

Global long-term sub-daily reanalysis of fluvial floods through high-resolution modeling

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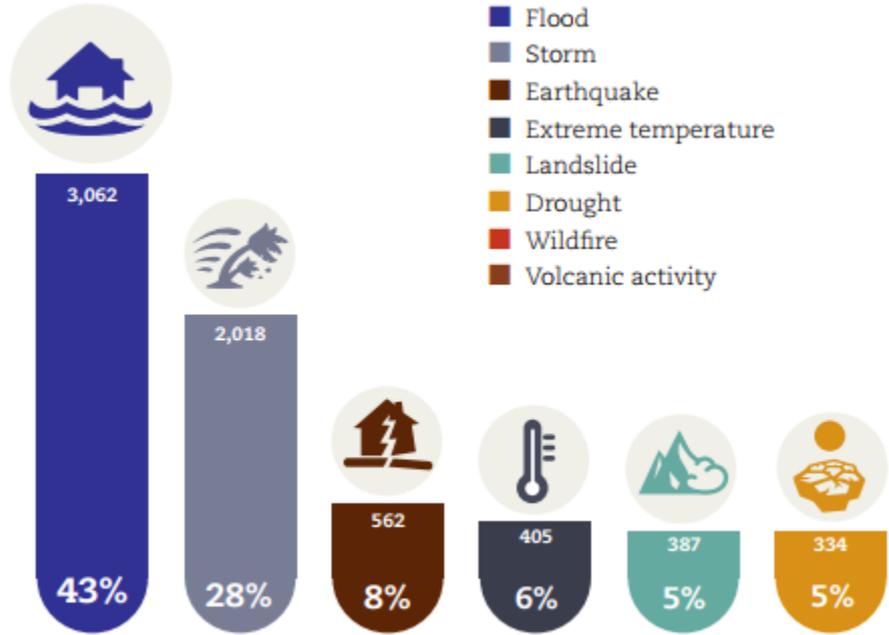
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Motivation

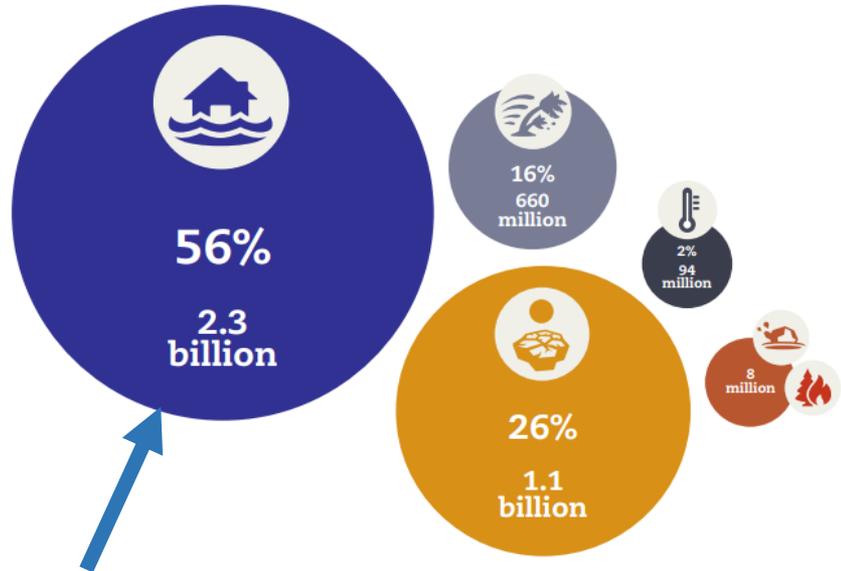
- Flood is one of the most devastating natural disasters of severe societal, economic, and environmental consequences.

Percentage of occurrences of natural disasters by disaster type (1995-2015)



Flood

Number of people affected by weather-related disasters (1995-2015)



Flood

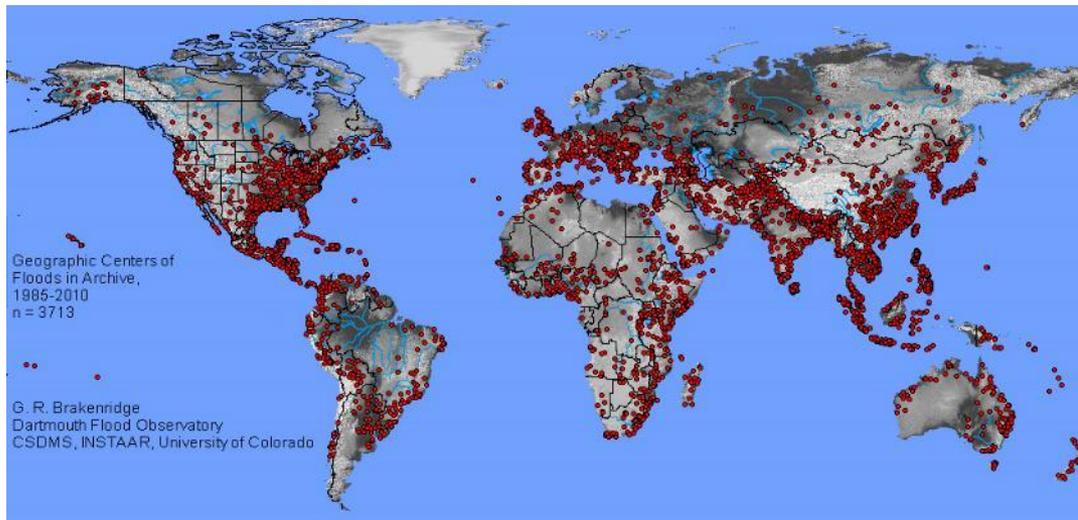
2015 UN Report

Motivation

- The characteristics of floods:
 - Happen within a very short time: **hours to days**
 - Happen within a very small area: **a few river reaches**
 - Wide geographic distributions **globally**

Geographic centers of floods (1985-2010)

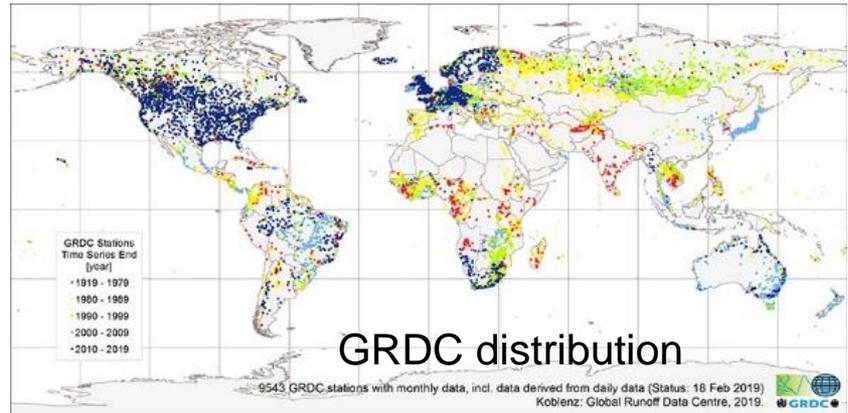
<http://floodobservatory.colorado.edu/Archives/index.html>



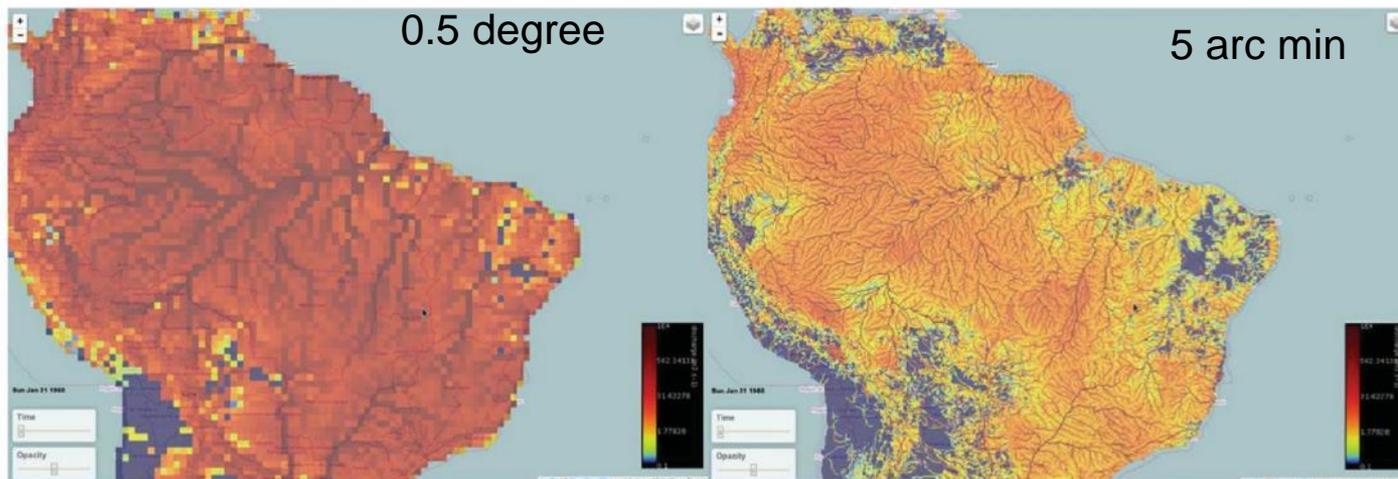
Grand challenges in global flood analysis

- In-situ observations: **limited availability**

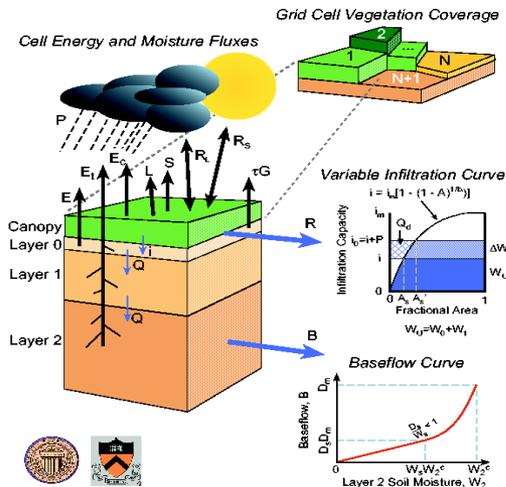
- Uneven distribution
- Decreasing gauges
- Daily & monthly records



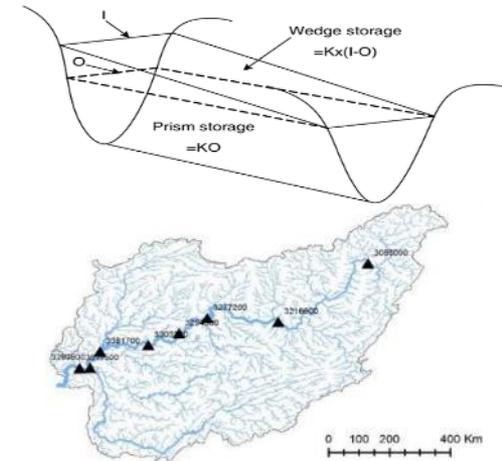
- Existing modeling efforts: **lack the sufficiently high spatial /temporal resolutions**



Global sub-daily modeling framework

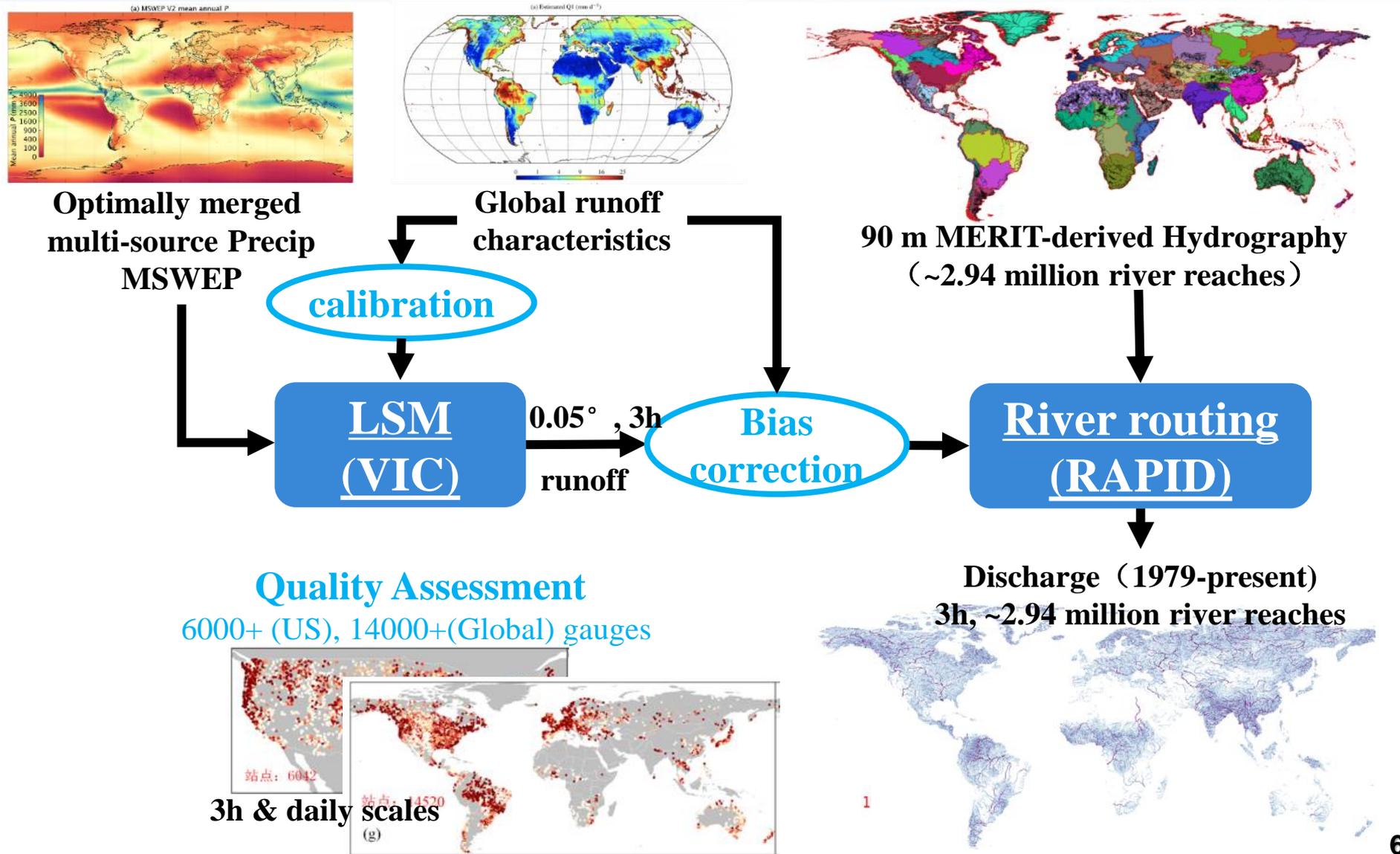


VIC + RAPID



1. Capture local and “flashy” events: **0.05° 3-hourly** + 90m DEM based rivers
2. Long-term historical reanalysis: 1979 – 2019
3. Potential for real-time monitoring and forecast

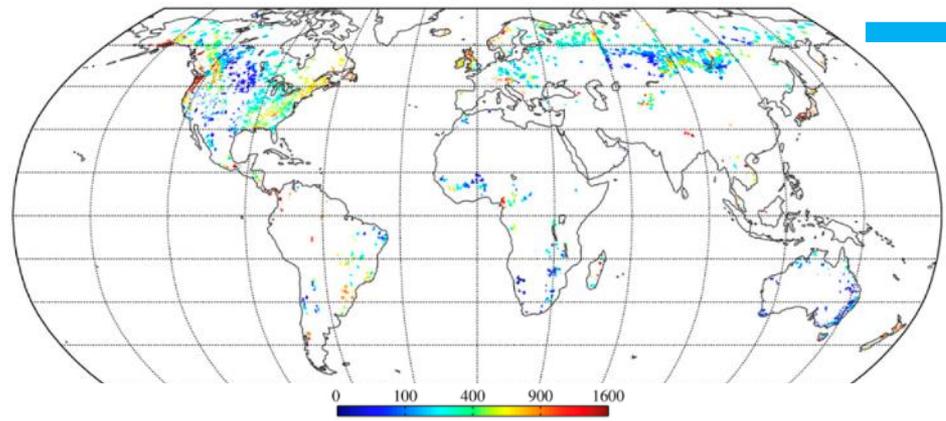
Global sub-daily modeling framework



Runoff calibration/bias correction target

- Global runoff characteristics -- GSCD

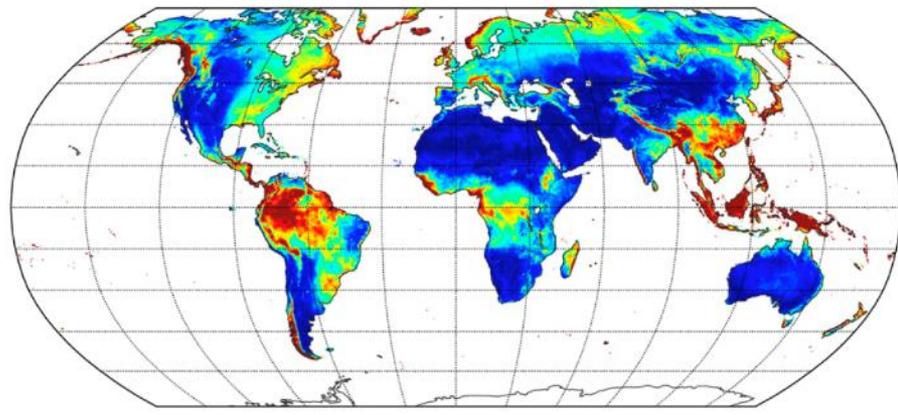
from >3,000 naturalized catchments



QMEAN (mm/yr)

Regionalization via ML: trained against 20 climate, topography, geology, land cover, soil factors

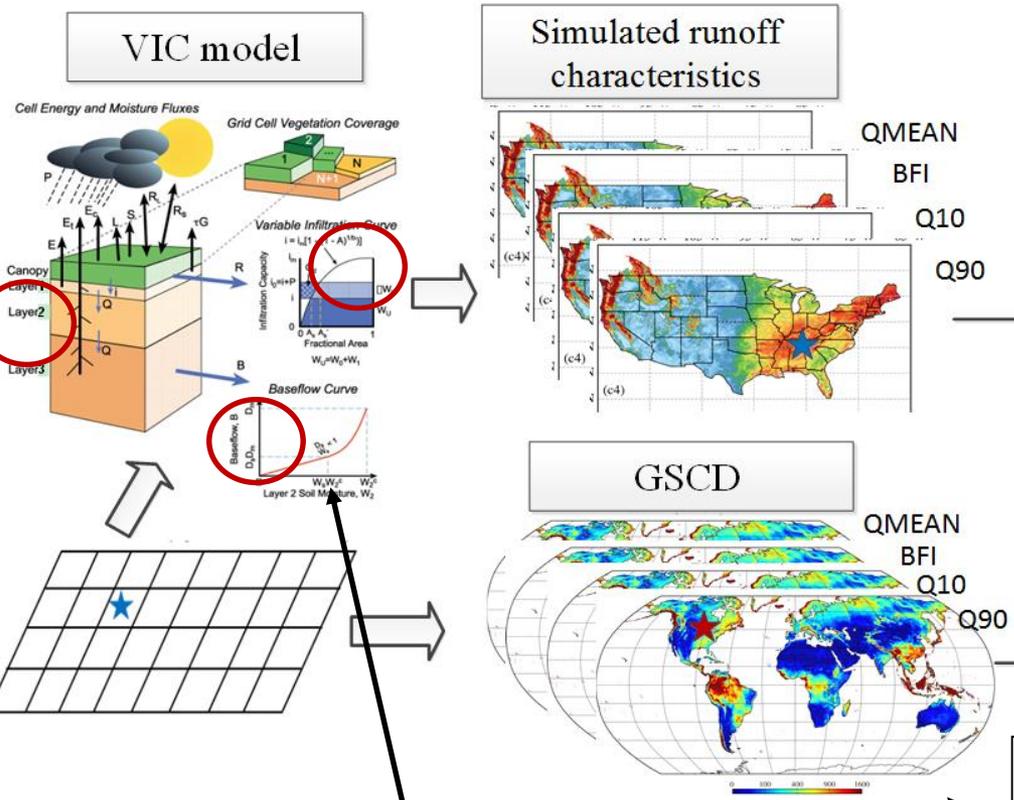
Similarly, Q_1 , Q_5 , Q_{10} , Q_{20} , Q_{50} , Q_{80} , Q_{90} , Q_{95} , Q_{99} , and BFI are derived globally (Testing R^2 : 0.55 – 0.93)



QMEAN (mm/yr)

Pixel-level model calibration

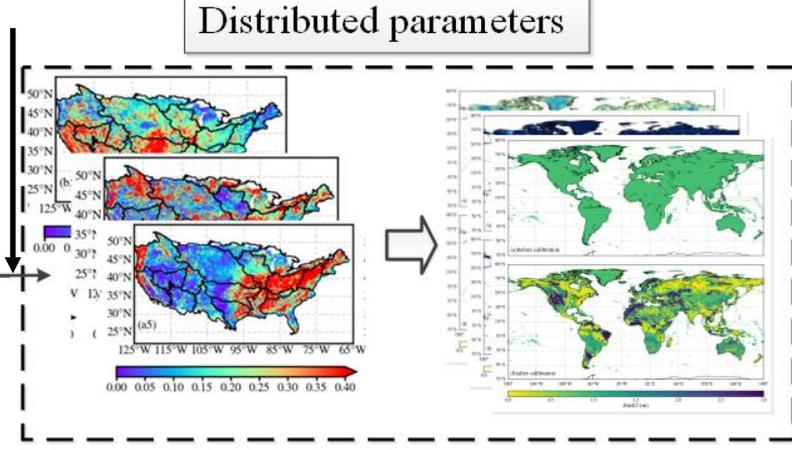
- Calibrate each pixel independently against runoff characteristics



Objective function

$$Obj = w_1 \left| \ln\left(\frac{Q_{MEAN}_m}{Q_{MEAN}_o}\right) \right| + w_2 \left| \ln\left(\frac{BFI_m}{BFI_o}\right) \right| + w_3 \left| \ln\left(\frac{Q_{10m}}{Q_{10o}}\right) \right| + w_4 \left| \ln\left(\frac{Q_{90m}}{Q_{90o}}\right) \right|$$

$$w_i (i = 1, 2, 3, 4) = \{0.6, 0.2, 0.1, 0.1\}$$

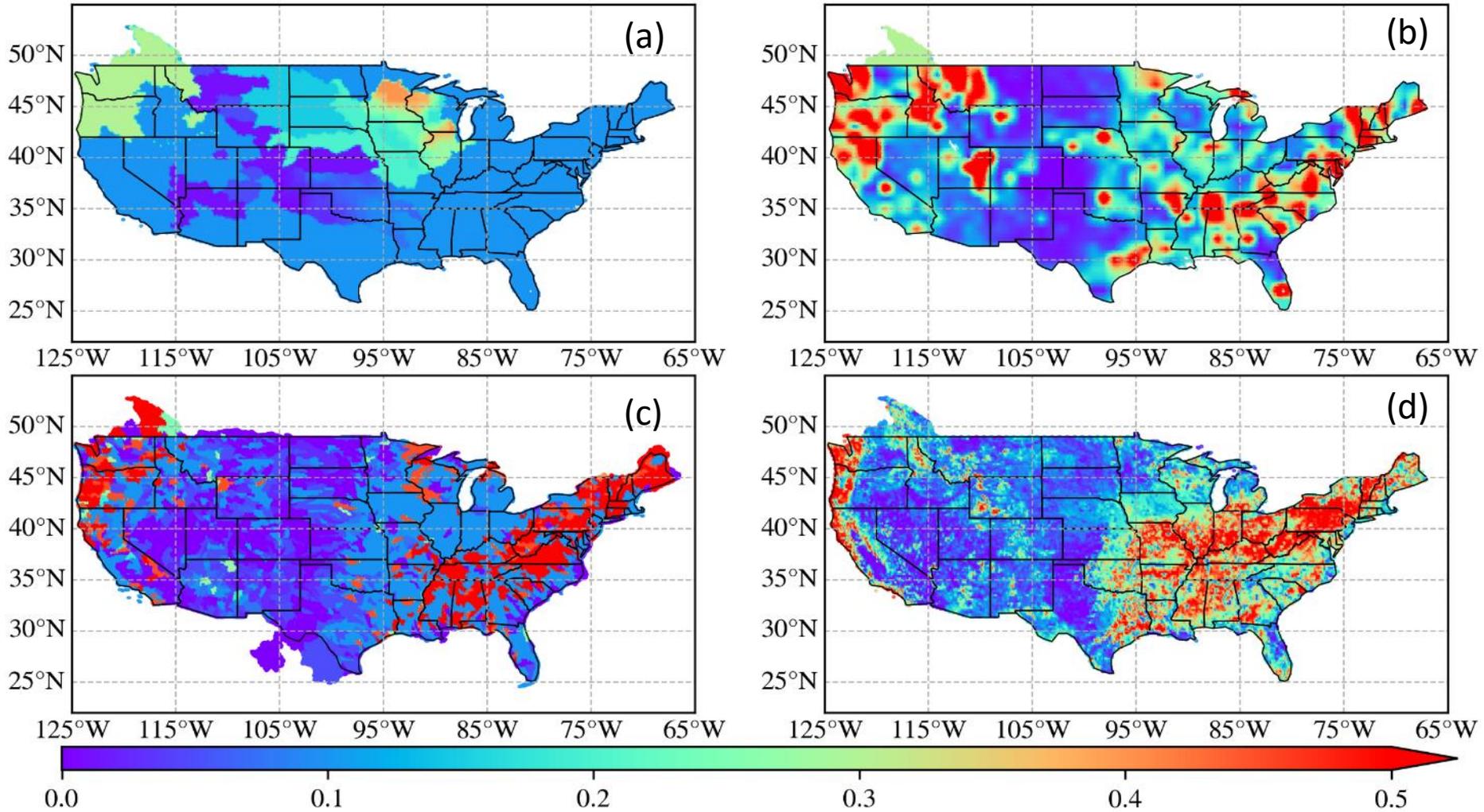


- Variable infiltration curver parameter b_i
- Thickness of soil layer 2 $thick_2$
- Fraction of the maximum velocity of baseflow where nonlinear baseflow begins D_s

- Four runoff characteristics
 - Q_{MEAN} : mean annual runoff per unit area (mm/yr)
 - BFI: baseflow index
 - Q_{10} : high runoff (mm/d)
 - Q_{90} : low runoff (mm/d)

Pixel-level model calibration

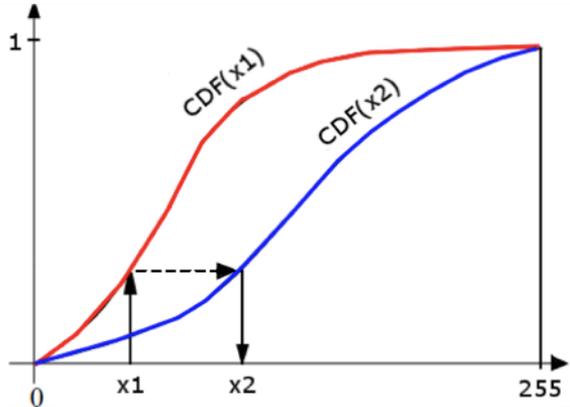
- Infiltration Curve Parameter in VIC model



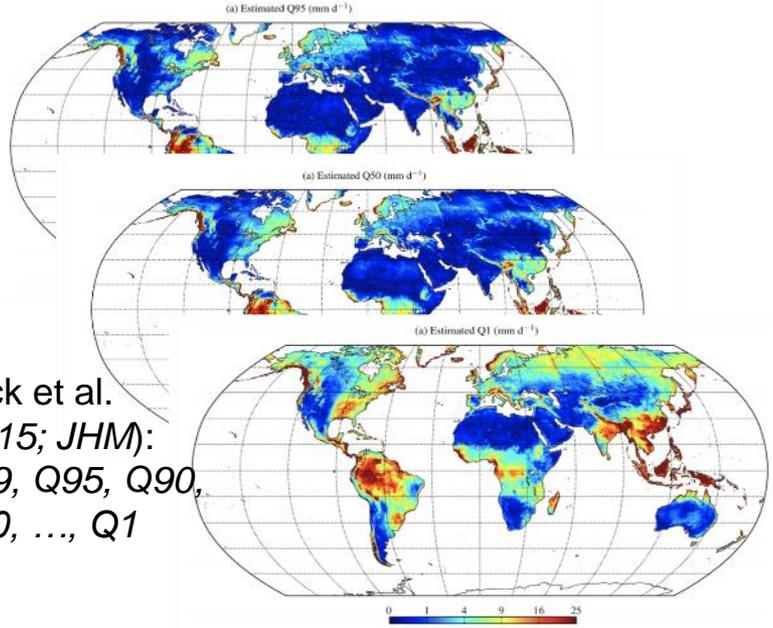
(a) Pre-calibration (NLDAS-2); (b) Troy et al., 2008; (c) Oubeidillah et al, 2014; (d) After calibration

Sparse CDF-matching for bias correction

- Traditional bias-correction: CDF matching

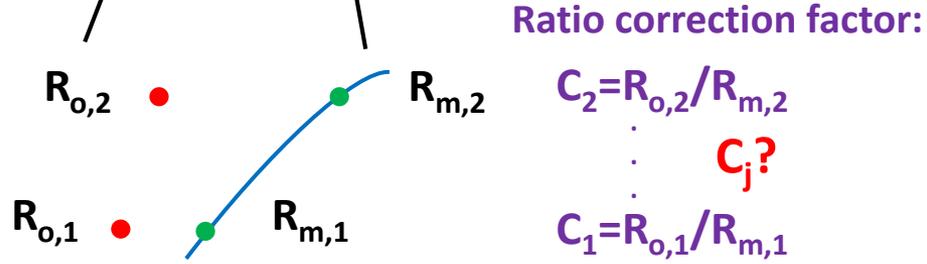
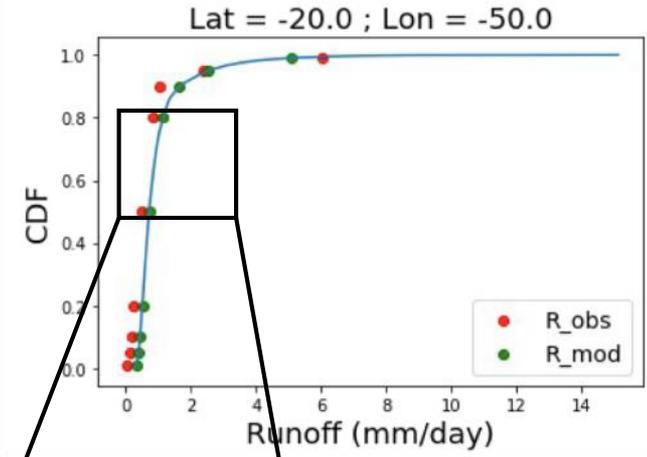


- Q characteristics from machine learning



Beck et al. (2015; JHM): Q99, Q95, Q90, Q50, ..., Q1

- What if no full CDF of the reference data?



Assume error is log-linear:

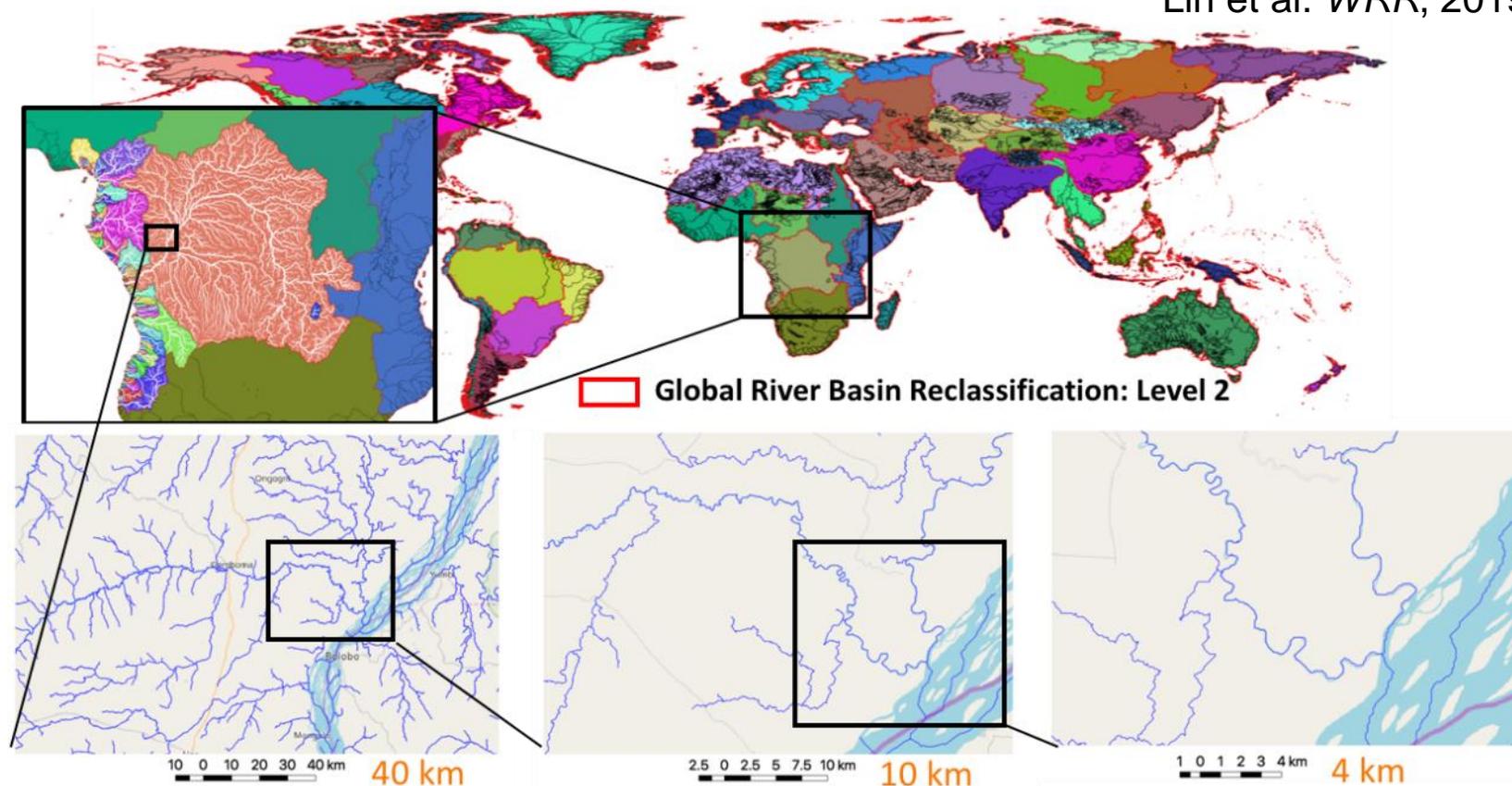
- $C_j = C_1^{1-j/N} \cdot C_2^{j/N}$
- j and N are the j-th element and total number of element between C₁ and C₂

Global river network from 90m MERIT DEM

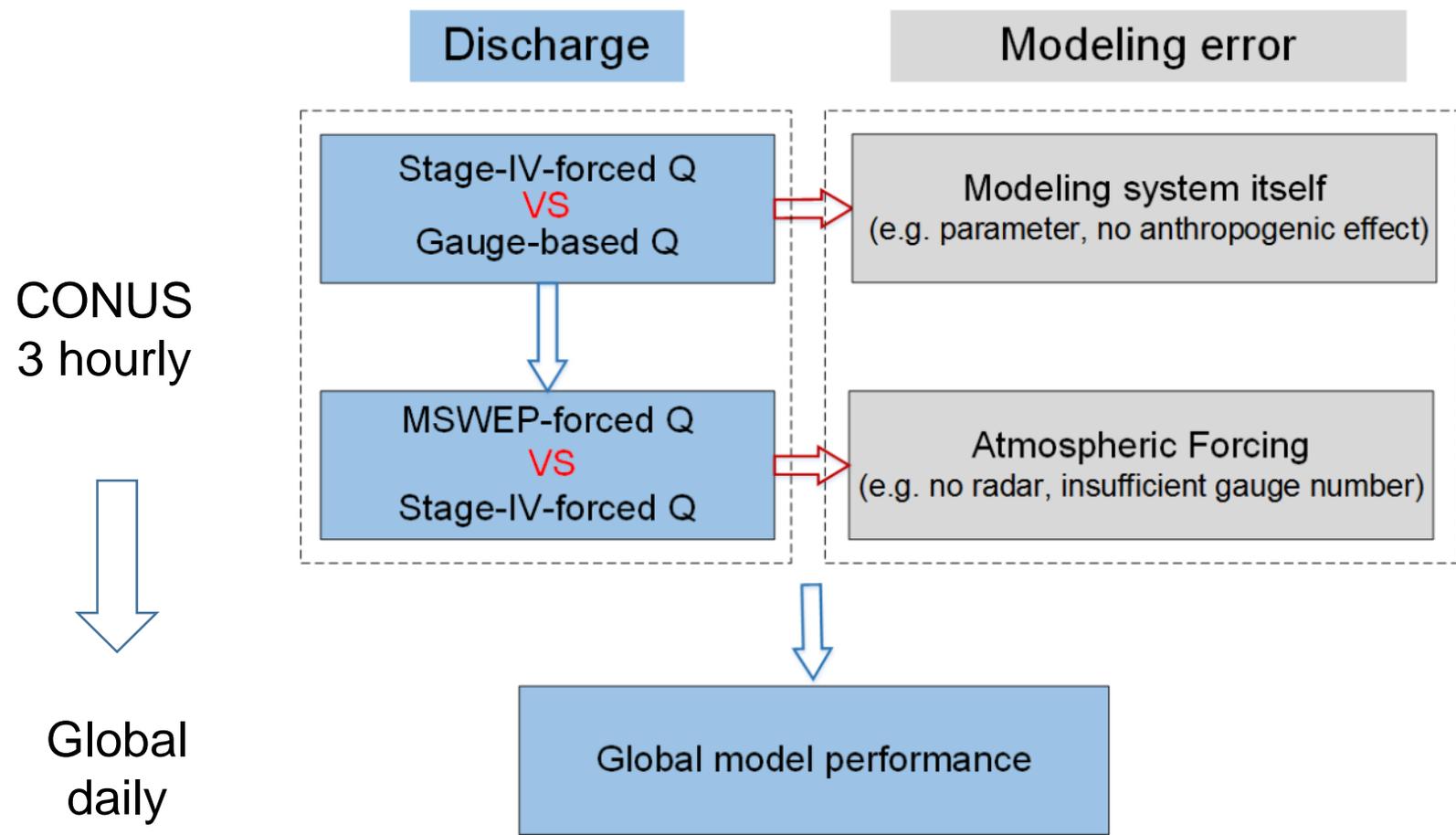
- MERIT Basins

- 2.94 million reaches & catchments + properties (e.g. COMID, slope, connectivity) organized at Level 1 (9 regions) and Level 2 (61 basins)
- Median = 6.8 km; Mean = 9.2 km; Total length= 2.6×10^7 km

Lin et al. *WRR*, 2019



Discharge skill assessment

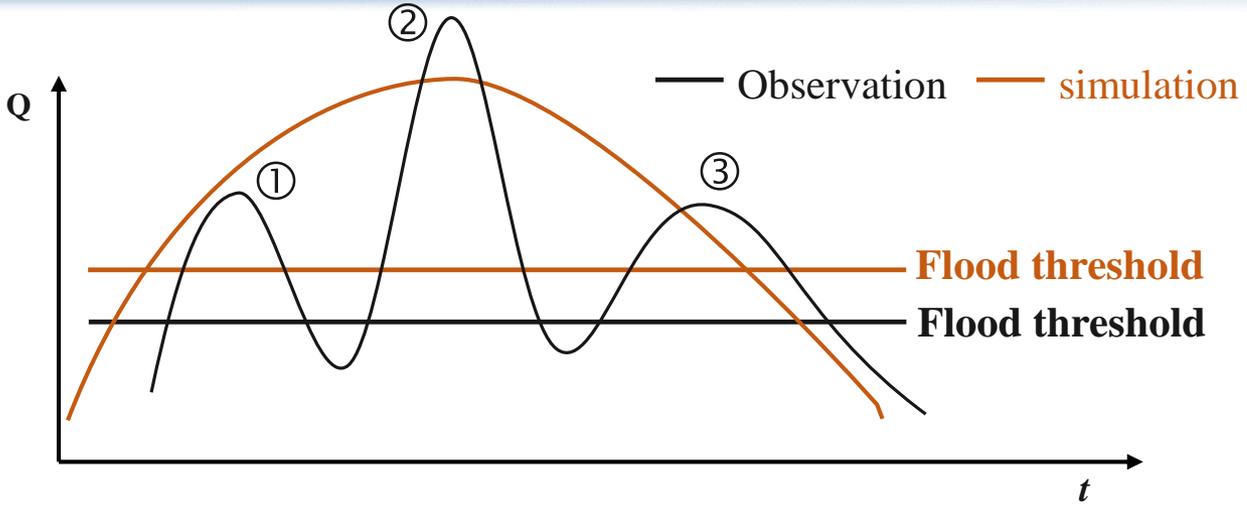


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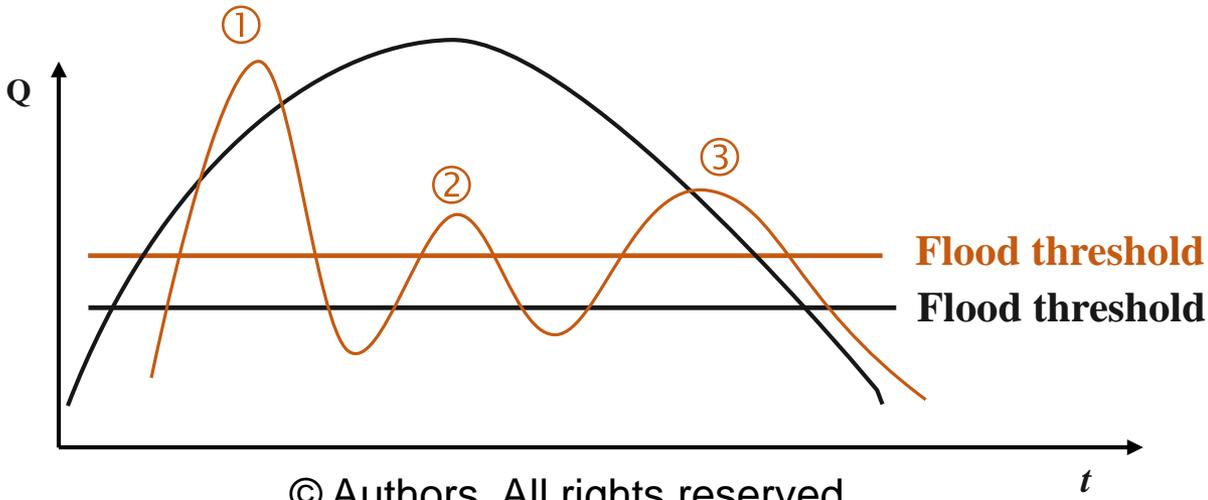
Metrics:

KGE and its 3 components: CC (Correlation Coefficient), RB (Relative Bias), RV (Relative Variability)

Flood-specific skill assessment



Event #② (the largest one) is treated as a hit event
Event #① & #③ are treated as missing events



Event #① (the largest one) is treated as a hit event
Event #② & #③ are treated as false events

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Metrics:

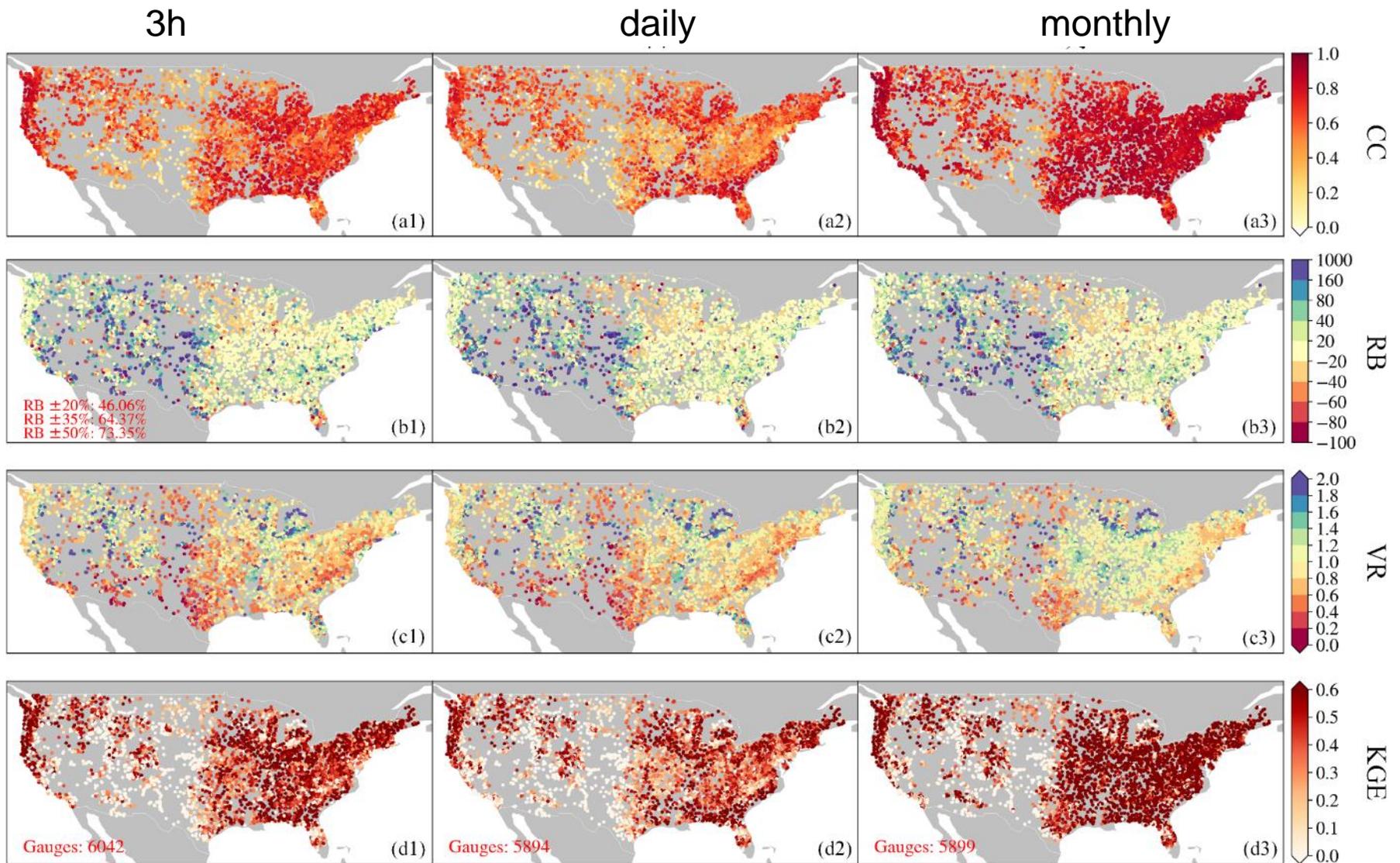
Flood detection capability: POD, FAR, CSI

Flood simulation statistics: flood volume/peak/timing errors

CONUS: Stage-IV vs Gauges

- Discharge skill assessment

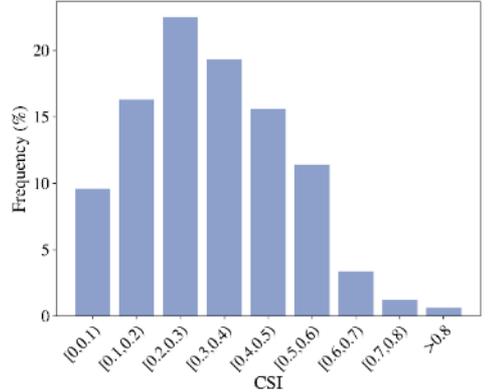
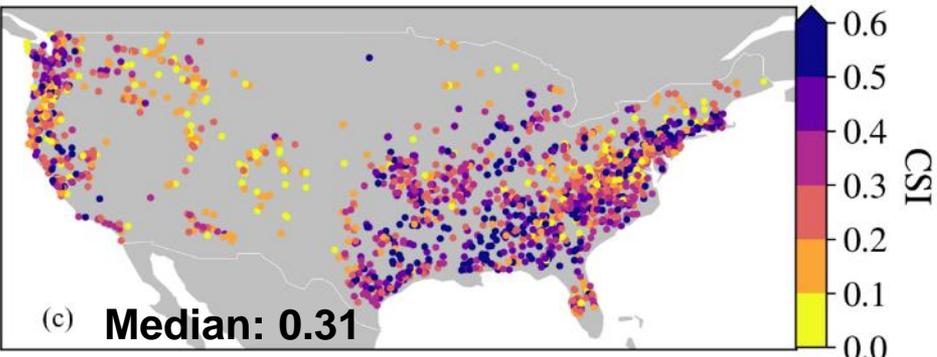
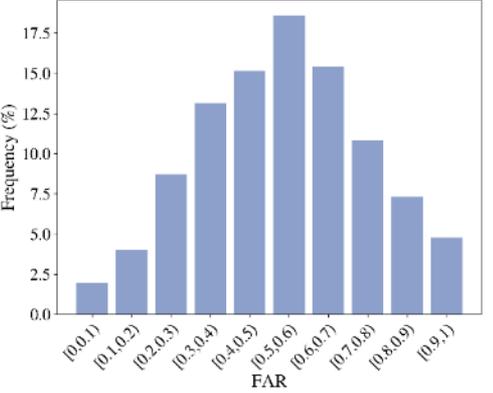
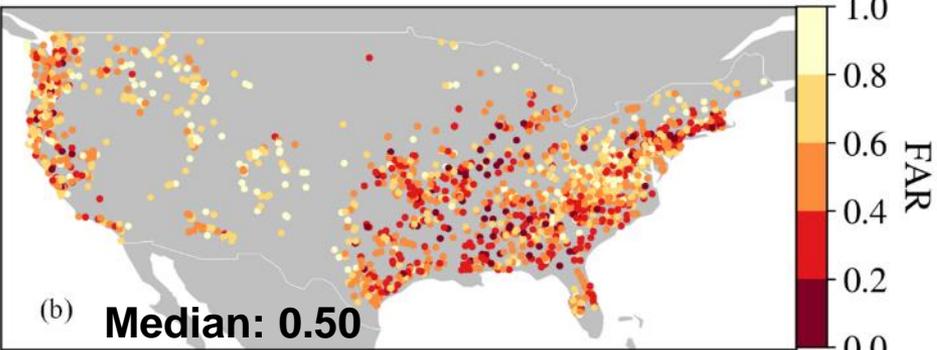
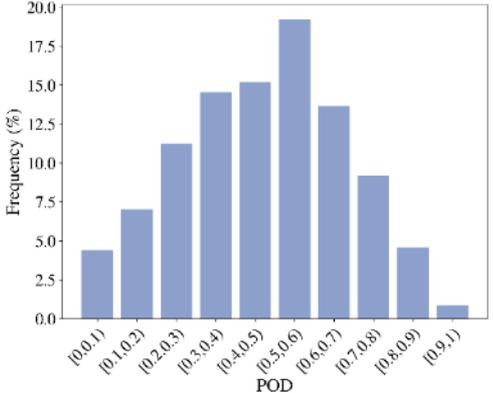
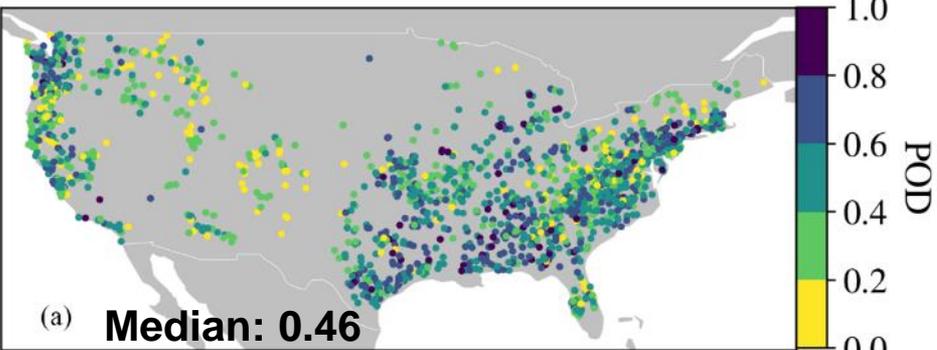
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CONUS: Stage-IV vs Gauges

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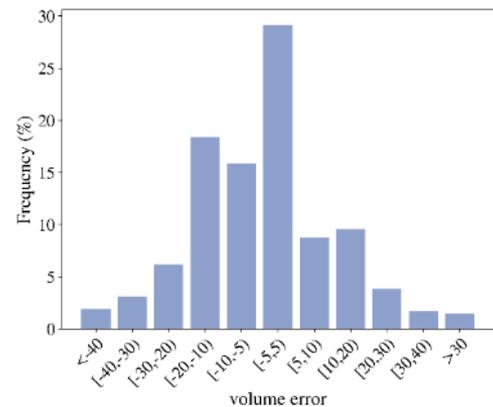
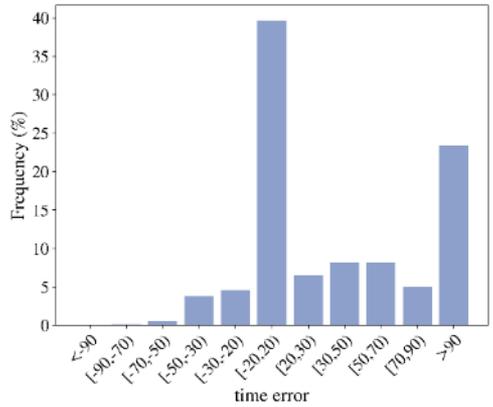
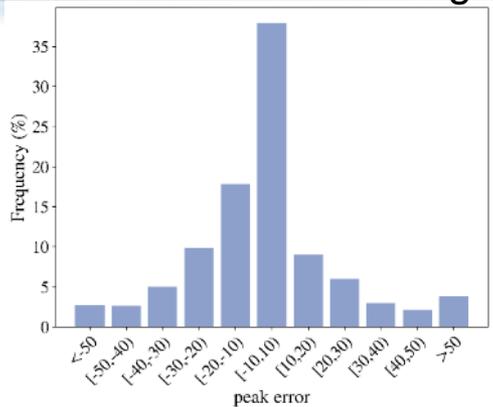
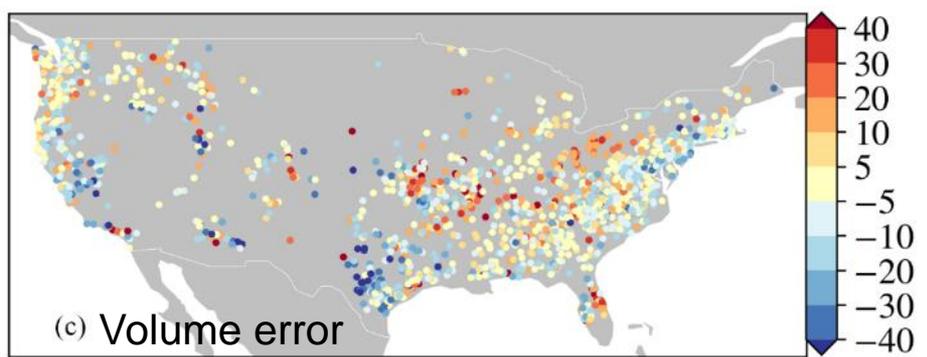
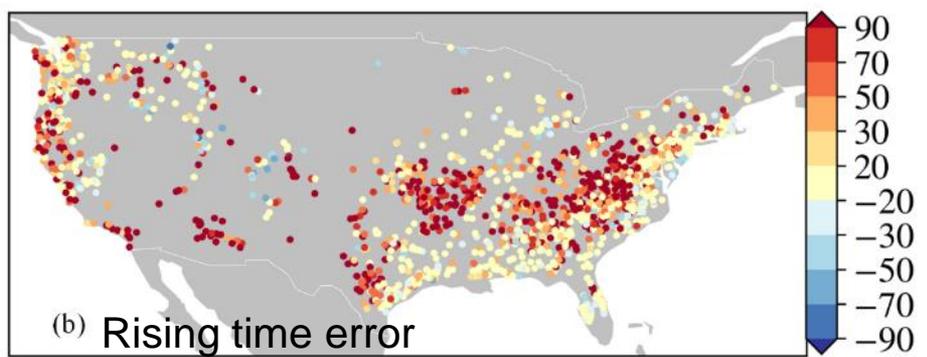
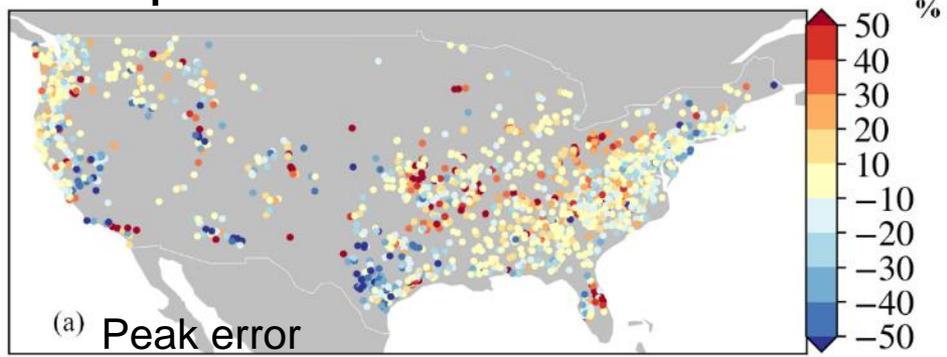
- Flood-specific skill assessment



CONUS: Stage-IV vs Gauges

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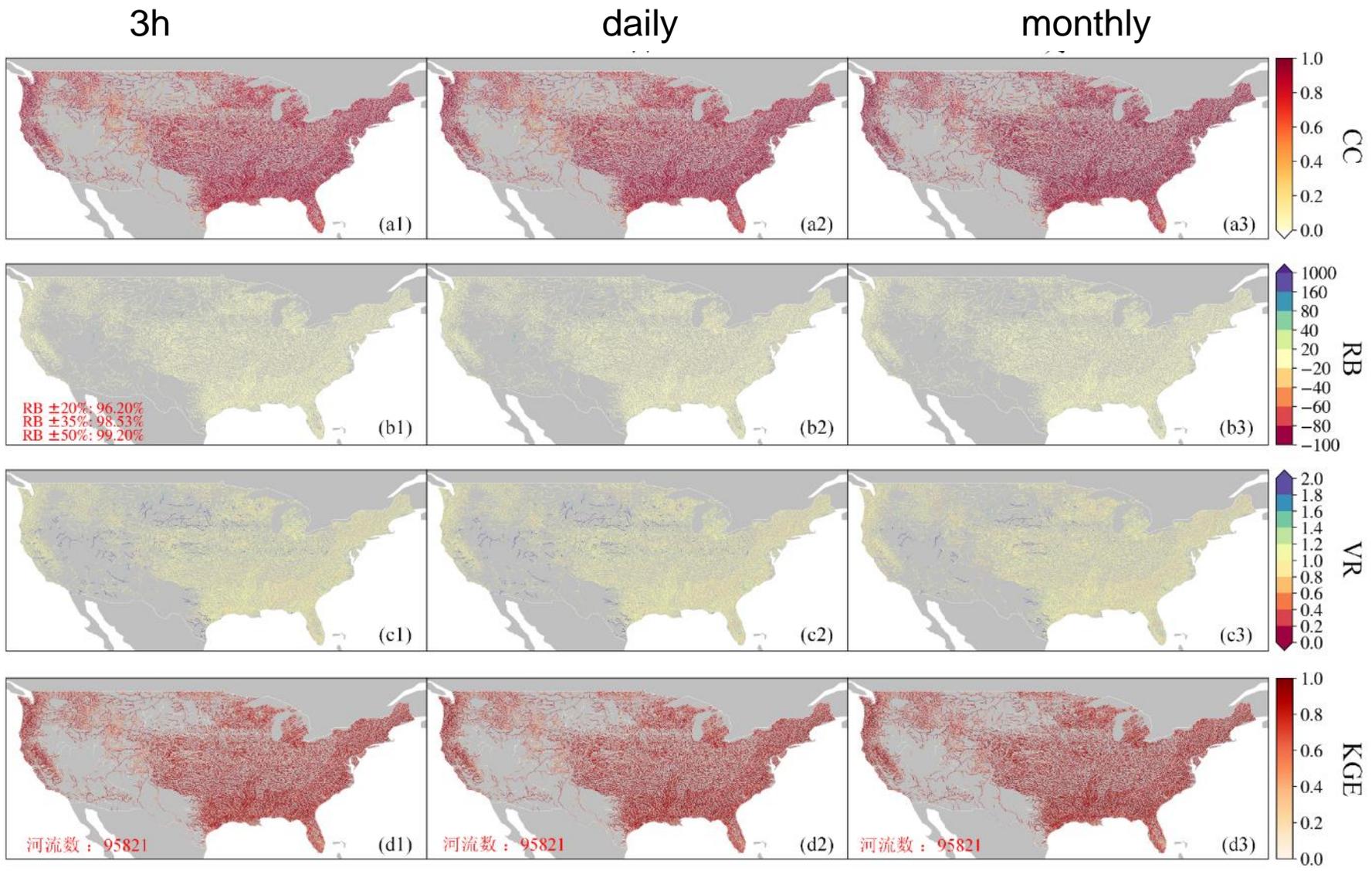
- Flood-specific skill assessment



CONUS: MSWEP vs Stage-IV

- Discharge skill assessment

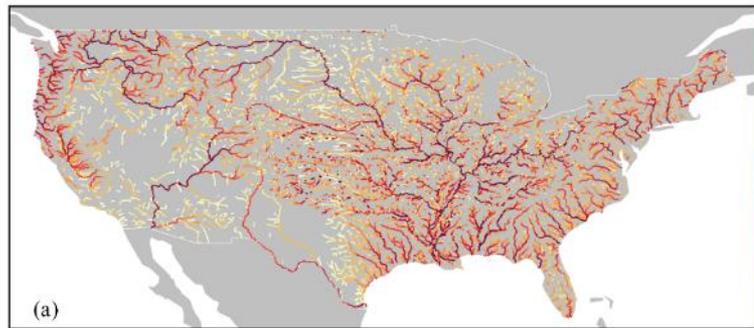
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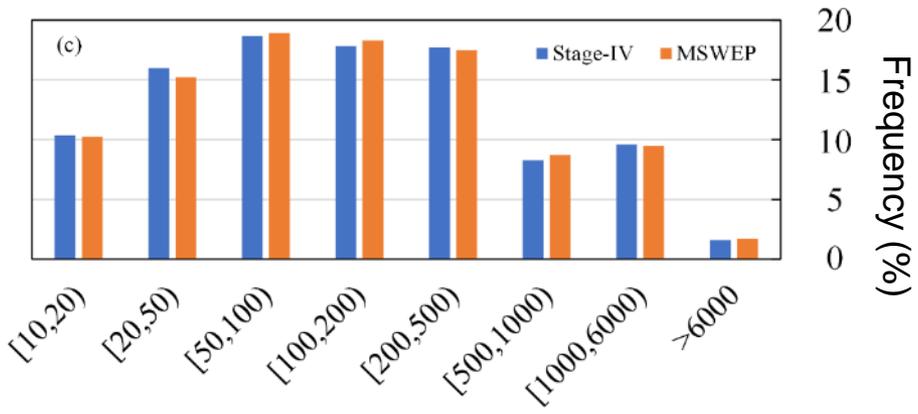
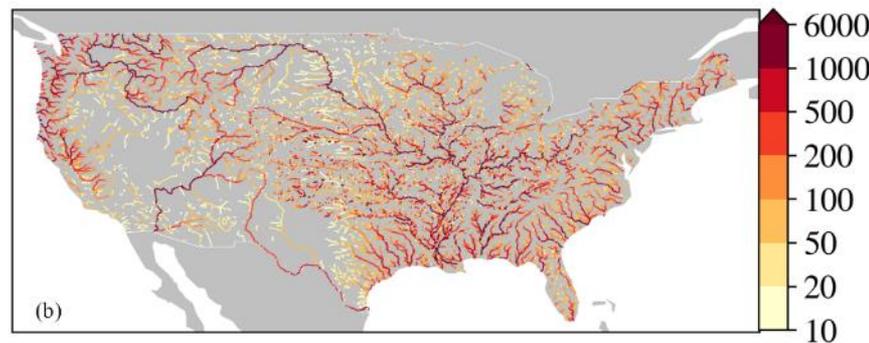
CONUS: MSWEP vs Stage-IV

- Flood-specific skill assessment

Stage-IV flood threshold



MSWEP flood threshold

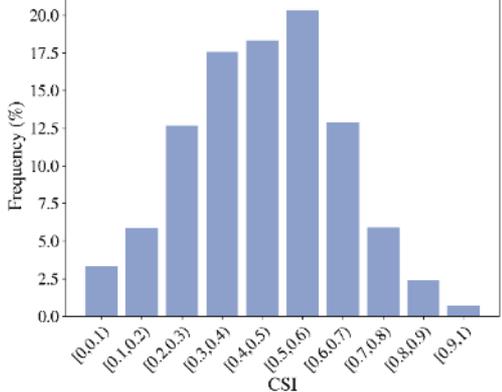
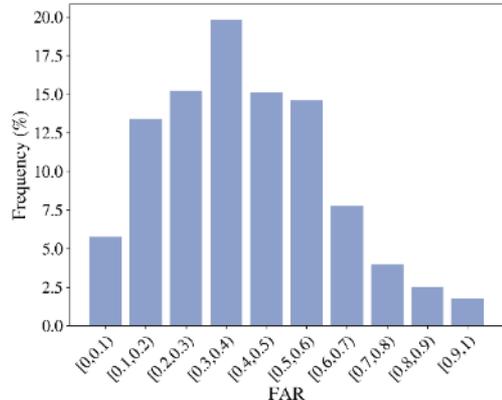
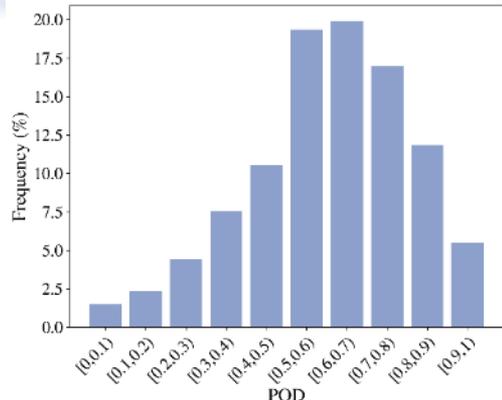
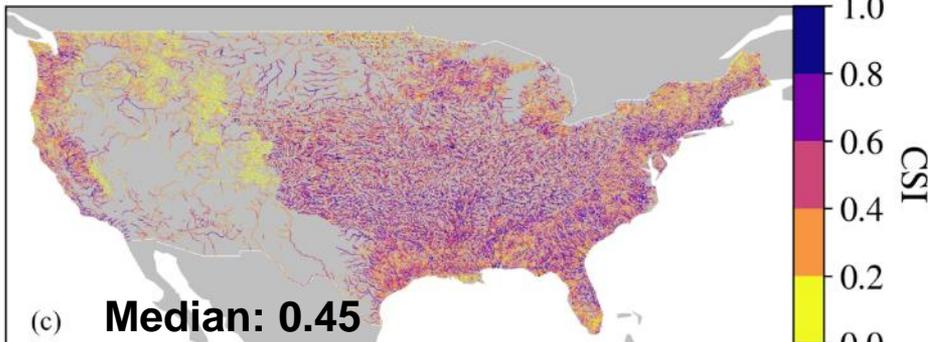
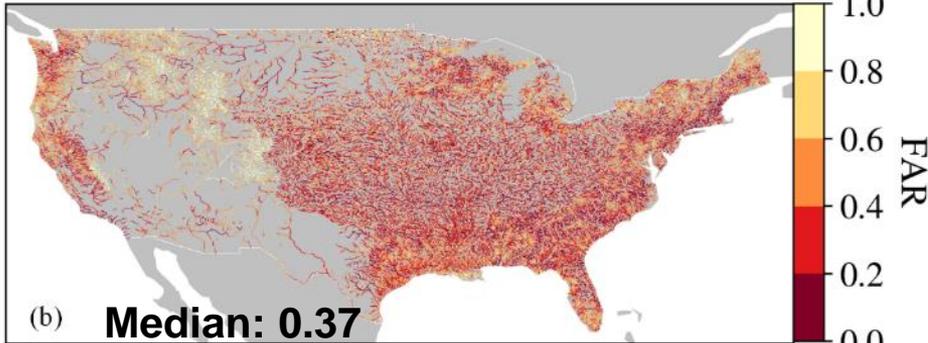
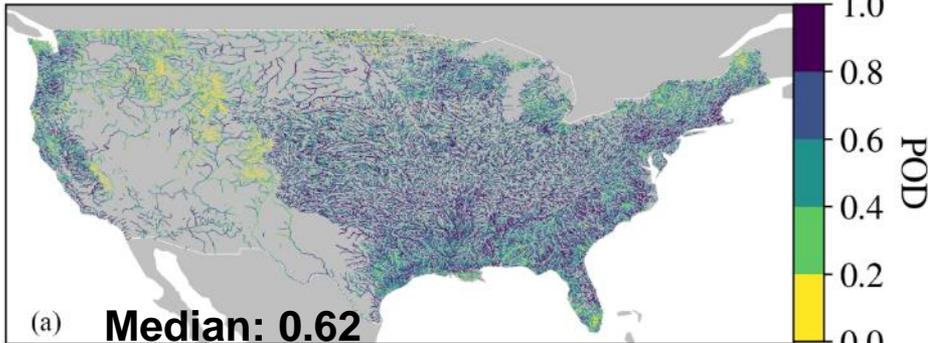


River reaches with stream order ≥ 3

CONUS: MSWEP vs Stage-IV

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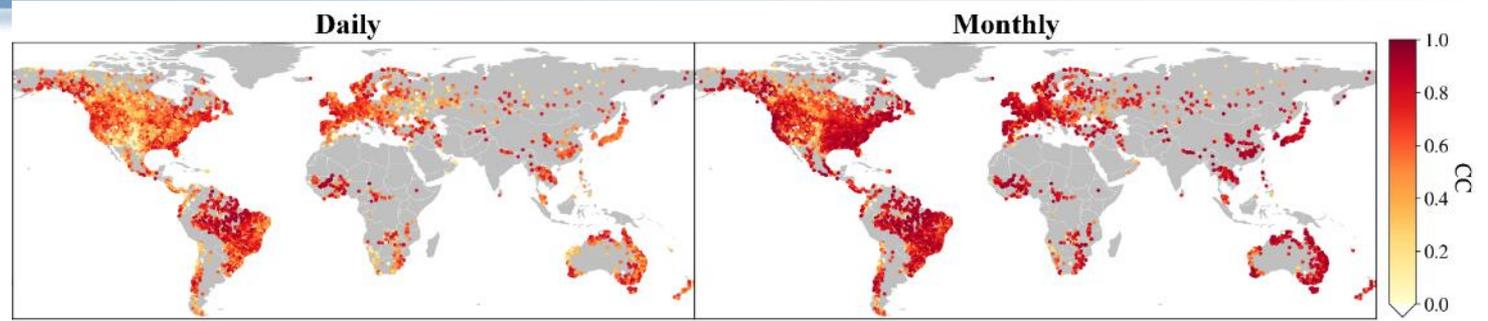
- Flood-specific skill assessment



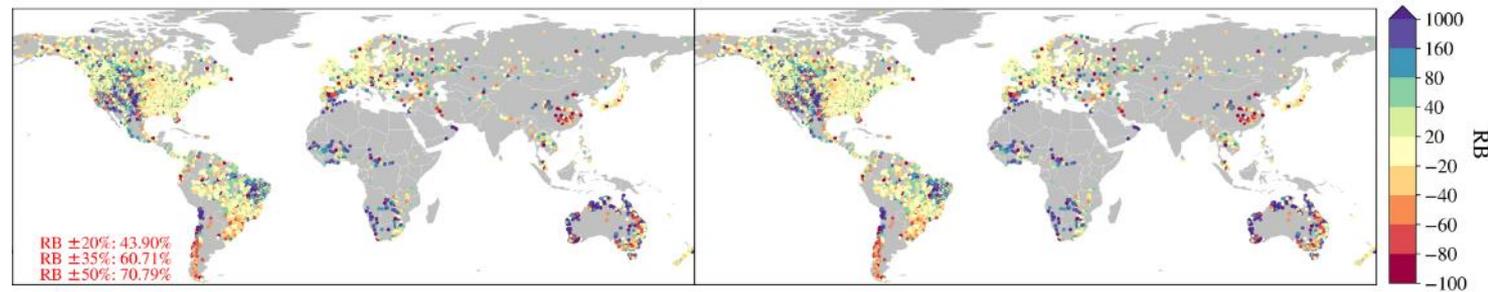
Global: daily/monthly skills

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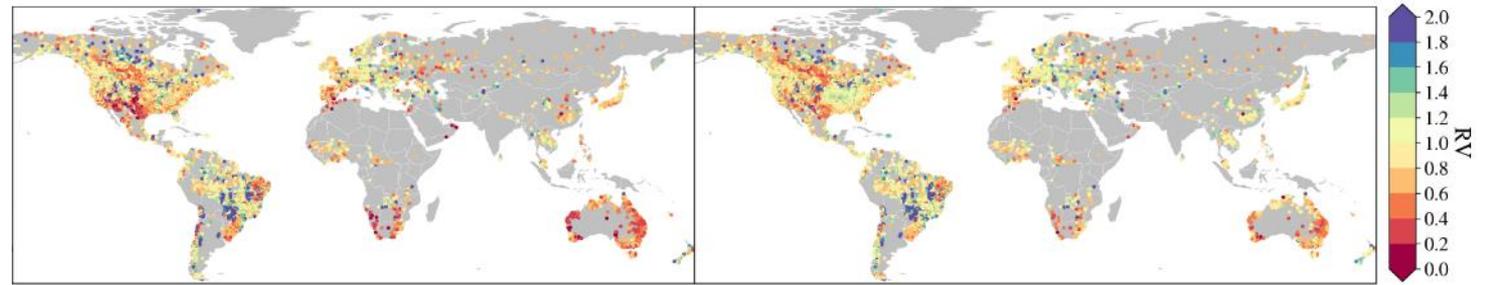
Correlation Coefficient



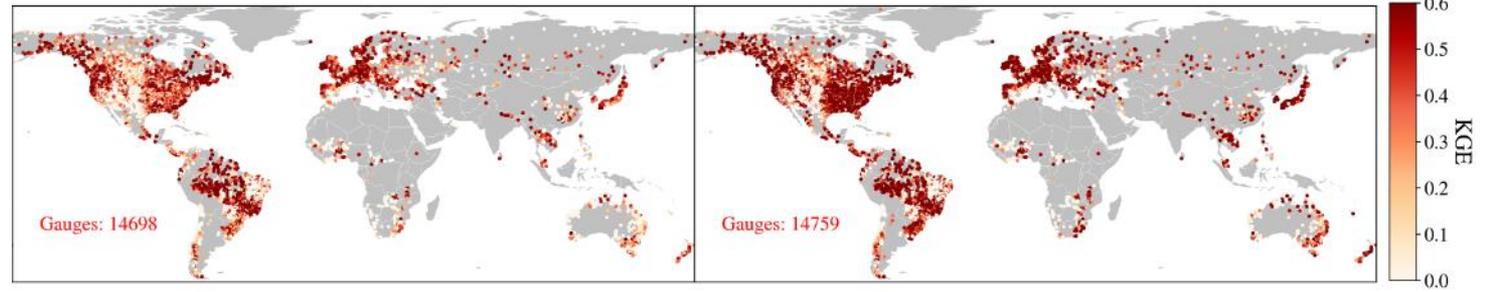
Relative Bias



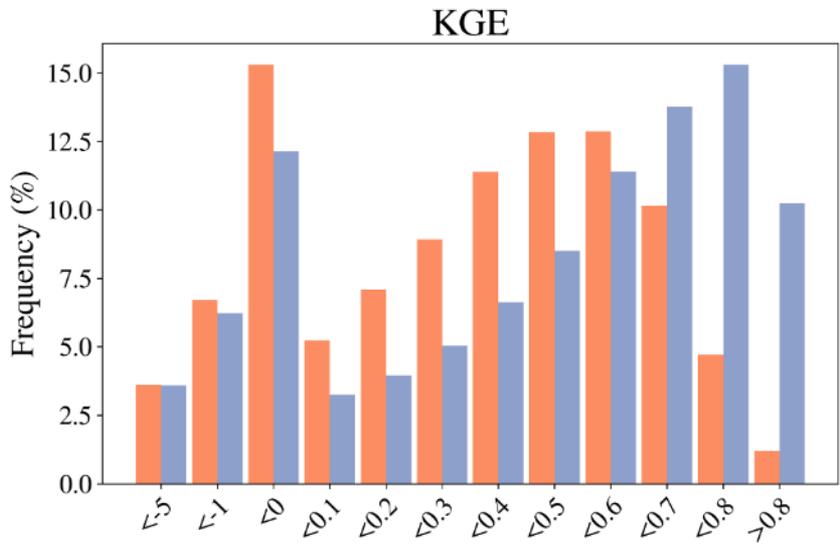
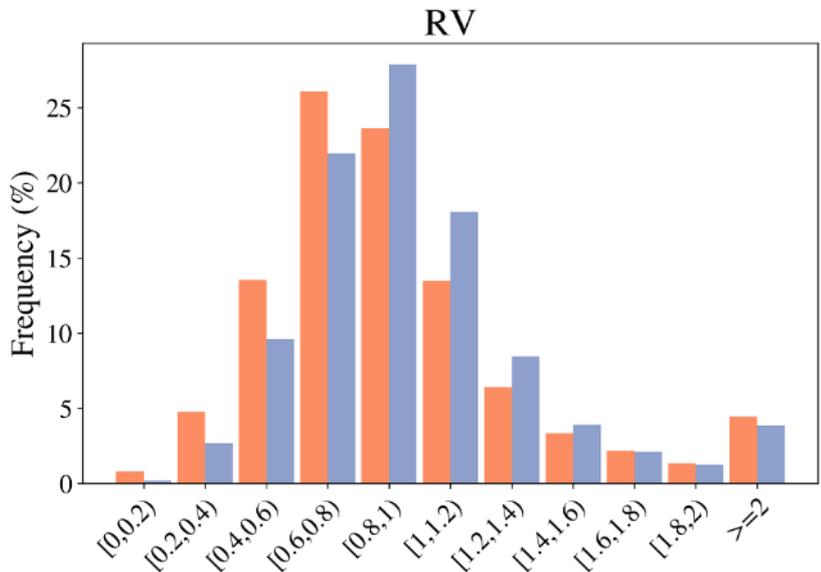
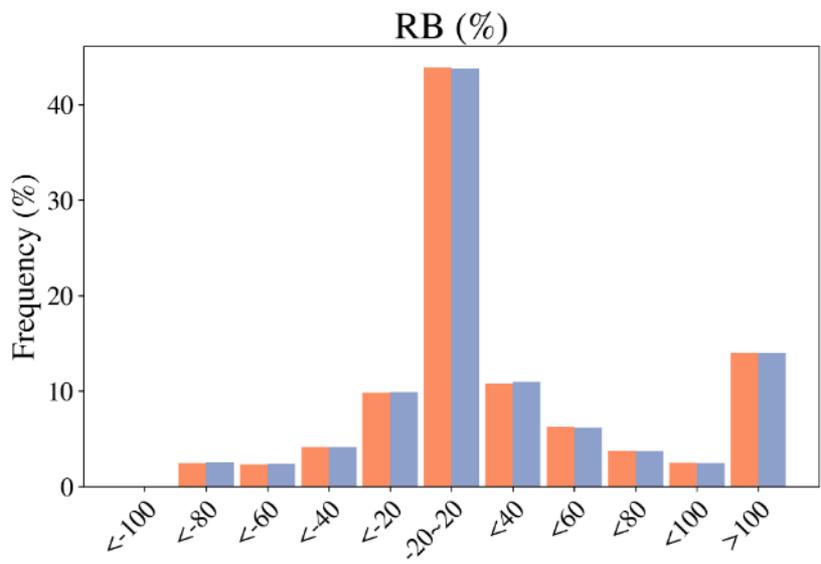
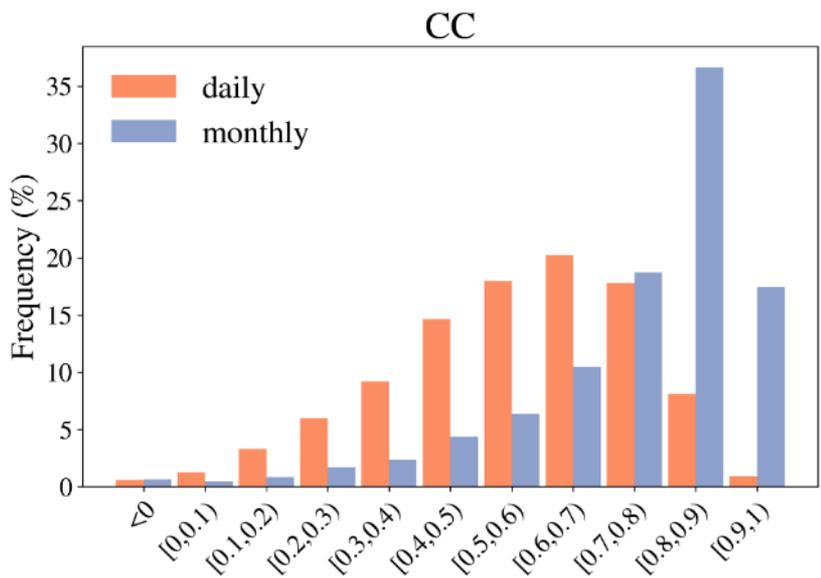
Relative Variability



KGE

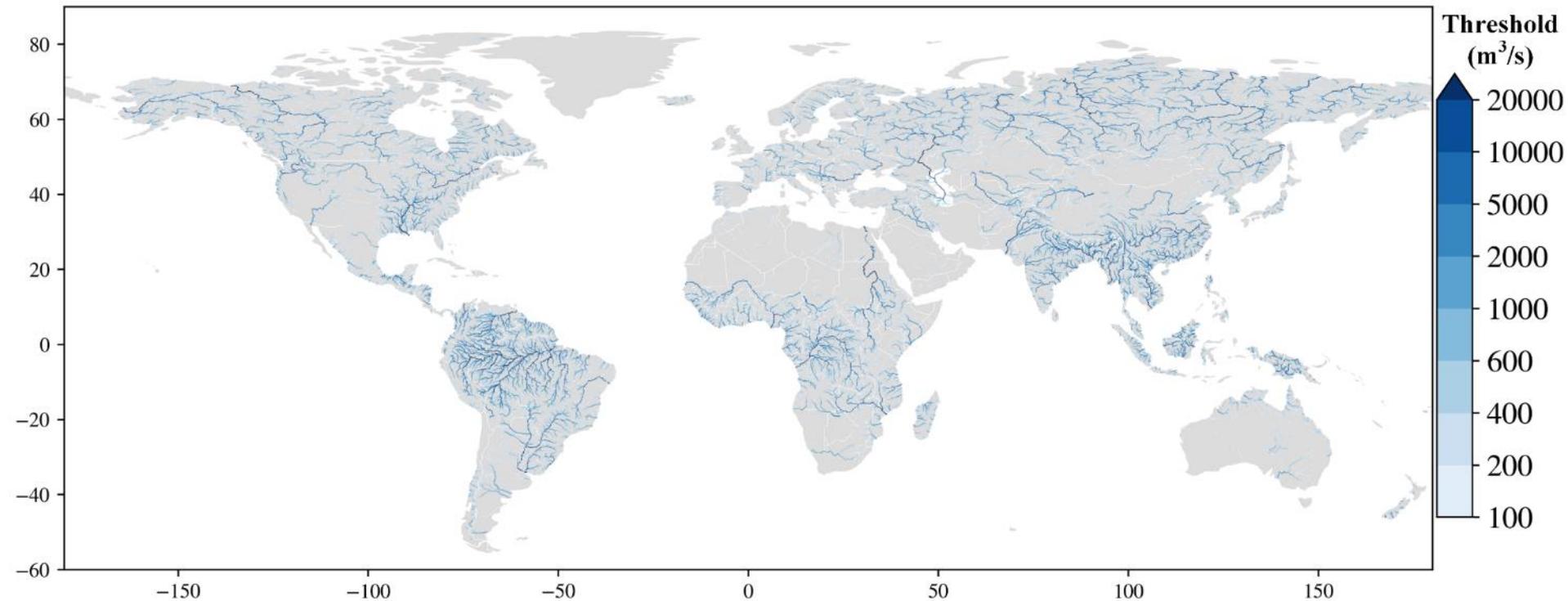


Global: daily/monthly skills



Global: flood analysis

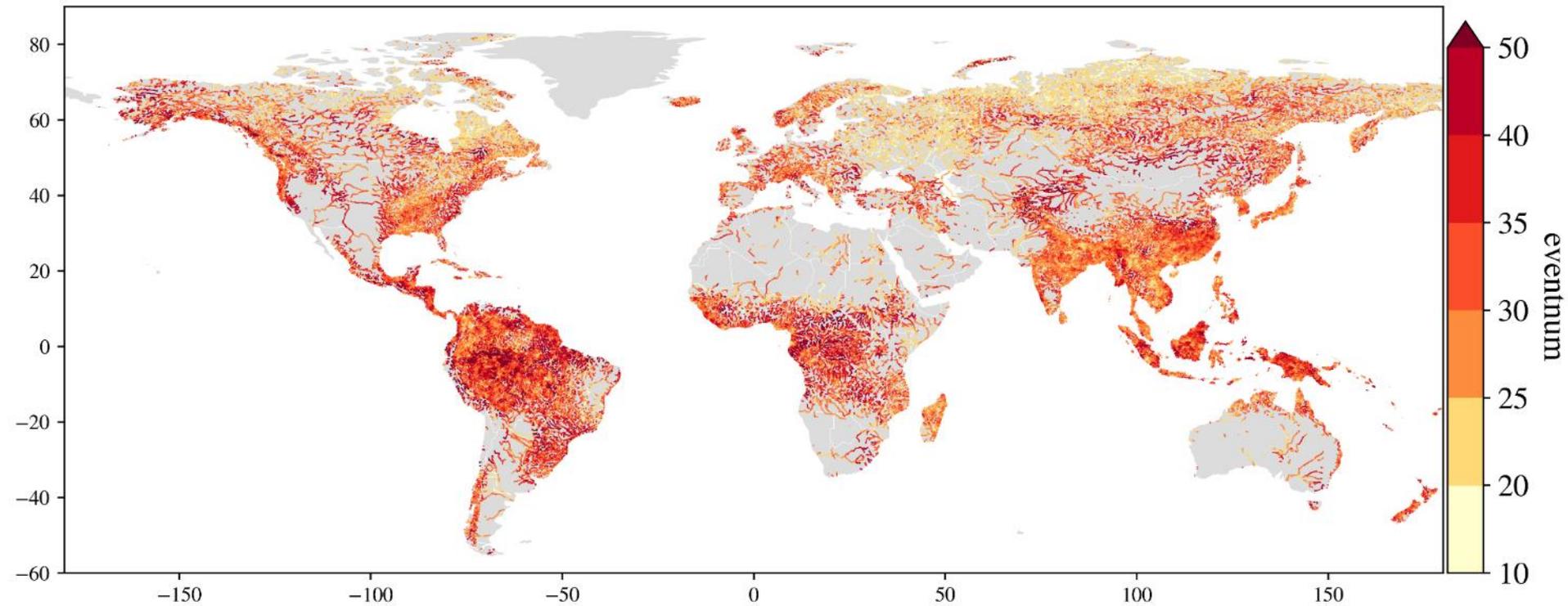
Global 3-hourly flood threshold (2-year return period)



River reaches with stream order ≥ 4 & threshold $\geq 100 \text{ m}^3/\text{s}$

Global: flood analysis

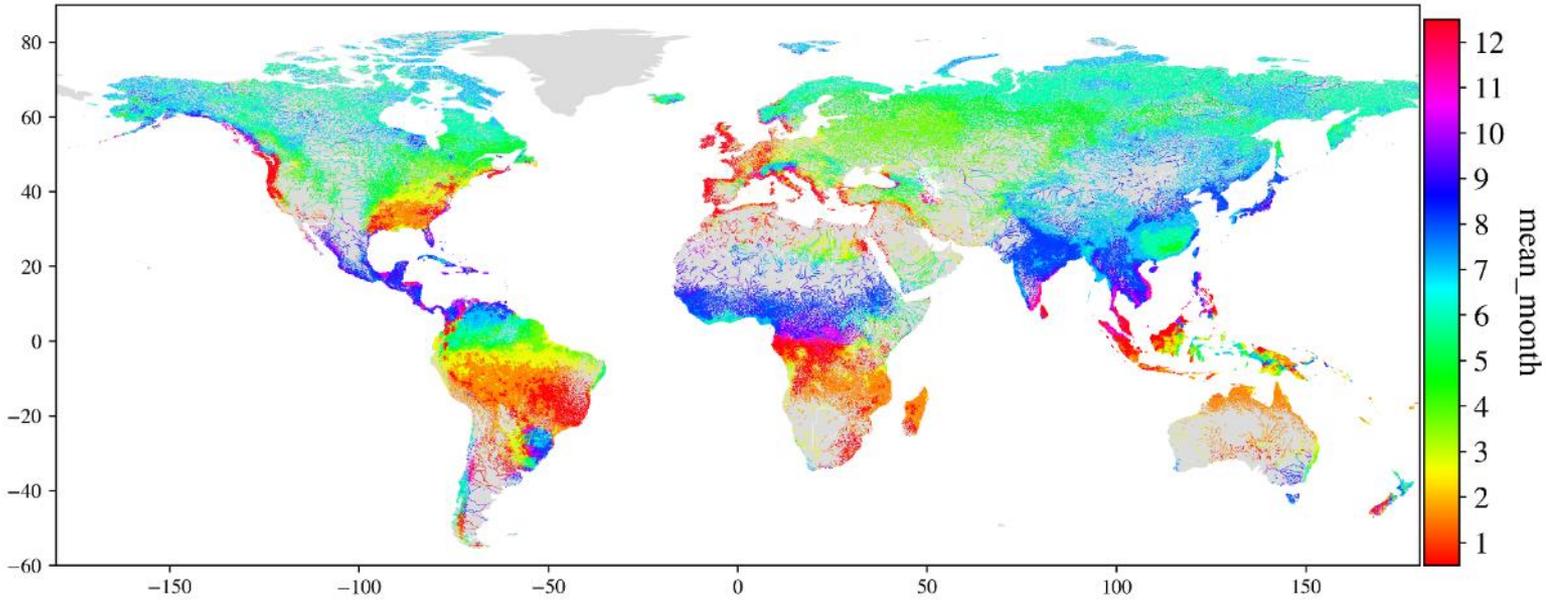
Number of flood events during 1980-2019



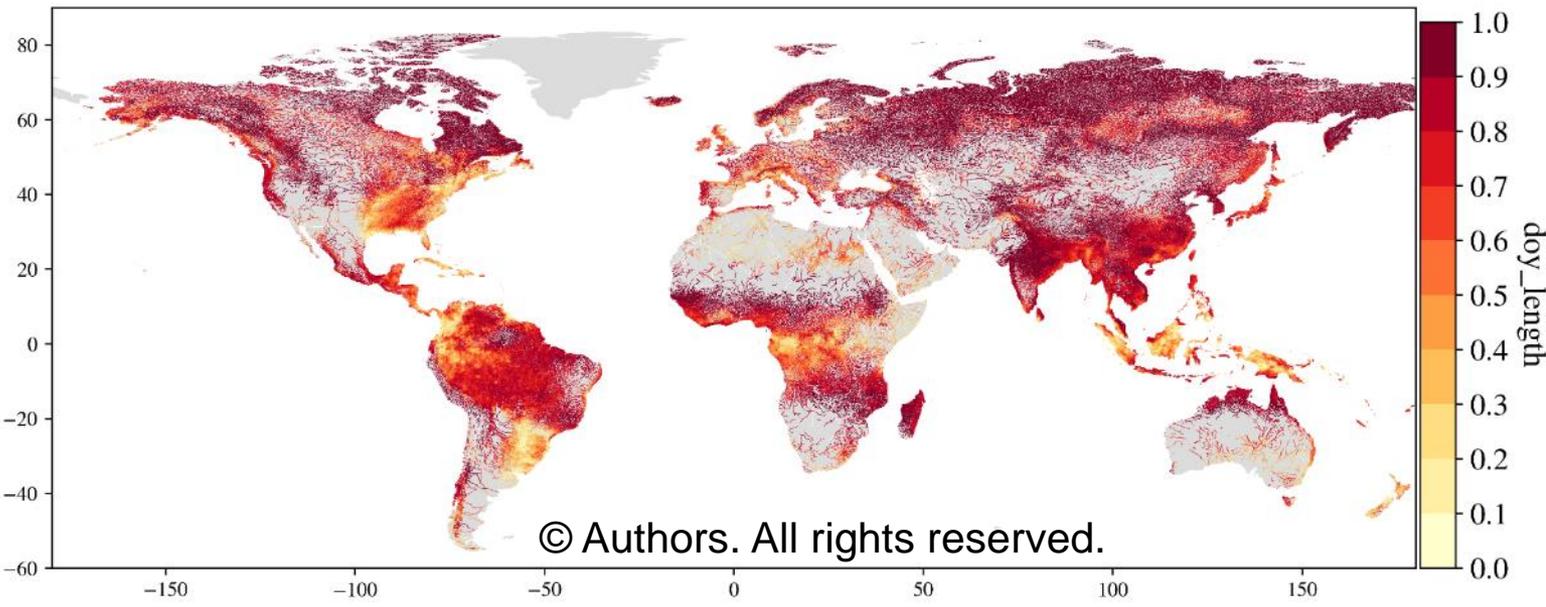
River reaches with threshold $\geq 100\text{m}^3/\text{s}$

Global: flood analysis

Flood Seasonality



Seasonal Concentration



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Conclusions and Outlook

- A carefully-designed modeling framework is implemented to generate **3-hourly river discharge record globally for 2.94 million river reaches derived from 90-m topography during 1980-2019**.
- The model can **reproduce the discharge time series well** at both 3-hourly and daily scales.
- A set of **global reach-level 3-hourly flood events** (above 2-year return period) for the period of 1980-2019 is generated.
- On going steps: further analysis on characteristics & physical mechanisms of global flood events.

Thanks to:

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- The members of the Terrestrial Hydrology Group and the Princeton CEE department for their support in completing this research.

References:

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