



Minimum distance estimation for max-stable models

R.A. Yuen[†] and Stilian Stoev, Department of Statistics, University of Michigan



Max-stable models

- For iid observations $Y^{(i)}(\mathbf{s})$, $i = 1, 2, \dots$ at fixed points $\mathbf{s} \in S$, we consider the limit of point-wise maxima

$$\left\{ \frac{1}{a_n(\mathbf{s})} \max_{i=1, \dots, n} Y^{(i)}(\mathbf{s}) - b_n(\mathbf{s}) \right\}_{\mathbf{s} \in S} \xrightarrow{d} \{X(\mathbf{s})\}_{\mathbf{s} \in S}, \text{ as } n \rightarrow \infty$$

where $a_n(\mathbf{s})$ and $b_n(\mathbf{s})$ are normalization functions.

- The limiting process $X := \{X(\mathbf{s})\}_{\mathbf{s} \in S}$ is a model for **worst case scenario** and must be max-stable (Resnick 1987):

Max-stable process

For independent copies $X^{(i)}(\mathbf{s})$, $i = 1, \dots, n$ of $X(\mathbf{s})$, there exists functions $c_n(\mathbf{s})$ and $d_n(\mathbf{s})$ such that

$$\left\{ \frac{1}{c_n(\mathbf{s})} \max_{i=1, \dots, n} X^{(i)}(\mathbf{s}) - d_n(\mathbf{s}) \right\}_{\mathbf{s} \in S} \xrightarrow{d} \{X(\mathbf{s})\}_{\mathbf{s} \in S}$$

- All max-stable processes have a spectral representation for their finite dimensional distribution functions (de Haan 1984):

$$\mathbb{P}(X(\mathbf{s}_1) \leq x_1, \dots, X(\mathbf{s}_d) \leq x_d) := F(\mathbf{x}) = \exp \left\{ \int_{\mathbb{W}} \left(\max_{j=1, \dots, d} \frac{w_j}{x_j} \right) H(d\mathbf{w}) \right\}$$

where the *spectral measure* H controls the dependence structure of X .

- Many flexible max-stable models have been proposed by specifying a parametric family of spectral measures, $\{H_\theta : \theta \in \mathbb{R}^p\}$. Examples include the well known Smith storm model (Smith 1990), Brown-Resnick (Brown and Resnick 1977) and the following extremal Gaussian.

Extremal Gaussian model (Schlather 2002)

$$F_\theta(\mathbf{x}) = \exp \left\{ - \int_{\mathbb{R}^d} \left(\max_{j=1, \dots, d} \frac{w_j}{x_j} \right) \frac{\sqrt{|\Omega_\theta|} e^{-\frac{1}{2} \mathbf{w}^\top \Omega_\theta \mathbf{w}}}{(\sqrt{2\pi})^{d-1}} d\mathbf{w} \right\}. \quad (1)$$

where Ω_θ is the precision matrix induced by a correlation function $\rho(\mathbf{s}_i, \mathbf{s}_j | \theta)$.

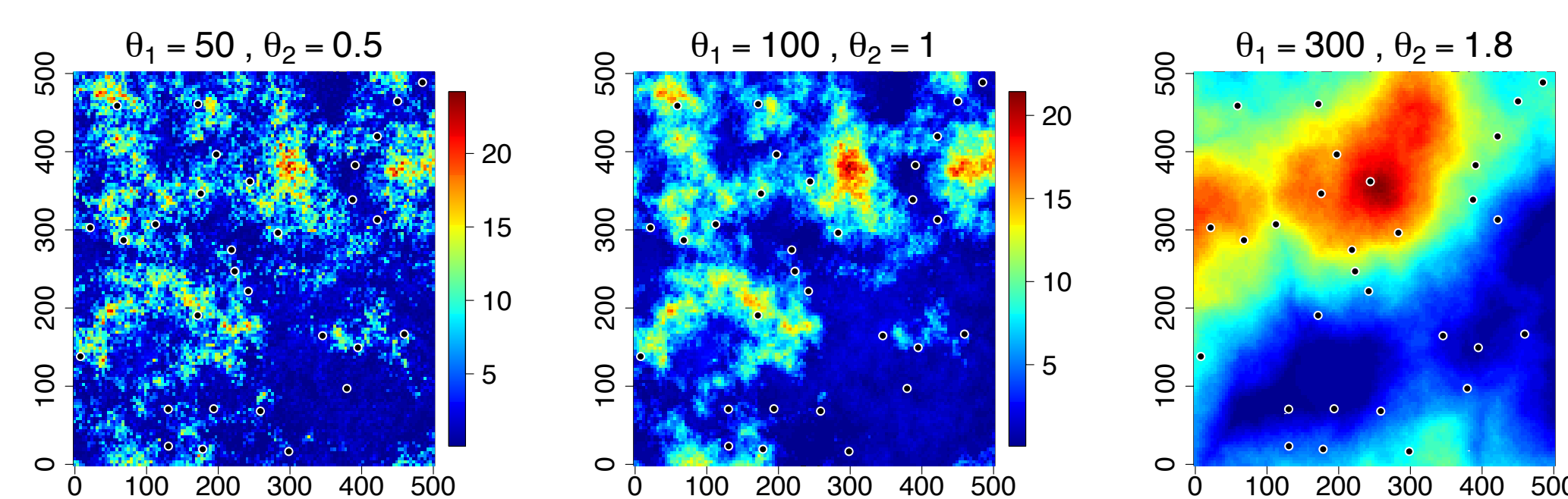


Figure 1: Three realizations from the extremal Gaussian model with stable correlation function: $\rho(\mathbf{s}_i, \mathbf{s}_j | \theta) = \exp \left[- (\|\mathbf{s}_i - \mathbf{s}_j\| / \theta_1)^{\theta_2} \right]$, $\theta_1 > 0, \theta_2 \in (0, 2]$

- Most useful max-stable models including (1) have **no tractable likelihood** when $d > 2$, making inference very challenging.
- Current state of art: Bivariate maximum composite likelihood estimator (MCLE) (Padoan et. al 2010)

Minimum distance estimation

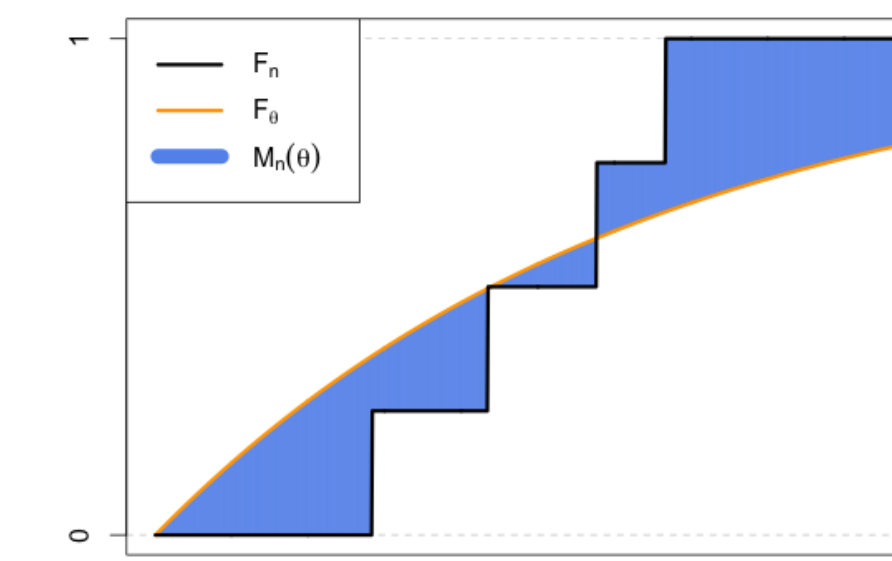
- Let $F_n(\mathbf{z}) = n^{-1} \sum_{i=1}^n \mathbb{I} \{X^{(i)}(\mathbf{s}_j) \leq z_j, j = 1, \dots, d\}$ be the d -dimensional empirical distribution function generated by a random sample $X^{(i)}(\mathbf{s}_1), \dots, X^{(i)}(\mathbf{s}_d)$, $i = 1, \dots, n$.
- Let μ be a tuning measure that emphasizes regions of the sample space.

Minimum distance criterion

$$M_n(\theta) = \int_{\mathbb{R}_+^d} (F_n(\mathbf{z}) - F_\theta(\mathbf{z}))^2 \mu(d\mathbf{z})$$

Minimum distance estimator

$$\hat{\theta}_n = \arg \min_{\theta \in \Theta} M_n(\theta)$$



- Subject to mild regularity conditions, $\hat{\theta}_n \xrightarrow{p} \theta_0$ and $\sqrt{n}(\hat{\theta}_n - \theta_0) \xrightarrow{d} \mathcal{N}(0, J_{\theta_0}^{-1} D_{\theta_0} J_{\theta_0}^{-1})$ where elements of the $p \times p$ matrices J_{θ_0} and D_{θ_0} are

$$(J_{\theta_0})_{ij} = \int_{\mathbb{R}_+^d} \frac{\partial}{\partial \theta_i} F_{\theta_0}(\mathbf{z}) \frac{\partial}{\partial \theta_j} F_{\theta_0}(\mathbf{z}) \mu(d\mathbf{z})$$

and

$$(D_{\theta_0})_{ij} = \int_{\mathbb{R}_+^d} \int_{\mathbb{R}_+^d} B_{\theta_0}(\mathbf{z}_1, \mathbf{z}_2) \frac{\partial}{\partial \theta_i} F_{\theta_0}(\mathbf{z}_1) \frac{\partial}{\partial \theta_j} F_{\theta_0}(\mathbf{z}_2) \mu(d\mathbf{z}_1) \mu(d\mathbf{z}_2)$$

with $B_{\theta_0}(\mathbf{z}_1, \mathbf{z}_2) = F_{\theta_0}(\mathbf{z}_1 \wedge \mathbf{z}_2) - F_{\theta_0}(\mathbf{z}_1) F_{\theta_0}(\mathbf{z}_2)$.

Simulation Study

- Using the model (1) with stable correlation function we set $\theta_0 = (100, 1)$ and simulated 100 replications at $d = 30$ uniformly sampled locations over a 500×500 grid. Realizations were generated using the R package **SpatialExtremes** (Ribatet 2012).
- For each replication, we generate samples of $n = 100$ and $n = 1000$.
- We specify an empirical measure for μ and numerically optimize the criterion $M_n(\theta)$.

Table: Empirical mean and standard deviation from 100 replications of the minimum distance estimator. Coverage rates are calculated numerically using plug-in estimates of the matrices $J_{\hat{\theta}_n}$ and $D_{\hat{\theta}_n}$.

	$\theta_1(100)$		$\theta_2(1)$	
n	100	1000	100	1000
mean	110.56	97.00	1.25	1.10
sd	113.73	32.89	0.63	0.34
.95 coverage	0.98	0.96	0.90	0.92

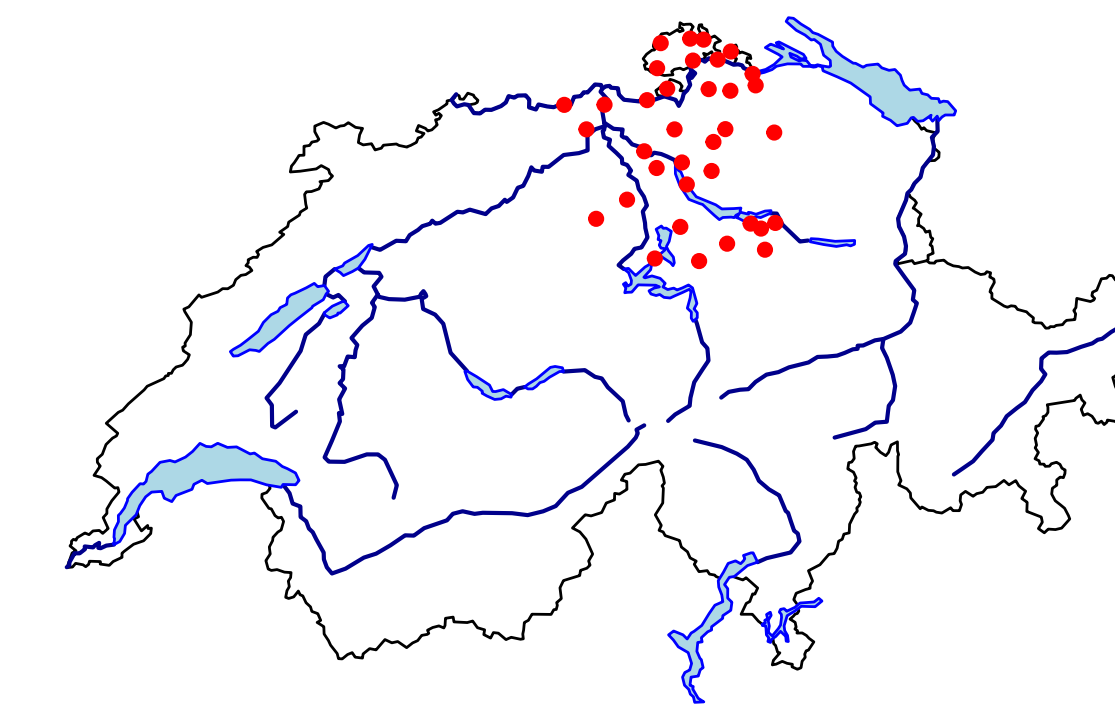
Application to Swiss rainfall

- We model maximum single day rainfall during summer months using the extremal Gaussian model (1) with Matérn correlation function

$$\rho(\mathbf{s}_i, \mathbf{s}_j | \theta) = \frac{(\|\mathbf{s}_i - \mathbf{s}_j\| / \theta_1)^{\theta_2}}{2^{\theta_2 - 1} \Gamma(\theta_2)} K_{\theta_2}(\|\mathbf{s}_i - \mathbf{s}_j\| / \theta_1), \quad \theta_1 > 0, \theta_2 > 0.$$

K_{θ_2} denotes the modified Bessel function of order θ_2 .

- Data are recorded from 1962-2008 at 35 observation locations near Zurich, Switzerland. (Data courtesy of R package **SpatialExtremes**)



- Summer maxima are first transformed to unit Fréchet margins. Each year is treated as an independent observation.

- Specifying an empirical measure for μ , we optimize the criterion $M_n(\theta)$ resulting in estimates

$$\hat{\theta}_1 = 18.46(25.58), \quad \hat{\theta}_2 = 0.5038(1.133).$$

Standard errors are in parentheses.

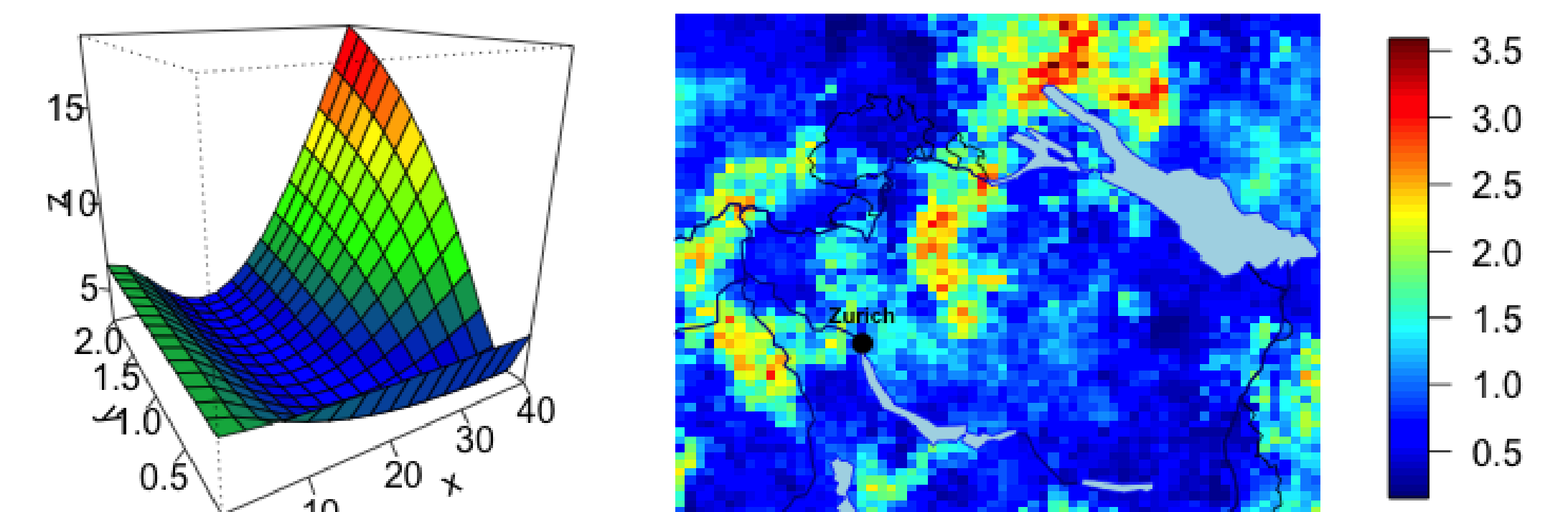


Figure 2: $M_n(\theta)$ criterion surface for Swiss rainfall data (left). A single realization from the fitted model (right)

For details on this research and other projects please visit:

<http://www.stat.lsa.umich.edu/~bobyuen>

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