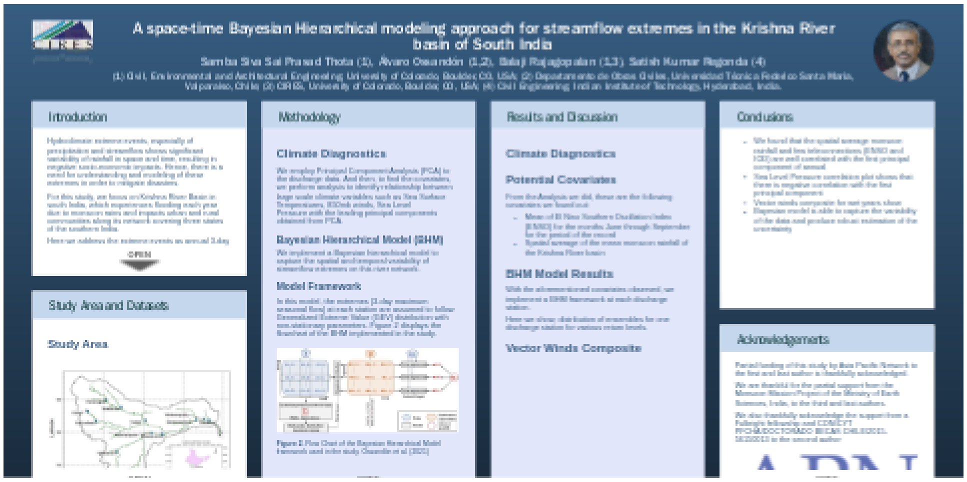
A space-time Bayesian Hierarchical modeling approach for streamflow extremes in the Krishna River basin of South India



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ABSTRACT

Hydroclimate extreme events, especially precipitation and streamflow, pose serious threats to life, livelihoods, and infrastructure. However, the extremes exhibit significant space-time variability and in conjunction with societal vulnerability and resiliency, resulting in varying levels of damage. Regardless, robust understanding and modeling of these extremes is crucial for effective hazard mitigation strategies. For this study, we focus on the Krishna River Basin in south India, which experiences flooding each year due to monsoon rains and impacts urban and rural communities along its network covering three States. We implement a Bayesian hierarchical model to capture the spatio-temporal variability of streamflow extremes on this river network. In this model, the extremes (3-day maximum seasonal flow) at each station are assumed to follow a Generalized Extreme Value (GEV) distribution with non-stationary parameters. The parameters are modeled as a linear function of suitable covariates. In addition, the spatial dependence of the streamflow extremes is modeled via a Gaussian copula. With suitable priors on the parameters, posterior distribution of the parameters and the predictive posterior distribution of streamflow (i.e., ensembles) at each location. Consequently, various return levels can also be obtained from these ensembles. We developed and tested the model on the monsoon seasonal 3-day max flow at 10-gauge stations for the period 1973 -2015. To find the covariates, we perform analysis to identify relationships between large-scale climate variables such as Sea Surface Temperatures, 850 mb winds, Sea Level Pressure, etc. Statistical learning methods will be employed for this analysis and as a result, obtain potential covariates that best relate to streamflow extremes in the basin. This modeling approach can be adapted to the seasonal and multidecadal projection of extremes, which will greatly help disaster mitigation planning efforts.

INTRODUCTION

Space-time variability of precipitation and streamflow extremes over India has major socio-economic impacts. Especially, floods, which result in significant loss of life and economic damage. Hence, there is a need for understanding and modeling of these extremes to help mitigate such impacts.

For this study, we focus on the Krishna River Basin in south India, which experiences frequent flooding due to (June-Sep) monsoon rainfalls. The impacts extend to populous urban and rural communities along its network covering three states.

The extreme events are modeled with seasonal 3-day maximum streamflow which captures the large-scale flood processes. Relationships are identified with basin rainfall and global climate variables. Consequently, these relationships are used to obtain potential covariates, which are used in a Bayesian Hierarchical model to capture the space-time variability of streamflow extremes and the attendant uncertainties.

STUDY AREA AND DATASETS

Study Area

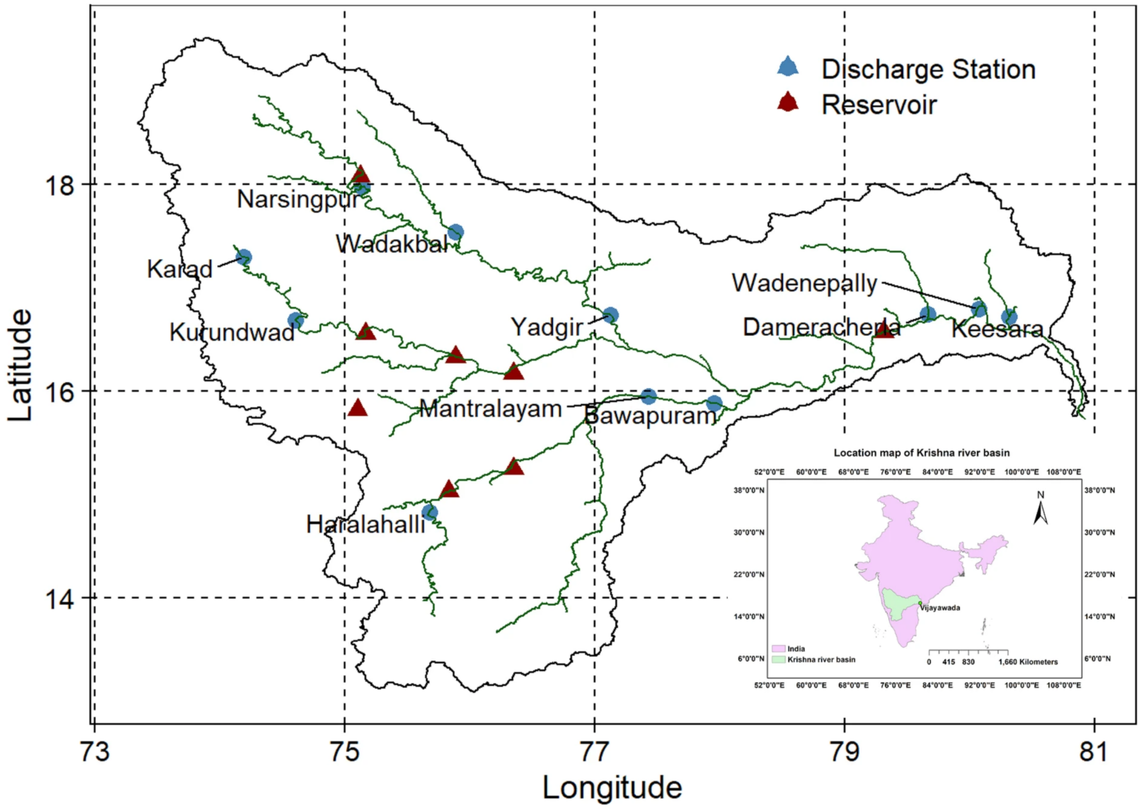

Figure 1. *Map of the Krishna River basin in India showing the locations of the eleven discharge sites and reservoirs*

- The Krishna River originates in the Western Ghats of India, flows East through the four states, and drains into the Bay of Bengal (Figure 1)
- The river has a length of ~ 1400 km and a drainage area of ~ 2,60,000 km2 (CWC, 2020)
- Krishna River basin is the second largest river basin in South India and fifth largest in India
- The basin has a semi-arid climate, and receives average annual rainfall of 850 mm (spatially varying 500–2000 mm)
- The maximum temperature varies between 20° C and 42°C and the minimum temperature between 8° and 30°C (S.Nandi et al., 2007)

Streamflow Data

- We obtained daily observed monsoon (Jun - Sep) discharge data from 1973 to 2015 at eleven gauge stations in the Krishna River Basin: Keesara, Yadgir, Wadakbal, Bawapuram, Karad, Wadenepally, Narsingpur, Haralahalli, Dameracherla, Kurundwad, Mantralayam from India Water Resource Information System (IWRIS).

Meteorological and Climate Data

- We used 0.25 degree gridded daily precipitation data from1973 to 2015 from the Indian Meteorological Data (IMD) (Pai et al., 2014)
- Sea Surface Temperatures and atmospheric circulation variables from NCEP-NCAR re-analysis (Kistler et al. 2001) is used for climate diagnostics

METHODOLOGY

Climate Diagnostics

We employed Principal Component Analysis (PCA) on the discharge data. The leading mode of variability (i.e. first PC) is used to select extreme years and perform climate diagnostics via composites and correlations with large scale climate variables – SST, 850 mb winds, Sea Level Pressure, etc.

Bayesian Hierarchical Model (BHM)

We implement a Bayesian hierarchical model to capture the spatial and temporal variability of streamflow extremes on this river network.

Model Framework

A Bayesian hierarchical model (Ossandón et al., 2021) was used to model the spatial and temporal variability of streamflow extremes on the network. In this model, the extremes (3-day maximum seasonal flow) at each station are assumed to follow a Generalized Extreme Value (GEV) distribution with non-stationary parameters as a function of covariates. The Gaussian Copula enables capture the spatial dependence. Figure 2 displays the flowchart of the BHM implemented in the study.

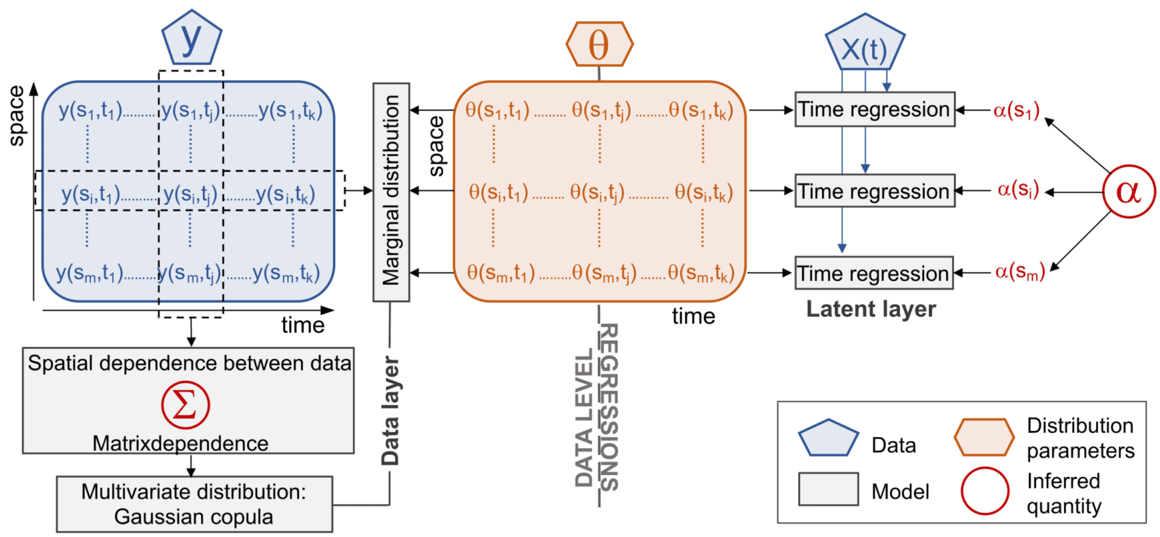

Figure 2. *Flow Chart of the Bayesian Hierarchical Model framework used in the study. Ossandón et al. (2021)*

With suitable priors on the parameters, posterior distribution of the parameters and the predictive posterior distribution of streamflow (i.e., ensembles) at each location are obtained.

RESULTS AND DISCUSSION

Climate Diagnostics

Principal Component Analysis was performed across the annual 3-day maximum discharge of the eleven stations considered in the study. The first two leading principal components (PCD1, PCD2) explained most of the variance (49%, 18% respectively) of the data.

Firstly, we computed the correlation between PCD1 and basin average monsoon (Jun-Sep) rainfall which yielded a correlation of 0.61. Furthermore, the correlation between PCD1 and the first principal component of basin wide monsoon rainfall yielded 0.46. Thus, this shows that basin average rainfall is a good indicator for the extreme discharge.

Then, we computed the correlation between PCD1 and Sea Surface Temperature anomalies for the monsoon months (Jun-Sep), which shows the region of El Nino Southern Oscillation Index (ENSO) is well correlated with the PCD1 (Figure 3).

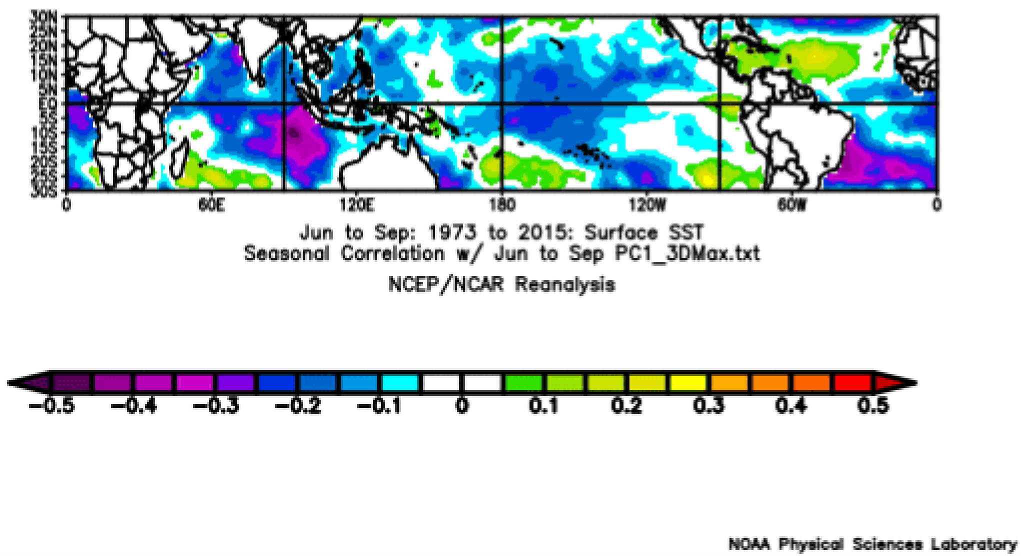

Figure 3. *Correlation of the first principal component with Sea Surface Temperature Anomalies for the monsoon months (Jun-Sep)*

To understand the climate mechanism behind these extremes, we generated composite maps of anomalies of sea level pressure and vector winds (at 850 mb) for wet years (top eleven years based on the PCD1 values) as shown in Figure 4a and Figure 4b respectively. Figure 4a shows low-pressure regions near the Krishna River basin region, which acts as a driving force for rainfall occurrence. Figure 4b shows the movement of winds from the Arabian Sea on the West (upstream of the basin) to the basin, which is part of strengthened monsoon jet, also consistent with ENSO teleconnection.

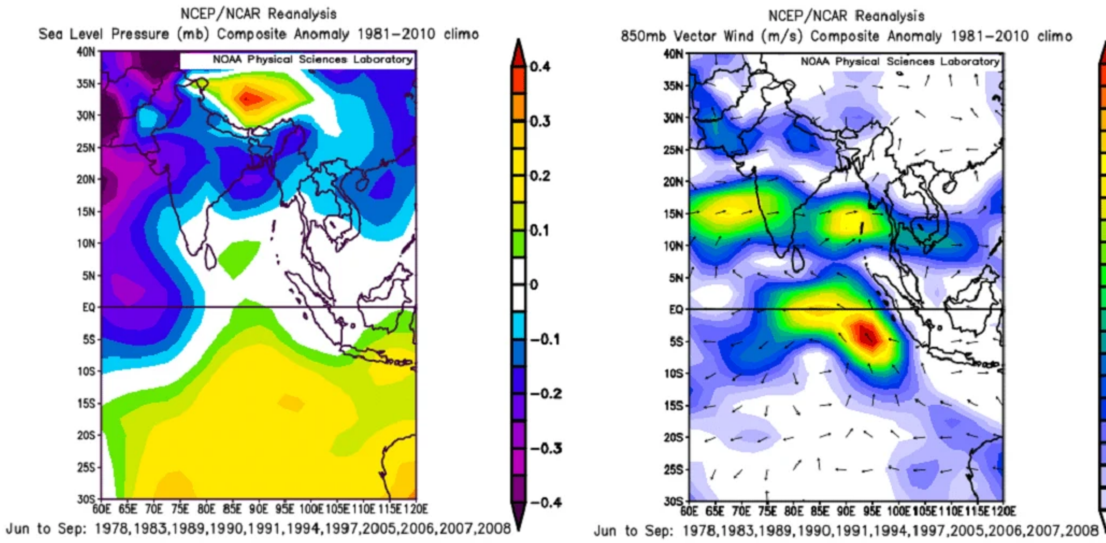

Figure 4a (left) and 4b (right) *Composite maps of Anomalies of Sea Level Pressure and Vector Winds at the Pressure level of 850 mb, respectively for monsoon season (Jun – Sep)*

Potential Covariates

From the climate diagnostics, these are the following covariates considered in the BHM:

- Mean of El Nino Southern Oscillation Index (ENSO) for the monsoon season (June-Sept) for the record period
- Spatial average of the mean monsoon rainfall of the Krishna River basin

BHM Model Results

With these covariates, we implemented the BHM framework obtaining the predictive posterior distribution of seasonal 3-day extremes at each location. We obtained posterior distribution of the parameters, and consequently, posterior distributions of various return levels. Figure 5 shows the posterior predictive distribution of return levels at Kurundwad (one of the upstream gauges without reservoir influence).

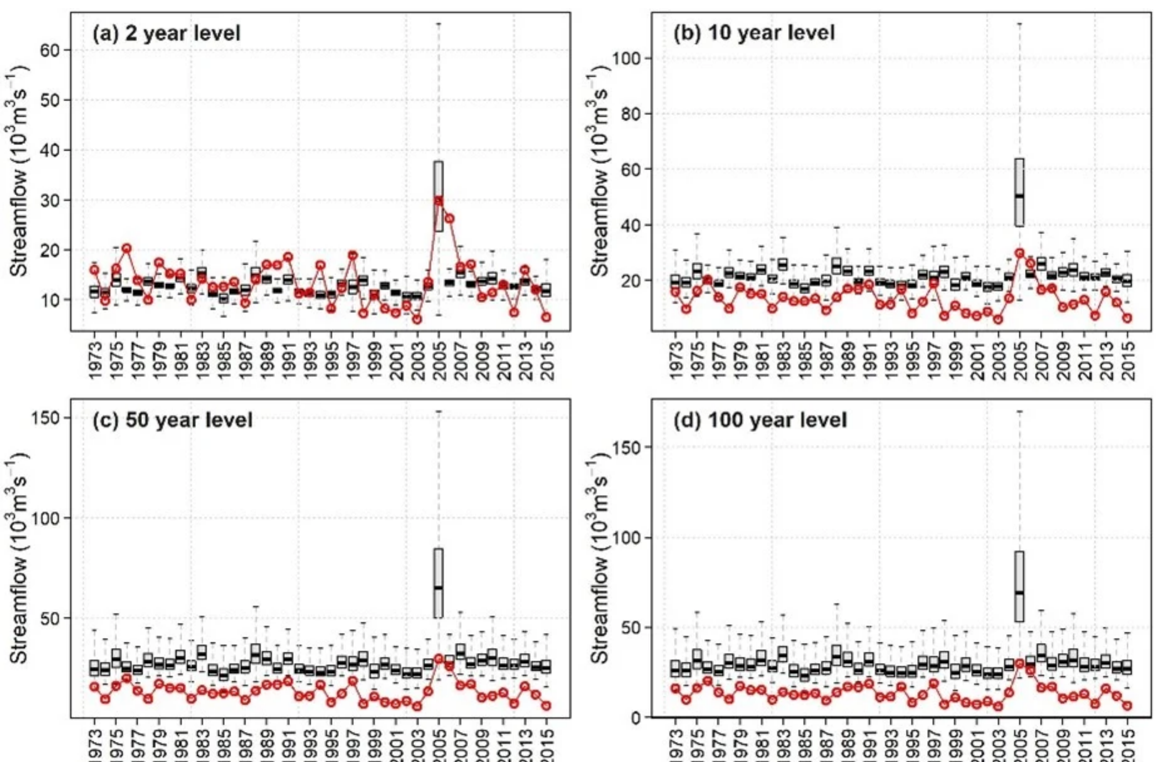

Figure 5. *Distribution of Ensembles of Maximum Discharge for the station Kurundwad. Red lines show the historical 3-day maximum streamflow, Whiskers the 95% credible intervals, boxes the interquartile range, and horizontal lines inside the boxes, the median of the ensembles.*

- BHM captures the temporal variability of the data and provides robust estimates of uncertainty
- High value in 2005 is caused by a huge rainfall event that is not reflected by all discharge gauges because of the influence of reservoir operations

CONCLUSIONS

- The variability of seasonal 3-day maximum streamflow in the Krishna River Basin is largely driven by ENSO. Further, it is strongly related to basin average rainfall. In that, a season with higher average rainfall favors higher extreme streamflow
- These two covariates in the BHM are able to capture the space-time variability quite well. The return levels can help planners in flood mitigation
- These two covariates are predicted a season ahead, typically, thus, enabling the BHM approach to be used for seasonal projection
- Reservoir operations influence streamflow extremes. Thus, the model needs to be implemented on headwater gauges for testing and validation
- Other covariates need to be explored, especially the role of antecedent land conditions, which can enhance skill

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