



# Early warning of hydrological extremes in India

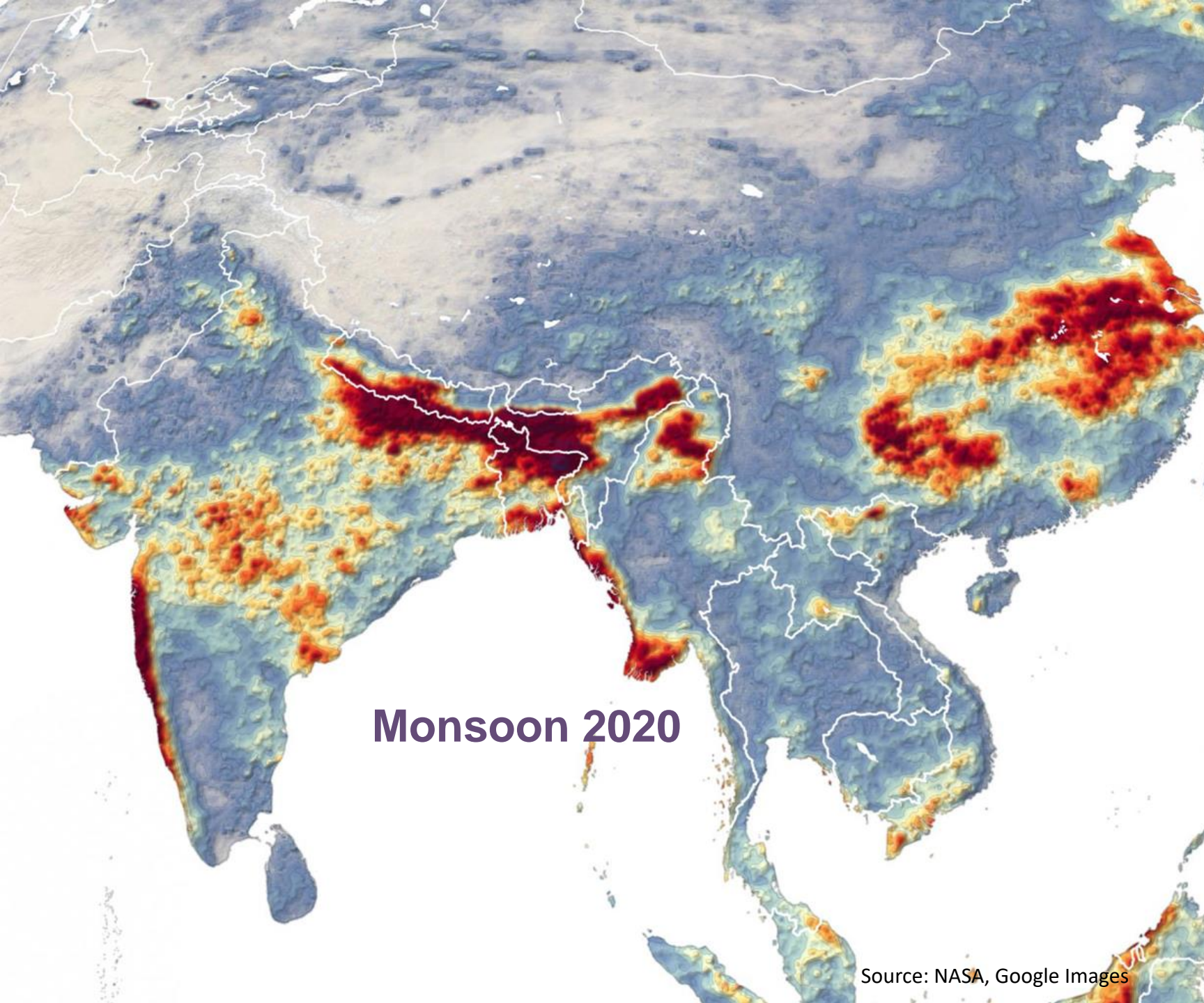
Vimal Mishra  
Indian Institute of Technology, Gandhinagar  
7 June, 2024





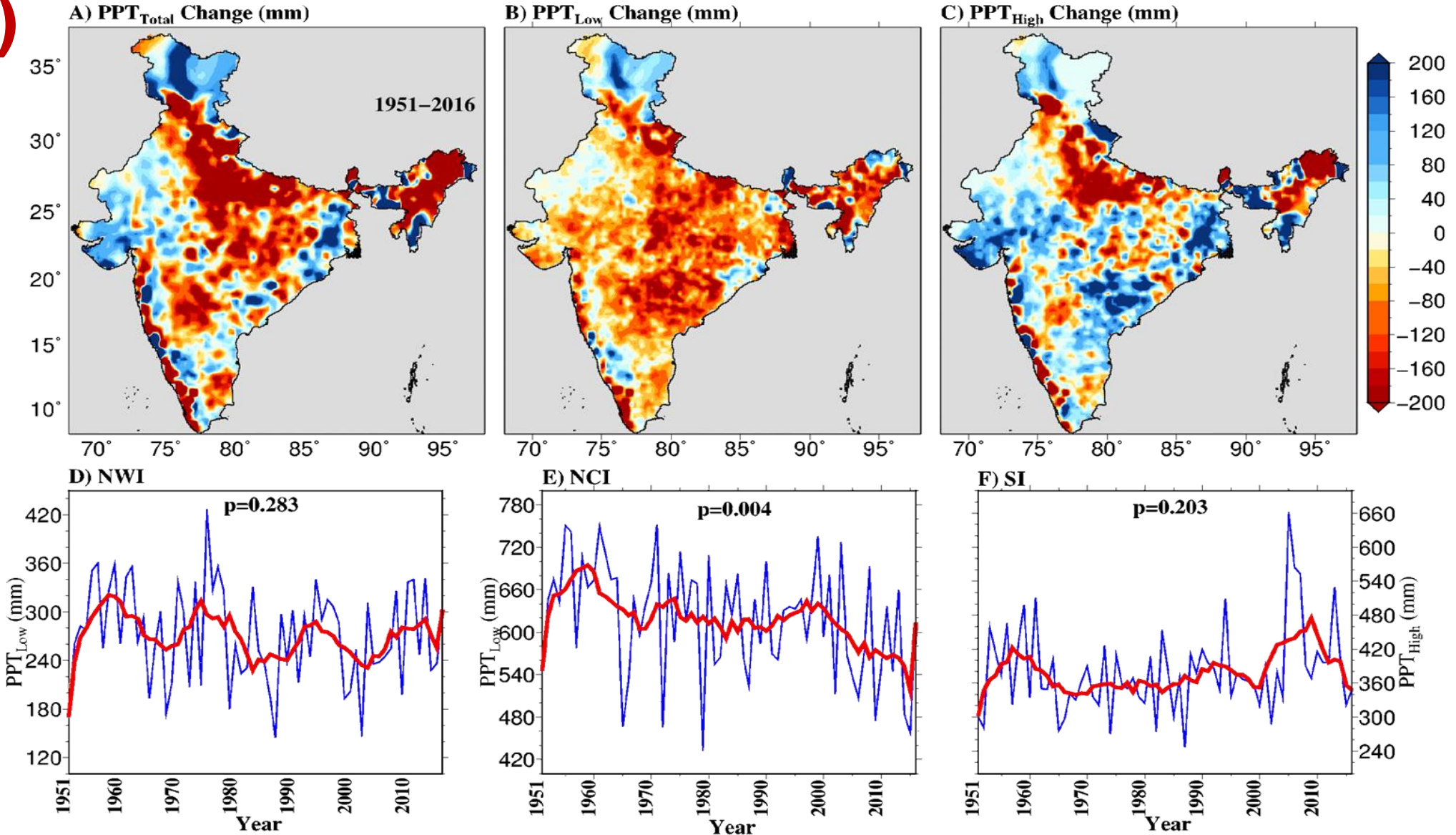
# Risk of hydroclimatic extremes

- **Air temperature (rise, irrigation/aerosols)**
- **Precipitation (mixed trends, more variability)**
- **Floods/flash floods (rise, more impacts)**
- **Droughts/flash droughts (intense, spatial/temporal variability)**
- **Compound extremes (hot-dry, wet-humid)**
- **Dry and moist heatwaves (rise, larger extents)**

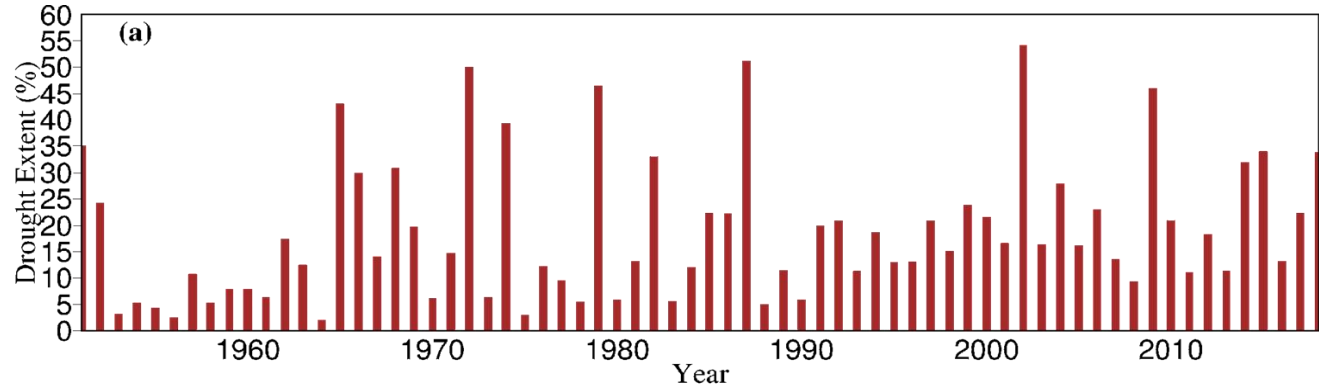


Source: NASA, Google Images

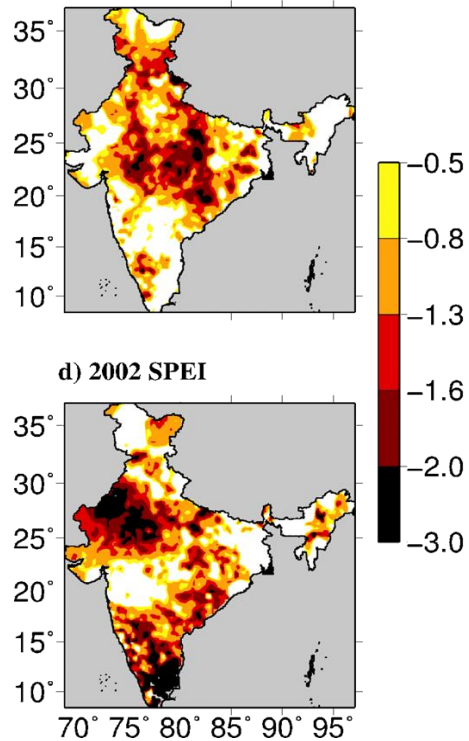
# Observed changes in rainfall characteristics (1951-2015)



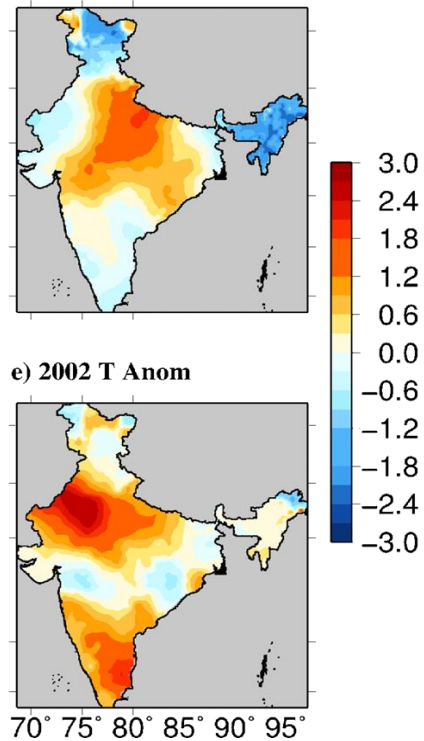
# Monsoon season droughts in India



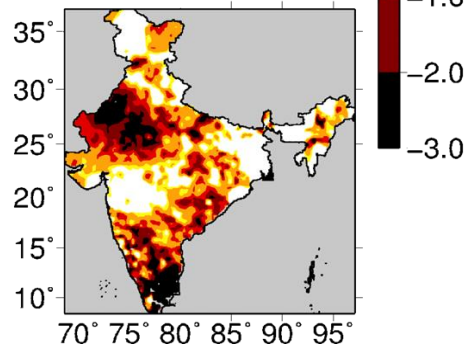
b) 1965 SPEI



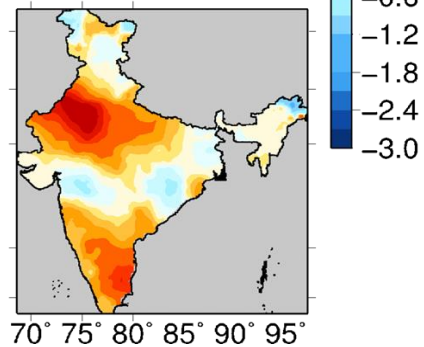
c) 1965 T Anom



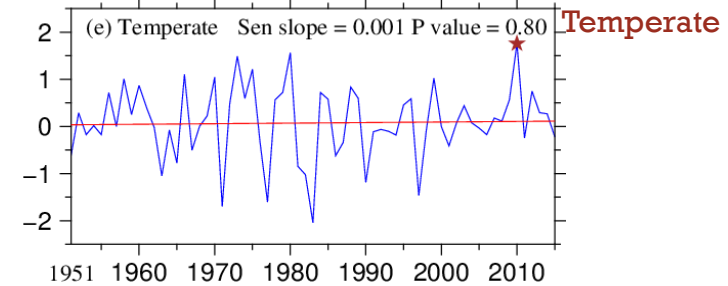
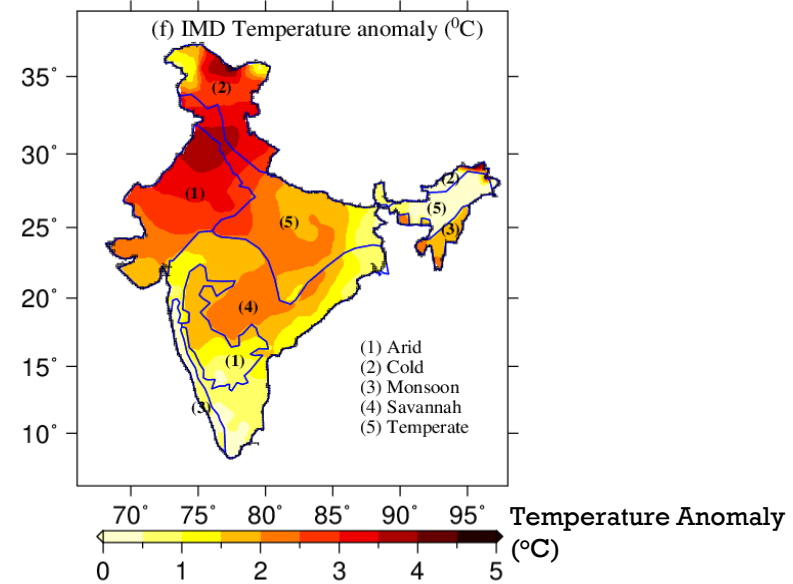
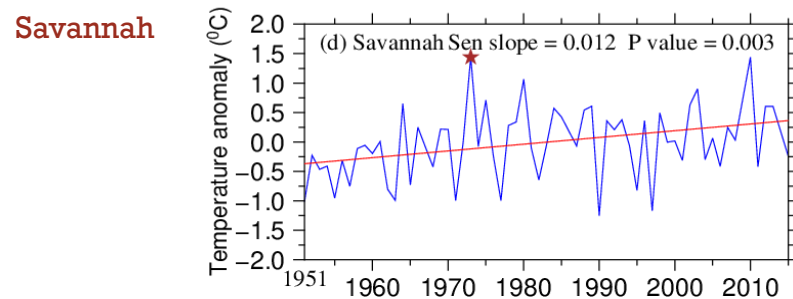
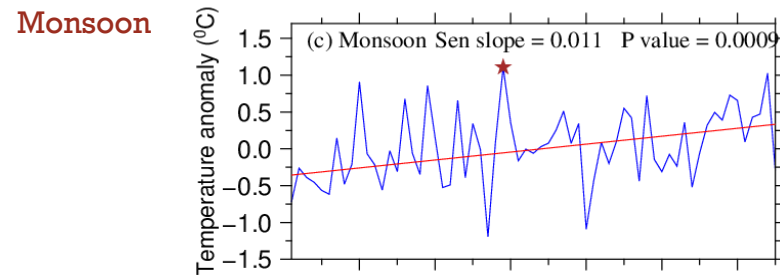
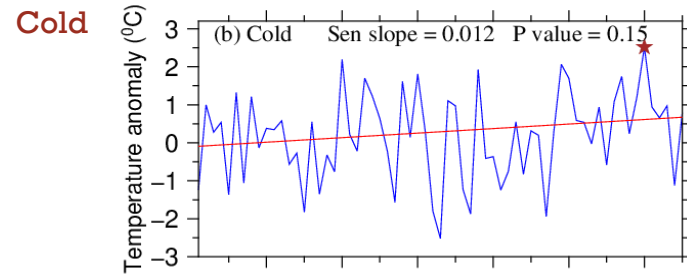
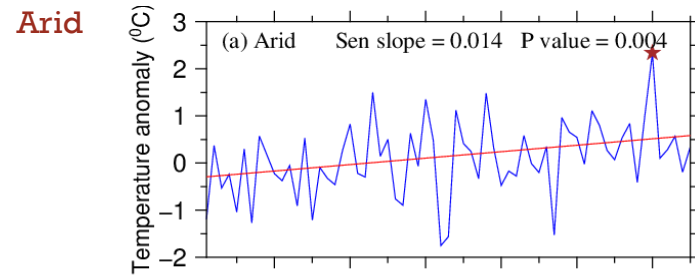
d) 2002 SPEI



e) 2002 T Anom

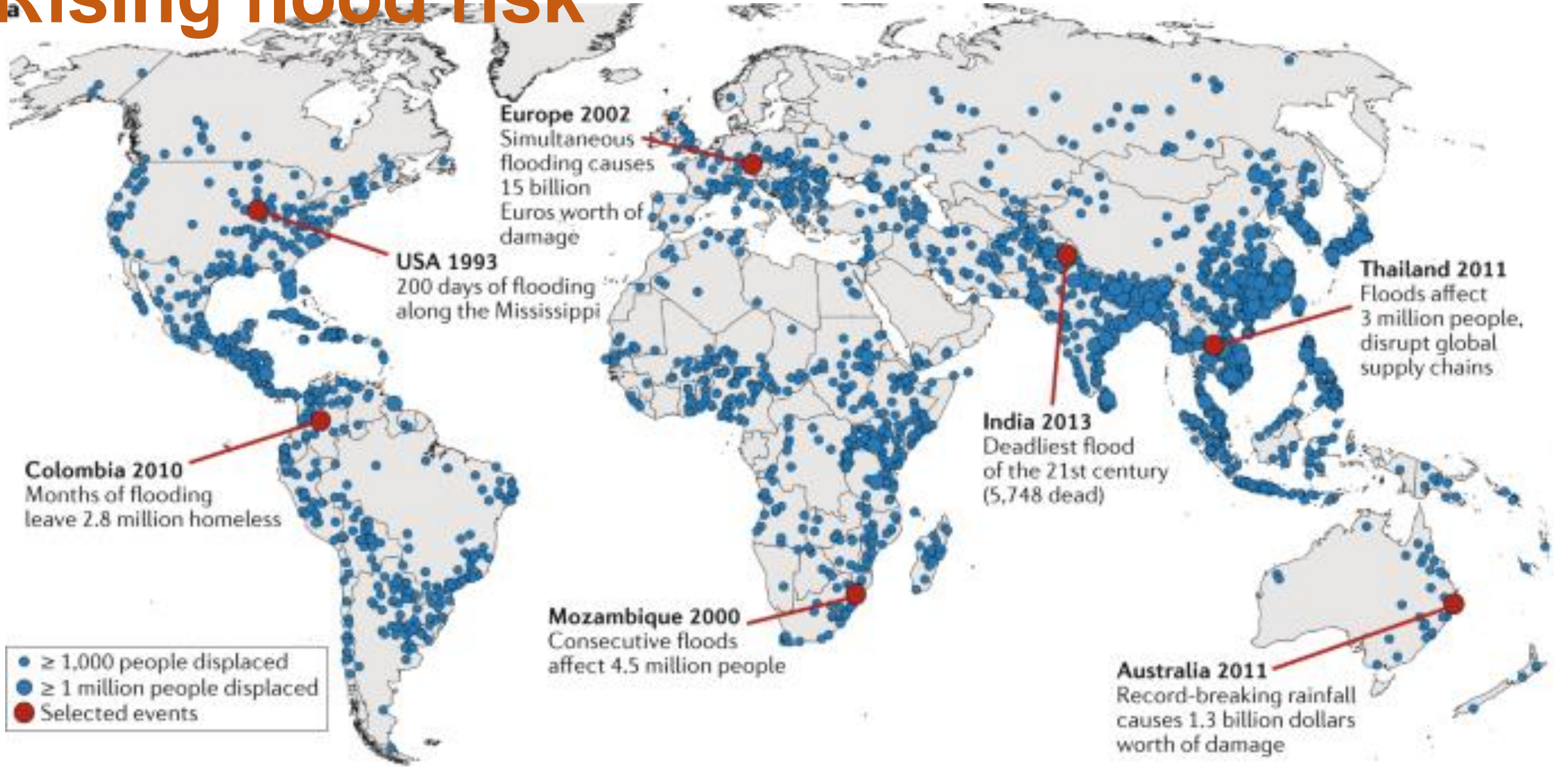


# Rising temperature and hottest summers



Climate zone	Year of hottest Summer
Arid	2010
Cold	2010
Monsoon	1979
savannah	1973
Temperate	2010

# Rising flood risk



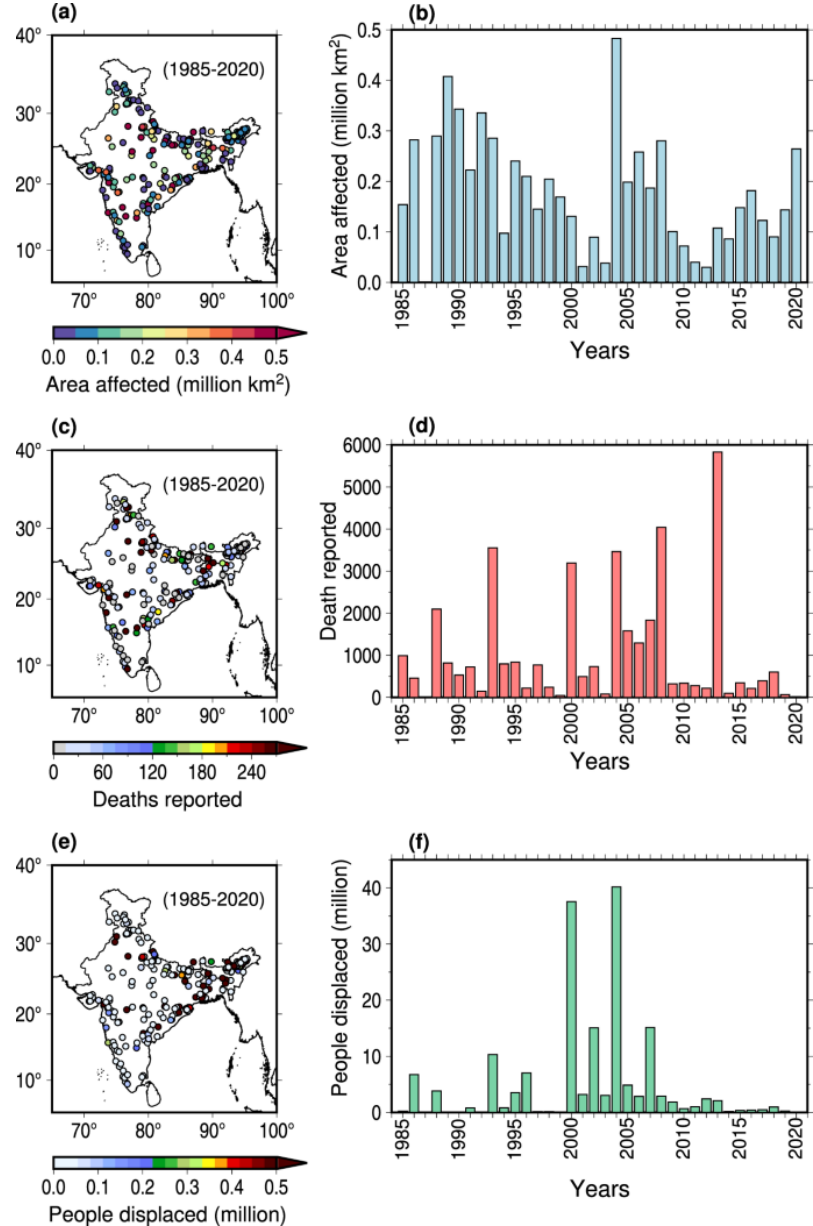
b



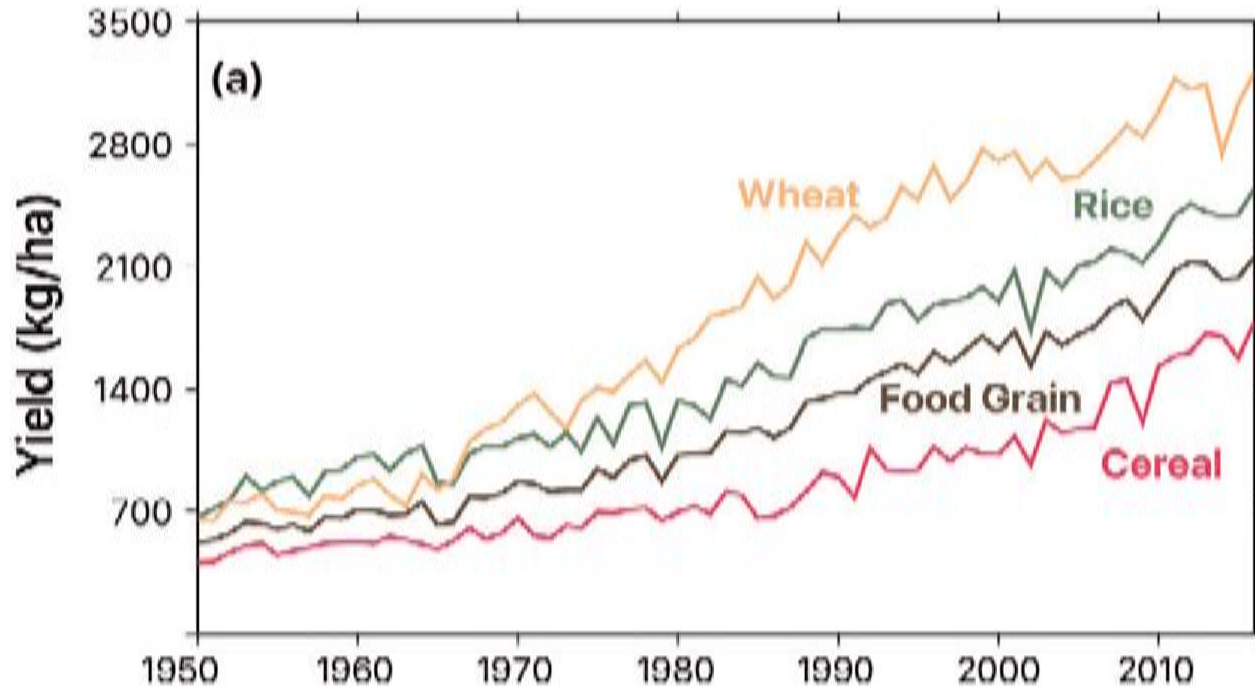
Merz et al., 2022



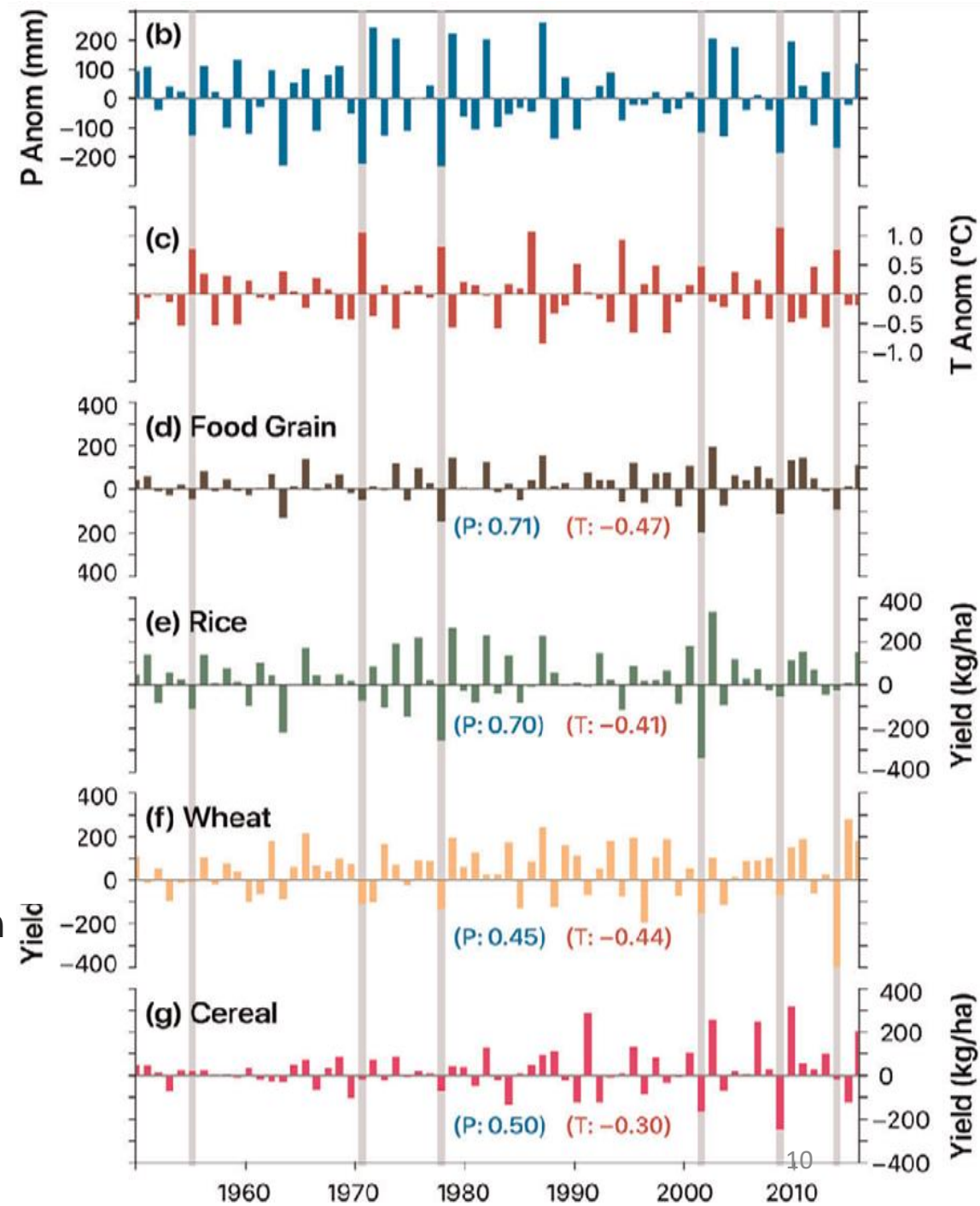
# Floods in India: area affected, mortality, and migration



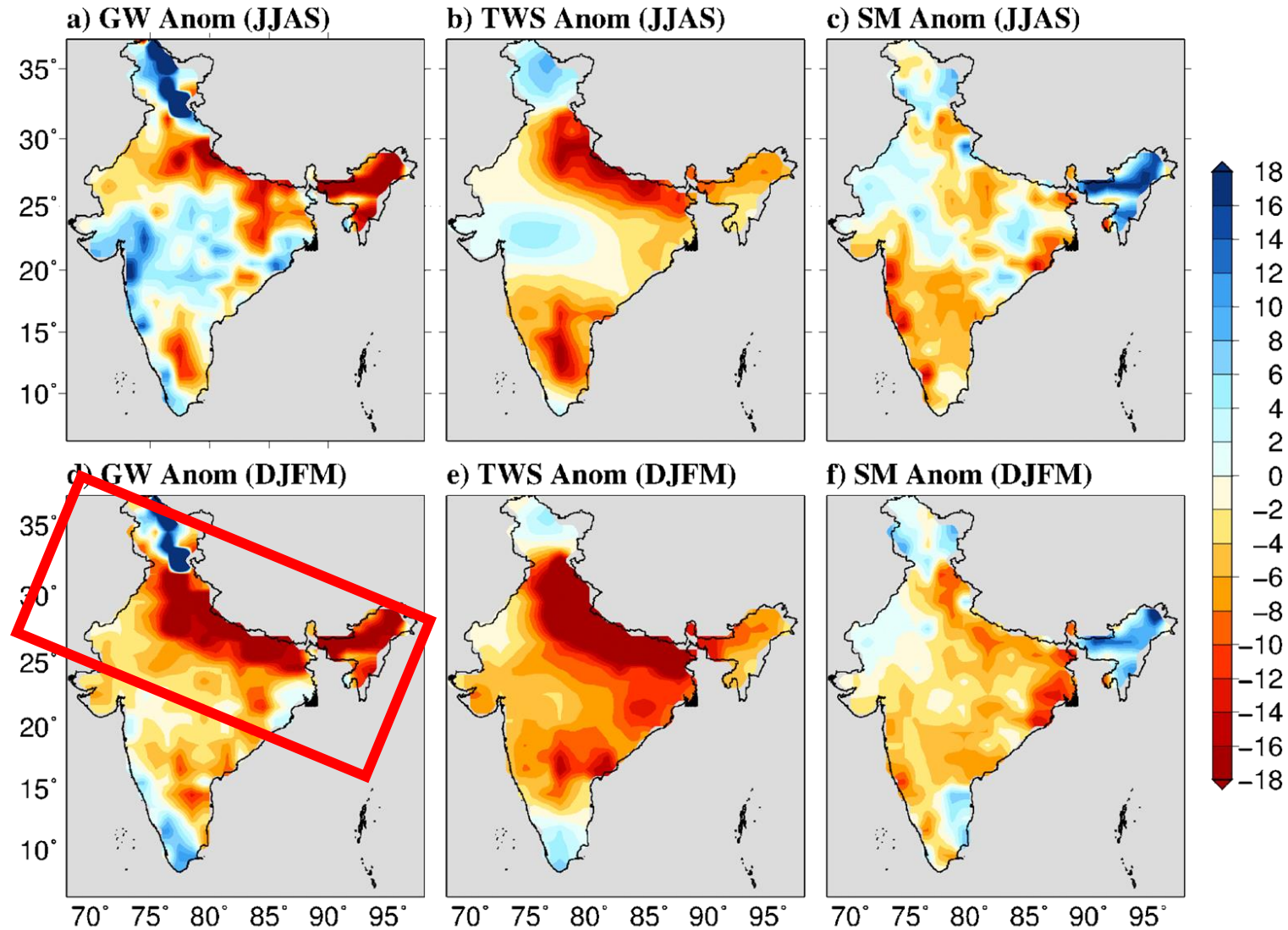
# Hot and dry monsoons and food grain yields



Changes in food production and associated links with monsoon precipitation and temperature over India.

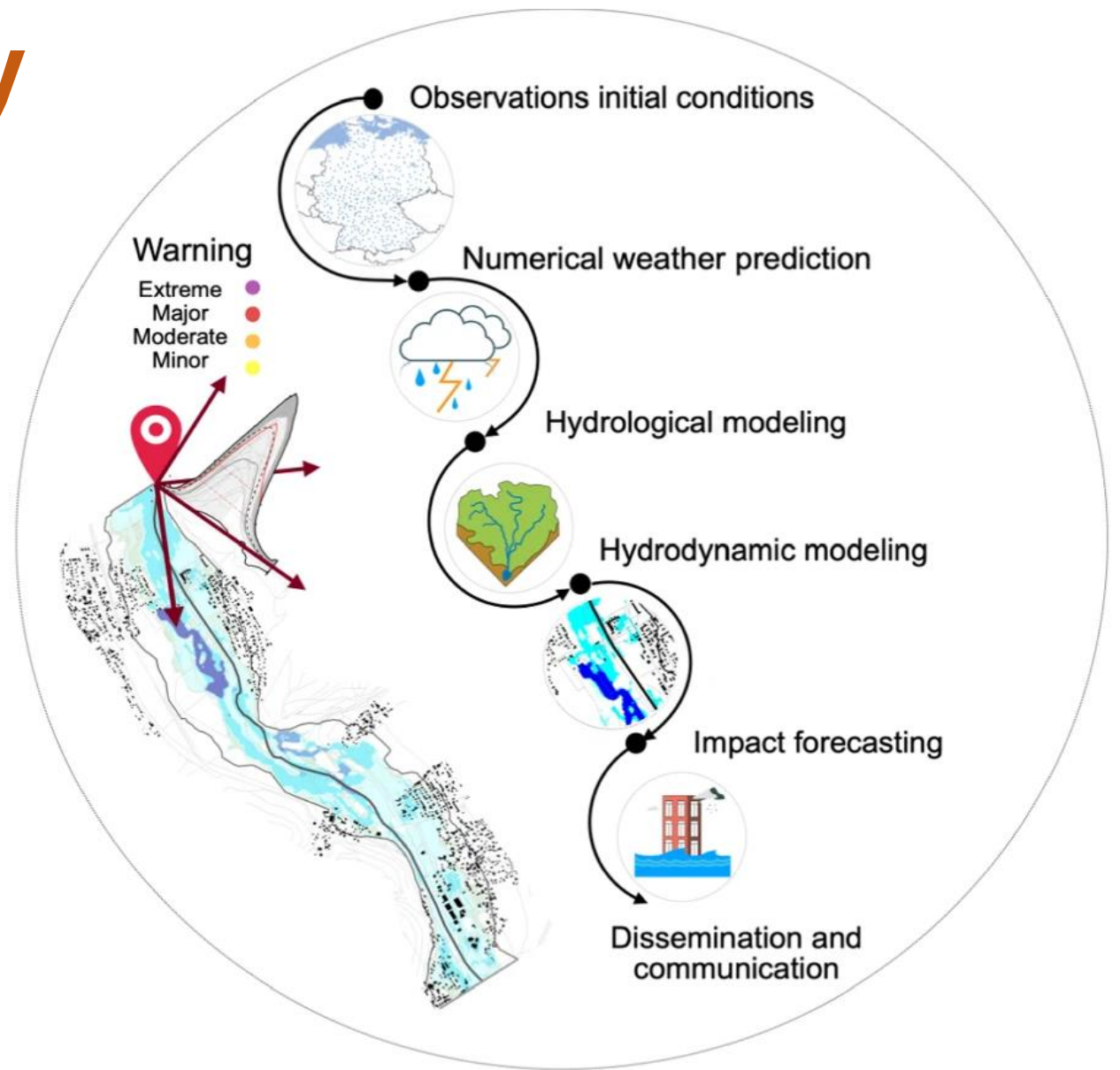


# The 2015 drought caused significant GW depletion in Gangetic Plain



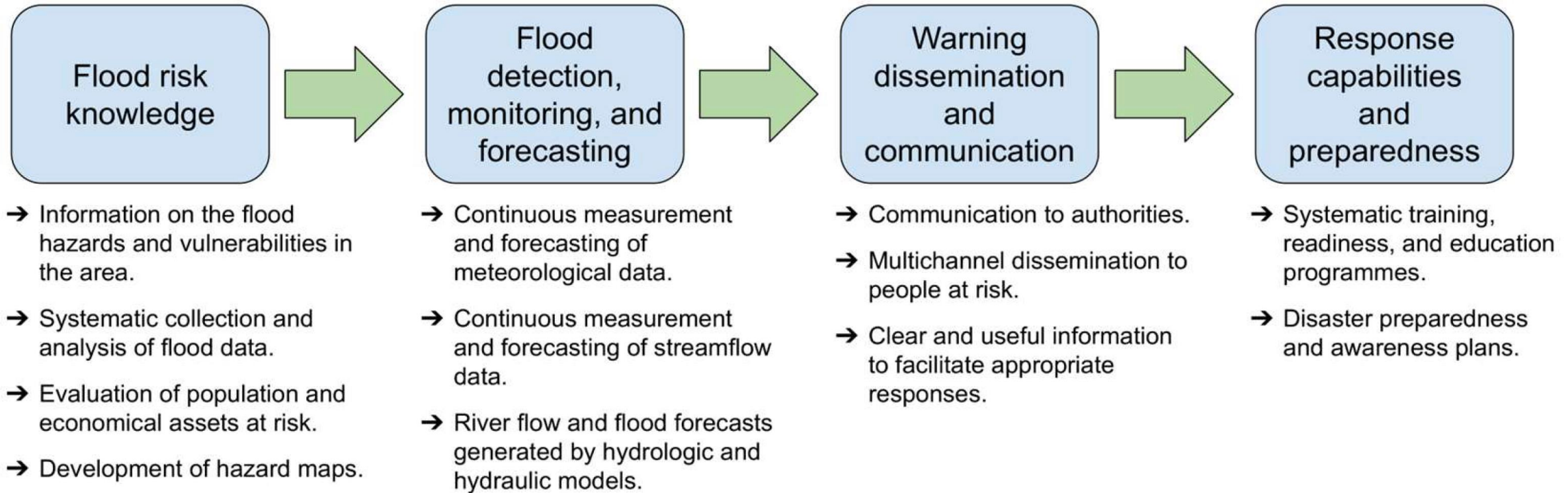
# Components of Early Warning System

1. Knowledge of the event
2. Modelling of the event
3. Detection, Monitoring, and Forecasting
4. Dissemination & Communication
5. Disaster Risk preparedness



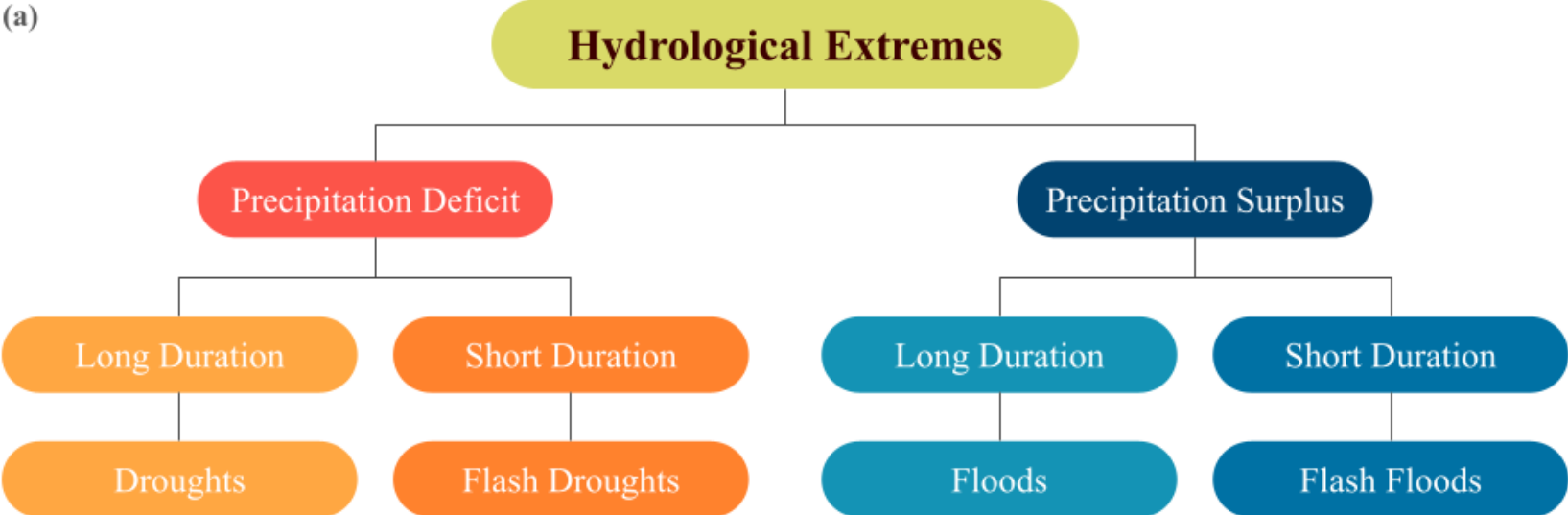
[Fig: A holistic end-to-end impact-based flood forecasting modelling chain. | Nature Communications](#)

# Components of Early Warning System

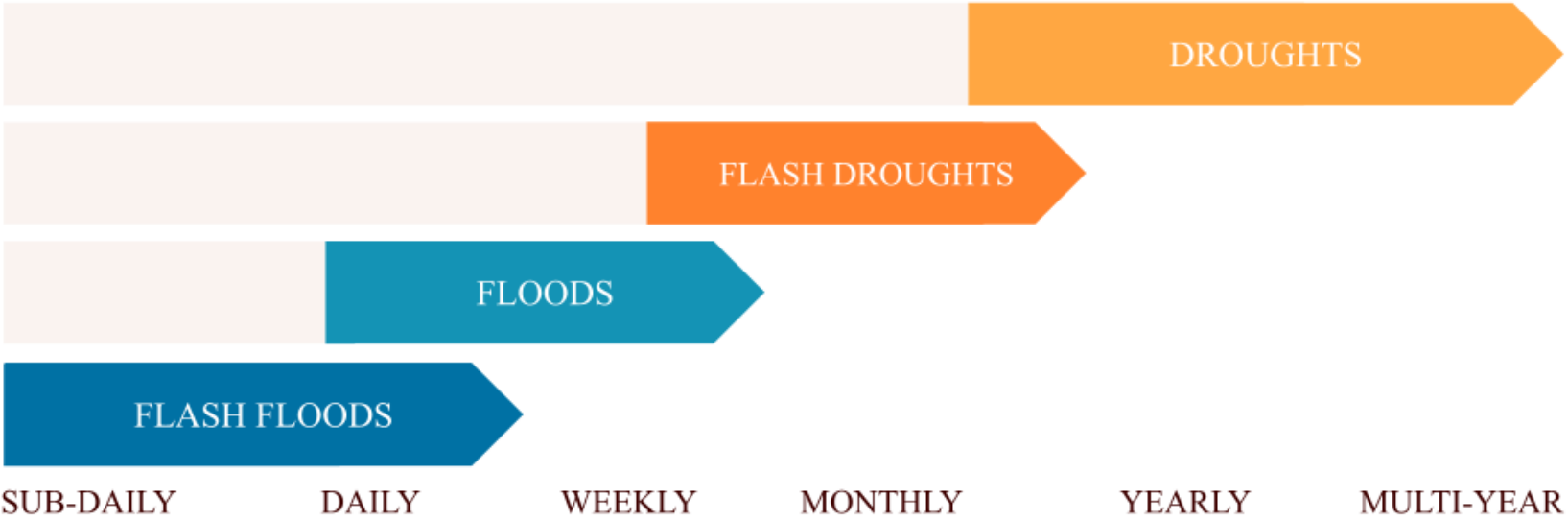


# Hydrological extremes: durations

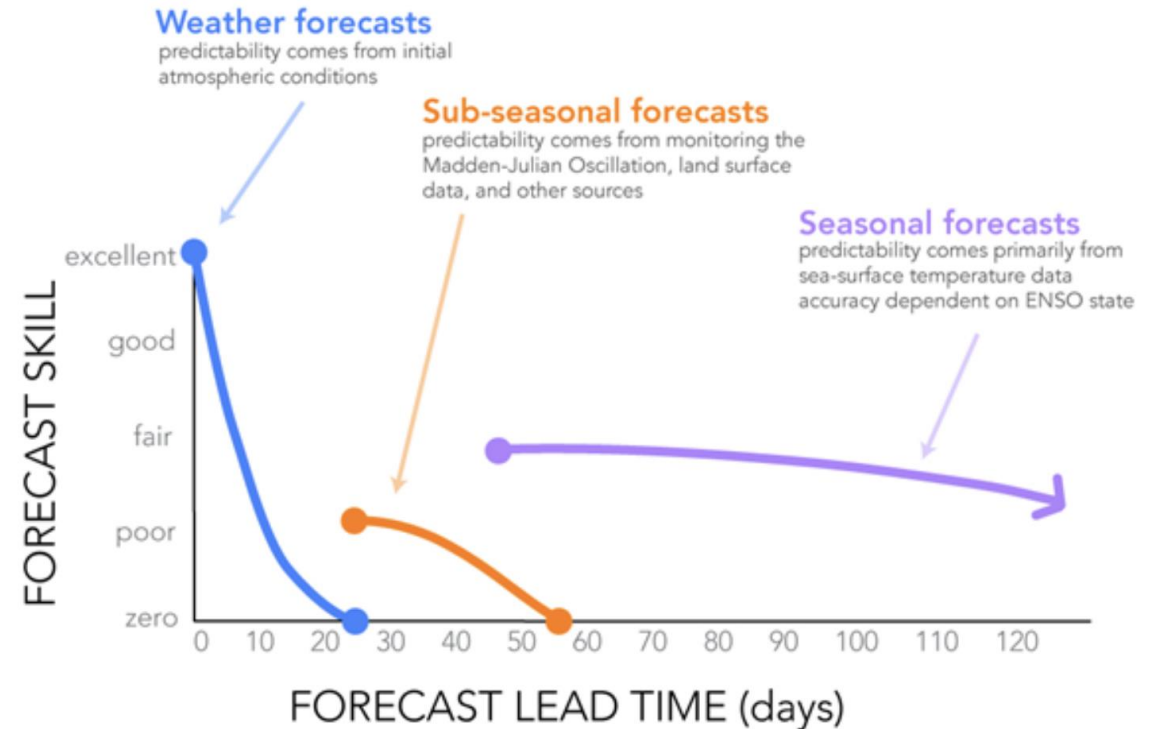
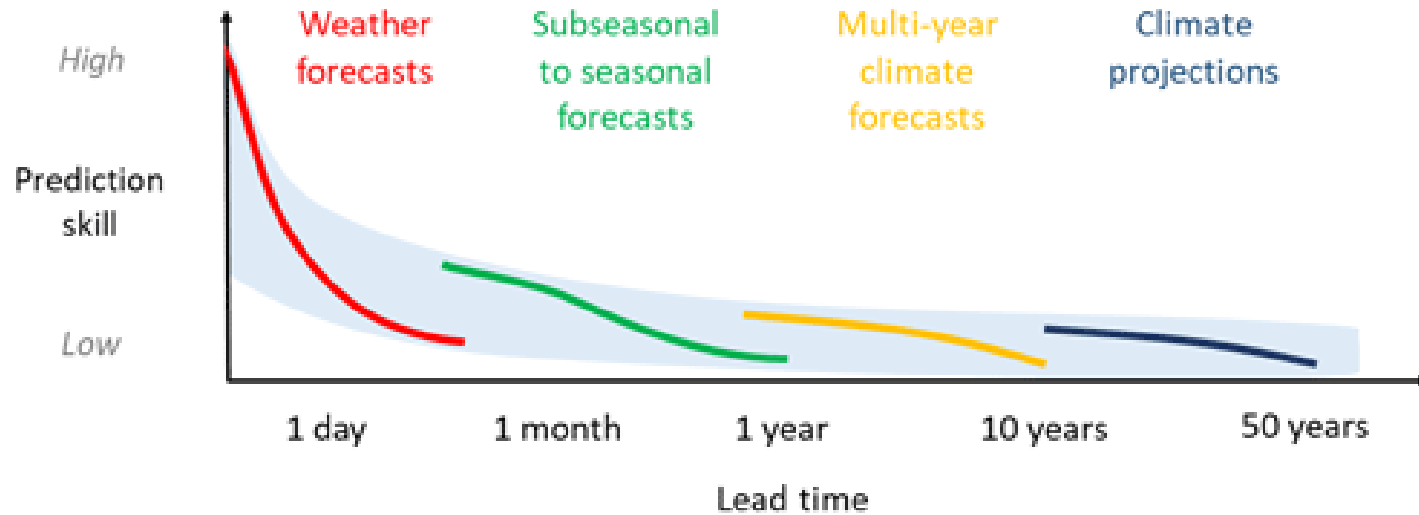
(a)



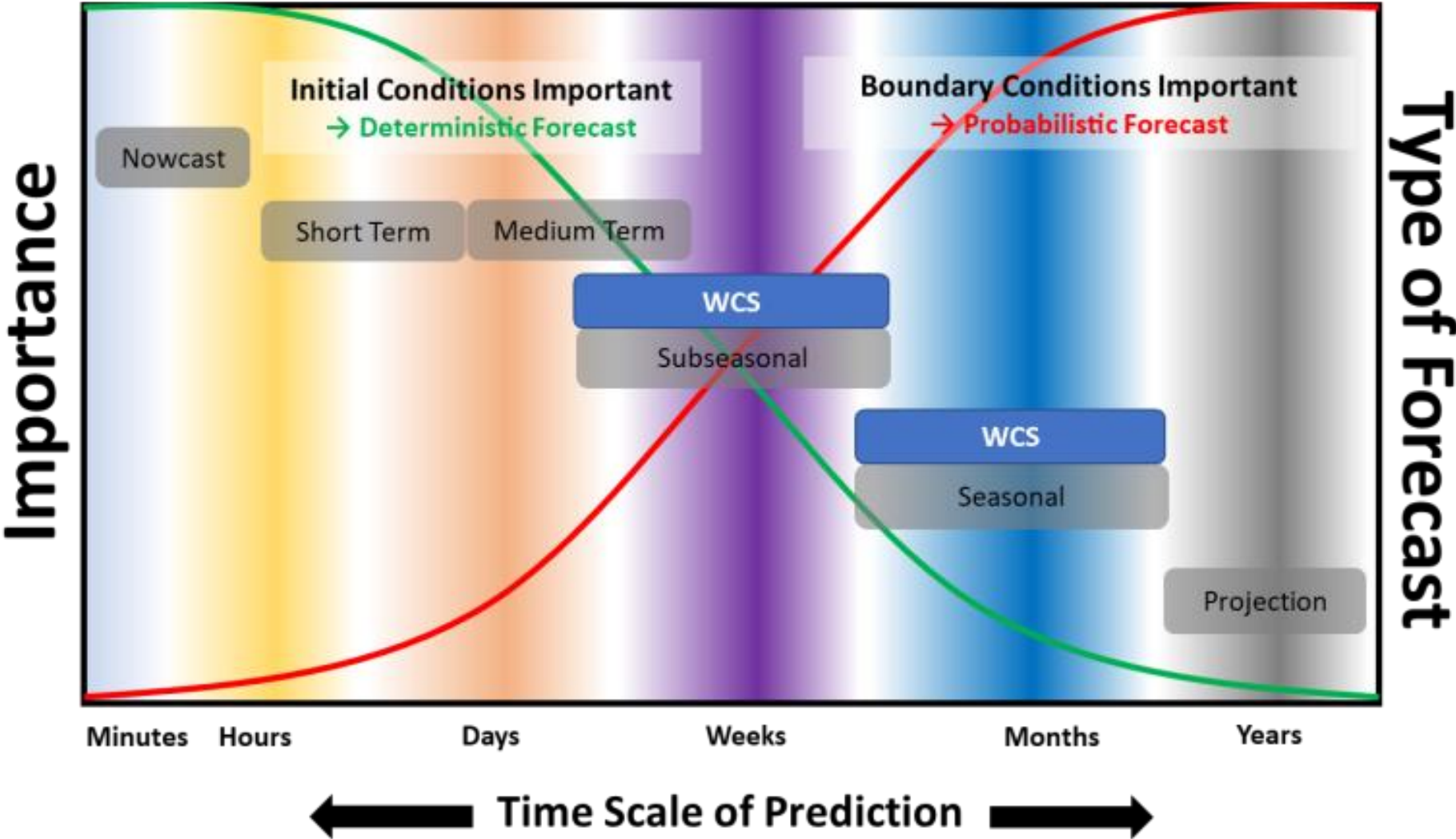
(b)



# Forecast lead time



# Hydrological prediction: role of initial condition





# Hydrological Ensemble Prediction

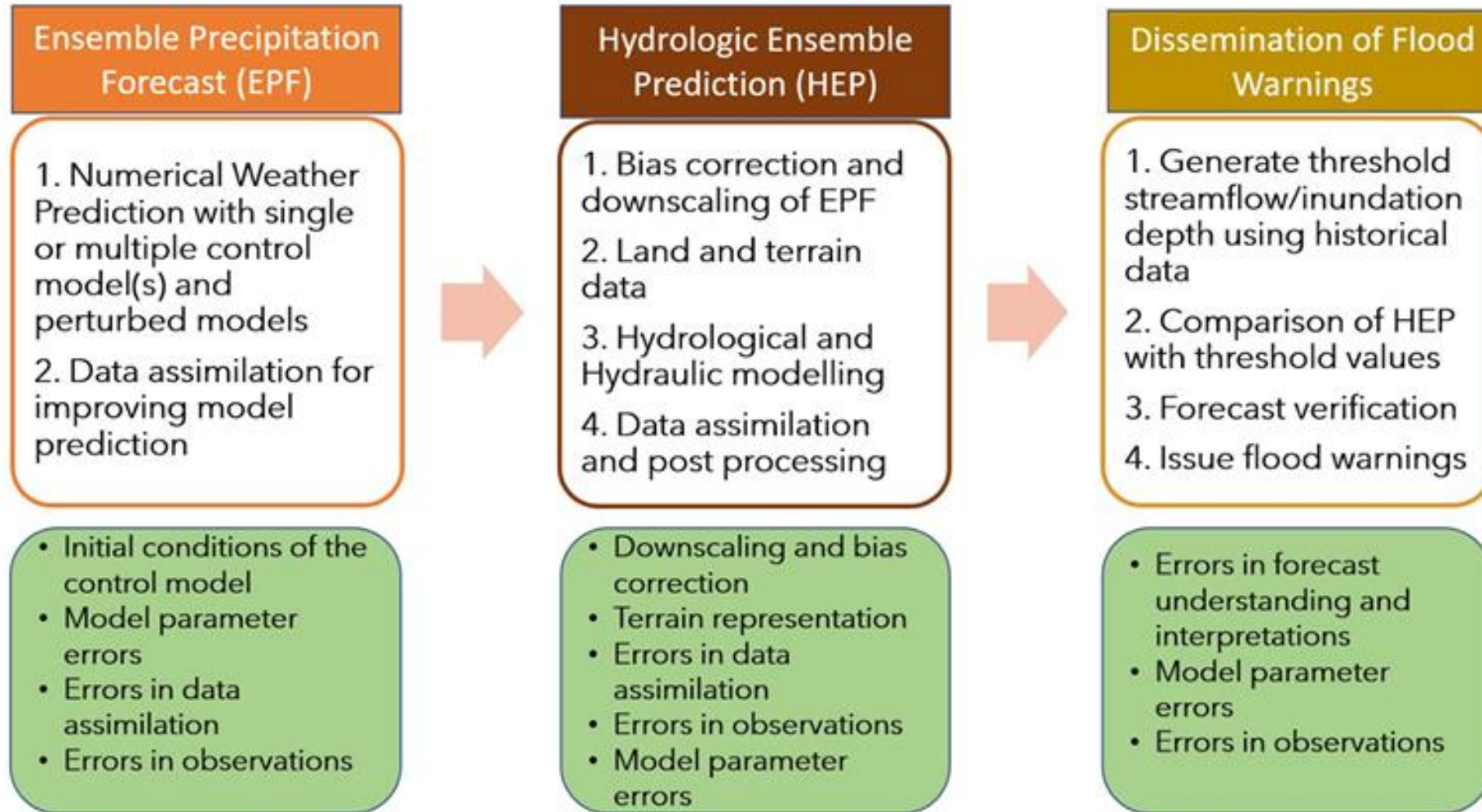
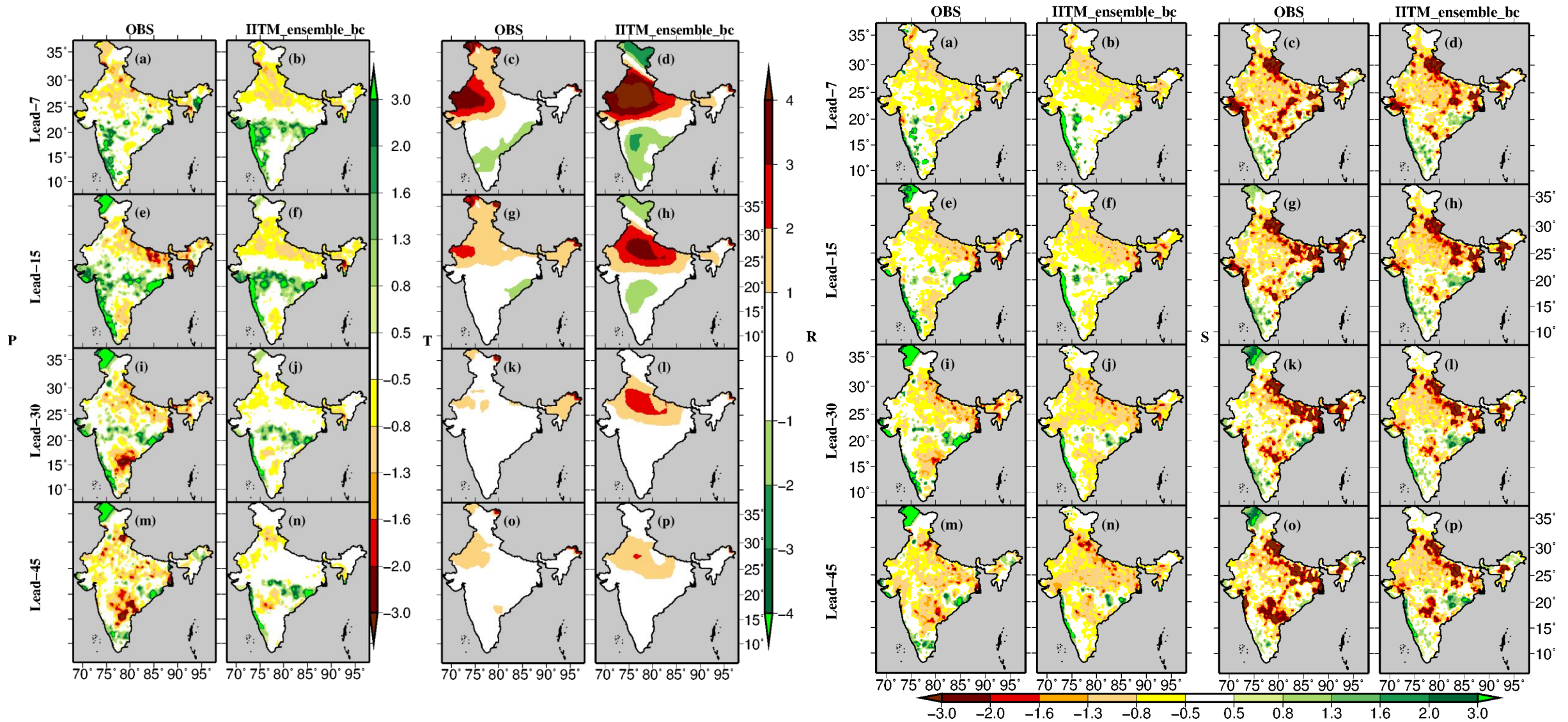
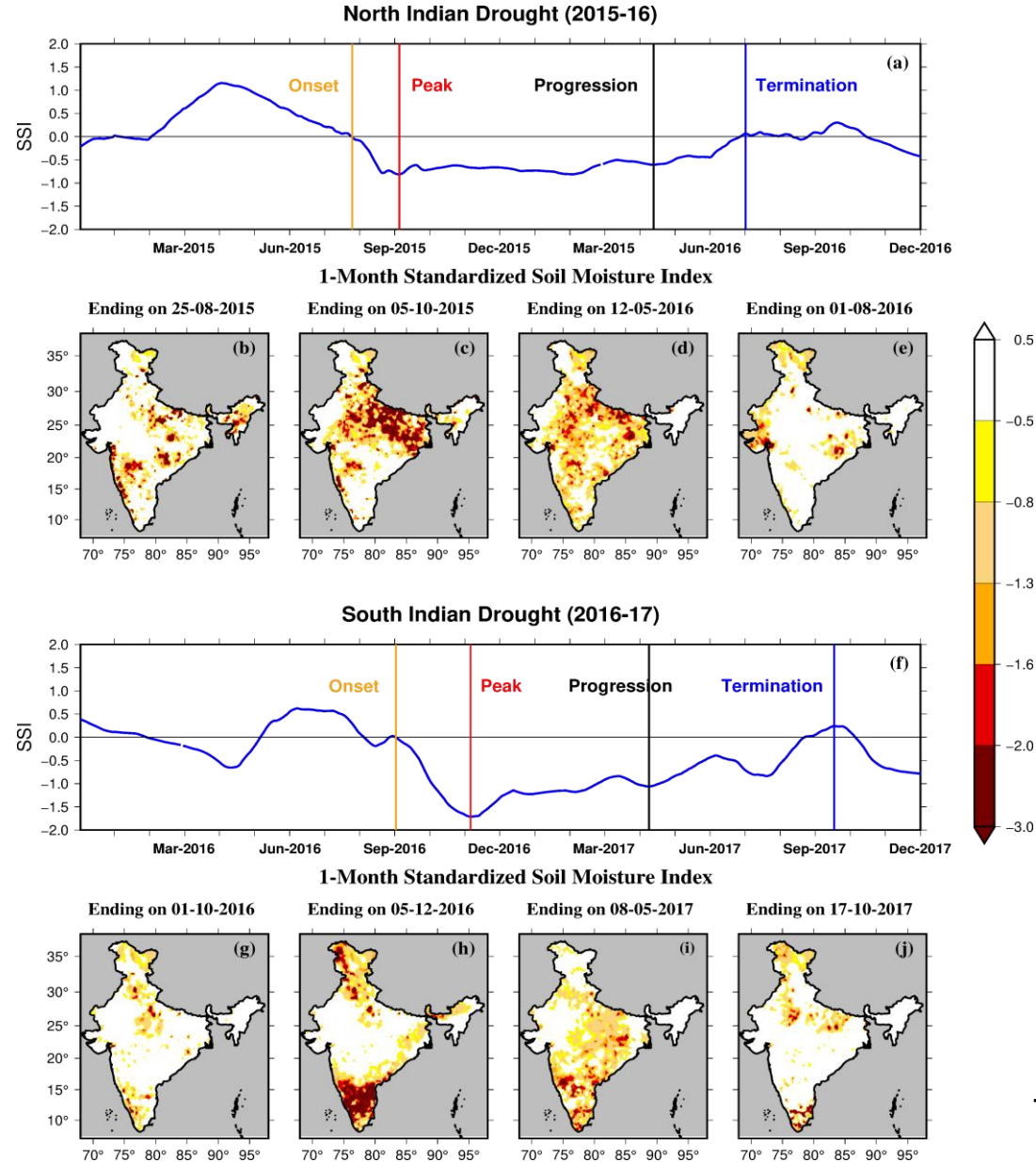


Figure. Schematic representation of hydrologic ensemble prediction (HEP) system used in flood forecasting.

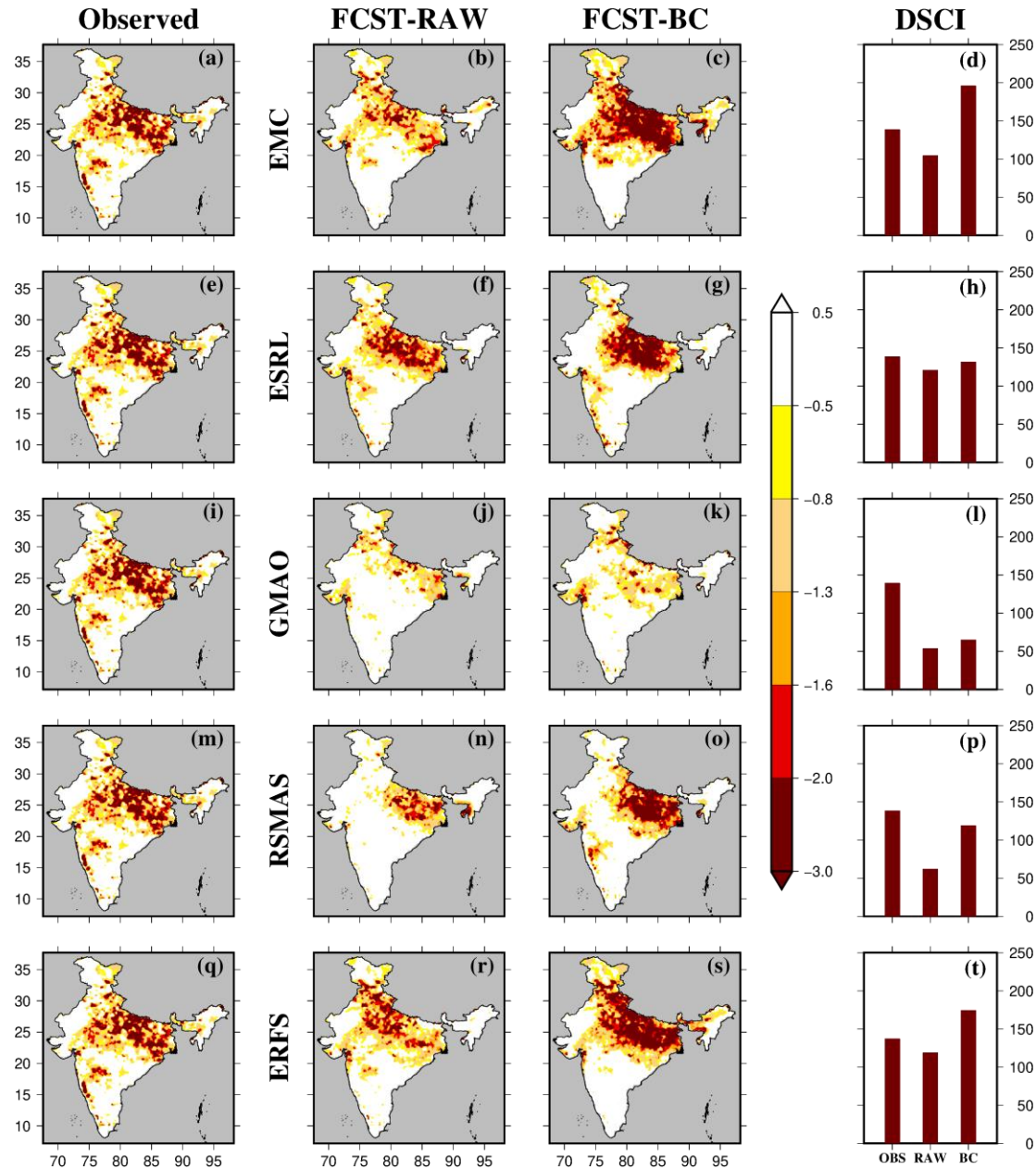
# Prediction of Drought : 15<sup>th</sup> July 2009



# Recent droughts (2015-2017)



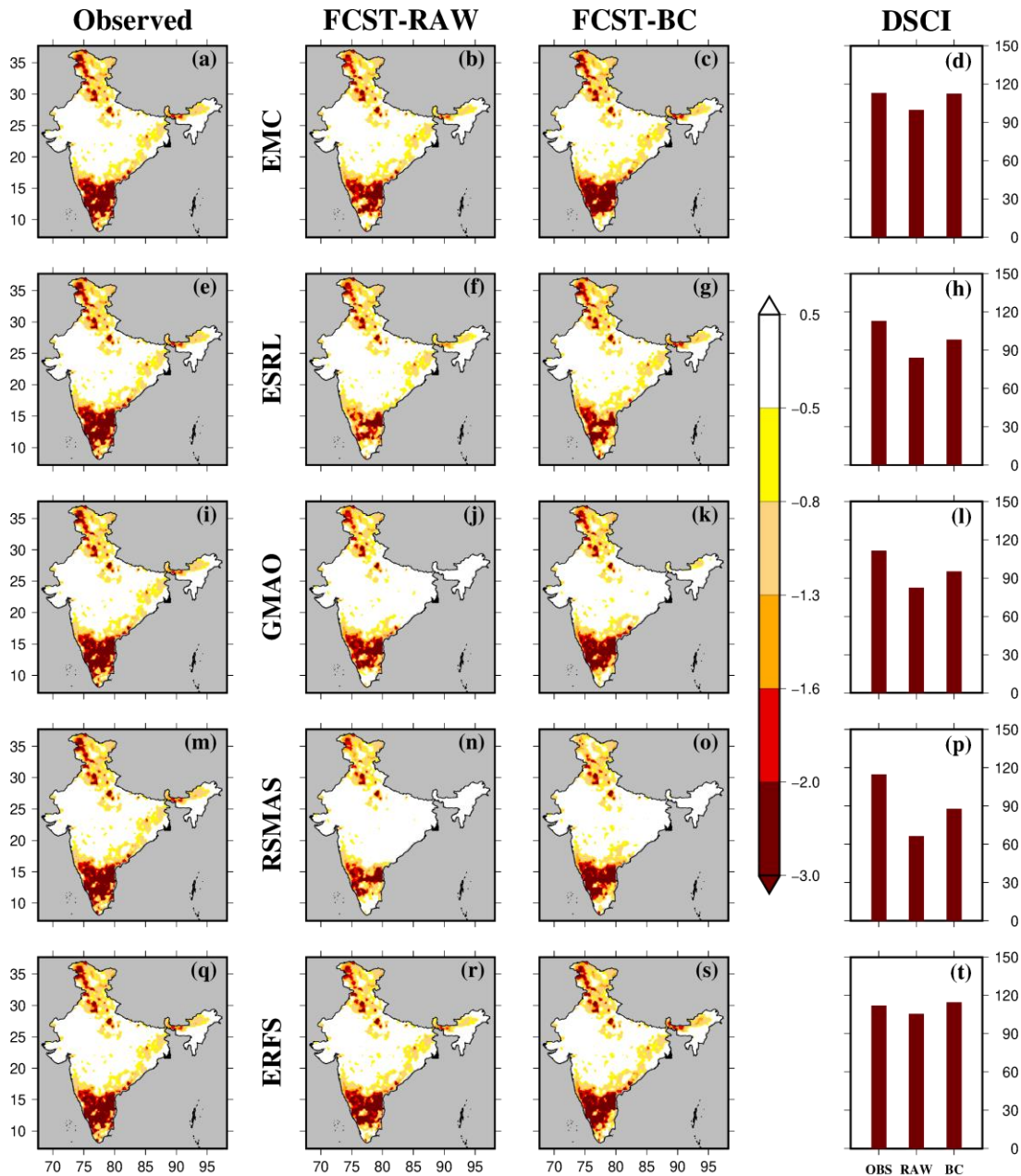
## Drought forecast of NIR



- FCST-RAW underestimated the intensity and areal extent of drought for all the models in NIR.
- FCST-BC slightly overestimated the drought intensity except for the GMAO and RSMAS models.
- Bias correction of meteorological forecast products showed a significant improvement in the skill of drought forecast in NIR.
- ESRL model performed best while GMAO model underestimated.

Fig. (a-c) Comparison of peak drought based on FCST-RAW SSI and FCST-BC SSI against observed SSI for North Indian drought in 2015-16. (d) DSCI values for observed, FCST-RAW and FCST-BC SSI

# Drought forecast of SIR

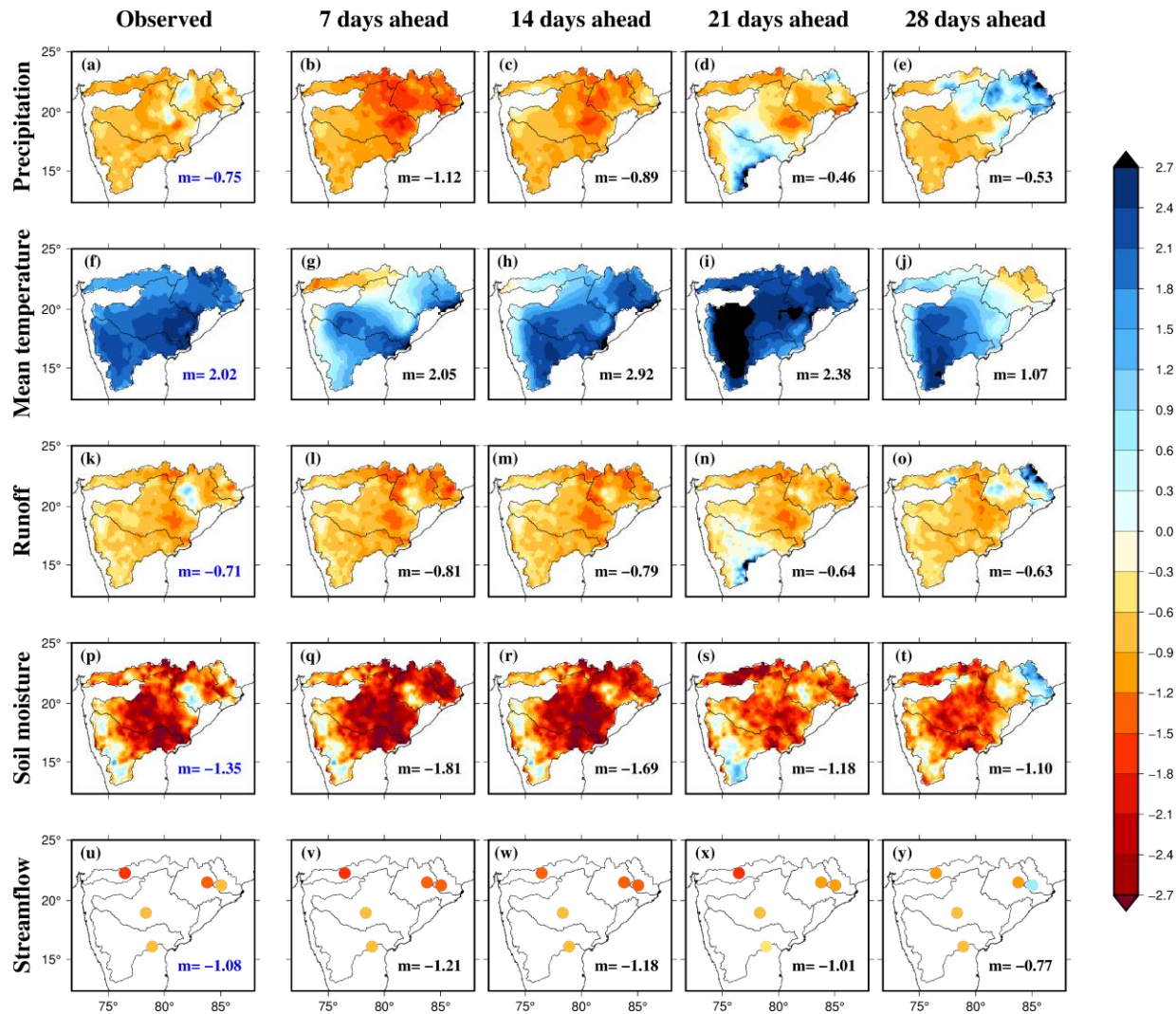


- FCST-RAW underestimated the intensity and areal extent of drought for all the models in SIR
- Bias correction of meteorological forecast products showed a significant improvement in the skill of drought forecast in SIR
- EMC model performed best while GMAO model underestimated

Fig. (a-c) Comparison of peak drought based on FCST-RAW SSI and FCST-BC SSI against observed SSI for South Indian drought in 2016-17. (d) DSCI values for observed, FCST-RAW and FCST-BC SSI

# Hydrological outlook

August 09, 2009



➤ Outlook is able to forecast the meteorological and hydrological variables well ahead 28 days lead time.

Fig. Comparison of observed and 7-, 14-, 21-, and 28-days ahead forecasted anomalies for hydrologic outlook for precipitation (FCST-BC), mean temperature (FCST-BC), runoff (FCST-BC-MET-HYD), soil moisture (FCST-BC-MET-HYD), and streamflow (FCST-BC-PP) for a selected extreme dry event occurred on August 09, 2009.

# Streamflow forecast

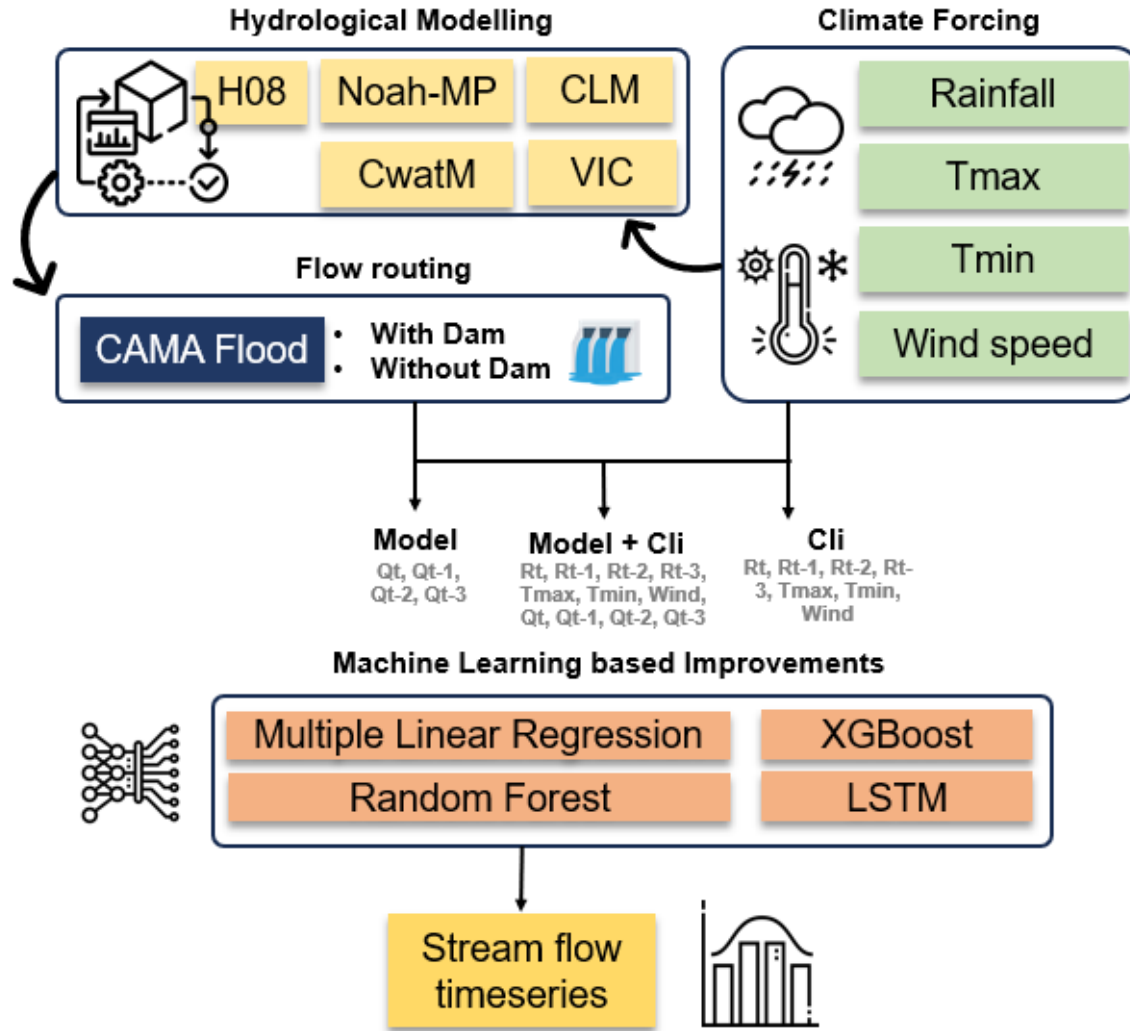
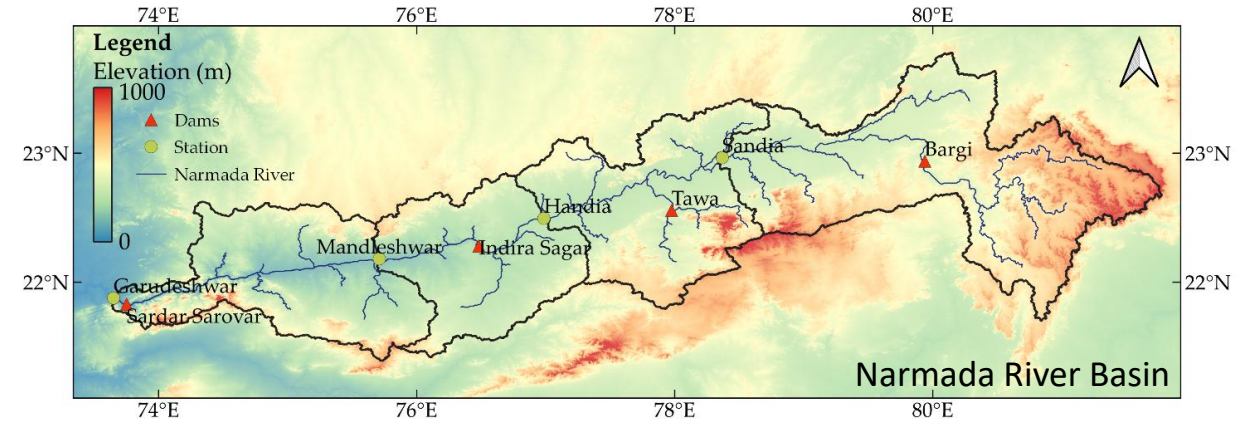


Figure. Proposed Methodology

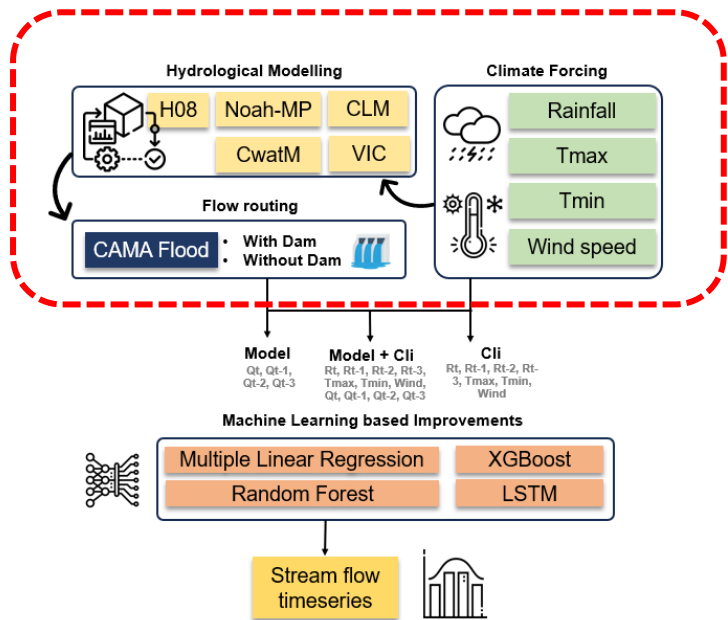


## Data and Models

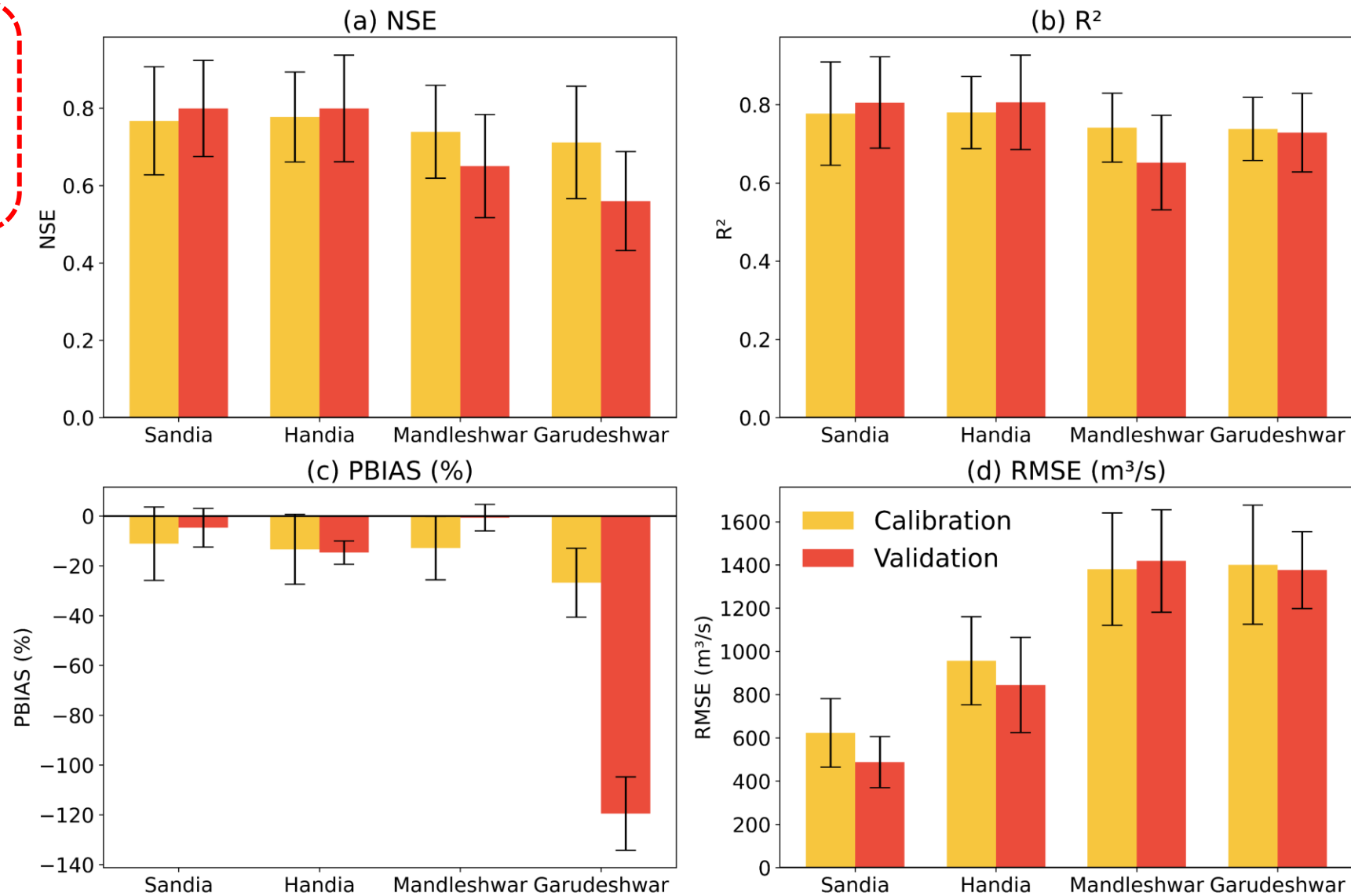
Climate Data	Source	Spatial Resolution	Temporal Resolution
<b>Rainfall</b>	IMD	0.25° x 0.25°	Daily (1986-2020)
Maximum	IMD	0.25° x 0.25°	Daily (1986-2020)
Temperature			
Minimum	IMD	0.25° x 0.25°	Daily (1986-2020)
Temperature			
Wind Speed	ERA5	0.25° x 0.25°	Daily (1986-2020)
Observed Discharge	India-WRIS	Station based at Sandia, Handia, Mandleshwar, and Garudeshwar Stations	Daily (1986-2016)
Model Discharge	(Kushwaha et al., 2021)	Mandleshwar, and Garudeshwar Stations	Daily (1986-2020)

# Performance Evaluation of Hydrological Models

With dam



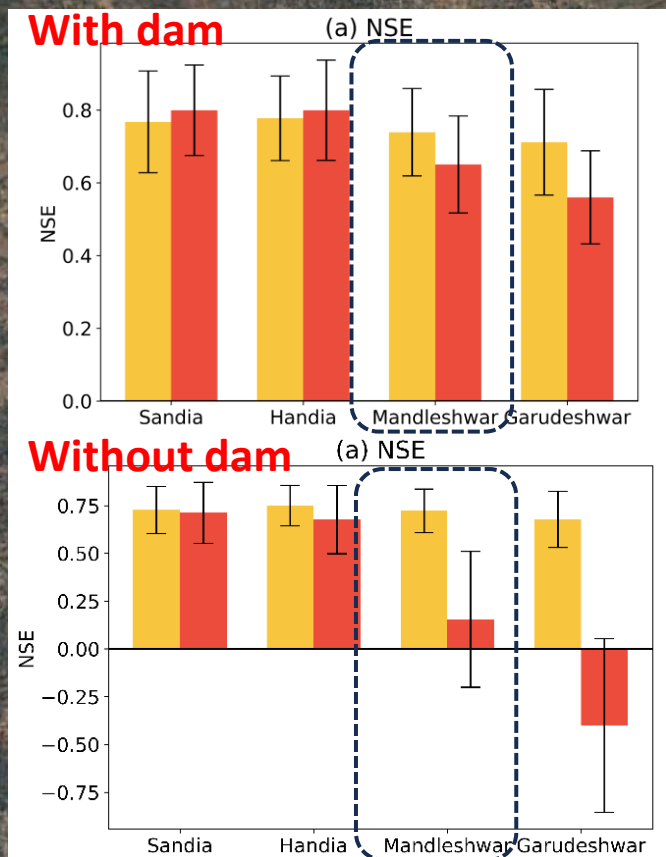
**Figure. Model performance parameters for traditional hydrological models.** Evaluation of multi-model simulated streamflow for with dam scenario at Sandia, Handia, Mandleshwar, and Garudeshwar using (a) NSE, (b)  $R^2$ , (c) PBIAS, and (d) RMSE. Yellow color shows statistics during the calibration, while orange shows during the evaluation. Error bars show variation within different HMs using one standard deviation.



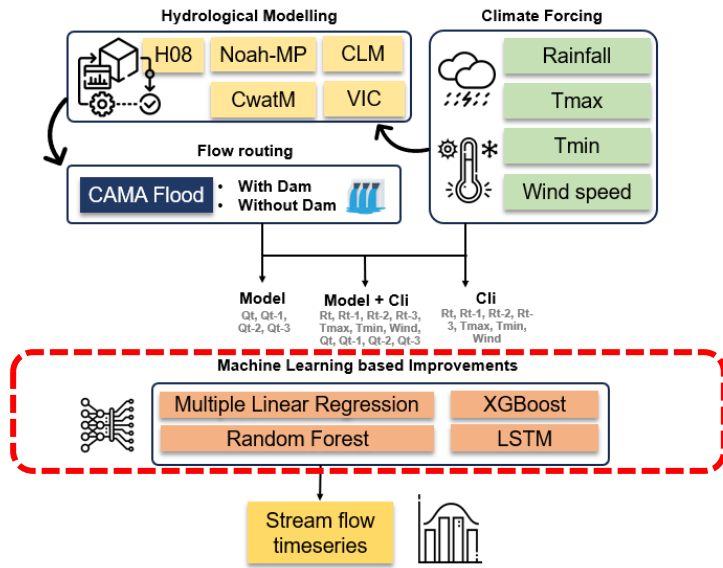


# Reservoir Influence

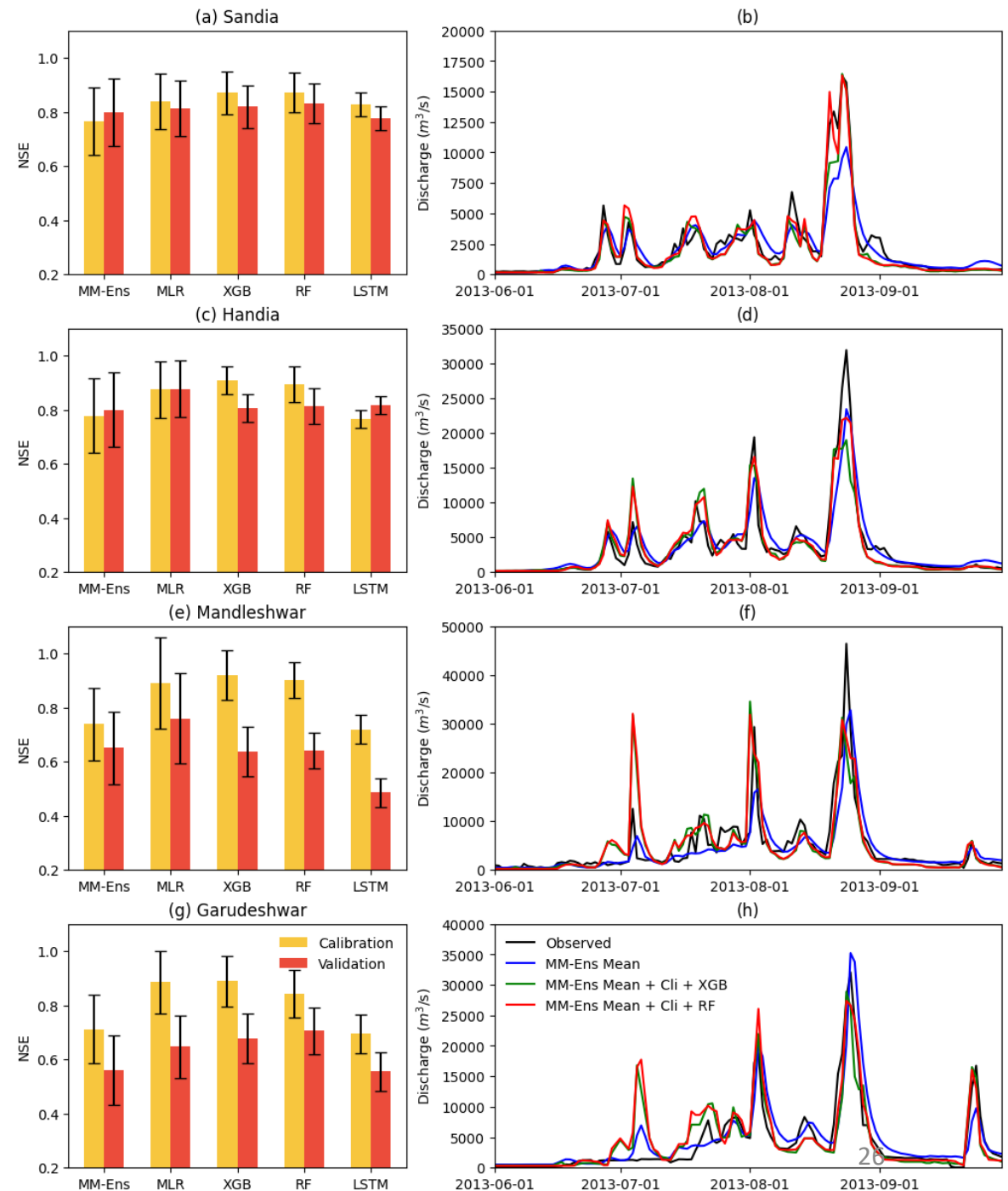
## Indirasagar Dam (2000 and 2004)



# ML based enhancements

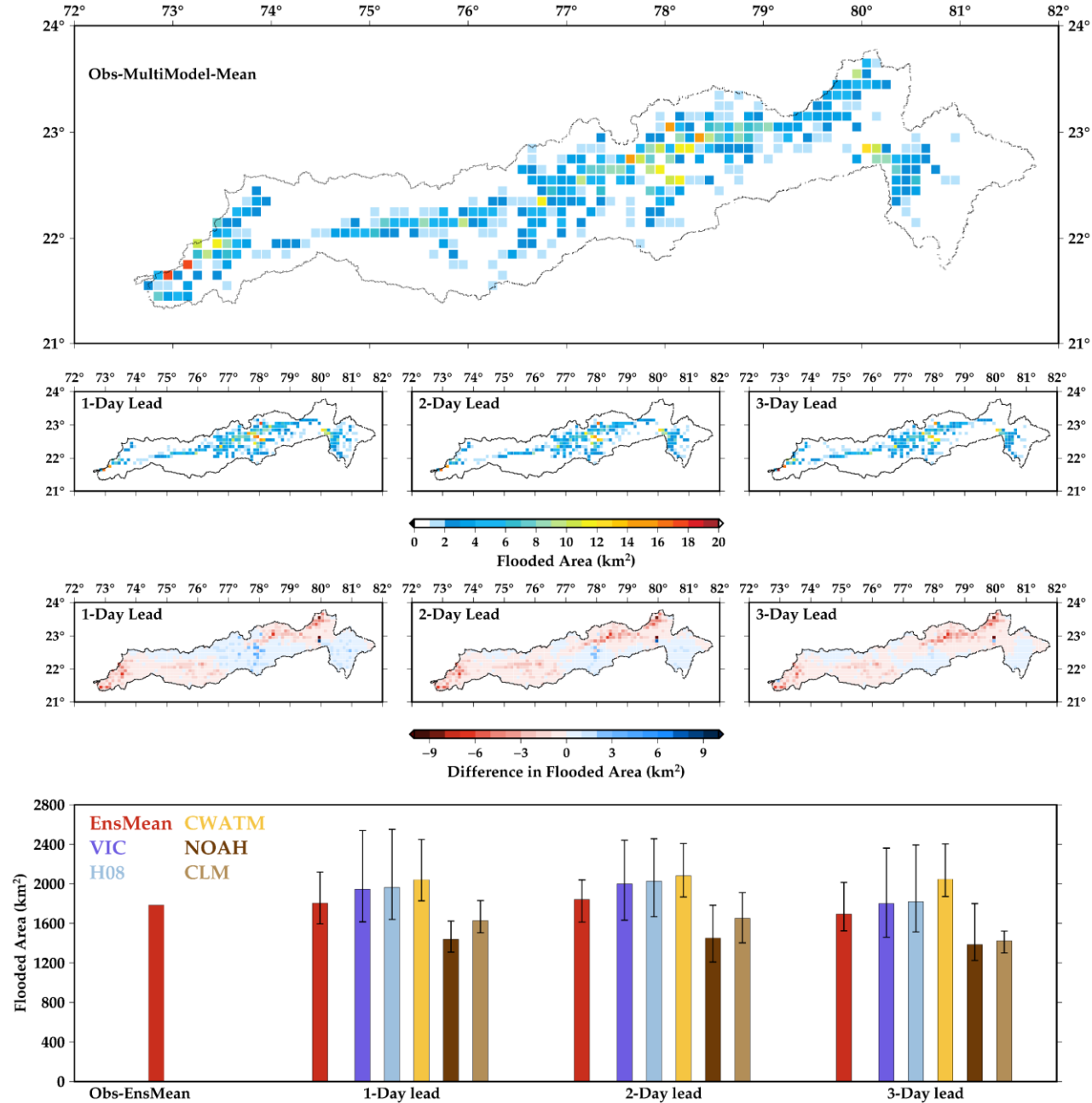


**Figure. Multi-model ensemble mean NSE and its improvement using ML methods.** Left panel shows multi-model ensemble mean NSE values with one standard deviation between various HMs using ML algorithms, including MLR, XGB, RF, and LSTM during calibration (yellow) and evaluation (orange) stage at (a) Sandia, (c) Handia, (e) Mandleshwar, and (g) Garudeshwar. Right panel shows timeseries of observed data (black), ensemble mean streamflow from multi models (blue), and XGB and RF based improvements (green and red, respectively) for the monsoon season (JJAS) of 2013 at (b) Sandia, (d) Handia, (f) Mandleshwar, and (h) Garudeshwar stations.





# Multi-model ensemble forecast of flood inundation



# Strengthening early warning: what we need?

1. High-resolution (5km), reliable precipitation and temperature forecast (Lead: sub-daily, daily, short-term, extended range, and sub-seasonal)
2. Spatial and temporal resolutions (high resolution helps but accuracy is more important)
3. Near-real time monitoring and availability of observations (data assimilation, ML based enhancements)
4. Hydrological models with proper representations of human interventions (irrigation, reservoirs, groundwater pumping)
5. Better forecast skills for extremes (AI/ML can help and so as improving the models)
6. Impact data
7. Need to move from deterministic to multi-model based probabilistic forecast