Role of hydrometeorological variables and catchment area to flood generation over the monsoonal climate region of India

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Abstract:

Indian River basins experience frequent flooding during the Indian summer monsoon and pose several challenges for the region's large population, yet the hydrometeorological and catchment-scale drivers that control flood processes remain poorly explored across India. To effectively manage flood risk in the densely populated Indian region, it is essential to understand how the temporal properties of precipitation and runoff generate floods across different aridity regimes within a large catchment, and which specific areas of a large, climatically heterogeneous basin generate the runoff that drives downstream flood peaks. In this study, we address these gaps and examine the role of hydrometeorological variables (such as precipitation and surface runoff) and catchment area in the flood

occurrence in the Godavari River basin (one of the largest river basins in the Indian Subcontinent) using observed and VIC-simulated datasets. Based on the temporal analysis of precipitation, runoff, and streamflow, we show that the majority of floods in the semi-humid sub-basins (Tekra, Pathagudam, Perur, and Polavaram) are predominantly associated with 10 to 11 days of accumulated precipitation, having multiple high-intensity precipitation events prior to flood. In contrast, the floods in the semi-arid region of Godavari (Mancherial sub-basin) are triggered by a single high-intensity precipitation day and are associated with short-duration (2 days) accumulated precipitation. In addition to temporal analysis, we performed Empirical Orthogonal Function (EOF) analysis using precipitation, runoff, and streamflow data to identify the specific sub-regions that disproportionately generate flood-causing runoff (flood-dominant catchment areas). Our results demonstrate that central and downstream areas of the basin contribute dominantly to flood occurrence, generating substantially higher runoff in the Tekra sub-basin. Overall, this study moves beyond basin-averaged flood attribution and advances understanding of flood-generating mechanisms over the Godavari River basin, which can be helpful for duration-informed forecasting and catchment-scale flood management during the monsoonal climate of the Indian Subcontinent.

Keywords: Flood mechanisms, Hydrometeorology, Catchment Characteristics, Godavari basin, Monsoonal climate.

Highlights

- **The majority of floods in the semi-humid regions of the Godavari River predominantly occur due to multiple high-intensity rainfall days**

- **Floods in the semi-arid Mancherial sub-basin are triggered by a single high-intensity precipitation event**
- **Central and downstream areas of the Godavari River basin dominate in the flood occurrence**
- **High runoff generation in the Tekra sub-basin plays an important role in downstream flooding in the Godavari River basin**

1. Introduction

Floods are among the costliest natural disasters, causing severe damage to infrastructure and socio-economic conditions. According to the World Bank report in 2006, floods caused damage of 163 million US$ annually during the 1999–2005 period in India. Moreover, flood occurrences have increased in India over the last few decades under a warming climate, affecting millions of people in the region (Ali et al., 2019; Gosain et al., 2006; Gupta and Nair, 2011; Milly et al., 2002). For instance, recent flood events in the Indian sub-continent (i.e., 2018 Kerala flood, 2014 Jammu and Kashmir flood, and 2013 Uttarakhand flood) caused enormous losses of property and human lives (Lindell et al., 2019; Mishra et al., 2018; Ray et al., 2019). Due to global warming, the frequency of high-intensity precipitation events has increased at the regional and global scales (Allan and Soden, 2007; Gosain et al., 2006; Guerreiro et al., 2018; Min et al., 2011; Nanditha and Mishra, 2024; Rogger et al., 2017; Trenberth et al., 2003; Ummenhofer et al., 2011), which instigated the increase in flood magnitude and frequency across the globe (Ali et al., 2019; Gosain et al., 2006; Gupta and Nair, 2011; Kundzewicz et al., 2014; Milly et al., 2002). Therefore, an improved understanding of

68 flood processes is required in the densely populated Indian sub-continent to reduce the
69 severe impact of flood events.

70 Flood mechanisms comprise multiple processes that control the intensity and
71 magnitude of river flow. In the monsoonal climate, the majority of floods occur primarily
72 due to high-intensity precipitation events (Ali et al., 2019; Garg and Mishra, 2019;
73 Nanditha et al., 2022; Nanditha and Mishra, 2022). However, static factors of catchment
74 properties (basin slope, geometry, land use and land cover, drainage density, drainage
75 area, and soil parameters) can also have an essential role in the flood generation
76 mechanism, apart from extreme precipitation (Blöschl et al., 2017, 2013; Merz and
77 Blöschl, 2003; Tarasova et al., 2019). For example, forest land cover generates less
78 runoff than arable land cover during storm events (Lane, 2017; Marc and Robinson,
79 2007). Recent study (Sharma and Mujumdar, 2024) found that baseflow contributes
80 significantly to the flood occurrence in Peninsular India.

81 To examine flood control processes, several causative processes and storylines
82 (e.g., high precipitation, rain on snow, cloudburst, excess runoff) have been used in
83 previous studies (Berghuijs et al., 2016; Keller et al., 2018; Li et al., 2019; Nanditha and
84 Mishra, 2022; Nied et al., 2014; Sharma and Mujumdar, 2024; Tarasova et al., 2019;
85 Viglione et al., 2010). These causative processes include the hydroclimatic, hydrological,
86 and hydrograph perspectives to better understand the flooding mechanisms (Tarasova et
87 al., 2019). Based on the causative classification, flood mechanisms, considering weather
88 systems, storm patterns, moisture transport, and weather circulation, are classified in the
89 hydroclimatic perspective (Blöschl et al., 2013; Grams et al., 2014). The hydrograph
90 perspective uses discharge time-series data to evaluate hydrographs that show distinct

flood-generation mechanisms (Tarasova et al., 2019). Under the hydrological perspective, hydrometeorological variables within the catchment, soil moisture information, and hydrological processes (i.e., saturation excess and infiltration) are considered (Berghuijs et al., 2016; Nied et al., 2014; Sikorska et al., 2015).

In some cases, multiple criteria were used in the evaluation of flood processes, for example, short-duration heavy rainfall and long-duration rainfall (with and without high-intensity rainfall) (Keller et al., 2018; Li et al., 2019; Nied et al., 2014; Tarasova et al., 2019). Additionally, the spatial variability of hydrometeorological variables within the catchment is also crucial to the flooding mechanism. For instance, Freyberg et al. (2014) found that a small portion of the catchment induces large streamflow in a pre-alpine catchment during rainy days, causing floods in the basin. Therefore, determining the flood-dominating catchment areas based on hydrometeorological and catchment properties prior to the peak flood is crucial for understanding flood processes. Overall, we need to thoroughly analyse the temporal and spatial properties of hydrometeorological variables to better understand flood generation mechanisms.

Flood mechanisms remain largely unexplored in large rivers within the monsoonal climate of India, which presents unique hydrometeorological and catchment conditions. For instance, large river basins in India have dry soil conditions in the pre-monsoon season and extremely wet soil conditions during the mid- and late monsoon. Moreover, large basins exhibit a variety of climate zones, topography, soil parameters, and vegetation cover, resulting in different hydrological responses during the monsoon season. Therefore, the goal of the present study is to understand the major flood-generating mechanisms across different aridity regimes within one of the largest river

basins in the Indian Subcontinent, the Godavari River basin. Using the Variable Infiltration Capacity [VIC; (Cherkauer et al., 2003; Liang et al., 1996, 1994)] simulated hydrological variables and observed meteorological datasets, first, we examine the temporal variability of hydrometeorological variables (precipitation and surface runoff) before the peak streamflow events to identify the dominating flood processes. Later, we evaluate the spatial variability of hydrometeorological variables to identify flood-dominant catchment areas associated with downstream flood events.

2. Study area

The Godavari River basin (Figure 1) is the second largest river basin in India, after the Ganges basin. The Godavari River witnessed many severe floods in the past decades (Garg and Mishra, 2019; Mujumdar et al., 1969; Rakhecha and Singh, 2017; Rakhecha, 2002), which affected the livelihood and life of millions of people in the basin. For instance, the floods during the years 1969 and 1976 in the Indravati (tributary of the Godavari River) stream posed severe damage in the basin (Garg and Mishra, 2019; Mujumdar et al., 1969; Rakhecha, 2002), which resulted in enormous loss of property and human lives. Similarly, the year 1986 flood in the downstream part of the river affected millions of people, with a loss of more than 250 lives (Rakhecha and Singh, 2017; The Hindu, 2011). Moreover, the high flow level in the Godavari River during 2019 displaced more than 17000 people of Andhra Pradesh (https://floodlist.com/asia/india-godavari-river-flood-andhra-pradesh-august-2019).

The Godavari river basin has a drainage area of approximately 312,800 km^2 and a river length of 1,465 km. The basin covers six Indian states (Maharashtra, Karnataka, Andhra Pradesh, Telangana, Chhattisgarh, and Odisha) and is located in peninsular India.

Godavari River originates from Triambakeshwar, a high-altitude (1067 m above sea level, masl) place in the Nasik district of Maharashtra. The river flows eastward from the Western Ghats to the Bay of Bengal across the Deccan Plateau (Figure 1). The basin exhibits significant elevation variability (Figure 1a), ranging from a flat plain (below 10 masl) to a hill range (above 1200 masl). Due to its low elevation, the downstream part of the basin has experienced numerous floods in the past. For instance, the irrigation department of Andhra Pradesh issued 22 flood warnings at Dowlaiswarm (a place near the river mouth) between 1962 and 1990 (Nageswara Rao, 2001). The basin also shows a large diversification in land use and land cover (LULC). The upper part of the basin is primarily covered by irrigated agricultural land, whereas the downstream region is covered by forest land (Figure 1b).

There is a large spatial variation in climate conditions across the basin. The annual mean temperature of the basin ranges from 20 to 30 °C and is primarily correlated with elevation (Figure 1c). The Godavari river basin receives most precipitation as rainfall (no snowfall), which occurs predominantly during the monsoon season (June to September), with large spatial variability in the annual mean (Figure 1d). The annual mean precipitation varies from 500 to 1200 mm, where the eastern part of the basin receives a large amount of rainfall, while the western part receives less than 600 mm of precipitation during the monsoon season (Figure 1d). Based on the Aridity Index (AI; the ratio of mean annual precipitation and mean annual potential evapotranspiration), the western part of the Godavari basin falls under the semi-arid region ($0.2 \leq AI < 0.5$) due to less rainfall (Figure S1), while the central and eastern parts of the basin fall under dry semi-humid and wet semi-humid regions, respectively (Figure S1). Detailed information

on basin elevation, land use and land cover (LULC), precipitation, and temperature can be found in Figure 1.

We selected five streamflow stations (Mancherial, Tekra, Pathagudam, Perur, and Polavaram; Figure 1a) for our analysis, which are located at major river reaches of the Godavari River. The Mancherial, Tekra, and Pathagudam stations are on reaches that drain into the reach measured by the Perur station, which in turn drains into the Polavaram station. Based on catchment area, Pathagudam is the smallest sub-basin at around 35,625 km^2, followed by Mancherial (84,375 km^2), Tekra (90,625 km^2), and Perur (226,250 km^2). Polavaram is the largest sub-basin, covering approximately 257,500 km^2.

3. Data and methods

3.1. Observed data

We used daily meteorological forcing for hydrological modelling to simulate streamflow from 1967 to 2019 in the Godavari River basin. Daily precipitation, minimum and maximum temperature, and wind speed datasets were used to develop the daily meteorological forcing. We obtained daily 0.25º gridded observed precipitation data from the India Meteorological Department [IMD, (Pai et al., 2014)]. IMD developed daily gridded precipitation data at 0.25º spatial resolution using the approximately 6995 stations located across the country using the inverse distance weighted interpolation scheme (Pai et al., 2015). Daily maximum and minimum temperature data were also obtained from the IMD at 1º spatial resolution based on 395 stations located across India (Srivastava et al., 2009). To maintain consistency in spatial resolution, maximum and

minimum temperature data were regridded to 0.25º using a lapse-rate relationship and digital elevation model (DEM) described by Maurer et al. (2002). The precipitation and temperature data from the IMD capture spatial and temporal variability well across India and have been widely used in previous studies (Chawla and Mujumdar, 2015; Garg and Mishra, 2019; Mahto and Mishra, 2019; Rajeevan et al., 2012; Shah and Mishra, 2016). The gridded wind data is not available from IMD. Therefore, we collected reanalysis wind speed data from the National Centers for Environmental Prediction- National Center for Atmospheric Research (NCEP-NCAR), which is available at 0.25º spatial resolution. Daily streamflow discharge data for model calibration and validation were obtained from the Central Water Commission (CWC) for the five selected gauging stations (Mancherial, Tekra, Pathagudam, Perur, and Polavaram), for the period 1967-2014. Streamflow data after 2014 have too many gaps and therefore could not be used for our analysis.

3.2. The Variable Infiltration Capacity (VIC) and routing models

The VIC model (Cherkauer et al., 2003; Cherkauer and Lettenmaier, 1999; Liang et al., 1996, 1994) is a physically based, land surface, grid-based hydrologic model that simulates energy and water fluxes at daily and sub-daily timescales for each grid cell (Gao et al., 2010). The hydrological model considers soil and vegetation parameters, including their sub-grid variability, and meteorological forcing (precipitation, maximum and minimum temperature, and wind speed data) to simulate surface runoff, baseflow, evaporation, and soil moisture. The sub-grid variability of soil and vegetation makes the VIC model more realistic than other physically-based models in heterogeneous topographic regions (Gao et al., 2012). Vegetation parameters for the VIC model were

extracted from the Advanced Very High-Resolution Radiometer (AVHRR) global land-cover information, which is available at 1km spatial resolution (Hansen et al., 2000; Sheffield and Wood, 2007). We used the Harmonized World Soil Database [HWSD; (Fischer et al., 2008)] soil data to develop soil parameters for the VIC model. For the given parameters and meteorological data, the VIC model uses the Xinanjiang model (Ren-Jun, 1992) and Richard's equation (Liang et al., 1994) to estimate the runoff and soil moisture, respectively. VIC considers three layers of soil. Out of the three, only the top two soil layers contribute to the estimation of surface runoff, while the bottom layer contributes to baseflow estimation.

Along with the VIC model, the stand-alone routing model from Lohmann et al., (1996) was used to route surface runoff and baseflow simulated by the VIC to desired locations over the basin. The model is based on two parts, routing within a grid cell and channel routing, where the first uses the unit hydrograph method while the second is performed using the linearized Saint-Venant equation. Both parts of the routing model are developed using the simple linear transfer function (Gao et al., 2010). The streamflow routing model assumes that surface runoff and baseflow exit a cell in a single flow direction, determined by the topography. Basin and sub-basin delineation and flow direction were computed from the Shuttle Radar Topography Mission elevation data (Digital Object Identifier (DOI) number: /10.5066/F7PR7TFT) for the routing model.

We used the previously calibrated VIC model of the Godavari River basin from Garg and Mishra (2019). Garg and Mishra (2019) calibrated the VIC model using the six soil parameters: Ds_{max} (maximum velocity of baseflow), Ds (Fraction of Ds_{max} where nonlinear baseflow begins), W_s (fraction of the maximum soil moisture where nonlinear

baseflow occurs), b_{inf} (shape of the variable infiltration capacity curve), and soil depths of the second and third layers; which control surface runoff, baseflow, evaporation (in bare soil), and soil moisture in the VIC model. The infiltration shape parameter (b_{inf}) and soil depths are used in the estimation of surface runoff, infiltration, soil moisture, and bare soil evaporation, while Ds_{max}, Ds, and W_s parameters are mainly used for baseflow estimation. More information on the VIC model, input datasets, and parameters can be obtained from Gao et al., (2010) and the Land Surface Hydrology Research Group at the University of Washington (http://uw-hydro.github.io/).

In this study, the calibrated VIC model (Garg and Mishra, 2019) was re-evaluated for the five stations using the updated observed daily streamflow data (Figures S2-S3, Table S1, S2). We re-evaluated the model performance for the Mancherial, Tekra, Pathagudam, Perur, and Polavaram stations of the Godavari River basins for the 1970-2014 period, where the first 10 years are the calibration period (Garg and Mishra, 2019) and the rest is the validation period (Figure S2, Table S1). The model performance was evaluated using the Nash–Sutcliffe efficiency [NSE; (Nash and Sutcliffe, 1970)], the coefficient of determination (R^2), and bias percentage at low (Bias_Q_5), mean (Bias_mean), and high (Bias_Q_{95}) streamflow values. These metrics (NSE, R^2, and Bias) show that the VIC model performs satisfactorily during the calibration period (Table S1, Figure S2), has acceptable performance during the validation period (Table S2, Figure S2), and maintains an acceptable performance across different flood years (Figure S3).

In the present study, we did not consider the interventions of human activities in the water cycle due to the limited availability of human intervention datasets. However, human activities in the basin do not affect natural river flow in most sub-basins, except in

the semi-arid region of the Mancherial sub-basin. A large number of reservoirs were constructed for water storage in this region, which affected the model performance, mostly after 1994. Therefore, the validation period was limited to 1980-1993 for the Mancherial station (Figure S2, Table S2). Such effects were not observed at the downstream stations of Perur and Polavaram, since the streamflow contribution of the semi-arid Mancherial basin is low relative to the rest of the basins. Overall, our results showed that the VIC-simulated natural streamflow compares well with the observed daily streamflow for all five stations during the calibration and validation periods and across different flood events (Figures S2 and S3, Tables S1 and S2). Therefore, the use of VIC (without human intervention) simulated streamflow is acceptable for our analysis.

3.3. Flood event characterization

To understand the flood generation mechanism, we evaluated two major aspects over the Godavari river basin (Figure 2): (i) temporal properties of flood-causing precipitation and surface runoff, and (ii) flood-dominating catchment area.

These analyses were based on observed precipitation data and VIC-simulated runoff and streamflow data. As the focus here is on floods, we identified independent high-streamflow events using the peak-over-threshold approach. First, we selected daily streamflow exceeding the 95^{th} percentile threshold to identify high-streamflow events. Later, we grouped the events that occurred with less than 10 days of separation (Brunner et al., 2020a, 2020b; Diederen et al., 2019) to identify the independent high-streamflow

event. If two or more high-streamflow events occurred together within each separation (within 10 days), we used the highest discharge value to make the event independent.

3.3.1. Temporal properties of flood-causing precipitation and surface runoff

Based on the duration of precipitation that leads to flood events, the events can be classified into long or short rain flood types (Berghuijs et al., 2016; Merz and Blöschl, 2003). Accordingly, we performed a temporal analysis of precipitation and runoff to identify the flood types. The correlation between the event peak discharge and basin area-averaged accumulated precipitation (before the peak streamflow) for different durations (range of 1-20 days) and lag times (0-7 days, representing the lag between the end of the precipitation window and the day of the peak streamflow) was estimated for all five sub-basins. A similar analysis was conducted by correlating the event peak discharge with the mean surface runoff prior to the peak.

The precipitation in the time windows found most correlated with the peak discharge was further analyzed to identify three flood-generation storylines, following the studies by Keller et al., (2017) and Berghuijs et al., (2016): (i) flood caused by a single high-intensity precipitation day; (ii) flood caused by multiple high-intensity precipitation days; and (iii) floods caused by low-to-medium intensity precipitation days. For this, we counted the number of high-precipitation days (above 99^{th} percentile) within the relevant window prior to the flood event. If the number is one, it is identified as caused by a single high precipitation day. If it is more than one, then the flood event is caused by multiple high-intensity precipitation days. Finally, if both conditions fail and there is no high-precipitation day prior to the flood, then the flood event is caused by multiple low-to-medium intensity precipitation days.

3.3.2. Flood-dominating catchment area

Next, we evaluated the dominated catchment area in flood generation by examining the spatial variability of precipitation and runoff (Figure 2). For that, we used the empirical orthogonal function (EOF) analysis and obtained the leading modes of spatial variability in precipitation and surface runoff (Mishra et al., 2012). EOF analysis identifies the dominant modes of spatio-temporal variability in a dataset by solving an eigenvalue problem derived from the spatio-temporal covariance matrix (Lorenz, 1956; Preisendorfer, 1988; Wilks, 2006; Navarra and Simoncini, 2010; Joliffe, 1986; Hannachi, 2022). Here, we first estimated the dominant spatiotemporal modes of variability in the gridded precipitation (surface runoff) to assess its coupling with peak discharge. To do so, we formed the spatial covariance matrix of N x N (where N is the number of grid points) using the following equation:

$$C = \frac{1}{t-1} P' P'^{T}$$

where P' is precipitation (runoff) anomaly; t is the number of peak events; and T represents the transpose matrix.

Further, the spatial covariance matrix (C) was decomposed as:

$$C e_k = \lambda_k e_k$$

where e_k and λ_k are the k^{th} spatial EOF and its associated eigenvalue, respectively (Lorenz, 1956). The fraction of total variance explained by each mode is $\lambda_k / \Sigma\lambda_j$. We also obtained the Principal Component (PC) time series by projecting the anomaly field onto each EOF:

316 $$a_k(t) = \sum_{i=1}^{N} P'_{i,t}.e_{k,i}$$

317 Finally, the coupling between each PC time series and the peak discharge anomaly was
318 quantified using the Pearson correlation coefficient. In the EOF analysis, we used
319 accumulated precipitation and mean surface runoff at each pixel for the time windows
320 that were most strongly correlated with peak discharge, as identified in step 1 above.

321 Lastly, we examine the role of antecedent soil moisture conditions in the runoff
322 generation mechanism. We categorize all flood events into dry and wet conditions based
323 on the soil moisture simulated for the soil layer (top 60 cm) before the time window
324 found most correlated with peak discharge. The 75th percentile threshold is computed
325 considering all occurrences of the same calendar day across the study period (1967–
326 2019). If soil moisture exceeds this threshold, the flood event is identified as a wet
327 condition; otherwise, it is identified as a dry condition. Thereafter, we analyzed the mean
328 runoff coefficient (surface runoff divided by precipitation) under wet and dry conditions
329 over the time window found in step 1.

330

331 **4. Results**

332 **4.1. High-intensity precipitation and Discharge Flood events**

333 Using the daily precipitation and simulated discharge data, we estimated the high-
334 intensity precipitation and streamflow values (precipitation and discharge values above
335 95th percentile; P_{95} and Q_{95}) for each month at the Mancherial, Tekra, Pathagudam, Perur,
336 and Polavaram stations, considering the 95th percentile threshold value of the period

1967-2019 (Figure S4). The majority of high-intensity precipitation (P_{95}) and streamflow (Q_{95}) occurred during the monsoon months (June-September; Figure S3a-e). The ratio of high-intensity streamflow to precipitation varies over time. The early months of monsoon (i.e., June and July) have a low ratio of Q_{95} and P_{95} compared to late monsoon months (i.e., August and September). Due to initially dry soil moisture conditions, most of the high-intensity precipitation that occurred in June and July did not produce high streamflow in the Godavari River. However, most high-intensity precipitation events lead to high streamflow in August and September due to wet soil moisture conditions during the late monsoon season (Figure S4). Moreover, we observed higher Q_{95} and P_{95} ratios in October in the Mancherial sub-basin, which is associated with wet conditions and the onset of the Northeast monsoon in the sub-basin (Mishra et al., 2021; Rajeevan et al., 2012a). Our preliminary analysis indicates a significant role of high-intensity precipitation and antecedent soil moisture conditions in the occurrence of high-intensity streamflow over the Godavari basin, consistent with the previous study by Garg and Mishra (2019).

To further understand the role of high-intensity precipitation and runoff in basin floods, we first identified flood events (independent high streamflow events, as described in the method section) for each sub-basin during the period 1967-2019 (Figure 3a). We found a total of 116, 107, 88, 105, and 104 independent high-streamflow events at the Mancherial, Tekra, Pathagudam, Perur, and Polavaram stations, respectively, during the period 1967-2019 (Figure 3a). Using the identified flood events, we analyzed the temporal and spatial variability of precipitation and runoff in further analysis to

understand the attribution of hydrometeorological variables and catchment area to flood generation.

4.2. Temporal properties of flood-causing precipitation and surface runoff

Next, we analyzed the temporal properties of precipitation before the peak streamflow of flood events. We found (Table 1, Tables S3-S7) that the highest correlation between basin-averaged accumulated precipitation and peak streamflow is for lags of 1-2 days and durations that vary between stations. Floods in the semi-arid Mancherial sub-basins were linked to short-duration (2 days) precipitation events (Table S3), while floods in other sub-basins (Tekra, Pathagudam, Perur, and Polavaram; Tables S4-S7) were well correlated with long-duration (10-11 days) precipitation. Similarly, we analyzed the temporal dynamics of surface runoff before the occurrence of peak streamflow (Table 2, Tables S8-S12). As expected, the Mancherial sub-basin showed the highest correlation with short-duration (2 days) mean runoff, whereas for the other sub-basins, the highest correlation was with long-duration (7-8 days) mean runoff (Table 2). The temporal properties of surface runoff are similar to those of precipitation but with a shorter time window, due to some precipitation being stored in soil. Overall, we found that the floods in large parts of the Godavari basin are associated with long-duration precipitation and surface runoff, except in the semi-arid Mancherial sub-basin, where floods are characterized by short-duration precipitation and surface runoff (Tables 1-2).

The precipitation over the time window presented above was further analyzed for the three different conditions (see Section 3.3.1). We found that for four out of five sub-basins (Tekra, Pathagudam, Perur, and Polavaram), the majority of flood events (around 40-50%) occurred due to multiple high-intensity precipitation (more than 99^{th} percentile)

382 days (Figure 3b). However, most of the floods in the semi-arid Mancherial sub-basin
383 resulted from single high-intensity precipitation events (Figure 3b). This is not surprising,
384 given the shorter precipitation duration found for Mancherial compared to the other sub-
385 basins. We also found that around 30-40% flood events in Mancherial, Perur, and
386 Polavaram sub-basins are associated with long-term low-intensity precipitation (Figure
387 3b). Overall, our results showed that the majority of flood events in the semi-humid
388 Tekra, Pathagudam, Perur, and Polavaram sub-basins occurred due to the higher
389 attribution of multiple high-intensity precipitation days. However, the majority of flood
390 events in the semi-arid Mancherial sub-basin occurred due to higher attribution of single-
391 day high-intensity precipitation (Figure 3, Table 1, 2).

392 **4.3. Flood-dominating catchment area**

393 Next, we identify the catchment area, which dominantly contributes to the flood
394 generation mechanism. The flood-dominating catchment area is identified based on the
395 spatial variability of hydrometeorological variables (precipitation and surface runoff
396 patterns) and catchment conditions before the peak streamflow. Using the EOF analysis,
397 we estimated the leading spatial patterns of variability in the accumulated precipitation
398 and mean surface runoff before the peak streamflow, where accumulation of precipitation
399 and mean runoff was based on the time-windows estimated in the previous analysis (i.e.,
400 2, 10, and 11 days for precipitation and 2, 7, and 8 days for runoff, Tables 1, 2).

401 Based on the EOF analysis, we captured the dominant pattern of accumulated
402 precipitation during the flood events. We found that floods in the Mancherial and Tekra
403 sub-basins are associated with precipitation occurring over the downstream areas of these
404 sub-basins, which are located in the central part of the Godavari basin (Figure 4a-c).

However, the leading spatial pattern (Mode-1) of accumulated precipitation covers the entire region of Pathagudam (Figure 4a-c). The Perur sub-basin also showed a similar spatial pattern in the EOF analysis for 10 and 11 days of accumulated precipitation and indicated high weightage over the central and downstream parts of the sub-basin during flood generation (Figure 4e-h). For the Polavaram sub-basin, we found a high dominance of the central and downstream part of the Godavari basin in the flooding mechanism (Figure 4i-k). Moreover, the correlation between peak streamflow and the leading mode (mode-1) of 10 or 11 days of accumulated precipitation is higher at Tekra, Pathagudam, Perur, and Polavaram sub-basins than the leading mode of 2 days of accumulated precipitation in the same basins (Figure 4d) due to long-rain type floods (Table 1). Furthermore, EOF analysis of mean surface runoff (Figure 5) showed a similar leading spatial pattern, although the area is slightly smaller than that of precipitation (Figure 4). In addition to EOF analysis, we computed pixel-based correlations between accumulated precipitation and peak streamflow (Figure S5), and between mean runoff and peak streamflow (Figure S5), for each sub-basin over the relevant duration. Our results showed spatial correlation patterns similar to those obtained from the EOF analysis. In addition, our analysis (Figure S5 and Figure S6) confirms the previous finding (Figure 4 and Figure 5) where higher correlations of peak streamflow in the Tekra, Pathagudam, Perur, and Polavaram sub-basins are with long-duration precipitation and runoff, compared to short-duration, while for the Mancherial station, the opposite behavior was found.

We further estimated the pixel-based runoff coefficient (ratio of surface runoff to precipitation) before peak streamflow for 2, 7, and 8 days durations under both dry and wet soil moisture conditions (Figure 6). We found that the Tekra basin showed the

highest runoff coefficient values compared to other parts of the basin for all durations and under both wet and dry conditions (Figure 6), indicating the dominance of the Tekra sub-basin in Godavari River flooding. We also found that the variation in runoff coefficient across durations is lower under dry conditions than under wet conditions (Figure 6). For instance, under wet conditions, the runoff coefficient values are higher for the 2 days duration and decrease slightly for the 7 and 8 days durations. The decrease in runoff coefficient for 7 and 8 days durations is due to the lower intensity of rainfall in a long-time span compared to 2 days duration rainfall. However, we found that runoff coefficient values are quite similar across all durations under dry conditions. Overall, our results highlight the flood-dominated area of the Godavari basin based on the hydrometeorology and catchment properties. Our analysis reveals that the central region of the Godavari basin and the Tekra sub-basin contribute significantly to flood generation, compared to other parts of the basin. Furthermore, these results can be used for flood management in the basin.

5. Discussion and Conclusions

Floods pose severe challenges to the infrastructure, ecology, and socio-economic development of the largely populated Indian Subcontinent. Moreover, the risk of floods has increased significantly under global warming (Ali et al., 2019; Arnell and Gosling, 2016; Dottori et al., 2018; Hirabayashi et al., 2013; Milly et al., 2002). Thus, efforts are required to better understand flood-generation mechanisms in the large river basins of the Indian Subcontinent during the monsoonal climate to support effective flood management. In this study, we examined the temporal and spatial variability of

hydrometeorological variables to identify the dominant flood-generating mechanisms and flood-contributing areas using the observed and VIC-simulated hydrological variables.

In our analysis, we considered two hydrometeorological variables, precipitation and surface runoff, across the basin to evaluate the flood-generation mechanism, in which high-intensity precipitation is the primary driver of flood occurrence. However, previous studies (Garg and Mishra, 2019; Sharma et al., 2018; Sharma and Mujumdar, 2024) showed that high-intensity precipitation and floods are not always linked due to initial hydrological conditions over the catchment. There is only 50 to 70% of high-intensity precipitation, which causes flooding in a basin (Garg and Mishra, 2019; Wasko and Sharma, 2017). Moreover, Sharma and Mujumdar (2024) showed that baseflow has a substantially stronger influence on flood magnitudes than soil moisture. Our results show that the attribution of high-intensity precipitation to flood generation varies with time. For instance, the majority of high-intensity precipitation events during the late monsoon season (August-September) cause flooding in the Godavari basin (Figure S3) due to wetter soil moisture conditions. Therefore, we used a bottom-up approach in our study to examine the temporal and spatial variability of hydrometeorological variables, i.e., we first identified the flood events, and then precipitation and surface runoff variables before the flood events were evaluated to understand their role in the flooding mechanism.

We evaluated the temporal properties of hydrometeorological variables (precipitation and surface runoff) to identify the flood types and processes (Keller et al., 2018; Merz and Blöschl, 2003) that predominantly occur over the Godavari basin in the monsoonal climate. We found that the majority of floods in the Godavari basin (except Mancherial Basin) are long-rain type floods (Keller et al., 2018; Merz and Blöschl,

2003), which are associated with the 10 to 11 (7 to 8) days long precipitation (mean surface runoff) with multiple high-intensity precipitation events. However, the majority of floods in the semi-arid Mancherial sub-basin are short-rain type. The majority area of the Godavari basin, associated with long-duration precipitation (surface runoff), falls in the semi-humid climate. The rivers in the humid climate can carry a large volume of water (or have a large storage capacity); therefore, a significant amount of rainfall is required for the flood occurrence (Merz and Blöschl, 2003). Previous studies (Hirschboeck et al., 2000; Merz and Blöschl, 2003; Nanditha and Mishra, 2022) have found that persistent rainfall in the region is the primary factor in generating long-rain type floods. Consistent with our results, Nandith and Mishra, (2024) showed that Multiday precipitation is the predominant driver of floods over the Indian Subcontinent. Similar to long-rain type floods (associated with humid climate), we observed that the short-rain type floods in the semi-arid Mancherial region are associated with the small storage capacity of the river in the region, which can be easily achieved with shorter rainfall. Therefore, to minimize the risk of flooding in the region, we require a forecasting system that can predict rainfall for 10 to 11 days duration in the semi-humid climate region. Moreover, we need to understand the occurrence of multiple concurrent extreme precipitation events in the future changing climate.

While the temporal properties of hydrometeorological variables have been widely evaluated to identify flood processes (Keller et al., 2018; Merz and Blöschl, 2003; Nanditha and Mishra, 2022), the spatial patterns of hydrometeorological variables and catchment conditions prior to peak streamflow are often overlooked. This study also evaluated the spatial variability of precipitation and surface runoff prior to peak

streamflow to delineate the dominant flood-generating areas using EOF and correlation analyses. We showed that accumulated precipitation (long- or short-duration) and mean surface runoff before peak streamflow predominantly occur over the central and downstream areas of the Godavari basin, which contribute to flood generation.

Apart from spatial patterns of precipitation and surface runoff prior to the flood, catchment properties also play an essential role in flood generation. We found that the majority area of the Tekra sub-basin generates more runoff compared to the other sub-basins. The high runoff ratio in the Tekra sub-basin can be associated with various catchment characteristics (such as high slope, conversion of forest to cropland (agricultural land cover), clay-dominant soils, etc.) in this semi-humid region, which results in a large fraction of precipitation contributing to the surface runoff and causing flooding in the downstream areas. Previous studies (Boardman et al., 2003; Holman et al., 2003; Lane, 2017; Marc and Robinson, 2007) showed that the high irrigation area, deforestation, and high slope accelerate the runoff generation mechanism, which causes high runoff in the basin.

With a limited understanding of flood processes in the Indian Subcontinent under monsoonal conditions, this study initiates a new discussion to better comprehend the mechanisms of flood generation in India, aiming to improve flood management. Using the same approach, we can identify the temporal and spatial variability of hydrometeorological variables in other Indian River basins, which can be used for numerous flood-control applications. Overall, our findings provide a better insight into the flood generation mechanism over a large river basin of the Indian Subcontinent during the monsoonal climate. Based on our study, we conclude the following:

1. The majority of floods in the Godavari river basin occurred during the monsoon season. However, during the late monsoon, the ratio of high flood events to high precipitation events is higher due to wet soil moisture conditions.
2. Four out of five sub-basins (except the Mancherial sub-basin) showed the dominance of long-duration type floods in the period 1967-2019. Long-duration rainfall (10-11 days) causes floods in the semi-humid regions of the Tekra, Pathagudam, Perur, and Polavaram sub-basins. However, Floods in the semi-arid Mancherial sub-basin are associated with short-duration (2 days) precipitation and surface runoff.
3. Floods in the Tekra, Pathagudam, Perur, and Polavaram sub-basins predominantly occur due to multiple high-intensity rainfall days. Therefore, long-duration type floods occurred in these sub-basins. Moreover, our analysis revealed that short-duration floods in the semi-arid Mancherial sub-basin are primarily associated with single-day high-intensity precipitation.
4. Based on the EOF and correlation analyses of precipitation and surface runoff, central and downstream areas of the basin dominate in the flood generation mechanism in the Godavari River, which highlights the importance of these areas in flood management in a future warming climate. Moreover, medium-term (10 to 11 days lead) precipitation forecasts in these regions will be useful for flood and reservoir management forecasting.
5. Our analysis also indicated the importance of the Tekra sub-basin in the high runoff generation in the Godavari basin. Due to favorable catchment characteristics, a large fraction of precipitation contributes to the surface runoff in

the Tekra sub-basin. Therefore, additional efforts (e.g., afforestation and sustainable infrastructure development) are needed in the Tekra sub-basin to improve flood management in the downstream region.

In the changing climate and land use land cover (urbanization and deforestation), the risk of floods is projected to increase over the Indian Subcontinent (Ali et al., 2019; Gosain et al., 2006; Gupta and Nair, 2011; Rogger et al., 2017; Shah et al., 2019). Moreover, the moisture-holding capacity of the atmosphere increases (Karl and Trenberth, 2003; Kharin et al., 2007) due to a warming climate, which leads to frequent, intense, and more extended extreme precipitation events (Ali et al., 2019, 2014; Roxy et al., 2017; Vittal et al., 2013). Therefore, reliable information on precipitation and runoff forecasts in the basin is crucial for effective flood mitigation. Since floods in semi-humid regions of the Godavari basin result from multiple high-intensity rainfall days, there is a need for high-skill medium-range precipitation forecasting (especially over the central and downstream regions of the basin) to mitigate flood risk in a warming climate. Moreover, a real-time soil moisture monitoring system is required in the Tekra basin (which experiences high runoff during the monsoon season) to mitigate flooding. In addition to a real-time monitoring and forecasting system, significant steps are needed to reduce the rapid runoff generation in the Tekra sub-basin using natural flood management methods for flood control in the downstream area of the basin (Lane, 2017). For instance, attenuation of surface runoff can be achieved through afforestation (Marc and Robinson, 2007), changes in arable land-use practices (Boardman et al., 2003), reductions in livestock density (Orr and Carling, 2006), and changes in tillage practices (Holman et al., 2003).

566 The flood-generating mechanisms cannot be fully understood by natural drivers of
567 floods (such as climate) and static catchment attributes alone. The current study does not
568 consider the extensive role of human activities on water resources and the simulation of
569 hydrological components, which can affect the flood-generating mechanisms (flood
570 propagation and attenuation) in the catchment (Boulange et al., 2021; Haddeland et al.,
571 2014). For instance, previous studies (Boulange et al., 2021; Han et al., 2019; Ruan et al.,
572 2024) have shown the roles of human activities and dynamic catchment attributes in
573 flood severity and exposure. Therefore, a similar study can be conducted separately in the
574 future to analyse the role of human activities (intensive agricultural practices, reservoir
575 operations, groundwater depletion, urbanization, etc.) in the occurrence of flood events.
576 Additionally, our study currently considers a limited number of observed streamflow
577 stations (five) on five major tributaries of the Godavari River Basin, which provides only
578 a limited understanding of flood mechanisms at a fine resolution (sub-catchment level)
579 for more robust flood mitigation measures. Based on the availability of long-term
580 streamflow data for other Godavari River streams, we can further improve understanding
581 of flood mechanisms and the dominant catchment-area contribution to flood generation in
582 the future using the framework discussed in our study. In this study, we used the
583 calibrated-VIC model for streamflow and runoff simulations, which also exhibits several
584 structural and parametric limitations when applied to predict extreme streamflow events
585 (Abdulla and Lettenmaier, 1997; Liang et al., 2003; Tsai et al., 2021). The VIC model
586 simulates runoff using a saturated-excess mechanism (Liang et al., 1994), which
587 underestimates excess runoff and infiltration estimations during intense monsoon events
588 (Beven, 2012). By considering multiple hydrological models (including human influence)

for streamflow prediction, we can reduce model limitations and develop a robust understanding of flood-generating mechanisms across India in the future.

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7. Author contributions:

SA and EM designed the study and wrote the manuscript. SA simulated the VIC model and performed the analysis. UG prepared the figures and partially contributed to the analysis.

8. Competing interests:

Authors declare no competing interests.

9. Data Availability:

All the datasets used in this study can be obtained from the corresponding author.

10. Code Availability:

Data processing scripts can be obtained from the corresponding author.

11. References:

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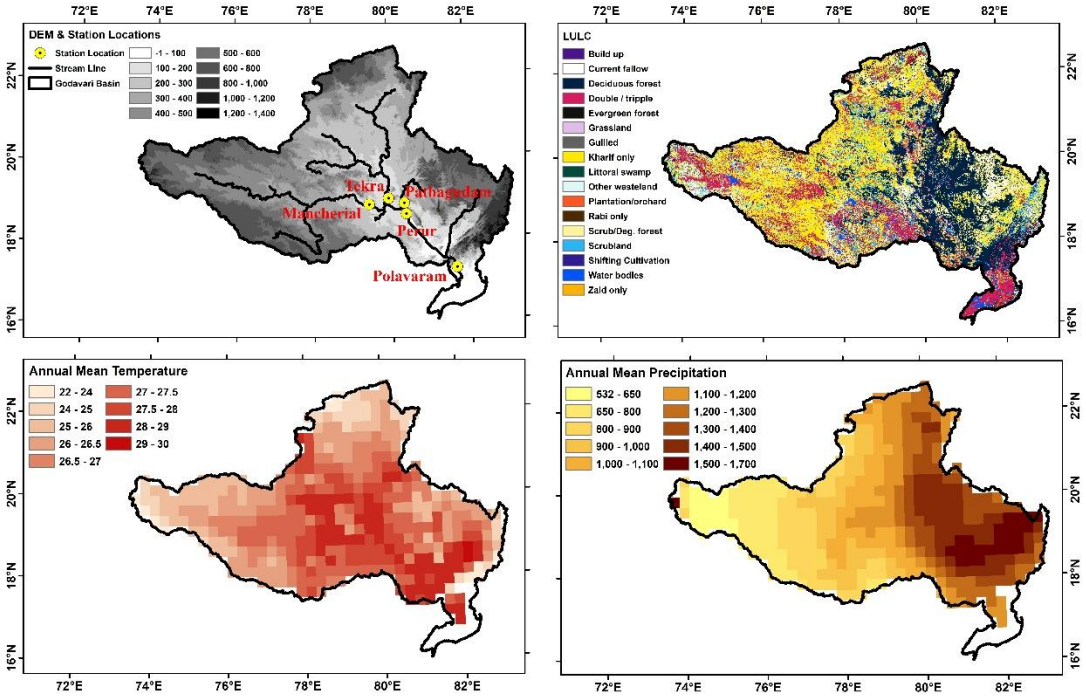
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12. Figures & Tables:



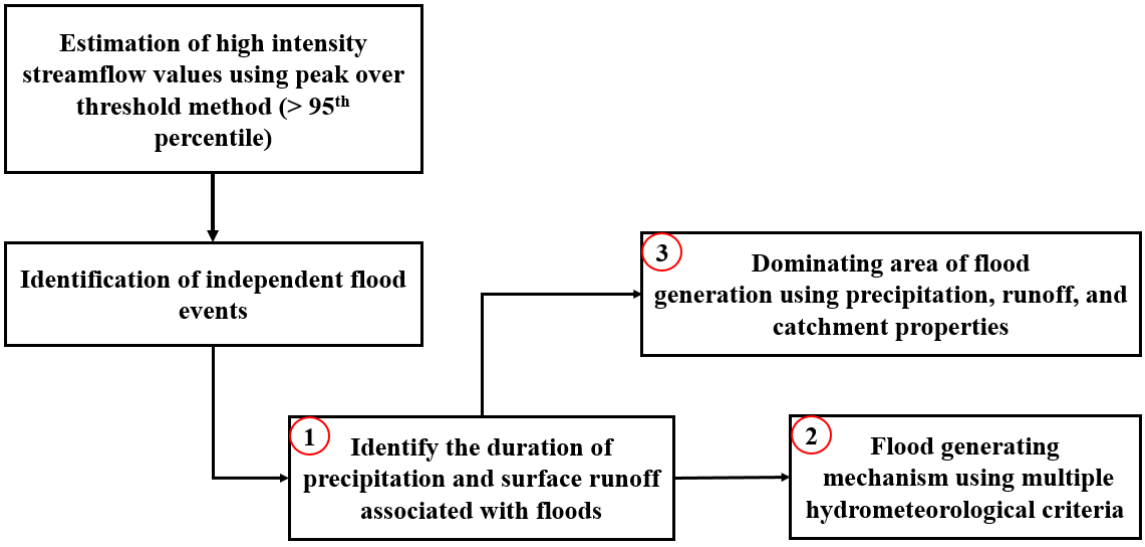
884

885 **Figure 1: Catchment and climate information of the Godavari River.** (a-b)

886 Topographic using the Digital Elevation Map (DEM) and Land use land cover (LULC)

887 information of the Godavari river basin. (c-d) Climate conditions over the basin using the

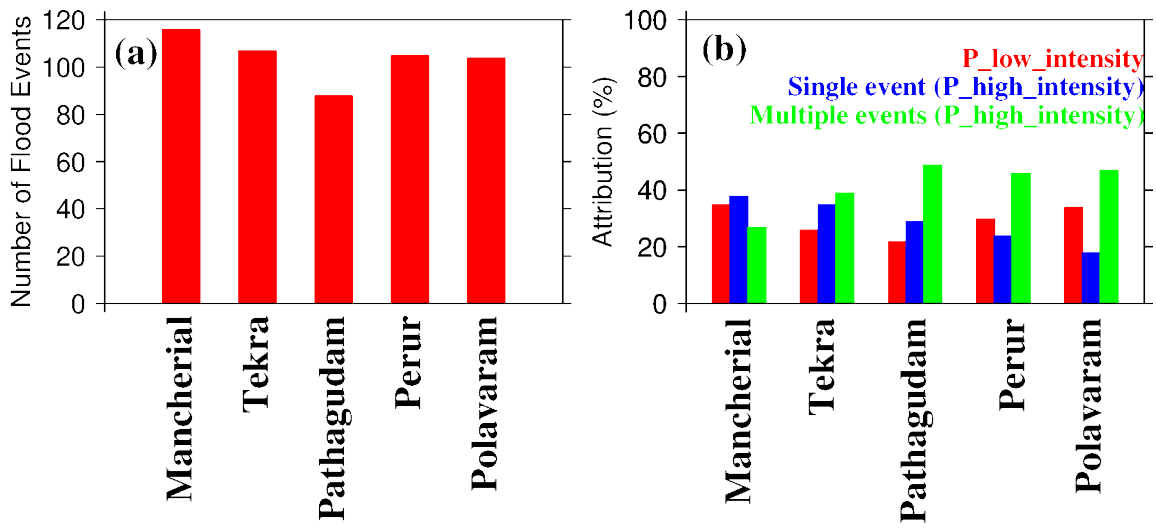
888 annual mean temperature and precipitation during 1967-2019.



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890 **Figure 2. Major steps used in the analysis.**

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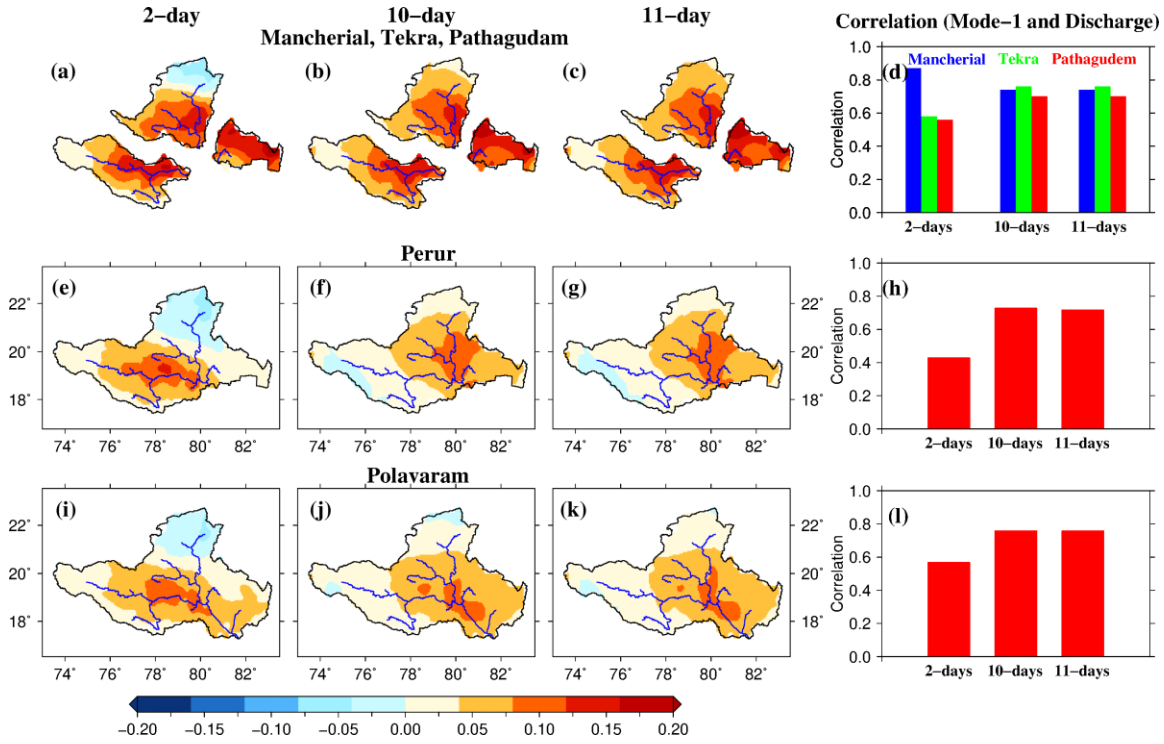
893 **Figure 3. Floods associated with multiple criteria of precipitation over the Godavari**

894 **River Basin.** (a) number of flood events in each sub-basin. (b) Attribution (%) of low-

895 intensity precipitation, single high-intensity precipitation, and multiple days' high-

896 intensity precipitation in flood generation.

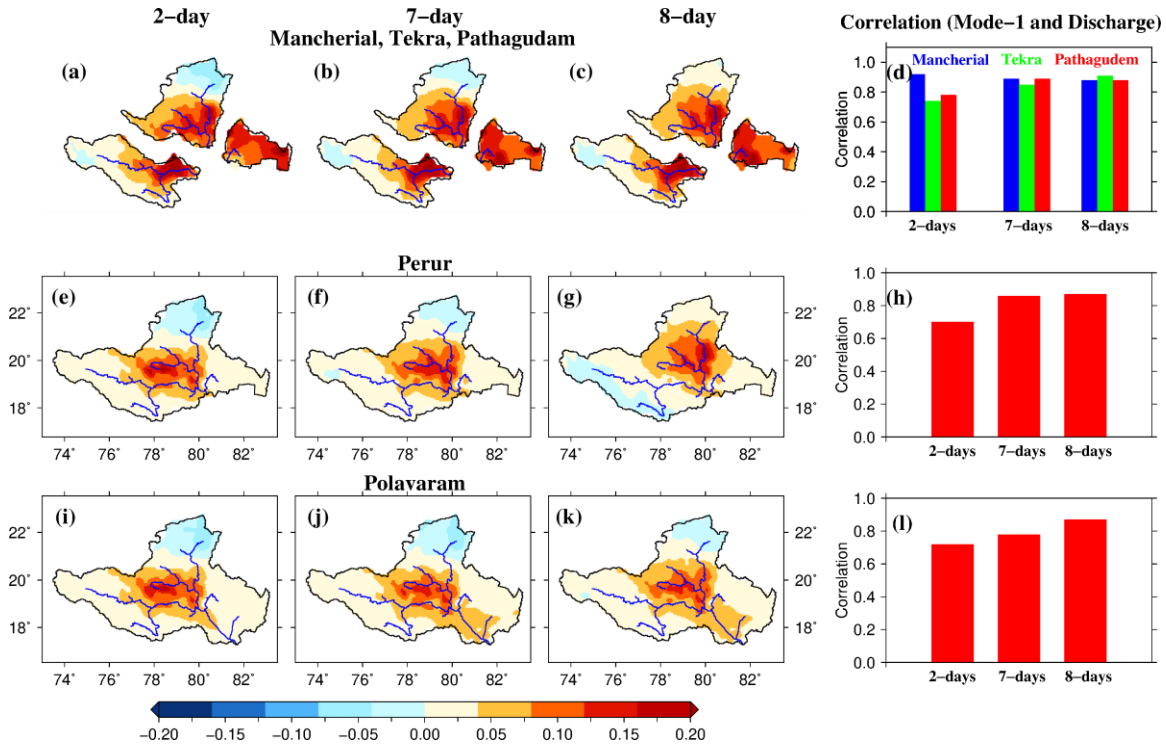
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899 **Figure 4:** The leading mode of variability in the accumulated precipitation during the high
900 streamflow events for the period 1967-2019 using the method of empirical orthogonal function
901 (EOF). (a-c) The first leading EOF mode of (a) 2 days, (b) 10 days, and (c) 11 days accumulated
902 precipitation for Mancherial (left), Tekra (middle), and Pathagudam (right) sub-basins. (d)
903 Correlation between the first leading mode and flood peak at Mancherial (left), Tekra (middle), and
904 Pathagudam (right) stations. (e-h) same as (a-d) but for the Perur sub-basin. (i-l) same as (a-d) but
905 for the Polavaram sub-basin.

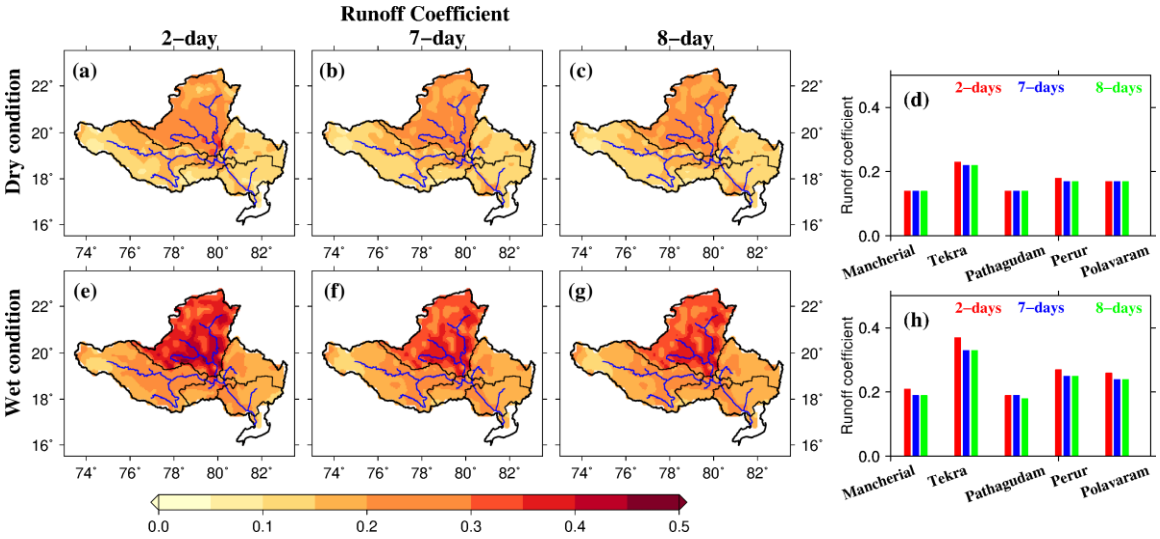
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908 **Figure 5.** The leading mode of variability in the mean runoff (excess precipitation) during the
909 extreme floods for the period 1967-2019 using the method of empirical orthogonal function (EOF).
910 (a-c) The first leading EOF mode of (a) 2 days, (b) 7 days, and (c) 8 days mean runoff for
911 Mancherial (left), Tekra (middle), and Pathagudam (right) sub-basins. (d) Correlation between the
912 first leading principal component (PC-1) and extreme floods at Mancherial (left), Tekra (middle),
913 and Pathagudam (right) stations during 1967-2019 for 2, 7, and 8 days mean runoff. (e-h) same as
914 (a-d) but for the Perur sub-basin. (i-l) same as (a-d) but for the Polavaram sub-basin.

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916

917 **Figure 6.** Runoff coefficient over the Godavari basin during the flood events in the period
918 1967-2019. (a-c) Variability in runoff coefficient values using (a) 2 days, (b) 7 days, and
919 (c) 8 days cumulative precipitation and mean runoff during dry condition flood events. (e-
920 g) Similar to (a-c), but with variability in runoff coefficient values during wet condition
921 flood events.

922

923 **Table 1:** Duration and lag (days) where the basin-averaged accumulated precipitation has
924 the highest correlation with simulated flood peak for high streamflow events at different
925 stations.

Station	**Lag-time**	**Duration**
Mancherial	2	2
Tekra	1	11
Pathagudam	2	10
Perur	2	10

Polavaram	2	11

926

927

928 **Table 2:** Duration and lag (days) where the basin-averaged simulated mean surface
929 runoff has the highest correlation with the simulated flood peak for high streamflow
930 events at different stations

Station	**Lag-time**	**Duration**
Mancherial	2	2
Tekra	1	8
Pathagudam	2	7
Perur	2	7
Polavaram	2	7

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