MILLIMAN WHITE PAPER

The impact of climate change on winter mortality: A complex phenomenon with an uncertain future

Winter temperature trends and suggestions for modeling their impact on mortality

Eve Titon
Tinhinane Talbi
Jeanne Bessiere

While some studies have been carried out on the prediction of heat waves and the resulting mortality,[1] there is relatively little work on the mortality risk associated with cold temperatures. In fact, the global rise in temperatures is leading to an increasing number of summer heat waves, with a consequent impact on mortality, while winter death rates have been declining overall since 1990.

However, the impact of low temperatures on the human body is complex: As human beings adjust their thermal optimum according to the climate, it is not certain that warmer winters will lead to a decrease in winter deaths in the future. Furthermore, the increasing volatility of temperatures in climate projections adds an additional layer of uncertainty, making the effects of these seasonal variations even more challenging to predict.

In this study, the mechanisms of the impact of changing winter weather conditions on the human body are detailed to define the climate variables of interest, as well as the appropriate models. Two models are then implemented and illustrated on French mortality data—a Lee-Carter model and a distributed lag non-linear model (DLNM)—to incorporate mortality attributable to winter weather conditions in a dynamic model.

How do cold temperatures affect mortality?

The impact of climate change on mortality is not only a major social issue, but also a major challenge for the healthcare sector and the life insurance industry. Heat waves are the main focus of attention, but cold temperatures account for much higher death rates than heat waves. Indeed, exposure to high temperatures over excessively long periods leads to a peak in mortality, mainly affecting the elderly. But exposure to low temperatures, often combined with high humidity, leads to epidemics of winter viruses, causing a large number of deaths every year. So, when it comes to modeling the evolution of winter deaths, it is a good idea to first understand the mechanisms involved, so as to determine the most appropriate types of modeling.

DEFINITION OF A COLD SNAP AND TRENDS

Météo France defines a cold snap as a “long-lasting and widespread cold spell.” It is characterized by a period of at least three days during which the national average temperature, as measured by the national heat indicator, falls below 2°C at least once and does not rise above 0.9°C for more than two days. The episode is interrupted when the national thermal indicator is above 2.2°C. Météo France has identified 46 cold snaps between 1947 and 2022 in France, noting that they are becoming “rarer, shorter, and less intense.” The four longest and most severe cold snaps—February 1956, January 1963, January 1985, and January 1987—occurred more than 30 years ago. According to Météo France, climate change is set to “reduce the number of abnormally cold days in winter throughout mainland France.”

1. Boumezoued, A., Elfassihi, A., Germain, V., & Titon, E. (December 19, 2022). Modeling the impact of climate risks on mortality. Milliman. Retrieved November 14, 2024, from https://www.milliman.com/en/insight/modeling-the-impact-of-climate-risks-on-mortality.

DRIAS climate projections predict a rise in average temperatures in mainland France between now and the end of the century,[2] ranging from 0.9°C to 1.3°C for the RCP (Representative Concentration Pathways) 2.6 scenario, and from 2.6°C to 5.3°C for the RPC 8.5 scenario, as well as a "continued decrease in cold extremes." In addition, according to IHME estimates,[3] the proportion of mortality attributable to low temperatures has shown a slight downward trend since 1990 in France and the rest of the world. This decrease in mortality could be explained by the global rise in temperatures, but also by more systematic vaccination campaigns and medical advances.

EXCESS WINTER DEATHS

How cold affects health and mortality

- **Direct effects**

  Exposure to cold has an immediate impact on mortality, particularly in the case of exposure to extreme cold, such as frostbite. Hypothermia, on the other hand, can occur at less extreme temperatures, in the case of prolonged exposure, for example, and is associated with aggravating factors such as alcohol.[4] A body temperature below 28°C endangers vital functions, particularly the cardiovascular system. Finally, trauma due to snow and ice conditions is also an immediate cause of deaths.

- **Indirect effects**

  Cold exposure is also associated with increased mortality from all nonaccidental causes, particularly cardiovascular disease, respiratory disease and infections.[36]

  Individuals first fall ill and then die. It is therefore less easy to identify the cold as the cause of death. What is more, while some illnesses, such as influenza, are seasonal, they are rarely listed as the cause of death on the death certificate. Instead, causes such as bacterial superinfections or exacerbations of preexisting conditions, like heart disease, are more commonly cited, even though influenza often plays a significant role in triggering these fatal outcomes, especially in vulnerable populations like the elderly.[7]

Cold-related mortality trend

The proportion of deaths attributable to low temperatures has been on a slight downward trend since 1990 in France and the rest of the world. Whereas 28.0 and 19.7 deaths per 100,000 were attributable to low temperatures in France and the rest of the world, respectively, in 1990, these numbers decreased to 24.2 and 18.8 deaths per 100,000 in 2021.[5]

The literature agrees on the existence of a U- or V-shaped temperature-mortality relationship ([6], [25], [34]), allowing the identification of a thermal optimum.

For each degree below the thermal optimum, mortality rises by 0.22% in the Netherlands [25], 1.6% in Valencia [6], and 4.2% in London [34]. Unlike the effects of heat, which are immediate, the impact of cold on mortality begins on the second day [10], lasts up to 23 days, and has no harvest effect [3]. The consequences of cold are felt as soon as there is a slight deviation from the thermal optimum, unlike the impact of heat, which occurs at extreme deviations [10]. Slight deviations from the thermal optimum also contribute more to excess mortality than extreme cold events.

The thermal optimum varies from region to region and may evolve over time, influenced by local factors such as the thermal efficiency of dwellings and adaptive behaviors. The increase in mortality associated with a drop of 1°C is higher in southern Europe than in northern Europe [16], higher in southern U.S. cities than in northern cities [11], and higher in southern French cities than in northern French cities [26]. This paradox of excess winter mortality [20] can be explained not so much by the difference in temperature magnitude between the north and the south, but by the thermal efficiency of dwellings and behavioral adaptations [22].

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2. DRIAS. Les futurs du climat. Retrieved November 18, 2024, from https://www.drias-climat.fr/.
3. Institute for Health Metrics and Evaluation. 2021 Global burden of disease (GBD) survey. Retrieved November 18, 2024 from https://vizhub.healthdata.org/gbd-results/.
4. L'Assurance Maladie. (November 13, 2023). L'hypothermie, un refroidissement parfois dangereux. Retrieved November 18, 2024, from https://www.ameli.fr/val-d-oise/assure/sante/themes/froid-pathologies-sante/hypothermie.
5. Institute for Health Metrics and Evaluation. 2021 Global burden of disease (GBD) survey. Retrieved November 18, 2024 from https://vizhub.healthdata.org/gbd-results/.

Cold also contributes more to excess mortality than heat ([10], [14]). Between 1998 and 2012, cold was 10 times more deadly than heat in 16 European countries [31]. The greater contribution of cold to mortality is explained by the number of days during which cold is active, which is much greater than for heat.

This regional and temporal variability makes projections more complex. Also, while cold contributes more to excess mortality than heat, future projections remain uncertain in the face of climate change.

Perspectives on future cold snap trends

Cold-related mortality could decline as average temperatures rise and heat waves become more frequent and intense [30]. The increase in the number of deaths attributable to heat would begin to exceed the reduction in the number of deaths attributable to cold by the end of the century in the RCP 6 scenario and by the second half of the 21st century in the RCP 8.5 scenario, particularly in the Mediterranean region [31]. However, there is a progressive adaptation to heat and a de facto maladaptation to cold ([1], [21]). This results in a shift to the right of the thermal optimum, or alternatively, an increase in sensitivity to cold: Cold spikes that may seem "average" today may turn out to be particularly deadly in the future. In this configuration, the impact of cold weather on mortality is difficult to determine and remains highly sensitive to the definition of the thermal optimum.

Moreover, even if the frequency and intensity of cold snaps are set to decline, cold alone cannot explain the seasonality of epidemics. Other social and environmental factors, such as individual behavior, photoperiod, ultraviolet rays, and humidity, are responsible for winter infections.

Cold temperatures, for example, are associated with an increase in the concentration of the population in confined spaces, as well as an increase in the use of heating. Influenza epidemics in Europe are linked to time spent indoors during the winter [28]. Heating, on the other hand, results in continuous air recirculation and low humidity, creating ideal conditions for the persistence of viral particles in the environment. The immune system is also weakened by photoperiod (i.e., variations in light exposure). By modifying melatonin and vitamin D levels, photoperiod is said to affect immunity levels ([24], [8], [13], [19], [40]). Finally, winter is characterized by ultraviolet rays being less abundant than in other seasons, while they are virucidal [12].

Thus, it would seem that rising temperatures resulting from climate change alone do not offer the prospect of the disappearance of winter epidemics: the impact of cold weather on mortality is likely to remain significant over time. Morevover, particularly low temperatures, which do not cause peak mortality today, could be much more deadly in the future, as the thermal optimum shifts. Consequently, modeling the impact of climate change on mortality must take cold snaps into account in the same way as heat waves or air pollution.

Calibrating the climate Lee-Carter model to model cold snaps

ADAPTATION OF THE CLASSICAL LEE-CARTER MODEL

In our study, we first implement a model that captures mortality attributable to climate factors. Building on the methodology used in Milliman White Paper [15], a model derived from the Lee-Carter framework [27] and adapted to isolate the mortality specifically attributable to climate risk, is proposed:

$$\ln \mu_{x,t} = \alpha_x + \beta_x^o \kappa_t^o + \delta_x^c C_t$$

The purpose of the term $\beta_x^o \kappa_t^o$ is to capture the global mortality that does not consider the climate cause. Note that $\boldsymbol{c}$ is related to the climate cause of mortality while $\boldsymbol{o}$ is related to other causes. Subsequently, in this article, we will refer to this model as the climate Lee-Carter model.

CLIMATE INDEX CONSTRUCTION AND FIT

The construction of the climate index involved data from three key sources: cold-attributable mortality data from the Global Health Data, all-cause mortality data from the Human Mortality Database, and climate data from Météo-France. The climate data, available monthly at the station level, were first aggregated to the national level and then averaged to align with the annual mortality data, focusing on two key periods: winter (January to March) and autumn (October to December). Following the literature, 15 climate variables were initially selected to construct the index. To explain mortality in year N, three time frames of all climate variables were used: winter variables from year N, autumn variables from year N, and autumn variables from year N-1. Since there were more predictors (15 variables for each of the three periods, resulting in 45 predictors) than data points (32), Lasso and Ridge penalized regression techniques were initially applied to narrow down the variables. However, these methods produced unstable results. To address this, the set of 45 variables was first reduced to 12 by eliminating those that were highly correlated. A stepwise variable selection algorithm based on AIC criteria was then used to identify the final set of predictors for constructing the climate index.

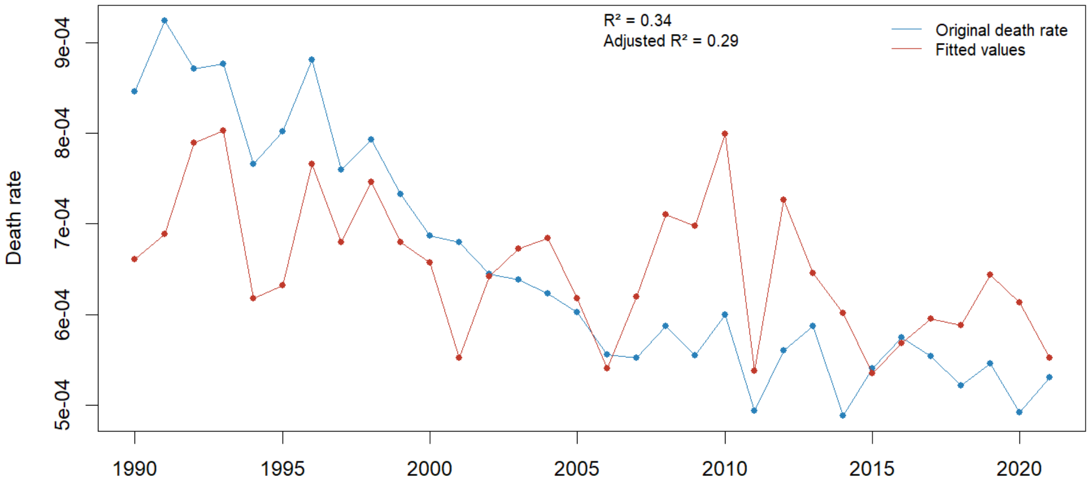
The final climate index C_t (Figure 1) is constructed using a regression between two climate variables and the climate mortality rates and is given by the equation below:

$$C_t = \alpha + b^T X_t$$

where α, b are the linear regression parameters, and $X_t = (X_t^1, X_t^2)$, represents the vector of climate variables for year t (namely October-December average of monthly total daily sunshine duration and of absolute monthly minimum daily temperature).

As we can see, it seems difficult to understand mortality due to low temperatures, using climate indicators constructed on an annual basis (low R^2, poor quality of fit).

FIGURE 1: CLIMATE INDEX AND SUBOPTIMAL TEMPERATURE DEATH RATE IN FRANCE (BOTH SEXES, INDIVIDUALS OVER 45)



CLIMATE LEE-CARTER FIT

The R^2 coefficients between the original death rates and the Lee-Carter models are shown in Figure 2. The two models are similar in the overall fit, with the climate Lee-Carter model showing a slightly better fit for ages above 55. Specifically, the climate model performs better than the Lee-Carter model for 51.52% of the ages (this figure increases to 89.40% of the ages when allowing of 0.50% in the R^2). However, the primary goal here is to incorporate the effects of cold waves while maintaining the model's performance, without necessarily aiming for an increase in R^2.

FIGURE 2: R^2 COEFFICIENTS BETWEEN THE MODEL AND EMPIRICAL DEATH RATES

	Climate Lee-Carter	Lee-Carter
45-55	89.99%	90.08%
55-65	91.34%	91.22%
>65	76.40%	76.40%
All ages	80.72%	80.71%

MODELING CHALLENGES RELATED THE CLIMATE LEE-CARTER MODEL

The goal of the climate Lee-Carter is to find a climate index that captures cause-specific mortality. In our case, several factors hinder its calibration, including cause-specific death data volume, quality, and frequency.

- **Data limitations:** The cause-specific death rate data is limited to a 32-point time series, making it difficult to divide the data into training, validation, and test sets.
- **Data quality:** Anomalies in death rate for ages under 45 also cut down on data depth and constrain calibration of the climate index to the upper age brackets.
- **Aggregation issues:** Aggregation and annualization of weather records to be consistent with the cause specific death annual data frequency may result in loss of information (smoothing the impact of local cold snaps and humidity peaks, mitigating the delayed effect of cold spells, blending the direct and delayed impacts of cold).
- **Linearity:** One might also investigate a nonlinear relationship between climate variables and mortality.

Addressing limitations: Lagged effects and infra-annual data

MODEL SPECIFICATION

This section presents alternative model specifications that aim to address some of the challenges faced by the climate Lee-Carter model. High temperatures in France are mainly observed in summer, enabling their impact on mortality to be modeled on an annual basis, using climate variables averaged over summer.[6] In contrast, low temperatures are dispersed throughout the year. Furthermore, while the impact of high temperatures on mortality is immediate and occurs only with significant deviations from the thermal optimum, the effects of low temperatures can begin with even slight deviations and may persist for up to a month. As a result, modeling on an annual basis does not seem suited to the impact of cold. An infra-annual lag model would allow to better account for the complex dynamics of temperature-related mortality, thereby improving the robustness of our findings compared to the climate Lee-Carter model.

While no research has focused on modeling the overall impact of winter (not solely temperatures but also humidity, insolation, precipitation, wind, etc.), several studies have examined the effects of temperature extremes, both high and low, using distributed lag models (Figure 3). The model's features are as follows:

$$\ln(D_t) = \alpha \ + g^n(X_t^n; L^n; \beta^n) + h^p\left(z_t^p; \gamma^p\right)$$

- **Data:** Daily or weekly all causes death count D_t for $t \in \{1; \dots; T\}$ and N climate variables X_t^n for $n \in \{1; \dots; N\}$.
- **Baseline model:** The death count D_t follows a quasi-Poisson distribution with overdispersion with log link, such that $\lambda_t = \mathbb{E}[D_t]$.
- **Adjustment:** Adjust death count for seasonal and long-term trends. (Recall that the objective of the model is to determine whether the variation in the number of deaths in the short term can be explained by climate factors. As this variation is dominated by seasonality and long-term trends, these effects must be accounted for. climate Denote $z_t = (z_t^1, \dots, z_t^P)$ a vector comprising P explanatory variables such as year, day of the week, or months. Some function of time h^p is fitted in the regression model, such as time stratified model, periodic function or flexible spline function.)
- **Mortality and climate variables relationship:** distributed lag model. We consider the L^i delayed impacts of climate variable X^i, that is $(X_{i,t}, X_{i,t-1}, \dots, X_{i,t-L^i})$ on death count D_t. For each lag $l \in \{1, \dots, L^i\}$, the relationship between mortality and climate variable X^i is described by f^i, a linear or nonlinear function (such as linear thresholds, quadradic, or natural cubic spline functions). The effect of climate variable X^i on death count D_t for day t is:

$$g^i\left(X_t^i; L^i; \beta^i\right) = \sum_{l=0}^{L^i} \beta^l f^i\left(X_{t-l}^i\right)$$

where β_l is the coefficient of the delayed impact l.

6. Milliman. (December 19, 2022). Modeling the impact of climate risks on mortality. Retrieved on November 18, 2024, from https://www.milliman.com/en/insight/modeling-the-impact-of-climate-risks-on-mortality.

Lag coefficients: constrained or unconstrained. In the above unconstrained distributed lag model, the lag terms are likely to exhibit significant correlation, which results in imprecise estimates—a notable drawback. This challenge can be mitigated by applying constraints to the estimates, specifically to the effects of the various lags. These constraints may take linear forms, such as in the lag-stratified distributed lag model, or nonlinear forms, involving smooth transitions in β coefficients through polynomial, cubic spline, or penalized spline functions.

FIGURE 3: USE CASE OF DISTRIBUTED LAG MODELS IN THE LITERATURE

	DISTRIBUTED LAG MODEL BASIS			
TEMPERATURE-MORTALITY MODEL BASIS	**UNCONSTRAINED**	**QUARTIC POLYNOMIAL**	**STRATA**	**NATURAL CUBIC SPLINE**
Linear	[37]	[37]	-	[41]
Quadratic	-	[9]	[11], [39]	
Natural cubic spline	-	-	-	[30], [31], [14], [17], [4]
Linear thresholds	[23], [18]	[4]	[25] [6],[34]	[35]

This table displays use cases of distributed lag models in the literature, along with the functions used to model the temperature-mortality relationship on one side and the lags on the other.

DATA, MODEL, AND CALIBRATION

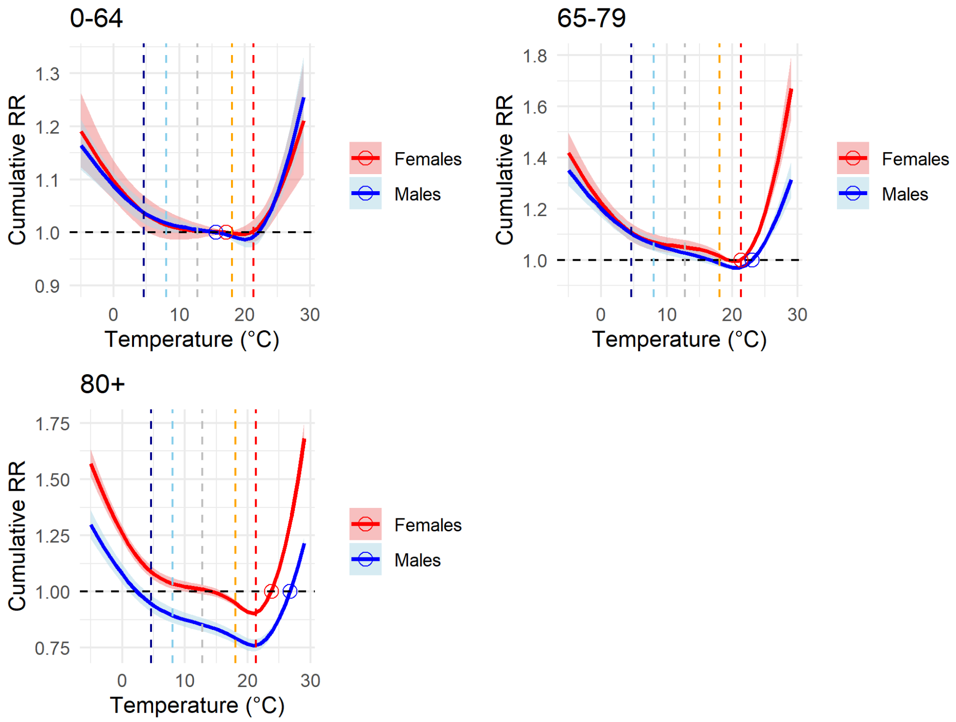
Daily national death count per age group and sex and national mean temperature indicator from 1990 to 2021 were used for this study. Daily national death count per age group and sex is regressed against daily mean national temperature within a quasi-Poisson regression framework with log link.

Following [17], the temperature mortality relationship is modeled with a natural cubic spline with three internal knots, placed at the 10th, 75th, and 90th percentiles of the daily temperature distribution within the observational period. Lagged effect up to 21 days are considered using a natural cubic spline with three internal knots placed at evenly spaced intervals on the log scale. We also control long-time trends and seasonality with two predictors: time and day of the week. Time is fitted as a natural cubic spline with 8 degrees of freedom per year, and a categorical variable indicating the day of the week is fitted with a linear relationship.

RESULTS

The cumulative temperature-mortality association over 21 days estimated with the DLNM are represented in Figure 4. The figure displays the temperature-related mortality in excess of the thermal optimum, which serves as the baseline model. The relative risk curves show a non-linear relationship between temperature and mortality, with sensitivity to both hot and cold temperature. In accordance with the literature, the effects of cold occur as soon as there is a slight deviation from median temperatures (below 50th percentile) and are incremental, while the effects of heat are more intense, but appear at more extreme temperature deviation (above 90th percentile). Sensitivity increases with age and shows differences between sex. Females tend to be more sensitive to extreme temperatures than males in the 65-79 and over 80 age groups.

FIGURE 4: DLNM RESULTS



The relative risks (RR) are calculated for the 1990-2021 period for women (red) and men (blue) across groups 0-64, 65-79, and 80+ with their 95% confidence intervals (shaded areas). The reference used for computing each subgroup RR is each subgroup minimum mortality temperature (thermal optimum, represented by a red circle for females and blue circle for males). The dark blue, light blue, grey, yellow and red dashed vertical lines show respectively the 10th, 25th, 50th, 75th, and 90th percentiles of the mean temperature distribution within the observation period.

CONCLUSION

This study emphasizes that each climate factor, due to its specific effects on mortality, requires a dedicated model. For example, heat waves produce immediate impacts, while cold has a more diffuse and lasting effect, justifying distinct modeling approaches for each. This need for adaptation opens the way for joint modeling, which would integrate the effects of multiple interacting climate factors, such as cold, heat, and air pollution.

Such a comprehensive approach would provide a more complete understanding of the impact of climate risks on mortality, considering the complex dynamics among the different elements.

Joint effects of climate risks on mortality

While it is valuable to model the impact of a single climate risk on mortality, such as cold, the interactions between different climate risks should also be considered. Modeling only one climate risk may not accurately reflect its true impact on mortality because climate risks often interact in complex ways. The overall effect of all climate risks on mortality is not simply the sum of individual impacts. Some climate risks have synergistic effects, either amplifying or mitigating the impact of others. For instance, the combination of cold and air pollution can significantly increase mortality. Up to 9.56% of non-accidental deaths in Xining were attributable to the joint exposure to cold waves and high levels of PM2.5 between 2016 and 2021 [33]. Conversely, cold temperatures can reduce mortality from malaria [5] by inhibiting the survival and transmission of both vectors and pathogens, as they have an optimal range for these processes [29],[33].

Modeling the joint impact of multiple climate factors on mortality is however a statistical challenge. Collinearities, non-linear relationships, and delayed effects complicate the modeling, inflate the variance of estimates, and reduce precision. While no previous research has considered the joint effects of temperature, pollution, and borne-vector diseases, time-stratified case-crossover designs with Cox, log-linear or logistic regressions have been used to model joint effect of ambient air pollutants, temperature, and humidity on mortality [42], of ozone and temperature on respiratory hospitalization [38], and of cold spells and fine particulate matters on mortality [32]. A time-series approach using a composite index, along the line of the Actuarial Climate Index (ACI) could also be considered [2].

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Appendix A: Detailed calibration of the climate Lee-Carter model

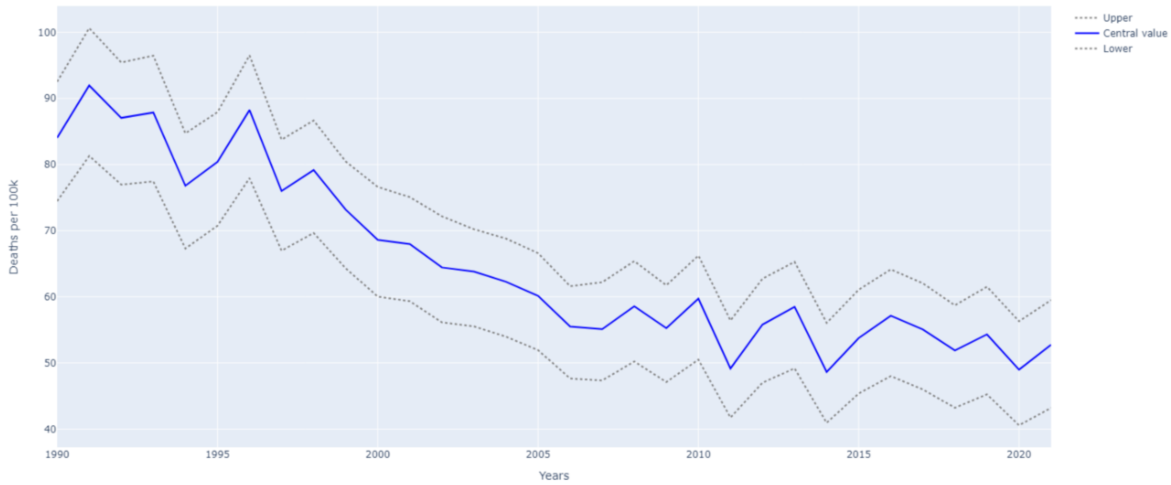
DATA

This study combines the use of three databases: one for the mortality linked to the specific cause (Global Health Data), one for the global national mortality (Human Mortality Database), and one for the climate variables.

Global Health Data (GHD)[7]:

This database is published by the Institute for Health Metrics and Evaluation (IHME). GHD provides annual death numbers estimates, classified by various criteria (age, location, year, sex), as well as by risk factors and cause of death. Particularly, the selection of death numbers relative to one specific risk is possible on this database. For example, on the “low temperature” risk factor, we can find all the deaths induced by suboptimal temperature, including deaths occurring from the increase in prevalence of lower respiratory infection, ischemic heart disease, or transport injuries. Recently, this database was updated to include two additional years (2020 and 2021), now offering a history from 1990 to 2021. These revisions came along with inconsistencies in the number of low-temperature-induced deaths in the under-45 age group. Consequently, our study will be limited to individuals over 45 years old.[8]

FIGURE A-1: FRENCH DEATH RATE ATTRIBUTABLE TO LOW TEMPERATURE EXPOSURE (BOTH SEXES, INDIVIDUALS OVER 45, 100 000)



Data source: GBD Database

Human Mortality Database (HMD)

This is the reference for death data used for actuarial purposes. It provides annual death numbers by country from 1816 to 2021.[9]

Climate and meteorological database:

This database contains various climate variables such as temperature, rainfall, sunshine duration, and wind-related data. The source of this data varies by country; for our study it is Météo France.[10] They provide monthly weather-related measures by stations located though France from 1864 to the current last month. To align with the annual and national grid of our mortality data, the climate variables need to be aggregated. Specifically, the climate variables from stations are averaged at the department level, then at the region level, and finally the regions are averaged to produce national climate variables. Moreover, to be consistent with the annual grid,

7. Institute for Health Metrics and Evaluation. (2021). Global Health Data Exchange. Retrieved November 18, 2024, from https://ghdx.healthdata.org/.

8. It should also be borne in mind that the years 2020 and 2021 had an impact on cold-related deaths (excluding COVID-19): confinements and barrier measures limited the spread of more traditional winter viruses.

9. Human Mortality Database. Retrieved November 18, 2024, from https://www.mortality.org/.

10. Météo France. Retrieved November 18, 2024, from https://meteo.data.gouv.fr/.

monthly national climate variables are averaged. To capture the effect of suboptimal temperatures, two relevant periods are defined: winter (January through March) and autumn (October through December). Consequently, the national monthly climate variables are averaged through January, February, and March and through October, November, December. Thus, each climate variable is represented by two annual measures: one for winter and one for autumn.

CONSTRUCTION OF A CLIMATE INDEX

Considering all the available climate variables, the goal is to select those that best explain mortality rates related to climate causes, particularly the impact of suboptimal temperature in this study.

We first selected 15 variables from the 124 provided by Météo France, in line with those mentioned in the literature, such as precipitations, minimal temperatures, number of days below 10 degrees, insolation, and wind force. Since we constructed two annual measures for each climate variable, we obtained 30 variables to explain mortality rates of year N. Additionally, following the literature, climate conditions from October to December of year N-1 may have a delayed impact on early year N mortality rates. Therefore, we also considered the set of 15 climate variables from this period. Finally, we reached a total of 45 predictors.

However, with only 32 data records for the response variable (specific cause of death), the predictor matrix is singular. It is necessary to narrow down the number of explanatory variables.

Penalized regression

Two penalized regressions with leave-one-out cross-validation are performed on the set of 45 predictors. Predictors for which the estimates are set to 0 are excluded from the predictors matrix, and a classic linear regression is then performed with the specific cause mortality rate.

A Lasso regression (least absolute shrinkage and selection operator) is fitted. Lasso uses L1 regularization to reduce the number of predictors, shrinking some coefficients to 0.

An elastic net regression is also conducted. Elastic net regression uses both L1 and L2 regularization, allowing better handling of highly correlated predictors, which is particularly the case with weather data.

A study of the stability of the climate index is carried out. We consider a sequence of data subsets each excluding one year, and re-estimate both penalized regressions on these subsets. The selection of climate indicators varies considerably, and the significance in the statistical student’s t-test of the coefficients estimated in the second step with the classical linear regression is low. This variability may be due to non-stationarity. To address this, we conduct a sequential unit root testing strategy on the whole dataset and stationarize five non-stationary series. The stability analysis of the index with stationarized data leads to the same previous conclusions.

Variables selection

The high correlation among weather data variables may also contribute to the instability of the climate index. Multicollinearity causes instability in coefficients estimates, making them highly sensitive to small data changes and complicating the interpretation of individual predictors effects due to cofounded variables influences.

To address this, we excluded highly correlated variables, such as the monthly number of days with a minimum daily temperature below -10°C, which is correlated at -86% with the monthly number of days with a minimum daily temperature below -5°C. We narrow down to four climate variables, which gives us 12 predictors to explain climate-related death rate of year N (again we have one indicator for January through March of year N, and two for October through December: one for year N and one for year N-1).

A stepwise selection algorithm based on AIC (Akaike Information Criterion) criteria was conducted. The stability study revealed that four to six climate indicators were consistently selected, but again, only half of the estimates were statistically significant according to student’s test. The multiple R-squared value was relatively low—around 40%—and the residuals were normally distributed, correlated, and homoscedastic at a significance level of 5%.

FIGURE A-2: STABILITY STUDY OF THE CLIMATE INDEX WITH A STEPWISE AIC VARIABLES SELECTION

DATA WITHOUT YEAR N	NUMBER OF SELECTED VARIABLES	NUMBER OF SIGNIFICANT VARIABLES	R2	NORMALITY OF RESIDUALS (P VALUE)	INDEPENDENCE OF RESIDUALS (P VALUE)	HOMOSCEDASTICITY OF RESIDUALS (P VALUE)
2021	6	3	41%	0,78	0,0000	0,13
2020	6	2	33%	0,88	0,0000	0,10
…	…	…	…	…	…	…
1991	5	4	45%	0,25	0,0000	0,23
1990	6	2	27%	0,50	0,0000	0,74
Mean	4,8	2,3	37%	0,74	0,0000	0,18
Min	3	2	27%	0,04	0,0000	0,04
Max	6	4	55%	0,99	0,0002	0,94
Whole dataset	6	2	34%	0,92	0,0000	0,09

The number of selected and significant variables does not include the intercept. The number of selected variables results from a stepwise AIC algorithm. The number of significant variables is the number of variables for which the linear regression between the cause specific death rate and the selected variables only are significant according to Student's t-test. The multiple R squared and tests on residuals are computed on the linear regression between the cause specific death rate and the significant variables only.

The climate index C_t (Figure A-4) is constructed using a regression between the climate variables shown in (Figure 3) and the climate mortality rates. The final climate index C_t is given by the following three-parameter linear equation:

$$C_t = \alpha + b^T X_t$$

where α,b are the linear regression parameters, and $X_t = (X_t^1, X_t^2)$, represents the vector of climate variables for year t.

FIGURE A-3: OCTOBER-DECEMBER AVERAGE OF MONTHLY TOTAL DAILY SUNSHINE DURATION (LEFT) AND OF ABSOLUTE MONTHLY MINIMUM DAILY TEMPERATURE (RIGHT)

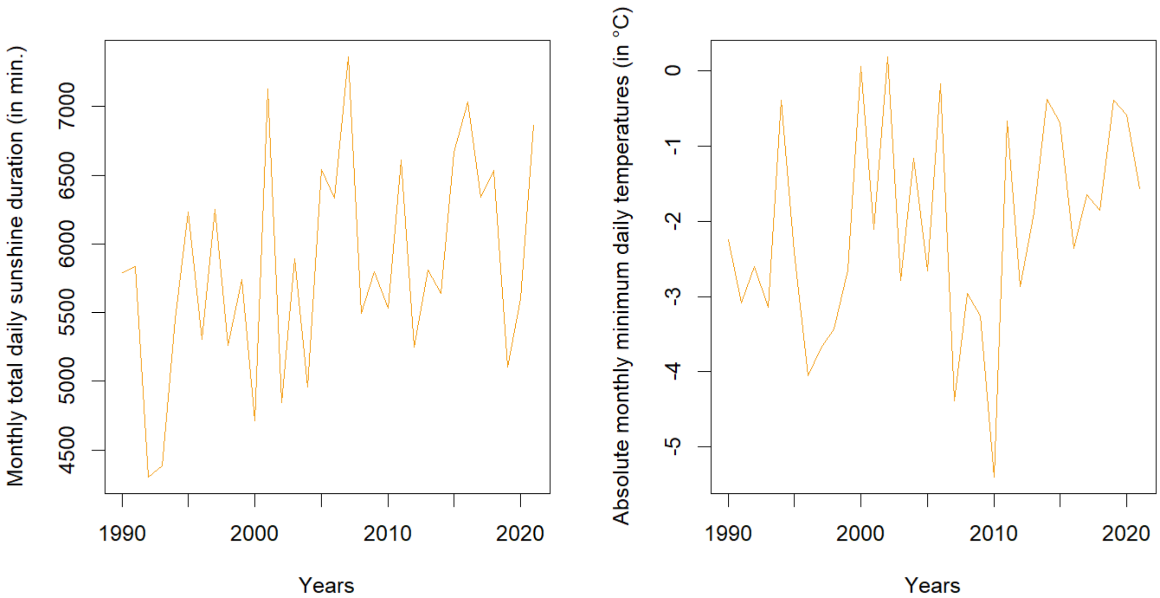
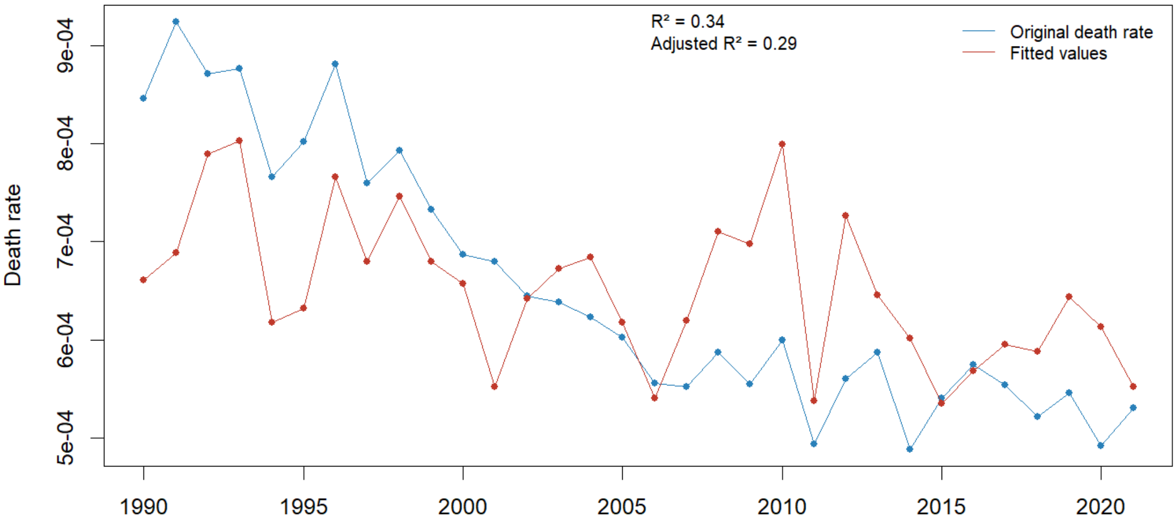


FIGURE A-4: CLIMATE INDEX AND SUBOPTIMAL TEMPERATURE DEATH RATE IN FRANCE (BOTH SEXES, INDIVIDUALS OVER 45)



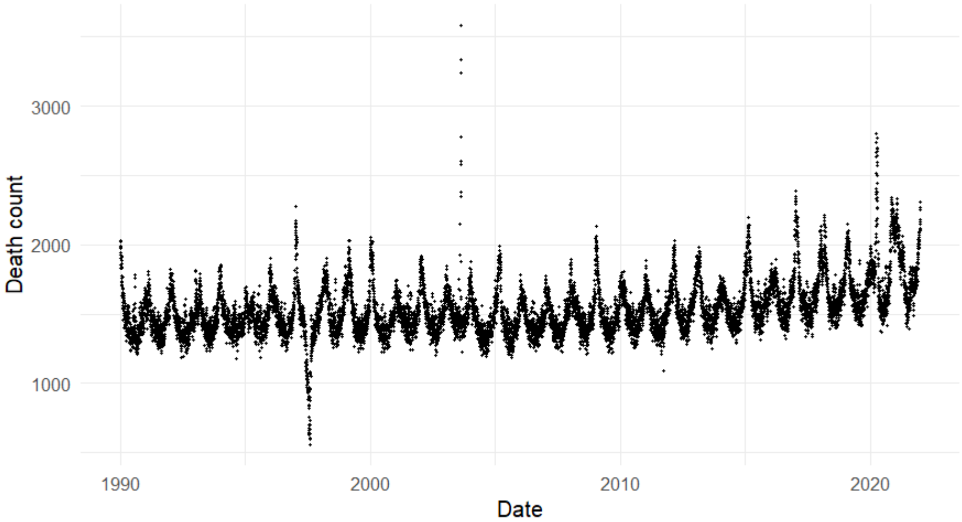
Appendix B: Detailed calibration of the DLNM

DATA

Two data sources were used for this study: one for mortality data and one for climate data.

- Insee daily death records provide daily death numbers in France from 1990 to 2021 with age and sex.[11] Data are aggregated per day, age, sex. Extreme values are observed in December 1996, June/July 1997, August 2003, and April 2020 (Figure B-1). While extreme values of 1996 are attributed to cold spells, 2003 to heat waves and 2020 to COVID, the outliers for summer 1997 are not recorded in Insee's monthly death records and therefore appear to be erroneous data. We perform a transformation on the data from June to July 1997 by replacing the daily death counts by sex and age group for each day $x \in [1, 2, \ldots, 31]$ of month $y \in [June\,; July]$ with the average for that day x of month y across the years $[1994; 1999]$. (Figure B-2).
- Météo France provides daily maximum and minimum temperature for 30 cities from 1990 to 2021. These temperatures are first averaged at the station level to compute daily mean temperatures, which are then aggregated to create a national mean temperature indicator.

FIGURE B-1: RAW DAILY DEATH COUNT IN FRANCE, ALL AGES, MALES AND FEMALES



11. National Institute of Statistics and Economic Studies (Insee). Retrieved November 18, 2024, from https://www.data.gouv.fr/fr/datasets/fichier-des-personnes-decedees/.

FIGURE B-2: ADJUSTED DAILY DEATH COUNT IN FRANCE, ALL AGES, MALES AND FEMALES

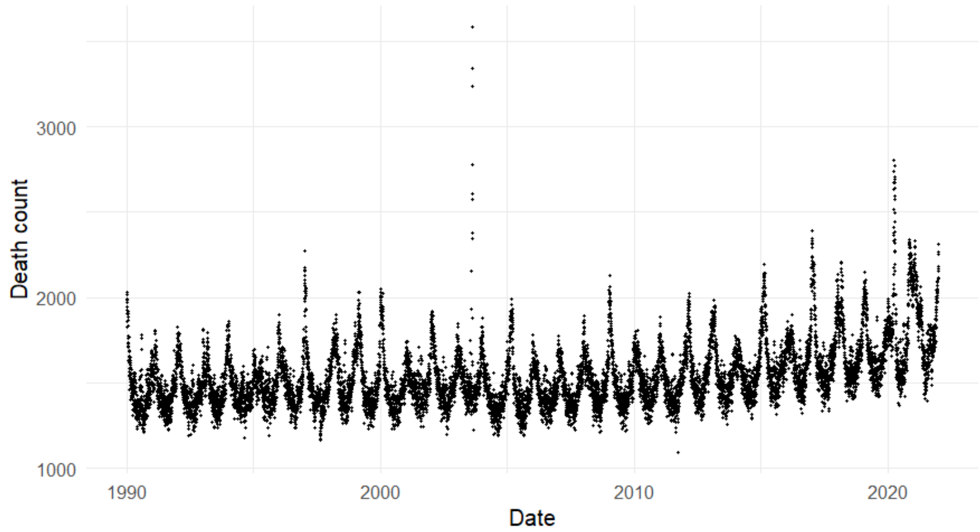
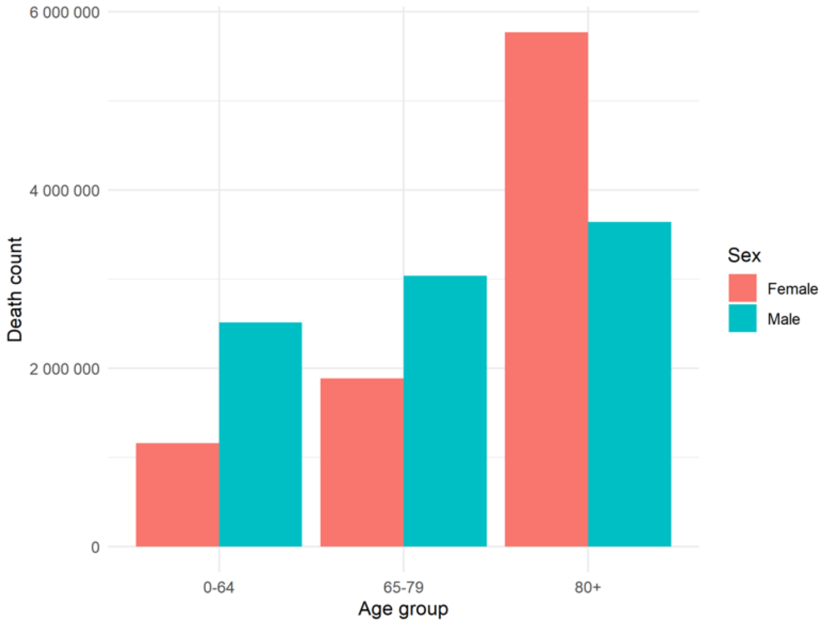


FIGURE B-3: DEATH COUNT PER AGE GROUP AND SEX BETWEEN 1990 AND 2021 IN FRANCE



CALIBRATION

Predictors

Predictors consist of one cross-basis function for the lagged effect of temperature, one control for long-time trend and one for seasonality.

Using the DLNM R package,[12] the temperature mortality lagged relationship is modeled with a cross-basis function. The temperature/mortality relationship is captured by a natural cubic spline with three internal knots, placed at the 10th, 75th, and 90th percentiles of the daily temperature distribution within the observational period, while the lagged effects are represented by a natural cubic spline with three internal knots placed at evenly spaced intervals on the log scale. We consider up to 21 lags.

12. DLNM: Distributed Lag Non-Linear Models. Retrieved November 18, 2024, from https://www.rdocumentation.org/packages/dlnm/versions/2.4.7.

We also control for long-time trends and seasonality with two predictors: time and day of the week. Time is fitted as a natural cubic spline with 8 degrees of freedom per year and a categorical variable indicating the day of the week is fitted with a linear relationship.

Model

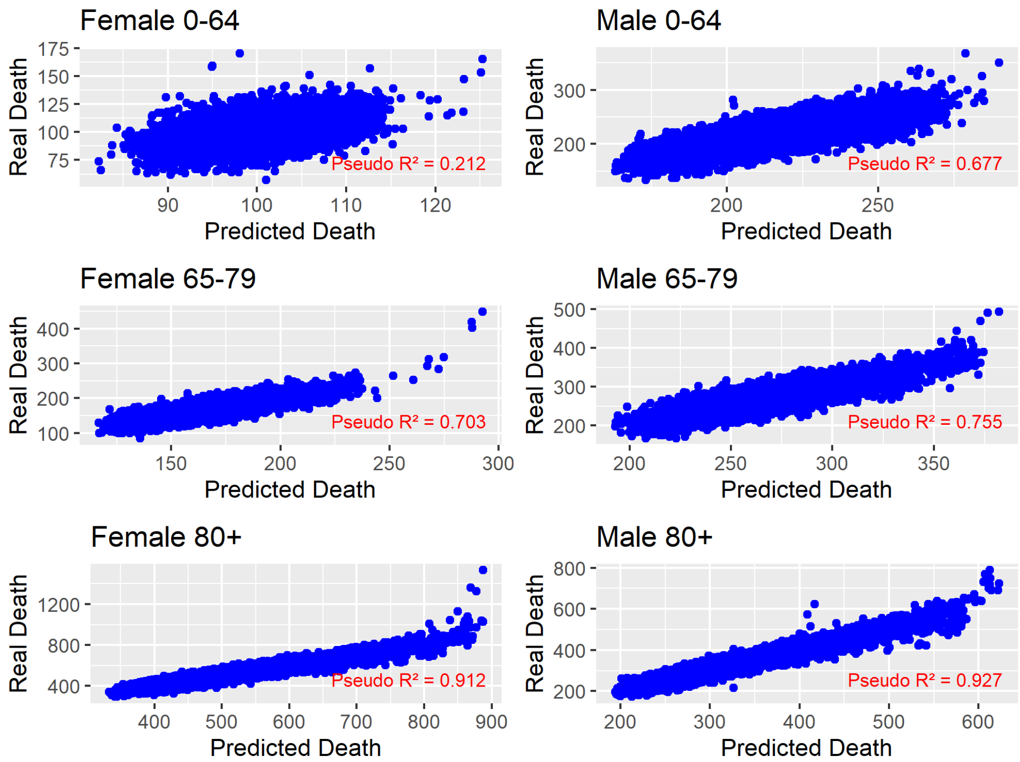
Daily national death count per age group and sex is then regressed against the cross-basis function of lagged daily mean national temperature and the two control variables within a quasi-Poisson regression framework with log link using the GLM function of stats R package.[13]

FIT

To assess the fit of the model, we compute the pseudo R^2 for each subgroup (B-4), that is the proportion of variation in the data explained by the model compared to the null model.

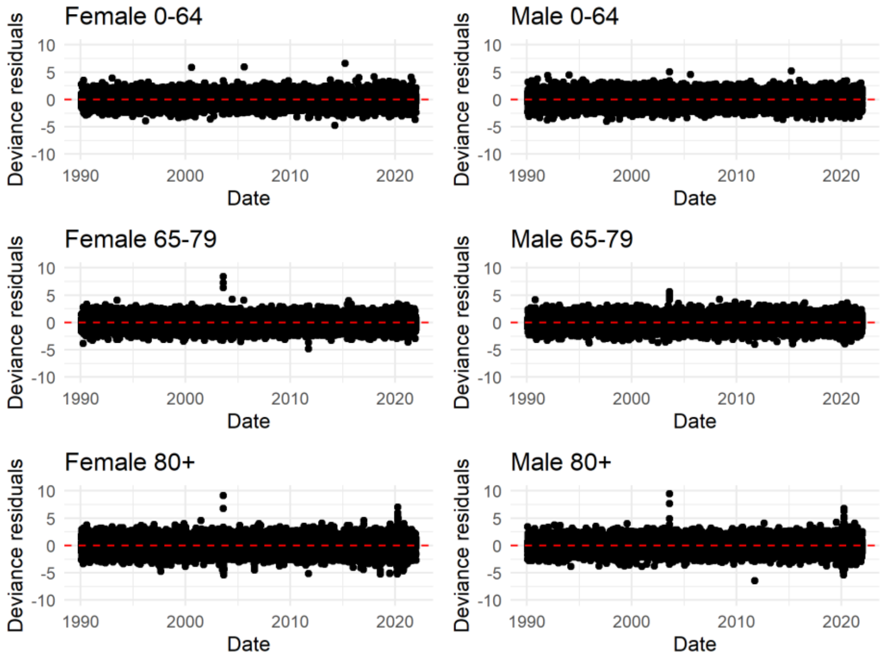
We observe a good fit for central and low values of death, while high extreme points are not well-captured. Analysis of the deviance residuals graphs against dates (Figure B-5 confirms this diagnostic and helps to localize extreme values (e.g., the 2003 heat wave and COVID). The model is well-suited to both sexes for ages above 65 but poorly performs on the 0-64 females' subgroup.

FIGURE B-4: FIT BETWEEN PREDICTED DEATH AND REAL DEATH OF THE QUASI-POISSON REGRESSION MODEL



13. See: Glm : Fitting Generalized Linear Models. RDocumentation at https://www.rdocumentation.org/packages/stats/versions/3.6.2/topics/glm.

FIGURE B-5: DEVIANCE RESIDUALS



RELATIVE RISK COMPUTATION

The RR are computed using the crosspred function of the DLNM package. This function requires the use of a centering value, used as a reference for prediction. This reference is the temperature value for which we consider the RR to be equal to 1. We used the MMT (minimum mortality temperature, or in other words, the thermal optimum) of each subgroup as the centering value.

Each MMT was computed as the temperature that minimizes the temperature/mortality relationship, represented by a second-degree polynomial.

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milliman.com

CONTACT

Eve Titon
eveelisabeth.titon@milliman.com

Tinhinane Talbi
tinhinane.talbi@milliman.com

Jeanne Bessiere
jeanne.bessiere@milliman.com

Milliman