Quentin Guibert
guibert@ceremade.dauphine.fr
https://www.ceremade.dauphine.fr/~guibert/

CEREMADE, Université Paris Dauphine - PSL

April 1, 2025 - Actuarial science seminar
National Bank of Belgium

The Impact of Temperature and Climate Change on Mortality

An extrapolation of temperature effects based on time series data in France

in collaboration with G. Pincemin and F. Planchet
The paper is available here: https://arxiv.org/abs/2406.02054

Agenda

Background

The effects of heat and cold on human body

- Temperatures have direct and indirect effects on human health.
- Hot and cold periods in temperate regions (Beker et al., 2018).
- Concept of MMT (Minimum Mortality Temperature) with spatial heterogeneity indicating different adaptation levels to temperatures (Yin et al., 2019).
- Many epidemiological studies estimated the temperature-attributable deaths.
- Concept of attributable mortality $\rightarrow$ Require daily or weekly mortality data (Gasparrini, 2014; Vicedo-Cabrera et al., 2019).
- Heatwaves $\nearrow$ and cold waves $\searrow$ during the 21st century (IPCC, 2023).
  BUT, complex projections with a lot of uncertainty, heterogeneity and combined effects due to human activity.

Problem set-up

Climate-related mortality in actuarial and demographic literature

- Largely unexplored in this actuarial literature, except some papers, e.g. Seklecka et al. (2017).
- Most stochastic mortality models are based on past dynamics (Lee and Carter, 1992; Barrieu et al., 2012; Dowd et al., 2020), e.g. the Lee-Carter model

$$\ln(\widehat{m}_{x,t}) = \alpha_x + \beta_x \kappa_t + \epsilon_{x,t}.$$

Specificity of temperature-attributable deaths

- The intensity of shocks is likely to be affected by climate change.
- Observed temperature-related shocks are punctual and generally non-catastrophic.
- They may be offset throughout the year → need to incorporate daily or weekly data.

Introduction

Main aims

- Coupling a multi-population mortality model with a climate epidemiology model.

To our knowledge, this is one of the first paper where a mortality model and an climate epidemiology model are combined.

Introduction

Main aims

- Coupling a multi-population mortality model with a climate epidemiology model.
- Measuring the effect of future temperatures on mortality trend, differentiating by sex and age.

To our knowledge, this is one of the first paper where a mortality model and an climate epidemiology model are combined.

Introduction

Main aims

- Coupling a multi-population mortality model with a climate epidemiology model.
- Measuring the effect of future temperatures on mortality trend, differentiating by sex and age.
- Integrating the uncertainty associated with future temperatures.

To our knowledge, this is one of the first paper where a mortality model and an climate epidemiology model are combined.

Introduction

Main aims

- Coupling a multi-population mortality model with a climate epidemiology model.
- Measuring the effect of future temperatures on mortality trend, differentiating by sex and age.
- Integrating the uncertainty associated with future temperatures.
- Measuring regional sensitivity differences.

To our knowledge, this is one of the first paper where a mortality model and an climate epidemiology model are combined.

Modeling framework

Notation and basic assumptions

- $\mu_{x,t}^{(g)}$, $E_{x,t}^{(g)}$, and $D_{x,t}^{(g)}$ represent, respectively, the force of mortality, observed exposure to risk, and observed number of deaths at age x and calendar year t.
- Two populations $g \in \{\text{female}, \text{male}\}$ in Metropolitan France.
- Crude central death rate of mortality $\widehat{m}_{x,t}^{(g)} = D_{x,t}^{(g)} / E_{x,t}^{(g)}$.

Modeling framework

Notation and basic assumptions

- $\mu_{x,t}^{(g)}$, $E_{x,t}^{(g)}$, and $D_{x,t}^{(g)}$ represent, respectively, the force of mortality, observed exposure to risk, and observed number of deaths at age x and calendar year t.
- Two populations $g \in \{\text{female}, \text{male}\}$ in Metropolitan France.
- Crude central death rate of mortality $\widehat{m}_{x,t}^{(g)} = D_{x,t}^{(g)} / E_{x,t}^{(g)}$.

Deaths attributable to temperatures

- Decomposition into two components

$$D_{x,t}^{(g)} = \widetilde{D}_{x,t}^{(g)} + \bar{D}_{x,t}^{(g)} \Rightarrow \widehat{m}_{x,t}^{(g)} = \widetilde{m}_{x,t}^{(g)} + \bar{m}_{x,t}^{(g)}$$

  where $\widetilde{D}_{x,t}^{(g)}$ and $\bar{D}_{x,t}^{(g)}$ are the number of deaths not attributable and attributable to temperature, respectively.

- Define the total attributable fraction related to temperatures as $\text{AF}_{x,t}^{(g)} = \dfrac{\bar{D}_{x,t}^{(g)}}{D_{x,t}^{(g)}}$.

Modeling framework

A multi-population model with temperature effects

- Consider the two-populations Li and Lee (2005) model for central deaths rates not attributable to temperature effects

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

Modeling framework

A multi-population model with temperature effects

- Consider the two-populations Li and Lee (2005) model for central deaths rates not attributable to temperature effects

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

- This choice is compatible with our data, but other models are possible.

Modeling framework

A multi-population model with temperature effects

- Consider the two-populations Li and Lee (2005) model for central deaths rates not attributable to temperature effects

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

- This choice is compatible with our data, but other models are possible.
- **Identifiability constraints**

$$\sum_{t \in \mathcal{T}_y} K_t = 0 \text{ and } \sum_{x \in \mathcal{X}} B_x^2 = 1,$$

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

Modeling framework

- Consider the two-populations Li and Lee (2005) model for central deaths rates not attributable to temperature effects

$$\ln\left(\widetilde{m}_{x,t}^{(g)}\right) = A_x + B_x K_t + \alpha_x^{(g)} + \beta_x^{(g)} \kappa_t^{(g)}.$$

- This choice is compatible with our data, but other models are possible.
- **Identifiability constraints**

$$\sum_{t \in \mathcal{T}_y} K_t = 0 \text{ and } \sum_{x \in \mathcal{X}} B_x^2 = 1,$$

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

- **Time series model with coherence assumption**

$$K_t = \delta + K_{t-1} + e_t \rightarrow \text{ RWD with drift}$$

$$\kappa_t^{(g)} = c^{(g)} + \phi^{(g)} \kappa_{t-1}^{(g)} + r_t^{(g)} \rightarrow \text{ AR(1) with drift and } |\phi^{(g)}| < 1.$$

Error terms are white noise with a mean of zero and a variance-covariance matrix $\boldsymbol{\Sigma}$.

Modeling framework

Poisson assumption and temperature-attributable deaths

- Poisson assumption for the number deaths not attributable to temperature

$$\widetilde{D}_{x,t}^{(g)} \sim \mathsf{Pois}\left(E_{x,t}^{(g)}\widetilde{m}_{x,t}^{(g)}\right).$$

Poisson assumption and temperature-attributable deaths

- Poisson assumption for the number deaths not attributable to temperature

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

- Knowing the attributable fraction $\text{AF}_{x,t}^{(g)}$, we also have a Poisson formulation for $D_{x,t}^{(g)}$ as

$$D_{x,t}^{(g)} \sim \text{Pois}\left(E_{x,t}^{(g)} T_{x,t}^{(g)} \widetilde{m}_{x,t}^{(g)}\right),$$

where $T_{x,t}^{(g)} = \left(1 - \text{AF}_{x,t}^{(g)}\right)^{-1}$.

Modeling framework

Poisson assumption and temperature-attributable deaths

- Poisson assumption for the number deaths not attributable to temperature

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

- Knowing the attributable fraction $\text{AF}_{x,t}^{(g)}$, we also have a Poisson formulation for $D_{x,t}^{(g)}$ as

$$D_{x,t}^{(g)} \sim \text{Pois}\left(E_{x,t}^{(g)} T_{x,t}^{(g)} \widetilde{m}_{x,t}^{(g)}\right),$$

  where $T_{x,t}^{(g)} = \left(1 - \text{AF}_{x,t}^{(g)}\right)^{-1}$.

- We consider $\ln\left(E_{x,t}^{(g)} T_{x,t}^{(g)}\right)$ as an offset term.

Poisson assumption and temperature-attributable deaths

- Poisson assumption for the number deaths not attributable to temperature

$$\widetilde{D}_{x,t}^{(g)} \sim \mathsf{Pois}\left(E_{x,t}^{(g)} \widetilde{m}_{x,t}^{(g)}\right).$$

- Knowing the attributable fraction $\mathsf{AF}_{x,t}^{(g)}$, we also have a Poisson formulation for $D_{x,t}^{(g)}$ as

$$D_{x,t}^{(g)} \sim \mathsf{Pois}\left(E_{x,t}^{(g)} T_{x,t}^{(g)} \widetilde{m}_{x,t}^{(g)}\right),$$

where $T_{x,t}^{(g)} = \left(1 - \mathsf{AF}_{x,t}^{(g)}\right)^{-1}$.

- We consider $\ln\left(E_{x,t}^{(g)} T_{x,t}^{(g)}\right)$ as an offset term.
- The model is estimated as a Poisson GLM through maximum likelihood estimation.

Modeling framework

The distributed lag non-linear model (DLNM) model for daily mortality

- We partition the age range $\mathcal{X}$ into $K \in \mathbb{N}^\star$ distinct strata $\mathcal{X}_k = [x_{k-1}, x_k), k \in \{1, \dots, K\}$.

The distributed lag non-linear model (DLNM) model for daily mortality

- We partition the age range $\mathcal{X}$ into $K \in \mathbb{N}^\star$ distinct strata $\mathcal{X}_k = [x_{k-1}, x_k), k \in \{1, \ldots, K\}$.
- For each day $d \in D^\star = \{1, 2, \ldots, 365, (366)\}$ of year t, let $D^{(g)}_{k,t,d}$ be the number of daily deaths aggregated on $\mathcal{X}_k$.

The distributed lag non-linear model (DLNM) model for daily mortality

- We partition the age range $\mathcal{X}$ into $K \in \mathbb{N}^\star$ distinct strata $\mathcal{X}_k = [x_{k-1}, x_k), k \in \{1, \dots, K\}$.
- For each day $d \in D^\star = \{1, 2, \dots, 365, (366)\}$ of year t, let $D^{(g)}_{k,t,d}$ be the number of daily deaths aggregated on $\mathcal{X}_k$.
- We consider a quasi-Poisson regression model with a log-link function

$$\ln(\mathbb{E}[D^{(g)}_{k,t,d}]) = \eta^{(g)}_k + s(\vartheta_{d,t}, L; \boldsymbol{\theta}^{(g)}_k) + z_{d,1}\zeta^{(g)}_{k,1} + \sum_{t \in \mathcal{T}_y} h_t(z_{d,t}; \boldsymbol{\zeta}^{(g)}_{k,t}), \quad k \in \{1, \dots, K\},$$

where:

The distributed lag non-linear model (DLNM) model for daily mortality

- We partition the age range $\mathcal{X}$ into $K \in \mathbb{N}^\star$ distinct strata $\mathcal{X}_k = [x_{k-1}, x_k), k \in \{1, \dots, K\}$.
- For each day $d \in D^\star = \{1, 2, \dots, 365, (366)\}$ of year t, let $D^{(g)}_{k,t,d}$ be the number of daily deaths aggregated on $\mathcal{X}_k$.
- We consider a quasi-Poisson regression model with a log-link function

$$\ln(\mathbb{E}[D^{(g)}_{k,t,d}]) = \eta^{(g)}_k + s(\vartheta_{d,t}, L; \boldsymbol{\theta}^{(g)}_k) + z_{d,1}\zeta^{(g)}_{k,1} + \sum_{t \in \mathcal{T}_y} h_t(z_{d,t}; \boldsymbol{\zeta}^{(g)}_{k,t}), \quad k \in \{1, \dots, K\},$$

where:

- $s(\vartheta_{d,t}, L; \boldsymbol{\theta}^{(g)}_k)$ is a cross-basis non-linear function, capturing the cumulated effect of the daily mean temperature $\vartheta_{d,t}$ over a maximum of L days,

The distributed lag non-linear model (DLNM) model for daily mortality

- We partition the age range $\mathcal{X}$ into $K \in \mathbb{N}^\star$ distinct strata $\mathcal{X}_k = [x_{k-1}, x_k), k \in \{1, \ldots, K\}$.
- For each day $d \in D^\star = \{1, 2, \ldots, 365, (366)\}$ of year t, let $D^{(g)}_{k,t,d}$ be the number of daily deaths aggregated on $\mathcal{X}_k$.
- We consider a quasi-Poisson regression model with a log-link function

$$\ln(\mathbb{E}[D^{(g)}_{k,t,d}]) = \eta^{(g)}_k + s(\vartheta_{d,t}, L; \boldsymbol{\theta}^{(g)}_k) + z_{d,1}\zeta^{(g)}_{k,1} + \sum_{t \in \mathcal{T}_y} h_t(z_{d,t}; \boldsymbol{\zeta}^{(g)}_{k,t}), \quad k \in \{1, \ldots, K\},$$

where:

- $s(\vartheta_{d,t}, L; \boldsymbol{\theta}^{(g)}_k)$ is a cross-basis non-linear function, capturing the cumulated effect of the daily mean temperature $\vartheta_{d,t}$ over a maximum of L days,
- $z_{1,d}$ is the day of the week indicator,

The distributed lag non-linear model (DLNM) model for daily mortality

- We partition the age range $\mathcal{X}$ into $K \in \mathbb{N}^\star$ distinct strata $\mathcal{X}_k = [x_{k-1}, x_k), k \in \{1, \dots, K\}$.
- For each day $d \in D^\star = \{1, 2, \dots, 365, (366)\}$ of year t, let $D^{(g)}_{k,t,d}$ be the number of daily deaths aggregated on $\mathcal{X}_k$.
- We consider a quasi-Poisson regression model with a log-link function

$$\ln(\mathbb{E}[D^{(g)}_{k,t,d}]) = \eta^{(g)}_k + s(\vartheta_{d,t}, L; \boldsymbol{\theta}^{(g)}_k) + z_{d,1}\zeta^{(g)}_{k,1} + \sum_{t \in \mathcal{T}_y} h_t(z_{d,t}; \boldsymbol{\zeta}^{(g)}_{k,t}), \quad k \in \{1, \dots, K\},$$

where:

- $s(\vartheta_{d,t}, L; \boldsymbol{\theta}^{(g)}_k)$ is a cross-basis non-linear function, capturing the cumulated effect of the daily mean temperature $\vartheta_{d,t}$ over a maximum of L days,
- $z_{1,d}$ is the day of the week indicator,
- $h_t(z_{d,t}; \boldsymbol{\zeta}^{(g)}_{k,t})$ are natural cubic B-splines for the day of the year variable to control the residual effect of seasonality.

Calibration

For each stratum $\mathcal{X}_k$, we consider a bi-dimensional spline function $s(\cdot,\cdot)$ as (ignoring k)

$$s(x_d, L; \boldsymbol{\theta}) = \sum_{l=0}^{L} f \cdot w(x_{d-l}, l; \boldsymbol{\theta}) = \boldsymbol{w}_{x,d}^\top \boldsymbol{\theta} = \left(\mathbf{1}_{v_x \cdot v_l}^\top \left(\left(\underbrace{\mathbf{1}_{v_l}^\top \otimes \boldsymbol{R}_{x,d}}_{\text{exposure dimension}}\right) \odot \left(\underbrace{\boldsymbol{C} \otimes \mathbf{1}_{v_x}^\top}_{\text{lag dimension}}\right)\right)\right)\boldsymbol{\theta},$$

where $f \cdot w$ is a cross-basis function, i.e. the bi-dimensional function space obtained by combining two independent sets of basis functions, and $\boldsymbol{\theta}$ a vector of parameters.

- **Hyperparameters:**
  - **exposure-response**: natural cubic B-spline with 3 internal knots (10-75-90th perc. daily avg. temp.)
  - **lag-response**: natural cubic B-spline with an intercept and 3 internal knots.
  - Lag L of 21 days.
- **Model estimation** through MLE (Wood, 2006). The variance-covariance matrix $\mathbb{V}[\boldsymbol{\theta}]$ is estimated through a parametric bootstrap technique (Vicedo-Cabrera et al., 2019).

Main indicators estimated on the calibration period

- The estimated attributable fraction (Gasparrini and Leone, 2014)

$$\widehat{\mathsf{AF}}^{(g)}_{k,t,d} = 1 - \exp\left(-\sum_{l=0}^{L} f \cdot w(\vartheta_{d,t}, l; \widehat{\boldsymbol{\theta}}^{(g)}_k)\right).$$

Main indicators estimated on the calibration period

- The estimated attributable fraction (Gasparrini and Leone, 2014)

$$\widehat{\mathsf{AF}}_{k,t,d}^{(g)} = 1 - \exp\left(- \sum_{l=0}^{L} f \cdot w(\vartheta_{d,t}, l; \widehat{\boldsymbol{\theta}}_k^{(g)}) \right).$$

- The estimated death counts attributable to temperature for each d and aggregated over a subperiod $\mathcal{D}_t \subseteq \mathcal{D}^\star$ for $x \in \mathcal{X}_k$

$$\widehat{\widehat{D}}_{x,t,d}^{(g)} = \widehat{\mathsf{AF}}_{k,t,d}^{(g)} \times \sum_{l=0}^{L} \frac{D_{x,t,d+l}^{(g)}}{L+1}, \quad \widehat{\widehat{D}}_{x,t}^{(g)} = \sum_{d \in \mathcal{D}_t} \widehat{\widehat{D}}_{x,t,d}^{(g)} \mathbb{1}_{\{d \in \mathcal{D}_t\}}$$

Main indicators estimated on the calibration period

- The estimated attributable fraction (Gasparrini and Leone, 2014)

$$\widehat{\mathsf{AF}}_{k,t,d}^{(g)} = 1 - \exp\left(- \sum_{l=0}^{L} f \cdot w(\vartheta_{d,t}, l; \widehat{\boldsymbol{\theta}}_k^{(g)}) \right).$$

- The estimated death counts attributable to temperature for each d and aggregated over a subperiod $\mathcal{D}_t \subseteq \mathcal{D}^\star$ for $x \in \mathcal{X}_k$

$$\widehat{\widehat{D}}_{x,t,d}^{(g)} = \widehat{\mathsf{AF}}_{k,t,d}^{(g)} \times \sum_{l=0}^{L} \frac{D_{x,t,d+l}^{(g)}}{L+1}, \quad \widehat{\widehat{D}}_{x,t}^{(g)} = \sum_{d \in \mathcal{D}_t} \widehat{\widehat{D}}_{x,t,d}^{(g)} \mathbb{1}_{\{d \in \mathcal{D}_t\}}$$

- The estimated total attributable fraction and the temperature adjustment over $\mathcal{D}_t$

$$\widehat{\mathsf{AF}}_{x,t}^{(g)}(\mathcal{D}_t) = \frac{\widehat{\widehat{D}}_{x,t}^{(g)}}{\sum_{d \in \mathcal{D}_t} D_{x,t,d}^{(g)}}, \quad \widehat{T}_{x,t}^{(g)}(\mathcal{D}_t) = \left(1 - \widehat{\mathsf{AF}}_{x,t}^{(g)}(\mathcal{D}_t) \right)^{-1}.$$

Adjusted exposure and death counts data

$$\mathcal{E} = \left\{ E_{x,t}^{(g)} \widehat{T}_{x,t}^{(g)}(\mathcal{D}^\star), x \in \mathcal{X}, t \in \mathcal{T}_y, g \in \mathcal{G} \right\}, \quad \mathcal{C} = \left\{ D_{x,t}^{(g)}, x \in \mathcal{X}, t \in \mathcal{T}_y, g \in \mathcal{G} \right\}.$$

Calibration steps (Li, 2013; Robben et al., 2022)

1. Estimate A_x, B_x, K_t from the Poisson log-likelihood under identifiability constraints

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

where $D_{x,t}^{\mathsf{agg}} = D_{x,t}^{(f)} + D_{x,t}^{(m)}$, $E_{x,t}^{\mathsf{agg}} = E_{x,t}^{(f)} \widehat{T}_{x,t}^{(f)}(\mathcal{D}^\star) + E_{x,t}^{(m)} \widehat{T}_{x,t}^{(m)}(\mathcal{D}^\star)$ and $\widetilde{m}_{x,t}^{\mathsf{agg}} = \exp(A_x + B_x K_t)$.

Adjusted exposure and death counts data

$$\mathcal{E} = \left\{ E_{x,t}^{(g)} \widehat{T}_{x,t}^{(g)}(\mathcal{D}^\star), x \in \mathcal{X}, t \in \mathcal{T}_y, g \in \mathcal{G} \right\}, \quad \mathcal{C} = \left\{ D_{x,t}^{(g)}, x \in \mathcal{X}, t \in \mathcal{T}_y, g \in \mathcal{G} \right\}.$$

Calibration steps (Li, 2013; Robben et al., 2022)

1. Estimate A_x, B_x, K_t from the Poisson log-likelihood under identifiability constraints

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

where $D_{x,t}^{\text{agg}} = D_{x,t}^{(f)} + D_{x,t}^{(m)}$, $E_{x,t}^{\text{agg}} = E_{x,t}^{(f)} \widehat{T}_{x,t}^{(f)}(\mathcal{D}^\star) + E_{x,t}^{(m)} \widehat{T}_{x,t}^{(m)}(\mathcal{D}^\star)$ and $\widetilde{m}_{x,t}^{\text{agg}} = \exp(A_x + B_x K_t)$.

2. Estimate the sex-specific parameters from the Poisson log-likelihood under identifiability constraints

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

Calibration

- Temperature dynamics are exogenous information from climate models.
- Time series model is as follow

$$\boldsymbol{Y}_t = \boldsymbol{\Upsilon} + \boldsymbol{\Phi}\boldsymbol{Y}_{t-1} + \boldsymbol{E}_t,$$

where

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

- The parameters $\boldsymbol{\Upsilon}$, $\boldsymbol{\Phi}$ and $\boldsymbol{\Sigma}$ are estimated through maximum likelihood based on the R-package **MultiMoMo** (Antonio et al., 2022).

Simulation procedure for each year $t \in \mathcal{T}_y^{\text{for}}$

1. Simulate $\widehat{\widetilde{m}}_{x,t}^{(g)}$ based on vector $\boldsymbol{Y}_t$.

Simulation procedure for each year $t \in \mathcal{T}_y^{\text{for}}$

1. Simulate $\widehat{\widetilde{m}}_{x,t}^{(g)}$ based on vector $\boldsymbol{Y}_t$.
2. Select a daily temperature trajectory $(\widehat{\vartheta}_{d,t})$ along a climate scenario.

Simulation procedure for each year $t \in \mathcal{T}_y^{\text{for}}$

1. Simulate $\widehat{\widetilde{m}}_{x,t}^{(g)}$ based on vector $\boldsymbol{Y}_t$.
2. Select a daily temperature trajectory $(\widehat{\vartheta}_{d,t})$ along a climate scenario.
3. Compute the predicted attributable fraction $\widehat{\mathsf{AF}}_{x,d,t}^{(g)}$ for each day d.

Simulation procedure for each year $t \in \mathcal{T}_y^{\text{for}}$

1. Simulate $\widehat{\widetilde{m}}_{x,t}^{(g)}$ based on vector $\boldsymbol{Y}_t$.
2. Select a daily temperature trajectory $(\widehat{\vartheta}_{d,t})$ along a climate scenario.
3. Compute the predicted attributable fraction $\widehat{\text{AF}}_{x,d,t}^{(g)}$ for each day d.
4. Project central mortality rates with temperature effects accumulated over the period $\mathcal{D}_t$

$$\widehat{\widehat{m}}_{x,t}^{(g)} = \widehat{\widetilde{m}}_{x,t}^{(g)} \left[1 + \sum_{d \in \mathcal{D}_t} \omega_{x,t,d}^{(g)} \widehat{\text{AF}}_{x,d,t}^{(g)} \left(1 - \widehat{\text{AF}}_{x,d,t}^{(g)}\right)^{-1} \mathbb{1}_{\{d \in \mathcal{D}_t\}} \right].$$

where $\omega_{x,t,d}^{(g)} = \widetilde{D}_{x,t,d}^{(g)} / \widetilde{D}_{x,t}^{(g)}$, a weight to be chosen, for the distribution of death counts not attributable to temperature.

Case study

Temperature data

- **Calibration period:** $\mathcal{T}_y = \{1980, \ldots, 2019\}$.
- Extract average daily temperatures of 14 cities from the GHCN database (NOAA).
- Compute average daily temperatures for Metropolitan France.

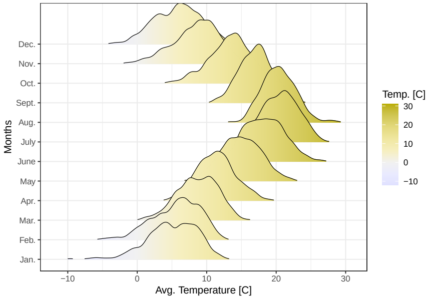


Figure: Distribution of average daily temperatures for each month of the year.

14 stations are located around Bordeaux, Brest, Caen, Clermont-Ferrand, Dijon, Lille, Lyon, Marseille, Nantes, Paris, Perpignan, Strasbourg, Toulouse and Tours.

Annual data from the HMD

- **Calibration period:** $\mathcal{T}_y = \{1980, \ldots, 2019\}$.
- **Age range:** $\mathcal{X} = \{0, \ldots, 105\}$.

Daily data from the Quetelet-Prodego Diffusion network (INSEE, 2020)

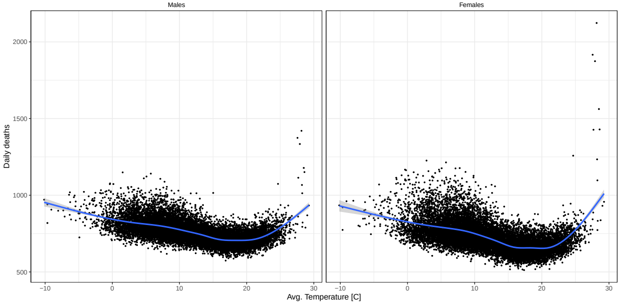
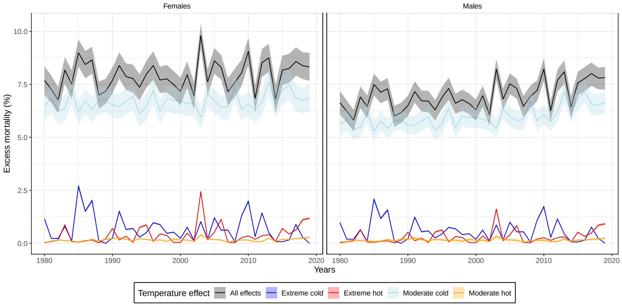


Figure: Representation of the daily death count according to the average daily temperature in France for women and men.

The DLNM estimation on 1980-2019

- $K = 4$ age buckets (0-64, 65-74, 75-84, and 85+) and split by sex.
- Hyperparameters are selected according to the literature.
- Extreme cold and hot: $[0\%, 2.5\%]$ and $[97.5\%, 100\%]$ quantiles.
- Moderate cold and hot: $]2.5\%, \text{MMT}[$ and $]\text{MMT}, 97.5\%[$ quantiles.



Estimation

Temperature-mortality association with the DLNM

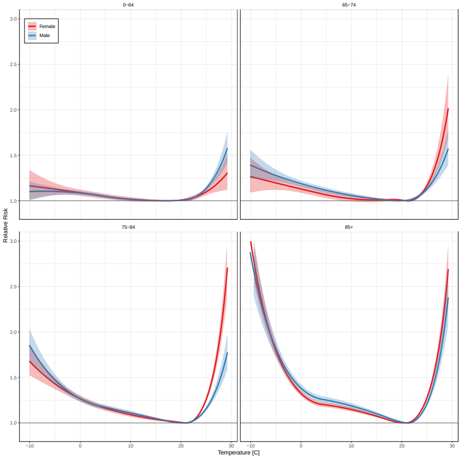


Figure: Cumulative relative risk of mortality over a 21-day period in Metropolitan France calculated for the years 1980-2019 for women (red) and men (blue) (95% CI with 1,000 Monte Carlo simulations)

Estimation

The Li-Lee model

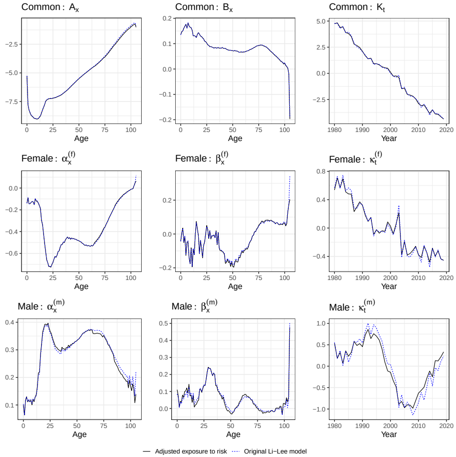


Figure: Estimated parameters $(\widehat{A}_x, \widehat{B}_x, \widehat{K}_t, \widehat{\alpha}_x^{(f)}, \widehat{\beta}_x^{(f)}, \widehat{\kappa}_t^{(f)}, \widehat{\alpha}_x^{(m)}, \widehat{\beta}_x^{(m)}, \widehat{\kappa}_t^{(m)})$ of the Li-Lee model for the calibration period 1980-2019 and ages between 0-105 for the entire population of Metropolitan France (Common), females (Female), and males (Male).

Simulation

- Projection of parameters $\widehat{K}_t$, $\widehat{\kappa}_t^{(f)}$, and $\widehat{\kappa}_t^{(m)}$ over the period 2020-2100.
- For both the original Li-Lee model and the Li-Lee model with ajusted exposure to risk.

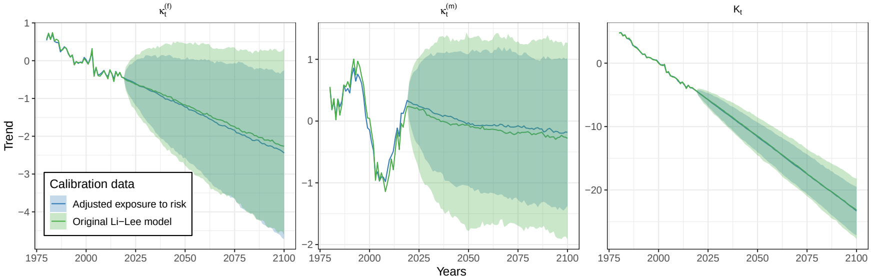


Figure: Projection of trend parameters $\widehat{K}_t$, $\widehat{\kappa}_t^{(f)}$, and $\widehat{\kappa}_t^{(m)}$ over the period 2020-2100 for the Li-Lee models with original exposure to risk and ajusted exposure to risk.

Simulation

- 12 climate models from the DRIAS → uncertainty about future temperatures.
- 3 Representative Concentration Pathway (RCP): RCP2.6, RCP4.5 and RCP8.5.
- 8 km resolution grid (SAFRAN) → 14 cities → average daily temperatures for Metropolitan France.

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

Simulation

Simulating temperatures effects

- Projection for each climate model and RCP scenario.
- Compute $\widehat{\mathrm{AF}}^{(g)}_{x,t}(\mathcal{D}_t)$ and aggregate by age and sex for facilitate visual analysis

$$\widehat{\mathrm{AF}}_t(\mathcal{D}_t) = \sum_{g\in\mathcal{G}}\sum_{x\in\mathcal{X}} \widehat{\mathrm{AF}}^{(g)}_{x,t}(\mathcal{D}_t)\frac{D^{(g)}_{x,2019}}{D_{2019}}, \text{ where } D_{2019} = \sum_{g\in\mathcal{G}}\sum_{x\in\mathcal{X}} D^{(g)}_{x,2019}.$$

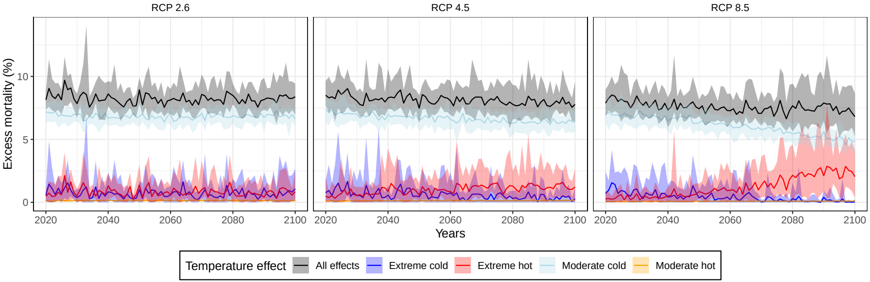


Figure: Temperature attributable fraction in Metropolitan France - Years 2020-2100 for both women and men.

Simulation

Impact of location - Perpignan

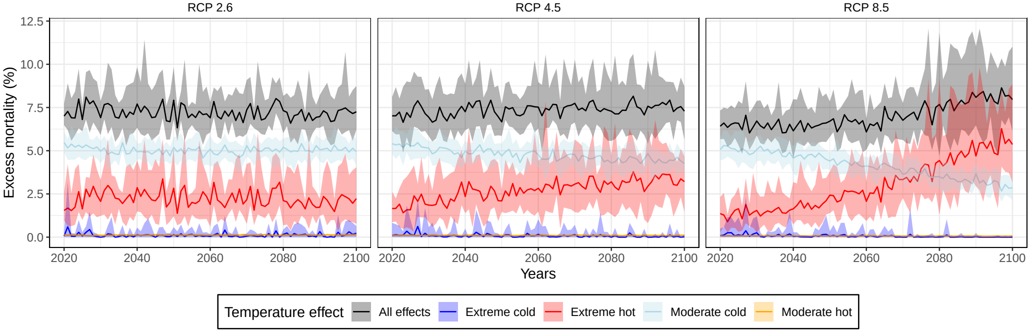


Figure: Temperature attributable fraction in Perpignan, simulated for the years 2020-2100.

- The total mortality rates attributable and non attributable to temperature effects

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

- Life expectancy lost (or gained) due to temperatures for a person of age x at date t due to the temperature effect

$$\Delta\widehat{e}_{x,t}^{(g)} = \sum_{k=1}^{t_{\max}} \left[\prod_{j=0}^{k-1} \left(1 - \widehat{\widetilde{q}}_{x,j}^{(g)}\right) - \prod_{j=0}^{k-1} \left(1 - \widehat{q}_{x,j}^{(g)}\right)\right].$$

Simulation

Life-years lost due to temperature

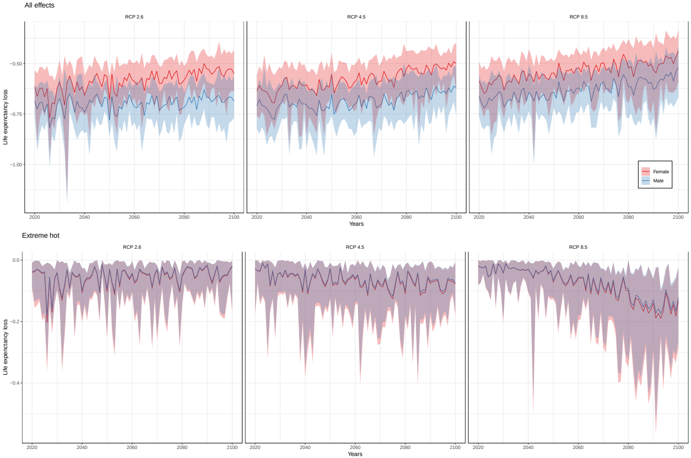


Figure: Life expectancy at birth lost in Metropolitan France, simulated for the years 2020-2100 for both women and men. We present both the loss related to all temperature effects and extreme hot effects only.

Simulation

Life-years lost due to temperature - Perpignan

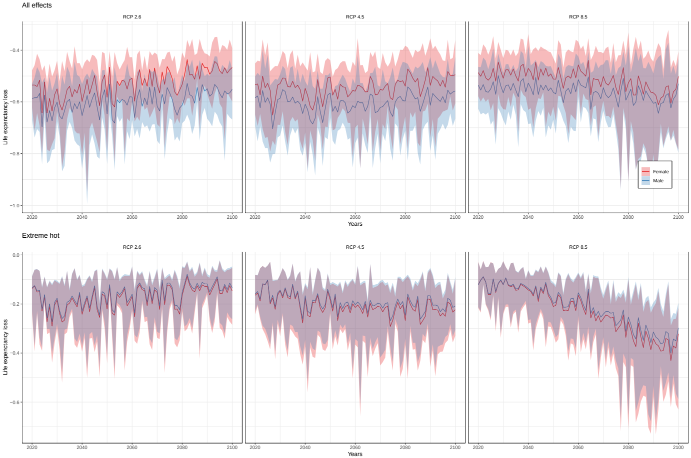


Figure: Life expectancy at birth lost in Perpignan, simulated for the years 2020-2100 for both women and men. We present both the loss related to all temperature effects and extreme hot effects only.

Conclusion

Main results

- A multi-population mortality model incorporating the effect of temperature changes on mortality.
- Assess gains or losses in projected life expectancy related to temperatures.
- Attenuation of the effect of cold temperature in RCP8.5 scenario.
- Increase of the effect of hot temperature in RCP8.5 scenario, especially in southern departments of France from 2050.

Limitations and extensions

- Strong assumption: we assume that populations do not adapt to their local environment:
  - Better (or worse) acclimatization to hot and cold temperatures.
  - House insulation, development of air conditioning, physiological process or immunity.
  - Prevention.
- Integrate other environmental variables (air pollution, the heat index, ...).
- Consider other regions, especially Southern Europe or the MENA region.

Thank you for your attention!

References I

- Antonio, K., Devriendt, S., and Robben, J. (2022). The MultiMoMo package. url: https://github.com/jensrobben/MultiMoMo.
- Barrieu, P., Bensusan, H., El Karoui, N., Hillairet, C., Loisel, S., Ravanelli, C., and Salhi, Y. (2012). Understanding, modelling and managing longevity risk: key issues and main challenges. *Scandinavian Actuarial Journal* 2012.3, pp. 203–231. doi: 10.1080/03461238.2010.511034.
- Beker, B. M., Cervellera, C., Vito, A. D., and Musso, C. G. (2018). Human Physiology in Extreme Heat and Cold. *Int Arch Clin Physiol* 1.1. doi: 10.23937/iacph-2017/1710001.
- Dowd, K., Cairns, A. J. G., and Blake, D. (2020). CBDX: a workhorse mortality model from the Cairns–Blake–Dowd family. *Annals of Actuarial Science* 14.2, pp. 445–460. doi: 10.1017/S1748499520000159.
- Gasparrini, A. (2014). Modeling exposure-lag-response associations with distributed lag non-linear models. *Statistics in Medicine* 33.5, pp. 881–899. doi: 10.1002/sim.5963.
- Gasparrini, A. and Leone, M. (2014). Attributable risk from distributed lag models. *BMC Medical Research Methodology* 14.1, p. 55. doi: 10.1186/1471-2288-14-55.
- Goes, J., Barigou, K., and Leucht, A. (2023). Bayesian mortality modelling with pandemics: a vanishing jump approach. doi: 10.48550/arXiv.2311.04920.

References II

INSEE (2020). État civil - Fichier détail Décès, INSEE (producteur), PROGEDO-ADISP (diffuseur). doi: 10.13144/lil-1605.

IPCC (2023). Key Risks across Sectors and Regions. *Climate Change 2022 – Impacts, Adaptation and Vulnerability: Working Group II Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Ed. by Pörtner, H.-O. et al. Cambridge University Press. doi: 10.1017/9781009325844.025.

Lee, R. D. and Carter, L. R. (1992). Modeling and Forecasting U. S. Mortality. *Journal of the American Statistical Association* 87.419, pp. 659–671. doi: 10.2307/2290201.

Li, J. (2013). A Poisson common factor model for projecting mortality and life expectancy jointly for females and males. *Population Studies* 67.1, pp. 111–126. doi: 10.1080/00324728.2012.689316.

Li, N. and Lee, R. (2005). Coherent mortality forecasts for a group of populations: An extension of the Lee-Carter method. *Demography* 42.3, pp. 575–594. doi: 10.1353/dem.2005.0021.

Liu, Y. and Li, J. S.-H. (2015). The age pattern of transitory mortality jumps and its impact on the pricing of catastrophic mortality bonds. *Insurance: Mathematics and Economics* 64, pp. 135–150. doi: 10.1016/j.insmatheco.2015.05.005.

References III

Martínez-Solanas, E., Quijal-Zamorano, M., Achebak, H., Petrova, D., Robine, J.-M., Herrmann, F. R., Rodó, X., and Ballester, J. (2021). Projections of temperature-attributable mortality in Europe: a time series analysis of 147 contiguous regions in 16 countries. *The Lancet Planetary Health* 5.7, e446–e454. doi: 10.1016/S2542-5196(21)00150-9.

Robben, J. and Antonio, K. (2024). Catastrophe risk in a stochastic multi-population mortality model. *Journal of Risk and Insurance* n/a. doi: 10.1111/jori.12470.

Robben, J., Antonio, K., and Devriendt, S. (2022). Assessing the Impact of the COVID-19 Shock on a Stochastic Multi-Population Mortality Model. *Risks* 10.2, p. 26. doi: 10.3390/risks10020026.

Seklecka, M., Pantelous, A. A., and O'Hare, C. (2017). Mortality effects of temperature changes in the United Kingdom. *Journal of Forecasting* 36.7, pp. 824–841. doi: 10.1002/for.2473.

Vicedo-Cabrera, A. M., Sera, F., and Gasparrini, A. (2019). Hands-on Tutorial on a Modeling Framework for Projections of Climate Change Impacts on Health. *Epidemiology (Cambridge, Mass.)* 30.3, pp. 321–329. doi: 10.1097/EDE.0000000000000982.

Wood, S. N. (2006). Generalized Additive Models: An Introduction with R. 1 edition. Boca Raton, FL: Chapman and Hall/CRC.

References IV

Yin, Q., Wang, J., Ren, Z., Li, J., and Guo, Y. (2019). Mapping the increased minimum mortality temperatures in the context of global climate change. *Nature Communications* 10.1, p. 4640. doi: 10.1038/s41467-019-12663-y.

Background

Temperature-attributable mortality

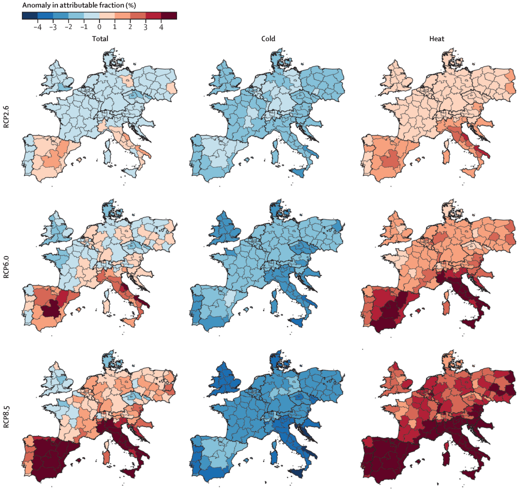


Figure: Attributable fraction anomalies by RCP scenario (2070–2099) (Martínez-Solanas et al., 2021)

Modeling framework

The Liu and Li (2015) model

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

where N_t is a Bernoulli variable and $J_{x,t}$ is the intensity of gaussian mortality jumps.

The Liu and Li (2015) model

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

where N_t is a Bernoulli variable and $J_{x,t}$ is the intensity of gaussian mortality jumps.

Integrating vanishing jump effects (Goes et al., 2023)

Bayesian formulation with gradually vanishing jump effects

$$\begin{aligned}\ln(\widehat{m}_{x,t}) &= \alpha_x + \beta_x \kappa_t + \beta_x^{(J)} J_t + \epsilon_{x,t} \\ J_t &= \alpha J_{t-1} + N_t Y_t,\end{aligned}$$

where Y_t, N_t and κ_t are random variables defined with a prior.

Catastrophe and volatility regime (Robben and Antonio, 2024)

Jumps for the residuals of the mortality improvement rates of population c

$$
\begin{aligned}
z_{x,t}^{(c)} &:= \ln \hat{m}_{x,t}^{(c)} - \ln \hat{m}_{x,t-1}^{(c)} - (\ln \mu_{x,t}^{(c)} - \ln \mu_{x,t-1}^{(c)}) \\
Z_{x,t}^{(c)} &= \beta_x^{(c)} Y_t^{(c)} + \epsilon_{x,t}^{(c)},
\end{aligned}
$$

where Y_t is null or a normal variable depending on the state of a Markov chain.

Specificity of temperature-attributable deaths

- The intensity of shocks is likely to be affected by climate change.
- Observed temperature-related shocks are punctual and generally non-catastrophic.
- They may be offset throughout the year → need to incorporate daily or weekly data.

The DLNM model

The DLNM models the relationship between a time series $(Y_d, d \in \mathcal{T})$ for a set of indices $\mathcal{T}$

$$\rho(\mathbb{E}\left[Y_d\right]) = \eta + \sum_{j=1}^{J} s_j(x_{d,j}, L; \boldsymbol{\theta}_j) + \sum_{m=1}^{M} r_m(u_{d,m}; \boldsymbol{\gamma}_m), + \sum_{p=1}^{P} h_p(z_{d,p}; \boldsymbol{\zeta}_p),$$

- $\rho(\cdot)$ is a monotonic link function, e.g. the log-link function for count data.
- each function $s_j(\cdot, \cdot)$ is a smooth bi-dimensional function that capture delayed effects of past exposures with a lag $L \in \mathbb{N}$ and a bi-dimensional cross basis function $f \cdot w$

$$s(x_d, L; \boldsymbol{\theta}) = \int_0^L f \cdot w(x_{d-l}, l; \boldsymbol{\theta}) dl \approx \sum_{l=0}^{L} f \cdot w(x_{d-l}, l; \boldsymbol{\theta}).$$

- $r_m\left(\cdot\right)$ are smooth univariate functions that capture the effects of confounding variables $\boldsymbol{u}_{d,m}$,
- $h_p(\cdot)$ are smooth univariate functions of categorical time variables that control residual seasonal effects.

Case study

Mortality data

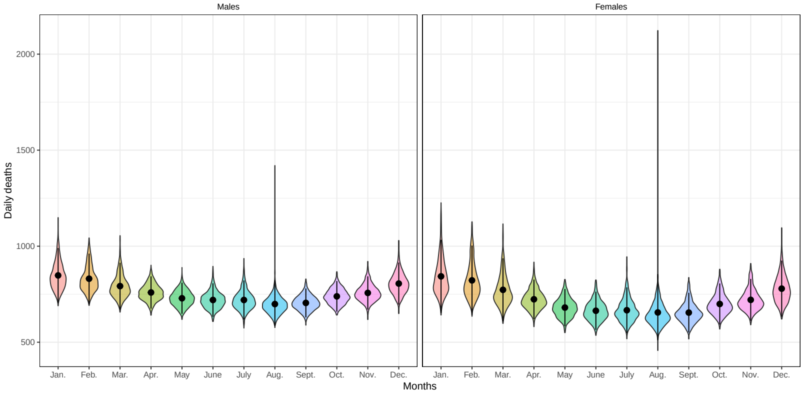


Figure: Probability density of the number of deaths by month of the year

Case study

Climate scenarios

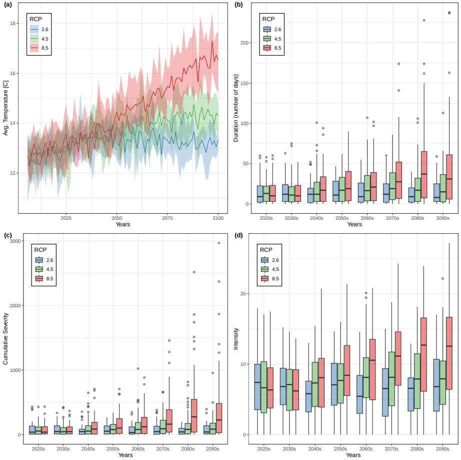


Figure: Projection of temperatures and heatwaves by RCP scenario in Metropolitan France over the period 2020-2100.

Estimation

The Li-Lee model

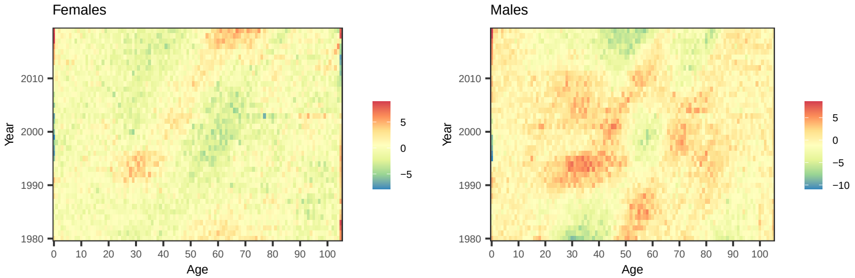


Figure: Pearson residuals of the Li-Lee model for the calibration period 1980-2019 and ages between 0-105 for the female and male populations of Metropolitan France. The model is fitted on temperature-ajusted risk exposures.

Estimation

DLNM model - Goodness of fit for females

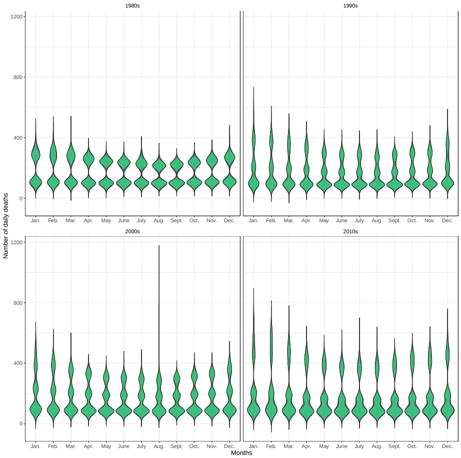


Figure: Monthly distribution of observed (blue) and predicted (green) numbers of deaths based on the DLNM model per year for women in metropolitan France for the years between 1980 and 2019. The distributions are grouped by decade.

DLNM model - Goodness of fit for males

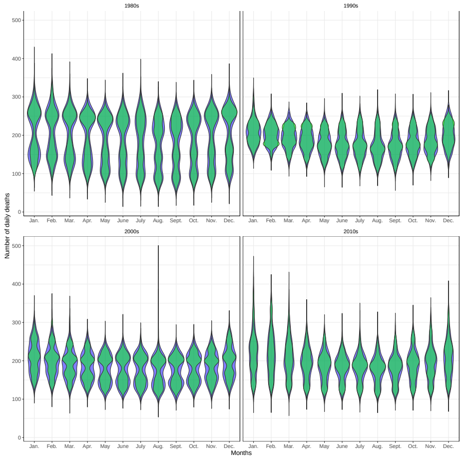


Figure: Monthly distribution of observed (blue) and predicted (green) numbers of deaths based on the DLNM model per year for men in metropolitan France for the years between 1980 and 2019. The distributions are grouped by decade.

Estimation

DLNM model - Goodness of fit

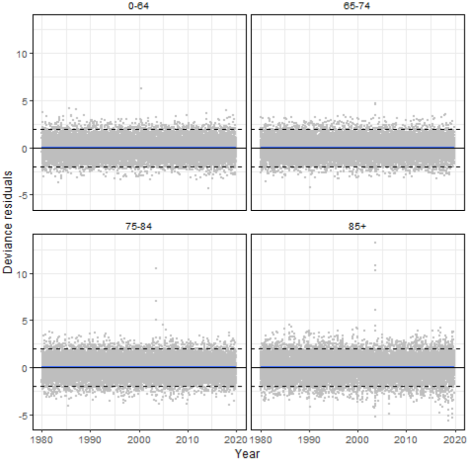


Figure: Representation of deviance residuals for DLNM models associated with age groups 0-64, 65-74, 75-84, and 85+ for women in metropolitan France for the years between 1980 and 2019.

Estimation

DLNM model - Goodness of fit

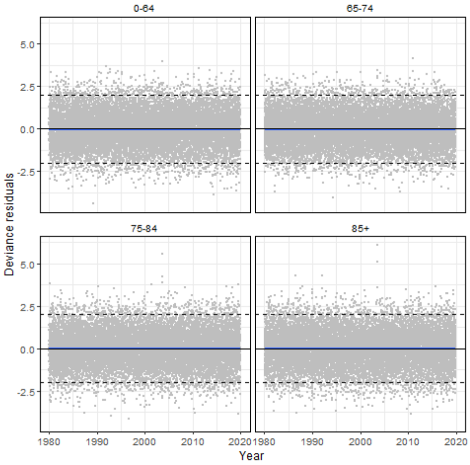


Figure: Representation of deviance residuals for DLNM models associated with age groups 0-64, 65-74, 75-84, and 85+ for men in metropolitan France for the years between 1980 and 2019.

Estimation

Temperature-mortality association with the DLNM for females

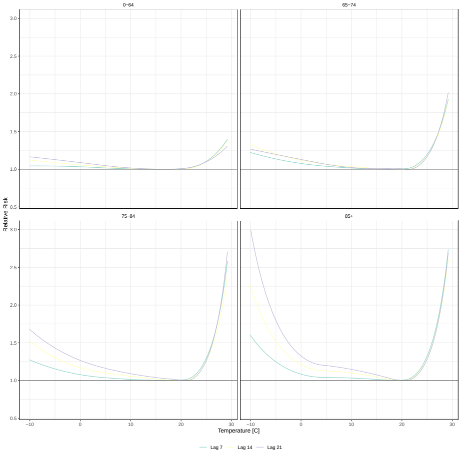


Figure: Cumulative relative risk of mortality over a 7, a 14 or 21-day period in Metropolitan France calculated for the years 1980-2019 for women across age groups 0-64, 65-74, 75-84, and 85+. Daily average temperatures are calculated for each city, and then an average of 14 cities is used to derive the daily average temperatures for Metropolitan France.

Estimation

Temperature-mortality association with the DLNM for males

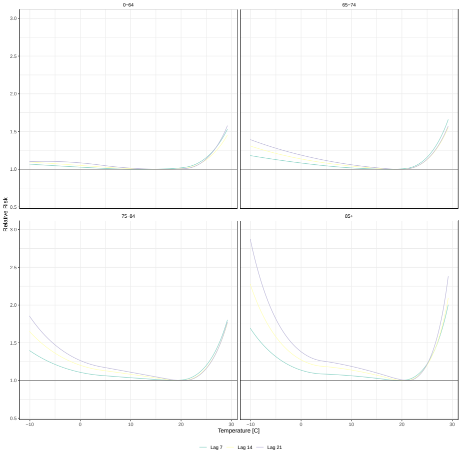


Figure: Cumulative relative risk of mortality over a 7, a 14 or 21-day period in Metropolitan France calculated for the years 1980-2019 for men across age groups 0-64, 65-74, 75-84, and 85+. Daily average temperatures are calculated for each city, and then an average of 14 cities is used to derive the daily average temperatures for Metropolitan France.