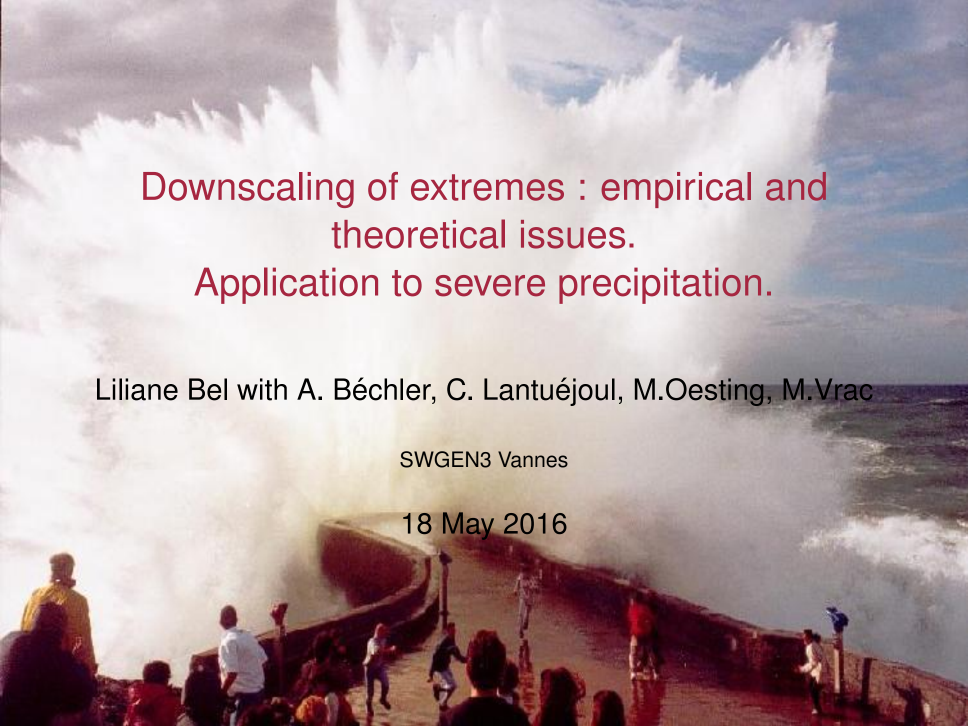


Downscaling of extremes : empirical and theoretical issues. Application to severe precipitation.

Liliane Bel with A. Béchler, C. Lantuéjoul, M.Oesting, M.Vrac

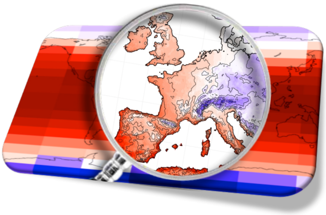
SWGEN3 Vannes

18 May 2016

Motivation

- $\approx \mathbf{30}$ **%** of the world economic activities are affected by the meteorological conditions (source: IPCC AR4)

- IPCC scenarios of climate change and GCMs :
  - Have a **coarse spatial resolution** (≈ 250 km)
    $\Longrightarrow$ Needs for *downscaling*
  - **Smooth** extreme values
    $\Longrightarrow$ Needs for correction to recover *extreme events*



Outline

Downscaling for Spatial Extremes

1. Statistical downscaling
2. Region of interest and data
3. Max-stable processes
4. Conditional distribution according to a single condition
5. Spatial Hybrid Downscaling

Outline

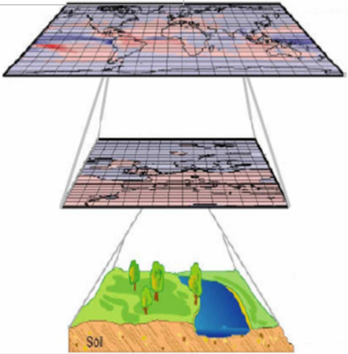
Downscaling for Spatial Extremes

1. Statistical downscaling
2.
3.
4.
5.

What is downscaling ???

≈ 250 km

Coarse atmospheric data
Precipitation, temperature, humidity, geopotential, wind, etc.



Definition:

Downscaling is the action of generating climatic or meteorological values and/or characteristics at a local scale, based on information (from GCM/reanalyses) given at a large scale.

Region, city, fields, station

Local variables (e.g., precip., temp.)
(small scale water cycle, impacts – crops, resources – etc.)

How to downscale?: The basics

≈ 250 km

Coarse atmospheric data
Precipitation, temperature, humidity, geopotential, wind, etc.

How to use the **coarse simulations** to produce **regional/local** climate features?

?

Region, city, fields, station

Local variables (e.g., precip., temp.)
(small scale water cycle, impacts – crops, resources – etc.)

How to downscale?: The basics

≈ 250 km

Coarse atmospheric data
Precipitation, temperature, humidity, geopotential, wind, etc.

Dynamical downscaling (RCMs):

- GCMs to drive regional models (5-50km) determining atmosphere dynamics
- Requires a lot of computer time and resources => Limited applications

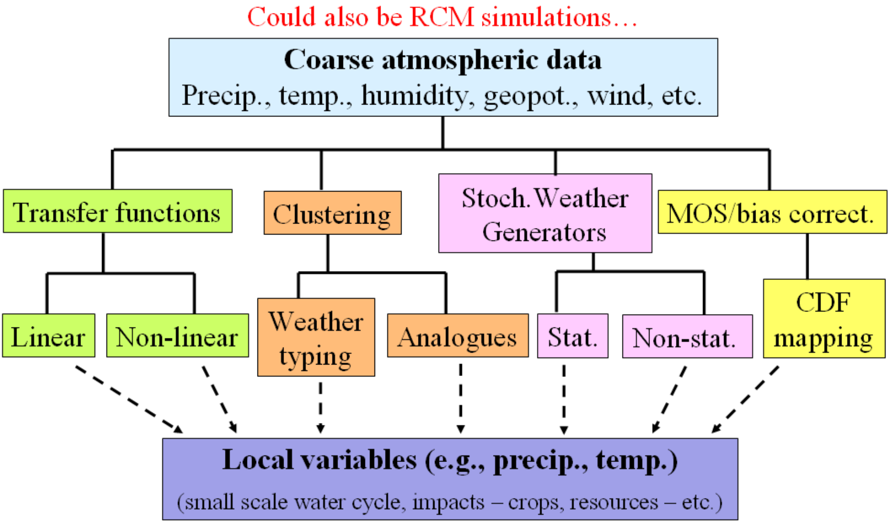
Statistical downscaling:

- Based on statistical relationships between large- and local-scale variables
- Low costs and rapid simulations applicable to any spatial resolution
- Uncertainties (results, propagation, etc)

Region, city, fields, station

Local variables (e.g., precip., temp.)
(small scale water cycle, impacts – crops, resources – etc.)

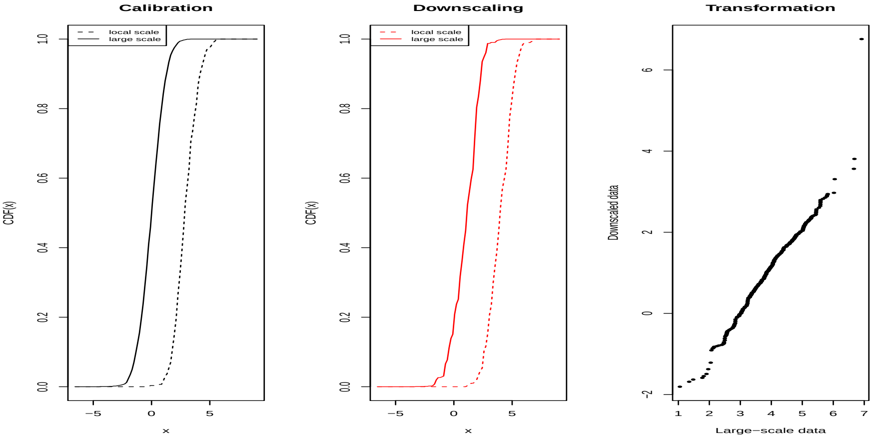
Main statistical approaches



Statistical downscaling : bias correction

CDF-Transform Method

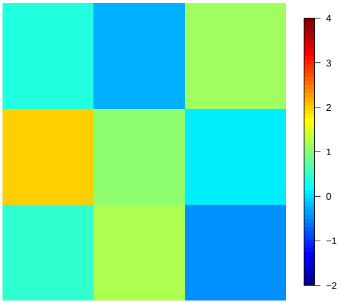
Build a bias correction by comparing the CDF of the high-scale variable and the one of the low-scale variable (Michelangeli et al., 2009).



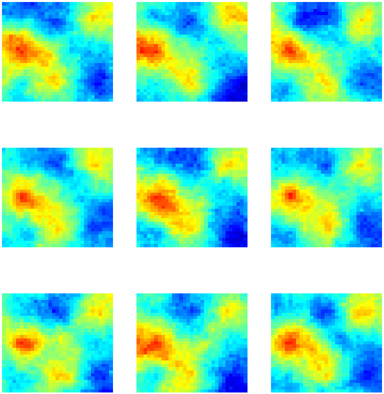
Statistical Downscaling for Spatial Extremes

Simulate spatial fields of extremes conditioning to large scale information

Large scale



Small scale



Statistical Downscaling for Spatial Extremes

Simulate spatial fields of extremes conditioning to large scale information

- Model for spatial extremes
- Conditional simulation for this model

Outline

Downscaling for Spatial Extremes

1.
2. Region of interest and data

3.

4.

5.

Low scale: *SAFRAN* data (Quintana-Segui et al., 2008)

Low scale daily precipitation data from SAFRAN analysis (1960–2007) on a grid with 8 km $\times$ 8 km-resolution (Quintana-Seguí et al., '08)

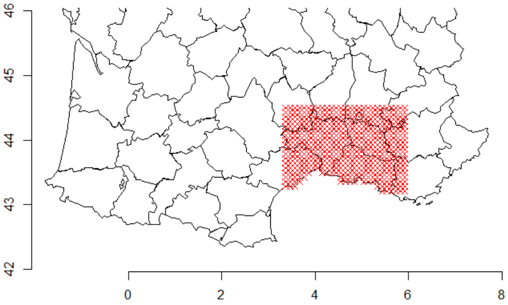


Figure: Study area of *SAFRAN* data subset.

Description:

- Cévennes region in SE of France
- Autumnal maximum of daily precipitation for 1960-2007.
- 457 points uniformly distributed.
- Grid data from interpolation.

Large scale: *MEDCORDEX-IPSL-WRF* data

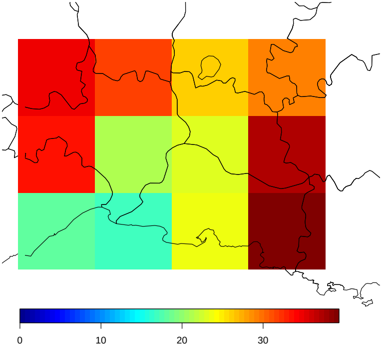


Figure: *MEDCORDEX-IPSL-WRF* maximum precipitation data for the year 1989 (in mm).

Description:

- RCM outputs of autumnal daily precipitation for 1989-2007.
- Grid resolution: about 50km.
- Area of interest is covered by 12 grid-cells.

Outline

Downscaling for Spatial Extremes

1.
2.
3. Max-stable processes
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5.

Spatial model for extremes

$\{Z(s), s \in \mathbb{S}\}$ random field , Z is **max-stable** if
there exist $a_n(s)$ and $b_n(s) > 0$, such that for all n, $(Z_i)_{i=1,n}$ ind copies Z,

$$\left\{\max_{i=1,n} \frac{Z_i(s) - a_n(s)}{b_n(s)}\right\}_{s\in\mathbb{S}} \stackrel{\mathcal{D}}{=} \{Z(s)\}_{s\in\mathbb{S}}$$

Asymptotic dependence at lag h

$$\chi(h) = \lim_{z \to z*} P(Z(s+h) > z | Z(s) > z)$$

$$\chi(h) > 0$$

Spatial extremes

De Haan construction

- (ξ_k, x_k) Poisson point process on $(0, +\infty) \times \mathcal{X}$, with intensity $\xi^{-2} d\xi \mu(dx)$,
- $W(.; s) : \mathcal{X} \mapsto [0, +\infty)$ functions $\int_{\mathcal{X}} W(x, s)\mu(dx) = 1$ for all $s \in \mathbb{S}$.

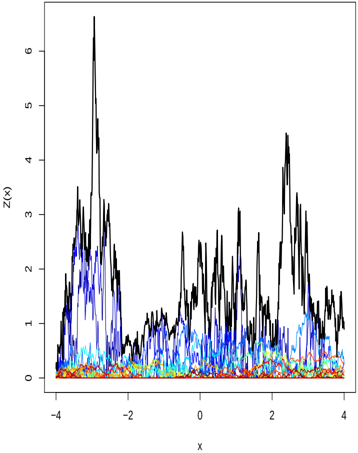
Then

$$Z(s) = \max_k \xi_k W(x_k, s)$$

is a max-stable process with Fréchet margins.

Models for maxima random fields.

Max-stable models



Max-stable models

- Smith (storm) processes
  $W_k(x_k, s) = \varphi(s - x_k)$
- Schlather processes
  $W_k(x_k, s) = \max(0, Y_k(s))$, Y_k
  Gaussian
- extremal-t processes $\xi^{-1+\alpha} d\xi \mu(dx)$,
  $W_k(x_k, s) = \max(0, Y_k(s))$, Y_k
  Gaussian
- Brown-Resnick processes
  $W_k(x_k, s) = \exp\left(Y_k(s) - \sigma^2(s)/2\right)\ Y_k$
  Gaussian stationary inc.

Data transformation

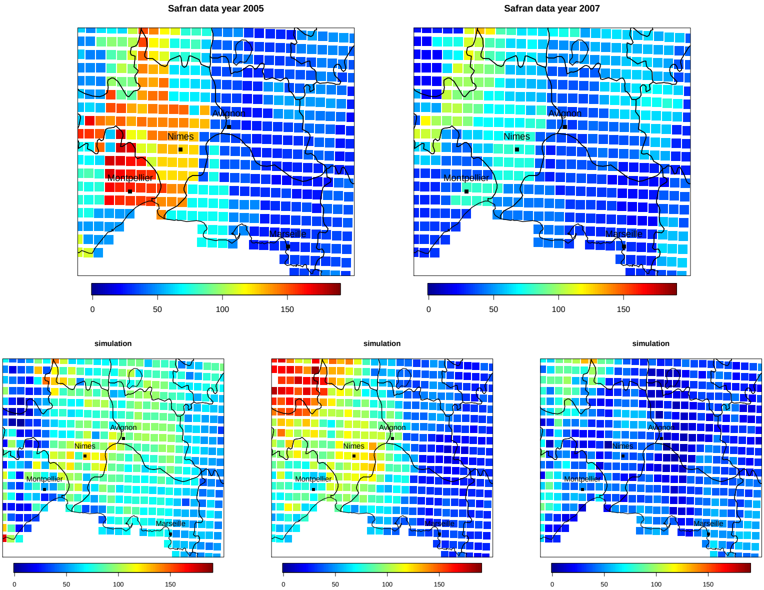
Max-stable model : t-extremal process with α-Fréchet margins.

Transformation of the data by modeling the GEV parameters:

$$\begin{aligned} \mu &= \mu_0 + \mu_1 * LON + \mu_2 * LAT \\ \sigma &= \sigma_0 + \sigma_1 * LON + \sigma_2 * LAT \\ \zeta &= \zeta_0 \end{aligned}$$

Parameters $(\mu_0, \mu_1, \mu_2, \sigma_0, \sigma_1, \sigma_2, \zeta, \alpha, \rho)$ estimated by composite likelihood

$$\begin{aligned} \mu &= \exp(-3.06 - 0.22LON + 0.18LAT) \\ \sigma &= \exp(-4.34 - 0.37LON + 0.21LAT) \\ \zeta &= 0.11 \\ \alpha &= 2.21 \\ \rho &= 1.23 \end{aligned}$$


Safran data year 2005
Safran data year 2007
Avignon
Nimes
Montpellier
Marseille
0
50
100
150
simulation
simulation
simulation

Outline

Downscaling for Spatial Extremes

1.
2.
3.
4. Conditional distribution according to a single condition
5.

Conditional Sampling for Max-Stable Processes

$$Z(s) = \max_{k \in \mathbb{N}} \xi_k W_k(s), \quad s \in K$$

Task: Simulate Z given some conditions on Z.

Condition~~s~~

- $\ell(Z) = z, \quad z > 0$

  for some positively homogeneous functional ℓ, i.e.

$$\ell(af) = a\ell(f), \quad a > 0,\ f \in C_+(K).$$

Examples for ℓ:
integral, point evaluation, maximum, minimum, ...

Conditional Sampling for Max-Stable Processes

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condition: $\ell(Z) = z, \quad z > 0$
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Difficulties:

- number of “active” functions may be arbitrarily large
- condition cannot be carried over to conditions on the Poisson point process
- condition cannot be expressed in terms of the exponent measure

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- condition cannot be expressed in terms of the exponent measure

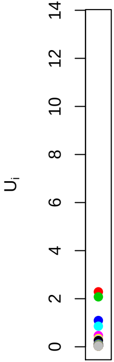
$\rightsquigarrow$ conditional distribution not tractable analytically

Our Approach: Sampling via MCMC techniques!

- $\{\xi_k\}_{k\in\mathbb{N}}$: Poisson point process with intensity $\xi^{-2}\,\mathrm{d}\xi$
- $\{W_k(\cdot)\}_{k\in\mathbb{N}}$: i.i.d. sample-continuous processes

$$Z(s) = \max_{k\in\mathbb{N}} \quad \xi_k W_k(s), \quad s \in K$$

Conditional Sampling for Max-Stable Processes



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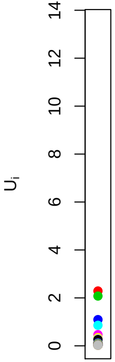
What about the distribution $\{\xi_k\}_{k\in\mathbb{N}}$?

- $\{\xi_k\}_{k\in\mathbb{N}}$ can be numbered s.t. $\xi_1 > \xi_2 > \ldots$
- then: $\xi_k =_d (E_1 + \ldots + E_k)^{-1}$ for $\{E_k\}_{k\in\mathbb{N}} \sim_{iid} \mathrm{Exp}(1)$



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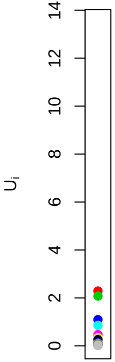
Assumption: $\sup_{s\in K} W_k(s) < C$ a.s. for some $C > 0$ $\quad (*)$

Then,

$$\xi_k \cdot C < \inf_{s\in K} Z(s)$$

$\Rightarrow \xi_k W_k(\cdot)$ cannot contribute to $Z(\cdot)$

Conditional Sampling for Max-Stable Processes



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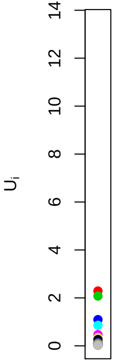
Define

$$N(\xi, \mathbf{W}) = \min\left\{k \in \mathbb{N} : \ \xi_k \cdot C < \inf_{s\in K} Z(s)\right\}.$$

Conditional Sampling for Max-Stable Processes



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$$Z(s) = \max_{k=1}^{N(\xi,\mathbf{W})} \xi_k W_k(s), \quad s \in K$$

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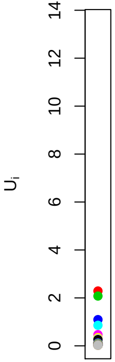

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Define

$$N(\xi, \mathbf{W}) = \min\left\{k \in \mathbb{N} : \ \xi_k \cdot C < \inf_{s\in K} Z(s)\right\}.$$

Note: W_k can always be chosen s.t. $(*)$ holds
(de Haan & Ferreira, '06, Oesting *et al, '13*)

Max-Stable Process

$$Z(s) = \max_{i=1}^{N(\mathbf{U},\mathbf{W})} \xi_k W_k(s)$$

Max-Stable Process

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Two-Step Procedure for Max-Stable Processes:

A Sample n from distribution of $N(\xi, \mathbf{W}) \mid \ell(Z) = z$

Max-Stable Process

$$Z(s) = \max_{i=1}^{N(\mathbf{U},\mathbf{W})} \xi_k W_k(s)$$

Two-Step Procedure for Max-Stable Processes:

A Sample $(\mathbf{w}, n)$ from distribution of $(\mathbf{W}, N(\xi, \mathbf{W})) \mid \ell(Z) = z$

Max-Stable Process

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B Sample ξ from distribution of $\xi \mid \mathbf{W} = \mathbf{w}$, $N(\xi, \mathbf{W}) = n$, $\ell(Z) = z$

Max-Stable Process

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Two-Step Procedure for Max-Stable Processes:

A Sample $(\mathbf{w}, n)$ from distribution of $(\mathbf{W}, N(\xi, \mathbf{W})) \mid \ell(Z) = z$
- by Metropolis-Hastings algorithm
- proposal distribution: unconditional distribution of $(\mathbf{W}, N(\xi, \mathbf{W}))$

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B Sample ξ from distribution of $\xi \mid \mathbf{W} = \mathbf{w}$, $N(\xi, \mathbf{W}) = n$, $\ell(Z) = z$
- Metropolis-Hastings algorithm
- conditional sampling for max-linear model

$$Z(s) = \max_{k=1}^{n} a_k(s) U_k = \mathbf{A} \odot \mathbf{U}$$

MCMC Algorithm for Max-Linear Models

$$Z(s) = \max_{k=1}^{n} a_k(s) U_k = \mathbf{A} \odot \mathbf{U}, \quad s \in K$$

Aim: Simulate $\mathbf{Y} = \left(\frac{U_2}{U_1}, \ldots, \frac{U_n}{U_1}\right) \mid \ell(Z) = z$.

Metropolis-Hastings Algorithm:

1. Choose starting value $\mathbf{y} \in (0, \infty)^{n-1}$.
2. Draw $\mathbf{y}^*$ from non-conditional distribution of $\mathbf{Y}$ as proposal for $\mathbf{y}$.
3. Set $\mathbf{y} = \mathbf{y}^*$ with probability

$$\min \left\{ 1, \quad \frac{\mathbb{P}(\mathbf{Y} \in \mathrm{d}\mathbf{y})\mathbb{P}(\mathbf{Y} \in \mathrm{d}\mathbf{y}^* \mid \ell(Z) = z)}{\mathbb{P}(\mathbf{Y} \in \mathrm{d}\mathbf{y}^*)\mathbb{P}(\mathbf{Y} \in \mathrm{d}\mathbf{y} \mid \ell(Z) = z)} \right\}.$$

4. Goto 2.

MCMC Algorithm for Max-Linear Models

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$$\min\left\{1, \frac{\left(\sum_{k=1}^{n} \frac{\ell(A \odot \mathbf{y}^*)}{y_k^*}\right)^n \exp\left(-\frac{1}{z} \sum_{k=1}^{n} \frac{\ell(A \odot \mathbf{y}^*)}{y_k^*}\right)}{\left(\sum_{k=1}^{n} \frac{\ell(A \odot \mathbf{y})}{y_k}\right)^n \exp\left(-\frac{1}{z} \sum_{k=1}^{n} \frac{\ell(A \odot \mathbf{y})}{y_k}\right)}\right\}.$$

4. Goto 2.

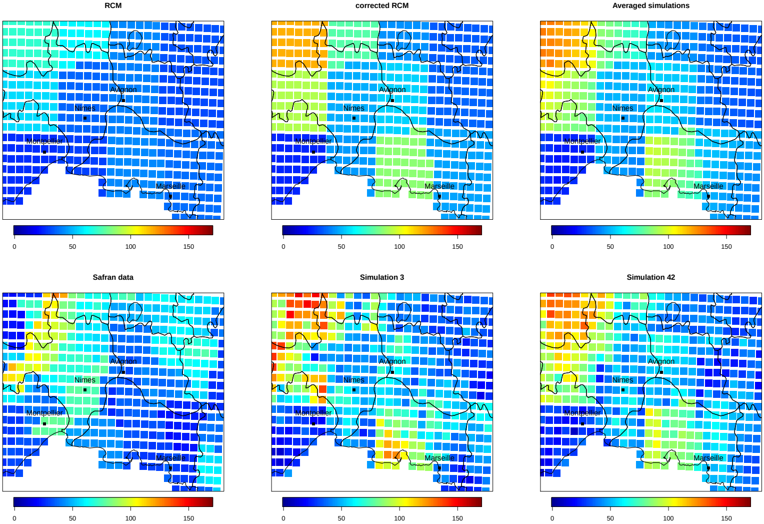
Application

Simulation conditional to each RCM grid-cell

- Standard downscaling (cdf-transform) for each Safran grid point covered by the RCM grid cell
- the averaged of the downscaled values is the conditioning value
- perform conditional simulations with the MCMC algorithm

Results

Year 2007



Outline

Downscaling for Spatial Extremes

1.
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5. Spatial Hybrid Downscaling

From conditional simulations to downscaling

Downscaling of the regional climate models (RCM) outputs

Climate model : cells $M_1, \ldots, M_n$

Objective: Simulate $(\mathbf{Z})_s | M_1 = m_1, \ldots, M_n = m_n$

From conditional simulations to downscaling

Downscaling of the regional climate models (RCM) outputs

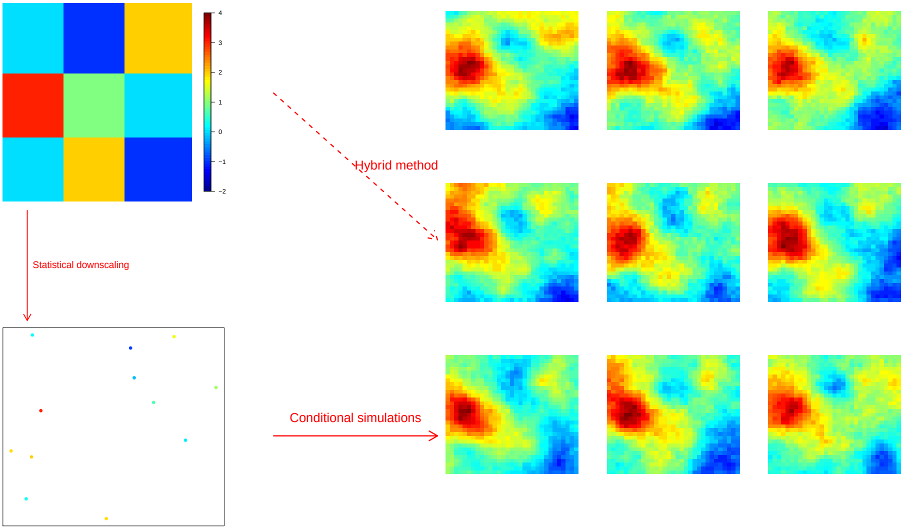
Climate model : cells $M_1, \ldots, M_n$

Objective: Simulate $(\mathbf{Z})_s | M_1 = m_1, \ldots, M_n = m_n$

Method: conditional simulations using downscaled values as conditioning points.

$\Rightarrow$ hybrid method

Hybrid Method : a physical and statistical approach



Hybrid Method : a physical and statistical approach

General Methodology:

- Choose a given number of points in the low scale dataset.
- Establish a statistical link (**transfer function**) between the high scale information (from GCM outputs) and these points (calibrated on the past)

Hybrid Method : a physical and statistical approach

General Methodology:

- Choose a given number of points in the low scale dataset.
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- Build with this transfer function some pseudo-observations at these given locations

Hybrid Method : a physical and statistical approach

General Methodology:

- Choose a given number of points in the low scale dataset.
- Establish a statistical link (**transfer function**) between the high scale information (from GCM outputs) and these points (calibrated on the past)
- Build with this transfer function some pseudo-observations at these given locations
- Perform a **conditional simulation algorithm** with the pseudo-observations as conditioning values.

Conditional simulations

Suppose that Z has been measured at a number of data points.

$$z_1 = Z(s_1), \dots, z_n = Z(s_n)$$

Objective: Simulate $(\mathbf{Z})_s | Z(s_1) = z_1 \dots, Z(s_n) = z_n$

$$Z(s) = \max_{k \geqslant 1} \xi_k W_k(s) = \max_{k \geqslant 1} \phi_k(s) = \max\Big(\max_{k=1,\ell} \phi_k^+(s), \max_{k \geqslant 1} \phi_k^-(s)\Big)$$

Algorithm

Dombry and Eyi-Minko (2012) propose:

(i) generate a partition $\mathcal{J}$ *given* $z_1, \dots, z_n$*;*
(ii) generate extremal random fields ϕ_i^+ *given* $\mathcal{J}$ *;*
(iii) generate sub-extremal random fields ϕ_i^- *.*

Comments on the generic algorithm

– Step *(i)*: Gibbs sampler, *Dombry et al, 2013*) rests on the computation of **multidimensional** integrals, that may be not numerically tractable.

– Step *(ii)*: Each extremal random field must be simulated under **equality** and **inequality** constraints. A rejection approach, may take very long time when the number of conditioning points is large.

Gathering steps 1 and 2

Instead of drawing a partition, draw directly the extremal random fields at **all conditioning points**

- avoid the calculation of integrals
- enables handling up to hundreds conditioning points instead of less than 30.

Choice of conditioning points

Basic choice: near the **center** of each grid-cell

Alternative choices

- choose a representative of the low-scale dataset with clustering algorithm.

  $\Rightarrow$ Partitioning Around Medoids (PAM)

- choose **randomly** one conditioning point into each grid-cell and **change** it for each simulation

  $\Rightarrow$ Stochastic Hybrid Method

Transfer functions and methods

Methods	TF	Cond. Sim.	Description
Interpolation	NO	NO	Bilinear interpolation of the RCM outputs values.
Linear downsc.	YES	NO	Model the low-scale variable by the mean of the high-scale variable over the 9 pixels around the point of interest.
Raw	NO	YES	Use directly RCM outputs as conditioning values.
CDF-t	YES	YES	Build a bias correction by comparing the CDF of the high-scale variable and the one of the low-scale variable.
Linear reg.	YES	YES	Same as *Linear downscaling* but only at the conditioning points.
Optimal	NO	YES	Use directly the real observations as conditioning points

Table: Different methods for building the pseudo-observations from the *Medcordex* and *Safran* datasets.

Results

Skill-Score: % of improvement compared to a reference method.

	Models	CRPSS	QSS_{95}	K-S SS	$RMSE_v$ SS
No simulations	Interpolation	-20.1%	-54.8%	-19.8%	-0.4%
	Linear downscaling	0%	0%	0%	0%
Conditional	Raw	14.0%	44.4%	10.4%	20.2%
	CDF-t	14.1%	**60.6%**	12.3%	**40.4%**
Simulations	Linear Regression	**20.1%**	53.4%	**15.0%**	22.5%
	Optimal	24.2%	70.7%	18.7%	52.9%

Table: Skill-Scores (with *Linear downscaling* as reference) of the hybrid algorithm with the different methods for building the pseudo-obs. from the MEDCORDEX dataset.

Results

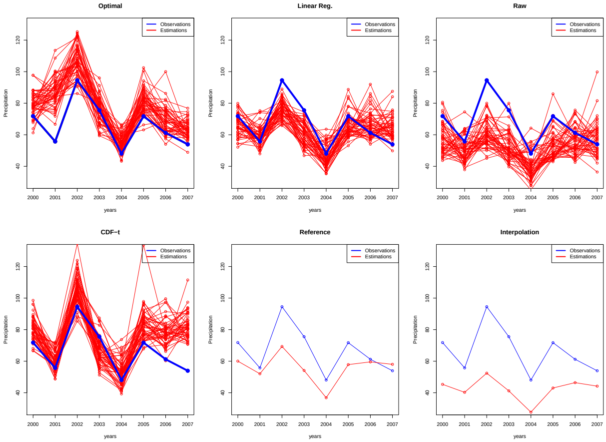

Figure: Annual means obtained by the 6 methods. The observed in blue and each trajectory in red is one conditional simulation.

Choice of the conditioning points

PAM

- Choice of conditioning points independent of the RCM model.
- 57 conditioning points
- Same order between the different methods ($\approx$ same skill-scores)
- Results not improved (higher scores).
  Reasons: the typicality of some conditioning points (alone in their clustering classes)

Stochastic Hybrid Method

- Choice of conditioning points depend on the RCM model
- No more case-by-case choice of conditioning points.
- Same order between the different methods ($\approx$ same skill-scores)
- Improved results (Scores)

Perspectives

Downscaling of MSP, theoretical distribution

- several conditions ?
- if not reachable, smoothing to avoid discontinuities when changing large scale grid-cell

Hybrid downscaling

- choice of the points (and number)

Both

- transfer functions
- other RCM

Describe the future evolution of the extreme precipitation according to different high-scale scenarios.

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