Estimation of Extreme Risk Measures from Heavy-tailed distributions

BY

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in collaboration with

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1. Nonparametric extreme risks measures

2. Estimators and asymptotics results

3. Extrapolation

4. Application
   - Tuning parameter selection procedure
   - Results

Definition of risk measures

- Let $Y \in \mathbb{R}$ be a random loss variable. For $\alpha \in (0,1)$, the Value-at-Risk of level α is the quantity $\mathrm{VaR}(\alpha)$ defined by

$$\mathrm{VaR}(\alpha) := \overline{F}^{\leftarrow}(\alpha) = \inf\{t, \overline{F}(t) \leq \alpha\},$$

where $\overline{F}^{\leftarrow}(.)$ is the generalized inverse of the survival function of Y.
$\mathrm{VaR}(\alpha)$ is the upper α-quantile of the loss distribution.

- The Conditional Tail Expectation of level $\alpha \in (0,1)$ is defined by

$$\mathrm{CTE}(\alpha) := \mathbb{E}(Y|Y > \mathrm{VaR}(\alpha)).$$

- The Conditional-Value-at-Risk of level $\alpha \in (0,1)$ introduced by Rockafellar et Uryasev [2000] is defined by

$$\mathrm{CVaR}_\lambda(\alpha) := \lambda \mathrm{VaR}(\alpha) + (1-\lambda)\mathrm{CTE}(\alpha),$$

with $0 \leq \lambda \leq 1$.

- The Conditional Tail Variance of level $\alpha \in (0,1)$ introduced by Valdez [2005] is defined by

$$\mathrm{CTV}(\alpha) := \mathbb{E}((Y - \mathrm{CTE}(\alpha))^2|Y > \mathrm{VaR}(\alpha)).$$

A new risk measure : the Conditional Tail Moment

The first purpose of this presentation is to unify the definitions of the previous risk measures. To this end, a new risk measure is introduced. The Conditional Tail Moment of level $\alpha \in (0,1)$ is defined by

$$\mathrm{CTM}_a(\alpha) := \mathbb{E}(Y^a | Y > \mathrm{VaR}(\alpha)),$$

where $a \geq 0$ is such that the moment of order a of Y exists.

All the previous risk measures of level α can be rewritten as

$$\begin{aligned}
\mathrm{VaR}(\alpha) &= \overline{F}^{\leftarrow}(\alpha), \\
\mathrm{CTE}(\alpha) &= \mathrm{CTM}_1(\alpha), \\
\mathrm{CVaR}(\alpha) &= \lambda \mathrm{VaR}(\alpha) + (1-\lambda)\mathrm{CTM}_1(\alpha), \\
\mathrm{CTV}(\alpha) &= \mathrm{CTM}_2(\alpha) - \mathrm{CTM}_1^2(\alpha).
\end{aligned}$$

$\Longrightarrow$ All the risk measures depend on the VaR and the CTM_a.

Framework : extreme losses and regression case

Our second aim is to adapt risk measures to extreme losses and to the case where a covariate $X \in \mathbb{R}^p$ is recorded simultaneously with the loss variable Y.

1. We replace the fixed level $\alpha \in (0,1)$ by a sequence $\alpha_n \underset{n\to\infty}{\longrightarrow} 0$.
2. Denoting by $\overline{F}(.|x)$ the conditional survival distribution function of Y given $X = x$, we define the Regression Value-at Risk by :

$$\mathrm{RVaR}(\alpha_n|x) := \overline{F}^{\leftarrow}(\alpha|x) = \inf\{t, \overline{F}(t|x) \leq \alpha\},$$

and the Regression Conditional Tail Moment of order a by :

$$\mathrm{RCTM}_a(\alpha_n|x) := \mathbb{E}(Y^a|Y > \mathrm{RVaR}(\alpha_n|x), X = x),$$

where $a > 0$ is such that the moment of order a of Y exists.

Rewriting risk measures

This yields the following risk measures :

$$\begin{aligned}
\mathrm{RCTE}(\alpha_n|x) &= \mathrm{RCTM}_1(\alpha_n|x), \\
\mathrm{RCVaR}_\lambda(\alpha_n|x) &= \lambda \mathrm{RVaR}(\alpha_n|x) + (1-\lambda)\mathrm{RCTM}_1(\alpha_n|x), \\
\mathrm{RCTV}_n(\alpha_n|x) &= \mathrm{RCTM}_2(\alpha_n|x) - \mathrm{RCTM}_1^2(\alpha_n|x).
\end{aligned}$$

$\Longrightarrow$ All the risk measures depend on the RVaR and the RCTM_a.

We defined the conditional moment of order $a \geq 0$ of Y given $X = x$ by

$$\varphi_a(y|x) = \mathbb{E}\left(Y^a \mathbb{I}\{Y > y\} | X = x\right),$$

where $\mathbb{I}\{.\}$ is the indicator function. Remarking that $\varphi_0(y|x) = \overline{F}(y|x)$ we have

$$\begin{aligned}
\mathrm{RVaR}(\alpha_n|x) &= \varphi_0^{\leftarrow}(\alpha_n|x), \\
\mathrm{RCTM}_a(\alpha_n|x) &= \frac{1}{\alpha_n}\varphi_a(\varphi_0^{\leftarrow}(\alpha_n|x)|x).
\end{aligned}$$

Objective : to estimate $\varphi_a(.|x)$ and $\varphi_a^{\leftarrow}(.|x)$.

Inference

Estimator of $\varphi_a(.|x)$:

We propose to use a classical kernel estimator given by

$$\widehat{\varphi}_{a,n}(y|x) = \sum_{i=1}^{n} K\left(\frac{x - X_i}{h_n}\right) Y_i^a \mathbb{I}\{Y_i > y\} \Bigg/ \sum_{i=1}^{n} K\left(\frac{x - X_i}{h_n}\right).$$

- In this context, h_n is a non-random sequence called the window-width such that $h_n \longrightarrow 0$ as $n \longrightarrow \infty$ and K is a density on $\mathbb{R}^p$.

Estimator of $\varphi_a^{\leftarrow}(.|x)$:

Since $\hat{\varphi}_{a,n}(.|x)$ is a non-increasing function, we can define an estimator of $\varphi_a^{\leftarrow}(\alpha|x)$ for $\alpha \in (0,1)$ by

$$\hat{\varphi}_{a,n}^{\leftarrow}(\alpha|x) = \inf\{t, \hat{\varphi}_{a,n}(t|x) < \alpha\}.$$

Heavy-tailed distributions

(F.1) We assume that the conditional survival distribution function of Y given $X = x$ is heavy-tailed and admits a probability density function.

It is also equivalent to stating that for all $\lambda > 0$,

$$\lim_{y\to\infty} \frac{\overline{F}(\lambda y|x)}{\overline{F}(y|x)} = \lambda^{-1/\gamma(x)}.$$

In this context, $\gamma(.)$ is a positive function of the covariate x and is referred to as the conditional tail index since it tunes the tail heaviness of the conditional distribution of Y given $X = x$.

Condition **(F.1)** also implies that for $a \in [0, 1/\gamma(x))$ and for all $y > 0$,

$$\mathrm{RCTM}_a(1/y|x) = y^{a\gamma(x)}\ell_a(y|x),$$

where for x fixed, $\ell_a(.|x)$ is a slowly-varying function at infinity, *i.e* for all $\lambda > 0$,

$$\lim_{y\to\infty} \frac{\ell_a(\lambda y|x)}{\ell_a(y|x)} = 1.$$

Karamata representation

It also appears that, under **(F.1)**, a sufficient condition for the existence of $\mathrm{RCTM}_a(1/.|x)$ is $a < 1/\gamma(x)$.

(F.2) $\ell_a(.|x)$ is normalized for all $a \in [0, 1/\gamma(x))$.

In such a case, the Karamata representation of the slowly-varying function can be written as

$$\ell_a(y|x) = c_a(x) \exp\left(\int_1^y \frac{\varepsilon_a(u|x)}{u} du \right),$$

where $c_a(.)$ is a positive function and $\varepsilon_a(y|x) \to 0$ as $y \to \infty$.

Here, we limit ourselves to assuming that for all $a \in (0, 1/\gamma(x))$,

(F.3) $|\varepsilon_a(.|x)|$ is continuous and ultimately non-increasing.

Others assumptions

A Lipschitz condition on the probability density function g of X is also required. For all $(x, x') \in \mathbb{R}^p \times \mathbb{R}^p$, the Euclidean distance between x and x' is denoted by $d(x, x')$ and the following assumption is introduced :

(L) There exists a constant $c_g > 0$ such that $|g(x) - g(x')| \leq c_g d(x, x')$.

The next assumption is standard in the kernel estimation framework.

(K) K is a bounded density on $\mathbb{R}^p$, with support S included in the unit ball of $\mathbb{R}^p$.

Finally, for $y > 0$ and $\xi > 0$, the largest oscillation of the conditional moment of order $a \in [0, 1/\gamma(x))$ is given by

$$\omega_n(y, \xi) = \sup \left\{ \left| \frac{\varphi_a(z|x)}{\varphi_a(z|x')} - 1 \right|, \; z \in [(1-\xi)y, (1+\xi)y] \text{ and } \; d(x, x') \leq h \right\}.$$

Main results

Theorem 1 :

Suppose **(F.1)**, **(F.2)**, **(L)** and **(K)** hold. Let us introduce $0 \le a_1 < a_2 < \cdots < a_J$ where J is a positive integer. For all $x \in \mathbb{R}^p$ such that $g(x) > 0$ and $0 < \gamma(x) < 1/(2a_J)$, let us introduce a sequence (α_n) with $\alpha_n \to 0$ and $nh^p\alpha_n \to \infty$ as $n \to \infty$. If there exists $\xi > 0$ such that $nh^p\alpha_n \left(h \vee \omega_n(\varphi_0^{\leftarrow}(\alpha_n|x), \xi)\right)^2 \to 0$, then, the random vector

$$\sqrt{nh^p\alpha_n}\left\{\left(\frac{\widehat{\mathrm{RCTM}}_{a_j,n}(\alpha_n|x)}{\mathrm{RCTM}_{a_j}(\alpha_n|x)} - 1\right)_{j\in\{1,\dots,J\}}, \left(\frac{\widehat{\mathrm{RVaR}}_n(\alpha_n|x)}{\mathrm{RVaR}(\alpha_n|x)} - 1\right)\right\}$$

is asymptotically Gaussian, centered, with a $(J+1)\times(J+1)$ covariance matrix $\|K\|_2^2\gamma^2(x)\Sigma(x)/g(x)$ where for $(i,j) \in \{1,\dots,J\}^2$ we have

$$\Sigma(x) = \left(\begin{array}{c|c} \frac{a_i a_j \gamma^2(x)(2-(a_i+a_j)\gamma(x))}{(1-(a_i+a_j)\gamma(x))} & \begin{array}{c} a_1\gamma^2(x)) \\ \vdots \\ a_J\gamma^2(x) \end{array} \\ \hline a_1\gamma^2(x)\cdots a_J\gamma^2(x) & \gamma^2(x) \end{array}\right).$$

Asymptotic normalities

Suppose the assumptions of Theorem 1 hold. Then, if $0 < \gamma(x) < 1/2$, we have

$$\sqrt{nh^p\alpha_n}\left(\frac{\widehat{\mathrm{RCTE}}_n(\alpha_n|x)}{\mathrm{RCTE}(\alpha_n|x)} - 1\right) \xrightarrow{d} \mathcal{N}\left(0, \frac{2(1-\gamma(x))\gamma^2(x)}{1-2\gamma(x)}\frac{\|K\|_2^2}{g(x)}\right)$$

$$\sqrt{nh^p\alpha_n}\left(\frac{\widehat{\mathrm{RCVaR}}_{\lambda,n}(\alpha_n|x)}{\mathrm{RCVaR}_\lambda(\alpha_n|x)} - 1\right) \xrightarrow{d} \mathcal{N}\left(0, \frac{\gamma^2(x)(\lambda^2+2-2\lambda-2\gamma(x))}{1-2\gamma(x)}\frac{\|K\|_2^2}{g(x)}\right)$$

The $\mathrm{RCTV}(\alpha_n|x)$ estimator involves the computation of a second order moment, it requires the stronger condition $0 < \gamma(x) < 1/4$,

$$\sqrt{nh^p\alpha_n}\left(\frac{\widehat{\mathrm{RCTV}}_n(\alpha_n|x)}{\mathrm{RCTV}(\alpha_n|x)} - 1\right) \xrightarrow{d} \mathcal{N}\left(0, V_{\gamma(x)}\frac{\|K\|_2^2}{g(x)}\right),$$

where

$$V_{\gamma(x)} = \frac{8(1-\gamma(x))(1-2\gamma(x))(1+2\gamma(x)+3\gamma^2(x))}{(1-3\gamma(x))(1-4\gamma(x))}.$$

A Weissman type estimator

- In Theorem 1, the condition $nh^p\alpha_n \to \infty$ provides a lower bound on the level of the risk measure to estimate.
- This restriction is a consequence of the use of kernel estimator which cannot extrapolate beyond the maximum observation in the ball $B(x,h)$.
- In consequence, α_n must be an order of an extreme quantile within the sample.

Definition

Let us consider $(\alpha_n)_{n\geq 1}$ and $(\beta_n)_{n\geq 1}$ two positives sequences such that $\alpha_n \to 0$, $\beta_n \to 0$ and $0 < \beta_n < \alpha_n$. A kernel adaptation of Weissman's estimator [1978] is given by

$$\widehat{\mathrm{RCTM}}^{W}_{a,n}(\beta_n|x) = \widehat{\mathrm{RCTM}}_{a,n}(\alpha_n|x)\left(\frac{\alpha_n}{\beta_n}\right)^{a\hat{\gamma}_n(x)}.$$

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Objective : to estimate $\gamma(x)$.

The Hill estimator

- Without covariate : Hill [1975]

Let $(k_n)_{n\geq 1}$ be a sequence of integers such that $k_n \in \{1 \ldots n\}$. The Hill estimator is given by

$$\hat{\gamma}_{n,\alpha_n} = \frac{1}{k_n - 1} \sum_{i=1}^{k_n - 1} \log(Z_{n-i+1,n}) - \log(Z_{n-k_n+1,n}),$$

where $k_n = \lfloor n\alpha_n \rfloor$ and $Z_{1,n} \leq \cdots \leq Z_{n,n}$ are the order statistics associated with *i.i.d.* realizations $Z_1, \ldots, Z_n$ of the random variable Z.

- With a covariate : Gardes and Girard [2008]

Let $(\alpha_n)_{n\geq 1}$ be a positive sequence such that $\alpha_n \to 0$. A kernel version of the Hill estimator is given by

$$\hat{\gamma}_{n,\alpha_n}(x) = \sum_{j=1}^{J} (\log(\widehat{\mathrm{RVaR}}_n(\tau_j \alpha_n | x)) - \log(\widehat{\mathrm{RVaR}}_n(\tau_1 \alpha_n | x))) \Bigg/ \sum_{j=1}^{J} \log(\tau_1/\tau_j),$$

where $J \geq 1$ and $(\tau_j)_{j\geq 1}$ is a decreasing sequence of weights.

Extrapolation

Theorem 2 :

Suppose the assumptions of Theorem 1 hold together with **(F.3)**. Let us consider $\hat{\gamma}_n(x)$ an estimator of the tail index such that

$$\sqrt{nh_n^p\alpha_n}(\hat{\gamma}_n(x)-\gamma(x)) \xrightarrow{d} \mathcal{N}\left(0, v^2(x)\right),$$

with $v(x)>0$. If, moreover $(\beta_n)_{n\geq 1}$ is a positive sequence such that $\beta_n \to 0$ and $\beta_n/\alpha_n \to 0$ as $n\to\infty$, we then have

$$\frac{\sqrt{nh_n^p\alpha_n}}{\log(\alpha_n/\beta_n)}\left(\frac{\widehat{\mathrm{RCTM}}^W_{a,n}(\beta_n|x)}{\mathrm{RCTM}_a(\beta_n|x)}-1\right) \xrightarrow{d} \mathcal{N}\left(0,(av(x))^2\right).$$

The condition $\beta_n/\alpha_n \to 0$ allows us to extrapole and choose a level β_n arbitrarily small.

Extrapolation

Daouia et al. [2011] have established the asymptotic normality of

$$\widehat{\mathrm{RVaR}}_n^W(\beta_n|x) = \widehat{\mathrm{RVaR}}_n(\alpha_n|x)\left(\frac{\alpha_n}{\beta_n}\right)^{\hat{\gamma}_n(x)}.$$

As a consequence, replacing $\widehat{\mathrm{RVaR}}_n$ by $\widehat{\mathrm{RVaR}}_n^W$ and $\widehat{\mathrm{RCTM}}_{a,n}$ by $\widehat{\mathrm{RCTM}}_{a,n}^W$ provides estimators for all risk measures considered in this presentation adapted to arbitrarily small levels.

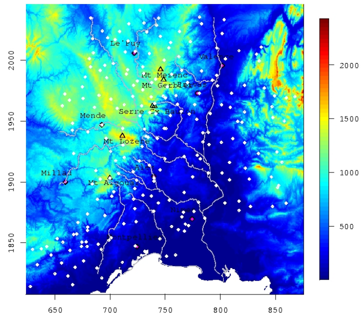
In particular we have $\mathrm{RCTE}(\alpha_n|x) = \mathrm{RCTM}_1(\alpha_n|x)$. Consequently we obtain

$$\widehat{\mathrm{RCTE}}_n^W(\beta_n|x) = \widehat{\mathrm{RCTE}}_n(\alpha_n|x)\left(\frac{\alpha_n}{\beta_n}\right)^{\hat{\gamma}_n(x)}.$$

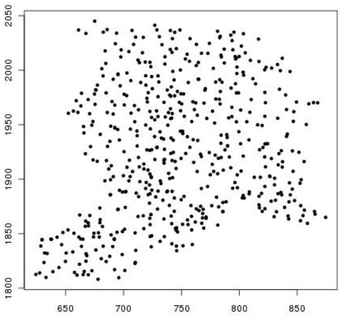
Application : $\widehat{\mathrm{RVaR}}_n^W$ and $\widehat{\mathrm{RCTE}}_n^W$.

Problem and data description

The Cévennes-Vivarais region



523 Stations / 1958–2000 / in mm



Objective : to choose (h_n, α_n).

A leave-one-out cross validation procedure to choose h_n and α_n : Step 1

- Double loop on $\mathcal{H} = \{h_i; i = 1, \dots, M\}$ and on $\mathcal{A} = \{\alpha_j; j = 1, \dots, R\}$.
- Loop on all stations $\{x_t; t = 1, \dots, N\}$.

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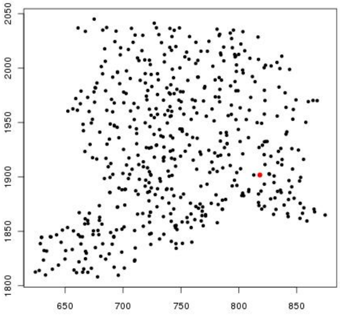
Place ourselves at the station x_t



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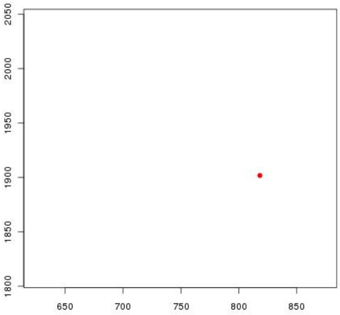
Remove all others stations



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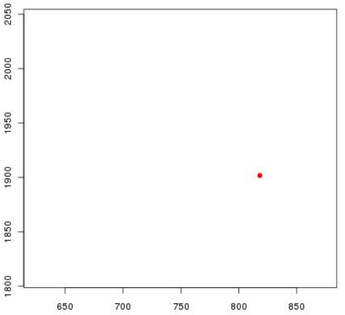

- Estimate $\gamma > 0$ using the classical Hill estimator.
- It only depends on α_j.
- The α_j are choosen such that we stay in the tail of the distribution $\max_{j \in \{1,\dots,R\}} (\alpha_j) < 0.1$

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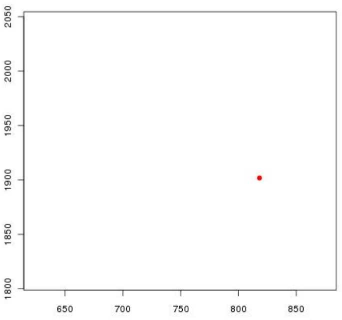

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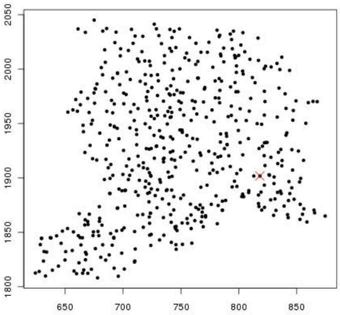
$\Longrightarrow$ We obtain $\hat{\gamma}_{n,t,\alpha_j}$

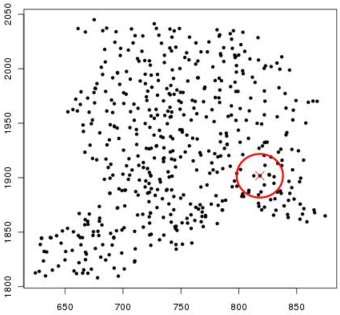
A leave-one-out cross validation procedure to choose h_n and α_n : Step 2

Remove the station x_t



A leave-one-out cross validation procedure to choose h_n and α_n : Step 2

Work in $B(x_t, h_i) \setminus \{x_t\}$



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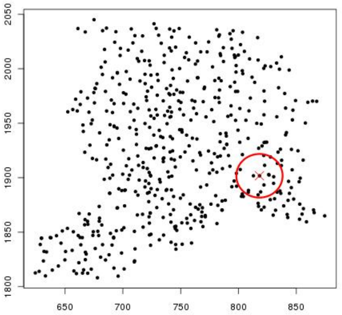

- Estimate $\gamma(x) > 0$ using the kernel version of the Hill estimator.
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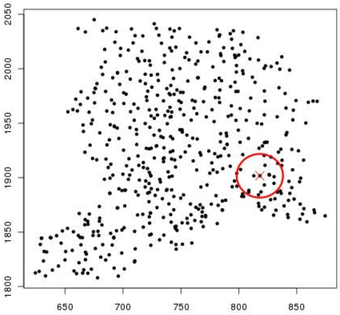

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$\Longrightarrow$ We obtain $\hat{\gamma}_{n,h_i,\alpha_j}(x_t)$

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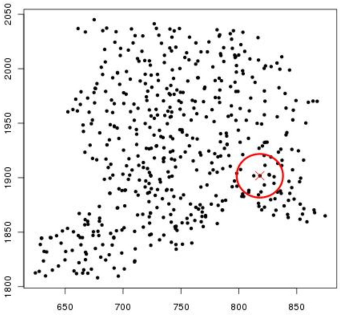

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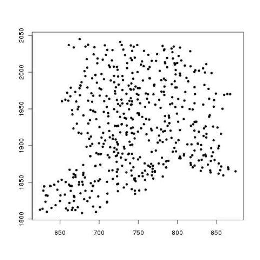
$\Longrightarrow$ We obtain $\hat{\gamma}_{n,h_i,\alpha_j}(x_t)$

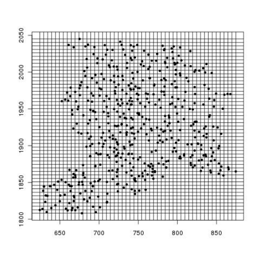
$$(h_{emp}, \alpha_{emp}) = \underset{(h_i,\alpha_j)\in\mathcal{H}\times\mathcal{A}}{\arg\min} \ \text{median}\{(\hat{\gamma}_{n,t,\alpha_j} - \hat{\gamma}_{n,h_i,\alpha_j}(x_t))^2, t \in \{1,\ldots,N\}\}.$$

Kernel interpolation

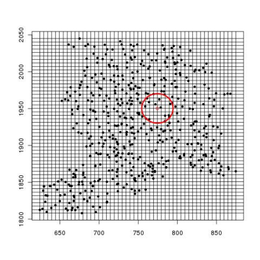
523 Stations



Regular grid : 200×200



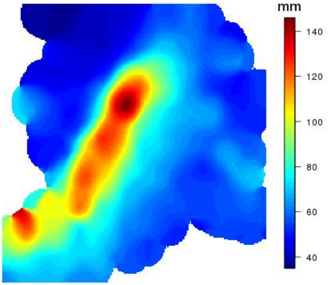
Work in $B(x, h)$



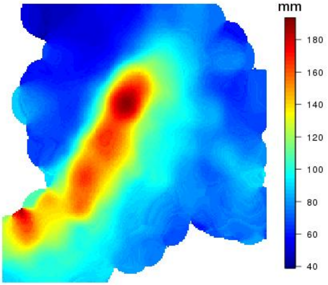
- Two dimensional covariate X function of the latitude and the longitude.
- Bi-quadratic kernel : $K(x) = \frac{15}{16}(1 - x^2)^2 \mathbb{I}_{\{|x| \leq 1\}}$.
- Harmonic sequence of weights : $(\tau_j)_{j \in \{1,\dots,9\}} = 1/j$.
- Results of the procedure $(h_{emp}, \alpha_{emp}) = (24, 1/(3 * 365.25))$.

Non extrapolated risk measures in the Cévennes-Vivarais region

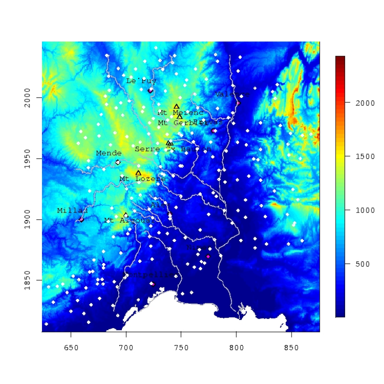
$\widehat{\mathrm{RVaR}}_n(1/(3 * 365.25)|x)$

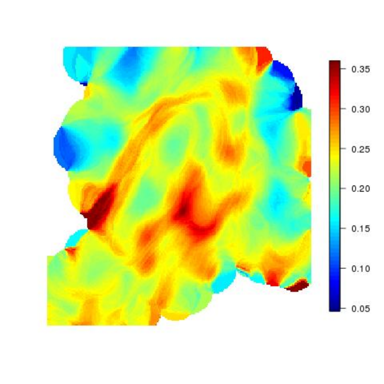


$\widehat{\mathrm{RCTE}}_n(1/(3 * 365.25)|x)$

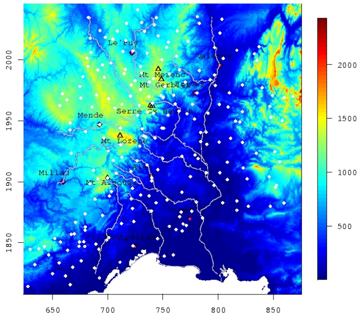


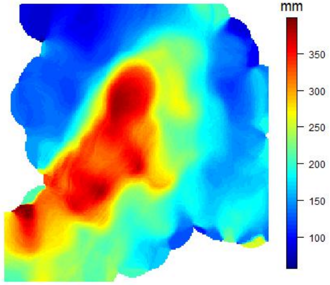
$\hat{\gamma}_{n,(1/(3*365.25))}(x)$ in the Cévennes-Vivarais region



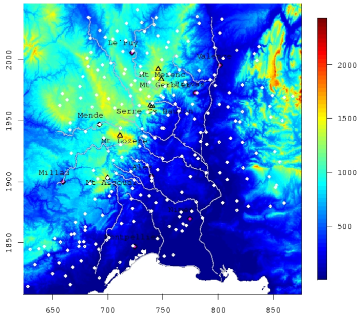


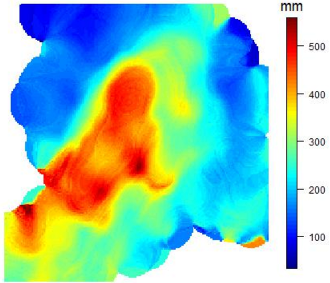
$\widehat{\mathrm{RVaR}}_n^W(1/(100 * 365.25)|x)$ *i.e.* a return level of 100 years





$\widehat{\mathrm{RCTE}}_n^W(1/(100*365.25)|x)$ corresponding to a return level of 100 years





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Thanks for your attention.