Modelos predictivos de excesos de mortalidad por olas de calor

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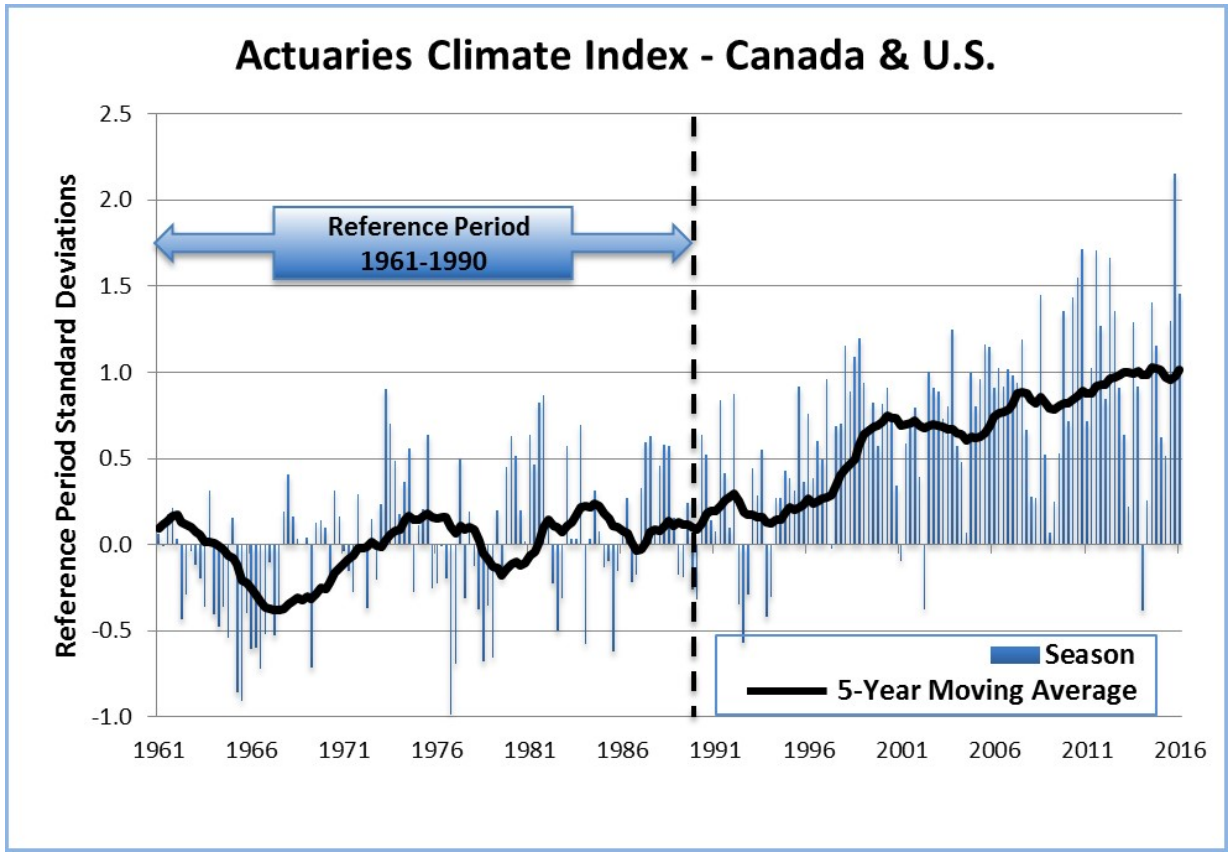
Introduction : Climate change and insurance

- Climate change challenges some fundamental principles of insurance : risk insurability, pooling, diversification, and risk transfer (Charpentier, 2008; Thistlethwaite and Wood, 2018; Courbage and Golnaraghi, 2022).
- Optimistic perspectives suggest that the insurance business could find in it an opportunity, through the development of new technical solutions (Rao and Li, 2023; Savitz and Gavriletea, 2019; Wagner, 2022).
- Pessimistically, climate change has forced already the strategic withdrawal of insurers in certain US markets, such as in California (Blood, 2023, APNews).

North American seasonal ACI values



Source : https://actuariesclimateindex.org/explore/

Impact on insurance costs

- In the Property & Casualty insurance sector, (Holzheu et al., 2021, SwissRe) forecasts increased frequency and severity of events due to climate change that will cost 30% to 63% more in insured catastrophe losses by 2040.
- This cost increase could even reach 90%–120% in specific markets, such as China, the UK, France and Germany.
- In all cases, it is important to add an actuarial perspective on the study of climate change and its impact on the insurance industry.

Actuarial climate indices

- The actuaries climate index™ (ACI) is linked to climate risks, a bit like the Consumer Price Index (CPI), which tracks the price variations of a basket of goods and services over time.
- Actuaries quantify and manage different types of risk. The ACI measures climate risk on the basis of a basket of extreme climate events and on variations of sea level.
- An index increase points to an increased number of extreme climate events.

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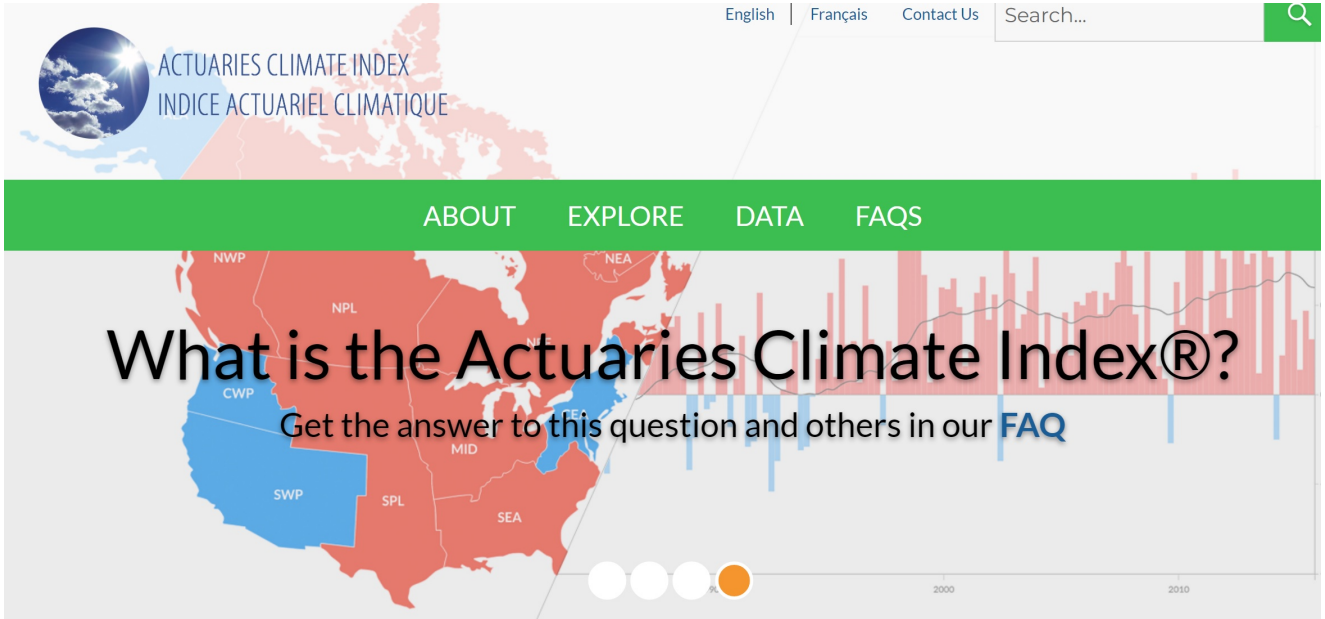
First launched in April 2019, version 1.0, current version 1.1 : https://actuariesclimateindex.org[1].

- The ACI is a pedagogical tool to help inform actuaries, decision makers, and the public in general, on climate trends and their potential consequences of climate change in the US and Canada.
- An objective measure of observed climate extremes and sea levels.
- A tool to follow climate trends, updated every 3 months, separately for 12 regions, for the 2 countries, and for the North American continent.

[1] Version 2.0 is currently in development : see https://www.pathlms.com/cas/courses/63730

ACI webpage

Sponsors: American Academy of Actuaries (AAA), Canadian Institute of Actuaries (CIA), Casualty Actuarial Society (CAS) and Society of Actuaries.



Source : https://actuariesclimateindex.org

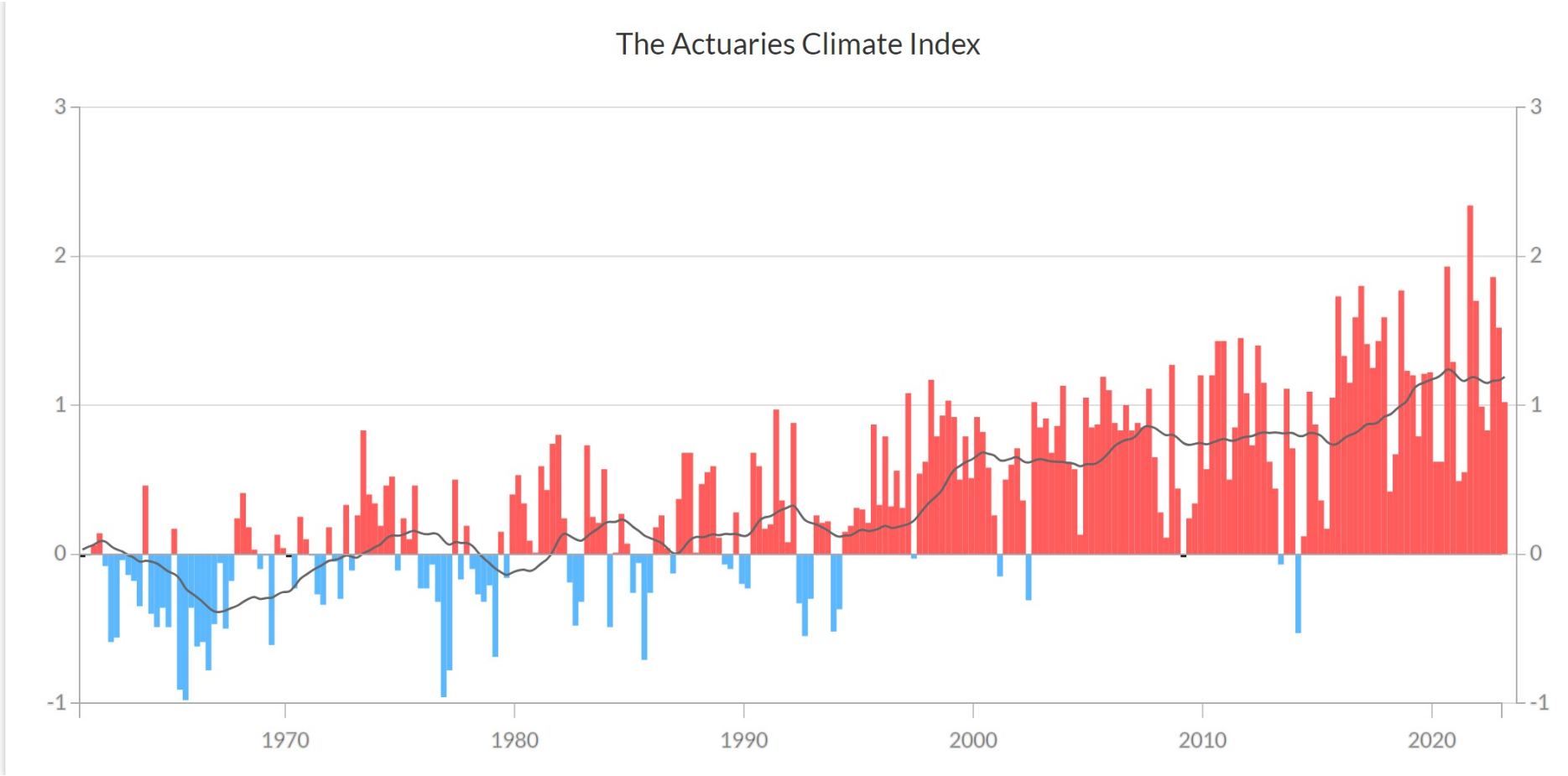
The North American ACI 6 components

- Frequency of extremes – high temperatures $> 90^{th}$ percentile of reference period.
- Frequency of extremes – low temperatures $< 10^{th}$ percentile of reference period.
- Maximum severity of heavy rains – 5 consecutive days in the month.
- Droughts : record period of consecutive days without rain ($<$ 1mm over 12 preceding months).
- Frequency of high winds, $> 90^{th}$ percentile or reference period (1961–90),
- Changes in sea levels.

$$ACI = \text{mean}(T90_{std} - T10_{std} + P_{std} + D_{std} + W_{std} + S_{std}).$$

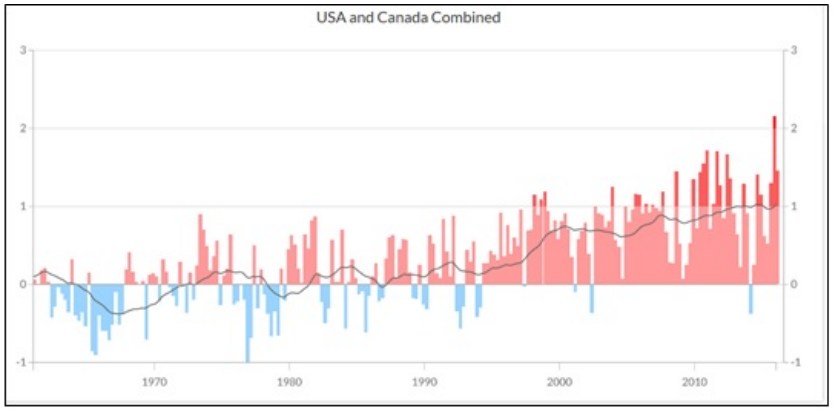
All relative to the reference period 1961-–1990 (standardised anomalies, like Z–scores: $T90_{std} = (T90 - \mu_{ref})/\sigma_{ref}$.

Actuaries climate index™ (ACI)

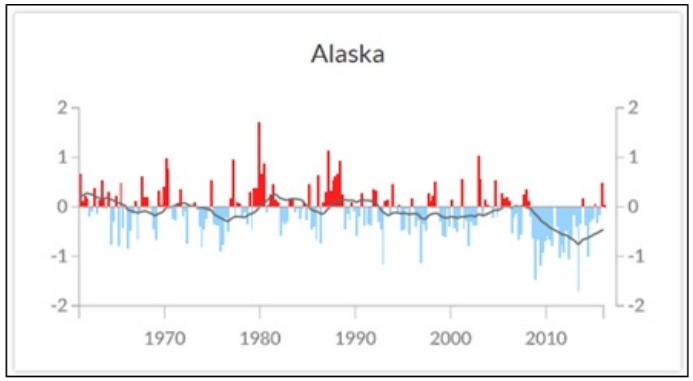


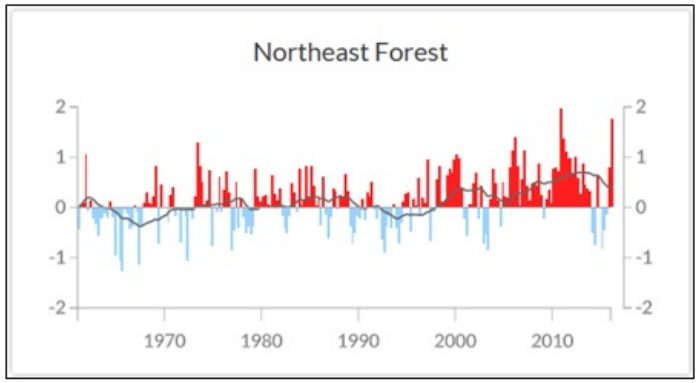
Source : (Zhou et al., 2023, AIAE)

ACI for Canada and the US : some regions



Note that the ACI for the U.S. and Canada is not a weighted average of the Canadian and U.S. indices. Standard deviations are calculated over the whole set of data for the location selected. The set for the U.S. and Canada is larger than either the U.S. or Canada alone, consequently it generates lower standard deviations. Similarly for a group of regions. A lower divisor results in higher standardized anomalies. Furthermore, the ACI for Canada or the U.S. is not the weighted average of their regions.





Source : https://actuariesclimateindex.org/wp-content/uploads/2018/04/guided_tour.pptx

The ACI ; what is it? - what it is not?

- The ACI does not explain the causes of climate change, and it does not predict future changes. It is based on real historical data, since 1961, from reliable sources ; for example the National Oceanic and Atmospheric Administration (NOAA) in the US.
- It provides a neutral and objective evaluation, in an analytical context, to study the different impacts of recent climate changes on risks and temperature increases.
- It measures extreme climate events, rather than their average ; because extremes have a greater impact on policyholders and their goods.

What can we learn from the ACI?

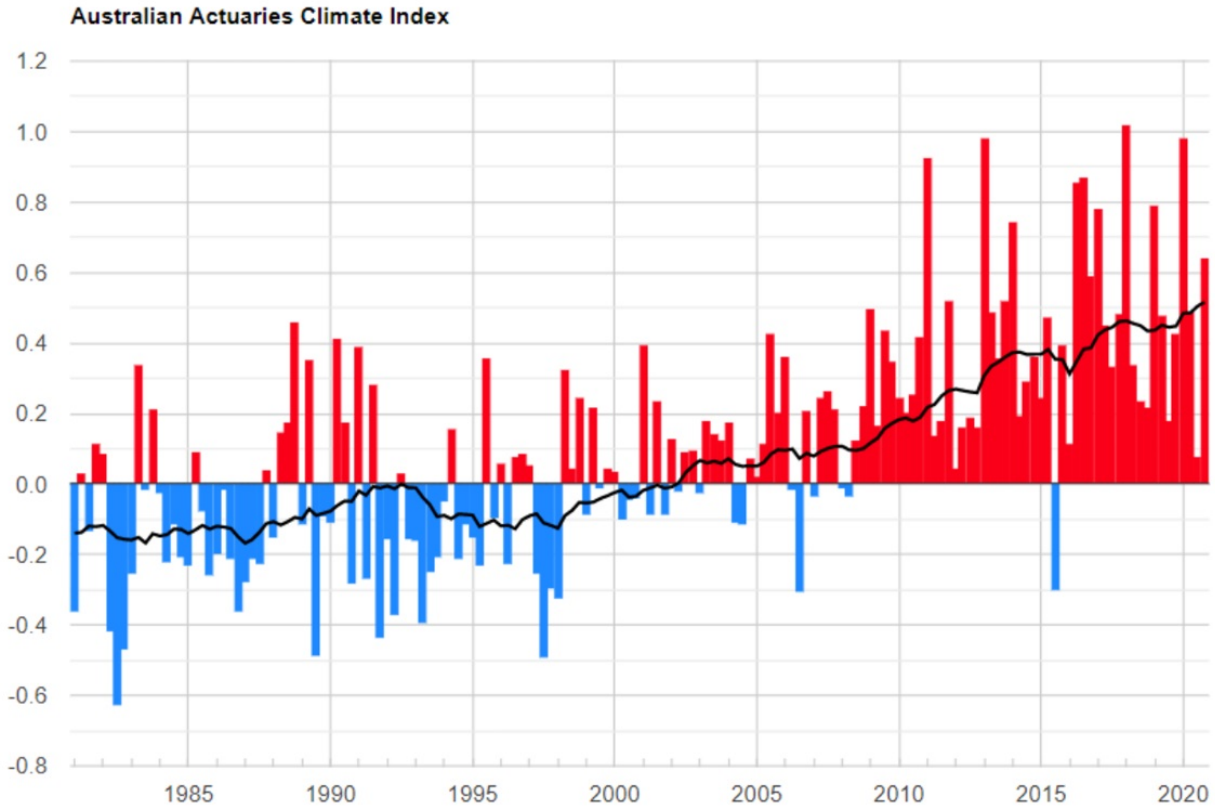
- Climate is defined over long periods: ACI accounts for changes in short term fluctuations, but in recent years, these fluctuations are mostly above average.
- The ACI methodology uses a 30-year reference period, from 1961 to 1990. Over this period, the mean index value is calibrated to zero. The monthly or seasonal values (meteorological seasons) measure quantitatively the climate risk variations, for the ACI or its 6 components.
- The 5 year moving average, that smooths monthly or seasonal fluctuations, increases constantly since 1990.
- We can observe the multiple effects of climatic risks ; their variations by region, component or season, allowing comparisons and informative micro analyses.

1.2 The Australian AACI

November 2018, sponsored by the Actuaries Institute Australia : https://www.actuaries.asn.au/microsites/climateindex.

- $AACI = \text{mean}(T_{std} + P_{std} + S_{std})$.
  T_{std} : Frequency of high and low temperatures $> 90^{th}$ percentile (standardised).
  P_{std} : Frequency of rain over 5 consecutive days $> 99^{th}$ percentile (standardised).
  S_{std} : Monthly maximum sea level (standardised).
- Eliminate separate $T10$ to reduce the weight of temperature variables, and D because it is highly correlated to P.
- Reference period : 1981–2010.

Australian Actuaries climate index (AACI)

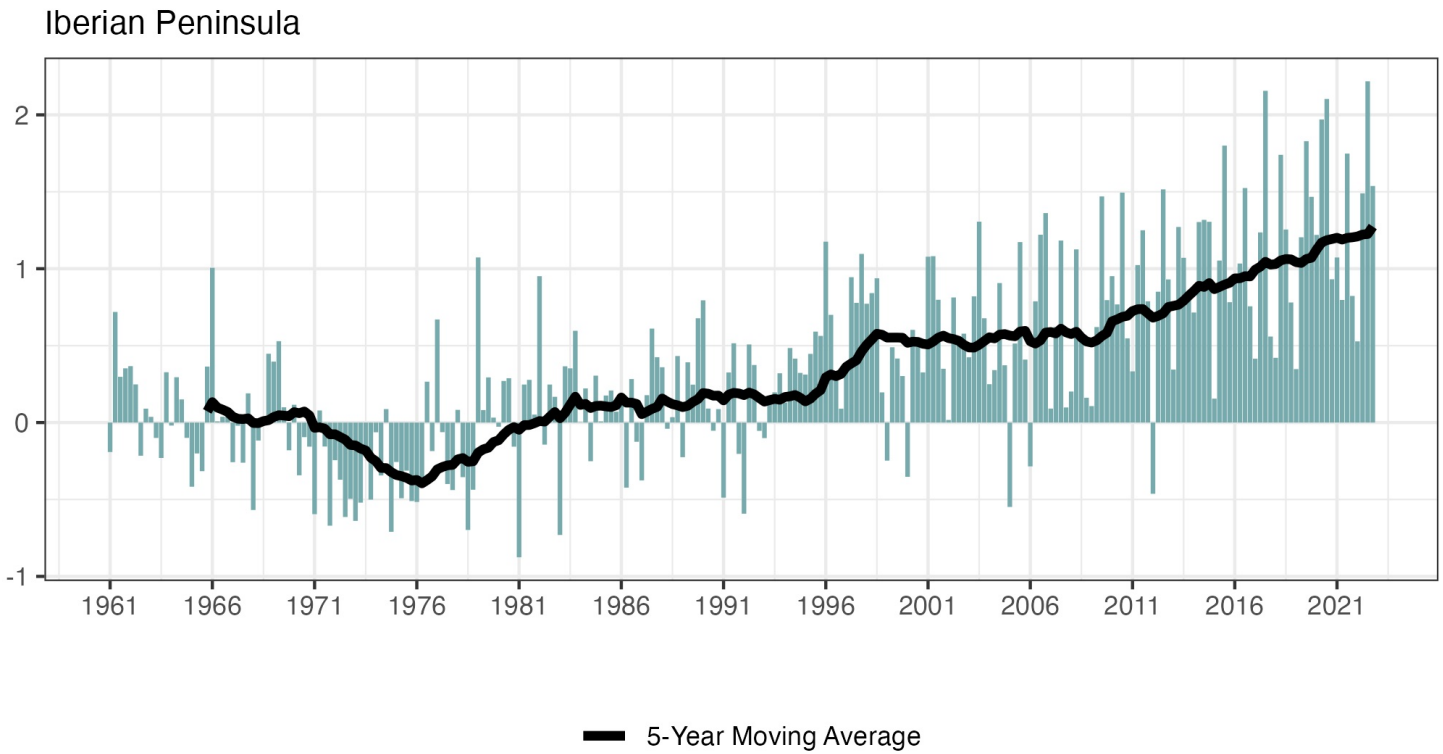


Source : https://actuaries.asn.au/microsites/climate-index/explore/component-graphs

1.3 The ACI for the Iberian Peninsula

- A first draft a Spanish version of the ACI was introduced in an oral presentation of the Spanish Institute of Actuaries (IAE).
- First defined over a different reference period (1975–1995 in general and 1993–2000 for sea levels).
- Their temperature variables differed also, see IAE (2023). It is now being standardized to ACI definitions, but with 5 variables, excluding the sea level.
- Using the North American ACI methodology and climate data for the Iberian Peninsula from the Copernicus ERA5-Land reanalysis database, (Zhou et al., 2023, AIAE) compare the values and trends of this first European index to the North American ACI.

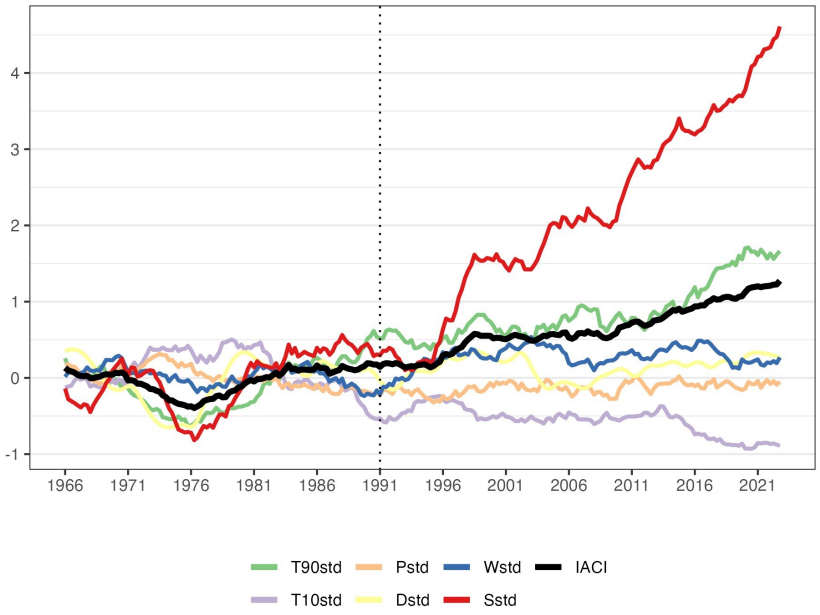
Iberian seasonal ACI values (IACI)



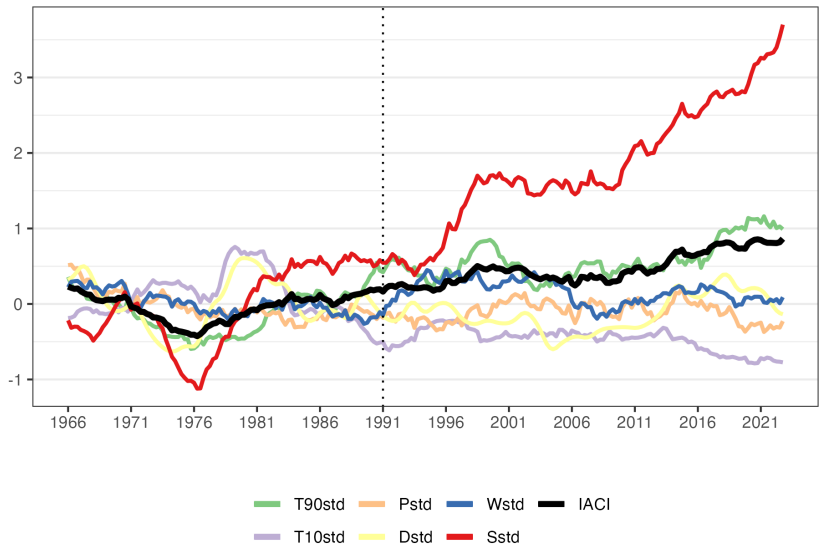
Source : (Zhou et al., 2023, AIAE)

Comparison IACI + 6 components : Spain vs Portugal

Spain (5-year averages)

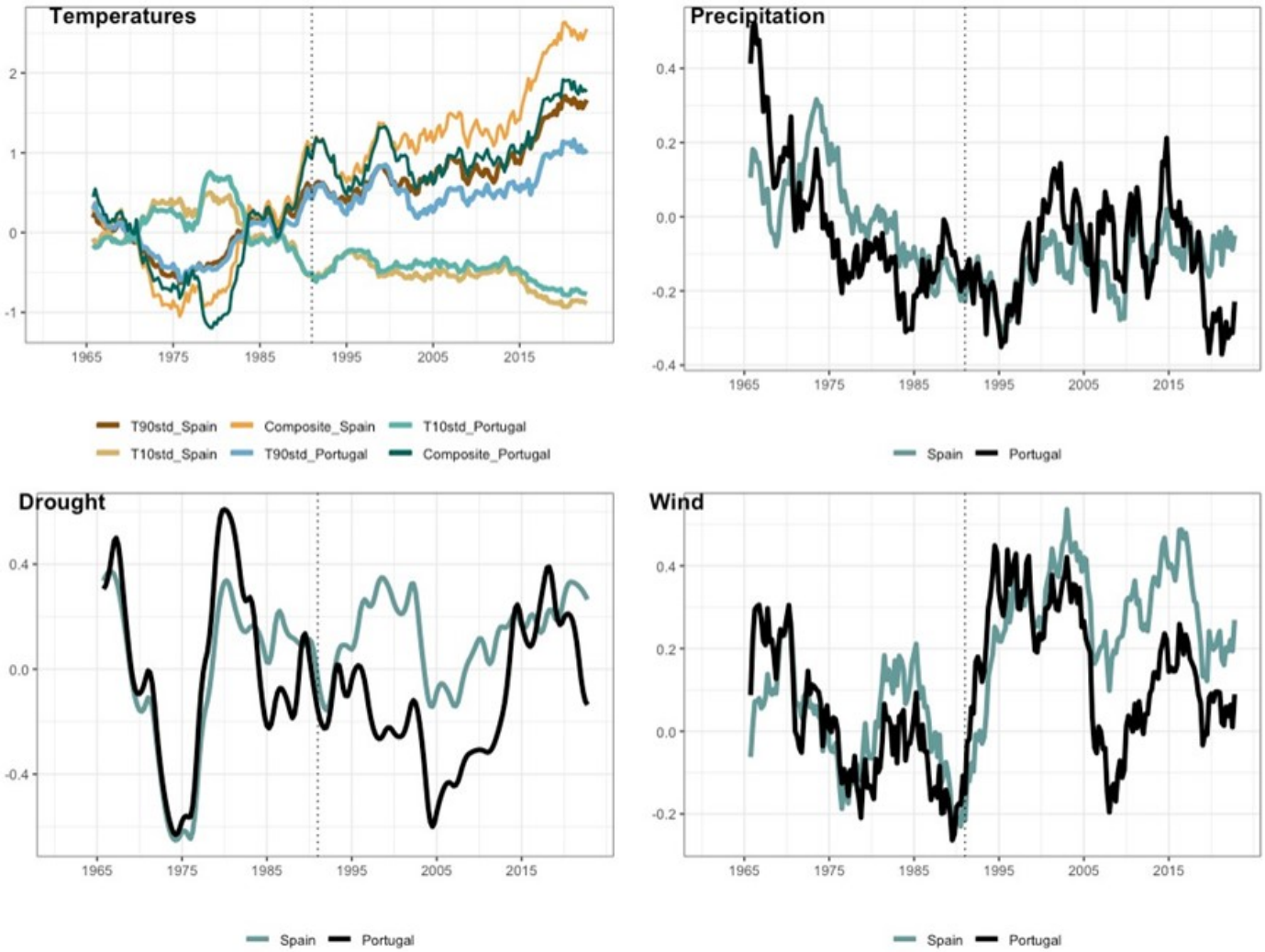


Portugal (5-year averages)



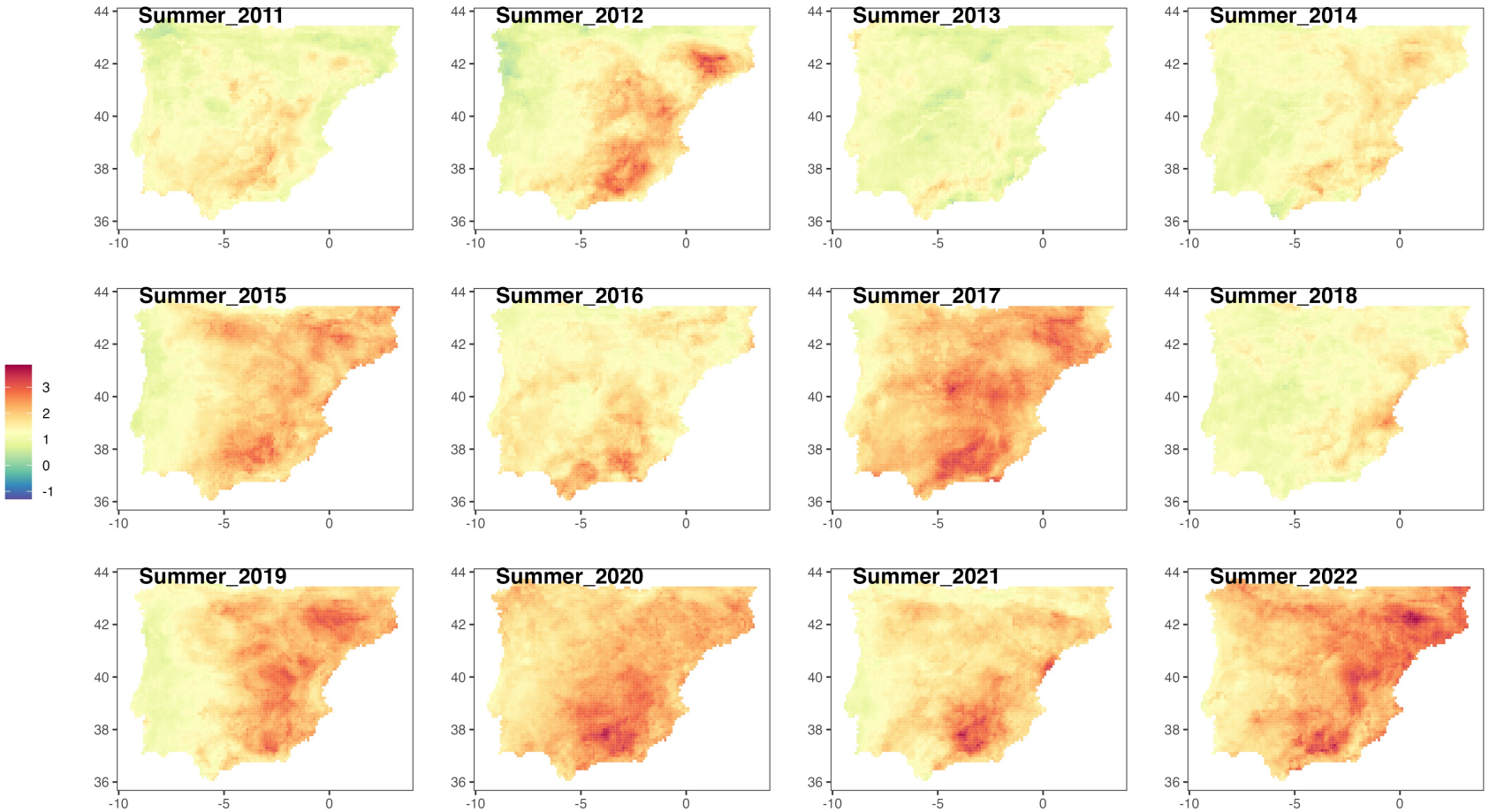
Source : (Zhou et al., 2023, AIAE)

Spain vs Portugal comparisons (5–year averages)



Source : (Zhou et al., 2023, AIAE)

Seasonal IACI comparisons : summers 2011 – 2022



Source : (Zhou et al., 2023, AIAE)

For more details about the IACI

Anales
del Instituto de Actuarios Españoles

4ª Época, Número 29, Año 2023/37-59

ON THE DEFINITION OF AN ACTUARIAL CLIMATE INDEX FOR THE IBERIAN PENINSULA

ACERCA DE LA DEFINICIÓN DE UN ÍNDICE CLIMÁTICO ACTUARIAL PARA LA PENÍNSULA IBÉRICA

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ABSTRACT

Climate change is defined as a long-term shift in climate patterns affecting the planet globally. The main consequences of climate change are a rise in average temperatures in many regions, and an increase in the frequency and intensity of extreme weather events, such as floods, droughts, storms, or hurricanes. Climate change is associated also with a rise in sea levels, more frequent and severe wildfires, a loss of biodiversity, and many other disruptions with serious economic impacts. These new risks are increasingly affecting both the frequency and severity of claims in different insurance branches. To help insurance companies predict and manage these new risks, actuaries have defined the Actuaries Climate Index™ (ACI), which combines information from several important weather variables from historical records of the United States and Canada. The ACI shows a significant increasing trend over the years. It is important to note, however, that the impact of climate change is not the same in all parts of the planet: different regions and countries are affected in different ways. Therefore, it is important to check if the ACI is as useful to assess climate risk outside the United States and Canada. In this paper, we follow the North American ACI methodology

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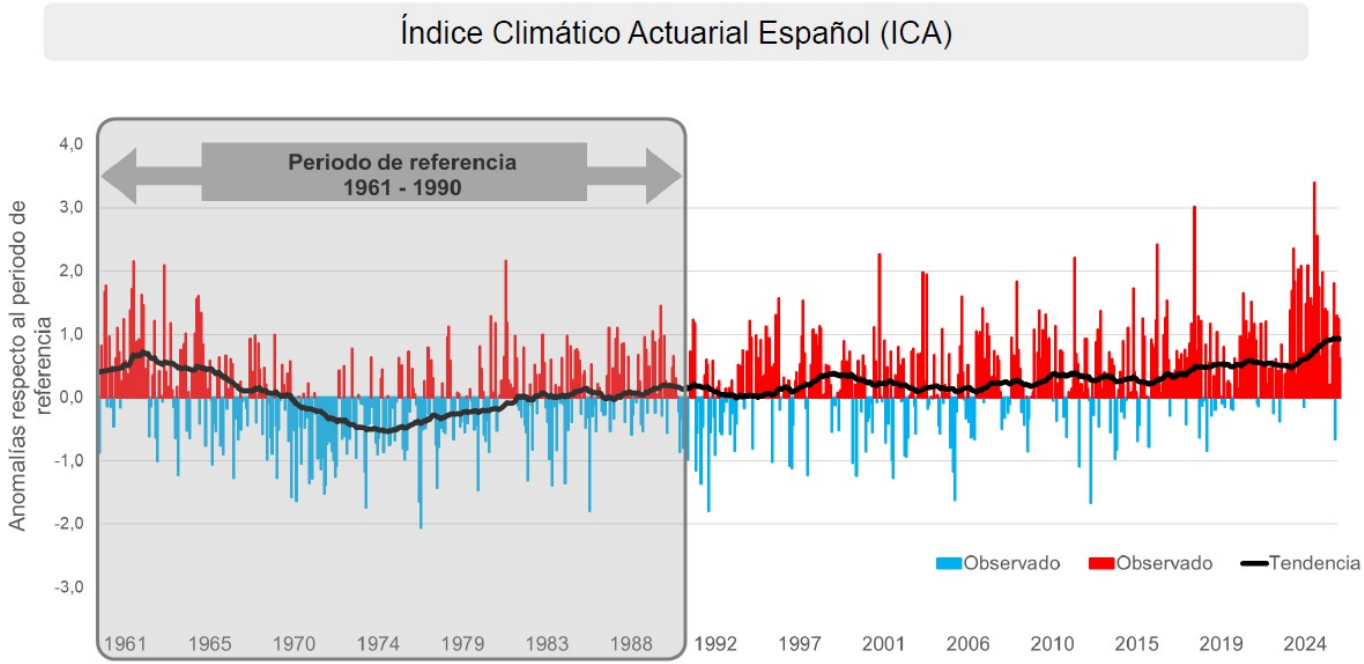
R–package : https://github.com/Nan-Z-byte/rIACI

IACI values : Iberian Actuarial Climate Index (IACI) v.0.2

For more details about the Spanish ACI of the IAE

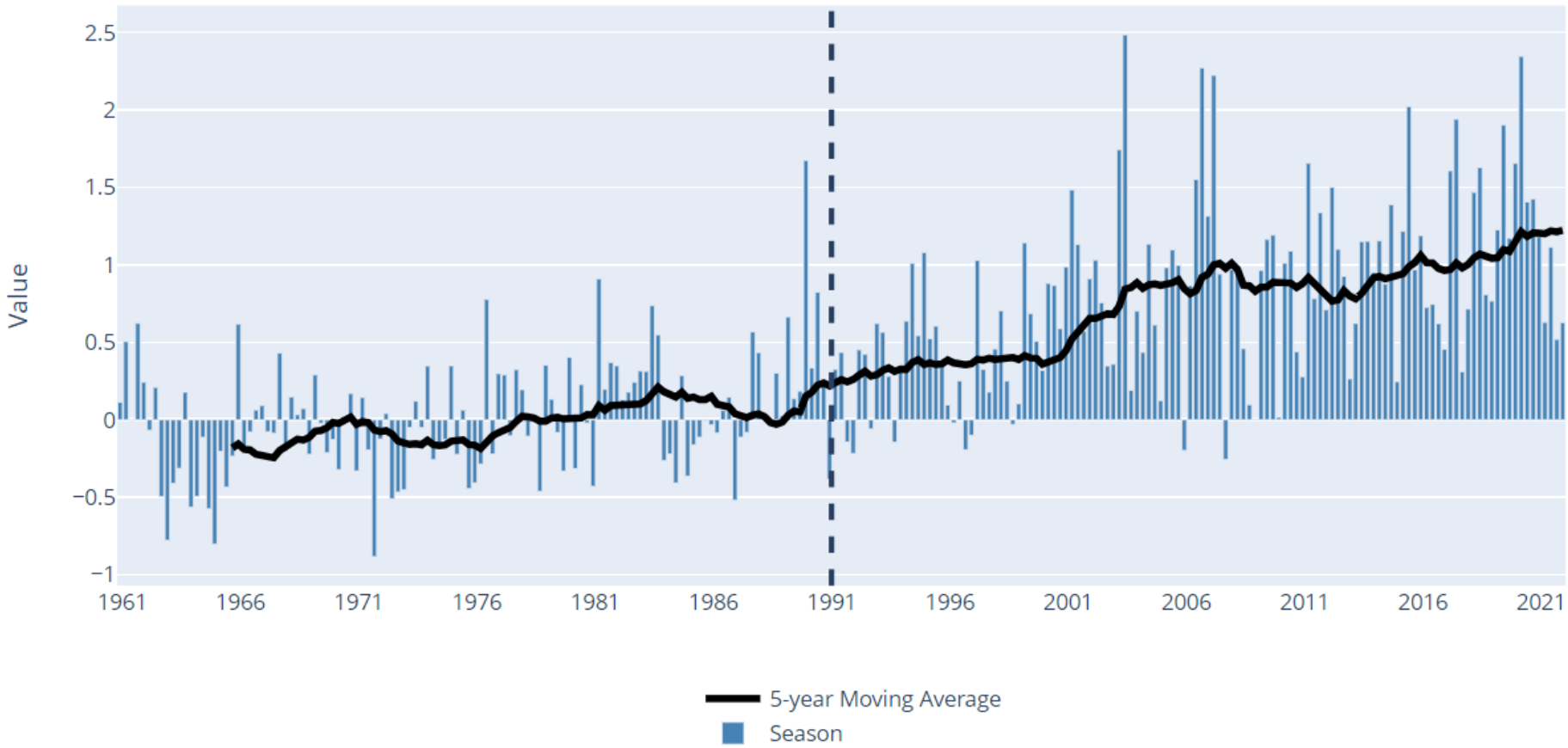


Source : https://actuarios.org/wp-content/uploads/2025/05/20250428-ICA.pdf

1.4 The French FACI

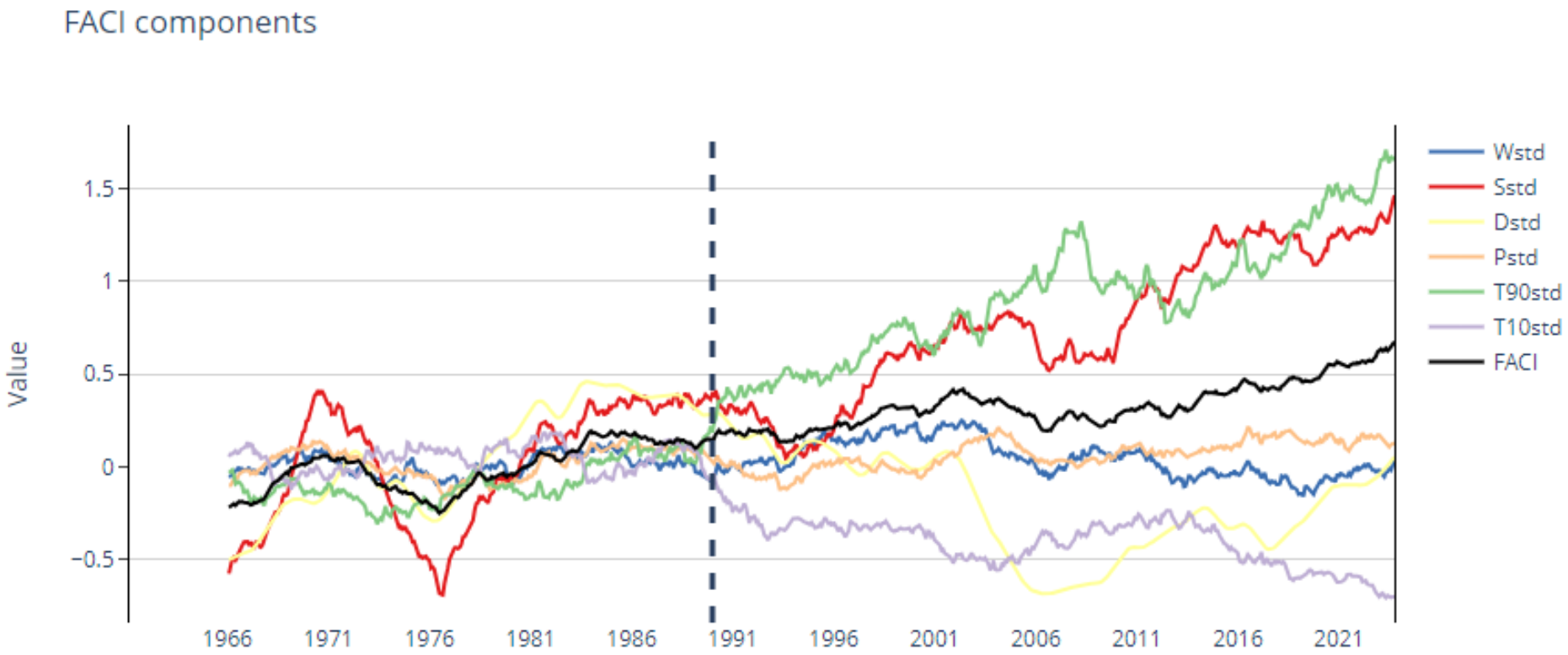
- (Garrido et al., 2023, preprint) calculate the French Actuarial Climate Index (FACI) with data extracted from the same ERA5-Land reanalysis database used for the IACI; see (Muñoz-Sabater et al., 2021, Copernicus).
- It is computed for over 10,000 cells forming the French grid of 0.1^0 of latitude $\times$ 0.1^0 of longitude (about 123.2 km^2).

French seasonal ACI values (FACI) 1961 -– 2022



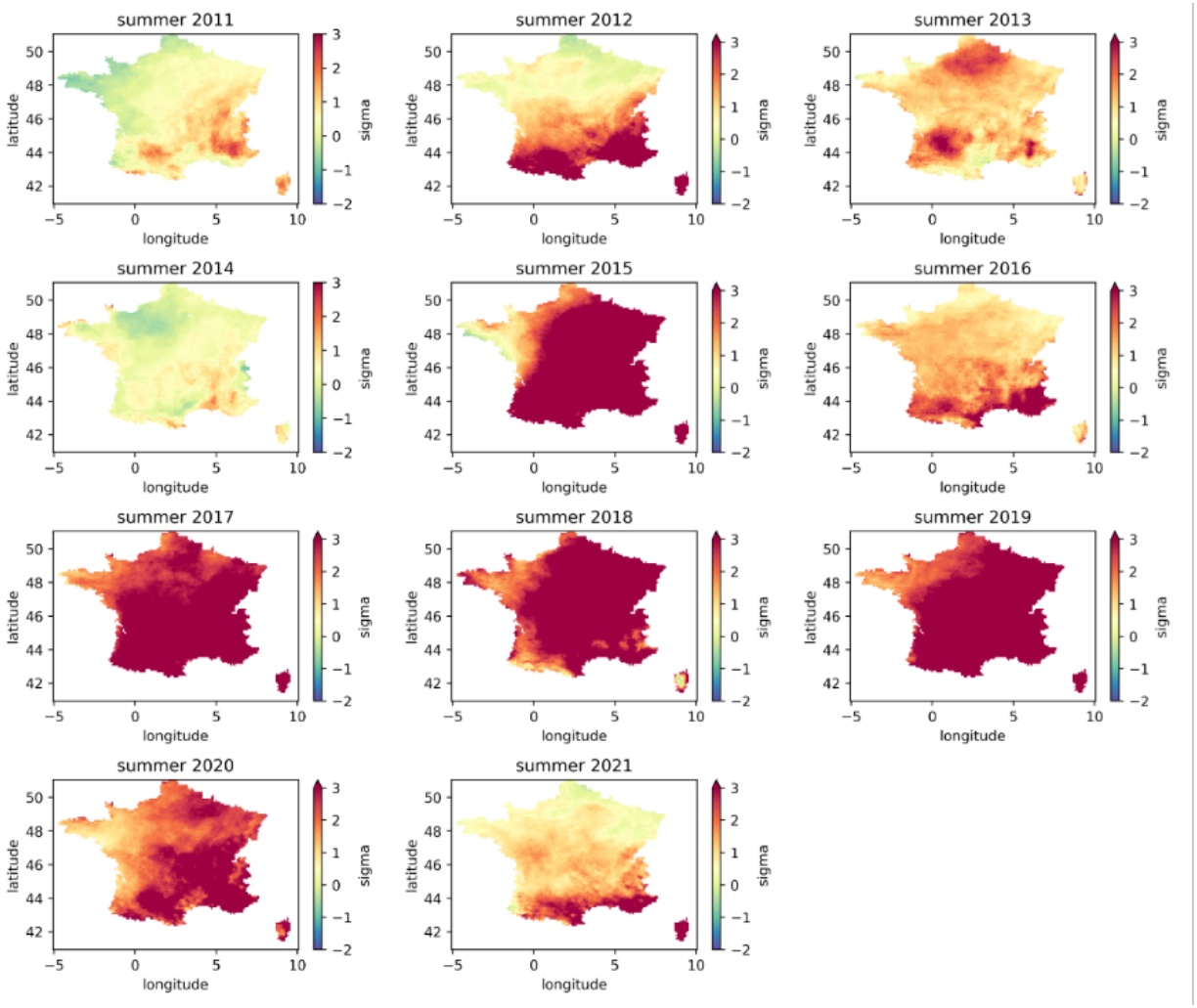
Source : (Garrido et al., 2023, preprint)

French FACI + 6 components (5–year averages)



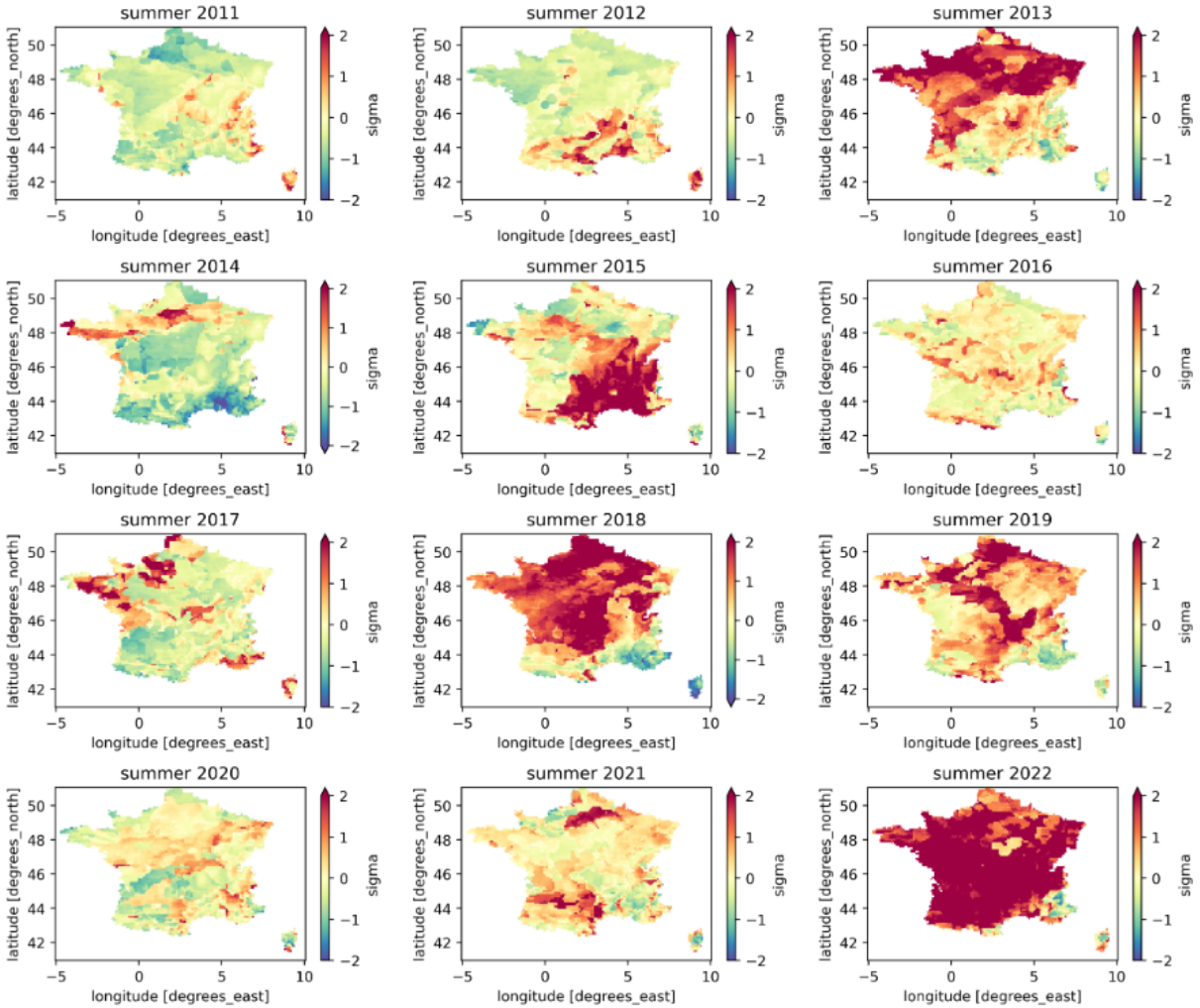
Source : (Garrido et al., 2023, preprint)

FACI T90 component : summers 2011 – 2021



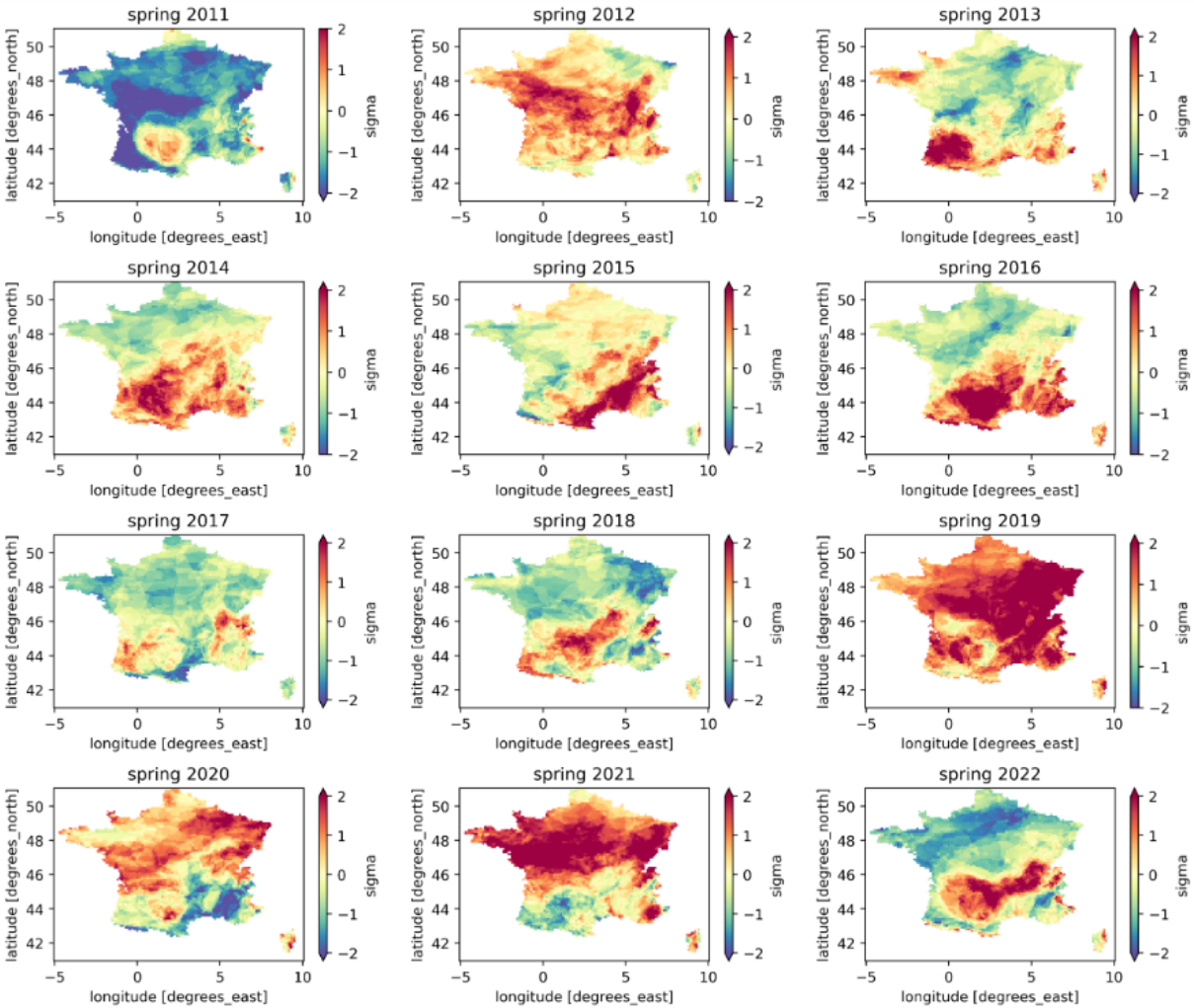
Source : (Garrido et al., 2023, preprint)

FACI drought component : summers 2011 -– 2022



Source : (Garrido et al., 2023, preprint)

FACI wind component : springs 2011 — 2022



Source : (Garrido et al., 2023, preprint)

For more details:
https://hal.science/hal-04684634/

R–package :
https://github.com/XavierMilhaud/ACI

Python–package :
https://github.com/XavierMilhaud/ACI-Python

Source : (Garrido et al., 2024, CNP)

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References I

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Courbage, C. and Golnaraghi, M. (2022). Extreme events, climate risks and insurance. *The Geneva Papers on Risk and Insurance - Issues and Practice*, 47:1–4.

Garrido, J., Milhaud, X., and Olympio, A. (2023). The definition of a French actuarial climate index; one more step towards a European index. *Preprint*.

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The Provincial Spanish Actuarial Index (pSACI).

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Universidad Complutense de Madrid

Modelos predictivos de excesos de mortalidad por olas de calor - Webinar IAE - 2025/06/11

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5 El SACI y el pSACI

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Índices Climáticos Actuariales y sus variantes

- Un índice climático actuarial es una representación cuantitativa del clima a través de la combinación de unos valores extremos que, se piensa, son relevantes para describir la variación climática e influyentes en la siniestralidad en seguros.
- Tiene interés actuarial estudiar esta variación climática desde dos puntos de vista:
  - Espacial: la variación en dominios geográficos que definan países, comunidades, provincias etc...
  - Temporal: la evolución del índice estacional, semestral, anual, etc...
  - Una combinación de ambos.

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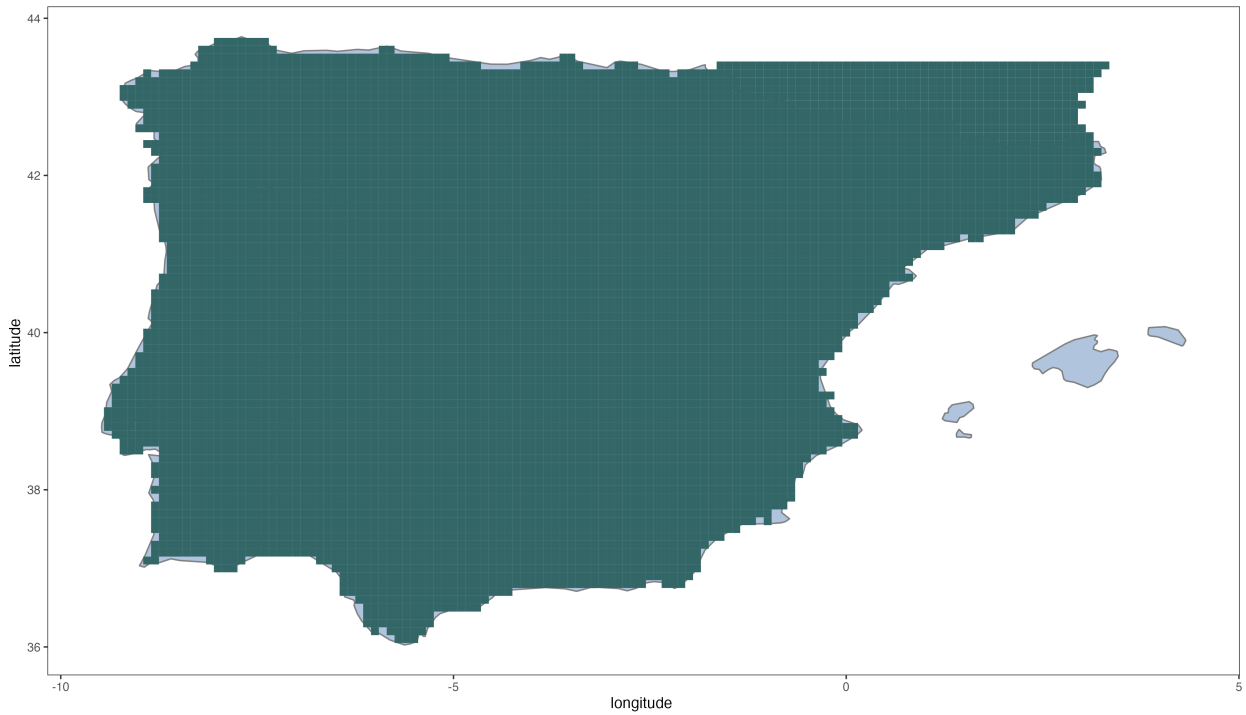
El IACI utiliza como "piezas"básicas las 6,526 celdas que aproximan la geografía de la península ibérica:

- Cada celda de 0.1°x0.1° ($\approx 123{,}2Km^2$) desde 36° a 47.7° lat.N., -9.5° a 3.3° long. E.
- En cada celda se usan los datos de **ERA5-Land reanalysis**, datos de altura del mar de **Permanent Service for Mean Sea Level**. **Datos mensuales.**
- Estos datos son combinados calculando **medias** a través del **tiempo** o/y del **espacio**.



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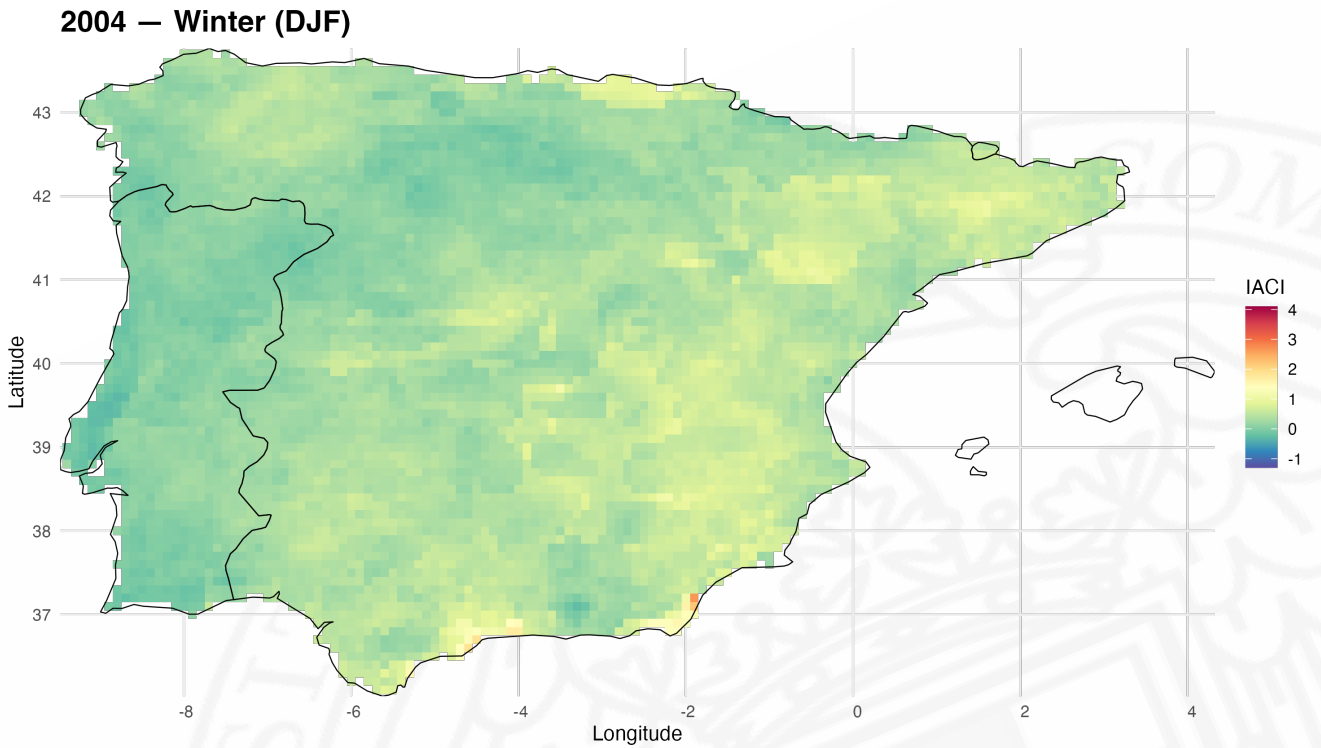
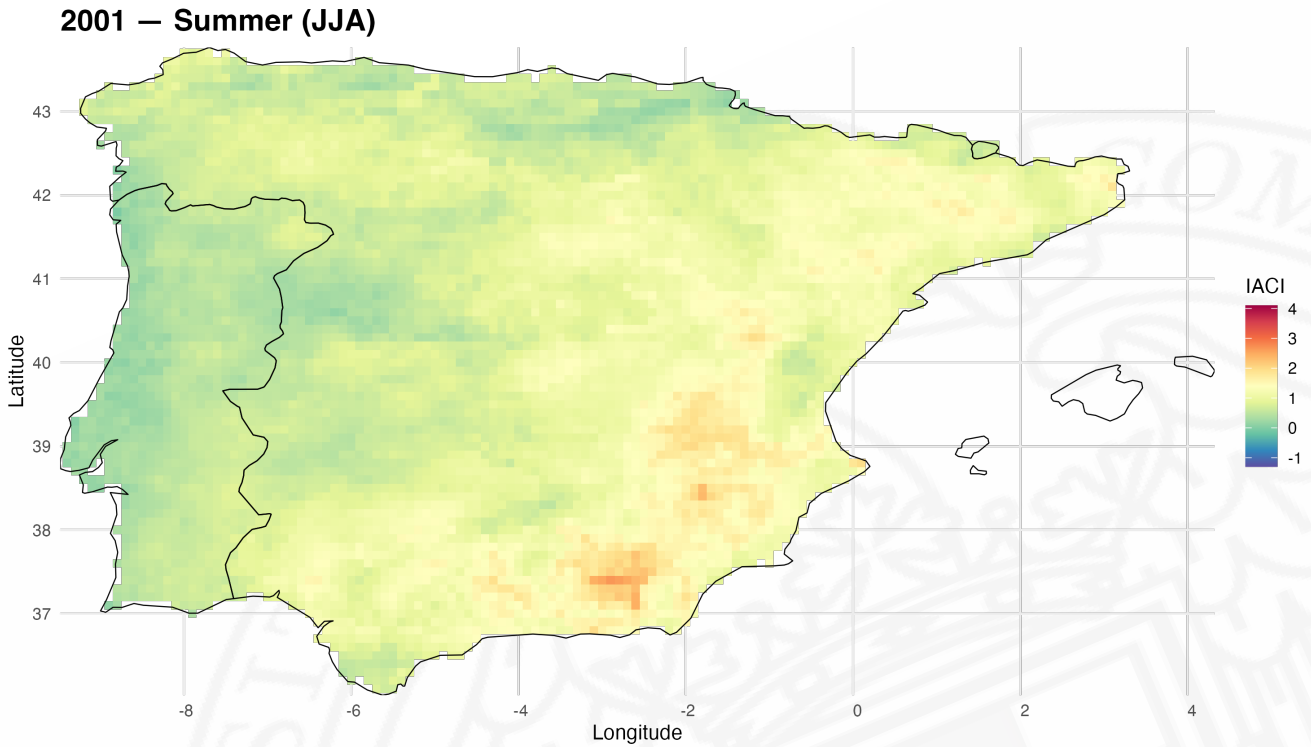
Índices estacionales

- Determinamos el periodo de interés (en meses).
- Determinamos las celdas que cubren la región geográfica de interés.
- Para cada una de las componentes del índice:
  - En cada celda, calculamos la media de todos los valores mensuales comprendidos en el periodo de interés, obeteniendo un valor medio en cada celda.
  - Calculamos la media de estos valores medios de todas las celdas, y estandarizamos respecto del periodo de referencia (le restamos la media del periodo de referencia y dididimos por su DT).
- Componemos el índice.

LA EVOLUCIÓN DEL IACI EN INVIERNO 2001–2023



LA EVOLUCIÓN DEL IACI EN VERANO 2001–2023



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- Determinamos las celdas que cubren la región geográfica de interés.
- Para cada una de las componentes del índice:
  - Para cada mes, calculamos la media de los valores de las celdas, obteniendo un valor medio.
  - Estandarizamos respecto del periodo de referencia (le restamos la media del periodo de referencia y dididimos por su DT).
- Componemos el índice.

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El Indice Climático Actuarial Español (SACI)

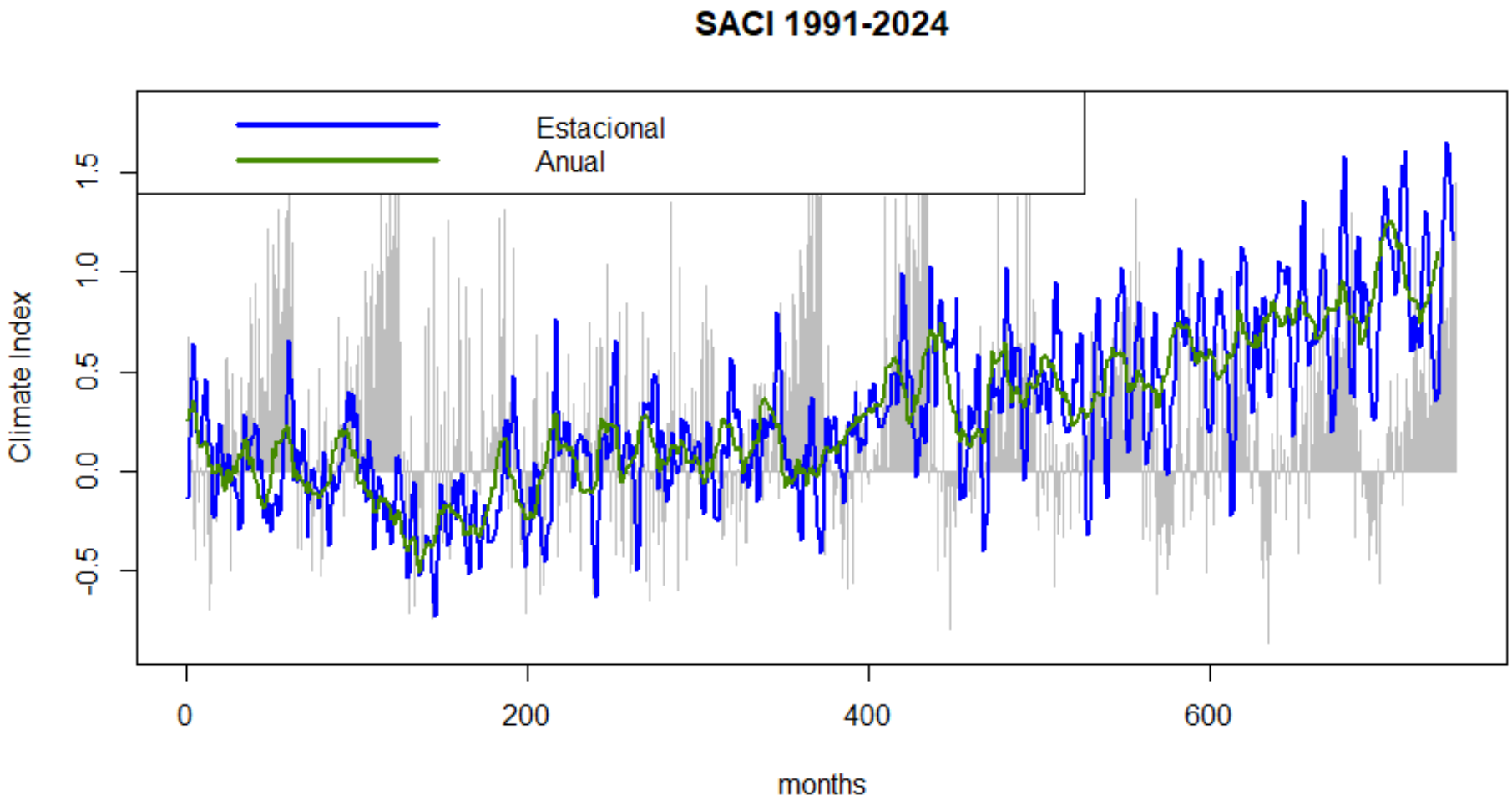

Figura: El índice climático Actuarial Español de 1991 a 2022 y sus medias móviles para 3 y 12 meses.

Indice Climático Actuarial Español provincial (pSACI)

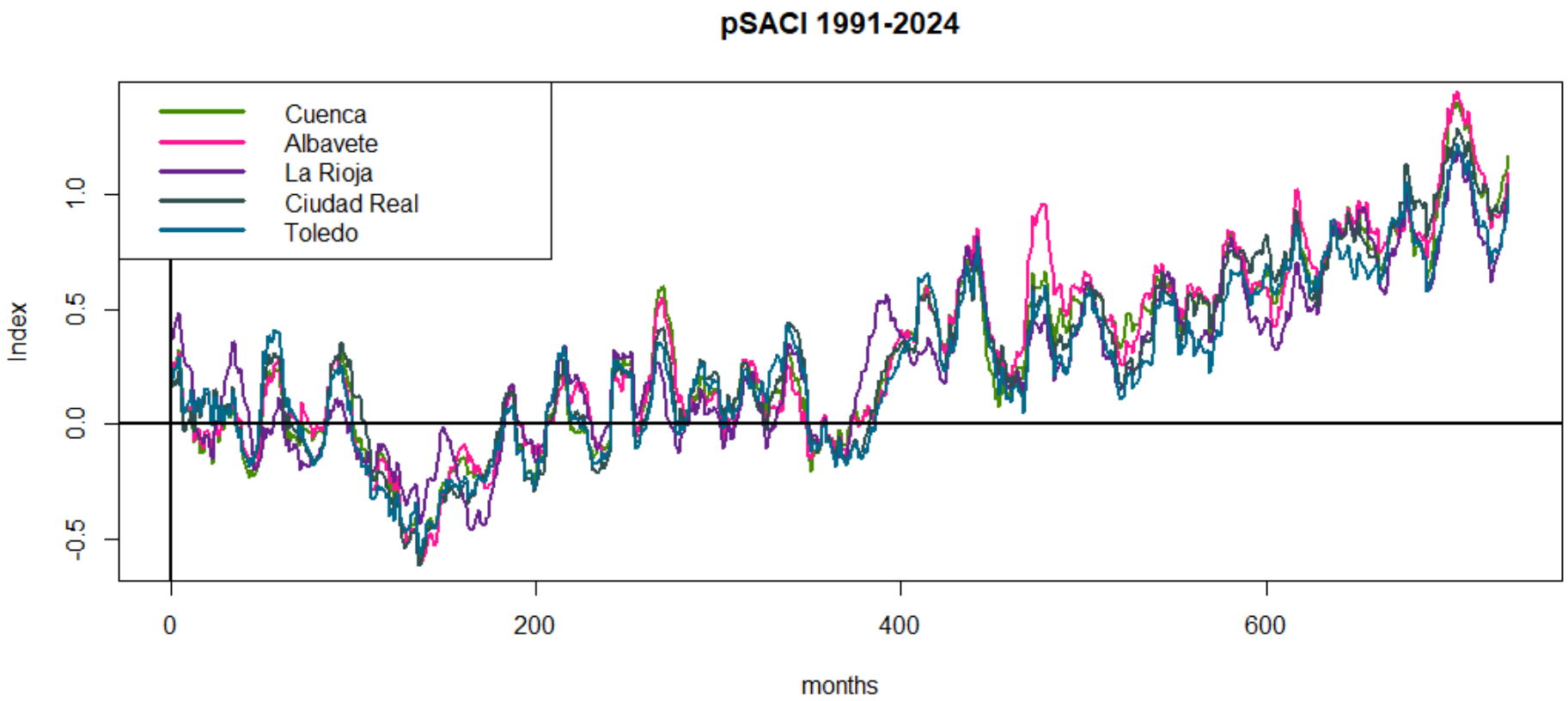

Figura: El pSACI de 1991 a 2022 para 5 provincias . Medias móviles de 12 meses.

Indice Climático Actuarial Español provincial (pSACI)

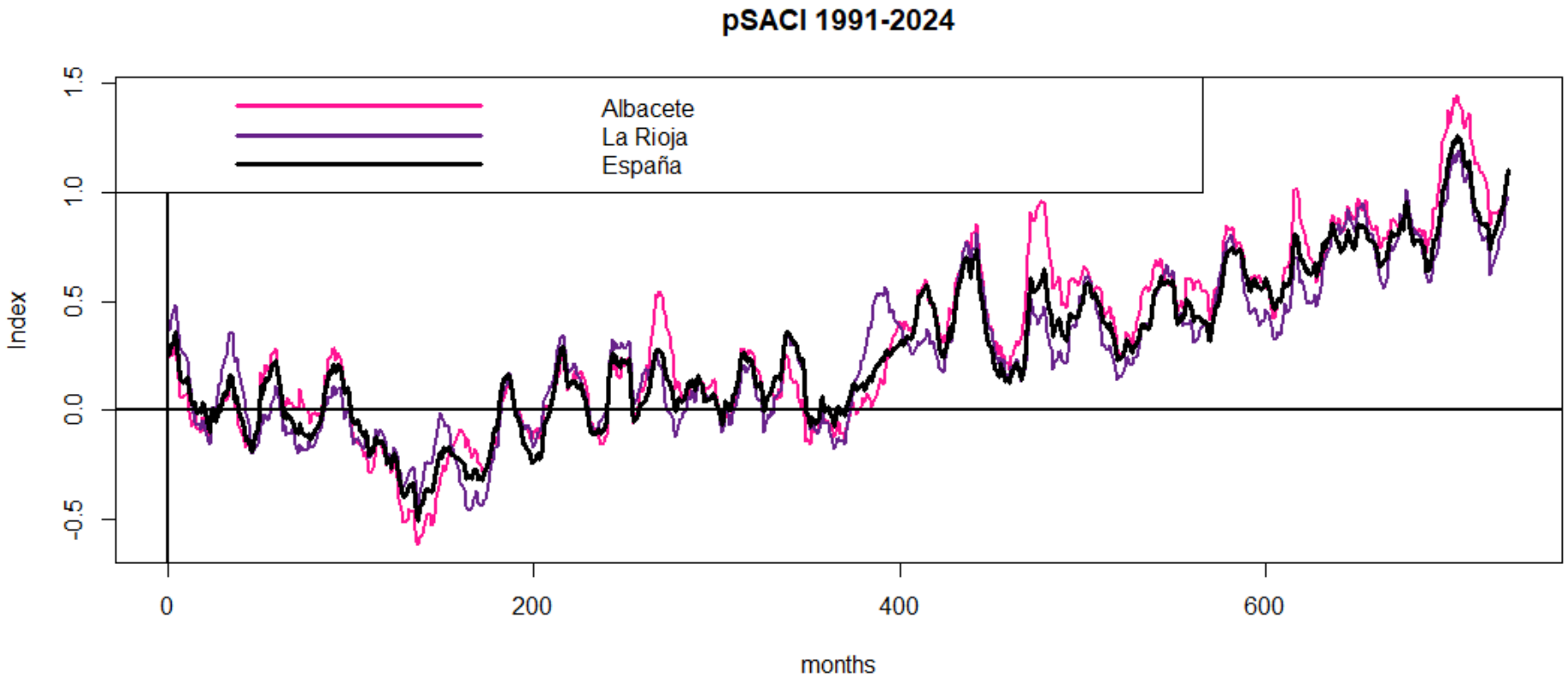

Figura: El pSACI de 1991 a 2022 para 2 provincias. Medias móviles de 12 meses. Detalle de la heterogeneidad espacial.

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1 Introducción

2 Metodología

3 Indices estacionales

4 Índices regionales (mensuales)

5 El SACI y el pSACI

6 Referencias

Referencias

- Zhou N., Vilar-Zanón J.L. 2025. Climate change and crop insurance: geographical heterogeneity in hailstorm risk for wine grapes in Spain. European Actuarial Journal. Springer. **10.1007/s13385-025-00419-6**. Open Access (a 09/06/2025 está por aparecer).
- Zhou N, Vilar-Zanón JL. 2024 Impact Assessment of Climate Change on Hailstorm Risk in Spanish Wine Grape Crop Insurance: Insights from Linear and Quantile Regressions. Risks. ; 12(2):20. **10.3390/risks12020020** . Open Access.

Webinar Modelos predictivos de excesos de mortalidad por olas de calor

José Garrido
José Luis Vilar
Ignacio Blasco

June 11th

comillas.edu

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1. Authors
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1. Authors

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2. Context

2. Context

- **National Plan of Preventive Actions for the Effects of Excess Temperature on Health Heat waves, produced by climate change:**
  - Deaths of **23,820 people** in Spain (2,382 deaths per year).
  - Between 2015 and 2024.

https://www.sanidad.gob.es/areas/sanidadAmbiental/riesgosAmbientales/calorExtremo/momoAltasTemperaturas.htm

- **ISCII Carlos III Study:**
  - The results showed that the risk of mortality attributable to heat waves grows between 9.1% and 10.7% for each degree that the ambient temperature rises above the threshold of impact on health.
  - This study associates **13,119 deaths** with heat waves, that is, 1,300 deaths per year.
  - Study carried out between 2000 and 2009 (ISCII Carlos III)

https://www.elconfidencialdigital.com/articulo/politica/sanidad-atribuye-cambio-climatico-24000-muertes-ultimos-diez-anos-espana/20250527123324965563.html

2. Context

- Results presented in the I Actual360 Congress and XVII Spanish-Italian Congress on Financial and Actuarial Mathematics
- Ongoing process (some results, but for sure more developments will be made)
- Heat exposure is linked to increased mortality.
- Modelling heat-related mortality is complex due to multiple influencing factors.
- Factors beyond temperature—like humidity, radiation, and wind—affect heat stress.
- Timing, intensity, and recovery periods of heat waves play crucial roles.
- Vulnerability factors (e.g., housing, healthcare, awareness) also affect outcomes.
- A common strategy is to separate environmental exposure from population vulnerability.
- Some studies simplify models by focusing only on temperature or temperature + humidity.
- This simplification works due to temperature's spatial consistency.
- The study tests this on Spanish data using micro-level mortality records.
- A climate index is used: IACI Index (includes temperature, precipitation, wind, sea level, by province).

2. Context

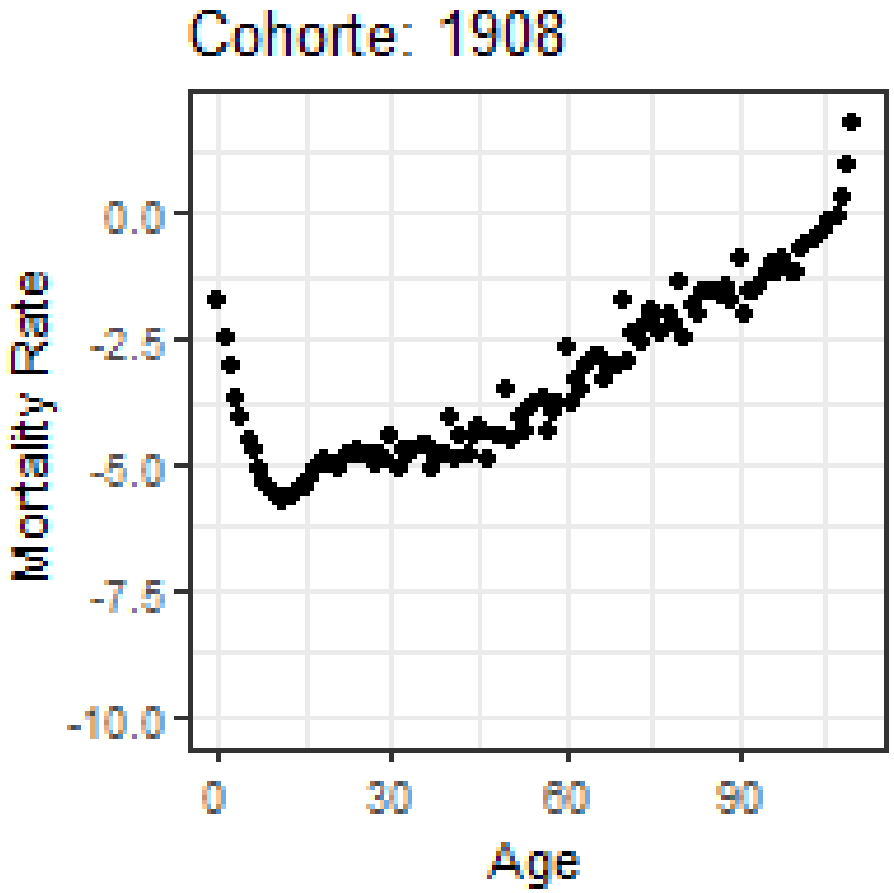
What age would you guess for the people in the photo?

2. Context

What age would you guess for the people in the photo?

Solution: it is a photograph taken in 1939. At the time of taking the photograph, the man who appears in the photograph was 61 years old and the woman, 52. The age adjusted for risk would surely be around 80-90 years ("What age would you guess ").

2. Context



- We have our graph that represents mortality rates as a function of age, for a given cohort (logarithmic scale).

Source: HMDB, Spain, unisex
Log scale

3. Inputs

INE Microdata

Microdata INE (requested in 2025)

- Individual deaths observed during the period [1975;2023] (49 years)
- Sets of data:
  - 1975-1979
  - 1980-1998
  - 1999-2008
  - 2009-2011
  - 2012-2023

INE Microdata

Useful fields analysis (selected fields)

- ***CPROI:*** province code of record. Numeric between 01 and 52 and equal to the code of the province in which it is being recorded.
- ***CMUNI:*** municipality code of record. Numeric, compatible with a geographic dictionary. "000", "999" and " " are not supported (writers suspect that the same principle as CMUNRE applies "for municipalities with more than 10,000 inhabitants").
- ***SEXO***: Sex. Numeric: 1 = male, 6 = female.
- ***MESDEF***: Month-date of death. Numeric, between 01 and 12.
- ***ANODEF***: Year-date of death. Numerical.
- ***CPRORE***: Province code of residence of the deceased. White or numeric between 01-52.
- ***CMUNRE***: Municipality, residence code of the deceased (for municipalities with more than 10,000 inhabitants)
- ***ECIV***: Marital status of the deceased (0, 1, 2, 3, 4) Not recorded, Single, Married, Widowed, Divorced
- ***AÑOSC***: Years old. Numerical.
- ***CBAS1***: 1st character of the code of basic cause. Alphabetic.
- ***CBAS23***: 2nd and 3rd character of the code of basic cause. Numerical.
- ***CBAS4***: 4th character of the code of basic cause
- ***CAUSAP***: Cause of perinatal mortality (93 groups)
- ***CAUSAINF***: Cause of infant mortality (54 groups) for children under 1 year of age
- ***NESTUDIOS***: Level of Education (see annex for detail)

INE Microdata

Sex distribution observed 2012-2023

	2023	2022	2021	2020	2019	2018
Total						
Total	436.124	464.417	450.744	493.776	418.703	427.721
Hombres	220.742	234.362	231.410	249.664	212.683	216.442
Mujeres	215.382	230.055	219.334	244.112	206.020	211.279
Check Hombres Microdatos	220.742	234.362	231.410	249.664	212.683	216.442
Check Mujeres Microdatos	215.382	230.055	219.334	244.112	206.020	211.279

	2017	2016	2015	2014	2013	2012
Total						
Total	424.523	410.611	422.568	395.830	390.419	402.950
Hombres	214.236	208.993	213.309	201.571	199.834	205.920
Mujeres	210.287	201.618	209.259	194.259	190.585	197.030
Check Hombres Microdatos	214.236	208.993	213.309	201.571	199.834	205.920
Check Mujeres Microdatos	210.287	201.618	209.259	194.259	190.585	197.030

	2011	2010	2009	2008	2007	2006
Total						
Total	387.911	382.047	384.933	386.324	385.361	371.478
Hombres	199.854	198.121	199.095	199.647	201.136	194.154
Mujeres	188.057	183.926	185.838	186.677	184.225	177.324
Check Hombres Microdatos	199.854	198.121	199.095	199.647	201.136	194.154
Check Mujeres Microdatos	188.057	183.926	185.838	186.677	184.225	177.324

INE Microdata

Sex distribution observed 2012-2023

	2005	2004	2003	2002	2001	2000
Total						
Total	387.355	371.934	384.828	368.618	360.131	360.391
Hombres	201.769	194.928	199.897	193.269	189.714	189.468
Mujeres	185.586	177.006	184.931	175.349	170.417	170.923
Check Hombres Microdatos	201.769	194.928	199.897	193.269	189.714	189.468
Check Mujeres Microdatos	185.586	177.006	184.931	175.349	170.417	170.923

	1999	1998	1997	1996	1995	1994
Total						
Total	371.102	360.511	349.521	351.449	346.227	338.242
Hombres	195.255	190.218	185.095	186.901	184.488	179.924
Mujeres	175.847	170.293	164.426	164.548	161.739	158.318
Check Hombres Microdatos	195.255	190.218	185.095	186.901	184.488	179.924
Check Mujeres Microdatos	175.847	170.293	164.426	164.548	161.739	158.318

	1993	1992	1991	1990	1989	1988
Total						
Total	339.661	331.515	337.691	333.142	324.796	319.437
Hombres	180.512	177.087	179.344	176.779	172.364	168.734
Mujeres	159.149	154.428	158.347	156.363	152.432	150.703
Check Hombres Microdatos	180.512	177.087	179.344	176.779	172.364	168.734
Check Mujeres Microdatos	159.149	154.428	158.347	156.363	152.432	150.703

INE Microdata

Sex distribution observed 2012-2023

	1987	1986	1985	1984	1983	1982
Total						
Total	310.073	310.413	312.532	299.409	302.569	286.655
Hombres	163.891	162.961	164.834	158.515	158.375	151.048
Mujeres	146.182	147.452	147.698	140.894	144.194	135.607
Check Hombres Microdatos	163.891	162.961	164.834	158.515	158.375	151.048
Check Mujeres Microdatos	146.182	147.452	147.698	140.894	144.194	135.607

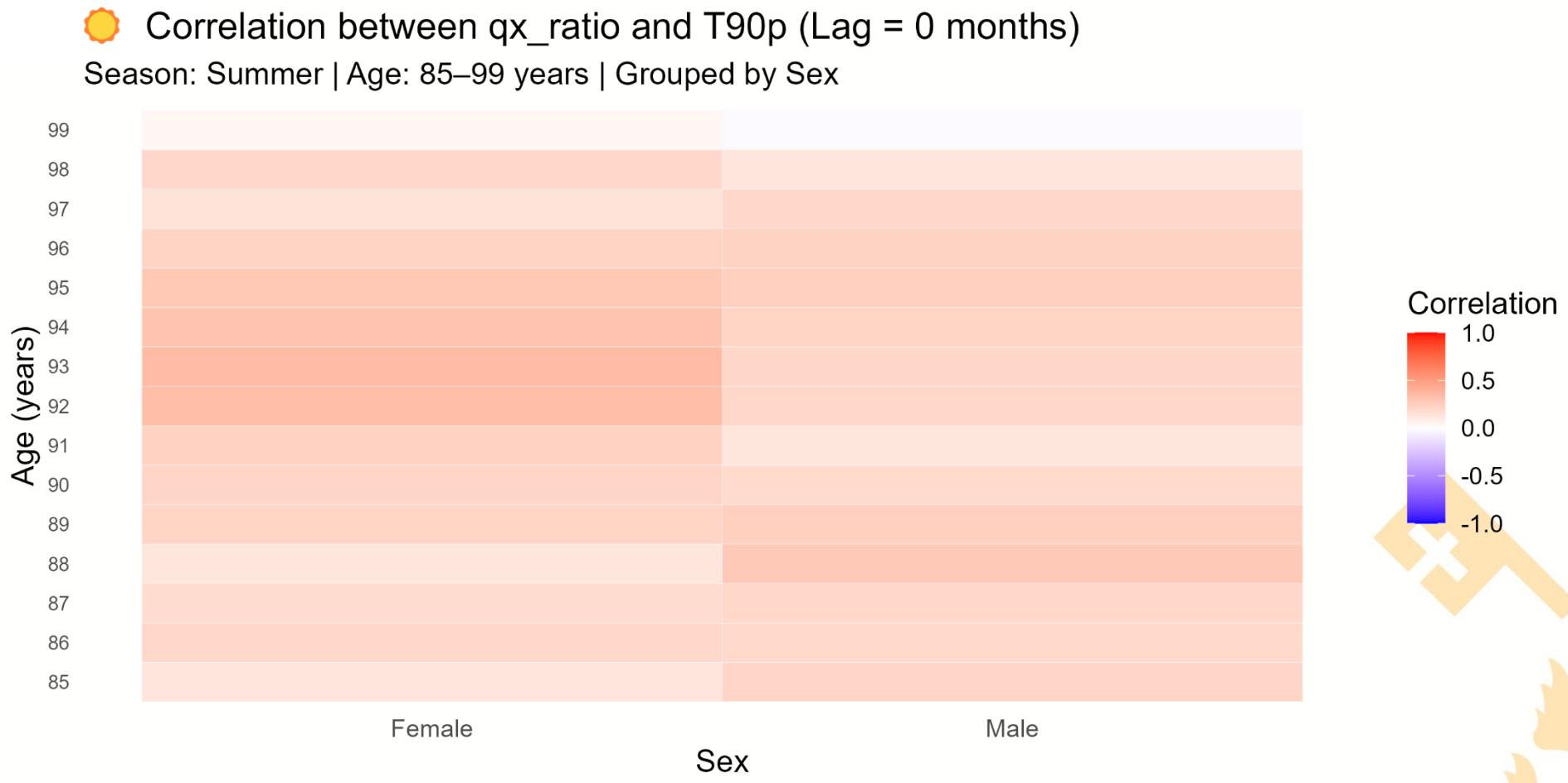
	1981	1980	1979	1978	1977	1976
Total						
Total	293.386	289.344	291.213	296.781	294.324	299.007
Hombres	154.437	152.225	153.573	155.541	153.870	155.979
Mujeres	138.949	137.119	137.640	141.240	140.454	143.028
Check Hombres Microdatos	154.437	152.225	153.573	155.541	153.870	155.979
Check Mujeres Microdatos	138.949	137.119	137.640	141.240	140.454	143.028
	VERDADERO	VERDADERO	VERDADERO	VERDADERO	VERDADERO	VERDADERO
	VERDADERO	VERDADERO	VERDADERO	VERDADERO	VERDADERO	VERDADERO

	1975
Total	
Total	298.192
Hombres	155.471
Mujeres	142.721
Check Hombres Microdatos	155.471
Check Mujeres Microdatos	142.721
	VERDADERO
	VERDADERO

Correlations

Heatwaves

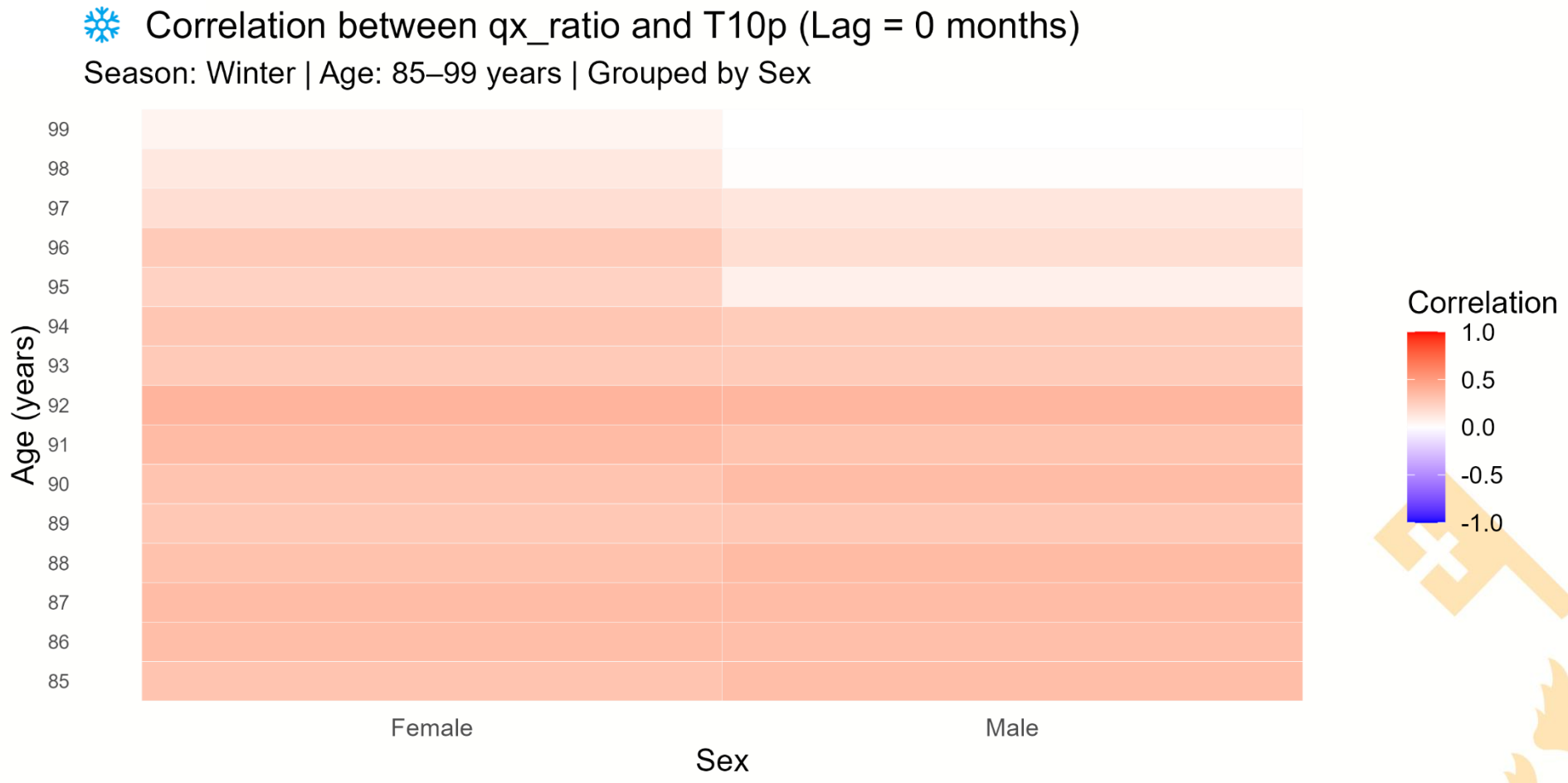
The impact of heatwaves on excess mortality seems more intense in males than females from 75 to 85. And from 85 to 92, heatwaves impact on females more intensely than on men …



Correlations

Cold waves

The correlation seems clear in old ages (>85 y.o. in males and >78 in females).



4. Algorithm

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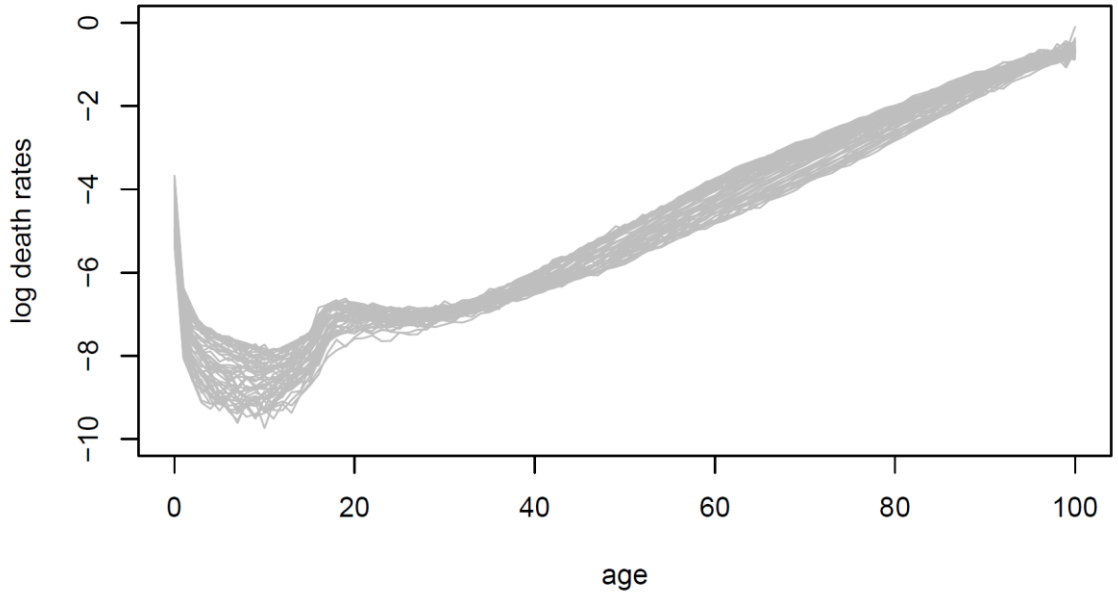
Our approach

1. Raw Data Import (Microdata & IACI). Filter from 1980, due to data completeness.
2. qx construction by month and sex. Include label for winter and summer months.
3. Two parallel algorithms:

   A. **Lee-Carter traditional fitting**. Objective: estimate excess of deaths:
      1. Lee-Carter for winter months (December, January and February) and summer months (June, July and August), and split by age and sex, considering the timestamp.
      2. Derivation of traditional Lee-Carter = qx_LC (winter_females, winter_males, summer_females, summer_males).
      3. Excess deaths according to a (traditional) Lee-Carter = max (deaths observed – deaths fitted ; 0) = max (deaths observed – qx_LC * Exposures ; 0).

   B. **GLM (Generalized Linear Model)**. Objective: explain death rates composition:
      1. Dataset for GLM: qx for age and IACI
      2. Variables selection
      3. GLM fitting

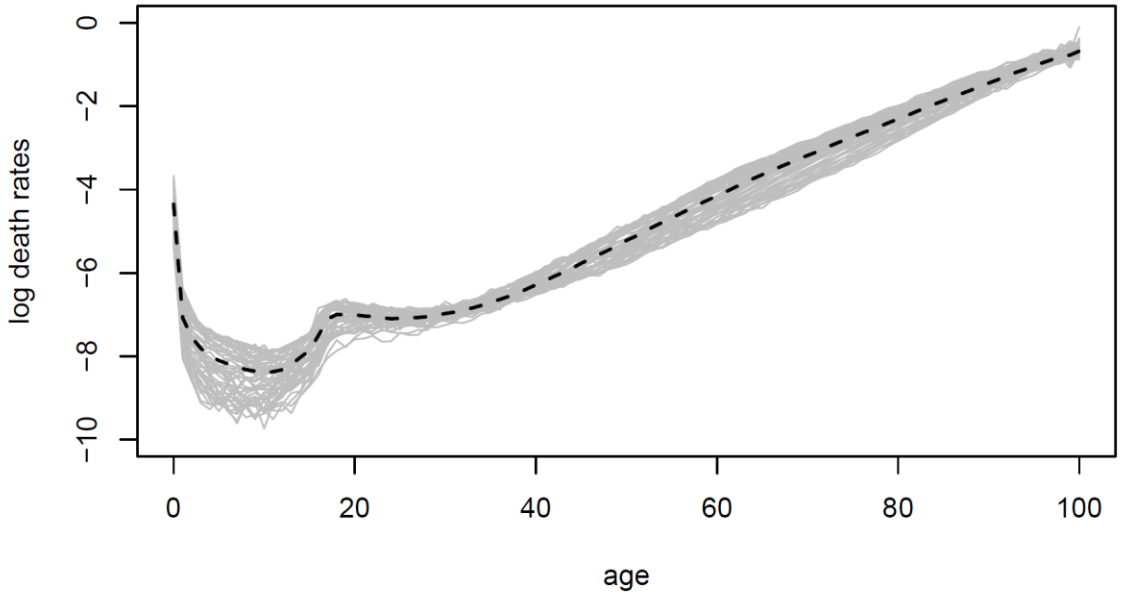
Lee-Carter



$$\log \mu_{xt} \quad =$$

Source: Andrés Villegas

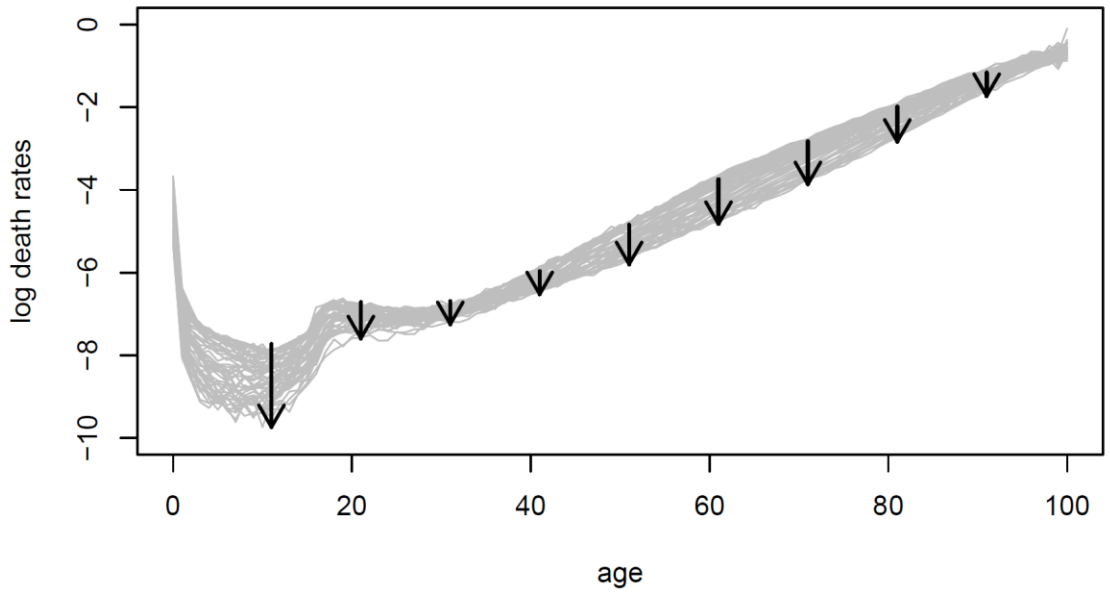
Lee-Carter



$$\log \mu_{xt} = \alpha_x$$

Source: Andrés Villegas

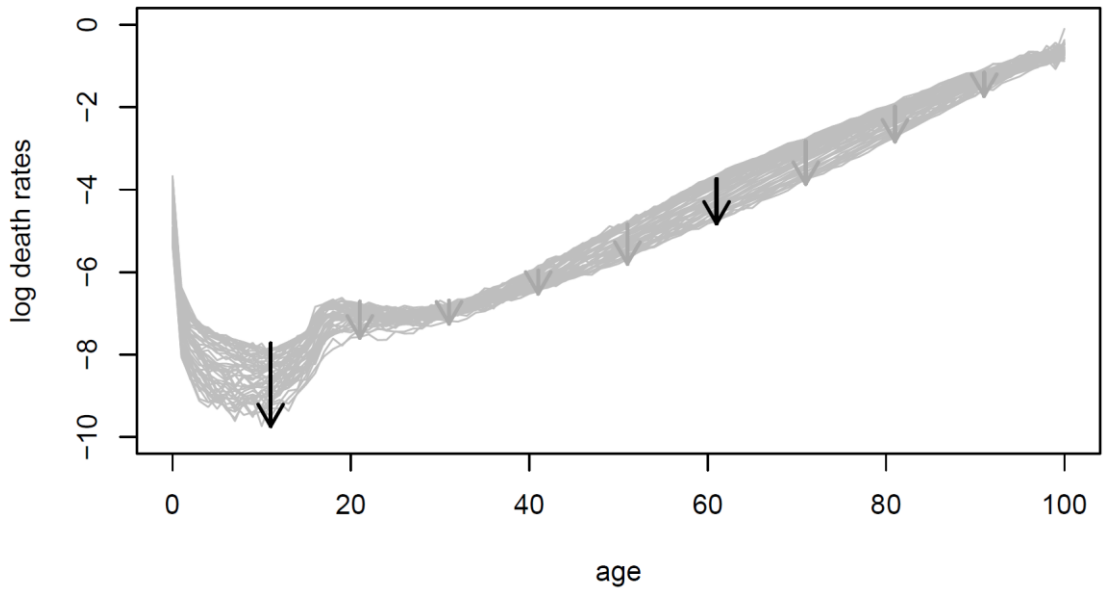
Lee-Carter



$$\log \mu_{xt} = \alpha_x + \kappa_t$$

Source: Andrés Villegas

Lee-Carter



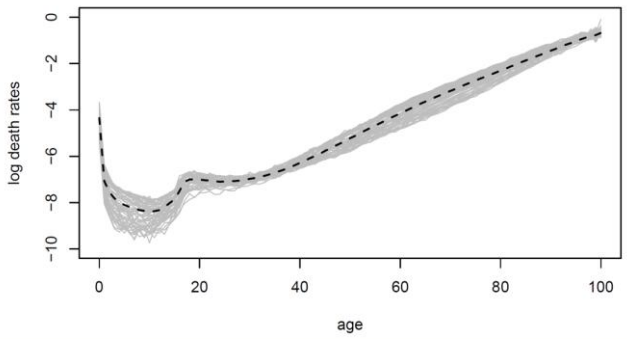
$$\log \mu_{xt} = \alpha_x + \beta_x \kappa_t$$

Source: Andrés Villegas

Lee-Carter

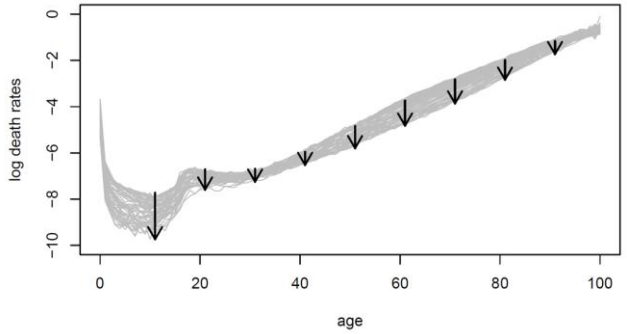
α_x

Coefficient that reflects the average behavior of mortality, for each age x.



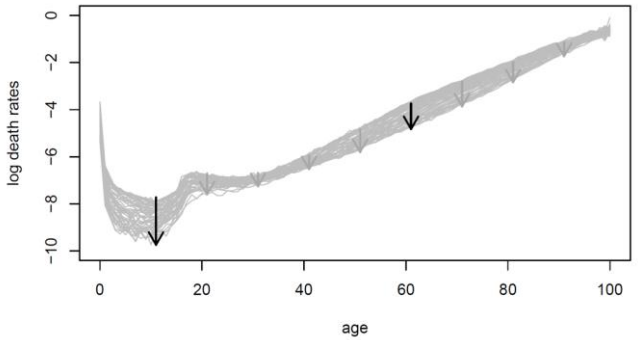
κ_t

General mortality rate, which evolves over time t (trend without discriminating by age).



$\beta_x \ \kappa_t$

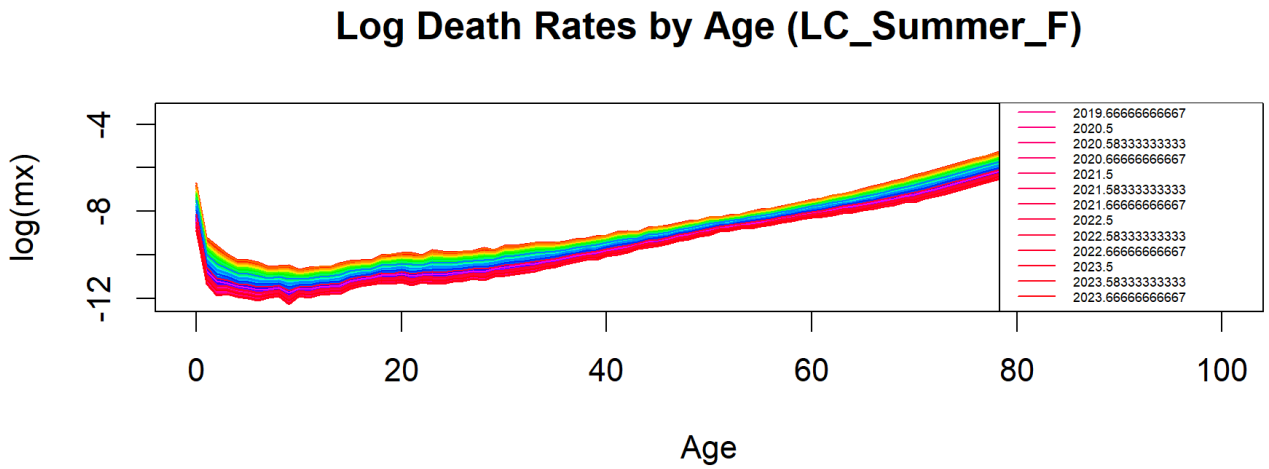
Beta is the coefficient that measures the sensitivity of ln(qx,t) to variations in kt. This is the trend particularized by age.



Source: Own elaboration based on Andrés Villegas

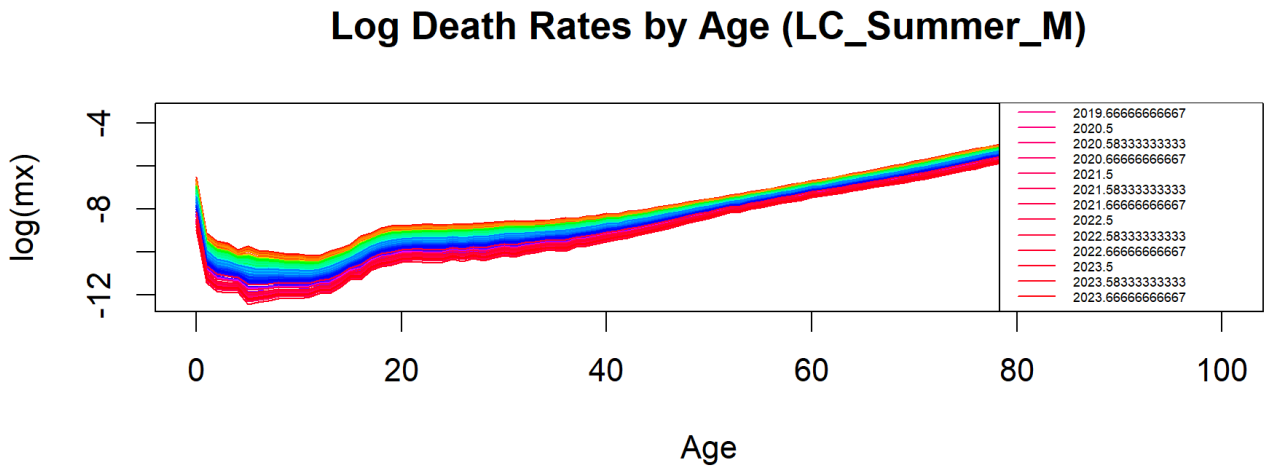
Lee-Carter for Summer Months (Jun, Jul, Aug)

Females



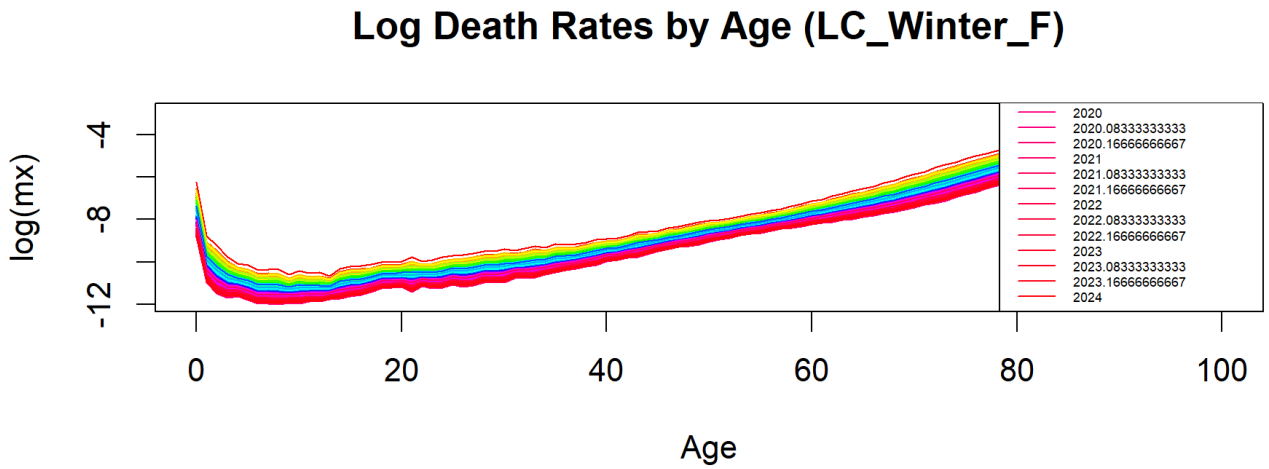
Lee-Carter for Summer Months (Jun, Jul, Aug)

Males



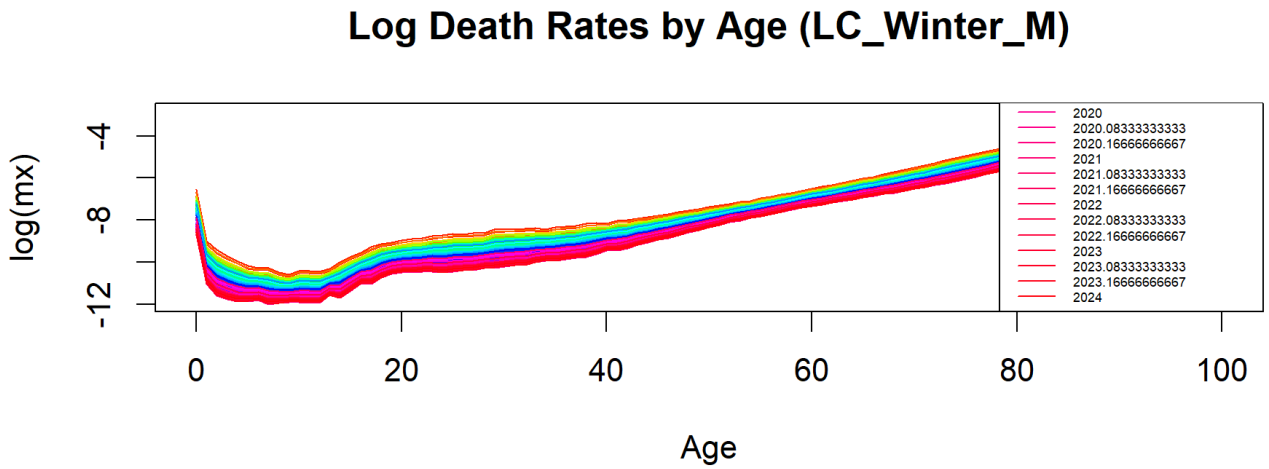
Lee-Carter for Winter Months (Dec, Jan, Feb)

Females



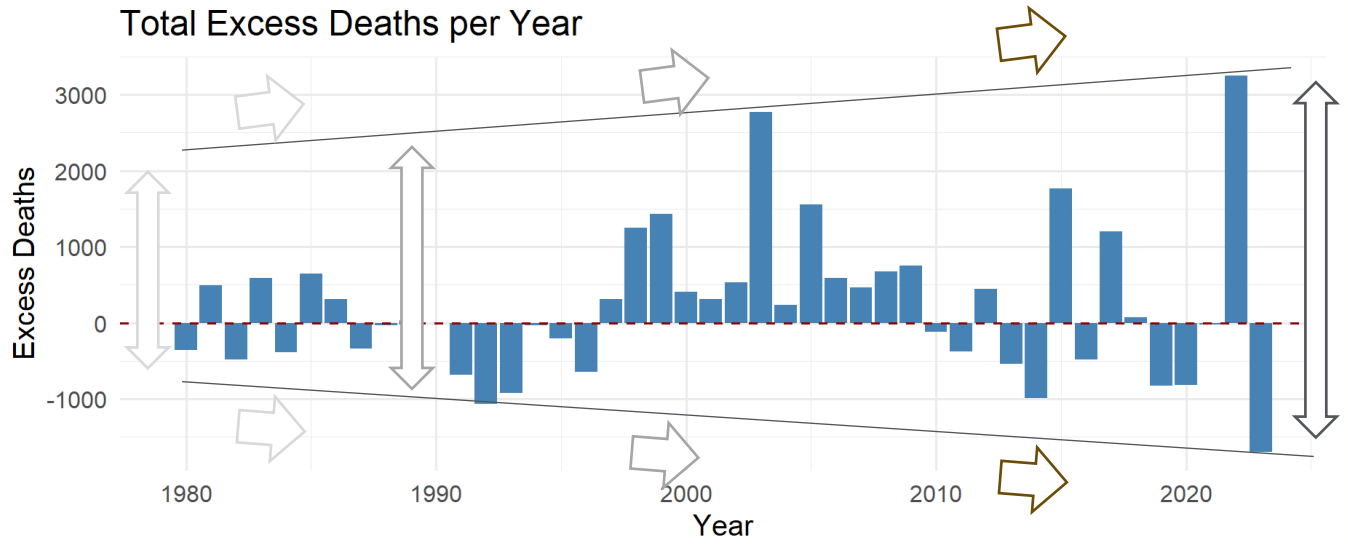
Lee-Carter for Winter Months (Dec, Jan, Feb)

Males



Lee-Carter Excess

Total Excess Deaths – Males and Females – Summer and Winter



- Wider margins when calculating excess of deaths.
- Heatwaves affect more and more the excess of deaths!
- But … how could this be considered in terms of death rates? … the population is greater in 2023 than in 1980 …

Models Summary

- **GLM (Generalized Linear Model):**
    - Assumes a linear relationship between predictors and a transformed outcome (via a link function).
    - Rigid in form: all covariates are included linearly or through explicitly defined interactions.
- **GAM (Generalized Additive Model):**
    - Extends GLM by allowing non-linear relationships through smooth functions (e.g., splines).
    - More flexible, ideal when you suspect unknown non-linear effects (e.g, Age, Year, …).
- **GNM (Generalized Nonlinear Model):**
    - A middle ground: supports custom nonlinear predictors (e.g., multiplicative terms) but without full spline-based smoothing.
    - Useful when you need more flexibility than GLM but want to avoid GAM's complexity.

All models tried (I)

- GLM (Gaussian, Identity Link): Linear regression on log(qx) with main and interaction effects:
  - T_extreme vs Season
  - Age vs Year
  - Sex
  - Simple, interpretable, but lower R^2.
- GLM (Gaussian, Log Link): Applies log link to qx, improving handling of non-linearity; more sensitive to outliers.
- GLM (Gamma, Log Link): Best performance for skewed mortality data. Models qx with Gamma distribution and log link, incorporating seasonal and age effects. High R^2 and lowest AIC.
- GLM (Gamma + IACI): Replaces T_extreme with the IACI climate index. Good fit, robust, interpretable, suitable for policy contexts focused on climate stress.
- GAM (Gaussian/Gamma): Adds splines over Age and Year to model smooth trends. Captures non-linear age effects; flexible but may overfit if not regularized.
- GNM (Gaussian): Generalized nonlinear model using linear predictors, fewer interactions. Easier interpretation than GAM, moderate fit.
- GLM (Poisson): Models Deaths with offset (log(Total * predicted_qx)). Suitable for count data; incorporates climate and demographic covariates. Needs accurate exposure estimates.
- Extended Climate GAM: Includes full set of climate indices (T90p, T10p, Rx5day, CDD, Sea). Best overall fit with Gamma family; useful for attributing climate drivers.
- Stepwise GLMs: Automated AIC-based selection for Gamma, Gaussian, Tweedie, Inverse Gaussian. Balances fit and parsimony. Tweedie and Gamma often selected.

All models tried (II)

- GLM (Poisson): Explicitly models counts of deaths using a log offset on expected counts. Suitable when the interest is in absolute mortality, with variance proportional to mean.
- GAM (Gamma): Uses smooth terms and tensor products to model complex non-linear interactions. Particularly useful in detecting gradual and sharp climate effects on mortality.
- Stepwise Gamma/InvGaussian: Based on AIC, retains only significant covariates among Age, Season, Sex, climate indices. Allows for interpretable and compact models with good predictive power.
- Tweedie GLM: Captures properties between Poisson and Gamma. Useful in overdispersed settings where mortality data exhibit many zeros and long right tails.
- Quasi-Poisson: Used for overdispersed count data but lacks true likelihood, hence no AIC. Useful for checking robustness of Poisson models.
- Consolidated GLMs: Include interactions like T_extreme, Age and Season. Highlights vulnerable age groups during extreme events (e.g., heatwaves).
- Climate Attribution GAM: Incorporates compound climate metrics (Rx5day, CDD, Sea). Reveals which weather phenomena drive excess deaths seasonally.
- **Best Model: Gamma GLM with log link, using**
    - T_extreme vs Season
    - Age vs Time
    - Sex
    - High R^2, low AIC, interpretable—ideal for policy modeling

GLM – Best model so far

The following is the Adapted climatic Lee-Carter model, on which our baseline is inspired on:

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)

Source: Milliman

The climatic Lee-Carter model could inspire a GLM based on the same idea.

Best Model so far

5. Results & Conclusions

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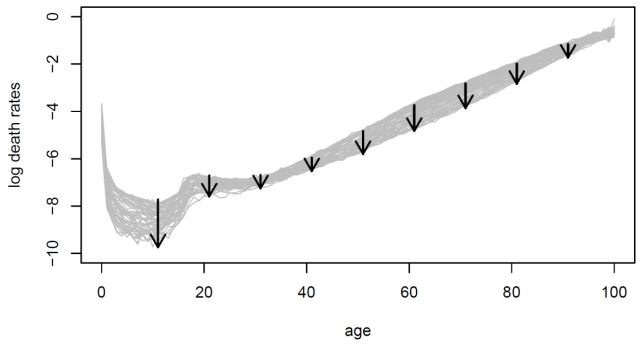
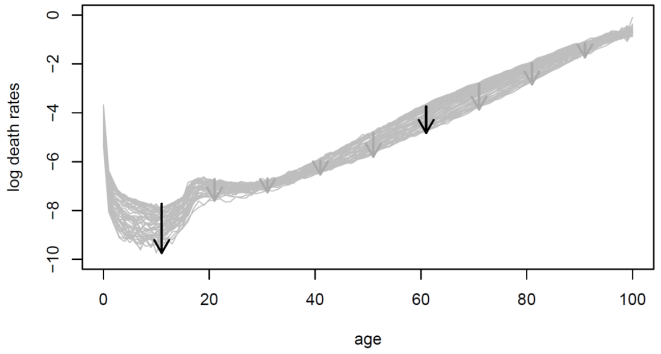
Lee-Carter – Excess. Overall results

- **Benchmark**: Ministry of Health = **23,820 people** in Spain (2,382 deaths per year).
    - Considering data from 2015-2024.
- **Model from this paper** = total **28,710 excess of deaths.** 2015-2023:
    - Considering data from 1980-2023 (Microdata INE). So, the differences come from different data used , but …
    - … are we considering our excess of deaths corrected by the trend in our analysis? Death rates should decrease with time, so the excess of deaths could be overestimated if we consider the oldest calendar years.
    - So, for this purpose, we incorporated both the trend and the effect of climate (see trend below):



$$\log \mu_{xt} = \alpha_x + \kappa_t$$



$$\log \mu_{xt} = \alpha_x + \beta_x \kappa_t$$

GLM (baseline)

- **For ages between 85 and 99 and monthly data from 1980 to 2023 (maybe weekly … as soon as possible).**
- T_extreme takes the value of T90 if the Season is Summer and T10p if the season is winter.

🔢 **Model Summary (Gamma GLM with Log Link)**
Significant Predictors:
Model Statistics:
- **Dispersion parameter (Gamma):** 0.03225164456
- **Null deviance:** 2034.843 on 7919 degrees of freedom
- **Residual deviance:** 262.427 on 7912 degrees of freedom
- **AIC:** -67373.967
- **Fisher Scoring Iterations:** 5

Variable	Significance
(Intercept)	***
T_extreme	***
Season_labelWinter	***
Edad_num	***
Year_Month	***
Sex_labelMale	***
T_extreme:Season_labelWinter	***
Edad_num:Year_Month	***

All coefficients are highly statistically significant (p < 0.001)

GLM (baseline)

Coefficients interpretation is the following (in blue, climate effects):

📈 **Model Coefficient Estimates**

Variable	Estimate
(Intercept)	-10.43912
T_extreme	0.03683
Season_labelWinter	0.35781
Edad_num	0.07121
Year_Month	-0.00025963
Sex_labelMale	0.17985
T_extreme:Season_labelWinter	0.03288
Edad_num:Year_Month	0.000002493

- **(Intercept) = -10.44**. Baseline log(qx) when all other variables are 0.Not directly interpretable by itself, but necessary for model scaling.
- **T_extreme = +0.0368**. Main effect of temperature extremes in summer (reference season). exp(0.0368) ≈ 1.0375. For each 1 percentage point increase in the frequency of extreme temperatures:
  - In summer (T90p): each 1% more of hot days → +3.75% increase in expected qx
  - In winter (T10p): each 1% more of cold days → +7.22% increase in expected qx even stronger effect (see interaction below)
  - 0.0368 (T_extreme) + 0.0329 (T_extreme_Season_labelWinter) = 0.0697
  - exp(0.0697) ≈ 1.0722 → ~7.22% increase in qx per 1% more cold days

- **Season_labelWinter = +0.358**: Winter months have about 43% higher baseline mortality than summer.

💡 So: **frequent heat in summer** and **frequent cold in winter** are both associated with **higher mortality**, but the impact is **stronger in winter**.

GLM (baseline)

Coefficients interpretation is the following:

- **Year_Month (temporal trend) = -0.0002596**. Mortality declines slightly over time — small, but significant:
  - exp(-0.0002596) ≈ 0.99974. So, for every additional month, the expected qx decreases by about 0.026%
  - exp(-0.0002596 × 12) = exp(-0.0031152) ≈ 0.99689. Each year, qx decreases by approximately by 1 - 0.99689 = 0.311%
  - exp(-0.0002596 × 120) = exp(-0.031152) ≈ 0.96935. Over 10 years, the expected mortality probability qx decreases by about 1 - 0.96935 = 3.07%
- **Sex_labelMale = +0'1798:** exp(0.1798) ≈ 1.197. Being male increases mortality risk by 1.197 -1 = ~20%

Sex	Multiplicative Factor	Relative Mortality (qx)
Female (baseline)	1.000	1.00% (if qx = 0.010)
Male	1.197	1.20% (if qx = 0.012)

- So, for every 1,000 individuals:
  - ~10 females would be expected to die
  - ~12 males would be expected to die
    → **~2 extra deaths per 1,000 due to sex alone**, under this model

GLM (baseline)

Coefficients interpretation is the following:

- **Edad_num = +0.0712.** Each additional year of age raises qx by about 7.4%.
- **Edad_num:Year_Month = +2.49e-6**
  - Interaction between age and time: aging effect intensifies slowly over time.
  - Though the coefficient is small, it is statistically significant and helps explain mortality evolution over decades.

GLM (baseline)

🧮 **Overall Interpretation**

- Age is the strongest driver: +7.4% qx per year.
- Extreme temperatures increase mortality, more so in winter.
- Being male increases mortality by ~20%.
- Seasonality matters: winter mortality is ~43% higher.
- There's a modest but significant long-term decrease in mortality over the decades:

- The age-time interaction hints at subtle demographic changes in mortality risk patterns: As calendar time moves forward, each additional year of age contributes slightly more to mortality than it did in the past.

GLM (baseline)

Metric	Value	Interpretation
AIC	−67,374	Improvement over the initial model ✅
Residual Deviance	262.4 (vs 2034.8 null)	Shows reasonable model fit ✅
Cox & Snell R^2	~87.5%	Explanatory power ✅
Coefficient Significance	All p < 2.2e-16	Strong statistical support ✅
Diagnostic Residuals	Mostly acceptable	Only mild heteroscedasticity and a few moderate outliers ⚠️

Other models (selection)

Model	AIC	Deviance	Cox & Snell R^2
GLM: Gaussian (Identity)	−4,186.93	272.69	0.86903
GLM: Gaussian (Log)	−59,575.39	0.25	0.74931
GLM: Gamma (Log)	−67,373.97	262.43	0.87574

Lowest AIC, solid deviance, and **highest valid R^2 (Cox & Snell)**

GLM vs IACI

```
Coefficients:
                             Estimate    Std. Error   t value   Pr(>|t|)
(Intercept)             -1.044051e+01  1.183909e-01 -88.18679 < 2.22e-16 ***
IACI                     2.948011e-02  6.784478e-03   4.34523 1.4087e-05 ***
Season_labelWinter       3.421904e-01  6.217851e-03  55.03355 < 2.22e-16 ***
Edad_num                 7.109786e-02  1.284941e-03  55.33162 < 2.22e-16 ***
Year_Month              -2.571780e-04  9.440435e-06 -27.24217 < 2.22e-16 ***
Sex_labelMale            1.796535e-01  4.105807e-03  43.75594 < 2.22e-16 ***
IACI:Season_labelWinter -1.446400e-01  8.488134e-03 -17.04026 < 2.22e-16 ***
Edad_num:Year_Month      2.500755e-06  1.024164e-07  24.41752 < 2.22e-16 ***
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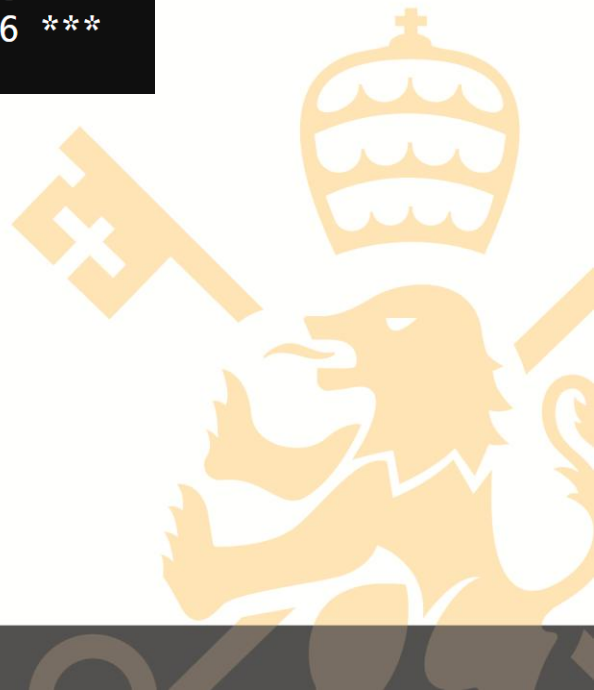

GLM vs IACI

Model	AIC	Deviance	Cox & Snell R^2
GLM: Gaussian (Identity)	−4,186.93	272.69	0.86903
GLM: Gaussian (Log)	−59,575.39	0.25	0.74931
GLM: Gamma (Log, T_extreme)	**−67,373.97**	**262.43**	**0.87574**
GLM: Gamma (Log, IACI)	**−67,162.79**	**269.48**	**0.87239**

Still Best Option

6. References

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Thanks

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Ignacio Blasco

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