



Designing life levels of Extreme Temperature by 2100

Séminaire ASNR et EDF R&D

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January 6th 2025



Climate Change :

- IPCC's Assessment Report released in 2022 : 1°C Global warming level attained.
- Increase in **frequency and intensity** of extremely hot events.[1]
- Increasing knowledge of the warming phenomena, using both **observations and climate models**.
- For adaptation needs, **local projections** are necessary.

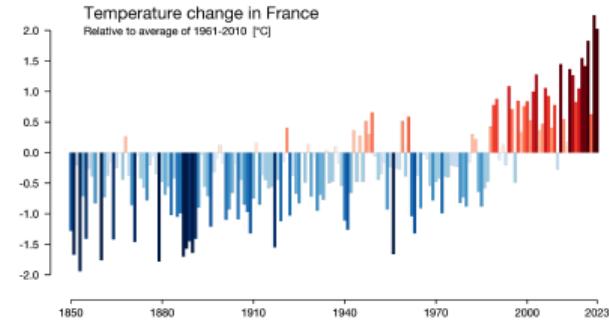


Figure: Anomaly of the annual mean temperature over France between 1850 and 2023. D'après:
[#ShowYourStripes](#)

Safety concerns :

- Reliability of **safety-significant equipment**.
- Building Codes using stationary return levels which may **vary during the building's life**.
- Danger for **Human's health** during heatwaves.

⇒ An **updated and well estimated index** is necessary .

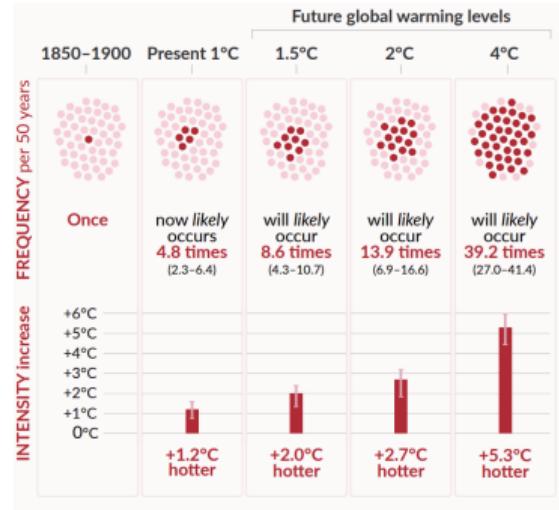


Figure: IPCC, 2021: Summary for Policymakers by Masson Delmotte, V et al.[3]

Our Goal: Defining the risk of extreme temperature levels excess by 2100 at a local scale.

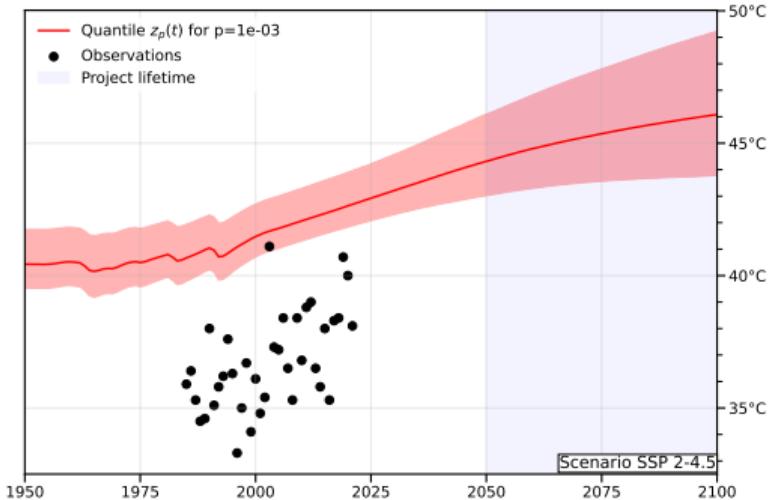
How?

- Adapting the stationary return level to a **non-stationary context**, considering the lifetime of the building.
- Estimating extreme temperature levels, integrating **information from climate models and local observations**, using tools based on Extreme Value Theory and a Bayesian framework.
- Providing a usable estimate taking **uncertainty** into account.
- Applying the method to **various places of interest**, such as Tricastin (South of France).

Issue:

Annual probability of excess **changes every year.**

Return Level is undefined.



Various index (S. Parey 2022):

- Design Life Level
- Equivalent Reliability
- Expected Waiting Time
- Statistical Upper Bound
- Average Design Life Level
- Expected Number of Events
- Amplification Factor

Needs:

- Separate the **period of interest** from the **return period** (annual probability $p = \frac{1}{T}$).
- Account for **non-stationnarity**, $Y_{2023} \neq Y_{2050}$.
- Applied similarly with or without stationarity.

Equivalent Reliability[4]:

For period $t_1 : t_2$ and annual probability p , \mathbf{z}_p is solution of :

$$P[\max(Y_{t_1}, Y_{t_1+1}, \dots, Y_{t_2}) \leq \mathbf{z}_p] = (1-p)^{t_2-t_1+1}$$

Constraints:

- **Extreme Values Analysis:** Annual Maxima, use of GEV distribution.
- **Non-stationarity:** Mean European Temperature as covariate for relationship with time and **scenario integration**.

$$Y \sim GEV(\mu_t, \sigma_t, \xi)$$

$$\begin{cases} \mu(t) = \mu_0 + \mu_1 X_t \\ \sigma(t) = \exp(\sigma_0 + \sigma_1 X_t) \\ \xi(t) = \xi_0 \end{cases}$$

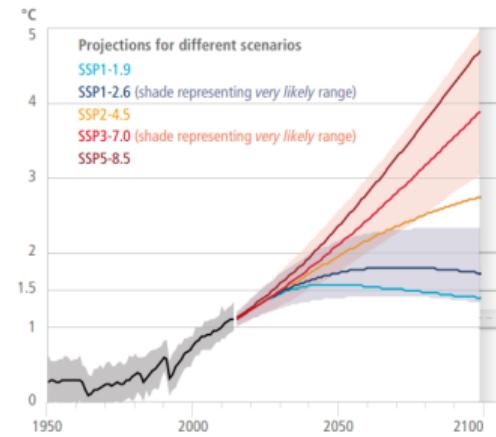
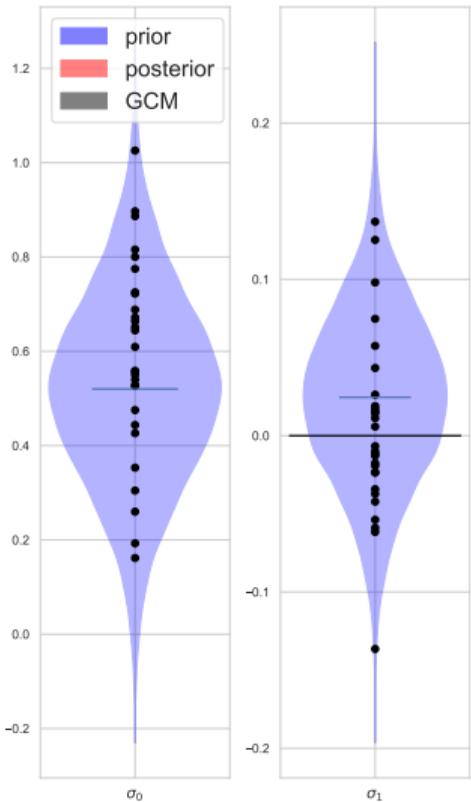


Figure: Global surface temperature changes for various scenarios. (IPCC, 2022)

Bayesian framework[5]

A-priori knowledge

- Include only information from **climate models**.
(historical and scenario).



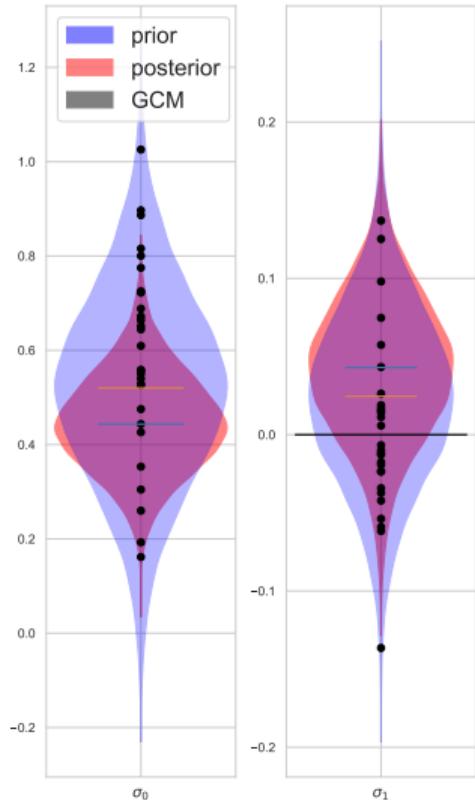
Bayesian framework[5]

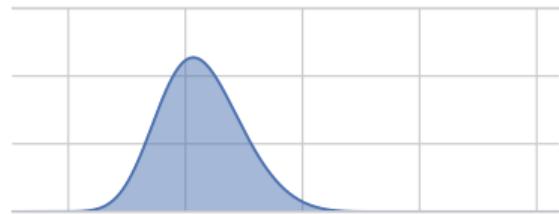
A-priori knowledge

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Updated using observations

- Maxima constraint using **Markov chain Monte Carlo** (NUTS).
- Using past local observations.

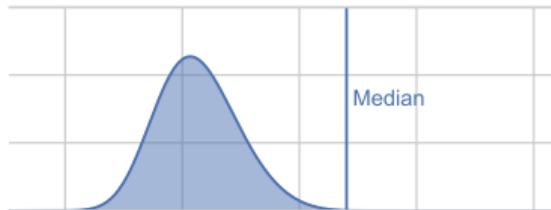




- Using all draws: for return levels
median

Median distribution Predictive distribution

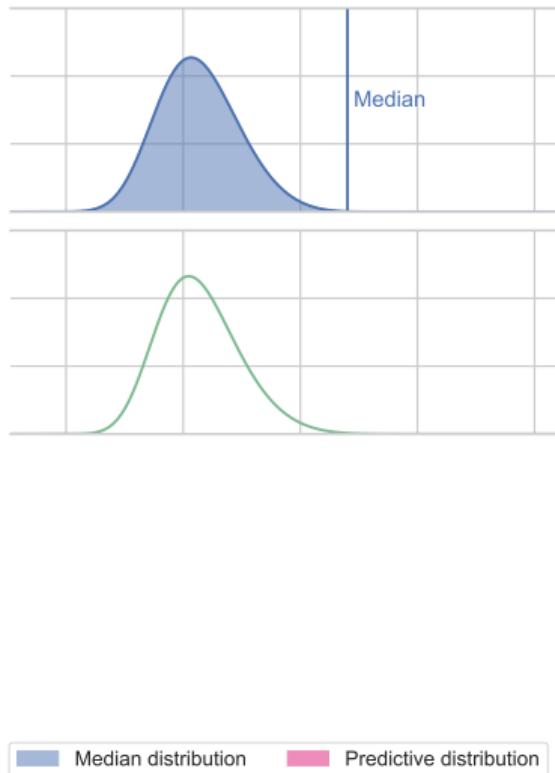
Predictive distribution - Illustration



- Using all draws: for return levels
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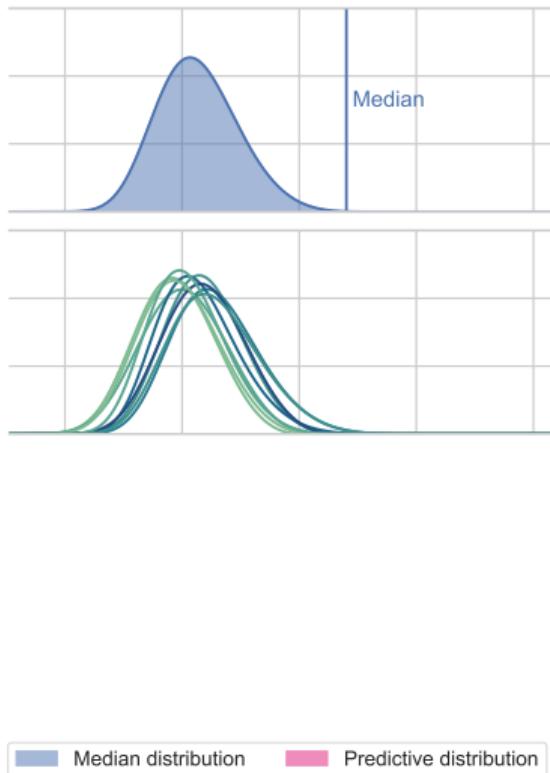
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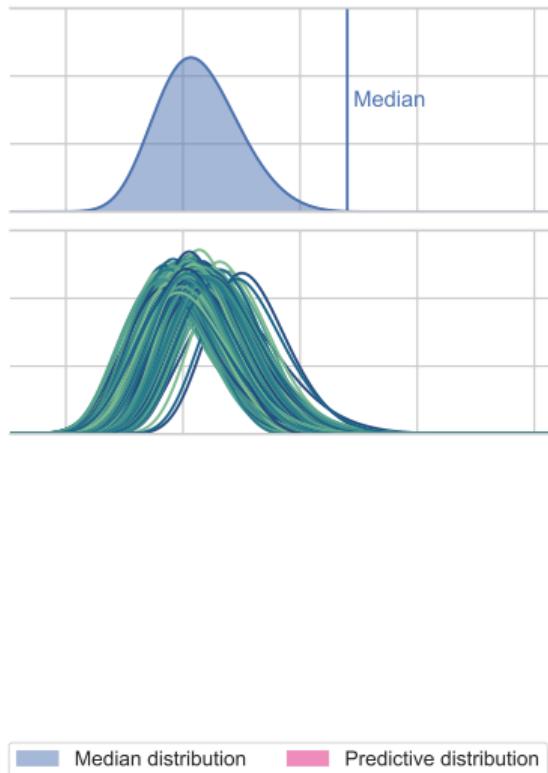


- Using all draws: for return levels **median**

Predictive distribution - Illustration

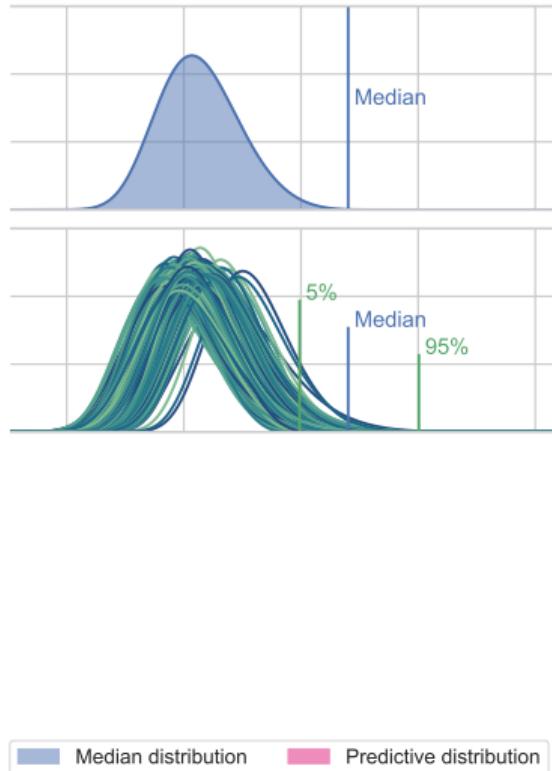


- Using all draws: for return levels **median**

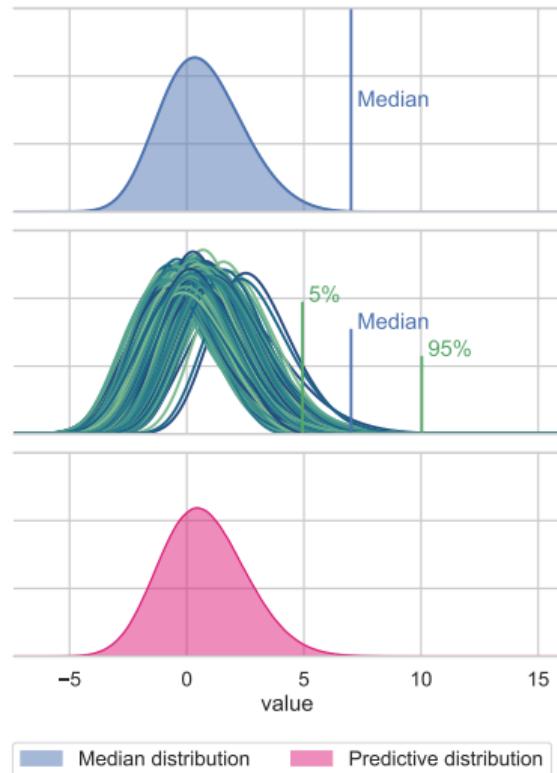


- Using all draws: for return levels **median** and **confidence intervals**

Predictive distribution - Illustration

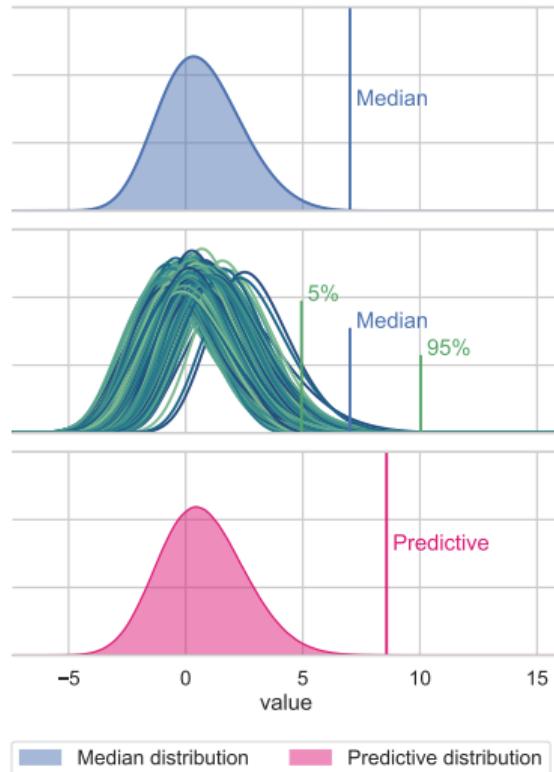


- Using all draws: for return levels **median** and **confidence intervals**
- Issue : Confidence Level is **another parameter** to choose.

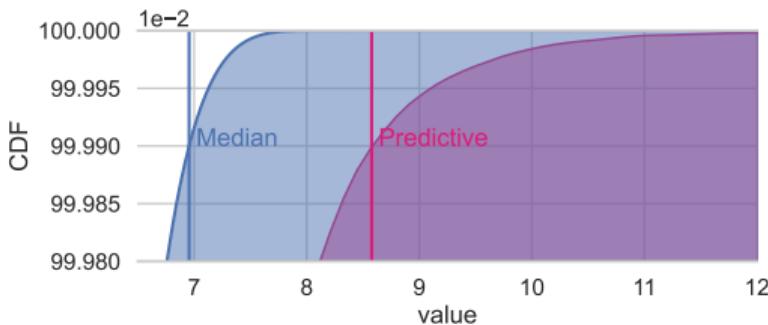


- Using all draws: for return levels **median** and **confidence intervals**
- Issue : Confidence Level is **another parameter** to choose.
- **Predictive distribution[2]:** One distribution **averaged** over the distribution of the model parameters.

$$P(Z \leq z|z_0) = \int_{\Theta} P(Z \leq z|\theta)\pi(\theta|z_0)d\theta$$



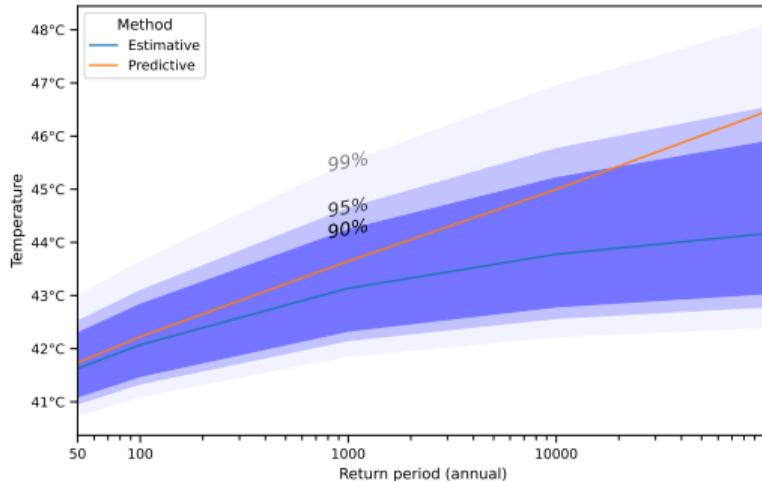
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Tricastin nuclear site :

- In the Rhône Valley (Topography)
- Active since 1980
- Elevation: 54m (Google Earth)

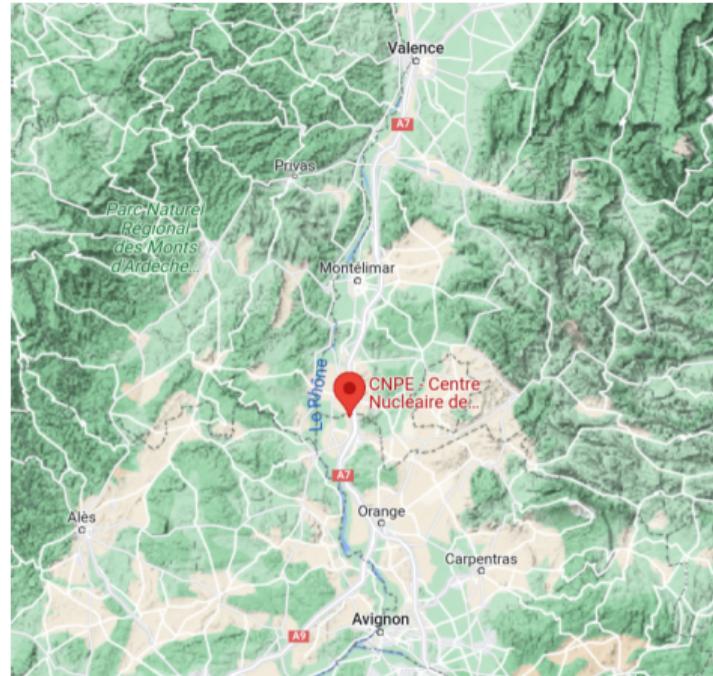


Figure: Situation of Tricastin Nuclear Powerplant

Climate models data:

- 28 **Global** climate models, CMIP6 generation.
- Numerous **historical and future scenario** runs , here SSP 1-1.9, SSP 2-4.5 and SSP 5-8.5.
- **Local Data:** TXX (Annual Maxima of daily maximum temperature).
- **Covariate Data:** Annual mean of mean temperature over continental Europe.
- Filtering to exclude **numerical explosions**

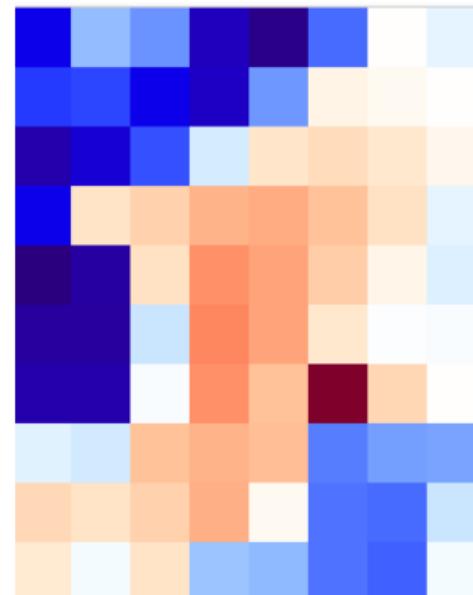


Figure: TX for 6th august 2066, model UKESM1-o-LL - France

Local meteorological data :

- Local observations (Pierrelatte station)
- 37 years available
- SQR Label (Limited disruptions), expert auditing.
- Alternative choices: Orange (60 years), Montélimar (60 years), Tricastin (16 years)
- No information on future evolution.

Covariate : Annual mean of mean temperature over continental Europe extracted from Crutem5 (gridded dataset).

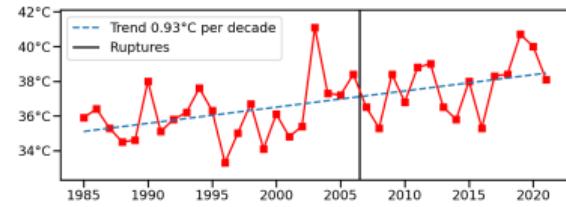
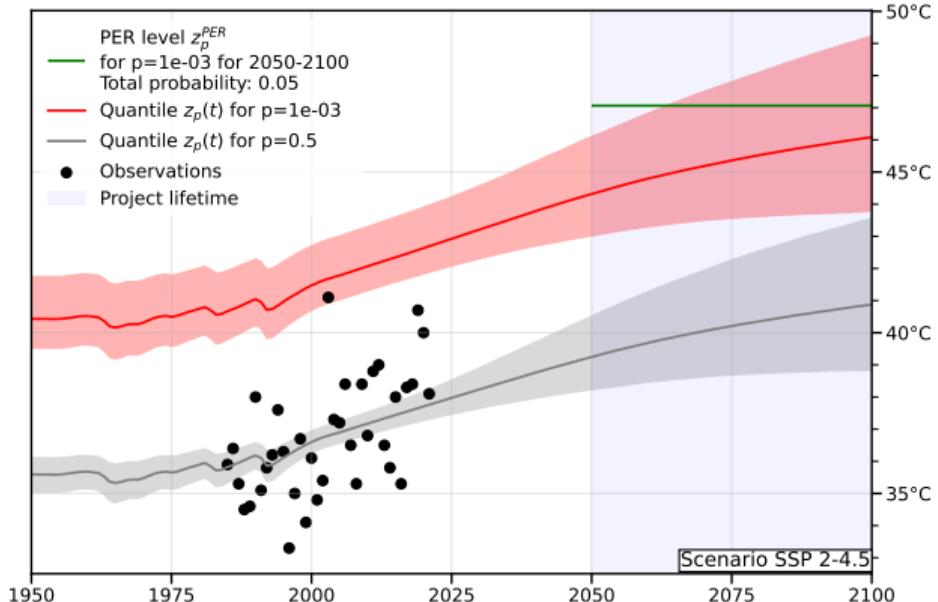


Figure: Annual Maxima for station Pierrelatte



Period of interest: **2050-2100**.

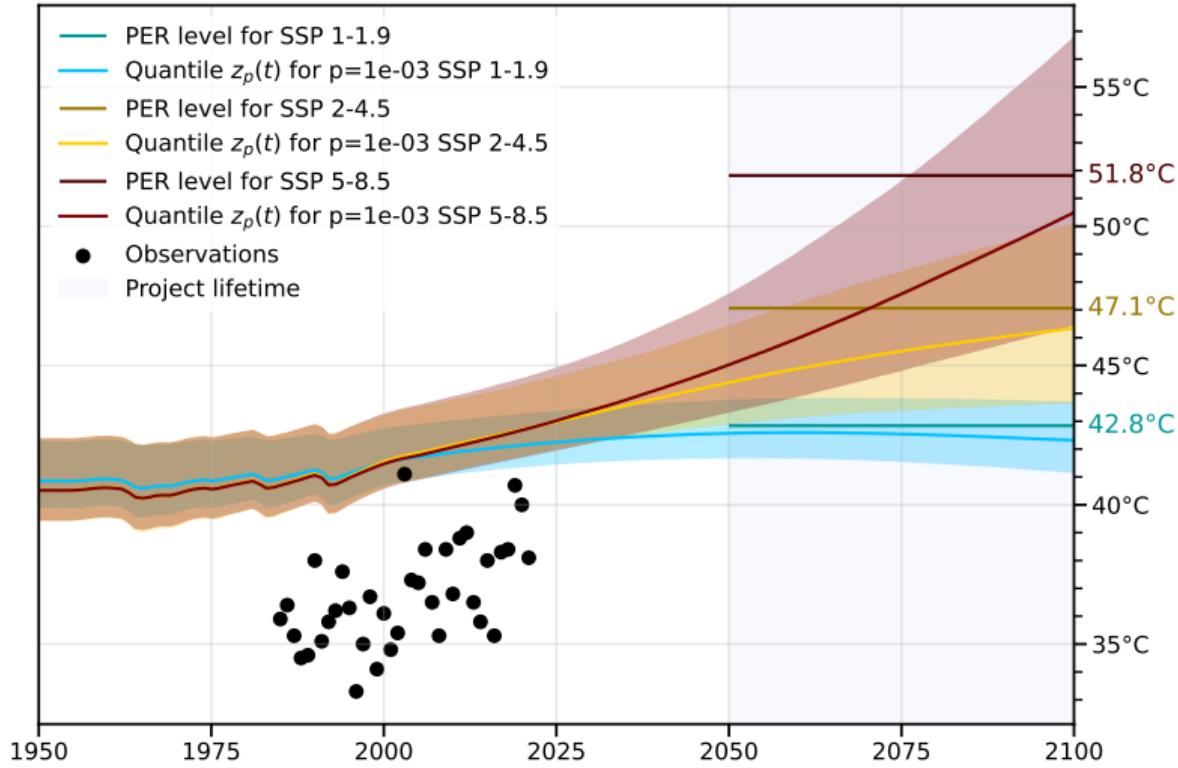
For an equivalent return level of 1000 years:

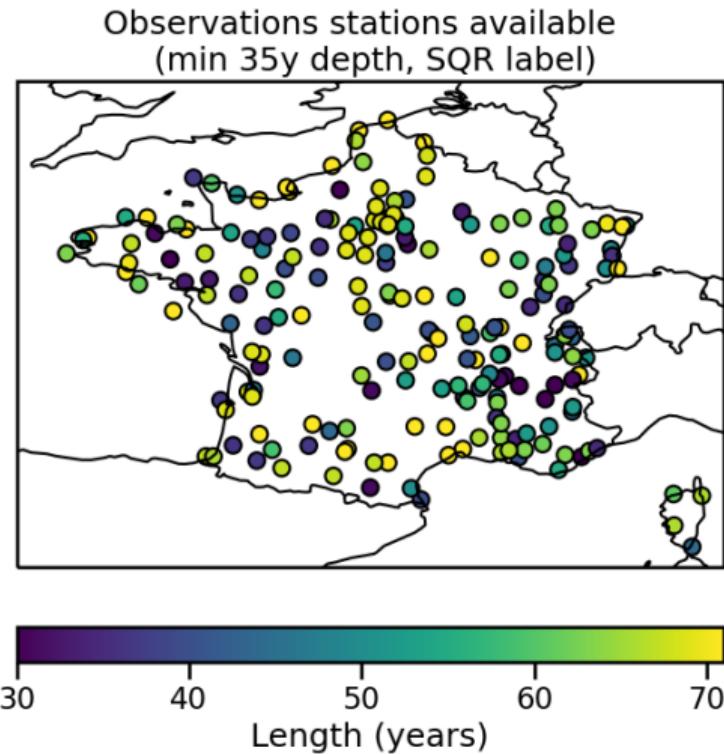
- Predictive is 47.1°C
- Median is 45.6°C with 48.4°C for 95% upper bound.

Interpretation

47°C has an annual probability of excess of $\frac{1}{1000}$ over 2050-2100.
Similarly, 47°C has a **5% probability of excess over 2050-2100**.

Applications to various scenarios





- Larger scale application to France. **Model data selection for coast stations ?**
- Testing various parametrizations and interventions on the prior. **How to evaluate a prior quality?**
- Change of support issue: if the point is non-average conditions (coast, montains, etc).

- Chose **Equivalent Reliability** as an index of interest.
- Adapted Robin and Ribes' (2020) bayesian estimation method.
- MCMC Algorithm: Large improvement in **time and precision**, comparison with alternatives.
- **Predictive** estimation taking parameter **uncertainty** into account.
- **First Application** at Tricastin.
- Many potential **avenues of improvement** (Data, Prior specification, model specification, etc).
- **Paper sent for review to Weather and Climate Extremes.**

- [1] Chapter 11: Weather and Climate Extreme Events in a Changing Climate.
- [2] S. Coles and J. Tawn.
Bayesian modelling of extreme surges on the UK east coast.
Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 363(1831):1387–1406, June 2005.
Publisher: Royal Society.
- [3] Intergovernmental Panel On Climate Change (Ipcc).
Climate Change 2021 – The Physical Science Basis: Working Group I Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change.
Cambridge University Press, 1 edition, July 2023.

- [4] Z. Liang, Y. Hu, H. Huang, J. Wang, and B. Li.
Study on the estimation of design value under non-stationary environment.
South-to-North Water Transfers Water Sci Tech, 14:50–53, 2016.
- [5] Y. Robin and A. Ribes.
Nonstationary extreme value analysis for event attribution combining climate models and observations.
Advances in Statistical Climatology, Meteorology and Oceanography, 6(2):205–221, Nov. 2020.
Publisher: Copernicus GmbH.

Designing life levels of Extreme Temperature by 2100

Thanks for listening.

Any questions?

■ Supplementary

- It's possible to calculate a physical upper bound for temperature, relying on moisture and instability of the air column.
- Both Zhang and Boos (2023) and Noyelle et al. (2023) calculated a physical upper bound for temperature using ERA-5 data on western Europe, higher than a GEV upper bound estimate on similar data.
- Using IPSL GCM data, Noyelle (2024) similarly found a physical upper bound 3 to 8°C higher than a GEV upper bound over 70 years.
- Exploration of the availability of necessary data for a multi-model analysis. Necessary first step for inclusion in our Bayesian framework.

Only need to be able to simulate from conditionnal distributions. (Maybe possible use of X_T)

Multivariate : $\psi = (\psi_1, \dots, \psi_d)'$, full conditionnals are $\pi(\psi_i|\psi_{-i}) = \pi_i(\psi_i)$

Description of algorithm:

- Initialisation: $k=1$, initial state of chain $\psi^{(0)}$
- Boucle: For new value $\psi^{(k)}$:
 - $\psi_1^{(k)} \sim \pi(\psi_1|\psi_{-1}^{(k-1)})$
 - $\psi_2^{(k)} \sim \pi(\psi_2|\psi_{-1,2}^{(k-1)}, \psi_1^{(k)})$
 - ...
 - $\psi_d^{(k)} \sim \pi(\psi_d|\psi_{-d}^{(k)})$

$\pi(\psi)$ is still the density of interest. We now have a transition kernel $p(\psi_{i+1}, \psi_i)$, easy to simulate from, to get successive values.

- Initialisation : k=1, initial state of chain $\psi^{(0)}$
- Boucle: For new value $\psi^{(k)}$:
 - Generate new proposed value ψ' using the kernel transition function.
 - Calculate Acceptance Probability (ratio) $A(\psi^{(k-1)}, \psi')$ of the proposed change of value:

$$A(\psi^{(k)}, \psi') = \min\left\{1, \frac{\pi(\psi')L(\psi'|\mathbf{x})p(\psi', \psi^{(k-1)})}{\pi(\psi^{(k-1)})L(\psi^{(k-1)}|\mathbf{x})p(\psi^{(k-1)}, \psi')}\right\}$$

- Accept $\psi^{(k)} = \psi'$ with probability $A(\psi^{(k)}, \psi')$ and keep $\psi^{(k)} = \psi^{(k-1)}$ otherwise.

Based on Bayesian Modelling of Extreme Rainfall Data from Elizabeth Smith
Gibbs concept (each parameter is updated in turn) and conditionals are MH (do we accept
the new value produced by the transition function?)

Avantage: Each parameter has his own trajectory (One may not move much and another a lot) + varying transition kernel (proportionnal) (not hard to do for simple MH too)
→ Less dependance than normal MH?.

Description of algorithm:

- Initialisation : $k=1$, initial state of chain $\theta^{(0)}$
- Boucle: For new value $\theta^{(k)}$:
 - In turn, for each parameter $\theta_j^{(k)}$
 - $\theta_j' = \theta_j^{(k-1)} + \varepsilon_j$
 - Accept or refuse using $A(\theta_j^{(k-1)}, \theta_j')$ with $\theta_{-j}^{(k)}$ seen as known.