Direct Impacts of Climate Change on Mortality in France

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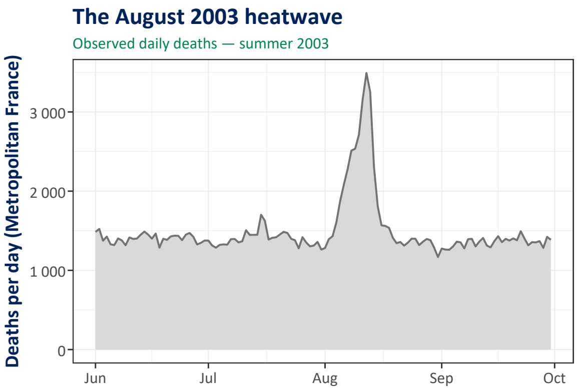
Motivation and study objectives

A public-health issue

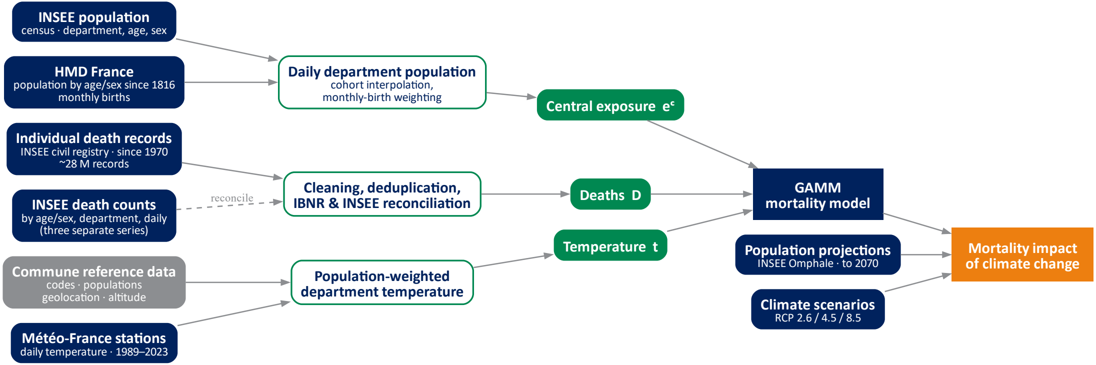
- Climate change has major implications for population health.
- The 2003 heatwave in France caused nearly **15,000 excess deaths**.
- Such events are expected to become more frequent and more severe.

Objectives of the study

- Assess the **direct** impact of climate change on mortality in metropolitan France.
- Rely on **open-source data only** (INSEE + HMD + Météo-France).
- Estimate a **daily mortality risk** that accounts for **local** temperature exposure.



Overview of Data Sources



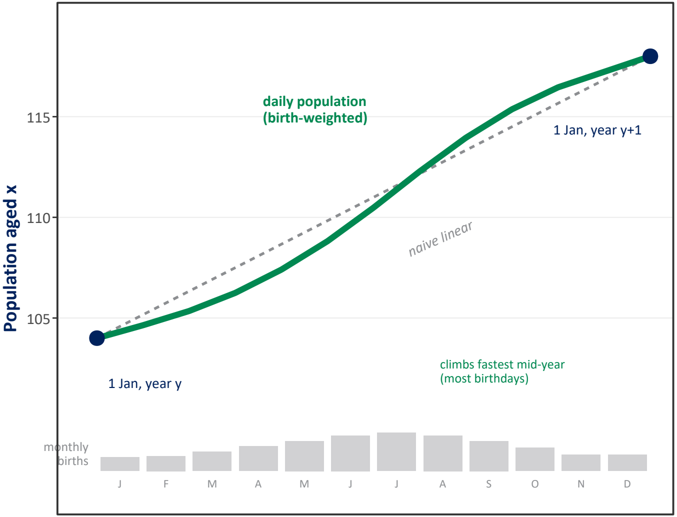
INSEE demographic data sources

- Two complementary INSEE products: the **population census** and the **civil-registry** death statistics.
- Daily death series are published **by age/sex** and **by department**, but **no series crosses these dimensions jointly**.

	Age	Sex	Department	Day	Source / span
Deaths · by age & sex	●	●			*HMD · 1816+*
Deaths · by department			●		*INSEE*
Deaths · daily				●	*INSEE*
Population · by age & sex	●	●			*HMD · 1899+*
Population · by department			●		*INSEE census*
Model input needed	×	×	×	×	*to reconstruct*

Building a daily, department-level population

- HMD corrects population counts above age 80 using the **extinct-cohort method** — same source as INSEE, but more internally consistent.
- The HMD **age distribution** is applied to the INSEE department-level population for each age band.
- **Daily** series are obtained by interpolating between the two cohorts sharing a given age in a year, refined with the **monthly distribution of births** (similar to HMD methodology).



The individual death records file

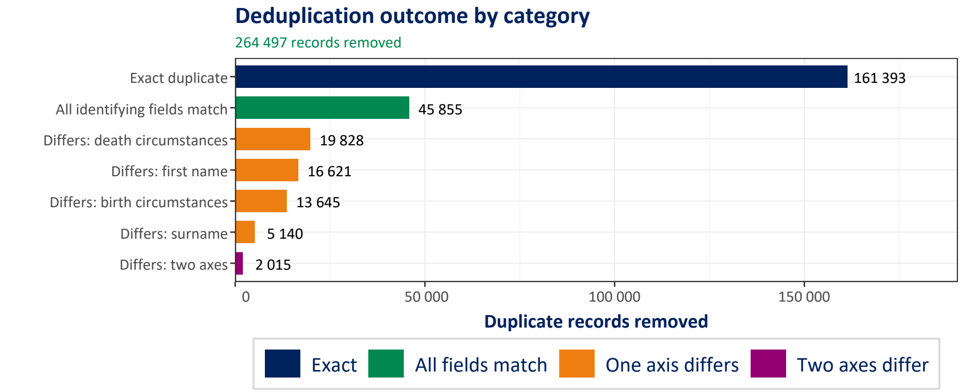
Birth date	Birth place	Death date	Death place	Sex
14/03/1932	Lyon (69)	02/08/2003	Lyon (69)	F
27/11/1945	Lille (59)	19/01/2017	Lille (59)	M
05/06/1928	Brest (29)	11/02/2009	Quimper (29)	F
21/09/1951	Nancy (54)	30/07/2019	Metz (57)	M
03/01/1939	Bordeaux (33)	16/12/2021	Bordeaux (33)	F
18/07/1924	Marseille (13)	09/08/2003	Marseille (13)	F
12/02/1957	Rennes (35)	25/05/2015	Paris (75)	M
30/10/1943	Strasbourg (67)	03/03/2012	Colmar (68)	M
08/04/1936	Toulouse (31)	21/11/2018	Toulouse (31)	F
25/12/1949	Rouen (76)	07/06/2020	Le Havre (76)	M

- Made available in **2019**, updated **monthly**.
- About **28 million records**.
- Each record carries the deceased's **birth date** and **sex**, and the **place and date of death**.

Reprocessing required

- Extensive cleaning and consistency controls are necessary before use.
- The data volume raises real **numerical and computational challenges**.

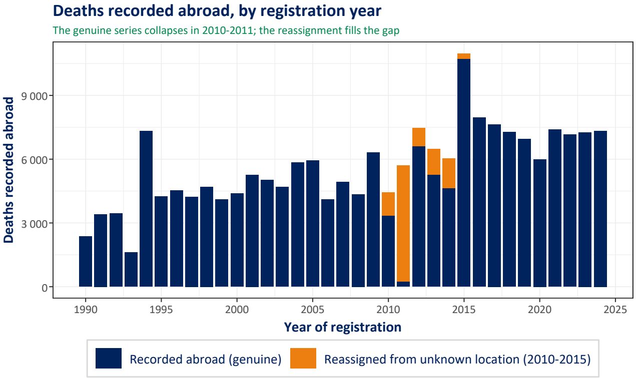
Deduplication



- **Principle** — candidate pairs are detected on identifying fields and merged.
- **Fuzzy matching** on names and first names absorbs spelling variants.
- Duplicates are characterised by which axis they disagree on: name, first name, birth circumstances, or death circumstances.

Other corrections & anomalies

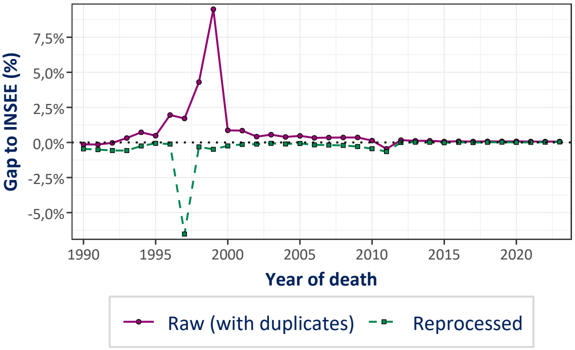
- About **10,000 deaths** registered in 2010-2015 had an **unknown place of death**; they are in fact deaths **abroad** and are reassigned to the abroad code.
- They fill a **gap**: the genuine abroad series collapses in 2010-2011 (see figure).
- Deaths abroad are **redistributed proportionally** by age, sex, and period; **IBNR** are computed separately for France and abroad.



Comparison with INSEE: annual & monthly gaps

Annual deaths relative to INSEE

Reprocessing brings the series onto INSEE



- Overall, the reprocessed series fit INSEE well in both **annual** and **monthly** views.
- A notable **data gap appears during summer 1997**.

Monthly gap to INSEE (%)

Reprocessed file vs INSEE; note the deficit in summer 1997

Year of death	1	2	3	4	5	6	7	8	9	10	11	12
	0,03	0,03	0,02	0,02	0,00	0,03	0,04	0,03	0,06	0,01	0,06	0,11
2022	-0,02	-0,01	-0,01	-0,02	-0,01	0,02	0,01	0,01	0,01	0,07	0,05	0,09
	0,00	-0,02	0,02	-0,04	-0,03	0,00	0,00	-0,01	-0,02	0,02	0,08	0,05
2020	0,00	-0,02	-0,04	-0,03	-0,01	-0,01	0,01	0,01	0,01	0,03	0,03	0,07
	0,00	-0,01	0,01	-0,03	0,03	0,03	0,01	0,01	0,01	0,02	0,04	0,12
2018	0,00	-0,02	0,01	0,00	-0,01	0,00	0,03	0,01	0,00	0,02	0,03	0,07
	-0,01	-0,02	-0,01	-0,03	-0,04	-0,06	-0,03	-0,03	-0,02	0,04	0,04	0,05
	-0,03	-0,04	-0,03	-0,05	-0,02	-0,02	0,03	0,02	0,02	0,04	0,08	0,09
2015	-0,04	-0,03	-0,02	-0,07	-0,03	-0,03	-0,03	-0,04	-0,02	0,00	0,01	0,06
	-0,02	-0,03	0,01	-0,04	0,01	-0,02	0,02	0,04	0,00	-0,02	0,05	0,14
2012	-0,02	-0,03	-0,02	-0,02	-0,02	-0,02	0,03	-0,01	0,05	0,02	0,10	0,16
	-0,03	-0,02	-0,06	-0,07	-0,04	-0,01	-0,04	0,02	0,00	0,01	0,05	0,14
	-1,07	-1,19	-1,22	-1,15	-0,64	-0,75	-0,61	-0,48	-2,84	0,58	0,36	0,97
2010	-0,11	-0,11	-0,10	-0,04	-0,12	-0,45	-0,50	-0,61	-0,50	-0,56	-0,60	-1,58
	-0,44	-0,34	-0,32	-0,31	-0,32	-0,22	-0,27	-0,35	-0,25	-0,30	-0,16	-0,18
2008	-0,40	-0,20	-0,20	-0,26	-0,23	-0,20	-0,19	-0,18	-0,23	-0,15	-0,17	-0,10
	-0,32	-0,27	-0,13	-0,18	-0,15	-0,23	-0,21	-0,20	-0,13	-0,11	-0,11	-0,17
	-0,34	-0,23	-0,10	-0,16	-0,17	-0,17	-0,22	-0,11	-0,11	-0,12	-0,13	-0,16
2005	0,02	-0,03	-0,06	-0,04	0,06	-0,07	-0,24	-0,09	-0,12	-0,04	-0,09	-0,19
	-0,14	-0,08	-0,09	0,04	-0,33	-0,10	-0,16	-0,09	-0,03	-0,07	-0,07	-0,13
2002	-0,08	-0,02	0,08	-0,05	-0,05	-0,07	-0,08	-0,10	-0,16	-0,02	-0,06	-0,15
	-0,24	0,04	-0,15	-0,14	-0,09	-0,16	-0,12	-0,15	-0,07	-0,10	-0,07	-0,14
	-0,08	-0,22	-0,11	-0,33	-0,11	-0,16	-0,15	-0,10	-0,18	-0,07	-0,06	-0,12
2000	-0,31	-0,24	-0,19	-0,27	-0,34	-0,26	-0,20	-0,27	-0,20	-0,14	-0,21	-0,29
	-0,40	-0,38	-0,33	-0,40	-0,55	-0,57	-0,49	-0,49	-0,57	-0,61	-0,57	-0,54
1998	-0,21	-0,14	-0,28	-0,21	-0,24	-0,28	-0,31	-0,41	-0,52	-0,36	-0,42	-0,43
	-0,13	-0,40	-0,17	-0,66	-2,98	-19,79	-43,77	-15,25	-0,07	-0,03	-0,02	0,03
	-0,04	-0,13	-0,10	-0,14	-0,13	-0,11	-0,08	-0,17	-0,14	-0,11	-0,10	-0,15
1995	-0,06	-0,08	-0,11	-0,14	0,05	-0,03	-0,08	-0,03	-0,04	-0,04	-0,07	-0,11
	-0,24	-0,18	-0,11	-0,39	-0,23	-0,28	-0,31	-0,21	-0,27	-0,27	-0,21	-0,29
	-0,74	-0,61	-0,42	-1,60	-0,17	-0,11	-0,32	-0,44	-0,37	-0,14	-0,28	-1,47
1992	-0,53	-0,52	-0,53	-0,60	-0,59	-0,54	-0,59	-0,60	-0,57	-0,52	-0,63	-0,66
	-0,43	-0,46	-0,56	-0,48	-0,54	-0,62	-0,49	-0,54	-0,54	-0,53	-0,48	-0,49
1990	-0,29	-0,37	-0,52	-0,44	-0,43	-0,43	-0,51	-0,49	-0,52	-0,46	-0,55	-0,52

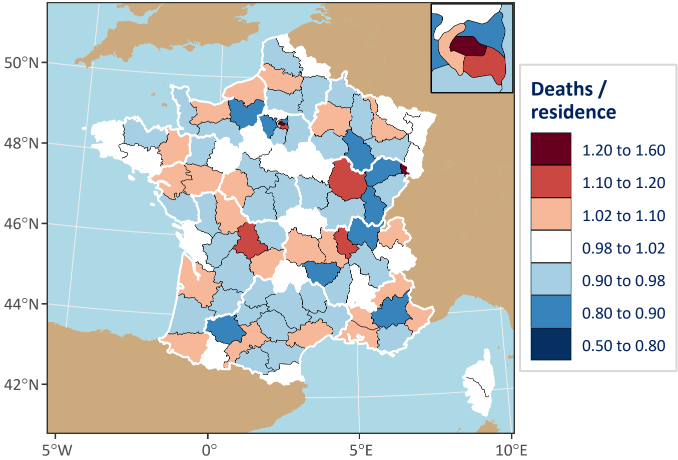
Month of death

Comparison with INSEE: gaps by department

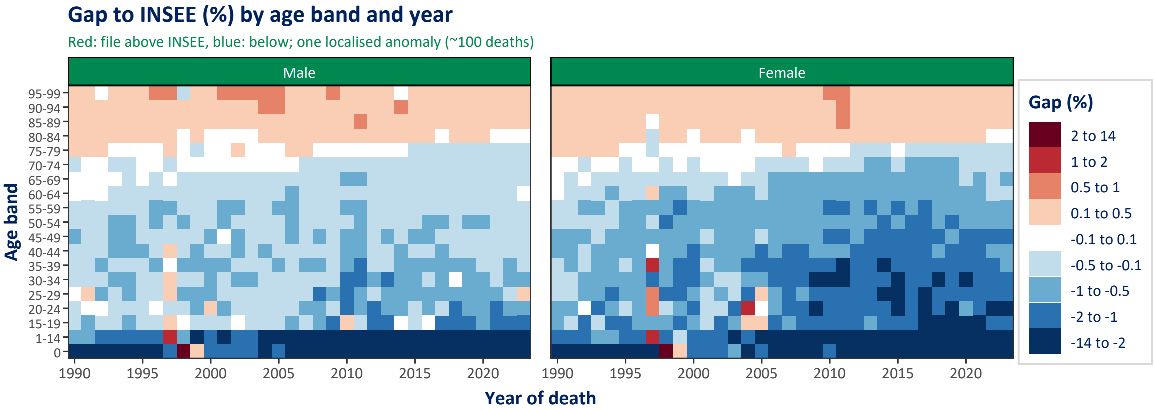
- Cross-department gaps are substantial: people often do not spend their **final days where they reside** — hospitals concentrate in large cities and reception capacity is uneven.
- Example: the opening of a **gerontology centre in department 90** shifts the local balance.
- Applying a **residence-to-death mortality ratio** largely removes the gaps (near-zero in recent years).
- For earlier years, residual gaps remain in some departments; we **renormalise onto the INSEE series**.

Place of death vs place of residence

Ratio > 1: department draws in deaths (hospitals, care centres)



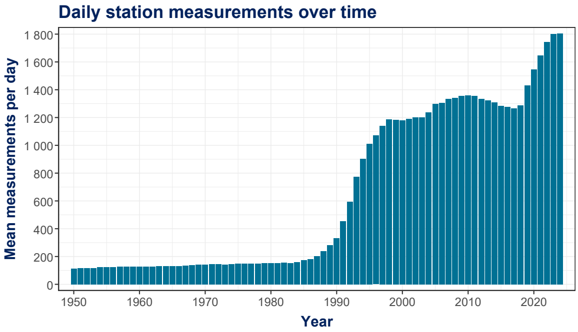
Comparison with INSEE: gaps by age band

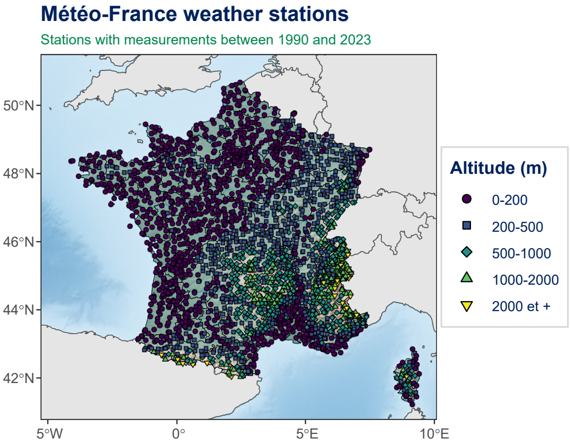


- Relative gaps by age band are **comparatively minor**; a **single anomaly** stands out but represents only about **100 deaths**.
- Going forward, we **align exactly to INSEE** by renormalising the mortality rate on **each axis**: month, department, and age band.

The Météo-France weather-station network

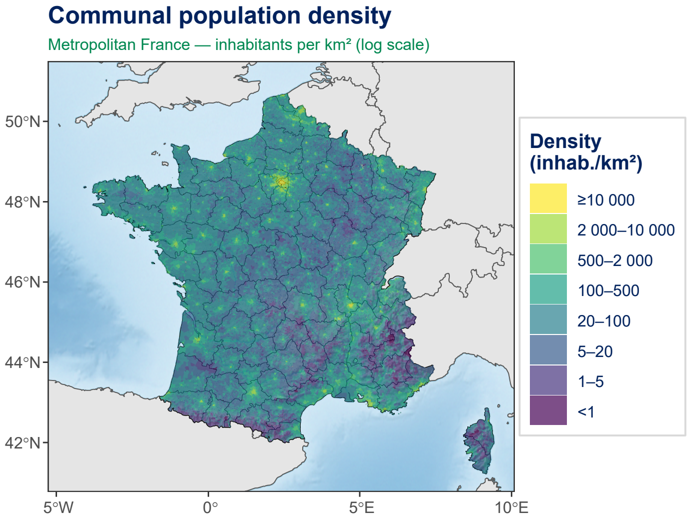
- The dataset draws on **2,719 contributing stations** (1950–2024), with coverage that grows markedly over time.
- Together they supply about **17.9 million daily temperature measurements**.
- These records are the basis for the daily department-level temperature.





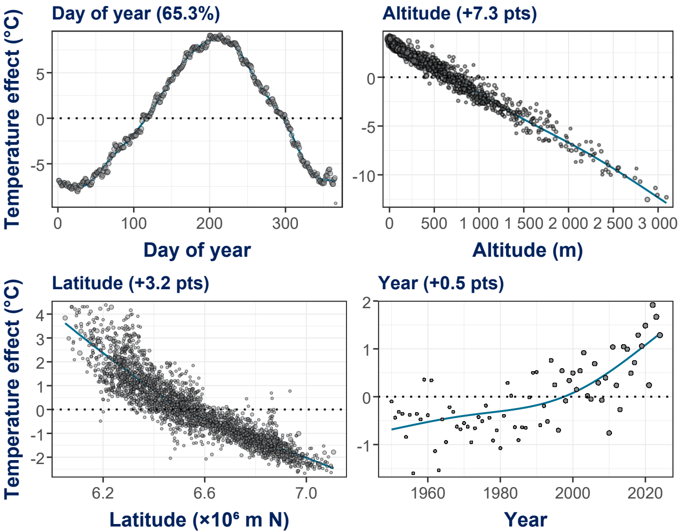
Goal: a population-weighted department temperature

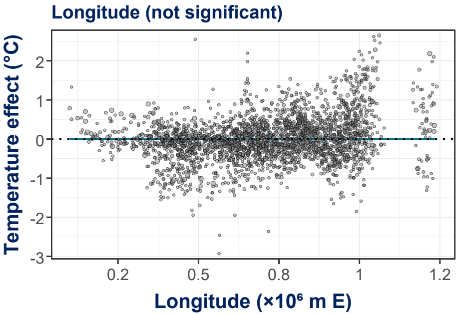
- Target: a **department temperature weighted by population at the commune level**.
- Annual **communal populations** are recovered and interpolated.
- Each commune is approximated by its **town hall**, whose **altitude** is read from the **AWS Terrain Tiles** elevation model (~75 m resolution, queried via the `elevatr` package).



Temperature modelling

- A model with **four explanatory variables explains 76.3 % of the variation** in temperature.
- **Longitude is not significant**, and cross-effects contribute little.
- The step mainly serves to **capture the altitude effect**, avoiding a complex 3D-surface smoothing of altitude.





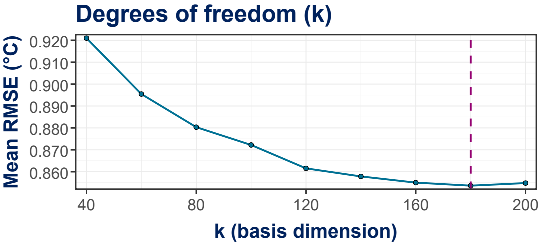
Modelling residual effects (2D smoothing)

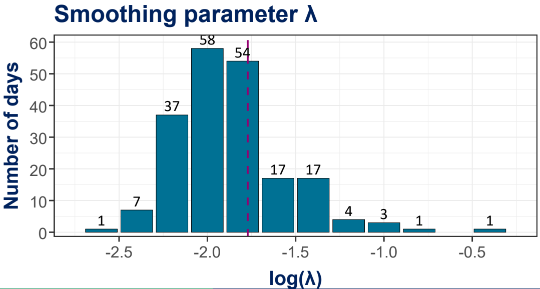
- The residual signal is captured by a **2D smoothing**.
- Tuning combines selection of the **optimal degrees of freedom** and of a **common smoothing parameter** λ.
- The share of additional variation explained is reported for three nested models, in **fit** and in **cross-validation**.

Share of temperature variation explained

Model	Fit	Cross-validation
Intercept only	0.0 %	0.0 %
+ 4 explanatory variables	76.3 %	76.3 %
+ 2D spatial smoothing	**98.9 %**	**98.6 %**

- Explained variation = R^2 (Gaussian deviance).
- 4-variable model: structural GAM, ∼30 df on 17.9 M obs. (fit ≈ CV).
- 2D smoothing: 5-fold cross-validation over held-out stations.





The GAMM framework

- The **Poisson distribution** arises naturally in duration models when individuals die independently and their death probabilities depend on the covariates considered.

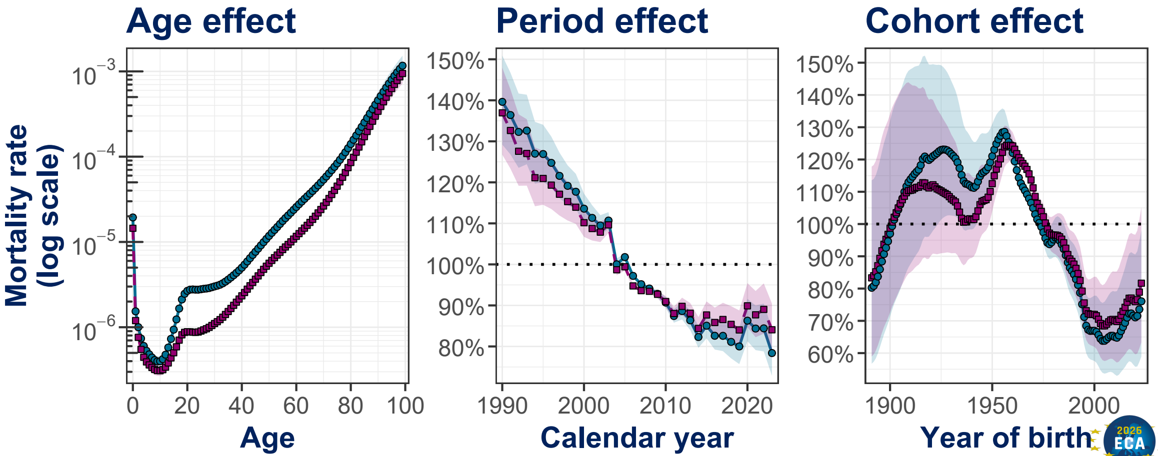
$$D_{x,y,d,s} \sim \mathcal{P}\left(e^c_{x,y,d,s}\, h_{x,y,d,s}\right)$$

- Here D is the death count, e^c the **central exposure-to-risk** and h the **force of mortality** (indexed by age, year, department and sex).
- **GAMM advantages**: flexibility, interpretability, and robustness to overfitting.

Comparison metric — the **deviance** of the daily death count at the scale of France (all ages, sexes and departments combined) is used to compare and rank every model.

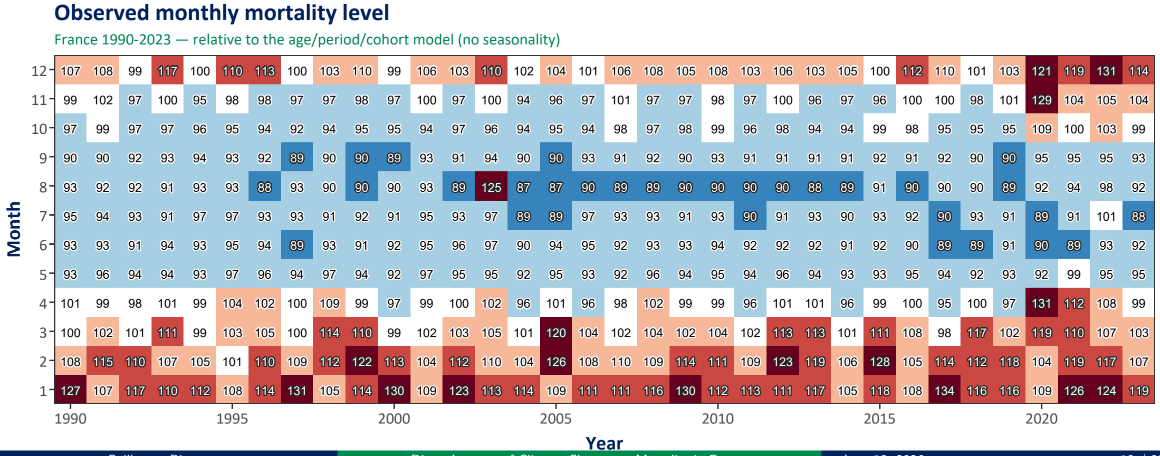
Age and calendar-year effects : the APC model

- The log-mortality is divided into **age** (α_x), **period** (β_y) and **cohort** (γ_{y-x}) effects : $\ln h_{x,y} = \alpha_x + \beta_y + \gamma_{y-x}$



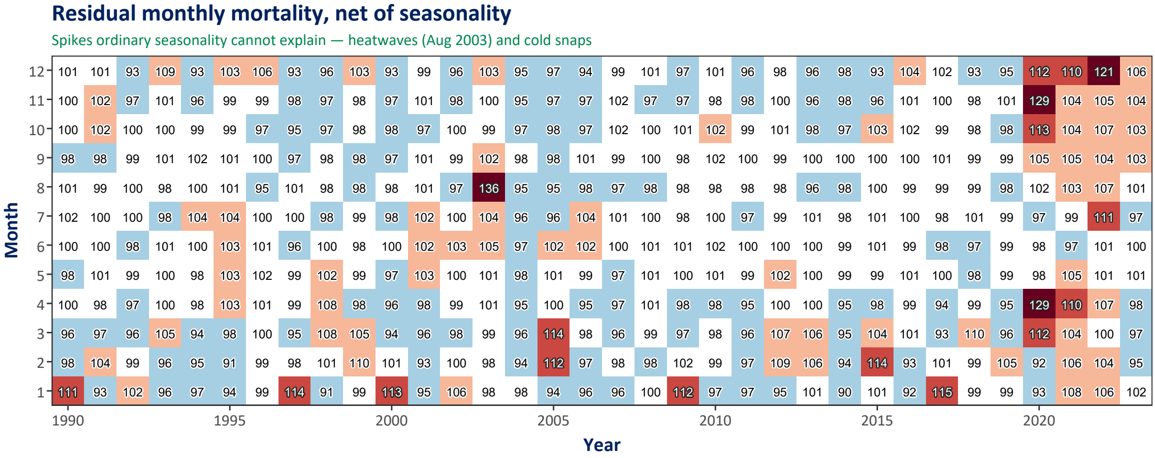
Revealing seasonality

- The raw monthly mortality reveals a strong, regular **seasonal cycle**: a marked **winter excess** and a milder **summer deficit**.
- Adding a **cyclic monthly component** to the model captures this pattern, with a marked winter excess and a milder summer deficit.



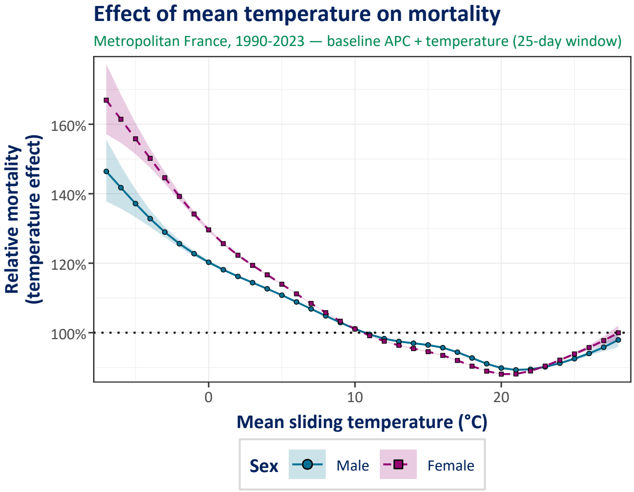
Residual temperature effects

- Net of seasonality, **unexplained events remain** — motivating the explicit inclusion of temperature.



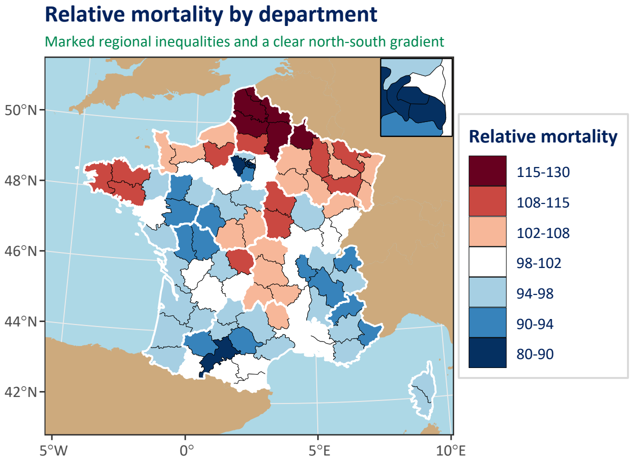
A simple temperature model

- Temperature is added as a smooth term; mortality rises at **both temperature extremes**, yielding a characteristic **U-shaped** relationship.
- The fit confirms a clear marginal contribution of temperature beyond seasonality.



Possible confounding with the department variable

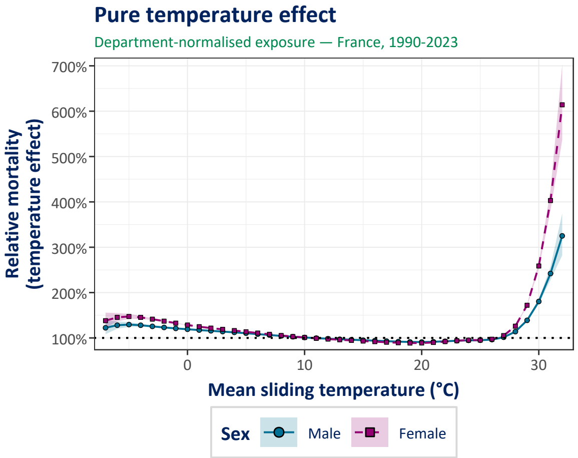
- Mapping **relative mortality by department** reveals marked **regional inequalities** and a clear **north–south gradient**.
- This gradient can be confounded with temperature and must be handled explicitly.



Department effect estimated on residuals (not jointly)

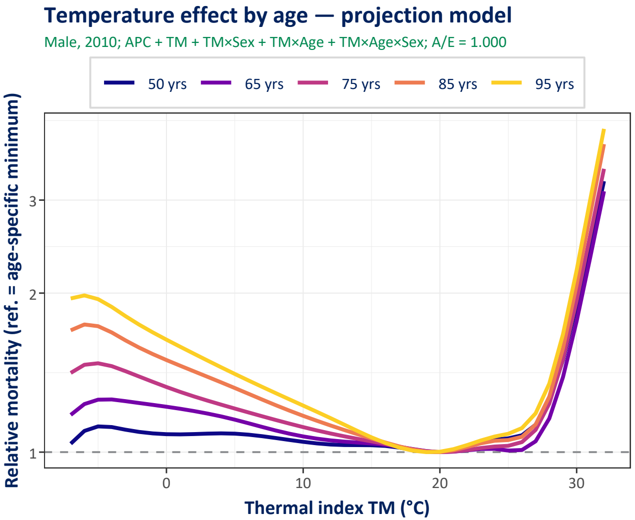
The department gradient is **not** fitted jointly with temperature. Instead it is estimated as a **residual** effect — the relative mortality by department once age, period, cohort (and optionally temperature) are accounted for.

- Temperature explains only ~**7 %** of the geographic gradient → the two are essentially **separable**.
- We therefore re-weight exposure by the empirical department factor r_{dep} and re-fit the **pure** temperature effect on normalised exposure.



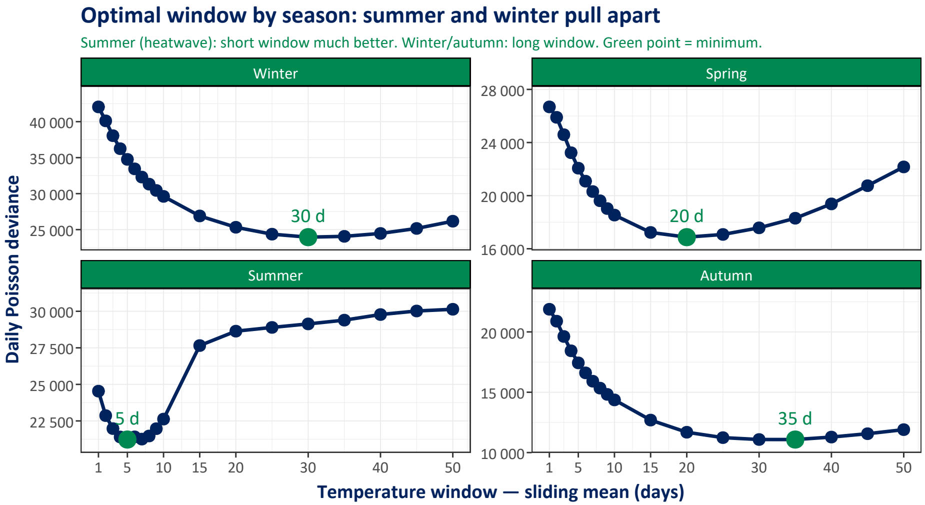
Adding the age interaction

- An **interaction between temperature and age** is also introduced.
- Result: heat and cold are **felt differently across age groups**, with the oldest most sensitive.



Selecting the optimal window

- Several **temperature-averaging windows** are compared on the deviance metric; the best trade-off is retained.

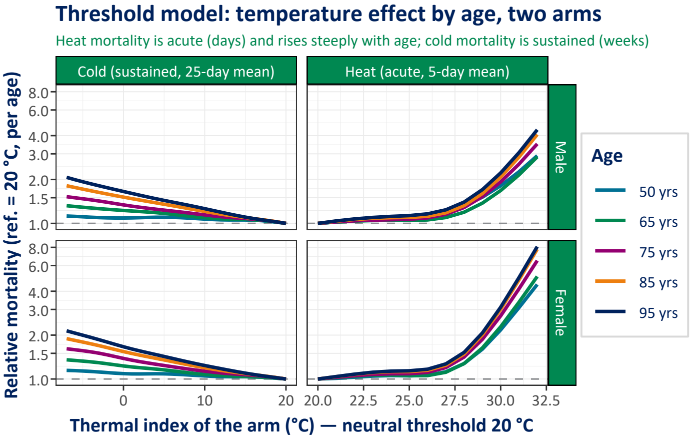


Two arms split at a neutral threshold

Rather than a single sliding window, we split the thermal signal into **two arms** at a neutral threshold of **20 °C**:

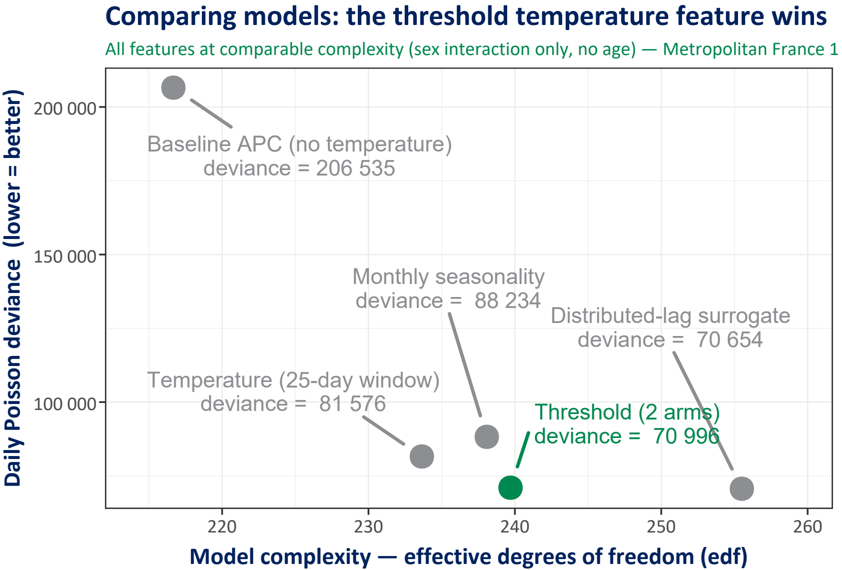
- **Heat arm** $= \max(\text{5-day mean}, 20)$ — acute, captures the days-long heatwave spike.
- **Cold arm** $= \min(\text{25-day mean}, 20)$ — sustained, captures weeks-long winter excess.

Each arm carries its own age and sex interaction. Decoupling by **value** (not calendar) makes the heat response transferable to future climates.



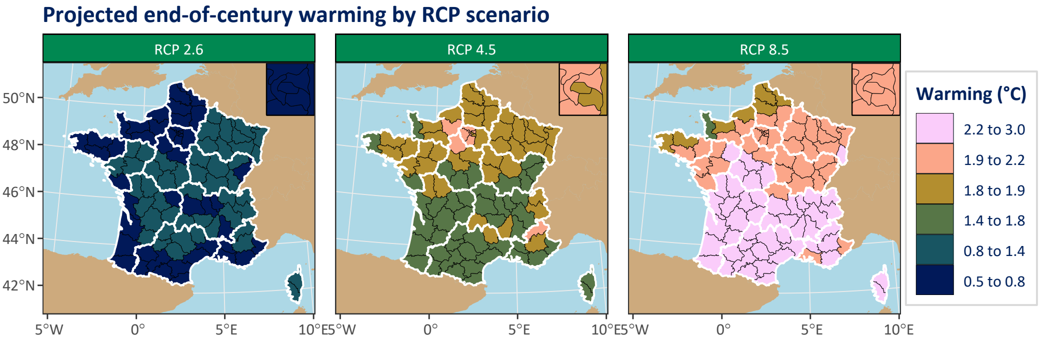
ılised exposure. Heat arm = max(5-day mean, 20); cold arm = min(25-day mean, 20).

Value added of the temperature model



DRIAS temperature projections

- Projections cover the **three RCP scenarios** — **RCP 2.6, 4.5 and 8.5** — where the number is the additional **radiative forcing** (in W/m²) reached by 2100, i.e. low, intermediate, and high emissions.
- The underlying climate models have known **characteristics and limits** — notably, their historical runs end in **2005**.
- Data are provided on an **8 km grid**.

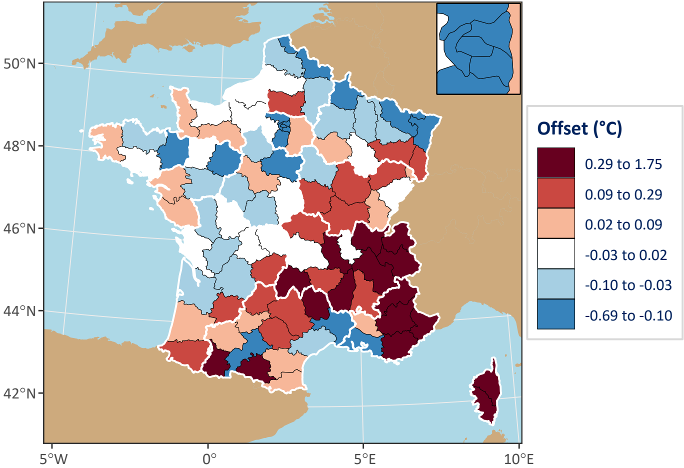


Mean 2071-2100 minus 1989-2005 baseline (°C) — DRIAS-2020, 8 km grid

Reconciling projected temperatures with Météo-France data

- **Simplified reconciliation**: take the temperature at the **nearest grid point**, rather than replicating the full Météo-France aggregation.
- A **department-level offset** corrects the **mountain bias**: populations live in valleys, which are warmer than the average altitude of the grid points.

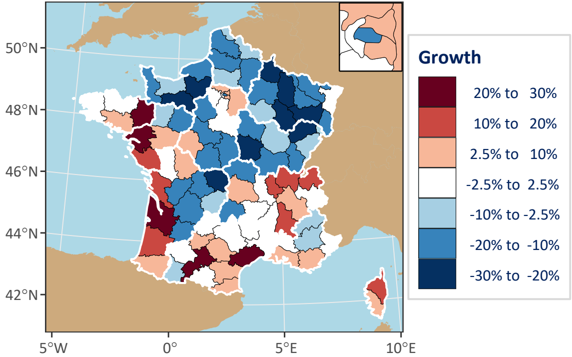
Reconciliation offset by department



seline temperature, 1989-2005 (°C) — mountain-bias correction (valleys warmer)

INSEE population projections

Projected population growth 2018 → 2070

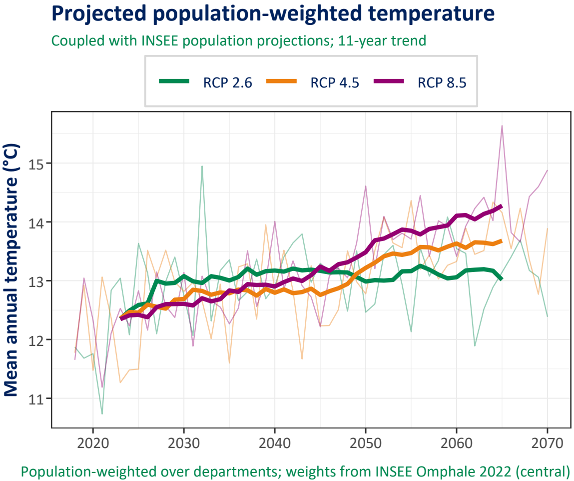


Source: INSEE Omphale 2022 — central scenario

These population projections depend on assumptions not only about **mortality** but also about **fertility** and **migration flows**.

Projected mean annual temperature under the 3 scenarios

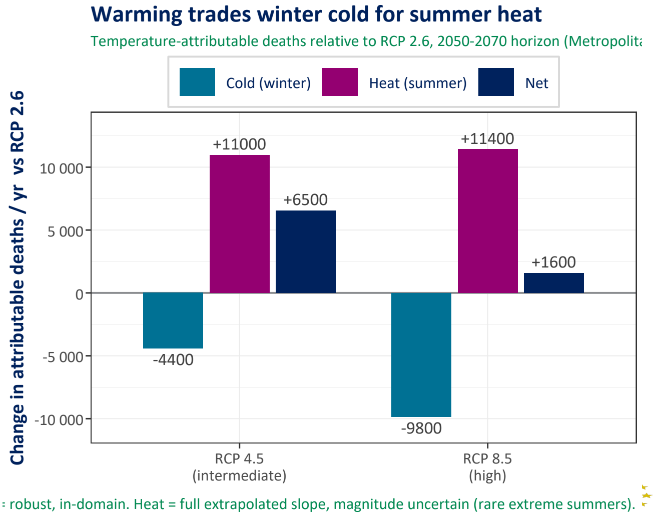
- The population-weighted temperature **couples** the climate signal with the **evolving population** (INSEE Omphale 2022, central scenario).
- Under all three RCP scenarios the weighted temperature **keeps rising to 2070**, with the scenarios fanning out — **RCP 8.5** warming fastest.
- Coupling re-weights toward the **departments where people will actually live**, reflecting projected ageing and internal migration.



Warming trades winter cold for summer heat

Coupling the threshold model with **DRIAS** temperatures and **INSEE Omphale** population to 2070, the robust signal is the **inter-scenario difference** (the shared baseline cancels):

- **Cold deaths fall** with warming — robust, in-domain (≈ −10 k/yr, RCP 8.5 vs 2.6).
- **Heat deaths rise** — direction sure, **magnitude uncertain** (rare extreme summers; response extrapolated without a ceiling).
- **Net** ≈ slightly up: the heat rise narrowly outweighs the cold decline.



Key takeaways

- Temperature is a **direct, measurable driver** of mortality: a **U-shaped** response, with excess in both **cold and heat**.
- A **two-arm threshold model** (split at **20 °C**) captures the signal well — and recovers documented events such as the **2003 heatwave**.
- The response is **strongly graded by age and sex** : the **oldest are by far the most sensitive**, and **women carry higher vulnerability to heat** than men.
- The **north–south department gradient is almost entirely non-thermal** (temperature explains only ≈ **7 %**) an may be accounted for **separately**.
- Warming **trades winter cold for summer heat**: to **2070** the robust signal is the **inter-scenario difference** — **cold deaths fall** (≈ −10 **k/yr**, RCP 8.5 vs 2.6) while **heat deaths rise** (direction certain, **magnitude uncertain**); the **net is slightly upward**.

Limitations & perspectives

- A **population-weighted temperature average** is used; a **DLNM** (distributed-lag non-linear model) would capture the effects more finely, but a bespoke implementation is required given the data volume and the treshold model remain a good approximation.
- Working from a **24-hour average** can mask sharp intraday swings — though daily maximum and mean are strongly correlated and indoor temperature has substantial inertia.
- **Humidity and wind**, which affect the body's ability to cool down, are not yet accounted for.
- Each scenario is a **single simulation with its own randomness**: an RCP 2.6 run may contain more severe heatwaves than an RCP 8.5 run. Drawing a **distribution of runs** would allow a calibrated impact range per warming scenario.
- Temperature also affects mortality through **indirect channels** : wider range of tropical diseases, agricultural impacts, impoverishment of the most exposed regions, and risks of humanitarian crises or conflict linked to climate migration. Those phenomena are likely to have a much stronger impact than the direct component.