



# Investigating Spatiotemporal Patterns of Soil Moisture - Precipitation Dependence over India

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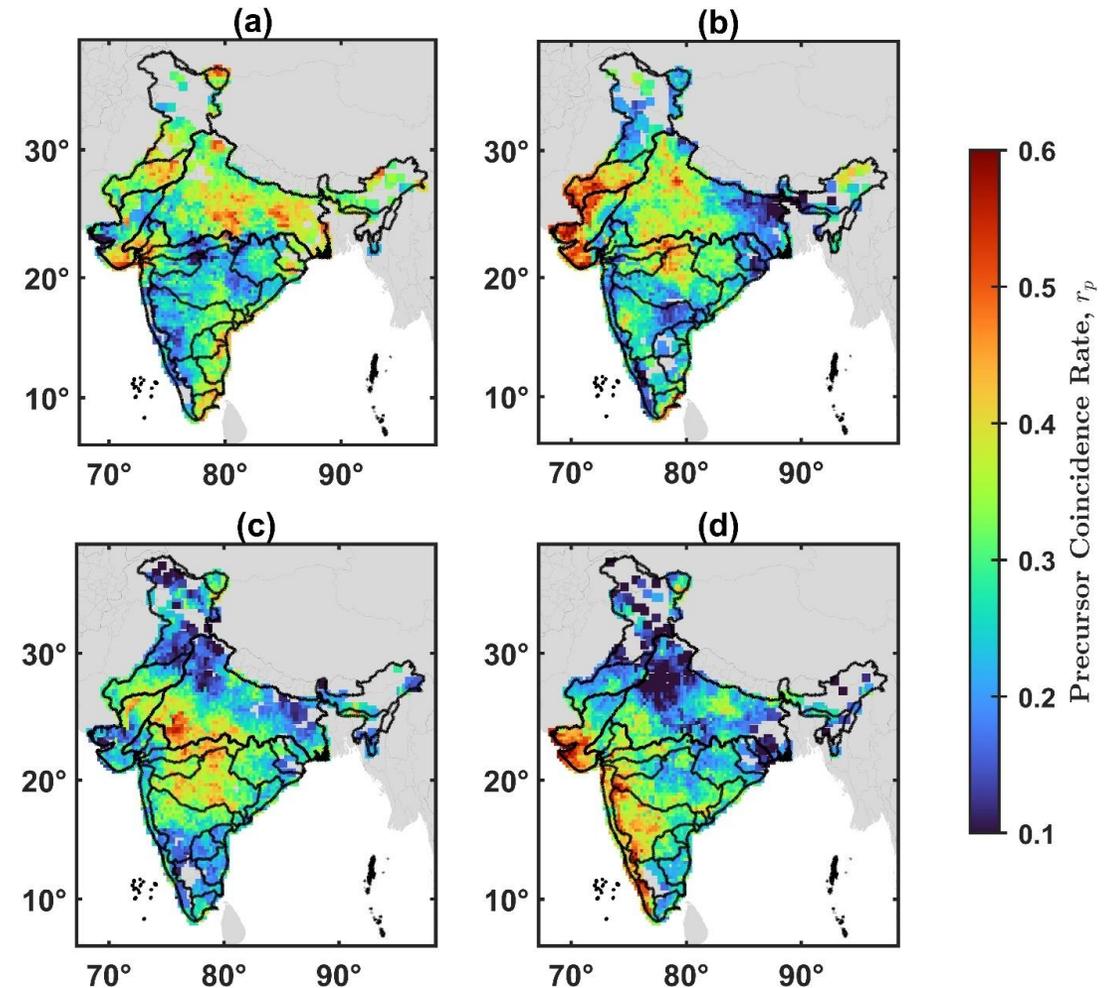
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In Hydrocomplexity: Addressing Challenges in Hydrology from a Holistic Perspective III Online Discussion Session (319)

22 June'22



# Learning from IPCC AR6

- **Climate Change** - impacted almost all phases of the global water cycle<sup>1</sup>
- Extreme Precipitation events have **increased** – past few decades<sup>1,2</sup>
- Observed increases in precipitation extremes – not directly translated to observed increases in **flooding**<sup>3,4</sup>
- Decrease in **antecedent soil moisture** – decline in observed flood discharge<sup>4</sup>
- **Preconditioned Compound Event**<sup>5</sup>

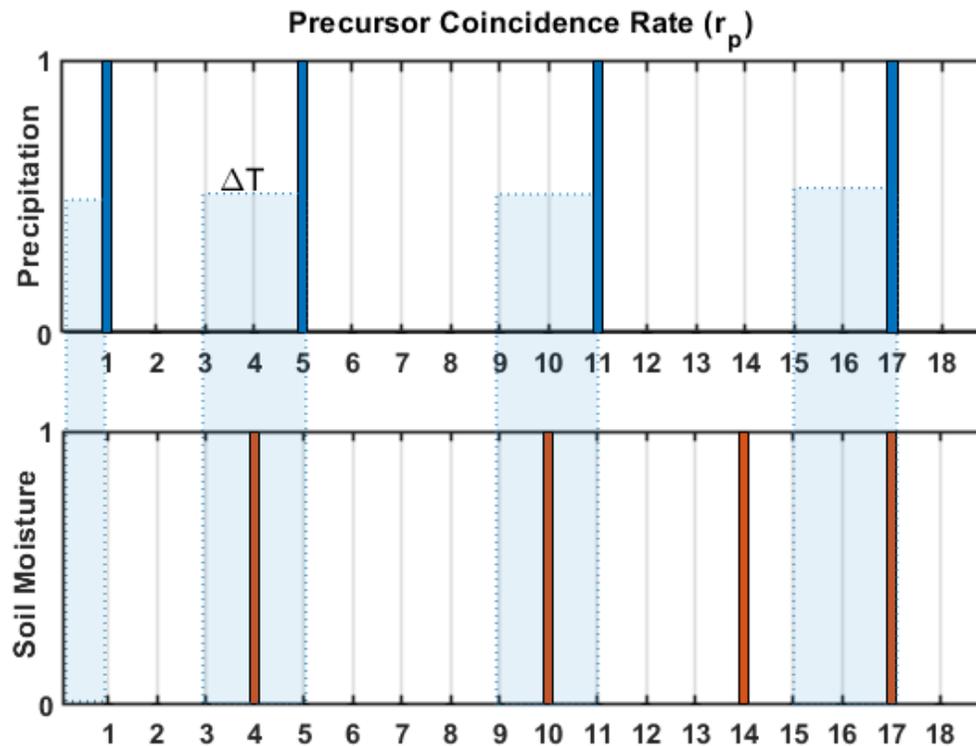
**IPCC AR6 – “*Low confidence in regional changes on flood frequency as it is strongly dependent on antecedent conditions!!!*”**

- 1) IPCC AR6 – 2021
- 2) Roxy et al., 2017
- 3) Sharma et al., 2018
- 4) Wasko et al., 2020
- 5) Zscheischler et al. 2020

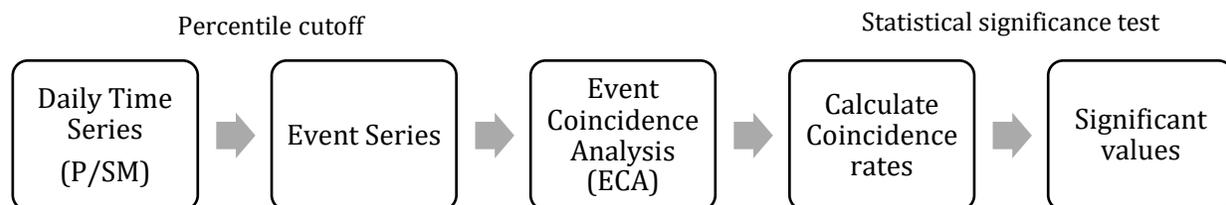
# Research Objectives

- R01** How to quantify and characterize the **spatiotemporal patterns** of SM –P dependence?
- R02** Does the SM-P patterns undergo **spatial/temporal shifts** over time?  
Do the **temporal evolution** correspond to **changing flood** patterns?

# Event Coincidence Analysis



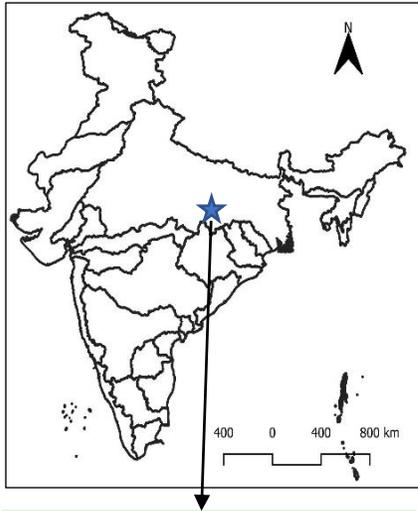
- Event Coincidence Analysis<sup>1,2,3</sup> (ECA) – quantifies and characterize - coincidences between event series
- Helps to consider the timings of well-defined events
- Two parameters - temporal tolerance interval  $\Delta T$  and joint time delay of  $\tau$
- Statistical significance test<sup>3</sup> to ensure that observed coincidences are not random
- Recent studies<sup>4</sup> – disentangled SM-P Covariation patterns using ECA



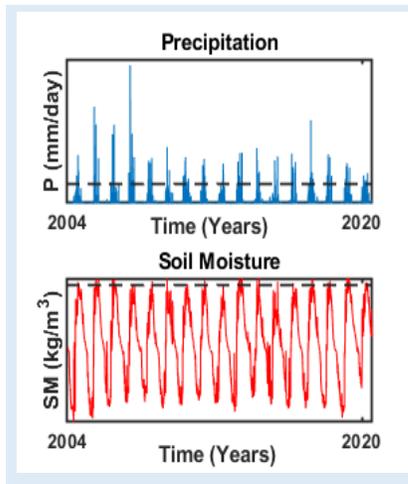
- 1) Donges et al., 2011, 2016
- 2) Siegmund et al., 2016
- 3) Siegmund et al., 2017
- 4) Sun et al. 2018

# Methodology & Data

## Step 1 – Data Preparation



## Step 2 – Percentile Cut-off



## Step 4 – Tail Dependence

Limit of Tail Dependence:

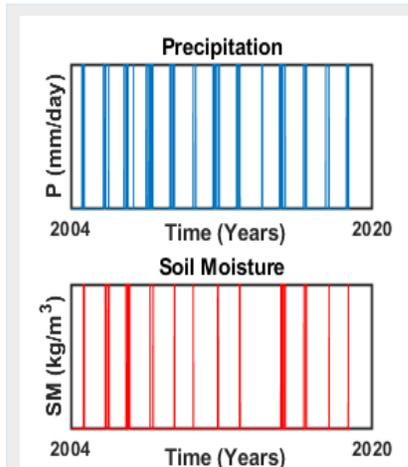
$$\chi = \lim_{u \rightarrow 1} P(F_Y(y) > u | F_X(x) > u)$$

Tail Dependence Measures:

$$\chi(u) = 2 - \frac{\log P(F_X(x) < u, F_Y(y) < u)}{\log P(F_X(x) < u)}$$

$$\bar{\chi}(u) = \sum_{0.90 < u \leq 0.95} \chi(u)$$

## Step 3 – Event Series



## Step 5 – ECA

Precursor coincidence rate

$$r_p = \frac{1}{N_p} \sum_{i=1}^{N_p} H \left( \sum_{j=1}^{N_{SM}} I_{[0, \Delta T]}((t_i^p - \tau) - t_j^{SM}) \right)$$

Trigger coincidence rate

$$r_t = \frac{1}{N_{SM}} \sum_{j=1}^{N_{SM}} H \left( \sum_{i=1}^{N_p} I_{[0, \Delta T]}((t_i^p - \tau) - t_j^{SM}) \right)$$

Significance test at  $\alpha = 0.05$

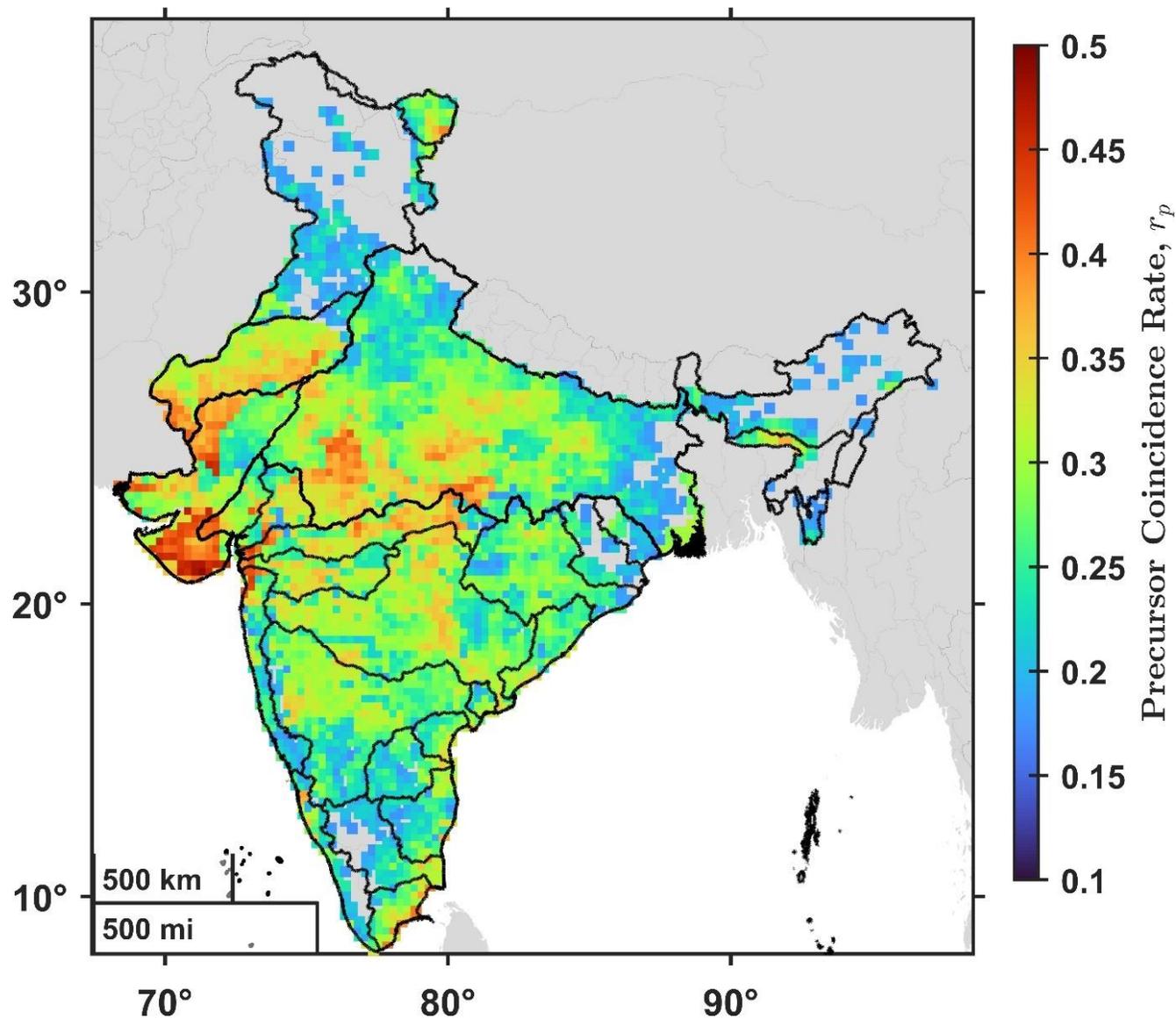
## Precipitation

- GPM – Global Precipitation Measurement
- $0.1^\circ \times 0.1^\circ$
- IMERG - Integrated Multi-satellite Retrievals for GPM
- IMERG – Version 06

## Soil Moisture

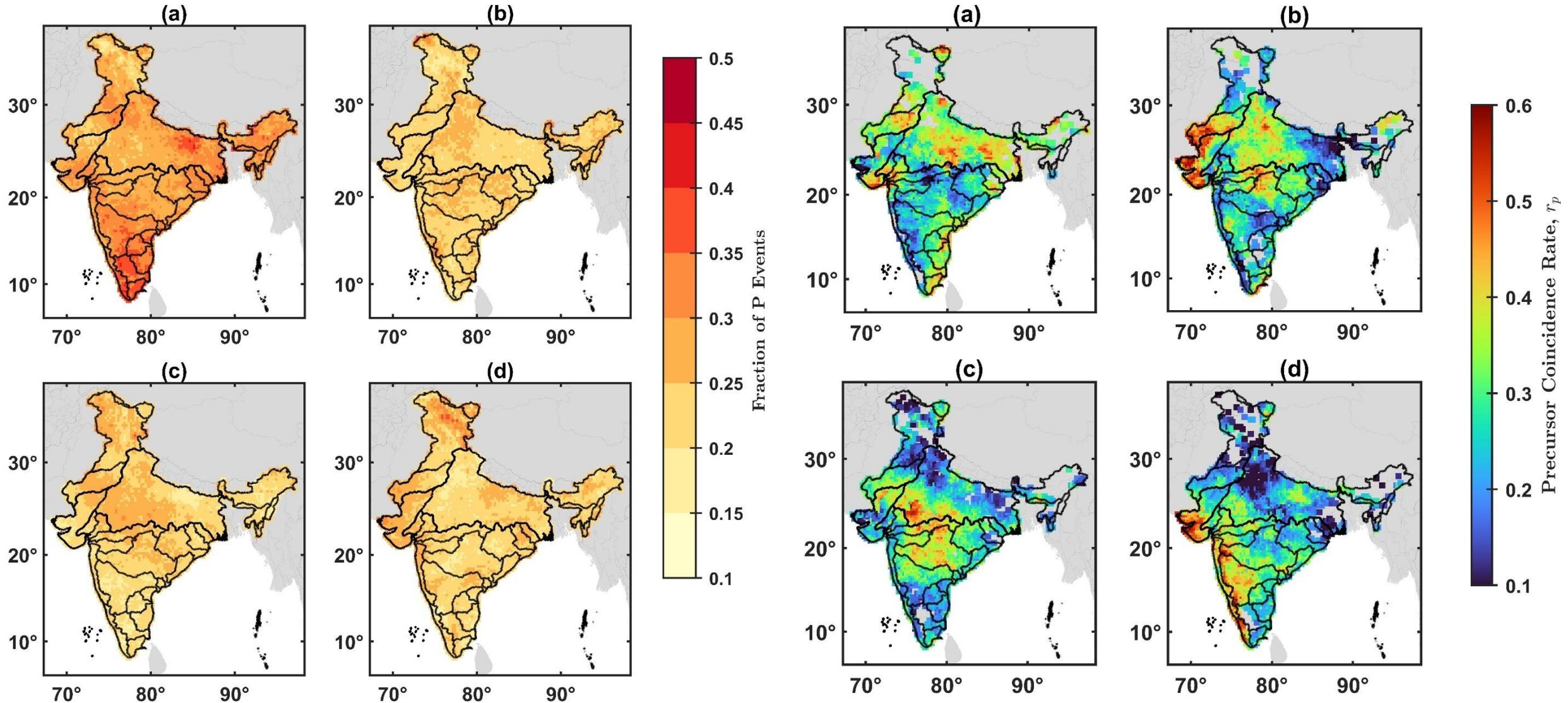
- NASA's Global Land Data Assimilation System
- $0.25^\circ \times 0.25^\circ$
- GLDAS – CLSM 2.2
- With GRACE-Data Assimilation

# Spatiotemporal evolution of SM-P

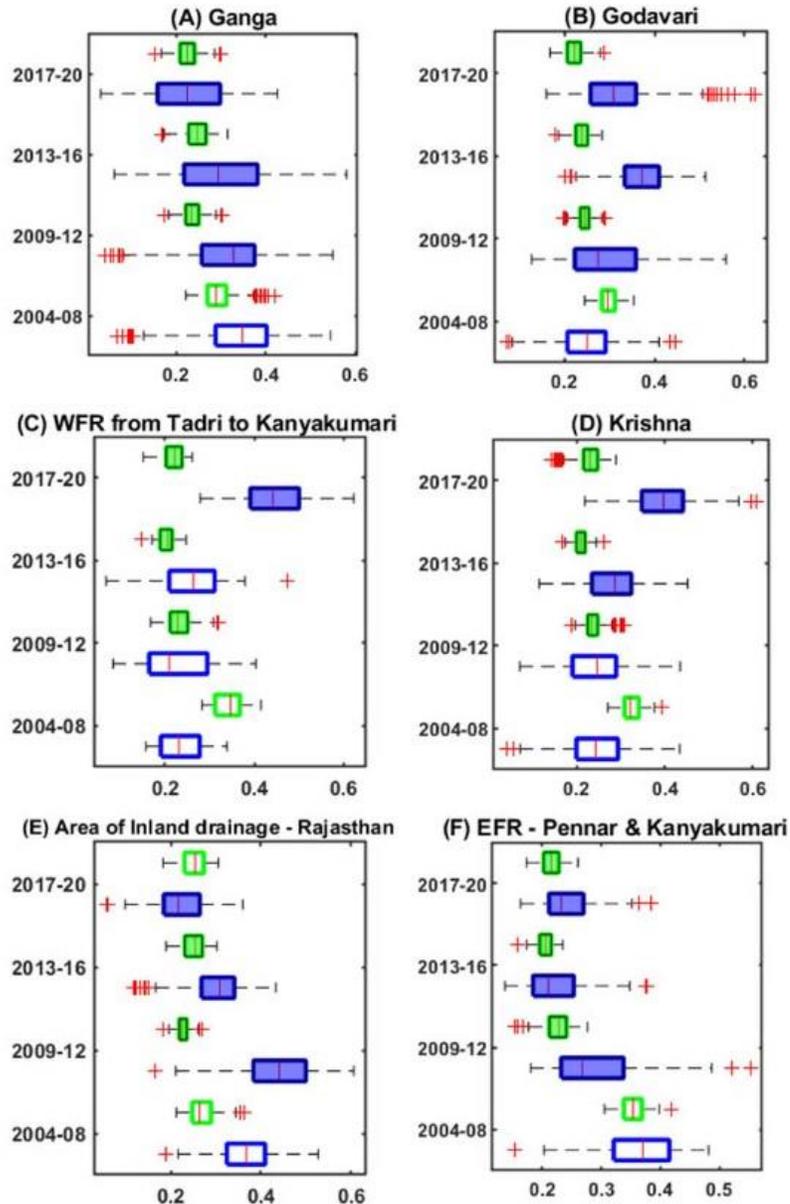


- Temporal Tolerance – 2 days
- Grid points with  $r_p > 0.40$  (40% of P events were preceded by SM event) - Ganga river basin (2A), West flowing rivers of Kutch and Saurashtra including Luni (18), inland drainage of Rajasthan (19), and Narmada river basin (12)
- SM-P preconditioning - weaken - towards the corners of the country
- Impact of **temporal evolution**?

# Spatiotemporal evolution of SM-P

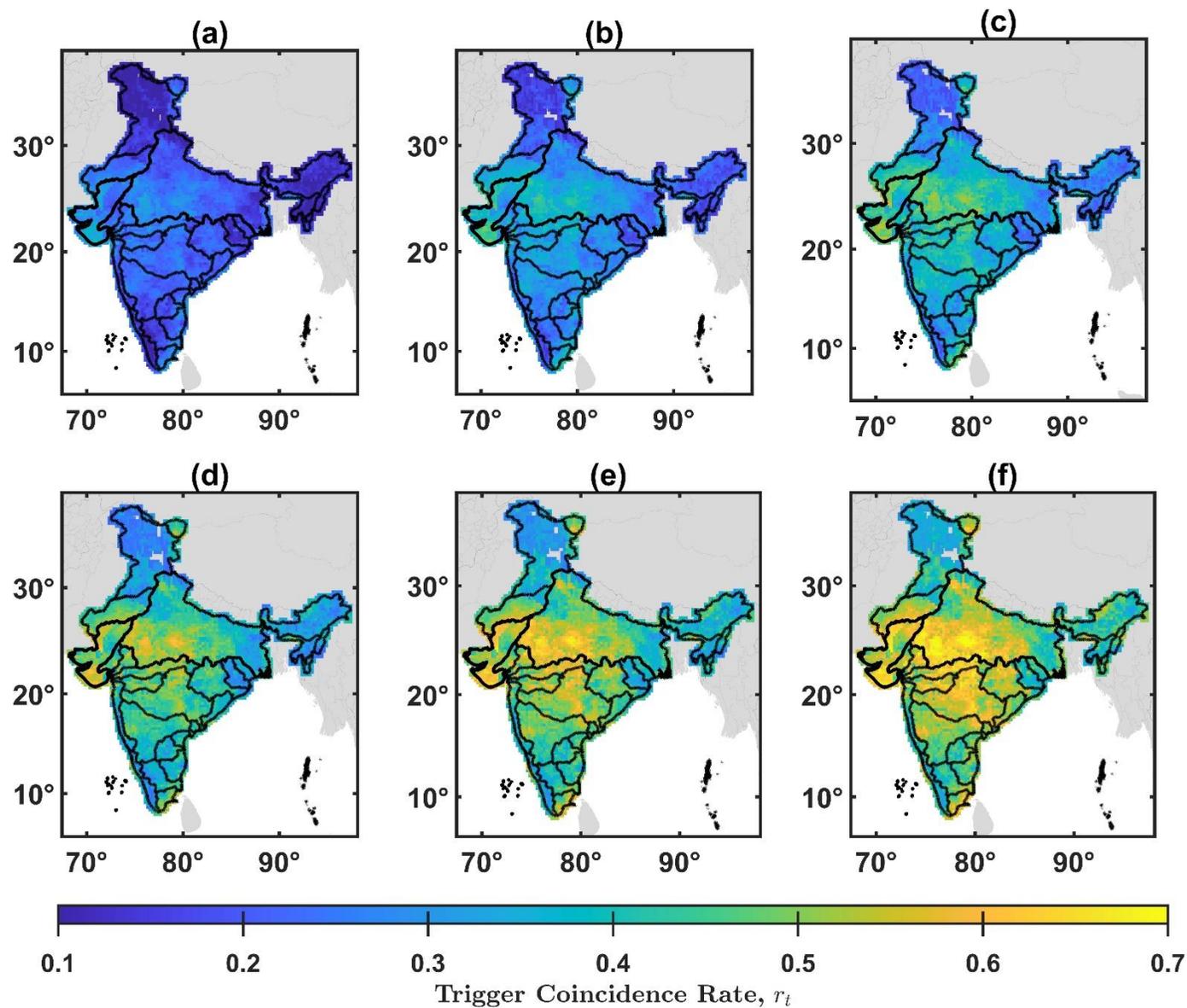


# Basin-scale Analysis



- SM-P preconditioning has undergone significant changes over the years
- Visualize the change in the hydrological regime and compare it with the influence of possible meteorological forcings
- Temporal evolution of precursor coincidence is seen to be insensitive to the changes in the proportion of P extreme events
- Intensification of precipitation
- Role of catchment conditions and other land-use factors

# Trigger Relationship between SM&P



- Possible SM-P coupled relationship
- Our regions matches - increased soil moisture - precipitation coupling in transitional regions between wet and dry climates
- Preliminary analysis only
- Difficulties in establishing causal relation from observational data

# Take Home Message

- ECA can be used as an additional tool in hydro-metrological studies
- Temporal Evolutions – disconnect between P events and precursor coincidence
- Possibly due to intensification of extreme precipitation, changing LULC
- Clustering of trigger hotspots - dominant atmospheric coupling mechanisms between P and SM.
- These locations can be regarded as proxies and provide additional information in forecasting extreme precipitation events



# Thank you!!

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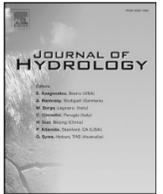
Journal of Hydrology 610 (2022) 127898



Contents lists available at [ScienceDirect](https://www.sciencedirect.com)

Journal of Hydrology

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Research papers

## Spatiotemporal dependence of soil moisture and precipitation over India

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<https://doi.org/10.1016/j.jhydrol.2022.127898>



### ARTICLE INFO

**Keywords:**  
 Event coincidence analysis  
 Precipitation  
 Soil moisture

### ABSTRACT

Anthropogenic climate change has impacted almost all phases of the global water cycle. Growing consensus asserts that extreme precipitation events will only rise in the years to come. However, an increase in extreme precipitation events does not necessarily correspond to higher flood risk. Much onus lies on the antecedent