Climate Change

- Increase in **frequency and intensity** of extremely hot events.
- Increasing knowledge of the warming phenomena, using both **observations and climate models**.

Safety concerns

- Reliability of **safety-significant equipment**.
- Danger for **Human's health and increased electricity** consumption during heatwaves.

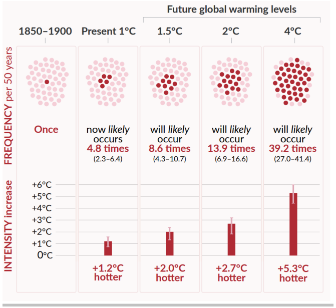

Figure: IPCC, 2021: Summary for Policymakers by MassonDelmotte, V et al.

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Our Goal: Estimating 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.
- Adapting the method to **various places of interest**, taking into account the inherent limitations of each zone.

Need: Separating the **period of interest** from the **return period** (annual probability).

Stationnary: Using $\mathbf{z}$, return level of period 100 years.

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For year 1 : $P[Y_1 \leq \mathbf{z}] = (1 - \frac{1}{\mathbf{T}}) = 0.99$
For year 2 :

Need: Separating the **period of interest** from the **return period** (annual probability).

Stationnary: Using $\mathbf{z}$, return level of period 100 years.
For year 1 : $P[Y_1 \leq \mathbf{z}] = (1 - \frac{1}{\mathbf{T}}) = 0.99$
For year 2 : $P[max(Y_1, Y_2) \leq \mathbf{z}] = (1 - \frac{1}{\mathbf{T}})^2$

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For year 2 : $P[max(Y_1, Y_2) \leq \mathbf{z}] = (1 - \frac{1}{\mathbf{T}})^2 = 0.98$
For year 50 : $P[max(Y_1, ..., Y_{50}) \leq \mathbf{z}] = (1 - \frac{1}{\mathbf{T}})^{50}$

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For year 50 : $P[max(Y_1, ..., Y_{50}) \leq \mathbf{z}] = (1 - \frac{1}{\mathbf{T}})^{50} = 0.60$

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Issue: With **non-stationnarity,** $Y_{2023} \neq Y_{2050}$.

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Issue: With **non-stationnarity,** $Y_{2023} \neq Y_{2050}$.
Equivalent Reliability: for period $[T_1, t_2]$, solution $\mathbf{z^{ER}_{T_2-T_1}}$ of :

$$P[Max_{t\in[\mathbf{T_1},\mathbf{T_2}]}(Y_t) \leq \mathbf{z^{ER}_{T_2-T_1}}] = (1 - \frac{1}{\mathbf{T}})^{\mathbf{T_2}-\mathbf{T_1}+1}$$

Constraints:

- **Extreme Values** Analysis: Annual Maxima, use of **GEV** distribution.
- **Non-stationarity**:Use of mean European Temperature as covariate allows for a better time relationship and **scenario integration**.

$$Y \sim \mathbb{P}_t = GEV(\mu_t, \sigma_t, \xi)$$

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

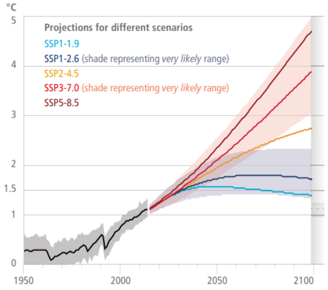


Figure: Global surface temperature changes for various scenarios. (IPCC, 2022)

Tricastin nuclear site :

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

Figure: Location of Tricastin Nuclear Powerplant

Climate Models

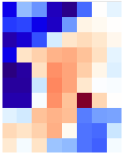


Figure: UKESM1-0-LL - France

- 28 Global climate models, CMIP6.
- **Historical and scenario** runs (SSP1-1.5, SSP2-4.5, SSP5-8.5).
- **Large grids** from 70 to 300 km.

Local observations

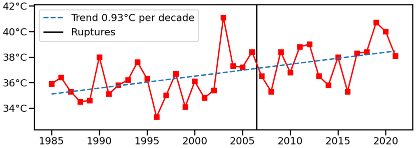


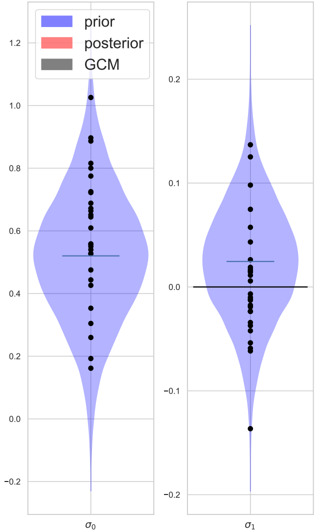
Figure: Annual Maximums in Pierrelatte

- 37 years long.
- **On site** information source.
- Good quality with few breaks.
- No knowledge on **future evolution**.

Bayesian framework

A-priori knowledge

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



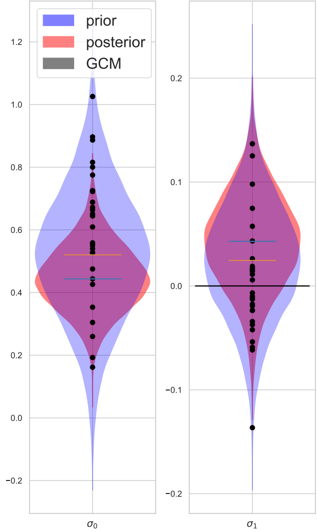
Bayesian framework

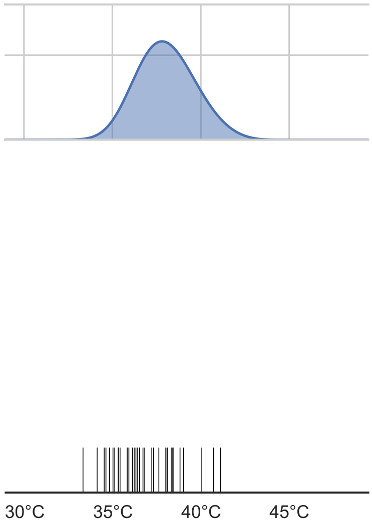
A-priori knowledge

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

Updated using observations

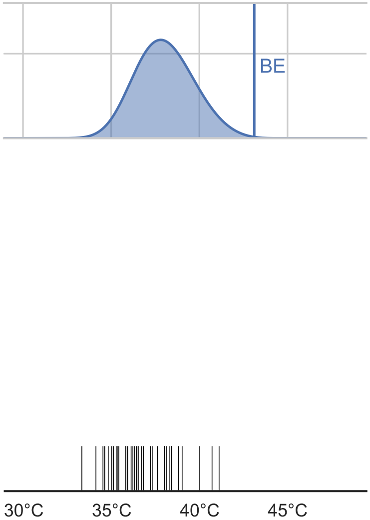
- Maxima constraint using **Markov chain Monte Carlo** (NUTS).
- Using past local observations.





- Best Estimate using **median** of all draws.

Predictive



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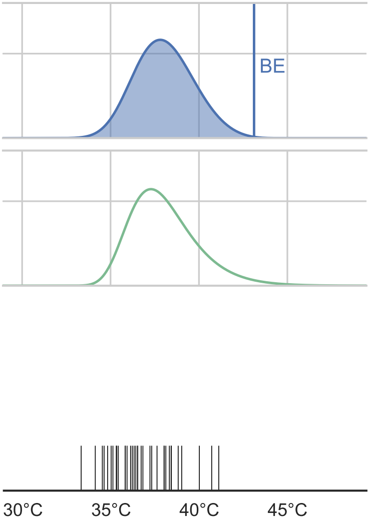

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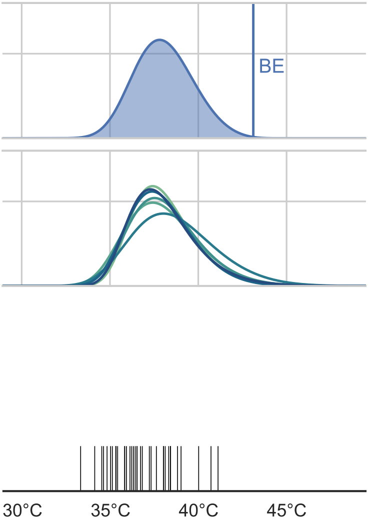

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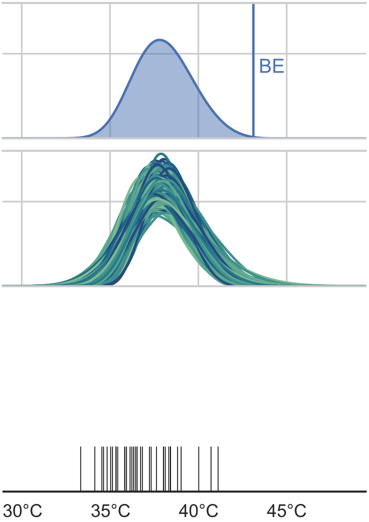
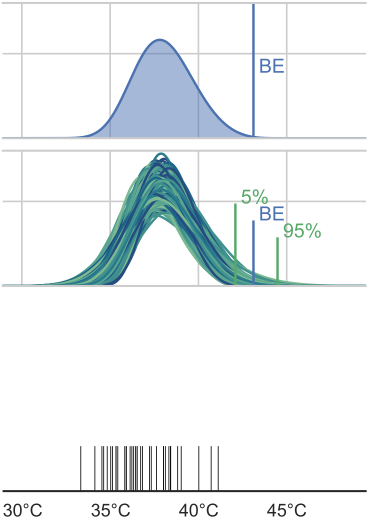


- Best Estimate using **median** of all draws.
- **Confidence intervals** using all draws.



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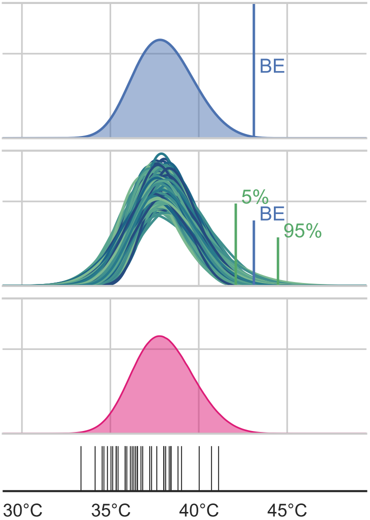
- **Issue** : Confidence Level is **another parameter** to choose.



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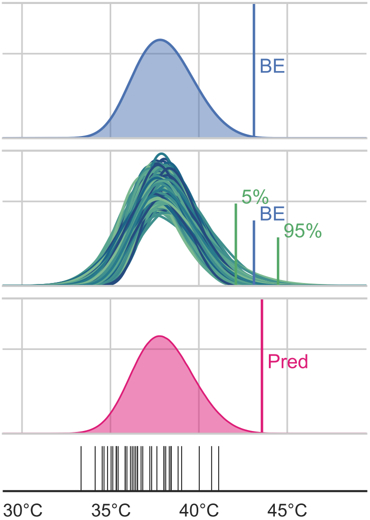

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- **Confidence intervals** using all draws.

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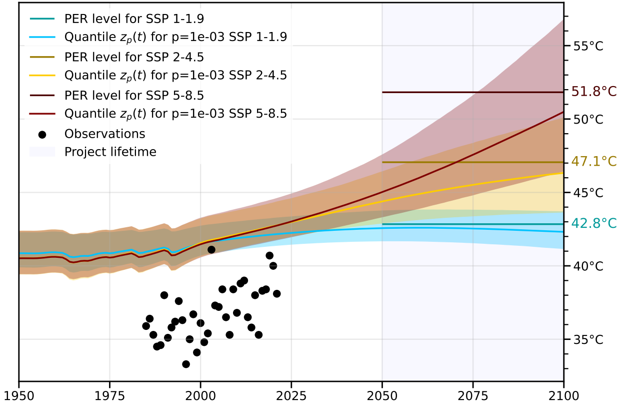
- One distribution blending all draws.
- One distribution **blending all draws**: Account for **estimation error** and **stochastic error**.



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

For an equivalent return level of 1000 years and scenario SSP2-4.5:

- 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**.

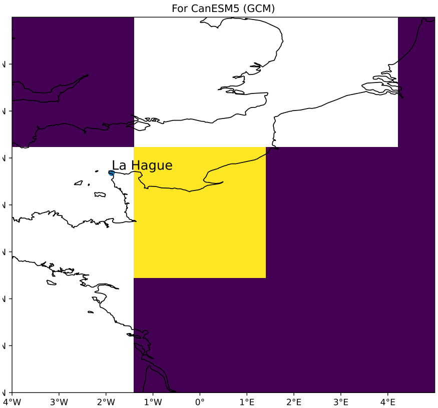
La Hague's reprocessing plant:

- Sea-side
- Specific climatology

Issue:

- Global climate models are **not representative of local effects**.
- Regional climate models (RCM) with **smaller grids (12 km) available**, but only a few .

Solution: Apply a correction on GEV parameters using the RCMs .



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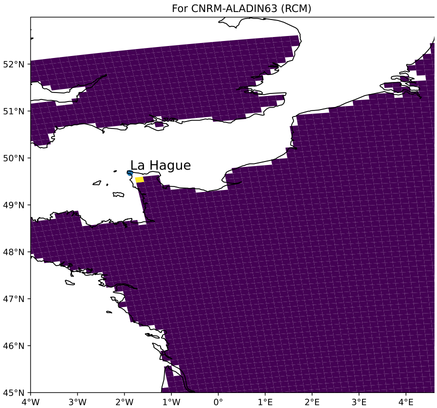
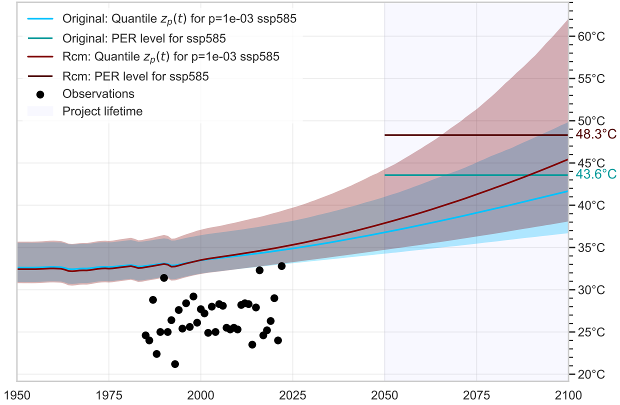


Hypothesis: the effect of the general circulation models' (GCMs) large grid over the GEV parameter fixed for each grid. -¿ Use high-resolution ALADIN data to **adjusts GEV parameters for grid effects**.

Data : CNRM-ALADIN63 (1850–2100, 12 km resolution), driven by CMIP5 GCM (Scenarios RCP2.6, RCP4.5, RCP8.5).

Methodology:

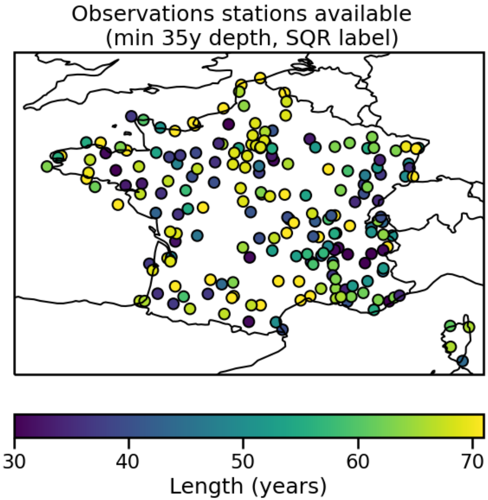
- By comparing **ALADIN-based** GEV estimates with **regridded GCM equivalents**, calculate an offset (Δ^{GCM_i}) for each GCM.
- Apply this offset to **correct GCM-derived parameters**.



Scenario of interest: **SSP5-8.5**. The correction leads to increased temperature levels.

For an equivalent return level of 1000 years:

- Difference in median return levels in 2100 is 3.4°C.
- Difference in EQR levels is 4.7°C.
- Increased variance in time due to local effects.



- Many stations available in France.
- What is the risk over continental France ?

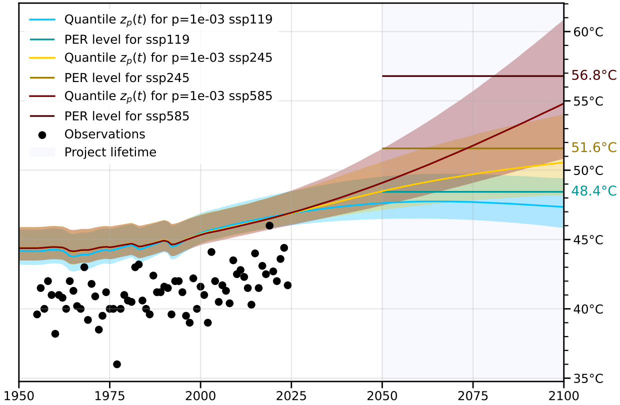


Figure: Equivalent Reliability, probabilité annuelle 0.01 sur 2050-2100

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

For an equivalent return level of 1000 years and scenario SSP2-4.5:

- Predictive is 51.6°C
- Median return level in 2100 is 50.7°C with 54°C for 95% upper bound.

Interpretation

For scenario SSP2-4.5, 51.6°C has a **5% probability of excess over 2050-2100**.

- Chose **Equivalent Reliability** as an index of interest.
- Adapted Robin and Ribes' (2020) Bayesian estimation method adding a **Predictive** estimation taking parameter **uncertainty** into account.
- **Paper sent for review to Weather and Climate Extremes**.
- **Application** at Tricastin, La Hague and France.
- Proposed a correction to **account for local effects** in specific applications (Paper currently being written).
- Currently applying the methodology to **various places of interest** (sites, countries, global temperature, etc.) for a future paper.
- Many potential **avenues of exploration** (bias correction, large scale application, etc.).

- Yiming Hu et al. “Concept of Equivalent Reliability for Estimating the Design Flood under Non-stationary Conditions”. en. In : Water Resources Management 32.3 (fév. 2018), p. 997- 1011. issn : 1573-1650. doi :10.1007/s11269-017-1851-y .
- Robin, Y. and Ribes, A.: Nonstationary extreme value analysis for event attribution combining climate models and observations, Adv. Stat. Clim. Meteorol. Oceanogr., 6, 205–221,https://doi.org/10.5194/ascmo-6-205-2020 , 2020.
- Packages python SDFC , NSSEA et CmdStanPy (STAN)
- Lee Fawcett et Amy C. Green. “Bayesian posterior predictive return levels for environmental extremes”. en. In : Stochastic Environmental Research and Risk Assessment 32.8 (août 2018), p. 2233-2252. issn : 1436-3259. doi : 10.1007/s00477-018- 1561- x

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:

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

  - 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)
$\rightarrow$ 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.