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Department of Civil and Environmental Engineering
Environmental Engineering Program

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

Andreas Langousis, ScD

Associate Professor and Head of the Geotechnical and Hydraulic Engineering Sectors
Department of Civil Engineering, University of Patras, Greece
Chair of the Precipitation and Climate Subdivision, EGU

with contributions from **Stergios Emmanouil, PhD Candidate**

Department of Civil and Environmental Engineering
University of Connecticut, USA

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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

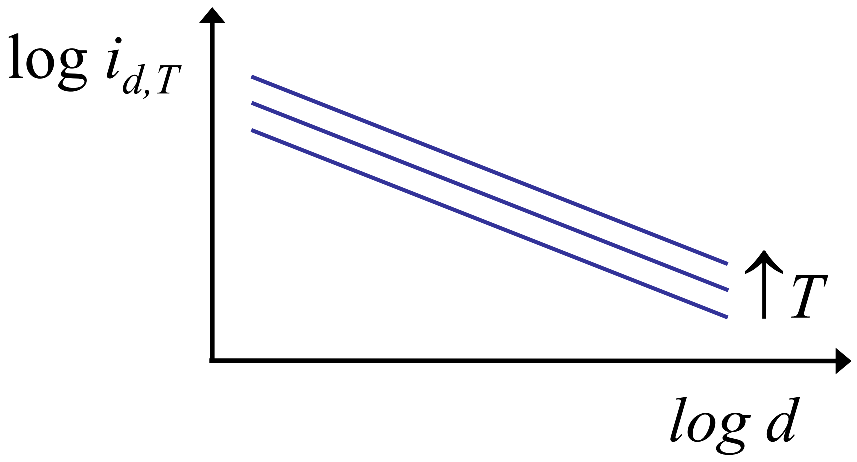
Definition of IDF Curves

I_d: average rainfall intensity over duration d

$I_{max,d}$: annual maximum of I_d

$i_{d,T}$: value exceeded by $I_{max,d}$ 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…***

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

IDF value

empirical function **e.g. d^{-c}** ***model parameter***

empirical function **e.g. $\propto T^k$, $\log T$**

➢ **Koutsoyiannis *et al.* (1998) approach:**

- **Select** ***c*** (e.g. using a homogeneity test) so that the *standardized historical annual maxima* $i_{max,d}/b(d)$ 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. $i_{max,d}/b(d) \sim \mathrm{GEV}(\mu, \sigma, k)$

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).

…condition k to be independent of d

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

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*** : $a_0(d) = h\, d^{-u}$ $z_0(d) = e\, d^{g}$

scale parameter probability of rain

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

…**match the mean** of the historical annual maxima

- ***Use larger portion of the available information, not just the annual maxima***

Methods of IDF Estimation

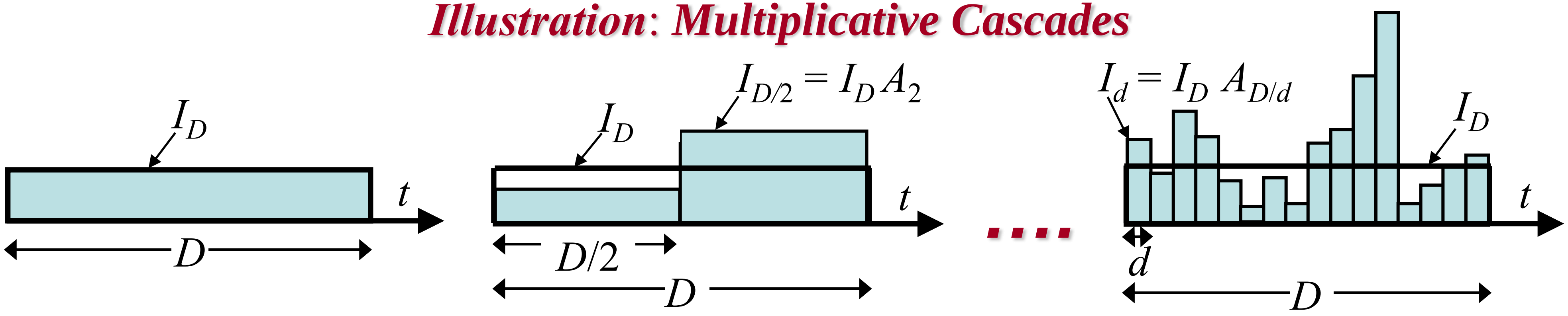
From stochastic models of rainfall

- 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



Advantages

- ✓ *Use information from the **full historical record***
- ✓ ***Robust** parameter estimation even from short records*
- ✓ ***Separable IDF scaling** for $d \to 0$ or $T \to \infty$* ⇨ $\boxed{i_{d,T} \sim T^{k} d^{-c}}$

Multifractal IDF Curves

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

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

$$r = D/d, \quad \gamma = \log_{rr_0}(i_{d,T}/\bar{I})$$

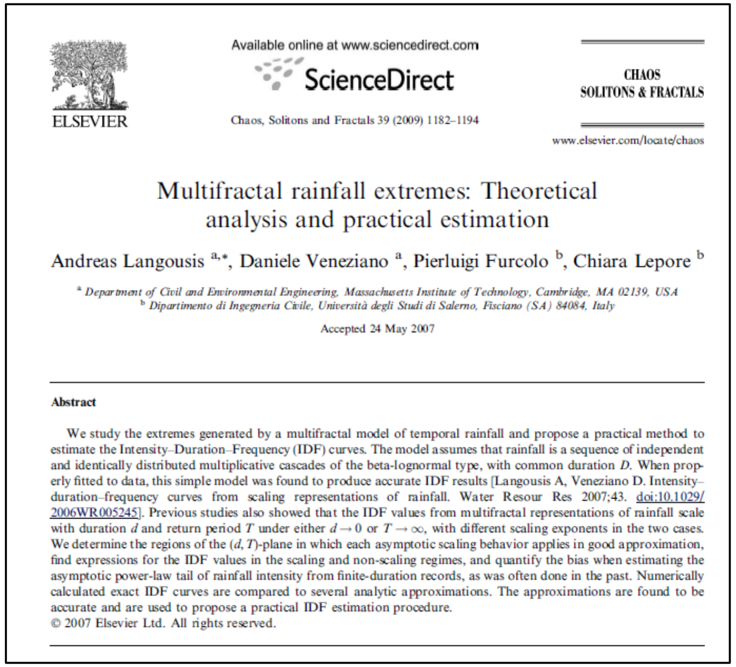
C_β : Fraction of ***intra-storm dry periods*** (*i.e.* $C_\beta = 0$ ⇨ compact rainfall)

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…***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Multifractal rainfall extremes: Theoretical analysis and practical estimation

Andreas Langousis [a,*], Daniele Veneziano [a], Pierluigi Furcolo [b], Chiara Lepore [b]
[a] Department of Civil and Environmental Engineering, Massachusetts Institute of Technology, Cambridge, MA 02139, USA
[b] Dipartimento di Ingegneria Civile, Università degli Studi di Salerno, Fisciano (SA) 84084, Italy

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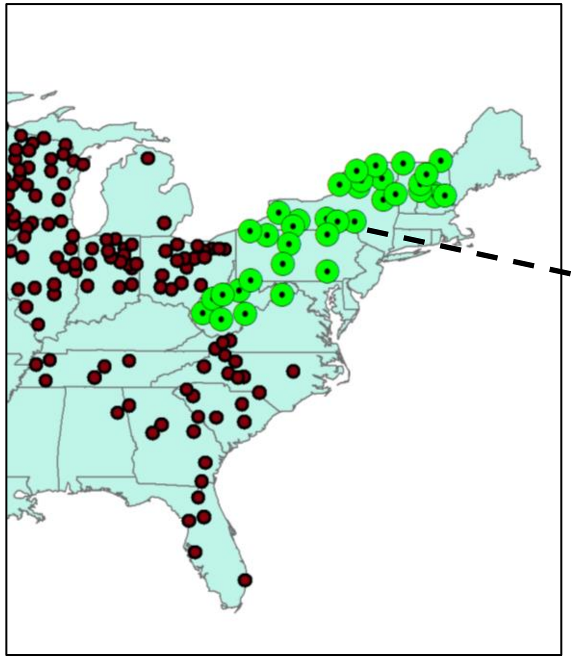
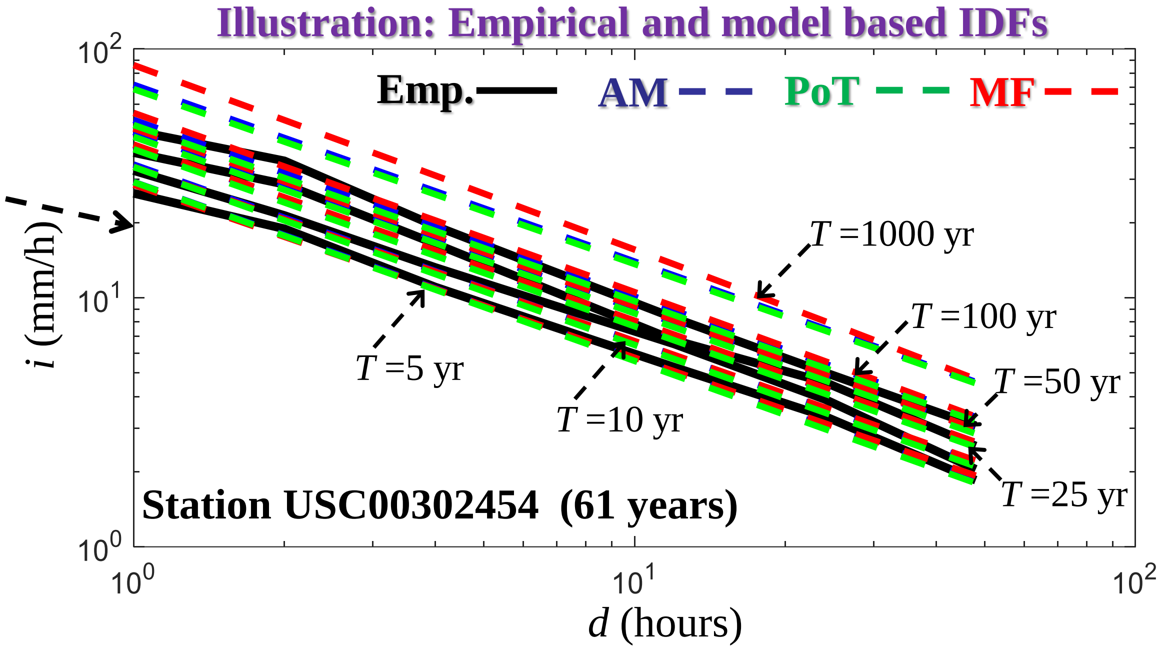
Abstract

We study the extremes generated by a multifractal model of temporal rainfall and propose a practical method to estimate the Intensity–Duration–Frequency (IDF) curves. The model assumes that rainfall is a sequence of independent and identically distributed multiplicative cascades of the beta-lognormal type, with common duration D. When properly fitted to data, this simple model was found to produce accurate IDF results [Langousis A, Veneziano D. Intensity–duration–frequency curves from scaling representations of rainfall. Water Resour Res 2007;43. doi:10.1029/2006WR005245]. Previous studies also showed that the IDF values from multifractal representations of rainfall scale with duration d and return period T under either $d \to 0$ or $T \to \infty$, with different scaling exponents in the two cases. We determine the regions of the (d, T)-plane in which each asymptotic scaling behavior applies in good approximation, find expressions for the IDF values in the scaling and non-scaling regimes, and quantify the bias when estimating the asymptotic power-law tail of rainfall intensity from finite-duration records, as was often done in the past. Numerically calculated exact IDF curves are compared to several analytic approximations. The approximations are found to be accurate and are used to propose a practical IDF estimation procedure.

Comparison of Alternative IDF Estimation Approaches



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



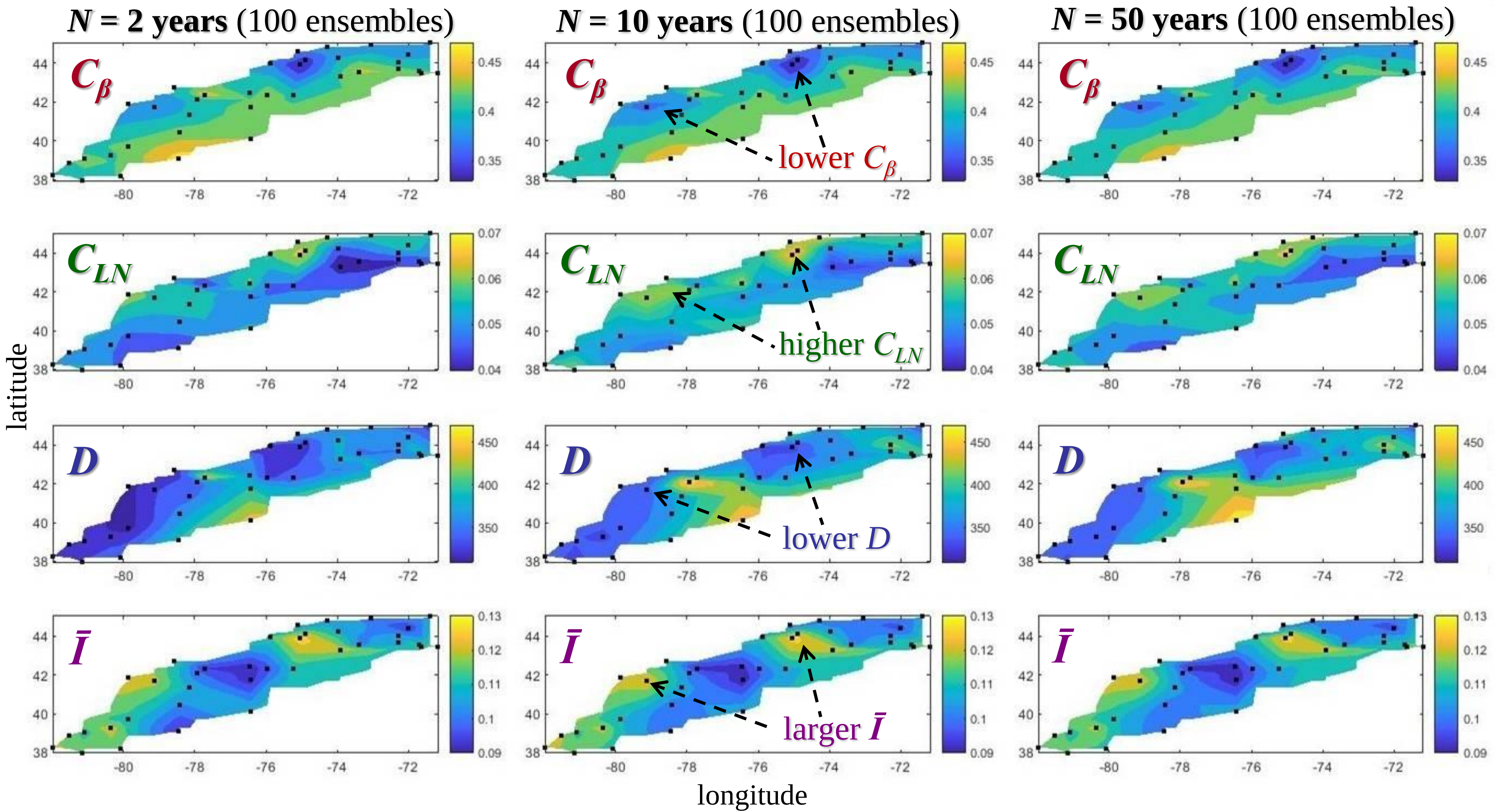
- **Use bootstrapping to:**
  - *Study the* ***uncertainty*** *in model* ***parameter estimation***
  - *Produce* ***parameter maps***
  - *Assess the* ***accuracy*** *and* ***robustness*** *of model based* ***IDF estimates***

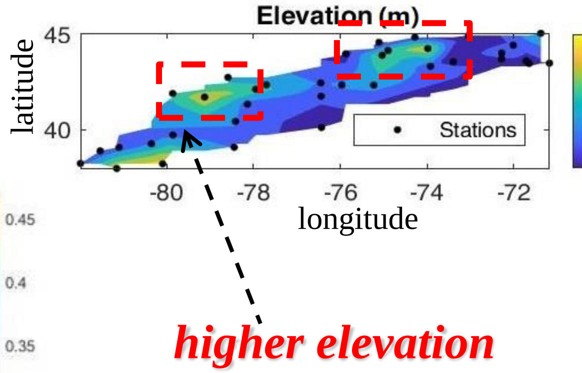
  ⇨ ***Benchmarking:*** *empirical IDFs from the full record length*

…vs IDF model and record length

MF Parameter Maps

- ✓ ***Robust parameter estimation irrespective of the sample length***



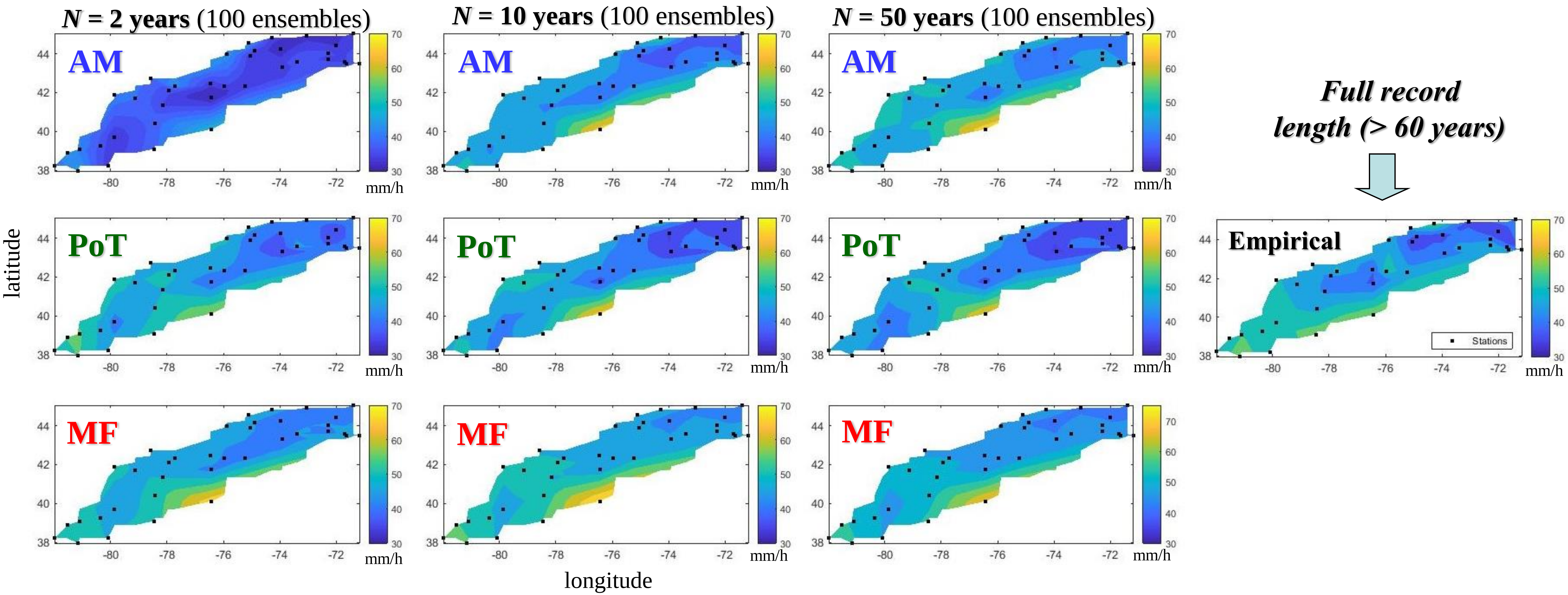


- ✓ ***Physically meaningful parameter setting explained by local topography and rainfall climatology***

Emmanouil, S., A. Langousis, E.I. Nikolopoulos, and E.N. Anagnostou (2020) Quantitative assessment of annual maxima, peaks-over-threshold (PoT) and multifractal parametric approaches in estimating intensity-duration-frequency (IDF) curves from short rainfall records, *Journal of Hydrology*, **589**, 125151, doi: 10.1016/j.jhydrol.2020.125151.

IDF estimates for T = 50 years

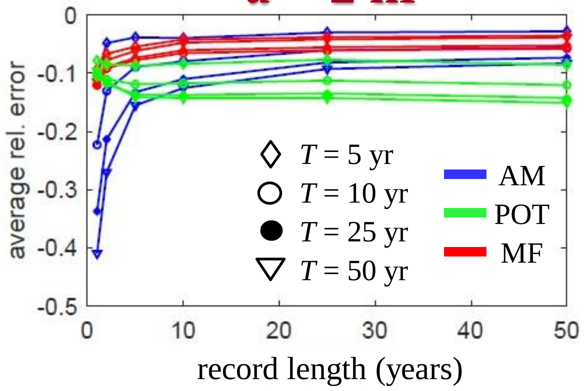
d = 1 hr



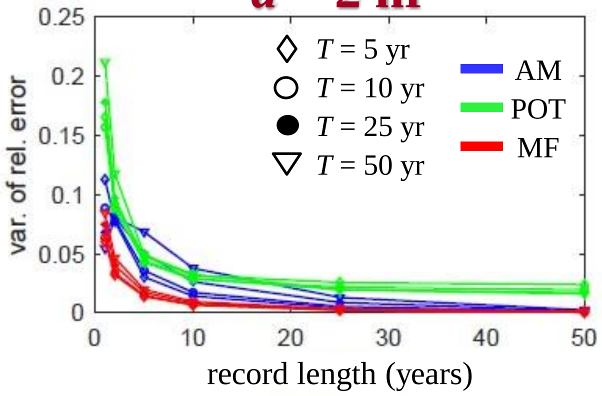
IDF estimation Bias – Variance – DRMSE

Relative bias | **Variance of relative error** | **DRMSE**

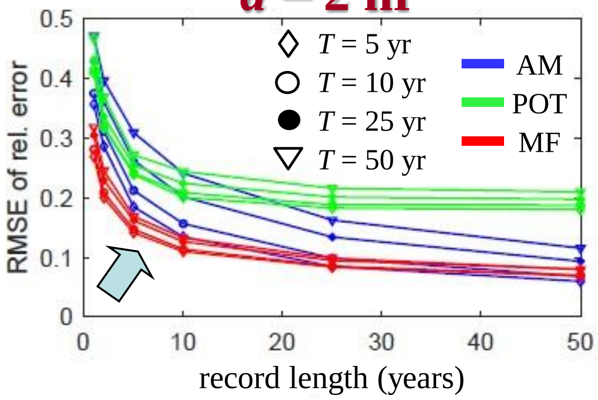
***d* = 2 hr**



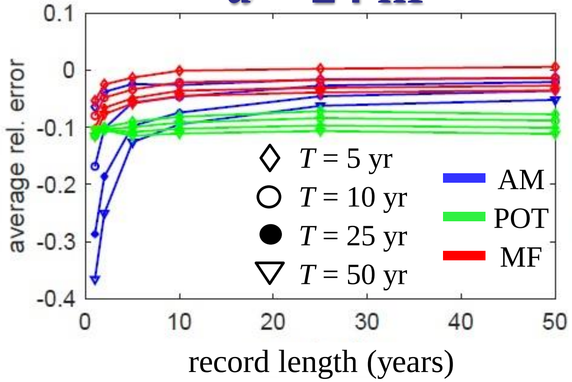
***d* = 2 hr**



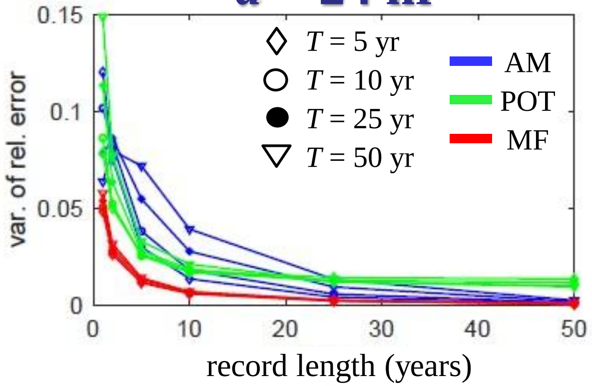
***d* = 2 hr**



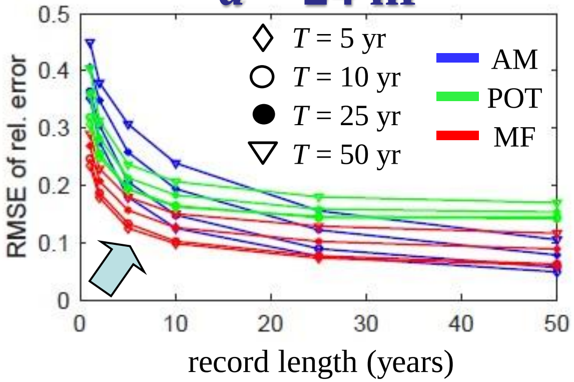
***d* = 24 hr**



***d* = 24 hr**



***d* = 24 hr**



✓ 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) ➔ **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.

- 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

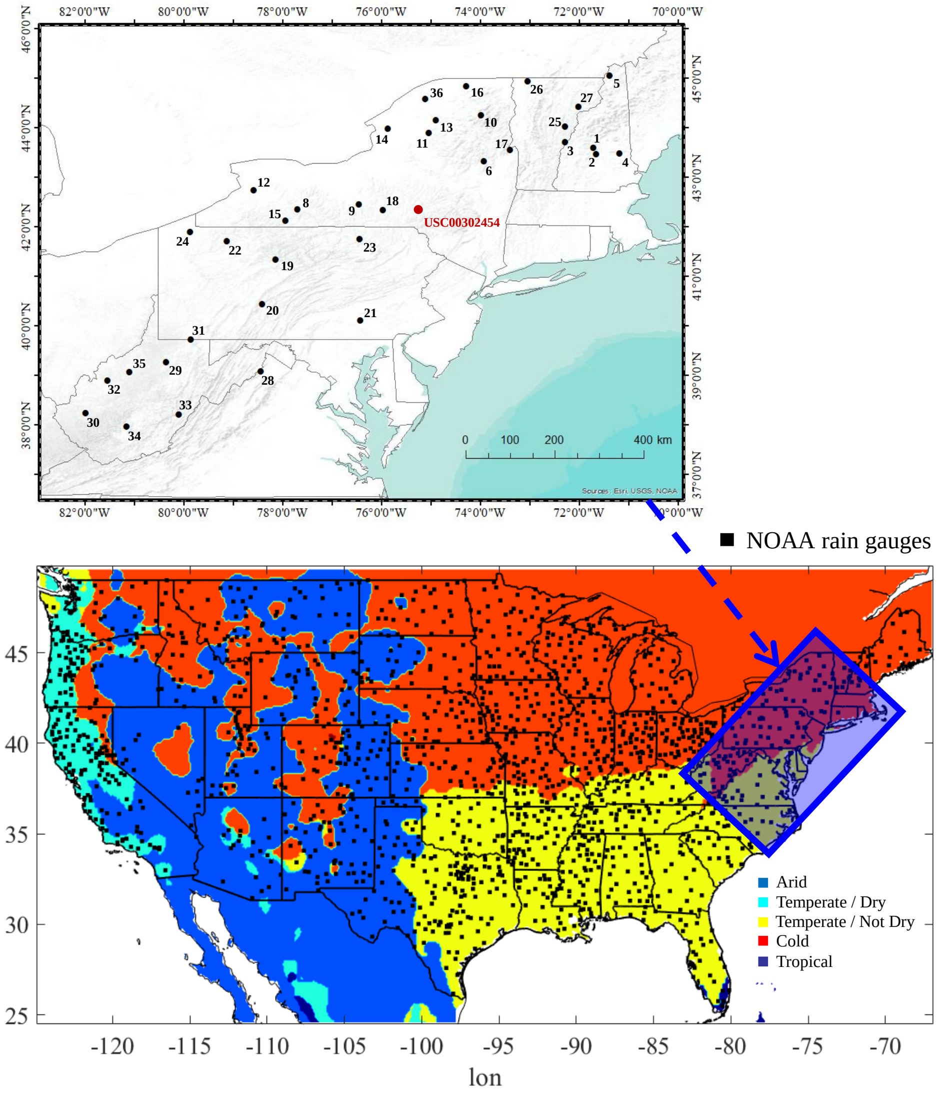
b) downscaling of a lower resolution product with extensive temporal coverage to finer spatial scales.

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**

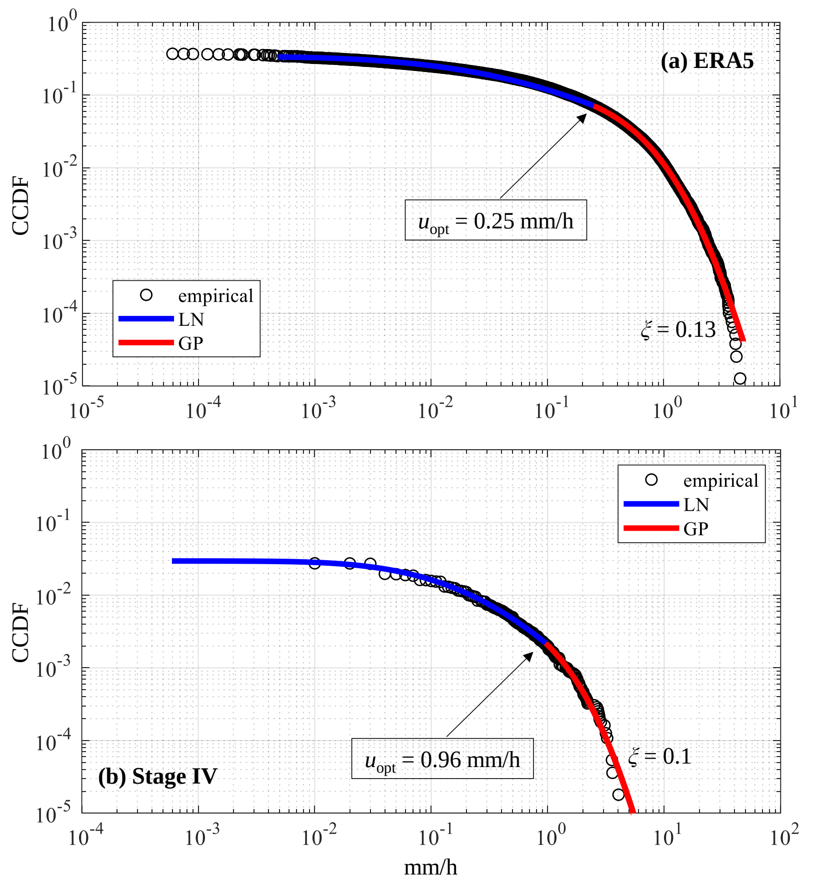
Particularly suited for **bias correction**

- ✓ **low sensitivity** to the intrinsic assumption of stationarity
- ✓ ability to **extrapolate** beyond the range of the available historical records

- ✓ **Two component** theoretical distribution model fitting
- ✓ Higher rainrates follow a **GP distribution model**
- ✓ Lower rainrates follow a **LN distribution model**

Advanced parametric Q-Q mapping framework

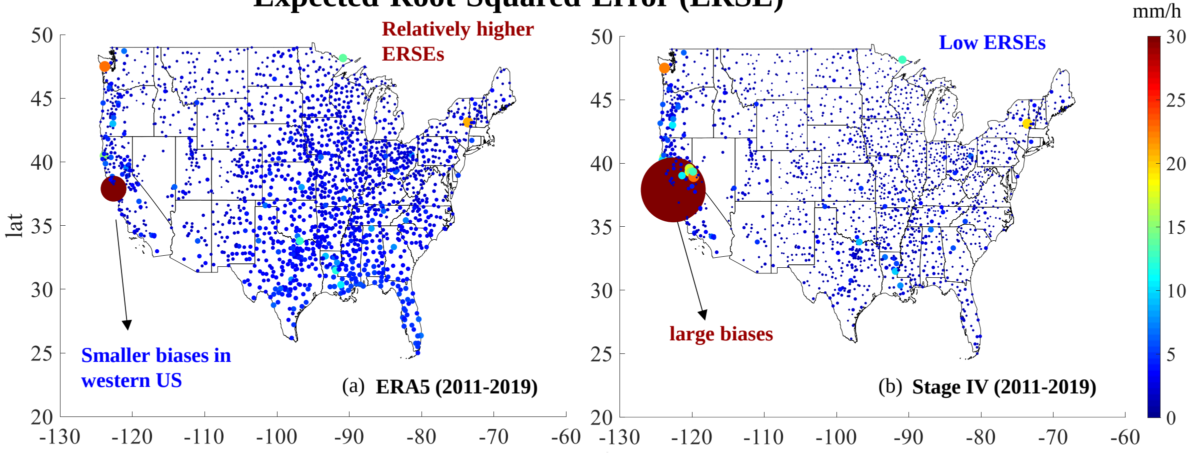
- maintains **continuity** of the distribution mixture by selecting an **optimal threshold** to shift between the distribution models used for higher and lower rainrates.

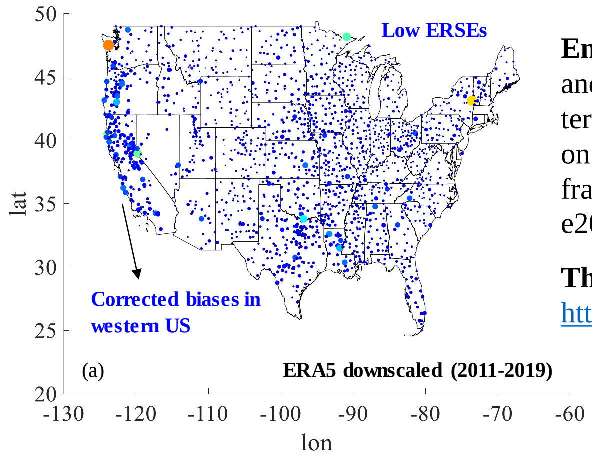


Findings

Statistical downscaling of atmospheric reanalysis precipitation data

Expected-Root-Squared-Error (ERSE)

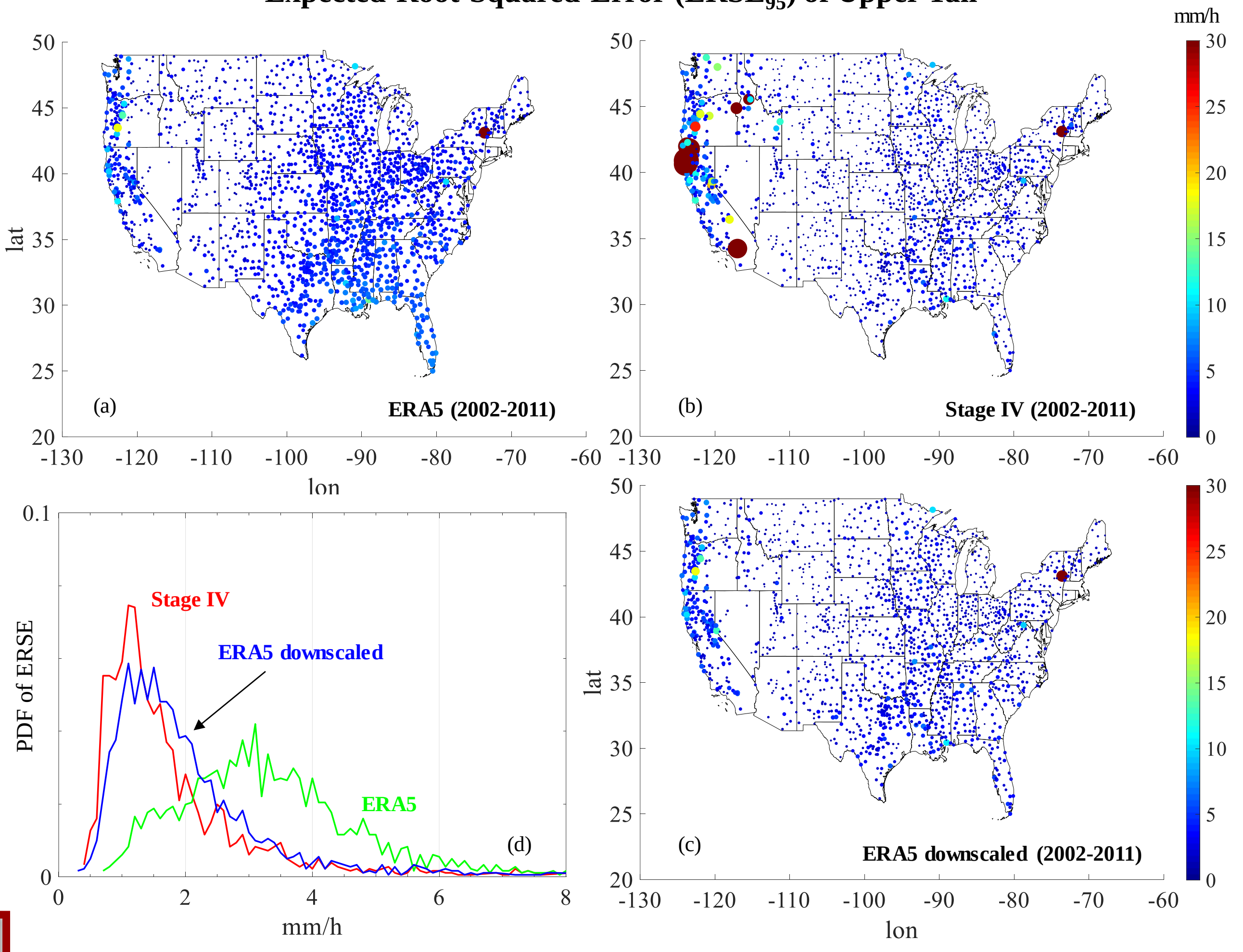




Emmanouil, S., A. Langousis, E.I. Nikolopoulos, and E.N. Anagnostou (2021). A CONUS-wide, long-term and high-resolution precipitation dataset based on a refined parametric statistical downscaling framework, *Water Resources Research*, **57**(6), e2020WR029548, doi: 10.1029/2020WR029548.

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

Expected-Root-Squared-Error ($ERSE_{95}$) of Upper Tail



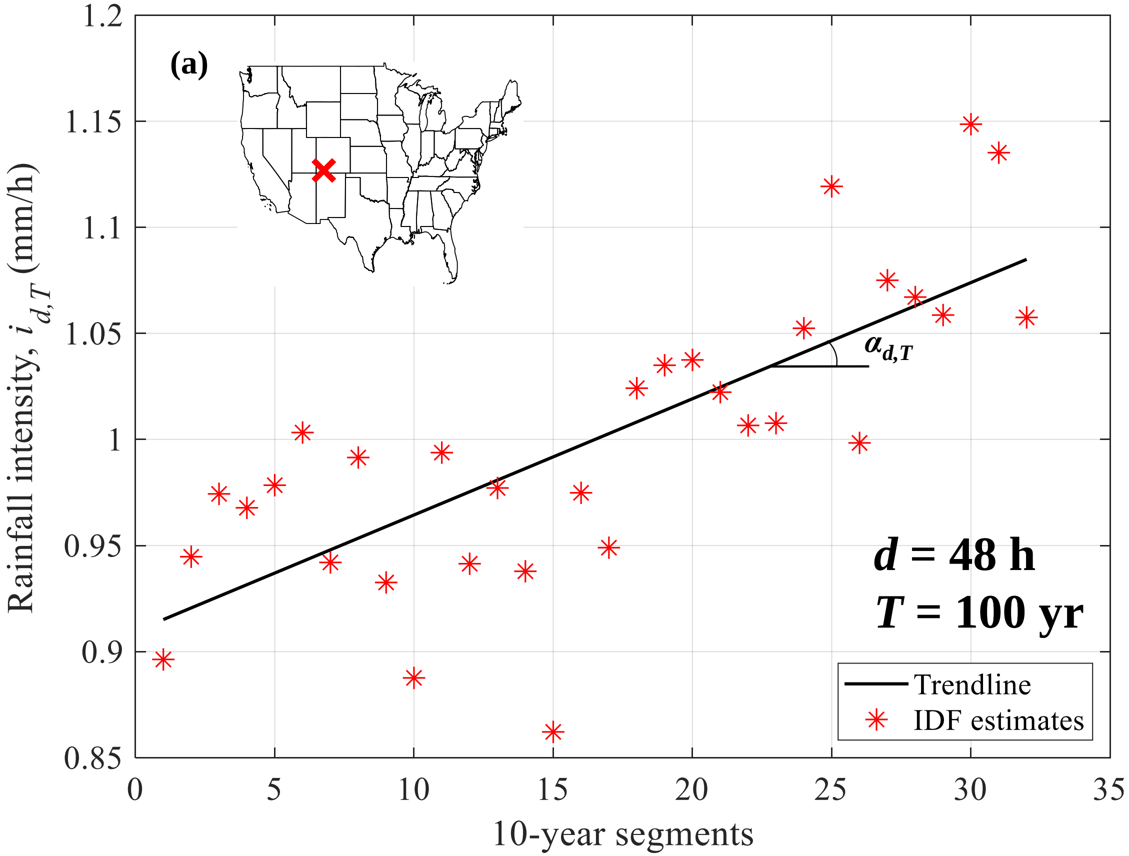
$$ERSE = \sqrt{\int_0^1 \left[F^{-1}(u) - F_0^{-1}(u)\right]^2 du}$$

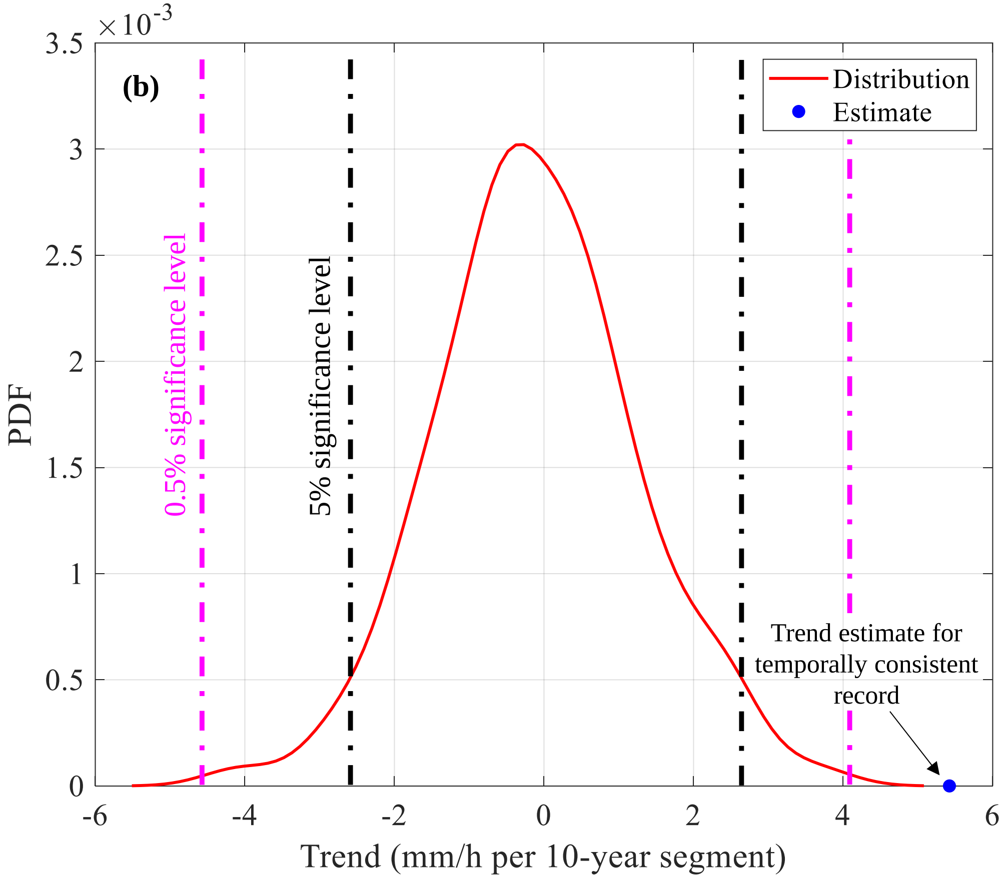
$$ERSE_{95} = \sqrt{\int_{0.95}^1 \left[F^{-1}(u) - F_0^{-1}(u)\right]^2 du}$$

- ✓ **Biases** in **western US** are **alleviated**.
- ✓ The product **benefits** from the strengths of the reference datasets.

Evaluating extreme rainfall trends based on reanalysis outputs

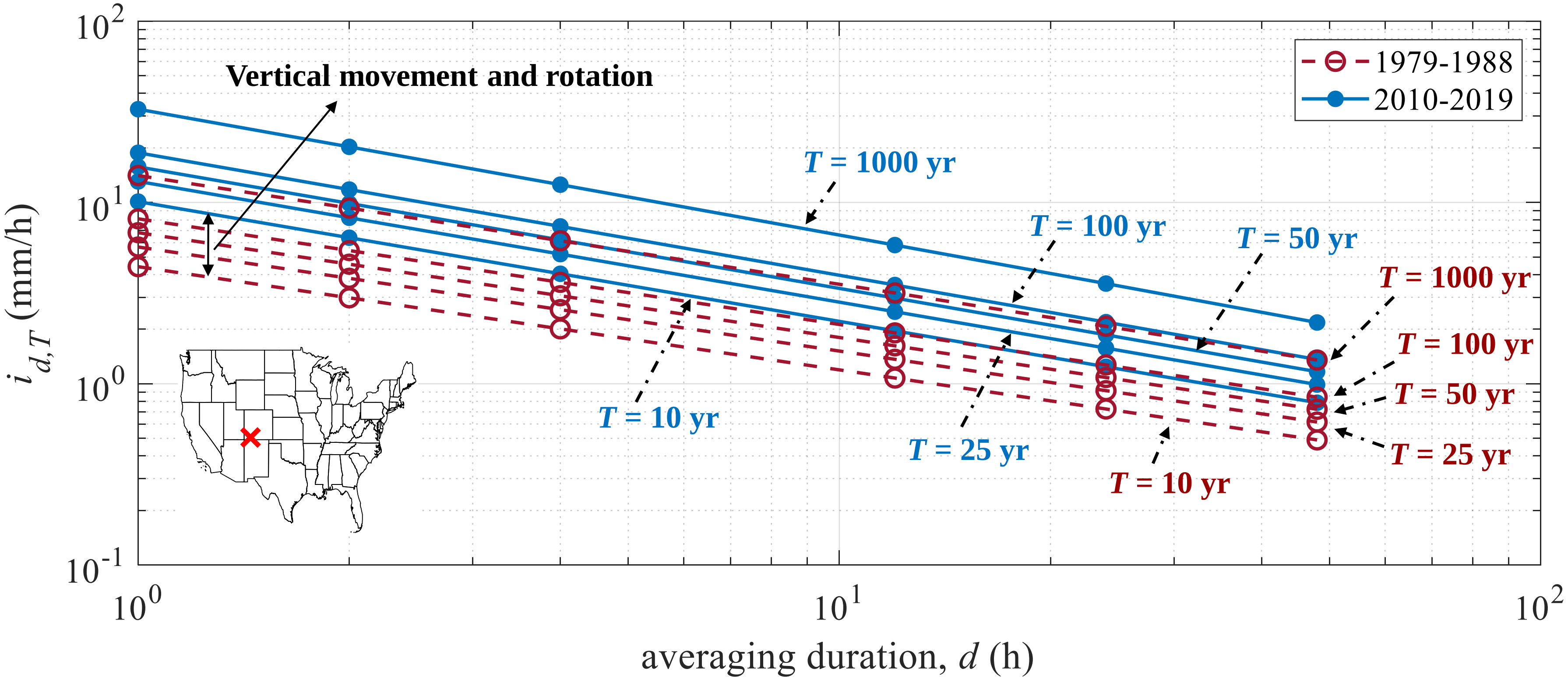
1) The continuous hourly rainfall timeseries is **split** into **sequential 10-year segments**, where climate conditions can be **assumed stationary**.
2) The **parametric multifractal (MF) analytical approximation** by Langousis *et al.* (2009) is employed to **each segment** to acquire rainfall intensity estimates for **return periods *T*** ranging from 2 years to more than 100 years.





Findings

Current extreme rainfall trends based on multifractal scaling arguments

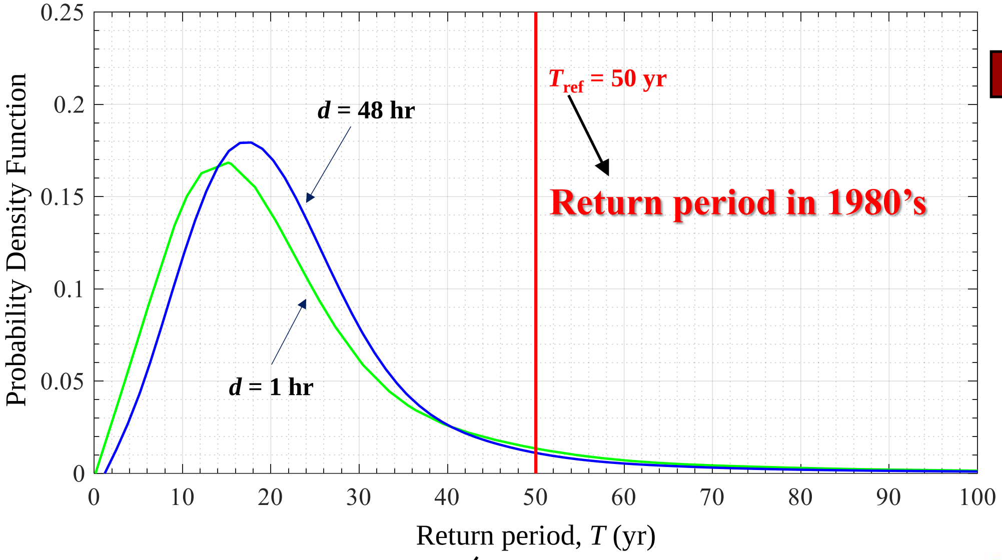


Emmanouil, S., A. Langousis, E.I. Nikolopoulos, and E.N. Anagnostou (2022). The spatiotemporal evolution of rainfall extremes in a changing climate: A CONUS-wide assessment based on multifractal scaling arguments, *Earth's Future*, (accepted).

- Beyond the **apparent effects** on the magnitude and frequency of intense precipitation events, **IDF curves tend to rotate**.
- Extent of changes **across averaging durations <u>differs</u>**.
- 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**.

Findings

Current extreme rainfall trends based on multifractal scaling arguments

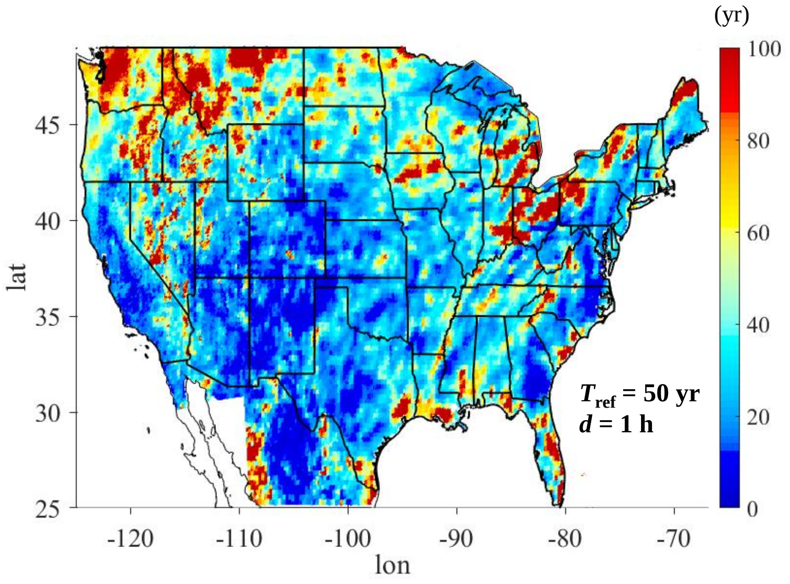


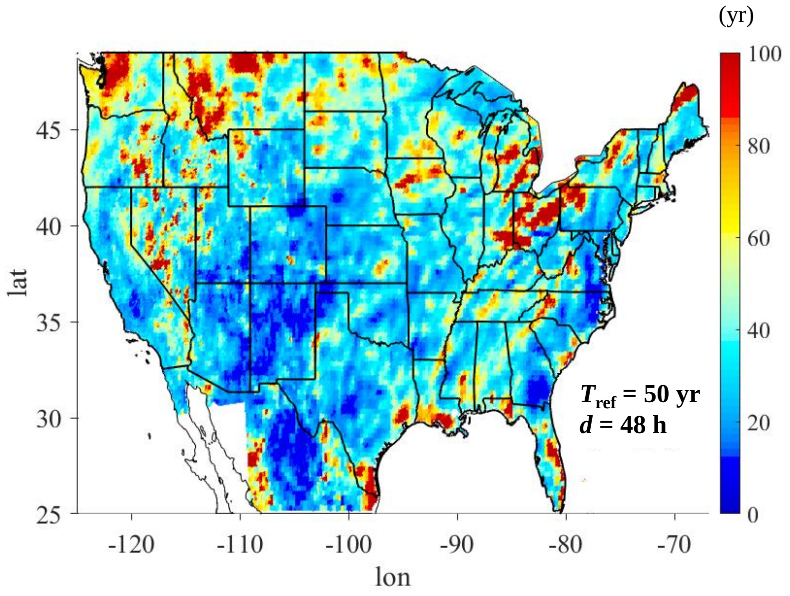
Return period levels in 2010's

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 yr**, could be overwhelmed **at least once** in a period of **1 to 20 yr**.





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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 → **future design considerations** 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.

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Thank you