

# Global High-resolution **A Priori** River Discharge for SWOT

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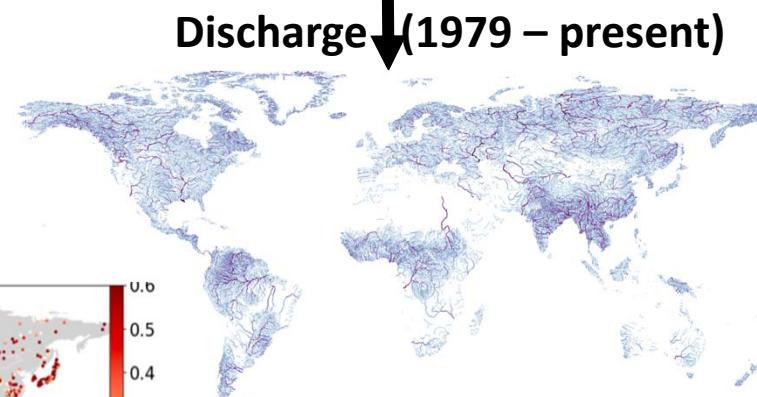
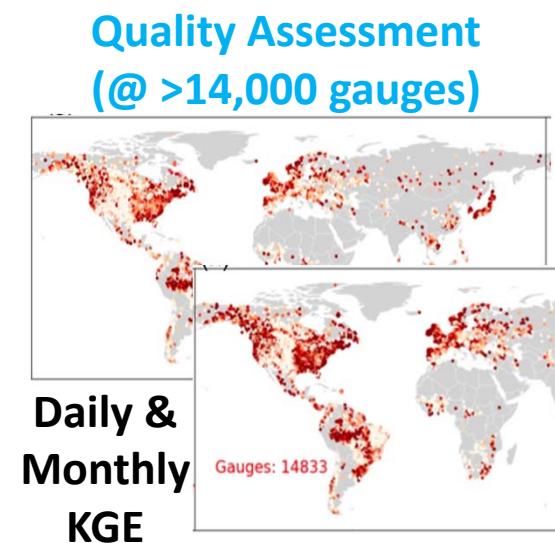
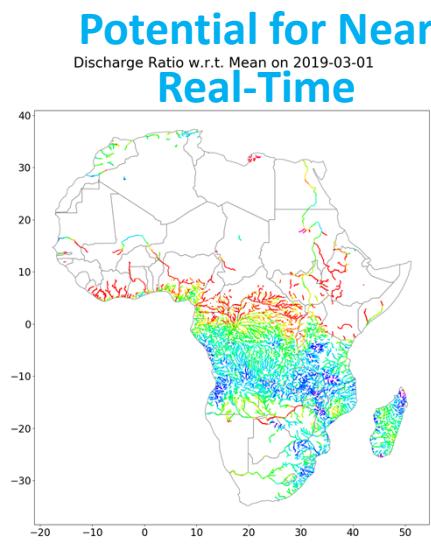
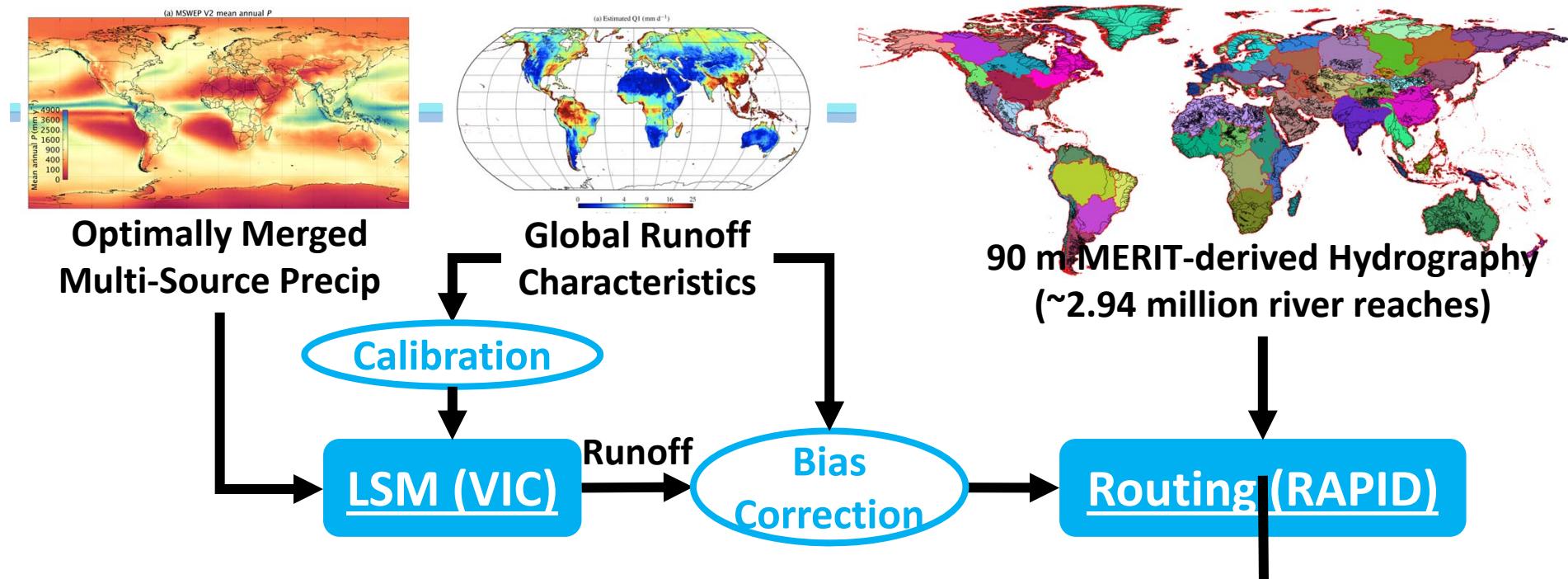
June 19<sup>th</sup>, 2019  
SWOT Science Team Meeting



# Motivations and Goals

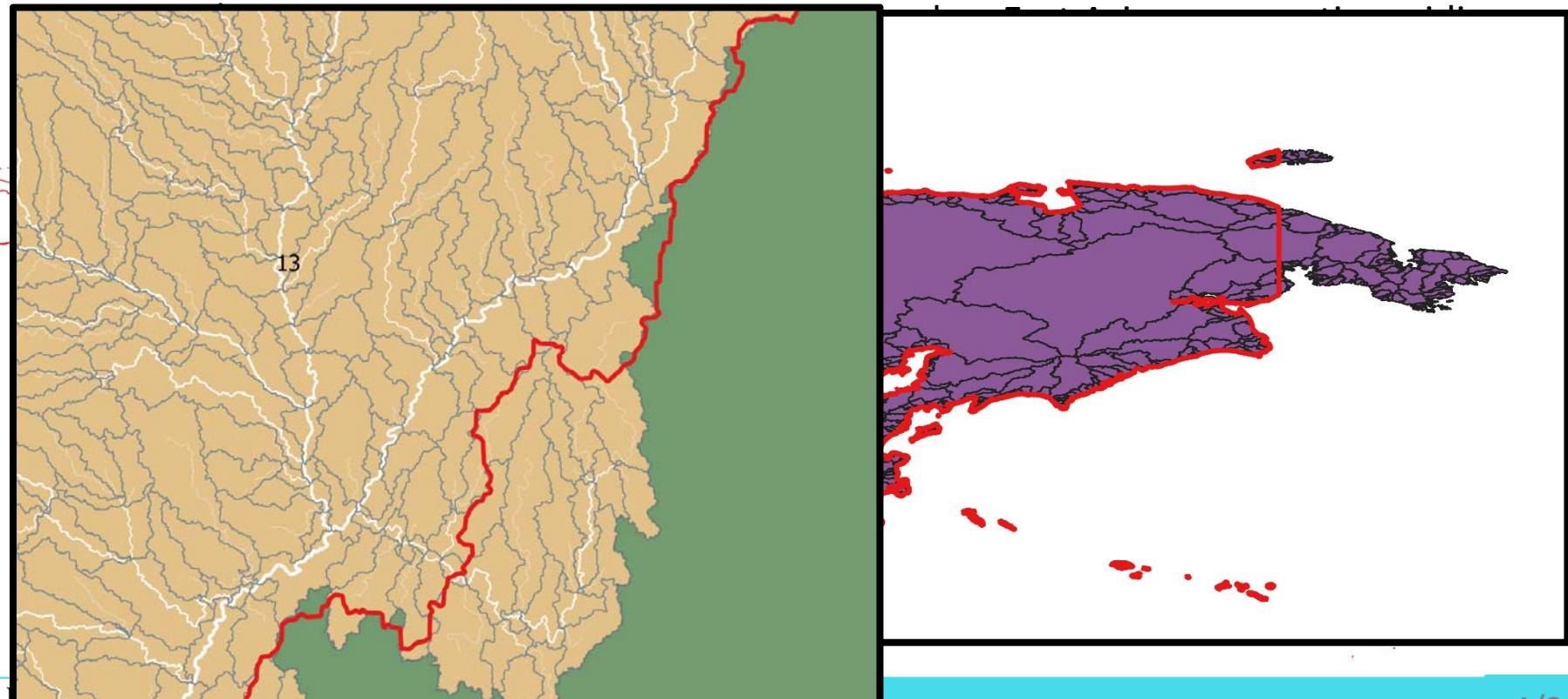
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- Discharge retrieval is an **under-constrained problem** (e.g. unknown channel geometry, roughness)
- Retrieval quality (e.g. bias, variability range) strongly depends on **prior information (talks by Garambois, Larnier, Frasson, ...)**
- Goal: **global best-quality a priori discharge** database through a carefully designed **modeling effort** (VIC/RAPID) at **high resolution**



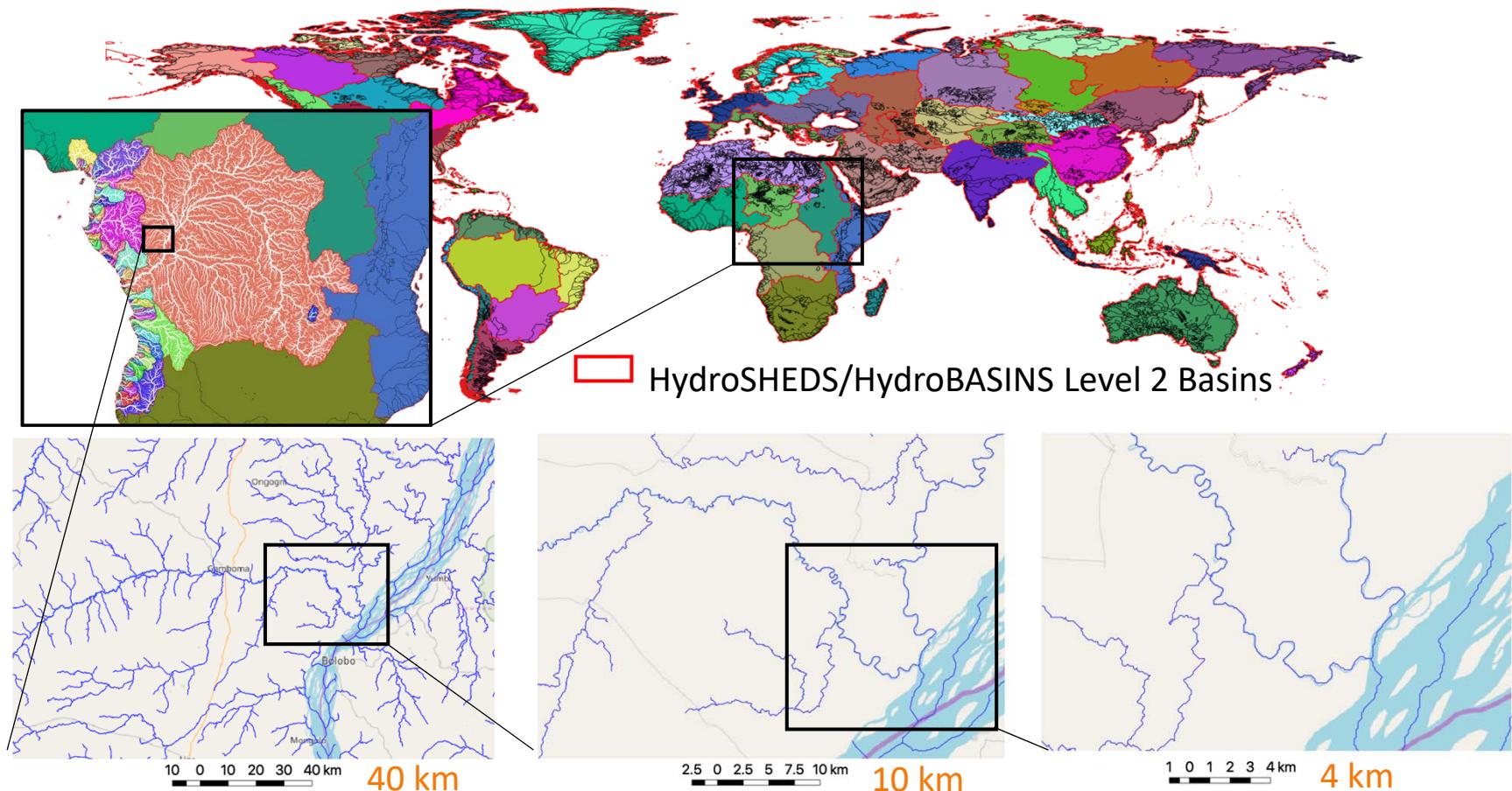
# Extract rivers/basins: MERIT-Hydro → MERIT-Basins

- MERIT (Multi-Error-Removed Improved-Terrain) DEM (Yamazaki et al. 2017)
  - Full global coverage (with  $\geq 60^\circ\text{N}$ );
  - 3s flow accum/dir (MERIT-Hydro, Yamazaki et al., 2019, WRR)
- ✓ Deriving global hydrography: vectorized 2.94 million river reaches & catchments
  - Channelization threshold: 25 km<sup>2</sup> drainage area
  - Basin/region definition: HydroBASINS level 1 and 2



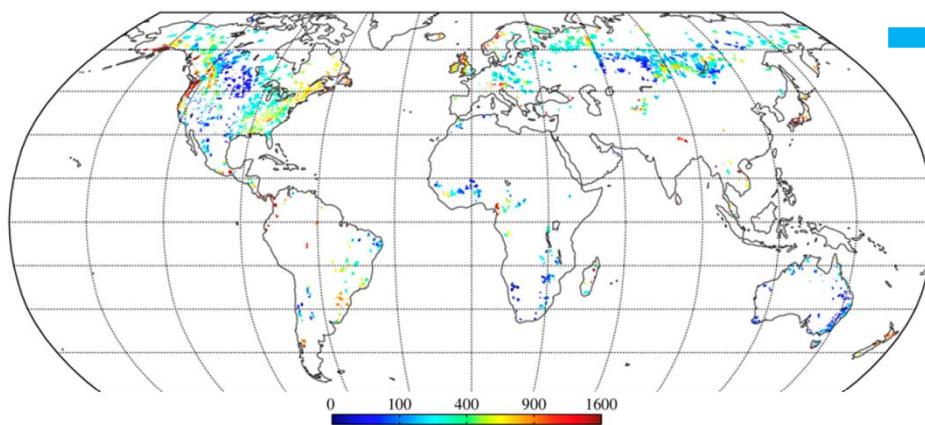
# Channel/network properties for modeling

- 2.94 M 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 =  $2.6 \times 10^7$  km**



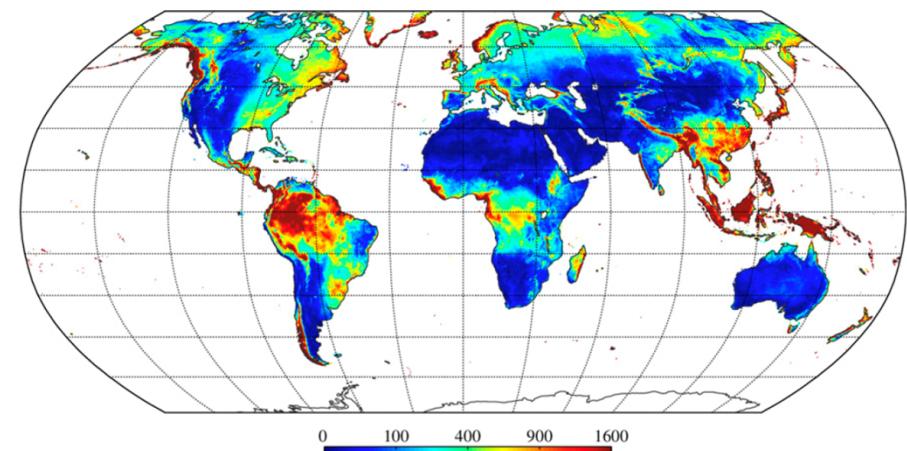
# Runoff characteristics derived from machine learning

$Q_{MEAN}$  from >3,000 naturalized catchments



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

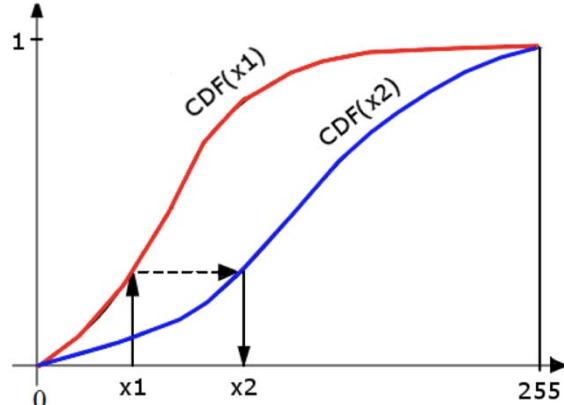
Similarly,  $Q_1$ ,  $Q_5$ ,  $Q_{10}$ ,  $Q_{20}$ ,  $Q_{50}$ ,  $Q_{80}$ ,  $Q_{90}$ ,  $Q_{95}$ ,  $Q_{99}$ , and BFI are derived globally  
(Testing  $R^2$ : 0.55 – 0.93)



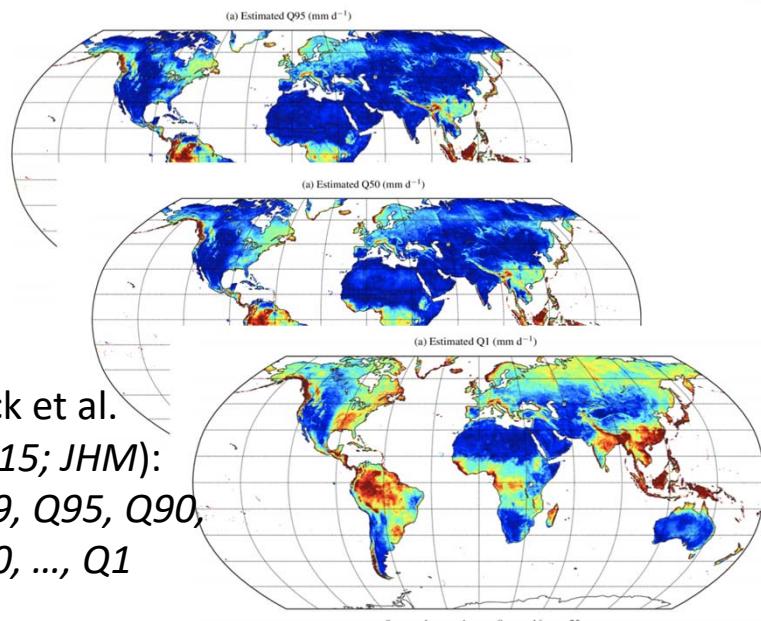
Beck et al. (2015; JHM)

# New bias correction method: “Sparse CDF Matching”

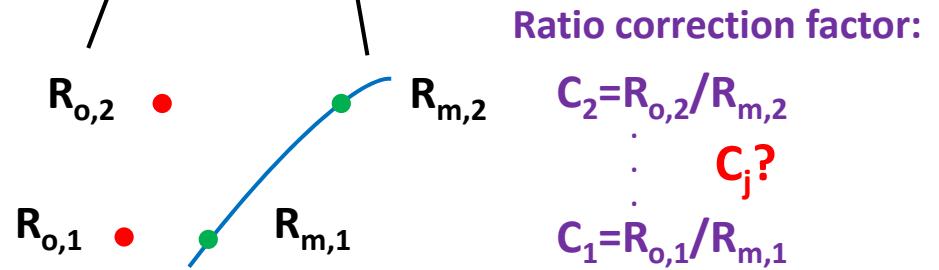
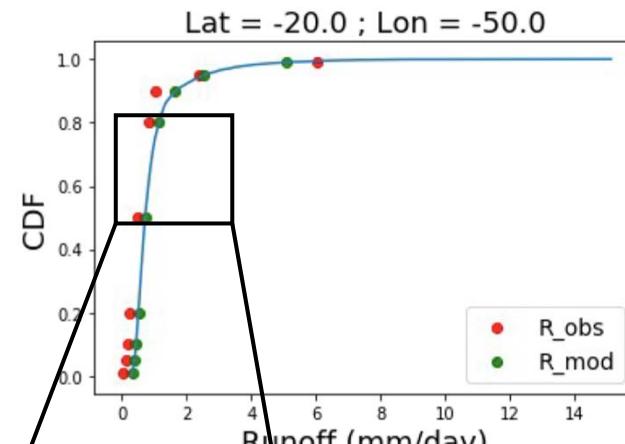
- Traditional bias-correction: CDF matching



- Q characteristics from machine learning



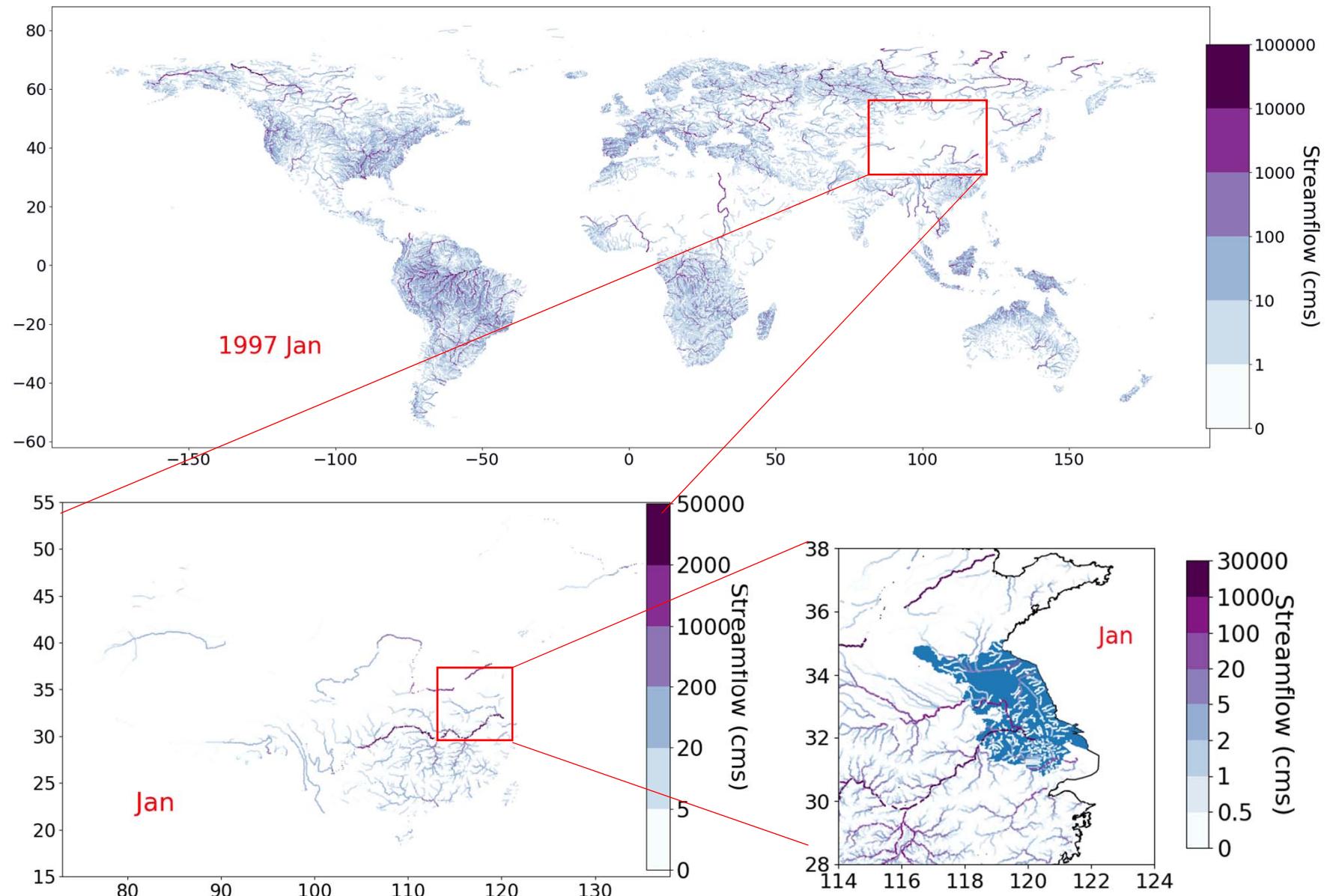
- What if no full CDF of the reference data?



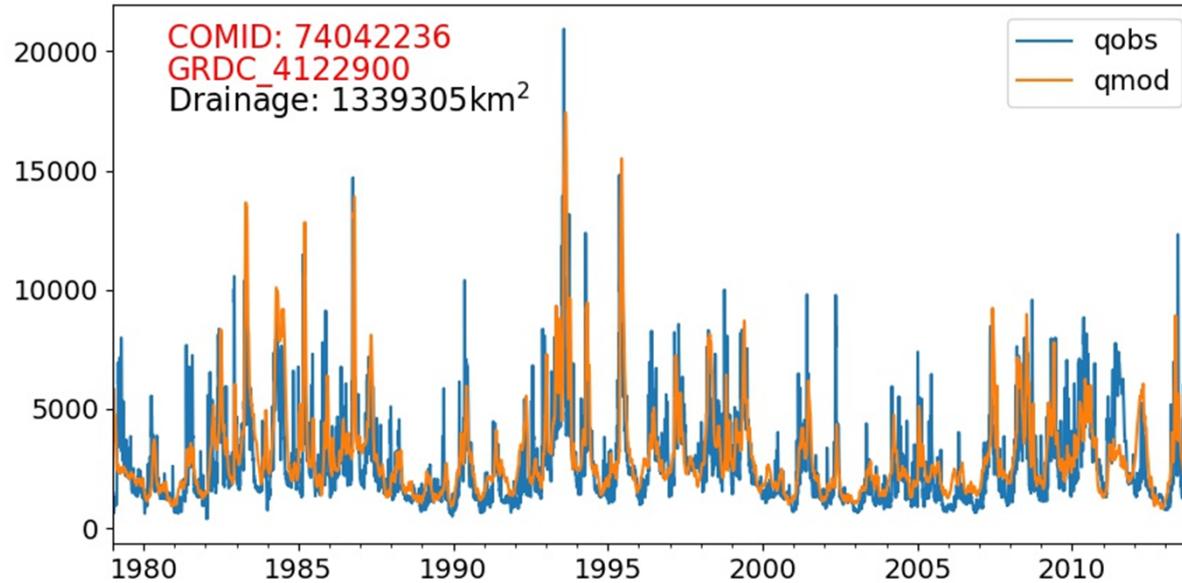
Assume error is log-linear:

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

# 40-year daily discharge @ $2.94 \times 10^6$ reaches



# Performance Metrics

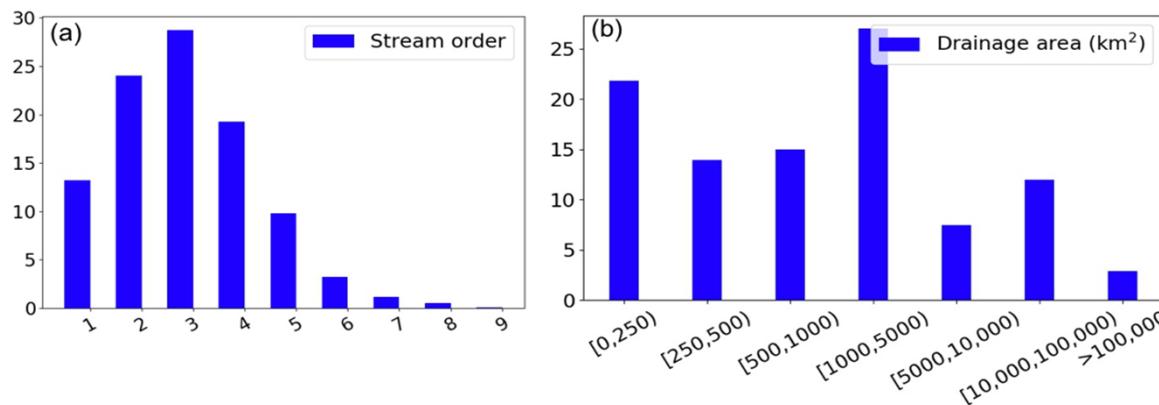
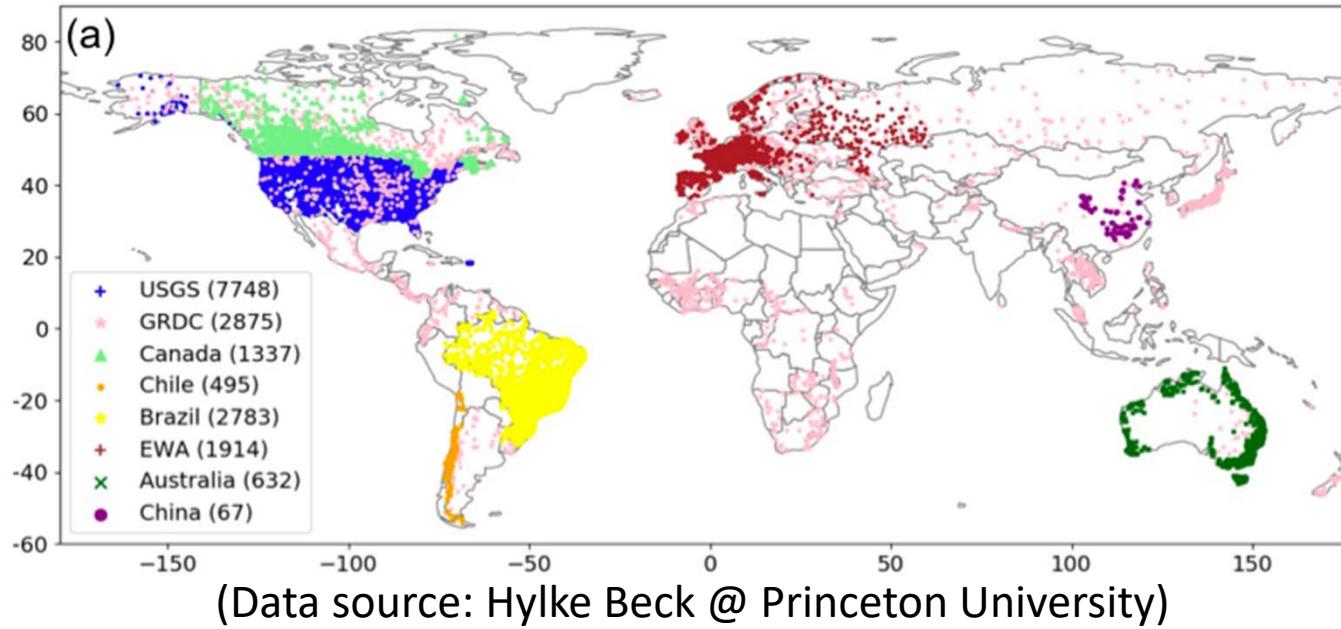


CC: 0.63  
BR: 1.14 (PBIAS: 11.4%)  
RV: 0.95  
KGE: 0.6

- **Correlation:**  $CC = \frac{cov(Q_m, Q_o)}{\sigma_{Q_m} \cdot \sigma_{Q_o}}$
- **Bias Ratio:**  $BR = \overline{Q_m}/\overline{Q_o}$ ; **Percentage Bias:** PBIAS =  $\frac{\overline{Q_m} - \overline{Q_o}}{\overline{Q_o}} \times 100\%$
- **Relative variability:**  $RV = (\sigma_{Q_m}/\overline{Q_m})/(\sigma_{Q_o}/\overline{Q_o})$
- **KGE** =  $1 - \sqrt{(CC - 1)^2 + (BR - 1)^2 + (RV - 1)^2}$

# Evaluation at >14,000 gauges globally

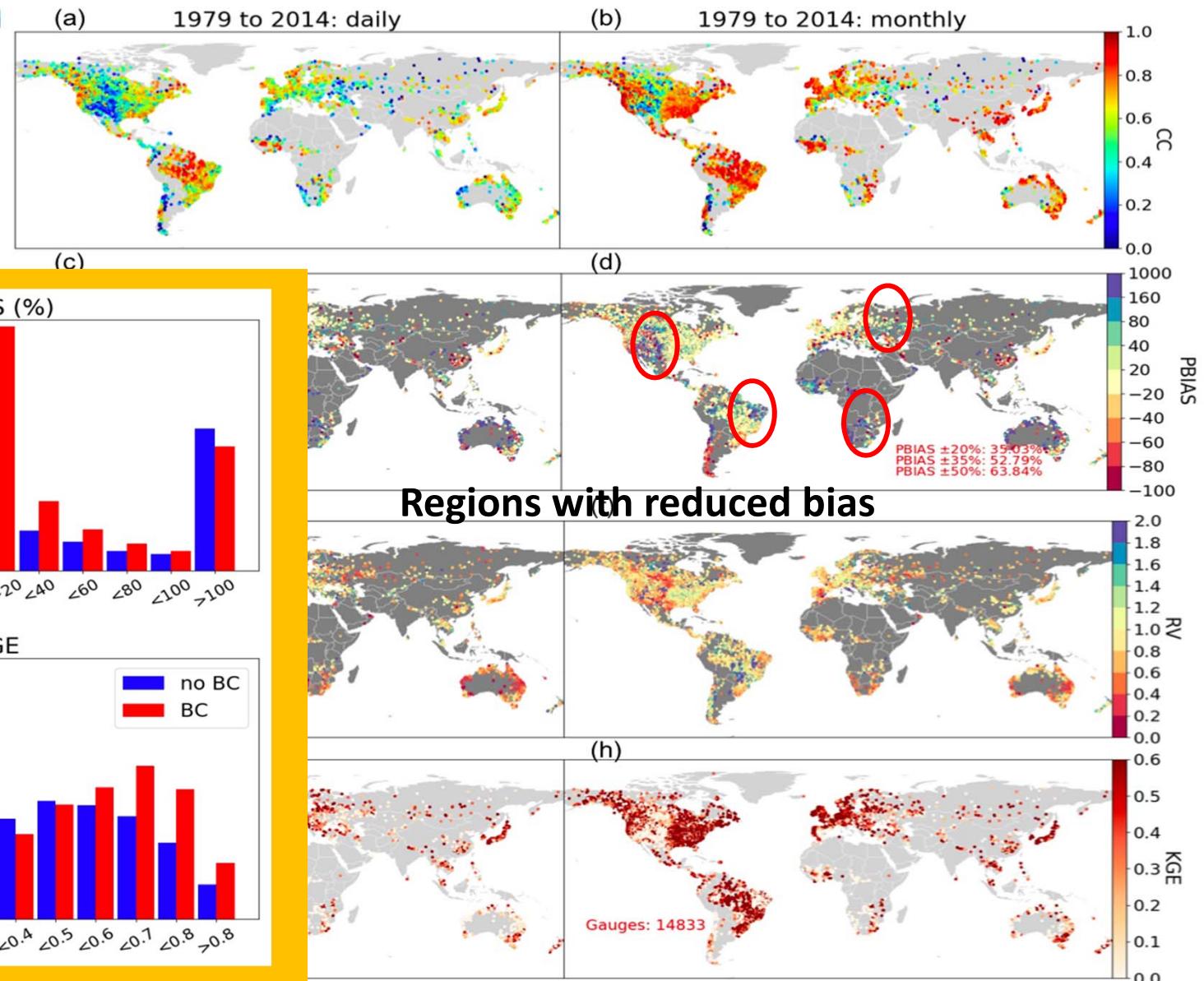
A global database of daily streamflow obs @ >21,000 gauges



- Uneven distribution
- Covering spectrum of stream orders (from small creeks to large streams)

# Performance (after Bias Correction)

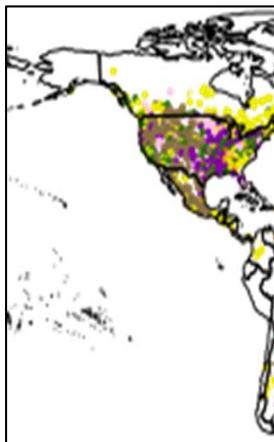
Correlation  
Coefficient



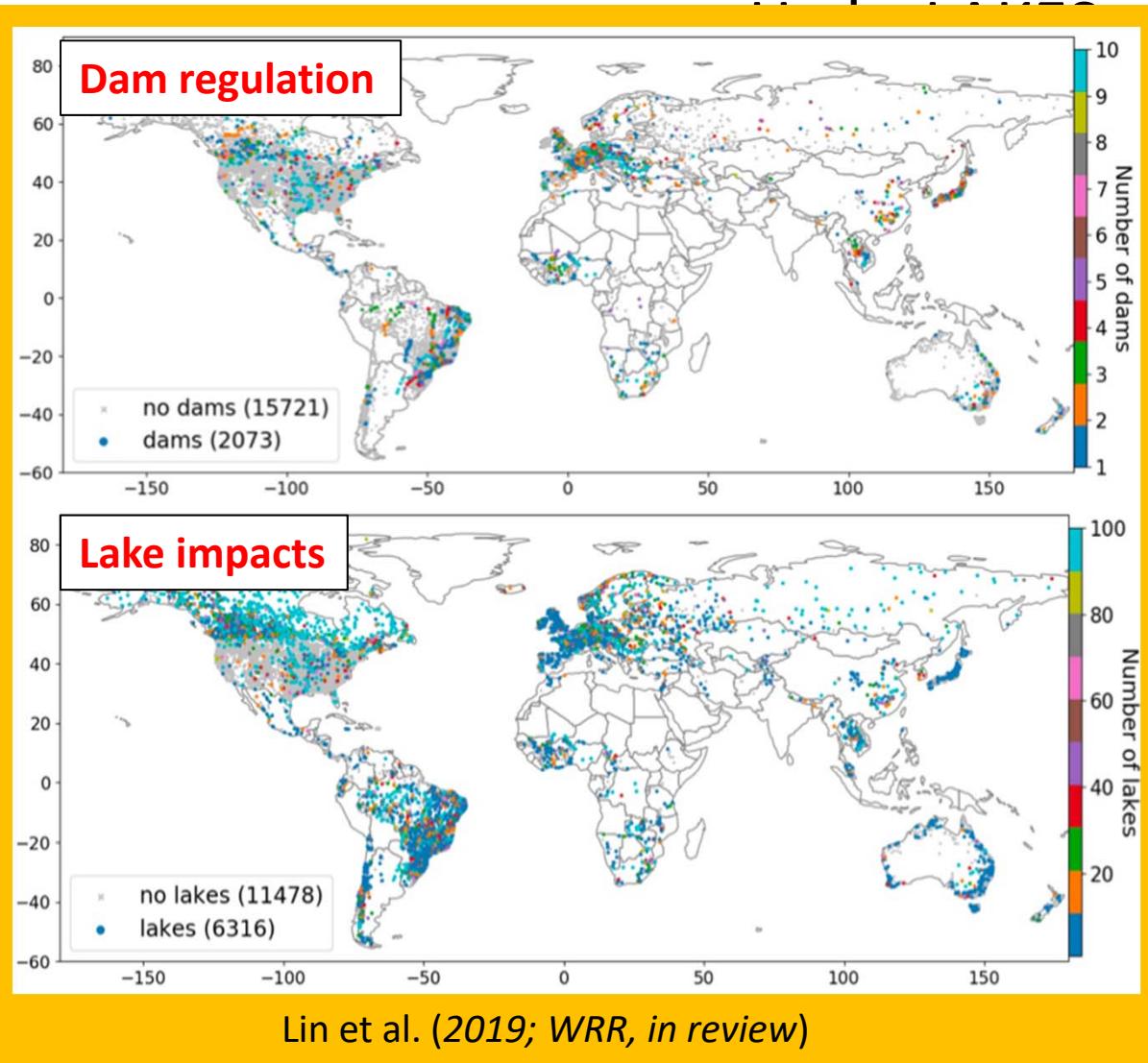
# Dam regulation and lake impacts

- GRaND

Lehner et al.

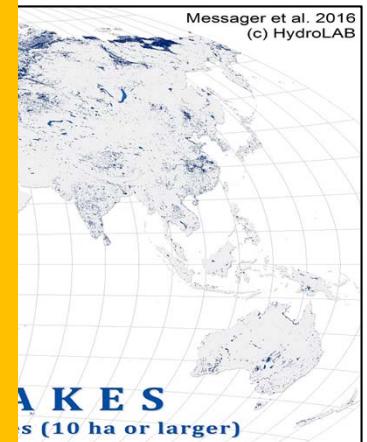


6,862 dams



Lin et al. (2019; *WRR, in review*)

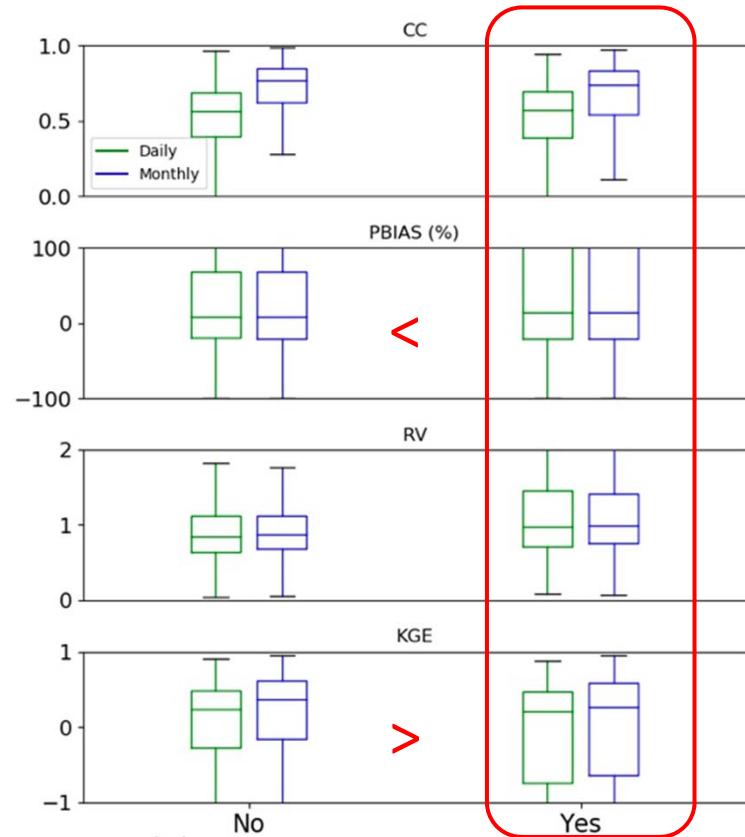
Communications)



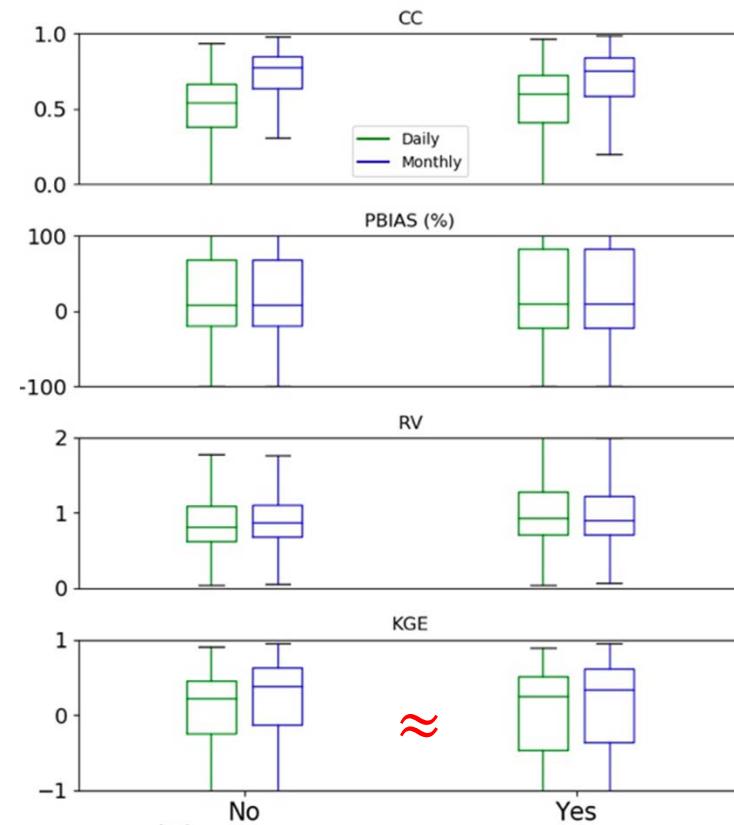
in 10 hectares

# Dam/lake impacts

## Dam regulations

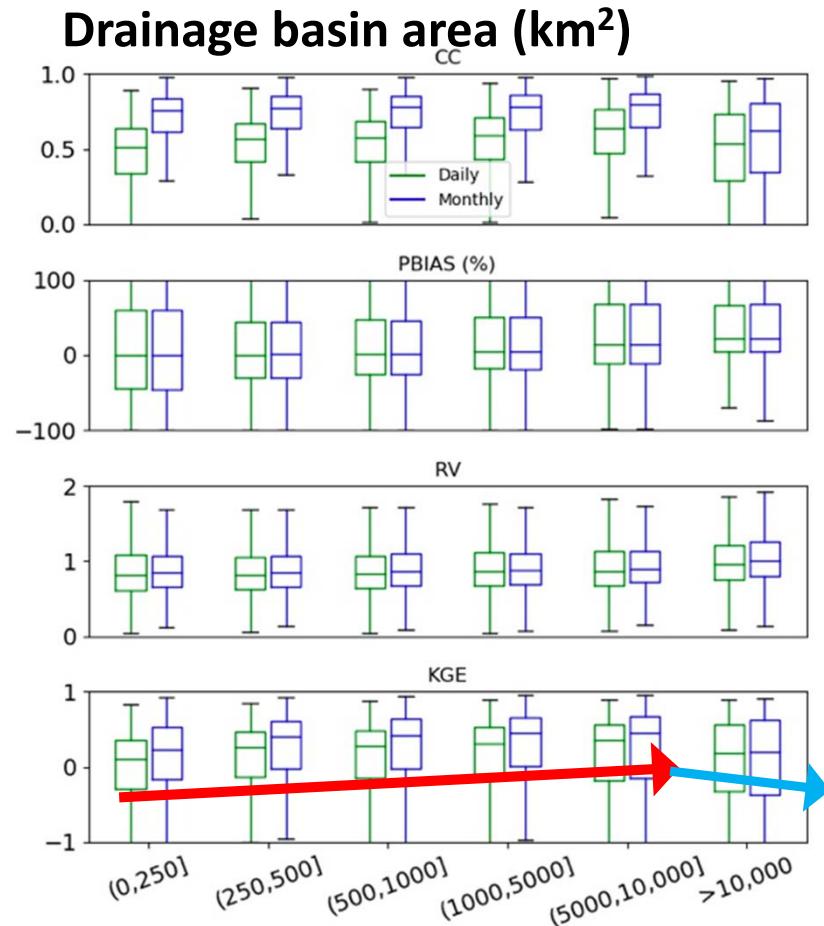


## Lake impacts

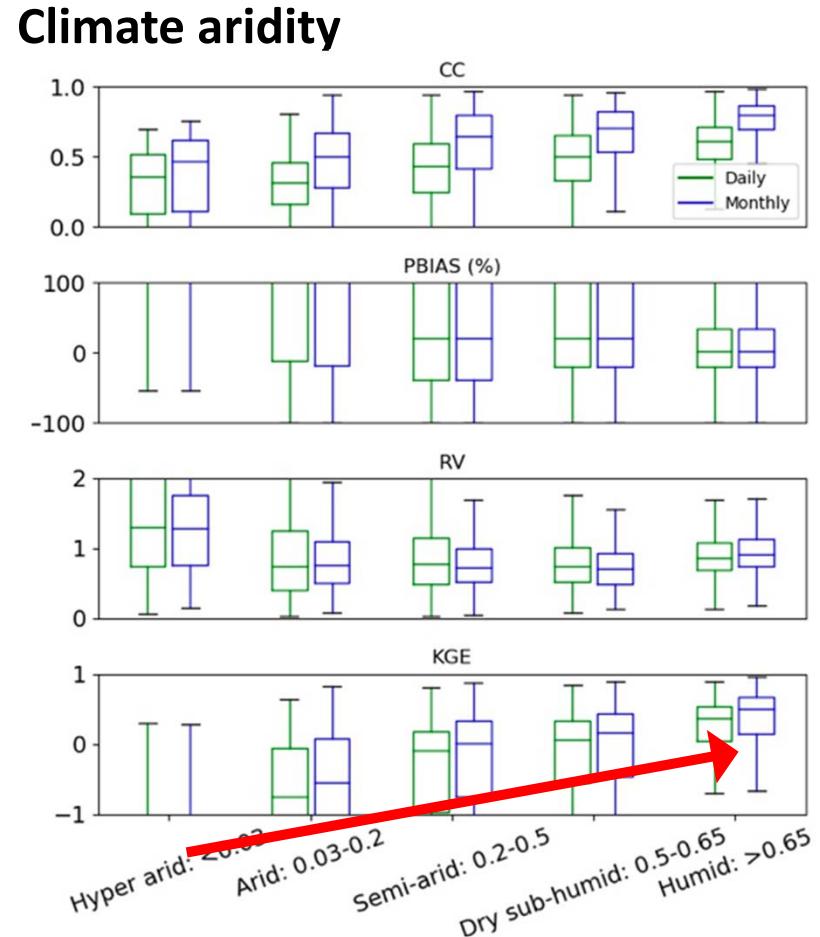


- Dams have stronger impacts than lakes
- Dams and lakes: smaller-than-expected influence

# Drainage area & aridity

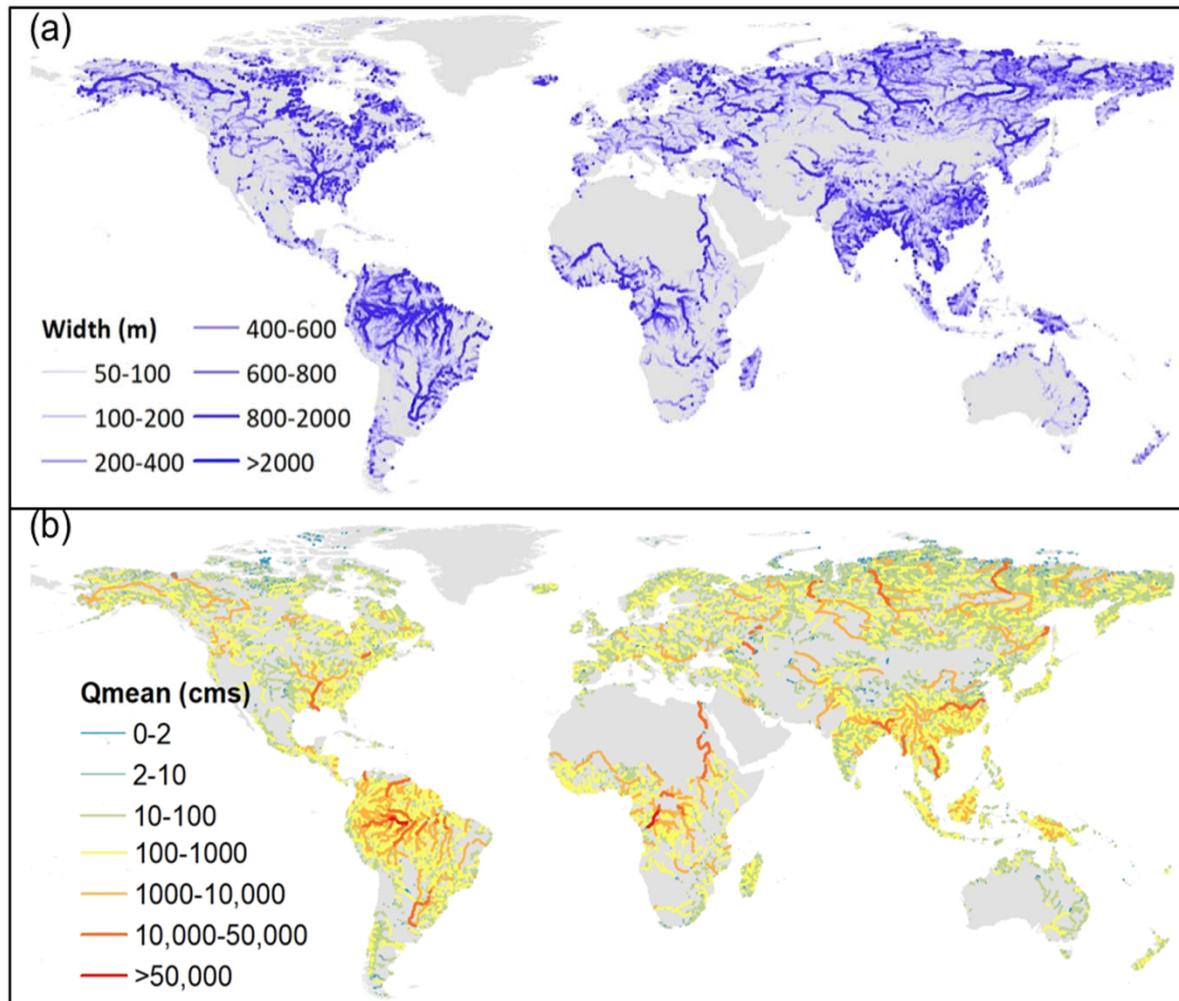


- Flow regulation issue
- Difficulty in dry region



# SWOT-Observable Reaches (8%, w>50m)

**8.8% reaches potentially observable by SWOT per GRWL**



- PBIAS:  
44% within  $\pm 20\%$   
76% within  $\pm 50\%$
- KGE:  
42%  $\geq 0.6$   
75%  $\geq 0.2$

# High-resolution VIC-RAPID vs. QWBM

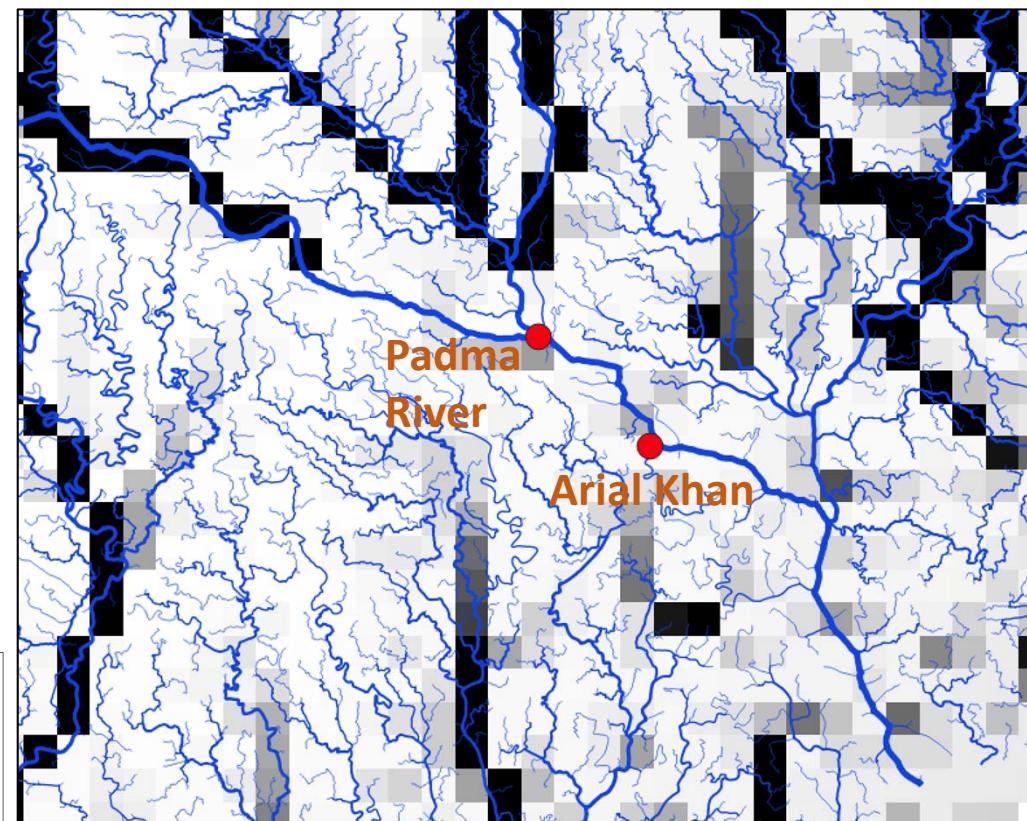
## Padma River (Pepsi 2):

QWBM underestimates  $Q_{\text{mean}}$ : incorrect hydrography along the coast (due to coarse resolution)

$Q_{\text{TRUE}}(\text{m}^3/\text{s})$ : 30017

$Q_{\text{WBM}}$ : 106

$Q_{\text{VIC\_RAPID}}$ : 30633



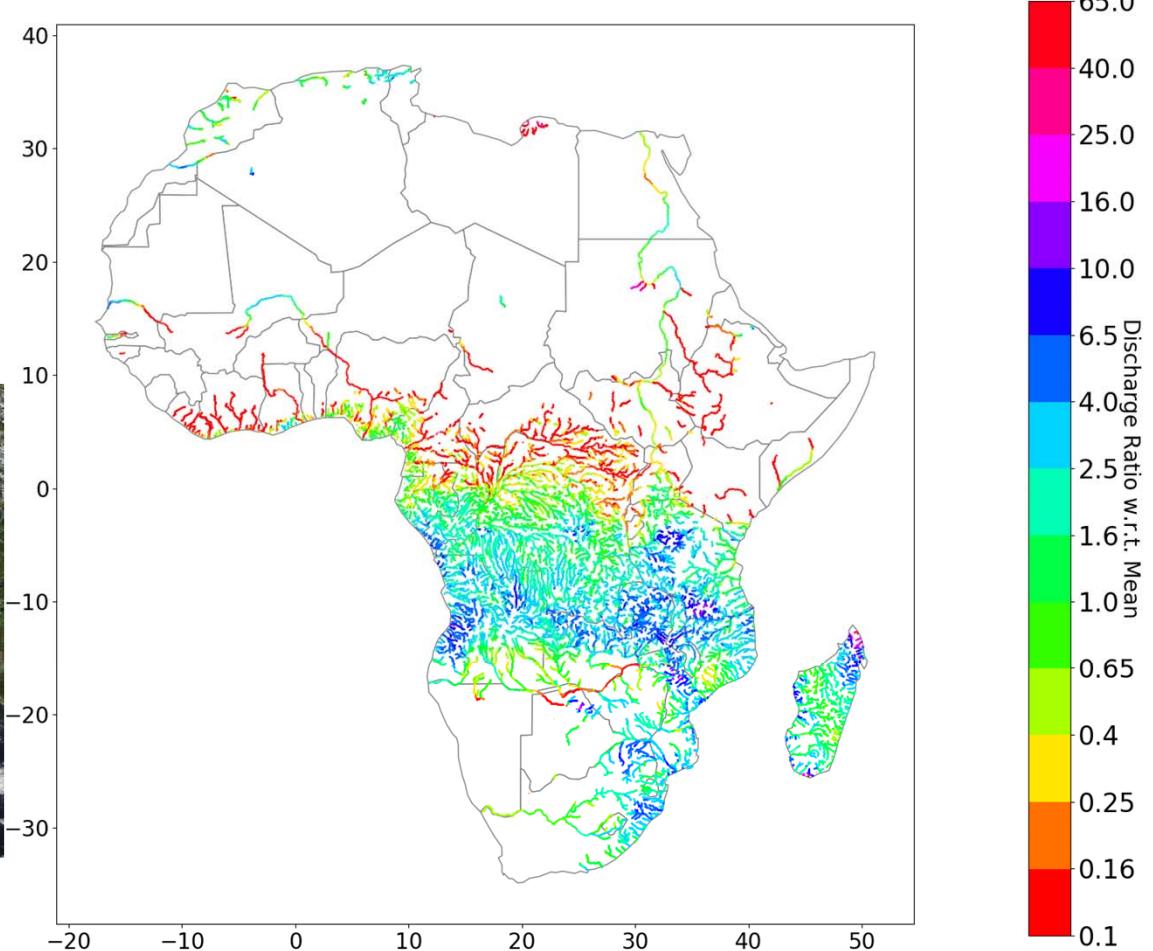
Black: QWBM  
Blue: MERIT-Basins

# Thanks for your attention!

- Tropical cyclone Idai in Africa in March 2019



Discharge Ratio w.r.t. Mean on 2019-03-01

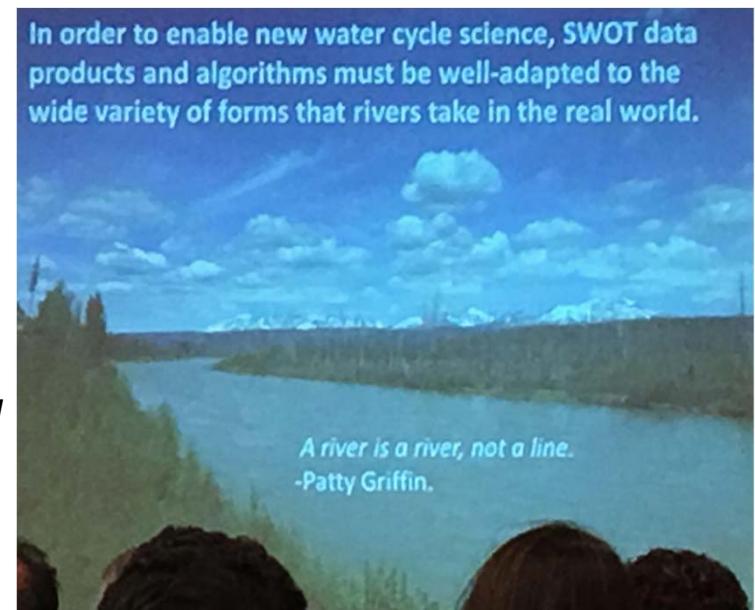


# Thank you for your attention!

- Questions? Comments?
- [mpan@princeton.edu](mailto:mpan@princeton.edu), [peirongl@princeton.edu](mailto:peirongl@princeton.edu)

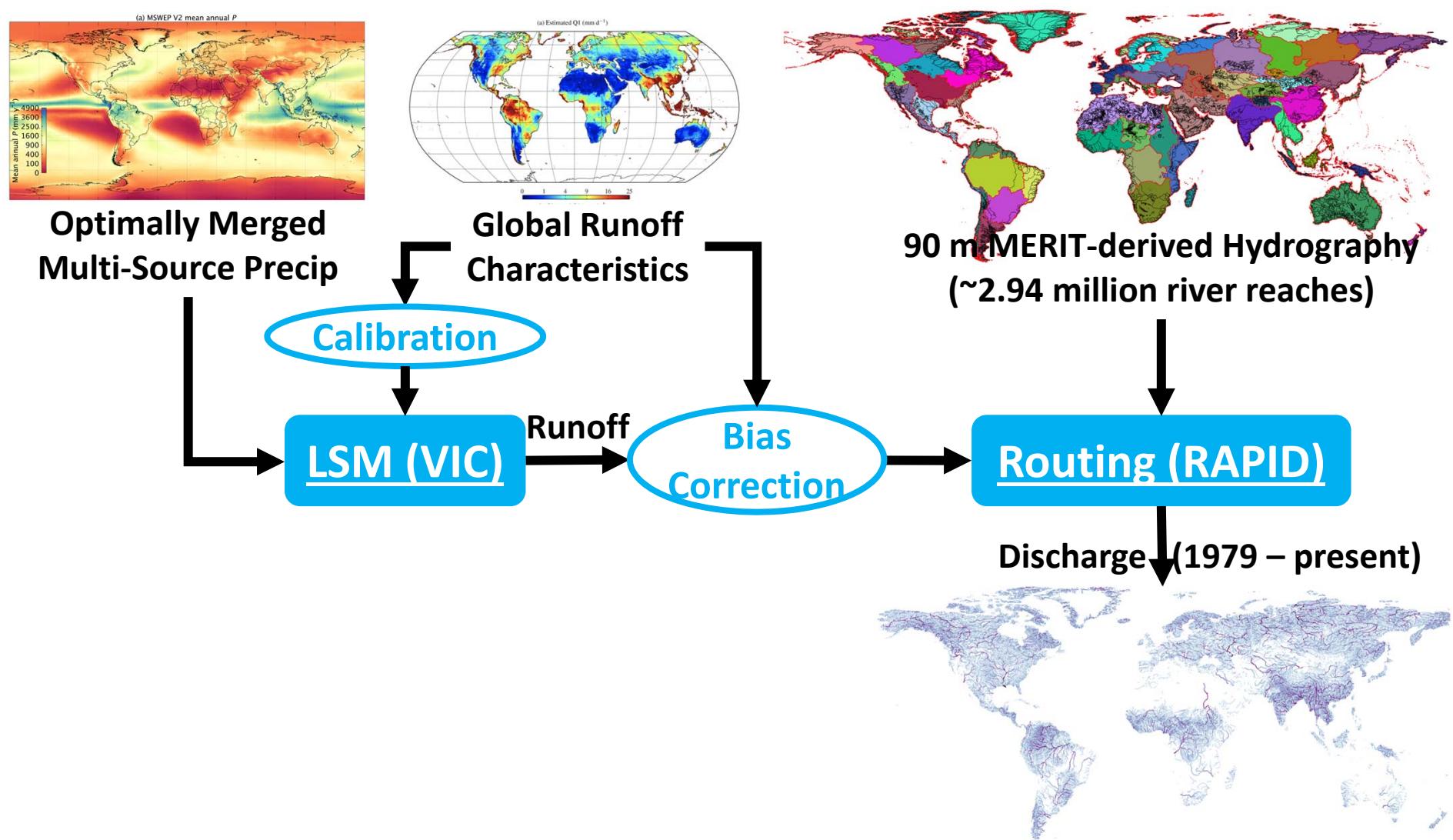
- Major references:

- Beck et al. (2015, *JHM*): Global maps of streamflow characteristics based on observations from several thousand catchments
- Beck et al. (2019, *BAMS*): MSWEP V2 global 3-hourly 0.1° precipitation: methodology and quantitative assessment
- Yamazaki et al. (2017, *GRL*): A *high-accuracy map of global terrain elevations*
- Yamazaki et al. (2019, *WRR*): A high-resolution global hydrography map based on latest topography datasets
- Yang et al. (2019, *WRR, in review*): In quest of calibration density and consistency in hydrologic modeling: distributed parameter calibration against Q characteristics
- Lin et al. (2019, *WRR, in review*): Step change in global reconstruction of naturalized river flows at 2.94 reaches

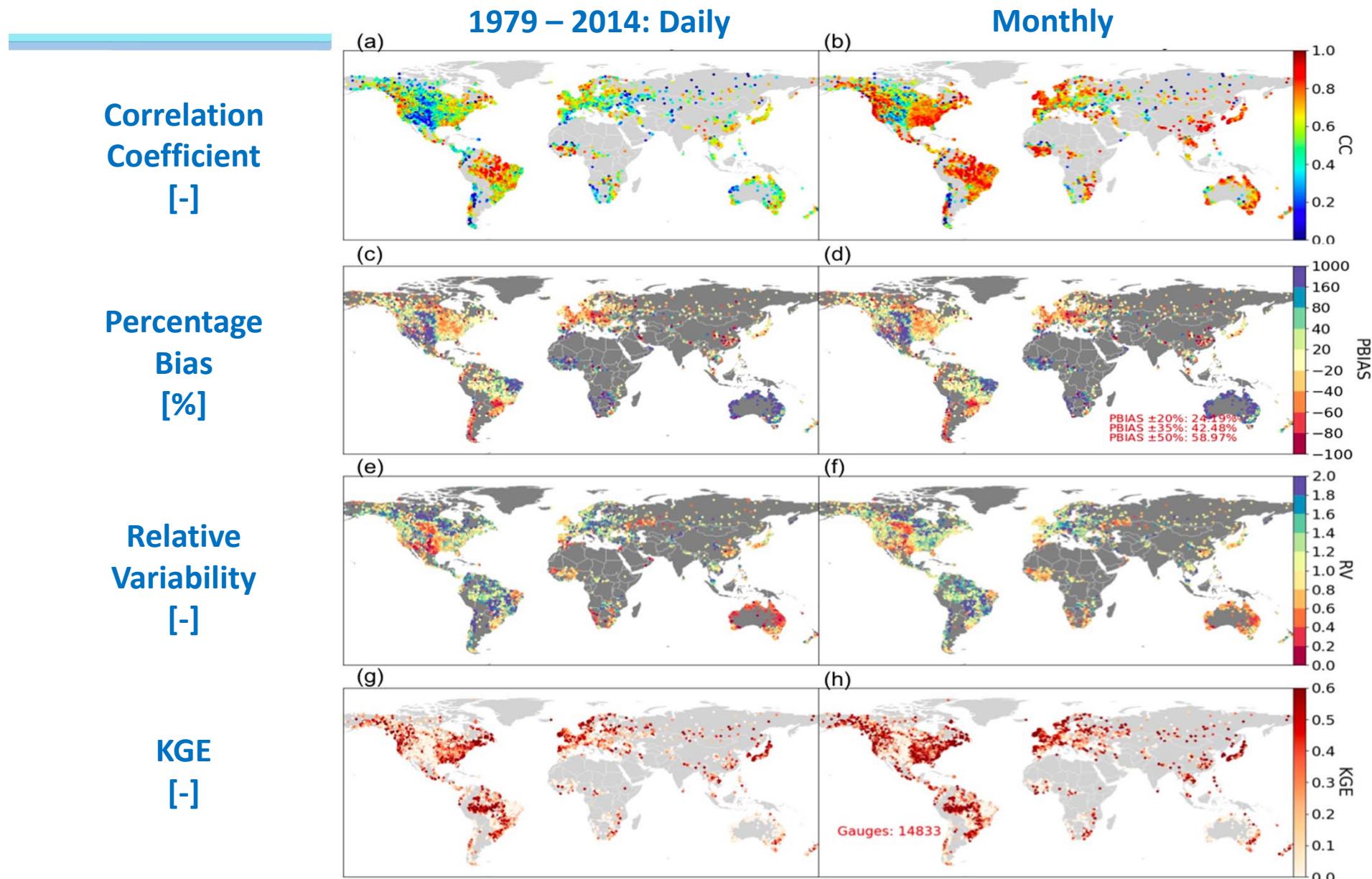


(Picture taken on 2018 SWOT ST Meeting)

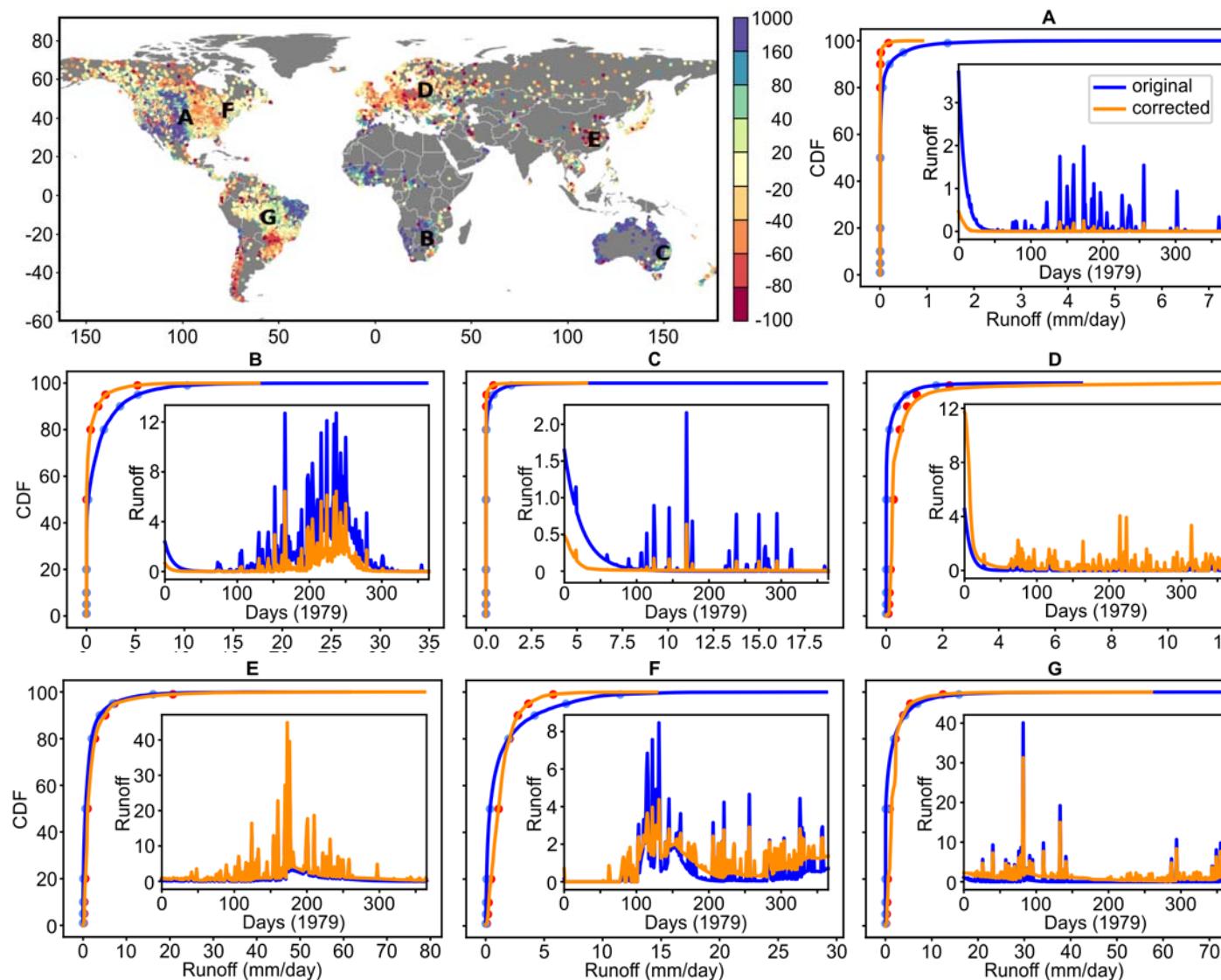
# Modeling Workflow



# Performance before Bias Correction



# Grid-by-grid Bias Correction



Regions: wet bias

(A, B, C)

Runoff → lower

Regions: dry bias

(D, E)

Runoff → higher

Regions: bias  $\pm 20\%$

(F, G)

Mean runoff →  
little change