Evaluating Climate Change Impacts on Mortality, Life Insurance, and Annuities

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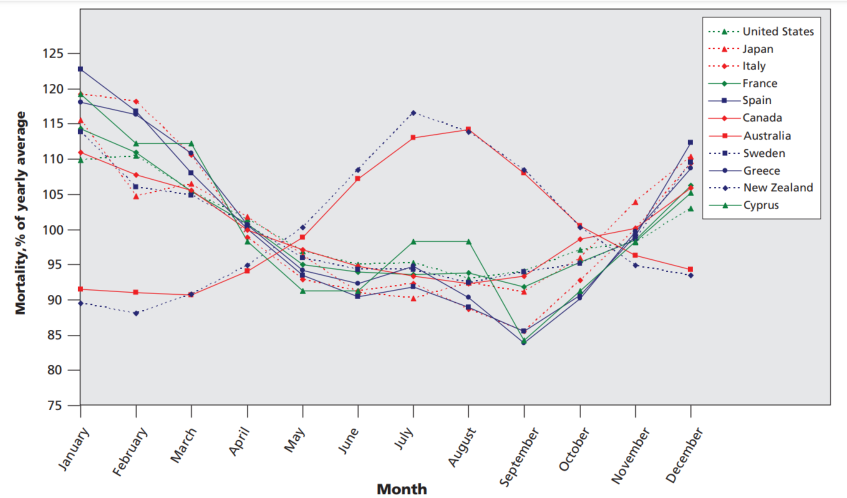
The Eighteenth International Longevity Risk and Capital Markets Solutions
London, September 7th 2023

Introduction

Extreme Temperatures and Human Mortality

- Wallemacq and House (2018) reported that more than 70,000 died during the 2003 European heatwave.
- Ballester et al. (2023) estimated that 61,672 (95% CI 37,643–86,807) deaths in Europe are heat-related between 30 May and 4 September 2022, the hottest summer season yet in Europe.
- The WHO has alerted that the frequency, duration, and magnitude of extreme temperature events have all increased over the world.
- While cold temperature extremes might not capture headlines as often as heatwaves, they also result in greater mortality.

Seasonal Variation in Mortality



Source: Falagas et al. (2009)

Research Questions

- What will human mortality look like under different emission scenarios?
- What are the implications for the life insurance and annuity sector?
- What are the challenges for such modelling work?

Relevant Literature from Actuarial Research

- Li and Tang (2022): Model extremal dependence between death counts and temperature
  - Focuses on excess mortality during extreme temperatures; does not consider potential winter mortality reductions due to warming
- Seklecka et al. (2017): Integrate temperature-related factors into a Lee-Carter-type model
  - Examines annual mortality data, making it challenging to discern the impact of temperature change across seasons.
- Naqvi and Hall (2018): Understand the effects of temperature changes on older-age mortalities in England & Wales and Scotland.
  - The use of monthly mean temperature and death data may lead to an underestimation of the impact of extreme heatwaves or cold snaps.

Relevant Literature from Environmental Epidemiology

- Numerous environmental epidemiological studies (Gasparrini et al., 2010, 2015, 2017; Zhao et al., 2021) have demonstrated strong evidence of a relationship between human mortality and non-optimal ambient temperature.
- Methodology frequently used: Distributed lag non-linear model (DLNM) that simultaneously captures non-linear exposure-response relations and temporal delayed effects of environmental stressors
- Limitations
  - Model death counts without considering the changing population size
  - Use very wide or no age bands
  - Focus on inference without assessing forecasting capabilities (potentially overfitting)
  - Restricted access to the dataset

Our Approach

- Focus on the mean predictions while being mindful of the inherent uncertainty in mortality rates and in climate models and projections
- Investigate the relationship between weekly mortality in different age groups and daily temperature for a local area
  - Use publicly available data
  - Adopt DLNM with population size incorporated and overfitting addressed
- Predict local temperatures under various SSP scenarios
  - Pattern scaling (relationship between global warming and local warming)
  - Time series modelling (allowing for seasonality, volatility, and autocorrelation)
- Obtain predicted mortalities using the temperature-mortality relationship and simulated local temperatures

Data

Dataset

- Weekly death counts in 2000-2019 obtained for five age bands (0-19, 20-39, 40-59, 60-79, and 80+) in ES3 and ES4 regions (Eurostat NUTS 1 region codes) from the Eurostat database

(a) ES3 COMUNIDAD DE MADRID

(b) ES4 CENTRO (ES)

Dataset

- Daily mean temperature for the grid closest to Madrid, obtained from the E-OBS gridded dataset
- The dilemma with the choice of region size
    - Small region: Mortality data is noisy, making it difficult to discern the temperature impact from the natural fluctuation in mortality.
    - Large region: Temperature patterns and their impact on mortality within individual subregions can vary significantly from one another.
- The global annual average surface temperature data in 1950-2022 from the National Centers for Environmental Information (NCEI)
- Projected global surface temperature under four future emission scenarios, namely SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5, from IPCC (2021).

Methodology

The Distributed Lag Non-linear Model (DLNM) (Gasparrini et al., 2010)

- Lags: Use past values in time series to predict future values
- Distributed Lag: The effects of a variable can spread out over multiple future time periods rather than being immediate and concentrated at a single time point.
- Basic structure:

$$Y_t = \beta_0 + \sum_{l=0}^{L} s_l(T_{t-l}, l; \boldsymbol{\eta}_l) + \varepsilon_t$$

  - Y_t: the response (e.g., death counts) at time t
  - T_{t-l}: a predictor (e.g., temperature) at lag l
  - $s_l(T_{t-l}, l; \boldsymbol{\eta}_l)$: a cross-basis function between T_{t-l} and l, parameterised by coefficients $\boldsymbol{\eta}_l$, capturing the nonlinear and lagged effect of the predictor
  - L: the maximum considered lag
  - ϵ_t: error term

The Distributed Lag Non-linear Model

- Why DLNM?
  - Health impacts persist days after exposure to extreme temperatures.
  - The 'harvesting' phenomenon: extreme temperatures can accelerate mortality for already vulnerable individuals.
  - Accurate assessments rely on models capturing both the temperature-mortality relationship and its temporal structure.
- Generalisations
  - Include multiple predictors with linear or nonlinear effects
  - Use link functions (e.g., logarithm) to relate predictors to $E(Y_t)$
  - Allow for different distributions (e.g., Poisson) for the response variable
- DLNM is a special case of a generalised additive model.

Mortality Modelling with DLNM

- Denote $D_{x,t}$, $E_{x,t}$ and $\mu_{x,t}$ as the death count, exposure-to-risk, and central mortality rate for age x at time t
- Using a log link with overdispersed Poisson distribution for DLNM, we model $D_{x,t}$ as follows

$$\ln E(D_{x,t}) = \ln E_{x,t} + \beta_0 + v(t) + \sum_{l=0}^{L} s_l(T_{t-l}, l; \boldsymbol{\eta}_l)$$

  - $v(t)$ is a smoothing function of time t capturing the time trend and seasonality of mortality.
  - In mortality modelling literature, we often assume that $D_{x,t} \sim \text{Poisson}(E_{x,t}\mu_{x,t})$ which leads to $\ln E(D_{x,t}) = \ln E_{x,t} + \ln \mu_{x,t}$
  - Our model implies that

$$\ln \mu_{x,t} = \beta_0 + v(t) + \sum_{l=0}^{L} s_l(T_{t-l}, l; \boldsymbol{\eta}_l)$$

Model Selection and Estimation

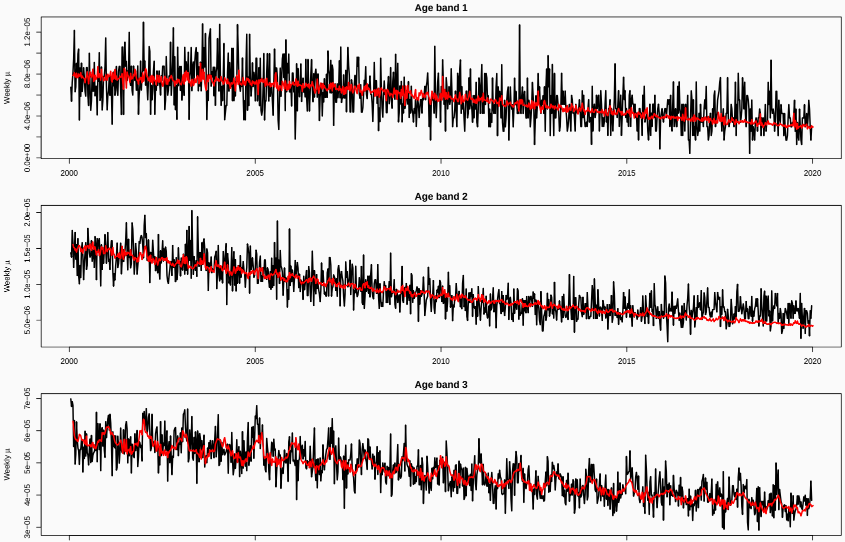
$$\ln E(D_{x,t}) = \ln E_{x,t} + v(t) + \beta_0 + \sum_{l=0}^{L} s_l(T_{t-l}, l; \boldsymbol{\eta}_l)$$

- t represents day.
- Weekly death counts: $D_{x,t}$, $t = 7, 14, 21, 28 \ldots$
  - Take week 5 death, represented by $D_{x,35}$, as an example
  - View week 5 death as the death on day 35
  - Assume $L = 30$. Temperatures in the past 30 days ($t = T_{35}, T_{34}, \ldots, T_6$) have an impact on the death count $D_{x,35}$

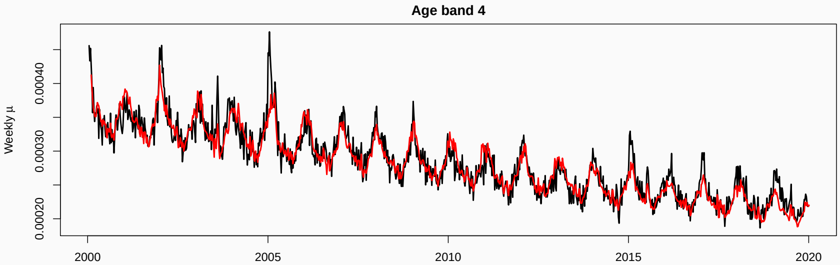
Model Estimation and Selection

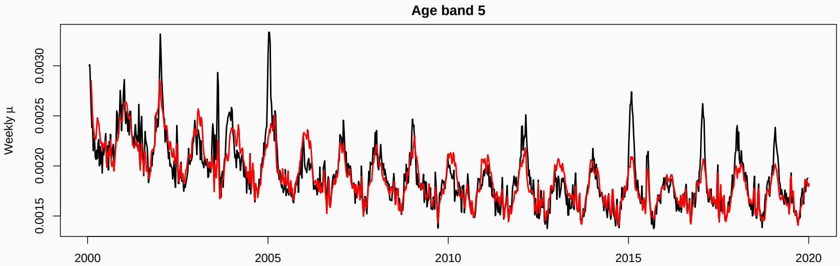
- Cross basis $s_l(T_{t-l}, l; \eta_l)$: natural cubic splines with 6 degrees of freedom (dof) for temperature T_{t-l} and 5 dof for lag l, selected by QBIC
- Smoothing function $v(t)$: natural cubic splines of 2 dof (two linear segments connected at the internal knot) selected by cross-validation
  - Environmental epidemiological studies suggest 7 dof per year of historic data to capture trend and seasonality (Gasparrini et al., 2010; Anderson and Bell, 2009).
  - We find that using 7 dof per year leads to unreasonable beyond-the-boundary behaviours (mortality trending up indefinitely).
- We perform model fitting for each age group separately.

Fitted Weekly Mortality



Fitted Weekly Mortality





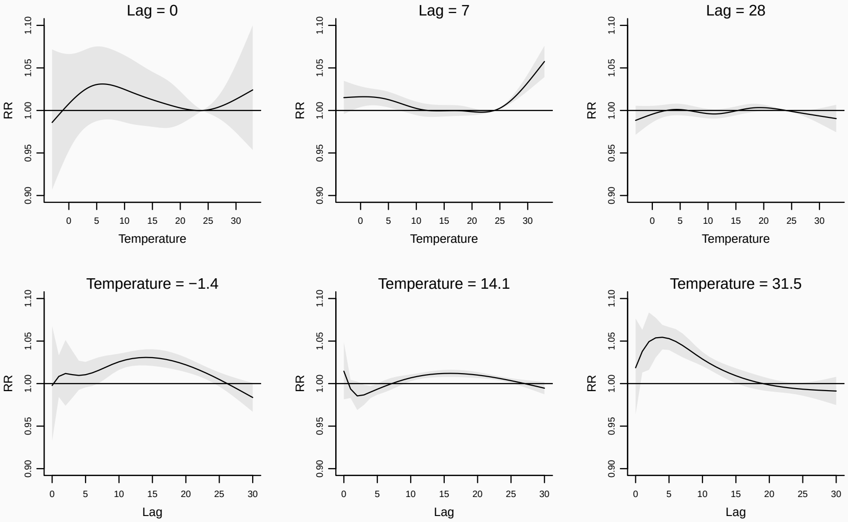
Estimated Temperature Impact on Mortality

- Relative risk: measures how the temperature (°C) on day $t - l$ affects the mortality on day t

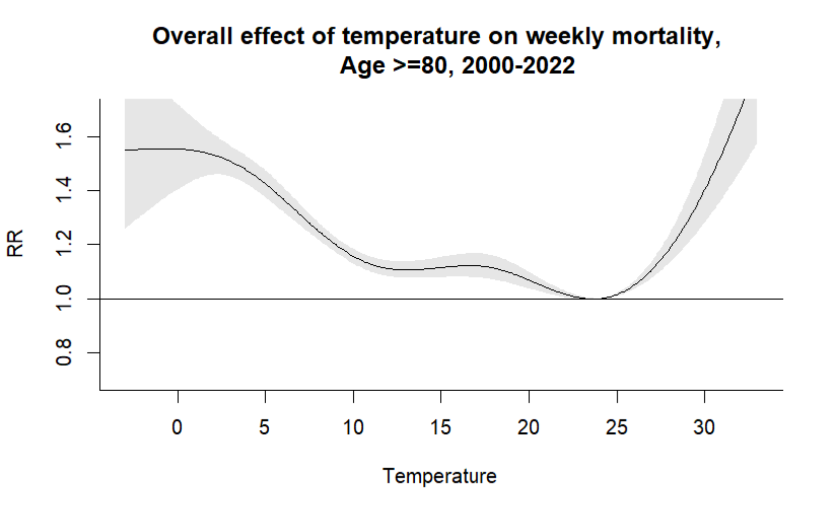
$$RR = \frac{\mu_{x,t} | T_{t-l} = T}{\mu_{x,t} | T_{t-l} = T_{ref}}$$

  - $RR > 1$: The mortality today, after exposure to temperature T from l days ago, is higher than the mortality after exposure to the reference temperature T_{ref} from l days ago
  - T_{ref} is the point of overall minimum mortality.
- We plot RR v.s. temperature at lags 0, 7, and 28 days; and RR v.s. lag at the temperatures of -1.4°C, 14.1°C, and 31.5°C (corresponding to 0.1, 50, and 99.9 percentiles of historical temperatures).
- The 95% confidence intervals of RRs are also shown.

Relative Risk - Age Band 5



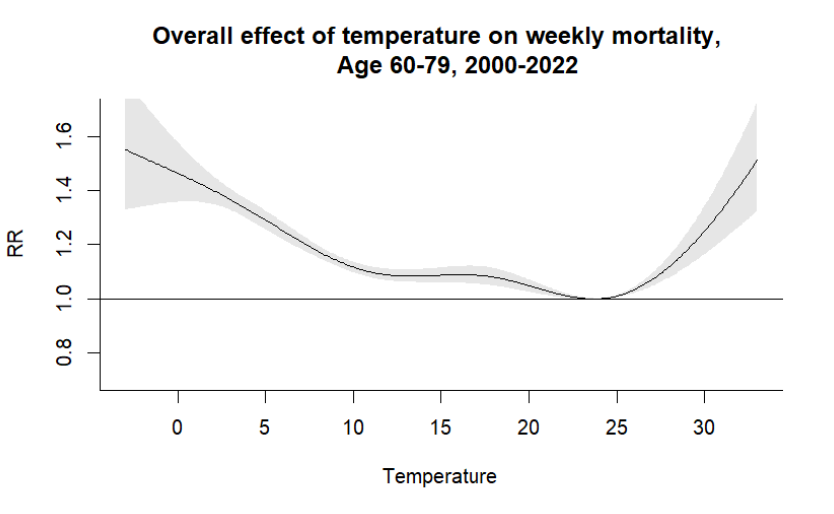
Relative Risk - Age Band 5



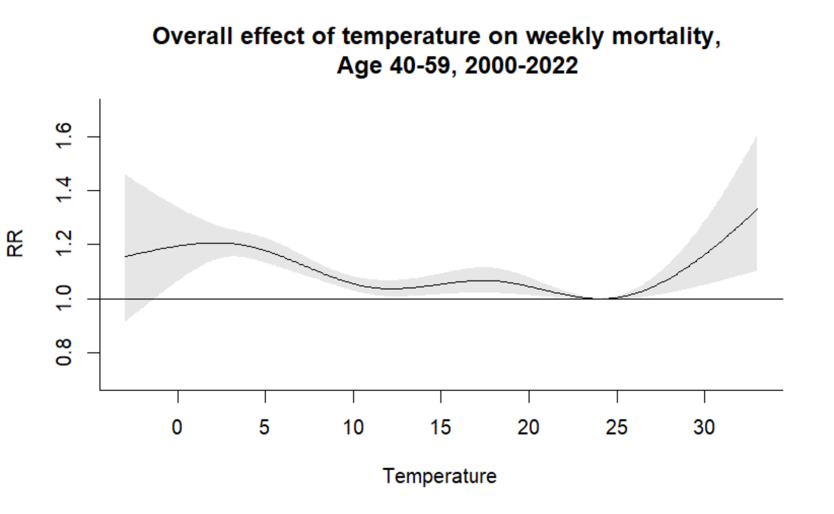
Relative Risk - Age Band 5

- Overall effect combines the temperature-mortality relationship over all lag orders.
- Characteristic U-shaped overall effect is observed for Madrid & Centro area. Both extreme cold and hot ambient temperatures are detrimental to human health.
- Wider confidence band at boundaries due to less data points related to extreme temperatures.

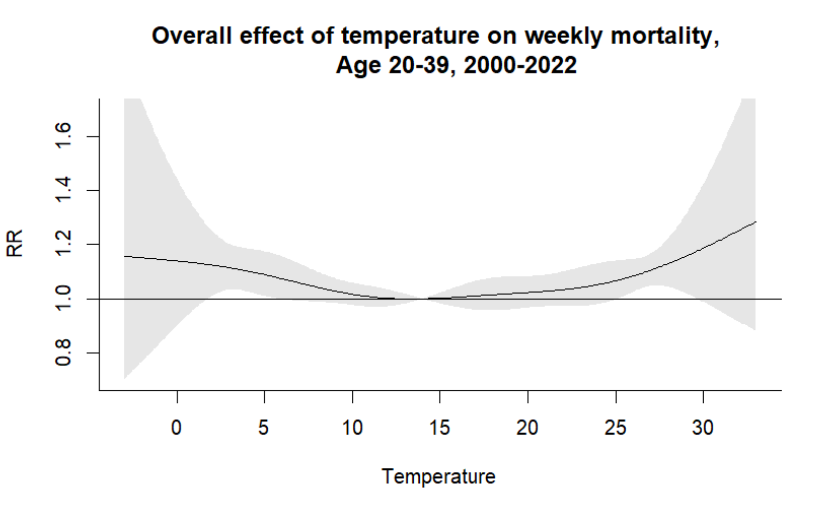
Relative Risk - Age Band 4



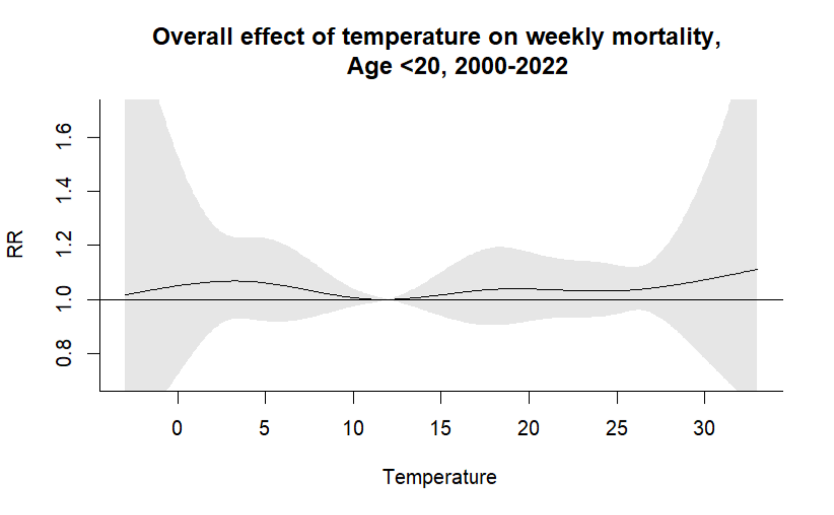
Relative Risk - Age Band 3



Relative Risk - Age Band 2

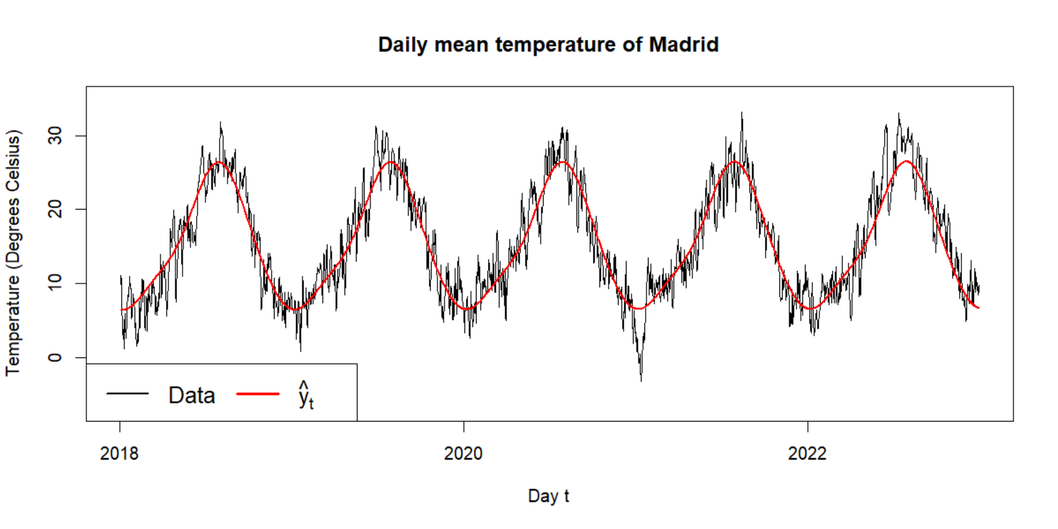


Relative Risk - Age Band 1



Temperature Predictions

Features of Temperatures



Time Series Temperature model - Without Climate Change Impact

- Features of temperature data
  - Seasonality in mean: Average temperature follows a yearly pattern due to seasons.
  - Autocorrelation: Today's temperature affects temperatures in the next few days.
  - Seasonality in volatility: Temperature variability also follows a yearly pattern.
  - Volatility clustering: High (or low) temperature variability periods tend to cluster together.
- We capture the features of temperature data with the s-AR-s-GARCH model (Campbell and Diebold, 2005).
- The seasonality in mean is represented by a Fourier series:

$$y_t = c_0 + \sum_{r=1}^{R} \phi_{c,r} \cos\left(2\pi r \frac{d(t)}{365}\right) + \sum_{r=1}^{R} \phi_{s,r} \sin\left(2\pi r \frac{d(t)}{365}\right)$$

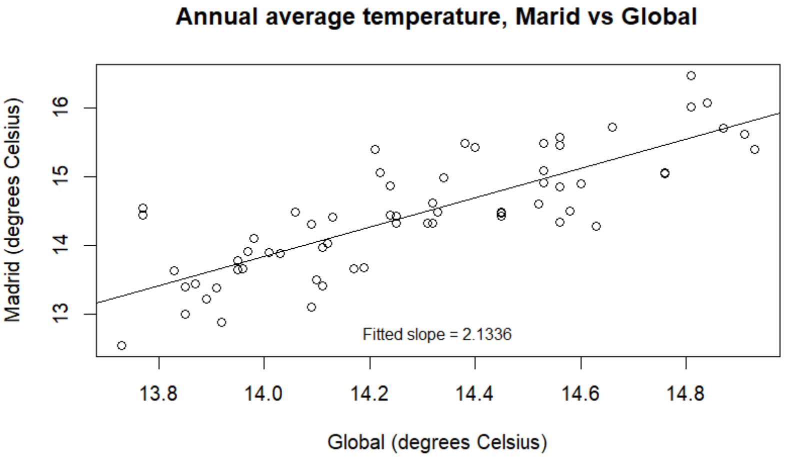
- We simulate future temperatures using this model to account for inherent fluctuations that may significantly affect mortality.

The Impact of Climate Change on Global Surface Temperature

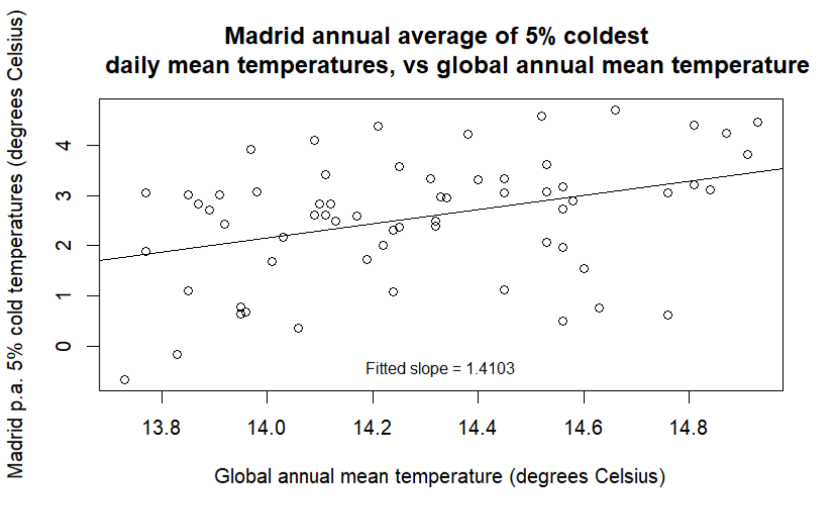
	Near term, 2021–2040		Mid-term, 2041–2060		Long term, 2081–2100	
Scenario	Best estimate (°C)	*Very likely* range (°C)	Best estimate (°C)	*Very likely* range (°C)	Best estimate (°C)	*Very likely* range (°C)
SSP1-1.9	1.5	1.2 to 1.7	1.6	1.2 to 2.0	1.4	1.0 to 1.8
SSP1-2.6	1.5	1.2 to 1.8	1.7	1.3 to 2.2	1.8	1.3 to 2.4
SSP2-4.5	1.5	1.2 to 1.8	2.0	1.6 to 2.5	2.7	2.1 to 3.5
SSP3-7.0	1.5	1.2 to 1.8	2.1	1.7 to 2.6	3.6	2.8 to 4.6
SSP5-8.5	1.6	1.3 to 1.9	2.4	1.9 to 3.0	4.4	3.3 to 5.7

Changes in global surface temperature relative to the period 1850–1900, reported in °C, for selected 20-year time periods and the five illustrative emissions scenarios considered. Source: IPCC (2021).

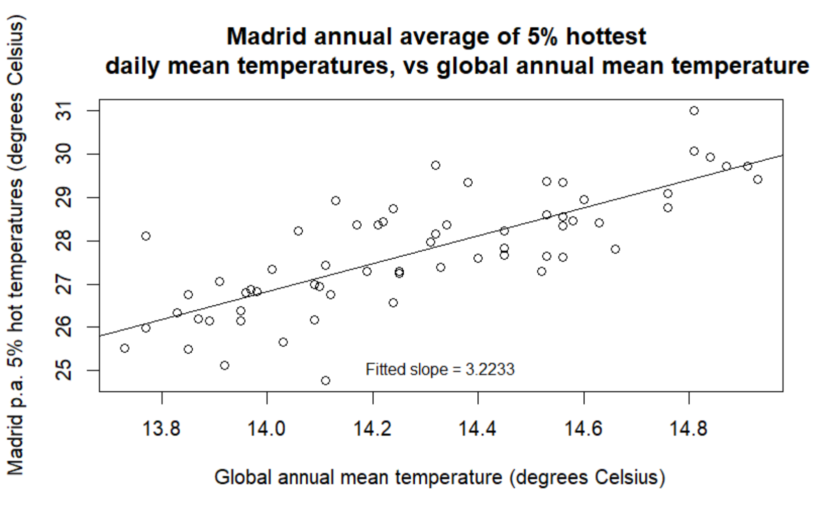
- It's essential to note that the effects of global warming can be highly regional.



Global Warming vs Regional Warming



Global Warming vs Regional Warming



Incorporating the Impact of Global Warming into Local Temperature Projections

- Pattern scaling (Tebaldi and Arblaster, 2014; Seneviratne et al., 2016)
  - Local annual temperature changes scale with global annual temperature shifts
  - A well-established method in climate science to down-scale the global pattern to a regional level
- The rate of change in regional extreme temperature differs from that of regional mean temperature.
- What causes the different rates of change in regional extreme temperature?
  - Are there changes in volatility?
  - Did the amplitude and phase of seasonal temperature cycles shift?
  - Or both?

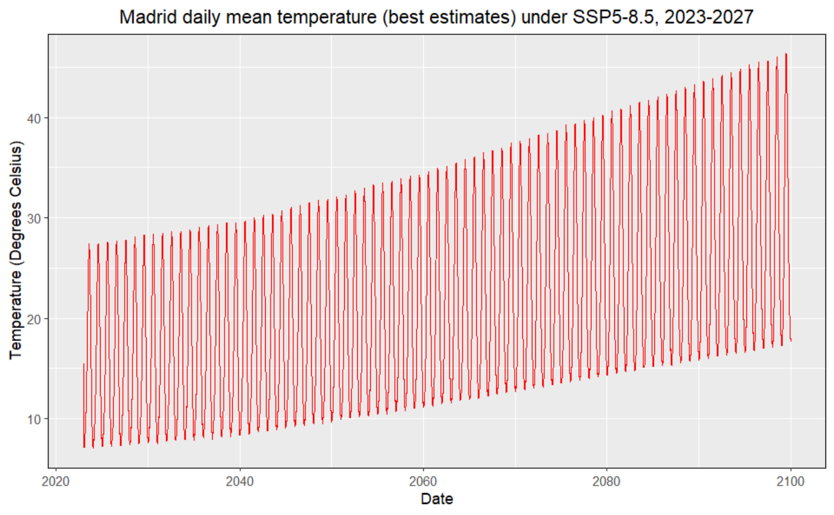
Incorporating Climate Change Impact into the Temperature Model

- ΔG_t represents the change in global annual mean temperature compared to a reference time point t_0
- Δy_t represents the change in regional mean temperature compared to a reference time point t_0
- We illustrate the case assuming the changing amplitude of the temperature cycle.

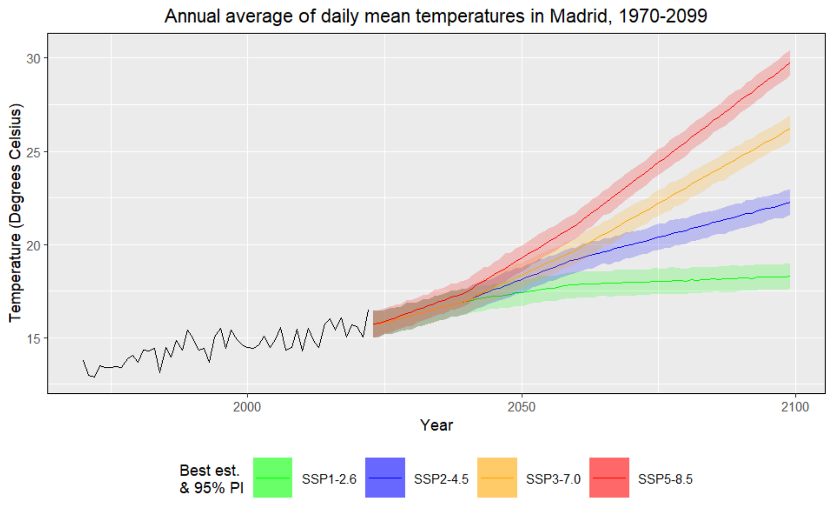
$$\Delta y_t \quad = \quad b_0 \Delta G_t + \sum_{r=1}^{R} \phi_{c,r} b_{c,r} \Delta G_t \cos\left(2\pi r \frac{d(t)}{365}\right) + \sum_{r=1}^{R} \phi_{s,r} b_{s,r} \Delta G_t \sin\left(2\pi r \frac{d(t)}{365}\right)$$

- Coefficients b_0, $b_{c,r}$, and $b_{s,r}$ are calibrated to ensure the projected speed of amplitude changes match the historical speed of change in regional mean and extreme temperatures.

Predicted Madrid Daily Mean Temperature



Simulated Temperatures for Madrid - Annual Average



Results

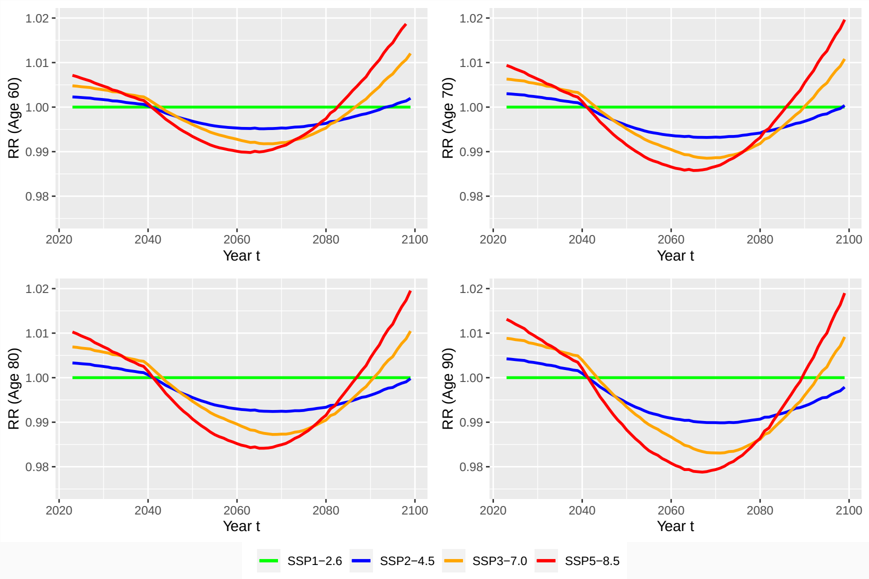
Mortality under Various SSP Scenarios

- For a given age x, we present the relative risk:

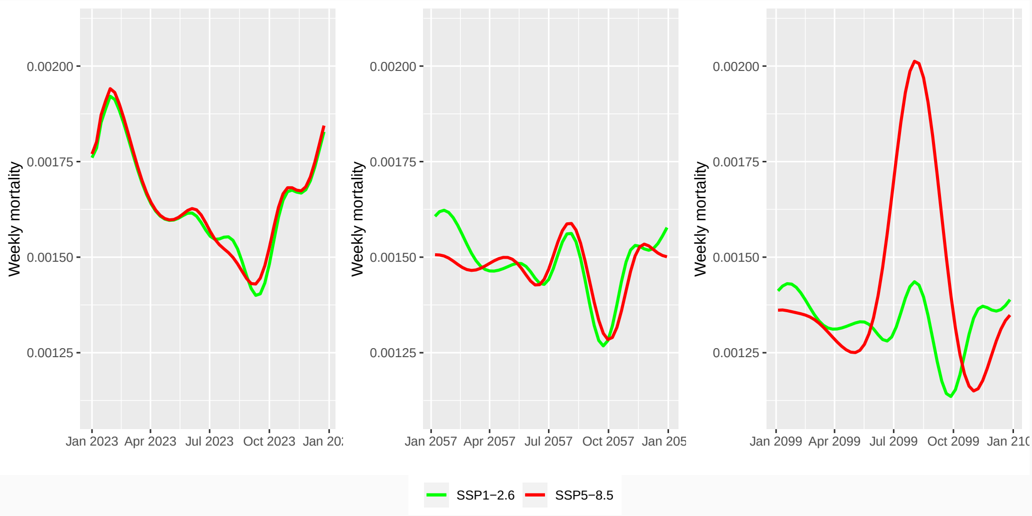
$$\frac{\mu_{x,t} \text{ under a specific SSP}}{\mu_{x,t} \text{ under the SSP1-2.6 scenario}}$$

- Keep in mind that SSP5-8.5 represents the most aggressive warming scenario.
- A milder winter reduces mortality, but a hotter summer increases it.
- We observe intersections among the relative risk curves across different SSPs.
    - From 2020-2040, deaths from hot summers outweigh the reduced winter deaths, making SSP5 the scenario with the highest mortality.
    - Beyond 2040, winter's mitigating effect on mortality prevails, causing a dip in deaths under SSP5.
    - However, as we project further, the fatalities from hot summers once again become more pronounced.

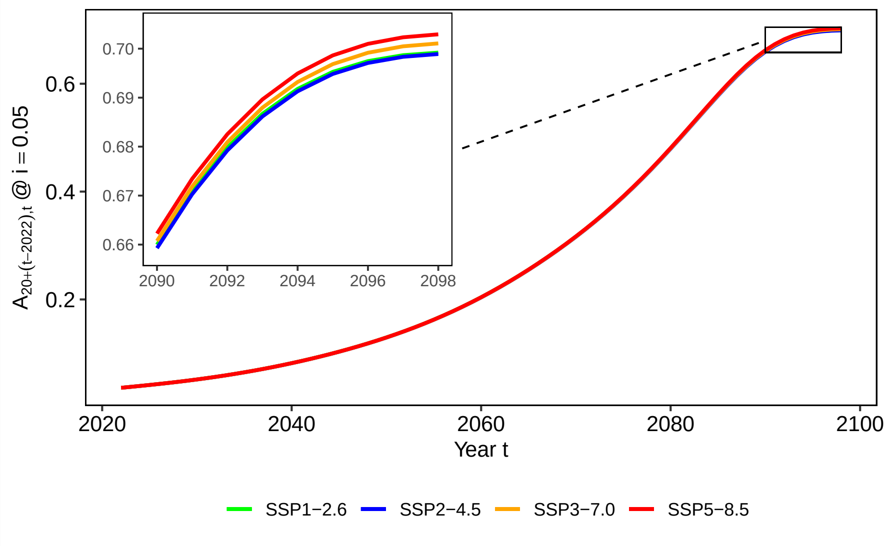
Relative Risk with Reference to Predicted Temperatures under SSP1-2.6



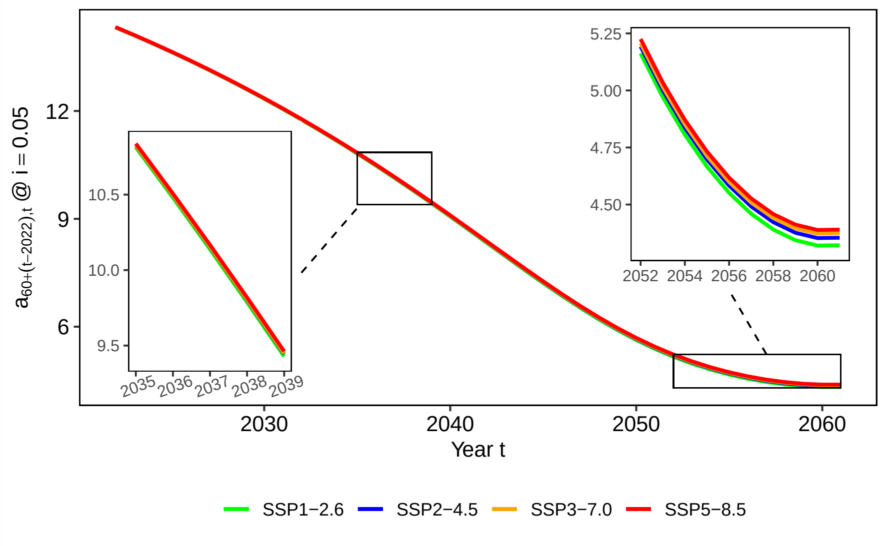
Seasonal Pattern in Mortality (Age 80+)



Climate Change Impact on Life Insurance Liability $A_{x+t,t}$



Climate Change Impact on Life Annuity Liability $a_{x+t,t}$



Conclusion and Future Research

Conclusion and Future Research

- We established a framework to assess climate change's impact on mortality
- Warmer winters potentially reduce moralities, while hotter summers increase them.
- The overall impact of warming climate shifts over time and varies across different emission scenarios.
- Analysing life insurance and annuity revealed that liability values only vary by a small amount across SSP scenarios.
- The shifting seasonal patterns could lead to large claims within specific seasons, even if the annual figures hold relatively steady.
- Uncertainties loom in future emission predictions and subsequent temperature shifts.
- Future research:
  - Extend our study to more regions
  - Address the underestimation of the consequences of heatwaves and cold snaps

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