Spatio-temporal modeling of urban extreme rainfall events at high resolution

Semdoc, IMAG, January 2025

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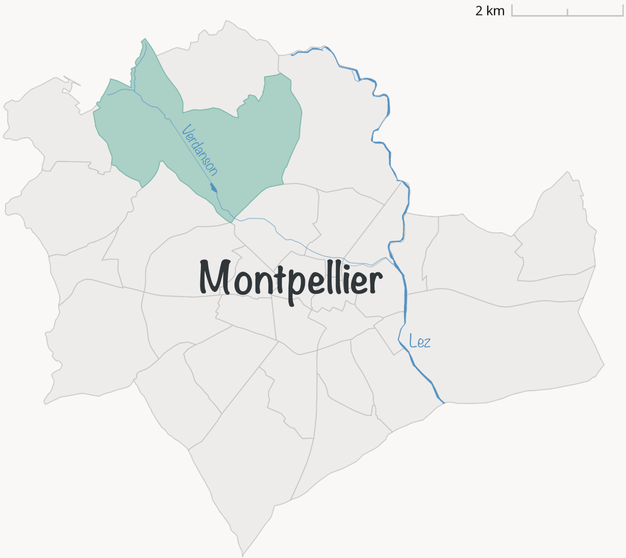
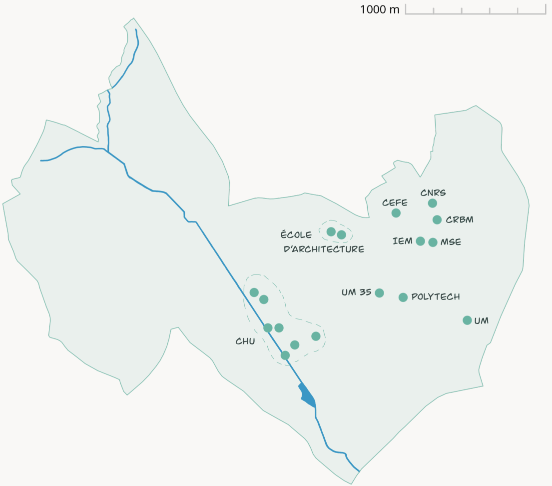
Floods in Montpellier, September 2022 and August 2015 (*Midi Libre*)

- Mediterranean events, localized rainfall
- Urban area, flood risks



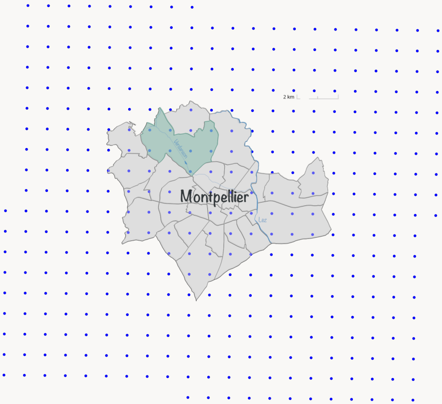
- North of Montpellier, *Hôpitaux-Facultés* district
- Verdanson water catchment, tributary of the Lez river



- **Source:** Urban observatory of HydroScience Montpellier (HSM)[1]
- **Time period:** $[2019, 2023[$
- **Temp. resol.:** 5 minutes
- **Spatial resol.:** 77 m to 1531 m

[1] Finaud-Guyot et al., 2023

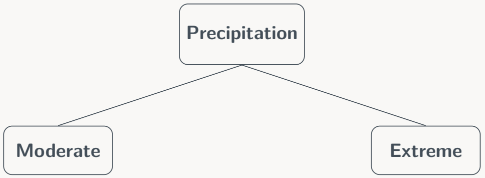
$\mathcal{S} = \{\textbf{17 rain gauges}\} \subset \mathbb{R}^2$ and $\mathcal{T} \subset \mathbb{R}_+$



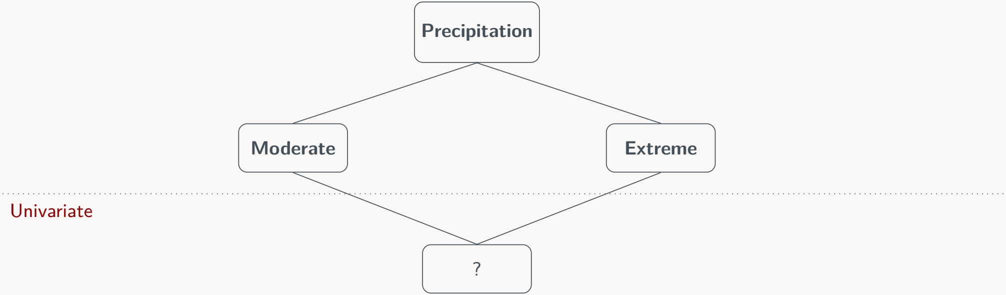
- **Source:** COMEPHORE, Météo France
- **Time period:** $[1997, 2023[$
- **Temporal resolution:** Every hour
- **Spatial resolution:** 1 km^2

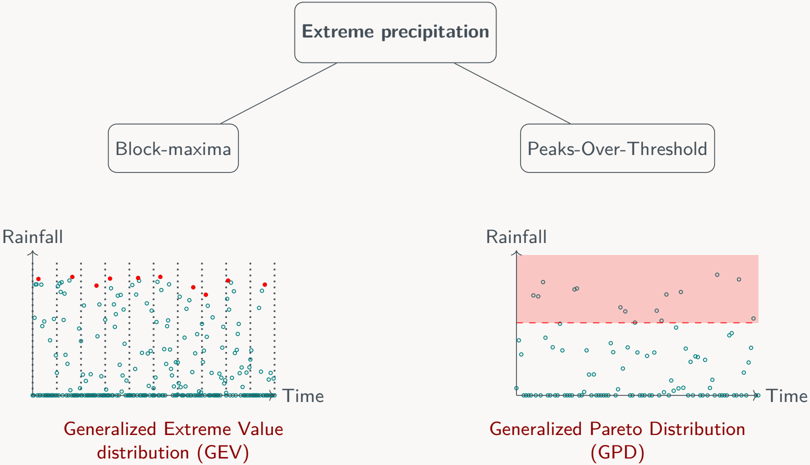
$\mathcal{S} = \{\textbf{400 pixels}\} \subset \mathbb{R}^2$ and $\mathcal{T} \subset \mathbb{R}_+$

More consistent data: HSM + COMEPHORE and Neural Network Downscaling.



Univariate


Precipitation
Moderate
Extreme
Univariate
?



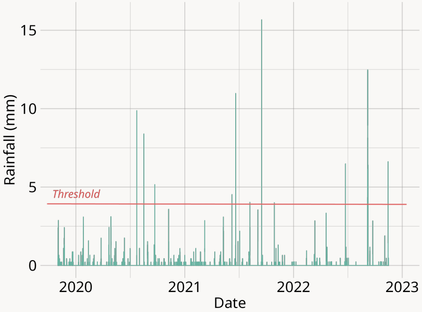
Extreme precipitation
Block-maxima
Peaks-Over-Threshold
Rainfall
Time
Generalized Extreme Value distribution (GEV)
Rainfall
Time
Generalized Pareto Distribution (GPD)

Generalized Pareto Distribution

$$\overline{H}_\xi\left(\frac{x-u}{\sigma}\right) = \begin{cases} \left(1+\xi\frac{x-u}{\sigma}\right)_+^{-1/\xi} & \text{if } \xi \neq 0\,, \\ e^{-\frac{x-u}{\sigma}} & \text{if } \xi = 0\,, \end{cases}$$

where $a_+ = \max(a, 0)$, $\sigma > 0$, $x - u > 0$

- Models extreme precipitation
- Depends on a threshold choice



Polytech

Generalized Pareto Distribution ⟶ **Extended GPD**[2]

$$\overline{H}_\xi\left(\frac{x-u}{\sigma}\right) = \begin{cases} \left(1+\xi\frac{x-u}{\sigma}\right)_+^{-1/\xi} & \text{if } \xi \neq 0\,, \\ e^{-\frac{x-u}{\sigma}} & \text{if } \xi = 0\,, \end{cases}$$

where $a_+ = \max(a,0)$, $\sigma > 0$, $x - u > 0$

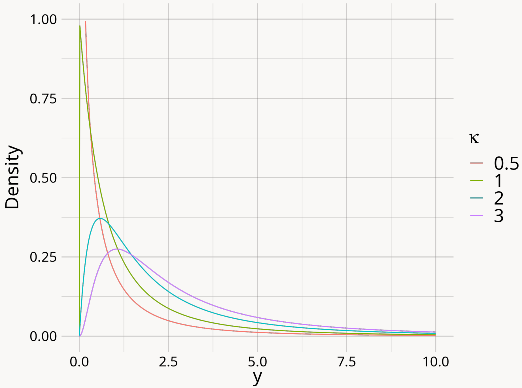
- Models extreme precipitation
- Depends on a threshold choice

$$F(x) = G\left(H_\xi\left(\frac{x}{\sigma}\right)\right),$$

where $G(x) = x^\kappa$, $\kappa > 0$

- Models **moderate and extreme** precipitation
- Avoids a threshold choice

[2]Naveau et al., 2016



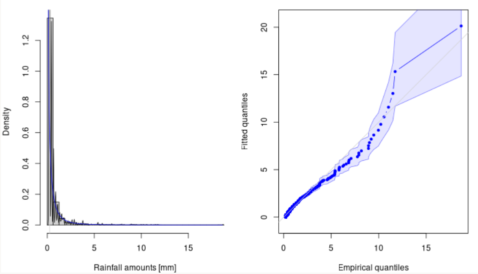
$\sigma = 1,\ \xi = 0.5$

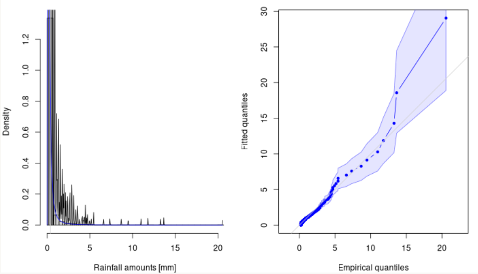
Extended GPD

$$F(x) = G\left(H_\xi\left(\frac{x}{\sigma}\right)\right),$$

where $G(x) = x^\kappa$, $\kappa > 0$

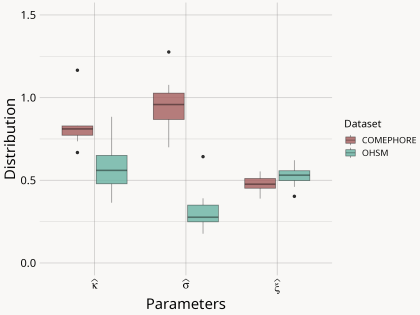
- Models **moderate and extreme** precipitation
- Avoids a threshold choice



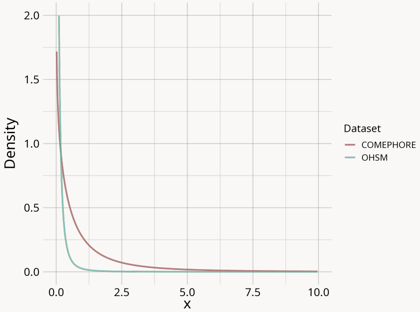


EGPD fitting for two rain gauges, CRBM (left) and CNRS (right) with left-censoring and 95% CI

Left-censoring: selected according to the RMSE criterion for each site individually[3]



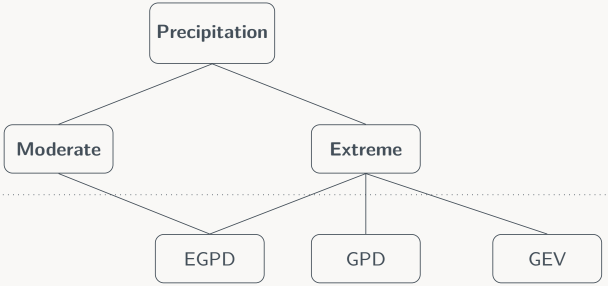
Parameter estimates



Density with mean parameters

EGPD fitting for two rain gauges, with parameter estimates and density with mean parameters

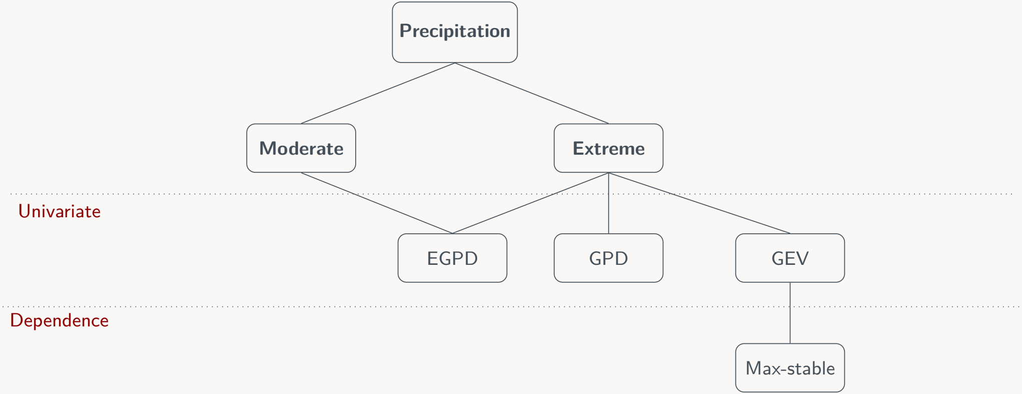
[3]Haruna et al., 2023

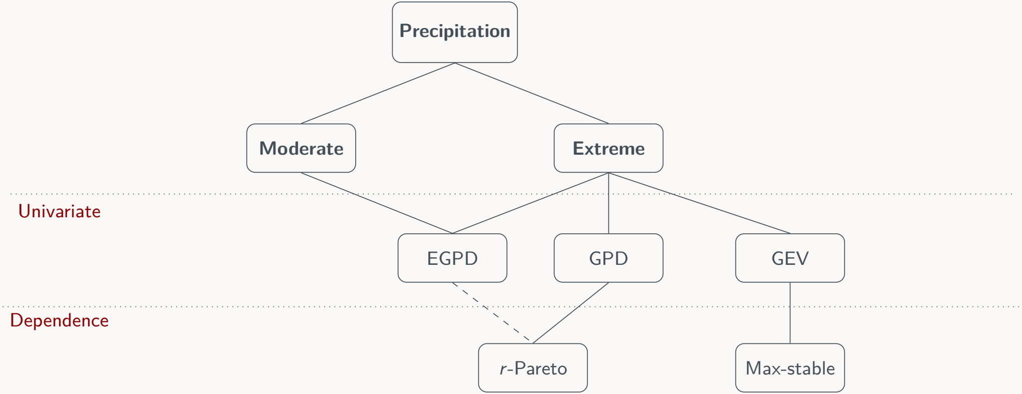


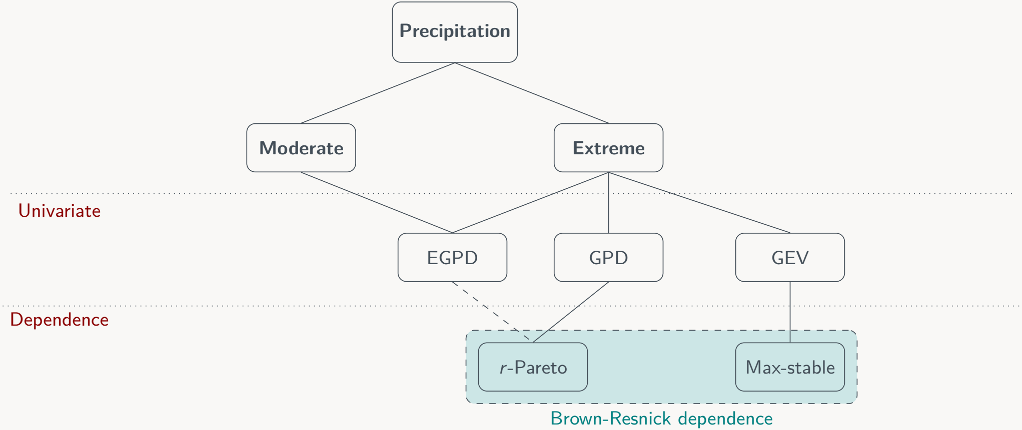
Univariate

Dependence

Spatio-temporal dependence modeling




Precipitation
Moderate
Extreme
Univariate
EGPD
GPD
GEV
Dependence
r-Pareto
Max-stable


Precipitation
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Max-stable
Brown-Resnick dependence

Rainfall random field: $\boldsymbol{X} = \{X_{\boldsymbol{s},t}\ ,\ (\boldsymbol{s}, t) \in \mathcal{S} \times \mathcal{T}\}$ stationary and isotropic

Let $\Lambda_{\mathcal{S}} \subset \mathbb{R}_+^2$ and $\Lambda_{\mathcal{T}} \subset \mathbb{R}_+$ be sets of spatial and temporal lags respectively.

Variogram

The spatio-temporal variogram of $\boldsymbol{X}$ is defined as

$$\gamma(\boldsymbol{h}, \tau) = \frac{1}{2} Var\left(X_{\boldsymbol{s},t} - X_{\boldsymbol{s}+\boldsymbol{h},t+\tau}\right),\ \boldsymbol{h} \in \Lambda_{\mathcal{S}}, \tau \in \Lambda_{\mathcal{T}}$$

- Describes the spatio-temporal variability
- Small $\gamma(\boldsymbol{h}, \tau)$: Strong dependence
- Large $\gamma(\boldsymbol{h}, \tau)$: Weaker dependence

Let $\Lambda_{\mathcal{S}} \subset \mathbb{R}_+^2$ and $\Lambda_{\mathcal{T}} \subset \mathbb{R}_+$ be sets of spatial and temporal lags respectively.

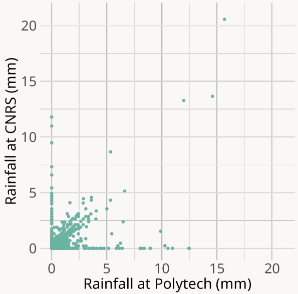
Spatio-temporal extremogram (Coles et al., 1999)

For all $\boldsymbol{h} \in \Lambda_{\mathcal{S}}, \tau \in \Lambda_{\mathcal{T}}$,

$$\chi(\boldsymbol{h}, \tau) = \lim_{q \to 1} \mathbb{P}(X^*_{\boldsymbol{s},t} > q \mid X^*_{\boldsymbol{s}+\boldsymbol{h},t+\tau} > q),$$

with $q \in [0, 1[$ and $X^*_{\boldsymbol{s},t}$ the uniform margins.

- $\chi(\boldsymbol{h}, \tau) \in [0, 1]$
- $\chi(\boldsymbol{h}, \tau) > 0$: asymptotic dependence
- $\chi(\boldsymbol{h}, \tau) = 0$: asymptotic independence



Extreme dependence measure

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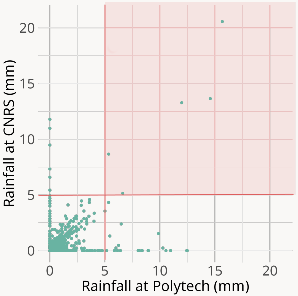


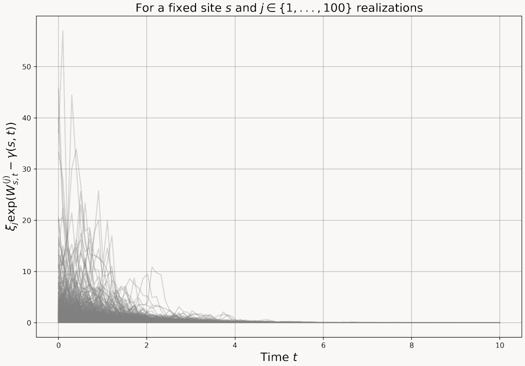
Rainfall random field: $\boldsymbol{X} = \{X_{\boldsymbol{s},t}\ ,\ (\boldsymbol{s}, t) \in \mathcal{S} \times \mathcal{T}\}$ stationary and isotropic

Spectral representation of a Brown-Resnick process (Brown and Resnick, 1977)

For all $\boldsymbol{s} \in \mathcal{S}$ and $t \in \mathcal{T}$,

$$Z_{\boldsymbol{s},t} = \bigvee_{j=1}^{\infty} \xi_j e^{W^{(j)}_{\boldsymbol{s},t} - \gamma(\boldsymbol{s},t)}$$

- $(\xi_j)_{j\geq 1}$: points of a Poisson process with intensity $\xi^{-2} d\xi$
- $\left(W^{(j)}\right)_{j\geq 1}$: independent replicates of an intrinsic stationary and isotropic Gaussian random field $\boldsymbol{W}$
- γ: spatio-temporal variogram of $\boldsymbol{W}$



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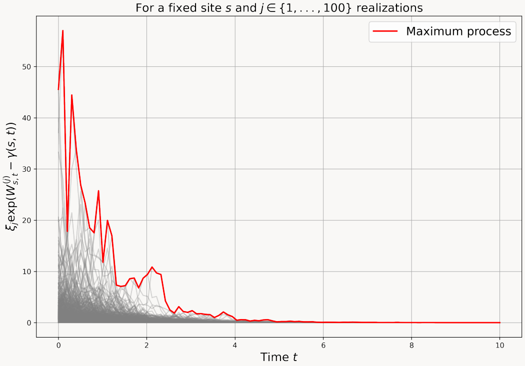
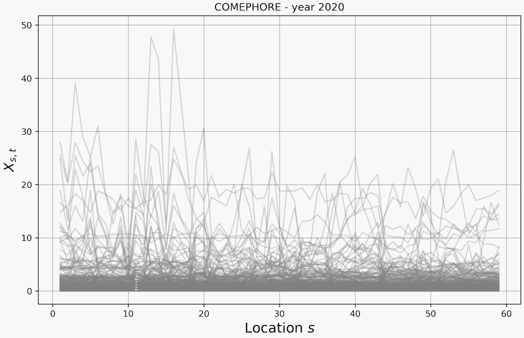


Definition (de Fondeville and Davison, 2018)

For all $\boldsymbol{s} \in \mathcal{S}$ and $t \in \mathcal{T}$, a risk function $r(\boldsymbol{X}) = X_{\boldsymbol{s}_0, t_0}$,

$$X_{\boldsymbol{s},t} \mid r(\boldsymbol{X}) > u \xrightarrow{d} Y_{\boldsymbol{s},t} \quad \text{with} \quad Y_{\boldsymbol{s},t} = uR_{\boldsymbol{s},t}e^{W_{\boldsymbol{s},t} - W_{\boldsymbol{s}_0,t_0} - \gamma(\boldsymbol{s}-\boldsymbol{s}_0, t-t_0)},$$

with $(\boldsymbol{s}_0, t_0)$ a given space-time location, u a high threshold and $R_{\boldsymbol{s},t} \sim \mathit{Pareto}(1)$.



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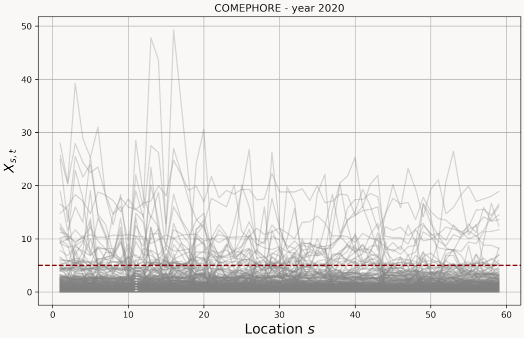

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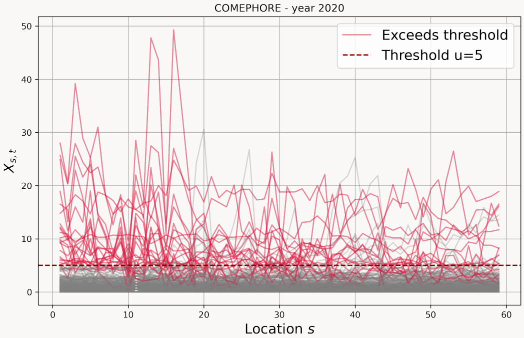

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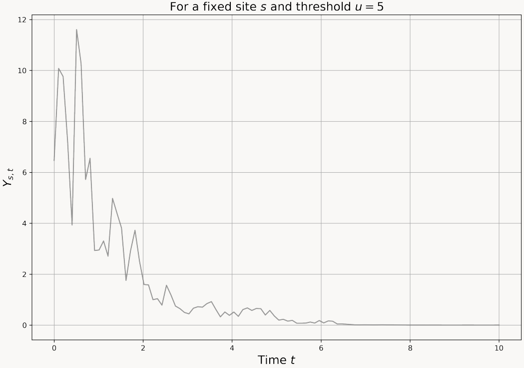


Let $\{X_{\boldsymbol{s},t} \mid r(\boldsymbol{X}) > u, \boldsymbol{s} \in \mathcal{S}, t \in \mathcal{T}\}$ converges in distribution to a r-Pareto process with $r(\boldsymbol{X}) = X_{\boldsymbol{s}_0,t_0}$.

Spatio-temporal r-extremogram

For all $\boldsymbol{h} \in \Lambda_{\mathcal{S}}, \tau \in \Lambda_{\mathcal{T}}$,

$$\begin{aligned} \chi_r(\boldsymbol{h}, \tau) &= \lim_{q \to 1} \mathbb{P}(X^*_{\boldsymbol{s}_0+\boldsymbol{h}, t_0+\tau} > q \mid X^*_{\boldsymbol{s}_0,t_0} > q) \\ &= \lim_{q \to 1} \mathbb{P}(X^*_{\boldsymbol{s}_0+\boldsymbol{h}, t_0+\tau} > q), \end{aligned}$$

with $q \in [0, 1[$ corresponding to threshold u and $X^*_{\boldsymbol{s},t}$ the uniform margins.

Spatio-temporal r-variogram of $\boldsymbol{W}$

For all $\boldsymbol{h} \in \Lambda_{\mathcal{S}}, \tau \in \Lambda_{\mathcal{T}}$,

$$\gamma_r(\boldsymbol{h}, \tau) = \frac{1}{2} Var\left(W_{\boldsymbol{s}_0,t_0} - W_{\boldsymbol{s}_0+\boldsymbol{h}, t_0+\tau}\right).$$

Let $\Lambda_{\mathcal{S}} \subset \mathbb{R}_+^2$ and $\Lambda_{\mathcal{T}} \subset \mathbb{R}_+$ be sets of spatial and temporal lags respectively.

Spatio-temporal extremogram with a Brown-Resnick dependence

Let $\boldsymbol{h} \in \Lambda_{\mathcal{S}}$ and $\tau \in \Lambda_{\mathcal{T}}$. We have

$$\chi(\boldsymbol{h}, \tau) = 2\left(1 - \phi\left(\sqrt{\frac{1}{2}\gamma(\boldsymbol{h}, \tau)}\right)\right)$$

with ϕ the std normal c.d.f. and γ the variogram of $\boldsymbol{W}$.

Dependence framework: Buhl et al., 2019

- Fractional Brownian motion
- Additive separability

$$\frac{\gamma(\boldsymbol{h}, \tau)}{2} = \beta_1 \|\boldsymbol{h}\|^{\alpha_1} + \beta_2 |\tau|^{\alpha_2},$$

with $0 < \alpha_1, \alpha_2 \leq 2\,,\ \beta_1, \beta_2 > 0.$

Case of additive separability: $\frac{\gamma(\boldsymbol{h},\tau)}{2} = \beta_1 \|\boldsymbol{h}\|^{\alpha_1} + \beta_2 |\tau|^{\alpha_2}, \quad 0 < \alpha_1, \alpha_2 \leq 2\,, \; \beta_1, \beta_2 > 0$

Spatio-temporal

$$\chi(\boldsymbol{h},\tau) = 2\left(1 - \phi\left(\sqrt{\tfrac{1}{2}\gamma(\boldsymbol{h},\tau)}\right)\right)$$

Transformation:

$$\eta(\chi) = 2\log\left(\phi^{-1}\left(1 - \tfrac{1}{2}\chi\right)\right)$$

Spatial

$$\eta\left(\chi(\boldsymbol{h},0)\right) = \log\beta_1 + \alpha_1 \log\|\boldsymbol{h}\|\,, \quad \boldsymbol{h} \in \Lambda_{\mathcal{S}}$$

Temporal

$$\eta\left(\chi(0,\tau)\right) = \log\beta_2 + \alpha_2 \log\tau\,, \quad \tau \in \Lambda_{\mathcal{T}}$$

Estimation of the separable variogram parameters

Case of additive separability: $\frac{\gamma(\boldsymbol{h},\tau)}{2} = \beta_1\|\boldsymbol{h}\|^{\alpha_1} + \beta_2|\tau|^{\alpha_2}, \quad 0 < \alpha_1, \alpha_2 \leq 2\,, \ \beta_1, \beta_2 > 0$

Spatio-temporal

$$\chi(\boldsymbol{h},\tau) = 2\left(1-\phi\left(\sqrt{\tfrac{1}{2}\gamma(\boldsymbol{h},\tau)}\right)\right)$$

Transformation:

$$\eta(\chi) = 2\log\left(\phi^{-1}\left(1-\tfrac{1}{2}\chi\right)\right)$$

Spatial

$$\eta\left(\chi(\boldsymbol{h},0)\right) := c_1 + \alpha_1 x_h\,, \ \ \boldsymbol{h} \in \Lambda_{\mathcal{S}}$$

Temporal

$$\eta\left(\chi(0,\tau)\right) := c_2 + \alpha_2 x_\tau\,, \ \ \tau \in \Lambda_{\mathcal{T}}$$

Weighted Least Squares Estimation (WLSE)

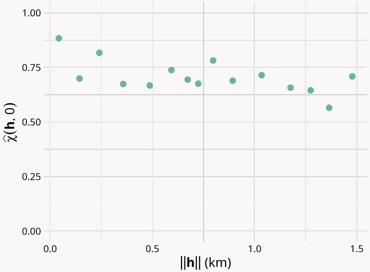
$$\begin{pmatrix}\widehat{c_i}\\ \widehat{\alpha_i}\end{pmatrix} = \text{argmin}_{c_i,\alpha_i} \sum\nolimits_x w_x \left(\eta\left(\widehat{\chi}\right) - (c_i + \alpha_i x)\right)^2$$

Empirical spatial extremogram

For a fixed $t \in \mathcal{T}$ and q a high quantile,

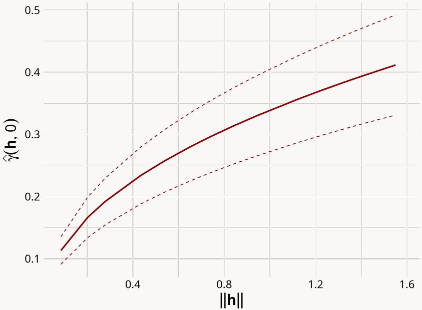
$$\widehat{\chi}_q^{(t)}(\boldsymbol{h}, 0) = \frac{\frac{1}{|N_{\boldsymbol{h}}|}\sum_{i,j \mid (\boldsymbol{s}_i, \boldsymbol{s}_j) \in N_{\boldsymbol{h}}} \mathbb{1}_{\{X^*_{\boldsymbol{s}_i,t} > q, X^*_{\boldsymbol{s}_j,t} > q\}}}{\frac{1}{|\mathcal{S}|}\sum_{i=1}^{|\mathcal{S}|} \mathbb{1}_{\{X^*_{\boldsymbol{s}_i,t} > q\}}},$$

where $C_{\boldsymbol{h}}$ are equifrequent distance classes and $N_{\boldsymbol{h}} = \left\{(\boldsymbol{s}_i, \boldsymbol{s}_j) \in \mathcal{S}^2 \;\middle|\; \|\boldsymbol{s}_i - \boldsymbol{s}_j\| \in C_{\boldsymbol{h}}\right\}$.



Transformation and WLSE

$\Longrightarrow$

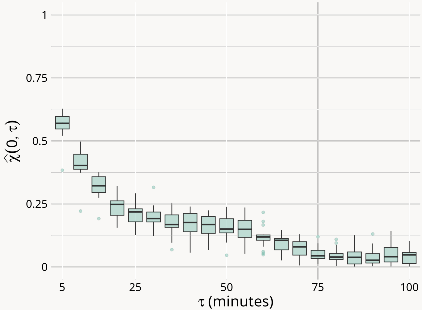


Spatial variogram $\widehat{\gamma}(\boldsymbol{h}, 0) = 2\widehat{\beta}_1 \|\boldsymbol{h}\|^{\widehat{\alpha}_1}$

Empirical temporal extremogram

For a location $\boldsymbol{s} \in \mathcal{S}$, a high quantile q and $t_k \in \{t_1, \dots, t_T\}$,

$$\widehat{\chi}_q^{(s)}(\mathbf{0}, \tau) = \frac{\frac{1}{T-\tau} \sum_{k=1}^{T-\tau} \mathbb{1}_{\{X^*_{\boldsymbol{s},t_k} > q, X^*_{\boldsymbol{s},t_k+\tau} > q\}}}{\frac{1}{T} \sum_{k=1}^{T} \mathbb{1}_{\{X^*_{\boldsymbol{s},t_k} > q\}}}$$



Transformation and WLSE

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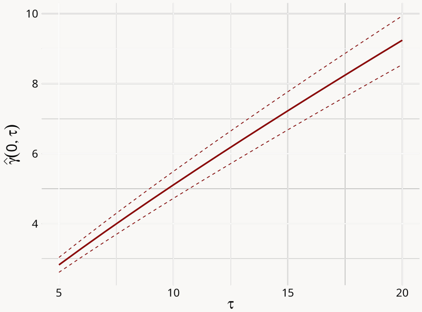


Temporal variogram $\widehat{\gamma}(\mathbf{0}, \tau) = 2\widehat{\beta}_2 |\tau|^{\widehat{\alpha}_2}$

Advection vector $\boldsymbol{V}$

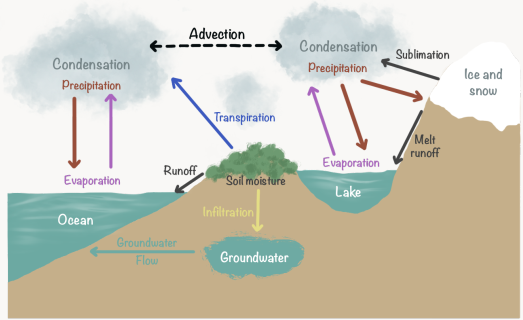
- Horizontal transport of air masses
- To relax the separability assumption

Lagrangian/Eulerian variogram

$$\gamma_L(\boldsymbol{h}, \tau) = \gamma(\boldsymbol{h} - \tau \boldsymbol{V}, \tau)$$

Dependence model

$$\frac{1}{2}\gamma_L(\boldsymbol{h}, \tau) = \beta_1 \|\boldsymbol{h} - \tau \boldsymbol{V}\|^{\alpha_1} + \beta_2 |\tau|^{\alpha_2}$$



Hydrologic cycle

Parameter optimization of $\boldsymbol{\Theta} = (\beta_1, \beta_2, \alpha_1, \alpha_2, \boldsymbol{V})$

Joint excesses for r-Pareto processes:

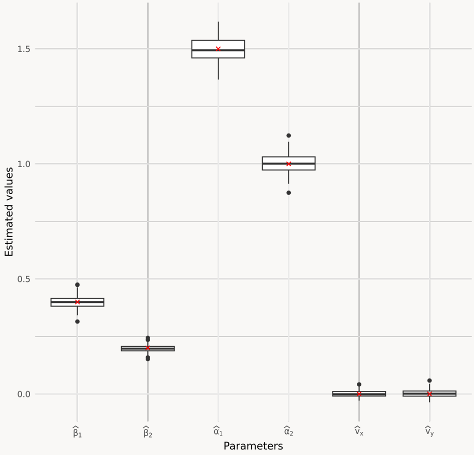
$$
\begin{aligned}
K_{\boldsymbol{h},\tau}(u) &= \sum_{s \in \mathcal{S}:(\boldsymbol{s},\boldsymbol{s}_0)\in\mathcal{N}(\boldsymbol{h})} \sum_{t\in\mathcal{T}:t-t_0=\tau} \mathbb{1}_{\{X_{\boldsymbol{s},t}>u, X_{\boldsymbol{s}_0+\boldsymbol{h},t_0+\tau}>u\}} \\
&\sim \mathcal{B}\left(\sum_{(\boldsymbol{s}_0,t_0)\in\mathcal{R}} \#\{s \in \mathcal{S} : (\boldsymbol{s},\boldsymbol{s}_0) \in \mathcal{N}(\boldsymbol{h})\}, \chi_{r,\boldsymbol{\Theta}}(\boldsymbol{h},\tau) \right), \text{ for a large } u
\end{aligned}
$$

with $\mathcal{R}$ a specific set of r-conditioning spatio-temporal locations.

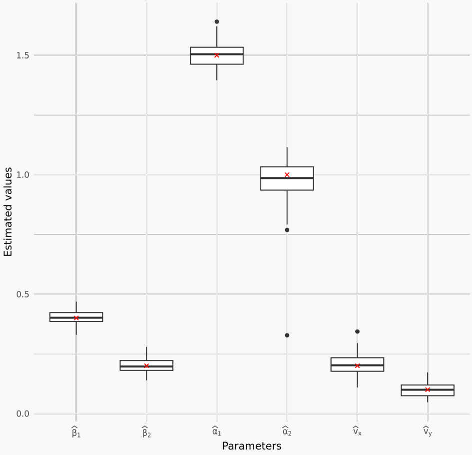
Composite log-likelihood:

$$
l_C(\boldsymbol{\Theta}) \propto \sum_{(\boldsymbol{s}_0,t_0)\in\mathcal{R}} \sum_{(\boldsymbol{s},\boldsymbol{s}_0)\in\mathcal{N}(\boldsymbol{h})} \sum_{t\in\mathcal{T}:t-t_0=\tau} k_{\boldsymbol{s},t} \log \chi_{r,\boldsymbol{\Theta}}(\boldsymbol{h},\tau) + (1-k_{\boldsymbol{s},t}) \log(1-\chi_{r,\boldsymbol{\Theta}}(\boldsymbol{h},\tau)).
$$

where $\chi_{r,\boldsymbol{\Theta}}(\boldsymbol{h},\tau)$ is the r-extremogram.



Without advection



With advection

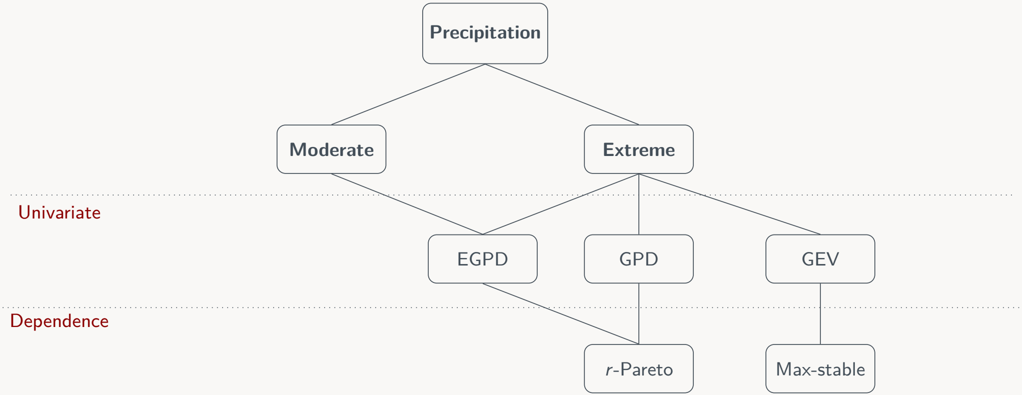
Parameter estimation on 100 simulations of 1000 replicates of r-Pareto processes with 25 sites and 30 time observations

Estimate constant advection $\widehat{\boldsymbol{V}}$

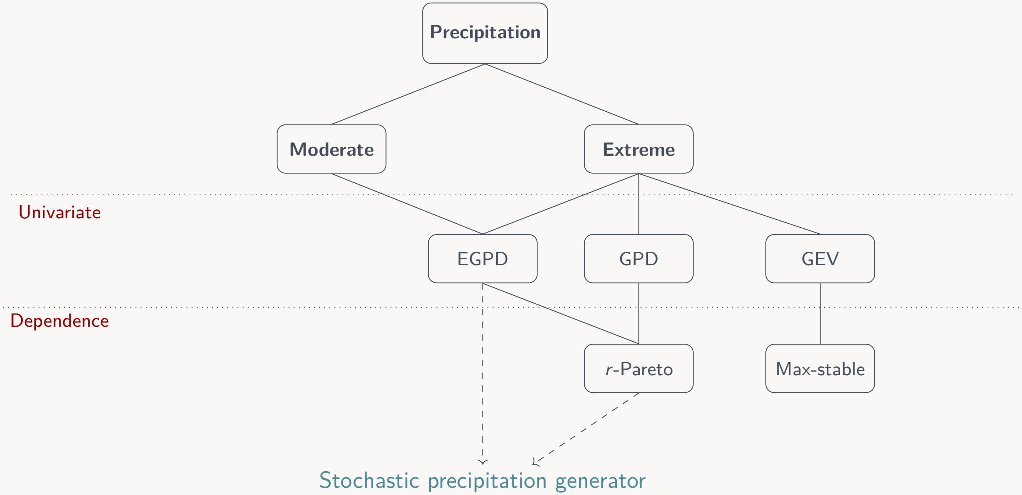
- Use **COMEPHORE** data.
- Initial parameters $\beta_1, \beta_2, \alpha_1, \alpha_2$: WLSE
- Initial advection: wind data

Estimate variogram parameters on HSM data

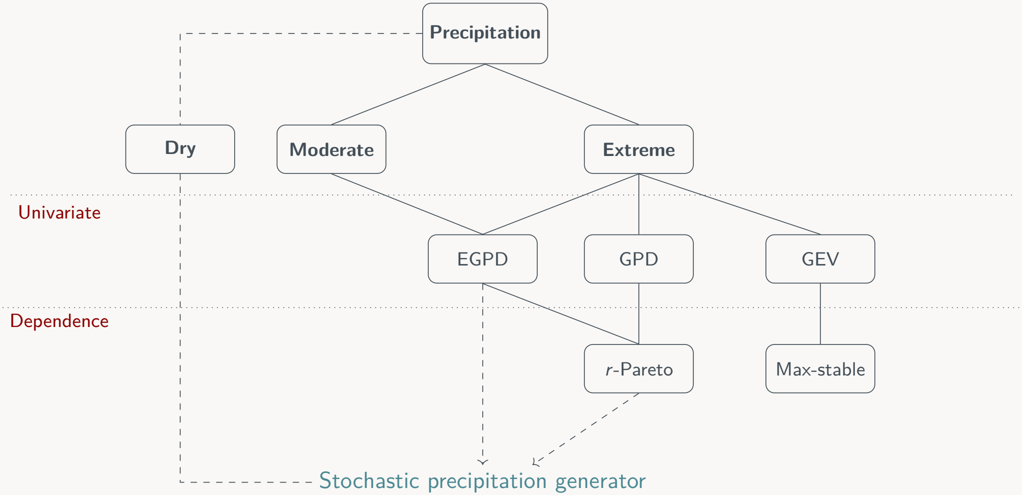
- Initial parameters $\beta_1, \beta_2, \alpha_1, \alpha_2$: WLSE
- Initial advection: $\widehat{\boldsymbol{V}}$ (from COMEPHORE)


Precipitation
Moderate
Extreme
Univariate
EGPD
GPD
GEV
Dependence
r-Pareto
Max-stable

Conclusion



Precipitation
Moderate
Extreme
Univariate
EGPD
GPD
GEV
Dependence
r-Pareto
Max-stable
Stochastic precipitation generator


Precipitation
Dry
Moderate
Extreme
Univariate
EGPD
GPD
GEV
Dependence
r-Pareto
Max-stable
Stochastic precipitation generator

Thank you for your attention!

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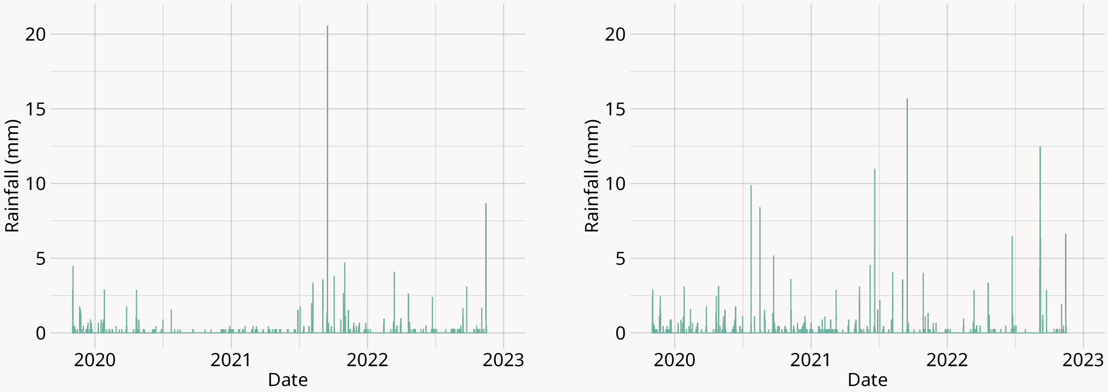
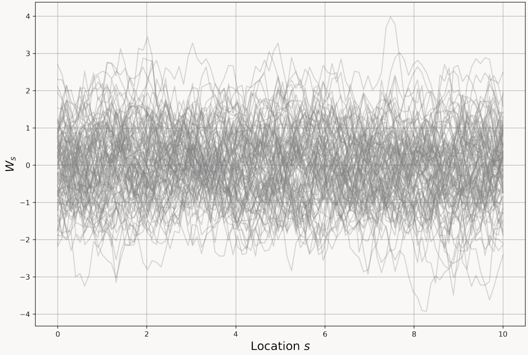
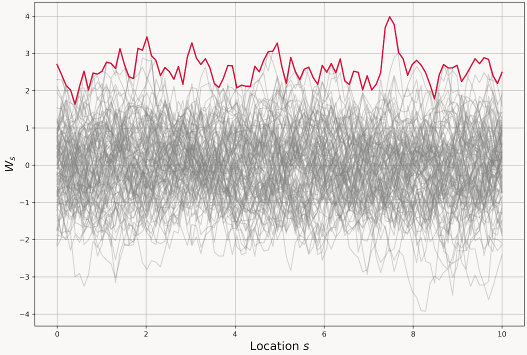


Rainfall amounts on CNRS and Polytech rain gauges



100 Gaussian processes



Maximum process in red