AGU FALL MEETING
New Orleans, LA & Online Everywhere
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Session H33I: Hydrometeorologic Extremes: Prediction, Simulation, and Change III Oral

Spatial-temporal Bayesian hierarchical model for summer monsoon precipitation extremes over India

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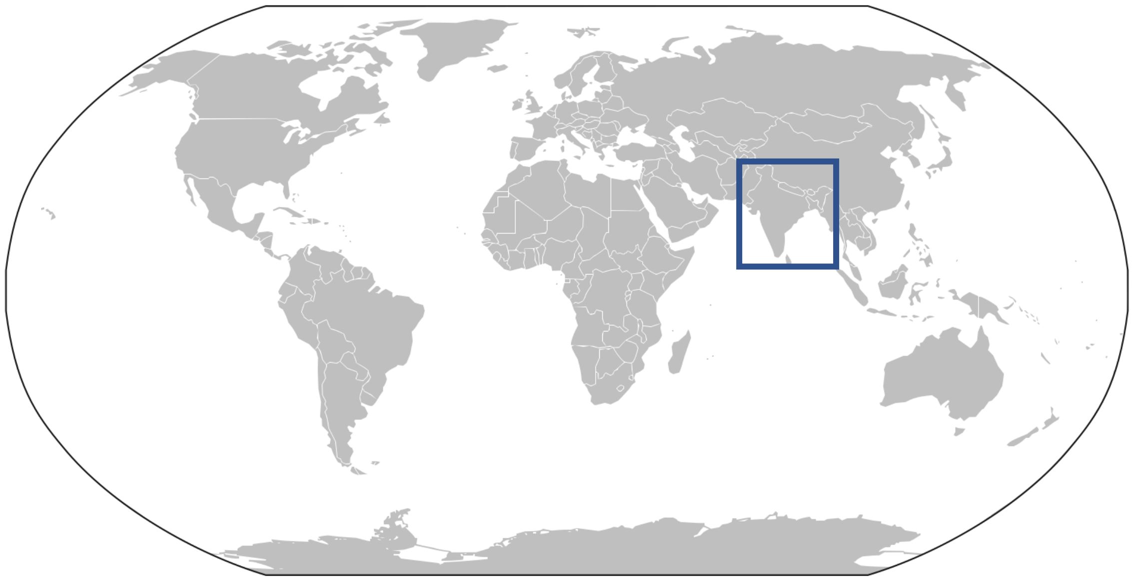
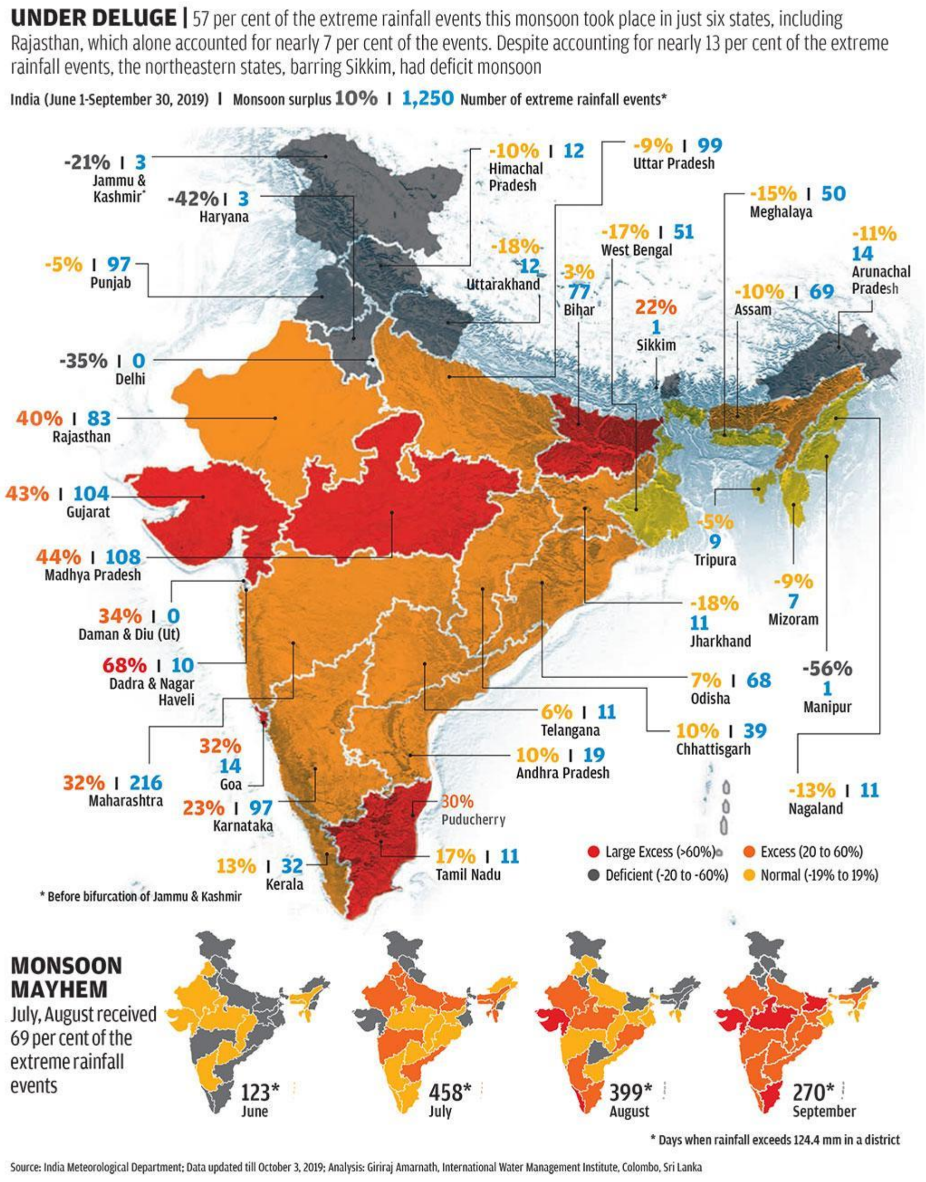
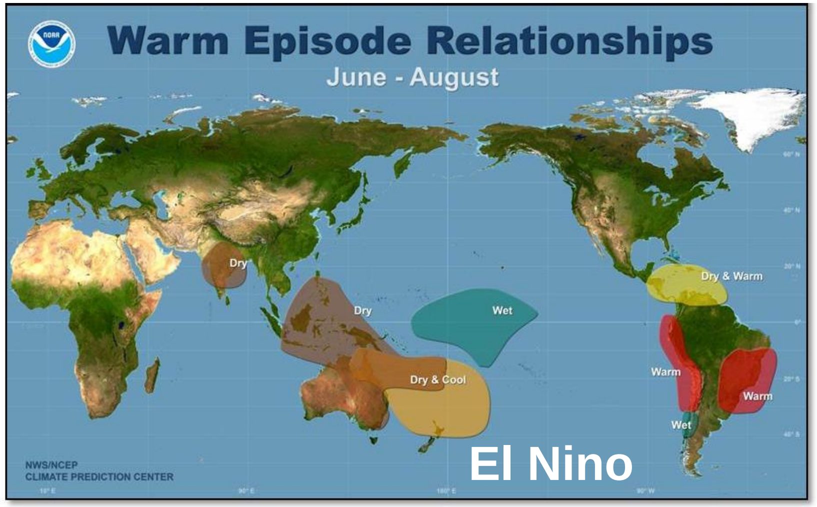
Motivation

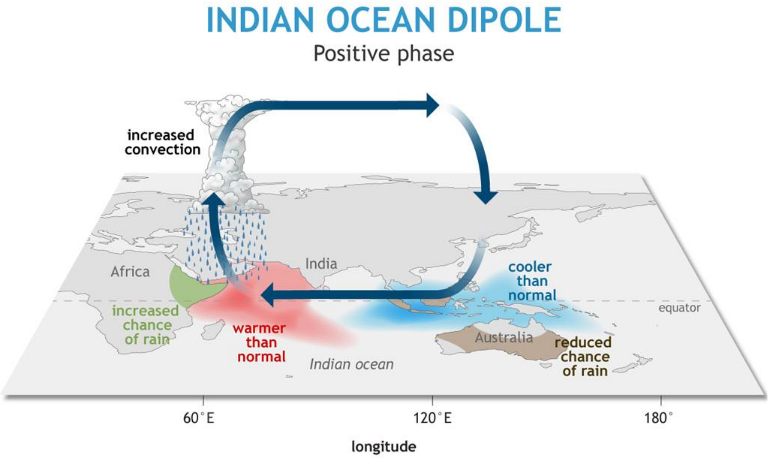


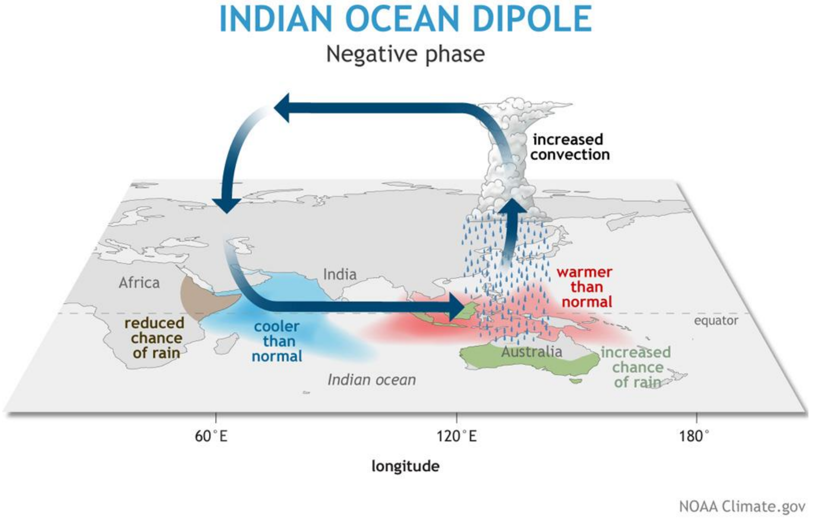
- India receives more than 80% of annual rainfall during the summer monsoon season (June-September)
- Floods occur mostly during this season (Rainfall-runoff basins)
- Understanding and modeling extreme precipitation is crucial for flood risk assessment and mitigation



Year to year variability of the rainfall over India is driven largely by ENSO and IOD



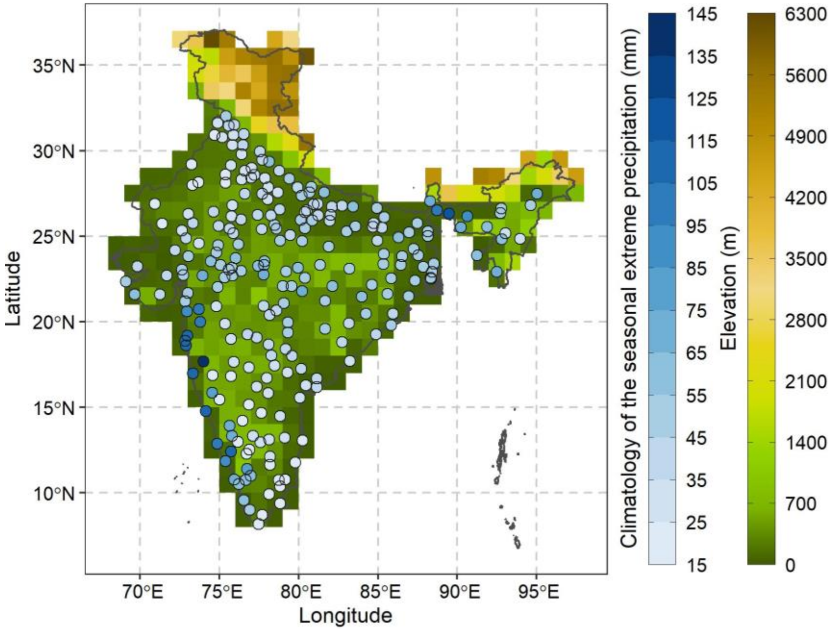




Data

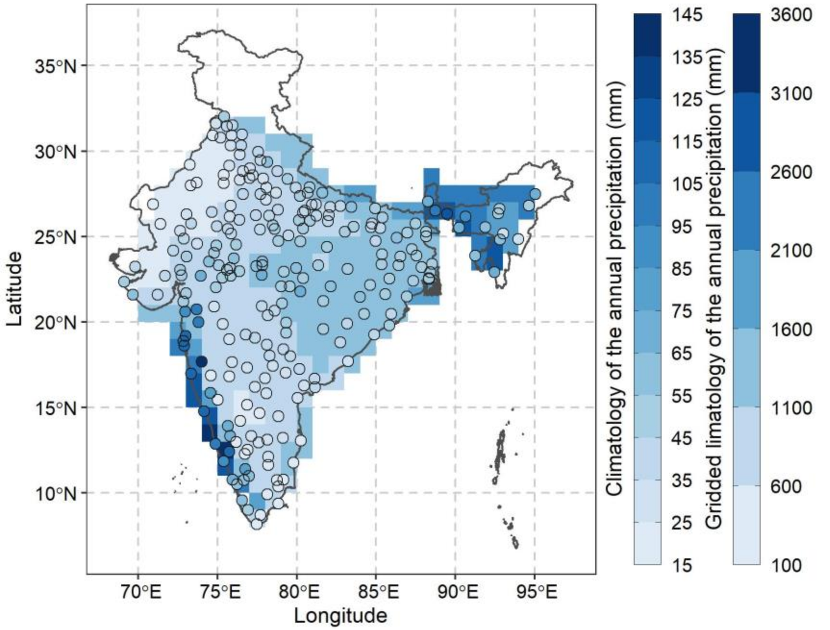
Precipitation

- Daily observed precipitation – The India Meteorological Department (IMD)
- Years: 1951-2017 (67 years), no. of sites 240
- 3-day summer (Jun-Sept) monsoon maximum precipitation



Potential Temporal Covariates (1951-2017)

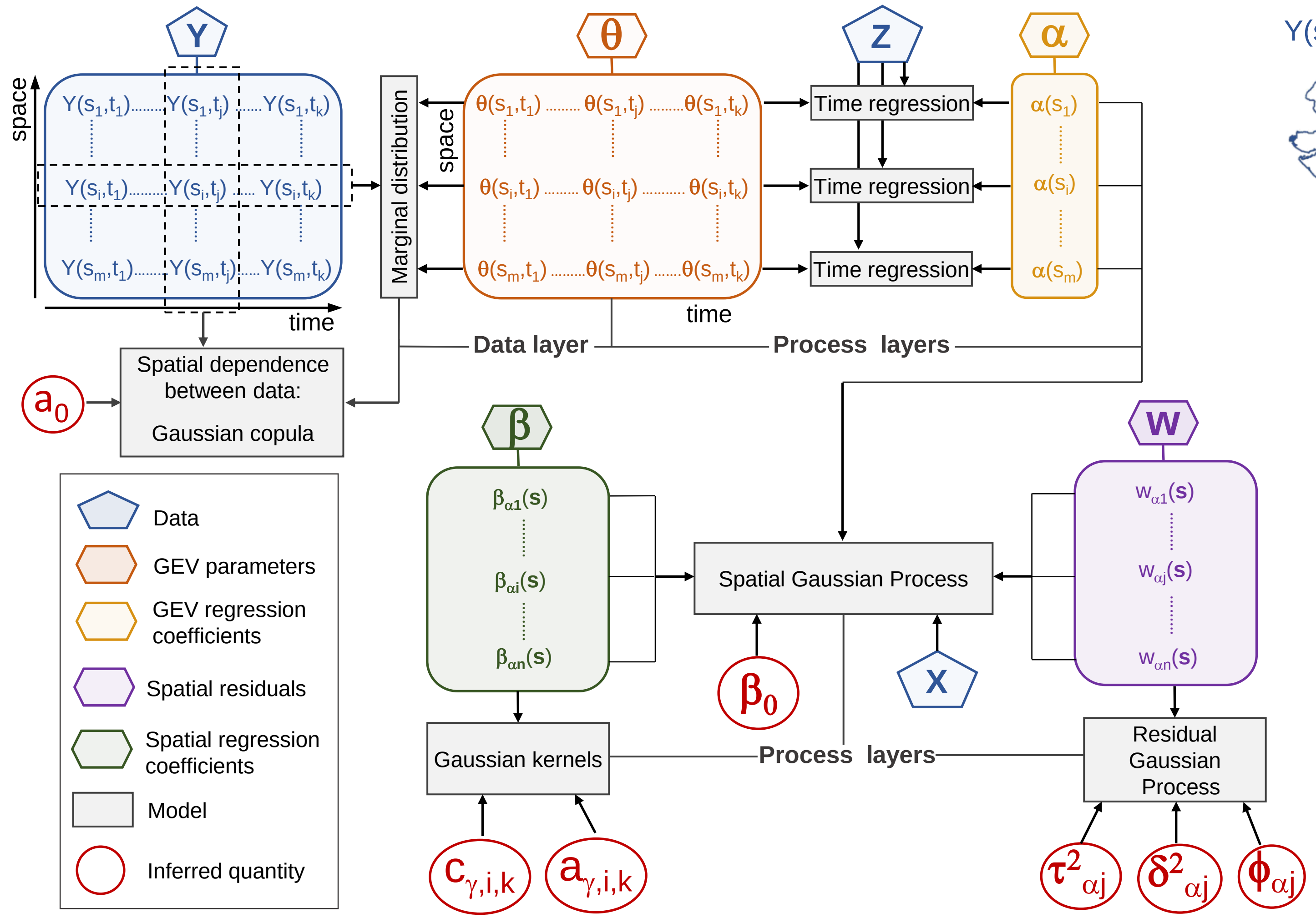
- Climate indices: ENSO, and IOD - NOAA
- Spatial Average Summer Monsoon Precipitation (SASP) – The India Meteorological Department (IMD)
- Monsoon season

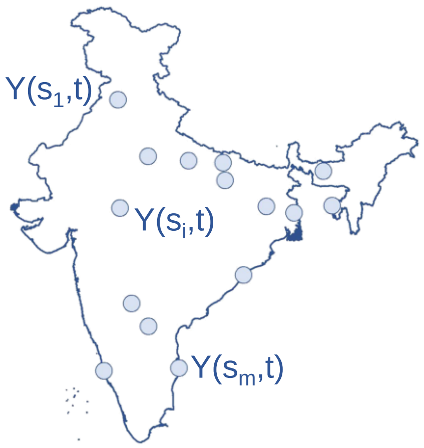


Spatial Covariates (1° spatial resolution)

- Elevation and Climatology of annual precipitation

General Bayesian Model Structure





For each time and location

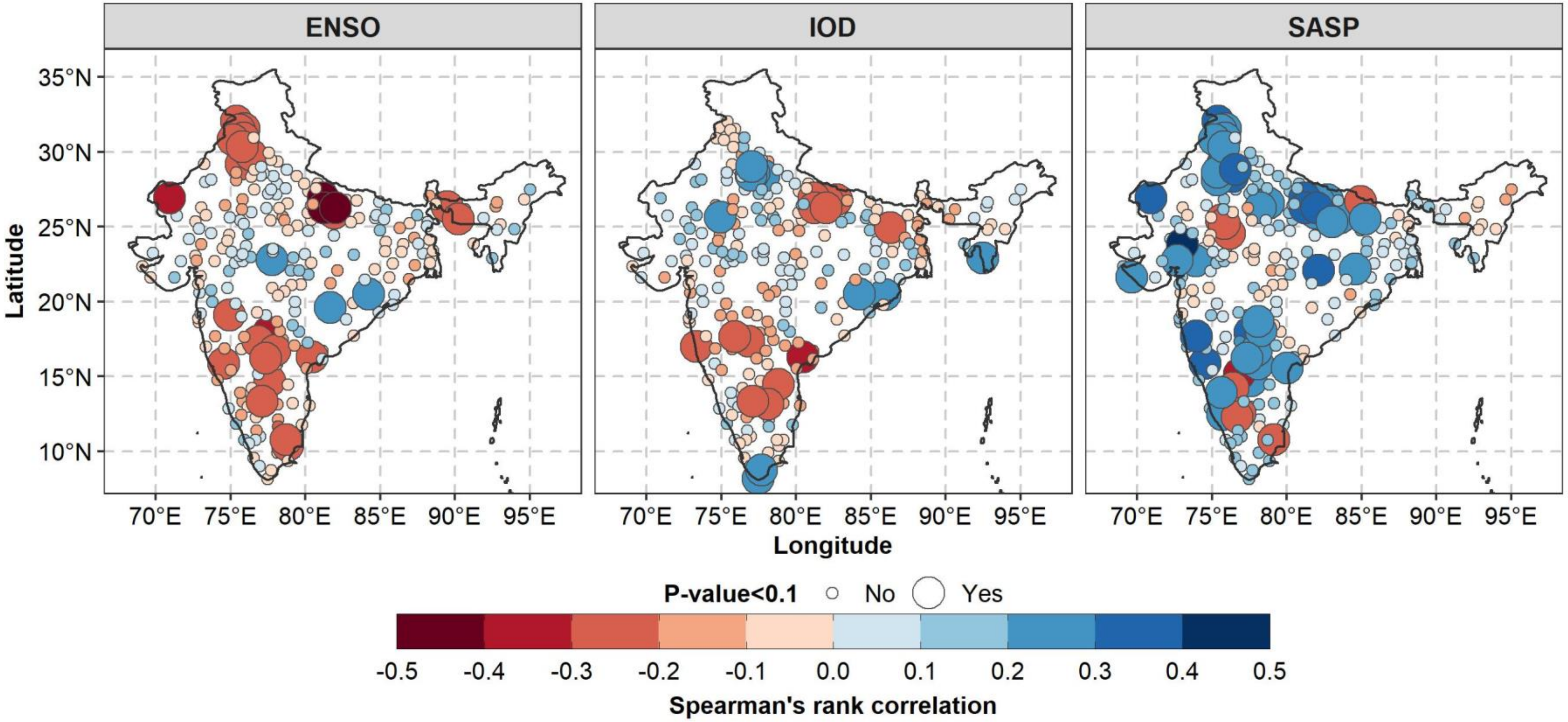
$$y(s_i, t_j) \sim GEV\left(\mu(s_i, t_j), \sigma(s_i, t_j), \xi(s_i, t_j)\right)$$

$$\boldsymbol{\theta}(s_i, t_j) = \left[\mu(s_i, t_j), \log \sigma\left(s_i, t_j\right), \xi(s_i, t_j)\right]$$

For each GEV regression coefficient

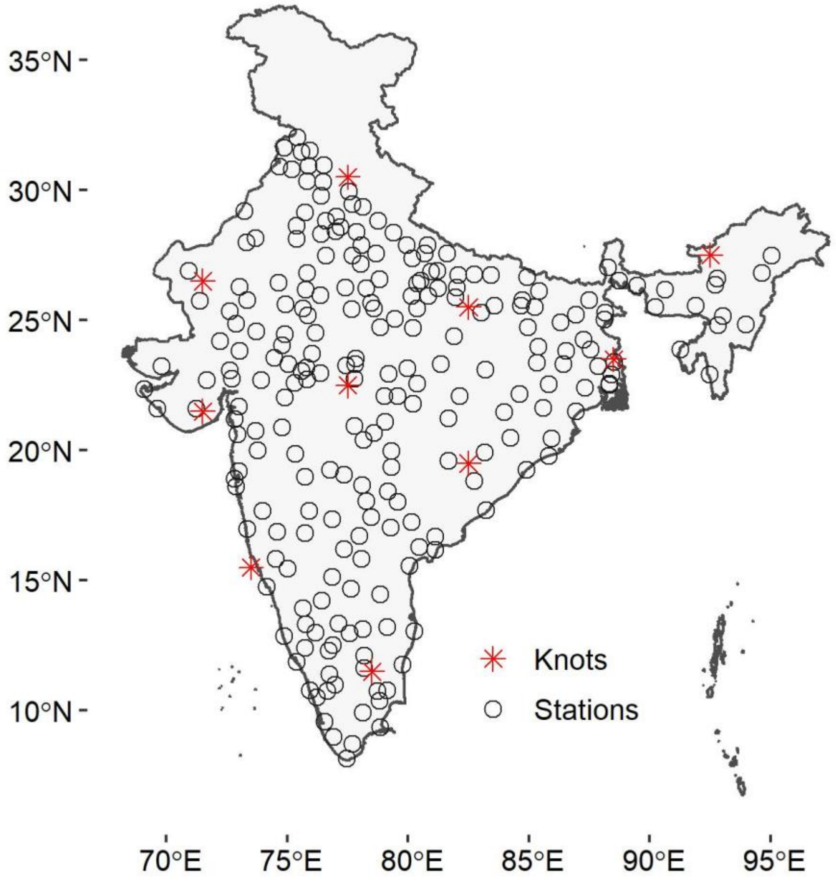
$$\boldsymbol{\beta}_\gamma(\mathbf{s}) = \left[\beta_{\gamma_1}(\mathbf{s}), \dots, \beta_{\gamma_p}(\mathbf{s})\right]^T$$

All the potential covariates show regions of strong correlation with summer maximum precipitation



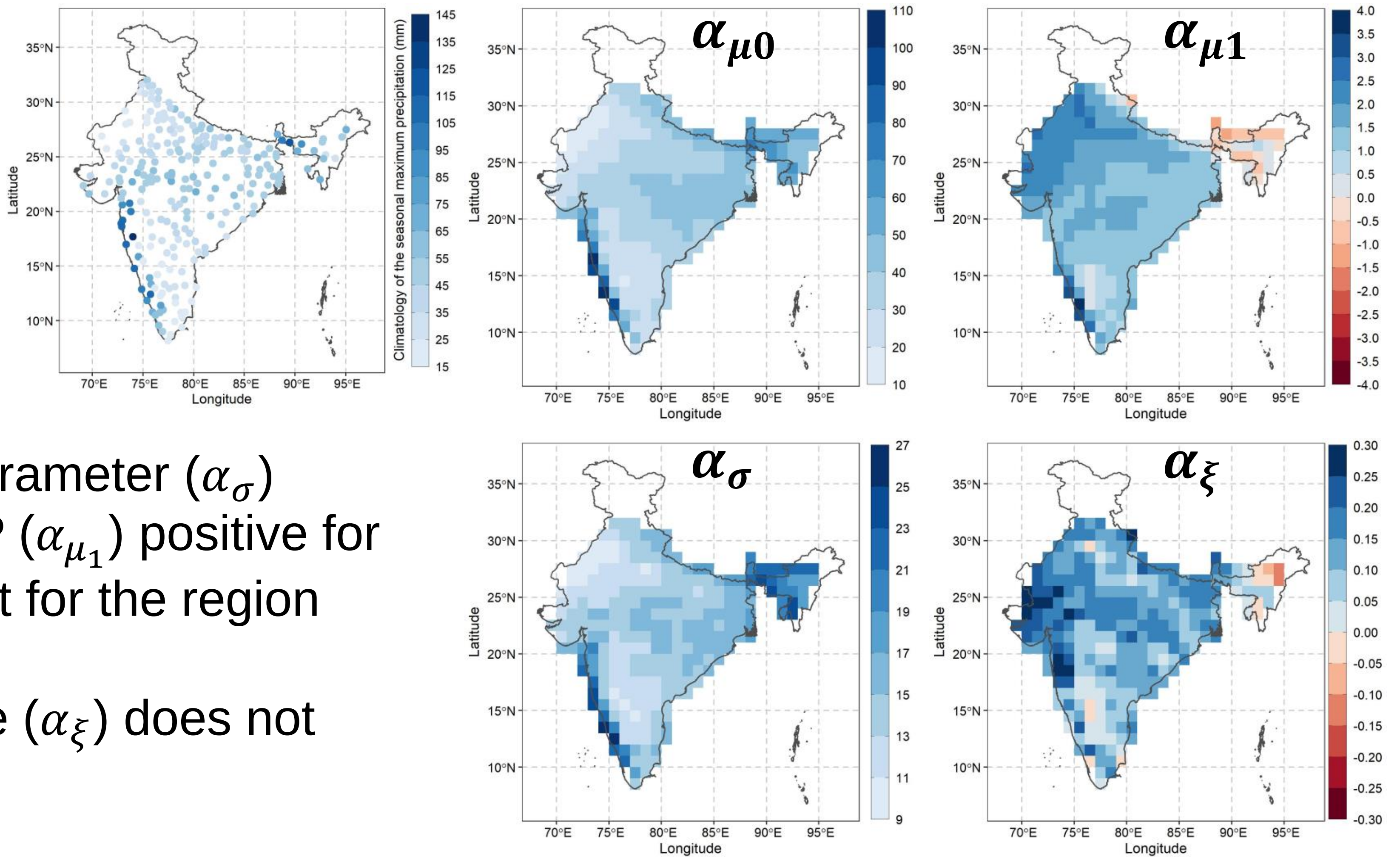
Model implementation

- Temporal covariates selected based on the lowest sum of AIC values at site (MLE)
  $\rightarrow$ SASP ($\alpha_{\mu 1}$)
- Only location was considered nonstationary
- For the Gaussian kernels, we used 10 knots and group size of 10 (Bracken et al., 2016)
- We used weakly informative normal priors.
- Posterior distributions estimated using the No-U-Turn Sampler (NUTS; Hoffman and Gelman 2014) for the Markov Chain Monte Carlo method (Gelman and Hill 2006).
- 3000 posterior samples (ensembles)



Posterior distribution of the GEV regression coefficients capture the spatial patterns of the data

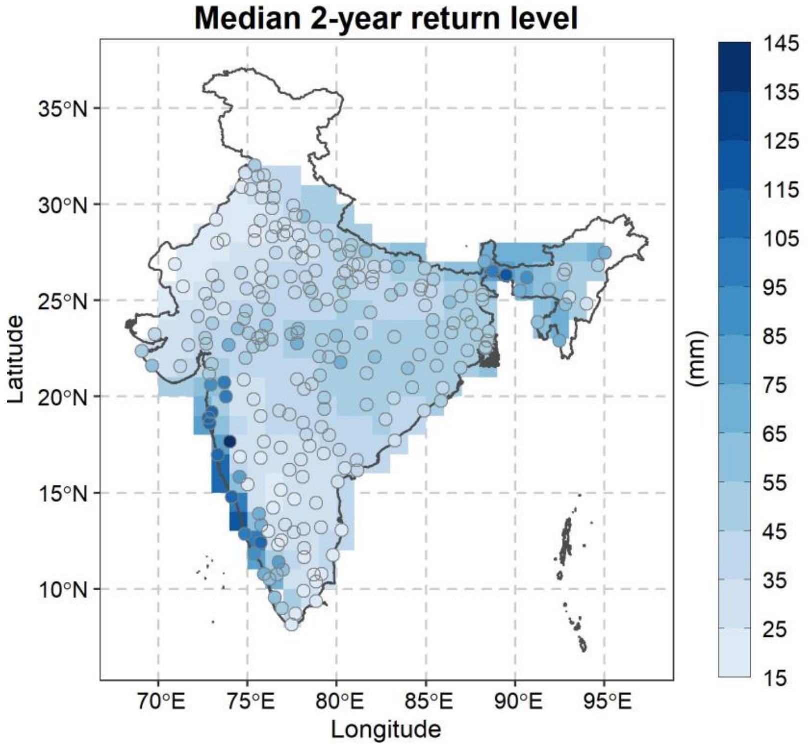
- Spatial pattern of the posterior median of the intercept of location parameter (α_{μ_0}) is consistent with seasonal maximum precipitation climatology

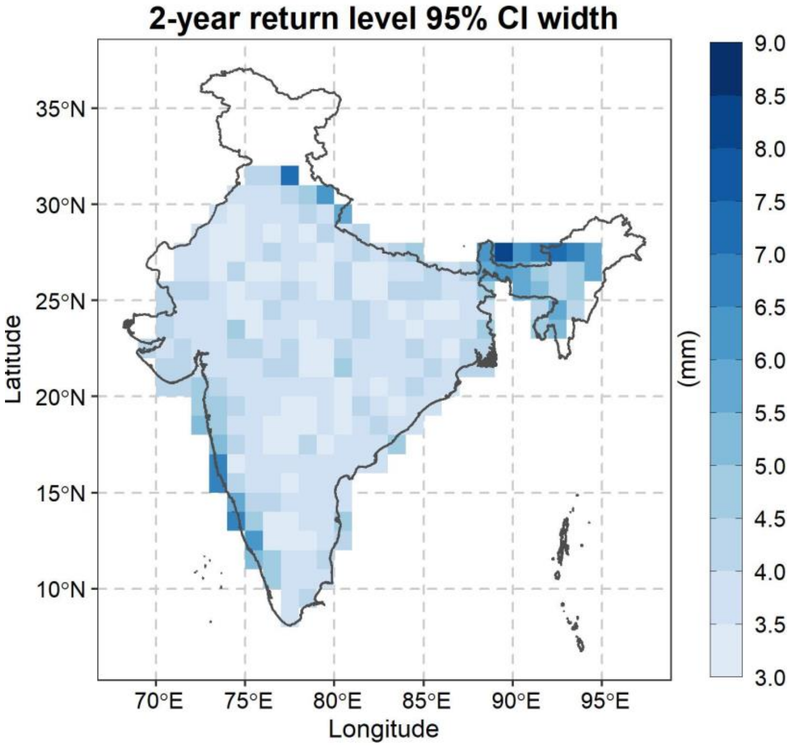


- Same pattern for scale parameter (α_{σ})
- Posterior median of SASP (α_{μ_1}) positive for most of the country except for the region close to the Himalayas
- Posterior median of shape (α_{ξ}) does not show any spatial pattern

Median of 2-year return level maximum precipitation captures the spatial patterns of the data

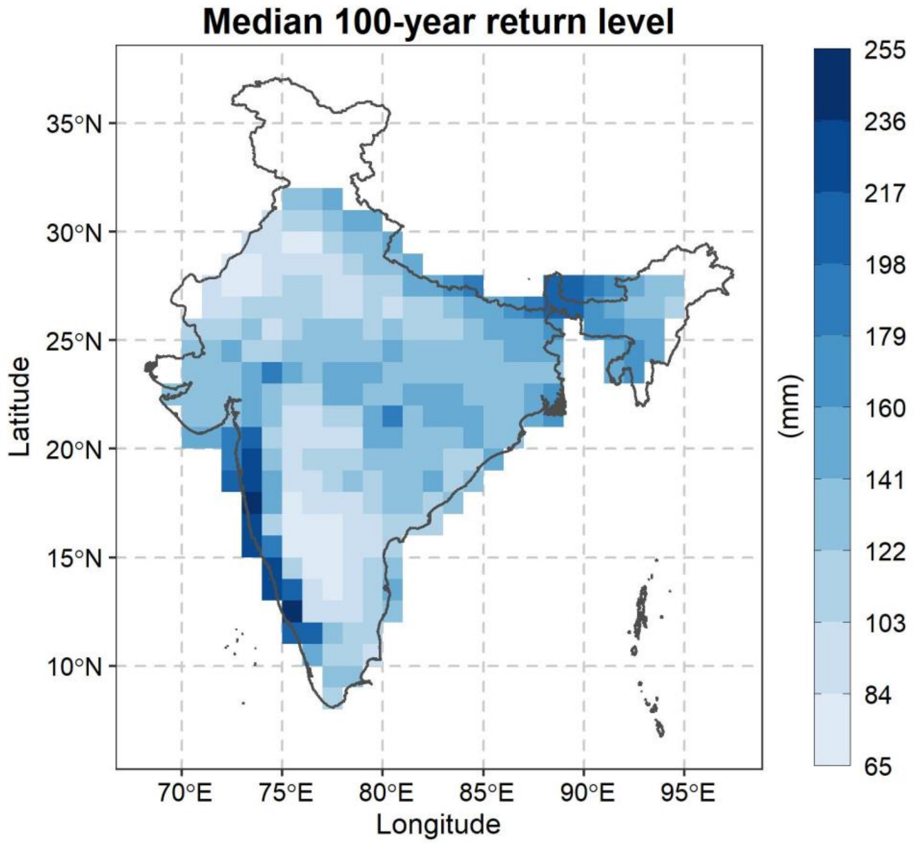
- BHM capture the spatial patterns of the observed summer maximum precipitation
- Small uncertainty for most of the domain with high values in the west coast and the mountain region close to the Himalayas

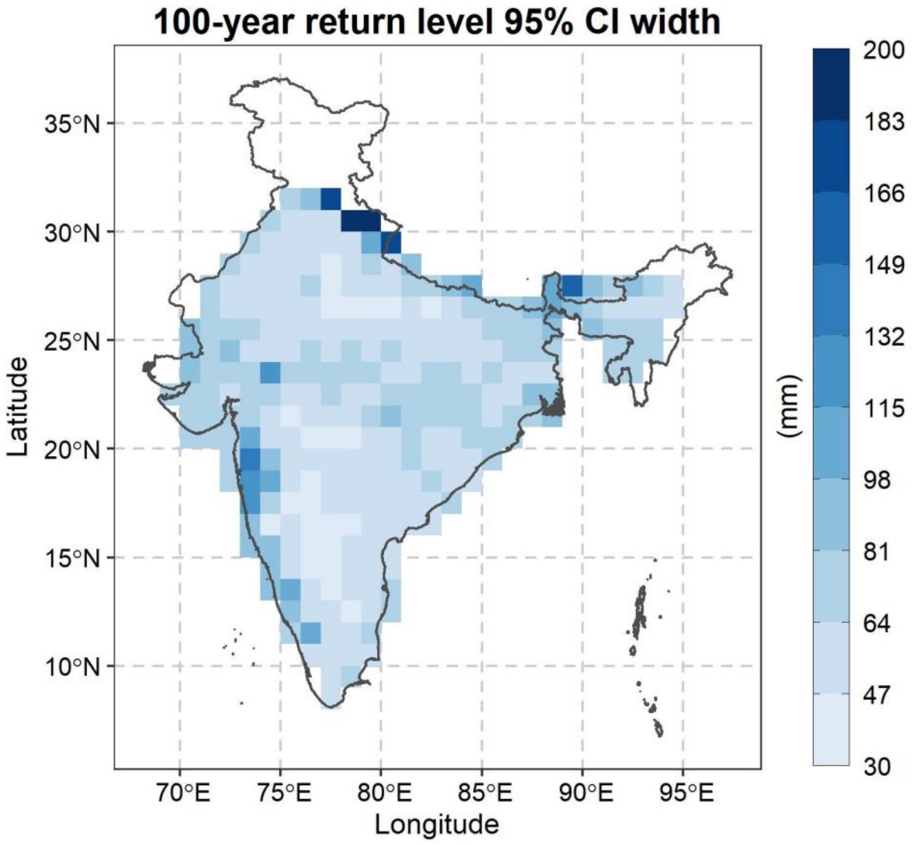




Median of 100-year return level maximum precipitation

- Similar pattern to the climatology of the observed summer maximum precipitation and the median of 2 years return level

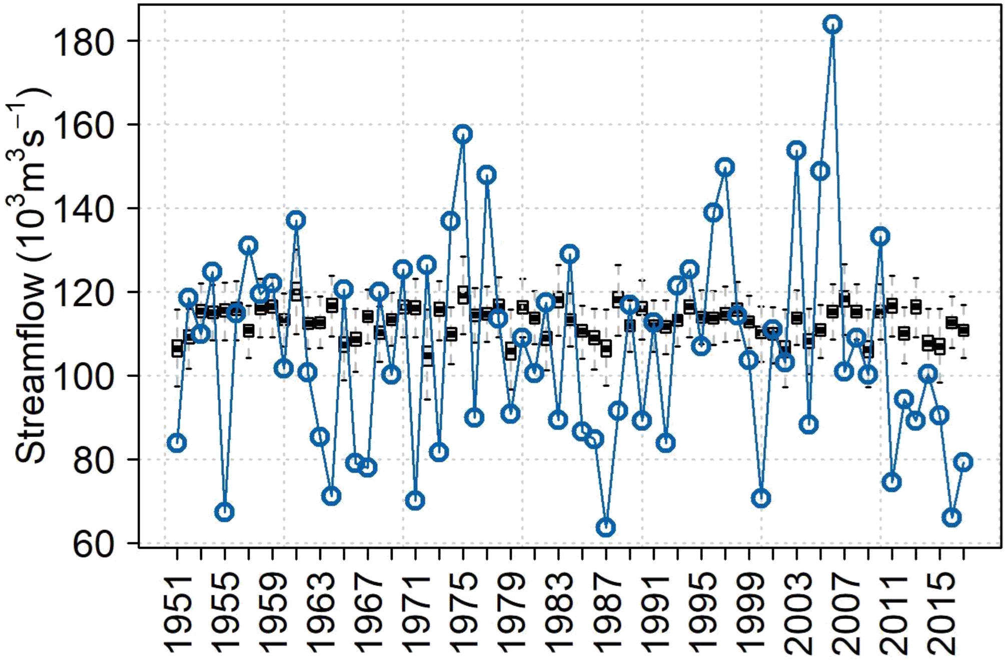




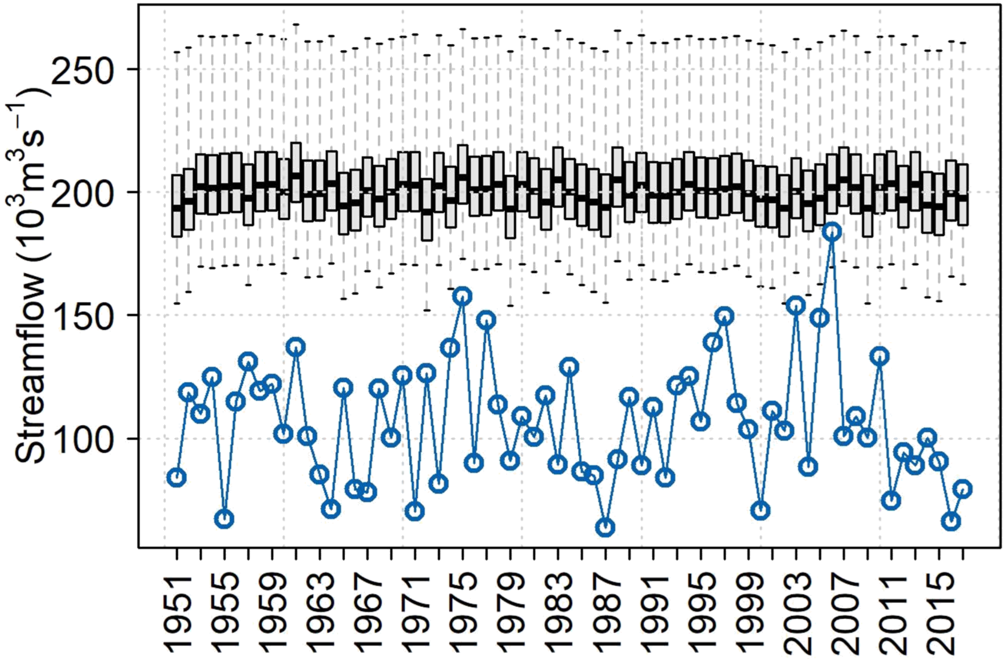
Time series of return levels

- BHM can generally capture the temporal variability of the data

2 years return level

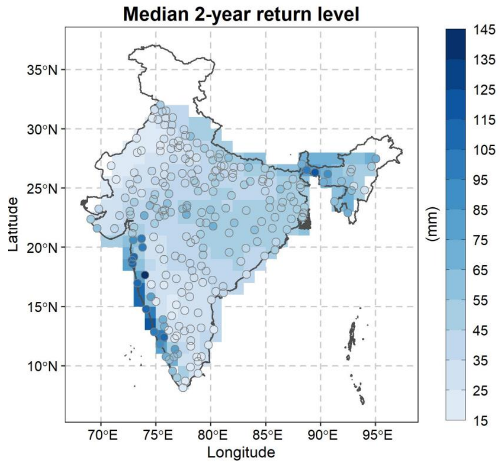


100 years return level

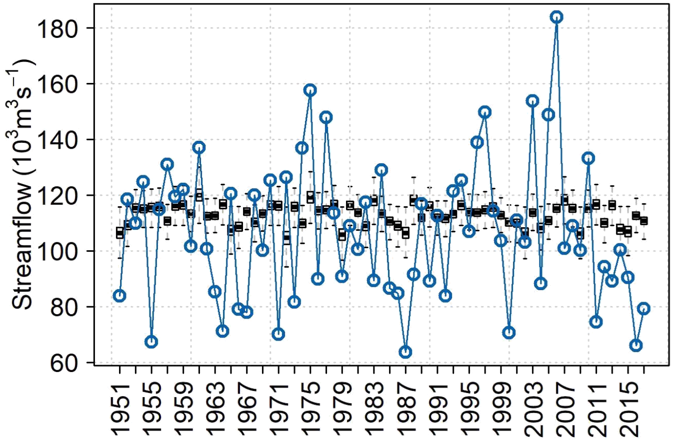


Conclusions

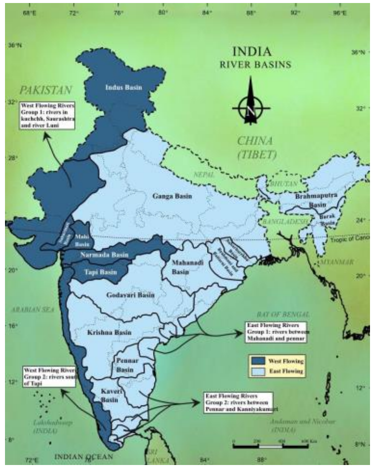
Captures the spatial pattern of the data



Provides temporal variability of the data by considering nonstationarity



The framework can be applied regionally to improve the results by considering tailored covariates



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