Robust estimation of rainfall extremes and their evolution in a changing climate: A CONUS-wide assessment based on multifractal theory

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Rainfall extremes and their evolution in a changing climate

- **Overarching objective:**
  - Assess the **evolution of extreme precipitation events** in a **changing climate**, over an **extensive high resolution** (say 4-km) **spatial grid**, various climatic regions, and over a **wide range of temporal scales**.

- **Requirements:**
  - Statistical framework for **robust estimation of rainfall extremes from short rainfall records** (say 10 years), **over a wide range of temporal scales** ⇒ **IDF curve estimation**
  - **High resolution** (e.g. hourly) **precipitation dataset** with extensive spatial coverage and record length (exceeding say 40 years) ⇒ **Statistical downscaling and bias correction of reanalysis products**
  - Apply the introduced **IDF estimation framework to sequential** (say 10-year) **segments** of the data to assess how extreme rainfall evolves over time. ⇒ **Detach from the stationarity assumption**

1. Use of **multifractal scaling arguments** for IDF estimation from short rainfall samples
2. **Statistical downscaling and bias correction** for robust extreme rainfall estimation at **fine spatiotemporal scales**.
3. Evaluation of **extreme rainfall trends** based on reanalysis outputs
   - Effects of climate change on extreme rainfall evolution based on historical information
Definition of IDF Curves

- $I_d$: average rainfall intensity over duration $d$
- $I_{\text{max},d}$: annual maximum of $I_d$
- $i_{d,T}$: value exceeded by $I_{\text{max},d}$ with probability $1/T$ (years)

**IDF Curves**
Methods of IDF Estimation
From the historical series of annual rainfall maxima (AM approach)

- **Separability assumption in d and T**

  \[ i_{d,T} = b(d) \alpha(T) \]

  • **Empirical function**
    - e.g. \( \alpha(T) \)
    - model parameter

  • **Koutsoyiannis et al. (1998) approach**:
    - **Select** \( c \) (e.g. using a homogeneity test) so that the standardized historical annual maxima \( \frac{i_{\text{max},d}}{b(d)} \) over all \( d \) belong to the same population.
    - **Obtain** \( \alpha(T) \) by fitting a theoretical distribution model with parameters independent of \( d \) to the standardized maxima; e.g. \( \frac{i_{\text{max},d}}{b(d)} \sim \text{GEV}(\mu, \sigma, k) \)

**Limitations:**

- **Estimation** of \( a(T) \) and \( b(d) \) using solely the series of annual maxima, discarding the largest portion of the available information in record.
- **Sensitivity** to outliers.
- **Pronounced statistical variability**, especially in the estimation of the distribution shape parameter ⇒ **extremes**

**Reduced performance in:**

- **Extreme rainfall estimation** from short records (e.g. \(< 25 \) years)
- **Regional frequency analysis** for estimation of distribution parameters at ungauged locations
Methods of IDF Estimation
From rainfall peaks above a properly selected threshold (PoT Approach)

Not particularly suited for IDF curve estimation... (see Emmanouil et al., 2020):

1) For each averaging duration $d$, determine the threshold $u_d$ above which the scaled excesses $I_{u(d),d} := [I_d - u(d)| I_d > u(d) ]$ follow a Generalized Pareto (GP) distribution model (see e.g. Langousis et al., 2016).

2) For each $d$, fit a GP model to the scaled excesses: $I_{u(d),d} \sim \text{GP} (u(d), a_{u(d)}(k))$

3) Reparameterize the resulting GP distributions to zero threshold, by adding a concentrated mass at zero and rescaling the shape parameter (Deidda, 2010).

4) Regress the parameters of the resulting GP model against $d$:

$$
i_{d,T} = \begin{cases} 
\frac{a_0(d)}{k} \left\{ \frac{1-(1-1/T)(d/1\text{yr})}{z_0(d)} \right\}^{-k}, & k \neq 0 \\
- a_0(d) \ln \left[ \frac{1-(1-1/T)(d/1\text{yr})}{z_0(d)} \right], & k = 0
\end{cases}
$$

Use larger portion of the available information, not just the annual maxima
Methods of IDF Estimation
From stochastic models of rainfall

➢ Fit a model to the *continuous* rainfall record

➢ *Calculate IDF curves from the fitted model* ⇒ typically through MC simulation

**Multifractal Rainfall Models:**
Temporal rainfall is said to be multifractal (MF) if the statistics remain *unchanged* when the observation axis is contracted by a factor \( r > 1 \) and the rainfall intensity is *multiplied* by some random variable \( A_r \).

**Illustration: Multiplicative Cascades**

\[
I_d = I_D A_{D/d}
\]

**Advantages**

✓ *Use information from the full historical record*

✓ Robust parameter estimation even from short records

✓ *Separable IDF scaling* for \( d \to 0 \) or \( T \to \infty \) →

\[
i_{d,T} \sim T^k d^{-c}
\]
Multifractal IDF Curves

Analytical solution for MF IDF curve estimation (Langousis et al., 2009):

\[ T_{r,\gamma} \approx \begin{cases} \frac{D}{r} \left[ (2\pi)^2 C_{LN} \left( \frac{\gamma C_{\beta}}{2 C_{LN}} + \frac{1}{2} \right) \ln(r_0) \right]^{1/2} (rr_0)^{C_{LN} \left( \frac{\gamma-C_{\beta}}{2 C_{LN}} + \frac{1}{2} \right) + C_{\beta}}, & \gamma \leq 2 - C_{\beta} - C_{LN} \\ \frac{D}{r} \left[ (2\pi)^2 \ln(rr_0) \left( \frac{1-C_{\beta}}{2 C_{LN}} \right)^2 \right]^{1/2} (rr_0)^{1 + (\gamma-1) \frac{1-C_{\beta}}{C_{LN}}}, & \gamma > 2 - C_{\beta} - C_{LN} \end{cases} \]

\[ r = \frac{D}{d}, \quad \gamma = \log_{rr_0}(i_d,T / \bar{I}) \]

\( C_{\beta} \): Fraction of intra-storm dry periods (i.e. \( C_{\beta} = 0 \) \( \Rightarrow \) compact rainfall)

\( C_{LN} \): Amplitude of the multiplicative fluctuations when it rains

\( D \): Average “storm” interarrival time (upper limit of multifractality)

\( \bar{I} \): Mean rainfall intensity

✓ 4-parameter model with physically meaningful setting...
Comparison of Alternative IDF Estimation Approaches

Available data: 36 raingauge stations in Northeast US with > 60 years of hourly recordings

Use bootstrapping to:

- Study the uncertainty in model parameter estimation
- Produce parameter maps
- Assess the accuracy and robustness of model based IDF estimates

Benchmarking: empirical IDF from the full record length vs IDF model and record length
Robust parameter estimation irrespective of the sample length

N = 2 years (100 ensembles)

N = 10 years (100 ensembles)

N = 50 years (100 ensembles)

higher elevation

Physically meaningful parameter setting explained by local topography and rainfall climatology

IDF estimates for $T = 50$ years

$d = 1 \text{ hr}$

$N = 2$ years (100 ensembles)  
$N = 10$ years (100 ensembles)  
$N = 50$ years (100 ensembles)  

Full record length (> 60 years)
For all $d$ and $T$ studied, the MF analytical approximation produces accurate and robust estimates even for sample lengths down to 1-2 years!
Statistical downscaling and bias correction of ERA5 atmospheric reanalysis product

- Assess hydroclimatic risk **multi-year precipitation datasets** at adequately **high spatial and temporal resolutions**

- Numerous precipitation datasets with **extensive spatial coverage** and record lengths (exceeding 40 years)

- The aforementioned **weaknesses** could be **remedied** by employing **high-resolution remote sensing-based rainfall estimates**.
  - The **temporal coverage** is usually in the range from 15 to 18 years

  **significant constraint** for water resources applications

- **Solution:**
  - a) **statistical correction** of the incorporated datasets, and
  - b) **downscaling** of a lower resolution product with **extensive temporal coverage** to **finer spatial scales**.

  - **atmospheric reanalysis:**
    - ERA5 offers robust global hourly precipitation estimates from **1979** to the current date over a **28 km** grid.
    - Rather **coarse** for physically based distributed hydrologic simulations.

- **ERA5** offers robust global hourly precipitation estimates from 1979 to the current date over a 28 km grid.
Data and Study Domain

1. Hourly rainfall measurements from NOAA
   - Includes 1818 rain gauge stations with extensive precipitation records (i.e., more than 40 years) over the entire CONUS (Wuertz et al., 2018).

2. ERA5 atmospheric reanalysis
   - Hourly rainfall estimates, over a 28-km, CONUS-wide grid.
   - Spanning back to 1979 (recently 1950, under a preliminary edition).

3. Stage IV radar-based precipitation estimates
   - Hourly rainfall estimates, over a 4-km, CONUS-wide grid.
   - Spanning back to 2002.
Brief description of statistical downscaling framework

➢ Parametric Quantile – Quantile (Q-Q) correction

✓ Two component theoretical distribution model fitting

✓ Higher rainrates follow a GP distribution model

✓ Lower rainrates follow a LN distribution model

➢ Particularly suited for bias correction

✓ low sensitivity to the intrinsic assumption of stationarity

✓ ability to extrapolate beyond the range of the available historical records

Advanced parametric Q-Q mapping framework

➢ maintains continuity of the distribution mixture by selecting an optimal threshold to shift between the distribution models used for higher and lower rainrates.
Findings
Statistical downscaling of atmospheric reanalysis precipitation data

**Expected-Root-Squared-Error (ERSE)**

- Smaller biases in western US
- Corrected biases in western US
- Relatively higher ERSEs
- Low ERSEs

**Expected-Root-Squared-Error (ERSE\textsubscript{95}) of Upper Tail**

- Low ERSEs
- Large biases


The full, CONUS-wide dataset can be found in: [https://doi.org/10.5061/dryad.8kprr4xnq](https://doi.org/10.5061/dryad.8kprr4xnq).

- **✓** Biases in western US are alleviated.
- **✓** The product benefits from the strengths of the reference datasets.
Evaluating extreme rainfall trends based on reanalysis outputs

1) The continuous hourly rainfall timeseries is split into sequential 10-year segments, where climate conditions can be assumed stationary.

2) The parametric multifractal (MF) analytical approximation by Langousis et al. (2009) is employed to each segment to acquire rainfall intensity estimates for return periods $T$ ranging from 2 years to more than 100 years.
Findings

Current extreme rainfall trends based on multifractal scaling arguments

➢ Beyond the apparent effects on the magnitude and frequency of intense precipitation events, **IDF curves tend to rotate.**

➢ Extent of changes **across averaging durations differs.**

➢ The dextrorotation reveals that changes in **shorter durations** tend to be more pronounced.
  - An indication that the **spatial structure of storms is evolving**, which can **alter catchment flood responses.**

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Findings
Current extreme rainfall trends based on multifractal scaling arguments

Current return period levels are **skewed to the right**

**Reduced non-exceedance probability levels**

Existing *infrastructure* designed to withstand catchment responses initiated by storms corresponding to $T = 50 \text{ yr}$, could be overwhelmed *at least once* in a period of 1 to 20 yr.

Conclusions

➢ Versatile downscaling technique

✓ Two-component theoretical distribution model.
✓ Maintains continuity of the distribution mixture.
✓ Automatic selection of an optimal threshold to shift between the models for higher and lower rainrates.
✓ Characterized by simplicity, versatility and computational effectiveness, while its data requirements are relatively low.

➢ Advanced multifractal framework

✓ Robustly provide IDF estimates even with small sample sizes (down to 2 years).
✓ Meaningful parameter setting that is explained by local topography and rainfall climatology.
✓ Applied to adequately short and sequential segments, where conditions can be fairly assumed stationary.

Extreme rainfall trends for various return periods \( T \) and durations \( d \).

➢ Existing infrastructure may be severely impacted by the effects of climate change.

➢ Observed trends

i. influenced by local topography and rainfall climatology,
ii. depend on the characteristic \( d \) and \( T \) of interest.
Future Research

➢ Evolving spatiotemporal patterns of intense precipitation should explicitly account for the nonstationary nature of the rainfall process.

➢ Climate model projections
   i. understand how the observed trends could evolve in future scenarios.
   ii. framework that accommodates the incorporation of the acquired extreme rainfall trend estimates to the design of critical infrastructure.

➢ Hydrological model outputs are largely affected by the spatial resolution of the rainfall input (see e.g., Perra et al., 2020)

➢ Most climate projections are offered at relatively coarse spatial scales (i.e., on the order of 25 km or more)

important to quantify the extent to which extreme rainfall trends are affected by the spatial resolution of the parent rainfall fields.
References

Thank you