Università
Ca'Foscari
Venezia

Robust and efficient estimation for the Generalized Extreme-Value distribution

Nathan Huet
Joint work with Ilaria Prosdocimi

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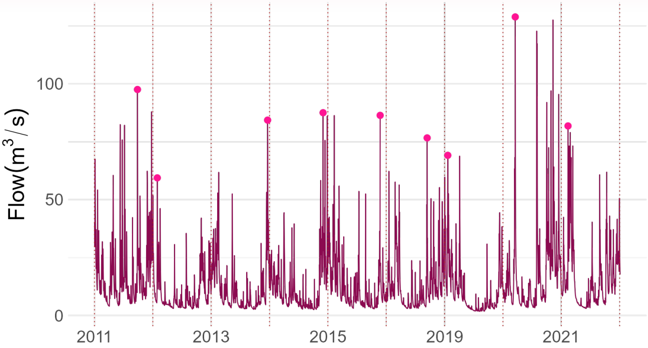
Motivation/Context



- working with extremes = limited sample size

⇝ estimating the parameters of a GEV distribution via maximum likelihood involves high sensitivity to outliers

⇝ **robust estimation methods**

Minimum density power divergence

[Basu et al., 1998]

Density Power Divergence $d_\alpha(g, f)$ between f and g:

$$d_\alpha(g, f) = \int_{\mathscr{X}} \left(f^{1+\alpha}(x) - \left(1 + \frac{1}{\alpha}\right) g(x) f^\alpha(x) + \frac{1}{\alpha} g^{1+\alpha}(x) \right) dx.$$

Minimum density power divergence θ_α for a parametric density model $\mathscr{F} = \{f(x; \theta), x \in \mathscr{X}, \theta \in \Theta\}$:

$$\theta_\alpha \in \mathrm{argmin}_{\theta \in \Theta} d_\alpha(g, f(\cdot; \theta)).$$

Minimum density power divergence estimator

Let $X_1, \ldots, X_n$ i.i.d. random element defined on $\mathscr{X}$. Denote by g_n their empirical density function.

Minimum Density Power Divergence Estimator (MDPDE) $\hat{\theta}_\alpha \in \Theta$ is defined as

$$\hat{\theta}_\alpha \in \mathrm{argmin}_{\theta \in \Theta} d_\alpha(g_n, f(\cdot; \theta))$$

◦ for $\alpha \to 0$, the MDPDE is the MLE (efficient)
◦ for $\alpha = 1$, the MDPDE is the L^2-estimator (robust)
$\rightsquigarrow$ for $\alpha \in]0,1[$ compromise between efficiency and robustness

MDPDE for GEV

◦ $X_1, ..., X_n$ i.i.d. GEV random variables; g_n their empirical density function.

◦ density model $\mathscr{F} = \{f(x;\mu,\sigma,\xi), x \in \mathbb{R}, (\mu,\sigma,\xi) \in \mathbb{R}\times]0,+\infty[\times\mathbb{R}\}$ with

$$f(x;\mu,\sigma,\xi) = \frac{1}{\sigma}\left(1+\xi\left(\frac{x-\mu}{\sigma}\right)\right)^{-(\xi+1)/\xi} \exp\left(-\left(1+\xi\left(\frac{x-\mu}{\sigma}\right)^{-1/\xi}\right)\right)\mathbb{1}\{x \in D_{\mu,\sigma,\xi}\}.$$

◦ MDPDE $(\hat{\mu}_\alpha, \hat{\sigma}_\alpha, \hat{\xi}_\alpha)$ for GEV

$$(\hat{\mu}_\alpha, \hat{\sigma}_\alpha, \hat{\xi}_\alpha) \in \operatorname{argmin}_{(\mu,\sigma,\xi)\in\mathbb{R}\times]0,+\infty[\times\left]-\left(\frac{1+\alpha}{\alpha}\right),+\infty\right[} d_\alpha(g_n, f(\cdot;\mu,\sigma,\xi))$$

◦ this approach has already been considered for Generalized Pareto distribution in [Juárez and Schucany, 2004]

Asymptotic Normality

Theorem. Let (μ_0, σ_0, ξ_0) be the target parameters. Suppose $\xi_0 > -(1+\alpha)/(2+\alpha)$, for fixed $\alpha > 0$. Then, there exists a consistent sequence of MDPDE $\{(\hat{\mu}_\alpha, \hat{\sigma}_\alpha, \hat{\xi}_\alpha)\}$ for (μ_0, σ_0, ξ_0). In addition,

$$\sqrt{n}(\hat{\mu}_\alpha - \mu_0, \hat{\sigma}_\alpha - \sigma_0, \hat{\xi}_\alpha - \xi_0)^\top \xrightarrow{d} \mathcal{N}\left(0, J_\alpha^{-1}(\mu_0, \sigma_0, \xi_0) K_\alpha(\mu_0, \sigma_0, \xi_0) J_\alpha^{-1}(\mu_0, \sigma_0, \xi_0)\right),$$

as $n \to +\infty$.

- for $\alpha \to 0$, we obtain the classic restriction $\xi_0 > -1/2$ for the asymptotic normality of the MLE [Bücher and Segers, 2017].
- for $\alpha > 0$, the region on which the asymptotic normality holds is enlarged as compared to the MLE.

Influence Function

Sensitivity Curve. For a sample statistic T,

$$SC_n(x) = \frac{T(X_1, ..., X_{n-1}, x) - T(X_1, ..., X_{n-1})}{(1/n)}.$$

Influence Function. For a sample statistic T,

$$IF(x) := \lim_{n \to +\infty} SC_n(x).$$

Example: for T the mean,

$$\begin{aligned} SC_n(x) &= \frac{mean_n(X_1, ..., X_{n-1}, x) - mean_{n-1}(X_1, ..., X_{n-1})}{(1/n)} \\ &= x - mean_{n-1}(X_1, ..., X_{n-1}) \\ &\to x - \mathbb{E}[X] = IF(x). \end{aligned}$$

Influence function of MDPDE for GEV

Theorem. Let $\theta_0 := (\mu_0, \sigma_0, \xi_0)$ be the target parameters. Suppose $\xi_0 > -(1+\alpha)/(2+\alpha)$, for fixed $\alpha > 0$. Then, the influence function of the MDPDE is given by

$$IF_\alpha(x, \theta_0) = J_\alpha^{-1}(\theta_0)\left[S(x;\theta_0) f^\alpha(x;\theta_0) - U_\alpha(\theta_0)\right],$$

and is bounded for $\alpha > 0$.

◦ Advantage over the MLE which has unbounded influence function.

◦ Decomposition:

$$IF_\alpha(x, \theta_0) = \Big(IF_{\alpha,\mu}(x, \theta_0), IF_{\alpha,\sigma}(x, \theta_0), IF_{\alpha,\xi}(x, \theta_0)\Big)^\top.$$

Illustration influence function

$\xi_0 = -0.3, \sigma_0 = 1, \mu_0 = 0$

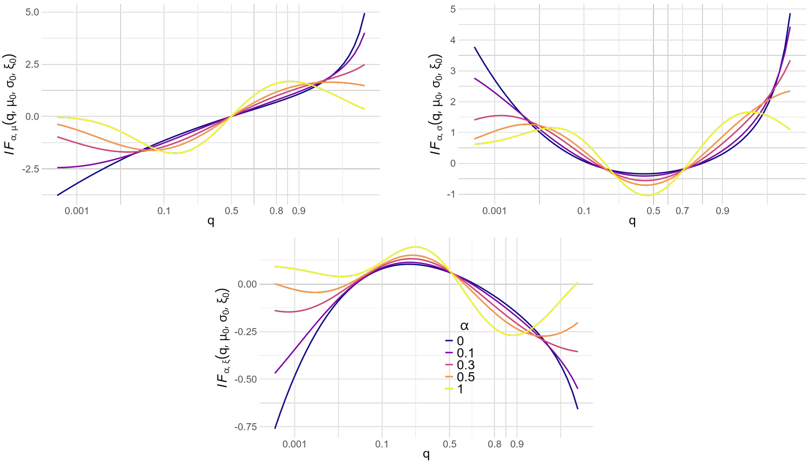


Figure: y-axis : componentwise MDPD influence functions.
x-axis : quantile level at which the functions are evaluated.

Illustration influence function

$\xi_0 = 0.3, \sigma_0 = 1, \mu_0 = 0$

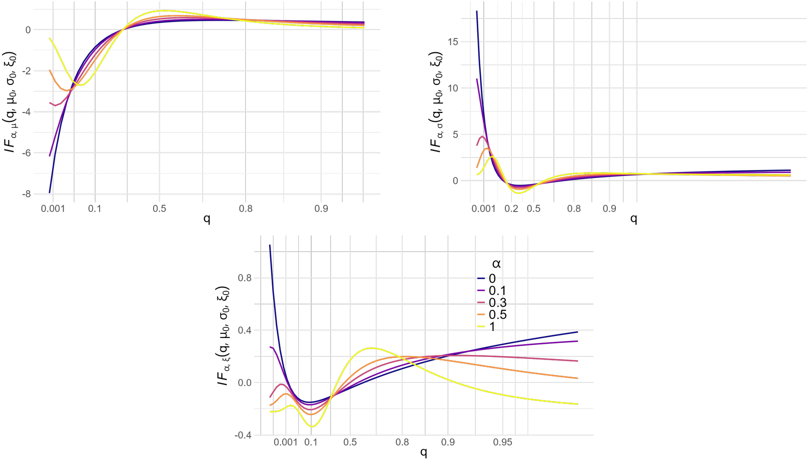


Figure: y-axis : componentwise MDPD influence functions.
x-axis : quantile level at which the functions are evaluated.

Experiments

Comparison of four estimators: MLE, MDPDE (with $\alpha = 0.05$), MDPDE (with $\alpha = 0.1$), MQE [Lin et al., 2024]

Contaminated model: $(1-\varepsilon)GEV(\mu_0, \sigma_0, \xi_0) + \varepsilon GEV(\mu_1, \sigma_1, \xi_1)$.

- true parameters: $\mu_0 = 0, \sigma_0 = 1, \xi_0 \in \{-0.3, 0, 0.3\}$
- contamination on scale parameter σ_1 and shape parameter ξ_1, **one at a time**;
- proportion of contamination : $\varepsilon = 0.1$; sample size : $n = 100$; number of replication : $d = 200$

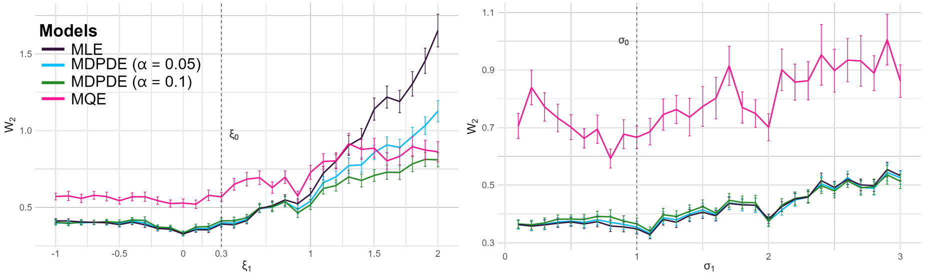
Performance measured according to the Wasserstein 2-distance

$$W_2(F_0, \hat{F}_0) = \left(\int_0^1 \left(F_0^{\leftarrow}(p) - \hat{F}_0^{\leftarrow}(p) \right)^2 dp \right)^{1/2},$$

where $F_0^{\leftarrow}$ is the true quantile function and $\hat{F}_0^{\leftarrow}$ the empirical quantile function estimated by each model.

Experiments : positive shape parameter

true : $\xi_0 = 0.3, \sigma_0 = 1, \mu_0 = 0$
contamination : $\mu_1 = 0, \varepsilon = 0.1$
model : $(1-\varepsilon)GEV(\mu_0, \sigma_0, \xi_0) + \varepsilon GEV(\mu_1, \sigma_1, \xi_1)$

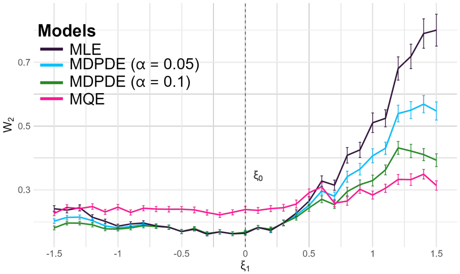


(a) $\sigma_1 = \sigma_0 = 1$, varying ξ_1 (b) $\xi_1 = \xi_0 = 0.3$, varying σ_1

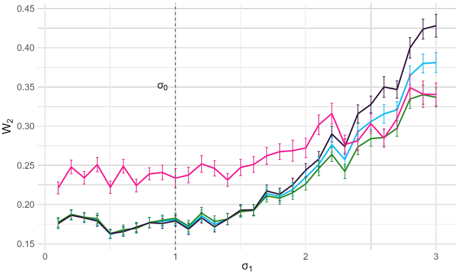
Figure: Average Wasserstein distance across various contaminated models.

Experiments : zero shape parameter

true : $\xi_0 = 0, \sigma_0 = 1, \mu_0 = 0$
contamination : $\mu_1 = 0, \varepsilon = 0.1$
model : $(1-\varepsilon)GEV(\mu_0, \sigma_0, \xi_0) + \varepsilon GEV(\mu_1, \sigma_1, \xi_1)$



(a) $\sigma_1 = \sigma_0 = 1$, varying ξ_1

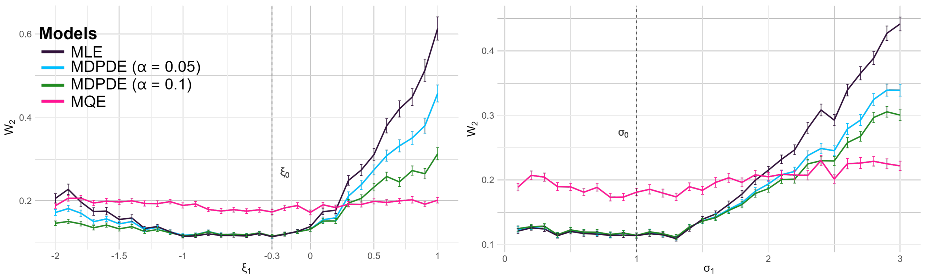


(b) $\xi_1 = \xi_0 = 0$, varying σ_1

Figure: Average Wasserstein distance across various contaminated models.

Experiments : negative shape parameter

true : $\xi_0 = -0.3, \sigma_0 = 1, \mu_0 = 0$
contamination : $\mu_1 = 0, \varepsilon = 0.1$
model : $(1-\varepsilon)GEV(\mu_0, \sigma_0, \xi_0) + \varepsilon GEV(\mu_1, \sigma_1, \xi_1)$

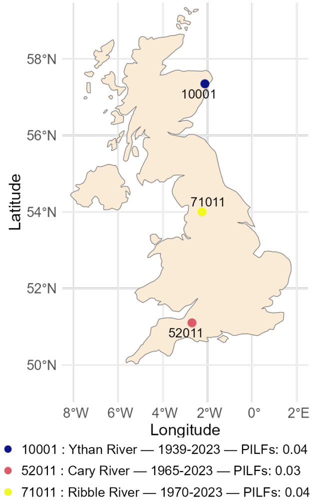


(a) $\sigma_1 = \sigma_0 = 1$, varying ξ_1 (b) $\xi_1 = \xi_0 = -0.3$, varying σ_1

Figure: Average Wasserstein distance across various contaminated models.

Application: flood frequency analysis in the UK

provided by the National River Flow Archive

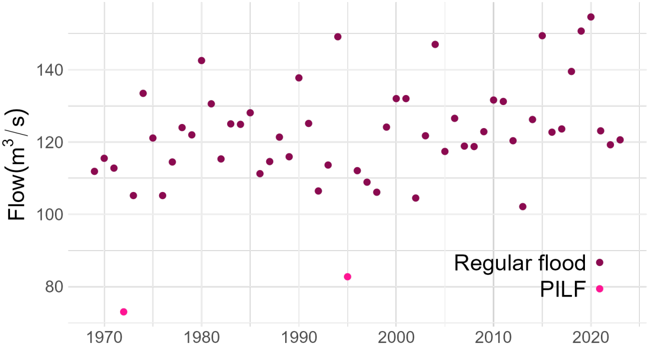


- Data : annual maximum river flows

Potentially Influential Low Floods (PILFs)

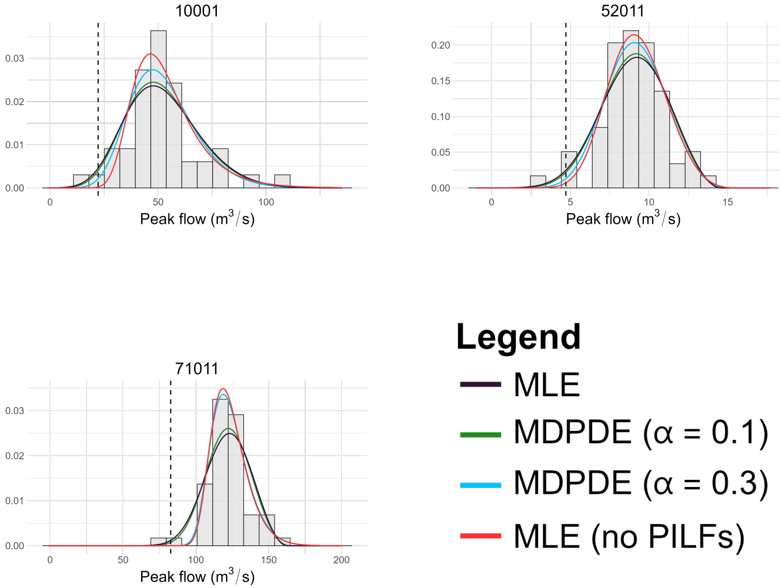
Why MDPDE? Presence of PILFs
$\rightarrow$ must be removed [England et al., 2018]

⚠ reduce the sample size even more

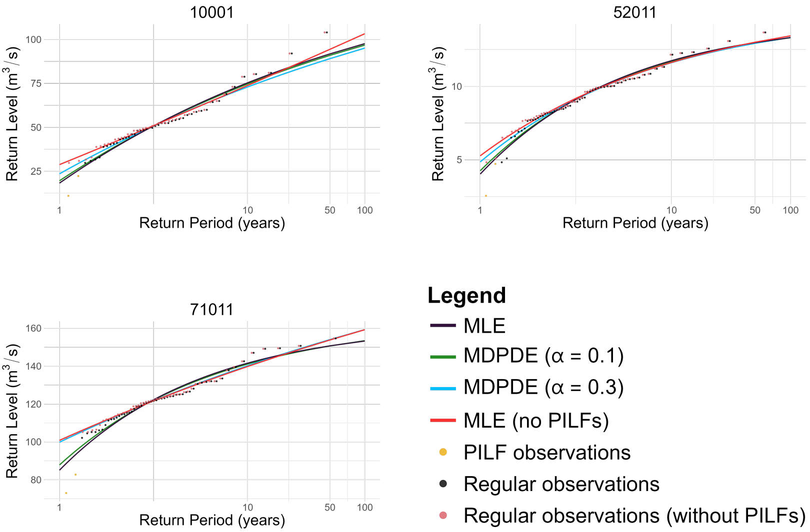


Comparison: MLE, MDPDE ($\alpha = 0.1$), MDPDE ($\alpha = 0.3$),
MLE without the PILFs

Density plots



Return curves



Future works/Open questions

- data-driven method to choose α for a good compromise between efficiency and robustness?
- extension to non-stationary case;
- other real-world applications?

References

- A. Basu, I. R. Harris, N. L. Hjort, and M. Jones., *Robust and efficient estimation by minimising a density power divergence*, Biometrika, 1998;
- A. Bücher and J. Segers, *On the maximum likelihood estimator for the generalized extreme-value distribution*, Extremes, 2017;
- J. F. England Jr, T. A. Cohn, B. A. Faber, J. R. Stedinger, W. O. Thomas Jr, A. G. Veilleux, J. E. Kiang and R. R. Mason Jr, *Guidelines for determining flood flow frequency—Bulletin 17C*, US Geological Survey, 2018;
- S. F. Juárez and W. R. Schucany, *Robust and efficient estimation for the generalized pareto distribution*, Extremes, 2004;
- S. Lin, A. Kong and R. Azencott, *Multi-Quantile Estimators for the parameters of Generalized Extreme Value distribution*, arXiv, 2024.

Thank you for your attention!

Appendix

MDPDE for GEV

MDPDE $(\hat{\mu}_\alpha, \hat{\sigma}_\alpha, \hat{\xi}_\alpha)$ minimizes

$$H_\alpha(\mu,\sigma,\xi) = \int_{S_{\mu,\sigma,\xi}} f^{1+\alpha}(x;\mu,\sigma,\xi)dx - \big(1+\frac{1}{\alpha}\big)\frac{1}{n}\sum_{i=1}^{n} f^{\alpha}(X_i;\mu,\sigma,\xi)$$
$$= \frac{1}{\sigma^\alpha}\Big(\frac{1}{1+\alpha}\Big)^{\alpha(\xi+1)+1}\Gamma\big(\alpha(\xi+1)+1\big) - \big(1+\frac{1}{\alpha}\big)\frac{1}{n}\sum_{i=1}^{n} f^{\alpha}(X_i;\mu,\sigma,\xi),$$

over $\mathbb{R}\times\mathbb{R}_{>0}\times\,\big]-\big(\frac{1+\alpha}{\alpha}\big),+\infty\big[$.

◦ this approach has already been considered for Generalized Pareto distribution in [Juárez and Schucany, 2004]

Involved quantities

(just for completeness)

Denote by $S(x;\mu,\sigma,\xi)$ and $i(x;\mu,\sigma,\xi)$ the score function and the information of the GEV distribution. Define the 3×3 matrices K_α and J_α as

$$K_\alpha(\mu,\sigma,\xi)=\int_{D_{\mu,\sigma,\xi}} S(x;\mu,\sigma,\xi)S^\top(x;\mu,\sigma,\xi)f^{1+2\alpha}(x;\mu,\sigma,\xi)dx-U_\alpha(\mu,\sigma,\xi)U_\alpha^\top(\mu,\sigma,\xi),$$

where

$$U_\alpha(\mu,\sigma,\xi)=\left[\begin{array}{c}\int_{D_{\mu,\sigma,\xi}} S_\mu(x;\mu,\sigma,\xi)f^{1+\alpha}(x;\mu,\sigma,\xi)dx\\ \int_{D_{\mu,\sigma,\xi}} S_\sigma(x;\mu,\sigma,\xi)f^{1+\alpha}(x;\mu,\sigma,\xi)dx\\ \int_{D_{\mu,\sigma,\xi}} S_\xi(x;\mu,\sigma,\xi)f^{1+\alpha}(x;\mu,\sigma,\xi)dx\end{array}\right],$$

and

$$J_\alpha(\mu,\sigma,\xi)=\int_{D_{\mu,\sigma,\xi}} S(x;\mu,\sigma,\xi)S^\top(x;\mu,\sigma,\xi)f^{1+\alpha}(x;\mu,\sigma,\xi)dx.$$