Assessing Climate-Driven Mortality Risk: A Stochastic Approach with Distributed Lag Non-Linear Models

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Motivation

- **Climate-driven mortality risks** have emerged as a growing concern in recent years.
- **Challenges** of quantifying and projecting climate-driven mortality risks:
  - Unable to capture short-term and long-term mortality effects simultaneously.
  - Mismatched frequency between climate data and mortality data.
- Our main objective:
  - Incorporating **climate variables and indices** into stochastic mortality models.
  - Proposing a new mortality model within **one-step approach** that captures **long-term** trends and **short-term** climate effects simultaneously.
  - Projecting mortality rates under different **representative concentration pathway (RCP) scenarios**.

Outline

Relevant Literature: Environmental and Epidemiological Research

- The mortality impact of various climate factors have been extensively studied:
  - Temperature (Armstrong, 2006).
  - Air pollution (Dominici et al., 2002).
  - Relative humidity (Armstrong et al., 2019).
  - Heat waves (Gasparrini and Armstrong, 2011).
- Distributed Lag Non-Linear Model (DLNM) (Gasparrini et al., 2010) are proposed to capture **non-linear** temperature effects on mortality rates.
  - DLNM does not allow for uncertainty in long-term mortality trends.

Relevant Literature: Actuarial Research

- Seklecka et al. (2017, 2019): Integrate annual Pearson's correlation between temperature and mortality into Lee–Carter model extension.
  - Fail to capture short-term and non-linear temperature effects.
- Li and Tang (2022): Apply peaks-over-threshold approach to model monthly death counts and extreme temperatures.
  - Lack the ability to **project** future mortality scenarios.
- Guibert et al. (2024): Introduce a two-stage approach to integrate DLNM into the Li and Lee (2005) model with projections under different RCP scenarios.
  - **Separation** of temperature effects and non-temperature effects is not guaranteed.
  - Annual mortality projection do not provide short-term effects on mortality rates.
- To address these issues, we propose a novel approach to incorporate climate-driven effects by DLNM into both single- and multi-population stochastic mortality models, which are called DLNM-LC and DLNM-LL model, respectively.

Research Questions

- How can climate variables and indices be incorporated as measures of climate-related risks?
- How can **mixed-frequency** climate-related risk factors and mortality rates be integrated into a mortality model by **one-step approach**?
- How to **quantify** the climate-driven mortality risks under **actuarial perspective**?
- What will mortality rates look like under different climate scenarios **in the future**?

Data: Mortality Data

- **Mortality data**: Weekly death counts $D(x,t,i)$ and annual population data $P(x,t,i)$ from Eurostat[1] over the period 2015–2019, for for age groups 20–64, 65–74, 75–84 and 85+ in three different NUTS regions: Attica (EL30, referred to as **Athens**[2]), Área Metropolitana de Lisboa (PT170, referred to as **Lisbon**), and Roma (ITI43, refer to as **Rome**). Assuming that weekly risk exposure remains constant over all 52 weeks of each year. The weekly mortality rate is:

$$m(x,t,i) = \frac{D(x,t,i)}{E(x,t,i)} := \frac{D(x,t,i)}{P(x,t,i)/52}. \tag{1}$$

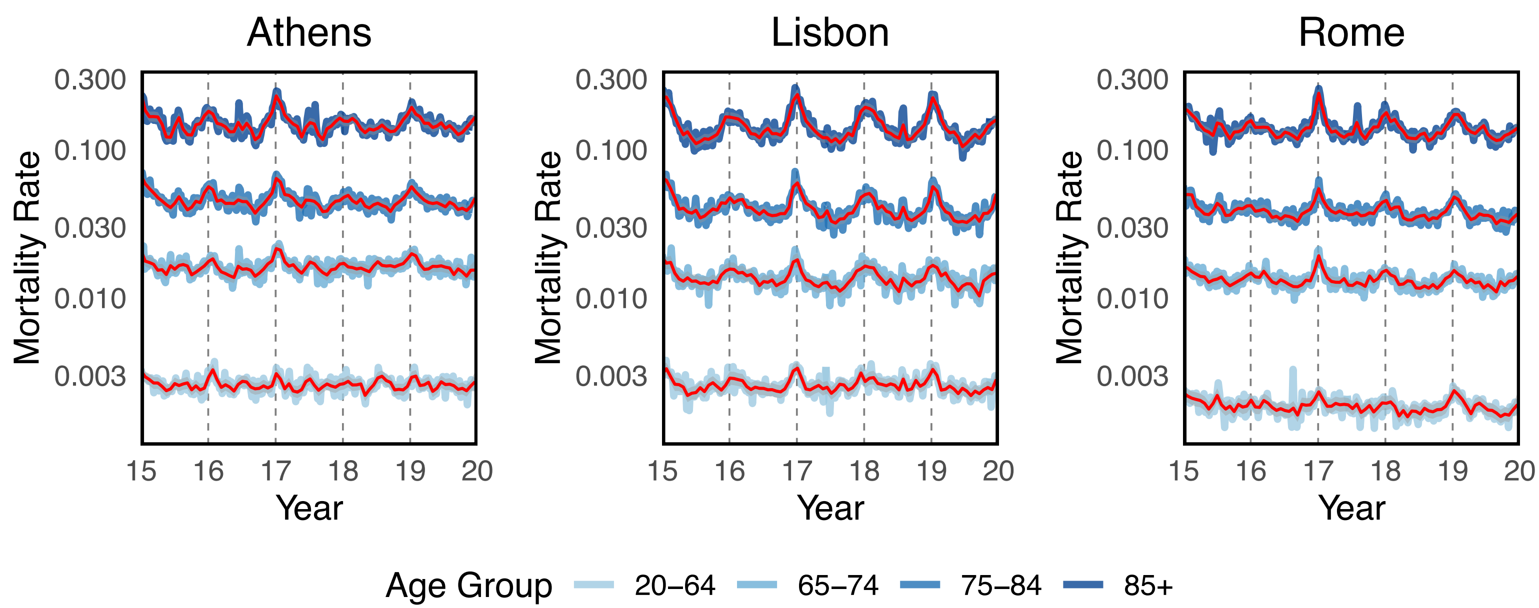


Figure 1: Historical weekly mortality rates (2015–2019).

[1] Data source: ec.europa.eu/eurostat/databrowser/view/demo_r_mweek3/default/table?lang=en.

[2] As the population of Attica is largely concentrated in Athens, we referred to the region simply as Athens.

Data: Climate index

- Several climate variables have been shown to significantly affect mortality rates.
  - Temperature variables and their lags (Robben et al., 2025) are **the most significant** variables related to climate-mortality risks.
  - Temperature, air pollutants, wind speed, radiation and humidity variables also have **joint effects** on mortality rates.
  - Extreme weather indicators can be considered.
  - The **time series features** of climate variables can be extracted.
- **Significant** climate variables and time series features can be **combined into a climate index** using either **statistical modeling** or **expert's opinion**.
- By expert's opinion, the Universal Thermal Climate Index (UTCI), which is a combinations of several climate variables, is utilized in the remainder of our paper.

Data: UTCI Data

The UTCI is defined as the **air temperature** (°C) under standard reference conditions that would elicit the same physiological response[3] as the actual conditions, depending on air temperature, **wind speed**, **humidity**, and **radiation** (Błażejczyk et al., 2013).

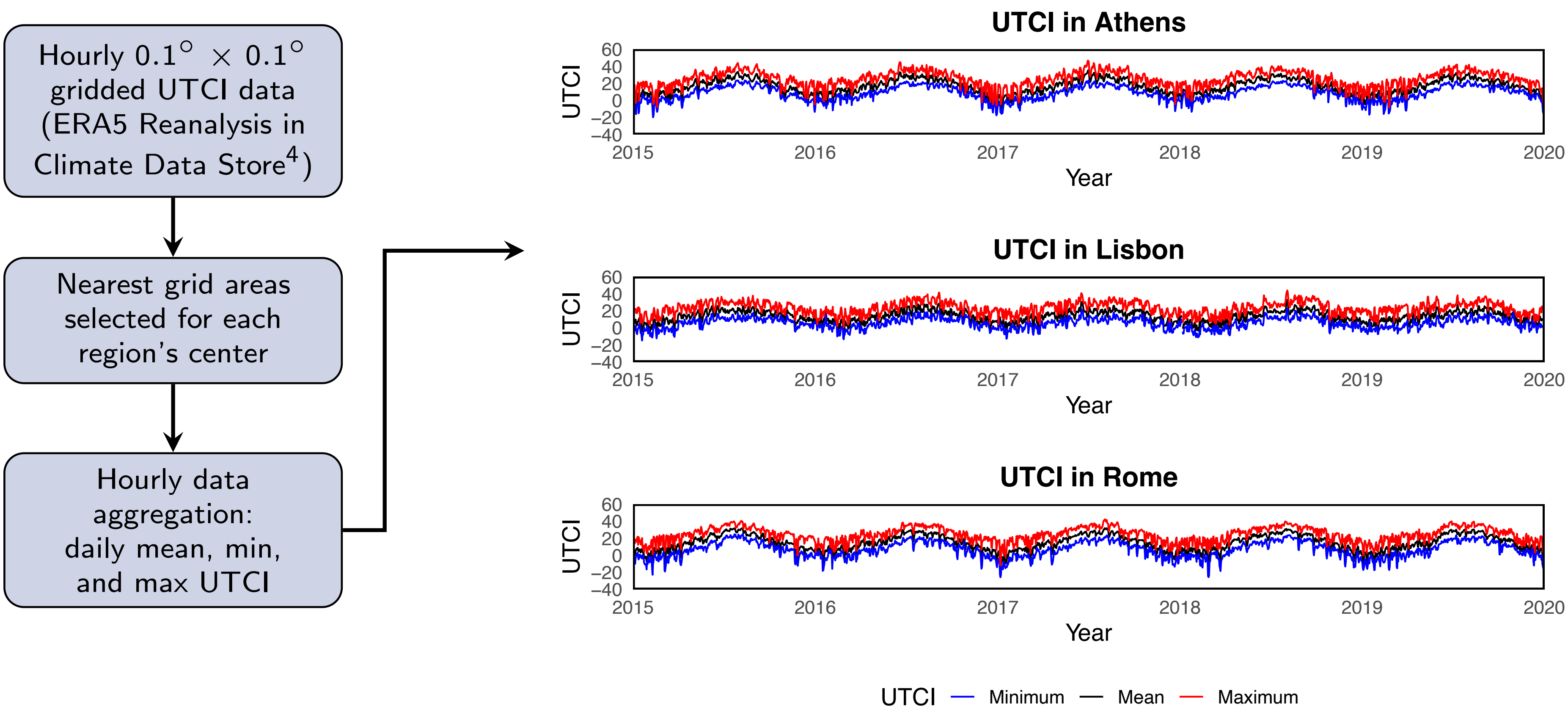


Figure 2: Data processing of historical daily UTCI (2015–2019).

[3] Examples of physiological responses include sweat production, shivering, skin wetness, skin blood flow, and mean skin and face temperatures.

[4] Data source: `cds.climate.copernicus.eu/datasets/reanalysis-era5-single-levels?tab=download`.

Data: Heat Wave Days and Cold Wave Days

- **The number of heat wave days** (HWD_t) and **cold wave days** (CWD_t) in week t are introduced to capture short-term mortality fluctuation due to extreme temperatures.
- We define heat and cold stress, expressed by a step function $g(U_\tau^j)$:

$$g(U_\tau^j) = \begin{cases} -1, & U_\tau^j < -13 \text{ (Significant cold stress)} \\ 0, & -13 \leq U_\tau^j \leq 32 \text{ (No significant thermal stress)} \\ 1, & U_\tau^j > 32 \text{ (Significant heat stress)} \end{cases}, \tag{2}$$

  - U_τ^{min}: Daily minimum UTCI on day τ.
  - U_τ^{max}: Daily maximum UTCI on day τ.
- We define the heatwave and coldwave indicator:

$$h_\tau = \mathbb{1}\{g(U_\tau^{\text{max}}) = 1\} \times \mathbb{1}\{g(U_\tau^{\text{max}}) = 1\} \times \mathbb{1}\{g(U_{\tau-2}^{\text{max}}) = 1\}, \tag{3}$$

$$c_\tau = \mathbb{1}\{g(U_\tau^{\text{min}}) = -1\} \times \mathbb{1}\{g(U_{\tau-1}^{\text{min}}) = -1\} \times \mathbb{1}\{g(U_{\tau-2}^{\text{min}}) = -1\}. \tag{4}$$

- The number of heatwave days and coldwave days in week t are defined as

$$\mathrm{HWD}_t = \sum_{\tau=1+7(t-1)}^{7t} h_\tau, \ \mathrm{CWD}_t = \sum_{\tau=1+7(t-1)}^{7t} c_\tau, \tag{5}$$

for $t = 1, \ldots, T$ where $\mathrm{HWD}_t, \mathrm{CWD}_t \in [0, 7]$.

Methodology: Mixed-Frequency DLNM

Following Gasparrini et al. (2010), we modify the **log link quasi-Poisson regression** as a mixed-frequency DLNM where mortality data has a lower frequency of week t and climate data has a higher frequency of day τ:

$$\log \mathbb{E}\left[y(t)\right] = \beta_0 + \sum_{\ell=0}^{L} s(X_{\tau_t-\ell}, \ell; \boldsymbol{\nu}, \boldsymbol{\eta}) + \boldsymbol{z}_t' \boldsymbol{\beta}, \qquad (6)$$

- $y(t)$: the response variable (*e.g.*, the number of death in week t).
- $X_{\tau_t-\ell}$: the exposure (*e.g.*, temperature) at the lag ℓ of reference day τ_t[5] for week t.
- $s(X_{\tau_t-\ell}, \ell; \boldsymbol{\nu}, \boldsymbol{\eta})$: 2-dimensional cross-basis smoothing function (*e.g.*, natural spline or B-spline) with degrees of freedom $\boldsymbol{\nu} = (\nu_1, \nu_2)$ and coefficients $\boldsymbol{\eta} \in \mathbb{R}^{\nu_1\nu_2}$.
- $\boldsymbol{z}_t'\boldsymbol{\beta}$: the effect of covariates $\boldsymbol{z}_t$ with the corresponding coefficients $\boldsymbol{\beta}$.

We represent the cross-basis function using the **mixed-frequency time-lag matrix**:

$$\begin{array}{c c}
 & \begin{array}{cccc} \text{Lag } 0 & \text{Lag } 1 & \cdots & \text{Lag } L \end{array} \\
\begin{array}{c} t=1 \\ t=2 \\ \vdots \\ t=N \end{array} & \begin{pmatrix} 7 & 6 & \cdots & 7-L \\ 14 & 13 & \cdots & 14-L \\ \vdots & \vdots & \ddots & \vdots \\ \tau_N & \tau_N - 1 & \cdots & \tau_N - L \end{pmatrix}.
\end{array}$$

$$\tau_t - \ell$$

[5] We set the reference day for each week to be the last day of that week.

Methodology: Li–Lee Model

The Li–Lee model (Li and Lee, 2005) is defined as follows:

$$\log m(x,t,i) = A(x,i) + B(x)K(t) + b(x,i)\kappa(t,i) + \epsilon(x,t,i), \tag{7}$$

with constraints

$$\sum_{x=1}^{N} B^2(x) = 1,\ \sum_{t=1}^{T} K(t) = 0,\ \sum_{x=1}^{N} b^2(x,i) = 1 \text{ and } \sum_{t=1}^{T} \kappa(t,i) = 0, \text{ for } i = 1,\dots,n.$$

- $A(x,i)$: the age-specific mean for region i.
- $K(t)$: the common time trend of mortality rates.
- $B(x)$: the age-specific loading associated with $K(t)$.
- $\kappa(t,i)$: the region-specific mortality trend for region i.
- $b(x,i)$; the age-specific loading associated with $\kappa(t,i)$ for region i.
- $\epsilon(x,t,i)$: the error term for region i.
- To estimate, the **product-ratio method** (Hyndman et al., 2013) is applied.
- The estimated parameter set of Li–Lee model is $\boldsymbol{\Theta}_{\text{LL}} := \{\hat{\boldsymbol{A}}, \hat{\boldsymbol{B}}, \hat{\boldsymbol{K}}, \hat{\boldsymbol{b}}, \hat{\boldsymbol{\kappa}}\}$.

Methodology: DLNM-LL Model

Under the multi-population setting, we propose DLNM-LL model. The model is specified:

$$\log m(x,t,i) = \underbrace{A(x,i) + B(x)K(t) + b(x,i)\kappa(t,i)}_{\textbf{Li–Lee component}} + \underbrace{\mathcal{S}_{x,i}\left(U_{\tau_{t,i}}, \ldots, U_{\tau_{t-L,i}}, \mathrm{HWD}_{t,i}, \mathrm{CWD}_{t,i}\right)}_{\textbf{DLNM component}} + \epsilon(x,t,i), \tag{8}$$

- We propose a **backfitting approach** to **jointly** estimate DLNM-LL model.
- The integrated DLNM component **isolates** and **quantifies** the climate-driven mortality risks for each region and age group.
- In Algorithm 1, we set maximum number of iterations $J = 20$ and convergence tolerance $\delta = 10^{-2}$.
- Based on Algorithm 1, the fitted log mortality rates in r^{th} recursion for age group x in time t:

$$\log \hat{M}(x,t,i) = \hat{A}^{(r)}(x,i) + \hat{B}^{(r)}(x)\hat{K}^{(r)}(t) + \hat{b}^{(r)}(x,i)\hat{\kappa}^{(r)}(t,i) + \sum_{j=0}^{r-1} \mathcal{S}_{x,i}^{(j)}\left(U_{\tau_{t,i}}, \ldots, U_{\tau_{t,i-L}}, \mathrm{HWD}_{t,i}, \mathrm{CWD}_{t,i}\right). \tag{9}$$

Algorithm 1: Backfitting DLNM–LL

Input: An $N \times T \times n$ mortality tensor $\boldsymbol{M} = [\boldsymbol{m}(x, t, 1), \ldots, \boldsymbol{m}(x, t, n)]$
Output: $\hat{\boldsymbol{A}}^{(r)}$, $\hat{\boldsymbol{B}}^{(r)}$, $\hat{\boldsymbol{K}}^{(r)}$, $\hat{\boldsymbol{b}}^{(r)}$, $\hat{\boldsymbol{\kappa}}^{(r)}$, and $\hat{\boldsymbol{M}}^{(r)}$, $r \in [1, J]$
Procedure: DLNM–LL($\boldsymbol{M}$)
$\hat{\boldsymbol{M}}^{(0)} \leftarrow \boldsymbol{M}$
$j \leftarrow 0$
while $j \leq J$ **do**
  $\hat{\boldsymbol{A}}^{(j)}, \hat{\boldsymbol{B}}^{(j)}, \hat{\boldsymbol{K}}^{(j)}, \hat{\boldsymbol{b}}^{(j)}, \hat{\boldsymbol{\kappa}}^{(j)} \leftarrow LL(\hat{\boldsymbol{M}}^{(j)})$
  $\boldsymbol{e}_i^{(j)} \leftarrow \log \hat{\boldsymbol{m}}^{(j)}(x, t, i) - \hat{\boldsymbol{A}}^{(j)}(x, i), \ \forall i$
  Decompose $\hat{\boldsymbol{e}}_i^{(j)} = \left[\hat{\boldsymbol{e}}_{1,i}^{(j)}, \ldots, \hat{\boldsymbol{e}}_{N,i}^{(j)}\right]$ by age group x
  Fit $\hat{\boldsymbol{e}}_{x,i}^{(j)} = \mathcal{S}_{x,i}^{(j)}\left(U_{\tau_{t,i}}, \ldots, U_{\tau_{t,i}-L}, \mathrm{HWD}_{t,i}, \mathrm{CWD}_{t,i}\right), \ \forall x, i$
  $\hat{\boldsymbol{e}}^{(j)} \leftarrow \left[\hat{\boldsymbol{e}}_{1,i}^{(j)}, \ldots, \hat{\boldsymbol{e}}_{N,i}^{(j)}\right]$
  $\log(\hat{\boldsymbol{M}}^{(j+1)}) \leftarrow \log(\hat{\boldsymbol{M}}^{(j)}) - \hat{\boldsymbol{e}}^{(j)}$
  if $j = J$ **or** ($j > 0$ **and** $\sup_{\boldsymbol{\theta} \in \boldsymbol{\Theta}_{LL}} \|\boldsymbol{\theta}^{(j)} - \boldsymbol{\theta}^{(j-1)}\|_\infty < \delta$) **then**
    $r \leftarrow j$
    break
  else
    $j \leftarrow j + 1$

Methodology: Quantification of Climate-Driven Mortality Risks

- We denote $\tilde{m}$ as the **estimated stochastic mortality component**:

$$\log \tilde{m}(x,t,i) = \log \hat{m}(x,t,i) - \sum_{j=0}^{r-1} \mathcal{S}_{x,i}^{(j)} \left(U_{\tau_{t,i}}, \ldots, U_{\tau_{t,i}-L}, \mathrm{HWD}_{t,i}, \mathrm{CWD}_{t,i} \right), \quad (10)$$

- **The ratio of the stochastic mortality component to total mortality**:

$$\frac{\hat{m}(x,t,i)}{\tilde{m}(x,t,i)} = \exp\left(\sum_{j=0}^{r-1} \mathcal{S}_{x,i}^{(j)} \left(U_{\tau_{t,i}}, \ldots, U_{\tau_{t,i}-L}, \mathrm{HWD}_{t,i}, \mathrm{CWD}_{t,i} \right) \right). \quad (11)$$

- **The climate loading** θ is defined as:

$$\theta(x,t,i) = 1 - \frac{\tilde{m}(x,t,i)}{\hat{m}(x,t,i)} = \frac{\hat{m}(x,t,i) - \tilde{m}(x,t,i)}{\hat{m}(x,t,i)}. \quad (12)$$

  - θ: **The proportion of climate-driven mortality relative to the total mortality.**
  - $\frac{1}{1-\theta}$: **Climate-related risk adjustment factor** applied to $\tilde{m}$.

Empirical Results: Stochastic mortality components

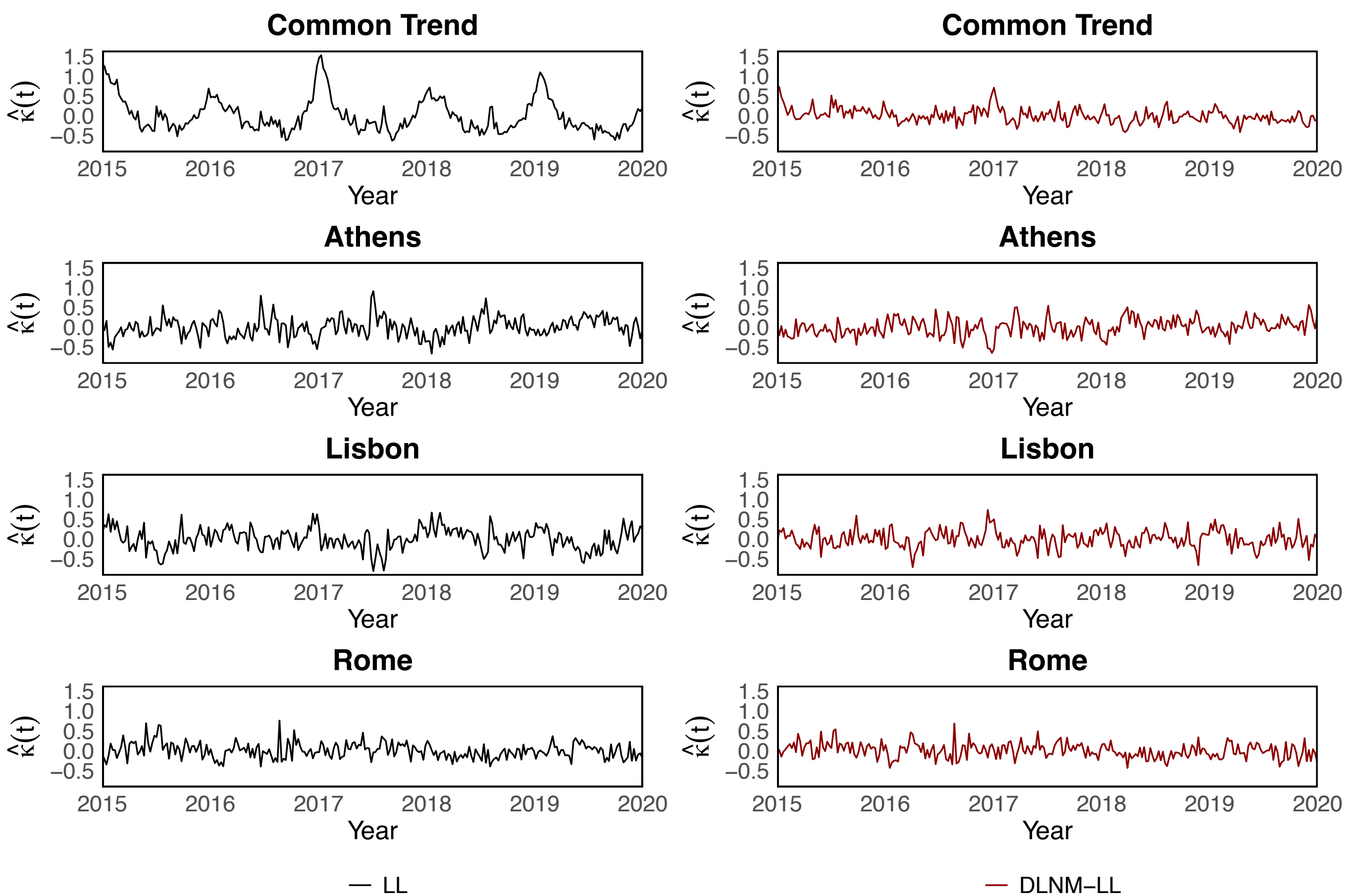
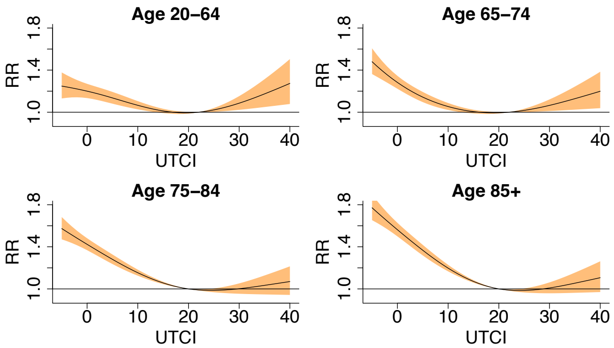


Figure 3: Fitted time-varying factors in multi-population models: LL (left); DLNM–LL (right).

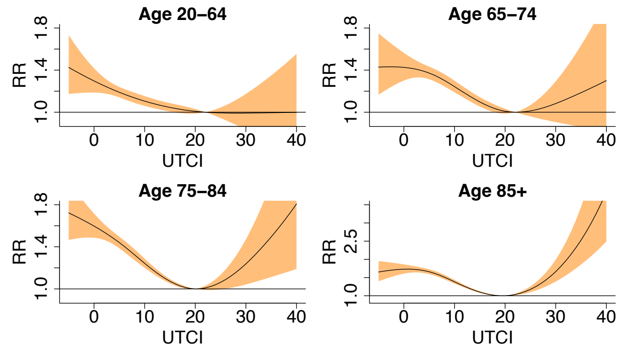
- **The climate-driven mortality is separated**: The stochastic mortality components do not exhibit obvious seasonal patterns (Take DLNM-LL model as an example[6]), since the seasonal patterns are primarily captured by DLNM components.

[6] Hereafter, we present results only for the DLNM–LL model.

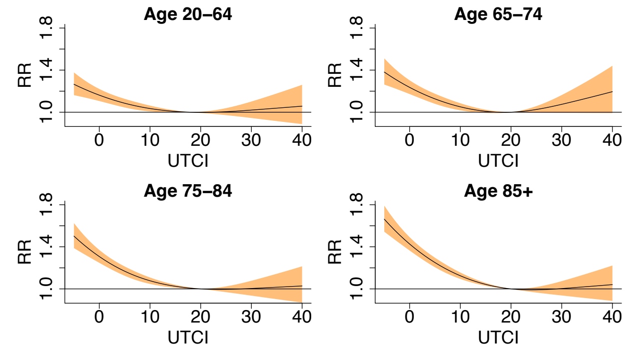
Empirical Results: Cross-Basis Function in DLNM Components



(a) Athens



(b) Lisbon



(c) Rome

Figure 4: Overall cumulative effects of UTCI on climate-driven mortality components (DLNM-LL).

- **The clear U-shaped relationship between relative risk (RR) and UTCI**.
  - Extreme cold and heat both elevate RR.
  - The UTCI range with minimum RR is about 18–25 °C across regions.
- The U-shaped curves confirm that **DLNM components capture climate effects** on mortality rates adequately.
- RR of extreme heat does not appear high in Athens and Rome: Evaluating extreme UTCI effects requires **both** cross-basis estimates and HWD_t and CWD_t parameters.

Empirical Results: HWD_t and CWD_t in DLNM Components

Age group	**Athens**		**Lisbon**		**Rome**	
	β_{HWD_t}	β_{CWD_t}	β_{HWD_t}	β_{CWD_t}	β_{HWD_t}	β_{CWD_t}
20–64	0.0135***	0.0071	0.0138**	0.0111***	0.0027	0.0086**
65–74	0.0093***	0.0112***	0.0196***	0.0048	-0.0125***	0.0010
75–84	0.0161***	0.0056**	0.0176***	0.0128***	0.0069*	0.0045
85+	0.0200***	0.0013	0.0192***	0.0140***	0.0146***	0.0072**

Level of significance: 0.01:***, 0.05:**, 0.1:*

Table 1: The coefficients of HWD_t and CWD_t in the DLNM component of the DLNM–LL model.

- Most coefficients of HWD_t and CWD_t are **positive** and **significant**. Older age groups (75–84, 85+) are more vulnerable under extreme UTCI condition.
- HWD_t effects are generally stronger than CWD_t: **Persistent extreme heat** is captured by HWD_t, which complements the cross-basis function.

Empirical Results: Expanding Window Cross-Validation

- **Expanding window cross-validation**: 10-fold expanding window, 102-week initial training sizes, 8-week expansion step, 78-week forecasting horizon with mean absolute error measure.

$$\mathrm{MAE}(x,i) = \frac{1}{10 \times 78} \sum_{j=1}^{10} \sum_{t=1}^{78} \left| m(x, 102+t+8j, i) - \hat{m}(x, 102+t+8j, i) \right|. \tag{13}$$

Athens	20–64	65–74	75–84	85+
Baseline LC	0.0258	0.1663	0.5253	2.1271
DLNM–LC	**0.0233**	**0.1370**	0.3921	**1.5268**
Baseline LL	0.0285	0.1830	0.5091	2.0056
DLNM–LL	0.0235	0.1544	**0.3764**	1.5413
Lisbon	20–64	65–74	75–84	85+
Baseline LC	0.0274	0.1519	0.4818	2.1166
DLNM–LC	0.0256	0.1646	0.5424	2.0999
Baseline LL	0.0275	0.1637	0.5040	2.0465
DLNM–LL	**0.0254**	**0.1381**	**0.4133**	**1.6763**
Rome	20–64	65–74	75–84	85+
Baseline LC	0.0197	**0.1209**	0.3609	1.7268
DLNM–LC	0.0211	0.1533	0.3748	1.7336
Baseline LL	**0.0195**	0.1280	0.3917	1.7444
DLNM–LL	0.0213	0.1509	**0.3313**	**1.3344**

Table 2: MAE for 10-fold expanding window cross-validation

Mortality Projection: RCP Scenarios and Future UTCI data

- **RCP scenarios**: The climate change scenarios that project future greenhouse gas concentrations and their radiative forcing levels through to the year 2100 (Van Vuuren et al., 2011).

Scenario	Description
RCP2.6	A stringent mitigation pathway to keep warming under $2^\circ C$ by **2100**, with deep cuts and net-negative CO_2.
RCP4.5	An intermediate stabilization scenario where CO_2 emissions peak around **2040** then decline.
RCP6.0	An intermediate pathway where CO_2 emissions peak around **2080** before declining.
RCP8.5	A high-emission, unmitigated scenario with CO_2 emissions growing unabated through the **21st century**.

Table 3: Description of four RCP scenarios.

- **Future input variables**: The input variables over the period 2031–2045 are collected from the Coupled Model Intercomparison Project Phase 5 (CMIP5) climate model[7].
- The regional-level mean radiant temperature data are not available in the climate model, we follow Di Napoli et al. (2020) to utilize historical MRT data from ERA-HEAT dataset to compute future UTCI data.

[7] Data source: `cds.climate.copernicus.eu/datasets/projections-cmip5-daily-single-levels?tab=download`. In CMIP 5 model, we select ensemble member r1i1p1 (initial condition) with two sub-climate models: CSIRO-MK3-6-O (Australia) and BCC-CSM-1-M (China).

Mortality Projection: Simulation Design

- We simulate two main components for 10,000 times to obtain the mean forecast, lower bound (2.5% quantile) and upper bound (97.5% quantile).
- **Stochastic mortality components**: time-varying factor $\kappa(t)$ for Lee–Carter model, and $\kappa(t, i)$ and $K(t)$ for Li–Lee model are simulated from time series model.
- The uncertainty of DLNM parameters are captured by **parametric bootstrapping**. Assume that the estimated parameters $\hat{\boldsymbol{\zeta}} := (\hat{\boldsymbol{\eta}},\ \hat{\boldsymbol{\beta}})$ follow a multivariate normal distribution:

$$\hat{\boldsymbol{\zeta}} \sim \mathcal{MVN}(\boldsymbol{\mu}_{\zeta}, \boldsymbol{\Sigma}_{\zeta}), \tag{14}$$

  - $\boldsymbol{\mu}_{\zeta}$: The true but unknown mean of the parameter vector.
  - $\boldsymbol{\Sigma}_{\zeta}$: The corresponding variance-covariance matrix.
- **DLNM components**: Applying bootstrapping for B times to obtain bootstrapped DLNM parameters $\hat{\boldsymbol{\zeta}}_b^* = (\boldsymbol{\eta}_b^*,\ \boldsymbol{\beta}_b^*)$ such that

$$\hat{\boldsymbol{\zeta}}_b^* \sim \mathcal{MVN}(\hat{\boldsymbol{\mu}}_{\zeta}, \hat{\boldsymbol{\Sigma}}_{\zeta}),\ b = 1, \ldots, B, \tag{15}$$

  - $\hat{\boldsymbol{\mu}}_{\zeta}$: The maximum quasi-likelihood estimator.
  - $\hat{\boldsymbol{\Sigma}}_{\zeta}$: The associated asymptotic covariance.

Mortality Projection: Weekly Mortality Rates

- **W-shaped seasonal pattern**: Higher winter mortality peak than the summer mortality peak, which is consistent with historical mortality rates.
- Lower winter mortality and higher summer mortality in RCP8.5 than in RCP2.6.

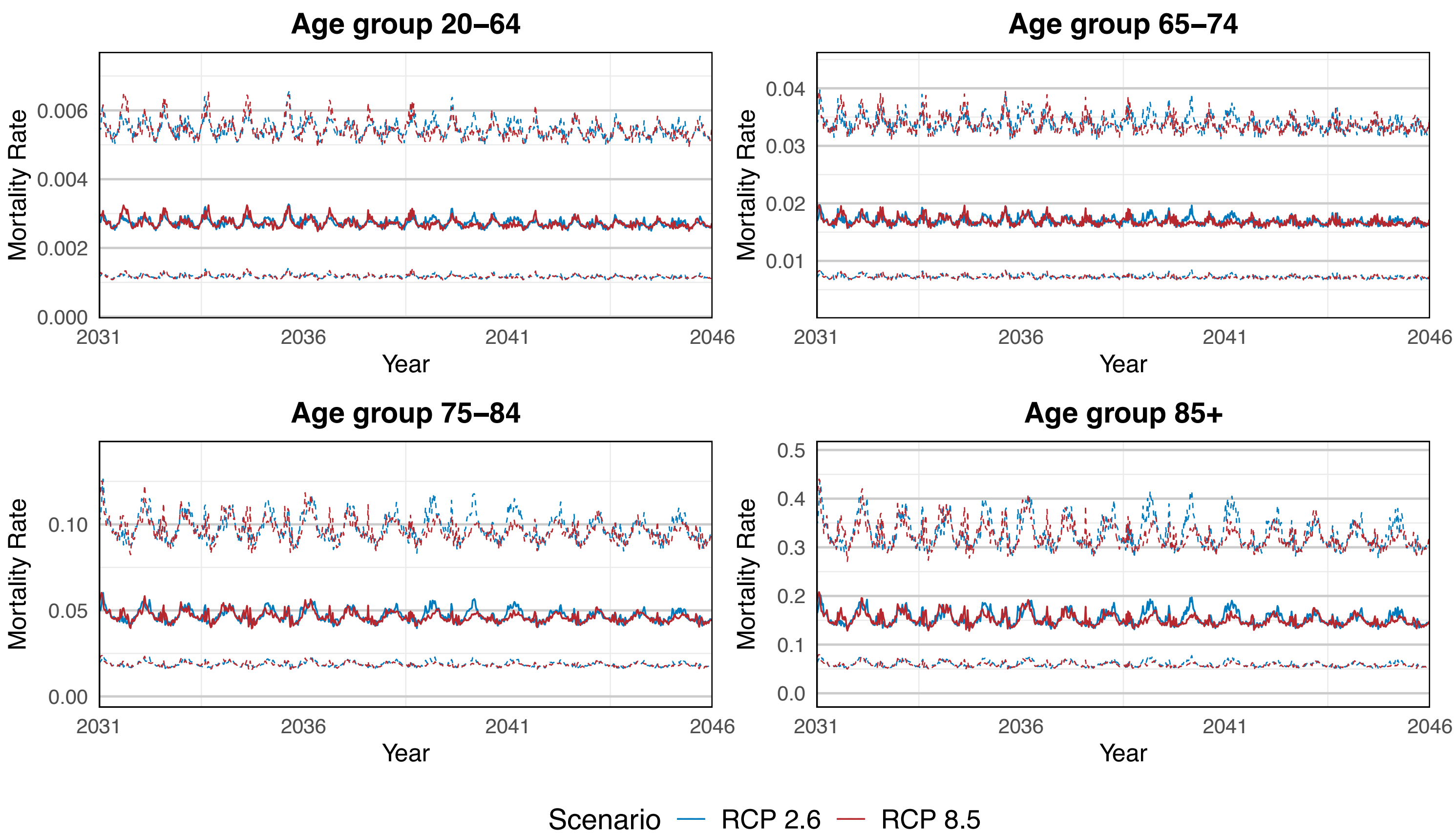


Figure 5: Weekly mortality projection for Athens (2031–2045) under DLNM-LL model.

- The projection highlights the **contrasting seasonal effects of climate change**, but the overall impact is less straightforward.

Mortality Projection: Annual Mortality Rates

- **Downward trend**: Mortality improvements from stochastic mortality components.
- **Combined impact of winter compensation and summer excess**: The domination of winter mortality compensation in the near future leads to temporary lower annual mortality rates under RCP8.5 than under RCP2.6.

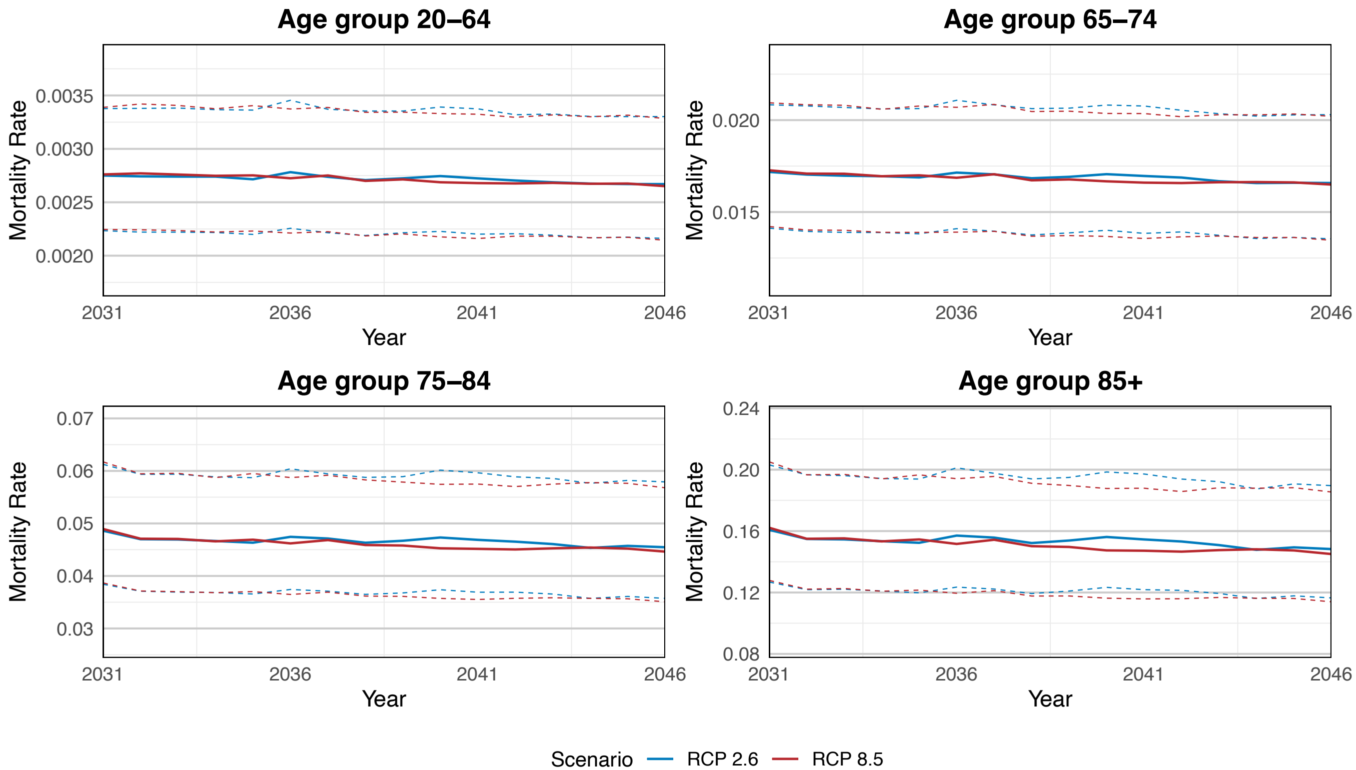


Figure 6: Annualized mortality projection for Athens (2031–2045).

- A small increase in UTCI temporarily decreases total mortality rates. As extreme summer heat intensifies, a large increase in UTCI potentially leads to a long-term increase in total mortality under RCP8.5.

Conclusion and Feature Research

- We propose a new stochastic climate-related mortality model in one-step approach.
- The proposed model effectively isolates and quantifies climate-driven mortality risks.
- We provide weekly and annual mortality projection under different RCP scenarios to reveal how different warming levels impact mortality rates.
- Potential feature research:
  - Apply different stochastic mortality components, such as Cairns-Blake-Dowd type models (Cairns et al., 2006).
  - Consider other exogenous variables (*e.g*, air pollutants and socio-economic variables).
  - Explore polling data across finer age groups and more geographical locations.

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Appendix

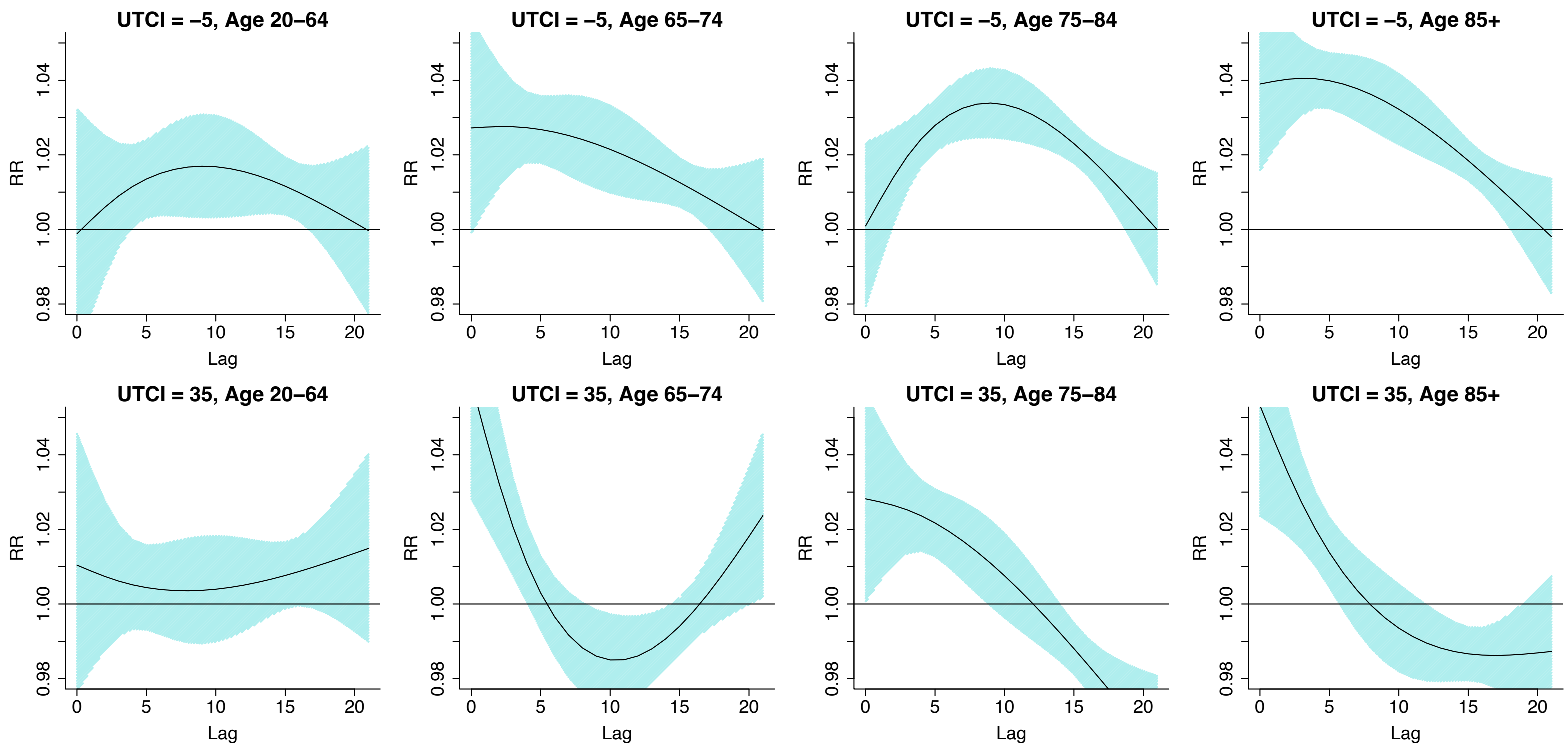

Figure 7: Lagged effects of UTCI on climate-driven mortality components (Athens, DLNM-LL)

- **Heat exposure**: **Immediate adverse effects** within the first five days of lag.
- **Cold exposure**: **Delayed long-lasting effects** on mortality. The relative risk gradually increases over time, peaking between five and ten days of lag before subsequently declining.
- **Age-related effects**: The effects are particularly pronounced in older populations.

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