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September 23, 2024 - JOCO 2024 - IAALS Session
Brussels (Belgium)

Impacts of 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 → Require daily or weekly mortality data (Gasparrini, 2014; Vicedo-Cabrera et al., 2019).
- Heatwaves ↗ and cold waves ↘ 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.

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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 $\widehat{m}_{x,t}^{(g)} = D_{x,t}^{(g)} / E_{x,t}^{(g)}$.

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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 without and with temperature effects.
- Define the total attributable fraction related to temperatures as $\theta_{x,t}^{(g)} = \bar{D}_{x,t}^{(g)} / D_{x,t}^{(g)}$.

Modeling framework

- Consider the two-populations Li and Lee (2005) model for central deaths rates without temperature effects

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

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

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

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

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

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- **Time series model with coherence assumption**

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

$$\kappa^{(g)}_t = c^{(g)} + \phi^{(g)} \kappa^{(g)}_{t-1} + r^{(g)}_t \rightarrow \text{ AR(1) with drift and } |\phi^{(g)}| < 1.$$

Errors terms are white noises with a mean of zero and a variance-covariance matrix $\mathbf{\Sigma}$.

Poisson assumption and temperature-attributable deaths

- Poisson assumption for the number of virtual deaths

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

Modeling framework

Poisson assumption and temperature-attributable deaths

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

- Knowing the attributable fraction $\theta_{x,t}^{(g)}$, we also have a Poisson formulation with log-link function for the overall number of deaths

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

where $T_{x,t}^{(g)} = (1 - \theta_{x,t}^{(g)})^{-1}$.

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- The mortality-related temperature component $T_{x,t}^{(g)}$ is an offset term.

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- The mortality-related temperature component $T_{x,t}^{(g)}$ is an offset term.
- The model is estimated as a Poisson GLM through maximum likelihood estimation.

Modeling framework

Quasi-Poisson regression model

Let $D^{(g)}_{k,t,d}$ be the number of daily deaths aggregated by K age groups and by sex for each day $d \in D^\star = \{1, 2, \ldots, 365, (366)\}$ of year t. We have

$$\ln(\mathbb{E}[D^{(g)}_{k,t,d}]) = \eta_k + s(\vartheta_{d,t}, L; \boldsymbol{\theta}_k) + \boldsymbol{u}_d \boldsymbol{\gamma}_k^\top + \sum_{p=1}^{P} h_p(z_{d,p}; \boldsymbol{\zeta}_k),$$

where:

- $s(\vartheta_{d,t}; l, \boldsymbol{\theta}_k)$ 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,
- $h_p(z_{d,p}; \boldsymbol{\zeta}_k)$ are natural cubic spline to account for seasonal variations, e.g year, day of the week or month as features.
- Confounding variables $\boldsymbol{u}_d$ can be integrated as a linear effect, e.g. pollutant.

The distributed lag non-linear generalized model (DLNM) is a gold standard in climate epidemiology (Gasparrini et al., 2010; Guo et al., 2014).

Calibration

Main indicators - Estimated on the calibration period

- Daily deaths attributed to temperatures

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

- The total attributed deaths over the period $D \subseteq D^\star$ for a year t

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

- The total attributable fraction

$$\theta^{(g)}_{x,t} = \frac{\bar{D}^{(g)}_{x,t}}{D^{(g)}_{x,t}} \Rightarrow T^{(g)}_{x,t} = (1 - \theta^{(g)}_{x,t})^{-1}.$$

Adjusted exposure and death counts data

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

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

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

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

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

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

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

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

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

Calibration

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

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

where

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

- The parameters $\boldsymbol{D}$, $\boldsymbol{\Phi}$ 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 $\widetilde{m}_{x,t}^{(g)}$ based on vector $\boldsymbol{Y}_t$.

Forecast

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

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

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

1. Simulate $\tilde{m}_{x,t}^{(g)}$ based on vector $\boldsymbol{Y}_t$.
2. Select a daily temperature trajectory $(\vartheta_{d,t})$ along a climate scenario.
3. Compute the daily effect of temperatures

$$\left(\exp\left(s(\vartheta_{d,t}; L, \widehat{\boldsymbol{\theta}}_k)\right) - 1\right).$$

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

1. Simulate $\tilde{m}_{x,t}^{(g)}$ based on vector $\boldsymbol{Y}_t$.
2. Select a daily temperature trajectory $(\vartheta_{d,t})$ along a climate scenario.
3. Compute the daily effect of temperatures

$$\left(\exp\left(s(\vartheta_{d,t}; L, \widehat{\boldsymbol{\theta}}_k)\right) - 1\right).$$

4. Project central mortality rates with temperature effects accumulated over period D

$$\widehat{m}_{x,t}^{(g)} = \tilde{m}_{x,t}^{(g)} \left[1 + \overbrace{\sum_{d \in D} \omega_{x,t,d}^{(g)} \left(\exp\left(s(\vartheta_{d,t}; L, \widehat{\boldsymbol{\theta}}_k)\right) - 1\right) \mathbb{1}_{\{d \in D\}}}^{\theta_{x,t}^{(g)}(D)/(1-\theta_{x,t}^{(g)}(D))} \right],$$

where $w_{x,t,d}^{(g)} = \widetilde{D}_{x,t,d}^{(g)} / \widetilde{D}_{x,t}^{(g)}$, a weight to be chosen, for the distribution of virtual deaths, e.g. $w_{x,t,d}^{(g)} = 1/D^\star$.

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.

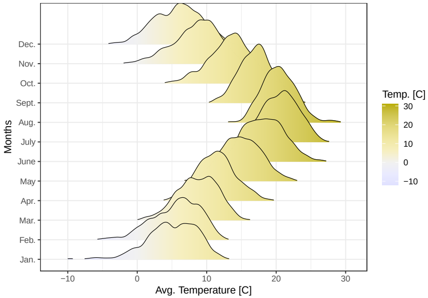


Figure: Distribution of average daily temperatures for each month of the year.

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)

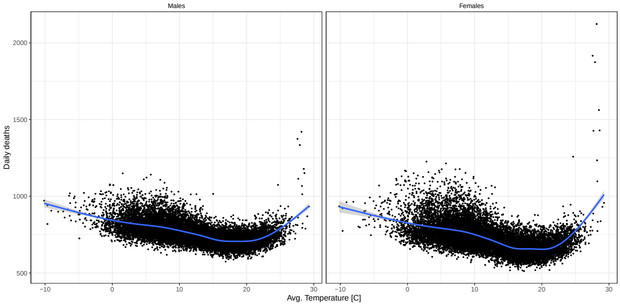


Figure: Representation of the daily death count according to the average daily temperature in France for women and men.

Estimation

Temperature-mortality association with the DLNM

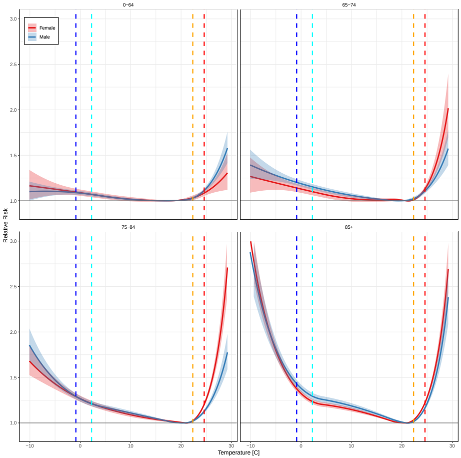
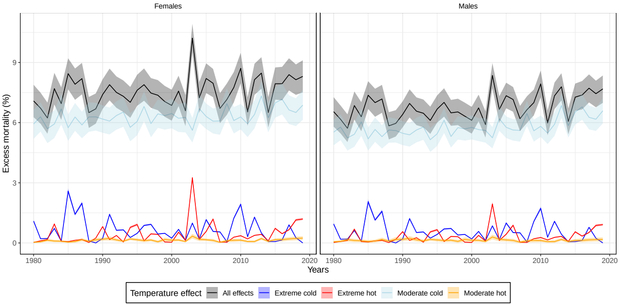


Figure: Cumulative relative risk of mortality over a 21-day period in Metropolitan France calculated for the years 1980-2019 for women (red) and men (blue) (95% CI with 1,000 Monte Carlo simulations)

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

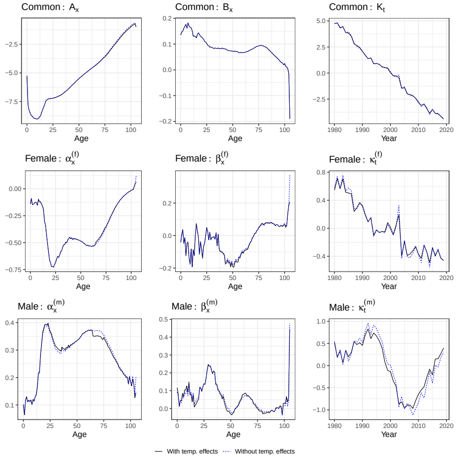


Figure: Estimated parameters $(\widehat{A}_x, \widehat{B}_x, \widehat{K}_t, \widehat{\alpha}_x^{(f)}, \widehat{\beta}_x^{(f)}, \widehat{\kappa}_t^{(f)}, \widehat{\alpha}_x^{(m)}, \widehat{\beta}_x^{(m)}, \widehat{\kappa}_t^{(m)})$ of the Li-Lee model for the calibration period 1980-2019 and ages between 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 models with and without temperature effects.

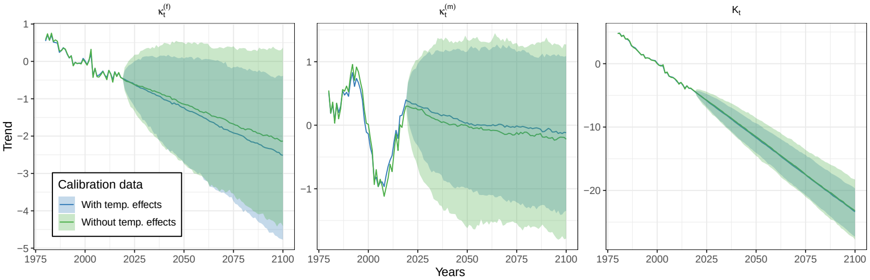


Figure: Projection of trend parameters $\widehat{K}_t$, $\widehat{\kappa}_t^{(f)}$, and $\widehat{\kappa}_t^{(m)}$ over the period 2020-2100 for the Li-Lee model for observed central death rates (with temperature effects) and central virtual death rates (without temperature effects).

- 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 $\theta^{(g)}_{x,t}(D)$ and aggregate by age and sex for facilitate visual analysis

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

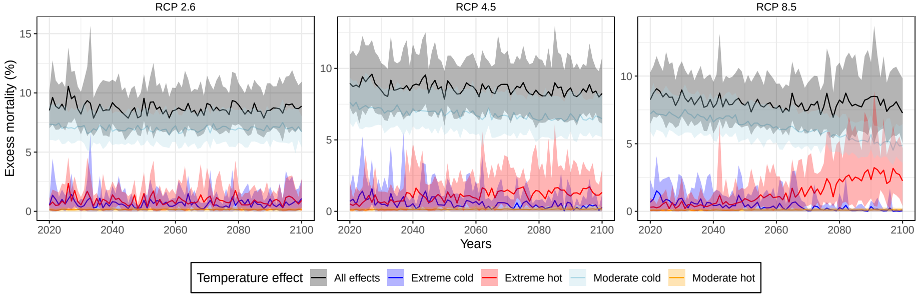


Figure: Temperature attributable fraction in Metropolitan France - Years 2020-2100 for both women and men.

Simulation

Impact of location - Perpignan

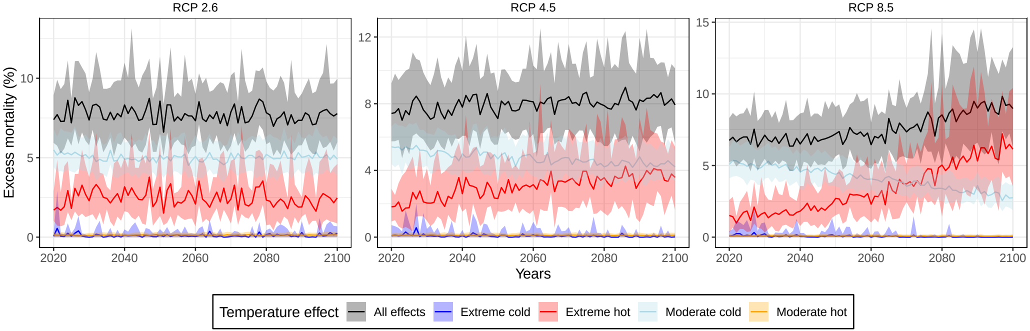


Figure: Temperature attributable fraction in Perpignan, simulated for the years 2020-2100.

Simulation

- The total mortality rates with and without temperature effects

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

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

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

Simulation

Life-years lost due to temperature

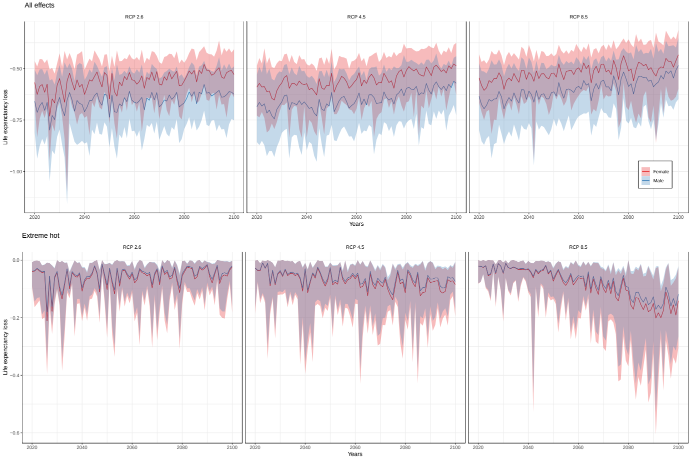


Figure: Life expectancy at birth lost in Metropolitan France, simulated for the years 2020-2100 for both women and men. We present both the loss related to all temperature effects and extreme hot effects only.

Simulation

Life-years lost due to temperature - Perpignan

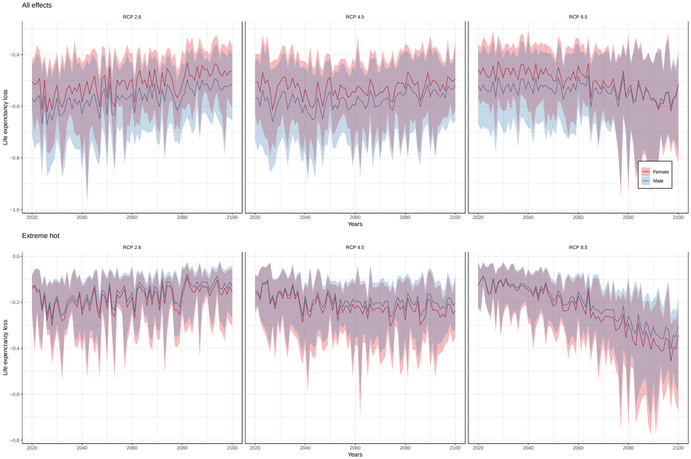


Figure: Life expectancy at birth lost in Perpignan, simulated for the years 2020-2100 for both women and men. We present both the loss related to all temperature effects and extreme hot effects only.

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!

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Background

Temperature-attributable mortality

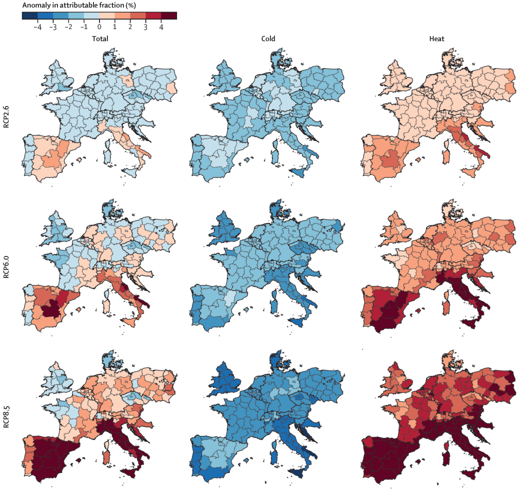

Figure: Attributable fraction anomalies by RCP scenario (2070–2099) (Martínez-Solanas et al., 2021)

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

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

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

Modeling framework

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.

Calibration

We consider a bi-dimensional spline function s as the surface of Relative Risk

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

where $f \cdot w$ is a bi-dimensional integrable function, and $\boldsymbol{\theta}_k$ a vector of parameters.

- **Specification:**
  - Cubic spline with internal knots placed at the 10th, 75th, and 90th percentiles of the daily temperature distribution.
  - Lag L of 21 days.
- **Estimation error:** the variance-covariance matrix $\mathbb{V}[\boldsymbol{\theta}_k]$ is estimated through a parametric bootstrap technique (Vicedo-Cabrera et al., 2019).

Case study

Mortality data

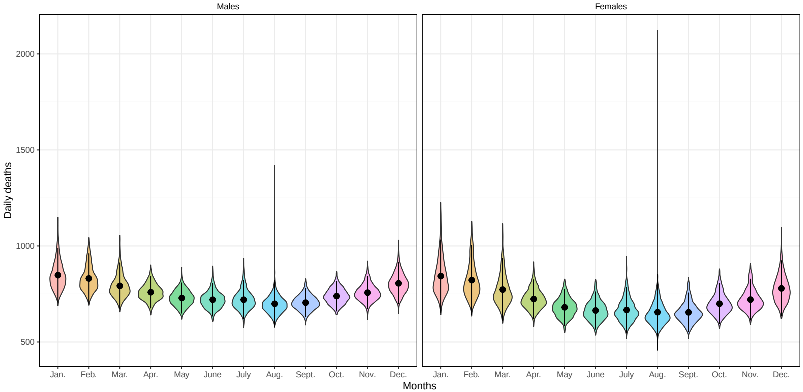

Figure: Probability density of the number of deaths by month of the year

Case study

Climate scenarios

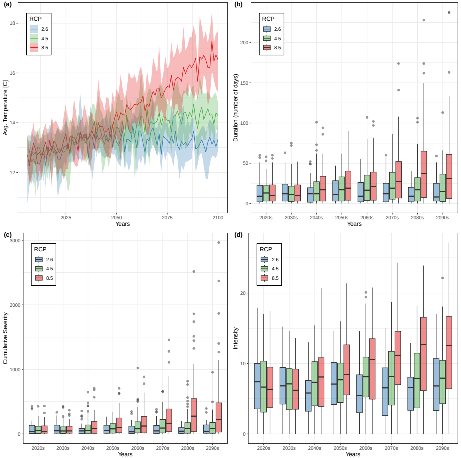

Figure: Projection of temperatures and heatwaves by RCP scenario in Metropolitan France over the period 2020-2100.

Estimation

The Li-Lee model

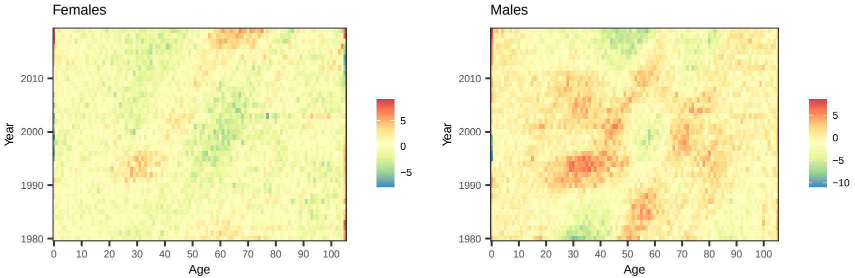

Figure: Pearson residuals of the Li-Lee model for the calibration period 1980-2019 and ages between 0-105 for the female and male populations of Metropolitan France. The model is fitted on temperature-ajusted risk exposures.

Estimation

DLNM model - Goodness of fit

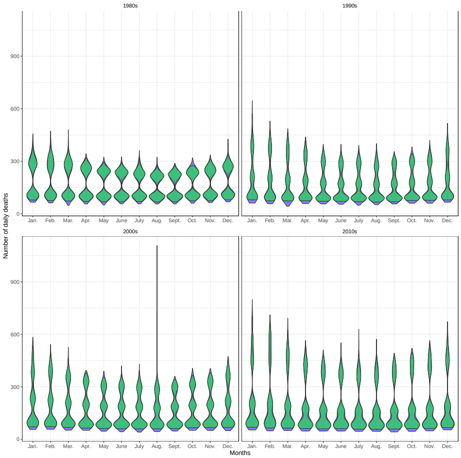

Figure: Monthly distribution of observed (blue) and predicted (green) numbers of deaths based on the DLNM model per year for women in metropolitan France for the years between 1980 and 2019. The distributions are grouped by decade.

Estimation

DLNM model - Goodness of fit

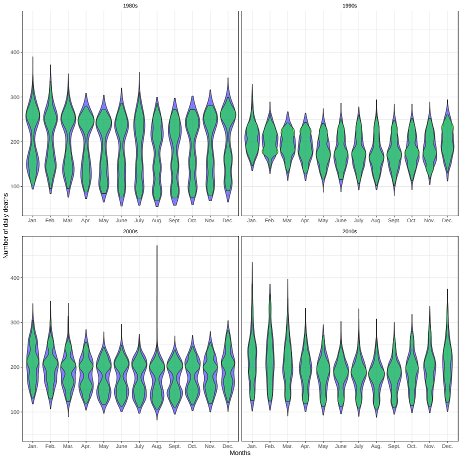

Figure: Monthly distribution of observed (blue) and predicted (green) numbers of deaths based on the DLNM model per year for men in metropolitan France for the years between 1980 and 2019. The distributions are grouped by decade.

Estimation

DLNM model - Goodness of fit

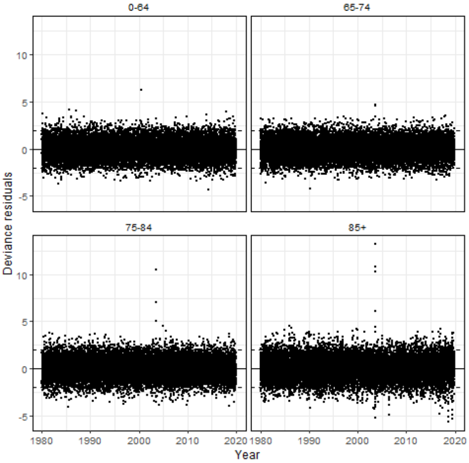

Figure: Representation of deviance residuals for DLNM models associated with age groups 0-64, 65-74, 75-84, and 85+ for women in metropolitan France for the years between 1980 and 2019.

Estimation

DLNM model - Goodness of fit

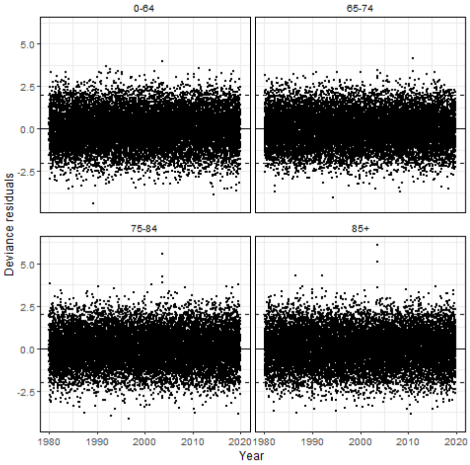

Figure: Representation of deviance residuals for DLNM models associated with age groups 0-64, 65-74, 75-84, and 85+ for men in metropolitan France for the years between 1980 and 2019.

Estimation

Temperature-mortality association with the DLNM

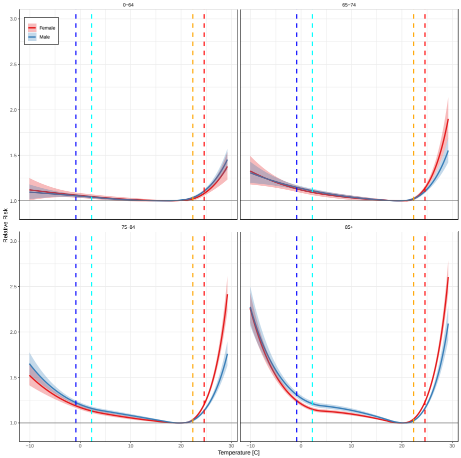

Figure: Cumulative relative risk of mortality over a 14-day period in Metropolitan France calculated for the years 1980-2019 for women (red) and men (blue) (95% CI with 1,000 Monte Carlo simulations)