Designing life levels of Extreme Temperature by 2100.

Valpred 5

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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.

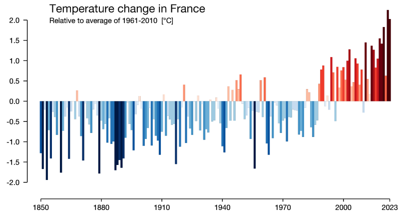


Figure: Anomaly of the annual mean temperature over France between 1850 and 2023. By: #ShowYourStripes

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.

$\Longrightarrow$ An **updated and well estimated index** is necessary .

Figure: Ultimate emergency diesel generators have to be secured against extrem temperatures – on the site of the Blayais power plant (Gironde) *by Florence Levillain /Signatures /Médiathèque IRSN*

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).

Tricastin nuclear site :

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

Figure: Situation of Tricastin Nuclear Powerplant

Issue:
In a stationary context, $z_p = F^{-1}(1-p)$.
With added non stationarity, a unique Return Level is undefined:

$$z_p(t) = F_t^{-1}(1-p)$$

Similarly, the Annual probability of excess **changes every year**.
Various alternatives (Expected Waiting Time, Average Design Life Level, Expected Number of Events, etc.)

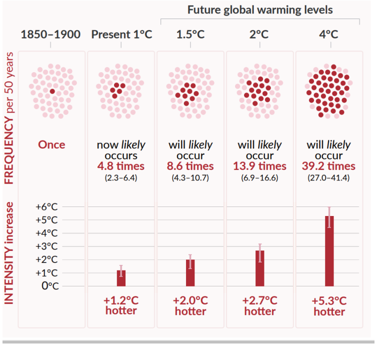


Figure: IPCC, 2021: Summary for Policymakers by Masson Delmotte, V et al.[3]

Needs:

- Assess Risk over the full **period of interest** $t_1 : t_2$ using Reliability:

$$R_{t_1:t_2}(z) = P[\max(Z_{t_1}, Z_{t_1+1}, ..., Z_{t_2}) \leq z]$$

- Separate the **period of interest** from the **return period** (annual probability $p = \frac{1}{T}$).
- Applied similarly with or without stationarity.
  Stationarity : $R_{t_1:t_2}(z) = (1-p)^{\mathbf{t_2 - t_1 + 1}}$

Equivalent Reliability[4]:
For period $t_1 : t_2$ and annual probability p, $\mathbf{z_p}$ is solution of :

$$R_{t_1:t_2}(z_p^{\mathrm{ER}}) = (1-p)^{\mathbf{t_2 - t_1 + 1}}$$

Constraints:

- **Extreme Values** Analysis: Annual Maxima, use of **GEV** distribution.

$$Z_t \sim GEV(\mu(t), \sigma(t), \xi)$$

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

- **Non-stationarity**: Mean European Temperature as covariate for relationship with time and **scenario integration**.

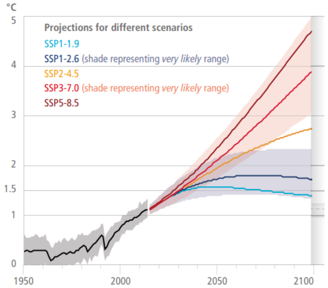


Figure: Global surface temperature changes for various scenarios. (IPCC, 2022)

Local meteorological data :

- **Local** observations (Pierrelatte station)
- 37 years available
- **Expert auditing:** Limited disruptions .
- **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 (grided dataset).

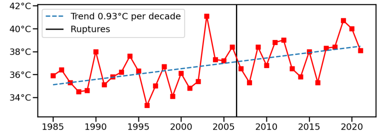


Figure: Annual Maxima for station Pierrelatte

Climate models data:

- 28 **Global** climate models (GCMs), 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**

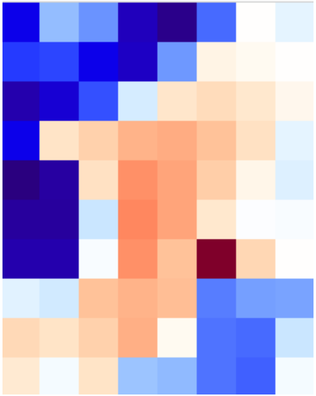
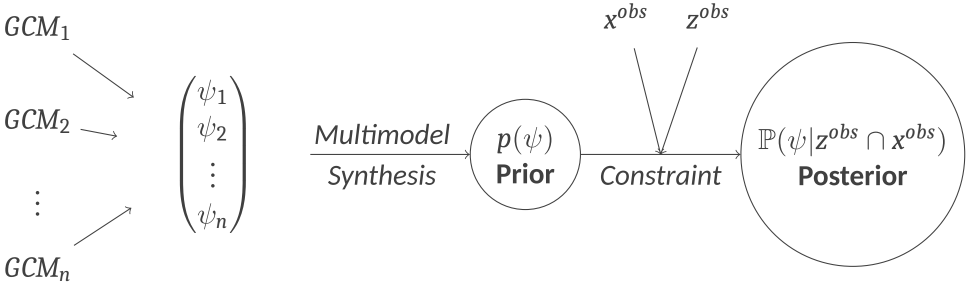


Figure: TX for 6th august 2066, model UKESM1-0-LL - France

Framework

Using $\psi = \{X_{1850} - X_{2100}, \mu_0, \mu_1, \sigma_0, \sigma_1, \xi\}$,
z^{obs} for local observations and x^{obs} for covariate observations.



Bayes Theorem:

$$\mathbb{P}(\psi|z^{obs} \cap x^{obs}) = \frac{\mathbb{P}[z^{obs}|(\psi|x^{obs})]\mathbb{P}(\psi|x^{obs})}{\mathbb{P}(z^{obs})}$$

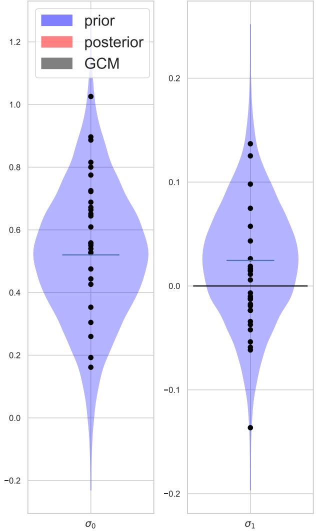
Bayesian constraint is done in **two steps**[5]:

- **Covariate constraint**: $\mathbb{P}(\psi|x^{obs})$ is calculated using a conjugate.
- **Local constraint** $\mathbb{P}(\psi|x^{obs}, z^{obs})$ is calculated by constraining $\mathbb{P}(\psi|x^{obs})$ with a **MCMC** chain.

Bayesian framework[5]

A-priori knowledge

- Maximum Likelihood GEV fit for each GCM.
- Multi gaussian prior includes only information from **climate models**. (historical and scenario).



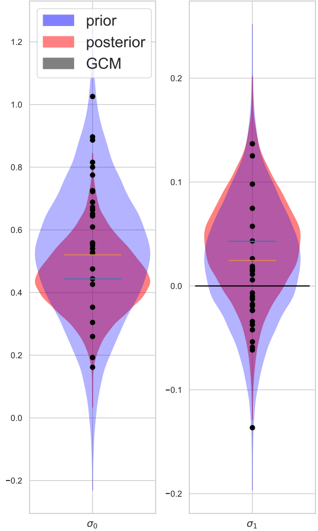
Bayesian framework[5]

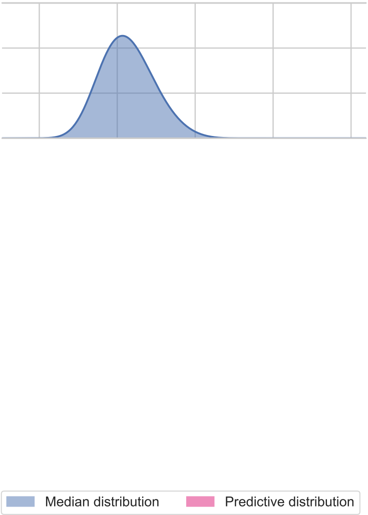
A-priori knowledge

- Maximum Likelihood GEV fit for each GCM.
- Multi gaussian prior includes only information from **climate models**. (historical and scenario).

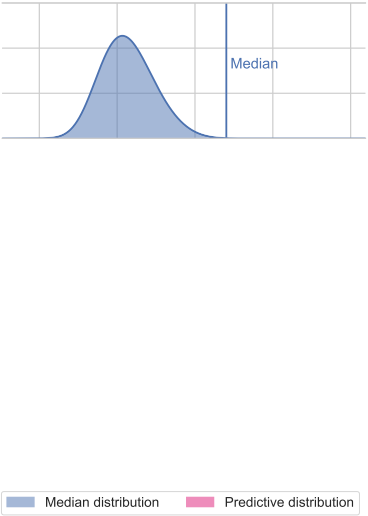
Updated using observations

- Covariate constraint using **a conjugate**.
- Maxima constraint using **Markov chain Monte Carlo** (NUTS) with past local observations.





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



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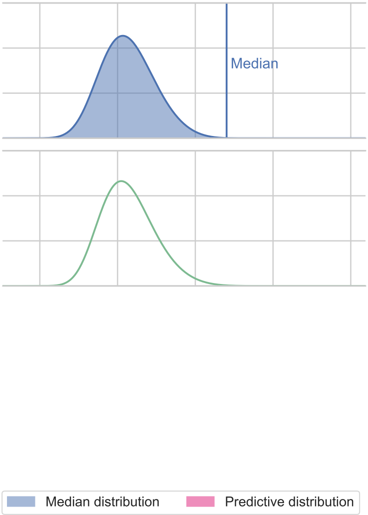

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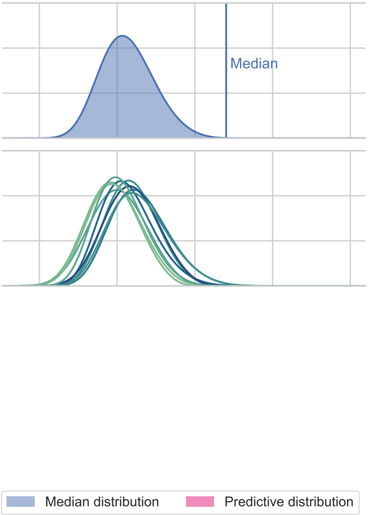

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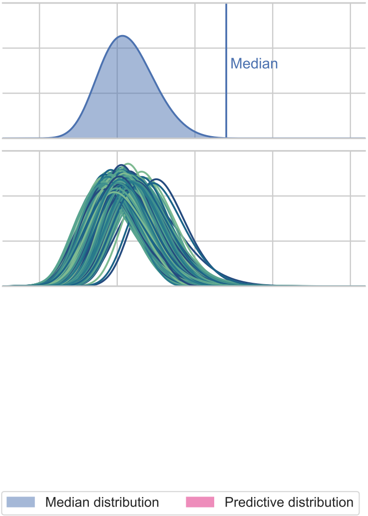
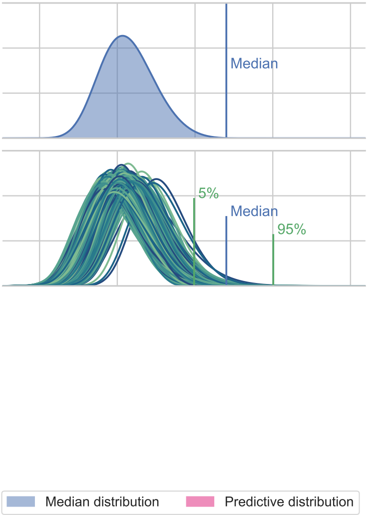
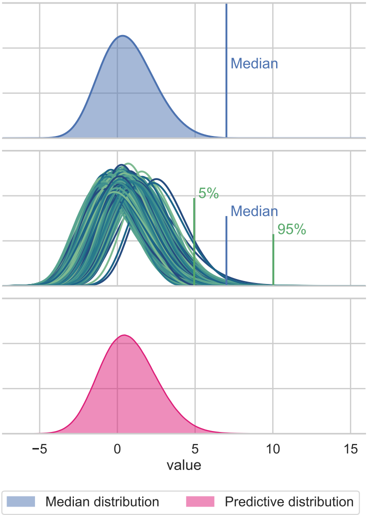


- Using all draws: for return levels **median** and **credibility intervals**

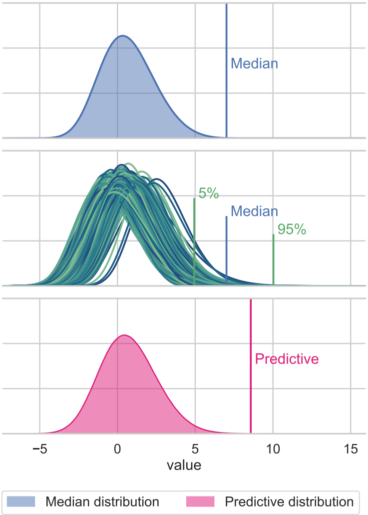


- Using all draws: for return levels **median** and **credibility intervals**
- **Issue** : Confidence Level is **another parameter** to choose.



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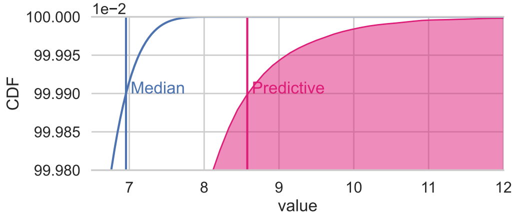

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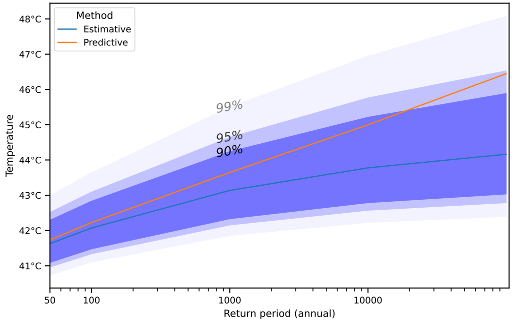
Predictive distribution - Illustration



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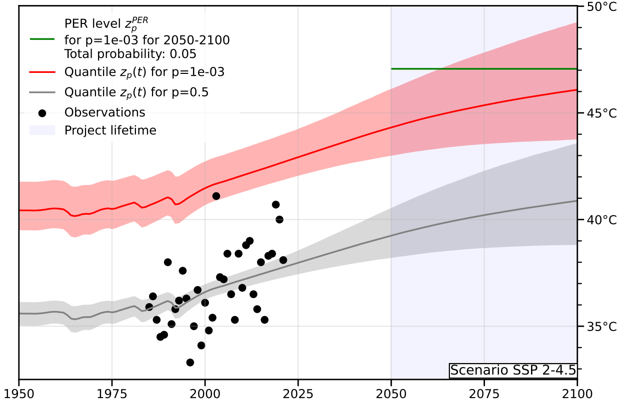


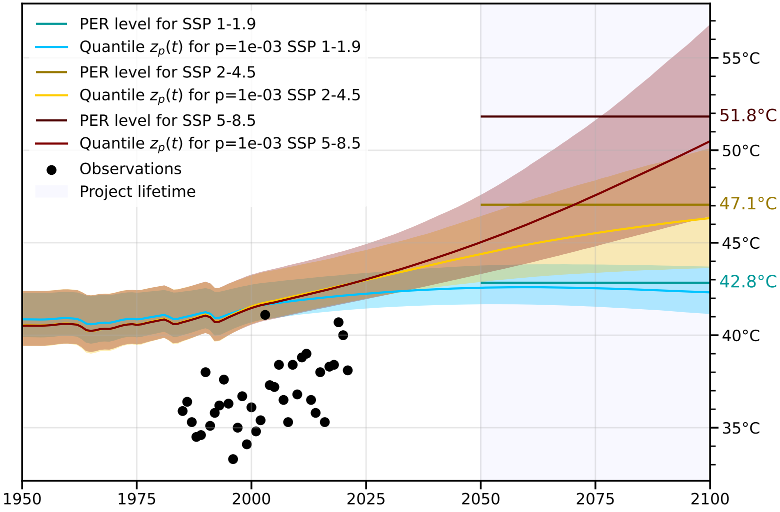
Period of interest: **2050-2100**.

For an equivalent return level of 1000 years:

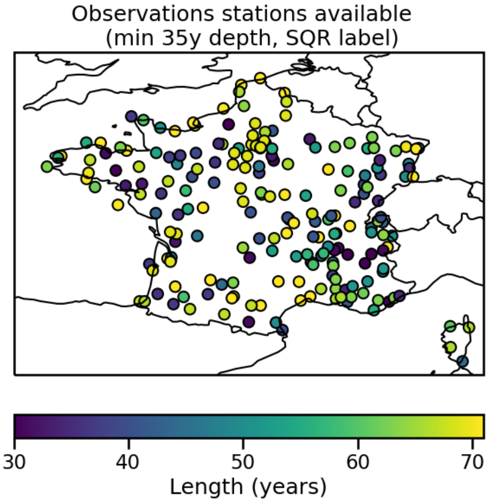
- Predictive is 47.1°C
- Median is 45.6°C with 48.4°C for 95% upper bound.

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**.



PER level for SSP 1-1.9
Quantile $z_p(t)$ for p=1e-03 SSP 1-1.9
PER level for SSP 2-4.5
Quantile $z_p(t)$ for p=1e-03 SSP 2-4.5
PER level for SSP 5-8.5
Quantile $z_p(t)$ for p=1e-03 SSP 5-8.5
Observations
Project lifetime
55°C
51.8°C
50°C
47.1°C
45°C
42.8°C
40°C
35°C
1950
1975
2000
2025
2050
2075
2100



- 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-avergae 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 for various scenarios.
- Current: Application to **all of France**.
- Many potential **avenues of improvement** (Data, Prior specification, model specification, etc).

[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 : $\psi = (\psi_1, \ldots, \psi_d)'$, 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 change of value:

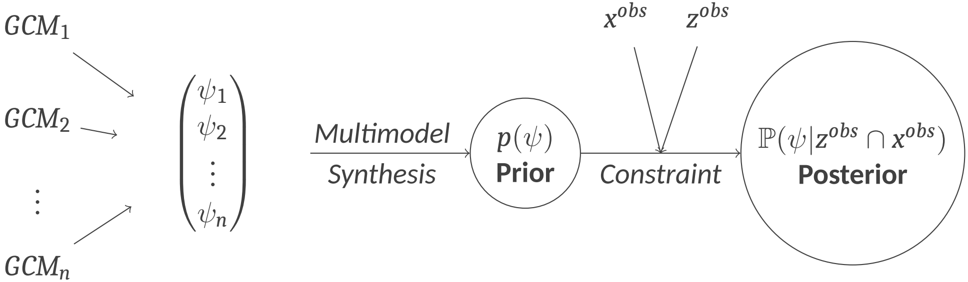
$$A(\psi^{(k)}, \psi') = min\{1, \frac{\pi(\psi')L(\psi'|x)p(\psi', \psi^{(k-1)})}{\pi(\psi^{(k-1)})L(\psi^{(k-1)}|x)p(\psi^{(k-1)}, \psi')}\}$$

  - 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.

Framework



GCM_1
GCM_2
$\vdots$
GCM_n
$\begin{pmatrix} \psi_1 \\ \psi_2 \\ \vdots \\ \psi_n \end{pmatrix}$
Multimodel
Synthesis
$p(\psi)$
Prior
x^{obs}
z^{obs}
Constraint
$\mathbb{P}(\psi | z^{obs} \cap x^{obs})$
Posterior