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Impacts of Climate Change on Mortality: An extrapolation of temperature effects based on time series data in France

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Abstract

Most contemporary mortality models rely on extrapolating trends or past events. However, population dynamics will be significantly impacted by climate change, notably the influence of temperatures on mortality. In this paper, we introduce a novel approach to incorporate temperature effects on projected mortality using a multi-population mortality model. This method combines a stochastic mortality model with a climate epidemiology model, predicting mortality variations due to daily temperature fluctuations, be it excesses or insufficiencies. The significance of this approach lies in its ability to disrupt mortality projections by utilizing temperature forecasts from climate models and to assess the impact of this unaccounted risk factor in conventional mortality models. We illustrate this proposed mortality model using French data stratified by gender, focusing on past temperatures and mortality. Utilizing climate model predictions across various IPCC scenarios, we investigate gains and loss in life expectancy linked to temperatures and the additional mortality induced by extreme heatwaves, and quantify them by assessing this new risk factor in prediction intervals. Furthermore, we analyze the geographical differences across the Metropolitan France.

Keywords: Climate change, Temperature, Heatwave, Mortality forecasting, Multi-population mortality model

1 Introduction

The study of past trends since the 19th century has demonstrated unprecedented improvements in human mortality worldwide. In the fields of actuarial science and demography, the analysis of these trends has led to a multitude of models and approaches aimed at studying the dynamics of mortality, see Lee and Carter (1992), Brouhns et al. (2002), Barrieu et al. (2012), Plat (2009), and Dowd et al. (2020) among others. These dynamics are complex and arise from numerous factors that are more or less shared among different population groups, such as health factors, lifestyles, and the performance of health systems. These elements typically emerge through socioeconomic analyses that reveal mortality disparities within a region, see for example Bonnet et al. (2023) or Cairns et al. (2024) for recent results.

Climate change and the disruptions caused by humanity to the environment will have consequences on human health and mortality (Pörtner et al., 2022), especially in Europe (Weilhammer et al., 2021). The WHO (2014) identify five main causes contributing to increase mortality in response to climate change: undernutrition, malaria, diarrhoeal disease, dengue, and heat. These causes will affect

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populations differently in the future depending on their level of education, access to healthcare, and age. For example, undernutrition primarily affects children under 15 years old, while heat mainly impacts mortality of the elderly. Malaria and diarrhoeal diseases are prevalent in children under 5 years, especially in South Asia and Africa. Heatwaves are expected to affect the entire world, with more than 68,000 heat-related deaths in Europe by 2030 without adaptation measures (Ballester et al., 2023). In these regions, the main mortality concerns among those listed by the WHO (2014) are actually heatwaves (Pottier et al., 2021) and vector-borne diseases (Semenza and Suk, 2018; Paz, 2020) with potential impacts on longevity and life expectancy. Recently, a significant number of studies have highlighted the impact of temperature fluctuations resulting from climate change on mortality (Gasparrini et al., 2015; Gronlund et al., 2018; Guo et al., 2018; Vicedo-Cabrera et al., 2018; Lee et al., 2020; Martínez-Solanas et al., 2021). With human activity, the rise in temperatures has accelerated since the pre-industrial era, reaching an average global increase of 1.1°C compared to the pre-industrial period (1850-1900) (Pörtner et al., 2022). These changes vary in magnitude according to latitude. For example, French population experienced exceptionally warm temperatures in 2022 (Haut Conseil pour le Climat, 2023) with consequences in terms of excess mortality (Ballester et al., 2023). According to IPCC projections, the direct impacts of temperature on human health are expected to intensify regardless of future climate trajectories. This could lead to changes in premature mortality due to temperature and adjustments in mortality trends related to the intra-annual death distribution. Under these conditions, it becomes crucial to study and incorporate the effects of climate change, particularly temperature, into the stochastic mortality models used for population projections. This is also a significant issue for insurers' and pension funds' models, as well as for supervisory authorities seeking to assess the vulnerability of financial institutions to climate change (ACPR, 2024). Therefore, the primary aim of this paper is to account for the effect of temperature variations on future projected mortality rates within the framework of multi-population stochastic mortality models.

The proposed model comprises two components, estimated separately. The first component is a conventional stochastic mortality model calibrated on historical trends. The second component is constructed using a climate epidemiology model. This last model is calibrated using daily temperature and mortality data allowing for the attribution of a fraction of deaths to the effects of temperature. By coupling these two models, our approach produces a stochastic mortality model accounting for the trend induced by temperatures. Our two-step approach provides significant flexibility to the mortality model, enabling projections that incorporate various climate scenarios concerning temperature evolution. Additionally, it allows for the measurement of gains or losses in life expectancy due to climate change. More precisely, we use daily temperature projections at different geographical levels and quantify the local and specific impact of temperature on mortality over specific periods of the year, e.g. isolating extreme temperatures. Furthermore, our approach also incorporates the uncertainty associated with various climate models.

The approach implemented in our article falls within the framework of modeling exogenous shocks to mortality rate dynamics. Starting from single-population mortality models, a relatively sparse literature has explored the introduction of stochastic shocks. Most of these models have been introduced to incorporate the effects of economic shocks (French and O'Hare, 2014) or pandemic shocks (Liu and Li, 2015; Robben et al., 2022; Goes et al., 2023) into the dynamics of mortality rates. In an insurance context, this may have substantial impacts on the amount of capital requirement, see e.g. (Planchet and Gautier de La Plaine, 2024) among others. Recently, Robben and Antonio (2024) introduce a model with mortality shocks based on a regime-switching model. Their approach considers a multi-population mortality model and mortality jumps that can occur in a regime of high volatility. So far, few stochastic mortality models have focused on integrating temperature-induced shocks. Seklecka et al. (2017) extend the framework of the Lee and Carter (1992) model by adding a component related to temperature-related mortality. This model is applied to data from the United Kingdom. Li and Tang (2022) implement an approach based on extreme value theory on US monthly data to model the dependence between extreme temperatures, both hot and cold, and excess mortality. For these different approaches, the generated mortality shocks are estimated from outliers observed generally in annual mortality rates. These outliers are generated by catastrophic events, such as pandemics, wars or other major events. In contrast, temperatures are responsible for lower-intensity mortality

fluctuations that vary spatially, incorporate lagged effects, and are observed over specific periods of the year. Additionally, compensations between the effects of hot and cold temperatures can be observed over a calendar year. It is almost universally observed that the mortality response to hot and cold temperatures follows a U- or V-shaped curve depending on the population (Kunst et al., 1993; Guo et al., 2014). These effects are generally modeled using daily data through time-series regression models that capture exposure–response associations. The distributed lag non-linear generalized model (DLNM)(Gasparrini et al., 2010; Gasparrini, 2014) is a reference in this field and has been used in numerous studies, see among others Gasparrini et al. (2015), Gasparrini et al. (2017), and Vicedo-Cabrera et al. (2021). It estimates the number of deaths attributable to temperatures over specific periods, accounting for different lag effects depending on whether the temperatures are hot or cold. In a prospective approach, these temperature variations should be studied simultaneously, as the number of deaths induced by cold temperatures is expected to decrease while that induced by hot temperatures is expected to increase in Europe due to the climate change (Martínez-Solanas et al., 2021).

The numerical application developed in this paper focuses on the use of a mortality model for two populations using the augmented common factor approach introduced by Li and Lee (2005). Many multi-population mortality models have been developed in the literature in recent years. Most of these models are based on the framework proposed by Lee and Carter (1992) or the CDB models (Cairns et al., 2006), as reviewed by Villegas et al. (2017). These models typically assume coherence or semi-coherence (Li et al., 2017) among several sub-populations. In our paper, we impose a coherence assumption between women and men in France regarding mortality not affected by temperatures. Although the long-term convergence hypothesis is challenging to demonstrate for women and men, this modeling illustrates the possibility of coupling the DLNM climate epidemiology model with a standard multi-population mortality model. This issue is indeed essential given the importance of multi-population mortality models (Antonio et al., 2017) and the need to account for geographical factors when modeling temperature dynamics.

The contribution of our paper is fourfold. First, we develop a new specification of a multi-population mortality model that incorporates the effect of temperature variations on central mortality rates. These effects require a preliminary phase of estimating temperature-attributable deaths using a DLNM model. By subsequently modeling deaths unaffected by temperature through a multi-population model, our approach associates temperature-related and non-temperature-related deaths while preserving the Poisson assumption of the number of deaths. To the best of our knowledge, this is a novel approach in the literature enabling an easy coupling of most single-population or multi-population mortality models with temperature. We illustrate it using the Li and Lee (2005) model on French mortality data. Once calibrated, our modeling framework can project future mortality by incorporating various temperature-related effects. Second, the temperature effects are calibrated by gender and age groups, allowing us to integrate their specific sensitivities to temperatures into the projections. Third, our multi-population mortality model is associated to temperature projections from 12 climate models across three Representative Concentration Pathways (RCP) scenarios for the period 2020-2100. Then, we evaluate the loss or gain in life expectancy due to future temperature trends in these different climate scenarios in France, highlighting the specific impact of extreme heatwaves. Furthermore, this approach allows us to measure the impact of uncertainties caused by different climate models. Fourth, we examine the sensitivity of mortality projections to the local temperature dynamics of various French cities. This reveals divergences and a potentially new source of heterogeneity in mortality projections.

This paper is organized as follows. Section 2 presents a brief review of the literature on the relationship between mortality and temperature. Section 3 introduces the notations used and discusses the approach taken in this paper compared to existing models incorporating exogenous shocks. We then describe our multi-population mortality model excluding temperature effects. Finally, we explain how temperature-attributable deaths are modeled. Section 4 details the various estimation procedures adopted, starting with the DLNM model. We then explain how to calculate the temperature-attributable fractions annually, followed by the estimation of the mortality model. Section 5 describes

the calibration of time series models used to project mortality trends. In addition, we present the projection of the attributable fractions based on climate scenarios and the life expectancy loss due to temperatures. In Section 6, we estimate and project the series of central death rates with and without the effect of temperatures. We then quantify the gains and losses in life expectancy induced by temperatures up to 2100 in Metropolitan France under different RCP scenarios and for different locations. Finally, Section 7 concludes the paper.

2 Background on temperature-mortality effects

This section presents a brief overview of the influence of temperatures on human mortality. These changes can have diverse consequences, directly impacting the body's function during extreme cold or heat situations, or indirectly affecting our environment-leading to issues such as disease outbreaks, food shortages, and deteriorating living conditions. Our specific focus lies in examining the effects of temperature fluctuations on mortality rates. For a comprehensive summary of other consequences of climate change on mortality, including aspects like vector-borne diseases, under-nutrition, and related factors, we refer to the sixth assessment report of the IPCC (Pörtner et al., 2022, TS.C.6).

2.1 The effects of heat and cold on human body

Human beings are homeotherms, equipped with various protective mechanisms to maintain stable internal temperatures. Prolonged exposure to high external temperatures can elevate internal heat, while cold temperatures can lower it (Beker et al., 2018). During periods of high heat, the body experiences several effects, including increased sweating, elevated heart rate, lower blood pressure, confusion, heat exhaustion, dehydration, heatstroke, heat rash, fainting, and heat edema, among other symptoms (WHO, 2018). To counter high temperatures, the body employs external mechanisms such as sweating and internal mechanisms that involve the production of specific proteins to safeguard internal cells (Bouchama and Knochel, 2002). However, these mechanisms have limitations and become inadequate with prolonged exposure. This can lead to more severe conditions like hyperthermia, identifiable through symptoms like rapid pulse, headaches, nausea, and loss of consciousness (Bouchama and Knochel, 2002). Severe dehydration is another consequence, carrying significant cardiovascular and pulmonary risks, potentially resulting in a rapid increase in body temperature and a heightened risk of fatality (WHO, 2004). The impact of heatstroke and dehydration during heatwaves can persist for up to three days post-exposure (Alsaqali et al., 2022). The risks escalate when high temperatures endure. Heatwaves pose greater threats when protective measures for vulnerable populations are lacking. Elderly individuals, those with existing health conditions, pregnant women, and outdoor workers face higher vulnerability. Consequently, targeted protection plans are implemented for these groups.

As with hot temperatures, cold temperatures elicit various physiological responses in individuals, see Ryti et al. (2016) for a review. Upon exposure to cold, initial symptoms include reduced blood circulation in extremities, arrhythmia, breathing challenges, muscle discomfort, and restricted mobility. Prolonged exposure to cold can lead to increasing levels of hypothermia. As the body temperature drops, the heart rate decreases, and severe bradycardia can occur when the internal temperature falls below 32°C, potentially resulting in fatality (Beker et al., 2018). Cold weather directly impacts heart and pulmonary health, notably affecting cardiovascular diseases (CVD). Particularly, mortality factors associated with cold weather include coronary heart disease, stroke and respiratory disorders. These health risks are notably prevalent in socioeconomically disadvantaged groups and regions with milder winters (Mercer, 2003).

2.2 Seasonal variations in mortality

The climate and seasonal variations significantly influence human mortality. Episodes of excess mortality can be observed during periods of heat, cold, or substantial temperature fluctuations, with

characteristics varying by region. These differences in mortality patterns can be considerable across studied areas, yet the temperature-mortality relationship is generally assessed as having a U or V-shaped-relationship (Kunst et al., 1993; Guo et al., 2014). Both heat and cold increase mortality risk: cold effects can persist over several weeks, while heat impacts are immediate but shorter-lived.

Each region exhibits an optimal temperature, known as the Minimum Mortality Temperature (MMT), see Yin et al. (2019) for a current and projected overview across the planet. This temperature corresponds to the point at which the death rate is lowest, reflecting the population’s acclimatization to its surroundings. The MMT varies significantly across countries, influenced by latitude, climate type, and average annual temperature, ranging from 14.2 to 31.1°C (Tobías et al., 2021). The observed MMT depends on the timeframe, serving as a crucial indicator of population adaptation. For instance, in France, the MMT is reported to have increased from 17.5°C (1968-1981) to 18.2°C (1996-2009) (Todd and Valleron, 2015). Globally, for every 1°C rise in average annual temperatures, the MMT increased by 0.8°C (Tobías et al., 2021). Of course, socioeconomic factors also influence these thresholds (Krummenauer et al., 2019).

Sensitivity to ambient temperatures varies by age, sex, health status, and social category (WHO, 2011). For example, the elderly (over 65 years) and young children (0-5 years) in tropical areas are particularly vulnerable to temperature fluctuations (Egondi et al., 2012). Among the elderly, women have a higher risk of heat-related mortality during heatwaves (Marí-Dell’Olmo et al., 2019; Yu et al., 2010). Geographic regions differ in their exposure to temperature variations and their capacity to respond to climate change, reflecting population acclimatization. Urban density within the same geographical area amplifies the risk of heat-related mortality, positively correlated with population density, air quality (e.g., fine particle concentration), or social inequality (Sera et al., 2019).

In countries with temperate and continental climates, mortality follows a distinct seasonal pattern (Madaniyazi et al., 2022). Mortality rates are higher in cold seasons compared to warm seasons, a trend observed globally but with varying seasonal amplitudes between regions. Temperature substantially explains this pattern, as stated in the literature (Pörtner et al., 2022), although the relation between mortality and temperatures can involve complex physiological aspects or indirect environmental and social aspects.

In tropical regions, besides temperature, rainfall plays also a crucial role. During monsoon periods, diseases like malaria, diarrheal diseases, or vector-borne illnesses spread more rapidly, significantly affecting women (Egondi et al., 2012). These diseases, identified by the World Health Organization (WHO) as major concerns related to climate change, contribute significantly to mortality (WHO, 2014).

Additionally, the human body’s cooling mechanisms, primarily reliant on perspiration, can be compromised if ambient humidity levels are either too low or too high. From a physiological standpoint, scientific studies have highlighted the potential health hazards associated with extreme temperatures in highly humid environments (Davis et al., 2016). However, epidemiological evidence regarding the consequences of wet-hot events seems remain less conclusive (Armstrong et al., 2019), while Fang et al. (2023) indicating an increased risk of mortality in the presence of dry-hot events.

2.3 Temperature related deaths : past and expectation

Over the period 1998-2017, the WHO estimates the number of heatwave induced deaths at over 166,000 worldwide, including 70,000 deaths in Europe in the summer of 2003 alone (WHO, 2017). The number of people exposed to heatwaves is also expected to continue to rise. In Europe, it is 9.3 million and would reach almost 300 million in 2100 in a +3°C scenario (Naumann et al., 2020). The annual number of deaths linked to heatwaves is currently estimated at more than 61,000 in Europe during the summer in 2022 and would be more than 120,000 in 2050 (Ballester et al., 2023). However, it is important to note that its results strongly depend on the definition given for a heatwave, see Appendix A.1. In European countries and Japan, where the proportion of older people in the population is increasing, the damage from heat could be even more severe in the long term. Indeed, the average temperature

of the planet has already increased by $+1.1^\circ\text{C}$ (Pörtner et al., 2022, TS.C.6) since the pre-industrial era and is expected to continue to rise under any scenario. Thus, extreme weather events such as heatwaves are expected to become more frequent while at the same time the probability of cold waves is expected to decrease (IPCC, 2023). The seasonality of deaths observed today in temperate climates could strongly evolve. Climate change will reduce extreme cold spells and winter seasons period (IPCC, 2023). This would conduct to reduce the cold exposure and cold fatalities (Madaniyazi et al., 2021; Naumann et al., 2020) when most of the temperature related deaths was caused by cold period (Gasparrini et al., 2015). In some parts of Europe, heat-associated health effects may even outweigh the effects of cold (Gronlund et al., 2018; Martínez-Solanas et al., 2021).

So far, no real mitigation or change in the distribution of annual deaths has already been observed in temperate countries (Cheng et al., 2019), which might explain a lesser focus in demographic or actuarial literature.

3 A multi-population mortality model with temperature effects

In this section, we explain our approach to incorporating temperature change into our mortality model. After introducing the data and notations (Section 3.1), we describe existing mortality models with jumps in Section 3.2. Section 3.3 presents the proposed dynamics for central (virtual) mortality rates excluding temperature effects, followed by the Poisson formulation used to estimate the model parameters. Finally, Section 3.4 describes the DLNM model used to estimate temperature-attributable deaths.

3.1 Notation

In the following, some notations are introduced for modeling mortality. Let $\mu_{x,t}^{(g)}$, $E_{x,t}^{(g)}$, and $D_{x,t}^{(g)}$ represent, respectively, the force of mortality, observed exposure to risk, and observed number of deaths for gender $g \in \{\text{female, male}\} = \mathcal{G}$ within the age range $[x, x + 1)$ and the calendar year $[t, t + 1)$, where $x \in \mathcal{X} = \{x_{\min}, \dots, x_{\max}\}$ denotes the set of integer ages, and $t \in \mathcal{T}_y = \{y_{\min}, \dots, y_{\max}\}$ represents the set of calendar years considered as the calibrated period for mortality models. In this paper, two populations, women and men, are considered in Metropolitan France. However, our approach can be extended directly to other population groups, e.g. two or more countries. For clarity, bold notations are used for vectors and matrices.

Common stochastic mortality models such as the Lee-Carter model (Lee and Carter, 1992) rely on the crude central death rate of mortality $\hat{m}_{x,t}^{(g)} = D_{x,t}^{(g)} / E_{x,t}^{(g)}$. It is equivalent to the estimated force of mortality $\hat{\mu}_{x,t}^{(g)}$ assuming a piecewise constant force of mortality. Traditional mortality models may also use the mortality rate $\hat{q}_{x,t}^{(g)} \simeq 1 - \exp(-\hat{\mu}_{x,t}^{(g)})$ under the classical piecewise constant force of mortality assumption.

This paper considers two distinct time scales. First, the mortality model component relating to temperatures is fitted daily within the calibration period $\mathcal{T}_d = \{d_{\min}, \dots, d_{\max}\}$ across the range of integer ages \mathcal{X} . Specifically, to evaluate the impact of temperature, we gather daily records of the number of deaths over the calibration period. These specific details are sourced from the *Institut national de la statistique et des études économiques* (INSEE, 2020), and we denote the number of deaths in day d of year t for gender g as $D_{x,t,d}^{(g)}$.

Second, the model forecasting annual mortality is calibrated using yearly data observed within the calibration period \mathcal{T}_y as we as a adjusted exposure to risk related to temperature effects. For that, we use annual mortality data derived from the series of observed numbers of deaths and observed exposure to risk, both available from the HMD (2024). It's noteworthy that the data series for observed exposure to risk are solely accessible on an annual basis. Further details on these data sources is provided in Section 6.1.

In the following sections, our focus lies on the dynamics of the annual number of deaths, denoted as $D_{x,t}^{(g)}$. We assume that they can be decomposed into two components

$$D_{x,t}^{(g)} = \tilde{D}_{x,t}^{(g)} + \bar{D}_{x,t}^{(g)}, \quad (1)$$

where $\tilde{D}_{x,t}^{(g)}$ represents the virtual number of deaths at age x and for year t without considering temperature effects, while $\bar{D}_{x,t}^{(g)}$ corresponds to the number of deaths attributable to temperature variations in year t at age x for gender g .

Additionally by dividing by $E_{x,t}^{(g)}$, we denote $\tilde{m}_{x,t}^{(g)}$ and $\bar{m}_{x,t}^{(g)}$ as the components of the crude central death rate excluding and including temperature effects, respectively, such as

$$\hat{m}_{x,t}^{(g)} = \tilde{m}_{x,t}^{(g)} + \bar{m}_{x,t}^{(g)}.$$

This relationship reveals two causes of mortality, with the mortality central death rate $\bar{m}_{x,t}^{(g)}$ associated with the temperature component of mortality. It captures a portion of the observed seasonal variations in daily deaths. We can also express it in a multiplicative form

$$\hat{m}_{x,t}^{(g)} = \frac{\tilde{m}_{x,t}^{(g)}}{1 - \theta_{x,t}^{(g)}}, \quad (2)$$

where $\theta_{x,t}^{(g)}$ is the total attributable fraction related to temperatures in year t at age x for gender g

$$\theta_{x,t}^{(g)} = \frac{\bar{D}_{x,t}^{(g)}}{D_{x,t}^{(g)}}. \quad (3)$$

This fraction will be calculated later based on the estimation of deaths $\bar{D}_{x,t}^{(g)}$ attributable to temperatures.

3.2 Existing extrapolative mortality models with exogenous effects and shocks

The Lee and Carter (1992) model stands as the most famous model for extrapolating mortality rates, see Basellini et al. (2022) for a review. This model assumes that the logarithm of mortality rates follows a stochastic dynamic learned from past mortality trends. Using previously introduced notations and omitting gender for simplicity in this section, the central death rates are modeled as

$$\ln(\hat{m}_{x,t}) = \alpha_x + \beta_x \kappa_t + \epsilon_{x,t}, \quad (4)$$

where α_x and β_x represent age-specific effect parameters, κ_t captures time-temporal factors reflecting the mortality trend in the logarithm of mortality rates over a past period, and $\epsilon_{x,t} \sim \mathcal{N}(0, \sigma_\epsilon^2)$, $\sigma_\epsilon > 0$ denotes residual terms. To ensure model identifiability, the following constraints can, for instance, be imposed during model estimation

$$\sum_{t \in \mathcal{T}_y} \kappa_t = 0 \text{ and } \sum_{x \in \mathcal{X}} \beta_x = 1. \quad (5)$$

This model relies on a two-step estimation process: first estimating the parameters of the model (4), and then estimating a time series model to describe the dynamics of $\hat{\kappa}_t$. For the first step, Lee and Carter (1992) estimate the parameters α_x as the averages of log mortality central rates over the past period. Parameters β_x and κ_t can be calibrated using a singular value decomposition (SVD) method. Alternatively, Brouhns et al. (2002) assume that the number of deaths follows a Poisson distribution expressed as

$$D_{x,t} \sim \text{Pois}(E_{x,t} \exp(\alpha_x + \beta_x \kappa_t)). \quad (6)$$

The estimation can then be conducted via maximum likelihood. Another route to estimate the Lee-Carter model, as suggested by Haberman and Renshaw (2012), relies on the use of mortality improvement rates. This approach has recently garnered interest, as seen in for instance in Hunt and Villegas (2023), due to its better performance (Mitchell et al., 2013). The second step assumes a random walk with drift or an ARIMA model for the series of $\hat{\kappa}_t$ estimated in the first step.

Starting from this basic framework, several strategies have been devised in the literature to incorporate exogenous effects into mortality models. Indeed, it can be intriguing to showcase the specific effect that certain phenomena have had on past trends in order to disrupt projected trends.

First, one approach relies on econometric models using factor analysis. For instance, French and O’Hare (2014) describes the dynamics of the logarithm of death rates as

$$\hat{m}_{x,t} = \boldsymbol{\lambda}_x \mathbf{F}_t + \epsilon_{x,t}, \quad (7)$$

where $\boldsymbol{\lambda}_x$ represents a vector of loading parameters associated with latent factor vectors \mathbf{F}_t . This type of approach can integrate various latent factors that could be linked to economic or health indicators to explain mortality trends. Another line of literature focuses on the use of shocks or jumps in mortality rate dynamics. These models have been particularly explored for modeling catastrophes, wars, or epidemics effects on mortality, notably during the COVID-19 pandemic, see Robben et al. (2022) for a review. Among these approaches, Liu and Li (2015) considers adding jumps to the Lee-Carter model

$$\ln(\hat{m}_{x,t}) = \alpha_x + \beta_x \kappa_t + N_t J_{x,t} + \epsilon_{x,t}, \quad (8)$$

where N_t is a Bernoulli variable identifying the occurrence of a temporary jump, i.e. over one year, at date t , and $J_{x,t}$ represents the intensity of a mortality jump at this date for age x as a multivariate normal vector. This model is estimated by initially identifying outliers in mortality rate series to determine the occurrence and the severity of jumps.

Incorporating jumps whose effects gradually disappear over several years is part of model enhancement. Recently, Robben and Antonio (2024) develop a multi-population approach comprising a regime-switching model with a high-volatility state where Gaussian shocks on the mortality trend can occur. Their model involves maximum likelihood estimation on improvement rates in several steps and requires preprocessing of data labeled as outliers. Another recent example is provided by Goes et al. (2023) who use a Bayesian formulation and consider the impact of shocks that gradually diffuse over several years.

However, these approaches may encounter difficulties in being extended to model the effect of future temperatures on mortality. As described in section 2, temperature variations produce different responses to heat and cold, with effects lasting only a few days or weeks at most. The shocks caused are thus punctual and offset each other throughout the year, making it challenging to distinguish specific temperature outliers based solely on annual statistics. Additionally, heatwave-type shocks are acute and can be partly or totally compensate throughout the year due to harvest effects, i.e. the decrease in mortality observed after a peak of heat-related mortality. This effect has been observed notably in the French population (Pascal et al., 2018), but is not systematically found in all studies. Another important aspect to consider is the increasing impact of climate change, particularly the consequences of rising temperatures and extreme heat events. This trend tends to limit the relevance of models whose shocks are estimated based on previous annual observations.

Currently, very few mortality models incorporating a temperature-related effect have been developed despite the abundance of epidemiological literature on the effects of heat, cold, or heatwaves on mortality, as discussed in Section 2. However, it is worth mentioning the work of Seklecka et al. (2017), who expand the Lee-Carter model by integrating an additional temperature-related factor. Their approach describes the evolution of the logarithm of mortality rates following a logic similar to that proposed by Plat (2009)

$$\ln(\hat{m}_{x,t}) = b_x^1 + k_t^1 + (\bar{x} - x)k_t^2 + (\bar{x} - x)^+ k_t^3 + ((a - x)^+ + \text{ct}_x(x - a)^+)^2 k_t^4 + \gamma_{t-x} + \epsilon_{x,t}, \quad (9)$$

where b_x^1 represents the shape parameter at age x of log-mortality rates, k_t^1 , k_t^2 , and k_t^3 are temporal effects applied respectively across all ages, a temporal effect varying by age, and a specific temporal

effect for ages below the average age \bar{x} . The coefficient ct_x includes the effect of temperature fluctuations for elderly ages (ages over a). A specific temporal effect k_t^4 accounts for the temperature effect. Finally, γ_{t-x} appears as a cohort effect. In this approach, the parameter a is determined by experts, e.g. Seklecka et al. (2017) set $a = 50$ for the United Kingdom, and the coefficient ct_x is calculated as the Pearson's correlation coefficient between temperatures and mortality rates for age x .

3.3 The coherent Li-Lee model for the virtual central death rates

The aforementioned limitations lead us to consider a more flexible framework to isolate the effect of temperatures. Our approach involves introducing a baseline stochastic mortality model without temperature effects. As we see as in Section 4.2, its implementation requires processing daily data to estimate the effects of seasonal temperature fluctuations on annual mortality.

First, we focus on modeling the virtual death rates devoid of temperature effects. A wide range of mortality models is conceivable for a single population or multiple populations. However, these models primarily focus on overall mortality and do not differentiate temperature-related effects. Our approach assumes that long term mortality trends are consistently observed in annual central death rates without temperature effects. Among the different mortality models, we opt for the Li and Lee (2005) model, also known as the Augmented Common Factor (ACF) model. Here, the dynamics of mortality is defined for one country and two genders.

Several reasons motivate this choice. Primarily, a model employing a biological coherence principle is favored here for projecting populations by gender. This choice allows us to observe whether the addition of a temperature component at a later stage diverges the mortality between men and women. In the context of multi-population mortality models, other authors emphasize a shared coherence assumption across multiple countries, see Dowd et al. (2011), Kleinow (2015), Li and Lu (2017), and Bergeron-Boucher et al. (2017) among others. The selection of the ACF model is justified by its status as a benchmark model in multi-population projections, building upon the Lee-Carter model. It's indeed one of the most commonly used mortality models across the literature, as highlighted by Antonio et al. (2017) for mortality projections in the Netherlands and Belgium. It is suitable for modeling mortality at all ages, whereas models like CDBX type models (Dowd et al., 2020) are generally better suited for retired populations. In addition, it should be noted that the approach subsequently developed to integrate the effect of temperatures is not dictated by the choice of the mortality model; other specifications are indeed entirely possible.

Building upon the previously introduced notations, we introduce our multi-population mortality model based on the Li and Lee (2005) model for the crude central death rates $\tilde{m}_{x,t}^{(g)}$ excluding temperature effects

$$\ln \tilde{m}_{x,t}^{(g)} = A_x + B_x K_t + \alpha_x^{(g)} + \beta_x^{(g)} \kappa_t^{(g)}. \quad (10)$$

This model imposes a common unisex trend K_t in the logarithm of crude central death rates over time and considering specific dynamics by gender $\kappa_t^{(g)}$. The parameters A_x and $\alpha_x^{(g)}$ represent a level parameter at age x for mortality, while the parameters B_x and $\beta_x^{(g)}$ modulate the trend of the logarithm of mortality rates by age and gender, respectively.

The assumption of long-term coherence is ensured by the dynamics given to the series K_t and $\kappa_t^{(g)}$

$$K_t = \delta + K_{t-1} + e_t, \quad (11)$$

$$\kappa_t^{(g)} = c^{(g)} + \phi^{(g)} \kappa_{t-1}^{(g)} + r_t^{(g)}. \quad (12)$$

Here, we consider a first-order autoregressive (AR) model with drift for $\kappa_t^{(g)}$ with estimated coefficients $c^{(g)}$ and $\phi^{(g)}$, and a random walk with drift (RWD) for K_t with a drift parameter δ . As proposed by Antonio et al. (2017) and Antonio et al. (2020), the innovation errors $(e_t, r_t^{(f)}, r_t^{(m)})$ is assumed to be a vector of Gaussian white noises with a mean of zero and a variance-covariance matrix Σ . The

parameters $c^{(g)}$, $\phi^{(g)}$ and $\phi^{(g)}$ are specific to gender g , and are estimated as described in Section 4.3. This specification ensures that the mortality of women and men does not diverge in the long run.

For calibrating this model, we apply the classical identifiability constraints for ensuring parameter uniqueness and efficient computations

$$\sum_{t \in \mathcal{T}} K_t = 0 \text{ and } \sum_{x \in \mathcal{X}} B_x^2 = 1. \quad (13)$$

$$\sum_{t \in \mathcal{T}_y} \kappa_t^{(g)} = 0 \text{ and } \sum_{x \in \mathcal{X}} (\beta_x^{(g)})^2 = 1, \text{ for } g \in \mathcal{G}. \quad (14)$$

Finally, building on the specification from Brouhns et al. (2002), we assume that the number of virtual deaths at age x and in year t for gender g follows a Poisson distribution

$$\tilde{D}_{x,t}^{(g)} \sim \text{Pois} \left(E_{x,t}^{(g)} \exp \left(\tilde{m}_{x,t}^{(g)} \right) \right). \quad (15)$$

This model cannot be estimated directly because virtual deaths are not observed and depend on how we define the mortality-related temperature component. Therefore, we reformulate the distribution of observed deaths knowing the attributable fraction $\theta_{x,t}^{(g)}$ defined in Equation (3). By noting $T_{x,t}^{(g)} = \exp \left(\bar{m}_{x,t}^{(g)} \right) = 1 + \theta_{x,t}^{(g)}$, we deduce a Poisson formulation with log-link function for $D_{x,t}^{(g)}$ as

$$D_{x,t}^{(g)} \sim \text{Pois} \left(E_{x,t}^{(g)} T_{x,t}^{(g)} \exp \left(\tilde{m}_{x,t}^{(g)} \right) \right). \quad (16)$$

From Equation (16), the model is estimated as a Poisson generalized linear model through maximum likelihood estimation, as described in Section 4.3, using $\ln \left(E_{x,t}^{(g)} T_{x,t}^{(g)} \right)$ as an offset term when we compute the predicted number of deaths

$$\mathbb{E} \left[D_{x,t}^{(g)} \right] = \ln \left(E_{x,t}^{(g)} \right) + \ln \left(T_{x,t}^{(g)} \right) + \tilde{m}_{x,t}^{(g)}.$$

The term $T_{x,t}^{(g)}$ is then calculated by determining the mortality attributable to temperatures.

3.4 Modeling daily deaths with the distributed lag non-linear model

We now seek to model the influence of temperature on the daily number of deaths. The so-called distributed lag models (DLMs) (Almon, 1965) are commonly employed by econometricians and epidemiologists to address the impact of delayed environmental factors on a response variable. From the aggregated temperature-mortality time series data, two traditional models is explored to capture the nonlinear correlation between temperature (U- or V-shaped) and mortality. Muggeo (2008) introduced the constrained segmented distributed lag (CSDL) model. This model assesses the effects of heat and cold using a fixed threshold within a Poisson regression framework. Recently, Pincemin (2021) implement it to measure the effect of temperatures on projected life expectancy of the French population.

Gasparrini et al. (2010) proposed a more versatile approach known as distributed lag non-linear generalized model (DLNM). This model, based on a quasi-Poisson regression, is adept at capturing nonlinear effects and has found extensive use in the epidemiological literature related to mortality and temperature. Notably, it has been employed in studies such as Gronlund et al. (2018), Guo et al. (2018), Vicedo-Cabrera et al. (2018), Lee et al. (2020), and Vicedo-Cabrera et al. (2021), among others. This model is able to reproduce lagged impacts induced by temperatures persist even after several days have elapsed. When a heatwave occurs, the most vulnerable, particularly the elderly, are the first to be affected. This group experiences an immediate increase in mortality, followed by a period of reduced mortality. Conversely, the effects of cold temperatures usually manifest after a delay of several days. Thus, it's crucial to utilize a statistical model that can effectively account for both immediate and delayed effects on a daily basis.

The DLNM is designed to examine the impact of exposure variables, e.g. temperature or air pollution, on univariate time series data of outcome, e.g. number of deaths, considering delayed effects and nonlinear relationships. However, it isn't explicitly designed to incorporate both age and time dimensions simultaneously. Hence, to address this limitation, we adopt an approach proposed by Vicedo-Cabrera et al. (2019) and introduce age and gender effects by fitting a model for age buckets and gender. To achieve this, we partition the age range \mathcal{X} into $K \in \mathbb{N}^*$ distinct strata $X_k = [x_{k-1}, x_k), k \in \{1, \dots, K\}$. We aggregate the observed number of deaths for gender g within each stratum X_k and denote it as $D_{k,t,d}^{(g)}$ for $k \in \{1, \dots, K\}$ on day $d \in D^* = \{1, 2, \dots, 365, (366)\}$ of year t over the period \mathcal{T}_d .

Let $\lambda_{k,t,d}^{(g)} = \mathbb{E}[D_{k,t,d}^{(g)}]$ represent the expected number of deaths for day d , $\vartheta_{d,t}$ denote the daily mean temperature of day d for year t , \mathbf{z}_d be a vector comprising P explanatory variables such as year, day of the week, or month, and \mathbf{u}_d be a vector of additional confounding variables like pollutants. We assume that $D_{k,t,d}^{(g)}$ follows a Poisson distribution with overdispersion and a canonical log-link. Utilizing these notations, the DLMN is implemented within each sub-group $k \in \{1, \dots, K\}$ as follows

$$\ln(\lambda_{k,t,d}) = \eta_k + s(\vartheta_{d,t}, L; \boldsymbol{\theta}_k) + \mathbf{u}_d \boldsymbol{\gamma}_k^\top + \sum_{p=1}^P h_p(z_{d,p}; \boldsymbol{\zeta}_k), \quad (17)$$

where $s(\vartheta_{d,t}; l, \beta_k)$ denotes a cross-basis (non-linear) function that simultaneously specifies the association between $\vartheta_{d,t}$ and its lag structure over a maximum of L days. The functions $h_p(z_{d,p}; \boldsymbol{\zeta}_k)$ are natural cubic spline capturing the effect of explanatory variables to account for seasonal variations. Confounding variables \mathbf{u}_d are specified using linear effects. The terms η_k , $\boldsymbol{\theta}_k$, $\boldsymbol{\gamma}_k$ and $\boldsymbol{\zeta}_k$ represent the parameters to be estimated. It's important to note that this specification does not incorporate the exposure to risk as an offset factor within the usual Poisson regression model as in Brouhns et al. (2002).

4 Estimation procedure

In this section, we employ a four-step methodology to integrate temperature variations into our estimation procedure. The initial stage of our approach draws from the established methodological framework commonly employed in environmental epidemiology, as seen in studies such as Gasparrini et al. (2017) or Vicedo-Cabrera et al. (2019). This step relies on a statistical approach that enables the association between temperature fluctuations and mortality from daily time series data. The subsequent step involves quantifying the surplus mortality and deaths directly attributable to temperature variations for past periods. These deaths are then considering for calculating an attributable fraction that we use to recalibrate the baseline mortality model in the third step. Finally, a time series model is introduced.

4.1 Estimating the DLNM model

We estimate the model given by (17) using the methodology described by Gasparrini (2014). For that, we consider a bi-dimensional spline function s

$$s(\vartheta_{d,t}; L, \boldsymbol{\theta}_k) = \int_0^L f \cdot w(\vartheta_{d-l,t}, l; \boldsymbol{\theta}_k) dl \approx \sum_{l=0}^L f \cdot w(\vartheta_{d-l,t}, l; \boldsymbol{\theta}_k), \quad (18)$$

where $f \cdot w$ is a bi-dimensional integrable function, known as the exposure-lag-response function. For instance, this function can be a natural cubic B-splines or B-splines of various degrees. Equation (18) can be expressed as a tensor product using the concept of cross-basis function, as detailed in Gasparrini et al. (2010). Hence, function s represents a surface of relative risk (RR) indicating the increase or decrease in mortality in response to a rise or fall in temperature relative to a certain threshold.

The uncertainty linked to the estimation of parameters θ_k in the spline function s can be measured through its variance-covariance matrix $\mathbb{V}[\theta_k]$. Subsequently, this estimated uncertainty is incorporated into our projections using a parametric bootstrap technique based on the assumption of a multivariate normal distribution for the estimated coefficients θ_k (Vicedo-Cabrera et al., 2019).

In this paper, we refer to recent literature in environmental epidemiology to measure the temperature-mortality relationship and calibrate this model. For the sake of comparability, our choice for the lag L and the function s is done consistently with this literature, rather than searching for hyperparameters best suited to our data. Based on works such as Gasparrini et al. (2017), Lee et al. (2020), and Martínez-Solanas et al. (2021), the association between mortality and temperature is modeled using a natural cubic spline. Three internal knots are placed at the 10th, 75th, and 90th percentiles of the daily temperature distribution within the observational period. This choice of a cubic spline allows for easier extrapolation of results to extreme temperatures. We also use a natural cubic spline with an intercept and three internal knots placed at evenly spaced intervals on the log scale. A maximum of 21 days is considered to account for delayed effects of both cold and hot temperatures. Finally, we retain two explanatory variables in the model (17): $z_{d,1}$ representing time, fitted as a natural cubic spline h_1 with 8 degrees of freedom per year to accommodate seasonality and long-term trends, and $z_{d,2}$ indicating the day of the week as a categorical variable with a linear relationship for h_2 . The study does not consider any confounding variables \mathbf{u}_d .

4.2 Excess of mortality and attributable risk

Based on the previously estimated model using temperature and daily death series, we calculate the historical count of deaths attributed to temperatures for each day of the year $d \in \mathcal{T}_d$, and age $x \in X_k$, $k \in \{1, \dots, K\}$ using the formula

$$\bar{D}_{x,t,d}^{(g)} = (1 - \exp(-s(\vartheta_d; L, \hat{\theta}_k))) \times D_{x,t,d}^{(g)} \quad (19)$$

where $\hat{\theta}_k$ is estimated as described in Section 4.1. The model's setup allows for a range of predictions that precisely gauge the influence of heat, cold, or specific events occurring on each days of subset $D \subseteq D^*$. It's important to note that the temperature effect is shared across all ages within the stratum X_k .

To determine the total attributed deaths due to temperatures for a calendar year $t \in \mathcal{T}_y$, we sum of the contributions from each day of a subperiod $D \subseteq D^*$ for a year $t \in \mathcal{T}_y$

$$\bar{D}_{x,t}^{(g)} = \sum_{d \in D} \bar{D}_{x,t,d}^{(g)} \mathbb{1}_{\{d \in D\}}.$$

In practice, the period D considered could correspond to the entire year, certain targeted months, heatwaves, or days above or below a certain temperature threshold. We can also assess heatwave effects by considering only the four hottest months of the year or on specific heatwave dates. In this paper, we consider $D = D^*$, i.e. deaths attributable to both cold and hot temperatures. The total attributable fraction is then estimated for each age $x \in X_k$ and year $t \in \mathcal{T}_y$ as

$$\theta_{x,t}^{(g)} = \frac{\bar{D}_{x,t}^{(g)}}{D_{x,t}^{(g)}}. \quad (20)$$

4.3 Estimating the mortality model for virtual deaths

Now, let's delve into our estimation approach for the stochastic mortality model (10) under constraints (13) and (14) as introduced in Section 3.3. After estimating the attributable fraction (20) over D , we calibrate our model using sets of exposure to risk adjusted by temperature effects and death count data

$$\mathcal{E} = \left\{ E_{x,t}^{(g)} T_{x,t}^{(g)}, x \in \mathcal{X}, t \in \mathcal{T}_y, g \in \mathcal{G} \right\}$$

$$\mathcal{D} = \left\{ D_{x,t}^{(g)}, x \in \mathcal{X}, t \in \mathcal{T}_y, g \in \mathcal{G} \right\}.$$

The estimation of the chosen model involves maximizing the following expression derived from the Poisson log-likelihood

$$\max_{A_x, B_x, K_t, \alpha_x^{(g)}, \beta_x^{(g)}, \kappa_t^{(g)}} \sum_{x \in \mathcal{X}} \sum_{t \in \mathcal{T}_y} \sum_{g \in \{f, m\}} \left(D_{x,t}^{(g)} \ln(\tilde{m}_{x,t}^{(g)}) - E_{x,t}^{(g)} T_{x,t}^{(g)} \tilde{m}_{x,t}^{(g)} \right),$$

where $\tilde{m}_{x,t}^{(g)} = \exp\left(A_x + B_x K_t + \alpha_x^{(g)} + \beta_x^{(g)} \kappa_t^{(g)}\right)$. The parameter estimation in the model through maximum likelihood can be calculated following an iterative procedure described, for instance, in Li (2013) or Chen and Millosovich (2018). In practice, we employ a simpler alternative suggested by Brouhns et al. (2002) based on a the conditional maximum-likelihood approach, see e.g. Li (2013) or Robben et al. (2022). Hence, the parameters are determined in two steps. Firstly, we estimate under constraints (13)

$$\max_{A_x, B_x, K_t} \sum_{x \in \mathcal{X}} \sum_{t \in \mathcal{T}_y} \left(D_{x,t}^{\text{agg}} \ln(\tilde{m}_{x,t}^{\text{agg}}) - E_{x,t}^{\text{agg}} \tilde{m}_{x,t}^{\text{agg}} \right),$$

where $D_{x,t}^{\text{agg}} = D_{x,t}^{(f)} + D_{x,t}^{(m)}$, $E_{x,t}^{\text{agg}} = E_{x,t}^{(f)} T_{x,t}^{(f)} + E_{x,t}^{(m)} T_{x,t}^{(m)}$ and $\tilde{m}_{x,t}^{\text{agg}} = \exp(A_x + B_x K_t)$.

Once these parameters are estimated and using the predicted values of $\tilde{m}_{x,t}^{\text{agg}}$, we secondly estimate the gender-specific parameters again by maximizing a Poisson log-likelihood under the constraints (14)

$$\forall g \in \mathcal{G}, \max_{\alpha_x^{(g)}, \beta_x^{(g)}, \kappa_t^{(g)}} \sum_{x \in \mathcal{X}} \sum_{t \in \mathcal{T}_y} \left(D_{x,t}^{(g)} \ln(\tilde{m}_{x,t}^{(g)}) - E_{x,t}^{(g)} T_{x,t}^{(g)} \tilde{m}_{x,t}^{(g)} \right).$$

As presented in Section 6.3, the parameters estimated for the mortality model described above on temperature-reprocessed data are quite similar to those estimated on non-adjusted exposure to risk.

4.4 Estimating the time series model

The dynamics of our model comprise two components: temperature dynamics and a time series model for forecasting the vector $(K_t, \kappa_t^{(f)}, \kappa_t^{(m)})$. In this article, we assume that temperature dynamics are exogenous information, with projected temperature series provided by climate models presented in Section 6.1. Here, we focus on calibrating the time series model described in Equations (11) and (12), rewritten in matrix form for all $t \in \mathcal{T}_y$ as

$$\mathbf{Y}_t = \mathbf{D} + \mathbf{\Phi} \mathbf{Y}_{t-1} + \mathbf{E}_t, \quad (21)$$

where

$$\mathbf{Y}_t = \begin{pmatrix} K_t \\ \kappa_t^{(f)} \\ \kappa_t^{(m)} \end{pmatrix}, \mathbf{D} = \begin{pmatrix} \delta \\ c^{(f)} \\ c^{(m)} \end{pmatrix}, \mathbf{\Phi} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & \phi^{(f)} & 0 \\ 0 & 0 & \phi^{(m)} \end{pmatrix} \text{ and } \mathbf{E}_t = \begin{pmatrix} e_t \\ r_t^{(f)} \\ r_t^{(m)} \end{pmatrix}.$$

Drawing from Antonio et al. (2017), the parameters \mathbf{D} , $\mathbf{\Phi}$ and $\mathbf{\Sigma}$ are estimated through maximum likelihood since $\mathbf{E}_t \sim \mathcal{N}_3(0, \mathbf{\Sigma})$. This estimation can be performed using the R-package **Multi-MoMo** (Antonio et al., 2022) by maximizing the three-dimensionnal Gaussian log-likelihood related to $(\mathbf{Y}_t)_{t \in \mathcal{T}_y}$.

5 Mortality forecast with temperature effect

In this section, we now aim to incorporate the effects of projected mortality. Indeed, daily projections of temperatures from climate models encompass changes in the intensity in both cold and hot periods, as well as in the severity and duration of heatwaves.

We consider the projection period on annual basis $\mathcal{T}_y^{\text{for}} = \{y_{\text{max}} + 1, \dots, y_{\text{max}} + H\}$ where y_{max} is the last year of the calibration set \mathcal{T}_y and $H \in \mathbb{N}^*$ is the projection horizon.

5.1 Forecasting the virtual mortality without temperature effect

Firstly, we describe the approach adopted to simulate a sample of central death rate trajectories $\tilde{m}_{x,t}^{(g)}$ for $x \in \mathcal{X}$, $g \in \mathcal{G}$ et $t \in \mathcal{T}_y^{\text{for}}$. For this purpose, we use Equation (10) with the estimated parameters $\hat{A}_x, \hat{B}_x, \hat{K}_t, \hat{\alpha}_x^{(g)}, \hat{\beta}_x^{(g)}$ and $\hat{\kappa}_t^{(g)}$ obtained as described in Section 4.3.

The mortality model for virtual deaths also involves the projection of the vector \mathbf{Y}_t , derived from Equation (21) using the estimated parameters $\hat{D}, \hat{\Phi}$ et $\hat{\Sigma}$, see Section 4.4. The dynamics of \mathbf{Y}_t are iteratively deduced by simulating the innovation errors \mathbf{E}_t from a multivariate Gaussian vector with zero mean and covariance matrix $\hat{\Sigma}$. Thus, we can obtain a Monte Carlo sample of trajectories $\tilde{m}_{x,t}^{(g)}$, allowing us to derive prediction intervals for any date $t \in \mathcal{T}_y^{\text{for}}$.

5.2 Forecasting temperature-Related Central Death Rates

Secondly, we focus on adding shocks to mortality resulting from daily temperature variations. Based on the usual methodology in ecological epidemiology (Vicedo-Cabrera et al., 2019), the excess of deaths can be deduced by using scenarios of temperatures available on a daily basis, see Section 6.1. Thus, considering the daily temperature trajectory (ϑ_d) given by an external climate scenario, we deduce the daily number of deaths attributed to temperatures for age $x \in X_k$, $k \in \{1, \dots, K\}$, gender $g \in \mathcal{G}$ and for any day $d \in D^*$ of the year $t \in \mathcal{T}_y^{\text{for}}$ using Equation (19). We rewrite it simply as

$$\bar{D}_{x,t,d}^{(g)} = \tilde{D}_{x,t,d}^{(g)} \left(\exp \left(s(\vartheta_{d,t}; L, \hat{\theta}_k) \right) - 1 \right).$$

Thus, the cumulative number of deaths over a subperiod $D \subseteq D^*$ for a year $t \in \mathcal{T}_y^{\text{for}}$ is expressed as

$$\bar{D}_{x,t}^{(g)} = \sum_{d \in D} \bar{D}_{x,t,d}^{(g)} \mathbb{1}_{\{d \in D\}}.$$

It is worth noting that a period D different to D^* can be considered when forecasting central mortality rates. This allows us to specifically measure the projected effects of hot and cold temperatures on mortality, distinguishing the compensations that occur throughout the year.

By using Equation (1), we obtain the following expression for the projected central mortality rates with temperature effects measured over period D of year $t \in \mathcal{T}_y^{\text{for}}$

$$\begin{aligned} \hat{m}_{x,t}^{(g)} &= \tilde{m}_{x,t}^{(g)} + \bar{m}_{x,t}^{(g)} \\ &= \tilde{m}_{x,t}^{(g)} + \frac{\tilde{D}_{x,t}^{(g)}}{E_{x,t}} \sum_{d \in D} \frac{\bar{D}_{x,t,d}^{(g)}}{\tilde{D}_{x,t}^{(g)}} \mathbb{1}_{\{d \in D\}} \\ &= \tilde{m}_{x,t}^{(g)} \left[1 + \sum_{d \in D} \omega_{x,t,d}^{(g)} \left(\exp \left(s(\vartheta_{d,t}; L, \hat{\theta}_k) \right) - 1 \right) \mathbb{1}_{\{d \in D\}} \right]. \end{aligned} \quad (22)$$

In Equation (22), the term $\tilde{m}_{x,t}^{(g)}$ corresponds to the forecasted central mortality rate without temperature effects. These effects are then added multiplicatively. The term $w_{x,t,d}^{(g)} = \tilde{D}_{x,t,d}^{(g)} / \tilde{D}_{x,t}^{(g)}$ corresponds to the weight associated with the distribution of virtual deaths over the period D of year t . These weights are unknown for future periods, but can be fixed by introducing a distribution assumption of deaths throughout the year. As the seasonality in death counts is mainly captured by temperature effects, it is reasonable to consider an uniform distribution for $\tilde{D}_{x,t,d}^{(g)}$. Under this usual assumption in actuarial literature, the hazard rate function is constant over the year and the weight can be fixed as $w_{x,t,d} = 1/D^*$. Other assumptions about the distribution of deaths could be considered, e.g. the historical distribution of virtual deaths observed empirically over a past period.

Furthermore, we recognize in expression (22) the projected total attributable fraction to temperature related to period D , which we denote

$$\theta_{x,t}^{(g)}(D) = \sum_{d \in D} \omega_{x,t,d}^{(g)} \left(\exp \left(s(\vartheta_{d,t}; L, \hat{\theta}_k) \right) - 1 \right) \mathbb{1}_{\{d \in D\}}. \quad (23)$$

It is worth noting that this quantity is not necessarily positive. Indeed, the reduction in cold-related mortality in a context of overall temperature increase can lead to a decrease in mortality during certain periods.

Finally, using Equation (22), we easily obtain an expression for the total mortality rates with and without temperature effects

$$q_{x,t}^{(g)} = 1 - \exp\left(-\widehat{m}_{x,t}^{(g)}\right), \widetilde{q}_{x,t}^{(g)} = 1 - \exp\left(-\widetilde{m}_{x,t}^{(g)}\right),$$

for all $x \in X_k, g \in \mathcal{G}, t \in \mathcal{T}_y^{\text{for}}$. Additionally, the periodic life expectancy at age x truncated at age t_{\max} , is given by

$$e_{x,t}^{(g)} = \int_x^{t_{\max}} e^{-\int_x^t \mu_{x,u}^{(g)} du} dt \approx \sum_{k=1}^{t_{\max}} \prod_{j=0}^{k-1} \left(1 - q_{x,t}^{(g)}\right).$$

In the presence of two causes of mortality, we examine the number of years of life expectancy lost (or gained) due to temperatures for a person of age x at date t due to the temperature effect

$$\Delta e_{x,t}^{(g)} = \int_x^{t_{\max}} e^{-\int_x^t \widetilde{\mu}_{x,u}^{(g)} du} dt - \int_x^{t_{\max}} e^{-\int_x^t \mu_{x,u}^{(g)} du} dt \approx \sum_{k=1}^{t_{\max}} \left[\prod_{j=0}^{k-1} \left(1 - \widetilde{q}_{x,t}^{(g)}\right) - \prod_{j=0}^{k-1} \left(1 - q_{x,t}^{(g)}\right) \right], \quad (24)$$

with the force of mortality $\mu_{x,t}^{(g)} = \widetilde{\mu}_{x,t}^{(g)} + \bar{\mu}_{x,t}^{(g)}$.

6 Assessing the impact of future temperatures on French mortality projections

Numerical illustrations presented in this case study have been carried out in the R statistical software (R Core Team, 2023). We use the DLNM model from package **dlnm** (Gasparrini, 2011). This package proposes a set of functions allowing the construction of the crossbasis transformation presented in Section 4.1, as well as many basis plot commands. The mortality projection is performed by adapting the R code from the **MultiMoMo** package (Antonio et al., 2022).

6.1 Data sources

In this section, we provide an illustration of our model using French mortality data for both women and men, both on a daily and annual basis. Daily mortality data are compared to past data on average national temperatures. Additionally, to project the future effect of temperatures, we utilize temperature scenarios from various climate models.

The calibration period chosen for this study corresponds to the range $\mathcal{T}_y = \{1980, \dots, 2019\}$. This selection allows us to focus on relatively recent temperature event. This calibration period ensures adaptability conditions comparable to those experienced by populations at the beginning of the forecasting period. Additionally, we choose to use temperature and mortality data up to the end of the year 2019 to avoid any undesirable effects of the Covid-19 pandemic on the mortality results. We concentrate our analysis on the age group $\mathcal{X} = \{0, \dots, 105\}$ available in the HMD. Older age groups are excluded due to the lower volumes of available data, which could compromise the stability of the results.

6.1.1 Temperature dataset for past periods

The temperature records come from the GHCN database (Climate Data Record (CDR) program, 2018). This database gathers more than 20 different sources and contains the main climatological information that can be observed at the surface of the globe, station by station. It undergoes several testing phases and validation processes to ensure the accuracy of its data.

The oldest data in the GHCN database can be up to 175 years old, and in the case of temperatures this poses various problems. The weather stations, over the years, have evolved technically, migrated from one location to another or may have been recalibrated. This is why internal recalibration algorithms and processes have been applied to this database. Finally, from this database, it is possible to select different meteorological stations of the globe.

In this paper, we select 14 stations related to major French cities: Bordeaux, Brest, Caen, Clermont-Ferrand, Dijon, Lille, Lyon, Marseille, Nantes, Paris, Perpignan, Strasbourg, Toulouse and Tours, to cover the French territory and the main part of the population over the calibration period. For each of them, daily records give access to the average, minimum and maximum temperature of each city. These three indicators are then aggregated to obtain their average at the scale of Metropolitan France, allowing for a comparison with the daily death count serie collected at an aggregated level for metropolitan France. Figure 1 presents the distribution of average daily temperatures over the observation period. It illustrates the temperature variations throughout the year as well as the range of values taken for each month of the year. We describe in Appendix A a historical overview of recent heatwaves in France and the definition used for their counting.

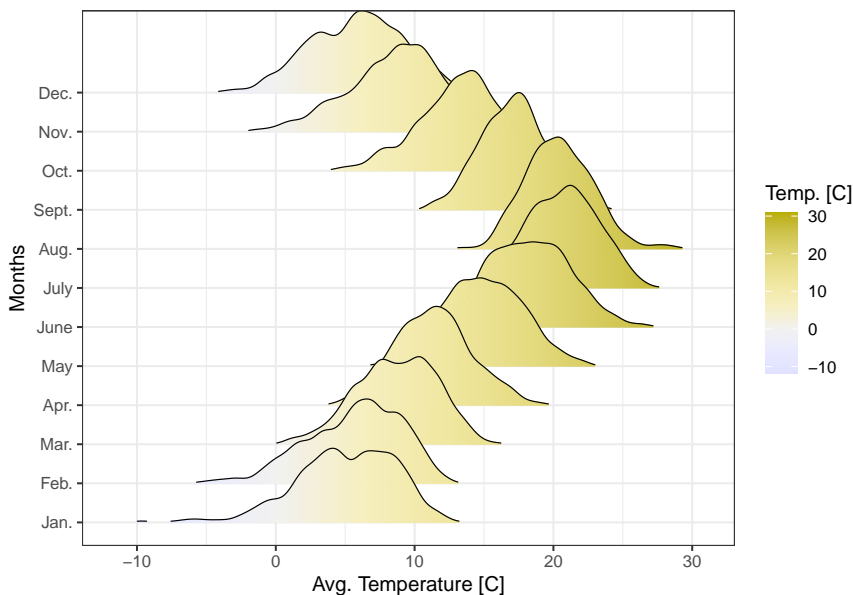


Figure 1: Distribution of average daily temperatures for each month of the year. The average daily temperatures are calculated city by city, and then an average of 14 cities is considered to derive average daily temperatures for Metropolitan France. Temperatures are expressed in degrees Celsius. Negative temperatures are represented in a blue color range, while positive temperatures are represented in a yellow color range. Calibration period 1980-2019, GHCN data.

6.1.2 Mortality datasets

Daily data. Our daily mortality data come from a specific inquiry made to the Quetelet-Prodego Diffusion network (INSEE, 2020), a French network of data centers for social sciences. This portal serves as a valuable resource for researchers and students. The data is acquired through a connection with the INSEE and is provided by the *Archives des Données Issues de la Statistique Publique* team.

Our request involves aggregating deaths from the civil registry. Various variables were accessible, including gender, age at death, socio-professional category, urban area, department, and region of death. The selected deaths are limited to metropolitan France, covering the years 1980 to 2019 and are provided on a daily basis. We select the age-period observation $\mathcal{X} = \{0, \dots, 105\}$ $\mathcal{T}_y = \{1980, \dots, 2019\}$ and the death counts at national level.

Figure 2 depicts the evolution of daily death counts over the period and compares them with the

daily average temperatures, for both women and men. This figure highlights the relationship between mortality and temperature by revealing a classical "U" shape: the daily death count tends to decrease with temperature until reaching a minimal level near 20°C. Beyond this average threshold over a day, mortality tends to increase with rising temperatures. The figure highlights a more pronounced association between heat and mortality for women.

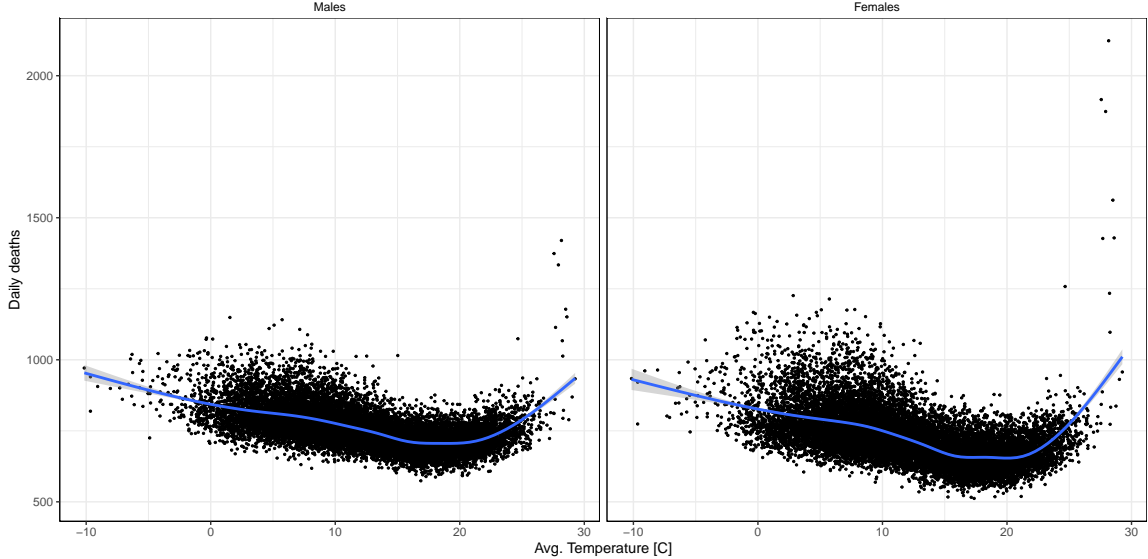


Figure 2: Representation of the daily death count according to the average daily temperature in France for women and men. The blue trend curve is obtained by smoothing using a generalized additive model with a confidence level of a 95%. The average daily temperatures are calculated city by city, and then an average of 14 cities is considered to derive average daily temperatures for Metropolitan France. Temperatures are expressed in degrees Celsius. Observation period: 1980-2019, based on GHCN data.

This relationship between mortality and temperature leads to observing seasonal cycles in the number of deaths. Figure 3 illustrates the distribution of deaths per month over the observation period for women et men. It highlights both the mortality associated with cold during the winter months, which can be marked by some extreme events, e.g., flu epidemics, and the peaks in mortality associated with heatwaves, notably an extreme event related to the summer heatwave of 2003. This figure underscores the greater variability in the number of deaths among women during the winter and in the height of summer.

Annual data. The annual mortality data considered are extracted from the Human Mortality Database (HMD, 2024). It enables the representation of the crude central death rate $\hat{m}_{x,t}^{(g)}$ for each age $x \in \mathcal{X}$, year $t \in \mathcal{T}_y$, and gender $g \in \mathcal{G}$.

6.1.3 Climate scenario dataset

In this paper, our daily future temperature projections are derived from twelve climate models for which we examine three climate change scenarios (Representative Concentration Pathway [RCP]2.6, RCP4.5, and RCP8.5) presented in the framework of the 5th IPCC Assessment Report (IPCC, 2014). These pathways depict the evolution of radiative forcing, which represents the difference between incoming solar radiation and outgoing infrared radiation. Radiative forcing is measured in $W.m^{-2}$.

The international CORDEX project aim to coordinate global research in terms of climate projections, its European branch EUROCORDEX made various simulations available in 2014. The outputs of these simulations have been improved and corrected in 2020 and are freely available through the DRIAS (2020) portal. The data available for Europe have a resolution of 7 to 10 km depending on the geographical areas, with different daily variables such as mean, minimum and maximum temper-

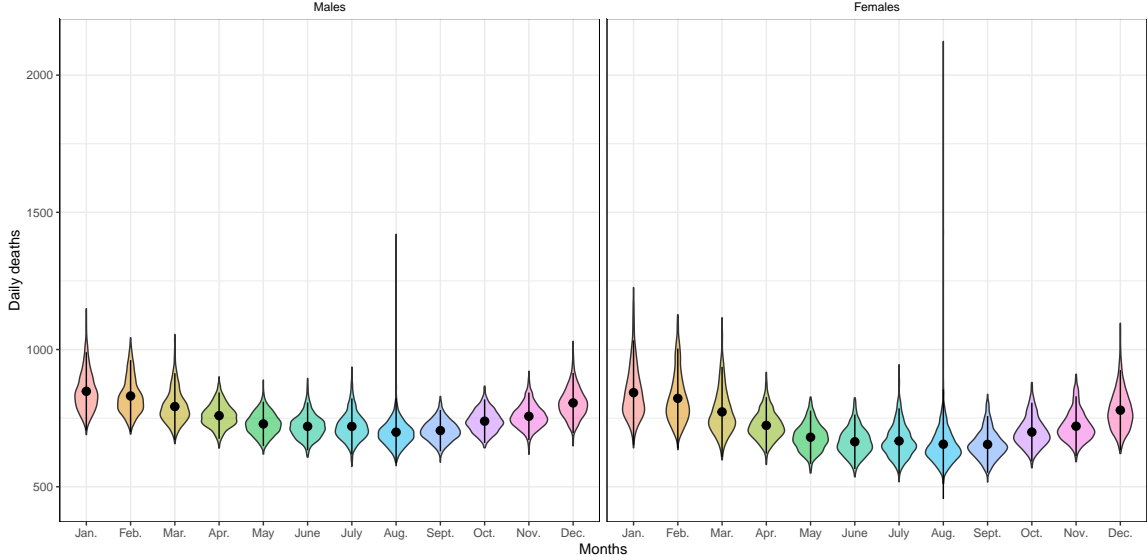


Figure 3: Probability density of the number of deaths by month of the year. The mean plus and minus the standard deviation is displayed as a pointrange. Daily average temperatures are calculated for each city, and then an average of 14 cities is used to derive the daily average temperatures for Metropolitan France. Temperatures are measured in degrees Celsius. Observation period: 1980-2019, based on GHCN data.

ature, total precipitation or wind speed. In our study, we extract temperature scenarios generated using global circulation models (GCMs) and regional circulation models (RCMs) described in Table 1. Temperature data is available in France on a daily time step over the period 2006-2100. It undergoes bias correction and statistical downscaling using the ADAMONT method (Verfaillie et al., 2017) to enable projections on an 8 km resolution grid (SAFRAN).

Table 1: List of climate models provided by the DRIAS

| Short Name | GCM | RCM | RCPs available | Period |
|----------------------|-----------|------------|------------------------|-----------|
| CNRM-CM5 / ALADIN63 | CNRM-CM5 | ALADIN63 | RCP8.5, RCP4.5, RCP2.6 | 2006-2100 |
| MPI-ESM / CCLM4-8-17 | MPI-ESM | CCLM4-8-17 | RCP8.5, RCP4.5, RCP2.6 | 2006-2100 |
| HadGEM2 / RegCM4-6 | HadGEM2 | RegCM4-6 | RCP8.5, RCP2.6 | 2006-2099 |
| EC-EARTH / RCA4 | EC-EARTH | RCA4 | RCP8.5, RCP4.5, RCP2.6 | 2006-2100 |
| IPSL-CM5A / WRF381P | IPSL-CM5A | WRF381P | RCP8.5, RCP4.5 | 2006-2100 |
| NorESM1 / REMO2015 | NorESM1 | REMO2015 | RCP8.5, RCP2.6 | 2006-2100 |
| MPI-ESM / REMO2009 | MPI-ESM | REMO2009 | RCP8.5, RCP4.5, RCP2.6 | 2006-2100 |
| HadGEM2 / CCLM4-8-17 | HadGEM2 | CCLM4-8-17 | RCP8.5, RCP4.5 | 2006-2099 |
| EC-EARTH / RACMO22E | EC-EARTH | RACMO22E | RCP8.5, RCP4.5, RCP2.6 | 2006-2100 |
| IPSL-CM5A / RCA4 | IPSL-CM5A | RCA4 | RCP8.5, RCP4.5 | 2006-2100 |
| CNRM-CM5 / RACMO22E | CNRM-CM5 | RACMO22E | RCP8.5, RCP4.5, RCP2.6 | 2006-2100 |
| NorESM1 / HIRHAM5 v3 | NorESM1 | HIRHAM5 v3 | RCP8.5, RCP4.5 | 2006-2100 |

To remain consistent with the observed mortality trends in 14 major cities described in Section 6.1.2, we extract daily averages, minimums, and maximums of temperatures for the points of the SAFRAN grid corresponding to these major cities. Subsequently, we calculate daily averages of these temperature indicators to reconstruct national averages. This simplification is adopted to have aggregated temperature trends enabling a connection with the selected stochastic mortality model at the scale of Metropolitan France. It is important to note that this simplification results in smoothing out certain regional temperature variations. It is conducted because we do not have access to historical daily death records by city or other areas.

Figure 4 depicts temperature trajectories from the three RCP2.6, RCP4.5, and RCP8.5 scenarios, as well as the distribution of indicators measuring the duration, cumulative severity, and intensity of

a heatwave for each decade, as defined in Appendix A.1. Figure 4.a illustrates a gradual increase in average annual temperatures, exacerbated for the RCP8.5 scenario from the 2040s-2050s. This overall temperature rise impacts not only the number but also the characteristics of heatwaves, which gain both in duration, severity, and intensity in the RCP4.5 and RCP8.5 scenarios. Specifically, we observe a similar trajectory of these characteristics for the 2020s and 2030s for all three scenarios, followed by an increase in the dangerousness of heatwaves starting from the 2040s in the RCP8.5 scenario. For these indicators (Figure 4.b to Figure 4.d), the increase in median values in the RCP4.5 and RCP8.5 scenarios is also accompanied by greater model volatility over time beyond the 2040s. The RCP2.6 scenario presents a relatively stable trajectory between 2020 and 2100. Additionally, we can observe a slight decrease in median values in the RCP2.6 scenario over the decades 2020 to 2040, with no clear trend thereafter. These observations are consistent with the findings on hot days presented by the IPCC (2022). Indeed, the regions identified as the most affected by this warming are central and eastern North America, central and southern Europe, and the Mediterranean region.

Regarding the RCP2.6 scenario, the HadGEM2/RegCM4-6 model predicts the most heatwaves, with 459 heatwaves recorded over the period 2020-2100. According to this model, the most severe heatwave occurs in 2047, lasting for 30 consecutive days with a cumulative severity of 209.4. In 2097, it predicts a heatwave with an intensity of 16.3. In scenario RCP4.5, the most pessimistic model in terms of heatwaves is the HadGEM2/CCLM4-8-17 model with a total of 1243 heatwaves. According to this model, the most severe heatwave occurs in 2062, lasting for 49 consecutive days with a cumulative severity of 572.0. In 2097, it predicts a heatwave with an intensity of 22.1. Finally, for scenario 8.5, this model is again the most pessimistic and predicts the most severe heatwave in 2088 (lasting for 89 consecutive days with a cumulative severity of 1099.5), as well as the most intense heatwave in 2094 with an intensity of 27.2. In comparison with these thresholds, the 2003 heatwave lasted 12 consecutive days, with a cumulative severity of 92 and an intensity of 9.2.

6.2 Estimation of temperature-mortality association with the DLNM

Using the approach outlined in Section 4.1, we calibrate model (18) over the period \mathcal{T}_y using daily temperature and death data with a lag of $L = 21$ days. In our study, we consider $K = 4$ age buckets to account for the differing sensitivities of women’s and men’s ages based on their specific MMTs: 0-64, 65-74, 75-84, and 85+. Sensitivity analysis regarding the parameter L is conducted in the appendix B.2, and does not challenge the obtained results for the body of the temperature distribution. However, we decide to observe responses over 21 days rather than 14 days in order to better capture long-term responses to heat and cold stress.

As explained in Section 4.1, we choose to adopt reference hyperparameters for the calibration of our DLNM models, as they provide a satisfactory fit to the data and facilitate comparisons with the literature. Alternatively, the search for the most accurate hyperparameters given to the data could be easily conducted by examining the Log-likelihood, the Bayes information criterion (BIC), and the Akaike information criterion (AIC). The goodness of fit of our DLNM models is assessed by comparing the distributions of observations and predictions, as well as the residuals of the Deviance, see Appendix B.1.

Figure 5 depicts the cumulative temperature-mortality association estimated with the DLNM model for both women and men, and for each age group, along with the corresponding 95% confidence intervals (CIs). These curves reveal a non-linear relationship between temperature and the Relative Risk (RR) of mortality over a 21-day period. The shapes of the curves are typical, showing sensitivity to both extreme cold and heat variations, above and below an optimal temperature range, i.e. the MMT, typically between 17 and 21°C, with little variation by gender. We observe that this sensitivity increases notably with age and exhibits differences between genders. For individuals over 85 years old, the responses to temperature variations are generally similar between women and men for both extreme cold and heat temperatures. For ages between 65 and 84 years, the RR for cold temperatures at the 1% percentile of the coldest temperatures exceeds the response to heat at the 1% percentile of the hottest temperatures. However, this risk significantly increases during the most extreme heatwaves.

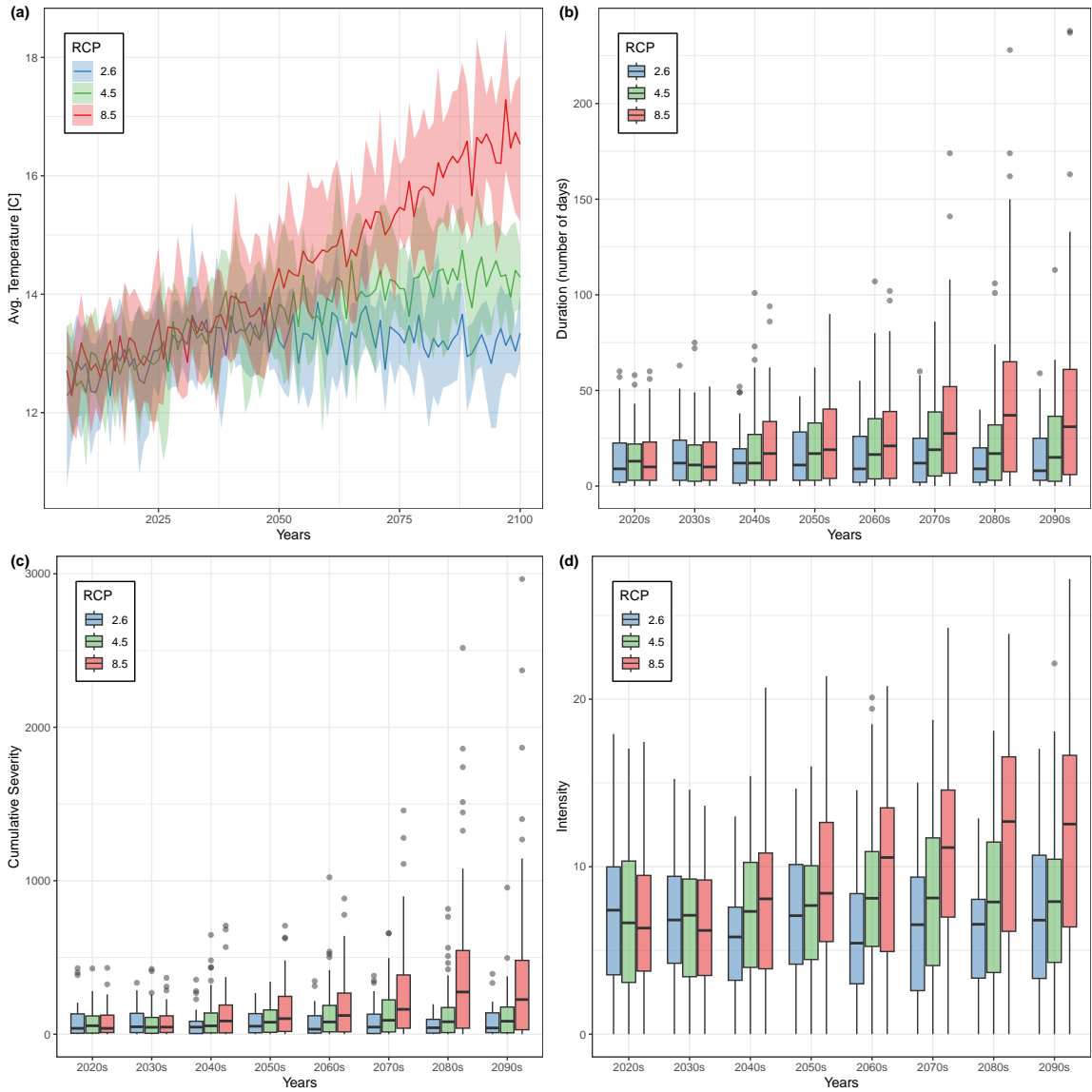


Figure 4: Projection of temperatures and heatwaves by RCP scenario in Metropolitan France over the period 2020-2100. (a) Annual average of daily temperatures by RCP scenario. Each curve is calculated as the average across available climate models. The shaded area corresponds to the 95% confidence intervals across all available climate models. (b) Distribution of heatwave duration per decade and per RCP scenario. (c) Distribution of cumulative heatwave severity per decade and per RCP scenario. (d) Distribution of heatwave intensity per decade and per RCP scenario. For each RCP scenario and each decade, the boxplots represent the distribution of duration, cumulative severity, and intensity calculated over the sample consisting of all years of the decade and across all available climate models. Daily average temperatures are calculated for each city, and then an average of 14 cities is used to derive the daily average temperatures for Metropolitan France. Temperatures are measured in degrees Celsius. Based on DRIAS data.

We also note a greater sensitivity of women to high temperatures and, conversely, a higher sensitivity of men to the coldest temperatures in these age groups. Regarding the age group 0-64 years, the curve for response to extreme heat is steeper for men.

Over the period from 1980 to 2019, we finally represent in Figure 6 the temperature attributable fraction for both women and men, defined in Equation (3), and aggregated over all ages to facilitate visualization. This fraction globally oscillates between 6% and 9% over the considered period, except for women where a peak appears for the 2003 extreme heatwave (Charpentier, 2011). This fraction is decomposed into different temperature effects, depending on the observed daily average temperatures.

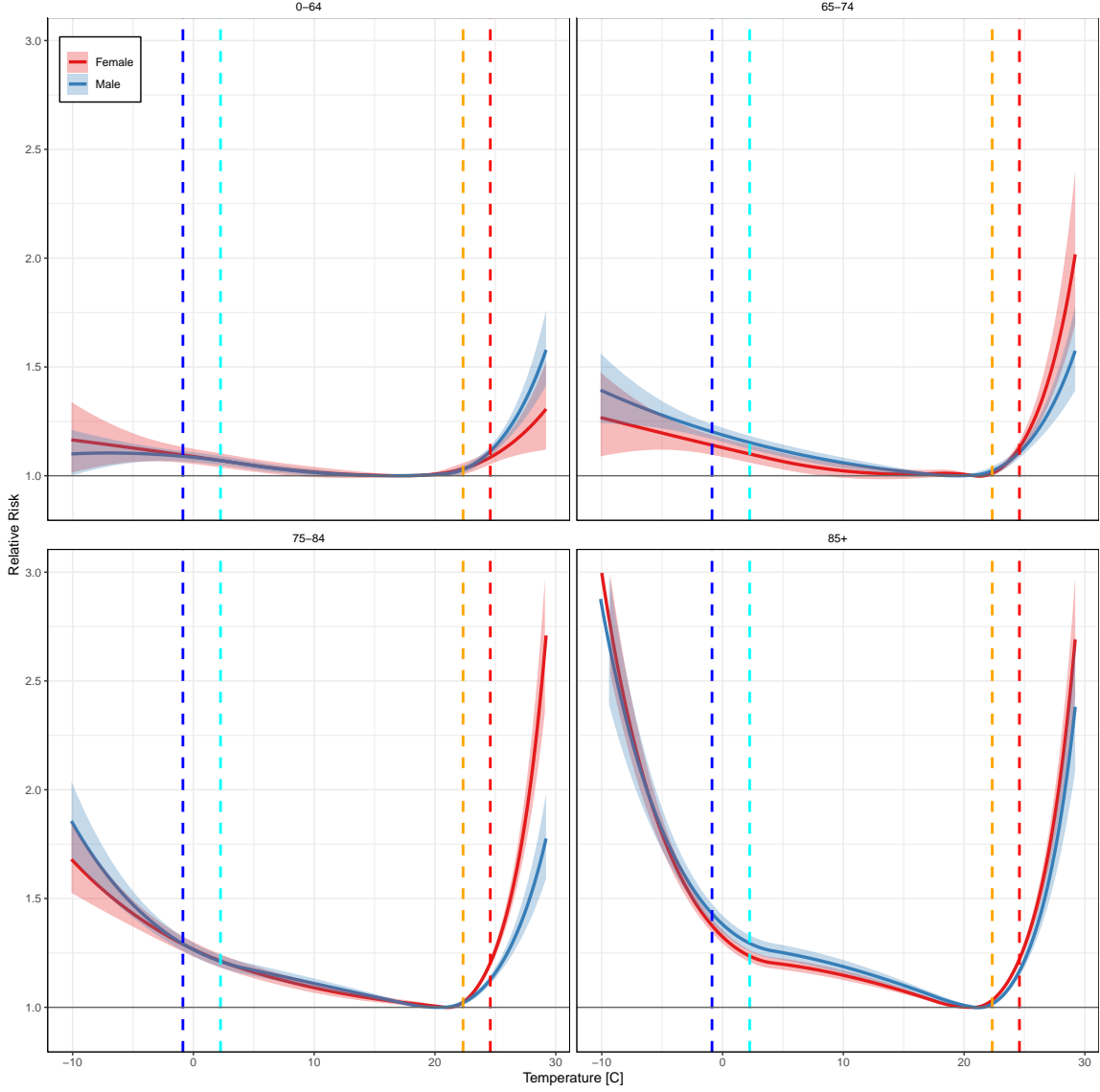


Figure 5: Cumulative relative risk of mortality over a 21-day period in Metropolitan France calculated for the years 1980-2019 for women (red) and men (blue) across age groups 0-64, 65-74, 75-84, and 85+, with their 95% confidence intervals (shaded areas). The dashed vertical lines represent the quantiles of daily mean temperatures at 1% (blue), 5% (cyan), 95% (orange), and 99% (red) calculated over the period 1980-2019. Daily average temperatures are calculated for each city, and then an average of 14 cities is used to derive the daily average temperatures for Metropolitan France. Temperatures are measured in degrees Celsius. Based on GHCN data.

Hot or cold temperature days corresponds to days D with average temperature above or below the MMT. Thus, similarly to Martínez-Solanas et al. (2021), we define moderate cold days (respectively moderate hot days) as cold days where the average temperature is below the 2.5% quantile (respectively above the 97.5% quantile)¹ of observed average temperatures over the period. Extreme cold (respectively extreme hot) days are those where the average temperature is below the 2.5% quantile (respectively above the 97.5% quantile). The most significant contribution to the attributable fraction for both women and men comes from moderate cold, while the effects of moderate hot temperatures are generally constant and very low. Extreme cold and hot events produce peaks in excess mortality in certain years, such as in 1985 and 2010 for cold effect, or in 2003 for the heatwave effect. We observe from around 2015 what appears to be the beginning of an upward trend in the extreme hot effect for

¹Over the observation period, the 2.5% quantile of the average temperature serie is 0.86°C and the 97.5% quantile is 23.44°C.

both women and men.

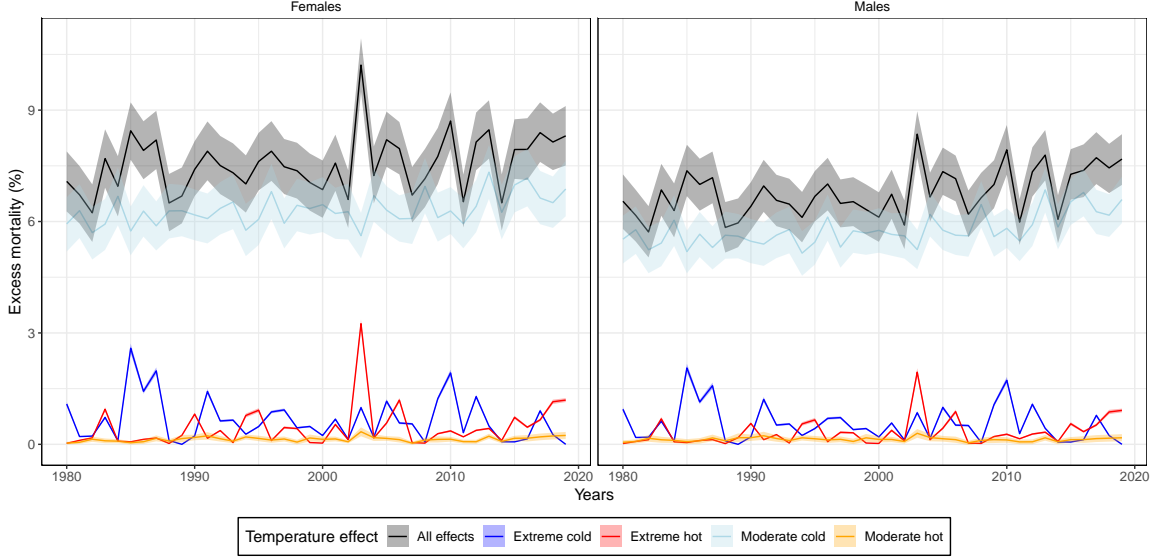


Figure 6: Temperature attributable fraction in Metropolitan France, calculated for the years 1980-2019 for both women and men across all age groups. These values, along with their 95% confidence intervals (shaded areas) are calculated through 1,000 Monte Carlo simulations of the DLNM coefficients. Each line corresponds to the average of these simulations. Attributable fraction is expressed in % for all effect, decomposed into moderate cold, moderate hot, extreme cold and extreme hot.

6.3 Calibrating and projecting the Li-Lee model

In this section, we present the estimates obtained for the Li-Lee model described in Section 4.3, in order to project the predicted values of the virtual central death rate $\tilde{m}_{x,t}^{(g)}$. To assess the impact of adjusting exposure to risk, we present both the results of the models (15) and (16). In both cases, our estimates of the Li-Lee model are obtained based on annual mortality data over the period \mathcal{T}_y .

Figure 7 illustrates the dynamics of the parameters of model (10). It first appears the close proximity between the estimated parameters with and without reprocessing exposures to temperature-attributable deaths. In particular, the temporal trend \hat{K}_t is not disrupted by this reprocessing. Although the impact is moderate, the most affected trend is visually that related to $\hat{\kappa}^{(m)}$.

Figure 8 examines the goodness of fit of the estimated Li-Lee model for model (16) by presenting the Pearson residuals of the fitted Poisson model. Although we have chosen a relatively simple mortality model, it adequately captures age and period effects for both female and male populations. We observe that some cohort effects are less well taken into account, especially for the male population. This limitation could potentially be addressed by using a model with a cohort component. However, including this effect generally introduces numerous other issues, such as less robustness than an Lee-Carter model and difficulties in projecting model parameters. Additionally, cohort effect modeling should be justified by arguments supporting the existence of real cohort effects in the data (Hunt and Blake, 2021). This situation is not straightforward concerning French data. For example, Boumezoued et al. (2020) shows a significant reduction in isolated cohort effects on the French population by incorporating information on monthly birth counts. Another reason is the diagonal trends in the female population appear relatively diffuse and limited. Since the issue of cohort effects is beyond the scope of this paper, we choose to retain a model capturing only age and period effects. It is also worth noting that our chosen specification for handling temperature-attributable deaths could easily be adapted to another stochastic mortality model.

The joint dynamics of the parameters $(\hat{K}_t, \hat{\kappa}_t^{(f)}, \hat{\kappa}_t^{(m)})$ are determined using the time series model described in Section 4.4, employing respectively a RWD process and two AR(1) processes. The

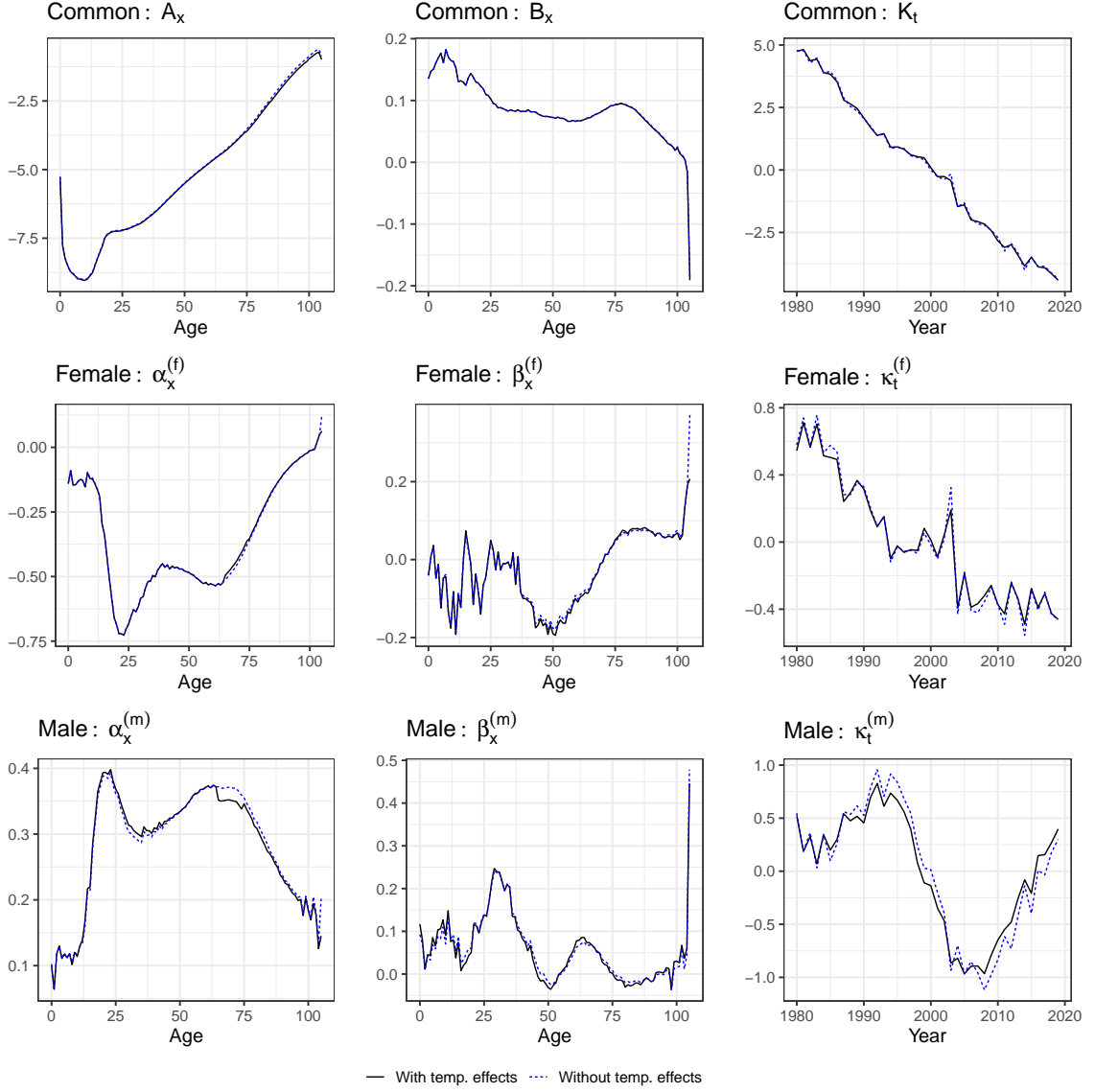


Figure 7: Estimated parameters $(\hat{A}_x, \hat{B}_x, \hat{K}_t, \hat{\alpha}_x^{(f)}, \hat{\beta}_x^{(f)}, \hat{\kappa}_t^{(f)}, \hat{\alpha}_x^{(m)}, \hat{\beta}_x^{(m)}, \hat{\kappa}_t^{(m)})$ of the Li-Lee model for the calibration period 1980-2019 and ages between 0-105 for the entire population of Metropolitan France (Common), females (Female), and males (Male). We distinguish between estimated parameters based on all observed deaths $D_{x,t}^{(g)}$ represented by black solid lines and virtual deaths $\tilde{D}_{x,t}^{(g)}$ reprocessed to account for temperature-attributable deaths in blue dashed lines.

estimated parameters from this model are presented in Table 2, both for the calibration performed on the observed data and for the data virtually reprocessed to exclude temperature-attributed deaths. Table 3 describes the correlation matrix of the residuals for these two sets of parameters.

To ensure compliance with the consistency constraint specified by the Lee-Li model, the dynamics of the processes $\hat{\kappa}_t^{(f)}$ and $\hat{\kappa}_t^{(m)}$ must remain stationary, i.e. the absolute value of $\phi^{(g)}$, $g \in \{f, m\}$, must be strictly lower than 1. This constraint is met during the maximum likelihood estimation of the model (21) regarding $\kappa_t^{(m)}$ and $\kappa_t^{(f)}$ for observed deaths. However, it is observed that the values of the coefficients $\phi^{(m)}$ and $\phi^{(f)}$ are very close to 1. Regarding $\phi^{(f)}$ when adjusting exposure to risk to the temperature effect $T_{x,t}^{(g)}$, the parameter values are slightly above 1. This undesirable situation would thus lead to projecting mortality rates for women diverging from the common trend K_t in the long term. To overcome this issue, Antonio et al. (2020) proposes reducing the calibration period of the model or increasing the lag of the autoregressive processes. Other strategies could be proposed, such as using a mortality model based on mortality increments (Hunt and Villegas, 2023) or employing a

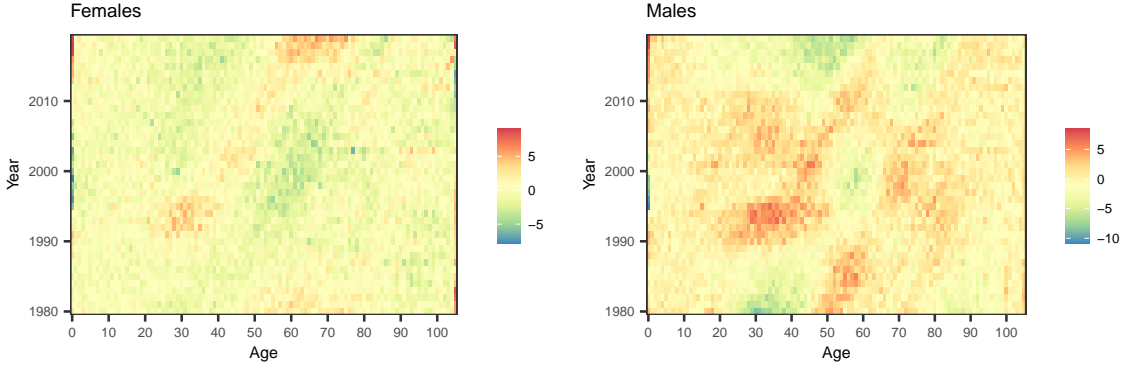


Figure 8: Pearson residuals of the Li-Lee model for the calibration period 1980-2019 and ages between 0-105 for the female and male populations of Metropolitan France. The model is fitted on observed deaths and temperature-adjusted risk exposures.

data-driven model, as seen in Guibert et al. (2019). However, this topic is beyond the scope of this paper, and we choose to address it more simply by constraining the coefficient $\phi^{(g)}$ to be strictly less than 1 during maximum likelihood maximization.

Table 2: Calibrated parameters in the Li-Lee model with observed deaths with and without temperature effects on the period 1980-2019 and age range 0-105.

| Calibration data | δ | $c^{(m)}$ | $\phi^{(m)}$ | $c^{(f)}$ | $\phi^{(f)}$ |
|-----------------------|----------|-----------|--------------|-----------|--------------|
| Without temp. effects | -0.234 | -0.0066 | 0.9692 | -0.0266 | 0.9963 |
| With temp. effects | -0.235 | -0.0034 | 0.9705 | -0.0258 | 0.9999 |

Table 3: Correlation matrix of residuals in the Li-Lee model observed deaths with and without temperature effects on the period 1980-2019 and age range 0-105.

| | Without temp. effects | | | With temp. effects | | |
|-------------|-----------------------|-------------|-------------|--------------------|-------------|-------------|
| | e_t | $r_t^{(m)}$ | $r_t^{(f)}$ | e_t | $r_t^{(m)}$ | $r_t^{(f)}$ |
| e_t | 1.0000 | -0.7393 | 0.9449 | 1.0000 | -0.5745 | 0.9342 |
| $r_t^{(m)}$ | -0.7393 | 1.0000 | -0.7152 | -0.5745 | 1.0000 | -0.5537 |
| $r_t^{(f)}$ | 0.9449 | -0.7152 | 1.0000 | 0.9342 | -0.5537 | 1.0000 |

Figure 9 finally presents the projection of parameters \hat{K}_t , $\hat{\kappa}_t^{(f)}$, and $\hat{\kappa}_t^{(m)}$ over the period 2020-2100, along with the 95% prediction intervals obtained by 1,000 Monte-Carlo simulation of innovation errors. These projections are shown for both models with and without temperature effects. More precisely, the trends without temperature effects correspond to the dynamic of virtual deaths. We first observe that the common trend K_t is virtually identical in terms of median for both parameter estimations. However, as expected, the projected uncertainty for the model built on observed mortality data without temperature corrections is wider than the trend for virtual central death rates. This is explained by adjustments in exposure to risk related to mortality peaks induced by temperature variations. Regarding the parameters $\hat{\kappa}_t^{(f)}$ and $\hat{\kappa}_t^{(m)}$, we notice the similarity between the forecasted series, and the same phenomenon in terms of uncertainty.

6.4 Simulating temperatures effects

We now focus on the simulation of attributable fractions to temperatures $\theta_{x,t}^{(g)}(D)$, as defined in equation (23). These attributable fractions depend on a period D that allows for distinguishing the effects of heat and cold over the year. These quantities are also calculated for each age group, gender and calendar year. To simplify notation, we do not include the index corresponding to the Monte-Carlo

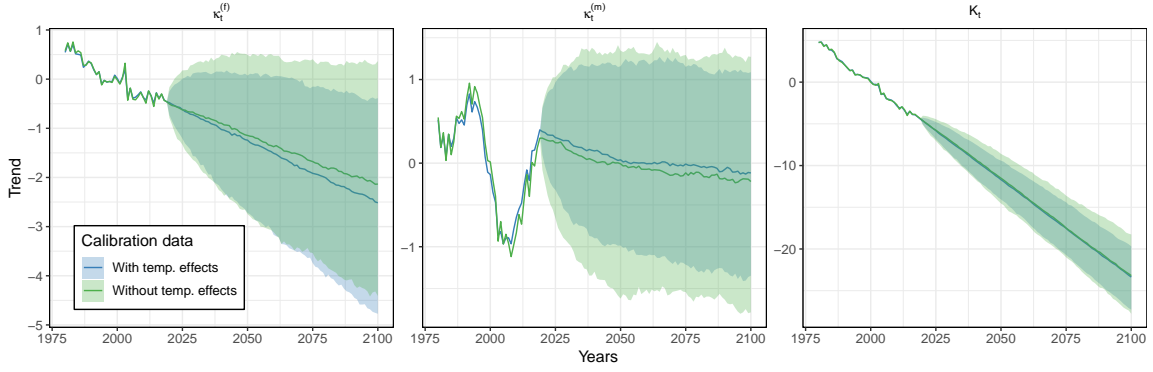


Figure 9: Projection of trend parameters \hat{K}_t , $\hat{\kappa}_t^{(f)}$, and $\hat{\kappa}_t^{(m)}$ over the period 2020-2100 for the Li-Lee model for observed central death rates (with temperature effects) and central virtual death rates (without temperature effects) for the calibration period 1980-2019 and ages between 0-105 for the entire population of Metropolitan France. The solid lines represent from 2020 the median of the projections. The 95% prediction intervals are constructed based on 1,000 Monte-Carlo simulations.

simulation numbers.

To facilitate visual analysis, we calculate an aggregated attributable fraction to temperatures using the distribution of deaths known at the end of 2019, as follows

$$\theta_t(D) = \sum_{g \in \mathcal{G}} \sum_{x \in \mathcal{X}} \theta_{x,t}^{(g)}(D) \frac{D_{x,2019}^{(g)}}{D_{2019}},$$

where $D_{2019} = \sum_{g \in \mathcal{G}} \sum_{x \in \mathcal{X}} D_{x,2019}^{(g)}$. The details of the attributable fractions to temperatures $\theta_{x,t}^{(g)}(D)$ per age bucket and gender are provided in Appendix C.1.

Figure 10 breaks down the evolution of attributable fractions related to hot and cold temperatures according to the RCP scenarios for the period 2020-2100 and all population. The presented 95% confidence intervals combine, for each RCP scenario, the estimation error associated with the coefficients θ_k , measured by 1,000 bootstrap replications, and the uncertainty related to different climate models listed in 1. Similar to Figure 6, we examine the evolution of components associated with moderate cold and hot days and extreme cold and hot days. Firstly, we observe a relatively stable overall effect of mean temperatures until the end of the century in the RCP2.6 scenario and a slightly decreasing effect in the RCP4.5 scenario for women and men. The RCP4.5 scenario is also characterized by a decrease in the effect of moderate cold and a progressive increase in the effect of extreme heat. It is noteworthy that there is an increase in the uncertainty of the effect of extreme heat over time.

The RCP8.5 scenario exhibits a different behavior. Specifically, it shows a more pronounced decrease over time than the RCP4.5 scenario in the effect of moderate cold temperatures, which is the main component of temperature-attributable mortality for both women and men. Concurrently, a marked increase in the effect of extreme heat is observed starting from the 2050s. However, as highlighted in Appendix C.1, this increase is not sufficient to reverse the overall declining trend in the effect of temperatures over the century for the males. For the female population, we observe a resurgence in the effect of temperatures towards the end of the century, as well as greater uncertainty in temperature-attributable mortality.

It is also noteworthy that the effects of temperatures vary according to geographical locations (Martínez-Solanas et al., 2021). To illustrate this pronounced effect between the north and south of France, we simulate the trajectory of attributable fractions for different French cities across the country, namely Brest, Marseille, Paris, Perpignan, and Strasbourg, using data from DRIAS. Detailed results are presented in Appendix C.2. For this purpose, we employ the DLNM model estimated on the daily mortality data of Metropolitan France as presented in Section 6.2. This is an approximation that could be improved by having access to time-series of death counts per city. Indeed, each of the

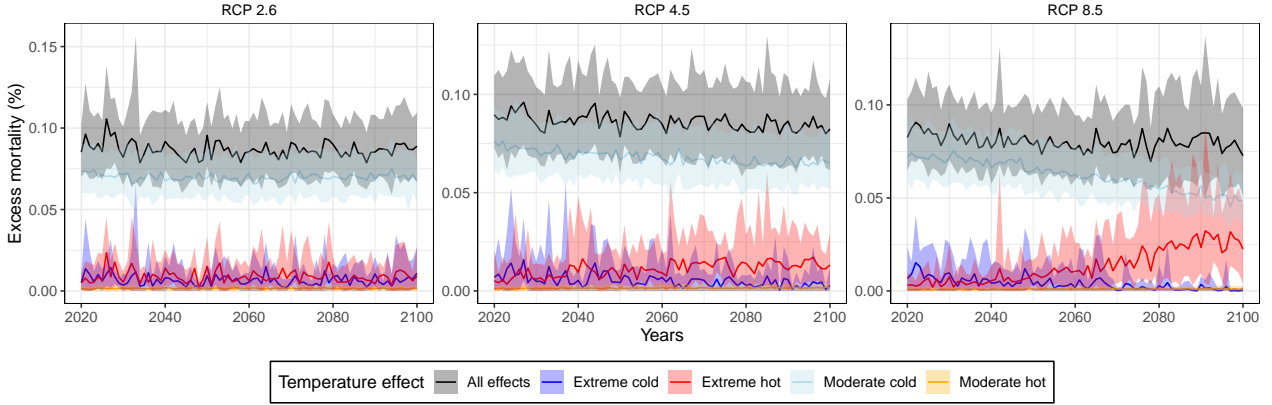


Figure 10: Temperature attributable fraction in Metropolitan France, simulated for the years 2020-2100 for both women and men across. These values, along with their 95% confidence intervals (shaded areas) are calculated through 1,000 Monte Carlo simulations of the DLNM coefficients and the ensemble of climate models. Each line corresponds to the average of these simulations. Attributable fraction is expressed in % for all effect, decomposed into moderate cold, moderate hot, extreme cold and extreme hot.

sub-populations residing there may have specific adaptation capacities to hot and cold temperatures, e.g. air conditioning or thermal insulation of buildings, which we do not account for.

These simulations reveal different sensitivities of each of these cities to extreme hot temperatures and moderate cold temperatures. For the city of Brest for example, the contribution of extreme hot temperatures to mortality remains very limited in the latter part of the century, even under the RCP8.5 scenario. On the other hand, the contribution of cold temperatures decreases gradually, which could tend to decrease the contribution of temperatures to mortality in this region. In contrast, the city of Perpignan appears significantly more exposed to extreme hot temperatures in the RCP4.5 scenario and in the RCP8.5 scenario.

6.5 Impacts on life-years lost due to temperature

Finally, we examine the effect of temperatures on the loss of life expectancy at birth. Figure 11 shows the loss of life expectancy at birth, as defined in Equation (24), for women and men between 2020 and 2100 due to temperatures in Metropolitan France. We specifically distinguish the overall temperature effects, which account for both hot and cold temperature-related mortality, and the sole effects of extreme hot temperatures. The different trajectories presented correspond to RCP2.6, RCP4.5 and RCP8.5 scenarios. These assessments are conducted under the assumption that populations and healthcare systems do not adapt to temperature changes throughout the century. Indeed, the challenging issue of adaptation and the evolution of the MMT is beyond the scope of this paper as recent literature suggest that populations can adapt to their local environment (Wu et al., 2024).

For the overall temperature effects, we first note that the loss of life expectancy for men is greater (in absolute value) than that for women. This difference is explained by men’s higher sensitivity to cold temperatures compared to women (Figure 5), especially in the age groups between 65 and 84 years. In the three RCP scenarios presented, rising temperatures would limit the contribution of cold to mortality. This would conduct to a general reduction of temperature-related life expectancy loss. We also observe in the RCP8.5 scenario a gradual reduction of the gap between women and men from 2050 onward due to increasing temperatures.

At the same time, attention must be paid to the evolution of life expectancy loss related to extreme hot temperatures. These excesses lead to reductions in life expectancy loss that generally do not exceed 0.1 years, except in a few exceptional years, under the RCP2.6 scenario. This loss does not show any particular trend throughout the century. The RCP4.5 scenario shows a slight but

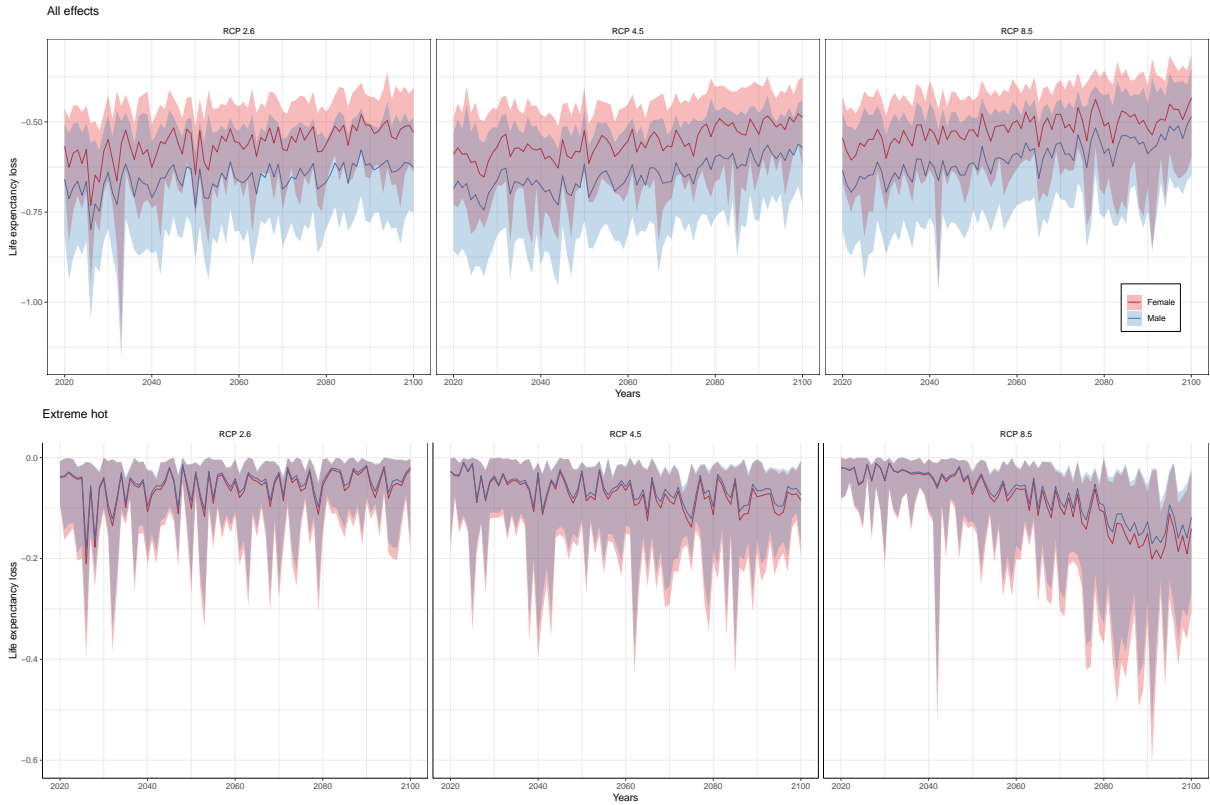


Figure 11: Life expectancy at birth lost in Metropolitan France, simulated for the years 2020-2100 for both women and men. We present both the loss related to all temperature effects and extreme hot effects only. These values, along with their 95% confidence intervals (shaded areas), are calculated through 1,000 Monte Carlo simulations of the DLNM coefficients, the Li-Lee model and the ensemble of climate models. Each line corresponds to the median of these simulations.

steady trend of reduction (in absolute value) in life expectancy loss for both women and men with the gradual increase in temperatures. The 95% uncertainty associated with our life expectancy loss predictions becomes wider from 2050 onwards in this scenario. On the other hand, the RCP8.5 scenario comprises an even greater worsening of life expectancy loss due to extreme heat from the second half of the century, potentially reaching nearly 0.2 years by 2100. The uncertainty associated with these predictions increases significantly over time due to the longer duration, severity, and intensity of heatwave episodes (Figure 4).

This situation at the scale of Metropolitan France varies according to geographical location. Thus, the same figures for temperature-related life expectancy loss are reproduced for Brest, Marseille, Paris, Perpignan and Strasbourg. For that purpose, we use the projections of central death rates, excluding temperature effects, as described in Section 5.2, and then apply the attributable fractions simulated from the temperature trajectories specific to each city using data from DRIAS. Detailed results are presented in Appendix D. For these different cities, the trajectory of temperature-related life expectancy loss clearly depends on the evolution of hot and cold contributions in each area of France. In the northern part of France, including Paris, Brest and Strasbourg, the life expectancy loss related to all temperature effects tends to decrease (in absolute value) in all RCP scenarios due to the reduced contribution of cold to mortality. In the RCP8.5 scenario where average temperatures tend to rise rapidly, the life expectancy loss seems to become lower more quickly. In the southern part of France (Marseille and Perpignan), the trajectory of life expectancy loss reduction is less clear in RCP2.6 and RCP4.5. In the RCP8.5 scenario for Perpignan, the temperature-related life expectancy loss increases (in absolute value) in the second half of the century. For this city, where extreme heat will be more frequent at the end of the century, the median life expectancy loss due to heatwaves alone reaches between 0.3 and 0.4 years.

7 Conclusion

Temperature changes linked to climate change create disturbances that will affect the frequency of observed deaths throughout the year. In this paper, we design a multi-population mortality model incorporating the effect of temperature changes on mortality. This framework includes a classic climate epidemiology model, known as the Distributed Lag Non-Linear Model (DLNM), which measure deaths attributable to hot and cold temperatures over different periods of the year. By coupling these two modeling frameworks and integrating temperature trajectories from various climate models, we project central death rates impacted by temperature effects and measure these impacts in terms of gains or losses in life expectancy.

Our results describe a situation dependent on both climate scenarios and the geographical location of populations. Specifically, the simulated gains or losses in life expectancy until the end of the century, particularly from 2050 in Metropolitan France, show a downward trend in mortality related to cold and an upward trend in mortality related to extreme heat. These two effects evolve in opposite directions and reveal a source of divergence between certain regions of France, especially under the RCP8.5 scenario. For all results, we incorporate multiple sources of uncertainty, including climate scenarios, prediction errors of the mortality model, and estimation errors of the DLNM model. The modeling framework established here and illustrated with French data offers an adaptable approach for other countries or regions, whether for demographic needs or for insurers, actuaries, or supervisory authorities interested in designing climate scenarios. Further research perspectives are opened by extending the multi-population mortality model to other countries or by refining the geographical resolution of the considered territory. For instance, some regions will be more affected than others by climate change, and more pronounced impacts of heat-related mortality are expected in Southern Europe or the MENA region (Hajat et al., 2023). Otherwise, the study of daily mortality or on finer time scales may encompass other environmental components such as air pollution or humidity, which we do not consider in this study. These factors introduce additional sources of uncertainty that should be addressed in future research. In this regard, the DLNM could be calibrated on multiple sites and additional environmental variables. Thus, a possible extension would be to model the simultaneous occurrence of mortality shocks related to temperature extremes and other environmental variables.

In this paper, we make the strong assumption that populations do not adapt to their local environment, which is debated in recent literature (Wu et al., 2024). Indeed, the number of deaths related to temperatures could decrease thanks acclimatization. This can result both from technology, e.g. improvement of house insulation, development of air conditioning, or by a physiological process, see Heiden et al. (2020) among others. Furthermore, prevention and protection plans could be set up to alert and guide the population on how to behave in the face of heatwaves. Concrete actions like changing working hours, opening air-conditioned reception areas, distributing water in public transport, monitoring the most vulnerable at home, and limiting or prohibiting outdoor sports activities could also affect heat-related mortality. Considering these acclimatization factors offers research perspectives to be explored in the construction of prospective scenarios.

Supplementary material: The results in this paper is obtained using R. Supplementary material related to this paper can be found at <https://github.com/qguibert/mortalityheatwaves>.

Author Contributions: Q.G., G.P. and F.P. design the study. Q.G. and G.P. collect, cure and verify the data. Q.G. designs the models and the methodology. Q.G. implements methods, produces results and visualizations. Q.G. and G.P. write the manuscript. F.P. edit the manuscript.

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A Heatwaves in France

Heatwaves represent a particular risk of acute mortality and their importance has increased over the past 20 years. To understand this phenomenon for the studied population, this appendix provides a synthetic overview of historical recent heatwaves in metropolitan France since 1950. Additional details are provided by Pincemin (2021).

A.1 Definition and characterization of heatwaves

Heatwaves do not have a single definition. Depending on the temperature distribution and the adaptation capacity of populations in the region concerned, the definitions and tolerance thresholds adopted may vary. In particular, the identification of a heatwave may depend on the climate, urbanization of the area concerned, as well as indicators measuring its intensity (average temperature, daytime or nighttime temperature, duration of the reference period, humidity rate, etc.).

In the context of this study on French population, we define a heatwave according to the criteria used for heatwave alerts by Météo France, the French national meteorological service. These criteria are also used by Santé Publique France (Santé Publique France, 2019b). Météo France defines a heatwave period as a period where the average of daily temperatures during the day and at night exceeds the 99.5% percentile of observations made between 1981 and 2010.

We introduce for $d \in D^*$

$$\bar{\vartheta}_d^{\max} = \frac{1}{3} \sum_{j=1}^3 \vartheta_{d-j}^{\max}, \quad \bar{\vartheta}_d^{\min} = \frac{1}{3} \sum_{j=1}^3 \vartheta_{d-j}^{\min},$$

where ϑ_d^{\max} and ϑ_d^{\min} are the aggregated maximum and minimum temperatures in metropolitan France for day d . This 3-day moving average is sometimes referred to as a biometeorological indicator. Thus, a day is marked by a heatwave if the minimum $\bar{\vartheta}_d^{\min}$ and maximum $\bar{\vartheta}_d^{\max}$ 3-day moving averages of temperatures exceed respective minimum r^{\min} and maximum r^{\max} thresholds.

Furthermore, we characterize each heatwave period, i.e. the set of days $D \subset D^*$, using the following indicators:

- the duration corresponds to the number of consecutive days above the alert thresholds, i.e., $|D|$,
- the cumulative severity corresponds to the sum of the daily severities sev_d over the heatwave period D

$$\text{sev}_d = |\vartheta_d^{\min} - r^{\min}| + |\vartheta_d^{\max} - r^{\max}|,$$

- the intensity of a heatwave corresponds to

$$\text{int} = \max_{d \in D} \{|\vartheta_d^{\min} - r^{\min}|\} + \max_{d \in D} \{|\vartheta_d^{\max} - r^{\max}|\}.$$

These indicators allow for triggering the appropriate level of alert in line with the danger associated with the heatwave, and for evaluating and ranking heatwaves among themselves.

A.2 History of recent heatwaves in France

Gradually, Western European countries such as France have experienced a decrease in the intensity and frequency of cold spells (Météo France, 2024). Conversely, heatwaves have become more frequent, and summers are increasingly hotter. In France, the major heatwaves of 1976 and 2003 resulted in an excess of 4,500 and 15,000 deaths, respectively. In recent years, heatwaves have occurred almost every single year with varying intensities. Some of them have had temperatures similar to the historical heatwave of 2003. In 2019 and 2020, they even reached the highest level of the alert plan for the first time in history.

Their consequences in terms of mortality are listed in Table 4, which contains data compiled from *Santé Publique France* and the Centre for Research on the Epidemiology of Disasters (CRED) Database. It is noteworthy that the dates and durations of each heatwave are calculated on average by department and are extracted from the annual reports of *Santé Publique France*. Considering the average for the entirety of France would result in a shorter duration of heatwaves. For comparative purposes, the CRED data is also included in this table. Significant differences in excess mortality attributed to these various events are observed depending on the data source, due to variations in the methodologies employed.

Table 4: Main heatwaves in metropolitan France since 1976. This table presents for each year the cumulative number of heatwave days and the attributed number of deaths, calculated on average per department by *Santé Publique France*. These data are extracted from the *Bulletins de Santé Publique France* (reports analyzing the departmental, regional, and national situation) on the relevant summers (Santé Publique France, 2018; Santé Publique France, 2019a; Santé Publique France, 2020) and from the publication of the Institut de Veille Sanitaire (2015). Data from the earlier years (1976, 1983, 2003, 2006) are sourced from a study on heatwaves since 1970 (Pascal et al., 2019). The CRED data is drawn from the EM'DAT database (Centre for Research on the Epidemiology of Disasters, 2021). This open and free database is a project of the Integrated Research on Disaster Risk. It is one of the three largest databases for disasters, along with MunichRe's NatCatSERVICE and SwissRe's Sigma. It is fed by numerous governmental and non-governmental sources, insurers and reinsurers, press agencies, specialized entities and various global organizations (United Nations, SwissRe, MunichRe, NOAA, etc.).

| Key information | Excess Death | |
|---|------------------------------|--------------------|
| | <i>Santé Publique France</i> | <i>Cred Em'Dat</i> |
| 1976 Late June – mid-July | 4,540 | - |
| 1983 July 9 – July 31 (22 days) | 2,900 | - |
| 2003 The summer of 2003 was the hottest in France and Europe in over 50 years, with exceptional intensity during the first half of August. This episode was associated with significant ozone pollution. | 14,800 | 19,490 |
| 2006 July 2006 witnessed a very intense heatwave, although less severe than in 2003, but with a longer duration. | 1,442 | 1,388 |
| 2015 Three waves unevenly distributed over the territory. The first was quite intense, affecting the north for 10 days. The second, lasting 11 days, was less intense and concentrated in the south-east. The last one, shorter, was very localized in some eastern and southern departments. | 2,040 | 3,275 |
| 2018 A two-week heatwave peaking in early August, exposing 70% of the French population. | 1,480 | - |
| 2019 Two very extensive and intense heatwaves. For the first time, several departments were under red alert during both waves. | 2,034 | 1,435 |
| 2020 Three heatwaves, one particularly severe in the north, resulting in a red alert for the second consecutive year, over a cumulative period of around ten days. | 1,924 | 1,924 |

In 2022, we observed an excess mortality of 73 deaths per million (26, 124), which corresponds to 4,807 (1,739, 8,123)² deaths (Ballester et al., 2023).

B Validation of the DLNM model

B.1 Goodness of fit for the DLNM model

The figures 12 and 13 compare the monthly distributions of observed and modeled death counts over the observation period for females and males. We observe a close similarity in the monthly distributions, notably during summers and winters. However, our models appear to fit less well to the left tails of the distribution, i.e. to the low values of the number of deaths, as well as to some extreme values of deaths in the spring and autumn. These variations in the number of deaths could possibly be explained by other factors not included in our model, e.g. air pollution, flu epidemics, etc.

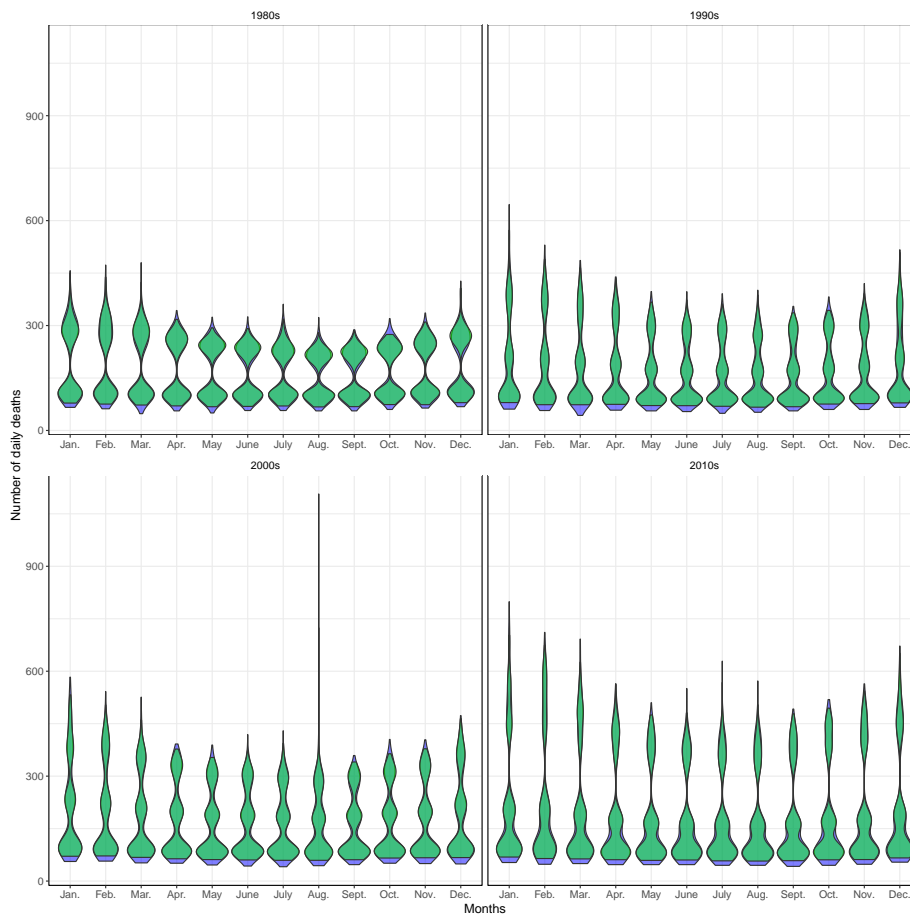


Figure 12: Monthly distribution of observed (blue) and predicted (green) numbers of deaths based on the DLNM model (17) per year for women in metropolitan France for the years between 1980 and 2019. The distributions are grouped by decade.

Figures 14 and 15 depict the analysis of deviance residuals by age group and indicate a relatively good fit to the data for women and men. It is worth noting a few extreme points that were not well captured by the model, such as the 2003 heatwave for 85+, which was an event of extreme magnitude.

²The values in parentheses represent the 95% confidence intervals.

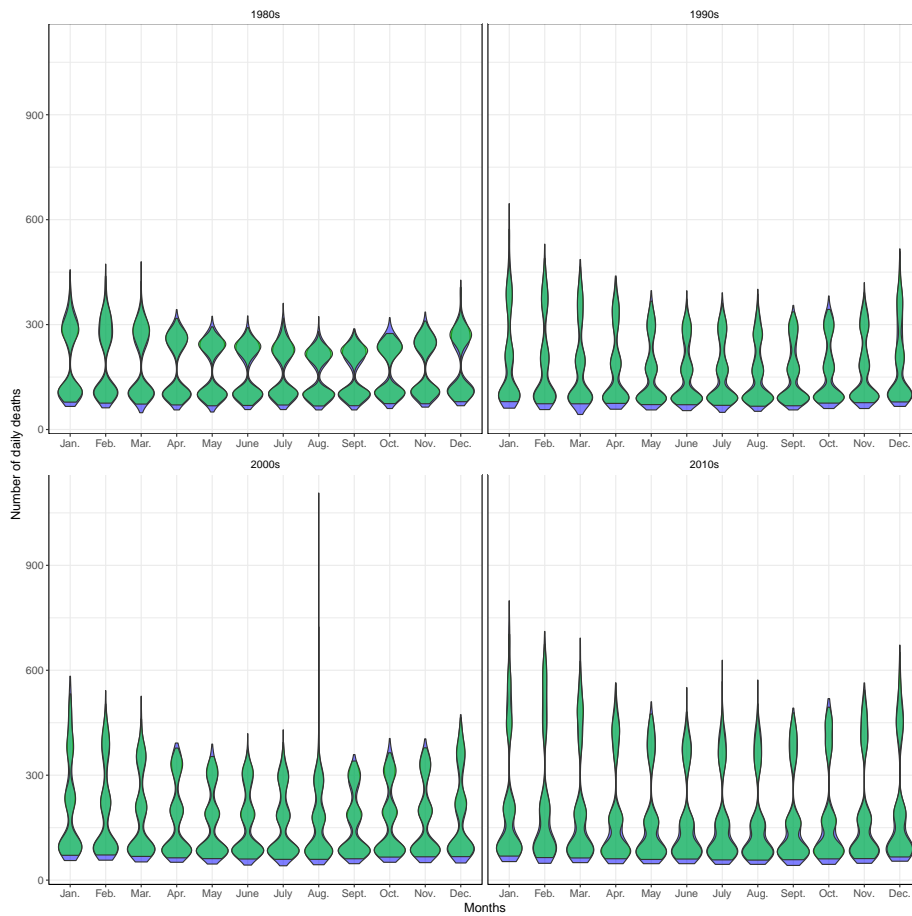


Figure 13: Monthly distribution of observed (blue) and predicted (green) numbers of deaths based on the DLNM model (17) per year for men in metropolitan France for the years between 1980 and 2019. The distributions are grouped by decade.

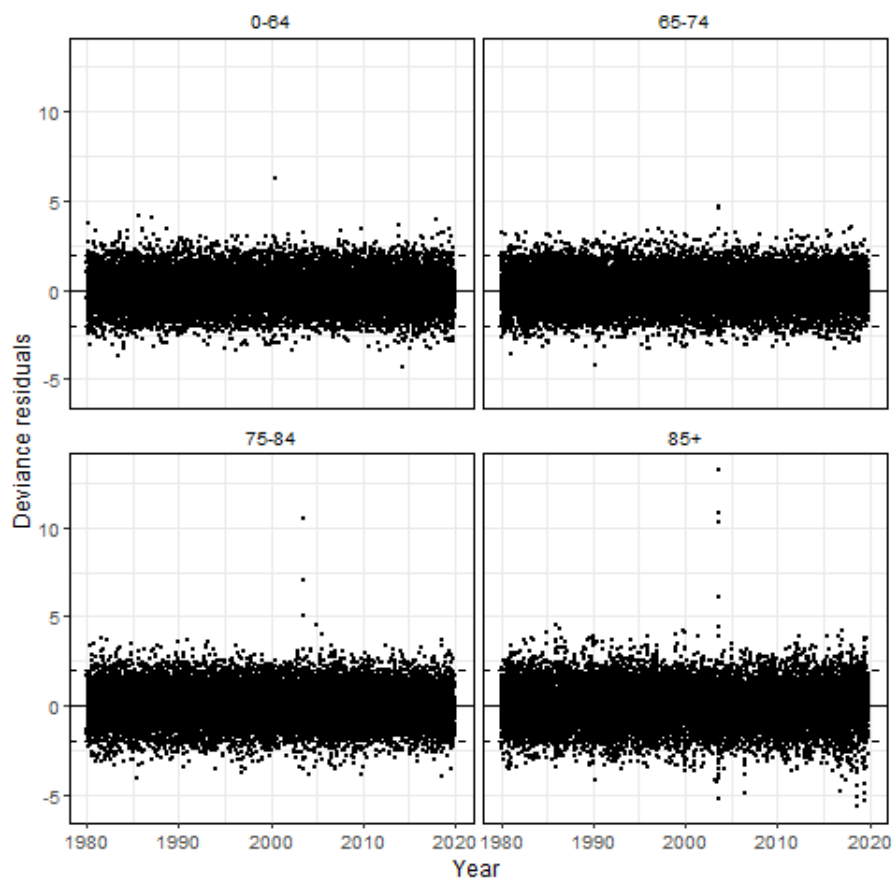


Figure 14: Representation of deviance residuals for DLNM models associated with age groups 0-64, 65-74, 75-84, and 85+ for women in metropolitan France for the years between 1980 and 2019.

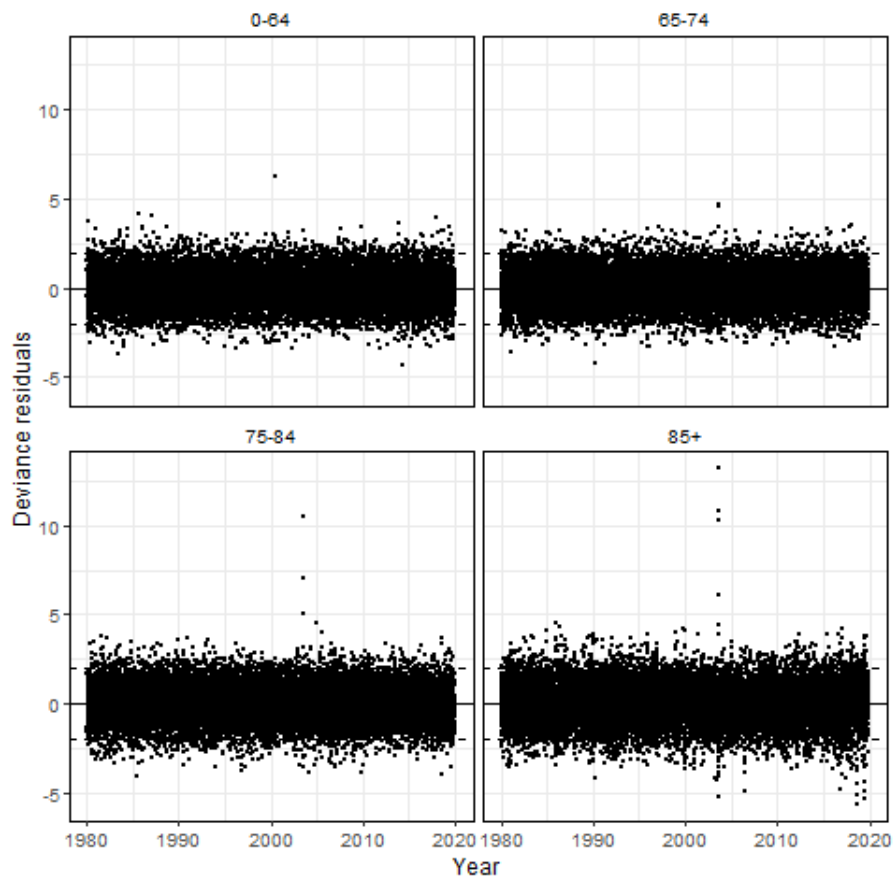


Figure 15: Representation of deviance residuals for DLNM models associated with age groups 0-64, 65-74, 75-84, and 85+ for men in metropolitan France for the years between 1980 and 2019.

B.2 Sensitivity analysis

In order to present the sensitivity to the number of days used to estimate the cumulative effects of the temperature-mortality association, we present in Figure 16 the response curves in terms of RR with a lag of 14 days. Compared to Figure 5, the Relative Risk (RR) of mortality over a 21-day period does not capture the longer-term effects related to periods of heat and cold, such as the harvesting effect associated with certain extreme heatwaves. This results in underestimated effects, mainly for the extremes of heat and cold periods.

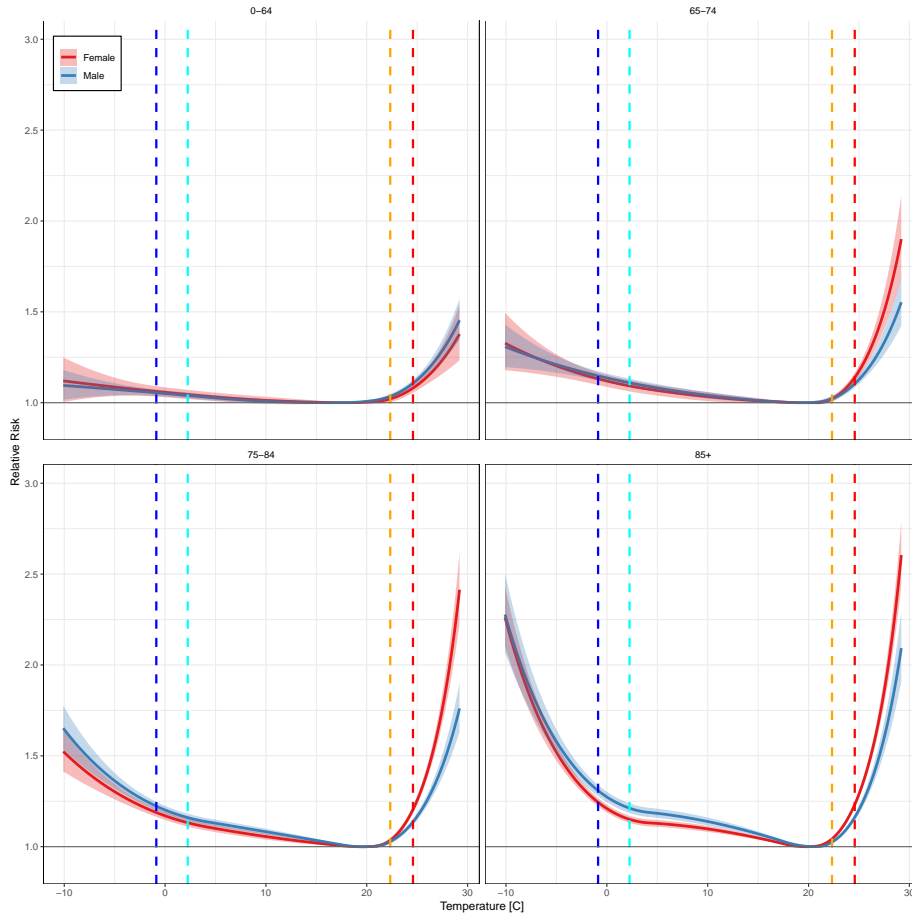


Figure 16: Cumulative relative risk of mortality over a 14-day period in Metropolitan France calculated for the years 1980-2019 for women (red) and men (blue) across age groups 0-64, 65-74, 75-84, and 85+, with their 95% confidence intervals (shaded areas). The dashed vertical lines represent the quantiles of daily mean temperatures at 1% (blue), 5% (cyan), 95% (orange), and 99% (red) calculated over the period 1980-2019. Daily average temperatures are calculated for each city, and then an average of 14 cities is used to derive the daily average temperatures for Metropolitan France. Temperatures are measured in degrees Celsius. Based on GHCN data.

C Additional figures on projected temperature-attributable fractions

C.1 Attributable fraction per age bucket and sex

Figures 17, 18, 19 and 20 describe the projected temperature-attributable fractions simulated by sex and age group.



Figure 17: Temperature attributable fraction in Metropolitan France, simulated for the years 2020-2100 for both women and men across for the age group 0-64. These values, along with their 95% confidence intervals (shaded areas) are calculated through 1,000 Monte Carlo simulations of the DLNM coefficients and the ensemble of climate models. Each line corresponds to the average of these simulations. Attributable fraction is expressed in % for all effect, decomposed into moderate cold, moderate hot, extreme cold and extreme hot.



Figure 18: Temperature attributable fraction in Metropolitan France, simulated for the years 2020-2100 for both women and men across for the age group 65-74. These values, along with their 95% confidence intervals (shaded areas) are calculated through 1,000 Monte Carlo simulations of the DLNM coefficients and the ensemble of climate models. Each line corresponds to the average of these simulations. Attributable fraction is expressed in % for all effect, decomposed into moderate cold, moderate hot, extreme cold and extreme hot.

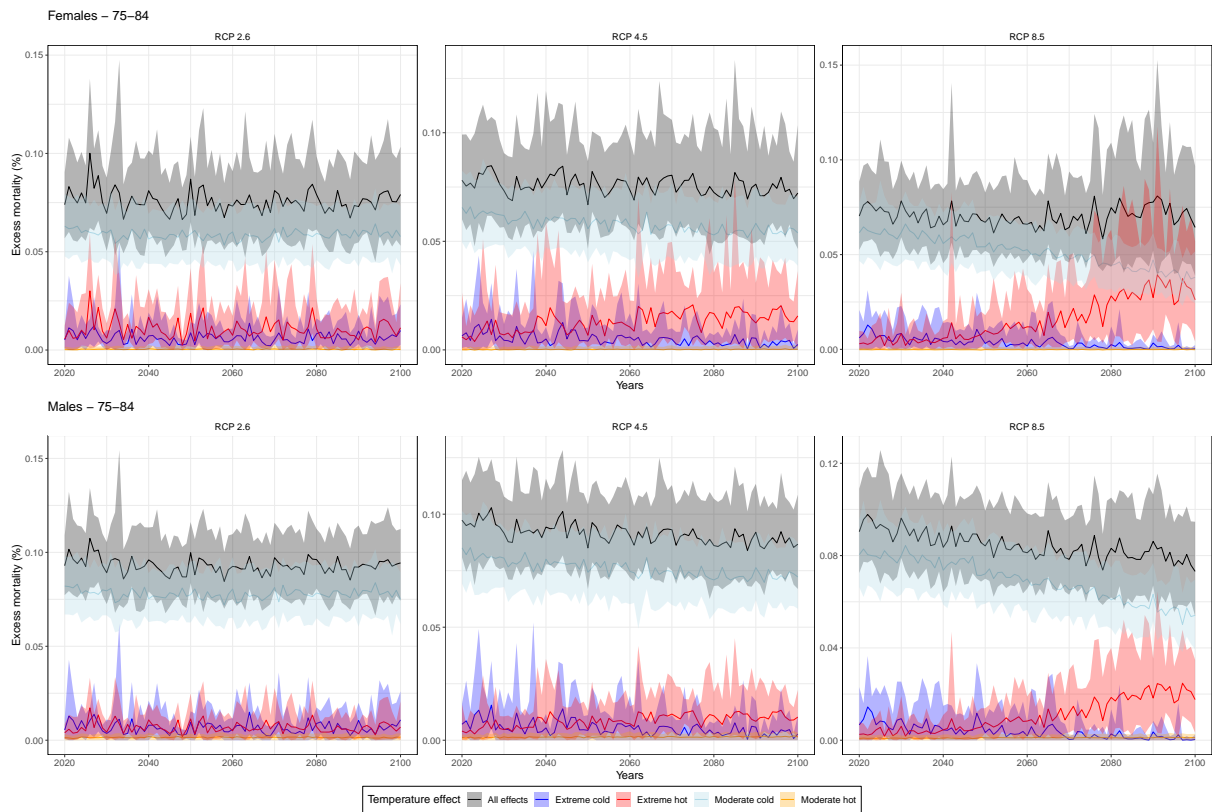


Figure 19: Temperature attributable fraction in Metropolitan France, simulated for the years 2020-2100 for both women and men across for the age group 75-84. These values, along with their 95% confidence intervals (shaded areas) are calculated through 1,000 Monte Carlo simulations of the DLNM coefficients and the ensemble of climate models. Each line corresponds to the average of these simulations. Attributable fraction is expressed in % for all effect, decomposed into moderate cold, moderate hot, extreme cold and extreme hot.

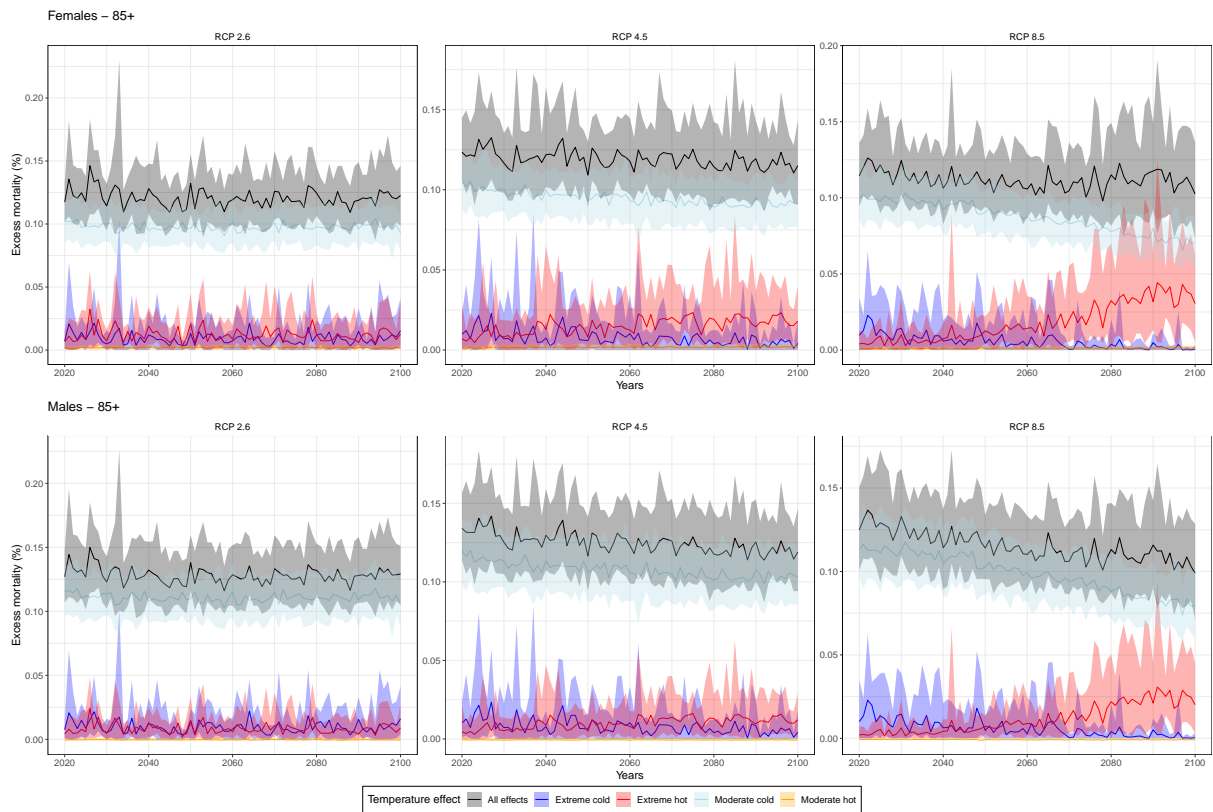


Figure 20: Temperature attributable fraction in Metropolitan France, simulated for the years 2020-2100 for both women and men across for the age group 85+. These values, along with their 95% confidence intervals (shaded areas) are calculated through 1,000 Monte Carlo simulations of the DLNM coefficients and the ensemble of climate models. Each line corresponds to the average of these simulations. Attributable fraction is expressed in % for all effect, decomposed into moderate cold, moderate hot, extreme cold and extreme hot.

C.2 Attributable fraction per city

In this appendix, Figures 21, 22, 23, 24 and 25 respectively present the projected fractions of deaths attributable to temperatures for the cities of Brest, Marseille, Paris, Perpignan and Strasbourg.

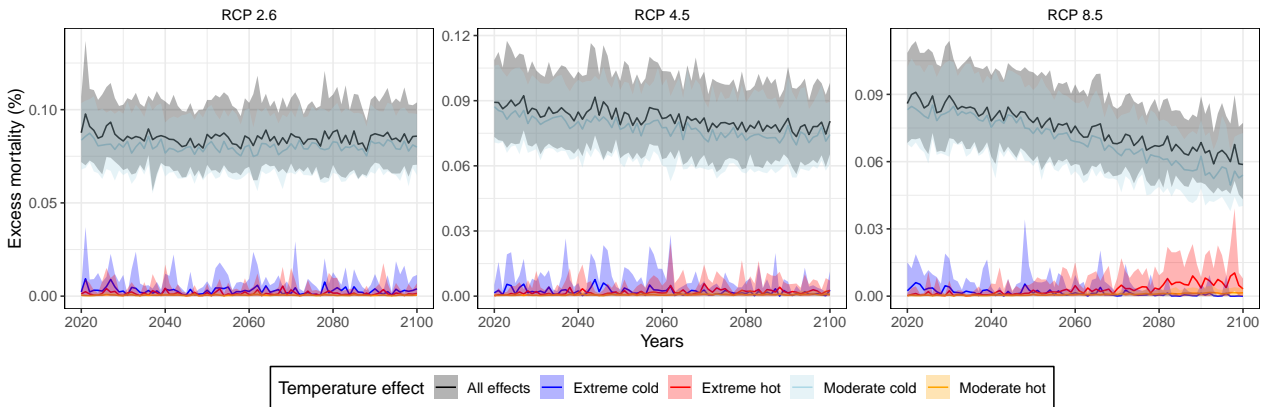


Figure 21: Temperature attributable fraction in Brest, simulated for the years 2020-2100 for both women and men across. These values, along with their 95% confidence intervals (shaded areas) are calculated through 1,000 Monte Carlo simulations of the DLNM coefficients and the ensemble of climate models. Each line corresponds to the average of these simulations. Attributable fraction is expressed in % for all effect, decomposed into moderate cold, moderate hot, extreme cold and extreme hot.

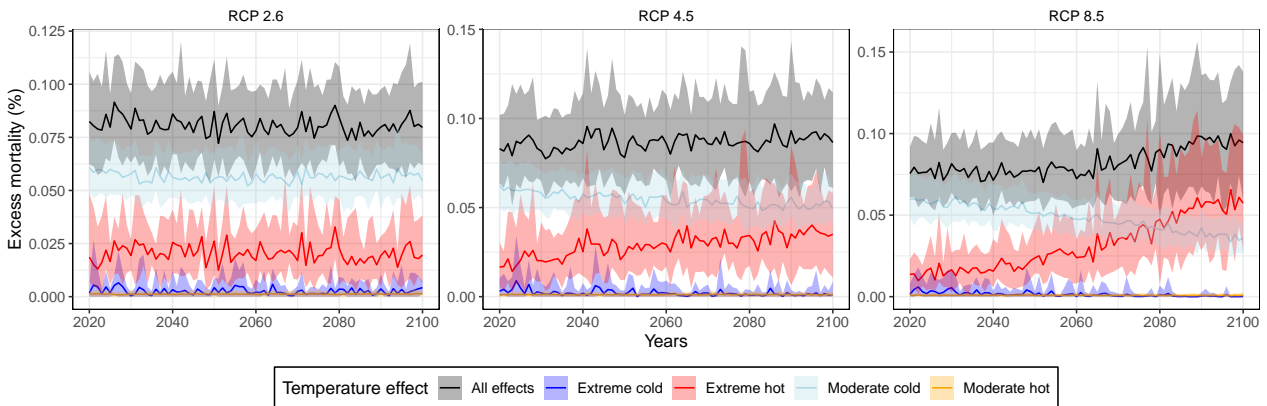


Figure 22: Temperature attributable fraction in Marseille, simulated for the years 2020-2100 for both women and men across. These values, along with their 95% confidence intervals (shaded areas) are calculated through 1,000 Monte Carlo simulations of the DLNM coefficients and the ensemble of climate models. Each line corresponds to the average of these simulations. Attributable fraction is expressed in % for all effect, decomposed into moderate cold, moderate hot, extreme cold and extreme hot.

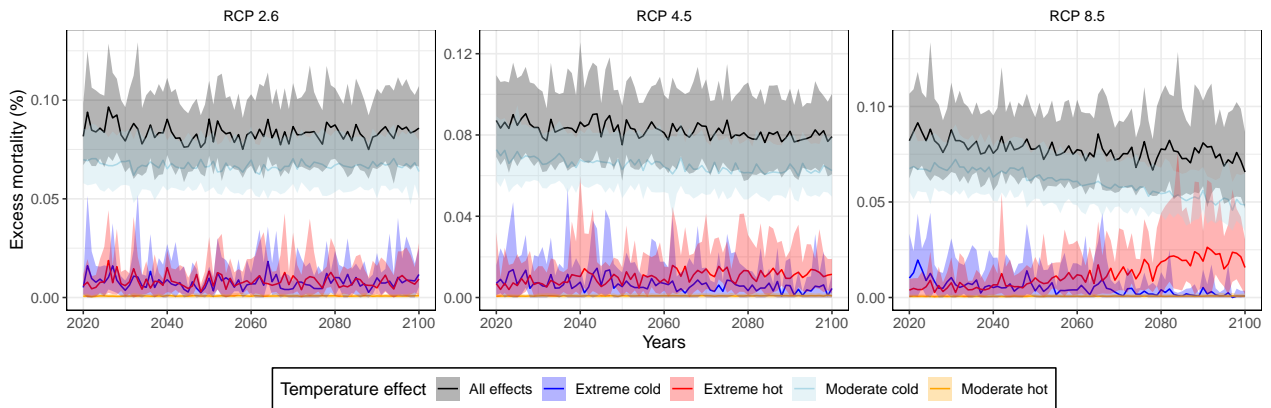


Figure 23: Temperature attributable fraction in Paris, simulated for the years 2020-2100 for both women and men across. These values, along with their 95% confidence intervals (shaded areas) are calculated through 1,000 Monte Carlo simulations of the DLNM coefficients and the ensemble of climate models. Each line corresponds to the average of these simulations. Attributable fraction is expressed in % for all effect, decomposed into moderate cold, moderate hot, extreme cold and extreme hot.

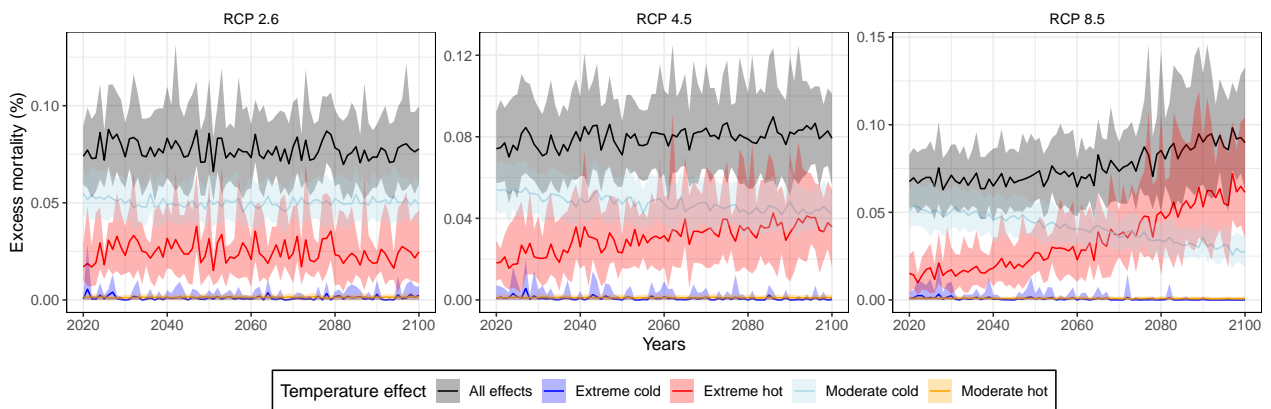


Figure 24: Temperature attributable fraction in Perpignan, simulated for the years 2020-2100 for both women and men across. These values, along with their 95% confidence intervals (shaded areas) are calculated through 1,000 Monte Carlo simulations of the DLNM coefficients and the ensemble of climate models. Each line corresponds to the average of these simulations. Attributable fraction is expressed in % for all effect, decomposed into moderate cold, moderate hot, extreme cold and extreme hot.

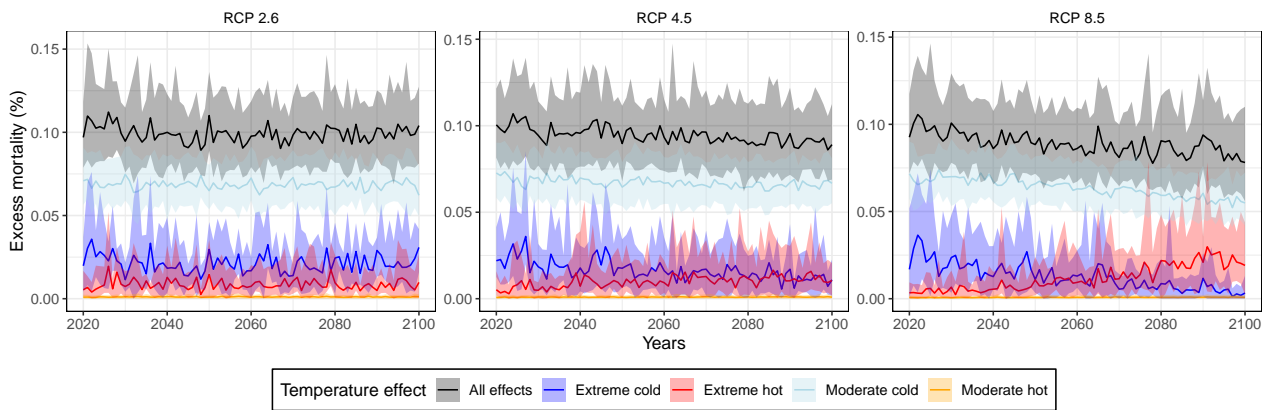


Figure 25: Temperature attributable fraction in Strasbourg, simulated for the years 2020-2100 for both women and men across. These values, along with their 95% confidence intervals (shaded areas) are calculated through 1,000 Monte Carlo simulations of the DLNM coefficients and the ensemble of climate models. Each line corresponds to the average of these simulations. Attributable fraction is expressed in % for all effect, decomposed into moderate cold, moderate hot, extreme cold and extreme hot.

D Additional figures on projected life expectancy losses by city

In this appendix, Figures 26, 27, 28, 29 and 30 respectively present the projected Life expectancy at birth losses attributable to overall temperatures and extreme hot temperatures for the cities of Brest, Marseille, Paris, Perpignan and Strasbourg.



Figure 26: Life expectancy at birth lost in Brest, simulated for the years 2020-2100 for both women and men. We present both the loss related to all temperature effects and extreme hot effects only. These values, along with their 95% confidence intervals (shaded areas), are calculated through 1,000 Monte Carlo simulations of the DLNM coefficients, the Li-Lee model and the ensemble of climate models. Each line corresponds to the median of these simulations.

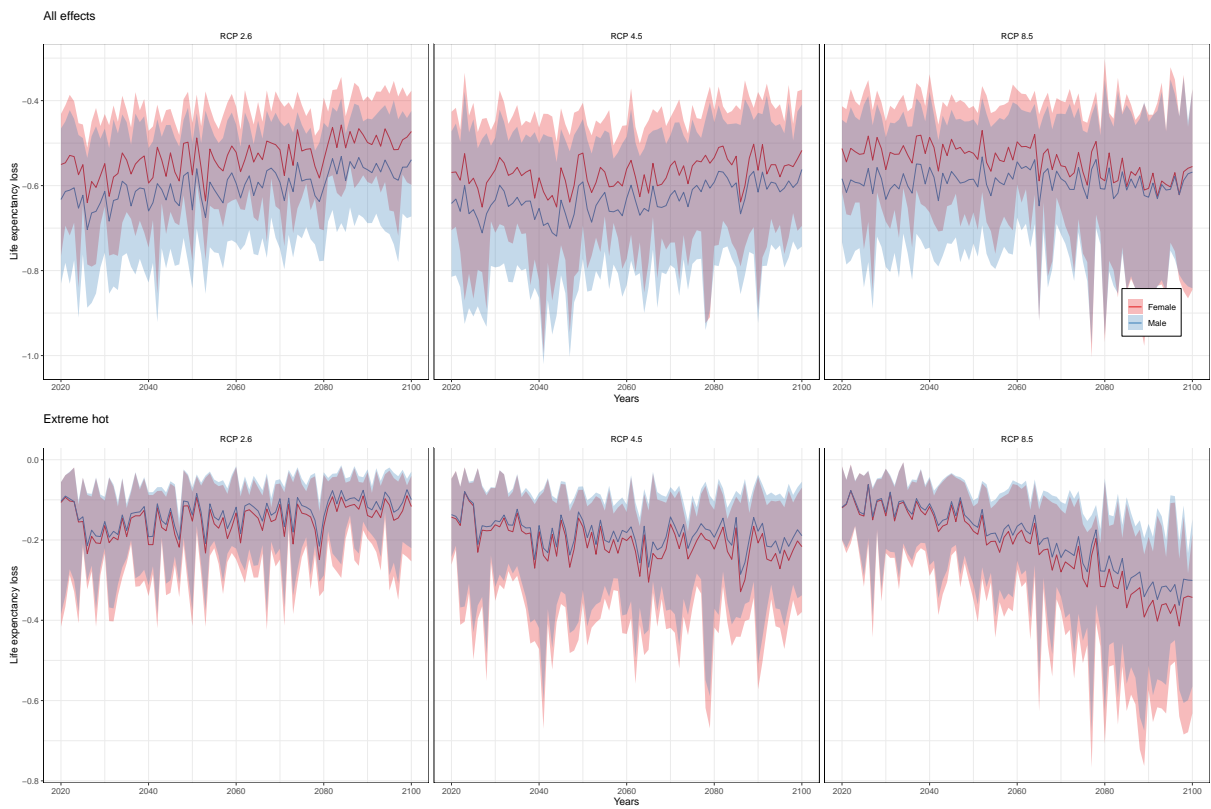


Figure 27: Life expectancy at birth lost in Marseille, simulated for the years 2020-2100 for both women and men. We present both the loss related to all temperature effects and extreme hot effects only. These values, along with their 95% confidence intervals (shaded areas), are calculated through 1,000 Monte Carlo simulations of the DLNM coefficients, the Li-Lee model and the ensemble of climate models. Each line corresponds to the median of these simulations.

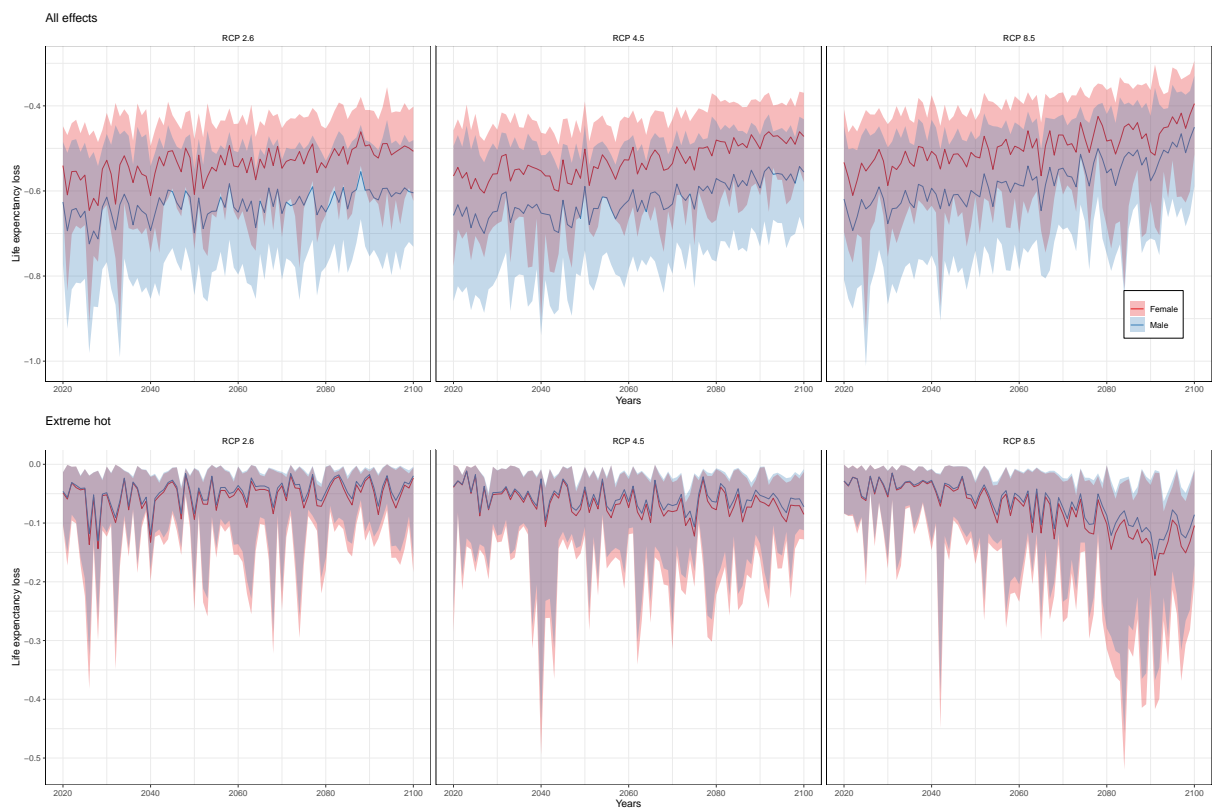


Figure 28: Life expectancy at birth lost in Paris, simulated for the years 2020-2100 for both women and men. We present both the loss related to all temperature effects and extreme hot effects only. These values, along with their 95% confidence intervals (shaded areas), are calculated through 1,000 Monte Carlo simulations of the DLNM coefficients, the Li-Lee model and the ensemble of climate models. Each line corresponds to the median of these simulations.

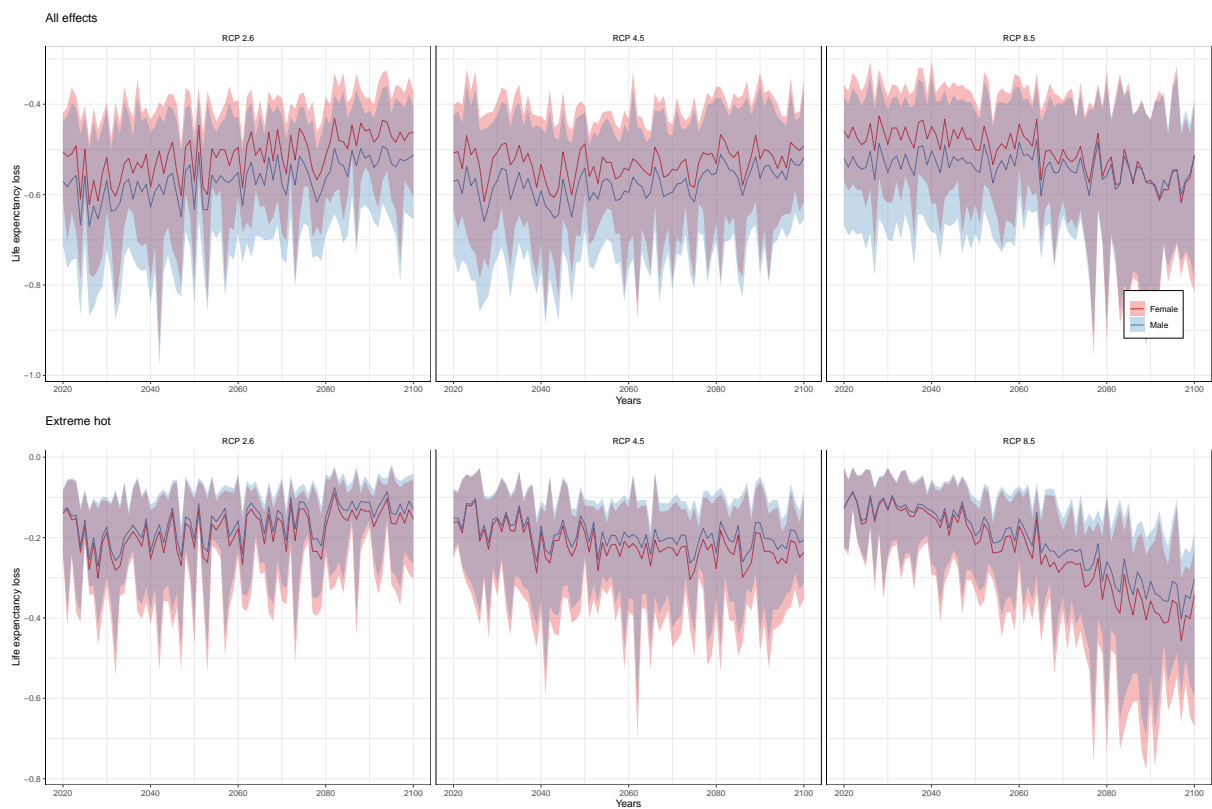


Figure 29: Life expectancy at birth lost in Perpignan, simulated for the years 2020-2100 for both women and men. We present both the loss related to all temperature effects and extreme hot effects only. These values, along with their 95% confidence intervals (shaded areas), are calculated through 1,000 Monte Carlo simulations of the DLNM coefficients, the Li-Lee model and the ensemble of climate models. Each line corresponds to the median of these simulations.

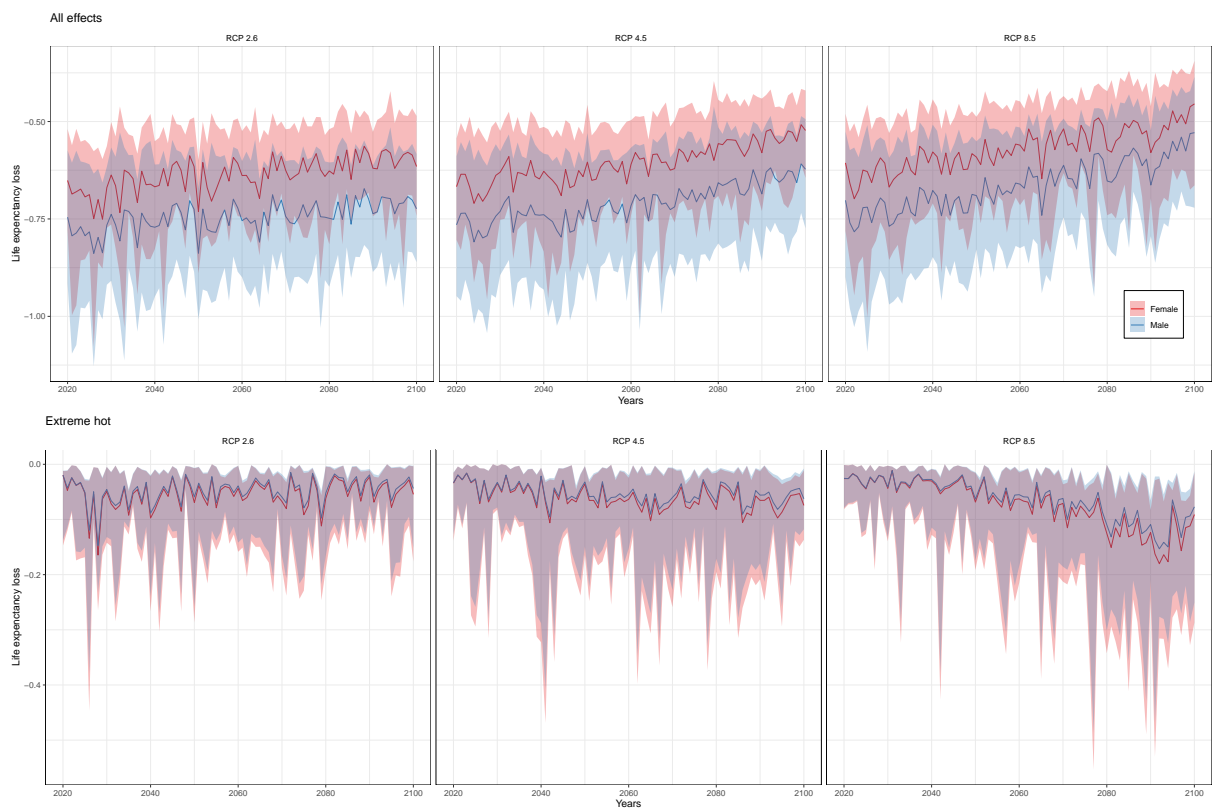


Figure 30: Life expectancy at birth lost in Strasbourg, simulated for the years 2020-2100 for both women and men. We present both the loss related to all temperature effects and extreme hot effects only. These values, along with their 95% confidence intervals (shaded areas), are calculated through 1,000 Monte Carlo simulations of the DLNM coefficients, the Li-Lee model and the ensemble of climate models. Each line corresponds to the median of these simulations.

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