

The definition of a French actuarial climate index; one more step towards a European index

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Abstract

Climate change is defined often as the long-term fluctuations in climate patterns affecting the planet globally. Its main observed consequences are a rise in average temperatures in many parts of the globe, and an increase in the frequency and severity of extreme weather events, such as floods, droughts, or wind storms. Climate change is also associated with a rise in sea levels, more frequent and more severe wildfires, a loss of biodiversity, as well as other disrupting events that can have a serious economic impact.

These new climate risks are increasingly affecting the frequency and the severity of claims in different insurance branches. In order to help insurance companies predict and manage climate risks, North-American actuaries have defined the Actuaries Climate Index™ (ACI), that combines information from several important weather variables in the historical records of United States and Canada. The ACI shows a significantly increasing trend over recent years.

Now that the ACI provides a factual and objective climate risk measure for North-America, the need arises to test if a similar tool can measure the impact of climate change in other parts of the planet, and if the change is similar or not. Despite the observed global nature of climate change, different regions and countries can be affected in different ways. As a first step it is important to check if the ACI methodology is useful to assess climate risk even outside the United States and Canada.

This paper proposes the use of the same ACI methodology to calculate an actuarial climate index with the climate data of France, which we call the French Actuarial Climate Index (FACI). The paper reviews the methodology and the data used to obtain the FACI, and with it studies the impact of climate change in France, including high-resolution analyses, per component, season and region. Together with the recent indices calculated for Spain and Portugal, this FACI represents one more step towards the definition of a European index.

Keywords— Climate change, France, Actuaries Climate Index™, French Actuarial Climate Index, Physical climate risk, Geographical grid, European Actuarial Climate Indices.

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[§]With the collaboration of Marie Hyvernaud, Alae Khidour and Esteban Mauboussin, from CNP Assurances, Paris, France, for the data analyses and computations.

1 Introduction

Climate change refers to long-term variations in temperature and in precipitation patterns, sea levels, and other aspects of Earth's system. Measuring and mitigating the effects of climate change are some of the most pressing and difficult challenges that society faces. It has heavy implications in the insurance sector, that is affected by increased frequency and severity in different lines of business.

According to the Intergovernmental Panel on Climate Change (IPCC), observed global surface temperatures from 2011 to 2020 were 1.1 °C higher than the average in the last half of the 19th century, with land surface temperature increasing by 1.59 °C; see (IPCC, 2023).

Climate change poses a range of enhanced hazards and dangers, including more frequent and intense extreme weather events, rising sea levels that threaten coastal areas, water scarcity and droughts, the disruption of ecosystems and the loss of biodiversity, adverse impact on agriculture and food security, public health risks, significant economic consequences, and displacement and migration of populations.

For insurance companies, any increase in extreme weather events, such as heat waves, wind storms, floods, wild-fires, and droughts, that can cause deaths and significant damages, would result in higher insurance claims, or added limitations in coverage. Moreover, if historical data are no longer representative due to changes in weather patterns, insurers need to reassess their risk models and to incorporate climate change projections and long-term climate risk assessments into their pricing, to accurately determine premiums.

1.1 Review of the literature

At the turn of this century the World Climate Research Program proposed several indices to help summarise useful information on climate change (see Peterson et al., 2001). In 2012, the Climate Index Working Group (CIWG) of the CAS Climate Change Committee summarised the scientific knowledge on climate change at the time, and proposed to develop a composite index, termed the Actuaries Climate Change Index (ACCI), to include information from several climate variables; see their report (Solterra Solutions, 2012). The development of the Actuaries Climate Index™ (ACI), that studies climate change in the United States and Canada, was then proposed by this same working group, in 2014. The ACI project was launched in November 2016.

The Actuaries Climate Index™, jointly developed by the Canadian Institute of Actuaries (CIA), the Society of Actuaries (SOA), the Casualty Actuarial Society (CAS), and the American Academy of Actuaries (AAA), uses climate data from North America (see ACI, 2018). It is intended to provide actuaries, public policy-makers, and the general public with a neutral, factual and helpful climate change index. A monitoring tool that could help us learn about climate change and to link it to its associated risks; see Figure 1.1.

Just as the Consumer Price Index (CPI) that tracks changes in the cost of a standard basket of goods and services over time, the ACI measures climate risks through a basket of extreme climate events and changes in sea level.

The focus is on extreme weather events, rather than averages; extremes have a larger impact on policyholders and their insured goods, as well as on society and the economy. The index is composed of six variables, each representing a monthly time series starting in 1961, and that is based on measurements from the National Oceanic and Atmospheric Administration (NOAA, Menne et al. (2012)), GHCN-DEX1 (CLIMDEX, Donat et al. (2013)), and the Permanent Service for Mean Sea

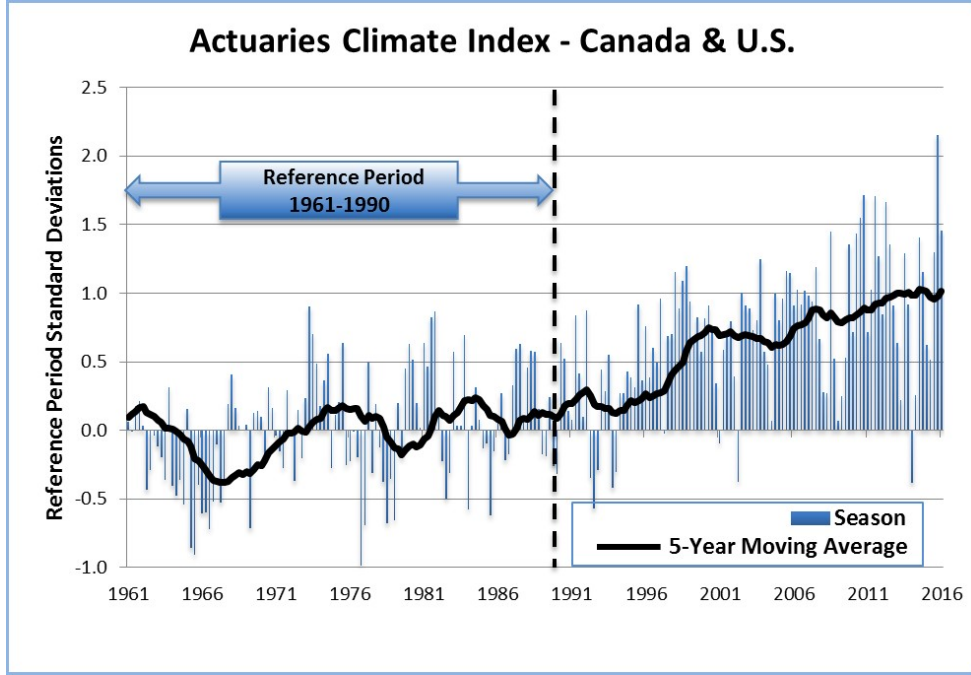


Figure 1.1. ACI values; 1961–1990 reference period to 2021

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

Level (Permanent Service for Mean Sea Level (PSMSL), 2023). More precisely

$$ACI = \frac{1}{6} \cdot (T90_{std} - T10_{std} + P_{std} + D_{std} + W_{std} + S_{std}), \quad (1.1)$$

where $T90_{std}$ and $T10_{std}$ are standardised variables that measure the frequency of extreme high and low temperatures, respectively, P_{std} measures the severity of extreme rainfall precipitations, D_{std} stands for extreme frequencies of consecutive dry days, W_{std} measures the frequency of days with extreme wind power and S_{std} tracks the anomalies in monthly seal level averages. See Appendix A for details.

Curry (2015) considers extending the application of the ACI formula to the UK, and more generally to Europe. He reviews the definition and underlying methodology of the ACI to find that it could be applied in these regions without change, although appropriate data for the region would be needed to do so.

In 2018 the Institute of Actuaries of Australia developed its own Australian Actuaries Climate Index (AACI), based on the same methodology as the North American ACI, to measure climate change in Australia; see AACI (2018). The AACI is calibrated also to a 0-average, but over a different reference period, 1981-2010. From Figure 1.2 we see that, like for the ACI, the seasonal values of the AACI are almost exclusively above average and that the index 5-year moving average has systematically increased since about 2001.

In addition, Nevruz et al. (2022) propose the application of the ACI in Turkey, adapting it to the local situation in Ankara, as to develop an index suitable for this region. They suggested that choosing the best grid data for their ACI was more important than changing how the index is calculated.

Bridging the gap between the physical risk and insurance, Pan et al. (2022) investigate the effectiveness of the ACI in predicting crop yields for (re)insurance rate making. They find that the ACI has significant predictive power for crop yields and yield losses, and they argue that a high-resolution index could benefit the insurance industry.

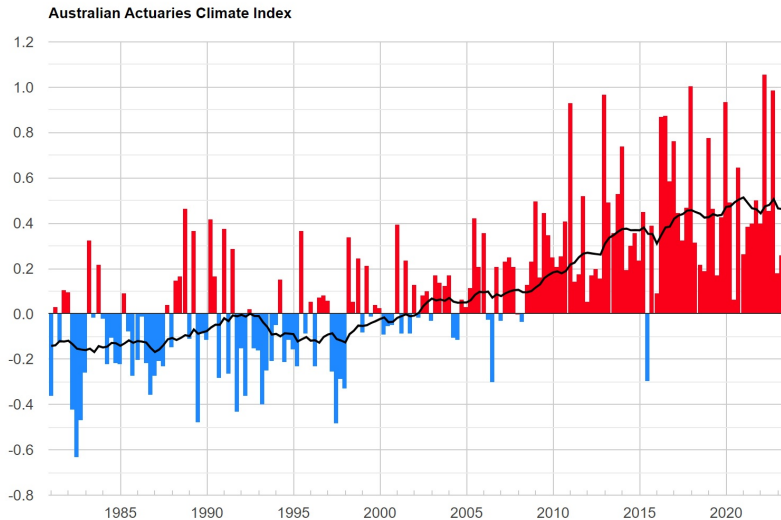


Figure 1.2. AACI values; 1981-2010 reference period to 2023

Source:

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

More recently, in an oral presentation at an event of the Spanish Institute of Actuaries (IAE), a first draft of a Spanish version of the ACI was defined, over a shorter and more recent reference period than for the ACI (1975-1995 in general and 1993-2000 for sea levels). Their temperature variables differ, using the average highs and average lows, as well as the composite index formula. Some details on this index are given in the presentation slides published online, see IAE (2023).

Finally, Zhou et al. (2023) use also the North American ACI methodology to build an actuarial climate index for the Iberian Peninsula, that they call the Iberian Actuarial Climate Index (IACI); see Figure 1.3 for its seasonal values and the 5-year moving averages. Their paper reviews in detail the methodology and the data used to obtain the IACI, and with it, they try to measure climate change in the Iberian Peninsula.

1.2 Extension to French climate data

Here metropolitan France is defined as the land area ranging from 41° to 51° north latitude and 6° east to 10° west longitude, excluding Belgium as well as Luxembourg to the north, Germany to the north east, Switzerland to the east, Italy and Monaco to the south east and Andorra and Spain to the south. Its largest island, Corsica, is included also in the data set, but not the French overseas territories.

We calculate the French Actuarial Climate Index (FACI) with data extracted from the ERA5-Land reanalysis database (see Copernicus Climate Change Service (C3S) Climate Data Store (CDS), 2022). Unlike the ACI for the United States and Canada which is calculated for 12 sub-regions, here the FACI is computed for over 10,000 cells forming the French grid of 0.1° of latitude \times 0.1° of longitude (about 123.2 km^2). We compare the French, Australian, Iberian and North American cases and show how the FACI tracks well the climate change of France through the years; see Figure 1.4. Then some high-resolution FACI analyses, show the evolution of each grid by index component, season, or region, through the years.

The rest of the paper is organised as follows; the extension of the North Amer-

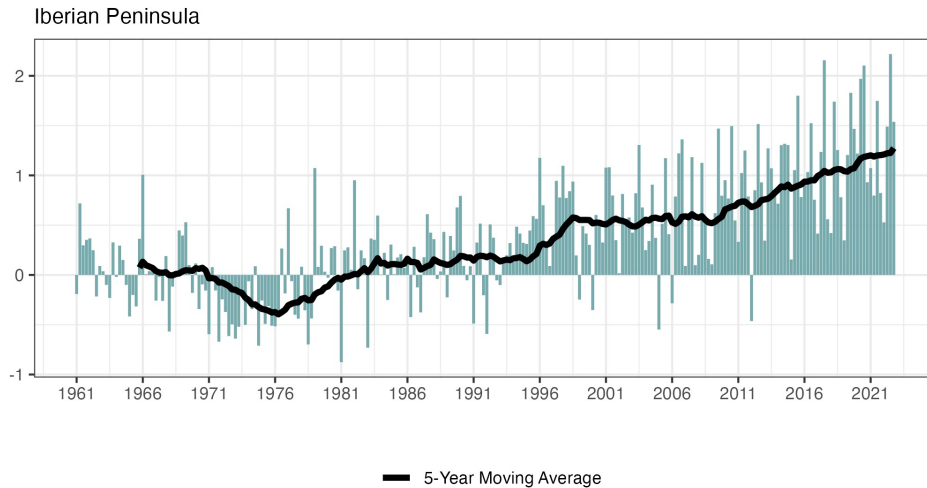


Figure 1.3. Seasonal IACI values; 1961-1990 reference period to 2022
 Source: Zhou, Vilar Zanón, Garrido, Heras Martínez (2023, AIAE)

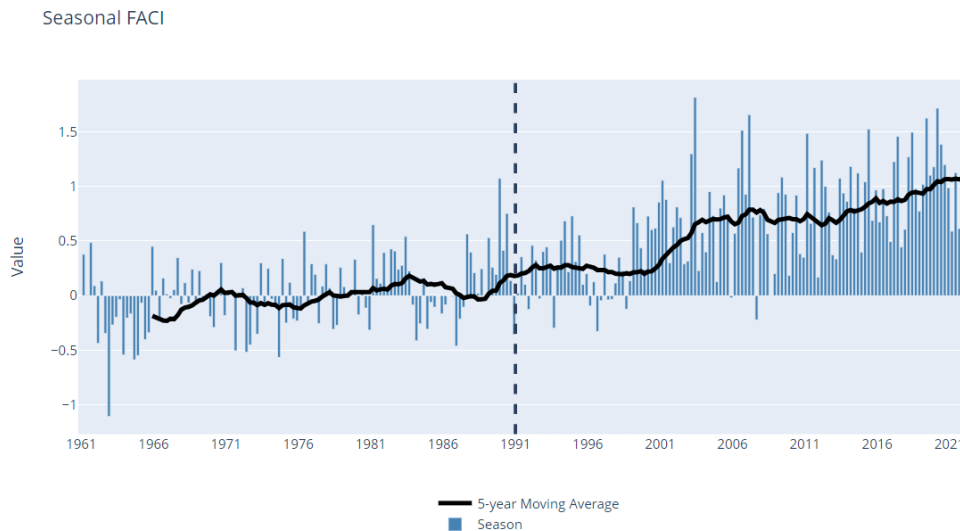


Figure 1.4. Seasonal FACI values; 1961-1990 reference period to 2022

ican ACI methodology to French data is presented in Section 2. Then a comparison of the FACI with the North American ACI, the indices for Australia and the Iberian Peninsula is given in Section 3. Section 4 gives several high-resolution FACI analyses. Finally, Section 5 proposes a possible application of FACI to parametric insurance. Some conclusive remarks and future developments wrap-up the paper, while additional technical details appear in the Appendices, for interested readers. In particular, Appendix A reviews in detail the methodology of the North American Actuaries Climate IndexTM (ACI) and its components.

2 The French Actuarial Climate Index

Now consider extending the North American ACI methodology to the climate data from France and Corsica.

To calculate the warm and cool temperature components of each grid cell in

France and Corsica, defined in Appendix A in Equations (A.1) and (A.2), respectively, set daytime as being 6h-22h and night-time as 22h-6h. The standardised anomalies of the temperature components, $T90_{std}$ and $T10_{std}$, are from Equations (A.3) and (A.4) and their seasonal values plotted in Figure 2.1.

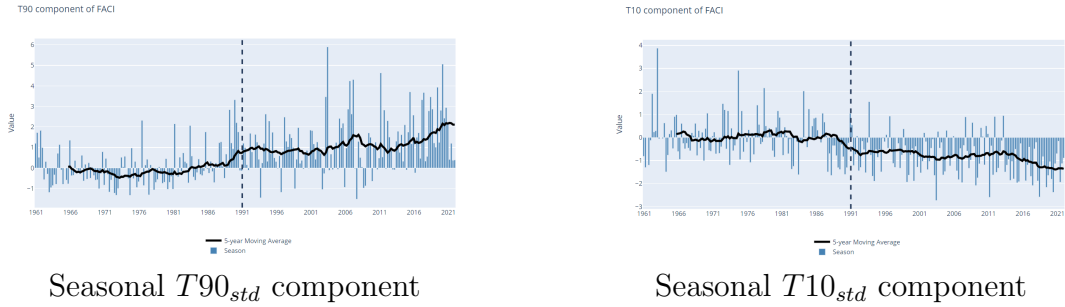


Figure 2.1. High and low temperature components of seasonal FACI

The 5-year moving averages of the standardised anomalies calculated for the two temperature components, $T90_{std}$ and $T10_{std}$, are plotted in Figure 2.2, depicting the changes in the frequency of extreme high and low temperature events.

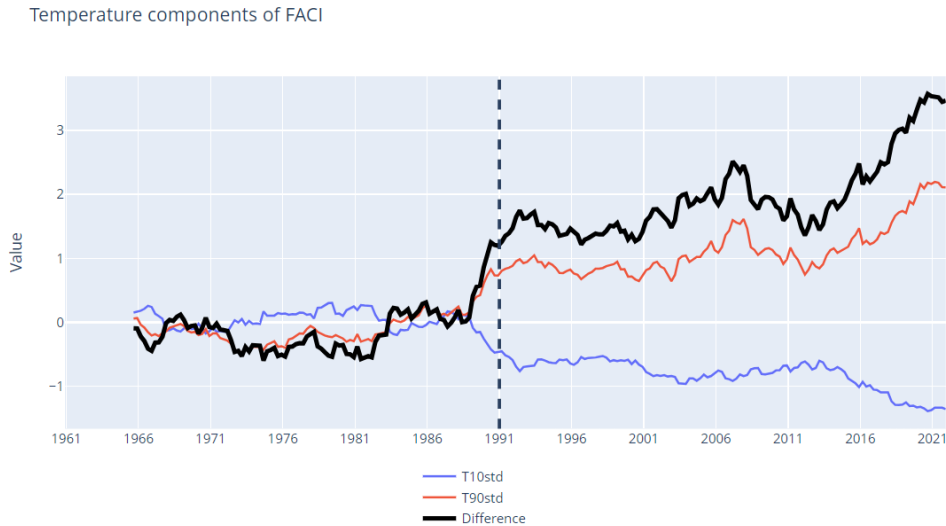


Figure 2.2. France: seasonal & 5-year moving average, temperature standardised anomalies

As for the North American ACI, note here the increase in the frequency of extreme warm temperature events (increase in $T90_{std}$) and the decrease in frequency of extreme cold temperature events (decrease in $T10_{std}$), starting just before the reference period end in 1990, causing the difference $T90_{std} - T10_{std}$ to grow. The black line represents the 5-year moving average of this difference, which helps better visualise the main trend.

The change in the frequency of extreme warm temperatures is opposite to that of extreme cold temperature events. It indicates that air temperatures are changing towards more extremes in highs and fewer in lows, that is, more warm days overall.

Next, consider Figure 2.3 that illustrates the standardised anomalies calculated for the precipitation component, P_{std} ; see (A.5) for the calculation formula.

Observe how the 5-year moving average has taken mainly only positive values since even before the reference period. Positive values of the standardised anomalies

indicate an increase in heavy precipitation events. Recent seasonal averages often go over 0.3, a value that can be interpreted to mean that the maximum 5-day rainfall has increased by 0.3 standard deviations, relative to the mean of the 1961-1990 reference period.

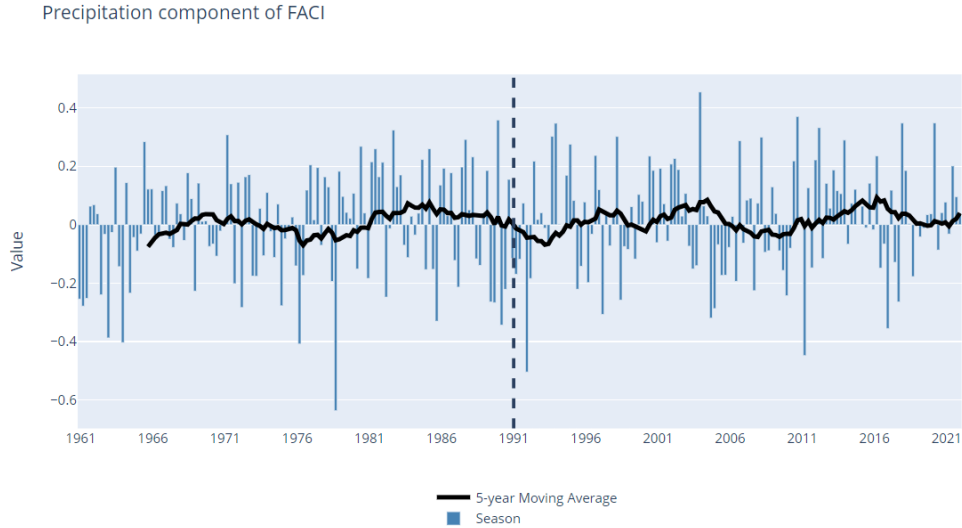


Figure 2.3. France: seasonal and 5-year moving average, maximum 5-day rainfall standardised anomalies

Then Figure 2.4 plots the D_{std} time series of the maximum consecutive dry days in France and Corsica; see the definition in (A.7). Their 5-year moving averages experienced a peak right around the end of the reference period, but since then their behaviour is almost comparable to what it was before 1990. Hence, no significant change in the length of periods without rainfall. Coupled to the increase in heavy precipitations observed in Figure 2.3, these 2 FACI components suggests a shift towards an overall increase in humidity in France and Corsica.

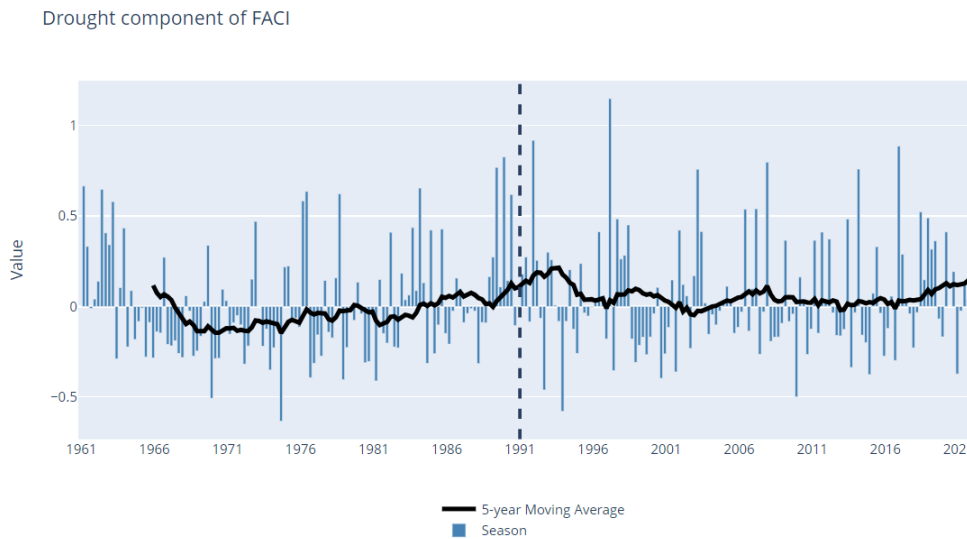


Figure 2.4. France: seasonal & 5-year moving average, consecutive dry days standardised anomalies

Figure 2.5 shows there has not been a significant change in the frequency of extremely windy days in France, after or during the reference period.

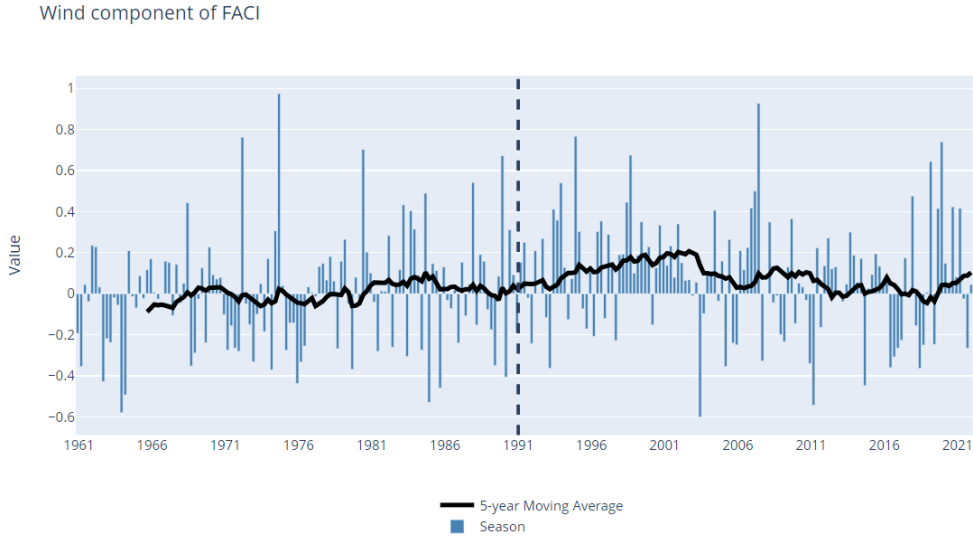


Figure 2.5. France: seasonal and 5-year moving average, wind power standardised anomalies

Finally, Figure 2.6 shows the seasonal standardised anomalies of the ocean and sea levels in France and Corsica. The values $\Delta S = S(j, k) - \mu_{ref}(j)$ have experienced a sharp increase after year 2000, and continues to increase progressively over time, although at a lower rate. The warming of earth's climate has melted ice sheets and glaciers, and the thermal expansion caused by warmer seawater has further exacerbated the rise of ocean and sea levels. These rising sea levels imply a series of risks for the coastal areas of France and Corsica, such as coastal erosion, flooding, and salinisation of freshwater resources.

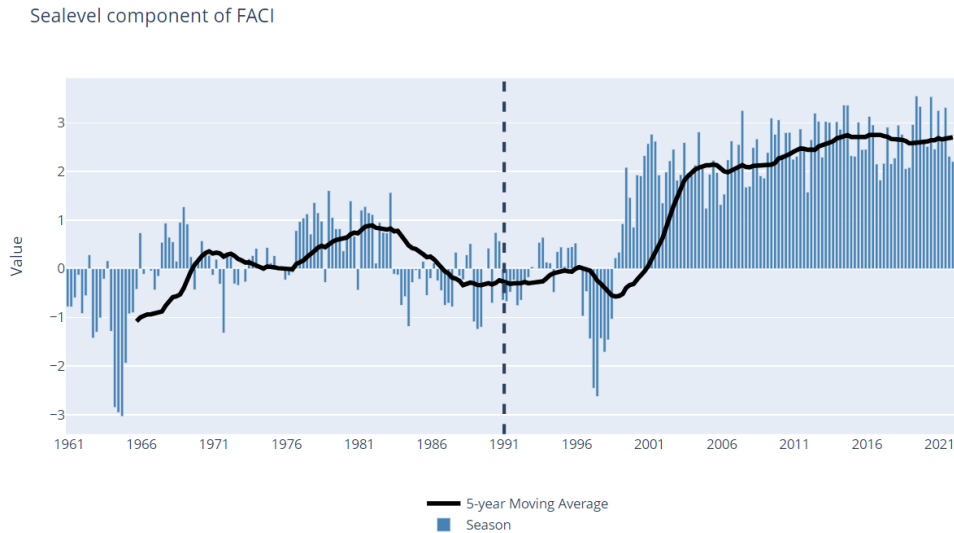


Figure 2.6. France: seasonal and 5-year moving average, sea level standardised anomalies

We observe seasonal volatility for some variables, such as wind, drought and precipitation, versus a certain continuity and an accumulation effect over time for other variables, such as temperature and sea level, passed 1990.

Curry (2015) uses a factor f_S as the fraction of the number of coastal to total

grid points, $0 < f_S \leq 1$, to adjust the ACI as follows:

$$ACI_{f-adj} = \frac{1}{6} \cdot (T90_{std} - T10_{std} + P_{std} + D_{std} + W_{std} + f_S S_{std}). \quad (2.1)$$

Considering the particular geography of France and Corsica, we argue that the ocean and sea level variable S_{std} is important for the entire region. Hence we set $f_S = 1$, as in the ACI, and defer to future work the study of estimating f_S as in Curry's extension of the ACI to the UK.

Figure 2.7 exhibits the 5-year moving seasonal averages of FACI together with its 6 components. Clearly the changes in sea level and temperatures dominate and are driving the increasing trend in FACI, while the other variables, precipitation, drought and wind power, have experienced little change over the study period.

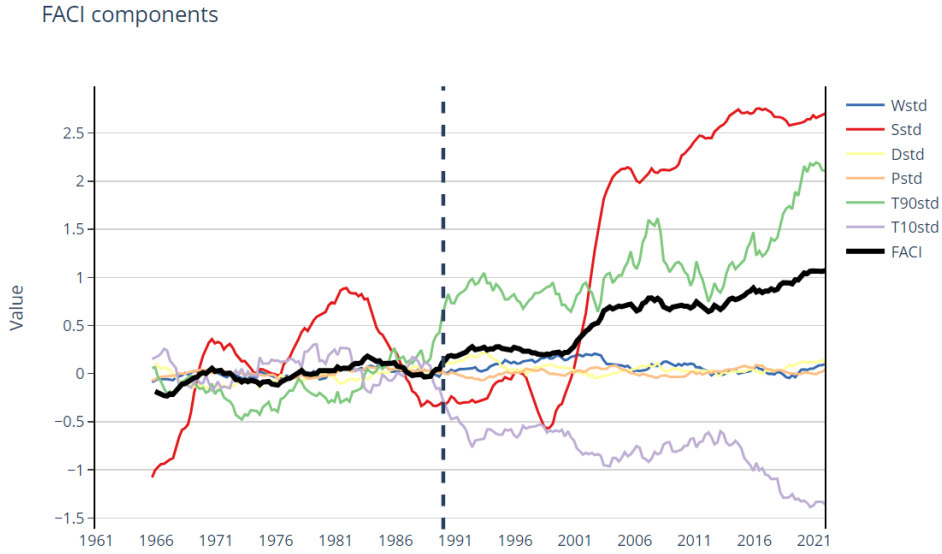


Figure 2.7. 5-year moving averages, FACI, and its 6 components

It is clear also from Figure 2.7 that some components are correlated. For instance, consider the 2 temperature variables, the highs ($T90_{std}$) curve and the lows ($T10_{std}$) curve form a mirror image one of another around 0; when $T90_{std}$ increases $T10_{std}$ decreases by a similar amount.

Figure 2.8 reports the correlation coefficients between the six FACI components. These are generally weak, except those of the frequency of extreme high and low temperatures, as seen above. Also, there is a significant negative correlation between the precipitation and drought variables, and a lesser positive correlation between precipitation and wind power, as well as an even more moderate correlation between sea level and the frequency of extreme temperatures; positive for high temperatures, and similar, but negative for low temperatures.

At this stage it is natural to question the validity of the methodology used to measure the change in these 6 climate variables. Not only with relation to the multicollinearity observed above, but even the use of standardised anomalies for variables that might not be symmetrically distributed around their mean. These issues are discussed in Appendix B, where the distributions of these 6 standardised anomalies are studied in detail.

Apart from the issue of the possible exclusion of some of the 6 components included in this first version of the FACI, it is also normal to consider the possible inclusion of additional important variables. For example, the North American ACI

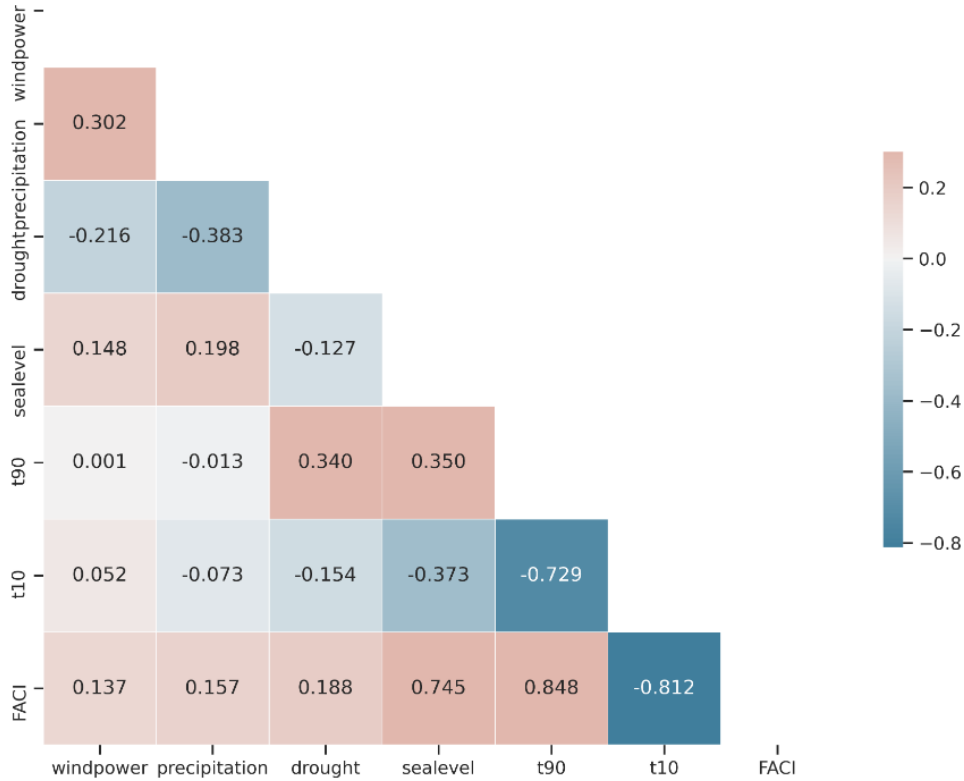


Figure 2.8. Correlation coefficients, 6 monthly FACI 6 components

does not include the ocean and sea temperatures, which could be a driver of change in France and Corsica.

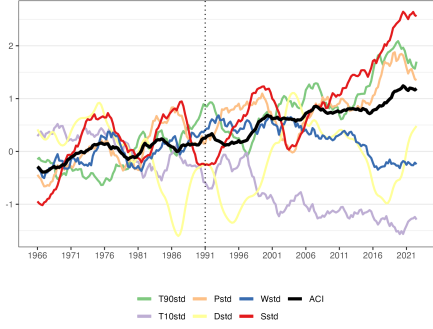
Before revisiting the methodology, the next section considers the comparison of the French actuarial climate index to the other indices currently available that all use the methodology of the North American ACI; the indices defined for the US, Canada, Australia, Spain and Portugal.

3 Index comparisons

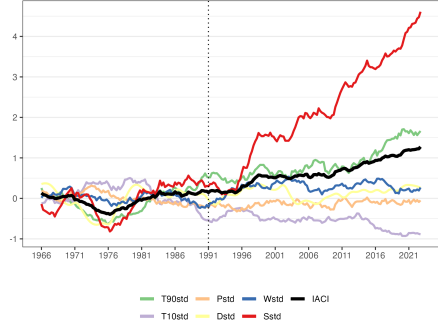
The index defined for the Iberian Peninsula (the IACI, for Spain and Portugal) is based on exactly on the same methodology of the North American ACI (for the US and Canada). So they can be compared directly with the FACI defined here. We do not include the index for Australia in this comparison. Although it was initially based also on the North American ACI methodology, it was revised keeping only 3 out the 6 climate variables, making it less comparable to the other indices.

Figure 3.1 combines the graph of the 5-year moving averages of the seasonal ACI and its 6 components, for the US and Canada (denoted USC in the graph captions), that appears in Figure A.1, to the graph of the 5-year moving averages of the seasonal IACI and its 6 components, for the Iberian Peninsula (denoted IP, see Zhou et al. (2023)). It also shows the same graph for France (denoted F), already shown in Figure 2.7.

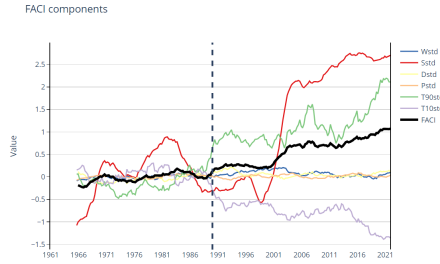
The first observation is that the change in sea level is dominant in all 3 graphs (red curve), with very similar increasing trends and a similar onset, at around the mid-90's. The Iberian Peninsula experienced the highest increase, with S_{std} currently at more than 4.5 standard deviations over its 0-mean. The US-Canada and France are currently at similar levels of 2.5, although US-Canada experienced one last large



USC: ACI and its 6 components



IP: IACI and its 6 components



F: FACI and its 6 components

Figure 3.1. Comparison of the indices for North America (USC), the Iberian Peninsula (IP) and France (F)

cyclical decrease before the early 2000's. Note also that ocean and sea level changes do depend on the region, within these countries. For instance, in Alaska the sea level 5-year moving averages have been constantly decreasing since 1961; see <https://actuariesclimateindex.org/maps/>. In addition, it is not clear how inland regions are affected by changes in ocean and sea level.

The next most dominant change, for all 3 graphs, is for the high temperature component (green curve). The $T90_{std}$ values are currently very similar in the US-Canada, the Iberian Peninsula and France, at 1.5, and exhibit similar trends, again with more oscillations in the US-Canada than in the other 2 graphs. Also, as already noted above, the low temperature component $T10_{std}$ exhibits a mirror image trend to that of $T90_{std}$, but over negative values. That is, both contribute significantly to the increasing trend in their respective composite indices.

The findings are quite different for the remaining 3 components; i.e. the maximum 5-day precipitation (P_{std}), the drought (D_{std}) and wind power (W_{std}). In the Iberian Peninsula and in France the 5-year seasonal averages of these 3 variables exhibit a stationary behaviour, with small oscillations around the 0-mean. In other words, they do not contribute as significantly to the increase in the IACI or in the FACI. Hence these indices increases are essentially due to the sea level, plus the high and low temperature components.

By contrast, North America experienced a significant increase in the maximum five-day precipitations (P_{std}) after the reference period. Its increasing trend shows some periodicity. With regards to droughts, the land areas of the US and Canada are very large, each region having different dry periods. Overall, the drought component (D_{std}) does not show a clear trend, but is slightly smaller since the reference period. Thus the trends in the precipitation (P_{std}) and drought (D_{std}) components indicate that the US and Canada have become wetter, compared to France and to the Iberian Peninsula.

Even if the contribution of each component of the Actuaries Climate Index™ the Iberian Actuarial Climate Index and the French Actuarial Climate Index is not equal, due to the differences in geography, their composite indices show a similar increasing trend. Moreover, the index values are themselves similar, ranging from -0.5 to 1.5. Particularly in recent years, all 3 composite indices have reached the value of 1. This indicates that climate change has led to a similar multiple of the standard deviation increase in the frequency and severity of extreme weather events, in comparison to the 1961-1990 reference period, that it be in France, the Iberian Peninsula or the US and Canada. In summary, the occurrence of extreme climate events is becoming increasingly common, overall, in all these three regions.

The above analysis compares the results obtained for France to those in two regions, North America and the Iberian Peninsula. Appendix C provides a finer analysis, by country, where the results for Canada are presented separately from those of the US and those of Portugal also are separate from those of Spain. Also the comparison is extended to include Australia, grouping all the actuarial climate indexes published so far.

4 High-resolution analyses; per region/season

Figures 4.1 to 4.4 show the evolution of the seasonal FACI over the last 12 years at a high resolution (cell-level, with cells at 0.1° of latitude \times 0.1° of longitude).

First consider the evolution of winter FACI seasonal values over the years 2011-2022.

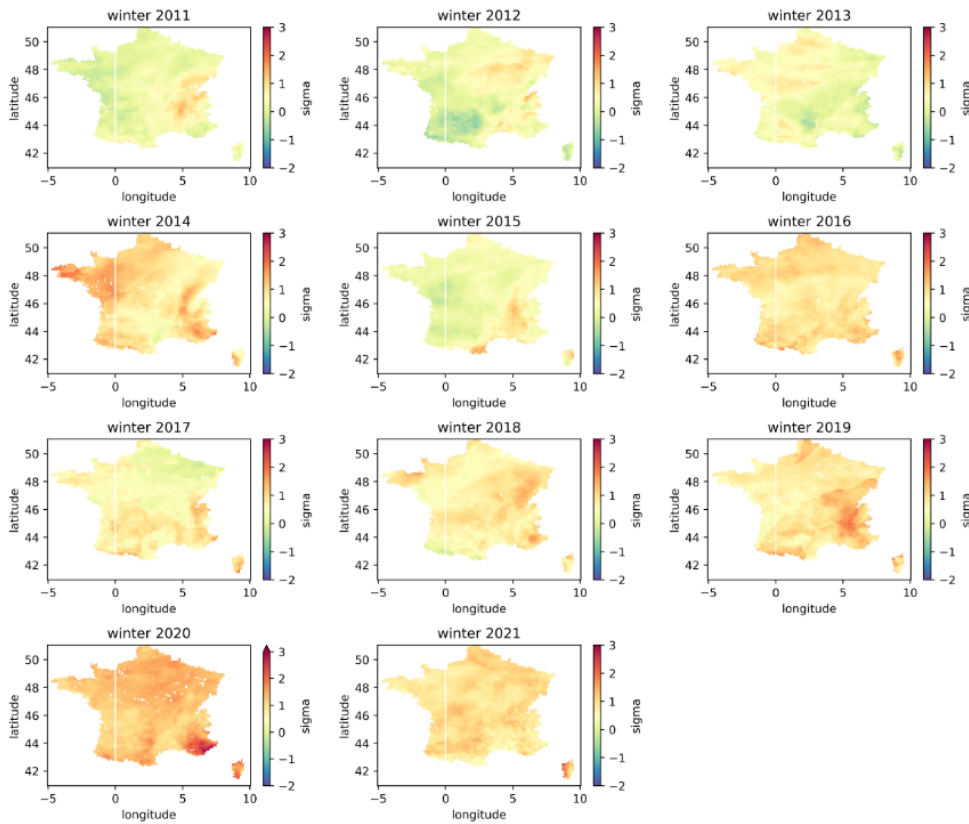


Figure 4.1. Winter FACI, 2011-2022

Given that at the time of publication the sealevel variable values were not available at most French tidal stations, passed the winter of 2022, we graph the spring,

summer and fall FACI values only for the 11 years 2011-2021.

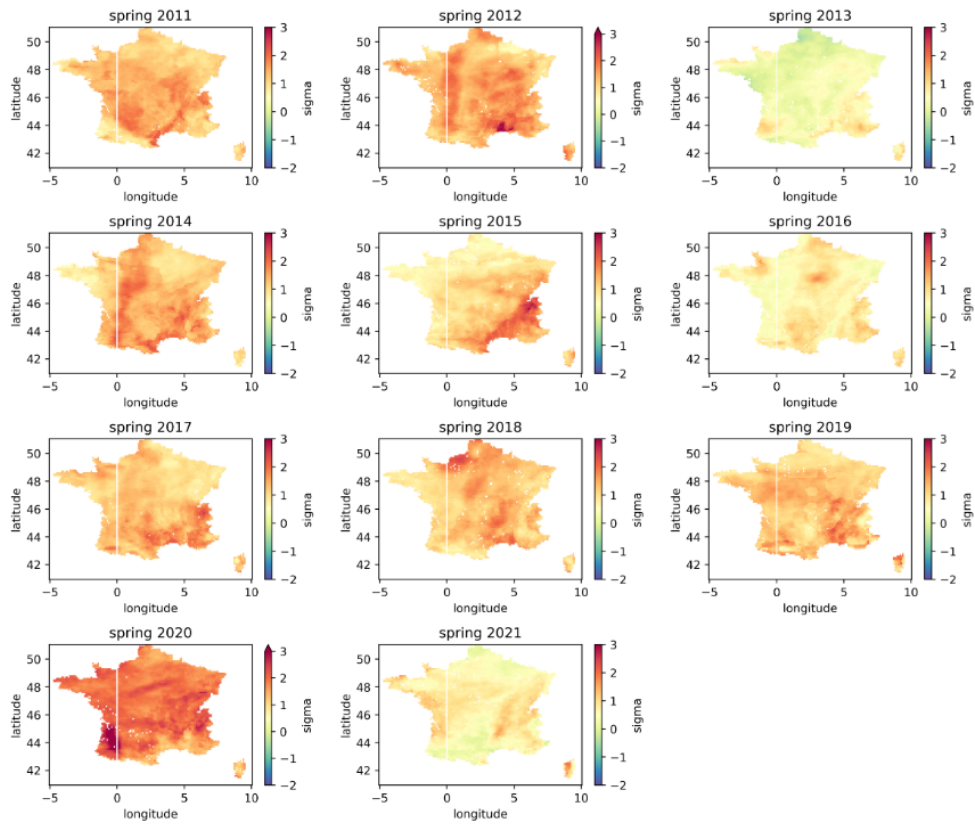


Figure 4.2. Spring FACI, 2012-2021

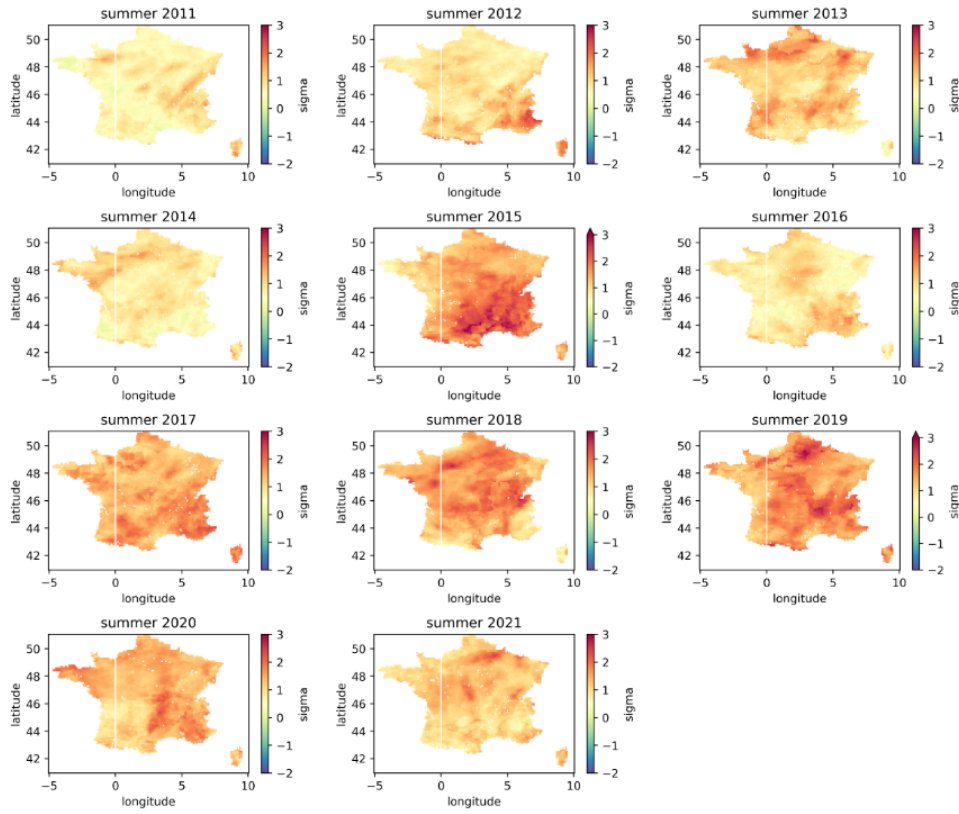


Figure 4.3. Summer FACI, 2012-2021

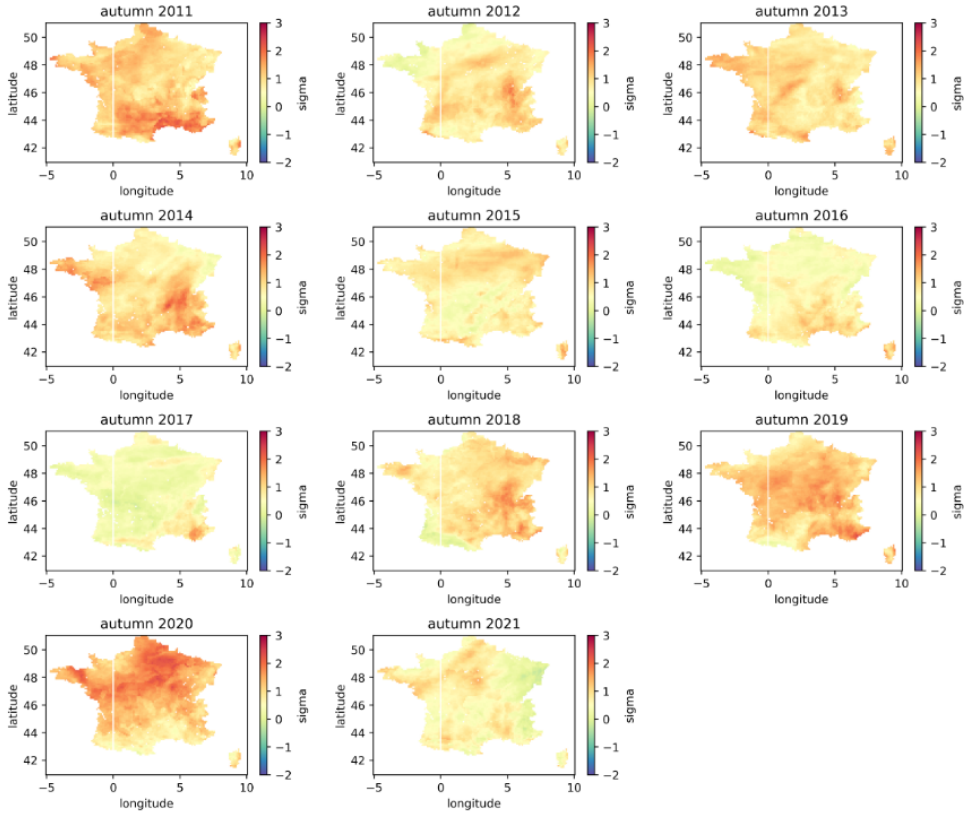


Figure 4.4. Autumn FACI, 2012-2021

First note how extreme climate events seem to occur more frequently during the

spring, across most of France (Figure 4.3). In some locations, the index reaches values of approximately 2. At a single component level, this would mean that the index has increased by an average of 2 standard deviations over the reference period average. For the composite FACI, that combines all 6 components, the interpretation is not as straightforward; here the standard deviation of the average of 6 possibly correlated components is not 1. It would be closer to $1/\sqrt{6}$ if they were independent. Hence, a seasonal index value of 2 is significantly high, as it is a possibly large multiple of $1/\sqrt{6}$.

However, note how the evolution of FACI varies across different cells within a region. Each individual grid cell is affected by climate change in a unique manner. This means that the impact of climate change in each specific area may differ. This heterogeneity also implies that the frequency of extreme climate events varies per region. This could indicate also that the level of vulnerability and/or adaptability to extreme weather conditions can differ from one cell to another.

To better separate the contribution of each component to FACI, Figures 4.5 to 4.4 plot the progress of the temperature, precipitation, drought and wind variables over the years 2011-2022.

4.1 Seasonal temperatures per region

First consider the high temperature $T90_{std}$ variable.

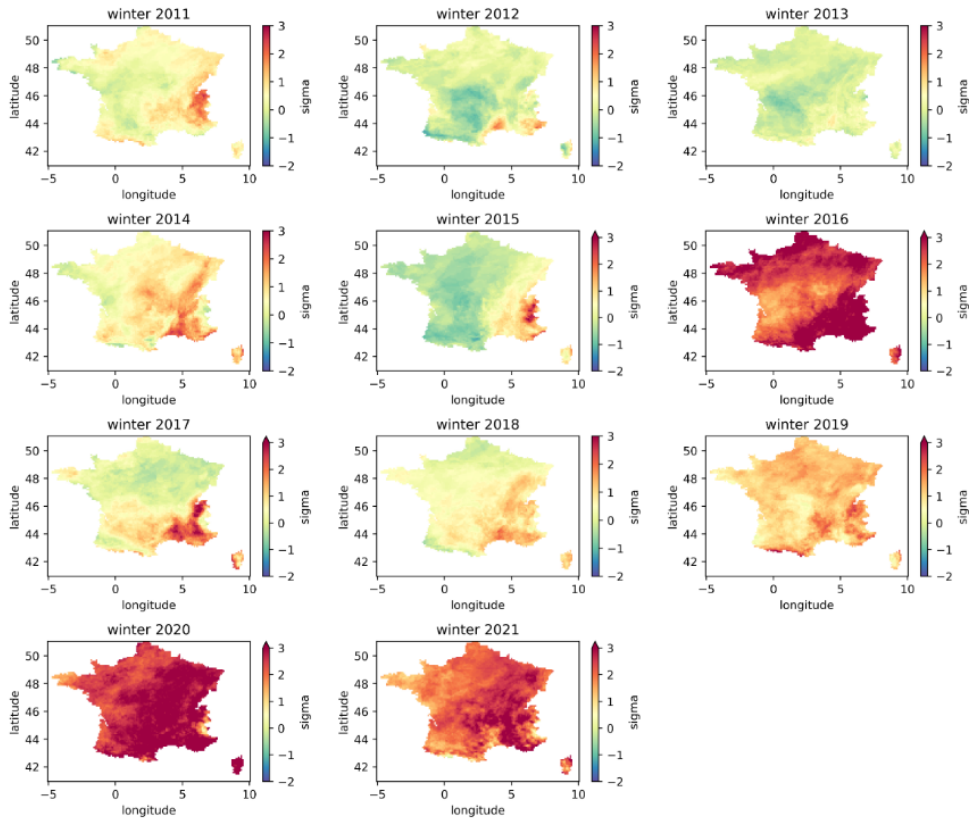


Figure 4.5. Winter seasonal $T90_{std}$ values, 2011-2022

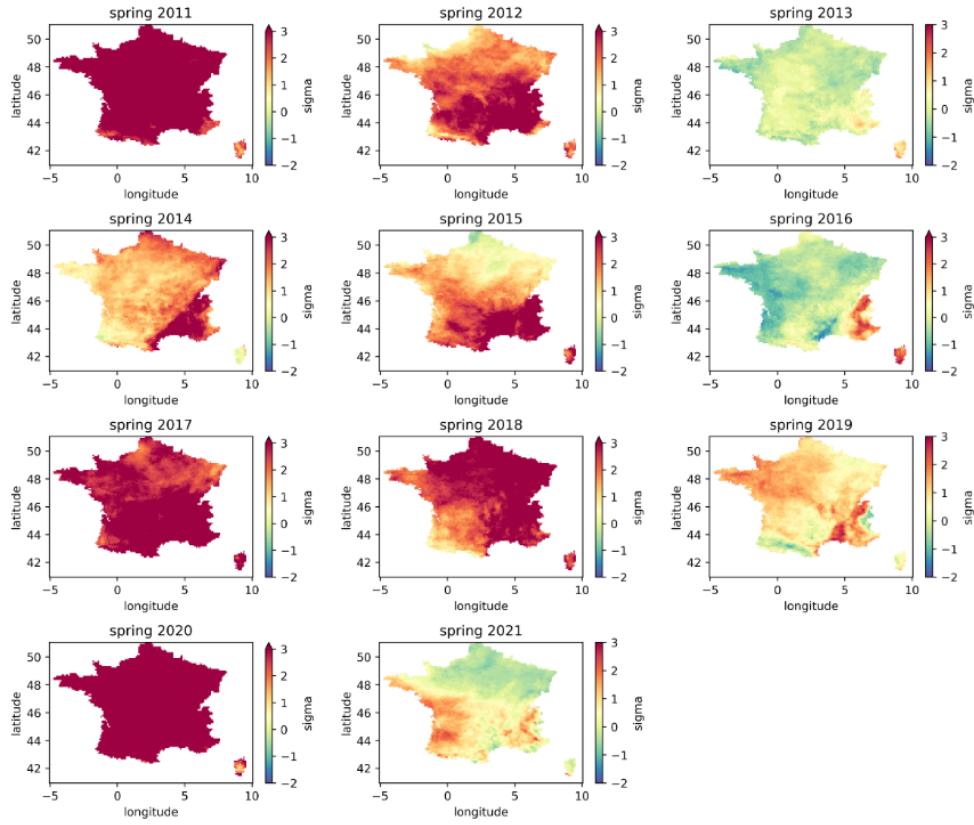


Figure 4.6. Spring seasonal $T90_{std}$ values, 2011-2022

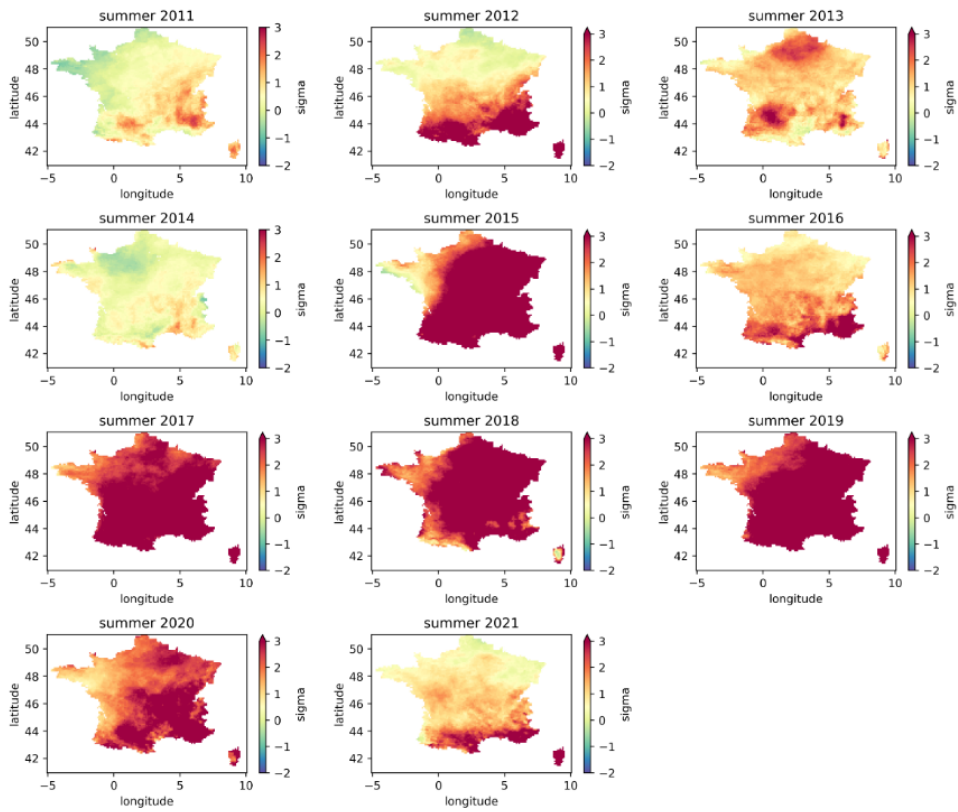


Figure 4.7. Summer seasonal $T90_{std}$ values, 2011-2022

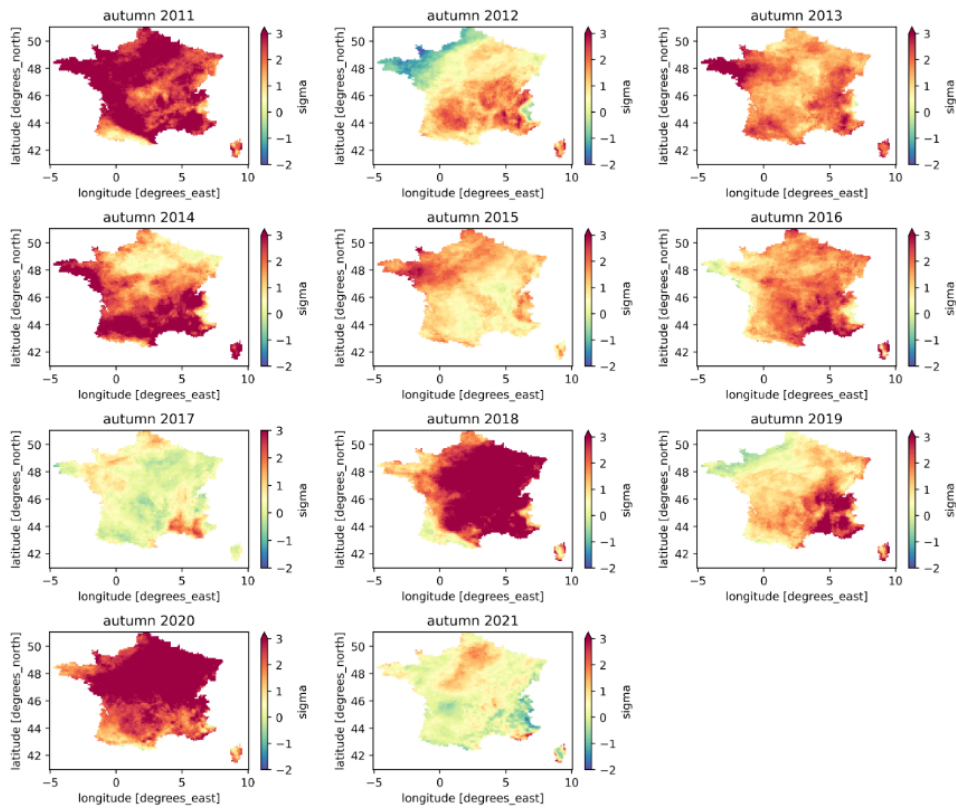


Figure 4.8. Fall seasonal $T90_{std}$ values, 2011-2022

Now consider the low temperatures $T10_{std}$. We plot $-T10_{std}$ instead, so that high values (in red) mean less frequent extreme lows, that is warmer days.

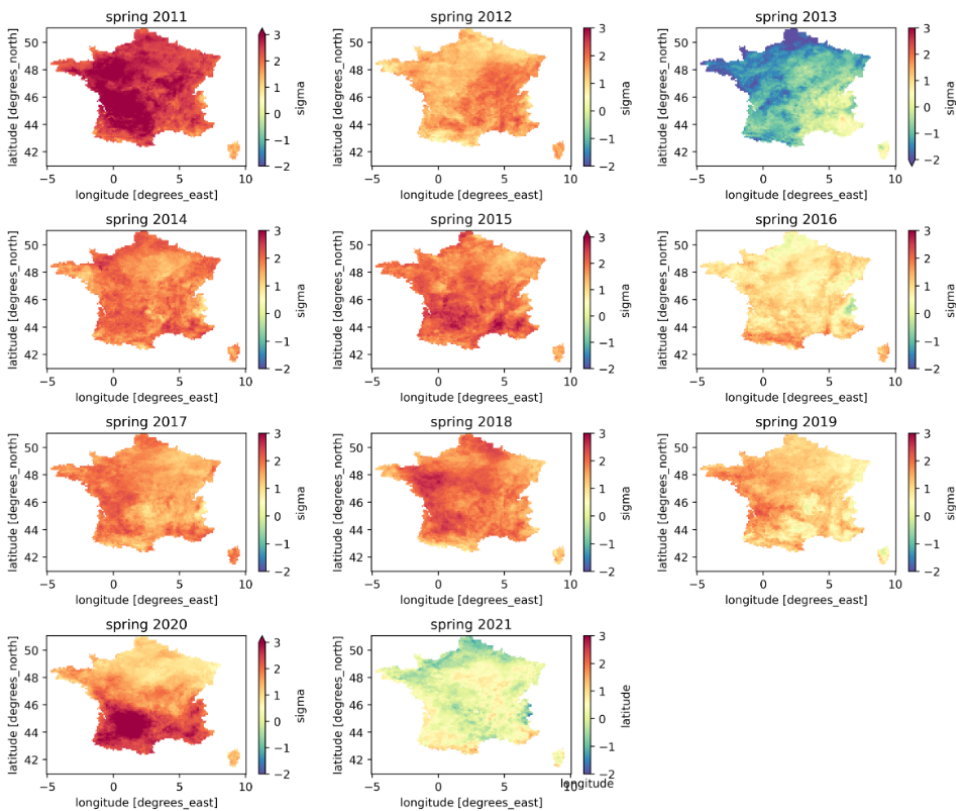


Figure 4.10. Spring seasonal $-T10_{std}$ values, 2011-2022

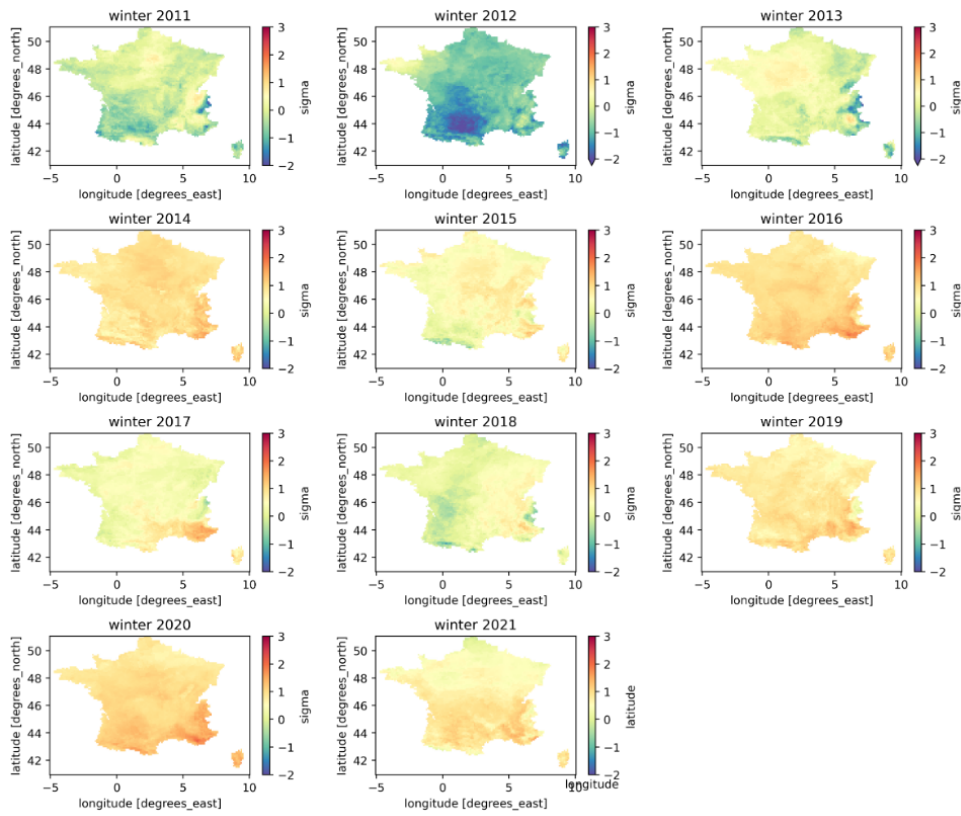


Figure 4.9. Winter seasonal $-T10_{std}$ values, 2011-2022

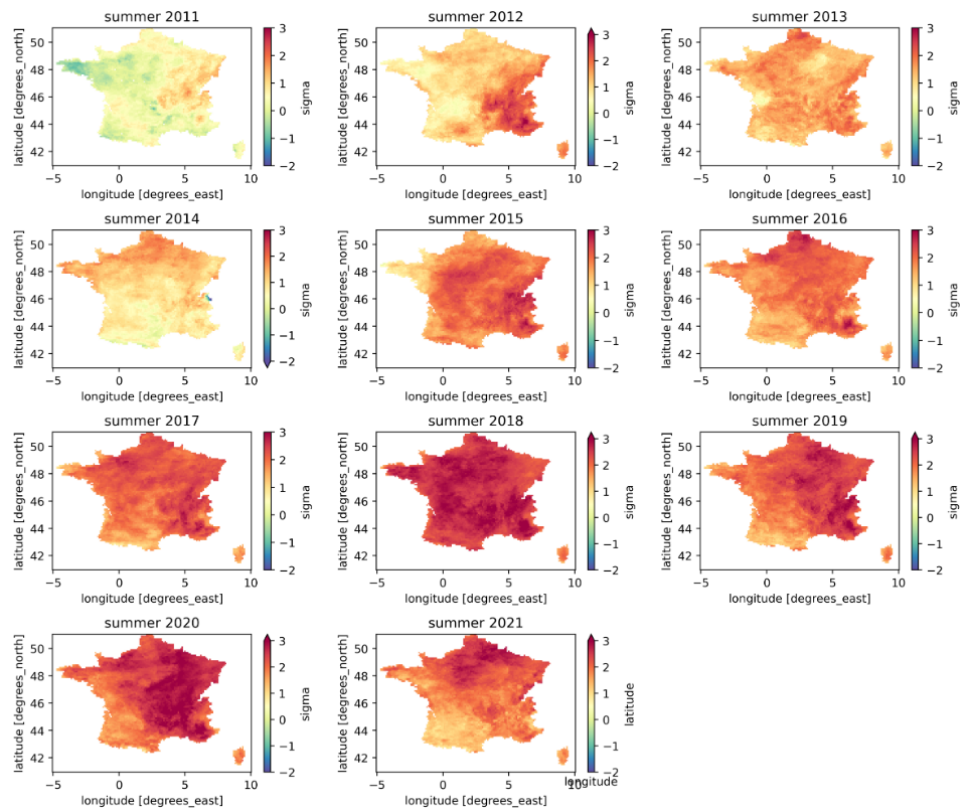


Figure 4.11. Summer seasonal $-T10_{std}$ values, 2011-2022

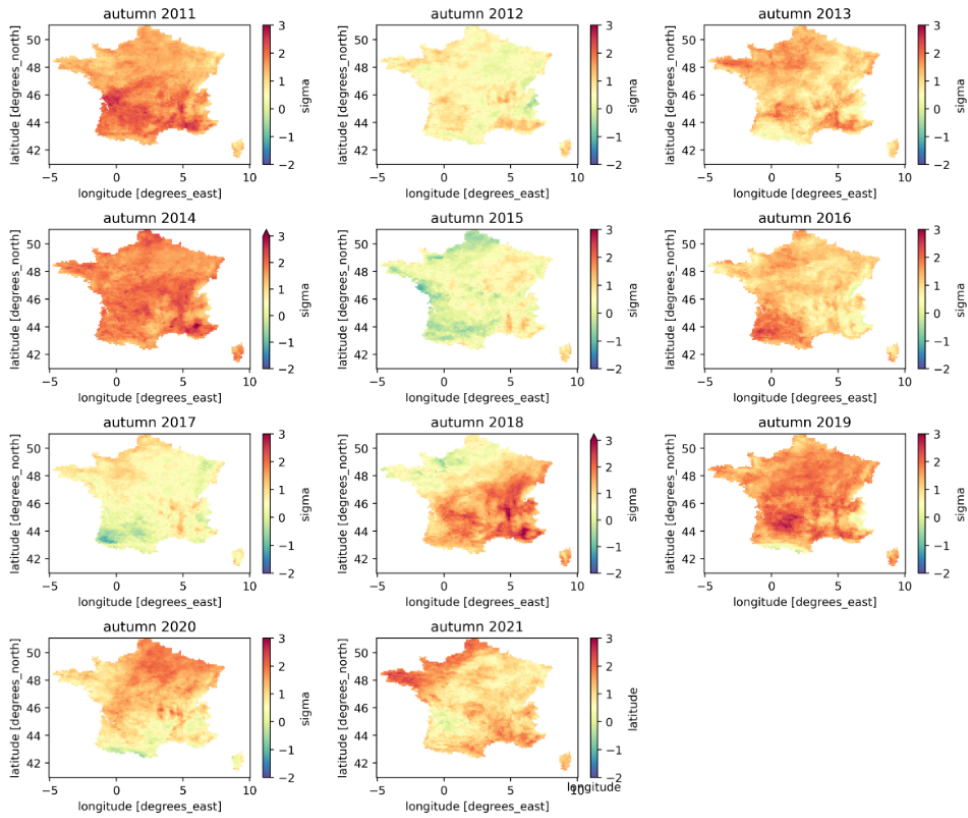


Figure 4.12. Fall seasonal $-T10_{std}$ values, 2011-2022

Note how summers are producing less frequent extreme low temperatures, at the same time as more frequent high temperatures (see Figure 4.7). To a certain extent, the same can be said about winters. The case of springs and falls is not as clear-cut.

4.2 Seasonal precipitations per region

The following plots are for the precipitations P_{std} variable.

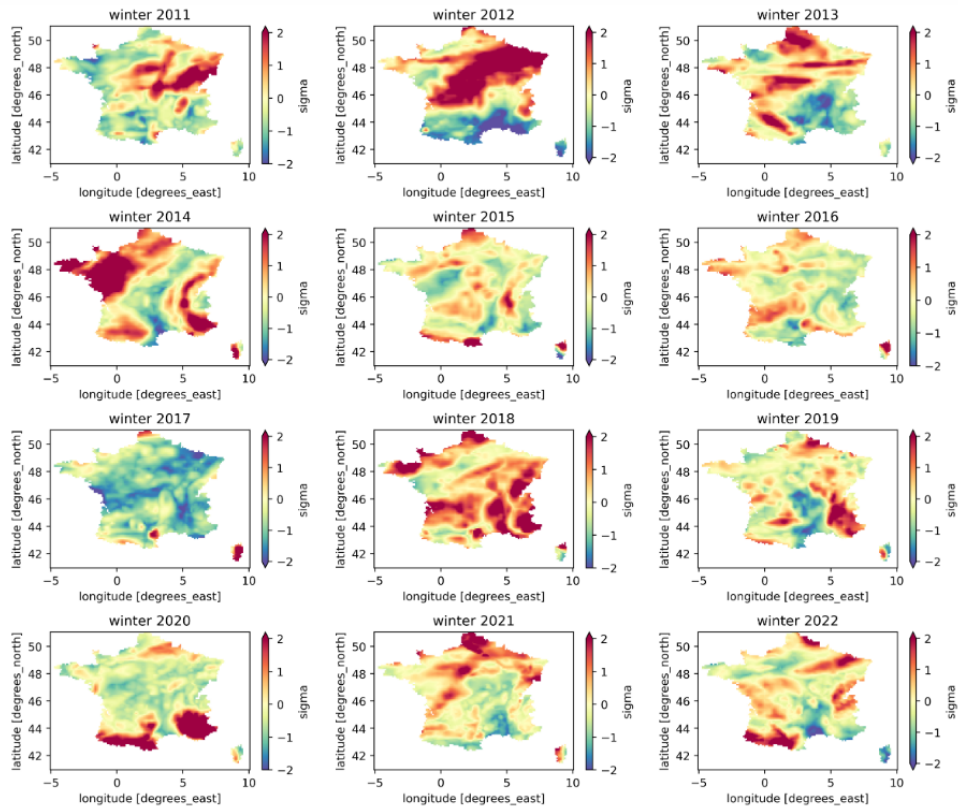


Figure 4.13. Winter seasonal P_{std} values, 2011-2022

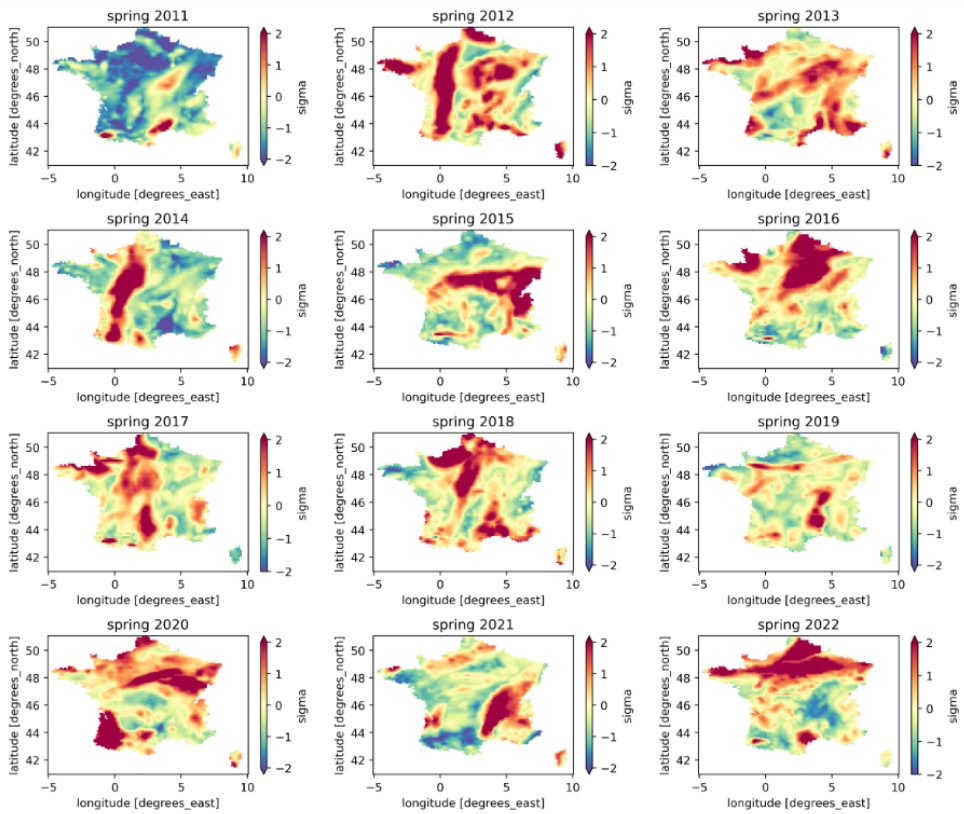


Figure 4.14. Spring seasonal P_{std} values, 2011-2022

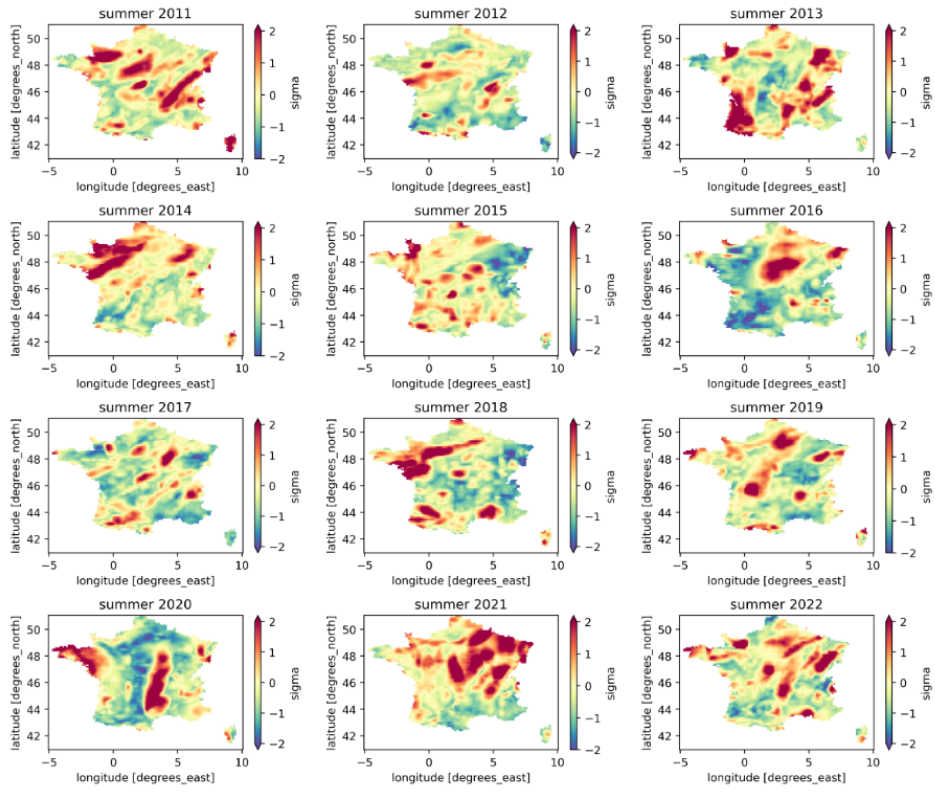


Figure 4.15. Summer seasonal P_{std} values, 2011-2022

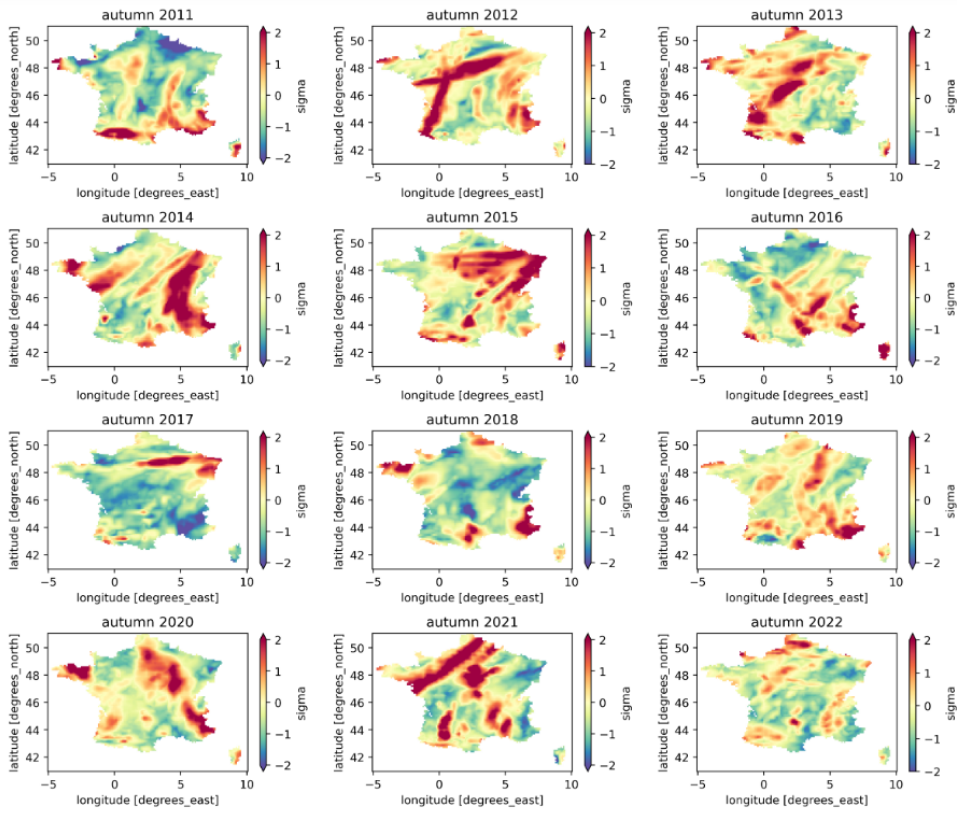


Figure 4.16. Fall seasonal P_{std} values, 2011-2022

4.3 Seasonal droughts per region

Now, this section gives the drought variable D_{std} plots.

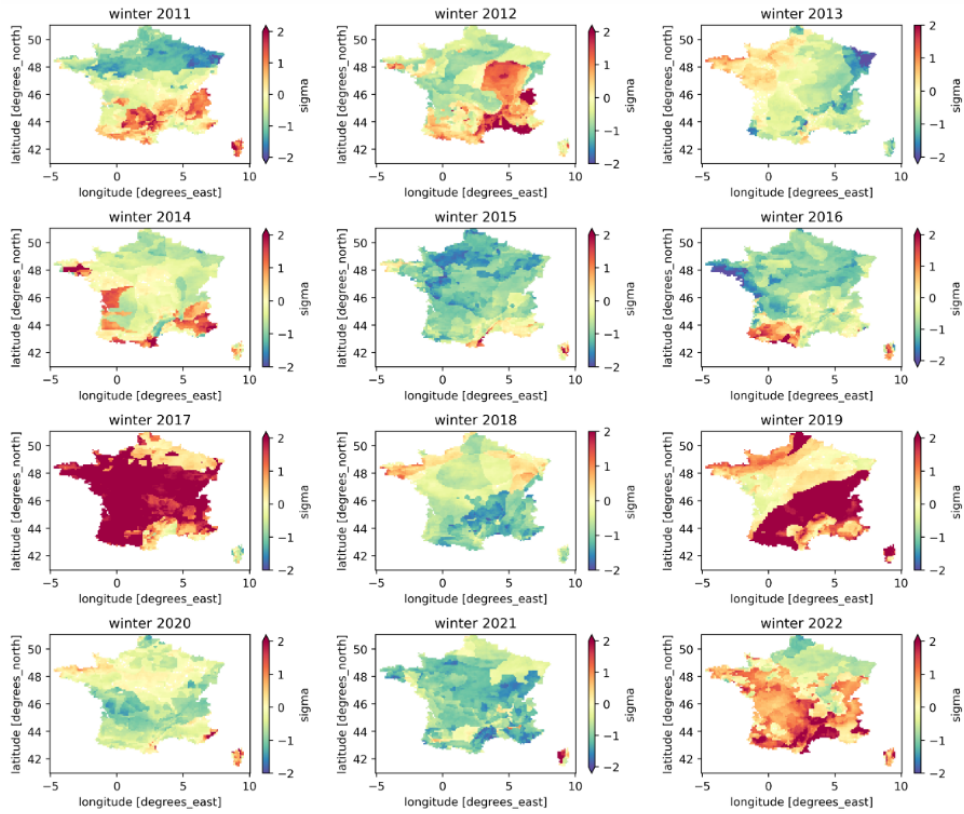


Figure 4.17. Winter seasonal D_{std} values, 2011-2022

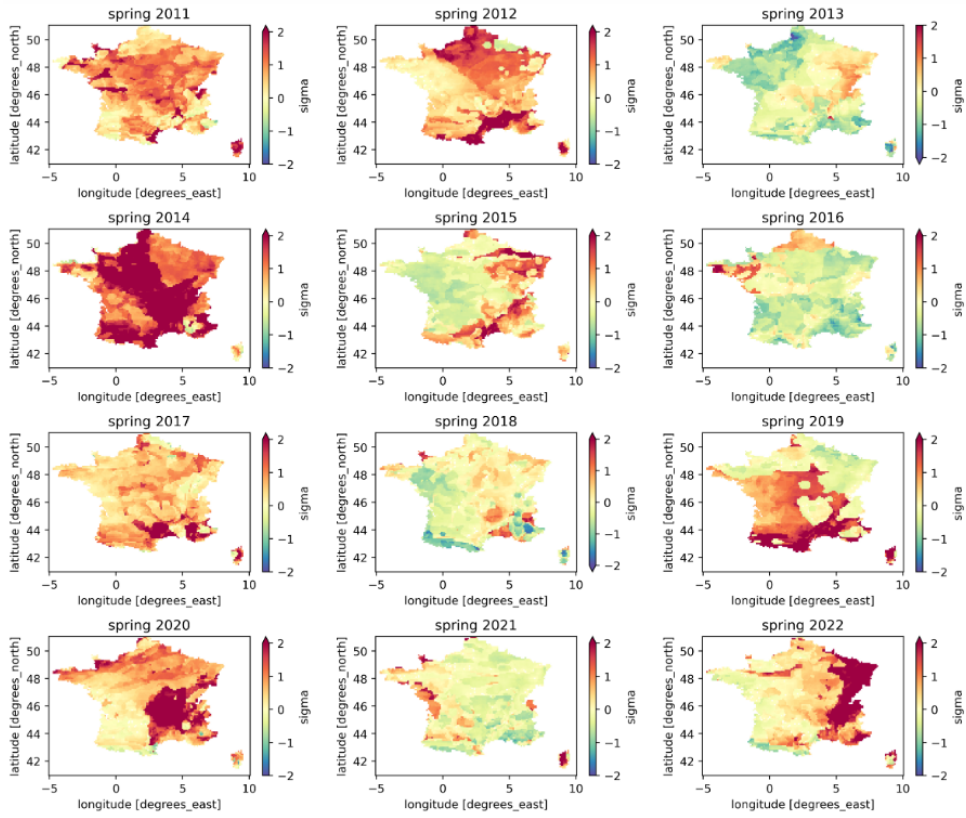


Figure 4.18. Spring seasonal D_{std} values, 2011-2022

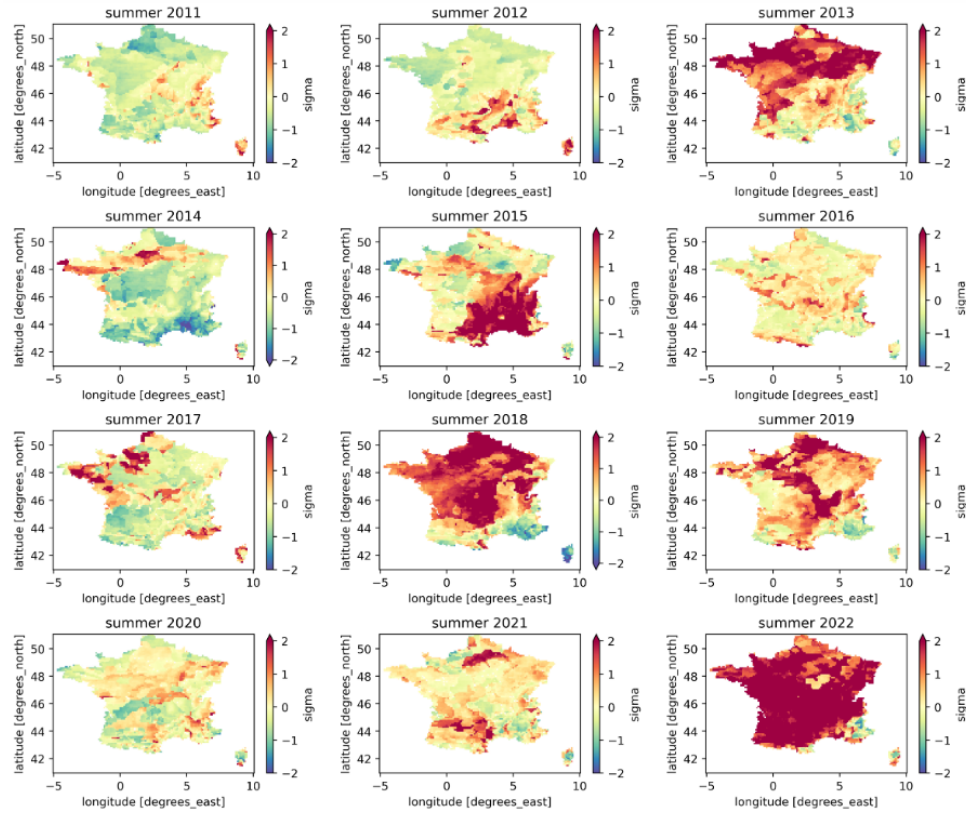


Figure 4.19. Summer seasonal D_{std} values, 2011-2022

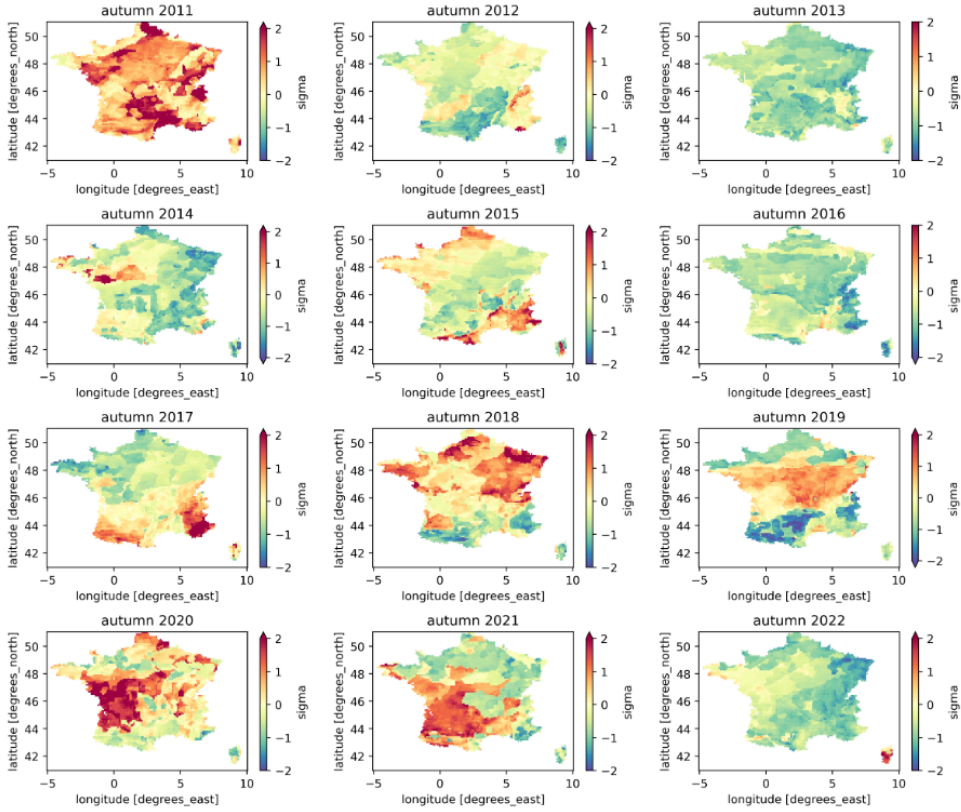


Figure 4.20. Fall seasonal D_{std} values, 2011-2022

5 Insurance application

Two main product types are available currently to transfer climate risks: climate derivatives and parametric insurance products. This section focuses on the latter type of cover. The main advantage of parametric insurance over climate derivatives is the product flexibility, while the main disadvantage is its price; climate derivatives being cheaper often, as they are traded on a stock market.

By contrast with a classical insurance product, parametric insurance contracts benefit payoffs are triggered by the value of a predetermined index, when it reaches a fixed threshold.

The application illustrated here uses the index defined above, the FACI, based on historical climate data for France and Corsica. With it we calculate premiums of parametric insurance covers of losses generated by climate events.

5.1 Definition of parametric insurance

Parametric insurance, also known as index insurance, defining characteristic is that its benefit payoff is triggered by a predetermined parameter or index value, while for a classical insurance, it is the occurrence of a loss that triggers the benefit payment.

Current parametric insurances are based mostly on climate indexes (sunshine hours, hurricane wind power, rainfall) whose values are easily obtained, as the information is available from meteorological reports. This type of insurance is popular with farmers seeking a harvest income guarantee. However, the idea can be extended to any risk for which the benefit can be based on an existing objective index.

The benefit payment process of a parametric insurance is the simplest. Any time that the index reaches the predetermined threshold in the contract, the benefit is

due and the insurer pays a lump sum that depends on by how much the index has exceeded the threshold. As such, the indemnity payment can be made very quickly, without the need for expert appraisal to evaluate the losses, or to force on the insured the burden of the proof of the damage incurred. In fact, the indemnity here does not depend on the loss incurred by the insured but rather by how much the index value overshoots the predetermined threshold. The idea being that, at least partly, the two concepts be linked.

5.2 Literature review

Several actuarial works consider the use of parametric insurance products and/or of climate derivatives. Vendé (2003) looks at the correlation between different climate indices in the rate making of a parametric cover for Cat. reinsurance. Denizot and Plouhinec (2008) evaluate the use of different temperature models in pricing climate derivatives. By contrast, Gilles and Finas (2011) consider the management of wind risk for the production of eolic electricity. They propose a solution based on mathematical finance to build appropriate climate derivatives. Nguyen and Ritleng (2014) study a parametric insurance product for the risk of heavy rainfall in Jamaica.

The Master's theses cited above base their analyses on purely meteorological indices, for non agricultural applications. Koch (2011) considers the creation of a crop yield parametric insurance product based on a climate index. Leprince (2001) describes two US crop insurance products, for yield and income, and their risk management use. Batisse and Mercuzot (2009) as well as Fosso and Seretti (2010) discuss the rate making process for agricultural crop insurance.

The underlying principle of parametric insurance is the construction of an index correlated with the variable of interest (e.g. sales, crop yields, crop quality, etc.). However, such an index must respect certain properties:

1. observable and easily measurable,
2. objective,
3. independently verifiable,
4. regularly communicated within a convenient delay,
5. coherent over time.

Such an index is not necessarily meteorological. For instance a region's crop yield published by an independent authority, and its structure, which can be complex (multi-index insurance, spatial and temporal flexibility, etc.), is created after an analysis of meteorological sensitivity of the variable of interest.

What emerges from the literature is that parametric insurance appears to be an adapted solution to manage non-catastrophic climate risk.

5.3 Parametric insurance market

Since November 2022, a highly specialised insurtech called Descartes Insurance, has received the certification awarded sparsely by the regulator, the Autorité de contrôle prudentiel et de résolution (ACPR), on the French market of parametric or index insurance. This player specialises in the design of insurance products that automatically pays indemnities to large enterprises or countries when a climatic event or a natural catastrophe occurs, simply because a predetermined index reaches a certain threshold. A niche market that is quickly forming in the last few years around start-ups, like Descartes, but also traditional insurers, like AXA through its subsidiary AXA Climate, reinsurers, like Swiss Re or Munich Re, and some large brokers.

In October 2022, Eunice Jesang, a Kenyan farmer from Makueni county, subscribed a crop insurance policy for her corn harvest. Her quotation allowed her to take part in the “Lemonade Crypto Climate Coalition”, a parametric crop insurance pilot program on blockchain, an initiative of the Lemonade Foundation. Their objective is to support millions of small farming producers, in world regions where traditional insurance against storms is not accessible, or not offered.

The specialised brokers Atekka have developed index insurance solutions also. Launched in Cognac in 2021, with the farming cooperative Océalia and the data provider Understory, their parametric insurance program against frost and hail that affect vineyards has already sold a dozen contracts. The frost cover for vines in Cognac worked well since its inception. Clients know from the contract signature that an indemnity will be paid, for example 30% of the insured capital, in case of a trigger if a temperature of -2 °C or less is recorded in their vineyards. The parametric solutions from Atekka complete traditional insurance. For larger cultures or winegrowers, classical multirisk climate insurance contracts are sold with a high deductible of 20 to 25%. Parametric insurance can be used to cover this deductible, that would otherwise be charged to the farmer.

Club Med also has used parametric insurance for its villages in the Caribbeans, threatened by hurricanes and earthquakes.

After creating, in February 2021, its practice in parametric insurance, the broker from Nantes, Bessé, joined AXA Climate in 2022 to develop parametric insurance solutions for agricultural subsidiaries.

5.4 Rate making process

The parametric insurance rate making process is similar to that of classical insurance. The usual desirable properties on premiums apply:

1. The charged premium should be larger than the net premium,
2. Premiums must be an increasing function of potential losses,
3. Premiums should be sub-additive in general, and additive for independent risks.

As for classical insurance, net premiums are adjusted by a risk loading, following some premium principle, to produce a loaded premium π . For example:

1. *The net premium principle* sets a loading θ that does not account for the risk of adverse loss (L) fluctuations around their expectation, $\mathbb{E}(L)$:

$$\forall L \in \mathcal{L}, \quad \pi(L) = (1 + \theta)\mathbb{E}(L), \quad \theta > 0, \quad (5.1)$$

2. *The variance principle* adds a term to account for fluctuations, but is not sub-additive:

$$\forall L \in \mathcal{L}, \quad \pi(L) = \mathbb{E}(L) + \theta\mathbb{V}(L), \quad \theta > 0,$$

3. *The standard deviation principle* replaces the variance, above, by the standard deviation. It is sub-additive:

$$\forall L \in \mathcal{L}, \quad \pi(L) = \mathbb{E}(L) + \theta\sqrt{\mathbb{V}(L)}, \quad \theta > 0, \quad (5.2)$$

The general rating formula for a basic parametric insurance product uses three variables: the entry point E , the exit point X and the marginal value of one index unit, say IV . The insurance benefit payoffs are determined by the following formula:

$$B = IV \times \mathbb{I}_{I > E} \times \min\{I - E, X - E\},$$

where B is the benefit value, \mathbb{I} is an indicator function and I is the index value.

This linear benefit formula is the most common on the market, where the index is correlated positively with the benefit payments. Here the entry and exit points help determine the part of the risk that is transferred to the insurance company, in a way reminiscent of an excess-of-loss reinsurance contract; see Figure 5.1 for an illustration using FACI as the index.

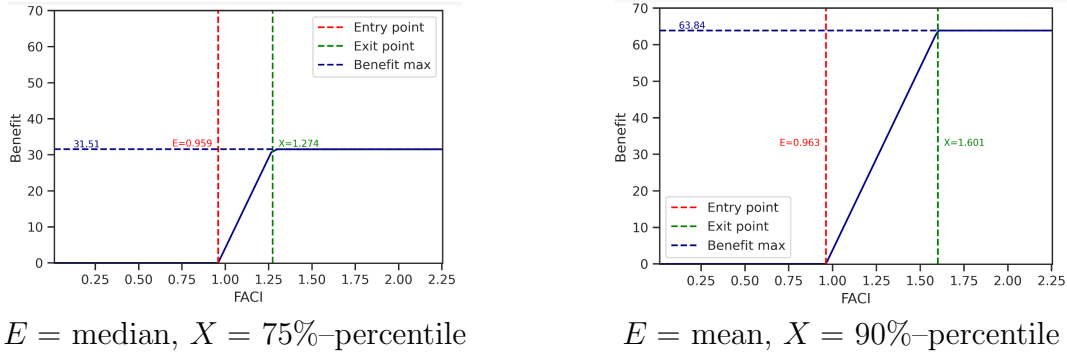


Figure 5.1. Parametric insurance benefit examples

The first contract parameters to fix are the entry and exit points, that trigger the benefit payments. The higher the exit point, the larger the premium charged for the cover. The more probable that the index value be between E and X , the higher the frequency and the size of the benefit payoffs.

A third parameter is the benefit calculation method. For example, the entry point E could be the first quartile, the median or any other a critical threshold, that if passed, it triggers a loss of $x\%$ of the expected yield (from a public institution, like the department of agriculture for crop insurance).

The exit point X could be, for example, a multiple of E , the third or a higher quartile. For crop insurance products commonly sold in the US, the expected yield is set as the last 5 years average crop, to which the maximum and minimum are subtracted (Olympic average).

Lastly, the current production value has to be evaluated. It can correspond to future prices on financial markets of insured crops or the farmer's fixed production costs. In the US all the surface yield insurance products are based on the future prices of the Chicago Board of Trade (CBOT).

There are different methods for the calculation of the premium itself. The first one is based on historical payoffs data. The objective here is not to model the index but use the historical empirical distribution of the payoffs it generated. For each year of historical data, the benefit is calculated as if the cover were in place. Then these are averaged over the past years. Here detrending is very important, so that the past losses distribution reflects that of future losses. Particular attention must be given to the quality, as well as the depth of the historical data available, to avoid overfitting. This method is commonly used to obtain a pure premium.

Another approach to calculate the pure premium is to fit a known parametric distribution to the empirical index distribution. In practice, the calculation is often performed via Monte Carlo simulations. This is the method illustrated here. Another possible estimation is through extreme value theory.

To control the profitability of the parametric insurance product, the insurer often uses economical and performance indicators, such as the loss ratio (observed losses over adjusted premiums charged). Depending on the specific risk, the loss ratio study can go back anywhere from 3 to 10 years. The lower the ratio, below 100%,

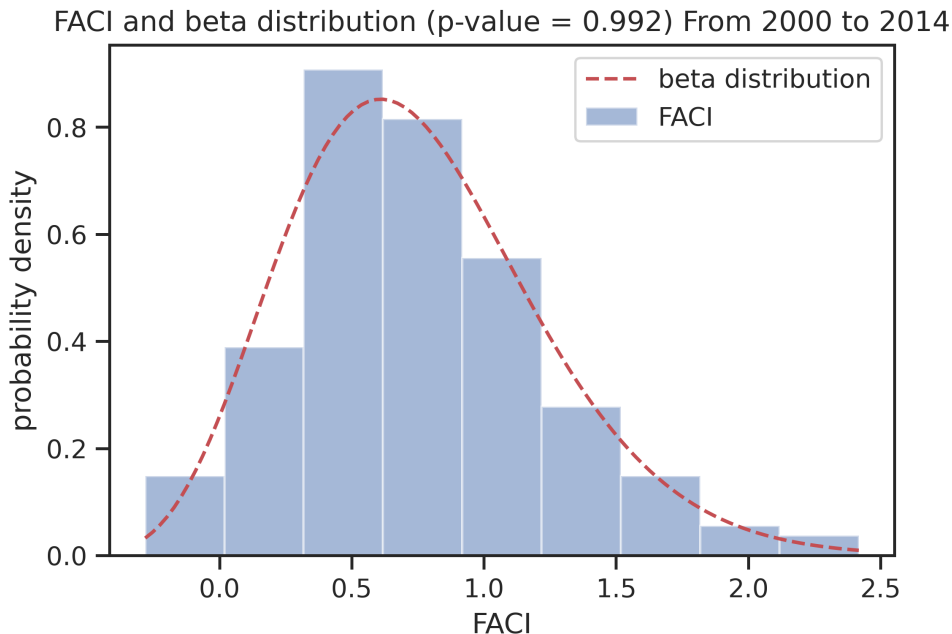


Figure 5.2. Fitted beta($\alpha = 8.43$, $\beta = 64.49$, $loc = -0.74$, $scale = 12.91$) density vs histogram on monthly FACI

the more profitable the product. Different learning and testing historical data sets are used for the premium calculation and loss ratio analysis, through backtesting.

5.5 Numerical illustration

FACI measures extreme weather events, in comparison to the 1961–1990 reference period. For the purposes of this numerical illustration we use a 2000–2014 learning period and a lower-resolution FACI, based on 0.25° of latitude \times 0.25° of longitude, keeping the high-resolution data for visualisations; see Figure D.1. Assume that a parametric insurance product is then defined and priced on January 1, 2015, based on this learning period data, providing a one-year coverage. The case of a seasonal or monthly coverage are also illustrated in Appendix D.

First, a parametric distribution is fitted to the monthly FACI values observed over the 2000–2014 learning period. Out of 17 fitted continuous distributions, the beta($\alpha = 8.43$, $\beta = 64.49$, $loc = -0.74$, $scale = 12.91$) yielded the highest p -value in Kolmogorov–Smirnov’s test. Figure 5.2 shows the fit, compared to the histogram of FACI values.

The fitted beta distribution is then used to price a one-year insurance coverage. Tables 5.1 and 5.2 give the empirical summary statistics and compare them to the theoretical beta values. Appendix D lists similar fits, but for monthly FACI indices to define a one-season or a one-month insurance coverage.

Minimum	25%-percentile	Median	75%-percentile	Maximum
-0.28	0.42	0.69	1.08	2.4

Table 5.1. Empirical summary statistics

Two parametric insurance coverages are illustrated, for benefits based on, 1. the entry point being the median $E = 0.959$ and the exit point being the 75%-percentile

Summary statistic	Theoretical	Empirical
Mean	3/4	3/4
Standard Deviation	0.4814	0.4805

Table 5.2. Summary statistics beta($\alpha = 8.43$, $\beta = 64.49$, $loc = -0.74$, $scale = 12.91$) vs empirical

$X = 1.274$, and 2. an entry point being the mean $E = 0.963$ and the exit point being the 90%-percentile $X = 1.601$, as in Figure 5.1.

First, 5,000 monthly FACI values are simulated, without a trend, from the beta density estimated over the 2000–2014 learning period, and tested for 2015; see Figure D.4. Two premium principles are illustrated; Formula 1 is the loaded pure premium in (5.1) and Formula 3 for the standard deviation principle in (5.2). Table D.1 reports the estimated parametric insurance benefit payoffs for these 2 premium formulas (denoted P.F.), comparing them to the simulated payoffs of an annual coverage in 2015, with a premium loading $\theta = 3\%$. In Appendix D.1 a more extensive comparison is given in Table D.1 for 3 different premium loadings, $\theta = 3\%$, 5% and 10%.

Parameters					Estimated benefit payoff						
E	E value	X (%)	X value	P.F.	Mean	Std	median	75%	min-max	Actual payoff	Pure prem.
med.	-0.062	75	0.331	1	170.18	57.86	168.76	208.67	0- 370.46	279.36	175.28
med.	-0.062	75	0.331	3	170.18	57.86	168.76	208.67	0- 370.46	279.36	171.92
med.	-0.062	90	0.626	1	227.17	85.23	222.53	283.53	0- 526.62	406.55	233.99
med.	-0.062	90	0.626	3	227.17	85.23	222.53	283.53	0- 526.62	406.55	229.73
med.	-0.062	99.5	1.481	1	262.87	111.45	253.87	333.42	0- 808.52	507.83	270.76
med.	-0.062	99.5	1.481	3	262.87	111.45	253.87	333.42	0- 808.52	507.83	266.22
mean	0	75	0.331	1	133.82	48.77	132.26	165.47	0- 308.22	229.57	137.84
mean	0	75	0.331	3	133.82	48.77	132.26	165.47	0- 308.22	229.57	135.28
mean	0	90	0.626	1	190.82	77.05	186.8	241.47	0- 462.64	356.76	196.54
mean	0	90	0.626	3	190.82	77.05	186.8	241.47	0- 462.64	356.76	193.13
mean	0	99.5	1.481	1	226.52	104.17	215.53	291.6	0- 746.79	458.04	233.31
mean	0	99.5	1.481	3	226.52	104.17	215.53	291.6	0- 746.79	458.04	229.64

Table 5.3. Parametric insurance – annual coverage premiums (X (%) in percent, $\theta = 3\%$, P.F. = Premium Formula, Std = standard deviation, prem. = premium)

Note how the actual payoffs exceed not only the mean or median estimated payoffs, but are generally close to the maximum of their range of simulated values. In addition, with small loadings, such as 3% to 10%, both the loaded pure premiums (Formula 1) and those based on a loading using the standard deviation (Formula 3), would have been insufficient to cover payoffs. Hence, the first conclusion is that to be solvent, an annual parametric insurance coverage with benefit payoffs based on FACI, requires risk loadings larger than 10%.

In many cases it makes more practical sense to design and sell parametric insurance based on a climate index only for a seasonal coverage, rather than on an annual basis. Table 5.4 reports the simulations results, obtained from the parametric distributions in Figure D.2 for a summer seasonal coverage only. All other parameters are as above, including a loading of $\theta = 3\%$. Illustrations for other loading values are reported in Table D.2 of the appendix, while Table D.3 gives the results for a fall seasonal coverage, Table D.4 for a winter coverage and Table D.5 for a spring coverage.

Parameters					Estimated benefit payoff					Actual payoff	Pure prem.
E	E value	X (%)	X value	P.F.	Mean	Std	median	75%	min-max		
med.	0.138	75	0.445	1	136.97	47.41	134.78	168.3	0- 304.89	92.25	141.08
med.	0.138	75	0.445	3	136.97	47.41	134.78	168.3	0- 304.89	92.25	138.39
med.	0.138	90	0.687	1	194.16	74.13	190.93	241.5	0- 473.21	136.56	199.99
med.	0.138	90	0.687	3	194.16	74.13	190.93	241.5	0- 473.21	136.56	196.39
med.	0.138	99.5	1.622	1	249.81	112.54	240.44	319.5	0- 826.78	190.55	257.31
med.	0.138	99.5	1.622	3	249.81	112.54	240.44	319.5	0- 826.78	190.55	253.19
mean	0.209	75	0.445	1	97.2	36.82	94.66	120.8	0- 233.93	70.96	100.12
mean	0.209	75	0.445	3	97.2	36.82	94.66	120.8	0- 233.93	70.96	98.31
mean	0.209	90	0.687	1	154.39	64.51	150.98	195.19	0- 409.35	115.28	159.03
mean	0.209	90	0.687	3	154.39	64.51	150.98	195.19	0- 409.35	115.28	156.33
mean	0.209	99.5	1.622	1	210.04	104.38	199.94	274.08	0- 770.01	169.27	216.35
mean	0.209	99.5	1.622	3	210.04	104.38	199.94	274.08	0- 770.01	169.27	213.18

Table 5.4. Parametric insurance – seasonal summer coverage premiums (X (%) in percent, $\theta = 3\%$, P.F. = Premium Formula, Std = standard deviation, prem. = premium)

Note how the actual payoffs are now much more in line with their estimated mean or median values. Furthermore, loaded premiums are now adequate for all loadings, even the smaller ones, and all premium loading formulas. The other conclusion emerging from this simulation study is hence that, for parametric insurance coverages defined on a climate index with seasonal variations, like FACI, it is more adequate to sell a seasonal coverage, here for the summer only, rather than an annual one, to reduce the high payoff variations due to seasonal fluctuations of the index.

A similar simulation analysis for a parametric insurance coverage sold on a monthly basis is possible using the parametric distributions fitted to each month in Figure D.3, but is not included here.

Conclusions

This paper applies the same methodology of the North American Actuaries Climate Index™ (ACI) to climate data from France and Corsica, in order to calculate the French Actuarial Climate Index (FACI). After reviewing the methodology and the data used to obtain the FACI, with it we study climate change in France since the 1961–1990 reference period, including high-resolution analyses, per component, per season and per region. Together with the recent indices calculated for Spain and Portugal, this FACI represents one more step towards the definition of a European index.

As an illustrative application of FACI, the paper concludes with the definition and pricing of a parametric insurance product that could be based on FACI. Two different benefit payoff formulas are illustrated, as well as different premium loadings. Annual and seasonal coverages are defined; the simulation study illustrating the better adequacy of premiums for seasonal coverages when the parametric insurance is based on an index, like FACI, that is subject to seasonal variations.

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Appendix A The North American Actuaries Climate Index (ACI)

Since we extend here the methodology of the Actuaries Climate Index™ (ACI) to French climate data, for completeness this section reviews the ACI methodology and its main results; see ACI (2018) for further details.

Originally defined for the United States and Canada, the ACI was produced jointly by several actuarial societies in North America. It combines six climate variables, see Table A.1, each being a monthly time series beginning in 1961.

Components	Notation	Definition
Warm temp.	$T90$	Frequency of temp. $> 90^{th}$ percentile
Cool temp.	$T10$	Frequency of temp. $< 10^{th}$ percentile
Precipitation	P	Max. rainfall/month in 5 consecutive days
Drought	D	Annual max. consecutive dry days
Wind speed	W	Frequency of wind speed $> 90^{th}$ percentile
Sea level	S	Change in sea level

Table A.1. Definition of the ACI components

The ACI uses a reference period from 1961 to 1990, as the basis to measure climate change. The data from this period produces the means and standard deviations used to standardise anomalies for each component, relative to 1961-1990. A monthly standardised anomaly is given by the difference between the given month's value and the corresponding month's average over the reference period, then dividing by its standard deviation over the reference period, like a Z-score. Figure 1.1 plots the seasonal ACI values plus their 5-year moving averages, from 1961 to 2016.

The ACI is calculated monthly, as well as on a seasonal basis. The latter is determined by taking meteorological seasonal averages, for example, the winter average is based on the calendar months of December, January, and February. Then the seasonal standardisation is just as for the monthly index.

A.1 Temperature components, $T90$ and $T10$

The two temperature components are defined as the frequency of temperatures above the 90^{th} percentile and below the 10^{th} percentile, relative to the data from the reference period of 1961 to 1990; see details in Table A.2.

Because warmer days and warmer nights tend to occur together, the ACI measures the average percentage of days when daytime high temperatures and night-time high temperatures are greater than the corresponding 90^{th} percentile, centred on a 5-day window, for the base period 1961-1990:

$$T90(j, k) = \frac{1}{2}[TX90(j, k) + TN90(j, k)], \quad (\text{A.1})$$

where $j = \text{Jan}, \text{Feb}, \dots, \text{Dec}$ and $k = 1961, 1962, \dots, 2022$.

The low temperature measure is calculated using a process similar to that used to calculate the frequency below the 10^{th} percentile:

$$T10(j, k) = \frac{1}{2}[TX10(j, k) + TN10(j, k)], \quad (\text{A.2})$$

where $j = \text{Jan}, \text{Feb}, \dots, \text{Dec}$ and $k = 1961, 1962, \dots, 2022$.

Notation	Explanation
$TX90$	Percentage of days when daytime max. temperature $> 90^{th}$ percentile of the reference period distribution for the relevant days
$TX10$	Percentage of days when daytime max. temperature $< 10^{th}$ percentile of the reference period distribution for the relevant days
$TN90$	Percentage of days when night-time min. temperature $> 90^{th}$ percentile of the reference period distribution for the relevant days
$TN10$	Percentage of days when night-time min. temperature $< 10^{th}$ percentile of the reference period distribution for the relevant days

Table A.2. Explanation of temperature indices

The standardised anomalies for high temperatures are calculated as the difference between the monthly frequency of warm temperatures > 90 -percentile and the average monthly frequency of warm temperature during the reference period, divided by the standard deviation over the reference period. The warm temperature $T90$ and the cool temperature $T10$ use the same algorithm:

$$T90_{std}(j, k) = \frac{T90(j, k) - \mu_{ref}T90(j)}{\sigma_{ref}T90(j)}, \quad (\text{A.3})$$

where $j = Jan, Feb, \dots, Dec$ and $k = 1961, 1962, \dots, 2022$, and $\mu_{ref}T90(j)$ is the average monthly frequencies of warm temperature for all months during the reference period, while $\sigma_{ref}T90(j)$ is the standard deviation of the warm temperatures during the reference period.

The standardised anomalies calculation method for the cold temperatures is consistent with that for warm temperatures

$$T10_{std}(j, k) = \frac{T10(j, k) - \mu_{ref}T10(j)}{\sigma_{ref}T10(j)}, \quad (\text{A.4})$$

where $j = Jan, Feb, \dots, Dec$, and $k = 1961, 1962, \dots, 2022$.

As the climate warms up, the occurrence of extreme cool temperatures decreases, and the temperature distribution shifts to the right. Hence, the sign of $T10_{std}$ is reversed in the calculation of the ACI to correctly reflect the risk (increasing the ACI when $T10_{std}$ decreases to further negative values).

Fewer extreme cold events indicate that the climate is changing, affecting plant and animal ecology and weather patterns. Increased melting of permafrost, increased infectious diseases transmission, and populations of pests and insects that were previously less likely to survive cooler temperatures are all thought to be associated with a reduction in the frequency of extreme cold events.

A.2 Precipitation component, P

The precipitation component focuses on extreme rainfall rather than average precipitation, using the maximum rainfall in any 5 consecutive days within a month, notated as $Rx5day(j, k)$. The percentage anomaly of maximum 5-day rainfall in a

month, relative to the reference period value for a given month, is given by:

$$P_{std}(j, k) = \frac{Rx5day(j, k) - \mu_{ref}Rx5day(j)}{\sigma_{ref}Rx5day(j)}, \quad (\text{A.5})$$

where, $j = Jan, Feb, \dots, Dec$ and $k = 1961, 1962, \dots, 2022$, while $\mu_{ref}Rx5day(j)$ is the average of all months during the reference period, and $\sigma_{ref}Rx5day(j)$ is the standard deviation during the reference period.

A.3 Drought component, D

Droughts are measured by the maximum number of consecutive dry days in each year, when the precipitation is less than 1 millimetre (denoted $CDD(k)$). Monthly values are obtained by linear interpolation of annual values:

$$CDD(j, k) = \begin{cases} \frac{12-j}{12}CDD(k-1) + \frac{j}{12}CDD(k) & j = 1, 2, \dots, 11, \\ CDD(k) & j = 12. \end{cases} \quad (\text{A.6})$$

The standardised anomaly calculations of CDD are similar to those for $Rx5day$:

$$D_{std}(j, k) = \frac{CDD(j, k) - \mu_{ref}CDD(j)}{\sigma_{ref}CDD(j)}. \quad (\text{A.7})$$

A.4 Wind Speed component, W

Daily wind speed measurements are converted to wind power, WP , using the relationship $WP(i, j) = 1/2\rho w^3$, where w is the daily mean wind speed and ρ is the air density (taken to be constant at $1.23\text{kg}/\text{m}^3$). Wind power is used because the destructive potential of wind is better explained by wind power than wind speed. The wind component measures the monthly frequency of daily mean wind power above the 90th percentile, denoted as $WP90$.

The wind power threshold $WP_u(i, j)$ is determined, for each day i and month j in the reference period at each grid point separately. The thresholds value is determined as the mean plus 1.28 standard deviations of $WP(i, j, k)$, for all 30 values of the same day and month in the 30-year reference period:

$$WP_u(i, j) = \mu_{ref}WP(i, j) + 1.28 \cdot \sigma_{ref}WP(i, j). \quad (\text{A.8})$$

The day counts when the mean wind exceeds the threshold are then expressed as a percentage of the number of days in the month, providing an exceedance frequency measure, for every month of every year, throughout the entire period:

$$I(i, j, k) = \begin{cases} 1 & WP(i, j, k) > WP_u(i, j), \\ 0 & \text{otherwise,} \end{cases} \quad (\text{A.9})$$

$$WP90(i, j, k) = \frac{\sum_{i=1}^{n(j)} I(i, j, k)}{n(j)}, \quad (\text{A.10})$$

where i represents the day, j the month, k the year, and $n(j)$ the number of days in the month j .

Then the standardisation is as usual:

$$W_{std}(j, k) = \frac{WP90(j, k) - \mu_{ref}WP90(j)}{\sigma_{ref}WP(j)}. \quad (\text{A.11})$$

A.5 Sea level, S

Monthly mean ocean and sea level measurements are obtained from tide gauges, which record changes in sea level relative to the sea floor (vertical measure). To avoid negative values, a revised local reference is defined, approximately 7 metres below mean sea level, (see Permanent Service for Mean Sea Level (PSMSL), 2023). It is important to note that the height of the land relative to sea level is subject to change due to crustal movements, and these measurements encompass the combined effects of land and ocean positional changes. The standardised anomalies in sea level are calculated using the following equation:

$$S_{std}(j, k) = \frac{S(j, k) - \mu_{ref}S(j)}{\sigma_{ref}S(j)}. \quad (\text{A.12})$$

A.6 The composite ACI index

The standardised anomalies of the six components above are then combined and averaged to produce the Actuaries Climate Index™; note that the minimum temperature anomaly $T10_{std}$ is subtracted, because the temperature probability distribution curve shifts to the right, as explained earlier:

$$ACI = \frac{1}{6}(T90_{std} - T10_{std} + P_{std} + D_{std} + W_{std} + S_{std}). \quad (\text{A.13})$$

Figure A.1 plots the 5-year moving averages of this composite ACI, as well as those of its 6 components.

Note the significant increasing trends in the ocean and sea level S_{std} and high temperature $T90_{std}$ moving averages, as well as in the ACI. Similarly, the low temperature $T10_{std}$ averages decrease significantly, given their negative signs they make an important positive contribution to the ACI.

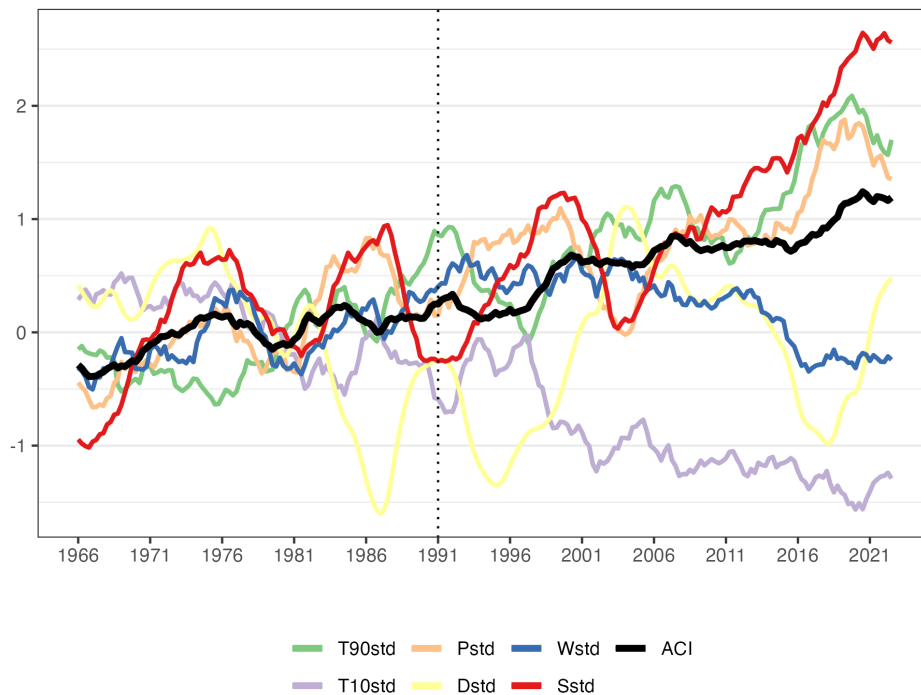


Figure A.1. 5-year moving averages, ACI, and its 6 components

Source: Zhou, Vilar Zanón, Garrido, Heras Martínez (2023, AIAE)

Appendix B The distribution of standardised anomalies

The methodology developed to define the North American ACI is based on the comparison of the standardised anomalies in 6 variables, during and after the 1961-1990 reference period. One might question if centring and standardising variables, by removing the mean and dividing by the standard deviation, is appropriate for variables that might not be symmetrically distributed around their mean. Especially when these variables measure extremes in the distribution rather than their average.

Figure B.1 plots the histograms of the standardised anomalies for each of the 6 FACI components, in blue for their value during reference period, and in red for the anomalies values after 1990.

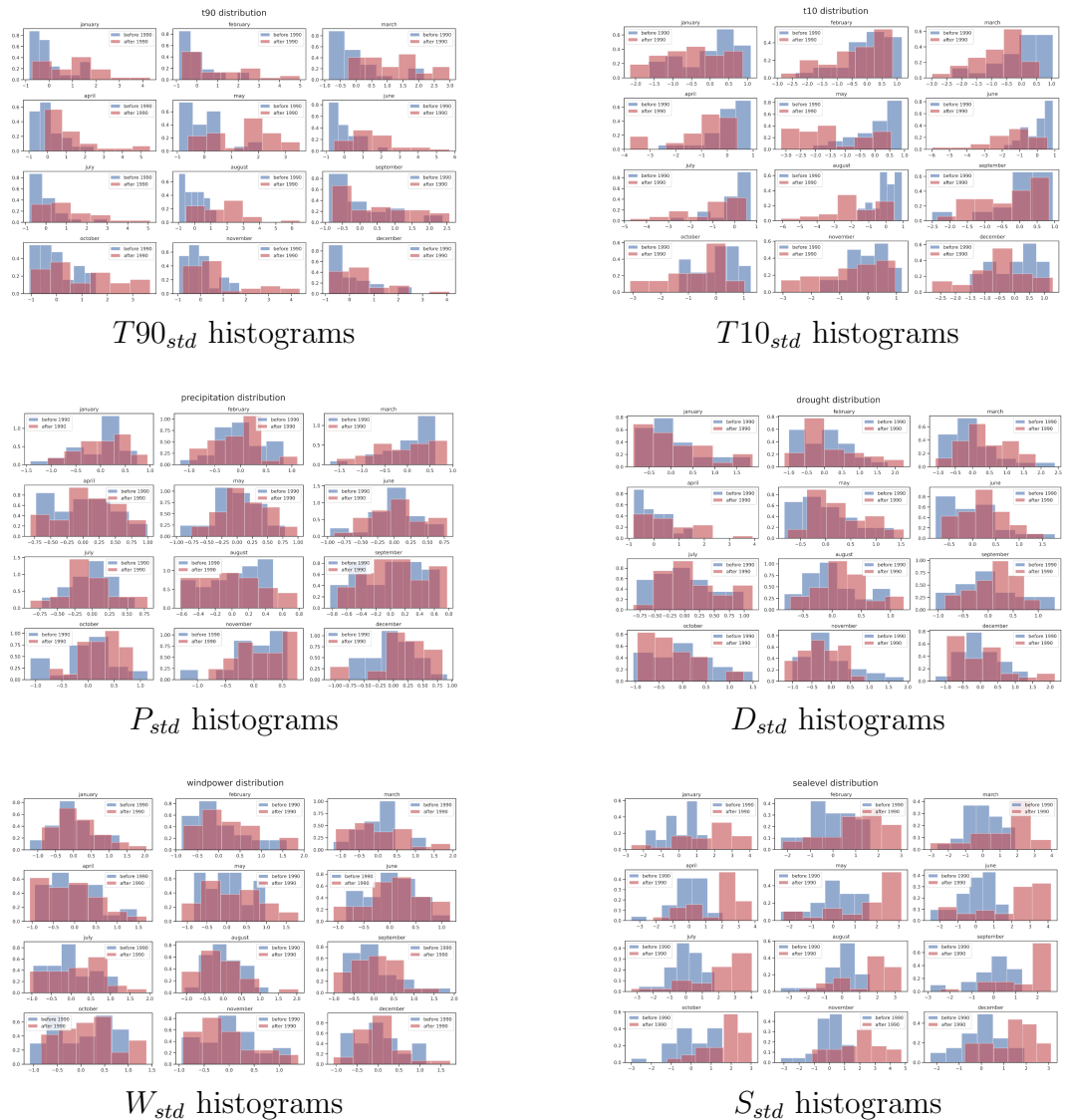


Figure B.1. Histograms of standardised anomalies, before and after 1990

These histograms vary substantially from one component to another, and between months. In general they are not symmetric about 0, neither before 1990 when that is their mean value, nor after 1990. It is better to proceed with the analysis one component at the time.

None of the histograms of the frequency of extreme warm temperature events ($T90_{std}$) are symmetric, and their right skewness is stronger before 1990 than after. What is clear is that the anomalies reach much larger positive values since 1990. The conclusions are similar for the frequency of extreme cold temperature events ($T10_{std}$), except that the skewness here is to the left and so is the range extension, reaching more negative values since 1990.

With regards to the the maximum 5-day precipitation (P_{std}) histograms, they vary less than those for temperature, perhaps with the exception of the end-of-the-year months, October, November and December. Here the left skewness gets stronger after 1990, that means that the Falls are either getting wetter, or the heavy rains come in later than during the reference period. Couple this to what is observed from the histograms for the the maximum number of consecutive days with a precipitation less than 1 millimetre (D_{std}). A drastic change in distribution, before and after 1998, occurs in the months of April, showing that it is mainly in the Spring that droughts are worse now in France and Corsica than during the reference period.

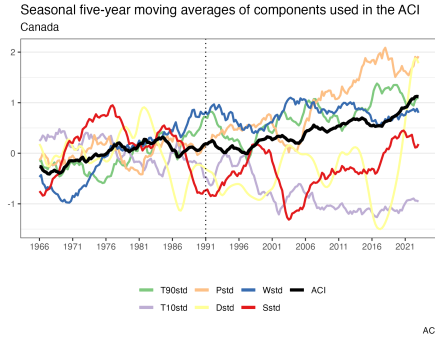
The mean daily wind power (W_{std}) histograms show a much longer right tail for most months, after 1990, in France and Corsica.

Finally, the ocean and sea level variable (S_{std}) exhibits the most significant change, before and after 1990. The distribution shifts to the right, uniformly, which produces a strong left tail in most months.

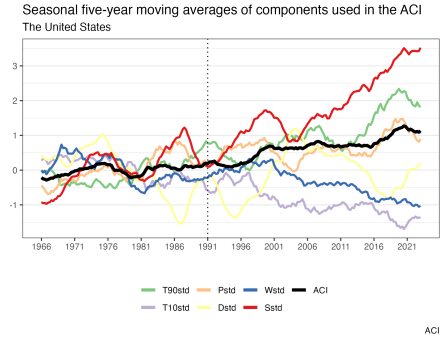
In summary, most components of the FACI are not symmetrically distributed, especially after 1990. Hence, the standardisation used for the North American ACI, subtracting the reference period mean and diving it by the standard deviation, is not the most appropriate for skewed observations. This aspect of the methodology will have to be revisited in future versions of the index for France.

Appendix C Country comparisons: Canada, the USA, Portugal, Spain and France

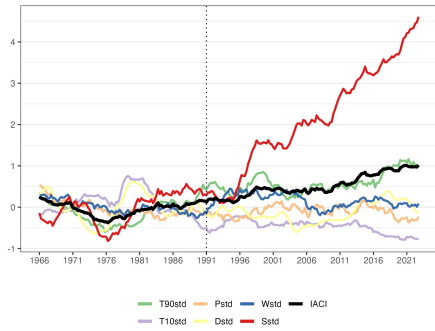
C.1 Indices and their 6 components



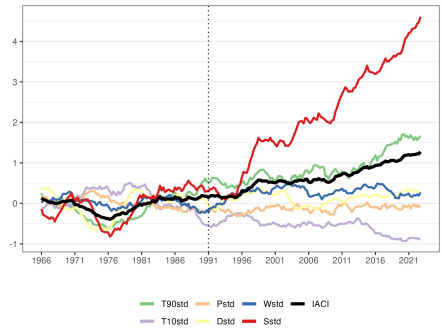
C: ACI and its 6 components



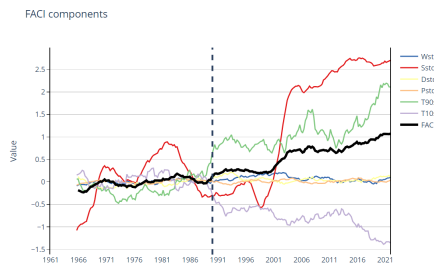
US: ACI and its 6 components



P: IACI and its 6 components



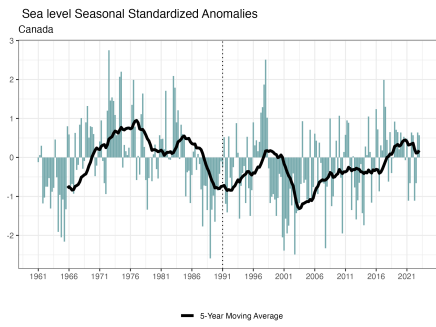
S: IACI and its 6 components



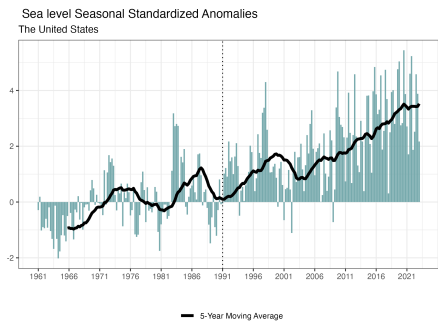
F: FACI and its 6 components

Figure C.1. 5-year averages: seasonal indices and 6 components, for Canada (C), USA (US), Portugal (P), Spain (S) and France (F)

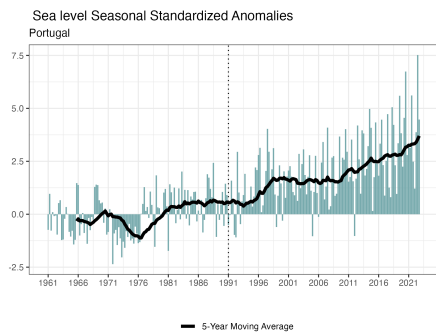
C.2 Sea level comparisons, S_{std}



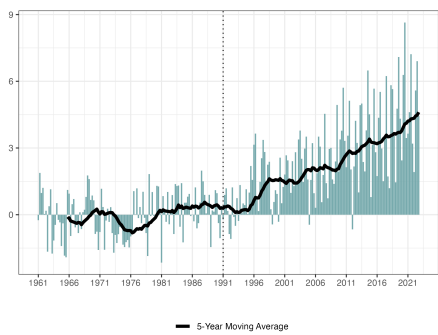
Canada: Sea level component



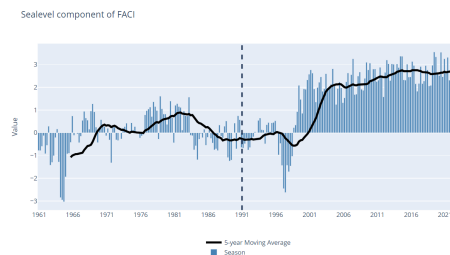
US: Sea level component



Portugal: Sea level component



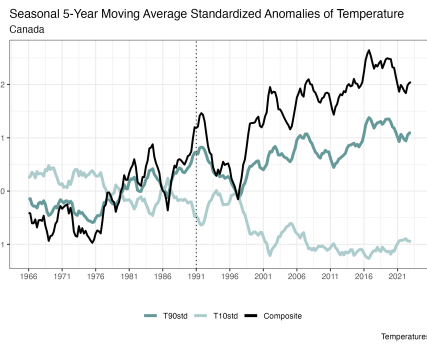
Spain: Sea level component



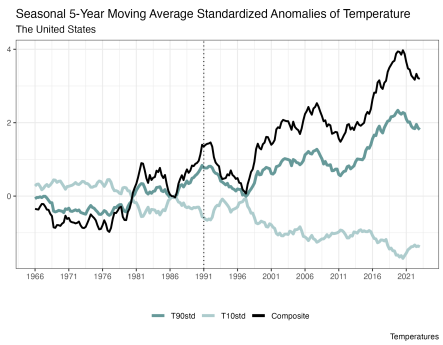
France: Sea level component

Figure C.2. 5-year averages: seasonal sea level component, for Canada, USA, Portugal, Spain and France

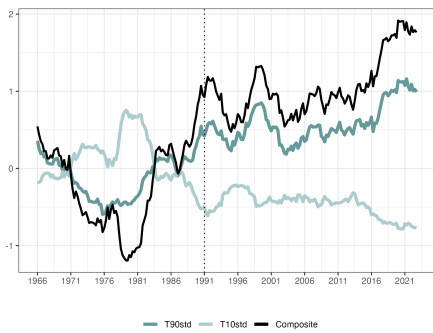
C.3 Temperatures $T_{90_{std}}$, $T_{10_{std}}$ and $T_{90_{std}} - T_{10_{std}}$



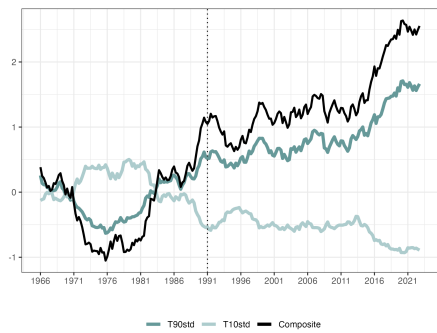
Canada: Temperature components



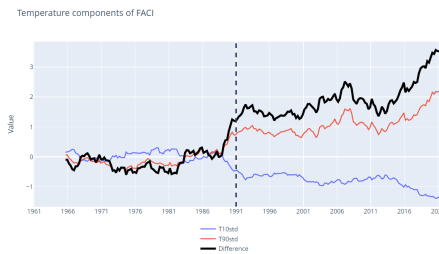
US: Temperature components



Portugal: Temperature components



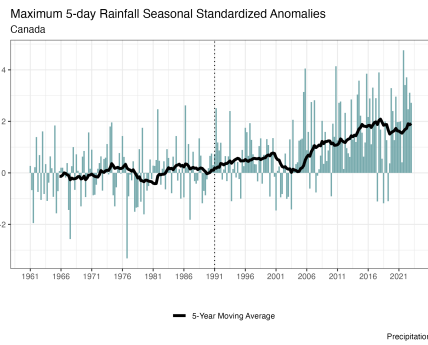
Spain: Temperature components



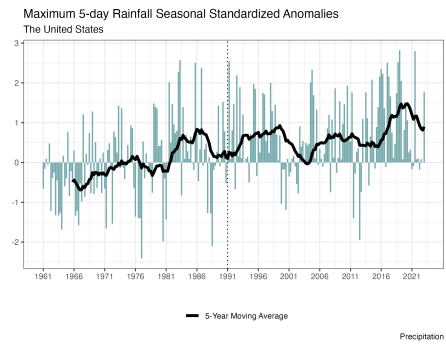
France: Temperature components

Figure C.3. 5-year averages: seasonal temperature components, for Canada, USA, Portugal, Spain and France

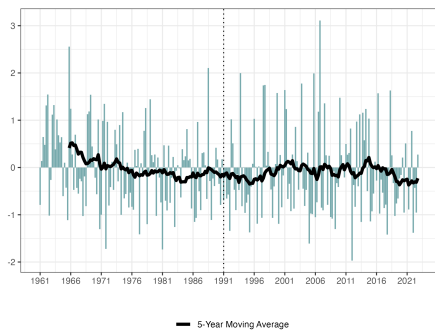
C.4 Precipitation component, P_{std}



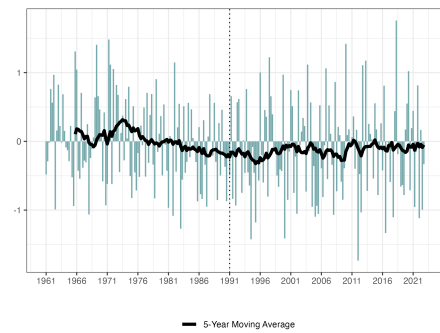
Canada: Precipitation component



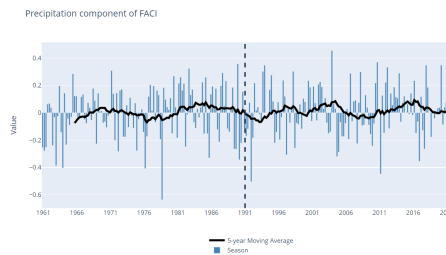
US: Precipitation component



Portugal: Precipitation component



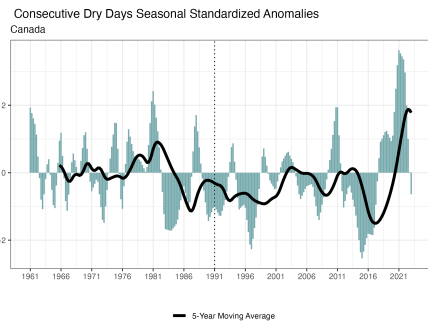
Spain: Precipitation component



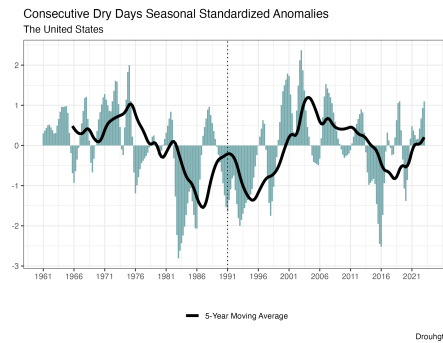
France: Precipitation component

Figure C.4. 5-year averages: seasonal precipitation component, for Canada, USA, Portugal, Spain and France

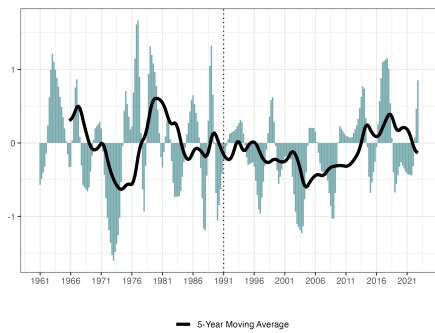
C.5 Drought component, D_{std}



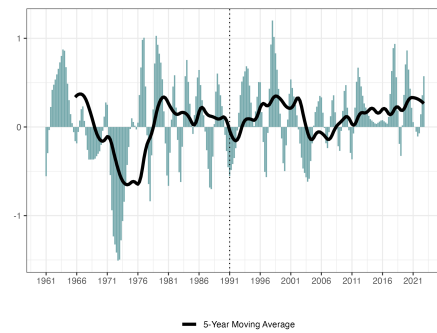
Canada: Drought component



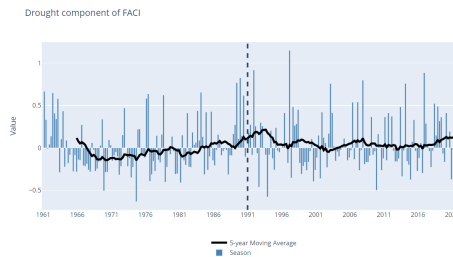
US: Drought component



Portugal: Drought component



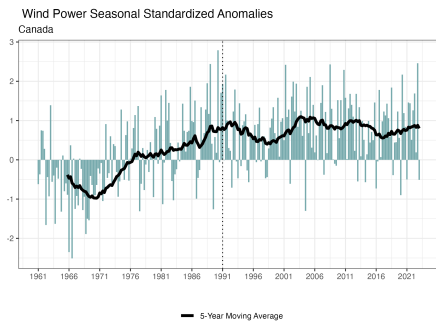
Spain: Drought component



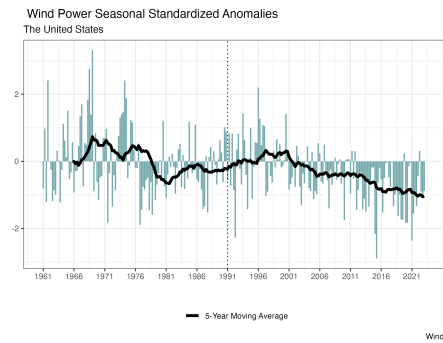
France: Drought component

Figure C.5. 5-year averages: seasonal drought component, for Canada, USA, Portugal, Spain and France

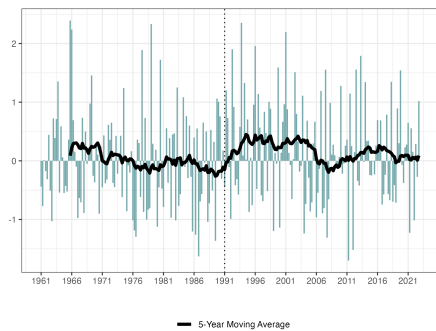
C.6 Wind component, W_{std}



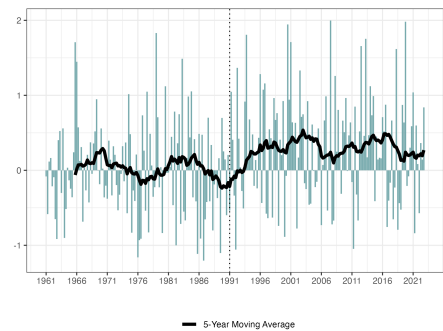
Canada: Wind component



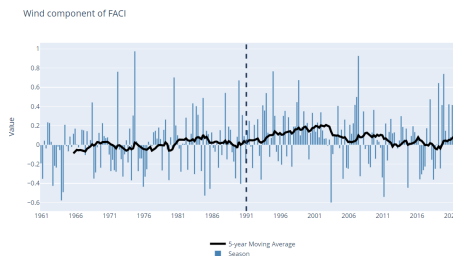
US: Wind component



Portugal: Wind component



Spain: Wind component



France: Wind component

Figure C.6. 5-year averages: seasonal wind component, for Canada, USA, Portugal, Spain and France

Appendix D Parametric insurance: fit of continuous distributions to monthly FACI values

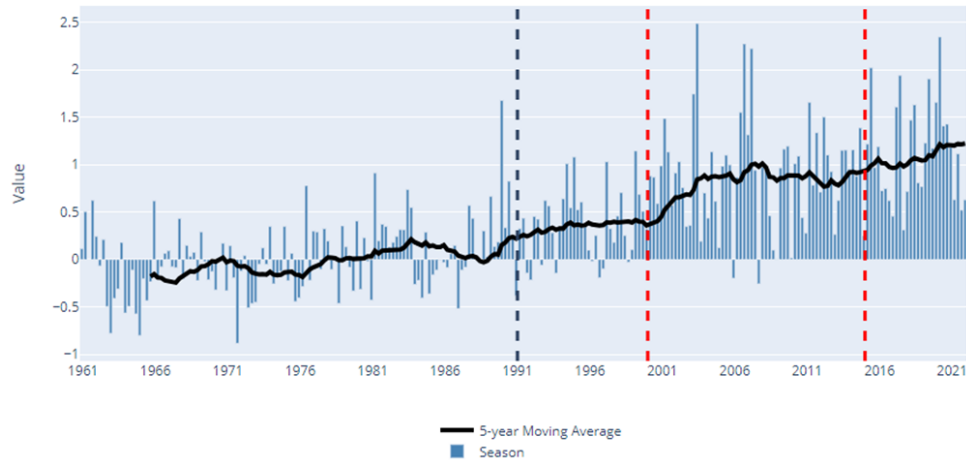


Figure D.1. Training period, monthly FACI values

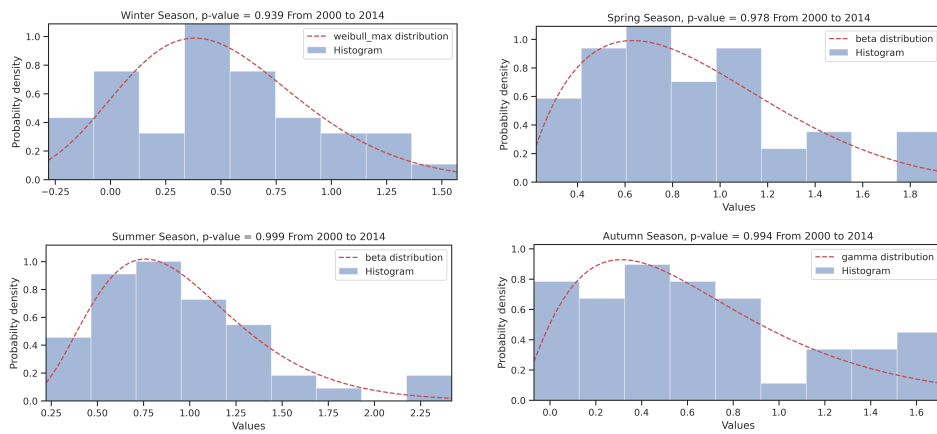


Figure D.2. Fitted parametric distributions, per season, to monthly FACI values over the 2000–2014 training period

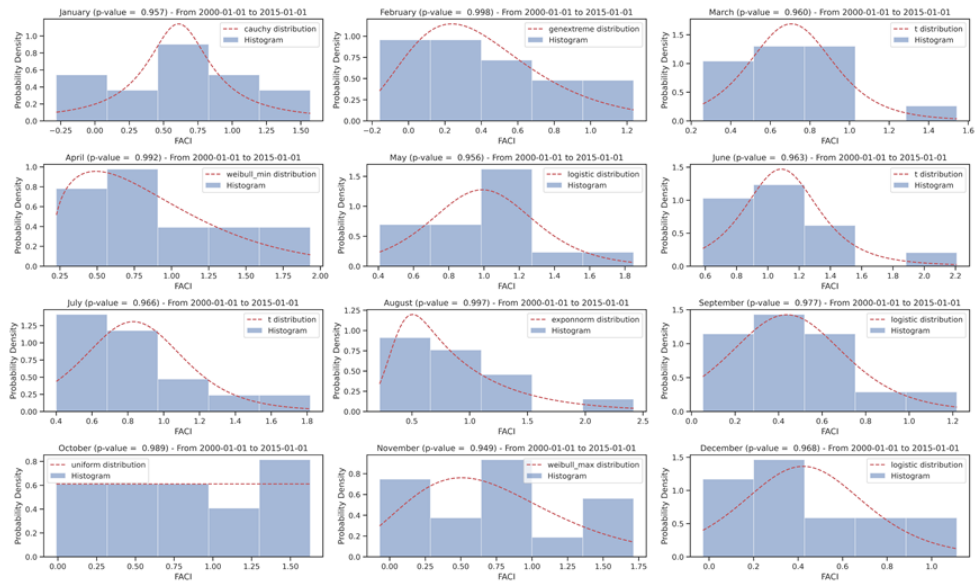


Figure D.3. Fitted parametric distributions, per month, to monthly FACI values over the 2000–2014 training period

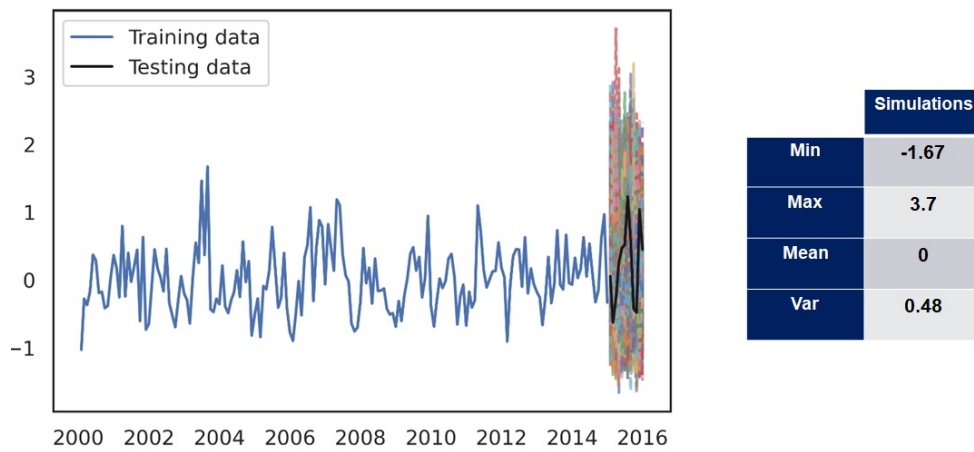


Figure D.4. Simulated monthly FACI values

Parameters						Estimated benefit payoff					Actual	Pure
E	E value	X (%)	X value	P.F.	θ (%)	Mean	Std	median	75%	min-max	payoff	prem.
med.	-0.062	75	0.331	1	3	170.18	57.86	168.76	208.67	0- 370.46	279.36	175.28
med.	-0.062	75	0.331	1	5	170.18	57.86	168.76	208.67	0- 370.46	279.36	178.69
med.	-0.062	75	0.331	1	10	170.18	57.86	168.76	208.67	0- 370.46	279.36	187.20
med.	-0.062	75	0.331	3	3	170.18	57.86	168.76	208.67	0- 370.46	279.36	171.92
med.	-0.062	75	0.331	3	5	170.18	57.86	168.76	208.67	0- 370.46	279.36	173.07
med.	-0.062	75	0.331	3	10	170.18	57.86	168.76	208.67	0- 370.46	279.36	175.97
med.	-0.062	90	0.626	1	3	227.17	85.23	222.53	283.53	0- 526.62	406.55	233.99
med.	-0.062	90	0.626	1	5	227.17	85.23	222.53	283.53	0- 526.62	406.55	238.53
med.	-0.062	90	0.626	1	10	227.17	85.23	222.53	283.53	0- 526.62	406.55	249.89
med.	-0.062	90	0.626	3	3	227.17	85.23	222.53	283.53	0- 526.62	406.55	229.73
med.	-0.062	90	0.626	3	5	227.17	85.23	222.53	283.53	0- 526.62	406.55	231.44
med.	-0.062	90	0.626	3	10	227.17	85.23	222.53	283.53	0- 526.62	406.55	235.70
med.	-0.062	99.5	1.481	1	3	262.87	111.45	253.87	333.42	0- 808.52	507.83	270.76
med.	-0.062	99.5	1.481	1	5	262.87	111.45	253.87	333.42	0-808.52	507.83	276.02
med.	-0.062	99.5	1.481	1	10	262.87	111.45	253.87	333.42	0- 808.52	507.83	289.16
med.	-0.062	99.5	1.481	3	3	262.87	111.45	253.87	333.42	0- 808.52	507.83	266.22
med.	-0.062	99.5	1.481	3	5	262.87	111.45	253.87	333.42	0- 808.52	507.83	268.45
med.	-0.062	99.5	1.481	3	10	262.87	111.45	253.87	333.42	0- 808.52	507.83	274.02
mean	0	75	0.331	1	3	133.82	48.77	132.26	165.47	0- 308.22	229.57	137.84
mean	0	75	0.331	1	5	133.82	48.77	132.26	165.47	0- 308.22	229.57	140.51
mean	0	75	0.331	1	10	133.82	48.77	132.26	165.47	0- 308.22	229.57	147.20
mean	0	75	0.331	3	3	133.82	48.77	132.26	165.47	0- 308.22	229.57	135.28
mean	0	75	0.331	3	5	133.82	48.77	132.26	165.47	0-308.22	229.57	136.26
mean	0	75	0.331	3	10	133.82	48.77	132.26	165.47	0-308.22	229.57	138.70
mean	0	90	0.626	1	3	190.82	77.05	186.8	241.47	0- 462.64	356.76	196.54
mean	0	90	0.626	1	5	190.82	77.05	186.8	241.47	0- 462.64	356.76	200.36
mean	0	90	0.626	1	10	190.82	77.05	186.8	241.47	0- 462.64	356.76	209.90
mean	0	90	0.626	3	3	190.82	77.05	186.8	241.47	0- 462.64	356.76	193.13
mean	0	90	0.626	3	5	190.82	77.05	186.8	241.47	0- 462.64	356.76	194.67
mean	0	90	0.626	3	10	190.82	77.05	186.8	241.47	0- 462.64	356.76	198.52
mean	0	99.5	1.481	1	3	226.52	104.17	215.53	291.6	0- 746.79	458.04	233.31
mean	0	99.5	1.481	1	5	226.52	104.17	215.53	291.6	0- 746.79	458.04	237.84
mean	0	99.5	1.481	1	10	226.52	104.17	215.53	291.6	0- 746.79	458.04	249.17
mean	0	99.5	1.481	3	3	226.52	104.17	215.53	291.6	0- 746.79	458.04	229.64
mean	0	99.5	1.481	3	5	226.52	104.17	215.53	291.6	0- 746.79	458.04	231.72
mean	0	99.5	1.481	3	10	226.52	104.17	215.53	291.6	0- 746.79	458.04	236.93

Table D.1. Parametric insurance – annual coverage premiums (X (%) and θ (%) in percent, P.F. = Premium Formula, Std = standard deviation, prem. = premium)

Parameters						Estimated benefit payoff					Actual payoff	Pure prem.
E	E value	X (%)	X value	P.F.	θ (%)	Mean	Std	median	75%	min-max		
med.	0.138	75	0.445	1	3	136.97	47.41	134.78	168.3	0- 304.89	92.25	141.08
med.	0.138	75	0.445	1	5	136.97	47.41	134.78	168.3	0- 304.89	92.25	143.82
med.	0.138	75	0.445	1	10	136.97	47.41	134.78	168.3	0- 304.89	92.25	150.67
med.	0.138	75	0.445	3	3	136.97	47.41	134.78	168.3	0- 304.89	92.25	138.39
med.	0.138	75	0.445	3	5	136.97	47.41	134.78	168.3	0- 304.89	92.25	139.34
med.	0.138	75	0.445	3	10	136.97	47.41	134.78	168.3	0- 304.89	92.25	141.71
med.	0.138	90	0.687	1	3	194.16	74.13	190.93	241.5	0- 473.21	136.56	199.99
med.	0.138	90	0.687	1	5	194.16	74.13	190.93	241.5	0- 473.21	136.56	203.87
med.	0.138	90	0.687	1	10	194.16	74.13	190.93	241.5	0- 473.21	136.56	213.58
med.	0.138	90	0.687	3	3	194.16	74.13	190.93	241.5	0- 473.21	136.56	196.39
med.	0.138	90	0.687	3	5	194.16	74.13	190.93	241.5	0- 473.21	136.56	197.87
med.	0.138	90	0.687	3	10	194.16	74.13	190.93	241.5	0- 473.21	136.56	201.58
med.	0.138	99.5	1.622	1	3	249.81	112.54	240.44	319.5	0- 826.78	190.55	257.31
med.	0.138	99.5	1.622	1	5	249.81	112.54	240.44	319.5	0- 826.78	190.55	262.3
med.	0.138	99.5	1.622	1	10	249.81	112.54	240.44	319.5	0- 826.78	190.55	274.79
med.	0.138	99.5	1.622	3	3	249.81	112.54	240.44	319.5	0- 826.78	190.55	253.19
med.	0.138	99.5	1.622	3	5	249.81	112.54	240.44	319.5	0- 826.78	190.55	255.44
med.	0.138	99.5	1.622	3	10	249.81	112.54	240.44	319.5	0- 826.78	190.55	261.06
mean	0.209	75	0.445	1	3	97.2	36.82	94.66	120.8	0- 233.93	70.96	100.12
mean	0.209	75	0.445	1	5	97.2	36.82	94.66	120.8	0- 233.93	70.96	102.06
mean	0.209	75	0.445	1	10	97.2	36.82	94.66	120.8	0- 233.93	70.96	106.92
mean	0.209	75	0.445	3	3	97.2	36.82	94.66	120.8	0- 233.93	70.96	98.31
mean	0.209	75	0.445	3	5	97.2	36.82	94.66	120.8	0- 233.93	70.96	99.05
mean	0.209	75	0.445	3	10	97.2	36.82	94.66	120.8	0- 233.93	70.96	100.89
mean	0.209	90	0.687	1	3	154.39	64.51	150.98	195.19	0- 409.35	115.28	159.03
mean	0.209	90	0.687	1	5	154.39	64.51	150.98	195.19	0- 409.35	115.28	162.11
mean	0.209	90	0.687	1	10	154.39	64.51	150.98	195.19	0- 409.35	115.28	169.83
mean	0.209	90	0.687	3	3	154.39	64.51	150.98	195.19	0- 409.35	115.28	156.33
mean	0.209	90	0.687	3	5	154.39	64.51	150.98	195.19	0- 409.35	115.28	157.62
mean	0.209	90	0.687	3	10	154.39	64.51	150.98	195.19	0- 409.35	115.28	160.85
mean	0.209	99.5	1.622	1	3	210.04	104.38	199.94	274.08	0- 770.01	169.27	216.35
mean	0.209	99.5	1.622	1	5	210.04	104.38	199.94	274.08	0- 770.01	169.27	220.55
mean	0.209	99.5	1.622	1	10	210.04	104.38	199.94	274.08	0- 770.01	169.27	231.05
mean	0.209	99.5	1.622	3	3	210.04	104.38	199.94	274.08	0- 770.01	169.27	213.18
mean	0.209	99.5	1.622	3	5	210.04	104.38	199.94	274.08	0- 770.01	169.27	215.26
mean	0.209	99.5	1.622	3	10	210.04	104.38	199.94	274.08	0- 770.01	169.27	220.48

Table D.2. Parametric insurance – seasonal summer coverage premiums (X (%) and θ (%) in percent, P.F. = Premium Formula, Std = standard deviation, prem. = premium)

Parameters						Estimated benefit payoff					Actual	Pure
E	E value	X (%)	X value	P.F.	θ (%)	Mean	Std	median	75%	min-max	payoff	prem.
med.	-0.158	75	0.166	1	3	139.59	48.73	137.32	171.09	0- 337.38	32.37	143.78
med.	-0.158	75	0.166	1	5	139.59	48.73	137.32	171.09	0- 337.38	32.37	146.57
med.	-0.158	75	0.166	1	10	139.59	48.73	137.32	171.09	0- 337.38	32.37	153.55
med.	-0.158	75	0.166	3	3	139.59	48.73	137.32	171.09	0- 337.38	32.37	141.05
med.	-0.158	75	0.166	3	5	139.59	48.73	137.32	171.09	0- 337.38	32.37	142.03
med.	-0.158	75	0.166	3	10	139.59	48.73	137.32	171.09	0- 337.38	32.37	144.46
med.	-0.158	90	0.649	1	3	236.53	95.63	230.06	298.66	0- 614.23	80.69	243.63
med.	-0.158	90	0.649	1	5	236.53	95.63	230.06	298.66	0- 614.23	80.69	248.36
med.	-0.158	90	0.649	1	10	236.53	95.63	230.06	298.66	0- 614.23	80.69	260.18
med.	-0.158	90	0.649	3	3	236.53	95.63	230.06	298.66	0- 614.23	80.69	239.4
med.	-0.158	90	0.649	3	5	236.53	95.63	230.06	298.66	0- 614.23	80.69	241.31
med.	-0.158	90	0.649	3	10	236.53	95.63	230.06	298.66	0- 614.23	80.69	246.09
med.	-0.158	99.5	0.959	1	3	262.81	113.32	252.98	334.17	0- 753.11	111.71	270.69
med.	-0.158	99.5	0.959	1	5	262.81	113.32	252.98	334.17	0- 753.11	111.71	275.95
med.	-0.158	99.5	0.959	1	10	262.81	113.32	252.98	334.17	0- 753.11	111.71	289.09
med.	-0.158	99.5	0.959	3	3	262.81	113.32	252.98	334.17	0- 753.11	111.71	266.21
med.	-0.158	99.5	0.959	3	5	262.81	113.32	252.98	334.17	0- 753.11	111.71	268.47
med.	-0.158	99.5	0.959	3	10	262.81	113.32	252.98	334.17	0- 753.11	111.71	274.14
mean	-0.079	75	0.166	1	3	97.69	36.93	97.74	122.21	0- 250.2	24.44	100.62
mean	-0.079	75	0.166	1	5	97.69	36.93	97.74	122.21	0- 250.2	24.44	102.57
mean	-0.079	75	0.166	1	10	97.69	36.93	97.74	122.21	0- 250.2	24.44	107.46
mean	0.079	75	0.166	3	3	97.69	36.93	97.74	122.21	0- 250.2	24.44	98.8
mean	-0.079	75	0.166	3	5	97.69	36.93	97.74	122.21	0- 250.2	24.44	99.53
mean	-0.079	75	0.166	3	10	97.69	36.93	97.74	122.21	0- 250.2	24.44	101.38
mean	-0.079	90	0.649	1	3	194.63	85.62	187.81	250.13	0- 534.97	72.77	200.47
mean	-0.079	90	0.649	1	5	194.63	85.62	187.81	250.13	0- 534.97	72.77	204.36
mean	-0.079	90	0.649	1	10	194.63	85.62	187.81	250.13	0- 534.97	72.77	214.09
mean	-0.079	90	0.649	3	3	194.63	85.62	187.81	250.13	0- 534.97	72.77	197.2
mean	-0.079	90	0.649	3	5	194.63	85.62	187.81	250.13	0- 534.97	72.77	198.91
mean	-0.079	90	0.649	3	10	194.63	85.62	187.81	250.13	0- 534.97	72.77	203.19
mean	-0.079	99.5	0.959	1	3	220.9	104	212.68	287.36	0- 673.85	103.78	227.53
mean	-0.079	99.5	0.959	1	5	220.9	104	212.68	287.36	0- 673.85	103.78	231.95
mean	-0.079	99.5	0.959	1	10	220.9	104	212.68	287.36	0- 673.85	103.78	242.99
mean	-0.079	99.5	0.959	3	3	220.9	104	212.68	287.36	0- 673.85	103.78	224.02
mean	-0.079	99.5	0.959	3	5	220.9	104	212.68	287.36	0- 673.85	103.78	226.1
mean	-0.079	99.5	0.959	3	10	220.9	104	212.68	287.36	0- 673.85	103.78	231.3

Table D.3. Parametric insurance – seasonal fall coverage premiums (X (%) and θ (%) in percent, P.F. = Premium Formula, Std = standard deviation, prem. = premium)

Parameters						Estimated benefit payoff					Actual payoff	Pure prem.
E	E value	X (%)	X value	P.F.	θ (%)	Mean	Std	median	75%	min-max		
med.	-0.303	75	-0.049	1	3	119.49	39.32	118.86	146.13	0- 266.05	50.7	123.08
med.	-0.303	75	-0.049	1	5	119.49	39.32	118.86	146.13	0- 266.05	50.7	125.47
med.	-0.303	75	-0.049	1	10	119.49	39.32	118.86	146.13	0- 266.05	50.7	131.44
med.	-0.303	75	-0.049	3	3	119.49	39.32	118.86	146.13	0- 266.05	50.7	120.67
med.	-0.303	75	-0.049	3	5	119.49	39.32	118.86	146.13	0- 266.05	50.7	121.46
med.	-0.303	75	-0.049	3	10	119.49	39.32	118.86	146.13	0- 266.05	50.7	123.42
med.	-0.303	90	0.348	1	3	199.78	78.25	195.69	250.4	0- 519.36	100.73	205.78
med.	-0.303	90	0.348	1	5	199.78	78.25	195.69	250.4	0- 519.36	100.73	209.77
med.	-0.303	90	0.348	1	10	199.78	78.25	195.69	250.4	0- 519.36	100.73	219.76
med.	-0.303	90	0.348	3	3	199.78	78.25	195.69	250.4	0- 519.36	100.73	202.13
med.	-0.303	90	0.348	3	5	199.78	78.25	195.69	250.4	0- 519.36	100.73	203.7
med.	-0.303	90	0.348	3	10	199.78	78.25	195.69	250.4	0- 519.36	100.73	207.61
med.	-0.303	99.5	0.746	1	3	219.18	92.95	213.4	276.48	0- 645.83	110.69	225.75
med.	-0.303	99.5	0.746	1	5	219.18	92.95	213.4	276.48	0- 645.83	110.69	230.13
med.	-0.303	99.5	0.746	1	10	219.18	92.95	213.4	276.48	0- 645.83	110.69	241.09
med.	-0.303	99.5	0.746	3	3	219.18	92.95	213.4	276.48	0- 645.83	110.69	221.96
med.	-0.303	99.5	0.746	3	5	219.18	92.95	213.4	276.48	0- 645.83	110.69	223.82
med.	-0.303	99.5	0.746	3	10	219.18	92.95	213.4	276.48	0- 645.83	110.69	228.47
mean	-0.258	75	-0.049	1	3	93.27	32.53	92.61	114.96	0- 216.81	41.75	96.07
mean	-0.258	75	-0.049	1	5	93.27	32.53	92.61	114.96	0- 216.81	41.75	97.94
mean	-0.258	75	-0.049	1	10	93.27	32.53	92.61	114.96	0- 216.81	41.75	102.6
mean	-0.258	75	-0.049	3	3	93.27	32.53	92.61	114.96	0- 216.81	41.75	94.25
mean	-0.258	75	-0.049	3	5	93.27	32.53	92.61	114.96	0- 216.81	41.75	94.9
mean	-0.258	75	-0.049	3	10	93.27	32.53	92.61	114.96	0- 216.81	41.75	96.53
mean	-0.258	90	0.348	1	3	173.56	72.52	168.98	220.31	0- 478.59	91.78	178.77
mean	-0.258	90	0.348	1	5	173.56	72.52	168.98	220.31	0- 478.59	91.78	182.24
mean	-0.258	90	0.348	1	10	173.56	72.52	168.98	220.31	0- 478.59	91.78	190.92
mean	-0.258	90	0.348	3	3	173.56	72.52	168.98	220.31	0- 478.59	91.78	175.74
mean	-0.258	90	0.348	3	5	173.56	72.52	168.98	220.31	0- 478.59	91.78	177.19
mean	-0.258	90	0.348	3	10	173.56	72.52	168.98	220.31	0- 478.59	91.78	180.82
mean	-0.258	99.5	0.746	1	3	192.96	87.63	186.95	246.63	0- 605.06	101.74	198.75
mean	-0.258	99.5	0.746	1	5	192.96	87.63	186.95	246.63	0- 605.06	101.74	202.61
mean	-0.258	99.5	0.746	1	10	192.96	87.63	186.95	246.63	0- 605.06	101.74	212.25
mean	-0.258	99.5	0.746	3	3	192.96	87.63	186.95	246.63	0- 605.06	101.74	195.59
mean	-0.258	99.5	0.746	3	5	192.96	87.63	186.95	246.63	0- 605.06	101.74	197.34
mean	-0.258	99.5	0.746	3	10	192.96	87.63	186.95	246.63	0- 605.06	101.74	201.72

Table D.4. Parametric insurance – seasonal winter coverage premiums (X (%) and θ (%) in percent, P.F. = Premium Formula, Std = standard deviation, prem. = premium)

Parameters						Estimated benefit payoff					Actual payoff	Pure prem.
E	E value	$X(\%)$	X value	P.F.	$\theta(\%)$	Mean	Std	median	75%	min-max		
med.	0.044	75	0.35	1	3	143.08	47.39	142.44	174.63	1.3- 313.37	52.05	147.38
med.	0.044	75	0.35	1	5	143.08	47.39	142.44	174.63	1.3- 313.37	52.05	150.24
med.	0.044	75	0.35	1	10	143.08	47.39	142.44	174.63	1.3- 313.37	52.05	157.39
med.	0.044	75	0.35	3	3	143.08	47.39	142.44	174.63	1.3- 313.37	52.05	144.51
med.	0.044	75	0.35	3	5	143.08	47.39	142.44	174.63	1.3- 313.37	52.05	145.45
med.	0.044	75	0.35	3	10	143.08	47.39	142.44	174.63	1.3- 313.37	52.05	147.82
med.	0.044	90	0.671	1	3	213.29	80.79	208.85	267.11	1.3- 527.47	63.48	219.68
med.	0.044	90	0.671	1	5	213.29	80.79	208.85	267.11	1.3- 527.47	63.48	223.95
med.	0.044	90	0.671	1	10	213.29	80.79	208.85	267.11	1.3- 527.47	63.48	234.61
med.	0.044	90	0.671	3	3	213.29	80.79	208.85	267.11	1.3- 527.47	63.48	215.71
med.	0.044	90	0.671	3	5	213.29	80.79	208.85	267.11	1.3- 527.47	63.48	217.33
med.	0.044	90	0.671	3	10	213.29	80.79	208.85	267.11	1.3- 527.47	63.48	221.37
med.	0.044	99.5	1.164	1	3	243.46	101.73	234.29	309.96	1.3- 654.26	63.48	250.77
med.	0.044	99.5	1.164	1	5	243.46	101.73	234.29	309.96	1.3- 654.26	63.48	255.63
med.	0.044	99.5	1.164	1	10	243.46	101.73	234.29	309.96	1.3- 654.26	63.48	267.81
med.	0.044	99.5	1.164	3	3	243.46	101.73	234.29	309.96	1.3- 654.26	63.48	246.51
med.	0.044	99.5	1.164	3	5	243.46	101.73	234.29	309.96	1.3- 654.26	63.48	248.55
med.	0.044	99.5	1.164	3	10	243.46	101.73	234.29	309.96	1.3- 654.26	63.48	253.63
mean	0.129	75	0.35	1	3	94.27	34.77	92.42	117.09	0- 221.78	35.17	97.1
mean	0.129	75	0.35	1	5	94.27	34.77	92.42	117.09	0- 221.78	35.17	98.98
mean	0.129	75	0.35	1	10	94.27	34.77	92.42	117.09	0- 221.78	35.17	103.7
mean	0.129	75	0.35	3	3	94.27	34.77	92.42	117.09	0- 221.78	35.17	95.31
mean	0.129	75	0.35	3	5	94.27	34.77	92.42	117.09	0- 221.78	35.17	96.01
mean	0.129	75	0.35	3	10	94.27	34.77	92.42	117.09	0- 221.78	35.17	97.75
mean	0.129	90	0.671	1	3	164.47	69.6	160.11	209.97	0- 434.64	46.61	169.41
mean	0.129	90	0.671	1	5	164.47	69.6	160.11	209.97	0- 434.64	46.61	172.7
mean	0.129	90	0.671	1	10	164.47	69.6	160.11	209.97	0- 434.64	46.61	180.92
mean	0.129	90	0.671	3	3	164.47	69.6	160.11	209.97	0- 434.64	46.61	166.56
mean	0.129	90	0.671	3	5	164.47	69.6	160.11	209.97	0- 434.64	46.61	167.95
mean	0.129	90	0.671	3	10	164.47	69.6	160.11	209.97	0- 434.64	46.61	171.43
mean	0.129	99.5	1.164	1	3	194.65	91.52	186.34	253.44	0- 561.43	46.61	200.49
mean	0.129	99.5	1.164	1	5	194.65	91.52	186.34	253.44	0- 561.43	46.61	204.38
mean	0.129	99.5	1.164	1	10	194.65	91.52	186.34	253.44	0- 561.43	46.61	214.11
mean	0.129	99.5	1.164	3	3	194.65	91.52	186.34	253.44	0- 561.43	46.61	197.39
mean	0.129	99.5	1.164	3	5	194.65	91.52	186.34	253.44	0- 561.43	46.61	199.22
mean	0.129	99.5	1.164	3	10	194.65	91.52	186.34	253.44	0- 561.43	46.61	203.8

Table D.5. Parametric insurance – seasonal spring coverage premiums ($X(\%)$ and $\theta(\%)$ in percent, P.F. = Premium Formula, Std = standard deviation, prem. = premium)