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

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Abstract

Hydroclimate extreme events, especially precipitation and streamflow extremes during wet seasons, pose severe threats to life, livelihoods, and infrastructure. Therefore, timely and skillful projections of attributes of seasonal streamflow extremes are imperative to plan mitigation strategies. In particular, the number of 'events' – i.e., exceedances of flow thresholds that result in flooding and the magnitude of such extremes during the season, will be of immense use to policymakers for early planning and implementation of flood risk mitigation and adaptation strategies. However, predicting seasonal extremes is challenging, particularly under spatial and temporal non-stationarity. To address this need, we develop a space-time model to project seasonal flow risk attributes using a Bayesian hierarchical modeling (BHM) framework in this study. In this model, the number of events exceeding a threshold during a season at a suite of gauge locations on a river network are modeled as Poisson margins. The seasonal daily maximum flows are modeled as a generalized extreme value (GEV). The rate parameters of the Poisson distribution and scale and shape parameters of the GEV are modeled as a linear function of suitable covariates. Gaussian Elliptical Copulas are applied to capture the spatial dependence. The best set of covariates is selected using the leave-one-out cross-validation information criteria (LOOIC). The modeling framework results in the posterior distribution of the risk attributes for each season and, thus, the uncertainties. We demonstrate the utility of this modeling framework to project the flood risk attributes during the summer peak monsoon season (July-August) at five gauges in the Narmada River basin of West-Central India. As potential covariates, we consider climate indices such as El Niño–Southern Oscillation (ENSO), the Indian Ocean Dipole (IOD), and the Pacific Warm Pool Region (PWPR) from the precedent season, which have shown strong teleconnections with the Indian monsoon. This spatiotemporal modeling framework helps in the planning of seasonal adaptation and preparedness measures as predictions of monsoon high flow risk occurrence become available up to 3 months before actual flood occurrence.

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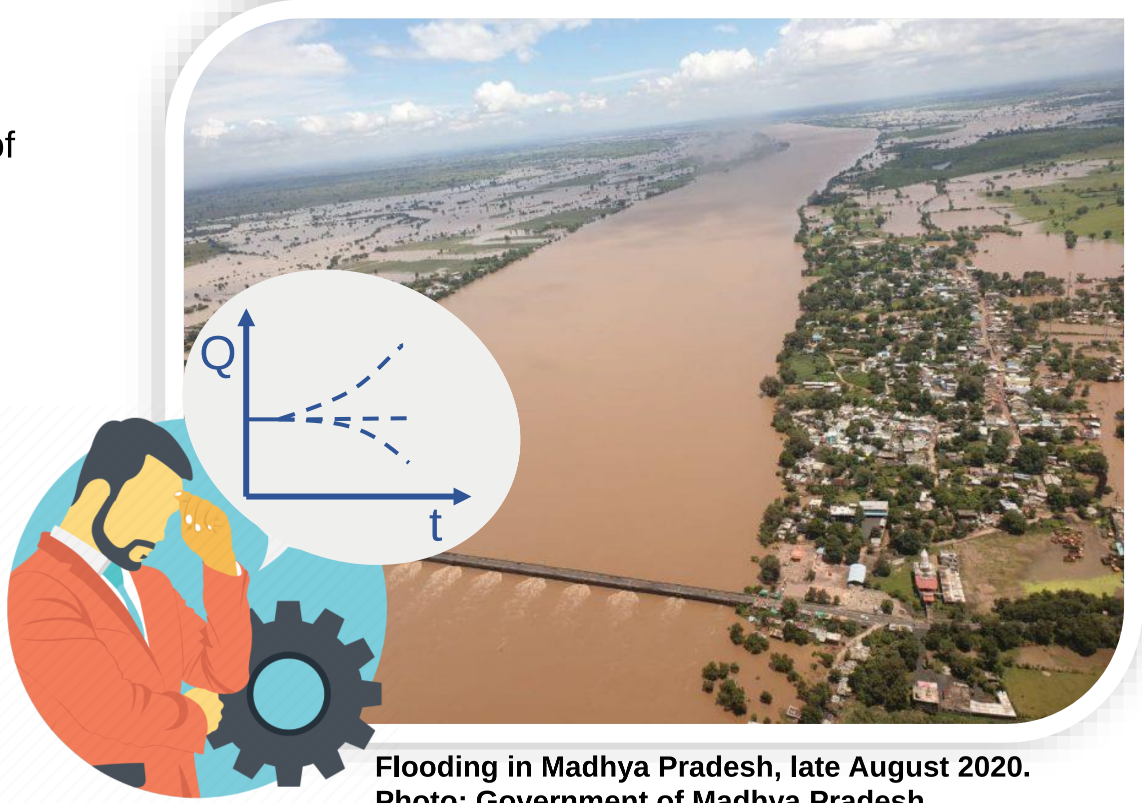

Flooding in Madhya Pradesh, late August 2020.
Photo: Government of Madhya Pradesh

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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

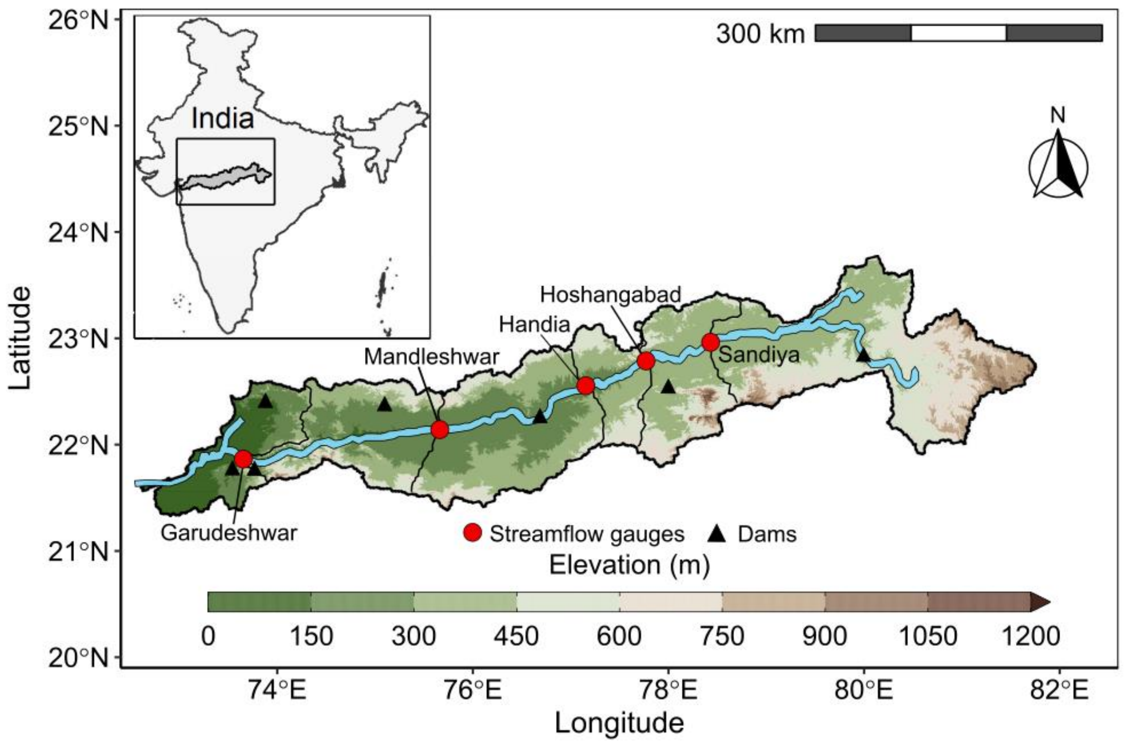
Precipitation

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

Climate Indices

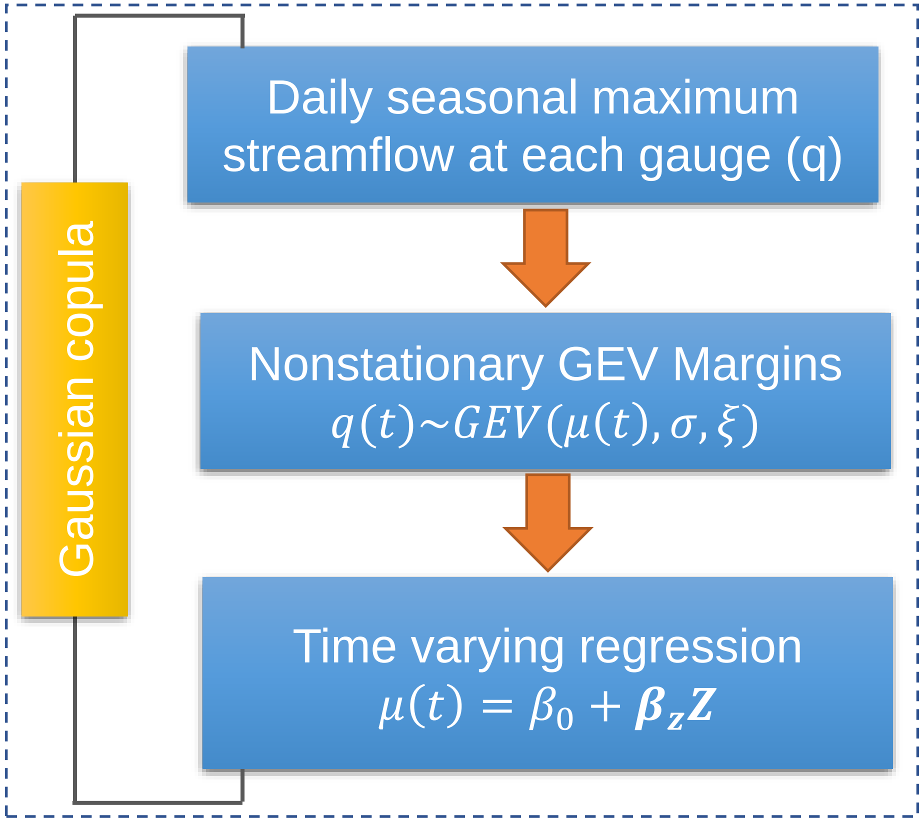
- Period: 1978-2018

The Narmada River Basin (NRB)

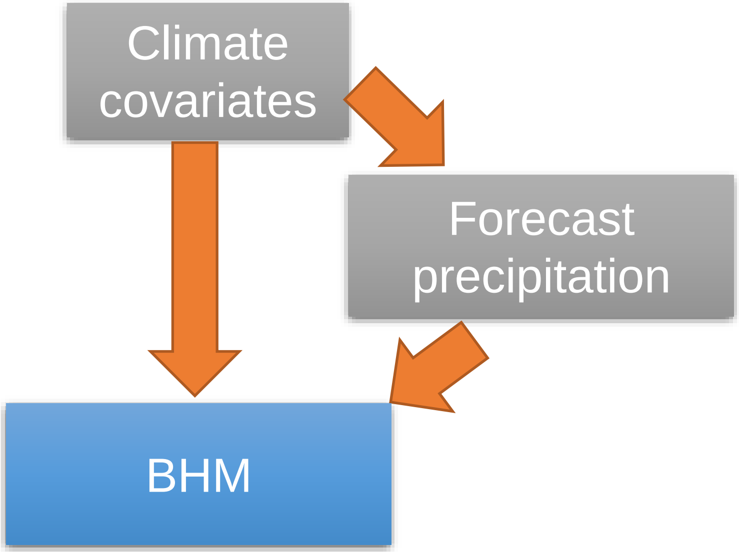


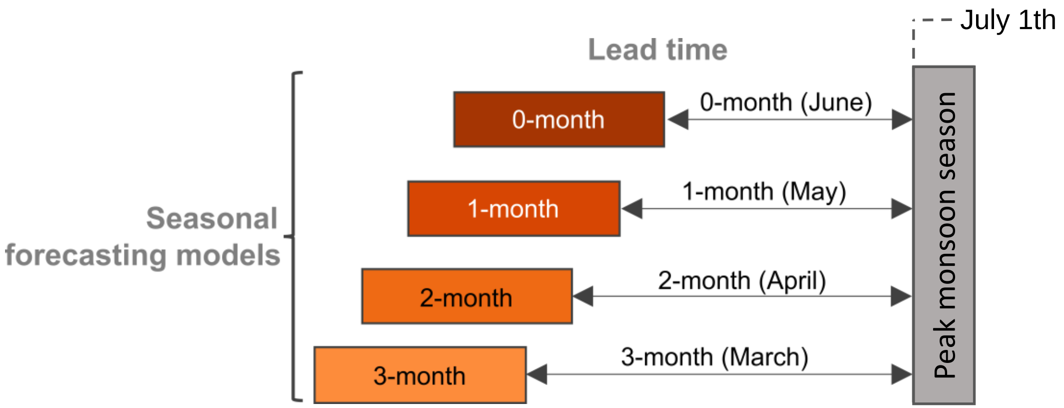
General Bayesian Model Structure

BHM



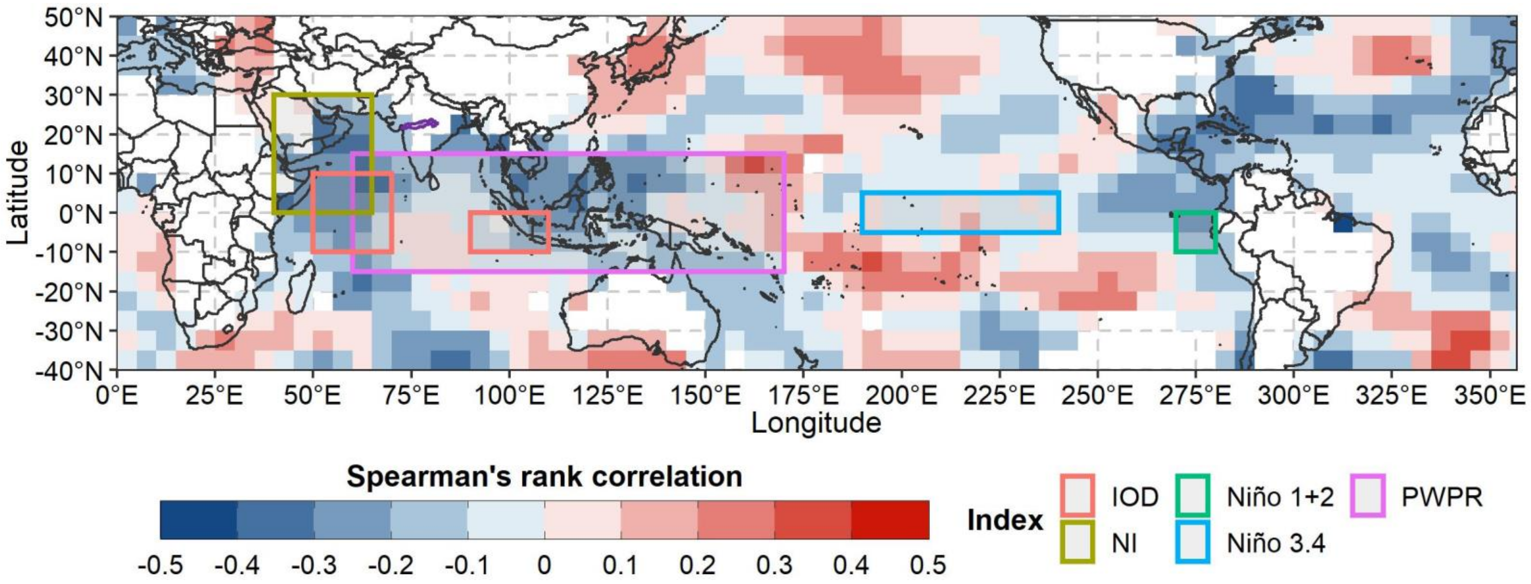
Based on Ossandon et al. (2022)





Covariates for each lead time

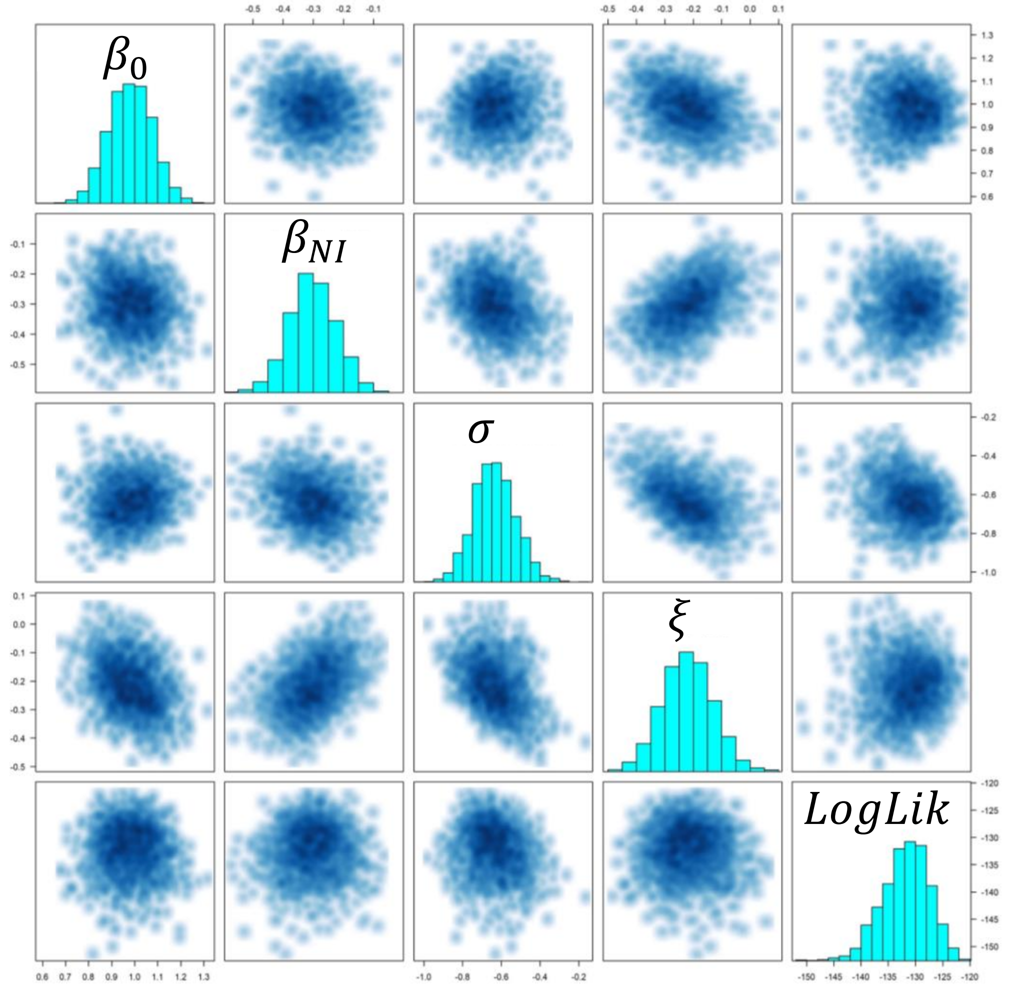
- IOD, PWPR, Nino1+2, Nino 3.4
- Basin average monsoon (July-August) total precipitation (AMTP) forecast
- We consider our own index (NI) for each lead time based on the region of highest correlation between the first PC of maximum streamflow and SST



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

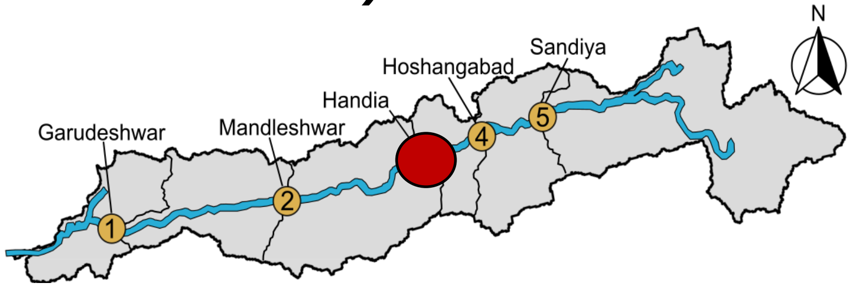
Hoshangabad, 1-month lead

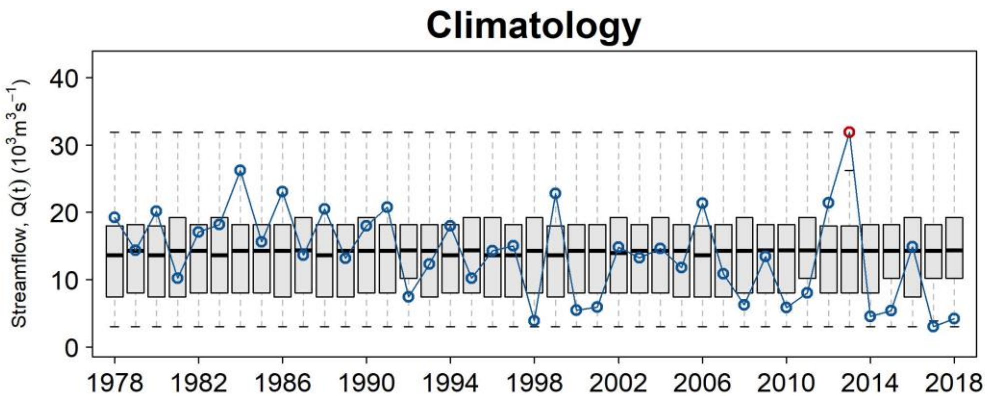


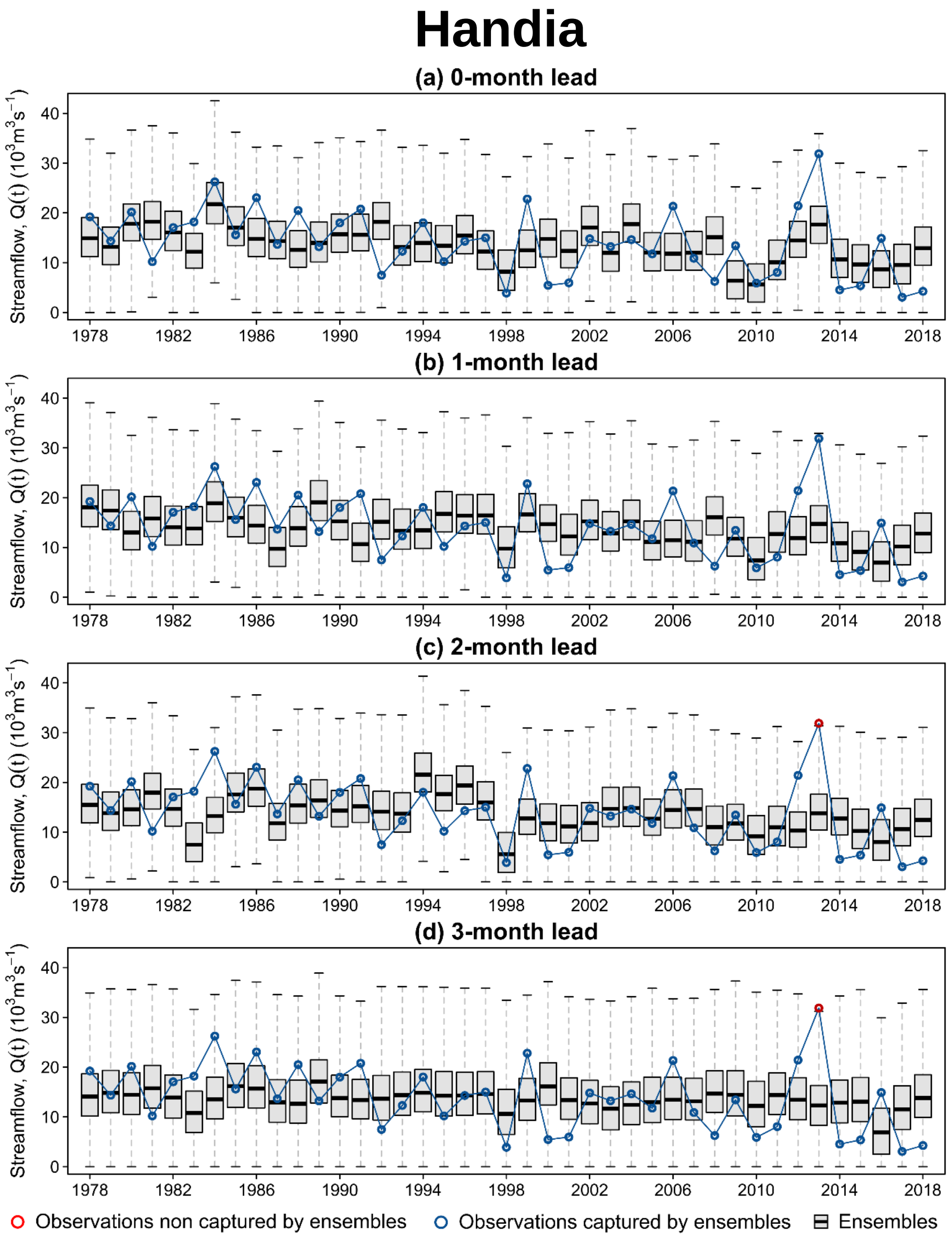
Lead time	Covariates	LOOIC
0-month	AMTP forecast, NI	247.4
1-month	NI	254.4
2-month	AMTP forecast, NI, PWPR	250.0
3-month	NI, PWPR	264.7

Results-cross validation

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



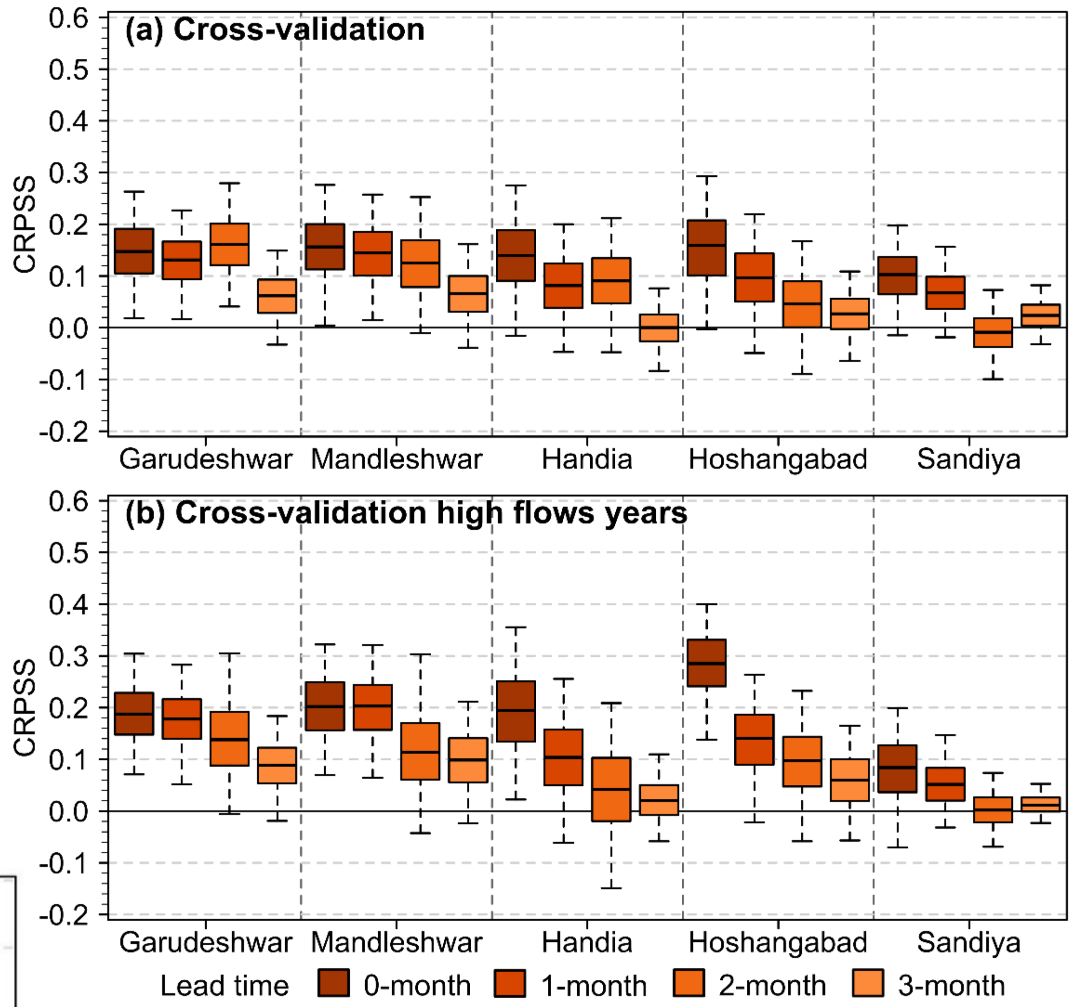


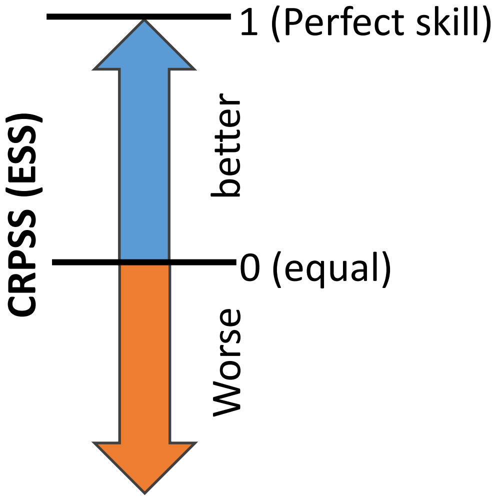


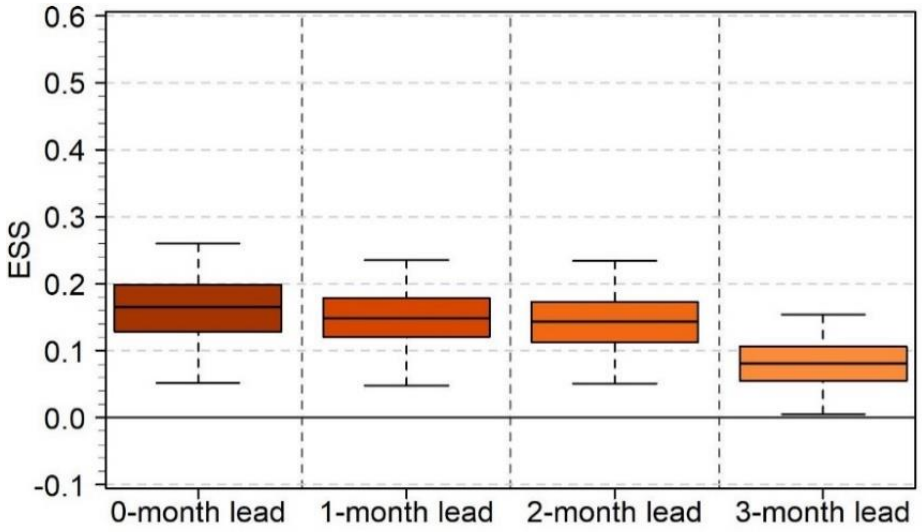
Model performance

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



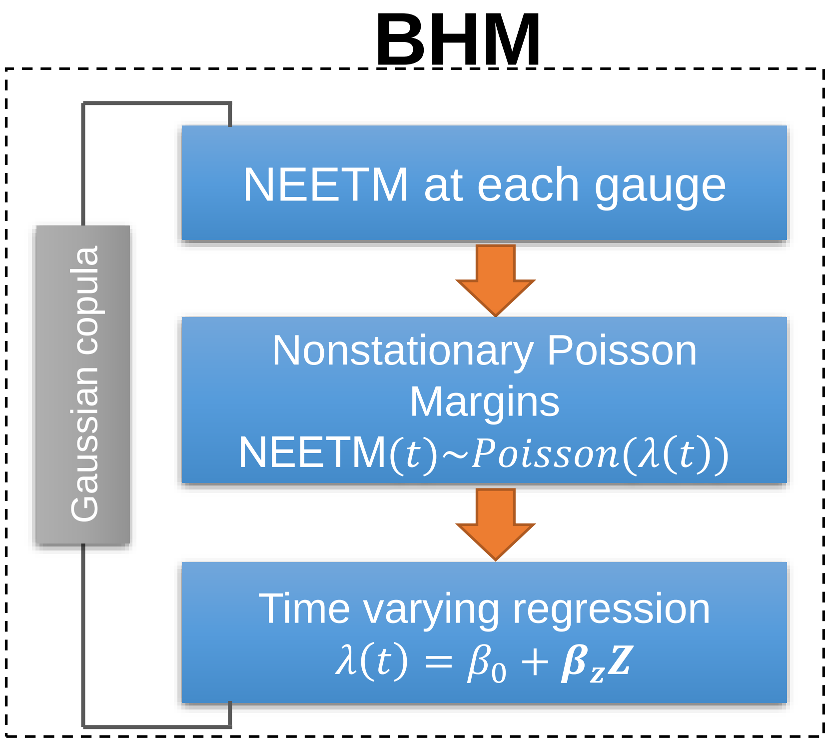


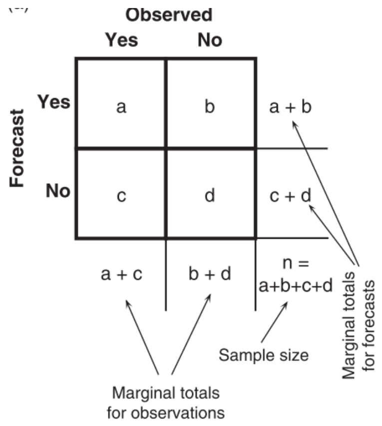


NEETM forecast

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

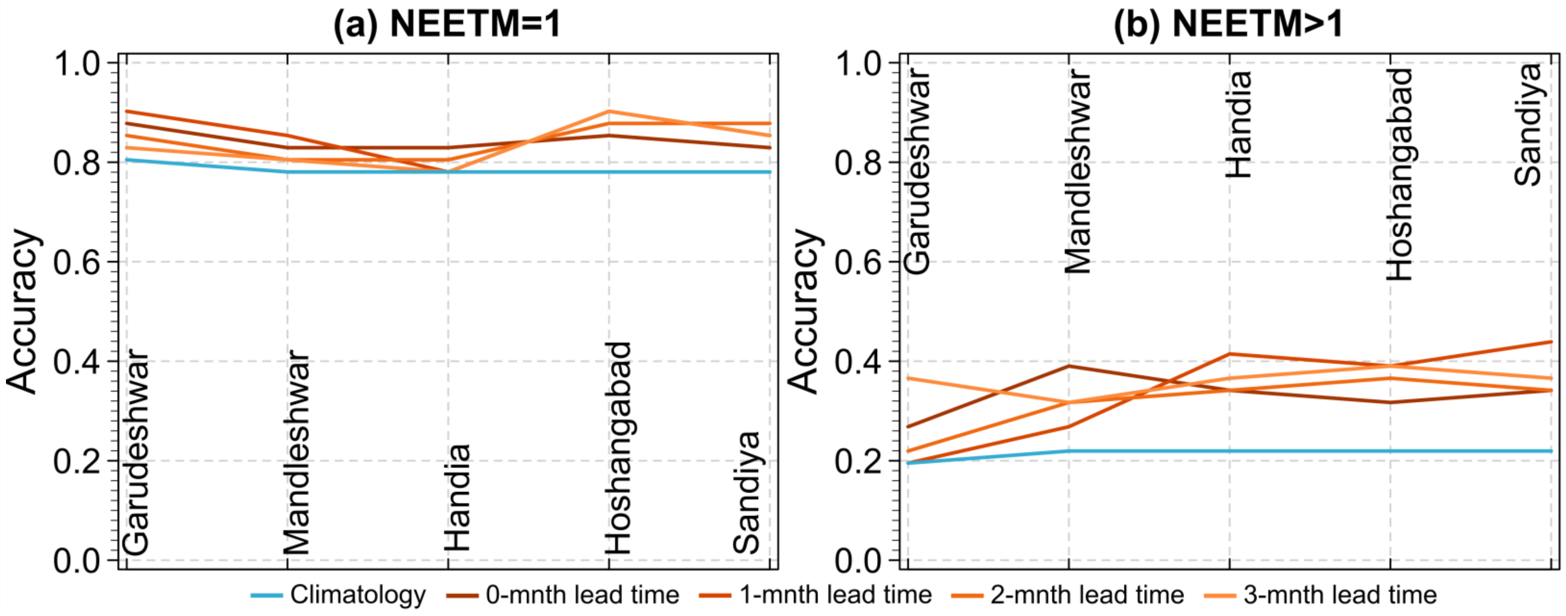
BHM provides higher accuracy Climatology to detect the occurrence of high flow events





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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