Reconstruction of instantaneous peaks in undisturbed catchments for enhanced flood frequency analysis across Contiguous United States

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Award ID:

I. Introduction and Objectives

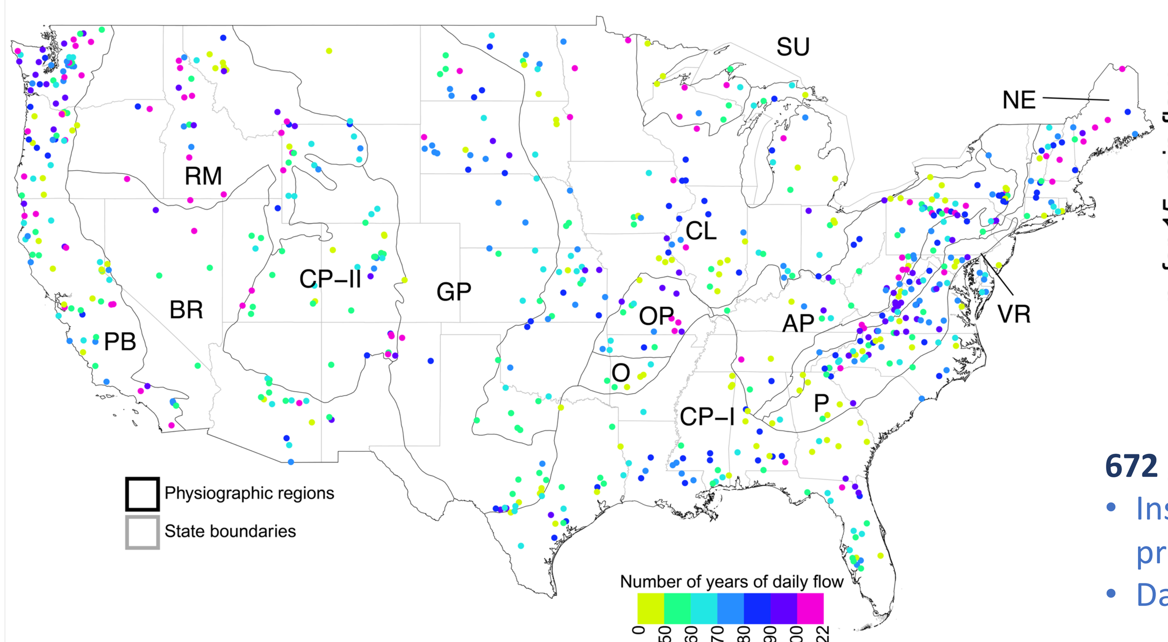
- Flood Frequency Analysis (FFA) is critical for infrastructure design, flood risk management and water system planning;
  - typically involves fitting a statistical distribution to peak flows (Q_p)
  - accuracy highly dependent upon the sample size
- Discharge records are mostly available as daily mean (Q_m) in USA, instantaneous observations are limited
- Daily mean in FFA can lead to underestimation of flood magnitudes

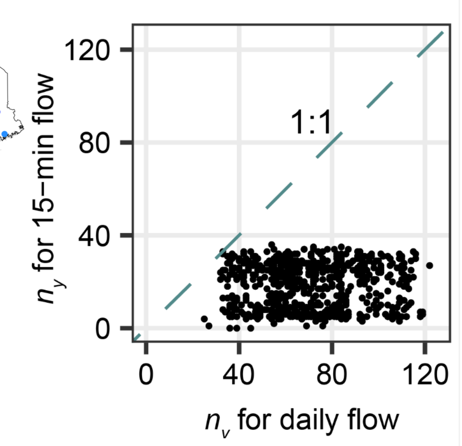
Objectives

- To increase the database of peak flows across Contiguous United States with gauge-dependent multi-linear regressions (MRs)
- To evaluate the utility of the reconstructed peaks in FFA

II. Study Area and Datasets

- USGS Geospatial Attributes of Gages for Evaluating Streamflow (GAGES II) Hydro-Climatic Data Network (**HCDN**) stream gauges





672 gages with near-natural flow
- Instantaneous flow: 1988 - present
- Daily mean: 1900s - present

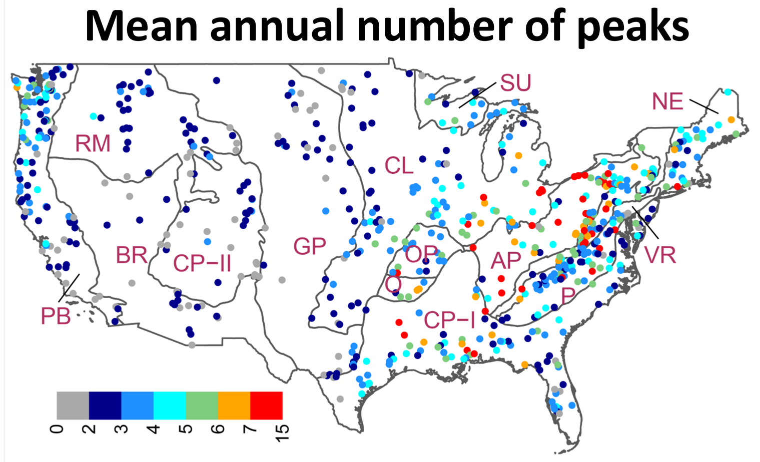
- NOAA Analysis of Record for Calibration (AORC) hourly, 1-km prec. in 1979-2020
- USGS National Hydrography Dataset (NHD) Plus for shapefiles of contributing basins

III. Methods

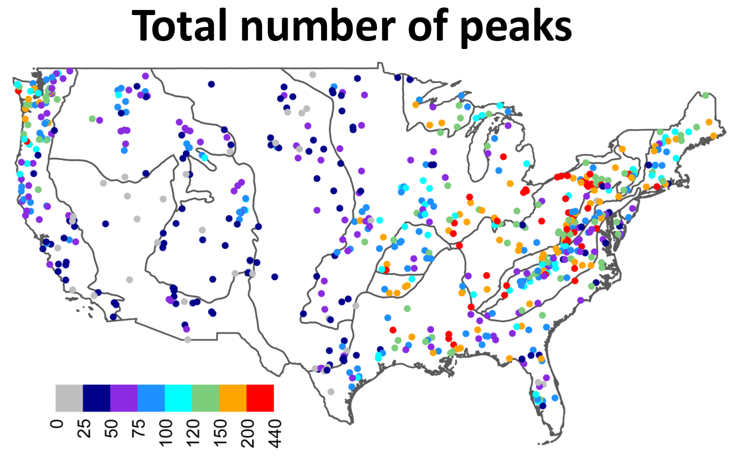
Peak flows and predictors

- Filtered Peak over Threshold (FPOT; Claps & Lao, 2003) for identifying peaks

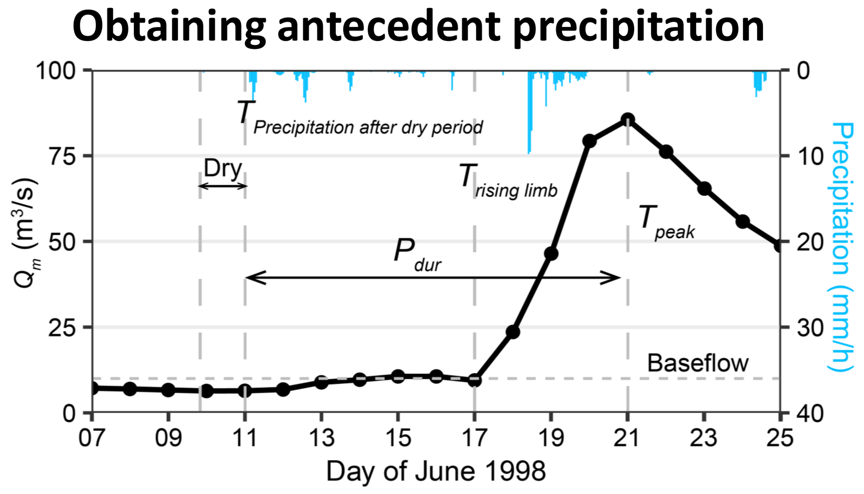
Mean annual number of peaks



Total number of peaks



Obtaining antecedent precipitation



Predictors

- Daily mean on the day of the peak ($Q_{m,s}$)
- Daily mean on the day before ($Q_{m,b}$)
- Daily mean on the day after ($Q_{m,a}$)
- Precipitation depth (P_{dep})
- Precipitation duration (P_{dur})

III. Methods

Multi-linear regression

$$\log(Q_p) = b_0 + b_1\log(Q_{m,s}) + b_2\log(Q_{m,b}) + b_3\log(Q_{m,a}) + b_4\log(P_{dep}) + b_5\log(P_{dur})$$

- Log-transformed variables - improved homoscedasticity and normality of residuals (e)

Significant predictors

- **Forward selection:** improvement of MSE
- **t-ratios:** p-value of t-ratio

Calibration and validation

- Monte-Carlo experiments
- 75% calibration, 25% validation
- Performance based on RRMSE and R²

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n} e_i^2 \qquad \text{R}^2 = 1 - \frac{\sum_{i=1}^{n} e_i^2}{\sum_{i=1}^{n}(Q_{p,i} - \bar{Q})^2} \qquad \text{RRMSE} = \left[\frac{1}{n}\sum_{i=1}^{n}\left(100 \times \frac{e_i}{Q_{p,i}}\right)^2\right]^{1/2}$$

Utility of reconstructed peaks in FFA

Scenarios for FFA

Scenario	$n_{y,obs}$ (years)	$n_{y,rec}$ (years)
Baseline 1	First n_y	0
Baseline 2	First n_y from Q_m	0
Baseline 3	First 15	0
Mixed 1	0	n_y
Mixed 2	First 10	Subsequent (n_y - 10)
Mixed 3	First 15	Subsequent (n_y - 15)

- At 357 gauges with 20 or more years of instantaneous data
- **Log-Pearson type 3 (LP3)** - with annual maxima
- **Generalized Pareto (GP)** - with FPOT peaks
- $T = 2, 4, 6, \ldots, 20$ *years*

- **Accuracy** based on RB and RRMSE between observed empirical ($x_{e,T}$) and distribution quantiles ($x_{d,T}$)

$$\text{RB}_T = \frac{x_{d,T} - x_{e,T}}{x_{e,T}} \times 100 \qquad \text{RB} = \frac{1}{10}\sum_T \text{RB}_T \qquad \text{RRMSE} = \sqrt{\frac{1}{10}\sum_T \text{RB}_T^2}$$

- **Uncertainty** based on relative width (w_T) of 90% confidence interval

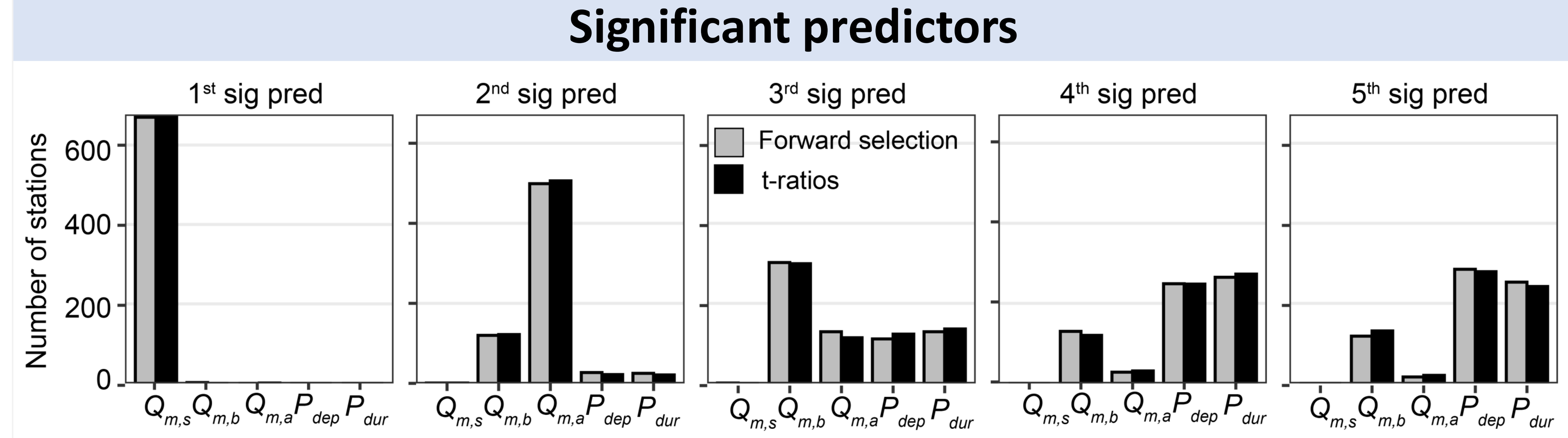
$$w_T = \frac{\left(x_{d,T}^{up} - x_{d,T}^{low}\right)}{x_{d,T}}$$

$x_{d,T}^{up}, x_{d,T}^{low}$ = upper, lower bounds of T-year quantile distribution

$x_{d,T}$ = T-year distribution quantile

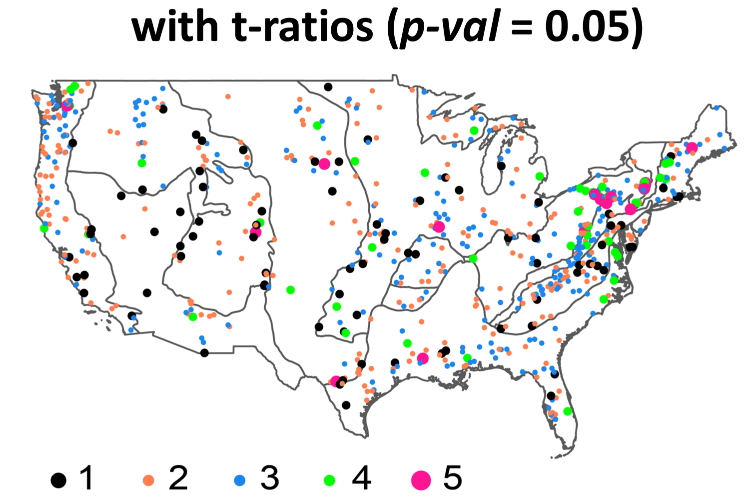
IV. Results

Significant predictors



- $Q_{m,s}$ is the most significant predictor at all sites, followed by $Q_{m,a}$ and $Q_{m,b}$
- P_{dep} and P_{dur}, mostly fourth and fifth significant predictors
- Similar results between forward selection and t-ratios

Number of significant predictors with t-ratios (*p-val* = 0.05)

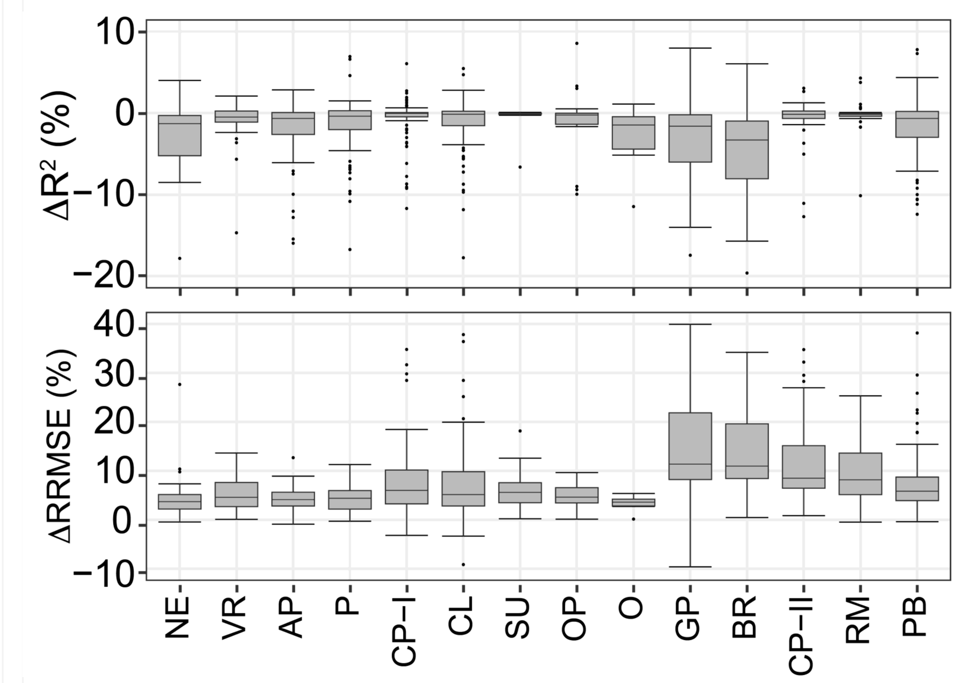


- 2 to 3 (2 to 4) significant predictors with t-ratios (forward selection)
- Minimum difference in performance of regression between the methods
- Precipitation predictors significant at 130 (19%) gauges
- Significant predictors from t-ratios selected

IV. Results

Robustness of multi-linear regressions

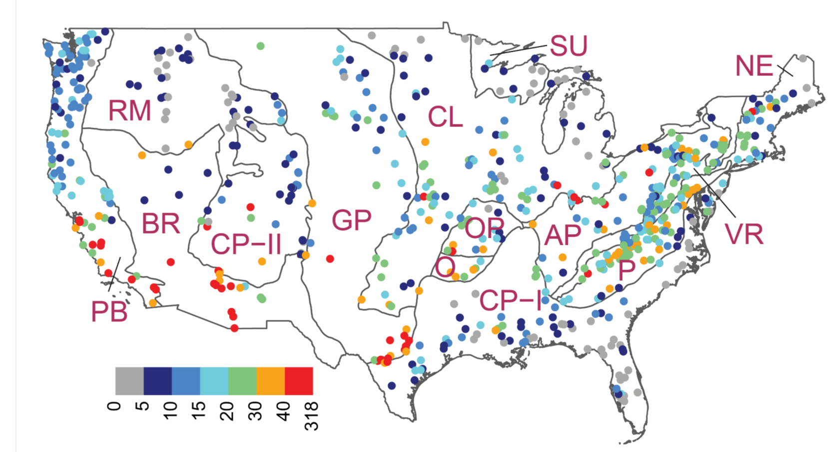
- Modest increase in RRMSE (0 - 20%) from calibration (*cal*) to validation (*val*); higher in BR, CP-II and GP and lower in O, AP and NE
- Minimum change in R²



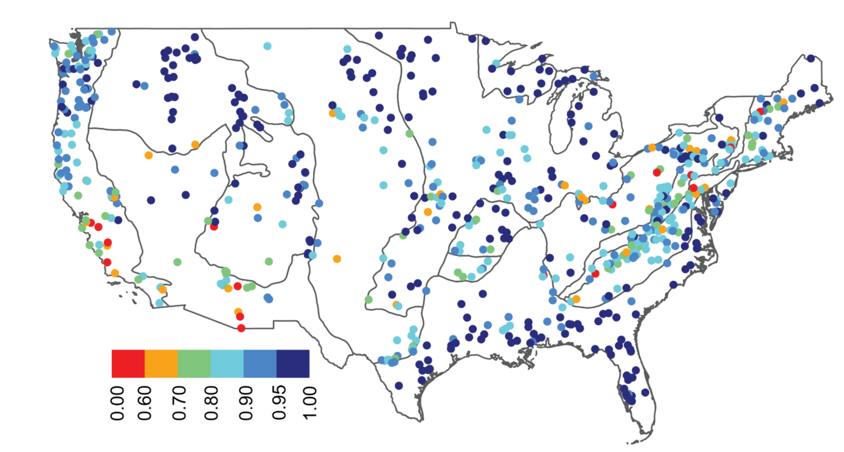
$$\Delta metric = \frac{val_{metric} - cal_{metric}}{cal_{metric}}$$

- Validation RRMSE < 20% at 70% of gauges
- RRMSE > 20% in southwestern, southeastern and Appalachian regions
- R² > 0.8 at 80% of gauges
- R² ~ 0.98: SU, CP-I and RM
- R² ~ 0.75: BR

Validation RRMSE



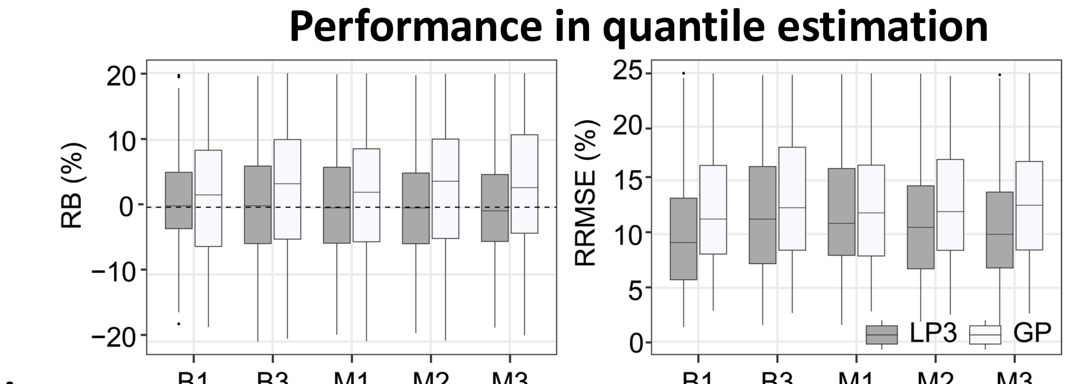
Validation R²



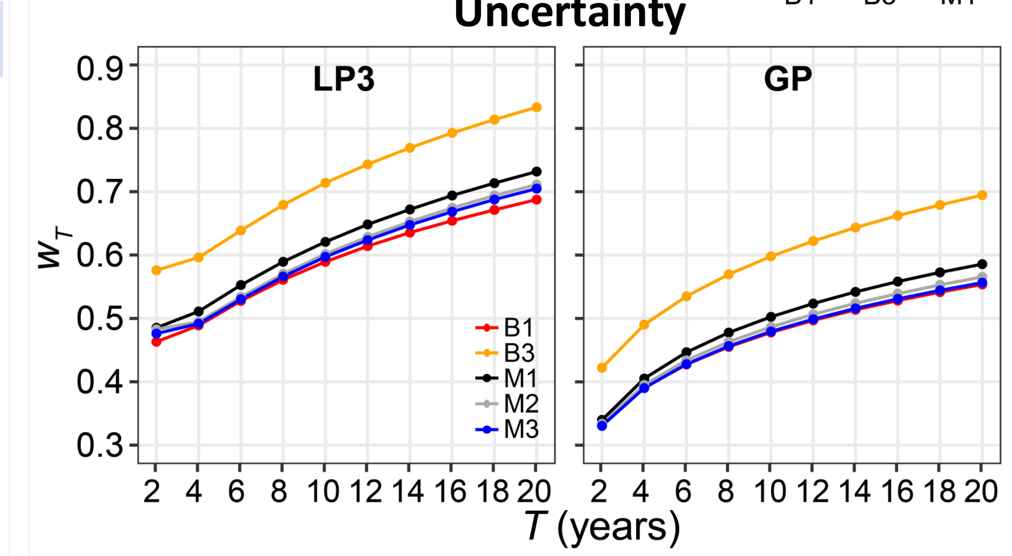
Utility of reconstructed peaks in FFA

- Daily mean in FFA underestimates the peaks (median RB = -25%) and a limited sample of peaks increases error by ~4%

Performance in quantile estimation



Uncertainty



- Mixed scenarios show improved performance in accuracy (Change in RRMSE < 2% with Baseline 1)
- Uncertainty of quantile estimates is reduced by 12% (Baseline 2 to Mixed 3)
- Lower uncertainty in GP

V. Conclusions

- In the multilinear regression, 2 to 3 predictors were sufficient, with flow predictors being dominant
- Performance of the multilinear regression is overall satisfactory, except for some gauges in southwestern, southeastern and Appalachian regions
- Adding reconstructed peaks to a limited sample of past observations lead to more reliable quantile estimates with reduced uncertainty

References

Claps, P. and Laio, F., 2003. Can continuous streamflow data support flood frequency analysis? An alternative to the partial duration series approach. *Water Resources Research*, *39*(8)