Refining European Extreme Precipitation Return Levels using Regionalized GEV Models

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Motivation

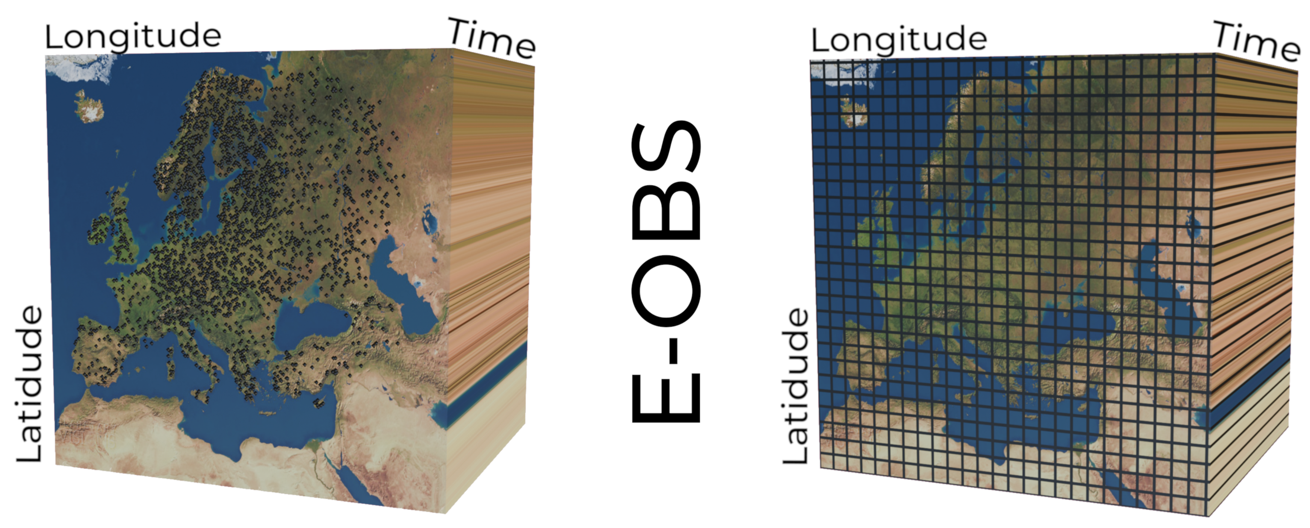
➢ **Extreme precipitation** events cause severe damage across Europe.
⟶ Need **climate**-aware models for extreme precipitation.

➢ Reliable **return level** estimation requires lots of data.
⟶ We need to pool data across space and time in a **regionalized** framework.

Our Proposition : A regionalized **GEV** with **space-time** adaptive **local** fits and automatic region discovery.

Data

➢ **E-OBS** Ensemble: **Daily**, **0.1°** gridded precipitation data across **Europe**
(25° N–75° N, 40° W–75° E), covering **1950–2024**.
Station-only interpolation.



➢ What do we do with it ?
We map GEV return levels Q(p) of **annual maxima** in space and time.
We want to get the best confidence intervals for future **attribution**.

Conclusion

➢ **Summary:** Weighted composite likelihood generalizes space-time likelihood, balancing bias and variance in return level estimation.

➢ **Key Point:** Weight choice is crucial. Simple kernels can't handle parameter anisotropy or discontinuities — neural networks may offer an elegant solution.

References

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Non-stationary GEV

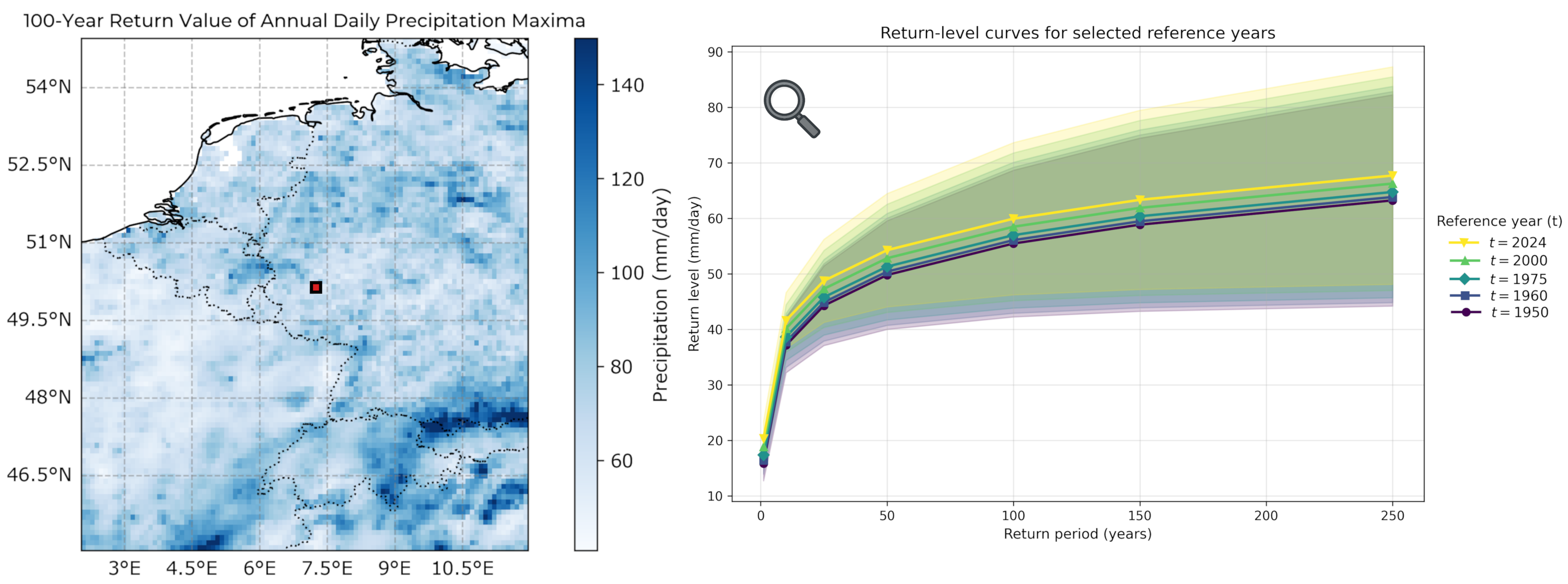
➢ Let $\mathbf{X}_{\mu,t}$, $\mathbf{X}_{\sigma,t}$ be the covariate matrices for the GEV parameters μ, σ with their coefficients vectors $\boldsymbol{\mu} = (\mu_0, \mu_1, \ldots, \mu_l)'$, $\boldsymbol{\sigma} = (\sigma_0, \sigma_1, \ldots, \sigma_l)'$.

➢ For T annual maximas , non-stationary log-likelihood :

$$\ell(\mu_t, \sigma_t, \xi_0) = \sum_{t=1}^{T} \log g(y_t; \mu_t, \sigma_t, \xi_0) \quad \text{with } \mu_t = \mathbf{X}_{\mu,t}\boldsymbol{\mu}, \quad \sigma_t = \mathbf{X}_{\sigma,t}\boldsymbol{\sigma}$$

with g the GEV density.

Global mean surface temperature anomaly (GMST) as covariate.
(Tradowsky et al., 2023).



Regionalisation

➢ Classical index-flood method : $Q_s(p) = \tilde{\mu}_s Q_R(p)$
with $\tilde{\mu}_s$ the index-flood; $Q_R(p)$ the regional quantile function.
⟶ **Issues :** Assumes constant $\xi_s, \frac{\mu_s}{\sigma_s}$, assumes temporal stationarity !

➢ Possible fix ? Spatio-temporal log-likelihood : ⟶ **Issue :** Non local.

$$\ell(\mu_{t,s}, \sigma_{t,s}; \xi_0) = \sum_{t=1}^{T} \sum_{s=1}^{S} \log g(y_{t,s}; \mu_{t,s}, \sigma_{t,s}, \xi_0)$$

Composite likelihood

➢ Our proposed solution :

$$\ell_w(\mu_{t,s}, \sigma_{t,s}, \xi_0) = -\frac{\sum_{t=1}^{T}\sum_{s=1}^{S} w_{t,s}\left[\log \sigma_{t,s} + \left(\frac{1}{\xi_0}+1\right)\log\left(1+\xi_0\frac{y_{t,s}-\mu_{t,s}}{\sigma_{t,s}}\right) + \left(1+\xi_0\frac{y_{t,s}-\mu_{t,s}}{\sigma_{t,s}}\right)^{-1/\xi_0}\right]}{\sum_{t=1}^{T}\sum_{s=1}^{S} w_{t,s}}$$

➢ Weights ? $w_{t,s} = (h_s h_t)^{-1} K_s\left(\frac{\|(x_s, y_s) - (x_0, y_0)\|}{h_s}\right) K_t\left(\frac{t - t_0}{h_t}\right)$

⟶ (So far) RBF kernels and product kernel.

⟶ (Next) Neural network weights + maximum likelihood post weighting.