

Beyond the Observed: A Stochastic Simulation Approach for Impact-Based Storylines

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Attribution of Extreme Weather Events



WAS THIS EVENT DUE TO CLIMATE CHANGE?

Human contribution to the European heatwave of 2003

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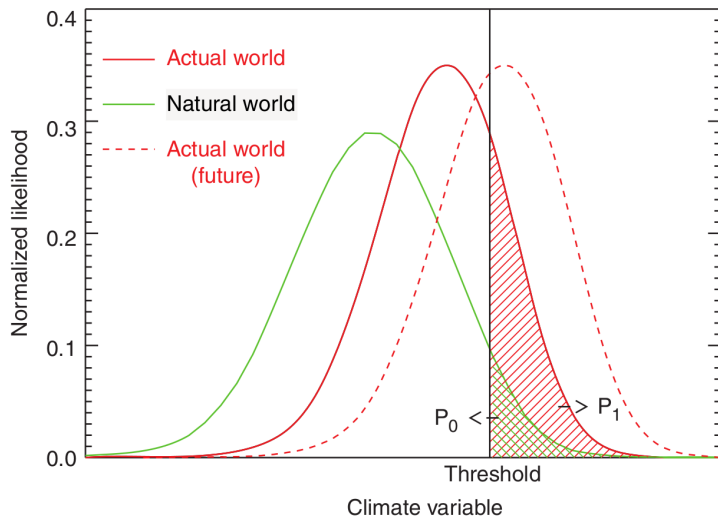
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The summer of 2003 was probably the hottest in Europe since at latest AD 1500¹⁻⁴, and unusually large numbers of heat-related deaths were reported in France, Germany and Italy⁵. It is an ill-posed question whether the 2003 heatwave was caused, in a simple deterministic sense, by a modification of the external influences on climate—for example, increasing concentrations of greenhouse gases in the atmosphere—because almost any such weather event might have occurred by chance in an unmodified climate. However, it is possible to estimate by how much human activities may have increased the risk of the occurrence of such a heatwave⁶⁻⁸. Here we use this conceptual framework to estimate the contribution of human-induced increases in atmospheric concentrations of greenhouse gases and other pollutants to the risk of the occurrence of unusually high mean summer temperatures throughout a large region of continental Europe. Using a threshold for mean summer temperature that was exceeded in 2003, but in no other year since the start of the instrumental record in 1851, we estimate it is very likely (confidence level >90%)⁹ that human influence has at least doubled the risk of a heatwave exceeding this threshold magnitude.

Fraction Attributable Risk (FAR)



Rapid attribution of extreme events and communication to the public:

- **World Weather Attribution (WWA):** Risk-based approach.
<https://www.worldweatherattribution.org/>
- **ClimaMeter:** Analog-based approach (story telling).
<https://www.climameter.org/>

Rapid Attribution: Use of Extreme Value Distributions

- **Generalize Extreme Value (GEV) distribution** for annual maxima.

$$G(z; \mu, \sigma, \xi) = \exp \left[- \left(1 + \xi \frac{z - \mu}{\sigma} \right)^{-1/\xi} \right],$$

with:

- **Location parameter** μ specifies center of distribution,
 - **Scale parameter** σ determines size of deviations,
 - **Shape parameter** ξ determines rate of tail decay.
- **Return period** T of event z_T is the average time (expressed in year) between two successive exceedances of z_T :

$$T = \frac{1}{1 - G(z_T)}.$$

- Conversely: **T -year return level** z_T .

Rapid Attribution: Use of Extreme Value Distributions

- WWA-protocol for rapid attribution in Philip *et al.* (2020).
- **Non-stationary GEV-distribution in a changing climate:**
Annual maximum temperature $\sim \text{GEV}[\mu(t), \sigma, \xi]$

$$\mu(t) = \mu_0 + \mu_1 \text{GMST}(t),$$

with:

- t : year
- $\text{GMST}(t)$: Global Mean Surface Temperature in year t (4-year running mean)
- μ_1 : Growth of the regional extremes per degree global warming.
- Present climate \Leftrightarrow Colder climate (-1.2°C).

Complexities of EEA: Low Signal-to-Noise Ratio

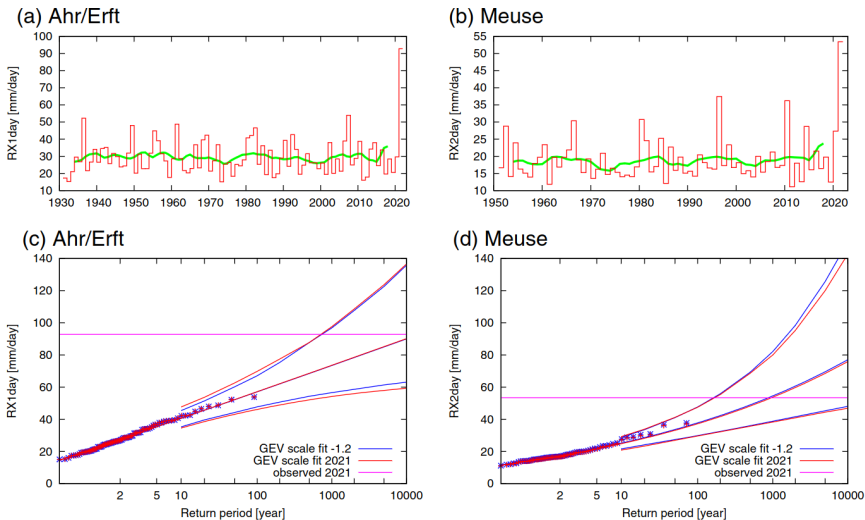


Figure: Taken from Tradowsky *et al.* (2023).

Complexities of EEA: Out-of-Distribution

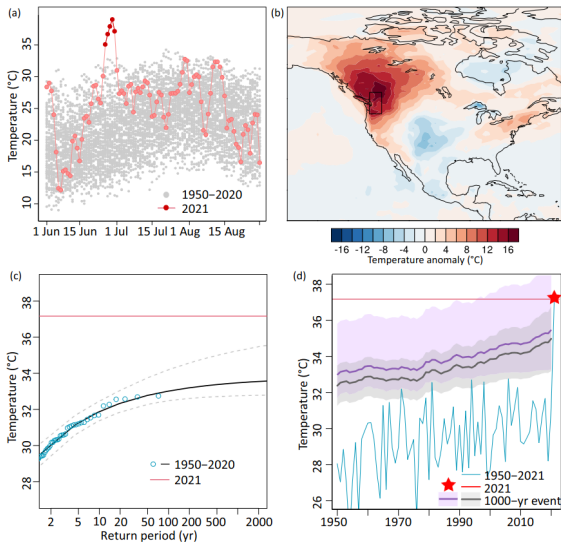


Figure: Taken from Fischer *et al.* (2023).

Review of *Shepherd (2016)* marks two main approaches:

- **1) Risk-Based Approach:**
 - e.g. Stott, Stone & Allen (2004).
 - Recent approaches: rapid attribution (Philip *et al.*, 2020)
- **2) Storyline Approach:** Identification of the chain of causal factors leading to the extreme event (Shepherd *et al.*, 2018).
 - **Pro:** good alternative if risk-based approach is too complex.
 - **Contra:** does not provide any probability.
- Examples of storylines based on:
 - Atmospheric analogs: Cattiaux J., *et al.* (2010)
 - Pseudo-Global-Warming experiments: Lackmann, G.M. (2015)
 - Ensemble boosting: Fischer E.M., *et al.* (2023)
 - Stochastic weather generation: Yiou (2014)

Stakeholder Workshop on “Tales of Future Weather”



Figure: <https://www.meteo.be/nl/info/nieuwsoverzicht/hoe-maken-wedsteden-weerbaar-tegen-hittegolven>

Storyline Approach with Ensemble Boosting: Pacific Northwest heatwave (June 2021)

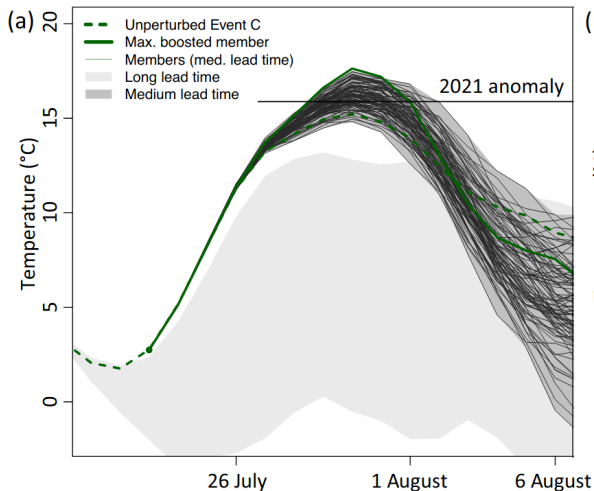
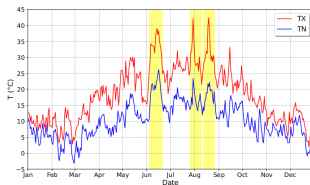
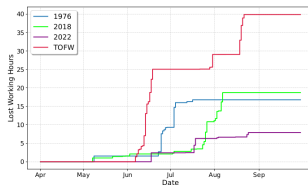


Figure: Taken from Fischer *et al.* (2023).

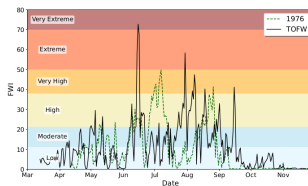
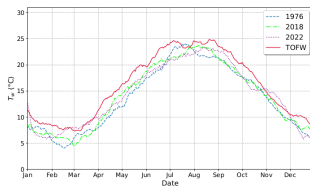
Storyline Approach with Local Impact Models



(a)

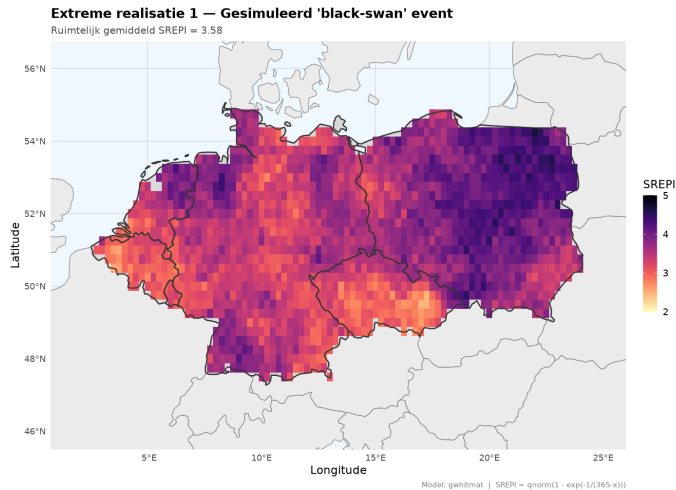


(b)



From: Niels Carlier (2025) *Constructing Tales of Future Belgian Heatwaves using Ensemble-Mining Strategies*, MSc. Thesis, UGent.

Storyline Approach for Wide-Spread Energy Droughts Using Spatial Extremes



From: Sarah Deleu, MSc. thesis student, UGent.

Storyline Approach with Phase-Randomisation

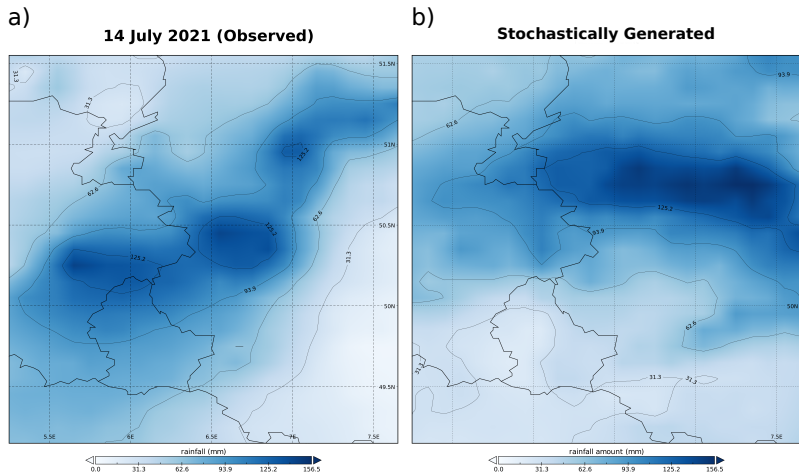
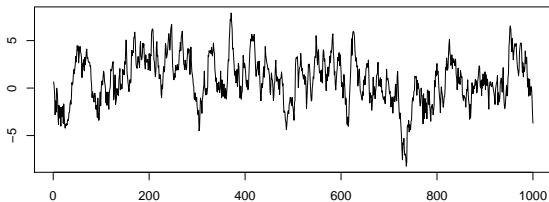


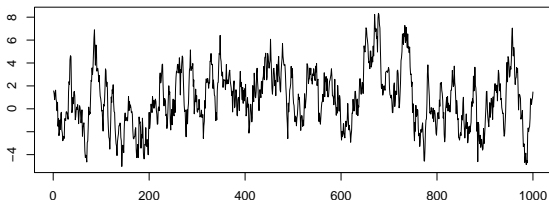
Figure: Taken from Van de Vyver (2024).

Phase-Randomisation (Schreiber & Schmitz, 2000)

Original Time Series



Phase-Randomised Time Series



Non-Extreme World

- Gaussian stationary process $Z(\mathbf{s}) \in \mathbb{R}^d$.
- **Semivariogram:**

$$\gamma_{ij} = \frac{1}{2} E [(Z(\mathbf{s}_i) - Z(\mathbf{s}_j))^2]$$

- **Semivariogram Matrix:**

$$\Gamma = \begin{pmatrix} \gamma_{1,1} & \dots & \gamma_{1,d} \\ \vdots & \ddots & \vdots \\ \gamma_{d,1} & \dots & \gamma_{d,d} \end{pmatrix}$$

Extreme World

- Regular varying $Z(\mathbf{s}) \in \mathbb{R}^d$.
- $Z(\mathbf{s}) = \Theta(\mathbf{s}) \times R$:
 - Direction: $\Theta(\mathbf{s}) = Z(\mathbf{s}) / \|Z(\mathbf{s})\|$
 - Intensity: $R = \|Z(\mathbf{s})\|$
- Extreme event: $R > r_0$
- **Tail Dependence Matrix:**
 $\Sigma = E[\Theta \Theta^T]$

$$= \begin{pmatrix} \sigma_{1,1} & \dots & \sigma_{1,d} \\ \vdots & \ddots & \vdots \\ \sigma_{d,1} & \dots & \sigma_{d,d} \end{pmatrix}$$

Non-Extreme World

- Spatio-temporal data is modelled with **Gaussian process**.
- Phase-randomisation preserves first-and second order moments (*e.g. mean, variance, auto-correlation, semivariogram*).

Extreme World

- Spatio-temporal **extreme** data is modelled with **Pareto-process**:
$$F_R(r) = 1 - (r/r_0)^{-\alpha}.$$
- **Phase-randomisation preserves tail dependence!**

Overview of the Algorithm

- **Input:** full spatio-temporal dataset $z[t, j]$, transformed to Pareto margins with tail-index α .
- **Decompose:** $z[t, j] = \theta[t, j] r(t)$.
- **Select extreme events** $x[t, j]$, defined as $r(t) > r_0$.
- **Phase-randomisation** of extreme events: $x[t, j] \rightarrow \tilde{x}[t, j]$.
- **Decompose:** $\tilde{x}[t, j] = \tilde{\theta}[t, j] \tilde{r}(t)$.
 \Rightarrow Recall **preservation empirical TPDM:**

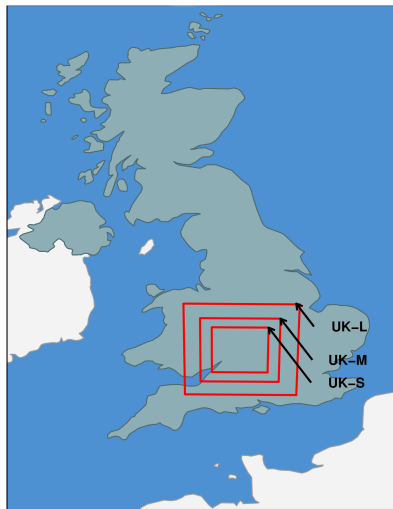
$$E[\Theta \Theta^T] = E[\tilde{\Theta} \tilde{\Theta}^T], \quad R > r_0.$$

- **New “surrogate” extreme events:**

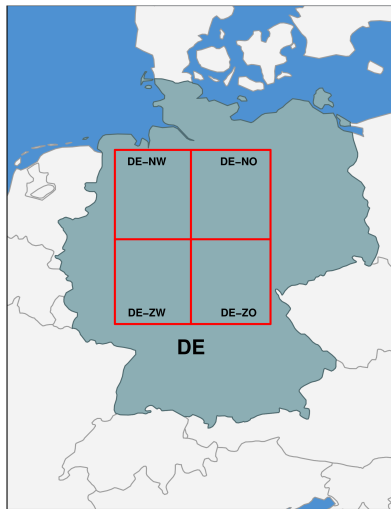
$$\tilde{\theta}(t, j) r^*(t), \quad \text{with} \quad r^*(t) \sim 1 - \left(r^*(t)/r_0 \right)^{-\alpha}.$$

Data and Study Domain

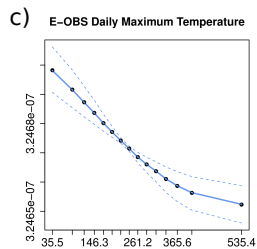
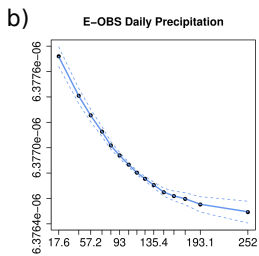
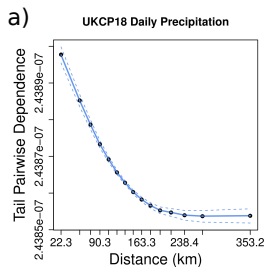
a) UKCP18



b) E-OBS

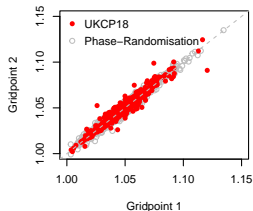


Performance Evaluation: Tail Dependence

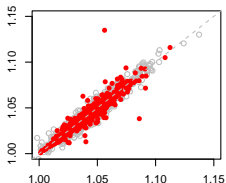


Performance Evaluation: Pair-wise Plots (UKCP18)

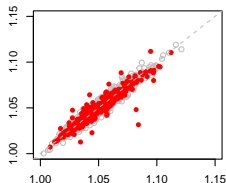
Distance between gridpoints: 2.2 km



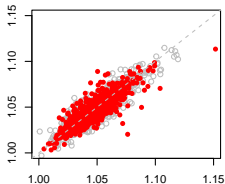
Distance between gridpoints: 4.2 km



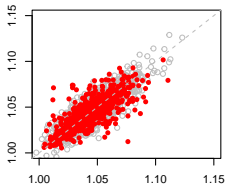
Distance between gridpoints: 5.8 km



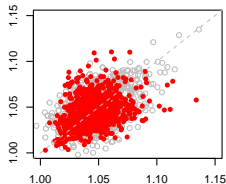
Distance between gridpoints: 11.1 km



Distance between gridpoints: 29.7 km

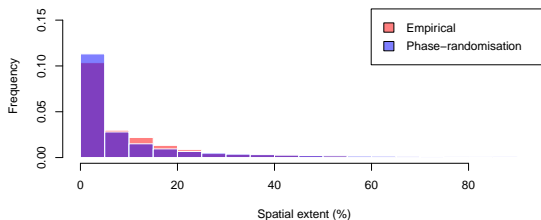


Distance between gridpoints: 57.4 km

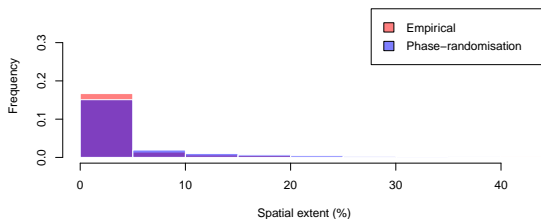


Performance Evaluation: Spatial Extent (UKCP18)

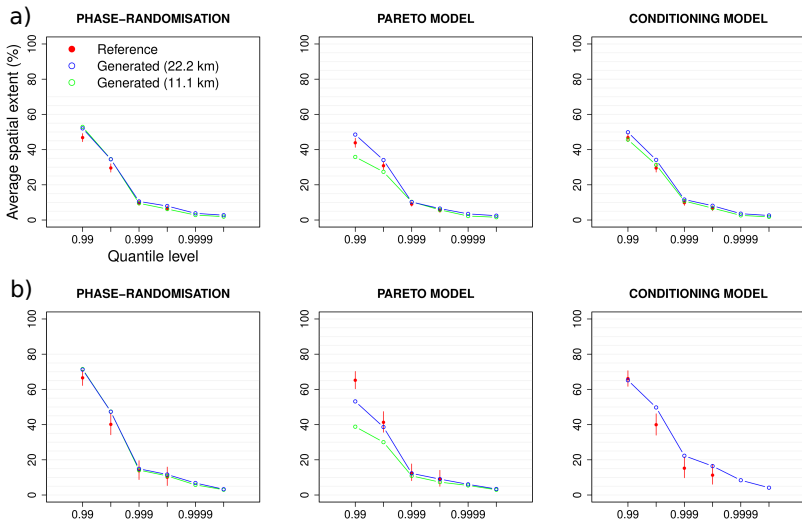
Probability density of spatial extent ($\tau=0.999$)



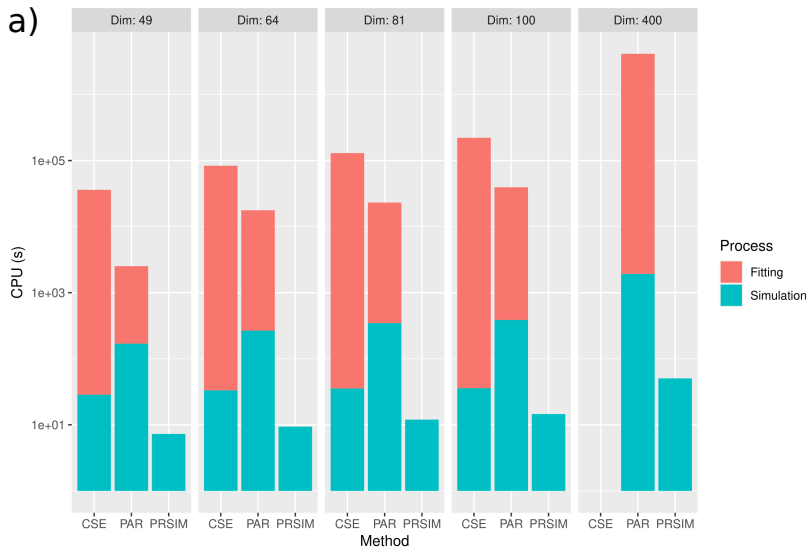
Probability density of spatial extent ($\tau=0.9999$)



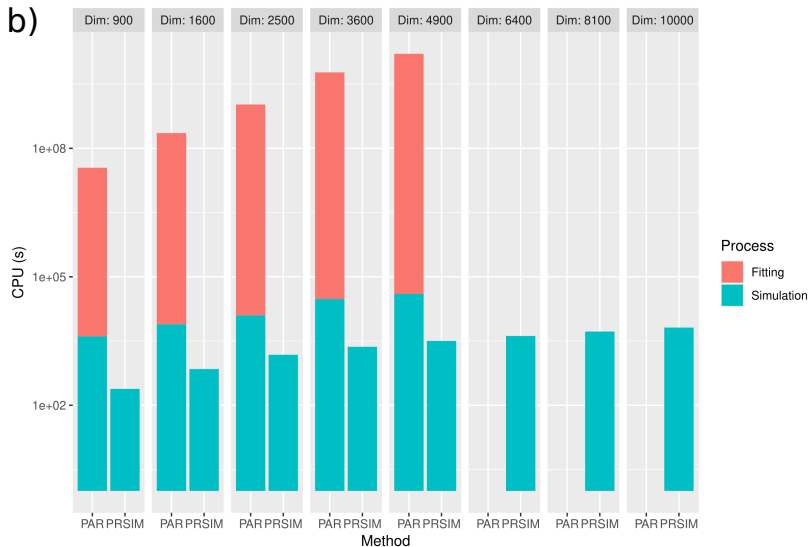
Performance Evaluation: Spatial Extent (E-OBS)



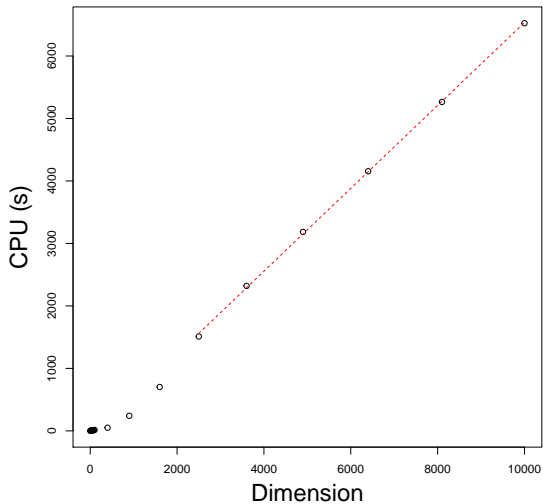
Scalability



Scalability



Scalability








Advantages

- New algorithm for generating high-resolution gridded datasets of synthetic extreme events.
- Realistic extreme patterns were generated with the same spatial dependence as observed extremes.
- The algorithm is fast, easy to implement and scalable to high dimensions.






Limitations

- Extreme event definition considers only widespread extremes, no highly-localised events.
- Overfitting issues.
- Some theoretical gaps...






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