Towards a Unified Framework in Hydroclimate Extremes Prediction in Changing Climate

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Hydroclimatic Extremes Management

Challenges

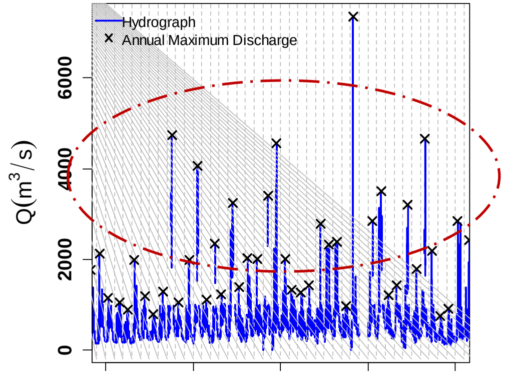
- ❑ Spatial Dependence
- ❑ Model structure uncertainty
- ❑ Non-stationarity
- ❑ Uncertainty in data and estimations
- ❑ More accurate predictions are needed
- ❑ Too complicated in practice
- ❑ Need for dynamic and up-to-date predictions

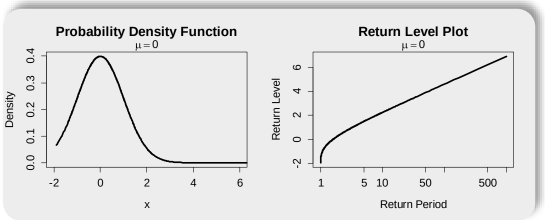
Traditional Flood Frequency Analysis

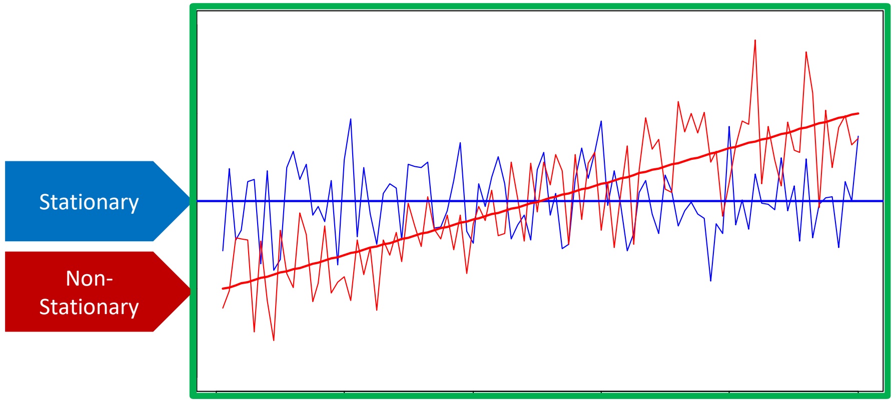
- ❑ Selection of a distribution
- ❑ Estimates the parameters
- ❑ Fitting to observed extremes
- ❑ Estimates flood quantiles (Q100)

Pros and Cons

- ❑ **Advantages**
  - ❖ Simple to use
- ❑ **Disadvantages**
  - ❖ Does not consider non-stationarity of floods
  - ❖ Does not consider spatial dependence between data
  - ❖ Does not consider the uncertainties associated with:
    - ❖ Model structure
    - ❖ Observations
    - ❖ Model estimations







Hydroclimatic Extremes Management

Challenges

- Spatial Dependence → ***Spatial Bayesian Hierarchical Model***
  Estimations in one location borrow information from other locations
- Model structure uncertainty → ***Bayesian Model Averaging***
  Conduct the modeling with various model structures
- Non-stationarity → ***Climate-informed Bayesian Hierarchical Model***
  Let model parameters change in time in accordance with climatic information
- Too complicated in practice → ***Plots, equations, and scale factors***
  Present tools that are simple to use and preserve model accuracy
- Need for dynamic and up-to-date prediction → ***Sequential Bayesian Hierarchical Model***
  A rethink about floods

Spatial Dependence

WATER RESOURCES RESEARCH, VOL. 49, 6656–6670, doi:10.1002/wrcr.20381, 2013

Analysis of runoff extremes using spatial hierarchical Bayesian modeling

Mohammad Reza Najafi[1] and Hamid Moradkhani[1]

"Everything is related to everything else, but near things are more related than distance things"
~ Tobler first law, 1970

- ❖ Models runoff extremes given their spatial variations:
  - ❖ Latitudes and longitudes
  - ❖ Drainage areas
  - ❖ Elevations
- ❖ Parameters of GPD distribution are modeled through a hierarchical Bayesian process
- ❖ Extreme floods are temporally independent
- ❖ Parameters are estimated by MCMC procedure

Drawbacks of Regional Flood Frequency Analysis

- ❖ Ignores the spatial component of the point data (geographic coordinates, elevation, …).
- ❖ Not incorporating additional data (covariates).
- ❖ Unable to explicitly estimate the uncertainties.

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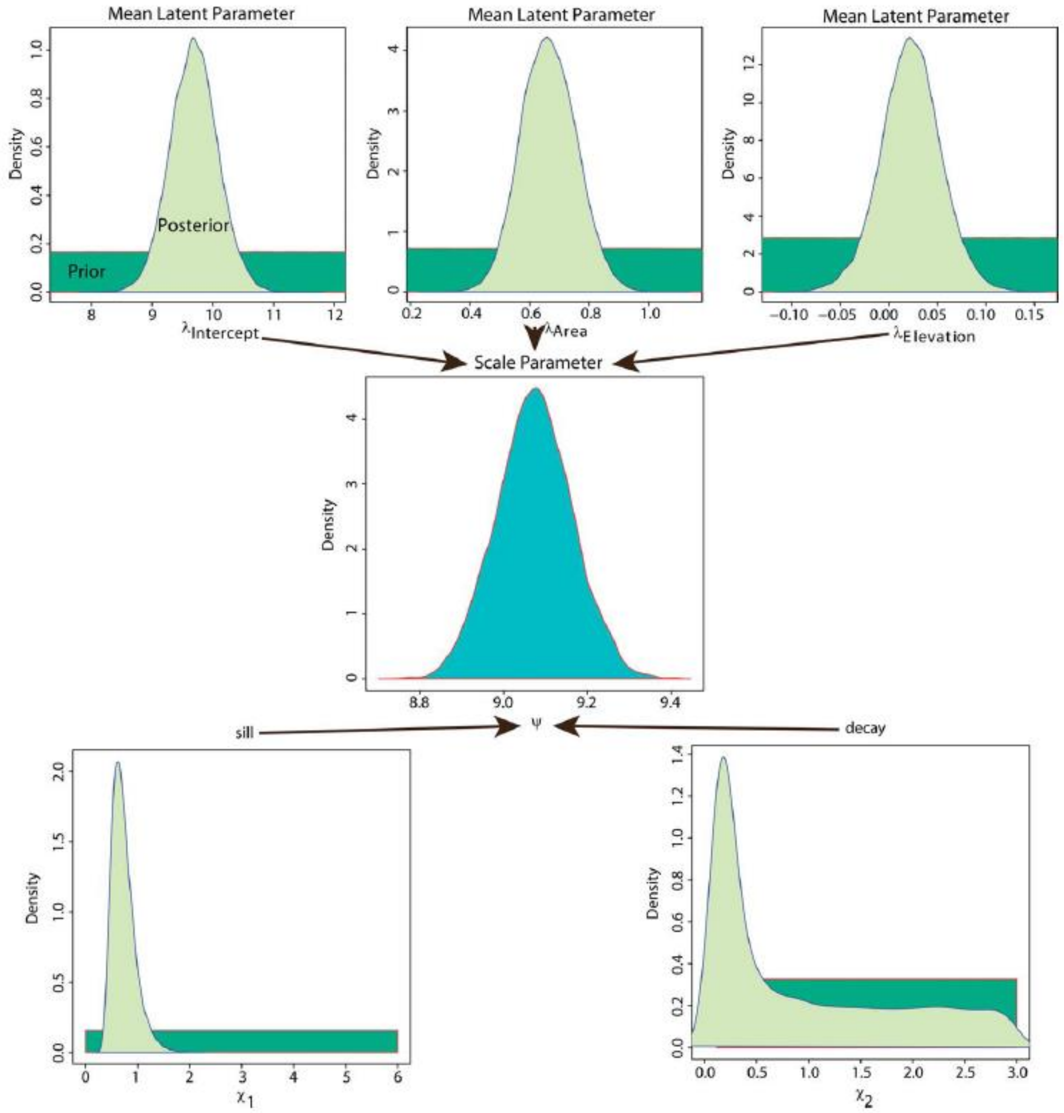
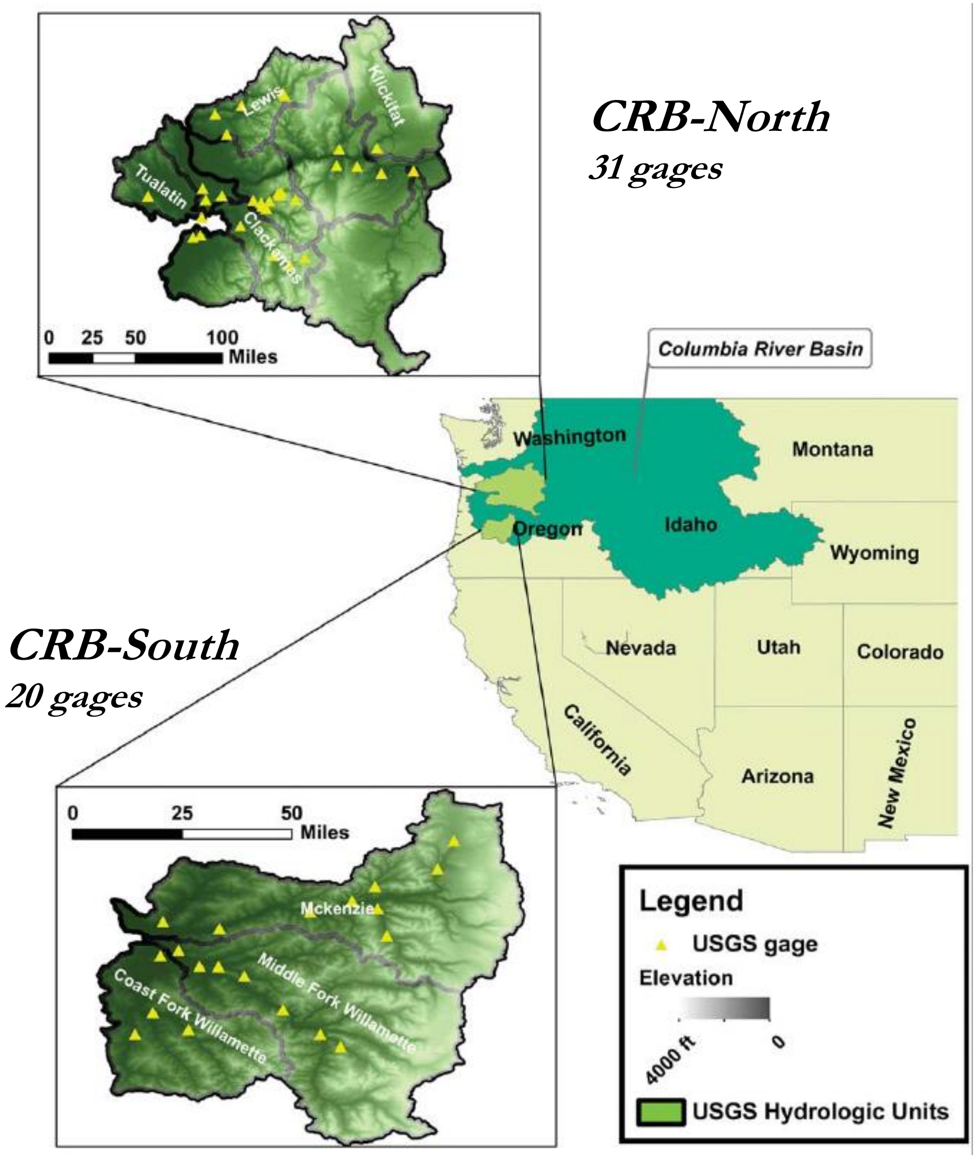
Model Structure



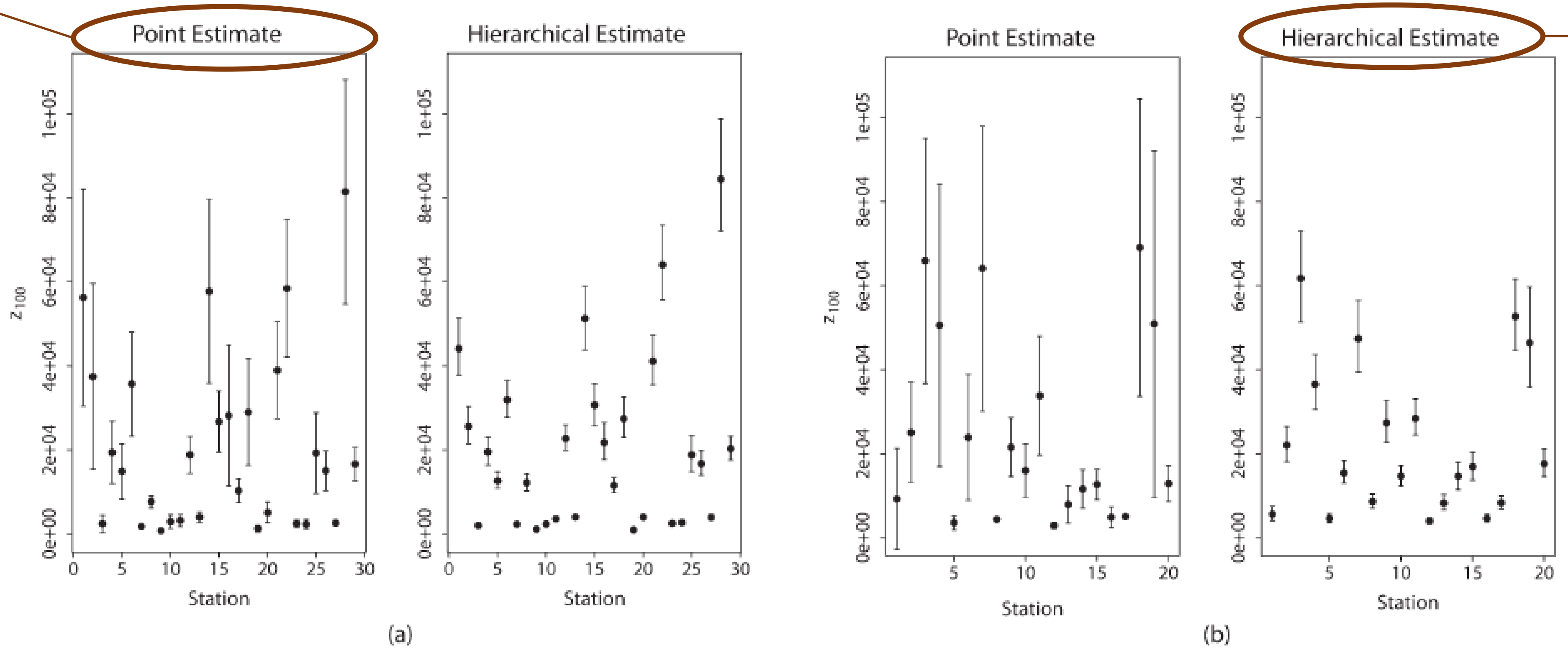
Study Area



Comparing 95% confidence intervals of 100-year flood

Separately fitted GPD Distribution

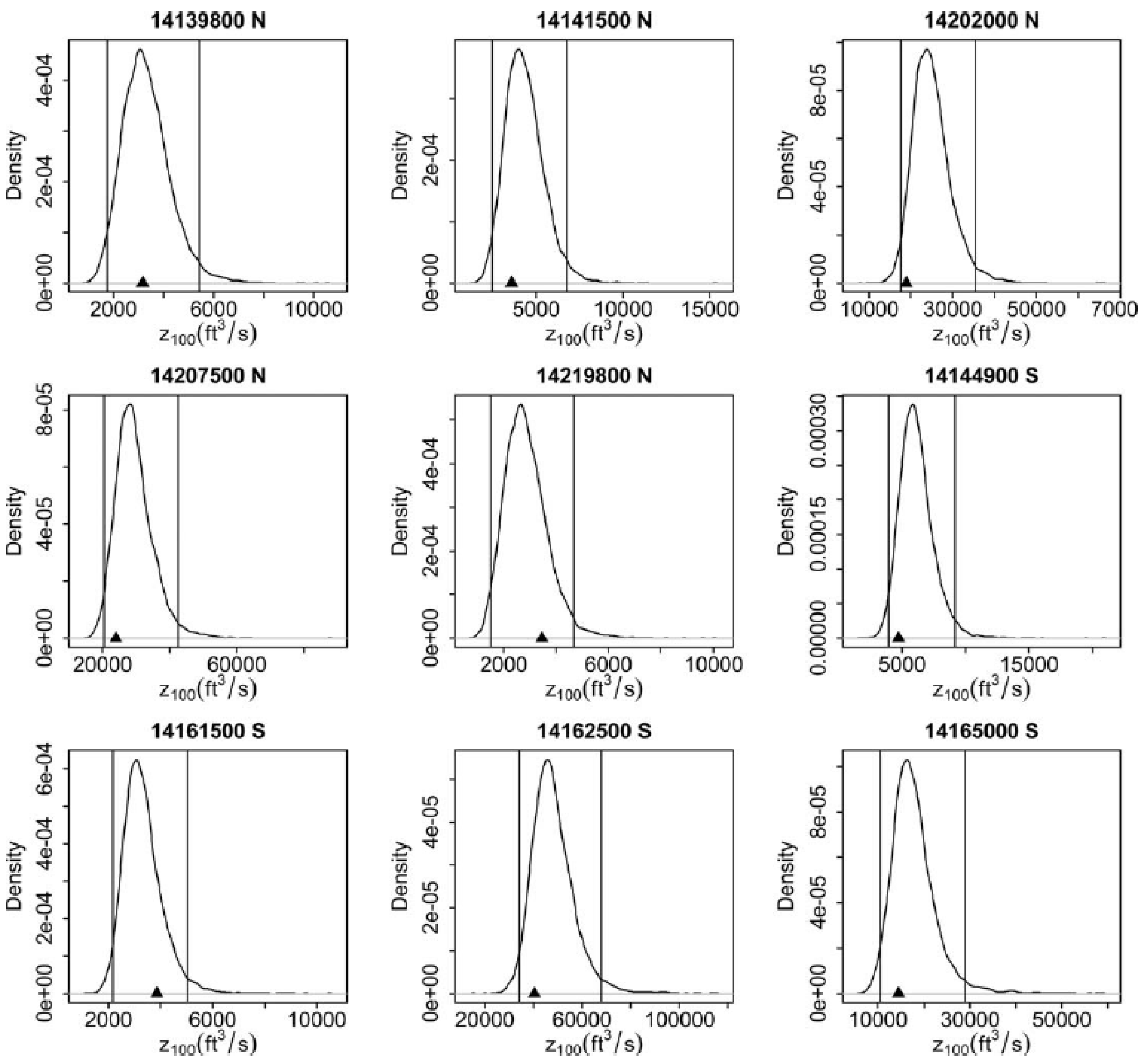
Spatial Bayesian Hierarchical Model



CRB-North

CRB-South

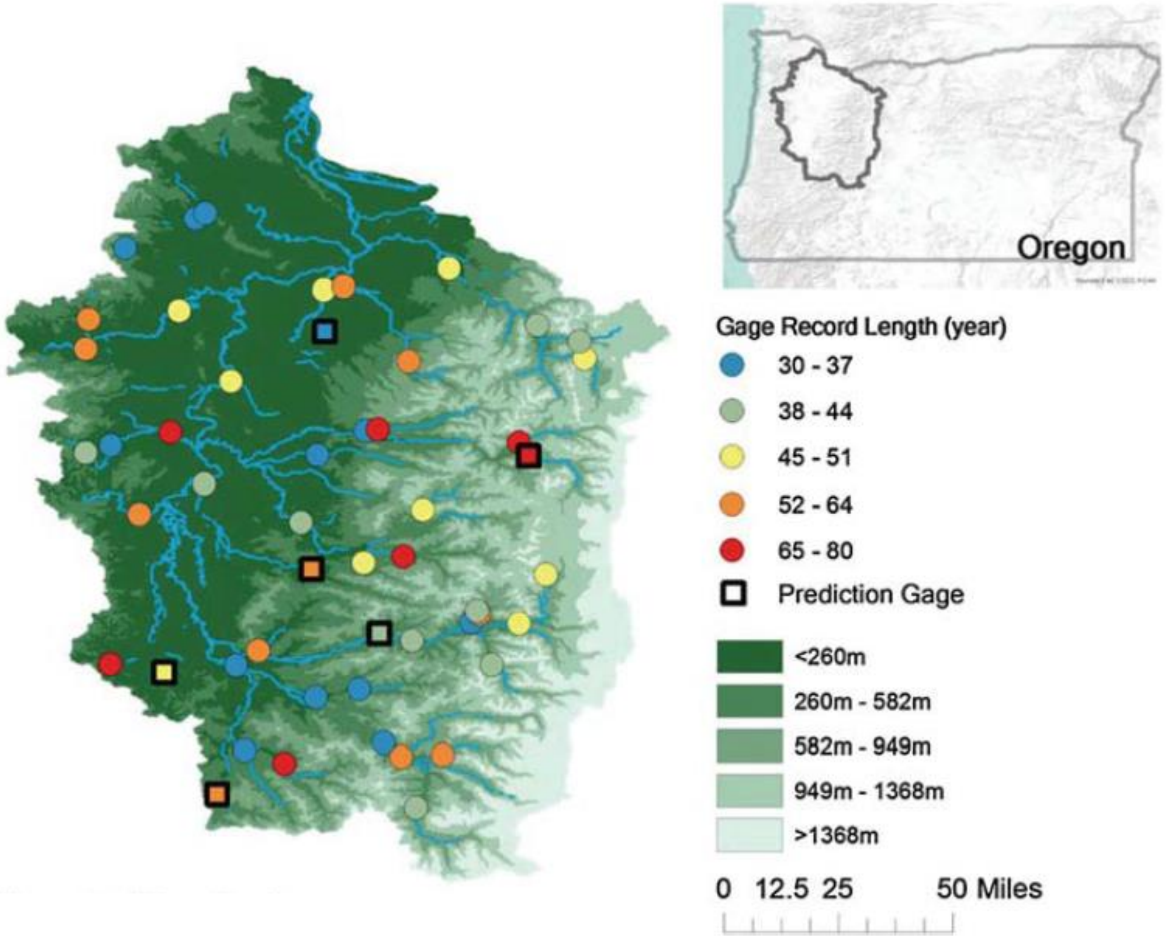
- The performance of the model is verified by predicting the 100-year return level floods for several test gages using the proposed model and comparing the results with at-site maximum likelihood estimations.
  - Significant increase in the precision
  - Satisfactory predictions for ungagged sites

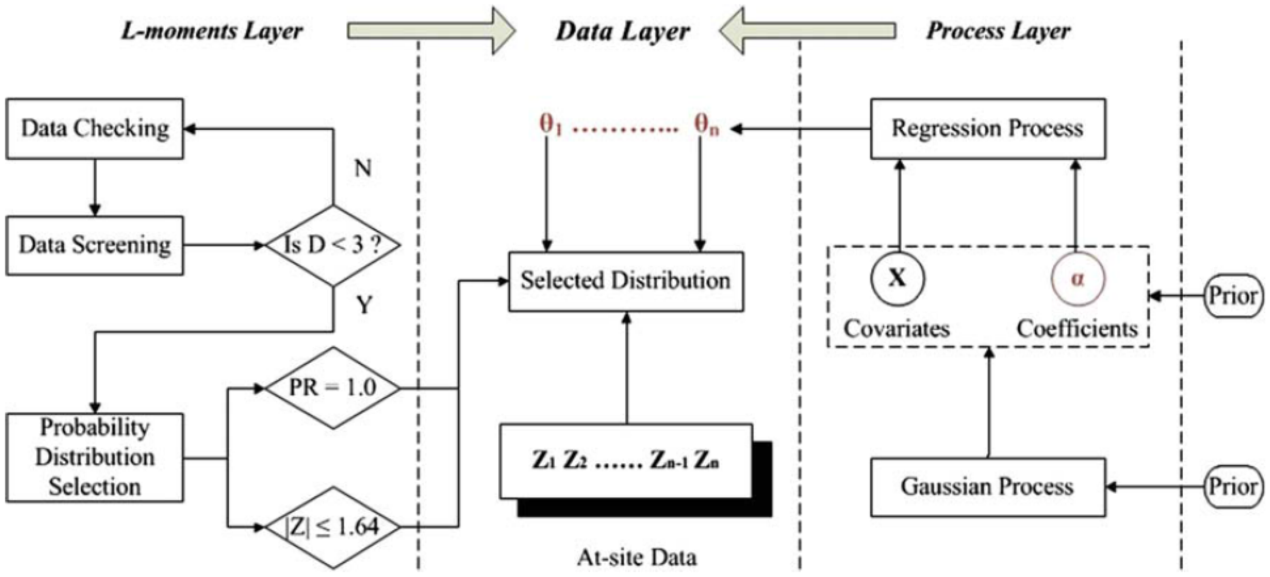


A regional Bayesian hierarchical model for flood frequency analysis

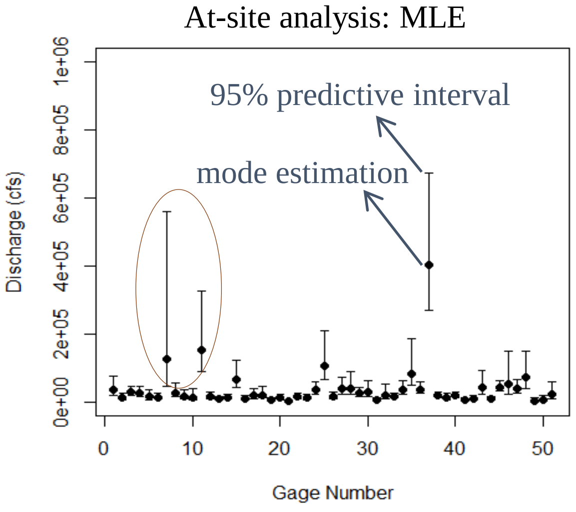
Hongxiang Yan · Hamid Moradkhani

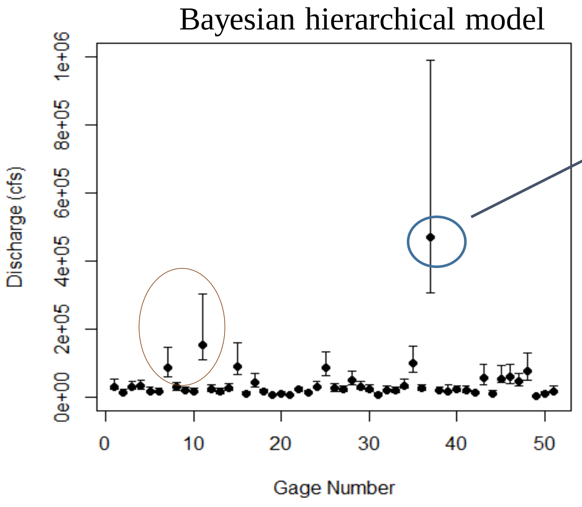
- Beyond three classical layers of the Bayesian Hierarchical Model, this study adds a layer called “L-moments layer”
- It uses L-moments theory to select a probability distribution.
- Overcomes subjective selection of a distribution.





Spatial Bayesian hierarchical model can reduce flood estimation uncertainty

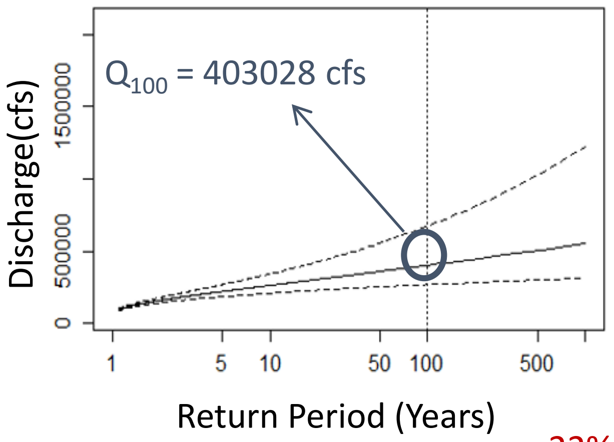




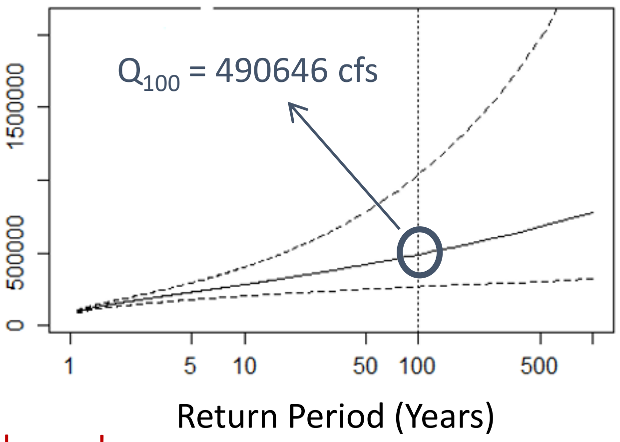
- USGS gage: 14191000
- Large contributing area (7270 mile^2)
- Historical flood happened in 1862 (not included)

Compared with at-site analysis, the Spatial Bayesian hierarchical model provides a more robust and accurate estimation

MLE: Without historic flood

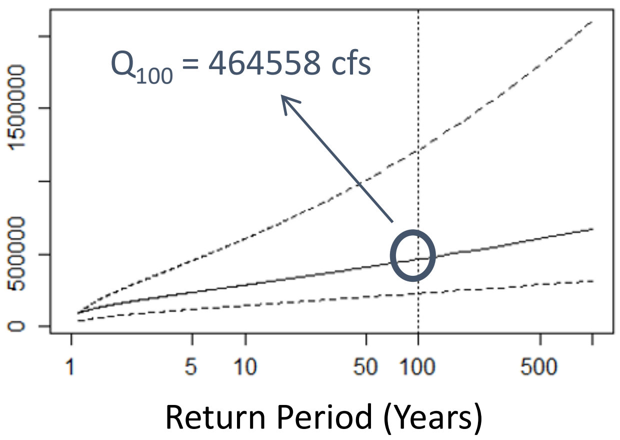


MLE: With historic flood

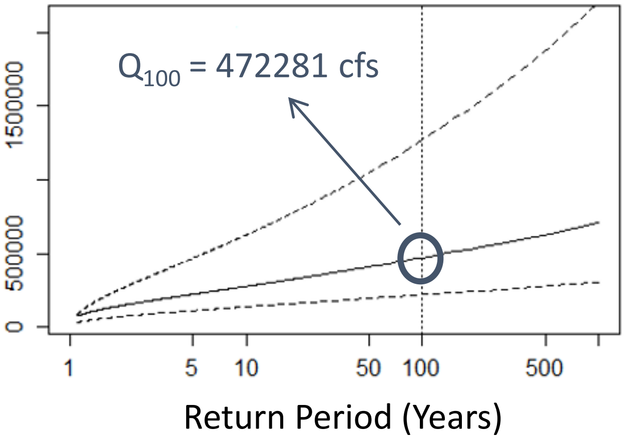


22% change!

Bayesian: Without historic flood



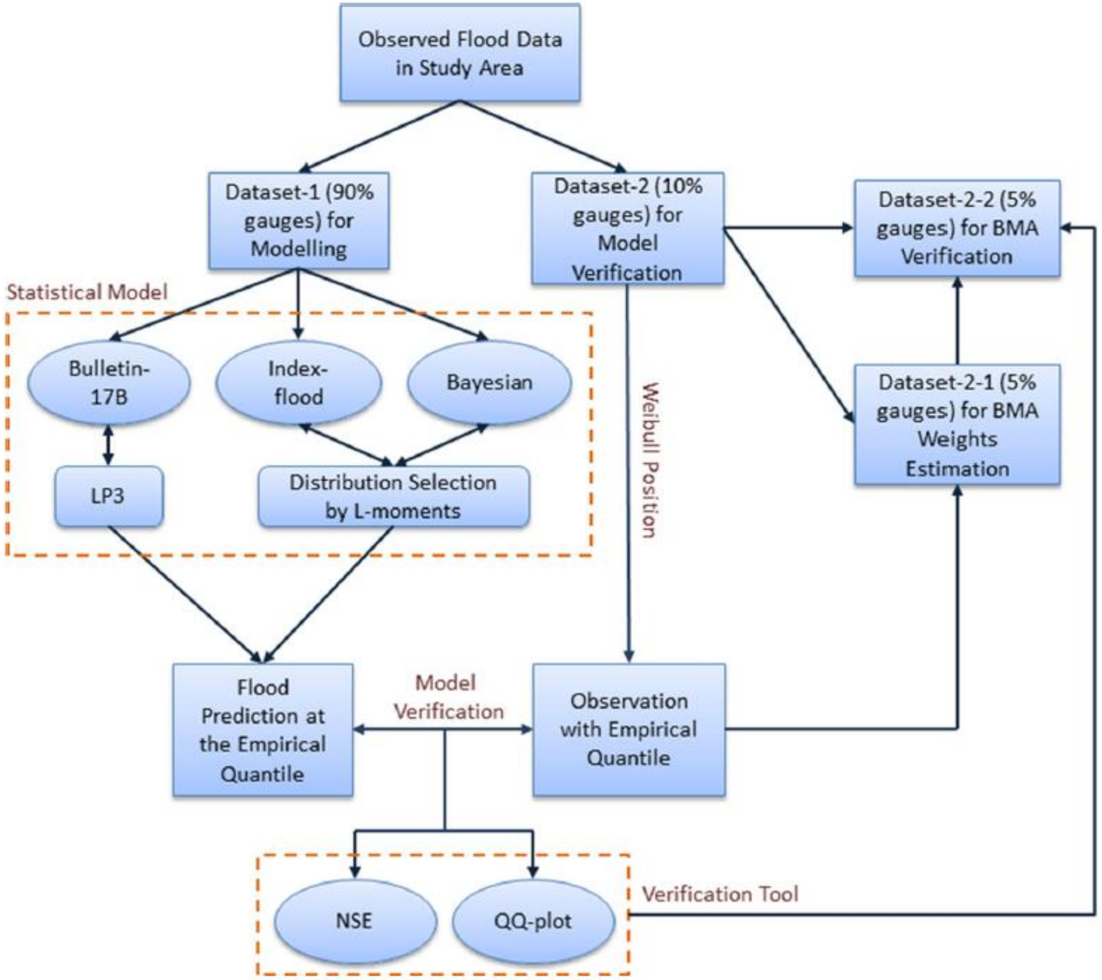
Bayesian: With historic flood

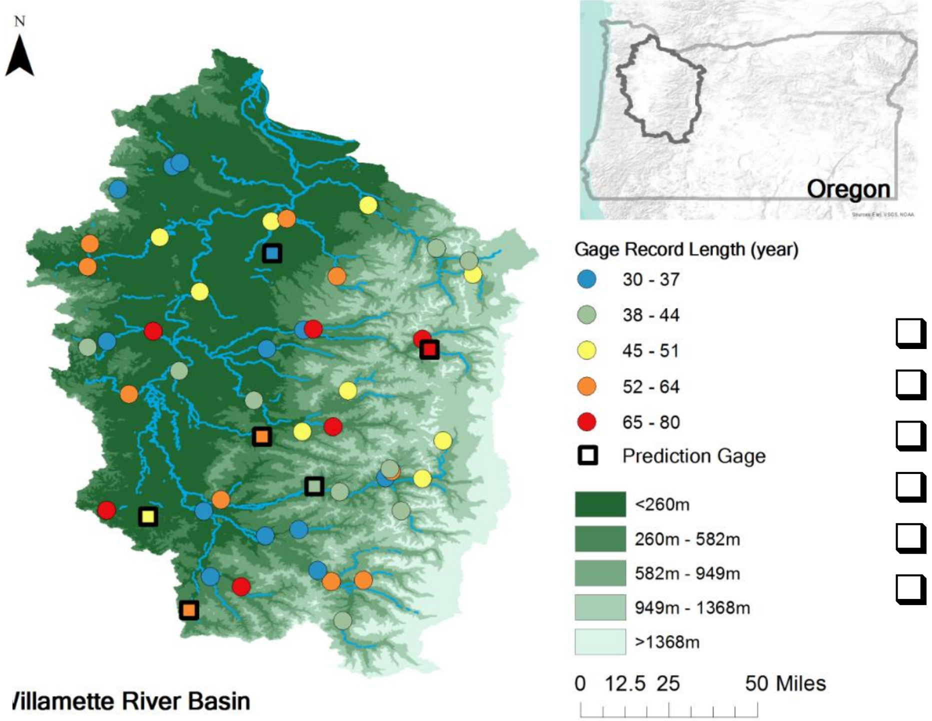


1.6% change!

Toward more robust extreme flood prediction by Bayesian hierarchical and multimodeling

Hongxiang Yan[1] · Hamid Moradkhani[1]



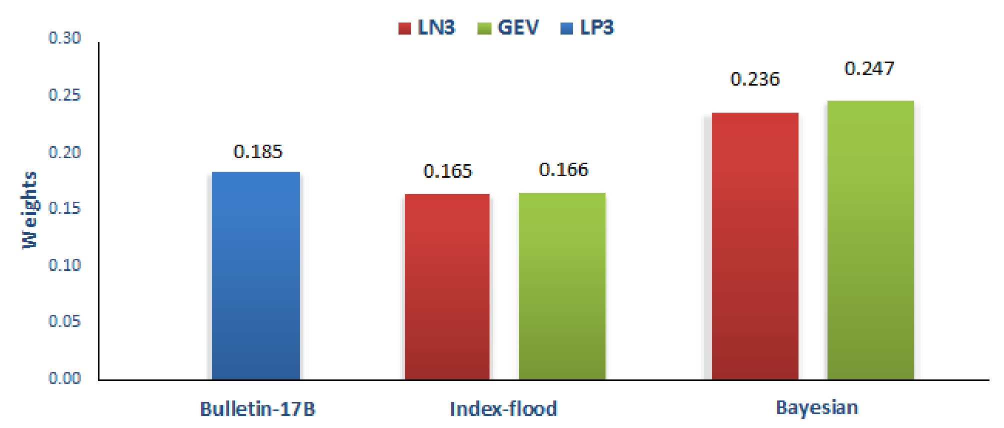


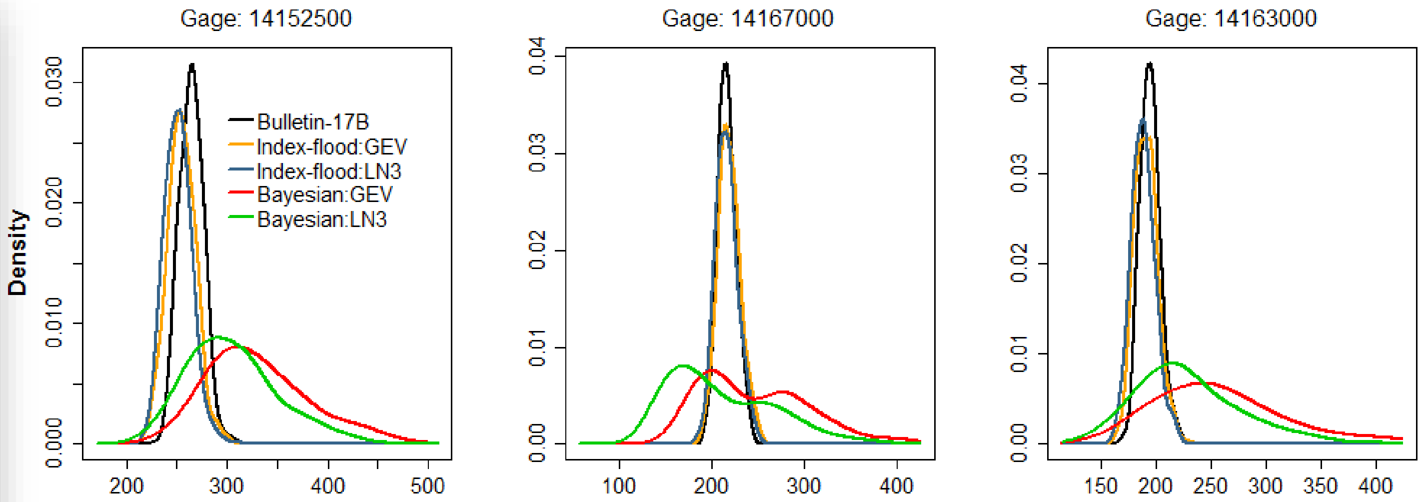
- ❑ 51 gages
- ❑ 6 gages for prediction
- ❑ At least 30 years of data
- ❑ Dam effect removed
- ❑ Not homogeneous
- ❑ RFA does not work

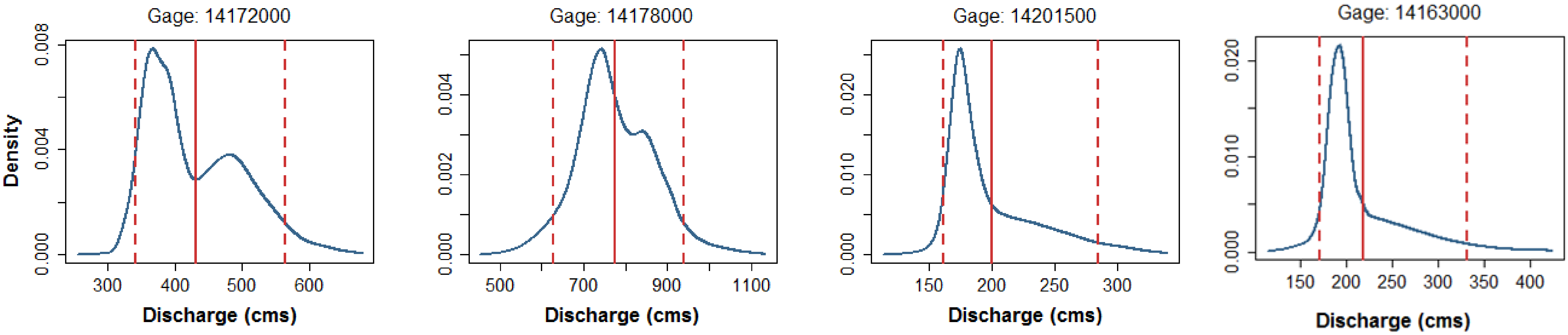
Highlights

- ❑ Each statistical model has its own drawbacks and assumptions and model structure dominates the extreme flood uncertainty
- ❑ The Bulletin-17B/C quantile method is based on at-site analysis
- ❑ The MLE estimator uncertainty relies on the Fisher information matrix
- ❑ The index-flood requires homogeneous assumption
- ❑ Spatial Bayesian hierarchical model has the isotropic assumption.

Model Structure Uncertainty

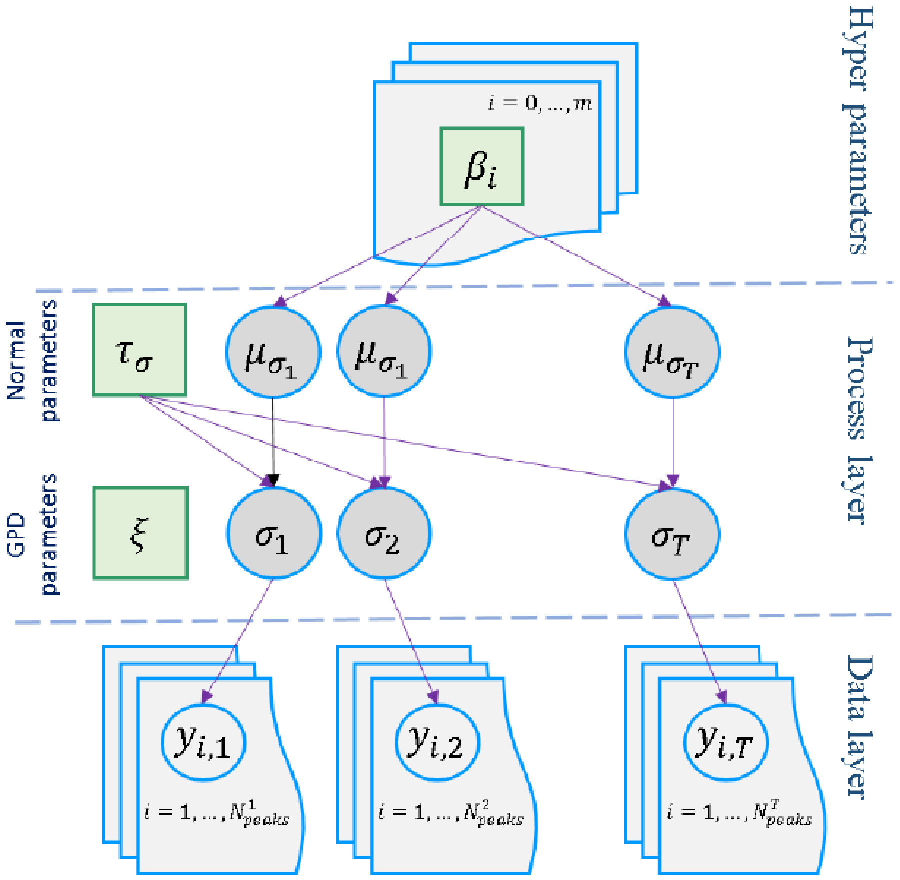


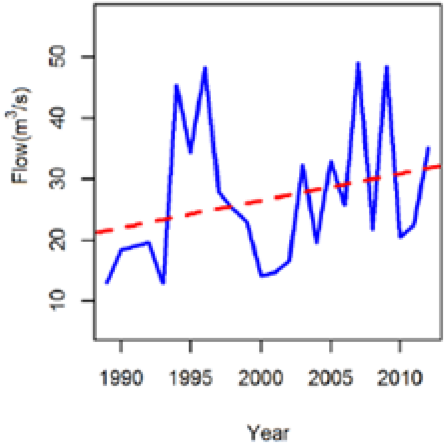


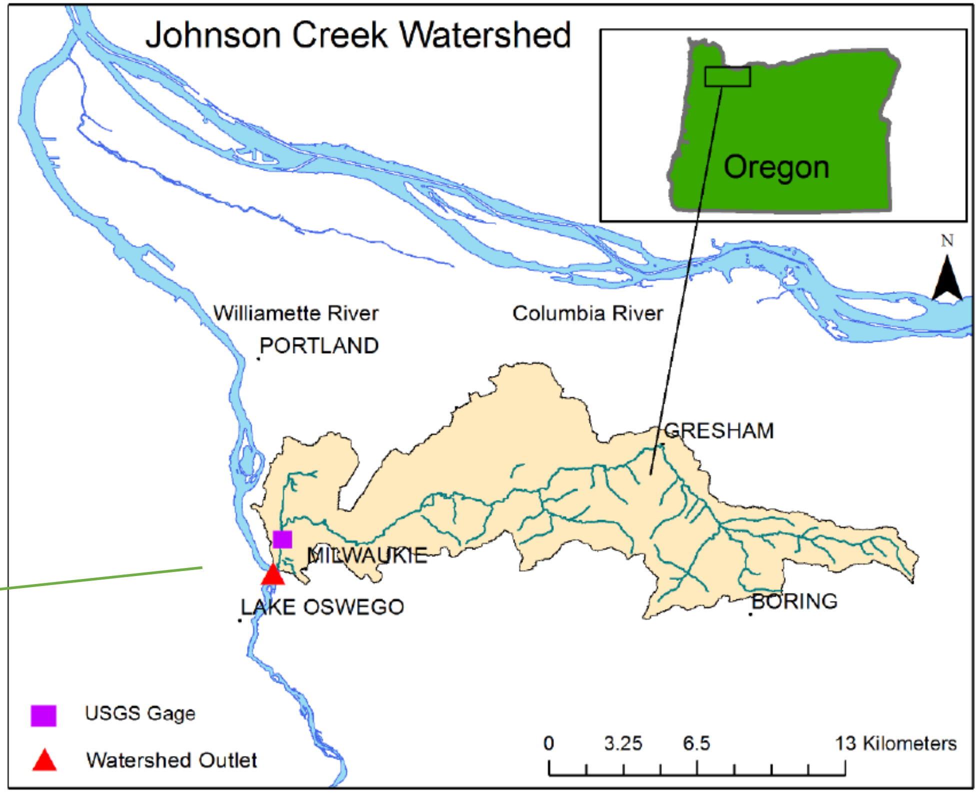


Towards a Practical Approach for Non-stationary Extreme Flood Prediction using a Climate Informed Bayesian Hierarchical model

Mahkameh Zarekarizi[1], Hamid Moradkhani, Hongxiang Yan, Cameron Bracken







Highlights

- Models Flood extremes using a Bayesian Hierarchical model
- Non-stationarity of floods are considered by letting model parameters vary in time.
- Parameters of the model vary in accordance with climate information.
- Parameters are estimated by MCMC procedure

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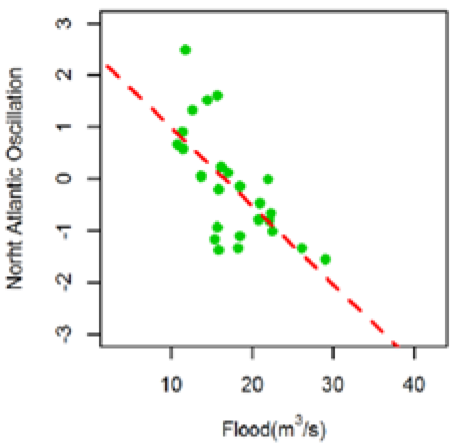
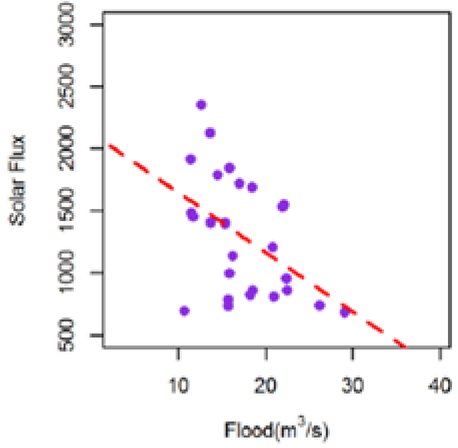
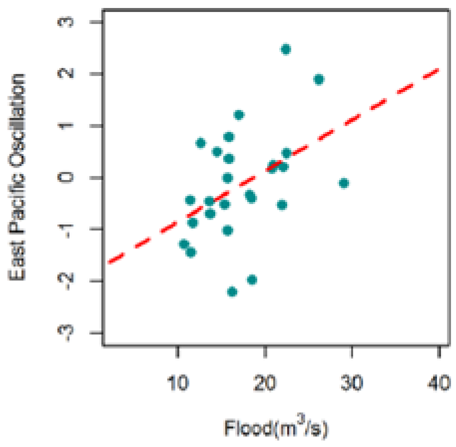
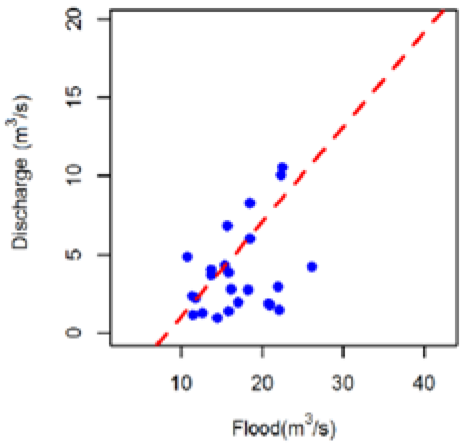
Covariates

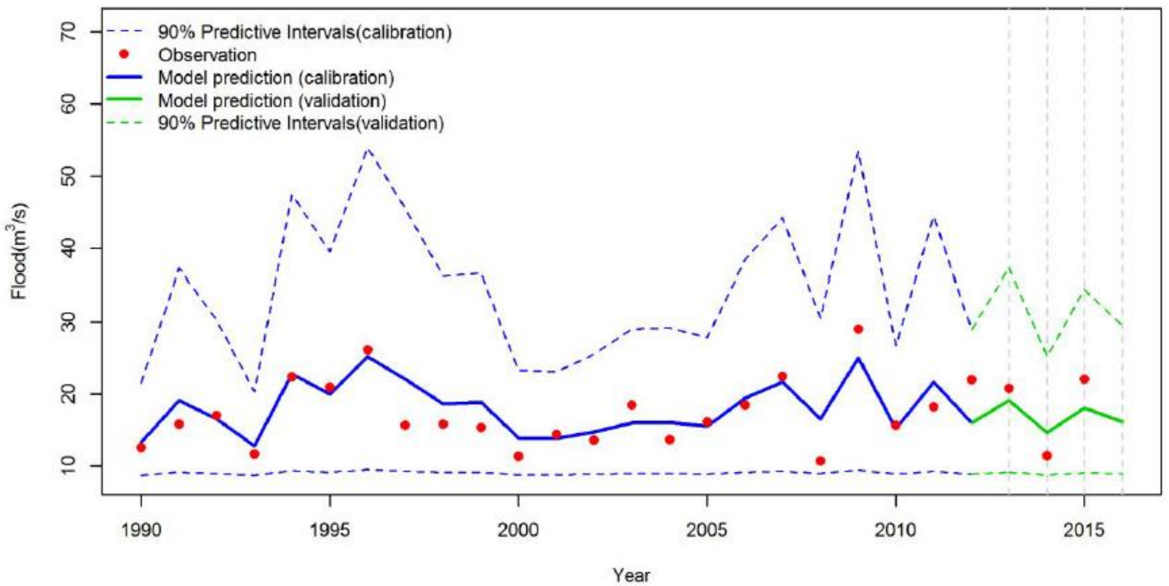




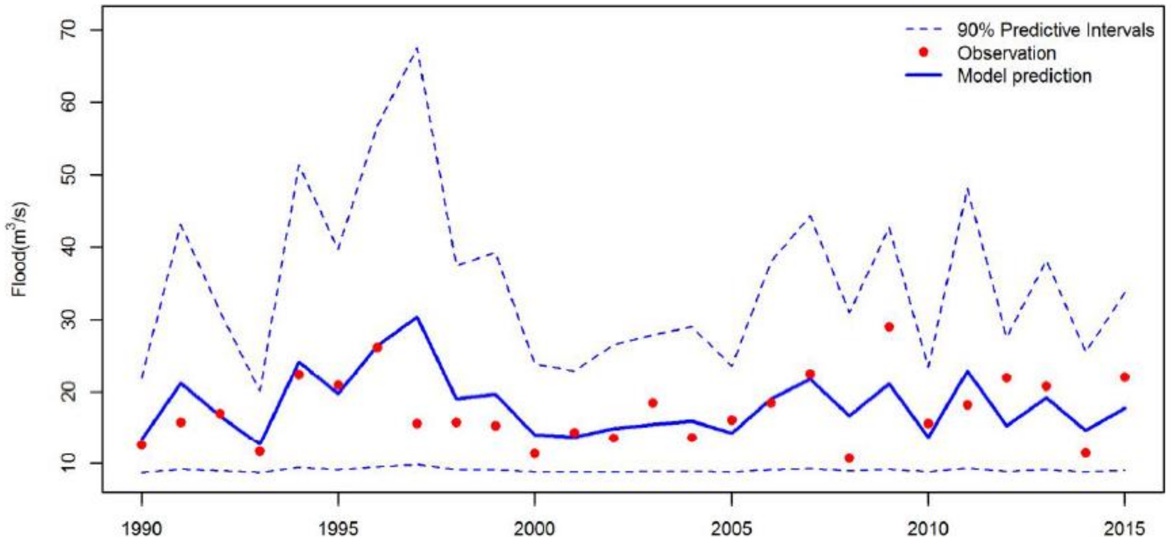




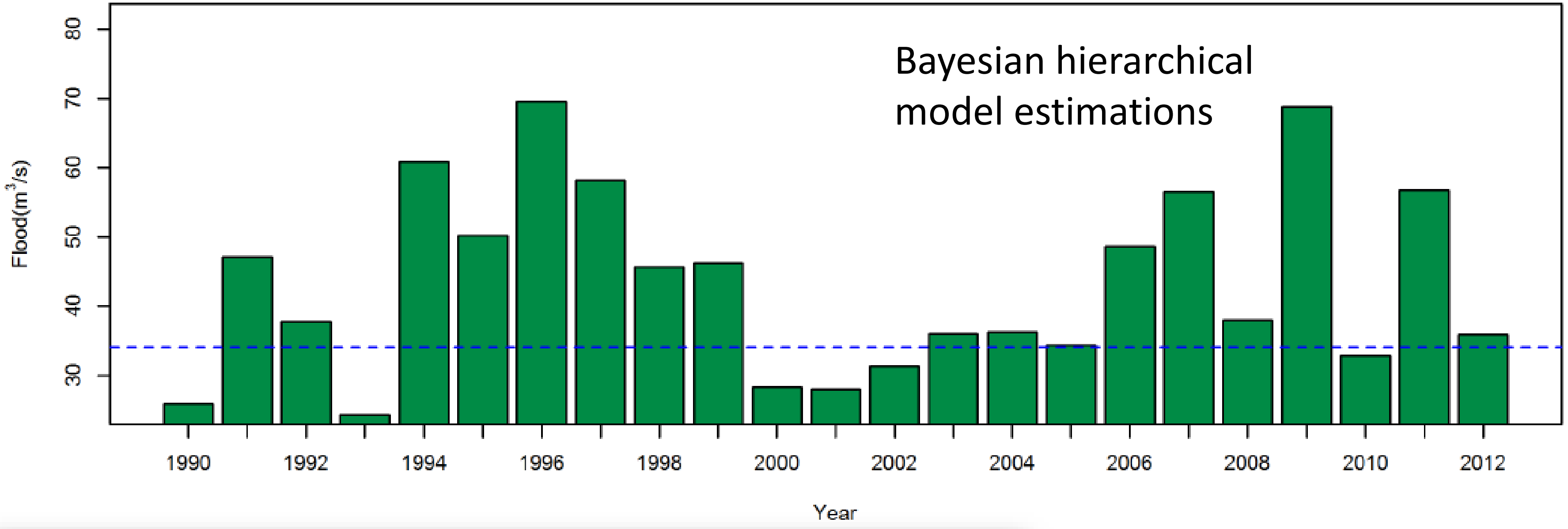
Predictions



Cross Validation



Non-Stationarity



Floods with exceedance probability of 1%

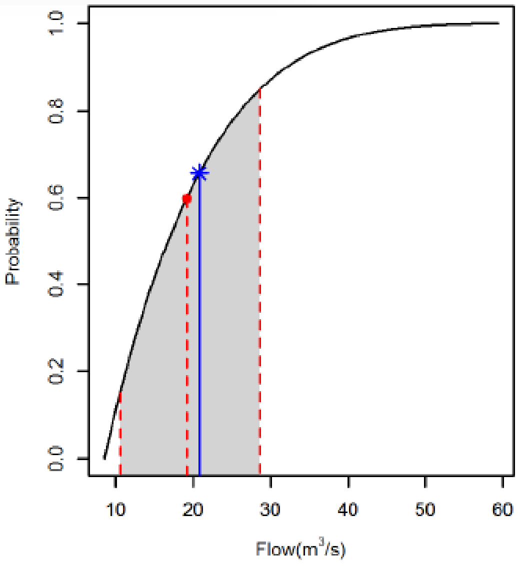
Stationary flood frequency model estimations

Model Predictions and predictive intervals

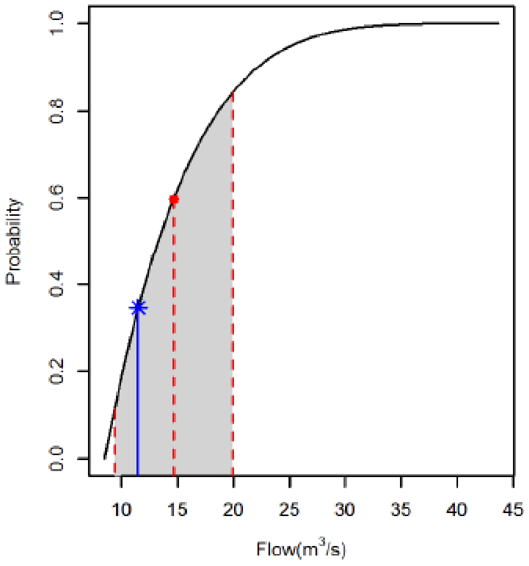
Observation

Predictive intervals
One standard deviation

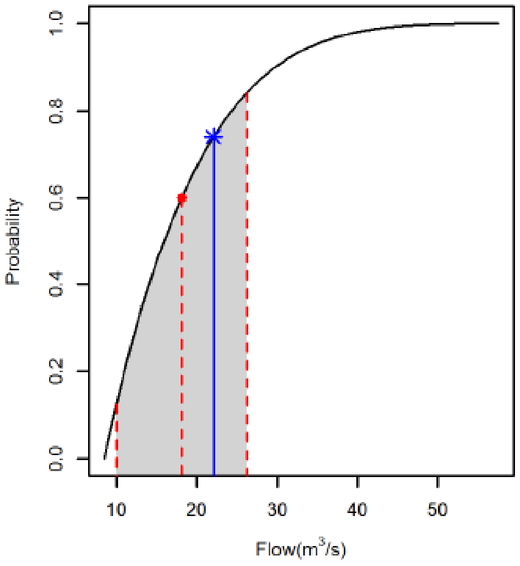
2013



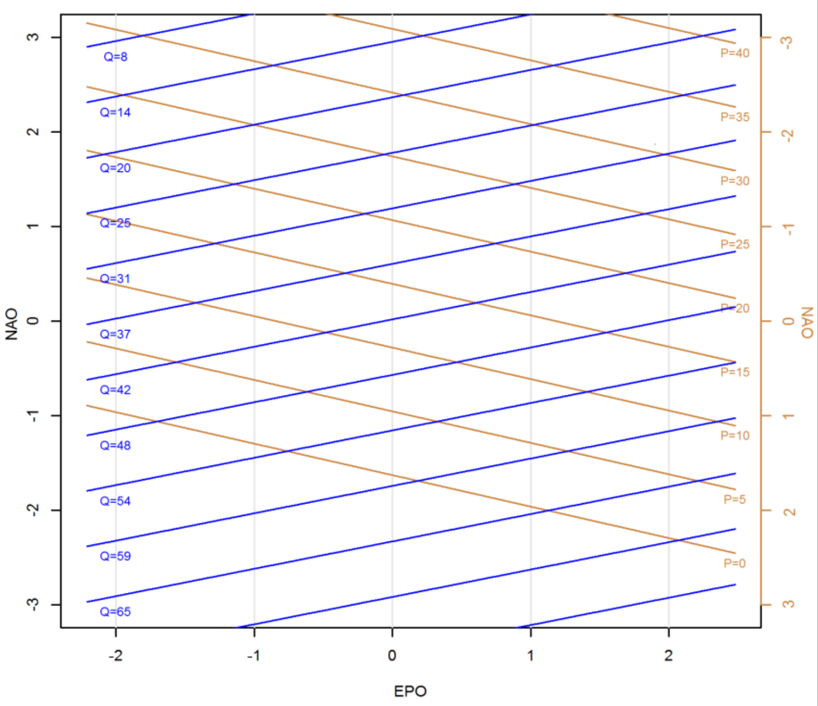
2014



2015



Early approximations of flood quantiles and probabilities given climatic information



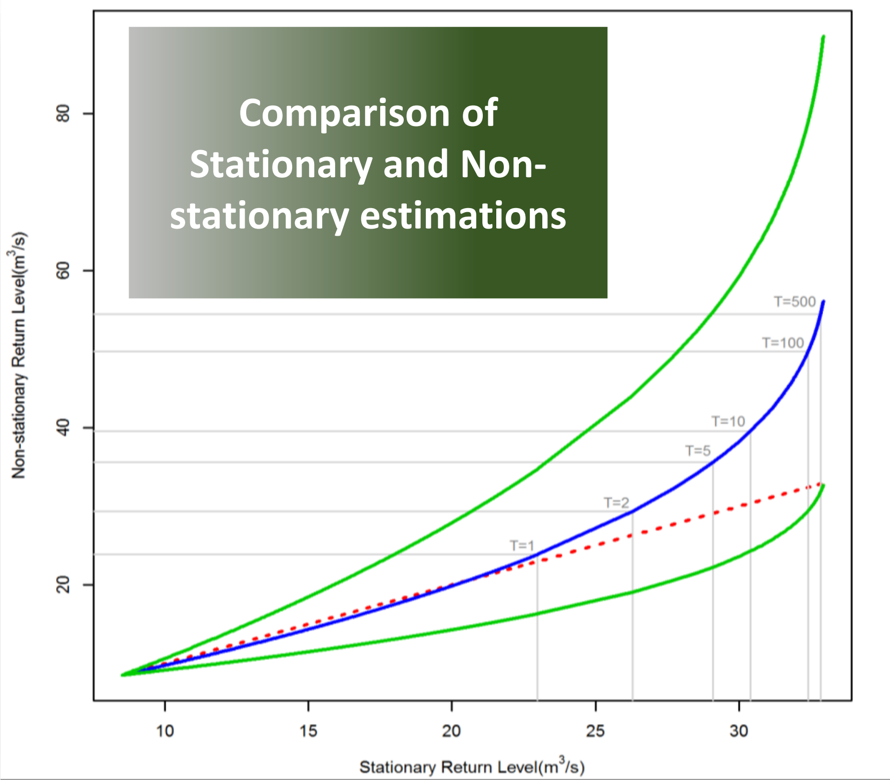
Simple Estimation of Flood Quantiles Using Climate Information

Return Period (year)	Predictive Equation (m^3/s)
500	$Q_{500} = (2257.17 - 271.61\ NAO - 0.46\ SF + 166.05\ EPO + 0.37\ q)/35.31$
200	$Q_{200} = (2094.07 - 248.97\ NAO - 0.42\ SF + 152.21\ EPO + 0.34\ q)/35.31$
100	$Q_{100} = (2257.18 - 271.61\ NAO - 0.46\ SF + 166.05\ EPO + 0.37\ q)/35.31$
80	$Q_{80} = (1899.33 - 221.95\ NAO - 0.37\ SF + 135.69\ EPO + 0.30\ q)/35.31$
50	$Q_{50} = (1785.23 - 206.11\ NAO - 0.34\ SF + 126.01\ EPO + 0.28\ q)/35.31$
20	$Q_{20} = (1530.62 - 170.78\ NAO - 0.29\ SF + 104.41\ EPO + 0.23\ q)/35.31$

Ratio of Stationary and Non-stationary estimations

Return Period (year)	Scaling Factor	Return Period (year)	Scaling Factor	Return Period (year)	Scaling Factor
1	1.038	50	1.469	300	1.621
2	1.116	60	1.487	400	1.642
5	1.223	70	1.501	500	1.658
10	1.302	80	1.513	600	1.670
20	1.377	90	1.523	700	1.681
30	1.420	100	1.532	800	1.690
40	1.448	200	1.590	1000	1.704

Comparison of Stationary and Non-stationary estimations



- Even after more than a century research of flood risk, unexpected failures and disasters due to "surprise floods" are frequent (Such as the Midwest U.S. flood and U.K. flood in 2015).

AGU PUBLICATIONS

Water Resources Research

RESEARCH ARTICLE
10.1002/2015WR017464

Charting unknown waters—On the role of surprise in flood risk assessment and management

B. Merz[1,2], S. Vorogushyn[1], U. Lall[3,4], A. Viglione[5], and G. Blöschl[5]

[1]GFZ German Research Center for Geosciences, Section 5.4 - Hydrology, Potsdam, Germany, [2]Institute of Earth and Environmental Science, University of Potsdam, Potsdam, Germany, [3]Columbia Water Center, Columbia University, New York, New York, USA, [4]Department of Earth and Environmental Engineering, Columbia University, New York, New York, USA, [5]Institute of Hydraulic Engineering and Water Resources Management, Vienna University of Technology, Vienna, Austria

Special Section:
The 50th Anniversary of Water Resources Research

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UK floods: 'Complete rethink needed' on flood defences

28 December 2015 | UK

UK Environment Agency (2015) proposed that a "complete rethink" is needed on flood defenses.

Following the direction of "rethink on flood risk analysis", a sequential Bayesian hierarchical (SBH) approach is proposed

Particle Filter Data Assimilation + **Bayesian Hierarchical Approach** = **Sequential Bayesian Hierarchical Approach**

Advantages

- Relax the Gaussian error assumption
- Fully quantify the flood system uncertainty
- Parameters are dynamically updated when new observations became available
- Able to track the possible system changes

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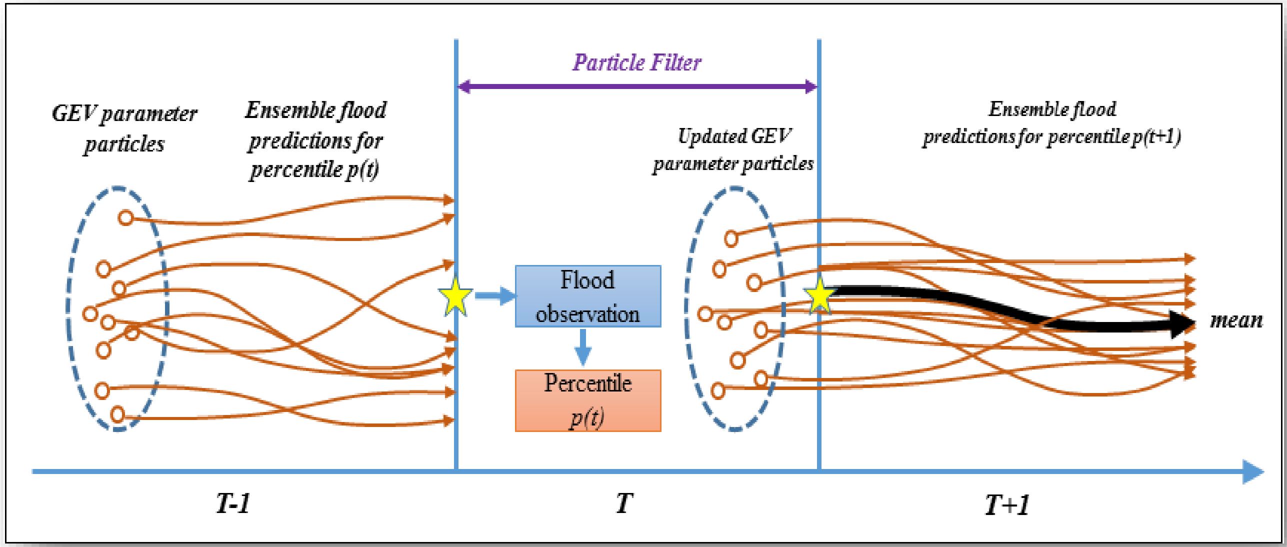
Framework



- Annual maximum streamflow are fitted to the generalized extreme value (GEV) distribution:

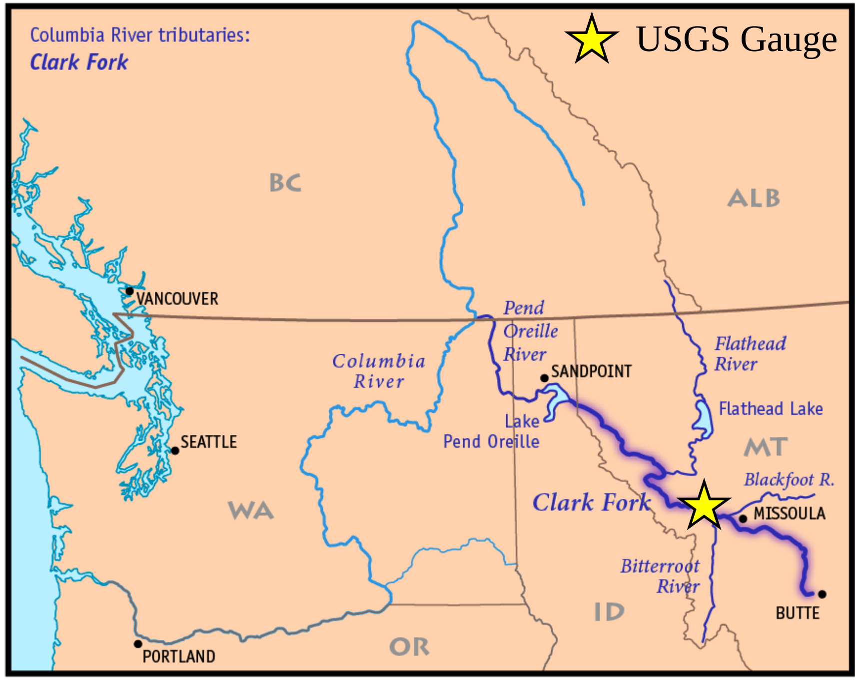
- The GEV non-stationary parameters for the three RCP scenarios are:

$$RCP2.6: \quad \mu_t = \begin{cases} C_1 + (t-1930)\times S_1 & 1930 < t \le 2050 \\ C_1 + (2050-1930)\times S_1 & 2050 < t \le 2100 \end{cases} \quad \sigma_t = \begin{cases} C_2 + (t-1930)\times S_2 & 1930 < t \le 2050 \\ C_2 + (2050-1930)\times S_2 & 2050 < t \le 2100 \end{cases} \quad \varepsilon = C_3$$

$$RCP6.0: \quad \mu_t = C_1 + (t-1930)\times S_1 \quad 1930 < t \le 2100 \quad \sigma_t = C_2 + (t-1930)\times S_2 \quad 1930 < t \le 2100 \quad \varepsilon = C_3$$

$$RCP8.5: \quad \mu_t = C_1 + (t-1930)^2\times S_1 \quad 1930 < t \le 2100 \quad \sigma_t = C_2 + (t-1930)^2\times S_2 \quad 1930 < t \le 2100 \quad \varepsilon = C_3$$

Study Area: Clark Fork River, Montana



The ultimate purpose is to estimate the posteriors for the parameter coefficients C and S for the location and scale parameters.

Sequential Bayesian Hierarchical

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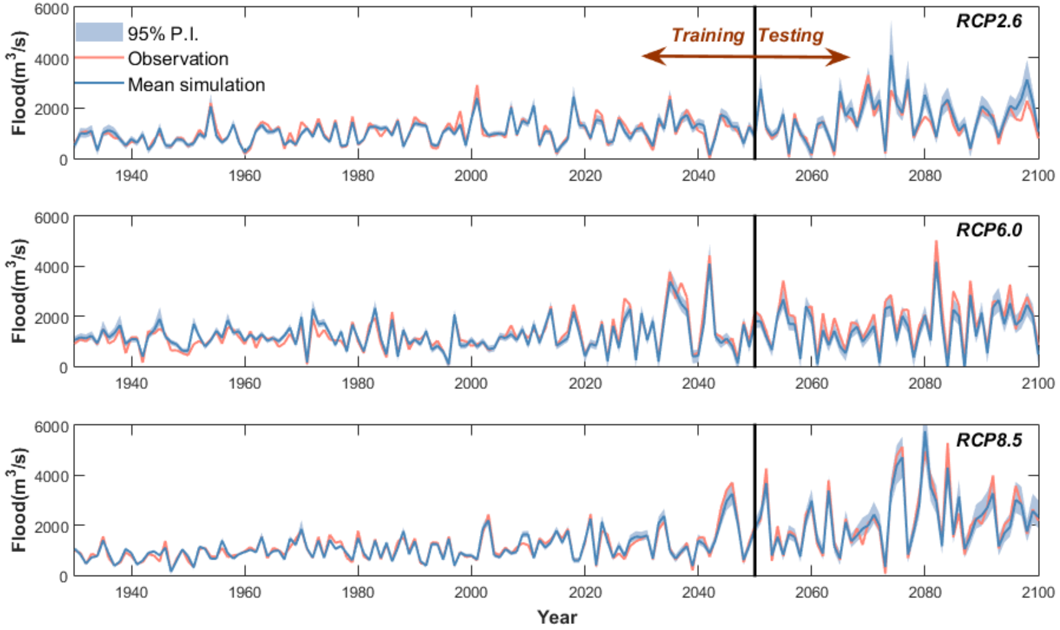
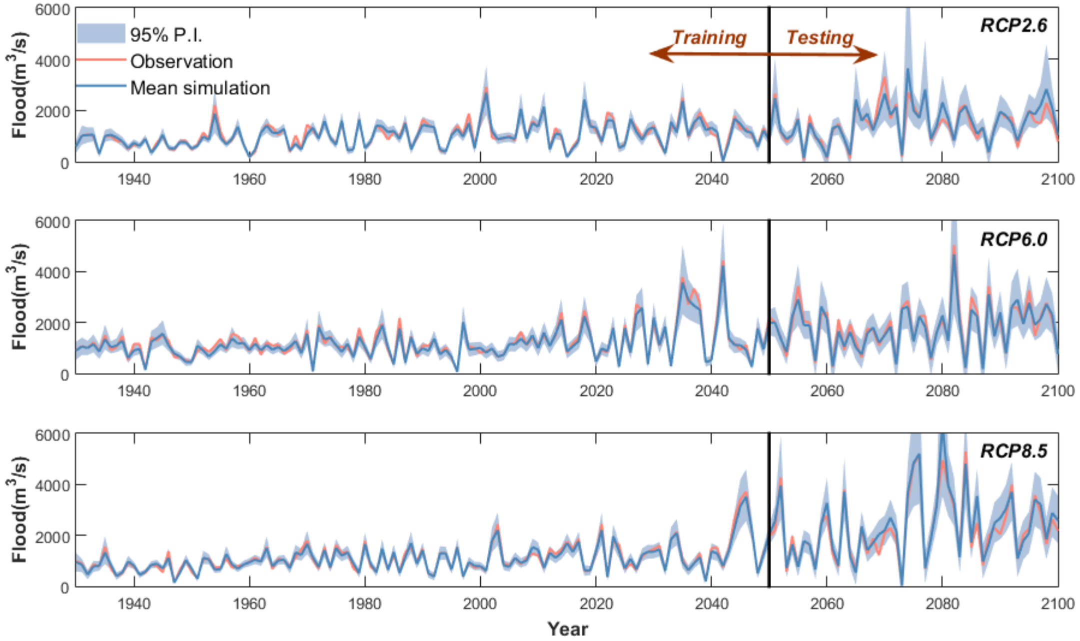
Synthetic Study Comparison Results

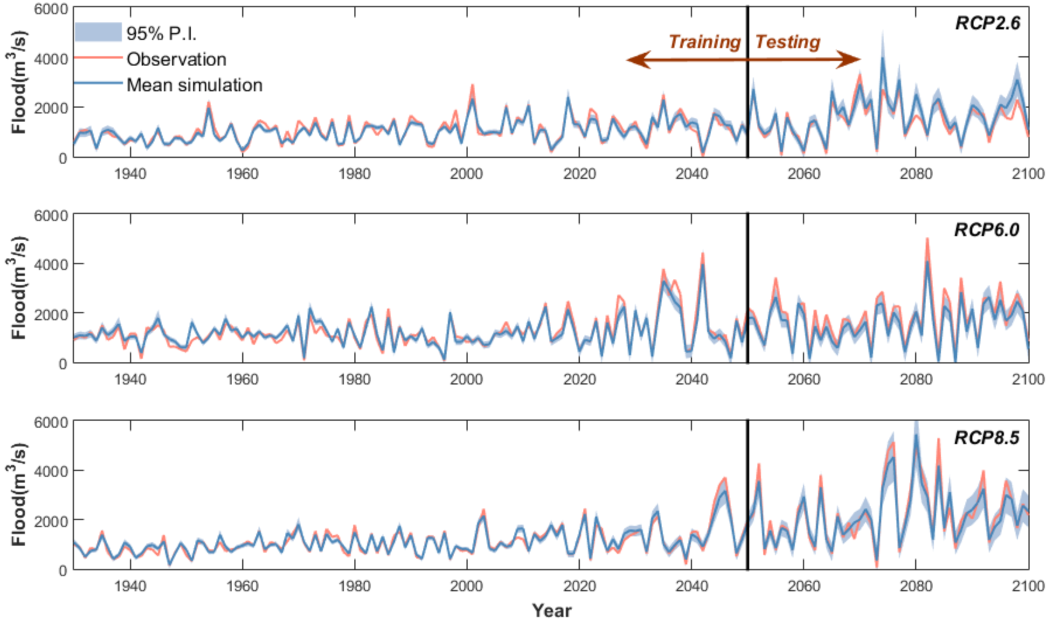
MCMC



SBH



MLE



Method	KGE	Scenario		
		RCP2.6	RCP6.0	RCP8.5
SBH	Training	0.94	0.91	0.92
	Testing	0.92	0.91	0.92
MLE	Training	0.85	0.86	0.88
	Testing	0.83	0.80	0.85
MCMC	Training	0.88	0.89	0.91
	Testing	0.81	0.80	0.89

Method	Surprise Flood Ratio (%)	Scenario		
		RCP2.6	RCP6.0	RCP8.5
SBH	Training	4.96	4.96	0
	Testing	0	0	0
MLE	Training	23.14	23.14	17.36
	Testing	2	32	8
MCMC	Training	19.84	21.49	23.14
	Testing	2	38	6

Surprise Flood Ratio

- ❖ Is used to assess the associated uncertainty of the predictions.
- ❖ If the predicted 95% uncertainty range cannot capture the synthetic observation, it is counted as one "surprise flood" event.

Conclusion

- ❖ The proposed sequential Bayesian hierarchical (SBH) approach was found to perform better than the MLE and MCMC methods.
- ❖ The parameter posteriors estimated from MLE and MCMC cannot represent the future posteriors under climate change.
- ❖ Conceptually, the SBH approach is able to capture the "flood terra incognita" and leads to no "surprise" flood event.
- ❖ The developed SBH here is not intended to replace any current flood risk methods, but to propose a "complete rethink" in non-stationary flood risk analysis.

References

- Merz, B., S. Vorogushyn, U. Lall, A. Viglione, and G. Blöschl. "Charting unknown waters—On the role of surprise in flood risk assessment and management." *Water Resources Research* 51, no. 8 (2015): 6399-6416.

- Reza Najafi, Mohammad, and Hamid Moradkhani. "Analysis of runoff extremes using spatial hierarchical Bayesian modeling." *Water Resources Research* 49, no. 10 (2013): 6656-6670.

- Yan, Hongxiang, and Hamid Moradkhani. "A regional Bayesian hierarchical model for flood frequency analysis." *Stochastic Environmental Research and Risk Assessment* 29, no. 3 (2015): 1019-1036.

- Yan, Hongxiang, and Hamid Moradkhani. "Toward more robust extreme flood prediction by Bayesian hierarchical and multimodeling." *Natural Hazards* 81, no. 1 (2016): 203-225.

Thank you