A space–time Bayesian hierarchical modeling framework for projection of seasonal high flow risk

Frontiers in Hydrology
Future of Water · 19–24 JUNE 2022
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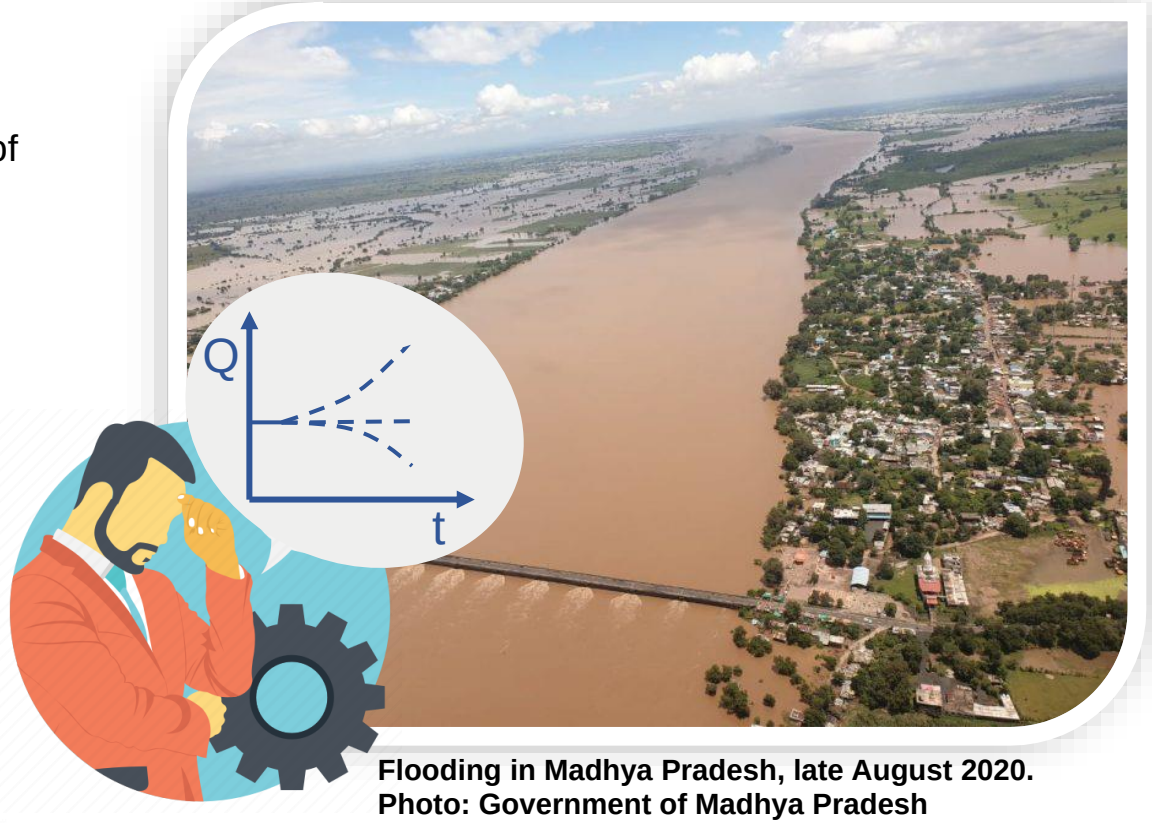

Flooding in Madhya Pradesh, late August 2020.
Photo: Government of Madhya Pradesh

Session 405: Interpreting and Attributing the Drivers of Hydrological Non-Stationarity II Oral

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Study Region and Data

Streamflow

- Daily observed streamflow during the peak monsoon season (July-August) – *India Water Resource Information System (IWRIS)*
- Period: 1978-2018 (37 years), no. of sites 5
- Daily maximum peak monsoon season (July-August) streamflow

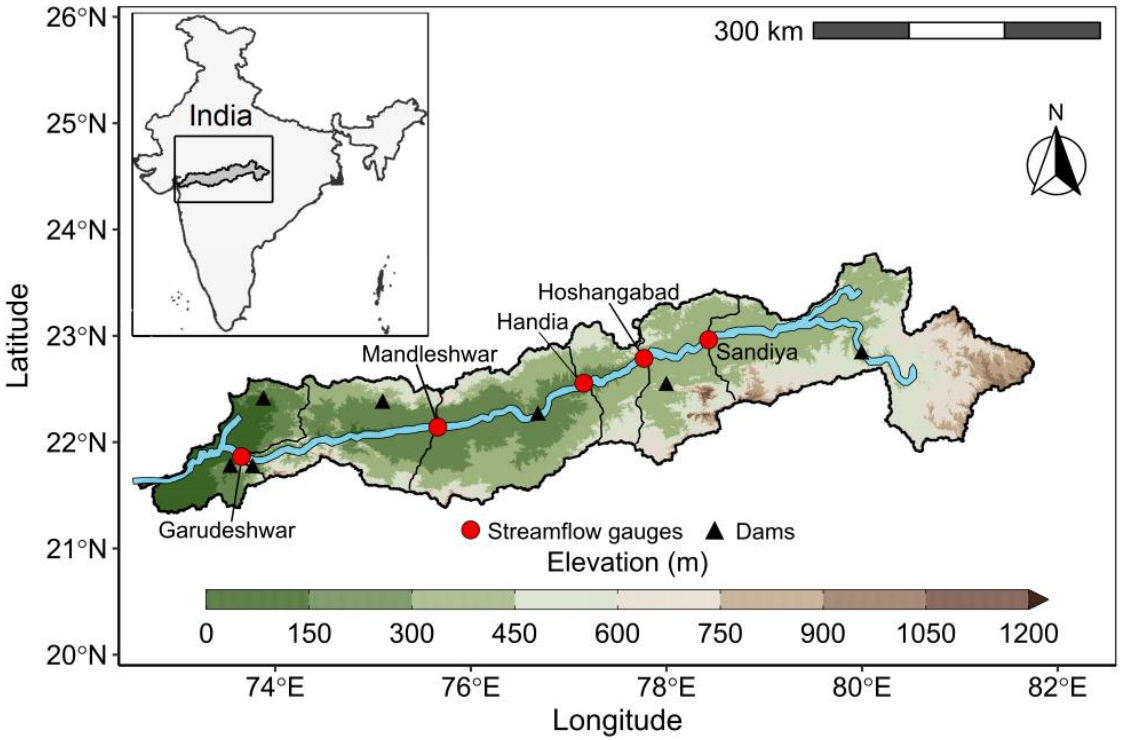
Precipitation

- Daily gridded precipitation - *India Meteorology Department (IMD)*
- Spatial Resolution: 0.25°
- Period: 1978-2018

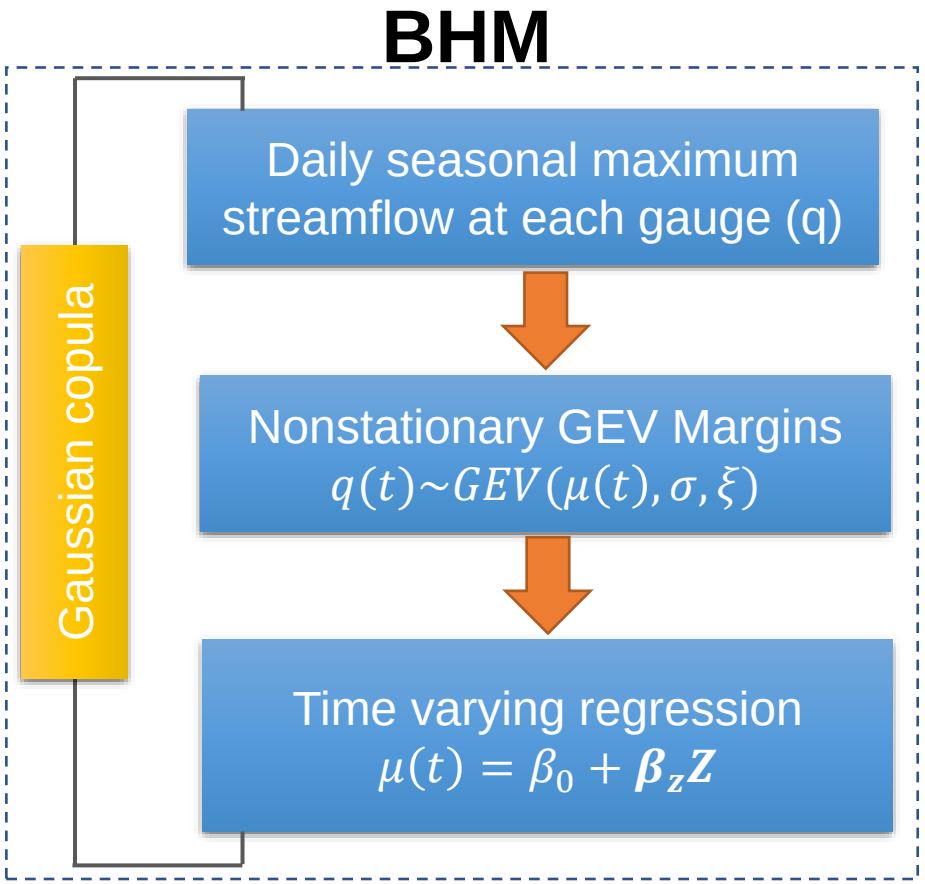
Climate Indices

- Period: 1978-2018

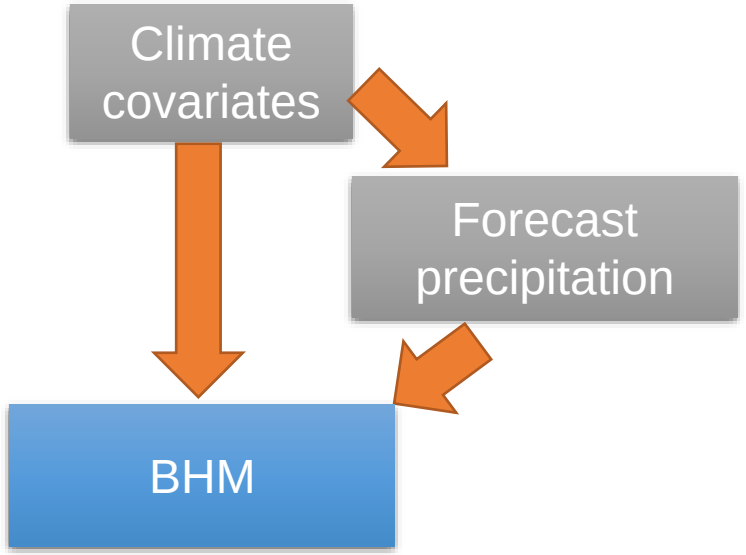
The Narmada River Basin (NRB)

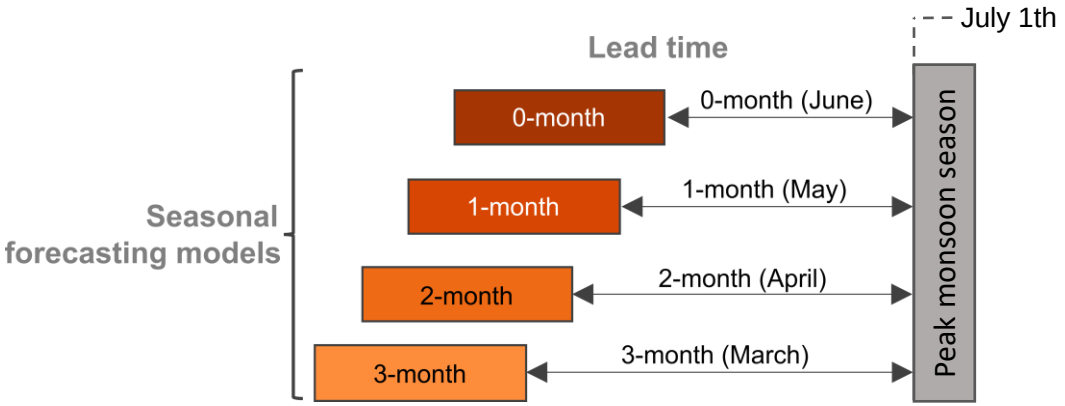


General Bayesian Model Structure



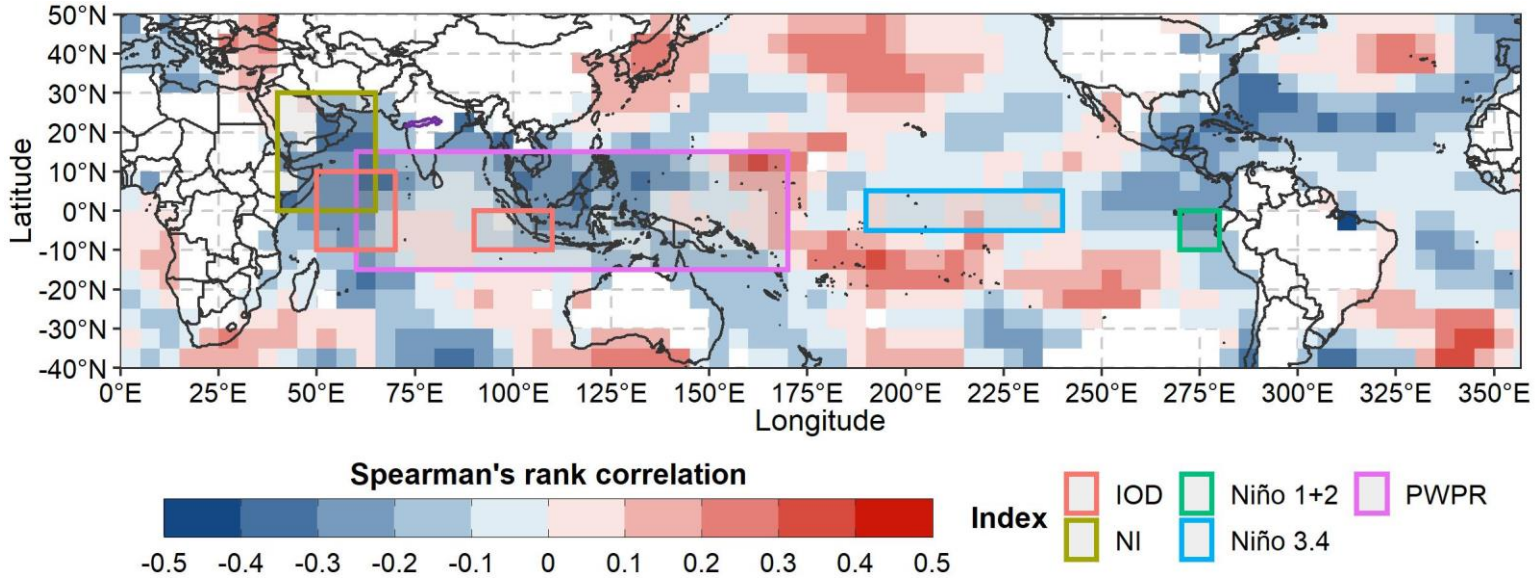
Based on Ossandon et al. (2022)





Covariates for each lead time

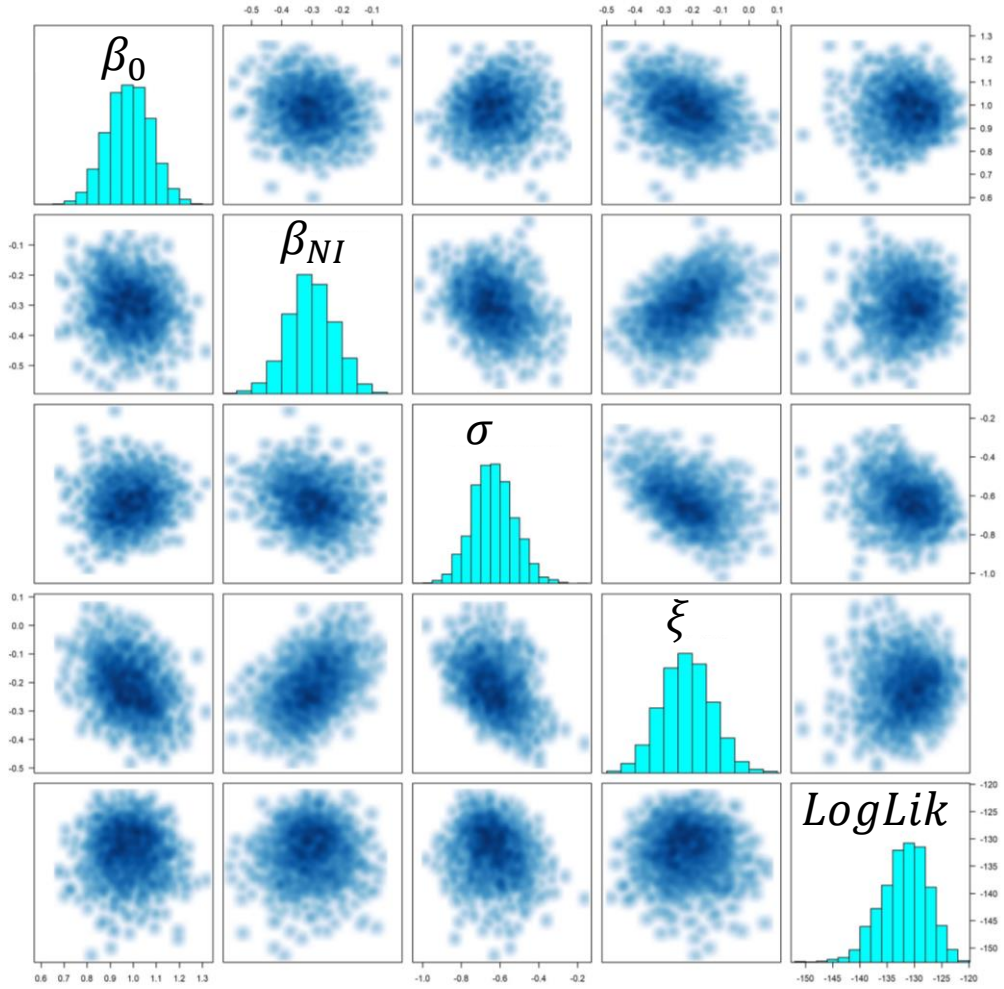
- IOD, PWPR, Nino1+2, Nino 3.4
- Basin average monsoon (July-August) total precipitation (AMTP) forecast
- We consider our own index (NI) for each lead time based on the region of highest correlation between the first PC of maximum streamflow and SST



Implementation and Model Fitting

- The BHNM implemented in STAN using MCMC
- Weakly informative independent priors for $\boldsymbol{\beta}$ and $\boldsymbol{\sigma}$
- 3000 samples for each parameter
- $\widehat{\boldsymbol{R}}$ statistic is below 1.1 for all the cases (ensure convergence)
- Best model was selected based on the lowest LOOIC value

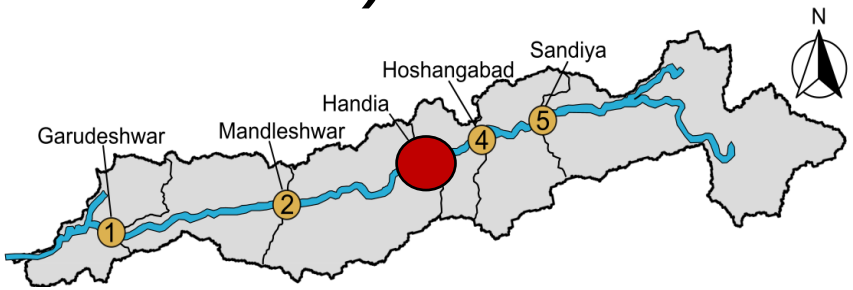
Hoshangabad, 1-month lead

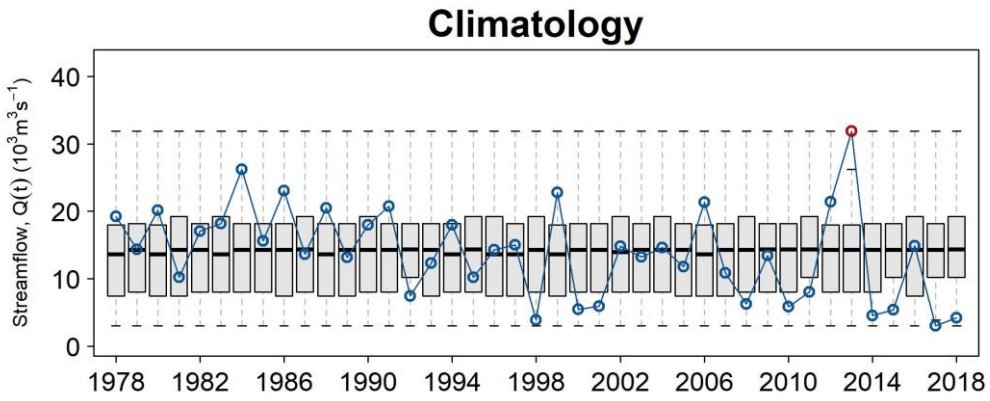


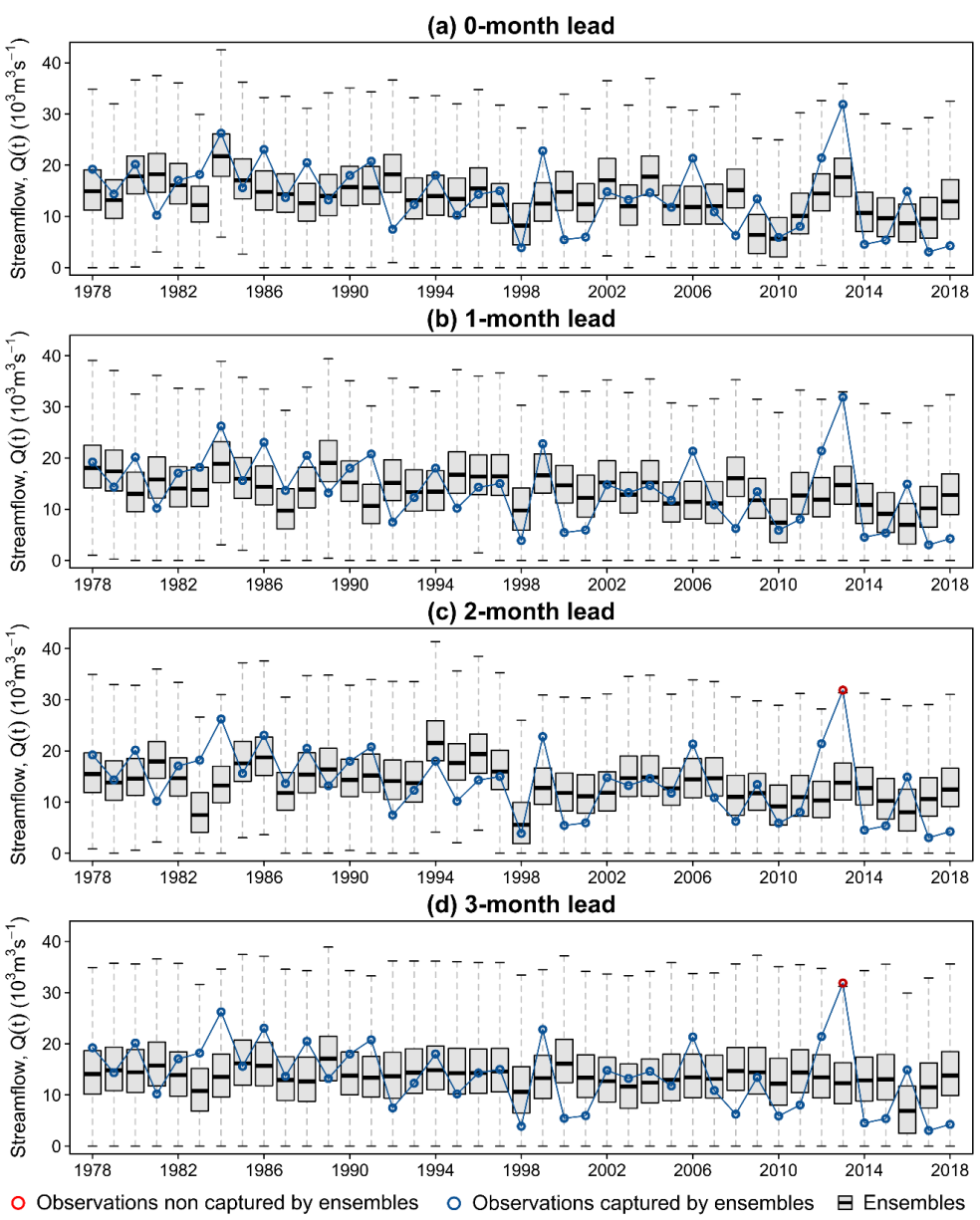
Lead time	Covariates	LOOIC
0-month	AMTP forecast, NI	247.4
1-month	NI	254.4
2-month	AMTP forecast, NI, PWPR	250.0
3-month	NI, PWPR	264.7

Results-cross validation

- BHM captures all the observations inside ensemble spread up to 1-month lead time (available on June 1)



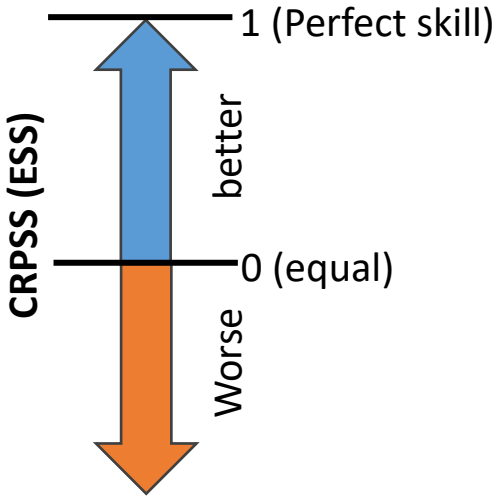


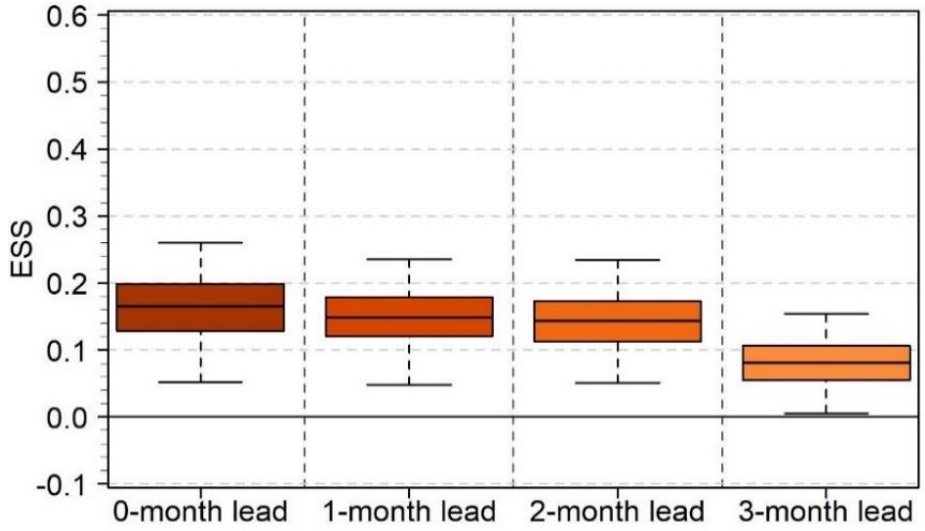


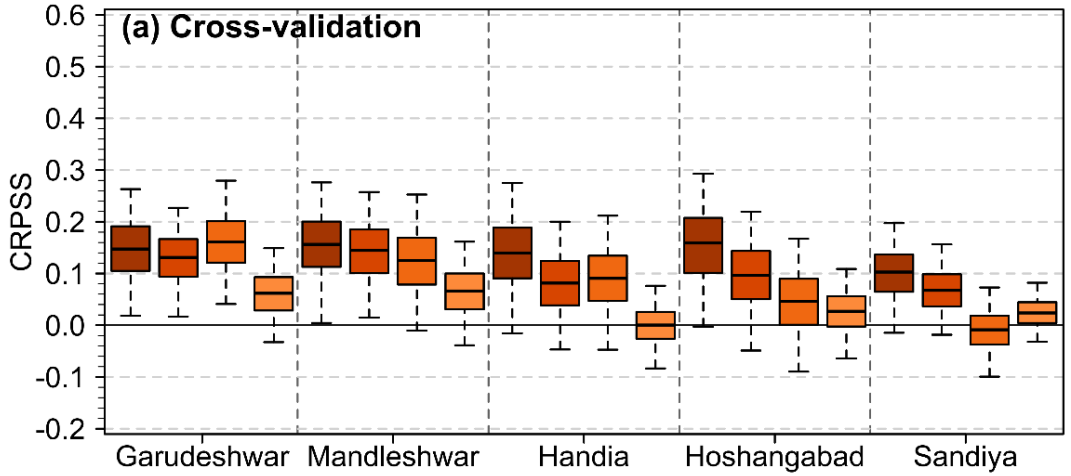
Model performance

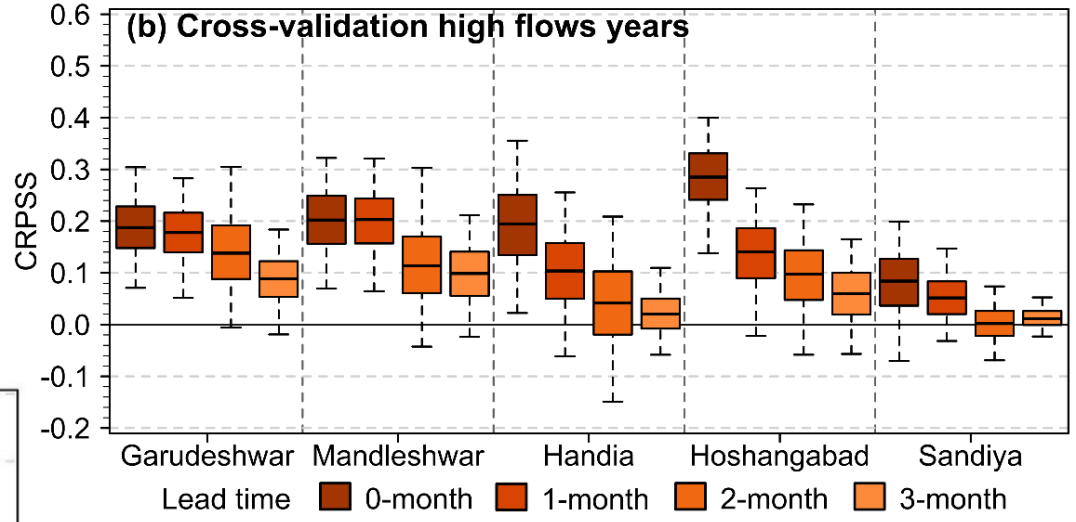
Distributional performance

- Skill decreases as the lead time increases
- Coherent forecast (no worse than climatology)
- For high flow years median CRPSS values above 0.1 up to 1-month lead
- Good spatial skill even up to 3-month lead





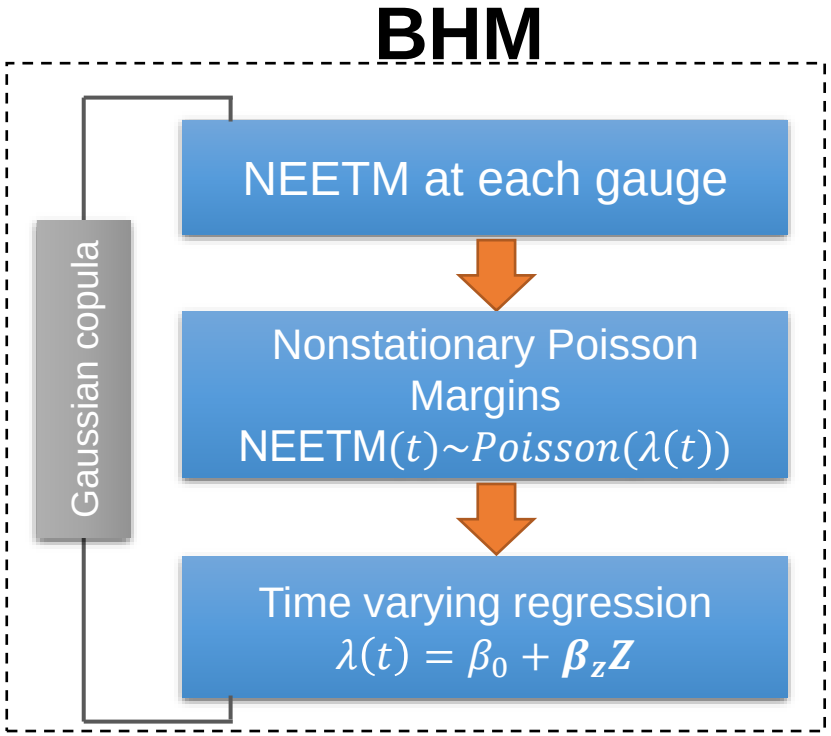


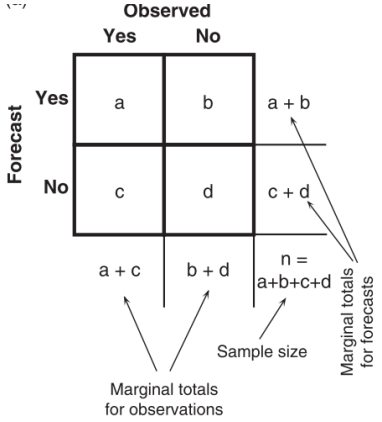


NEETM forecast

- **NEETM**: Number of Events that Exceed a Threshold during monsoon season (July-August)
- Same structure but with a Poisson margin at each site

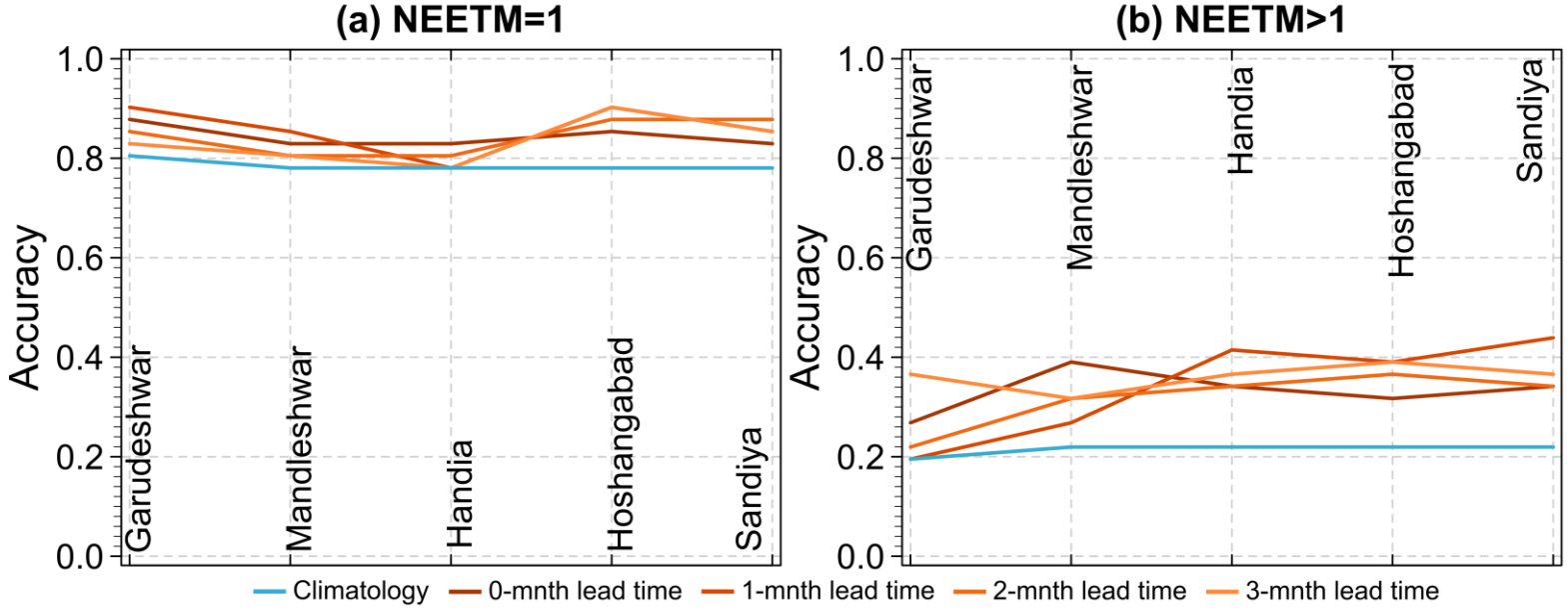
BHM provides higher accuracy Climatology to detect the occurrence of high flow events





Source: Wilks (2011)

$$Accuracy = \frac{a+d}{sample\ size}$$



Summary and Conclusions

- We implemented a BHM for forecasting of seasonal streamflow extremes in the NRB
- The model provides robust and reliable streamflow forecast ensembles up to 1-month lead time and beyond
- The first effort to model seasonal streamflow extremes in the NRB and India
- This can be combined with daily forecast (ossandon et al. 2022)

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