Modeling the impact of climate risk on mortality

Longevity 18

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SEPTEMBER 8, 2023

Presentation based on the paper:
https://www.milliman.com/en/insight/modeling-the-impact-of-climate-risks-on-mortality

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Introduction

Motivations and goals

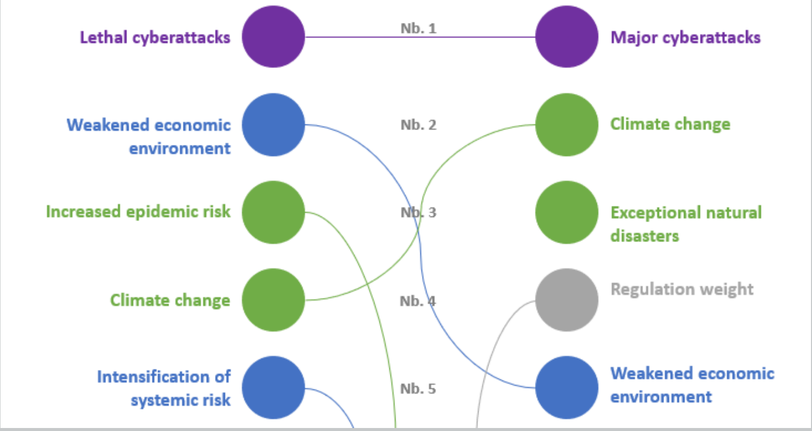
Context

- Objectives of Paris Agreements: to keep global warming well below +2°C compared to the pre-industrial era by 2100 and to tackle the effects of climate change.
- Mobilization of actors in relation to climate change (GIEC, COP21, EIOPA,France Assureurs - ex FFA, ACPR).
- ACPR stress tests provide mortality trajectories that account for air pollution and vector-borne diseases

Objectives

- To bring elements of understanding of the new stakes linked to this climate change.
- Production of a toolbox allowing:
  - To understand the risks linked to a climatic evolution and the repercussions on the activity of the insurers
  - To propose notions of 1-year horizon risk and new relevant modeling of this risk.
- To study the deformation of mortality shocks in relation to reference shocks.

Ranking of emerging risks according to France Assureurs (ex FFA) for 2022 (with 2021 comparison)



SOURCE : CARTOGRAPHIE PROSPECTIVE 2022 de l'assurance France Assureurs (01-2022)

Mapping climate risks impacting mortality

Examples of climate impacts on mortality

Food and water insecurity

- Food and water insecurity: changes in temperatures, rainfall, and weather generally, may affect crop production and many other aspects of agriculture.
- Water supply may be heavily reduced by drought.
- The quality of drinking water sources may also be compromised by extreme storm events.
- Large locust storms, caused by huge rainfall in areas where they breed, may result in significant crop damage.
- These events would likely result in increases in the probability of disease and a negative impact on life expectancy.

Temperature change and volatility

- Changes in temperatures may be subject to a higher volatility (extreme values)
- Conditions relating to high temperatures could be exacerbated by the increased likelihood and severity of heatwaves
- The impact is not the same for all ages (younger and older people are the most affected).

Pandemics and vector-borne infectious diseases

- Prevalence of pandemics or outbreaks of disease such as malaria, due to a wider spread of disease-carrying insects.
- Increased exposure to existing diseases, as rising global temperatures can lengthen the season and increase the geographic range of disease-carrying insects. This effect is exacerbated given the difficulty e.g. to counteract exploding mosquitos populations

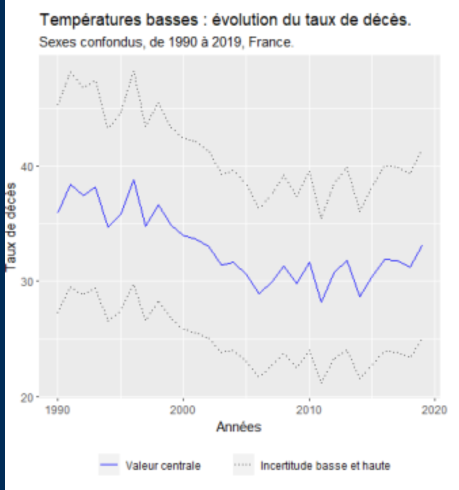
Mapping climate risks impacting mortality

Declination for the case of France

Temperature change and volatility

- Non-optimal temperatures: heat waves
  - Direct mortality (sunstroke, dehydration, etc.)
  - Indirect mortality (deterioration of vital organs, mainly in older population)
- Non-optimal temperatures : cold waves

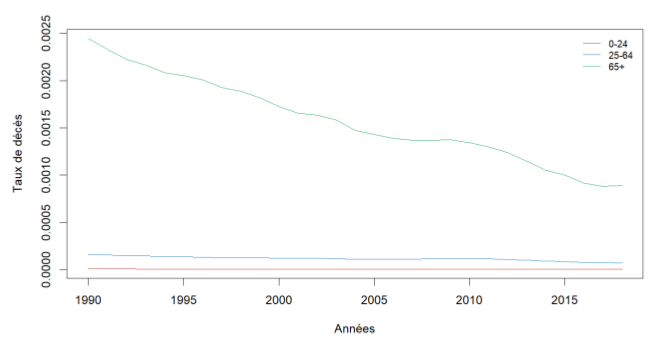
Trends in death rates for low temperatures (all genders, 1990-2019, France)



Air pollution and increasing allergens

- Asthma, respiratory allergies
- Tracheal, bronchus and lung cancer
- Ischemic heart disease
- Stroke
- Chronic obstructive pulmonary disease
- Diabetes melltitus type 2

Air pollution death rates (all genders, 1990-2019, France)

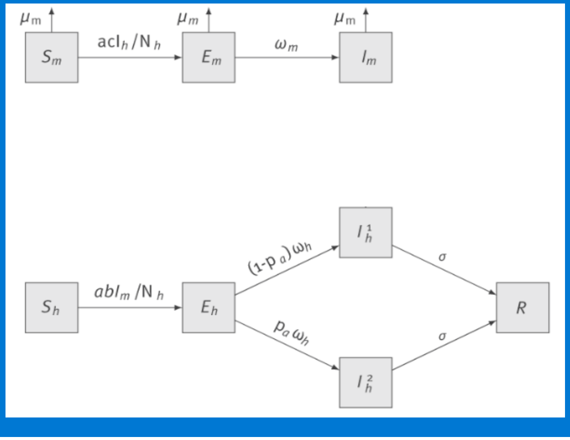


Changes in vector ecology

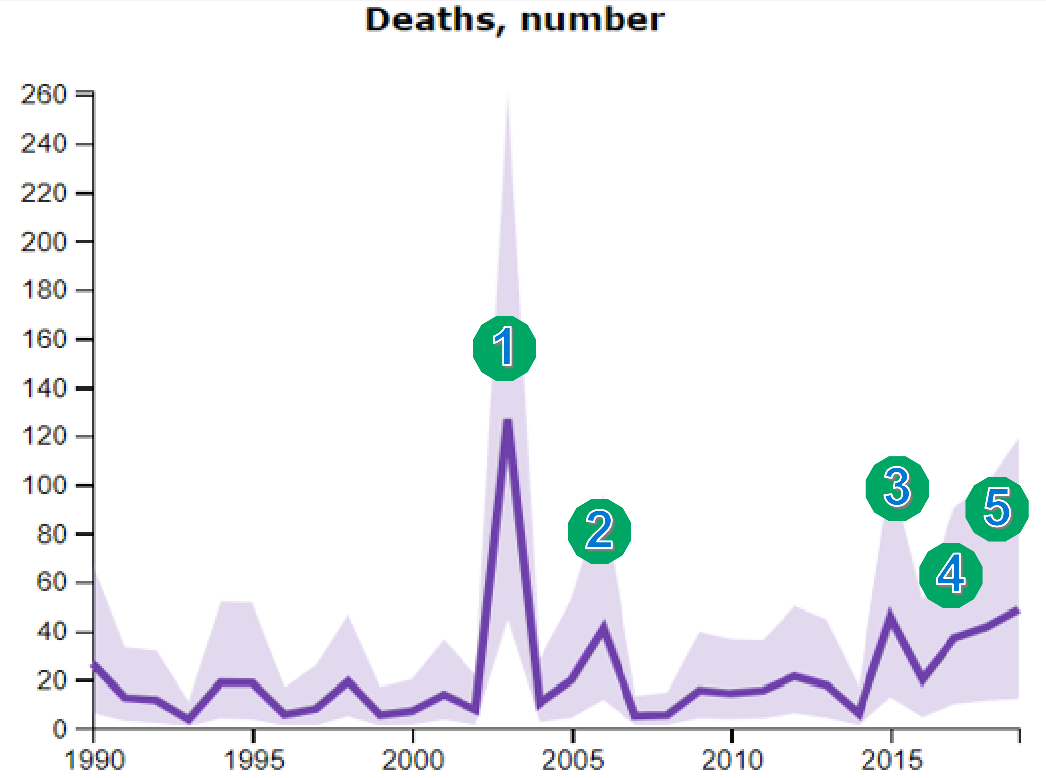
- Malaria, dengue fever , lyme disease, Zika virus, Other mosquito diseases
- Number of deaths rising, but still low
- SIR-type modeling

Modeling example for vector-borne diseases

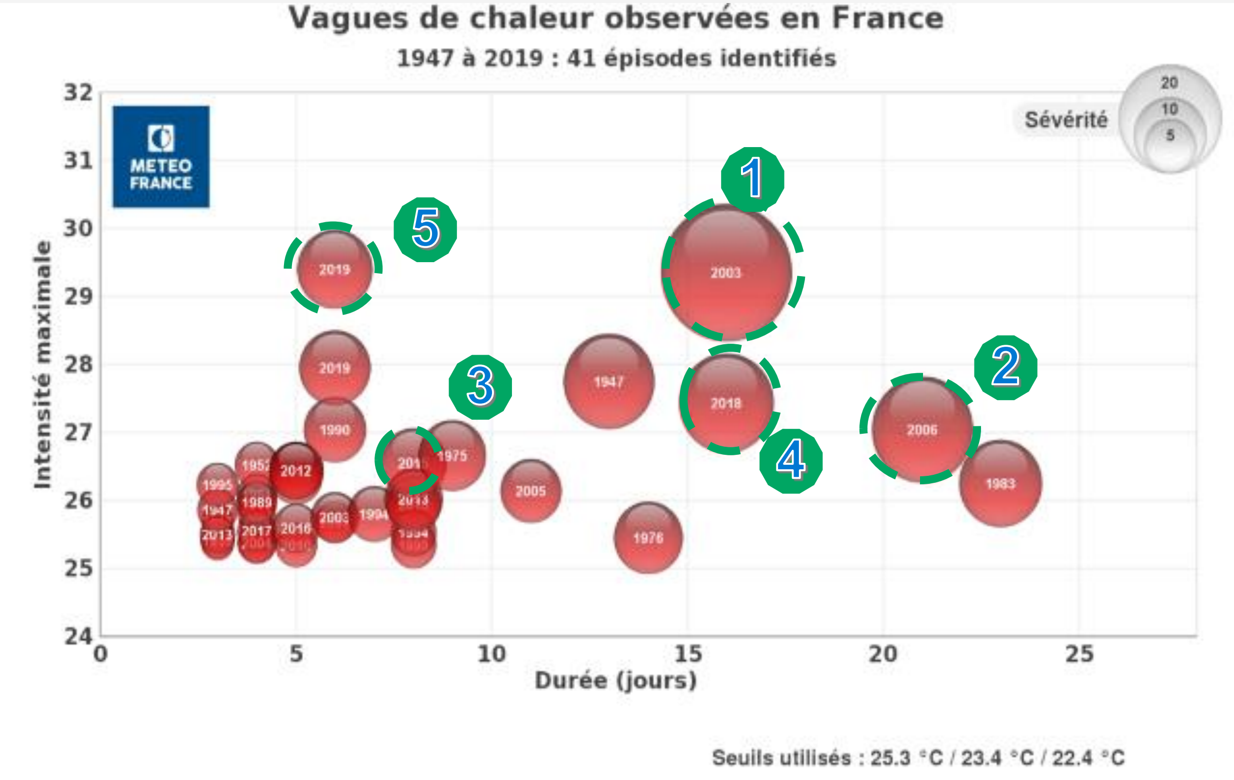
source: Sochacki, Thomas, et al. Imported chikungunya cases in an area newly colonised by Aedes albopictus: mathematical assessment of the best public health strategy.



Relation between Heat Waves and deaths in France



Death rate for the cause "exposure to high temperatures", ages: 55+, all genders



Heat waves in France. From 1947 to 2019: 41 heat waves observed

modeling climate-related mortality

Example of mortality modeling taking into account climate risks

Model features

- Choice of the model : few mortality data available and low frequency of extreme weather events.
- Proposal for a model capturing cause-related mortality.
- Division into age groups : exemple sur le cas de la France → Young people (0-25 years), Working people (25-65 years), Retired people (65 years and over).

Classical Lee-Carter model

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

- α_x : describes average age specific pattern by age of mortality
- κ_t is the time-varying index for the general mortality
- β_x : the coefficient which measures sensitivity of ln(μ_(x,t)) at age group x to changing the index κ_t
- The term β_x κ_t captures the joint tendency of age-specific mortality rates to evolve over time.

Adapted climatic Lee-Carter model

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

- $\mu_{x,t}$ is the total mortality**.**
- **C_t : indicator related to climatic variables**
- **The notation** c refers to the climatic cause studied
- The notation o refers to other causes than the one considered (called by c)

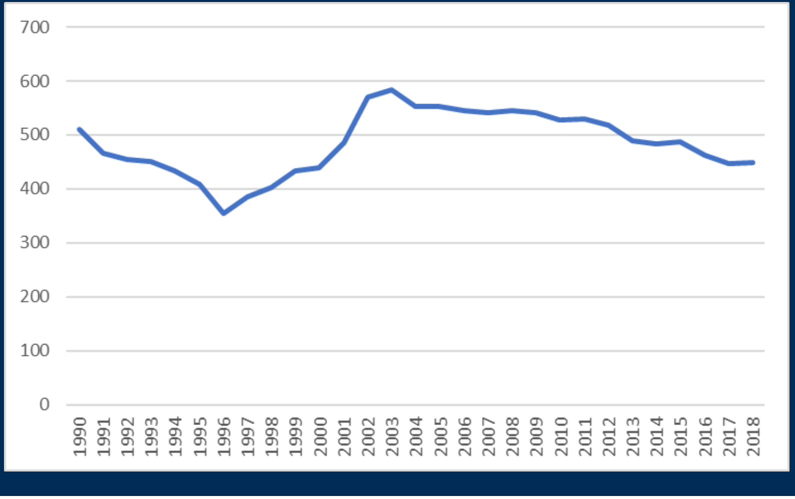
Data presentation

Mortality and climate data

Human Mortality Database (HMD)

- The HMD is the reference for mortality data for Actuarial subjects
- Annual periodicity from 1990 to 2018.

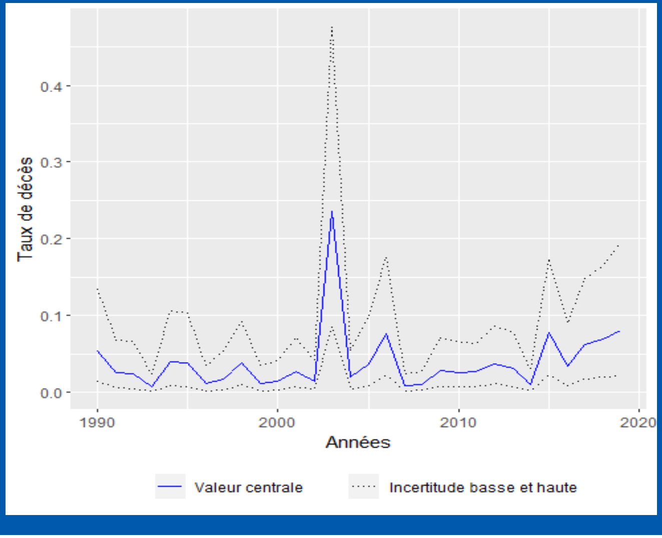
Trends in death rates for France
(all genders, 1990-2018, France, age:55)



Global Health Data (GHD)

- The GHD gathers numbers of deaths classified by different parameters (age, territory, years, etc.) and particularly by cause of death.
- Annual periodicity from 1990 to 2019.

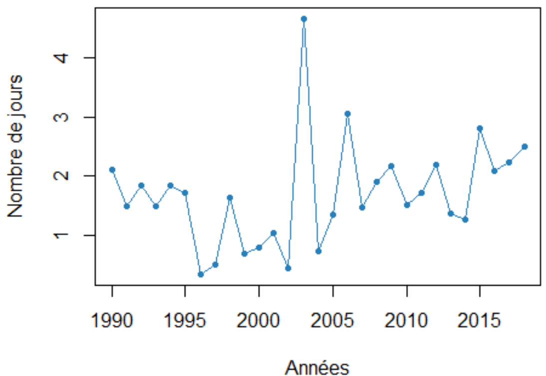
Evolution of death rates for high temperatures (sexes combined, 1990-2019, France)



Météo France

- Climate database containing for example the number of days above a certain temperature (30°C, 35°C, 40°C), rainfall levels, wind speed, sunshine time or minimum, maximum or average temperatures.
- Annual periodicity from 1990 to 2021.

Number of days with temperatures above 35°C over the summer period for France



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Integration of climate risk in the mortality model

Step 1 : Estimation of the mortality related to climate risk

1. Calibration of α_{c_i} using a Classic Lee-Carter model on global mortality rates (all-cause) . The parameter α_{c_i} is a vector containing three parameters, one for each age class.

$$\ln\left(\mu_{c_i,t}\right) = \alpha_{c_i} + \beta_x^o \kappa_t^o + C_t \delta_{c_i}$$

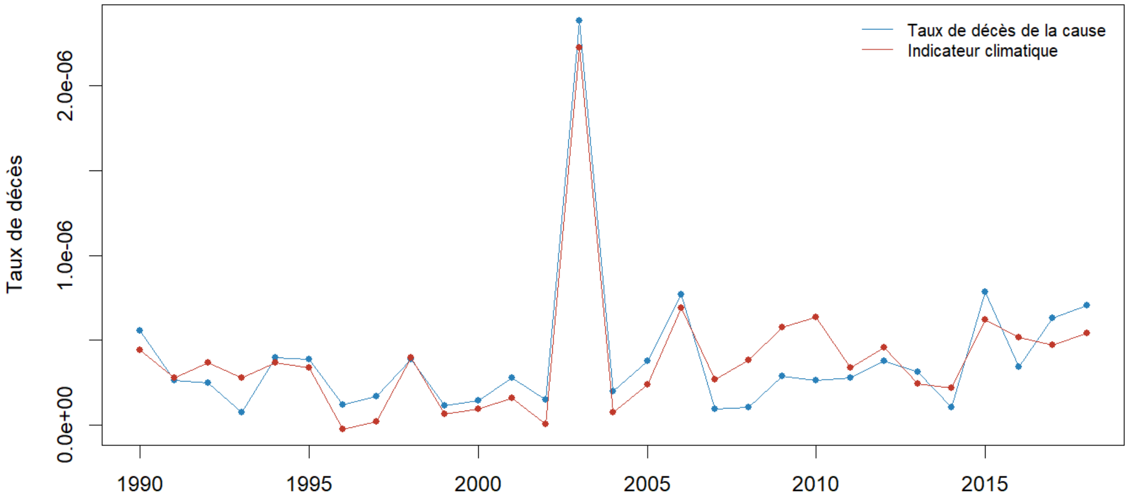
3. Calibration of δ_{c_i} by minimizing residuals: $R_{c_i,t} = \ln\left(\mu_{c_i,t}\right) - \alpha_{c_i} - \delta_{c_i} C_t$, where $\mu_{c_i,t}$ are the global mortality rates.

Note that during the calibration process, a "peak" function can be used to accentuate the excess mortality of each age group.

2. Calibration of the Climate Index (a, b, c) using a linear regression between the climate cause death rates and the climate variables T_t^{35} and T_t^{40} (average of the number of days with temperature above 35°C/40°C during the summer period of year t).

$$C_t = \left(a + bT_t^{35} + cT_t^{40}\right)$$

Presentation of the climate indicator based on death rates due to high temperatures



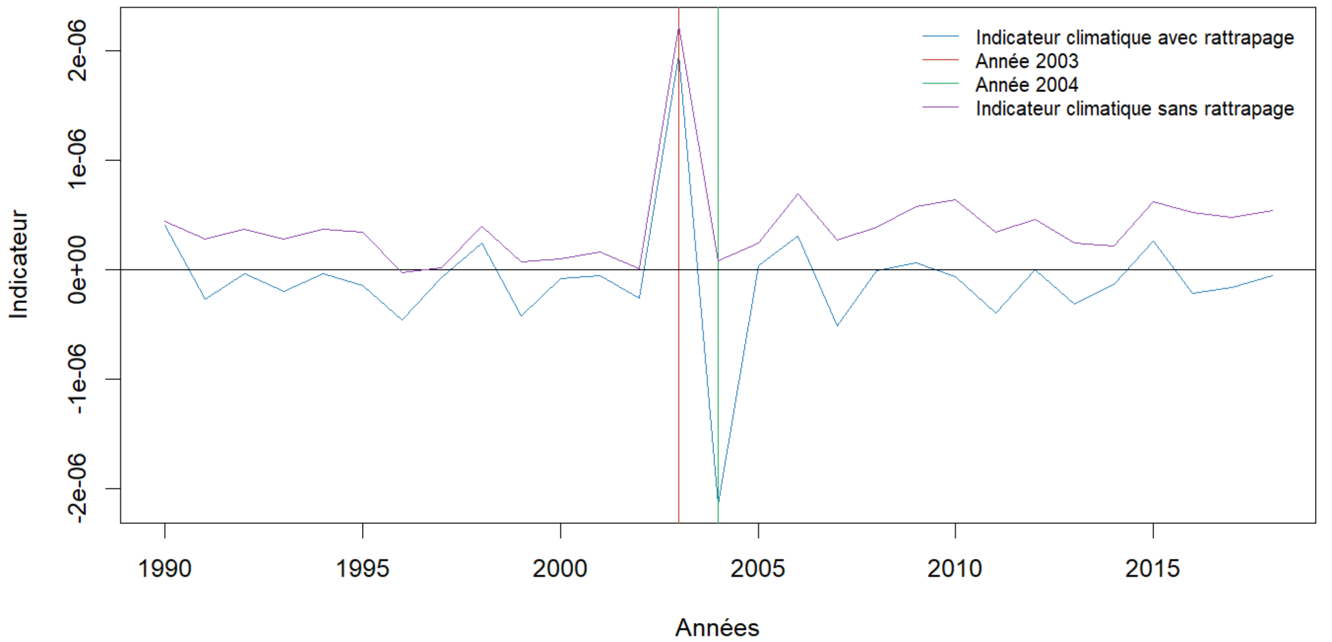
Integration of climate risk in the mortality model

Step 2 : Integration of the catch-up effect

→ Definition: The catch-up (or harvest) effect refers to the fact that weaker people are mainly affected by an event that causes excess mortality in the general population. Without the event, these people would have died within days or weeks that followed. Therefore, the event is followed by a period of under-mortality.

$$\ln(\mu_{c_i,t}) = \alpha_{c_i} + \beta_x^o \kappa_t^o + \delta_{c_i} CI_t$$

Presentation of the climate indicator based on death rates due to high temperatures



Calibration of α, β : This step integrates the harvest effect by replacing C_t by CI_t. The catch-up effect parameters α and β are estimated using least squares minimization. $CI_t = \left(a + \alpha(bT_t^{35} + cT_t^{40}) + \beta(bT_{t-1}^{35} + cT_{t-1}^{40})\right)$

Integration of climate risk in the mortality model

Step 3 : Calibration of the global age-continuous mortality rates

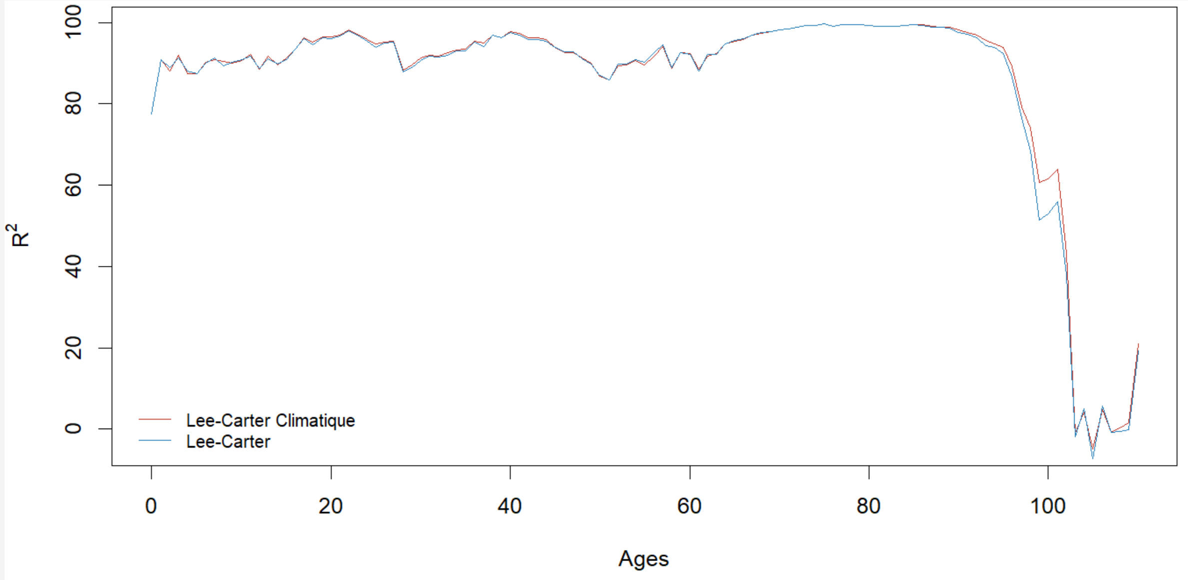
$$\ln(\mu_{c_i,t}) = \alpha_{c_i} + \beta_x^o\kappa_t^o + \delta_{c_i}C_t \quad \Rightarrow \quad ln(\mu_{x,t}) = \alpha_x + \beta_x^o\kappa_t^o + \delta_x CI_t$$

1. Conversion of age class parameters to constant age parameters.

2. Application of a Lee-Carter model on the final residuals to find the coefficients α_x, β_x^o and κ_t^o.

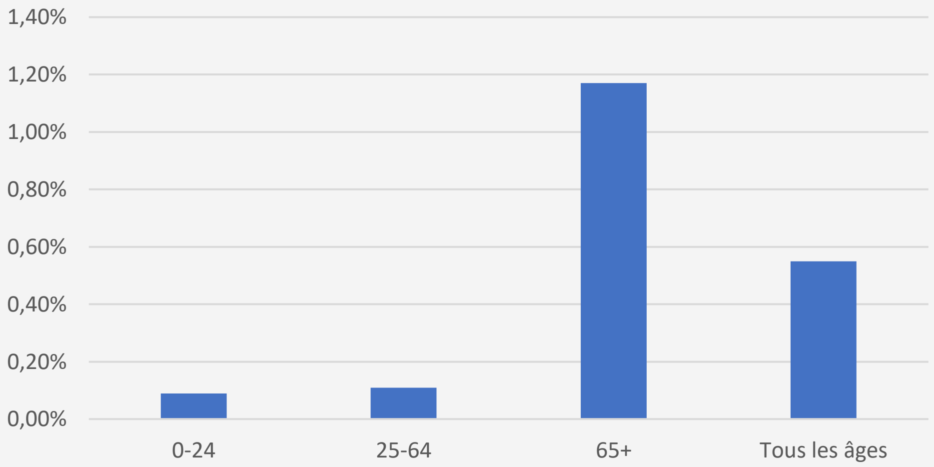
3. Comparison of conventional LC and climatic LC models in terms of AIC, BIC and R^2.

*Correspondence on ages according to the **R^2** metric for the two Lee-Carter models on real rates*



- The climate model is better than the Lee-Carter model on 61.82% of the ages (and on 93.64% of the ages if we consider a tolerance of 0.5% on the R^2).

*Performance differences between the conventional and climate models for the **R^2** metric on real rates*



Projections and shocks calculation

Correspondence between models and projections

- **Projections :** Use of autoregressive models
  - Climate model:

$$\left(T_t^{35}, T_t^{40}, \kappa_t\right) = \left(T_{t-1}^{35}, T_{t-1}^{40}, \kappa_{t-1}\right) + (\mu_1, \mu_2, \mu_3) + C\left(\epsilon_t^1, \epsilon_t^2, \epsilon_t^3\right)$$

  - Classical model:

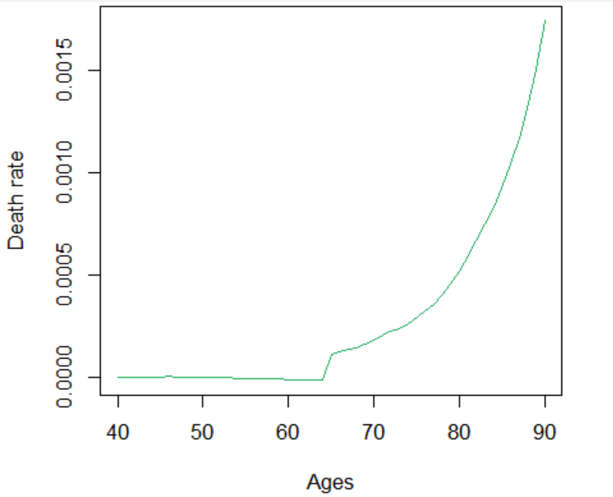
$$\kappa_t = \kappa_{t-1} + \theta + \varepsilon_t$$

- **Shock calculations**: The age-shocked life expectancy is defined according to (EIOPA)

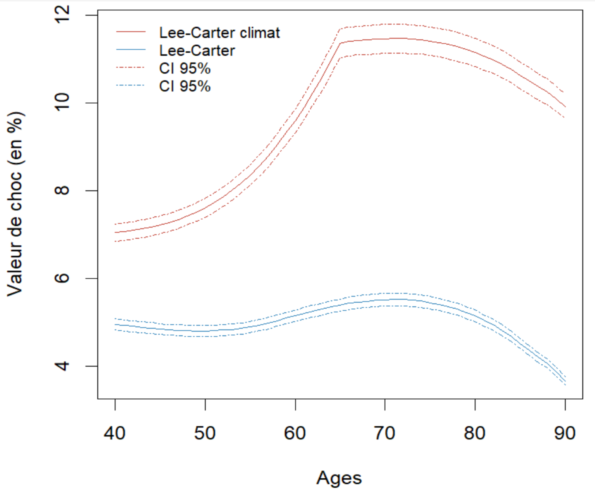
$$e_x^h(t) = \frac{1}{2} + \sum_{k=1}^{+\infty} \prod_{s=0}^{k-1} \left(1 - (1+h) q_{x+s}(t+s)\right)$$

$$h_{\inf}(x) = \underset{h \in]-1,1[}{\operatorname{argmin}} \left(e_x^h(t) - e_x^{0.5\%}(t)\right)^2$$

Impact de la cause climatique (40-90 ans)



Shock values (40-90 ans)



- **Results**
  - Over the whole interval, climate shocks are on average 6.12% more important than conventional shocks.
  - Construction of a confidence interval centred around the mean: the mean shock over the study age interval is thus 11.11 ± 0.24% for the climate model and 5.29 ± 0.11% with the classic Lee-Carter model.

Applying the same modeling framework to other countries

Model calibration on the US

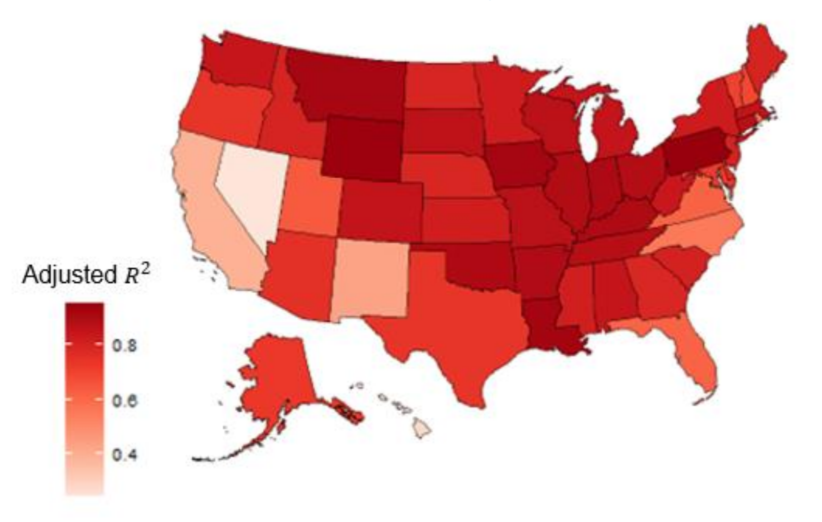
US model features

- Study at state level.
- Climate index calculated by state, based on all available climate variables: not all states are affected in the same way by heat waves.
  - For some states, death rates are too low to be captured by climate variables.
  - For others, the model developed fits very well → Oklahoma

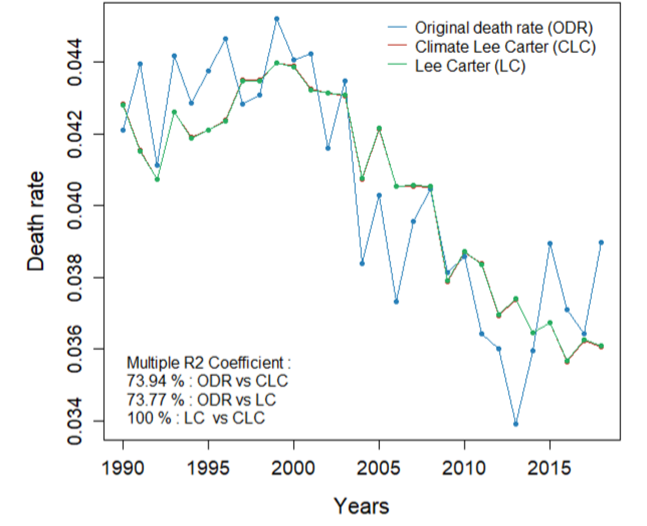
Results

- Same conclusions as for France.
- The climate model estimates slightly better than the classic Lee-Carter model, in terms of R^2 per age and in terms of AIC and BIC.

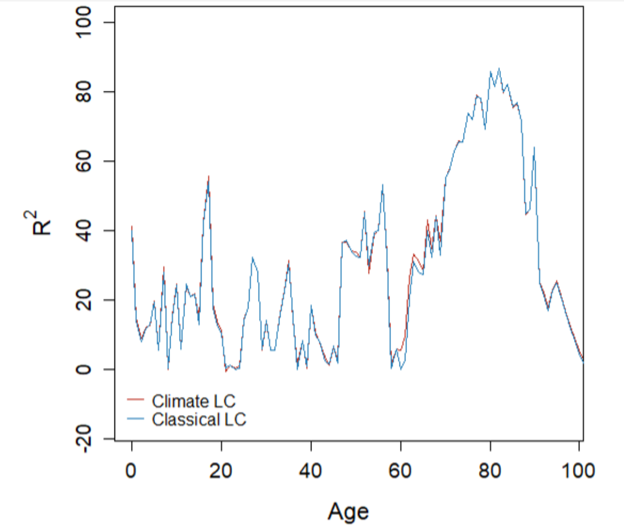
R^2 of linear regression of climatic mortality rates on climatic variables, by state



Comparison of estimated and empirical death rates for Oklahoma - age 75



Results – R^2 by age



Conclusion

What our work has enabled us to achieve so far?

- A map of climate risks and their impacts on mortality
  - Associated ICD10 codes
  - An adaptation of this mapping to the specific case of France
- A simple modeling framework for mortality due to climatic risks causing a relatively large number of deaths, and which are highly correlated with the available climatic variables.
- modeling approaches for other climatic factors with an impact on mortality.

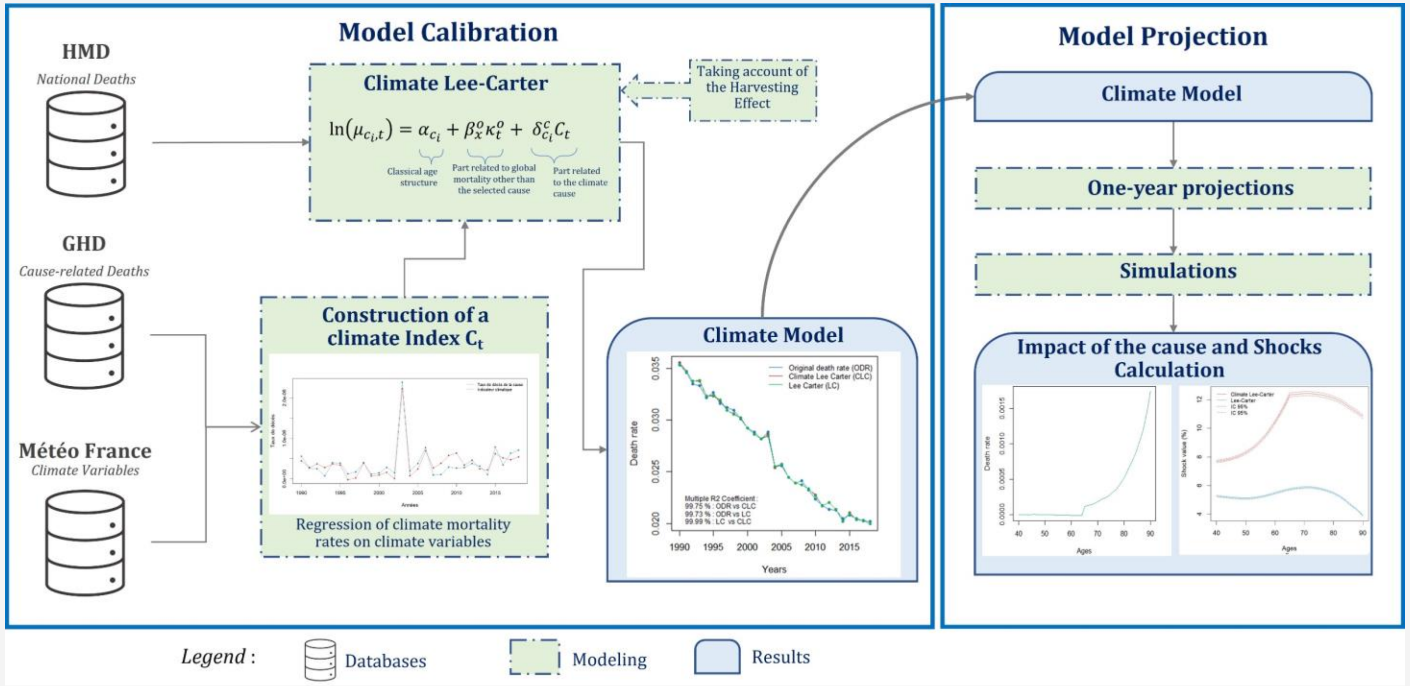
What are the next steps?

- For a given country, complete the exercise:
  - Modeling the mortality due to each of the climatic causes identified.
  - Aggregate them by modeling the correlations between the different causes of death.

  → Obtention of a mortality model taking into account the main climatic risks.
- Integrate this model into an economic scenario generator.

How can this work be used for?

- For information purposes
- To project mortality
- To define climate stress tests or internal models



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Thank you

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