Climate-driven mortality projections under different scenarios

Application: Forecasting the impact of high temperatures on mortality in the Netherlands

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Most climate scenarios project average temperatures over a given time horizon. However, key climatic factors such as extreme temperatures or air pollution have distinct effects on health and mortality, requiring the use of other, more precise climatic variables. To address this issue, this study develops an advanced methodology for deriving mortality scenarios from conventional climate projections. By integrating critical climate indicators and refining existing approaches, this framework enhances the accuracy of climate-related mortality projections, offering a more comprehensive assessment of future risks.

Climate change is widely recognized as one of the most pressing global challenges, with deep impacts on ecosystems, human societies, and economic systems. Among its many consequences, heatwaves—and more broadly, extreme temperatures—play a particularly significant role. According to reports from the Intergovernmental Panel on Climate Change (IPCC)[1], these events are increasing in both intensity and frequency, leading to direct health impacts, including a rise in mortality, particularly among vulnerable populations.

An increasing number of research studies are addressing these critical issues, aiming to understand and quantify the impact of extreme temperatures on human mortality. While these studies have shed light on some underlying mechanisms and established correlations between climatic events and mortality variations, the subject remains only partially explored. Most of this research focuses primarily on developing explanatory models based on historical data, highlighting significant relationships between past temperatures and mortality. However, few studies have produced long-term projections, despite the crucial role of such projections in anticipating future consequences.

Some actuarial studies have explored mortality projection by incorporating climatic variables, but they have often been limited to using average temperature as the sole explanatory factor or relying on preexisting projections from public databases whose scope remains constrained. While these approaches are valuable, they underscore the need to develop more specialized methodologies capable of fully leveraging available climate data to better capture local variations and broader impacts.

In this study, we present the results of modeling the impact of heatwaves on mortality in the Netherlands.

Data sources

This study draws on multiple well-established public databases, enabling a robust analysis of the relationship between climate dynamics, demographic trends, and observed mortality:

- Mortality data: Sourced from the Human Mortality Database (HMD),[2] which provides detailed age- and sex-specific mortality rates.
- Climate data: Derived from the Royal Netherlands Meteorological Institute (KNMI) observations and projections,[3] incorporating key variables such as mean temperature, minimum temperature, and the number of tropical days.
- Heat-attributable mortality rates: Extracted from the Global Burden of Disease (GBD) study,[4] offering a comprehensive assessment of the link between temperature fluctuations and mortality patterns.

1. Groupe d’experts intergouvernemental sur l’évolution du climat [Intergovernmental Panel on Climate Change]. (March 20, 2023). Ce qu’il faut retenir du 6e rapport d’évaluation du GIEC. Retrieved January 22, 2025, from https://www.ecologie.gouv.fr/sites/default/files/documents/20250_4pages-GIEC-2.pdf.
2. Human Mortality Database. (2024). Netherlands total population. Retrieved January 21, 2025, from https://www.mortality.org/Country/Country?cntr=NLD.
3. Koninklijk Nederlands Meteorologisch Instituut [Royal Netherlands Meteorological Institute]. (2024). Daggegevens van het weer in Nederland. Retrieved January 21, 2025, from https://www.knmi.nl/nederland-nu/klimatologie/daggegevens.
4. Global Health Data Exchange. (2024). 2021 Global Burden of Disease (GBD) study: Results. Retrieved January 21, 2025, from https://vizhub.healthdata.org/gbd-results/.

To ensure data integrity, we applied a truncation at age 94 because of missing values for older age groups in certain periods. Additionally, COVID-19-related deaths from 2020 and 2021 were excluded to prevent distortions in the analysis of long-term climate-related mortality trends.

Calibration: A climate-adapted version of the Lee-Carter model

The chosen model for explaining mortality while accounting for the impact of high temperatures builds upon an extended version of the Lee-Carter model, augmented with a climatic component.[5] This climate-adjusted Lee-Carter model is formulated as follows:

$$\ln(\mu_{x,t}) = \alpha_x + \beta_x \kappa_t + \delta_x C_t + \varepsilon_{x,t} \,,$$

where x represents age, μ denotes the mortality rate, and α_x, β_x, and κ_t are the parameters of the Lee-Carter model. The term C_t represents the climatic indicator for year t, capturing the impact of the studied climatic variables on mortality.

In this study, we propose alternatives to the initial calibration method introduced in the original formulation of the modeling framework. The term C_t is adjusted using a generalized additive model (GAM), which is defined as follows:

$$g(E[Y]) = \beta_0 + f_1(x_1) + f_2(x_2) + \ \dots + f_{\mathrm{p}}(x_p),$$

where g is the link function, β_0 represents the intercept, and $f_{\mathrm{i}}(x_{\mathrm{i}})$ are nonparametric smoothing functions applied to the predictors x_{i}. These functions enable a flexible modeling approach by capturing the relationship between each predictor and the dependent variable without imposing a predefined functional form.

To achieve this, we used thin-plate splines with penalization. These splines operate by minimizing a measure of surface deformation that smooths the data while adapting to the structure of the observations. We introduced a penalization parameter to regulate model complexity and prevent overfitting.

The most significant climatic variables selected by the model (in the case of Dutch data) are:

- The number of tropical days, defined as the number of days when the maximum temperature exceeds 30°C.
- The annual average of daily mean temperatures.
- The annual average of daily minimum temperatures.

To model the interactions between these highly correlated variables, we used a smooth tensor product. This approach captures the joint and nonlinear effects of the three variables without assuming their independence.

Temporal variables: Projection methodology and extreme value modeling

In long-term modeling, forecasting climatic variables is crucial for anticipating the impacts of climate change. While official climate scenarios provide essential insights into global and regional trends in long-term average temperatures, they do not include projections of the specific climatic variables required for the model. To project the climatic indicator, derived from temperature-related variables, time series of mean and minimum temperatures were decomposed into three key components: trend, seasonality, and noise. Additionally, the projection of the number of tropical days was conducted using extreme value theory (EVT) to better capture rare but impactful temperature events. Moreover, the regular temporal parameter of the Lee-Carter model ($\boldsymbol{\kappa_t}$) and the residual component ($\boldsymbol{\varepsilon_{x,t}}$) were projected to estimate future mortality rates, ensuring a comprehensive approach to climate-related mortality forecasting.

SELECTION OF THE DECOMPOSITION MODEL

Three primary time series decomposition models are widely used in the literature:[6]

- Additive decomposition: A simple approach suited for time series with a stable seasonal pattern that remains constant over time.
- Multiplicative decomposition: Appropriate for series where seasonal fluctuations scale proportionally with the trend.
- STL decomposition (seasonal-trend decomposition using locally estimated scatterplot smoothing [LOESS]): A highly flexible method capable of capturing complex dynamics, though it requires more precise calibration.

5. Boumezoued, A., Elfassihi, A., Germain, V. & Titon, E. (December 19, 2022). Modelling the impact of climate risks on mortality [White paper]. Milliman. Retrieved January 21, 2025, from https://www.milliman.com/-/media/milliman/pdfs/2022-articles/12-16-22_modelling-the-impact-of-climate-risks-on-mortality.ashx.

6. Hyndman, R. J., and Athanasopoulos, G. (2021). Forecasting: Principles and practice (3rd ed.). OTexts. Retrieved September 11, 2024, from https://otexts.com/fpp3/.

An analysis of the seasonal components of temperature time series revealed stable mean levels and consistent seasonal fluctuation patterns. This finding supports the selection of an additive approach,

$$Y_t = T_t + S_t + N_t,$$

where Y_t represents the time series under study, T_t denotes the long-term trend, S_t corresponds to the seasonal component, and N_t represents the residual component.

TREND COMPONENT

The trend component is based on KNMI projections for average temperatures,[7] with an adjustment applied to minimum temperatures to maintain a consistent mean difference of 4°C. These projections rely on the KNMI'23 scenarios, which downscale global climate trends identified by the IPCC to a regional level. They incorporate emission trajectories from the Shared Socioeconomic Pathways (SSPs), providing forecasts of climate variables through the end of the century. KNMI'23 defines two main climate scenarios: a low-emission scenario "L" (SSP1-2.6) aligned with the Paris Agreement targets and a high-emission scenario "H" (SSP5-8.5) reflecting a trajectory with no significant emission reductions. Each scenario is further divided into two variants: a wet scenario "n" characterized by wetter winters and slightly drier summers, and a dry scenario "d" marked by significantly drier summers.[8]

For this study, only the Hd and Ld scenarios were selected due to their relevance in evaluating the impact of high temperatures on mortality.

SEASONAL COMPONENT

The seasonal component was analyzed using Fourier analysis, which revealed a stable annual cycle but with a gradual intensification of peak values over time. To capture this evolving dynamic, an adjustment was applied to values exceeding the 90th percentile, ensuring that the increasing amplitude of extreme temperatures was reflected while preserving a stable reference seasonal cycle. For modeling purposes, we assumed the seasonal component was identical for both mean and minimum temperatures, given their strong statistical coherence. This assumption is supported by high correlation coefficients and a well-synchronized pattern of seasonal variations between the two temperature variables.

RESIDUAL COMPONENT

In an ideal model, the residuals from additive decomposition should exhibit a purely random structure with no significant correlations, indicating that the trend and seasonal components fully capture the underlying data dynamics. However, statistical tests revealed signs of residual autocorrelation, heteroscedasticity, and nonnormality, suggesting that additional structure remained within the residuals.

To address these patterns, we modeled the noise component using a hybrid ARIMA-APARCH approach, enabling the simultaneous capture of temporal dependence and conditional heteroscedasticity in the residuals.

For projections, we used historical residuals as a reference, with iteratively adjusted conditional variance to maintain realistic fluctuations. To prevent unrealistic underestimation of future variability, we introduced a variance floor, set at the 70th percentile of historical variance. Additionally, a trend factor of 0.0001 was applied to the variance projections to reflect a gradual increase in uncertainty over time. At each step, random noise scaled by the square root of the projected conditional variance was added, ensuring that future residual variations were dynamically and robustly integrated into the model.

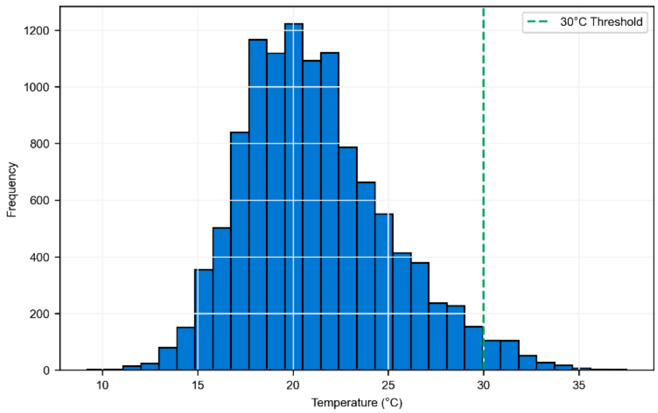
MODELING THE NUMBER OF TROPICAL DAYS

Tropical days are rare events. An analysis of the distribution of daily summer maximum temperatures (June–August) shows that temperatures exceeding 30°C lie beyond the 95th percentile of historical data, set at 28.6°C. This confirms the extreme nature of these occurrences and justifies the application of EVT to model them.

7. van Dorland, R., Beersma, J., Bessembinder, J., Bloemendaal, N., van den Brink, H., Brotons Blanes, M., Drijfhout, S., et al. (March 8, 2024). KNMI national climate scenarios 2023 for the Netherlands (Scientific report WR-23-02, version 2). Royal Netherlands Meteorological Institute. Retrieved January 22, 2025, from https://cdn.knmi.nl/system/data_center_publications/files/000/071/902/original/KNMI23_climate_scenarios_scientific_report_WR23-02.pdf.

8. Ibid.

FIGURE 1: HISTOGRAM OF MAXIMUM TEMPERATURES



We used a Poisson process to model tropical days, allowing for the projection of the number of days on which maximum temperatures exceed a critical threshold, set at the 95th percentile of historical summer maximum temperatures. This approach treats these extreme events as random occurrences, with an annual mean frequency calibrated using data from the past 10 years while incorporating future climate scenarios.

To estimate the magnitude of exceedances beyond 30°C, we employed a generalized Pareto distribution (GPD). This method enables the simultaneous projection of both the frequency and severity of extreme temperature events, providing a robust framework for assessing future heat extremes.

OTHER PARAMETERS

The temporal parameter κ_t, which represents long-term mortality trends, was projected using an ARIMA(0,1,0) model. While alternative models, such as exponential smoothing state space (ETS), demonstrated strong predictive performance, we selected ARIMA for its simplicity and effectiveness in capturing trends and the persistence of past mortality patterns.

The residual component $\varepsilon_{x,t}$, which accounts for unexplained fluctuations, was projected separately for each age x. These residuals, defined as the difference between observed and predicted logarithmic mortality rates ($\ln(\mu_{x,t}) - \ln(\hat{\mu}_{x,t})$), follow a normal distribution with a mean of zero and an age-specific standard deviation, calibrated using historical data. To incorporate future uncertainty, 1,000 stochastic simulations were performed, ensuring a robust and comprehensive assessment of variability in mortality projections.

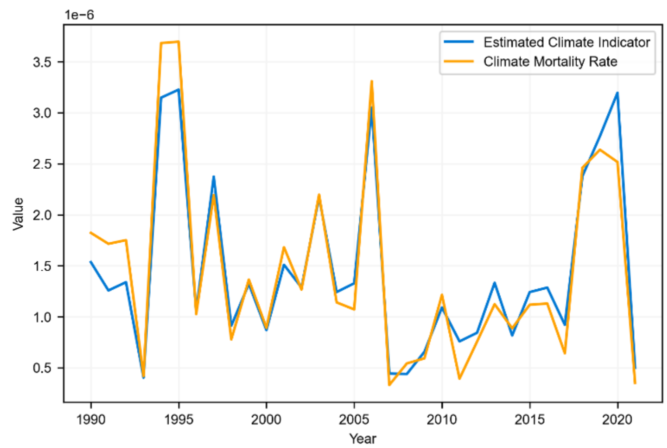
Results

MODEL CALIBRATION AND CLIMATE VARIABLE PROJECTION

Adjustment of the climatic indicator

The climatic indicator $\boldsymbol{C_t}$, representing mortality rates attributable to high temperatures, was adjusted using a GAM. The model exhibited strong explanatory power, achieving an explained deviance of 92.61%, which indicates an excellent fit to the observed data and robust predictive capability.

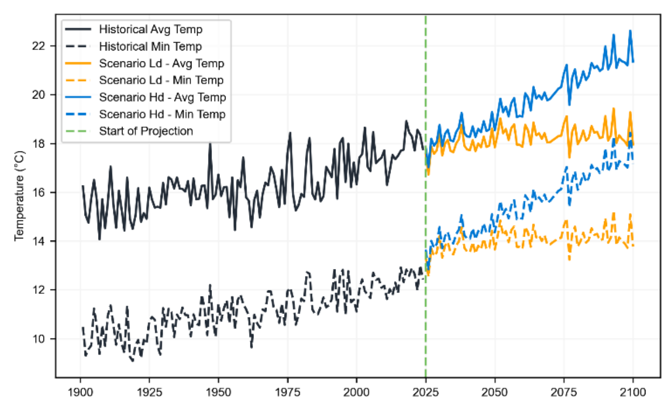
FIGURE 2: ADJUSTMENT OF THE CLIMATIC INDICATOR



Projection of climate variables

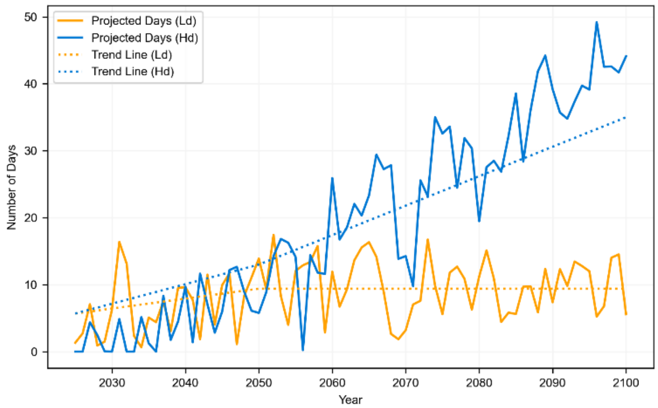
Projections derived from KNMI scenarios indicate substantial changes by 2100. Under the Hd (high emissions and dry summer) scenario, summer temperatures are expected to rise significantly, reaching an average of nearly 22°C by the end of the century. Additionally, minimum temperatures are projected to increase, highlighting the need to assess their impact, given the cumulative effects of sustained nighttime heat on mortality.

FIGURE 3: PROJECTION OF MEAN AND MINIMUM TEMPERATURES BY 2100



Furthermore, the number of tropical days - days when maximum temperatures exceed 30°C - is expected to rise dramatically. Under the Hd scenario, this figure could reach 50 days per year by 2100, compared with fewer than 10 today. This sharp increase significantly heightens the risk of prolonged exposure to extreme heat, with direct consequences for mortality and public health.

FIGURE 4: PROJECTION OF THE NUMBER OF TROPICAL DAYS BY 2100



These projections highlight the increasing exposure to extreme climatic conditions, which is expected to lead to an increase in heat-related mortality.

MODEL PROJECTIONS

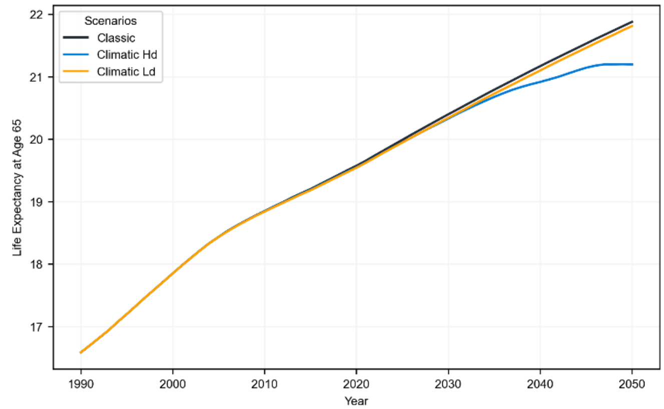
Impact of high temperatures on life expectancy

Results from the climate-adjusted Lee-Carter model, which incorporates the effects of high temperatures, indicate a continued increase in cohort life expectancy at age 65 across the two climate scenarios analyzed. These projections are evaluated against a classic scenario, based on the standard Lee-Carter model without climate-related adjustments, serving as a baseline for comparison. Despite the overall upward trend, elevated temperatures lead to a noticeable slowdown in longevity gains, with distinct long-term effects:

- Hd scenario (high emissions, dry summers): Shows a significant long-term divergence, highlighting the cumulative impact of extreme temperatures on mortality.
- Ld scenario (low emissions, dry summers): Remains closer to conventional projections but exhibits a slight decline due to moderate climate effects.

This climate-driven effect results in a slower pace of longevity gains. Under the Hd scenario, life expectancy at age 65 is projected to be 0.7 years lower than in the baseline scenario by 2050, underscoring the detrimental impact of prolonged heat exposure on mortality trends.

FIGURE 5: TRENDS IN LIFE EXPECTANCY AT AGE 65



Calculation of mortality shocks

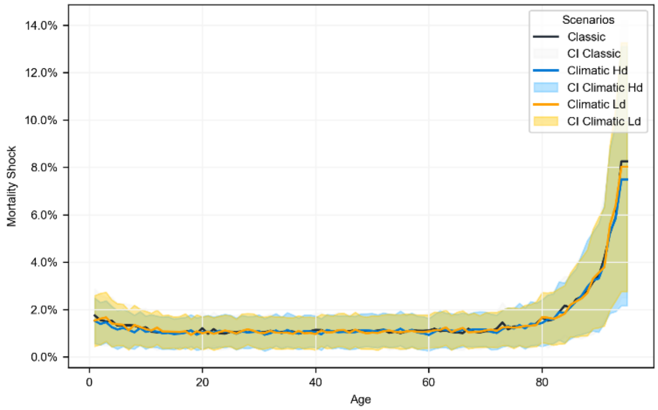
Mortality shocks were estimated following the European Insurance and Occupational Pensions Authority (EIOPA) methodology[9] for the three scenarios (baseline, Hd climate, Ld climate) at both a one-year horizon and the ultimate horizon. In this context, a mortality shock represents an adjustment to mortality rates to account for extreme deviations in life expectancy. The shock factor is determined by minimizing the difference between shock-adjusted life expectancy and the realization of the 0.5% percentile of simulated life expectancies without the shock.

We used the empirical quantile method to derive confidence intervals.

- One-year horizon: The mortality shock curves across the three scenarios are remarkably similar, indicating that short-term mortality shocks exhibit low sensitivity to climate variations. Additionally, a notable increase in mortality shocks is observed at older ages. This effect arises from a structural bias linked to the dynamics of residual life expectancy: As age increases, remaining life expectancy shortens, and its distribution naturally contracts around lower values. As a result, the 0.5% quantile approaches its lower bound more gradually than baseline life expectancy, leading to reduced sensitivity to fluctuations in the shock factor. In other words, at advanced ages, further reductions in life expectancy require larger shock factor adjustments due to the already elevated baseline mortality rates.

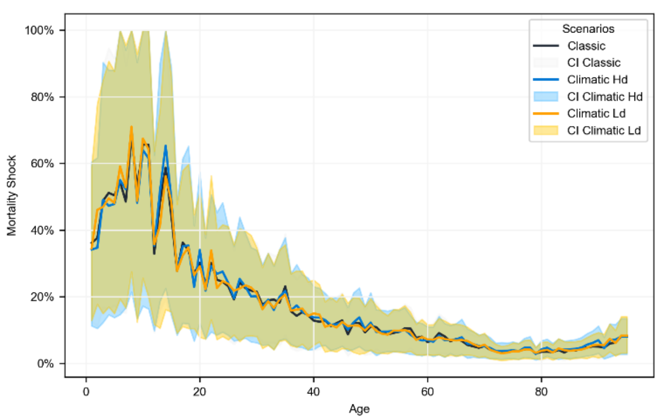
9. European Insurance and Occupational Pensions Authority. (February 28, 2018). EIOPA's second set of advice to the European Commission on specific items in the Solvency II delegated regulation. Retrieved January 22, 2025, from https://www.eiopa.europa.eu/publications/eiopas-second-set-advice-european-commission-specific-items-solvency-ii-delegated-regulation_en.

FIGURE 6: MORTALITY SHOCKS BY AGE AT A ONE-YEAR HORIZON



- At the ultimate horizon, the methodological biases previously discussed gradually diminish. For ages after 80, mortality shock curves converge toward more consistent values, aligning with expected projections, including those published by EIOPA.[10] This convergence reflects the progressive adjustment of long-term mortality shocks, providing a more representative view of projected mortality trends. When comparing the three scenarios, the Hd climate scenario results in an average increase in mortality shocks of 0.23% compared with the baseline scenario, while the Ld climate scenario leads to a more moderate rise of approximately 0.08%. Although these differences remain small, they highlight the differentiated impact of climate conditions on mortality projections. The Hd scenario, based on more pessimistic climate assumptions, amplifies mortality shocks over time, whereas the Ld scenario, reflecting a more moderate climate evolution, results in a less pronounced impact.

FIGURE 7: MORTALITY SHOCKS BY AGE AT THE ULTIMATE HORIZON



Sensitivity analysis

The sensitivity analysis evaluated the impact of methodological and parametric assumptions on life expectancy projections, revealing notable differences in model responsiveness under various climate scenarios:

- The severe climate scenarios (Hd) are particularly sensitive to assumptions regarding heat-related mortality rates and the modeling approach for the temporal parameter $\boldsymbol{\kappa_t}$. For instance, variations in heat-attributable mortality can lead to a life expectancy reduction of up to 2.4 years by 2060. Likewise, the choice of model—ARIMA or ETS—for $\boldsymbol{\kappa_t}$ has a significant impact on projections. The ETS model, which places greater emphasis on recent trends, produces more pessimistic scenarios compared with ARIMA.
- The moderate climate scenarios (Ld) exhibit greater stability, with life expectancy trajectories remaining relatively unaffected by variations in assumptions.

These findings emphasize the critical influence of mortality rate assumptions and temporal dynamics in shaping projections, particularly under extreme climate conditions.

Discussion

This study evaluated the impact of high temperatures on mortality through a climate-adapted extension of the Lee-Carter model, incorporating key climatic variables to enhance the accuracy of mortality projections across different scenarios. The results underscore an increased sensitivity of mortality to extreme temperatures, particularly among vulnerable populations such as people over 65. By integrating specific climate indicators, including the number of tropical days, this approach addresses the limitations of conventional models, which often rely solely on average temperature analyses and fail to capture the full complexity of heat-related mortality risks.

Projections based on KNMI’23 climate scenarios suggest a notable increase in mortality rates between 2050 and 2100, particularly in scenarios with more frequent and intense heatwaves. However, we must acknowledge several methodological constraints. These include the truncation of data at age 94, the simplified assumption of a constant difference between minimum and mean temperatures, and the implicit assumption of residual stationarity, which remains unverified in this framework.

10 Ibid.

Looking ahead, several avenues for further research could refine and expand these findings. Investigating geographical disparities, particularly between urban and rural areas, would offer deeper insights into how infrastructure, exposure conditions, and adaptive behaviors influence mortality risks. Incorporating insurance portfolio characteristics could further enrich the analysis by accounting for adverse selection effects. Additionally, a gender-based differentiation could provide a more detailed understanding of how biological and behavioral factors influence vulnerability to extreme temperatures. Finally, broadening the model to account for other climate-related risks, such as air pollution or cold snaps, would offer a more comprehensive assessment of future health impacts in the context of climate change.

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