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**.
- Building Codes using stationary return levels which may **vary during the building's life**.

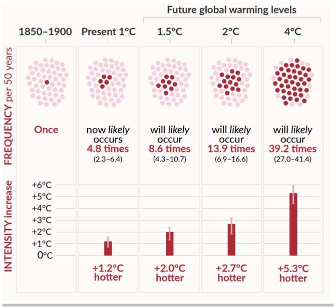


Figure: IPCC, 2021: Summary for Policymakers by MassonDelmotte, V et al.

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 = $\frac{1}{T}$).
- Account for **non-stationnarity,** $Y_{2023} \neq Y_{2050}$.
- Applied similarly with ou without stationarity.

Our choice: 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**.

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

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

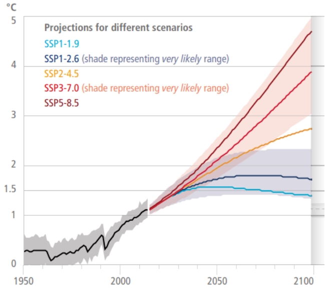


Figure: Global surface temperature changes for various scenarios. (IPCC, 2022)

Climate Models

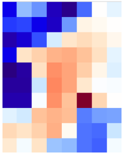


Figure: UKESM1-0-LL - France

- 28 Global climate models, CMIP6.
- **Historical and scenario** runs (SSP 5-8.5).
- **Large grids**

Local observations

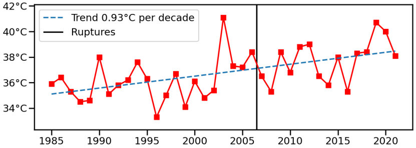


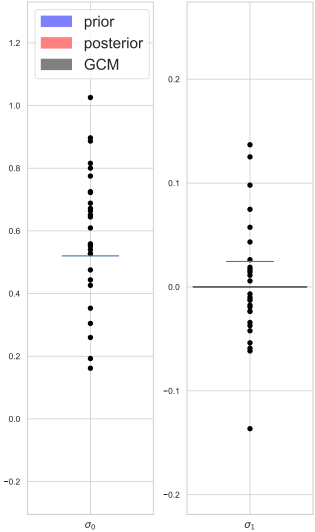
Figure: Annual Maximums in Pierrelatte

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

Bayesian framework: a-priori knowledge updated using observations.

Step 1: Prior creation

- Create **Multi-model distribution** (Multivariate Gaussian).
- Include only information from climate models.



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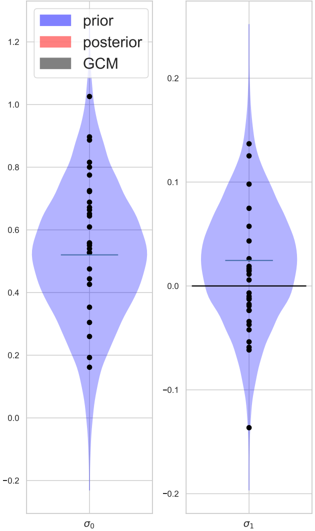


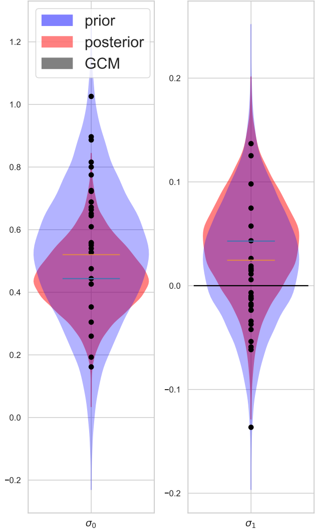
Bayesian framework: a-priori knowledge updated using observations.

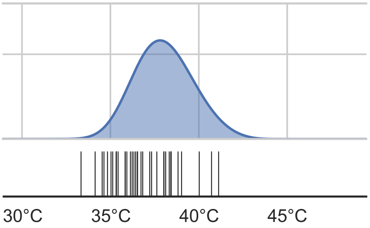
Step 1: Prior creation

- Create **Multi-model distribution** (Multivariate Gaussian).
- Include only information from climate models.

Step 2: Constraint using observations

- Maxima constraint using **Markov chain Monte Carlo** (NUTS).
- Large number of draws obtained.





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

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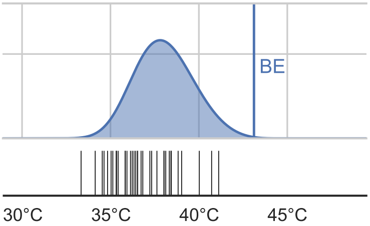

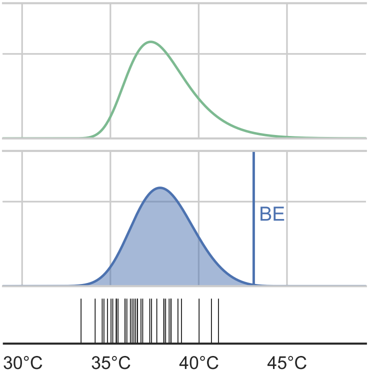

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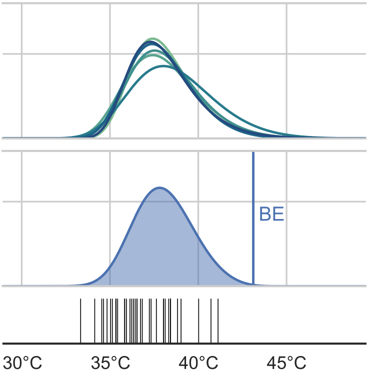

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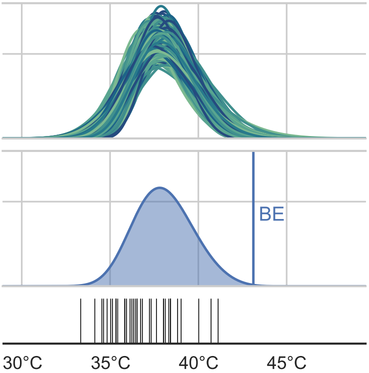
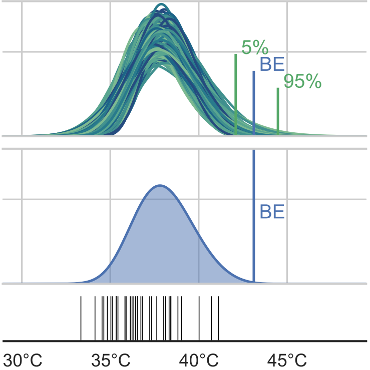


- Best Estimate using **median** of all draws.
- **Confidence intervals** using all draws.



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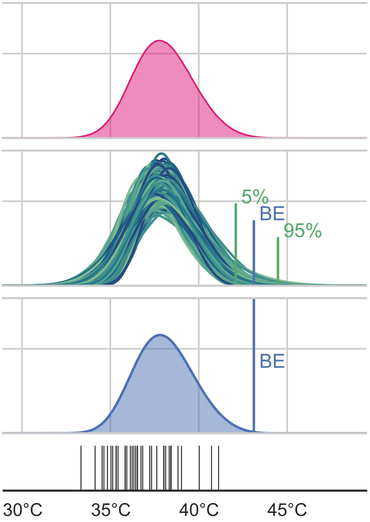
- **Issue** : Confidence Level is **another parameter** to choose.



- Best Estimate using **median** of all draws.
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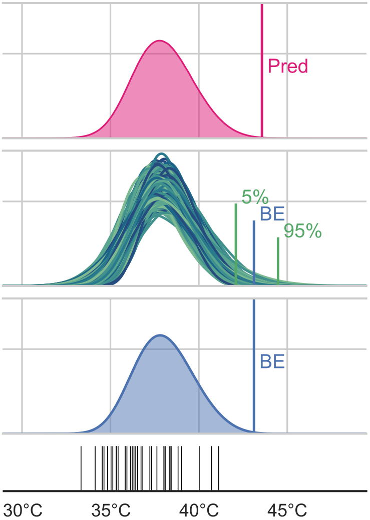
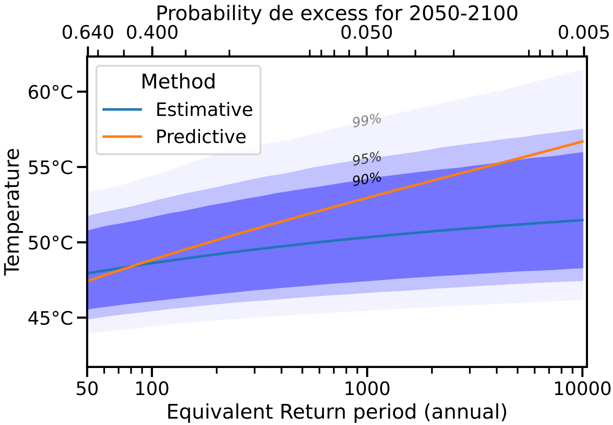
- One distribution blending all draws



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

- **Issue** : Confidence Level is **another parameter** to choose.
- One distribution blending all draws
- **Predictive**: One value with all parameter uncertainty integrated.



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

For an equivalent return level of 1000 years:

- Predictive is 52.9°C
- Median is 50.3°C with 55.5°C for 95% upper bound.

Interpretation

53°C has an annual probability of excess of $\frac{1}{1000}$ over 2050-2100.
Similarly, 53°C has a 5% probability of excess over 2050-2100.

- Chose **Equivalent Reliability** as quantity of interest.
- Adapted Robin and Ribes' (2020) 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).

- 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

Extreme Temperature in France by 2100

Thanks for listening.
Any questions?

- Slides supplémentaires

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

Multivariate : $\psi = (\psi_1, \ldots, \psi_d)'$, 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 changeof 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.