

# Functional peaks-over-threshold analysis with an application to extreme European winter storms

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# Motivation

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3s maximum wind gust of the storm Lothar during winter 1999

- ▶ 169 km/h maximum observed windspeed in Paris (Parc Montsouris).
- ▶ Estimated loss around 8 billion dollars.



# Motivation

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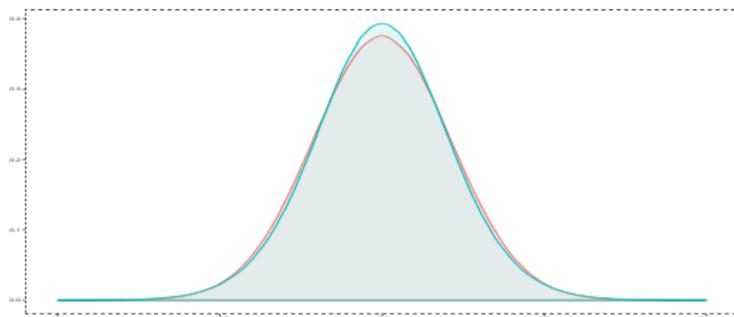
- ▶ Classical techniques for risk estimation rely on historical catalogues and climate models:

⇒ Cannot generate completely new extreme events.

- ▶ Aim to develop a windstorm generator producing storms with
  - ▶ unobserved intensities, i.e., extrapolation above known levels;
  - ▶ unobserved patterns, i.e., new storm tracks and shapes.



## Motivation: geostatistical tools?



- ▶ Gaussian (red) and  $t_{20}$  (blue) density functions matched to have probabilities 0.05 for  $|X| > 1.96$ .
- ▶ Ratio of  $t_{20}$ /Gaussian probabilities for  $|X| > x$ :

x	2	3	4	5	6	7
Ratio of probabilities	1.01	1.7	6.1	58	1589	1.7e5

- ▶ Gaussian distribution has a quick tale decay which may strongly underestimate rare events:

⇒ Not suitable for extrapolation!



## Motivation: geostatistical tools?

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- ▶ For a threshold  $u > 0$  and a bivariate vector with Fréchet margins and Gaussian copula,

$$\Pr(X_1 > u \mid X_2 > u) \sim C \times u^{-(1-\rho)/(\rho+1)} (\log u)^{-\rho/(1+\rho)},$$

and

$$\lim_{u \rightarrow \infty} \Pr(X_1 > u \mid X_2 > u) = 0.$$

where  $-1 < \rho < 1$  is the correlation coefficient.

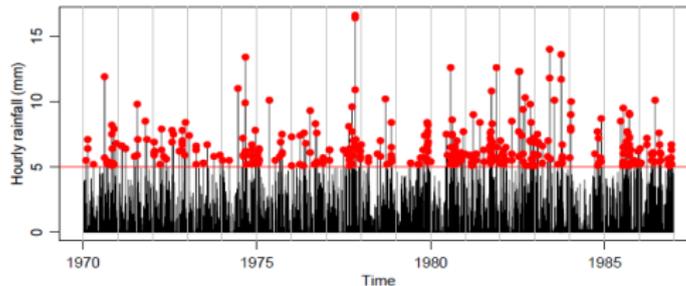
- ▶ With a Gaussian spatial model, the extent of an extreme event decreases as  $u$  increases:

⇒ Strength of dependence should not depend on the intensity.

# Extreme value theory (EVT)

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- ▶ Extreme value theory describes the tail of the distribution.
- ▶ Historically it was developed for "block maxima", i.e., to model annual/monthly maxima with the Generalized Extreme Value (GEV) distribution.
- ▶ Max-stable processes, the functional equivalent of GEV, are mathematically very complex and thus limited application to few dozens of locations.
- ▶ To model single events, an alternative is the peaks-over-threshold analysis.



# Univariate extreme value theory (EVT)

## Peaks-over-threshold models

For any random variable  $X$ , there exist sequences  $a_n > 0$  and  $b_n$  such that

$$\left. \begin{array}{l} n \Pr \left[ \frac{\{X - b_n\}_+}{a_n} > x \right] \\ n \Pr \left[ \frac{\{b_n - X\}_+}{a_n} > x \right] \end{array} \right\} \rightarrow \nu_\xi(x), \quad n \rightarrow \infty,$$

and  $\nu_\xi$  is either degenerate or

$$\nu_\xi(x) = \begin{cases} \left(1 + \xi \frac{x - \mu}{\sigma}\right)^{-1/\xi}, & 1 + \xi(x - \mu)/\sigma \geq 0, \quad \xi \neq 0; \\ \exp\left(-\frac{x - \mu}{\sigma}\right), & x \geq 0, \quad \xi = 0. \end{cases}$$

with,  $\mu \in \mathbb{R}$ ,  $\sigma > 0$ .

$\xi$ , the tail index, determines the strength of the tail and its support:

- ▶  $\xi > 0$ : Fréchet type with  $x \geq \mu$ ,
- ▶  $\xi = 0$ : Gumbel type with  $x \geq \mu$ ,
- ▶  $\xi < 0$ : Weibull type with  $x \in (\mu; \mu - \sigma/1/\xi)$ ;



## Univariate results for threshold exceedances

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For a large enough threshold  $u < \inf\{x : F(x) = 1\}$ , we can use the approximation

$$\Pr(X - u > x \mid X > u) \approx \begin{cases} (1 + \xi x / \sigma)_+^{-1/\xi}, & \xi \neq 0, \\ \exp(-x/\sigma), & \xi = 0, \end{cases}$$

where  $\sigma = \sigma(u) > 0$  and  $a_+ = \max(a, 0)$ :

⇒ The conditional distributions of exceedances over a high threshold can be approximated by a GP distribution.

## (Generalized) functional regular variation

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- ▶ Let  $\{X(s)\}_{s \in S}$  be a stochastic process with sample paths in the space of continuous functions  $C(S)$ , where  $S \subset \mathbb{R}^d$ .
- ▶ Suppose there exist  $\xi \in \mathbb{R}$ , sequences  $a_n > 0$  and  $b_n$  with  $\lim_{n \rightarrow \infty} a_n(s) = \infty$  for all  $s \in S$ , such that

$$\left. \begin{aligned} n \Pr \left[ \left\{ 1 + \xi \left( \frac{X - b_n}{a_n} \right) \right\}^{1/\xi} \in \cdot \right] \\ n \Pr \left[ \exp \left( \frac{X - b_n}{a_n} \right) \in \cdot \right] \end{aligned} \right\} \rightarrow \Lambda(\cdot), \quad n \rightarrow \infty. \quad (1)$$

- ▶  $\Lambda$  is a measure on  $C_+(S) \setminus \{0\}$  satisfying

$$\Lambda\{x \in tA\} = t^{-1} \Lambda\{x \in A\}, \quad t > 0, \quad A \in C(S) \setminus \{0\}.$$

- ▶ Condition (1), which we write  $X \in \text{GRV}(\Lambda)$ , is a form of functional regular variation (Hult and Lindskog, 2005).

## Risk functional and $r$ -exceedances

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- ▶ For a monotonic increasing functional  $r$ , an  $r$ -exceedance over a threshold  $u \geq 0$  is an event  $\{r(x) \geq u\}$ .
- ▶  $r$  is called a risk functional. Common examples are
  - $\sup_{s \in S} X(s)$  for events where  $X$  exceeds a threshold at least one location;
  - $\sum_{t=1}^T \int_S X_t(s) ds$  for spatio-temporal accumulation;
  - $\sqrt{\int_S X(s)^2 ds}$  when the risk is determined by the energy inside a system;
  - $X(s_0)$ , with  $s_0 \in S$  for risks at a specific location, for instance a dam or a power plant.
- ▶ For simplicity of exposure, we now further suppose that  $r$  is linear.

## Limiting distribution of $r$ -exceedances

### Theorem (de Fondeville and Davison, 2018)

Let  $r$  be a risk functional and let  $X \in \text{GRV}(\Lambda)$ . Then there exist  $\xi \in \mathbb{R}$  and a measure  $\sigma_{\text{ang}}$  on

$$\mathcal{S}_{\text{ang}} = \{x \in \mathcal{C}(\mathcal{S}) : \|x\|_1 = 1\},$$

such that for any  $\mathcal{W} \subset \mathcal{S}_{\text{ang}}$ , and  $\rho \geq 0$ ,

$$n\Pr \left[ \frac{r(X) - r(b_n)}{r(a_n)} > \rho, \frac{X - r(b_n)}{\|X - r(b_n)\|_{\text{ang}}} \in \mathcal{W} \right] \rightarrow \left( 1 + \xi \frac{x - \mu}{\sigma} \right)^{-1/\xi} \sigma_{\text{ang}}(\mathcal{W}),$$

as  $n \rightarrow \infty$ , for  $\xi \neq 0$ , and

$$n\Pr \left[ \frac{r(X) - r(b_n)}{r(a_n)} \geq \rho, \exp \frac{X - r(X)}{r(a_n)} \in \mathcal{W} \right] \rightarrow \exp \left( -\frac{x - \mu}{\sigma} \right) \sigma_{\text{ang}}(\mathcal{W}),$$

for  $\xi = 0$ .



### Generalized r-Pareto process (de Fondeville and Davison, 2018)

A generalized r-Pareto process  $P$  is defined by

$$P = \begin{cases} R \frac{W}{r(W)}, & \xi \neq 0, \\ R + \log W - r(\log W), & \xi = 0, \end{cases} \quad (2)$$

where

- ▶  $R$  is a univariate generalized Pareto variable with tail parameter  $\xi$ , and distribution function

$$\Pr(R > \rho) = \left\{ 1 + \xi \frac{\rho - u}{\sigma} \right\}^{-1/\xi}, \quad \rho \geq u \geq 0,$$

with  $\sigma > 0$ ;

- ▶  $W$  is the stochastic process

$$W = A\{R_1 Q\}^\xi + B.$$

where  $A > 0$ ,  $B \in C(S)$  with  $r(A) = 1$  and  $r(B) = 0$ ,  $R_1$  is a unit Pareto distribution and  $Q$  is a stochastic process on  $\{x \in C_+(S) : \|x\|_1 = 1\}$  with probability measure  $\sigma_{\text{ang}}$ .

## Properties of generalized $r$ -Pareto processes

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- ▶  $r$ -Pareto processes are the only possible limits of rescaled threshold exceedances for a regularly varying stochastic process. This means for a large enough threshold  $u > 0$ ,

$$\Pr(X - u \in \cdot \mid r(X) > u) \approx \Pr(P \in \cdot).$$

- ▶ The  $r$ -exceedance distribution of  $P$  is

$$\Pr\{r(P) \geq \rho\} = \left\{1 + \xi \frac{\rho - u}{\sigma}\right\}^{-1/\xi}, \quad \rho \geq u.$$

- ▶ The generalized  $r$ -Pareto process has generalized Pareto marginals above a sufficiently high threshold  $u_0 \geq 0$ :

$$\Pr\{P(s_0) \geq \rho \mid P(s_0) \geq u_0\} = \left\{1 + \xi \frac{\rho - \mu(s_0)}{\sigma(u_0)}\right\}^{-1/\xi}, \quad \rho \geq u_0,$$

with  $\sigma(u_0) > 0$  and  $\mu(s_0) \in \mathbb{R}$ .

## Density function of exceedances

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- ▶ In practice, choose a high threshold vector  $u > 0$  such that the density function of the  $r$ -exceedances  $f_{\theta}^r$  can be approximated by its limit

$$f_{\theta}^r(x) \approx \frac{\lambda_{\theta}^r(x)}{\Lambda_{\theta}\{A_r(u)\}}, \quad x \in A_r(u),$$

with  $A_r(u) = \{x \in C(S) : r(x) \geq u\}$  and where

$$\Lambda_{\theta}\{A_r(u)\} = \int_{A_r(u)} \lambda_{\theta}^r(x) dx, \quad u \geq 0.$$

- ▶ For most models, the limiting measure  $\Lambda$  and its partial derivatives are known in Cartesian coordinates.
- ▶ Direct maximum likelihood estimation is in general not recommended and dimensionally limited because it requires  $\Lambda_{\theta}\{A_r(u)\}$ .
- ▶ Model estimation in "moderately high" dimensions is possible within the framework of proper scoring rules (de Fondeville and Davison, 2017).



## The gradient scoring rule

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- ▶ An adaptation of the gradient scoring rule (de Fondeville and Davison, 2017) allows statistical inference using partial derivatives, with respect to  $x_1, \dots, x_\ell$ , of the log-density function,

$$\delta_w(\lambda_{\theta,u}^r, x) = \sum_{i=1}^{\ell} \left( 2w_i(x) \frac{\partial w_i(x)}{\partial x_i} \frac{\partial \log \lambda_{\theta,u}^r(x)}{\partial x_i} + w_i(x)^2 \left[ \frac{\partial^2 \log \lambda_{\theta,u}^r(x)}{\partial x_i^2} + \frac{1}{2} \left\{ \frac{\partial \log \lambda_{\theta,u}^r(x)}{\partial x_i} \right\}^2 \right] \right),$$

where  $w : A_r(u) \rightarrow \mathbb{R}_+^\ell$  is a weighting function differentiable on  $A_r(u)$  and vanishing on the boundaries of  $A_r(u)$ .

- ▶ Maximization of  $\delta_w$  gives an asymptotically unbiased and normal estimator.

## Brown–Resnick model

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- ▶ Recall that for  $\xi \neq 0$ ,  $P$  is

$$P = R \frac{A(R_1 Q)^\xi + B}{r\{A(R_1 Q)^\xi + B\}}$$

- ▶ Suppose  $W$  follows a log-Gaussian distribution with stationary increments and semi-variogram  $\gamma$ .
- ▶ The  $\ell$ -dimensional intensity function is

$$\lambda_\theta^r(x) = \frac{|\Sigma_\theta|^{-1/2}}{x_1^2 x_2 \cdots x_\ell (2\pi)^{(\ell-1)/2}} \exp\left(-\frac{1}{2} \tilde{x}^T \Sigma_\theta^{-1} \tilde{x}\right), \quad x \in \mathbb{R}_+^\ell \setminus \{0\},$$

where  $\tilde{x}$  is the  $(\ell - 1)$ -dimensional vector

$$\{\log(x_j/x_1) + \gamma_\theta(s_j - s_1) : j = 2, \dots, \ell\}^T,$$

and  $\Sigma_\theta$  is the  $(\ell - 1) \times (\ell - 1)$  matrix

$$\{\gamma_\theta(s_i - s_1) + \gamma_\theta(s_j - s_1) - \gamma_\theta(s_i - s_j)\}_{i,j \in \{2, \dots, \ell\}}.$$

## Measure of extremal dependence

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- ▶ The extremogram  $\pi(h)$  is a tool to measure the strength of dependence ( $\sim$  variogram for extremes);

$$\pi(h) = \Pr \left[ X(s+h) > u \mid \left\{ X(s) > u \right\} \cap \left\{ r \left( \frac{X}{u} \right) > 1 \right\} \right].$$

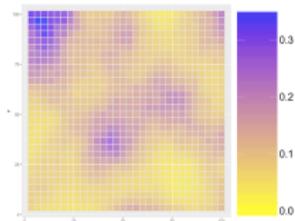
- ▶ For the Brown–Resnick model,

$$\pi(h) = 2 \left[ 1 - \Phi \left\{ \left( \frac{\gamma(h)}{2} \right)^{1/2} \right\} \right],$$

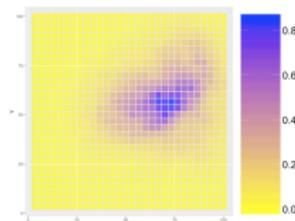
where  $\gamma$  is a valid semi-variogram and  $\Phi$  is the cumulative distribution function of a Gaussian random variable.

# Variogram and extremogram

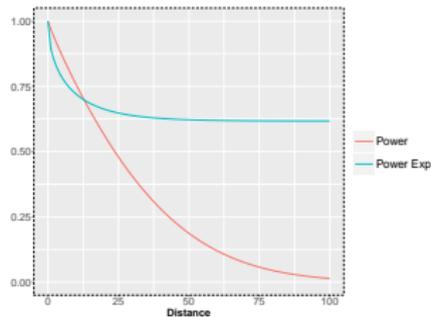
Simulation of generalized r-Pareto process with  $\int_S X(s)ds \geq 100$ .



$$\gamma(h) = \sigma \left[ 1 - \exp \left\{ - \left( \frac{h}{\tau} \right)^\alpha \right\} \right]$$



$$\gamma(h) = \left( \frac{h}{\tau} \right)^\alpha$$



Theoretical  $\pi(h)$  for two different variograms

## Application: Extreme European winter storms

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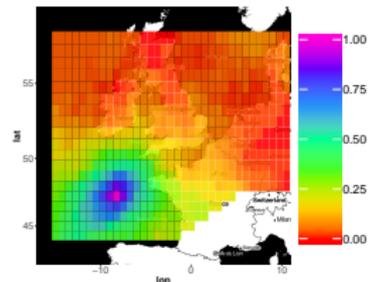
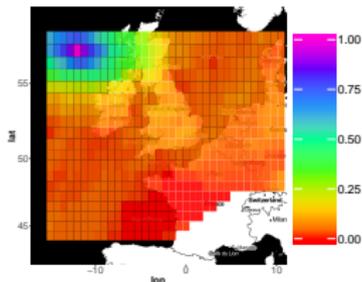
- ▶ 3s maximum windgust every 3 hours for the period 1979 to 2016 from ERA-Interim reanalysis model.
- ▶ Storms are defined as an exceedance of an 24 hours temporal aggregation of the spatial mean:

$$r(X) = \sum_{i=1}^8 \int_S X(s) ds.$$

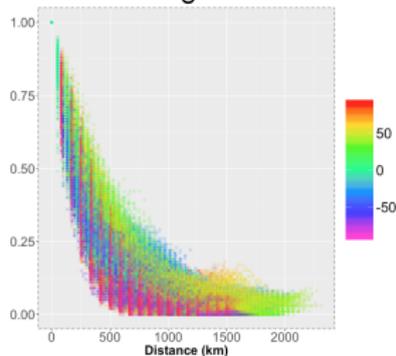
- ▶ Time frame is centered on the 24 hour maximum of the spatial mean.
- ▶ 200 events are used to fit a Pareto process.

# Application: Extreme European winter storms

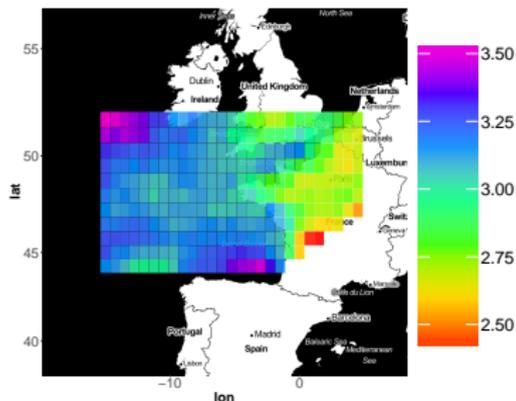
Estimated  $\pi(h)$  for two different locations



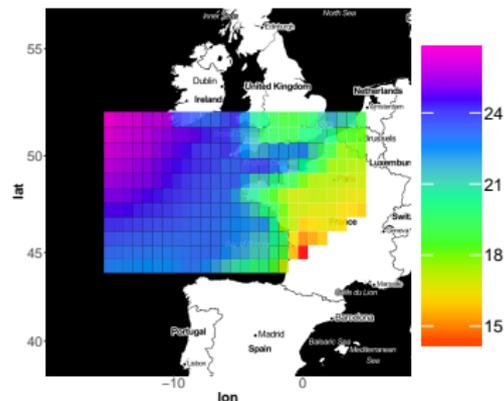
Extremogram cloud



# Extreme European winter storms: Marginal model



Scales



Locations



## Application: Extreme European winter storms

- Variogram model:

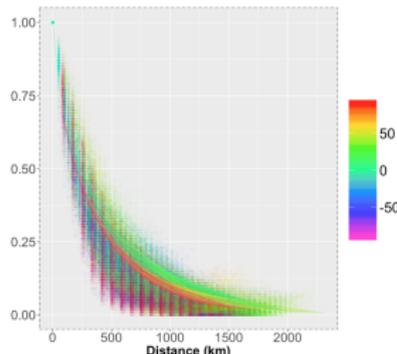
$$\gamma(s_i, s_j, t_i, t_j) = \left\| \frac{\Omega\{s_i - s_j + V(t_i - t_j)\}}{\tau} \right\|_2^\kappa, \quad s_i, s_j \in S, \quad t_i, t_j \in \{0, \dots, 21\},$$

with  $0 < \kappa \leq 2$ ,  $\tau > 0$ , wind vector  $V \in \mathbb{R}^2$  and anisotropy matrix

$$\Omega = \begin{bmatrix} \cos \eta & -\sin \eta \\ a \sin \eta & a \cos \eta \end{bmatrix}, \quad \eta \in \left(-\frac{\pi}{4}; \frac{\pi}{4}\right], \quad a > 0.$$

- Estimated parameters

$\kappa$	$\tau$	$a$	$\eta$	$V_1$	$V_2$
1.17	348.6	1.25	-0.02	0.25	-0.01



## Application: European extra-tropical cyclones

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Simulated extreme windstorm over Europe

## Summary and discussion

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- ▶ Classical geostatistics should be avoided when modelling extreme events.
- ▶ Generalized  $r$ -Pareto process is the functional equivalent of the generalized Pareto distribution and allows one to model  $r$ -exceedances.
- ▶ The Brown–Resnick model uses classical variogram models, while the corresponding stochastic process is heavy-tailed.
- ▶ Inference using the gradient scoring rule enables inference in "moderately high" dimensions and is limited by matrix inversion.
- ▶ We developed a (too) simple spatio-temporal generator for extreme windstorms in Europe.
- ▶ Ongoing work:
  - ▶ Marginal modelling;
  - ▶ Complex dependence structure to better capture the characteristics of the dependence structure.



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# Risk functional

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## Risk functional

A monotonic increasing functional  $r : \mathcal{C}(S) \rightarrow \mathbb{R}$  satisfying

$$r \text{ continuous at } \{B - A\xi^{-1}\} \quad \text{and } r(B - A\xi^{-1}) < 0, \quad \xi > 0$$

$$r(x) \rightarrow -\infty, \quad x \rightarrow -\infty \quad \xi \leq 0,$$

and for which there are functions  $A > 0$  and  $B$  such that

$$\lim_{n \rightarrow \infty} \sup_{s \in S} \left| \frac{a_n(s)}{r(a_n)} - A(s) \right| = 0, \quad \lim_{n \rightarrow \infty} \sup_{s \in S} \left| \frac{b_n(s) - r(b_n)}{r(a_n)} - B(s) \right| = 0,$$

is called a risk functional.

## Properties of generalized r-Pareto processes

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- ▶ The  $r$ -exceedance distribution of  $P$  is

$$\Pr \{r(P) \geq \rho\} = \left\{ 1 + \xi \frac{\rho - u}{\sigma} \right\}^{-1/\xi}, \quad \rho \geq u.$$

- ▶ The generalized  $r$ -Pareto process has generalized Pareto marginals above a sufficiently high threshold  $u_0 \geq 0$ :

$$\Pr \{P(s_0) \geq \rho \mid P(s_0) \geq u_0\} = \left\{ 1 + \xi \frac{\rho - u_0 A(s_0) - B(s_0)}{\sigma(u_0)} \right\}^{-1/\xi}, \quad \rho \geq u_0,$$

with  $\sigma(u_0) = \sigma A(s_0) + \xi \{u_0 - A(s_0)u - B(s_0)\}$ .

## The gradient score

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### Proposition (de Fondeville and Davison, 2017)

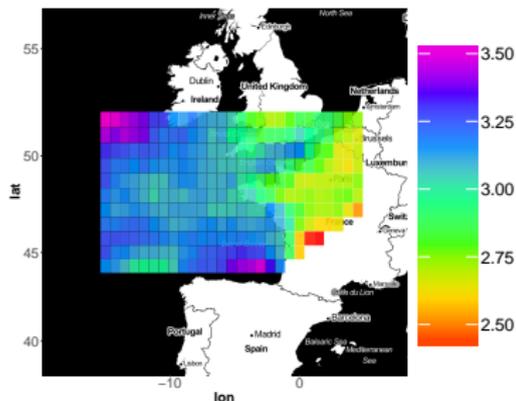
The scoring rule  $\delta_w(\lambda_{\theta, u}^r, \cdot)$  is strictly proper, i.e., the estimator

$$\hat{\theta}_{\delta}^r\{x^1, \dots, x^n\} = \arg \max_{\theta \in \Theta} \sum_{m=1}^n \epsilon \left\{ r \left( \frac{x^m}{u_n} \right) > 1 \right\} \delta(\lambda_{\theta, u_n}^r, x^m), \quad (3)$$

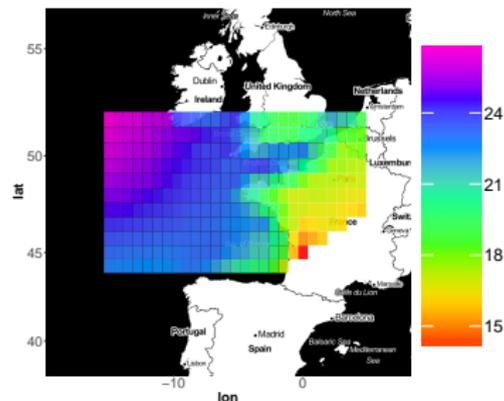
where  $\epsilon\{\cdot\}$  is the indicator function and  $x^1, \dots, x^n$  are sampled from the random vector  $X$  with normalized marginals, is consistent and asymptotically normal as  $n \rightarrow \infty$  and  $u_n \rightarrow \infty$  with  $N_{u_n} = o(n)$ .

In a simulation study, we compared the gradient scoring rule with spectral likelihood and censored likelihood.

# Extreme European winter storms: Marginal model



Scales



Locations