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Title: The changing magnitude and timing of riverine floods in India

Short Title: Trends in Floods across India

Sai Kiran Kuntla[1], Manabendra Saharia[1,2*], Sharad Kumar Jain[3]

[1]Department of Civil Engineering, Indian Institute of Technology Delhi, Hauz Khas, New Delhi 110016, India

[2]Yardi School of Artificial Intelligence, Indian Institute of Technology Delhi, Hauz Khas, New Delhi 110016, India

[3]Department of Civil Engineering, Indian Institute of Technology Roorkee, Roorkee 247667, India

*Corresponding author. Email: msaharia@iitd.ac.in

Abstract

Riverine floods represent the most frequent and destructive type of floods worldwide. Despite encompassing some of the most densely populated floodplains and mounting concerns about floods and droughts, no study has examined the trends in flood discharge observations in India. Using the most representative records of streamflow in India till date, we identified a decreasing trend in flood magnitude in 74% of the gauging stations across the country and regional variation in the change of the timing of floods. Besides, we investigated if any continental-scale climate signals lead to these trends in the country. It is found that decreasing precipitation and soil moisture have resulted in reduced flood magnitude during the monsoon season by an average of 17% per decade in the West and Central Ganga basin. Contrastingly, flood magnitude is increasing by 8% per decade during pre-monsoon in the Malabar coast due to increasing precipitation. Simultaneously, the early precipitation in the lower Yamuna basin and delayed precipitation in the Upper Ganga basin have led to earlier and later floods in these regions, respectively. Our investigation into the potential correlations between changes in flooding and catchment characteristics reveal that there is a dampening of flood discharges within basins situated in arid climates. Furthermore, small catchments (<1000 km^2) experienced increased flood magnitudes which has implications for flash floods, with a concurrent reduction in flood magnitudes in large catchments. Understanding these substantial shifts in magnitude and

timing of floods is important as they can exert strong influence on disaster management and water resources planning.

Teaser

Study reveals decreasing flood magnitudes and regional flood timing shifts across India, exploring underlying factors.

1. Introduction

Floods are causing increasing human and economic losses worldwide, with regional differences, and India is expected to experience indirect economic losses greater than the global average (*1*, *2*). Moreover, the impact of floods has been severe in the country, with 113,390 human casualties reported between 1975 and 2015, averaging 2765 deaths per year (*3*). The intensification of heavy precipitation events likely due to an increase in atmospheric water holding capacity by 7% per 1°C of warming has played a significant role in flood occurrence, but the response of land surfaces at different scales can modulate the flood responses (*4*). Given the significant impact of floods on human lives, infrastructure, and economic development, a comprehensive understanding of the changing nature of flooding using a long instrumental record is necessary for hydrological risk analysis, understanding the flood generation mechanisms, water resources planning and management, and for assessment of climate change impacts(*5*, *6*).

Many attempts have been made globally to explore the changes in flood hazard based on large-scale hydrological models(*7–9*). However, the outcomes of these studies may not represent the actual variability, may have high uncertainty, and are inherently subjected to the limitations of global hydrological models(*10*, *11*). Moreover, regional patterns cannot be precisely inferred from global studies. Many times, the intensification of extreme precipitation events globally(*12–14*) is used as a proxy for assessing flood hazard(*15*). However, caution must be exercised as many global and regional studies have reported decreasing trends in streamflow despite the increase in extreme precipitation(*15–18*). This diverging trend of precipitation and streamflow highlights the complex nature of flood generation and the impact of multiple factors(*19*, *20*). Studying streamflow trends – magnitude and timing - from past observational records is one of the best approaches to derive the hypothesis on changing flood hazard at any spatial scale(*6*, *16*, *21*, *22*). However, the availability, quality, and consistency of observational streamflow data over a long period is necessary for such an analysis. Therefore, such large-sample studies at large spatial scales are limited to the developed regions of the world where long-term observation data exists. A few global studies exploring trends in streamflow magnitude(*15*) and timing(*6*), have used limited data from Asia, Africa, Eastern Europe, and South America (except Brazil). But no data was used from India, one of the worst affected regions from recent hydrometeorological disasters. In India, long-series of observed streamflow data exist at limited gauging sites.

Out of these, a large number of sites fall in the river basins whose data are classified and hence, it is very difficult for researchers to obtain the data and publish the results.

Chug et al. (2020) found that the frequency of extreme flow events has doubled in North India during 1980–2003 with a statistically significant rising trend in annual maximum flows. This change in streamflow is likely to be caused by increasing precipitation extremes during summer and winter seasons. Das et al. (2022) examined the changing trends in annual maximum flows during 1966–2015 at 38 gauging stations in the Godavari catchment of India and found increasing trends in the northern stations located in the Wainganga, Wardha and Indravati sub-basins. At the same time, declining trends were observed in the upstream, central and downstream parts of the Godavari catchment. However, most reported observational studies in India concerning streamflow trends are catchment-scale(*23*, *25*–*27*) or regional-scale studies(*22*, *28*–*30*) and have relied on point data but not catchment-scale attributes. Moreover, the heterogeneity of catchment characteristics, analysis periods, chosen hydrological indices, and methods influence their conclusions. Consequently, they are limited in their ability to provide holistic information on the changing nature of flooding in the country.

Unavailability of observational data of adequate fidelity for the whole country and the reasons mentioned earlier, a comprehensive study describing the changing magnitude and timing of riverine floods at pan-India scale does not exist in the scientific literature. Therefore, there is a pressing need for a cohesive, nationwide, consistent, and thorough investigation of flooding trends and their underlying mechanisms. This study has conducted a homogenous and comprehensive analysis of flooding magnitude and timing trends and their causative mechanisms at a pan-India scale to facilitate improved understanding, management, and mitigation of riverine floods. This study was taken up after a painstaking effort to collate four decades of data from 173 gauge stations spread across the country, making it the most spatial representative, large-sample observational study in India.

2. Results

2.1. Regional patterns of change in the magnitude and timing of floods

Floods are a common occurrence in India during the monsoon season, which accounts for nearly 80% of the country's annual rainfall(*31*, *32*). In this study, 85% of the floods identified across all stations were recorded during the monsoon season between June and September. Our analysis reveals clear regional patterns in the changing nature of the magnitude and timing of floods across India. Figure 1 shows a decreasing trend in flood magnitude across most of the country during the monsoon season, which is also evident at the annual scale (Figure S1). Specifically, 74% (128) of the gauging stations exhibited a decreasing trend in flood magnitude. In contrast, only 26% (45) of the gauging stations out of a total 173 across the country showed an increasing trend.

Many factors, both natural and human induced, influence river flooding at a location over an extended period of time. Natural factors such as climate change(*8*, *21*) and natural hazards such as earthquakes and landslides can reshape river courses, leading to changes in flow pattern(*33*). Further, human-induced changes, such as urbanization(*34*), land use and cover alterations(*35*), river training(*36*), and engineering projects such as dam construction(*37*, *38*), also contribute to changes in flood dynamics. Studying the complex interplay of all these factors with observed flooding trends is beyond the scope of this study. Nevertheless, we have made an effort to identify any potential relationships between changing precipitation patterns, soil moisture levels, and observed flooding variables in the identified hotspots. Hotspots are regions with a considerable number of gauge stations that do not have dams in their catchment and have a cluster of strong trends (high percentage of change) in observed series. A cluster of catchments with a strong decreasing trend, i.e., a high percentage of change per decade, was observed over the central region of the Ganga basin (Hotspot M1) during the monsoon season (Figure 1) with an average decrease of 17% per decade. At the same time, a consistent decreasing trend in the magnitude of floods over the Narmada basin is observed in monsoon, possibly due to the construction of dams in this region during the study period(*39*). Blöschl et al. (2019) reported a similar high decrease in flood discharges in western Russia at 18% per decade between 1960-2010.

In contrast, the West flowing rivers from Tadri to Kanyakumari (Chaliyar, Periyar, Bharathapuzha, Vamanapuram, etc.) in the Malabar coast (Hotspot M2) showed an increasing trend at an average rate of 8% per decade in pre-monsoon floods in the region (inset in Figure 1(a)). In the Marathwada region of the Deccan plateau, which has been experiencing severe droughts in recent times(*40*, *41*), river flows were found to be decreasing at an average rate of 8% per decade during the monsoon season and 31% in pre-monsoon, based on data from three stations in the region.

In terms of flood timing, the cluster of catchments covering the lower Yamuna basin (Hotspot T1, Figure 1) located southwest of Ganga showed a decreasing trend across the monsoon, i.e., a shift towards an earlier calendar day, or floods occurring early. In contrast, catchments in the upper Ganga (Hotspot T2) exhibit a significant trend towards later floods (floods are delayed). On an annual scale, catchments in the southern region of the country tended to experience floods later, while those in the central region tended to have earlier floods.

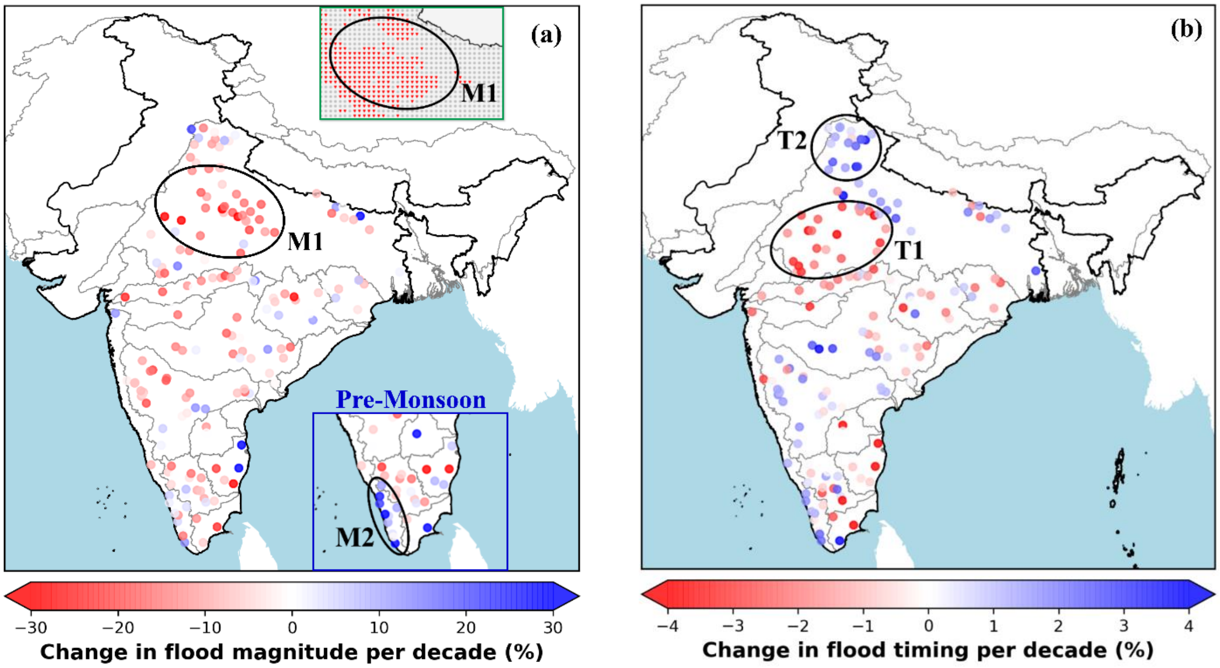

Figure 1: Trends in (a) flood magnitude and (b) timing in monsoon (June-September) between 1970 and 2010 based on the Theil-Sen slope estimator. The inset figure in (a) with a blue border in the right lower corner corresponds to flood magnitude trends in pre-monsoon over Hotspot M2. The inset figure in (a) with a green border in the right upper corner corresponds to the significant trends (red-decreasing; grey-no trend) in gridded monsoon mean precipitation over Hotspot M1 between 1970 and 2010 based on Modified Mann-Kendall test (P<0.05) (*42*). *Annual and other seasonal trends are available in the supplementary file.*

2.2. Evolution of floods and their drivers

We focus on the catchments in the hotspots to infer the causes of changes in flood magnitude and timing. Given that multi-day precipitation and soil moisture have been identified as the primary drivers of flooding in India(*20*, *43*), we studied the long-term evolution of these drivers using a ten-year moving average filter, jointly with flooding variables, and temperature as a proxy for a warming climate. The patterns in the evolution of flood discharge and drivers (Figure 2) and the statistical significance between them (Table 1) demonstrate that the decrease in flood magnitude over central Ganga (Hotspot M1) is associated with the decline in precipitation and soil moisture, highlighting the crucial role of precipitation and soil moisture in flood generation. In fact, the role of soil moisture in runoff generation has been recognized in existing studies (*17*, *44*, *45*). In addition, the temporal occurrence of flood in M1 follows precipitation and soil moisture (Figure S2) confirming their importance in setting flood magnitudes across the region. Moreover, a significant decreasing trend at 5% significance level in monsoon mean precipitation is observed between 1970 and 2010 over most grid points in Hotspot M1 (inset in Figure 1(a)). This clearly suggests the crucial role of precipitation behind decreasing flood magnitudes over this region. Furthermore, the decrease in the annual and monsoon precipitation over central Ganga is also reported in other studies(*46*, *47*), which suggests that this trend may be associated with Indian ocean warming and the presence of atmospheric aerosols in the region.

Conversely, the increase in flood magnitude over the West flowing rivers from Tadri to Kanyakumari basin in the Malabar coast of the country (M2) (inset in Figure 1(a)) can be attributed to the increasing magnitude of precipitation during the pre-monsoon. Notably, the flood magnitudes over the catchments of Hotspot M2 show a clear pattern and strong positive correlation (Spearman rank correlation coefficient r = 0.88) with precipitation, indicating that an increase in the magnitude of precipitation is leading to an increase in flood discharge. This observation is further supported by the evolution plot of the day of flood occurrence and precipitation during the same period over M2 (Figure S2), which also suggests that early occurrence of precipitation leads to early pre-monsoon floods over M2. In M2, all floods are rainfall generated and temperature does not seem to have any influence on floods. Intense pre-monsoon rains over the catchments of the West flowing rivers across M2 have been reported in recent articles and published studies(*48*–*51*). Moreover, when the positive dipole mode index (DMI) and the positive ENSO index (SOI) coincide, an observed increase in positive rainfall anomaly during 1991-2020 was noticed over the southwest Indian peninsular region (*49*).

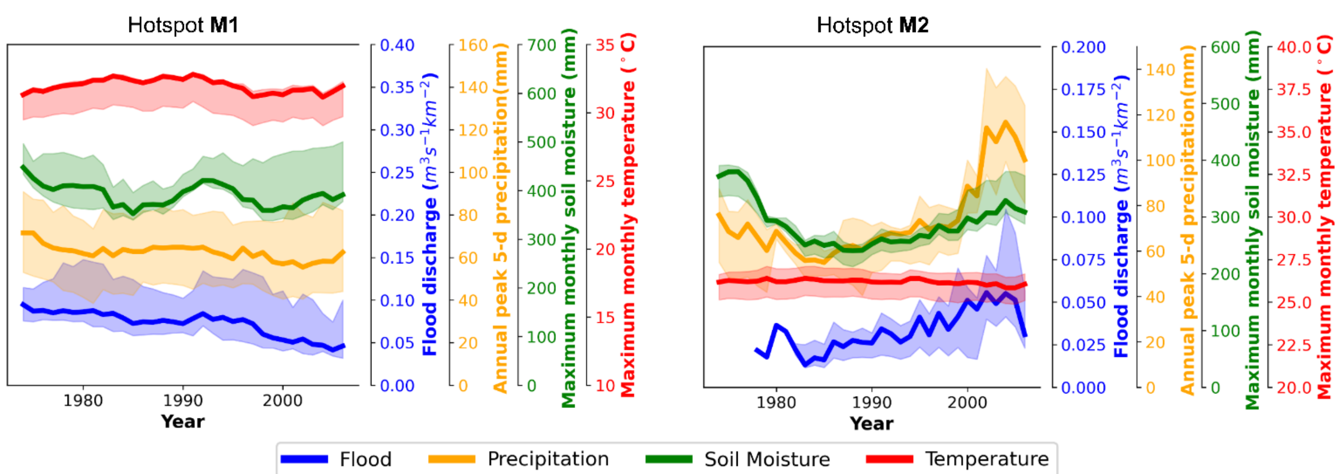

Figure 2: Long-term temporal evolutions of flood magnitude along with its drivers for hotspots with clear regional patterns. The data represents observed floods (blue), peak 5-day precipitation (orange), peak monthly soil moisture (green), and peak monthly temperature (red). Solid lines show the median, and the shaded region shows the variability within the hotspots (25th and 75th percentile). All data were subjected to a 10-year weighted moving average filter.

Table 1: Spearman's rank correlation coefficient (r) between hotspot medians of the annual series of flood discharge and timing with their drivers

	Magnitude		**Timing**	
Hotspot	M1	M2	T1	T2
Precipitation	0.60	**0.88**	**0.72**	**0.56**
Soil Moisture	**0.64**	0.62	0.44	0.17
Temperature	0.34	-0.68	-0.04	0.11

On the other hand, the timing of floods in the two hotspots, the lower Yamuna basin (T1) and upper Ganga basin (T2) exhibit a close correlation with the pattern of the observed precipitation. In the lower Yamuna basin (located in to the southwest of Ganga basin) (T1), earlier precipitation leads to early floods while delayed precipitation results in later floods over the upper Ganga basin (T2). In the entire Himalayan belt, including the Upper Ganga basin, rainfall contributes significantly more to streamflow than snowfall and glacier melt(*52*). Moreover, substantial evidence suggests a strong correlation between precipitation extremes and streamflow in the T2 region(*23*, *53*, *54*). Figure 3 shows the variations in flood timing and its drivers for hotspots T1 and T2, displaying a good match.

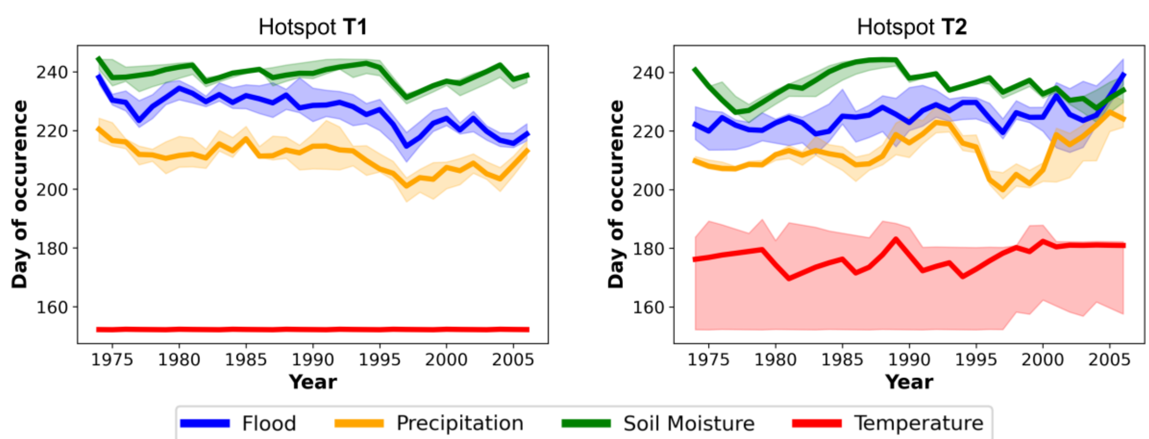

Figure 3: Long-term temporal evolutions of flood timing along with its drivers for hotspots with clear regional patterns. *Please refer to the caption of Figure 2 for the description of the plots.*

2.3. Changes in 100-year flood discharge

To further investigate the impact of these changes in observed flows in the context of flood management, we estimated the trend in 100-year flood discharge between 1970 and 2010. Our analysis reveals that regional trends in observed annual floods and nonstationary 100-year return period flood discharge are almost similar (Figure 4). The inference from Figure 4(a) is that the 100-year flood discharge has decreased by more than half during these 40 years at many locations in the Western and central Ganga basin. Consequently, the frequency of the 1970 100-year flood will increase in these regions (Figure 4(b)). In contrast, a few stations in the Upper Ganga basin and the southwest of the country show an increase in the 1970 100-year flood discharge and a decrease in the frequency of its occurrence.

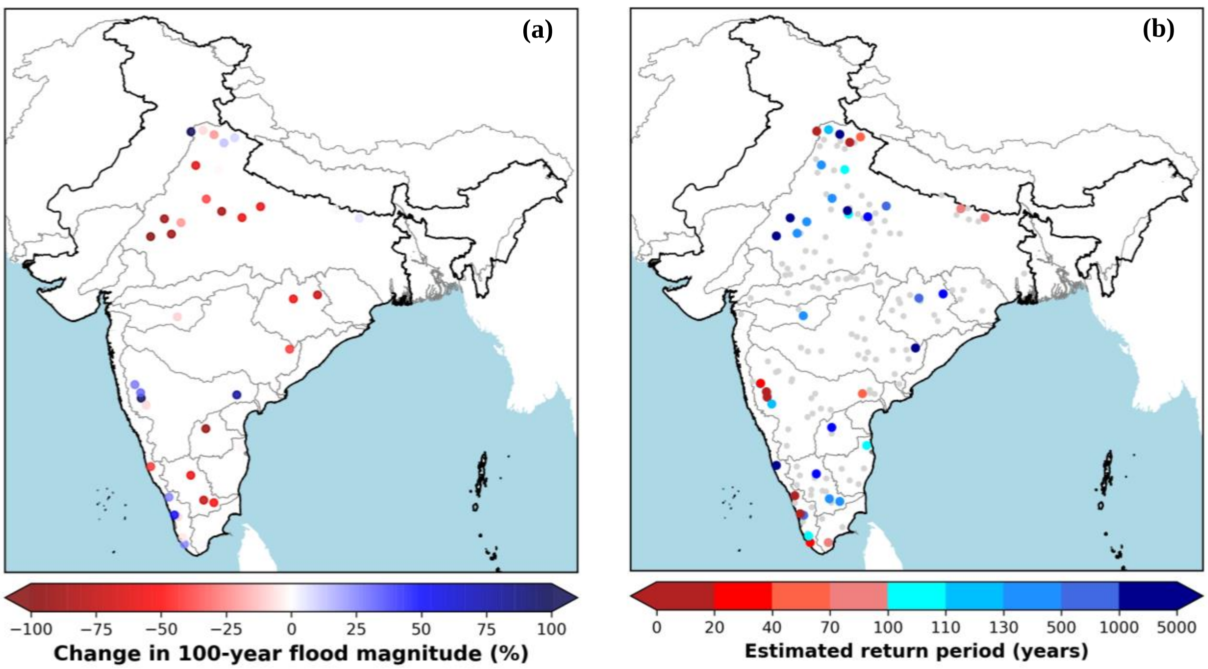

Figure 4: Estimated (a) percentage change in the magnitude of 1970 100-year flood discharge in 2010**.** and (b) return period in 2010 for the 1970 100-year flood discharge. Grey-colored points represent stationary stations.

2.4 Relationship between floods and catchment characteristics

We investigate how the trends in the magnitude and timing of flood are associated with specific geographical or climatic characteristics. To examine the role of climate, catchments are categorized based on the dominant Köppen-Geiger climate class (i.e., covering more than 50% of the catchment area). There are 88 Tropical climate-dominated catchments, 43 temperate, 34 Arid, and 2 polar, among others. Since there are only 2 Polar catchments, and 6 catchments do not have any specific dominant climate in them, they are not considered in this analysis.

Figure 5 depicts a significant decrease in flood magnitude over arid climates during all seasons. No specific pattern is inferred regarding shifts in timings in any particular climate class (Figure S3). The decrease in flood magnitude in arid regions can be attributed to climate change(*55*, *56*) and various anthropogenic activities(*27*, *30*). Drylands are more sensitive to global warming and its impacts, leading to increasingly arid conditions(*55–57*).

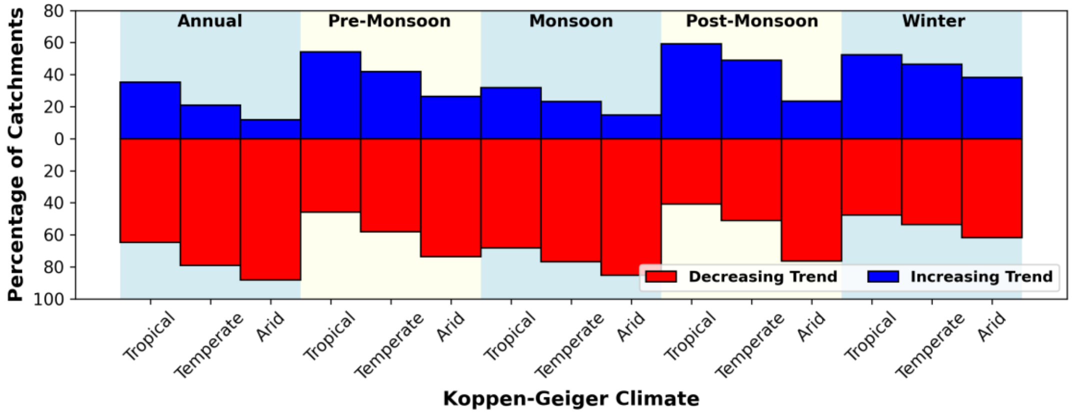

Figure 5: Percentage of catchments with decreasing and increasing trends in flood magnitude in each climate over different seasons.

Interestingly, there exists a clear relationship between the catchment area and the observed percentage change in flood magnitude per decade (Figure 6). The flood magnitudes over larger catchments are observed to be decreasing at higher rates, and as the catchment size decreases the rate of change is also decreasing. And it is predominantly an increasing trend in small catchments (area less than 1,000 sq.km.). In general, large catchments (>10,000 sq.km.) are more susceptible to cumulative pressure from widespread anthropogenic activities, which can lead to significant alterations in hydrological processes and reductions in streamflow. On the other hand, no specific pattern is observed between the trend of flood magnitude and mean elevation of the catchment suggesting no influence of mean elevation of the catchment on the changing nature of flood magnitude. At the same time, from Figure S4, neither the catchment area nor the mean elevation of the catchment has any notable relationship with the trends of flood timing.

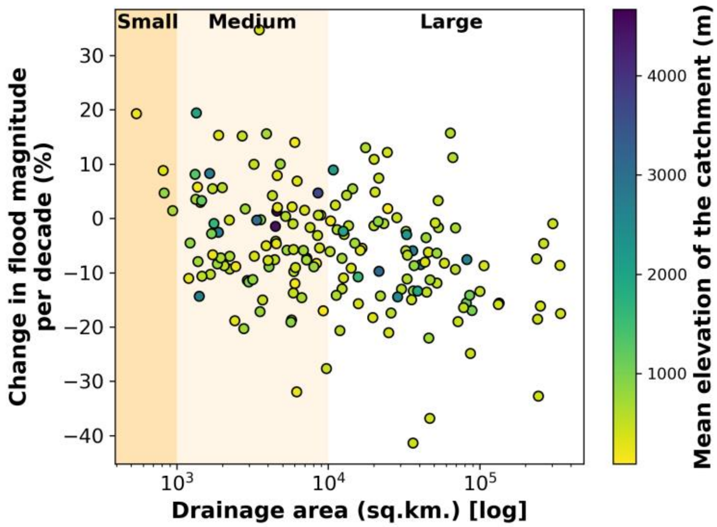

Figure 6: Drainage area vs. percentage change in flood magnitude per decade based on the Theil-Sen slope all the catchments. Points are color-coded based on the mean elevation of the catchment. The background is based on the size of catchments: small (less than 1,000 sq.km.), medium (1,000 – 10,000 sq.km.), and large (10,000 sq.km.)

3. Discussions

Overall, this study sheds light on the decreasing flood magnitudes across three-fourths of the country, with a notable 17% per decade decline in Ganga basin. Additionally, it highlights distinct regional patterns in flood timing, underscoring the complexity of flood dynamics. If these changes in flood magnitude and timing trends are not understood and accounted for, significant economic and environmental consequences could emerge, given that reservoir filling, ecosystems, and communities are adapted to the typical seasonal flooding patterns. For instance, diminished flood magnitudes can lead to lower reservoir storages, adversely impacting water supply, irrigation, and hydropower generation. Additionally, earlier-than-expected floods, such as those seen in the Upper Ganga region, can result in catastrophic outcomes since the entire flood management system will need to be re-designed. Increasing discharges and early floods on the Malabar coast (Hotspot M2) in the pre-monsoon season may have severe implications for agriculture as it is a significant crop harvesting time. Focusing on hotspots, we identify the critical role of multiday precipitation and soil moisture patterns for changes in flood characteristics in those regions. At the same time, geographical and climatic factors play pivotal roles, with arid climates experiencing significant decreases in flood magnitudes, and an interesting trend emerges, revealing an amplification of the decrease in flood magnitudes as the catchment area increases. These findings and insights on changes in the 100-year return period of floods during the last 40 years would enhance our scientific understanding of flood dynamics in India and play a crucial role in flood risk management and mitigation strategies tailored to the diverse regional characteristics of the country.

4. Materials and Methods

4.1 Data

Streamflow data

Good-quality time series of streamflow for a considerable period is vital for change detection studies(*58*). The observed streamflow data used in this study is obtained from the Central Water Commission (CWC) of India. This study is the first in the country based on such a large sample of observational streamflow records. Only those gauge stations were selected in this study which had at least 30 years of data with a minimum of 350 daily values each year, ensuring robustness(*59*). This requirement also meets the data availability criteria for trend analysis, which states that stations considered should at least have 70% of the years in the study period. The years from 1970 to 2010 were selected as the common period for the analyses due to the availability of the maximum data that met the above criteria, ensuring optimal spatial representativeness. Additionally, using a common period facilitates intercomparison among catchments. Based on these criteria, 173 gauge stations are selected, ensuring considerable representation of the catchments covering diverse physiographic characteristics. Moreover, extreme data indices are very sensitive to missing data. Hence, extensive efforts have been made to obtain, curate, and collate the long-term streamflow time series datasets over the country. In some cases, CWC estimates the peak flows by using rating curves. Hence, the peak flow data may have uncertainty of about 10-15%.

Catchment characteristics

Shapefiles were generated for the catchments corresponding to the 173 gauge stations by considering the location of gauge stations as their outlet/pour point. Next, shapefiles were used to compute the catchment area and basin-scale variables from the raw gridded datasets. The mean elevation over the catchments was calculated utilizing the shapefiles and SRTM void-filled DEM data of 3 arc-second (~90 m) resolution.

Precipitation and Temperature

The global ERA5 reanalysis hourly precipitation and 2m temperature data are aggregated to daily and average monthly values, respectively, and used to compute the basin-scale precipitation and temperature over all the catchments in this study. ERA5 gridded products have been available from 1959 – present at a resolution of 0.25° x 0.25°. Reanalysis integrates model data with global observations to create a global dataset that is full and consistent(*60*). Though India Meteorological Department (IMD) precipitation and temperature datasets also cover the given period, their spatial extent is limited to the national boundary of India. Ours is a basin-scale study and the catchments of some gauging stations in the Ganga basin (which are included in this study) fall outside the territory of India. Hence, the IMD observation dataset is not suitable for this study. Apart from this, it has been observed in the previous studies that ERA5 precipitation and temperature products are consistent with the observational record(*61–63*) and outperform other reanalysis products for hydrologic applications in India(*64*).

Köppen-Geiger climate classes

Köppen-Geiger climate classes are useful for combining climatic conditions determined by several variables and their seasonality. In this study, we used the main climates of the Köppen-Geiger map produced by Kottek et al. (2006), which is processed utilizing mean monthly precipitation and temperature data for the years 1951 to 2000 from the Global Precipitation Climatology Centre (GPCC) and the Climatic Research Unit (CRU) of the University of East Anglia, respectively.

Soil moisture

Basin-scale monthly mean soil moisture is derived using Climate Prediction Center (CPC) soil moisture V2 data products from Physical Science Laboratory (PSL). This data is available at a resolution of 0.5° x 0.5° on a monthly scale for the period 1948 to present.

4.2 Methodology

Identifying floods

To examine the trends of both flood magnitude and timing, the annual peak was selected as the metric, which has been widely used in hydroclimatic studies due to its straightforward interpretation(*5*, *6*, *66*, *67*). Specifically, we extracted annual peak discharges (APD) and their corresponding occurrence day of the year (APD_DOY) (ordinal day – 1 for 1st January and 365 (366) for 31st December) are extracted from the daily streamflow time series data for the whole analysis period. Here, the APD metric is considered flood magnitude, and its occurrence day is considered flood timing.

Changes in flood magnitude and timing

To evaluate the changing nature of flooding magnitude and timing at individual catchments, we have employed Theil-Sen's Slope Estimator(*68*). The Sen-slope estimator has been widely used in various hydrometeorological time series trend analysis (*21*, *69*, *70*). It helps to find the magnitude of trends in terms of percentage per decade using Equation 1. This allows trend estimates comparison between catchments of different sizes and climates and diminishes model biases trends(*69–71*).

$$T_c = \frac{\tau_c}{\bar{x}_c} \text{ x } 10 \; years \text{ x } 100 \qquad (1)$$

where T_c is the trend at catchment c in units of percent per decade, τ_c is the Theil-Sen slope estimator, and $\bar{x}_c$ is the mean of the index time series.

Changes in 100-year flood discharge

The trends in flood magnitude suggest that their exists trends in 100-year flood discharge (*21*, *72*). The 100-year flood discharge was estimated for each station by employing GEV distribution. GEV distribution combines the Gumbel, Fréchet, and Weibull distributions into one continuous probability distribution. It is one of the most widely used distributions in flood frequency analysis (*73*). The probability distribution function of the GEV distribution for the block maxima is given by Equation 2:

$$F(z) = \exp\left[-\left\{1 + \tau\left(\frac{z-\mu}{\sigma}\right)\right\}^{\frac{-1}{\tau}}\right] \qquad (2)$$

Where μ is the location parameter, σ is the scale parameter, τ is the shape parameter. These parameters were estimated from the annual maximum flood discharge using the MLE (Maximum Likelihood) method. The 'extRemes' package in R(*74*) environment was used to fit a GEV distribution to data on floods with 100-year return periods. A log-link function was implemented to guarantee a positive scale parameter. For this study, location and scale parameters were made to change linearly with the covariate time (t) (*75*, *76*). Shape parameter was assumed to be constant because introducing a covariate in shape parameter leads to too much error in its estimation (*77*).

$$\mu(t) = \mu_o + \mu_1 t \; ; \sigma(t) = \sigma_o + \sigma_1 t \qquad (3)$$

The following four types of models were fitted to the flood data: -

1. Both location and scale are considered constant, and the model is stationary.
2. The location parameter varies with time, and the scale parameter is considered constant.
3. The location parameter is constant, while the scale parameter is a function of time.
4. Both the location and scale parameters of the GEV distribution vary with time.

Akaike information criterion (AIC) is used for selecting the optimal GEV model, as it is a versatile and reliable tool suitable for both stationary and nonstationary data(*78*). The fit with the least AIC value of all four fits was declared the best-fitting GEV distribution, and based on the best-fitted GEV distribution, the changes in the magnitude of 100-year floods with time were computed.

References

1. B. Merz, G. Blöschl, S. Vorogushyn, F. Dottori, J. C. J. H. Aerts, P. Bates, M. Bertola, M. Kemter, H. Kreibich, U. Lall, E. Macdonald, Causes, impacts and patterns of disastrous river floods. *Nat Rev Earth Environ* **2**, 592–609 (2021).

2. F. Dottori, W. Szewczyk, J.-C. Ciscar, F. Zhao, L. Alfieri, Y. Hirabayashi, A. Bianchi, I. Mongelli, K. Frieler, R. A. Betts, L. Feyen, Increased human and economic losses from river flooding with anthropogenic warming. *Nature Climate Change* **8**, 781–786 (2018).

3. M. Saharia, A. Jain, R. R. Baishya, S. Haobam, O. P. Sreejith, D. S. Pai, A. Rafieeinasab, India flood inventory: creation of a multi-source national geospatial database to facilitate comprehensive flood research. *Nat Hazards* **108**, 619–633 (2021).

4. H. Douville, K. Raghavan, J. Renwick, R. P. Allan, P. A. Arias, M. Barlow, R. Cerezo-Mota, A. Cherchi, ThianY. Gan, J. Gergis, D. Jiang, A. Khan, W. P. Mba, D. Rosenfeld, J. Tierney, O. Zolina, "Water Cycle Changes" in *Climate Change 2021: The Physical Science Basis. Intergovernmental Panel on Climate Change (IPCC)* (Cambridge University Press, Cambridge, 2021; https://www.ipcc.ch/report/ar6/wg1/chapter/chapter-8/)*Intergovernmental Panel on Climate Change*, pp. 1055–1210.

5. I. Mallakpour, G. Villarini, The changing nature of flooding across the central United States. *Nature Climate Change* **5**, 250–254 (2015).

6. C. Wasko, R. Nathan, M. C. Peel, Trends in Global Flood and Streamflow Timing Based on Local Water Year. *Water Resources Research* **56**, e2020WR027233 (2020).

7. N. W. Arnell, S. N. Gosling, The impacts of climate change on river flood risk at the global scale. *Climatic Change* **134**, 387–401 (2016).

8. Y. Hirabayashi, R. Mahendran, S. Koirala, L. Konoshima, D. Yamazaki, S. Watanabe, H. Kim, S. Kanae, Global flood risk under climate change. *Nature Clim Change* **3**, 816–821 (2013).

9. R. Dankers, N. W. Arnell, D. B. Clark, P. D. Falloon, B. M. Fekete, S. N. Gosling, J. Heinke, H. Kim, Y. Masaki, Y. Satoh, T. Stacke, Y. Wada, D. Wisser, First look at changes in flood hazard in the Inter-Sectoral Impact Model Intercomparison Project ensemble. *Proceedings of the National Academy of Sciences* **111**, 3257–3261 (2014).

10. A. Sood, V. Smakhtin, Global hydrological models: a review. *Hydrological Sciences Journal* **60**, 549–565 (2015).

11. P. J. Ward, B. Jongman, P. Salamon, A. Simpson, P. Bates, T. De Groeve, S. Muis, E. C. de Perez, R. Rudari, M. A. Trigg, H. C. Winsemius, Usefulness and limitations of global flood risk models. *Nature Clim Change* **5**, 712–715 (2015).

12. J. Lehmann, D. Coumou, K. Frieler, Increased record-breaking precipitation events under global warming. *Climatic Change* **132**, 501–515 (2015).

13. S. M. Papalexiou, A. Montanari, Global and Regional Increase of Precipitation Extremes Under Global Warming. *Water Resources Research* **55**, 4901–4914 (2019).

14. M. K. Roxy, S. Ghosh, A. Pathak, R. Athulya, M. Mujumdar, R. Murtugudde, P. Terray, M. Rajeevan, A threefold rise in widespread extreme rain events over central India. *Nat Commun* **8**, 708 (2017).

15. H. X. Do, S. Westra, M. Leonard, A global-scale investigation of trends in annual maximum streamflow. *Journal of Hydrology* **552**, 28–43 (2017).

16. L. Mediero, D. Santillán, L. Garrote, A. Granados, Detection and attribution of trends in magnitude, frequency and timing of floods in Spain. *Journal of Hydrology* **517**, 1072–1088 (2014).

17. A. Sharma, C. Wasko, D. P. Lettenmaier, If Precipitation Extremes Are Increasing, Why Aren't Floods? *Water Resources Research* **54**, 8545–8551 (2018).

18. C. Wasko, R. Nathan, Influence of changes in rainfall and soil moisture on trends in flooding. *Journal of Hydrology* **575**, 432–441 (2019).

19. S. K. Kuntla, M. Saharia, P. Kirstetter, Global-scale characterization of streamflow extremes. *Journal of Hydrology* **615**, 128668 (2022).

20. L. Stein, F. Pianosi, R. Woods, Event-based classification for global study of river flood generating processes. *Hydrological Processes* **34**, 1514–1529 (2020).

21. G. Blöschl, J. Hall, A. Viglione, R. A. P. Perdigão, J. Parajka, B. Merz, D. Lun, B. Arheimer, G. T. Aronica, A. Bilibashi, M. Boháč, O. Bonacci, M. Borga, I. Čanjevac, A. Castellarin, G. B. Chirico, P. Claps, N. Frolova, D. Ganora, L. Gorbachova, A. Gül, J. Hannaford, S. Harrigan, M. Kireeva, A. Kiss, T. R. Kjeldsen, S. Kohnová, J. J. Koskela, O. Ledvinka, N. Macdonald, M. Mavrova-Guirguinova, L. Mediero, R. Merz, P. Molnar, A. Montanari, C. Murphy, M. Osuch, V. Ovcharuk, I. Radevski, J. L. Salinas, E. Sauquet, M. Šraj, J. Szolgay, E. Volpi, D. Wilson, K. Zaimi, N. Živković, Changing climate both increases and decreases European river floods. *Nature* **573**, 108–111 (2019).

22. A. Kuriqi, R. Ali, Q. B. Pham, J. Montenegro Gambini, V. Gupta, A. Malik, N. T. T. Linh, Y. Joshi, D. T. Anh, V. T. Nam, X. Dong, Seasonality shift and streamflow flow variability trends in central India. *Acta Geophys.* **68**, 1461–1475 (2020).

23. D. Chug, A. Pathak, J. Indu, S. K. Jain, S. K. Jain, A. P. Dimri, D. Niyogi, S. Ghosh, Observed Evidence for Steep Rise in the Extreme Flow of Western Himalayan Rivers. *Geophysical Research Letters* **47**, e2020GL087815 (2020).

24. S. Das, S. J. Sangode, A. M. Kandekar, Increasing and decreasing trends in extreme annual streamflow in the Godavari catchment, India. *Current Science* **122** (2022).

25. N. S. Abeysingha, M. Singh, V. K. Sehgal, M. Khanna, H. Pathak, Analysis of trends in streamflow and its linkages with rainfall and anthropogenic factors in Gomti River basin of North India. *Theor Appl Climatol* **123**, 785–799 (2016).

26. P. P. Jena, C. Chatterjee, G. Pradhan, A. Mishra, Are recent frequent high floods in Mahanadi basin in eastern India due to increase in extreme rainfalls? *Journal of Hydrology* **517**, 847–862 (2014).

27. R. Nune, B. A. George, P. Teluguntla, A. W. Western, Relating Trends in Streamflow to Anthropogenic Influences: A Case Study of Himayat Sagar Catchment, India. *Water Resour Manage* **28**, 1579–1595 (2014).

28. S. Das, Dynamics of streamflow and sediment load in Peninsular Indian rivers (1965–2015). *Science of The Total Environment* **799**, 149372 (2021).

29. D. K. Panda, A. Kumar, S. Ghosh, R. K. Mohanty, Streamflow trends in the Mahanadi River basin (India): Linkages to tropical climate variability. *Journal of Hydrology* **495**, 135–149 (2013).

30. P. J. Sharma, P. L. Patel, V. Jothiprakash, Impact of rainfall variability and anthropogenic activities on streamflow changes and water stress conditions across Tapi Basin in India. *Science of The Total Environment* **687**, 885–897 (2019).

31. B. Parthasarathy, A. A. Munot, D. R. Kothawale, All-India monthly and seasonal rainfall series: 1871–1993. *Theor Appl Climatol* **49**, 217–224 (1994).

32. D. A. Mooley, B. Parthasarathy, Fluctuations in All-India summer monsoon rainfall during 1871–1978. *Climatic Change* **6**, 287–301 (1984).

33. E. McEwan, Earthquakes can change the course of rivers – with devastating results, *PreventionWeb* (2023). https://www.preventionweb.net/news/earthquakes-can-change-course-rivers-devastating-results-we-may-now-be-able-predict-these.

34. S. Suriya, B. V. Mudgal, Impact of urbanization on flooding: The Thirusoolam sub watershed – A case study. *Journal of Hydrology* **412–413**, 210–219 (2012).

35. S. K. Kuntla, An era of Sentinels in flood management: Potential of Sentinel-1, -2, and -3 satellites for effective flood management. *Open Geosciences* **13**, 1616–1642 (2021).

36. D. Skublics, G. Blöschl, P. Rutschmann, Effect of river training on flood retention of the Bavarian Danube. *Journal of Hydrology and Hydromechanics* **64**, 349–356 (2016).

37. S. Talukdar, S. Pal, Impact of Dam on Flow Regime and Flood Plain Modification in Punarbhaba River Basin of Indo-Bangladesh Barind Tract. *Water Conserv Sci Eng* **3**, 59–77 (2018).

38. S. K. Kuntla, M. Saharia, S. Prakash, G. Villarini, Precipitation inequality exacerbates streamflow inequality, but dams moderate it. *Science of The Total Environment*, 169098 (2023).

39. S. K. Jain, P. C. Nayak, Y. Singh, S. K. Chandniha, Trends in rainfall and peak flows for some river basins in India. *Current Science* **112**, 1712–1726 (2017).

40. S. Swain, S. K. Mishra, A. Pandey, D. Dayal, Assessment of drought trends and variabilities over the agriculture-dominated Marathwada Region, India. *Environ Monit Assess* **194**, 883 (2022).

41. M. Zachariah, S. Kumari, A. Mondal, K. Haustein, F. E. L. Otto, Attribution of the 2015 drought in Marathwada, India from a multivariate perspective. *Weather and Climate Extremes* **39**, 100546 (2023).

42. S. Yue, C. Y. Wang, Applicability of prewhitening to eliminate the influence of serial correlation on the Mann-Kendall test. *Water Resources Research* **38**, 4-1-4–7 (2002).

43. J. S. Nanditha, V. Mishra, Multiday Precipitation Is a Prominent Driver of Floods in Indian River Basins. *Water Resources Research* **58**, e2022WR032723 (2022).

44. M. G. Grillakis, A. G. Koutroulis, J. Komma, I. K. Tsanis, W. Wagner, G. Blöschl, Initial soil moisture effects on flash flood generation – A comparison between basins of contrasting hydro-climatic conditions. *Journal of Hydrology* **541**, 206–217 (2016).

45. Q. Ran, J. Wang, X. Chen, L. Liu, J. Li, S. Ye, The relative importance of antecedent soil moisture and precipitation in flood generation in the middle and lower Yangtze River basin. *Hydrology and Earth System Sciences* **26**, 4919–4931 (2022).

46. M. A. Bollasina, Y. Ming, V. Ramaswamy, Anthropogenic Aerosols and the Weakening of the South Asian Summer Monsoon. *Science* **334**, 502–505 (2011).

47. M. K. Roxy, K. Ritika, P. Terray, R. Murtugudde, K. Ashok, B. N. Goswami, Drying of Indian subcontinent by rapid Indian Ocean warming and a weakening land-sea thermal gradient. *Nat Commun* **6**, 7423 (2015).

48. K. N. Krishnakumar, G. S. L. H. V. Prasada Rao, C. S. Gopakumar, Rainfall trends in twentieth century over Kerala, India. *Atmospheric Environment* **43**, 1940–1944 (2009).

49. M. Mathew, K. Sreelash, A. A. Jacob, M. M. Mathew, D. Padmalal, Diverging monthly rainfall trends in south peninsular India and their association with global climate indices. *Stoch Environ Res Risk Assess* **37**, 27–48 (2023).

50. OnManorama, Kerala gets 85% excess summer rain, decade's second highest. Still, water level in dams safe, *OnManorama* (2022). https://www.onmanorama.com/news/kerala/2022/05/31/excess-rain-monsoon-weather-climate-dams-summer-rain.html.

51. The Hindu, Summer rainfall highest in 50 years, *The Hindu* (2021). https://www.thehindu.com/news/national/kerala/summer-rainfall-highest-in-50-years/article34700975.ece.

52. A. F. Lutz, W. W. Immerzeel, A. B. Shrestha, M. F. P. Bierkens, Consistent increase in High Asia's runoff due to increasing glacier melt and precipitation. *Nature Clim Change* **4**, 587–592 (2014).

53. B. Bookhagen, Appearance of extreme monsoonal rainfall events and their impact on erosion in the Himalaya. *Geomatics, Natural Hazards and Risk* **1**, 37–50 (2010).

54. S. Swarnkar, P. Mujumdar, Increasing Flood Frequencies Under Warming in the West-Central Himalayas. *Water Resources Research* **59**, e2022WR032772 (2023).

55. J. Huang, Y. Li, C. Fu, F. Chen, Q. Fu, A. Dai, M. Shinoda, Z. Ma, W. Guo, Z. Li, L. Zhang, Y. Liu, H. Yu, Y. He, Y. Xie, X. Guan, M. Ji, L. Lin, S. Wang, H. Yan, G. Wang, Dryland climate change: Recent progress and challenges. *Reviews of Geophysics* **55**, 719–778 (2017).

56. R. P. Allan, H. Douville, An even drier future for the arid lands. *Proceedings of the National Academy of Sciences* **121**, e2320840121 (2024).

57. N. Skliris, J. D. Zika, G. Nurser, S. A. Josey, R. Marsh, Global water cycle amplifying at less than the Clausius-Clapeyron rate. *Sci Rep* **6**, 38752 (2016).

58. S. Yue, Z. W. Kundzewicz, L. Wang, “Detection of Changes” in *Changes in Flood Risk in Europe* (CRC Press, 2012).

59. ECA&D, R. N. M. I. KNMI, Algorithm Theoretical Basis Document (ATBD). (2013). https://www.ecad.eu/documents/atbd.pdf.

60. H. Hersbach, B. Bell, P. Berrisford, S. Hirahara, A. Horányi, J. Muñoz-Sabater, J. Nicolas, C. Peubey, R. Radu, D. Schepers, A. Simmons, C. Soci, S. Abdalla, X. Abellan, G. Balsamo, P. Bechtold, G. Biavati, J. Bidlot, M. Bonavita, G. Chiara, P. Dahlgren, D. Dee, M. Diamantakis, R. Dragani, J. Flemming, R. Forbes, M. Fuentes, A. Geer, L. Haimberger, S. Healy, R. J. Hogan, E. Hólm, M. Janisková, S. Keeley, P. Laloyaux, P. Lopez, C. Lupu, G. Radnoti, P. Rosnay, I. Rozum, F. Vamborg, S. Villaume, J. Thépaut, The ERA5 global reanalysis. *Q.J.R. Meteorol. Soc.* **146**, 1999–2049 (2020).

61. J.-P. Baudouin, M. Herzog, C. A. Petrie, Cross-validating precipitation datasets in the Indus River basin. *Hydrology and Earth System Sciences* **24**, 427–450 (2020).

62. H. Sun, F. Su, T. Yao, Z. He, G. Tang, J. Huang, B. Zheng, F. Meng, T. Ou, D. Chen, General overestimation of ERA5 precipitation in flow simulations for High Mountain Asia basins. *Environ. Res. Commun.* **3**, 121003 (2021).

63. J. K. Vishal, S. I. Rani, Location-specific verification of near-surface air temperature from IMDAA regional reanalysis. *J Earth Syst Sci* **131**, 179 (2022).

64. S. S. Mahto, V. Mishra, Does ERA-5 Outperform Other Reanalysis Products for Hydrologic Applications in India? *Journal of Geophysical Research: Atmospheres* **124**, 9423–9441 (2019).

65. M. Kottek, J. Grieser, C. Beck, B. Rudolf, F. Rubel, World Map of the Köppen-Geiger climate classification updated. *Meteorologische Zeitschrift*, 259–263 (2006).

66. H. X. Do, Y. Mei, A. D. Gronewold, To What Extent Are Changes in Flood Magnitude Related to Changes in Precipitation Extremes? *Geophysical Research Letters* **47**, e2020GL088684 (2020).

67. S. Westra, L. V. Alexander, F. W. Zwiers, Global Increasing Trends in Annual Maximum Daily Precipitation. *Journal of Climate* **26**, 3904–3918 (2013).

68. P. K. Sen, Estimates of the Regression Coefficient Based on Kendall’s Tau. *Journal of the American Statistical Association* **63**, 1379–1389 (1968).

69. L. Gudmundsson, M. Leonard, H. X. Do, S. Westra, S. I. Seneviratne, Observed Trends in Global Indicators of Mean and Extreme Streamflow. *Geophysical Research Letters* **46**, 756–766 (2019).

70. L. Gudmundsson, J. Boulange, H. X. Do, S. N. Gosling, M. G. Grillakis, A. G. Koutroulis, M. Leonard, J. Liu, H. Müller Schmied, L. Papadimitriou, Y. Pokhrel, S. I. Seneviratne, Y. Satoh, W. Thiery, S. Westra, X. Zhang, F. Zhao, Globally observed trends in mean and extreme river flow attributed to climate change. *Science* **371**, 1159–1162 (2021).

71. K. Stahl, L. M. Tallaksen, J. Hannaford, H. a. J. van Lanen, Filling the white space on maps of European runoff trends: estimates from a multi-model ensemble. *Hydrology and Earth System Sciences* **16**, 2035–2047 (2012).

72. J. L. Salinas, A. Castellarin, S. Kohnová, T. R. Kjeldsen, Regional parent flood frequency distributions in Europe – Part 2: Climate and scale controls. *Hydrology and Earth System Sciences* **18**, 4391–4401 (2014).

73. V. P. Singh, "Generalized Extreme Value Distribution" in *Entropy-Based Parameter Estimation in Hydrology*, V. P. Singh, Ed. (Springer Netherlands, Dordrecht, 1998; https://doi.org/10.1007/978-94-017-1431-0_11)*Water Science and Technology Library*, pp. 169–183.

74. E. Gilleland, R. W. Katz, extRemes 2.0: An Extreme Value Analysis Package in R. *Journal of Statistical Software* **72**, 1–39 (2016).

75. D. Faulkner, S. Warren, P. Spencer, P. Sharkey, Can we still predict the future from the past? Implementing non-stationary flood frequency analysis in the UK. *Journal of Flood Risk Management* **13**, e12582 (2020).

76. M. Šraj, A. Viglione, J. Parajka, G. Blöschl, The influence of non-stationarity in extreme hydrological events on flood frequency estimation. *Journal of Hydrology and Hydromechanics* **64**, 426–437 (2016).

77. N. L. O'Brien, D. H. Burn, A nonstationary index-flood technique for estimating extreme quantiles for annual maximum streamflow. *Journal of Hydrology* **519**, 2040–2048 (2014).

78. A. C. F. Xavier, G. C. Blain, M. V. B. de Morais, G. da R. Sobierajski, Selecting "the best" nonstationary Generalized Extreme Value (GEV) distribution: on the influence of different numbers of GEV-models. *Bragantia* **78**, 606–621 (2019).

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Author contributions

Conceptualization: SKK, MS

Methodology: SKK, MS

Investigation: SKK

Visualization: SKK

Funding acquisition: MS

Writing – original draft: SKK

Writing – review & editing: SKK, MS, SKJ

Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data and materials availability

The datasets in this study are available from the following sources:

- Streamflow data from India Water Resources Information System (WRIS): https://indiawris.gov.in/wris/#/RiverMonitoring.
- Precipitation and temperature from the ERA5 reanalysis products: https://doi.org/10.24381/cds.adbb2d47
- Soil moisture data from the Climate Prediction Center (CPC) dataset: https://www.psl.noaa.gov/data/gridded/data.cpcsoil.html
- Koppen-Geiger climate classification from http://koeppen-geiger.vu-wien.ac.at/present.htm
- SRTM DEM from USGS earth explorer: https://earthexplorer.usgs.gov/

Science Advances

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Supplementary Materials for

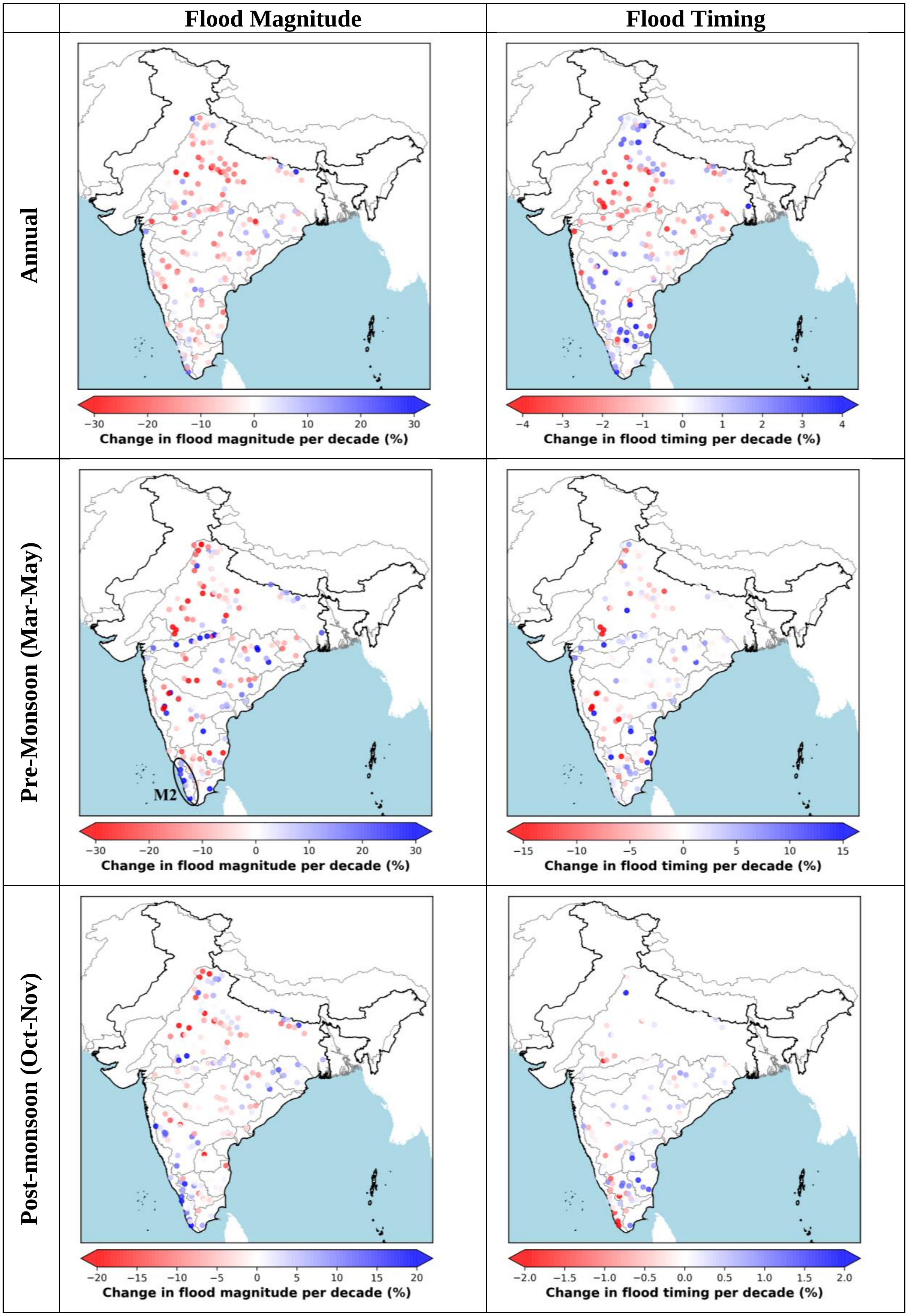
The changing magnitude and timing of riverine floods in India

Sai Kiran Kuntla *et al.*

Corresponding author. Email: msaharia@iitd.ac.in

This PDF file includes:

Figures S1 to S5
Table S1


Flood Magnitude
Flood Timing
Annual
Pre-Monsoon (Mar-May)
Post-monsoon (Oct-Nov)
−30 −20 −10 0 10 20 30
Change in flood magnitude per decade (%)
−4 −3 −2 −1 0 1 2 3 4
Change in flood timing per decade (%)
M2
−30 −20 −10 0 10 20 30
Change in flood magnitude per decade (%)
−15 −10 −5 0 5 10 15
Change in flood timing per decade (%)
−20 −15 −10 −5 0 5 10 15 20
Change in flood magnitude per decade (%)
−2.0 −1.5 −1.0 −0.5 0.0 0.5 1.0 1.5 2.0
Change in flood timing per decade (%)

Winter (Dec–Feb)

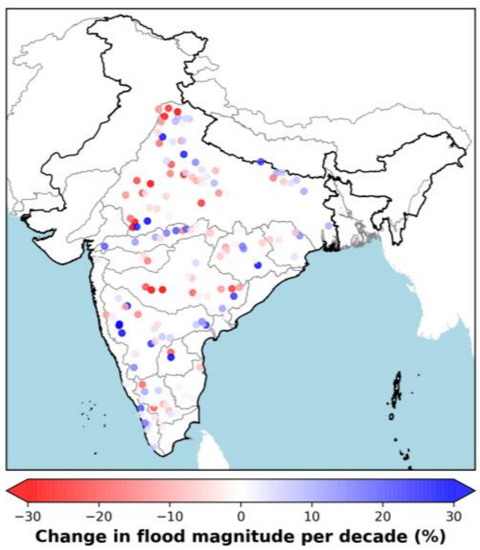


Figure S1: Annual and seasonal trends in flood magnitude and timing between 1970 and 2010 based on the Theil-Sen slope estimator

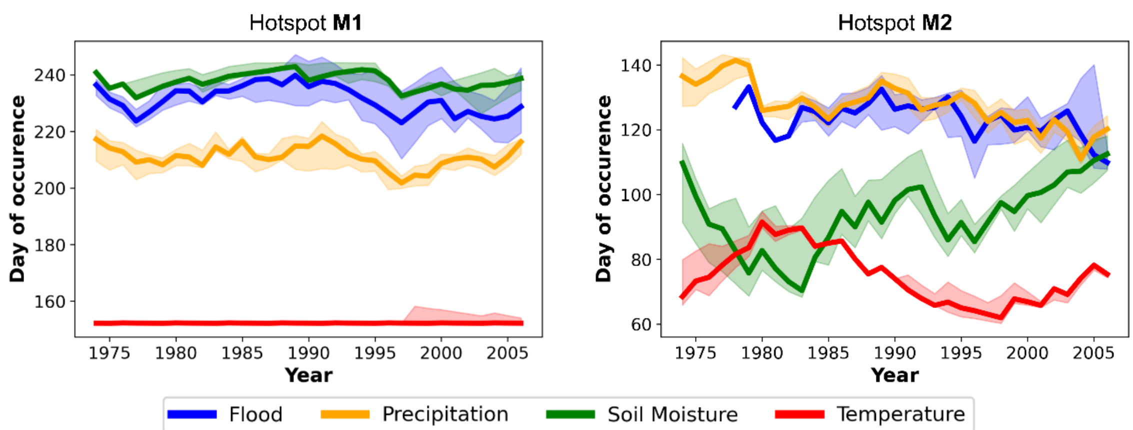


Figure S2: Long-term temporal evolutions of flood timing along with their drivers for hotspots with a clear regional pattern in flood magnitude (Hotspot M1, and M2). The data represents observed floods (blue), peak 5-day precipitation (orange), peak monthly soil moisture (green), and peak monthly temperature (red). Solid lines show the median, and the shaded region shows the variability within the hotspots (25th and 75th percentile). All data were subjected to a 10-year weighted moving average filter.

Table S1: Spearman's rank correlation coefficient (r) between the median of flood timing and their drivers over hotspots of catchments showing a significant trend in flood magnitude.

	Timing	
Hotspot	M1	M2
Precipitation	0.61	0.72

Soil Moisture	0.77	-0.20
Temperature	-0.07	0.05

Timing

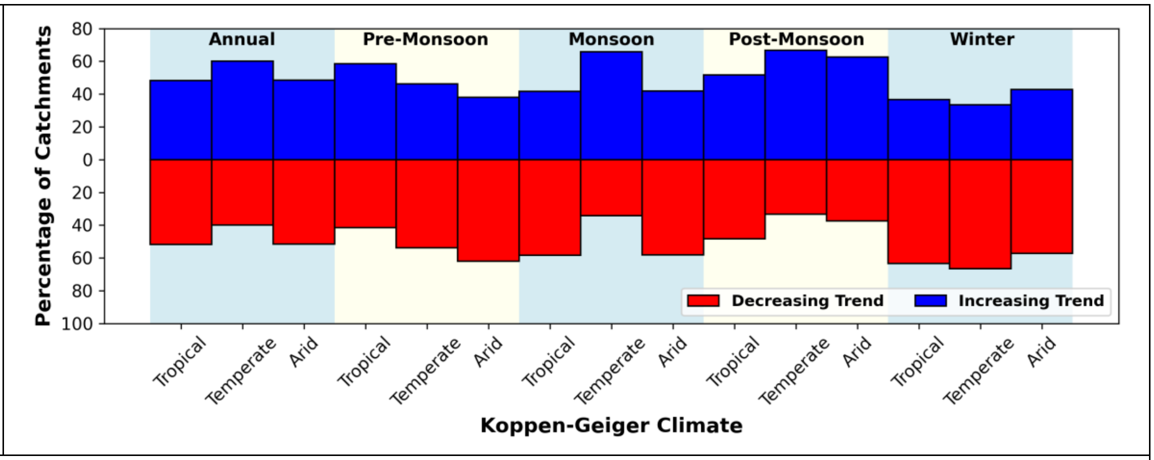


Figure S3: Percentage of catchments with decreasing and increasing trends in food timing in each climate over different seasons.

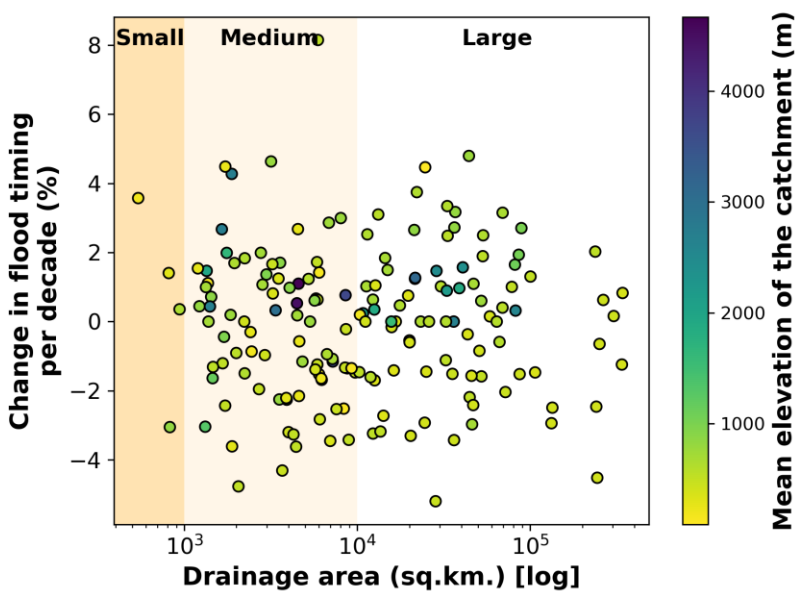
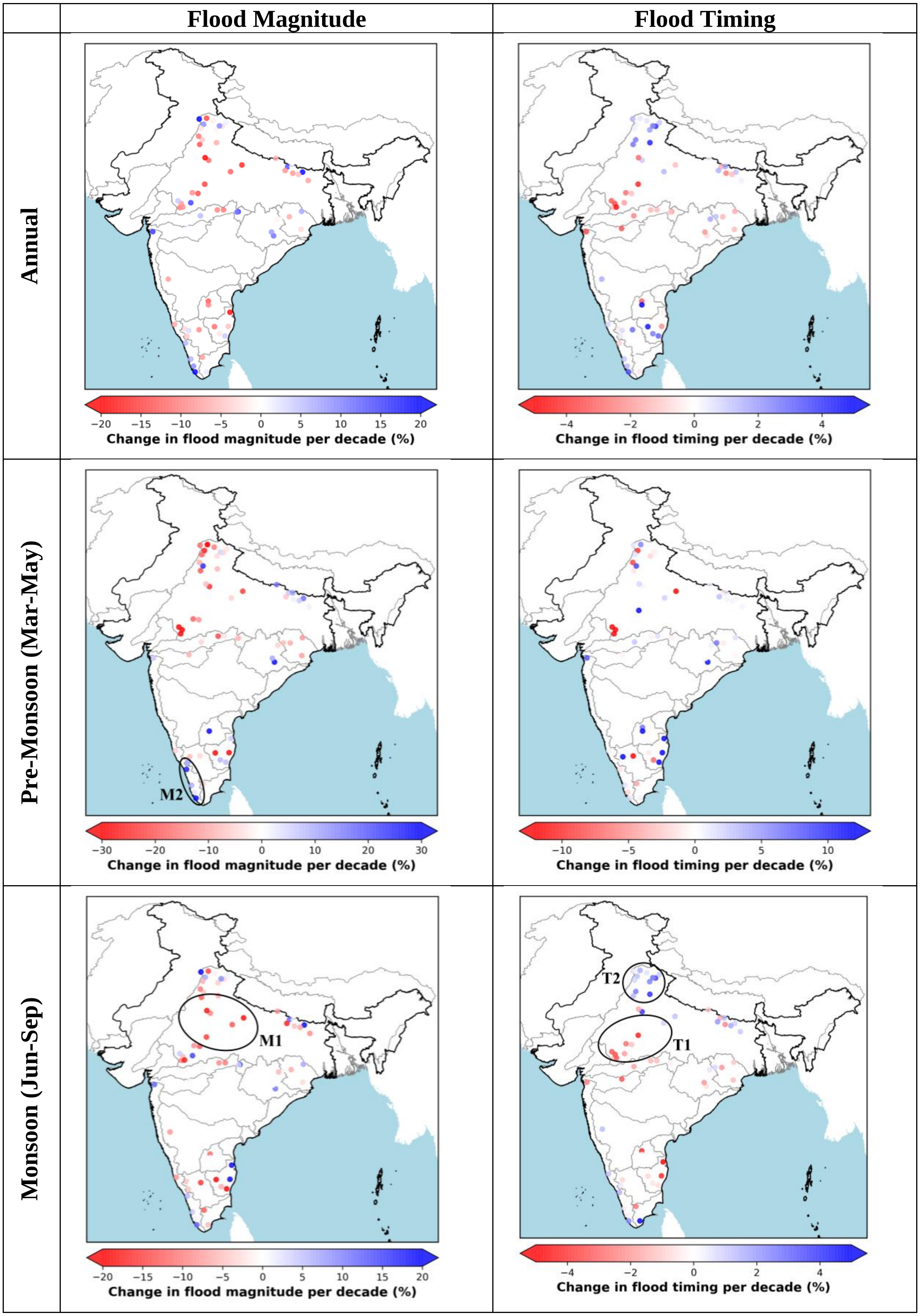


Figure S4: Drainage area vs. percentage change in flood magnitude per decade based on *the* Theil-Sen slope estimator over all the catchments. Points are color-coded based on the mean elevation of the catchment. *The b*ackground is color-coded based on the size of catchments: small (less than 1,000 sq.km.), medium (1,000 – 10,000 sq.km.), and large (more than 10,000 sq.km.).


Flood Magnitude
Flood Timing
Annual
Pre-Monsoon (Mar-May)
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−20 −15 −10 −5 0 5 10 15 20
Change in flood magnitude per decade (%)
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−30 −20 −10 0 10 20 30
Change in flood magnitude per decade (%)
−10 −5 0 5 10
Change in flood timing per decade (%)
M1
T2
T1
−20 −15 −10 −5 0 5 10 15 20
Change in flood magnitude per decade (%)
−4 −2 0 2 4
Change in flood timing per decade (%)

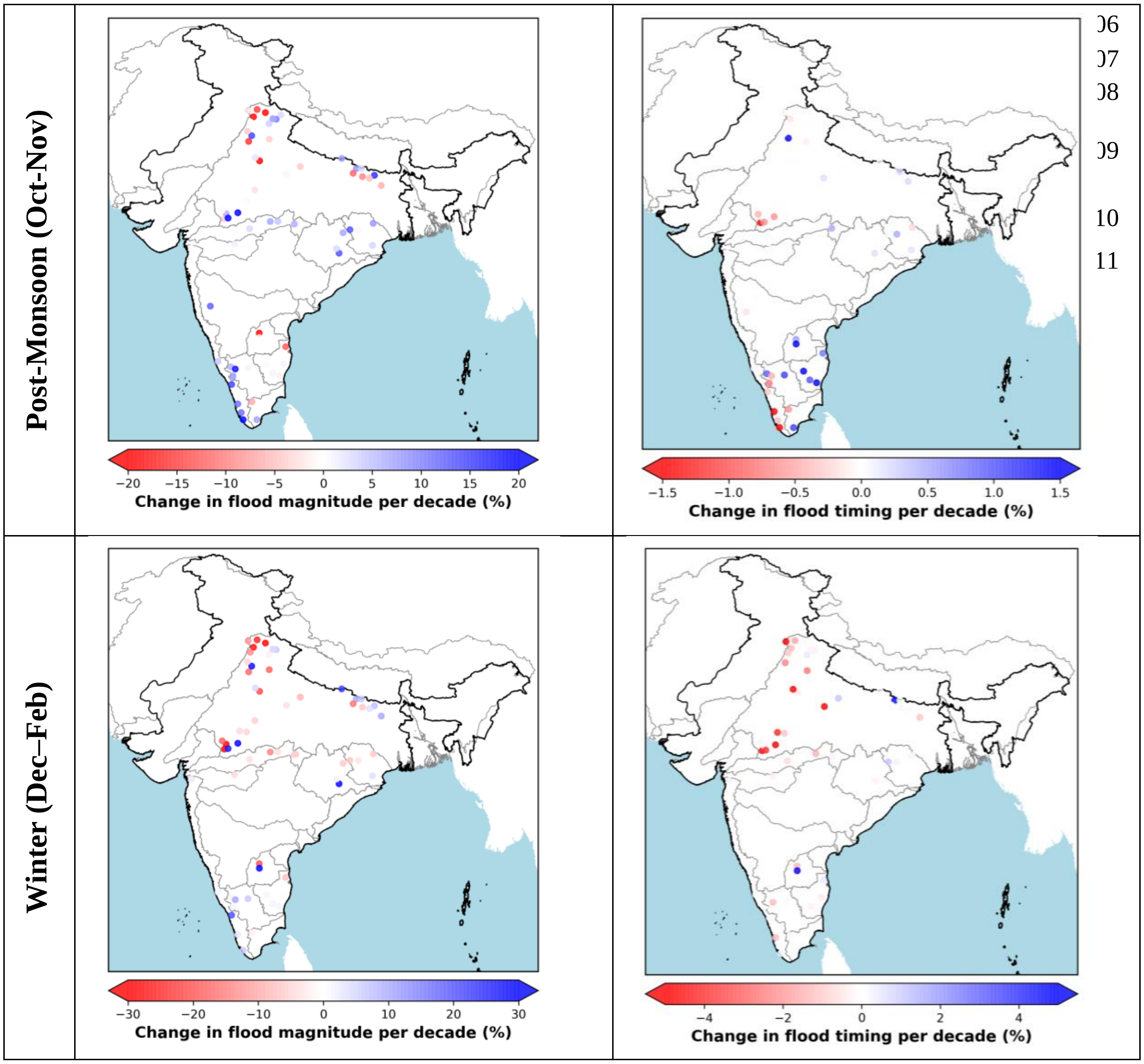

Figure S5: Annual and seasonal trends in flood magnitude and timing between 1970 and 2010 based on the Theil-Sen slope estimator over stations whose catchments do not have any dams within their boundary.