

# Flood risk assessment for Indian sub-continental river basins

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## Abstract

Floods are among India's most frequently occurring natural disasters, which disrupt all aspects of socio-economic well-being. A large population is affected by floods during almost every summer monsoon season in India, leaving its footprint through human mortality, migration, and damage to agriculture and infrastructure. Despite the massive imprints of floods, sub-basin level flood risk assessment is still in its infancy and requires advancements. Using hydrological and hydrodynamical models, we reconstructed sub-basin level observed floods for the 1901-2020 period. Our modelling framework includes the influence of 51 major reservoirs that affect flow variability and flood inundation. Sub-basins in the Ganga and Brahmaputra River basins witnessed substantial flood inundation extent during the worst flood in the observational record. Major floods in the sub-basins of the Ganga and Brahmaputra occur during the late summer monsoon season (August-September). Beas, Brahmani, upper Satluj, Upper Godavari, Middle and Lower Krishna, and Vashishti sub-basins are among the most influenced by the dams, while Beas, Brahmani, Ravi, and Lower Satluj are among the most impacted by floods and the presence of dams. Bhagirathi, Gandak, Kosi, lower Brahmaputra, and Ghaghara are India's sub-basins with the highest flood risk. Our findings have implications for flood risk assessment and mitigation in India.

## 1. Introduction

Flood risk to both natural and human systems is projected to increase due to climate change (IPCC, 2014, 2022). Extreme weather and climate extremes have increased under warming climate, leading to an increased frequency of natural hazards like floods, droughts, heat waves, cyclones, and heavy rains. Hydroclimatic extremes affect humans and infrastructure (Eidsvig et al., 2017; Peduzzi et al., 2009). Due to high vulnerability and lower adaptive capacity, developing countries are often the most impacted by extreme weather events. Further, developing countries usually take longer to recover from the hazards due to low climate resilience. Globally, floods are among the most devastating natural hazards (Ghosh & Kar, 2018). Among all flood types, riverine floods occur most frequently (Kimuli et al., 2021) and often cause substantial damage to agriculture and infrastructure. A considerable fraction of the population and infrastructure are exposed to flooding, which will also increase due to the projected increase in the magnitude and frequency of floods (Winsemius et al., 2018).

The increase in flood magnitude due to the warming climate has resulted in considerable economic losses (C. M. R. Mateo et al., 2014; Willner et al., 2018). The total financial loss will likely increase by 17% in the next 20 years due to climate change (Willner et al., 2018). Besides agriculture, floods significantly affect the built environment and transportation infrastructure (Kalantari et al., 2014). For instance, more than 7% of road and railway assets

37 globally are exposed to a 100-year return period flood (Koks et al., 2019). In Asia, about 75% of the population  
38 is exposed to riverine floods (Varis et al., 2022). India falls among the top ten most flood-affected countries in  
39 Asia and the Pacific (Kimuli et al., 2021). In addition, India is also among the top-ten countries that experienced  
40 the highest human mortality due to floods. Considerable population exposure, climate change, and rapid growth  
41 and development in flood-prone areas contribute to increased losses from floods.

42 In India, state administration takes decisions to mitigate floods while the central government provides financial  
43 aid under severe conditions (Jain et al., 2017). The state authorities develop action plans to minimize flood  
44 damage. Therefore, identifying the regions with higher flood risk is essential for planning and mitigation. Flood  
45 impacts can be quantified according to the affected population, gross domestic product (GDP), and agricultural  
46 practices (Ward et al., 2013). The flood risk assessment framework suggested by the Intergovernmental Panel on  
47 Climate Change (IPCC) has been extensively applied at the regional and global scales (Allen et al., 2016; IPCC,  
48 2014; Roy et al., 2021). The risk can be quantified as a function of vulnerability, hazard, and exposure (IPCC,  
49 2014). To control the risk, reducing vulnerability is considered a short to the mid-term goal (V. Mishra et al.,  
50 2022), while reducing hazards and exposure are long-term goals (Birkmann & Welle, 2015). Flood risk assessment  
51 can assist in identifying the regions at high risk due to higher vulnerability, hazard, and exposure, which can be  
52 used for developing a framework, methodology, and guidelines for flood mitigation and damage assessment.

53 A flood risk assessment performed on a global scale may not help in identifying the flood risk-prone regions at a  
54 country scale due to the coarser spatial resolution (Bernhofen et al., 2022). Due to complex geomorphological  
55 characteristics and diverse climatic conditions, India is considered a relatively high flood-risk region (Hochrainer-  
56 Stigler et al., 2021). Therefore, estimating flood risk on a finer scale (e.g. sub-basin level) is essential for reliable  
57 flood risk assessment. There have been studies on regional or river basin scales (Allen et al., 2016; Ghosh & Kar,  
58 2018; Roy et al., 2021); however, those do not provide flood risk at a sub-basin scale in India. In addition, the  
59 impact assessment of floods on transport infrastructure (rail and road infrastructure) still needs to be improved in  
60 the country (Pathak et al., 2020; P. Singh et al., 2018). In addition, the role of dams and reservoirs in the flood  
61 risk assessment should be addressed (Hirabayashi et al., 2013; Yamazaki et al., 2018a). Dams and reservoirs  
62 considerably influence streamflow variability and can attenuate flood peaks (Dang et al., 2019; Vu et al., 2022;  
63 Zajac et al., 2017). In contrast, dam operations and decisions can also worsen the flood situation in the downstream  
64 regions. For instance, recent flooding in Kerala and Chennai was partly attributed to reservoir operations (V.  
65 Mishra & Shah, 2018). India has more than 5300 large dams regulating river flow (National Register of Large  
66 Dams (NRLD), 2019), affecting ecosystems, natural resources, and livelihoods (Acreman, 2000). Reservoirs  
67 impact flow regulation, magnitude, timing, and extent of flooding in the downstream regions. Therefore, flood  
68 risk assessment without considering the role of reservoirs can be inappropriate in the basins that are highly affected  
69 by the presence of dams.

70 We use the H08 (Hanasaki et al., 2018) global hydrological model combined with the CaMa-Flood (Yamazaki et  
71 al., 2011) model for the sub-basin level flood risk assessment in India considering the role of reservoirs. The  
72 CaMa-Flood model combined with the H08 model has been used for several river basins globally (Boulange et  
73 al., 2021; C. M. R. Mateo et al., 2013). The CaMa-Flood model performs well in simulating flood dynamics  
74 (Chaudhari and Pokhrel, 2022; H. Dang et al., 2022; Gaur & Gaur, 2018; Hirabayashi et al., 2013, 2021; Yamazaki  
75 et al., 2018; Yang et al., 2019). The CaMa-Flood model takes runoff as input simulated from any hydrological

76 model and can simulate flood depth and inundation. In India, almost all the major rivers are influenced by  
77 reservoirs (Lehner et al., 2011). Therefore, the major scientific questions that we address are: 1) How does the  
78 flood risk vary at the sub-basin level in India during the 1901-2020 period? 2) Which are the sub-basins where  
79 the presence of reservoirs considerably influences the flood risk? To address these questions, we use long-term  
80 observations (1901-2020) from India Meteorological Department (IMD) along with a hydrological modelling  
81 framework.

## 82 **2. Data and Methods**

### 83 **2.1 Datasets**

84 We used observed gridded precipitation (Pai et al., 2014) and daily maximum and minimum temperatures  
85 (Srivastava et al., 2009) from India Meteorological Department (IMD). We obtained gridded daily precipitation  
86 at 0.25° from IMD for the 1901-2020 period that was developed using station-based rainfall observations from  
87 more than 6900 gauge stations (Pai et al., 2014). The gridded rainfall product has been widely used for  
88 hydrological studies (Kushwaha et al., 2021; Shah & Mishra, 2016) and it captures the key features of the summer  
89 monsoon variability and orographic rainfall over the western Ghats and foothills of the Himalayas. We obtained  
90 daily 1° gridded maximum and minimum temperatures from IMD (Srivastava et al., 2009). The gridded  
91 temperature dataset is developed using observations from 395 stations located across India. Bilinear interpolation  
92 was used to convert the 1° gridded temperature to 0.25° resolution to make it consistent with the gridded  
93 precipitation. For the regions outside India, we obtained observational meteorological datasets (rainfall and  
94 temperature) at 0.25 degrees from Princeton University (Sheffield et al., 2006). Gridded datasets from Sheffield  
95 et al. (2006) compare well against the IMD observations and have been used in hydrological applications in India  
96 (Shah & Mishra, 2016).

97 Observed daily streamflow at gauge stations and reservoir live storage were obtained from India Water Resources  
98 Information System (India-WRIS). We considered the influence of 51 major reservoirs located in different river  
99 basins to examine the impact of reservoirs on floods using the CaMa-Flood model (Figure S1). The information  
100 of dams was obtained from the National Register of Large Dams (NRLD) [Table S1]. We used the Global Surface  
101 Water (GSW) extent to estimate flood occurrences at a monthly timescale (Pekel et al., 2016). Simulated flood  
102 occurrences during the period of the GSW database (1985-2020) were used to validate the performance of the  
103 hydrological model in simulating flood extent (Pekel et al., 2016). In addition, we obtained reported flood details  
104 from the Emergency Events Database (EM-DAT, <http://www.emdat.be/>) and Dartmouth Flood Observatory  
105 (DFO, <http://floodobservatory.colorado.edu/>). EM-DAT is developed by the Centre for Research on the  
106 Epidemiology of Disasters (CRED), while the University of Colorado manages DFO. We used population data  
107 from Global Human Settlement Layers (GHLS) to estimate flood exposure. Finally, we used roadway and railway  
108 network data to assess the impact of floods on the infrastructure.

### 109 **2.2 H08-CaMa-Flood combined model**

110 We used the H08 (Hanasaki et al., 2018) global hydrological model to simulate hydrological variables. The H08  
111 is a distributed global water resources model comprising six sub-models: land surface hydrology, river routing,  
112 reservoir operation, crop growth, environmental flow, and water abstraction. The model estimates baseflow using  
113 a leaky bucket method, while runoff is calculated based on saturation excess non-linear flow (Hanasaki et al.,

114 2008). The H08 model can be run separately or combined with any hydrodynamic model to perform flow routing.  
115 The H08 model uses precipitation, air temperature, short and longwave radiations, wind speed, surface pressure,  
116 and specific humidity as input meteorological forcing. Soil parameters for the H08 model were obtained from  
117 Harmonized World Soil Database (HWSD). We forced the H08 model with the input meteorological forcing at  
118 0.25° spatial and daily temporal resolution. We combined the H08 land surface model with the CaMa-Flood  
119 model. The CaMa-Flood model has been previously combined with the H08 model to obtain flood inundation  
120 estimates (C. M. Mateo et al., 2014).

121 The CaMa-Flood (version 4.1) is a hydrodynamic model (Yamazaki et al., 2011), which simulates river-floodplain  
122 dynamics (Yamazaki et al., 2013). The CaMa-Flood model has been extensively used for better performance in  
123 simulating discharge and flood peaks (Zhao et al., 2017). The CaMa-Flood model considers the role of dams and  
124 reservoirs for streamflow and flood inundation simulations (Chaudhari & Pokhrel, 2022; C. M. Mateo et al., 2014;  
125 Pokhrel et al., 2018). We ran the CaMa-Flood model at a finer spatial resolution (0.1°) using the H08-simulated  
126 runoff (0.25°) as input. We calibrated the combined model (H08 and CaMa-Flood) for India's eighteen major river  
127 basins for at least one gauge station each, considering the influence of 51 major dams. The gauge stations were  
128 selected in the farthest downstream of the river basin based on the availability of observed streamflow. The  
129 influence of reservoir operations was simulated using the CaMa-Flood model and evaluated against the observed  
130 daily live reservoir storage.

131 Large-scale global hydrological models do not perfectly capture the observed trends and variations as these are  
132 often not well calibrated at river basin scale (Krysanova et al., 2018). The H08 model performs well when  
133 calibrated at the river basin scale rather than coarser domains such as climate zones (Chuphal & Mishra, 2023;  
134 Yoshida et al., 2022). Here, we manually calibrated the H08 model by adjusting four key parameters that  
135 considerably influence streamflow for each river basin, which include single-layer soil depth, gamma, bulk  
136 transfer coefficient, and tau (Hanasaki et al., 2008; Raghav & Eldho, 2023). A more detailed discussion about the  
137 calibration parameters of H08 are discussed in Dangar & Mishra (2021). Different sets of combinations of  
138 calibration parameters within a range were used to calibrate the H08 model. The employed sets of parameters for  
139 the 18 river basins in the Indian sub-continent are listed in Table S2. The calibrated parameters account for the  
140 effect of human interventions because the model calibration is performed against the observed streamflow rather  
141 than the naturalized streamflow (Duc Dang et al., 2020). We evaluated the model performance using the  
142 coefficient of determination ( $R^2$ ) and Nash-Sutcliffe Efficiency (NSE) for daily streamflow and reservoir live  
143 storage. In addition, we compared the simulated and satellite-based observed flood occurrences. The satellite-  
144 based flood occurrence is calculated using the Global Surface Water (GSW) dataset (Pekel et al., 2016), available  
145 for the 1984-2020 period. We forced the well-calibrated combined (H08 and CaMa-Flood) models with observed  
146 meteorological forcing from India Meteorological Department (IMD) at 0.25° spatial resolution to conduct  
147 simulations from 1901 to 2020. The H08 model simulated runoff is used in CaMa-Flood to rout flood dynamics  
148 at six arc-minutes (0.1 degrees). We generated the flood depth maps for the historical worst flood at the sub-basin  
149 level. The worst flood is based on the highest magnitude of river flow observed at the subbasin outlet. The  
150 generated flood depths at 6 arc-minutes (0.1°) were further downscaled to 1 arc-minute (~0.185 km) resolution  
151 using the downscaling module available within the CaMa-Flood.

152 We used C-ratio (Nilsson et al., 2005; Zajac et al., 2017) to assess the potential impact of dams along a river. The  
153 C-ratio is an identifier calculated as the ratio of total maximum storage capacity of the upstream reservoirs to the  
154 mean annual discharge at a gauge station in the downstream region (Nilsson et al., 2005; Zajac et al., 2017). We  
155 calculated the C-ratio at the outlets of each sub-basins that are influenced by the presence of dams. A C-ratio of  
156 less than 0.5 indicates that the sub-basin is minimally affected by the presence of dams. Further, to identify sub-  
157 basins susceptible to flood inundation resulting from dam operations, we multiplied the percentage of flooded  
158 area in each sub-basin by its corresponding C-ratio. This enabled us to identify the sub-basins that experience  
159 substantial flood inundation and are considerably impacted by the presence of reservoirs. Finally, we estimated  
160 the exposed rail and road infrastructure affected by floods. The flooded area overlapped over the road and railway  
161 network to estimate the network length affected by floods in a sub-basin. We considered the flooded area of the  
162 observed worst flood. The subbasins with the highest rail and road infrastructure exposure to floods were  
163 identified.

### 164 **2.3 Risk assessment**

165 We estimated flood risk using hazard, exposure, and vulnerability based on the common framework adopted by  
166 the United Nations in the Global Assessment Reports of the United Nations Office for Disaster Risk Reduction  
167 (UNISDR, 2011, 2013). A similar framework was used in previous studies for flood risk assessments (C. M. R.  
168 Mateo et al., 2014; Tanoue, 2020; Winsemius et al., 2013). We multiplied the normalized values of hazard,  
169 exposure, and vulnerability to estimate the risk as:

$$170 \quad \text{Risk} = \text{Vulnerability} * \text{Exposure} * \text{Hazard} \quad \dots \dots (1)$$

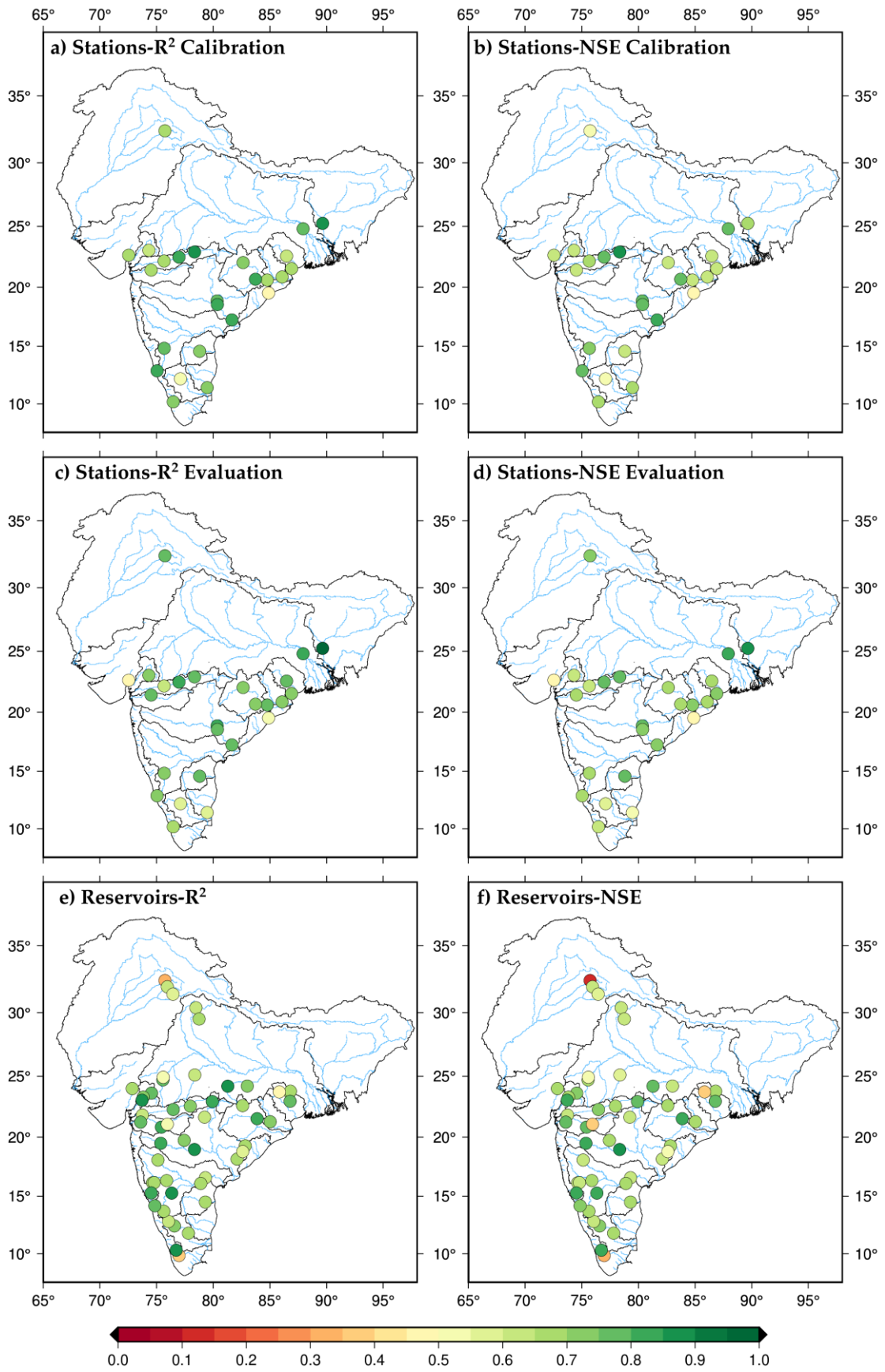
171 The flood risk assessment can help identify the hotspots and prioritize climate adaptation (de Moel et al., 2015).  
172 Among the three components, vulnerability is a degree of damage to a particular object at flood risk with a  
173 specified amount and present on a scale from 0 to 1. We obtained the vulnerability index for each district from  
174 the “Climate Vulnerability Assessment for Adaptation Planning in India Using a Common Framework”, a report  
175 developed by the Department of Science and Technology  
176 (<https://dst.gov.in/sites/default/files/Full%20Report%20%281%29.pdf>). The vulnerability of each district is  
177 calculated using 14 indicators, each with equal weights. The indicators capture both sensitivity and adaptive  
178 capacity. We estimated the vulnerability index of each sub-basin by taking the spatial mean of the vulnerability  
179 of the districts falling into the sub-basins. Exposure is termed as assets and population in a flood-exposed area  
180 resulting in flood damage (Marchand et al., 2022). The population dataset is a critical component in performing  
181 exposure estimation. The exposure is defined as the fraction of the population exposed to the flood extent (Smith  
182 et al., 2019). We completed the flood exposure estimate using the Global Human Settlement Layers (GHSL)  
183 population dataset (Joint Research Centre (JRC) et al., 2021), which is available at a resolution of 30 arc-seconds  
184 for 1975, 1990, 2000, 2014 and 2015. We used the population data for the year 2015 throughout this study. We  
185 rescaled the population data to 6 arc-minutes to make it consistent with the flooded area simulated from the  
186 combined model. We estimated the hazard as the exceedance probability of a flooded area exceeding half of the  
187 historical maximum flooded area in the last 50 years. We used normalized vulnerability, exposure, and hazard to  
188 estimate the risk.

### 189 **3. Results**

### 190 3.1 Calibration and evaluation of hydrological models

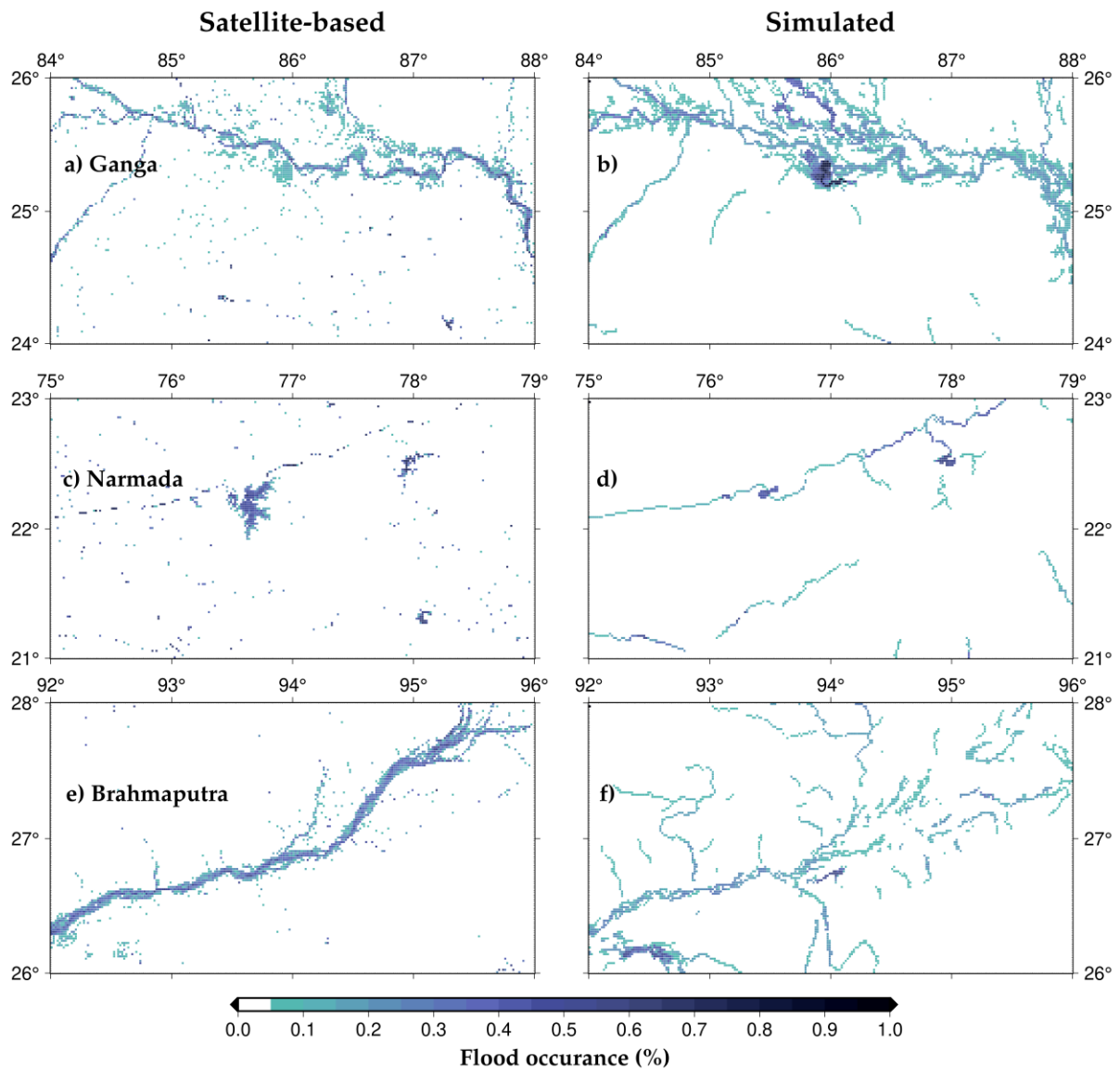
191 We calibrated and evaluated the performance of the H08 and CaMa-Flood combined models against the observed  
192 daily streamflow (Figure 1). Due to the unavailability of daily observed streamflow for the three transboundary  
193 river basins (Indus, Ganga and Brahmaputra), we used observed monthly streamflow to calibrate the model. In  
194 addition, we evaluated the model performance for daily live storage of the 51 reservoirs after the calibration  
195 against the observed flow (Figure 1). The model exhibited good skills ( $R^2 > 0.6$  and  $NSE > 0.6$ ) for almost all the  
196 river basins except Cauvery, East Coast, Northeast Coast, and Sabarmati. The model also performed well with  
197 NSE greater than 0.6 for more than 80% of the selected reservoirs in simulating daily live storage for the selected  
198 reservoirs. We estimated the bias and timing error in simulating peak discharge at all the selected gauge stations  
199 (Figure S2). We calculated the bias in the model simulated annual maximum streamflow against the observed  
200 annual maximum streamflow for the time periods for which observations are available. We excluded the  
201 transboundary rivers (Ganga, Brahmaputra and Indus) as timing error (in days) could not be estimated due to the  
202 unavailability of daily observed flow. While other gauge stations exhibited moderate bias, gauge stations in  
203 Cauvery, Sabarmati, and Mahi rivers basins show a considerable dry bias. Contrary to several other stations where  
204 the mean timing error was below two days, the Sabarmati river basin displayed a comparatively higher mean  
205 timing error. The relatively poor performance of the model in these river basins can be attributed to the lack of  
206 long-term observations as well as substantial human interventions that can affect the observed flow.

207 We compared model-simulated, and satellite-based observed flood occurrence for the 1984-2020 period (Figure  
208 2). In addition, we compared the model-simulated flood events against Sentinel-1 SAR and MODIS satellite-  
209 based imagery for a few flood events based on the satellite data availability (Figures. 3, S3, S4). We found that  
210 the model simulated flood extent captures the satellite based flood extent. However, we note that the model  
211 overestimated the flood extent in Ganga river basin and underestimated in Brahmaputra river basin, therefore,  
212 showing a non-systematic bias. Moreover, a considerable difference in the flood extent based on the two satellite  
213 datasets was observed, which highlights the observational uncertainty in the estimation of flood extent. In general,  
214 the model exhibits satisfactory performance in simulating flood extent against the satellite-based observations.  
215 However, the model overestimates flood extent in the Ganga basin, which could be attributed to the influence of  
216 cloud contamination and dense vegetation cover on satellite-based flood estimates (Chaudhari & Pokhrel, 2022).  
217 On the other hand, the model underestimates the flood occurrence in the upstream region of the Brahmaputra  
218 River. This could be due to limitations in model parameterization, as observed flow is limited in the transboundary  
219 river basins. Despite the good performance against the observed streamflow, the simulated flood extent has a  
220 considerable bias, which can be attributed to satellite-based flood extent mapping limitations and the model's  
221 ability to capture the flood extent accurately. The model-simulated flood extent shows a good agreement against  
222 the reported flood from EM-DAT and DFO databases (Figure S5). In addition, the simulated flood extent also  
223 showed a good agreement with the reported flood in cities in the Brahmaputra and Ganga River basins. Given the  
224 limitation in the streamflow and flood extent observations, the hydrological models perform satisfactorily and can  
225 be used for the sub-basin level risk assessment.



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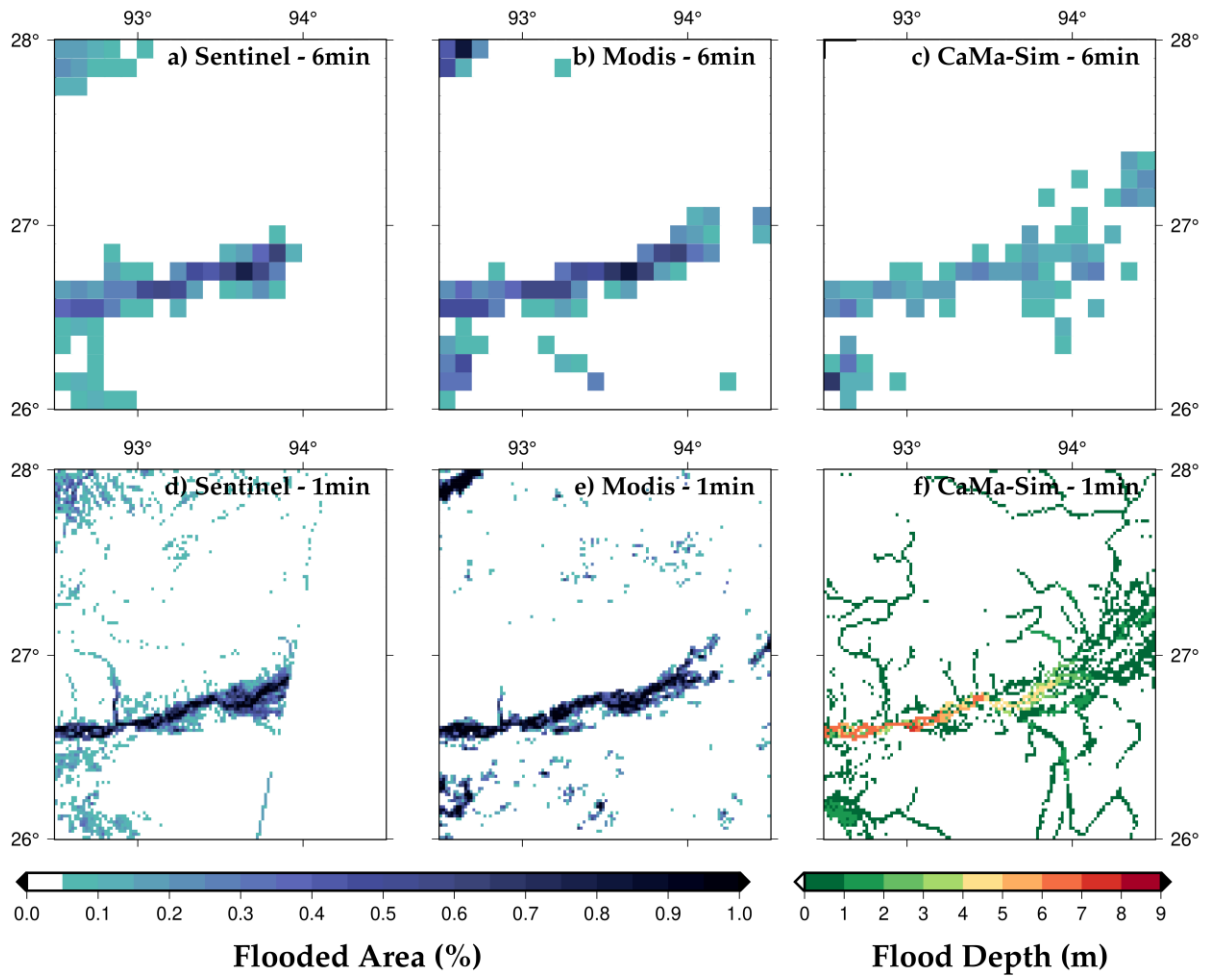
227 **Figure 1: Calibration and evaluation of the combined model for daily river flow and reservoir storage at**  
 228 **gauge stations and daily live storage of reservoirs**



229

230 **Figure 2: Simulated flood occurrences compared with satellite-based flood occurrence for different**  
 231 **regions in Ganga, Narmada and Brahmaputra River basin.**





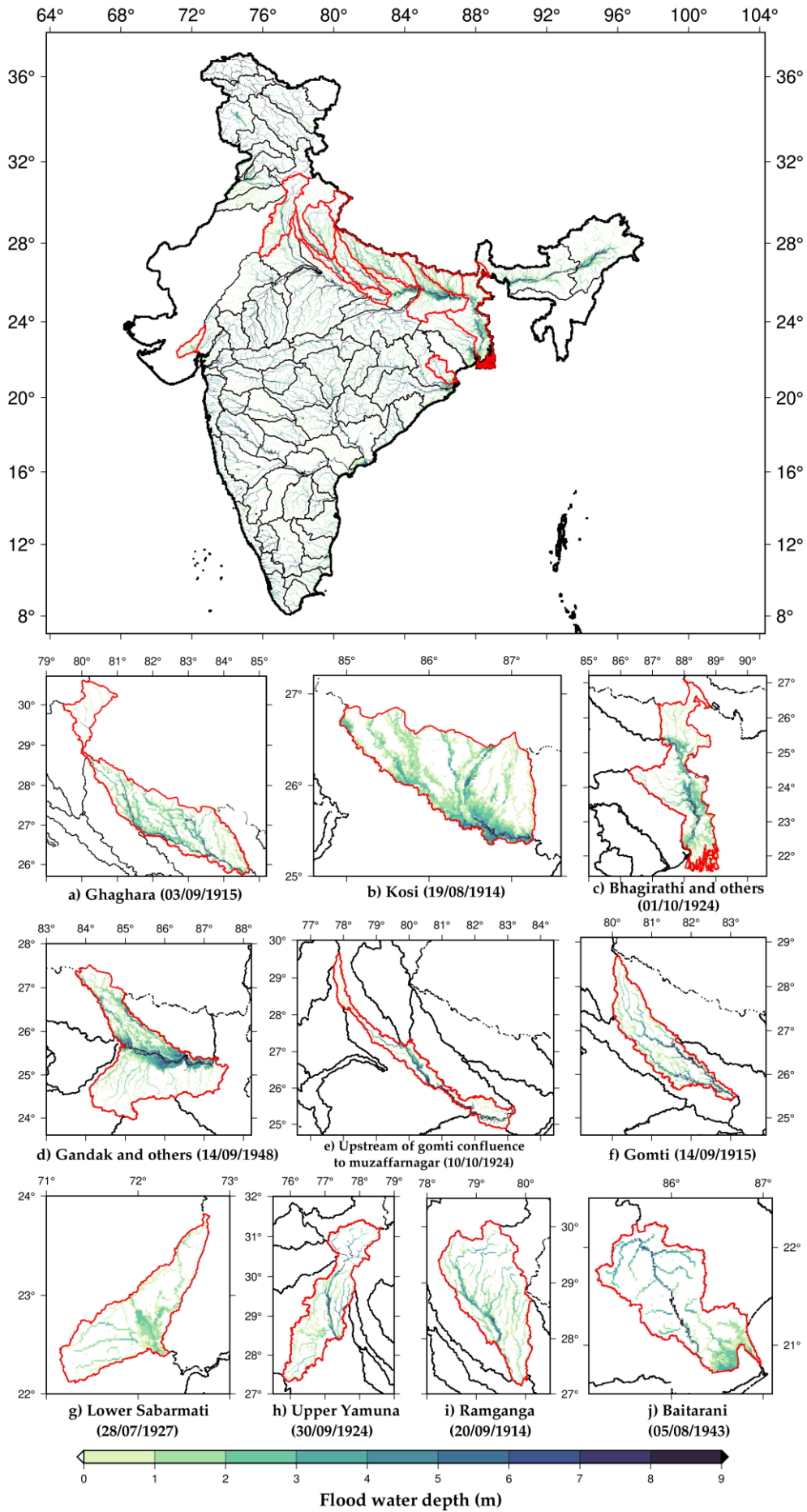
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233 **Figure 3: Simulated flood extent compared with Sentinel-1 SAR and MODIS satellite-based flood extent**  
 234 **for the 2016 flood event in the Brahmaputra river**

235 **3.2 Estimation of the observed flood extent**

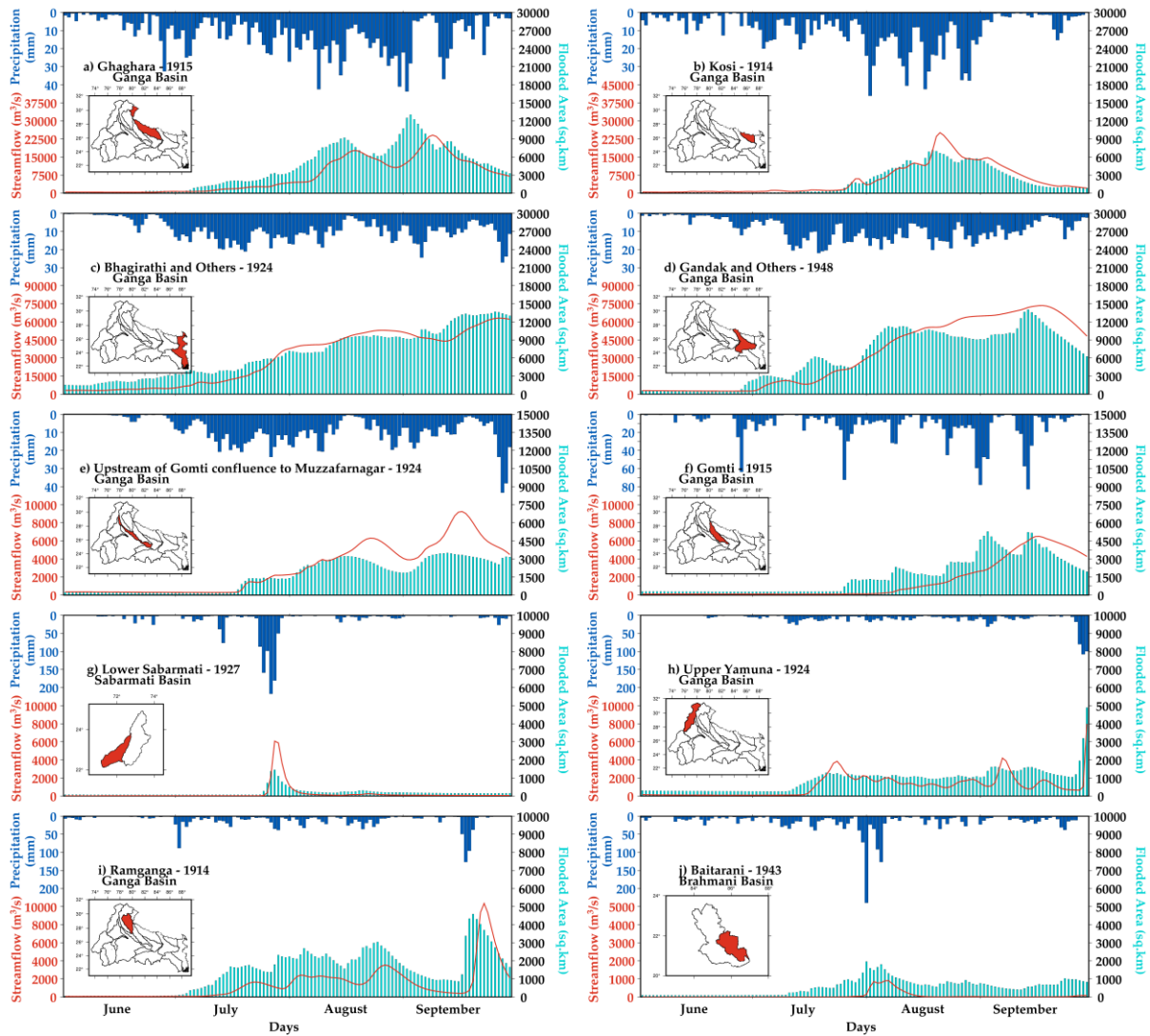
236 Next, we reconstructed the flood inundation for the observed worst flood for each sub-basin for the 1901-2020  
 237 period in India. The inundation extent for the worst flood can help us identify the sub-basin with higher flood risk.  
 238 We estimated flood depth and inundated area for each sub-basin for the worst flood during the last 120 years  
 239 (Figure 4). In addition, we identified the occurrence of the worst flood at the sub-basin level during the 1901-2020  
 240 period. We highlighted ten sub-basins that experienced the highest fractional area affected by the worst flood.  
 241 Sub-basins in the Ganga and Brahmaputra rivers are among the most highly influenced by the worst flood. For  
 242 instance, Ghaghra, Kosi, Bhagirathi, Gandak, Gomti, lower Sabarmati, upper Yamuna, Ramganga, and Baitarani  
 243 sub-basins had the highest fractional area affected by the worst flood during 1901-2020 (Figure 4). The fractional  
 244 area of sub-basins in the semi-arid western India is less affected compared to those located in the Ganga basin.  
 245 For example, the lower Sabarmati sub-basin of the Sabarmati River basin is among the sub-basins that are highly  
 246 influenced by the observed worst flood. We also find that the worst flood in the same year did not affect all the  
 247 sub-basins within a river basin (Figure S6). For instance, all the highly influenced sub-basins experienced the  
 248 worst flood in different years in the Ganga basin (Figure 4). Most of the top flood-affected sub-basins experienced  
 249 floods during August-September in the summer monsoon season. Overall, the flood extent due to the worst flood

250 is substantially greater in the sub-basins of the Ganga and Brahmaputra river basins compared to other basins in  
251 India (Figure 4). Ganga river basin also has the highest population density among all the basins in the Indian sub-  
252 continent, which makes it vulnerable for the flood risk.



254 **Figure 4: Flood depth map for the observed worst flood for each sub-basins, highlighting the sub-basins**  
255 **with maximum flood inundated area (%) (a) Ghaghara – Ganga River basin (b) Kosi – Ganga River basin**  
256 **(c) Bhagirathi and others – Ganga River basin (d) Gandak and others – Ganga River basin (e) Upstream**  
257 **of Gomti confluence to Muzaffarnagar – Ganga River basin (f) Gomti – Ganga River basin (g) Lower**  
258 **Sabarmati – Sabarmati River basin (h) Upper Yamuna – Ganga River basin (i) Ramganga – Ganga River**  
259 **basin (j) Baitarani – Brahmani River basin**

260 Next, we examined the precipitation, streamflow, and flood-affected area (%) for the ten sub-basins that had the  
261 highest fractional flood affected area for the worst flood during 1901-2020 (Figure 5). As floods mostly occur  
262 during the summer monsoon season in India (V. Mishra et al., 2022; Nanditha & Mishra, 2021), we examined the  
263 temporal variability of precipitation, and streamflow during the monsoon season of the worst flood year. Nanditha  
264 and Mishra (2022) reported that multi-day precipitation is India's most robust driver of floods. Moreover, extreme  
265 precipitation and wet-antecedent conditions trigger floods in India (Nanditha & Mishra, 2022). We find that the  
266 Ghaghara sub-basin of the Ganga river experienced the worst flood in September 1915, affecting more than 10,000  
267 km<sup>2</sup> area of the sub-basin. A multi-day rainfall in late August and early September (1915) caused the worst flood  
268 in the basin. The Kosi sub-basin of the Ganga river experienced the worst flood in August 1914, which affected  
269 more than 5000 km<sup>2</sup> of the basin (Figure 5). Similarly, Bhagirathi and other sub-basins in the Ganga river basin  
270 were affected by the worst flood in late September 1924, which inundated more than 12000 km<sup>2</sup> of the sub-basin.  
271 Similarly, Gandak and Gomti river basins experienced the worst floods in 1948 and 1915, respectively. Our results  
272 agree with the information presented in previous studies (Agarwal & Narain, 1991; Fredrick, 2017; Joshi, 2014;  
273 D. K. Mishra, 2015; A. Singh et al., 2021). We find that most of the sub-basins of the Ganga river basin are prone  
274 to large extents of flood inundation. Moreover, the worst floods in most sub-basins were caused by multi-day  
275 precipitation, a prominent driver of floods in the Indian sub-continental river basins (Figure 5).

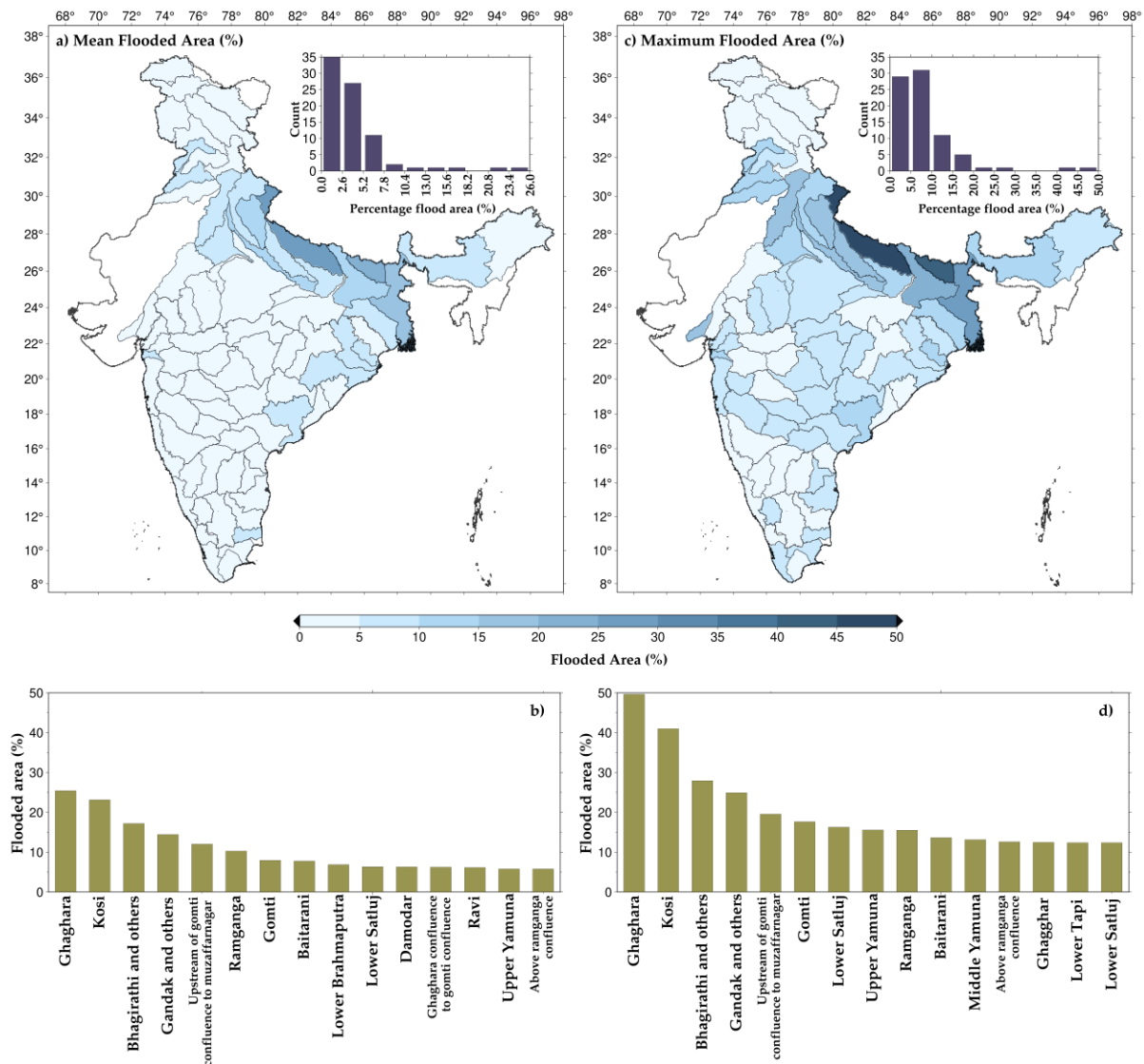


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277 **Figure 5: Daily upstream precipitation (mm, blue), the H08 model simulated streamflow (red) at the sub-**  
 278 **basin outlet (m<sup>3</sup>/s), and flooded area (km<sup>2</sup>, green) for the summer monsoon (June-September) period of**  
 279 **the corresponding worst flood year. (a) Ghaghara - Ganga River basin (b) Kosi - Ganga River basin (c)**  
 280 **Bhagirathi and others - Ganga River basin (d) Gandak and others - Ganga River basin (e) Upstream of**  
 281 **Gomti confluence to Muzaffarnagar - Ganga River basin (f) Gomti - Ganga River basin (g) Lower**  
 282 **Sabarmati – Sabarmati River basin (h) Upper Yamuna – Ganga River basin (i) Ramganga – Ganga River**  
 283 **basin (j) Baitarani – Brahmani River basin**

284 To further examine the flood-affected area at the sub-basin level, we estimated the mean annual maximum flooded  
 285 area (Figure 6a) and historical maximum flooded area using the H08-CaMa flood models (Figure 6b). Most of the  
 286 highly flooded sub-basins are in the Ganga River basin. While the mean annual maximum flooded area for the  
 287 top flood-affected sub-basins ranged between 10 to 15%, their maximum flooded area varied between 30 to 40%.  
 288 Other than sub-basins from the Ganga river basin, Baitarani, lower Tapi, lower Godavari, Brahmani, and lower  
 289 Mahanadi also showed a considerable mean flooded area during the 1901-1920 period. In the case of the maximum  
 290 flooded area, Gandak, Kosi, and Ghaghara confluence to Gomti confluence sub-basins exhibited more than 20%  
 291 flooded area. Sub-basins from the other river basins, such as lower Tapi, lower Narmada, Baitarani, and lower

292 Satluj, are in the top fifteen sub-basins with the highest flooded area. The sub-basins in the Ganga and  
 293 Brahmaputra rivers are the most flood-affected. Moreover, the Ganga and Brahmaputra rivers experience the  
 294 highest floods among all the river basins (Mohanty et al., 2020; Mohapatra & Singh, 2003).



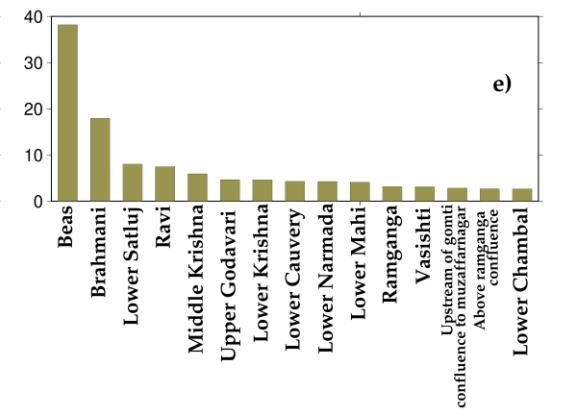
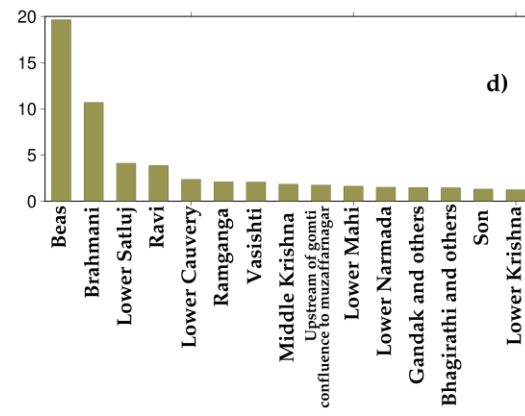
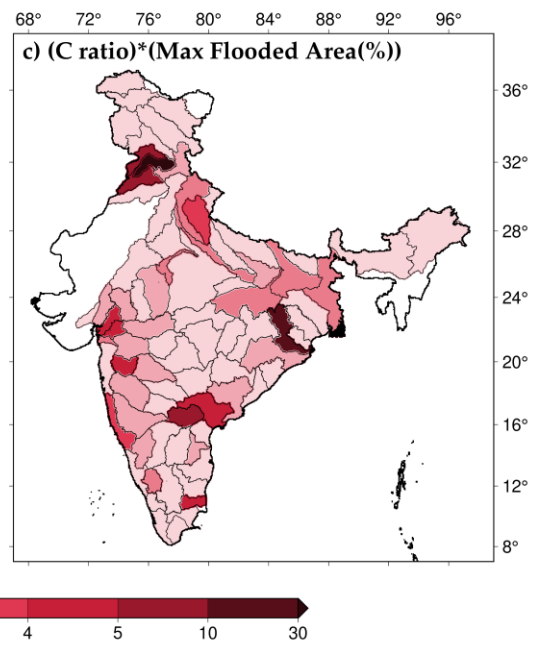
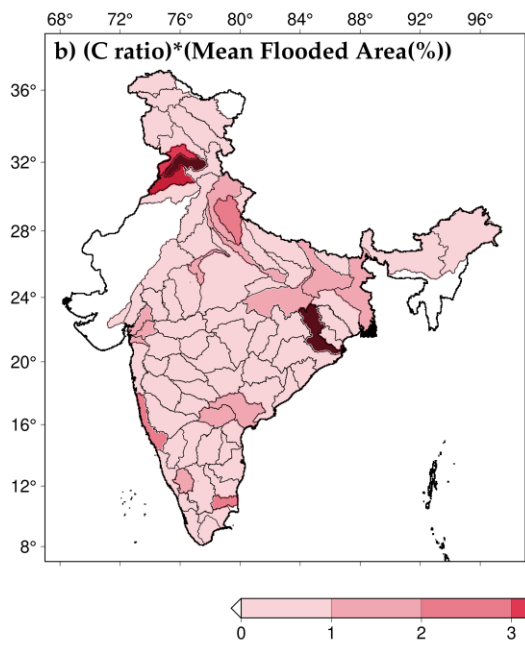
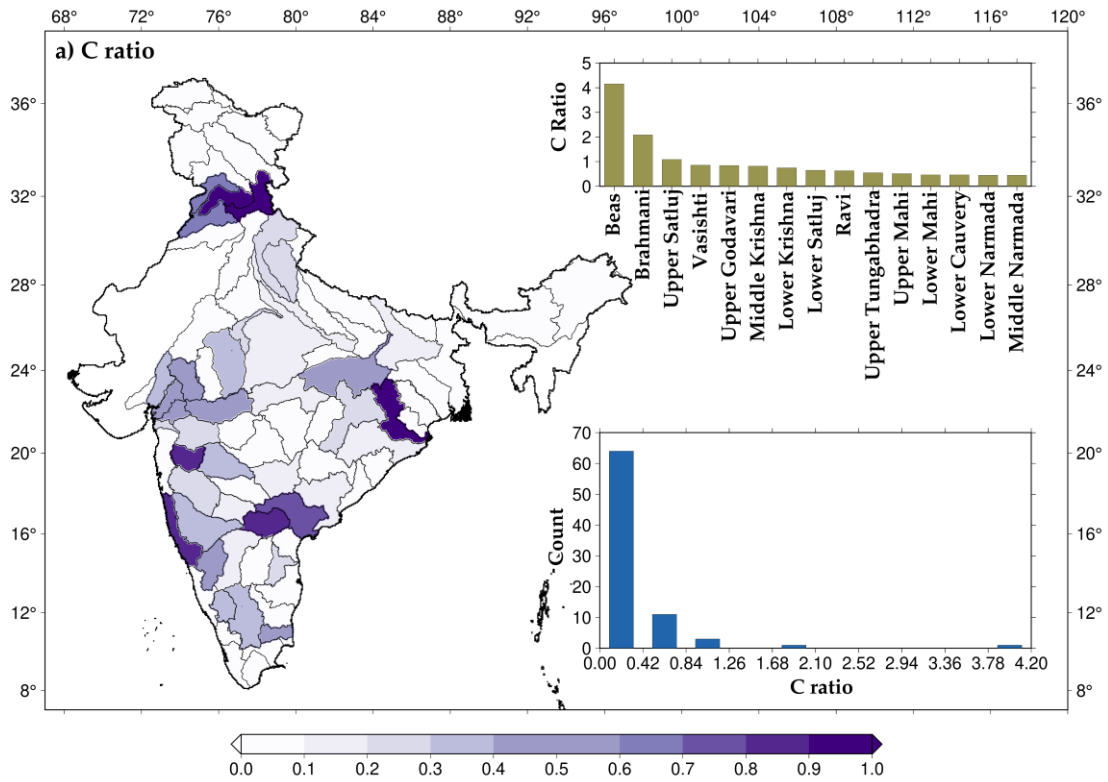
295  
 296 **Figure 6: (a) Mean of annual maximum flooded area (percentage) between 1901-2020 and the overall**  
 297 **distribution (b) highlighting the top fifteen sub-basin. (c) Historical maximum flooded area (percentage)**  
 298 **and the overall distribution (d) highlighting the top fifteen sub-basin.**

299 **3.3 Influence of reservoirs on flood extent**

300 We selected and considered 51 major reservoirs to examine their influence on flood risk based on the availability  
 301 of the observed storage data. We estimated C-ratio for each sub-basin considering the river flow at the outlet to  
 302 investigate the impact of reservoirs on streamflow. C-ratio can vary between zero to infinity, and higher values  
 303 indicate the prominent effect of dams on river flow. We identified sub-basins with a greater influence on dams  
 304 based on the C-ratio. We find that Beas, Brahmani, upper Satluj, Upper Godavari, Middle and Lower Krishna,  
 305 and Vashishti are among the most influenced by the dams. Beas sub-basin has the highest C-ratio (4.16) among  
 306 all the sub-basin in the Indian sub-continent (Figure 7a). Out of the 80 sub-basins, only eleven have C-ratio greater

307 than 0.5. 64 out of 80 sub-basins have a C-ratio between zero to 0.42 (Figure 7a). We considered only 51 major  
308 reservoirs in our analysis. However, there are several major and minor dams for which observed data is  
309 unavailable. Therefore, the influence of reservoirs based on the C-ratio might need to be considered. However,  
310 our analysis indicates that dams in a few sub-basins can significantly alter the river flow and flood risk. For  
311 instance, dams effectively alter extreme flow's timing, duration, and frequency (Mittal et al., 2016). C-ratio alone  
312 may not effectively capture the influence of dams on floods; therefore, we multiplied the fractional area affected  
313 by floods and the C-ratio for each sub-basins. For instance, if a sub-basin is considerably affected by dams and  
314 has a large flood extent, the value of the multiplied ratio will be higher. The multiplier ratio can effectively identify  
315 the sub-basins with high flood-affected areas and flow regulated by the reservoirs. We find that Beas, Brahmani,  
316 Ravi, and Lower Satluj are among the highly influenced by floods and the presence of reservoirs. Overall, the  
317 sub-basins with higher C ratio and the highest flood-affected area are across the Indian subcontinent. Central India  
318 has sub-basins that are relatively less affected by floods and the presence of dams.



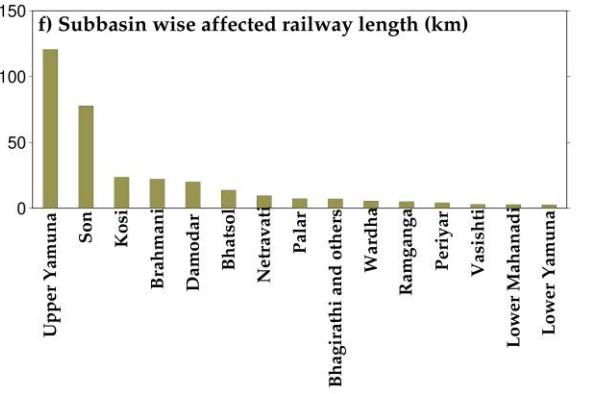
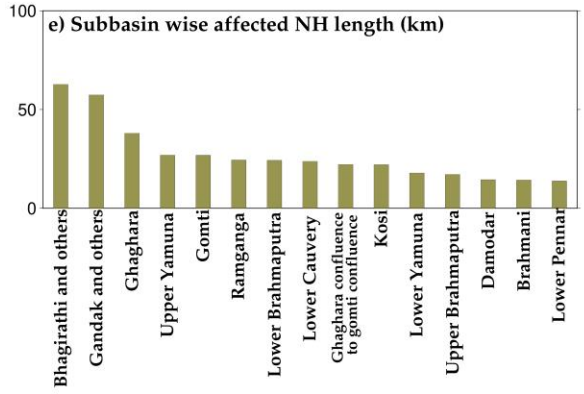
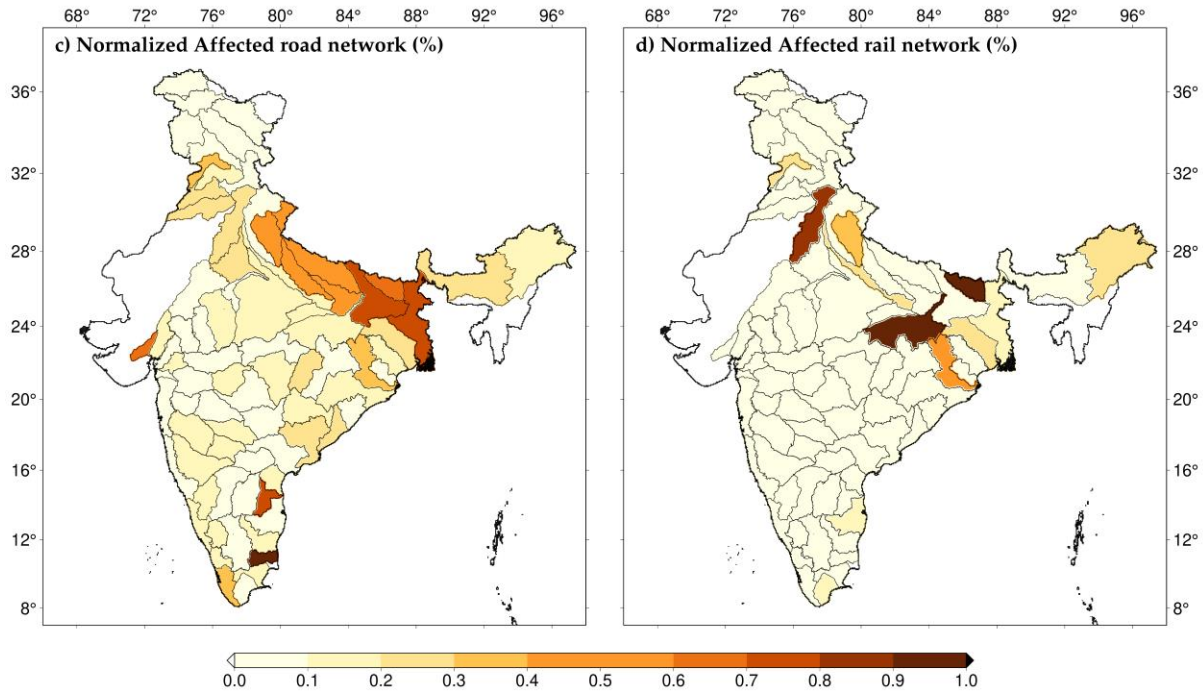
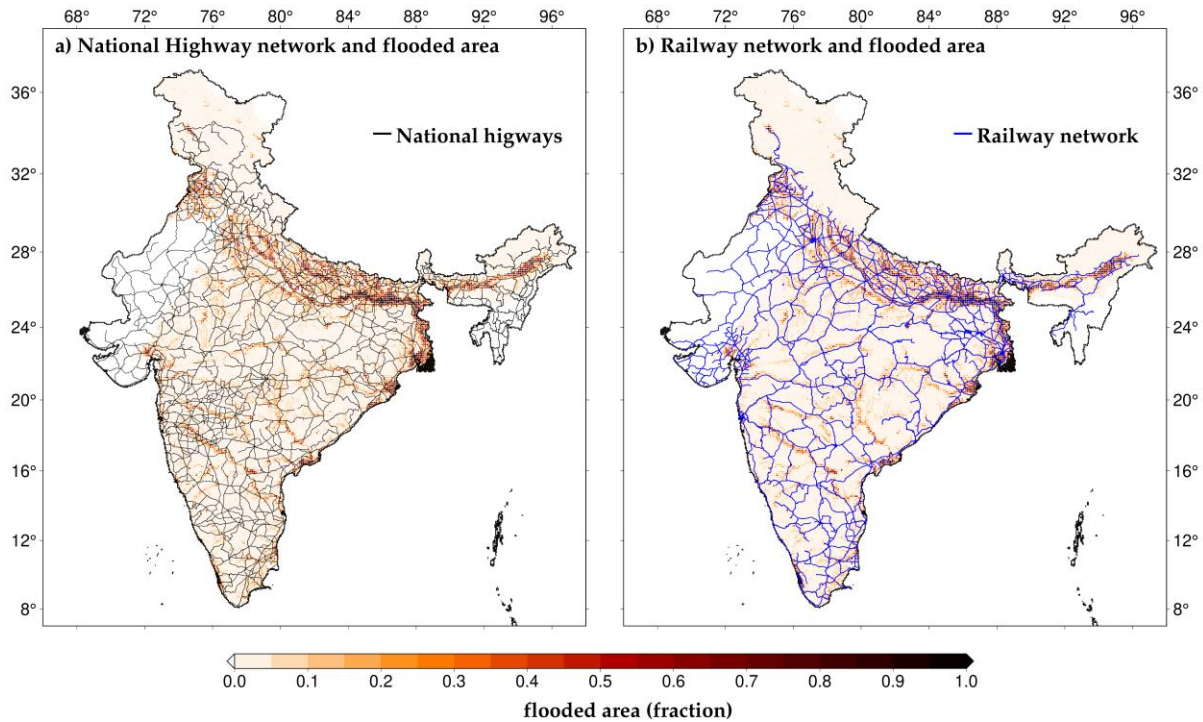




320 **Figure 7: (a) Sub-basin wise C-ratio, top fifteen sub-basins and distribution of sub-basins based on C-ratio**  
321 **values (b) Mean of annual maximum flooded area (percentage) multiplied with C-ratio (d) highlighting top**  
322 **15 sub-basins (c) Historical maximum flooded area (percentage) multiplied with C-ratio (e) highlighting**  
323 **top 15 sub-basins.**

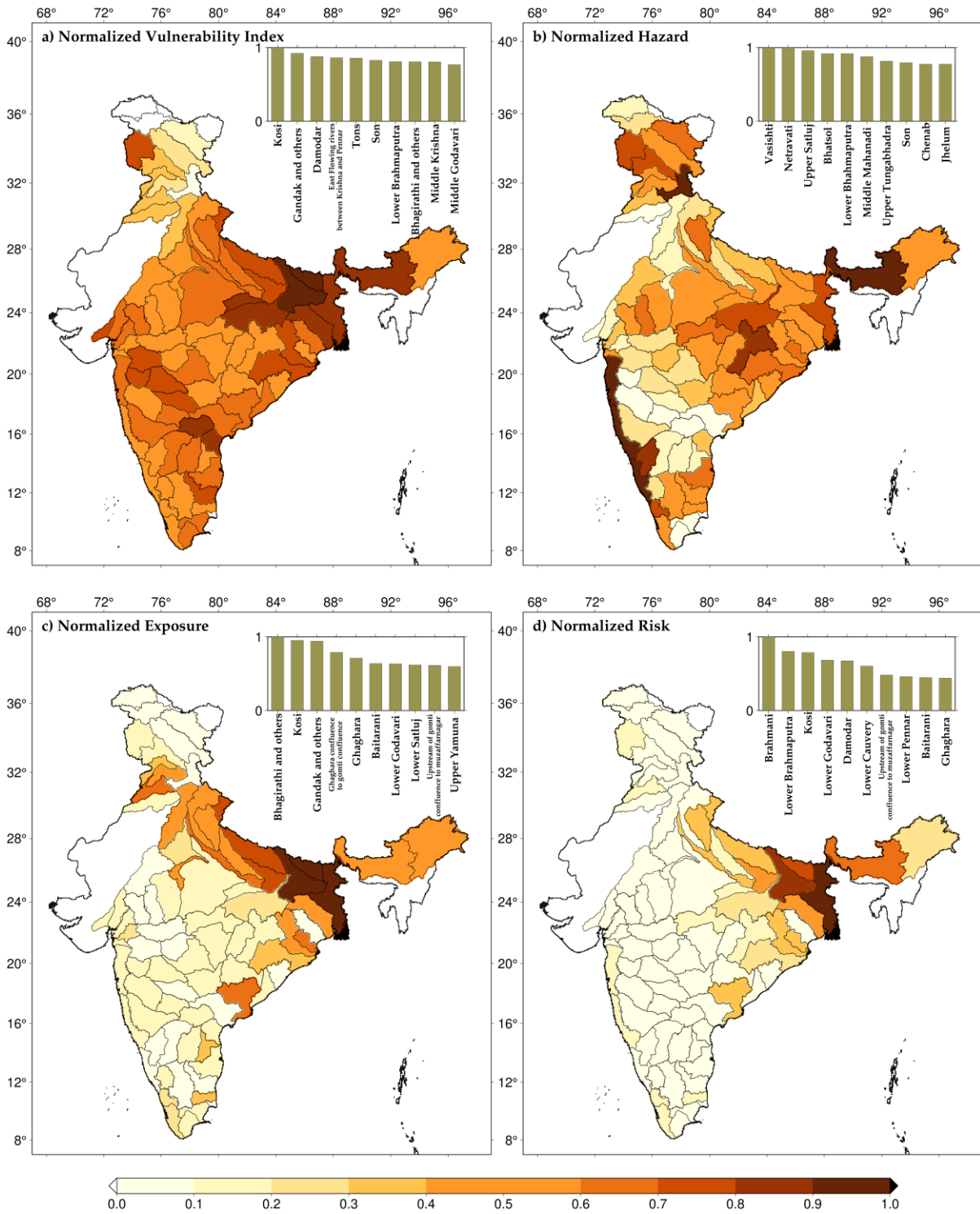
#### 324 **3.4 Sub-basin level flood risk assessment**

325 Next, we identified the roads (national highways) and railway exposure to riverine floods for each subbasin.  
326 Climate change will adversely affect rail and road networks (Hooper & Chapman, 2012; Padhra, 2022). A  
327 considerable length of roads is affected due to surface flooding resulting from high-intensity rain (Koks et al.,  
328 2019). Therefore, we examined the impact of floods on rail and road infrastructure in India. We estimated the  
329 length of the road and railway network potentially affected by the worst flood that occurred during 1901-2020.  
330 We overlapped the road and rail network over the flooded area and estimated the network length exposed to floods  
331 (Figures 8a-b). The estimated length for each sub-basin was normalized between zero and one (Figures 8c-d). We  
332 find that the road network can be the most affected by the floods in the Gandak, Kosi and Ghaghara confluence  
333 to Gomti confluence in the Ganga river basin. On the other hand, a considerable part of the rail network can be  
334 affected by floods in Son, Kosi, and Upper Yamuna subbasins. Moreover, in Bhagirathi and Gandak river basins,  
335 more than 50 km of road network falls in the flood-prone regions (Figure 8e). There are ten sub-basins in which  
336 more than 20 km of road network falls in flood-prone areas of India. Similarly, over 20 km of the rail network is  
337 in the flood-affected areas of the six sub-basins (Upper Yamuna, Son, Kosi, Brahmani) [Figure 8f].



339 **Figure 8: Flood impacts on roads and railways infrastructure. (a-b) National Highways network and**  
340 **Railway network overlapped over the flooded area in worst flood cases, (c-d) subbasin wise normalised**  
341 **flood affected road and railway network (percentage), (e-f) top 15 subbasins with most affected national**  
342 **highways and railway length (km).**

343 Finally, we estimated sub-basin level flood risk using normalized vulnerability, hazard, and exposure (Figure 9).  
344 Vulnerability for each sub-basin in India was assessed using the national vulnerability assessment data available  
345 at the district level. We estimated hazard probability considering 50% of the inundated area for the worst flood as  
346 a benchmark. The likelihood of flood inundated areas in a sub-basin exceeding the benchmark was used in the  
347 risk assessment. Similarly, we used the worst flood extent and gridded population data to estimate flood exposure.  
348 The sub-basins in north-central India have a relatively higher vulnerability calculated using the socio-economic  
349 indicators. The vulnerability is relatively lower in north India and the Western Ghats. Kosi, Gandak, and Damodar  
350 sub-basins have the highest vulnerability. We find that hazard probability is higher in the sub-basins of  
351 Brahmaputra, rivers in the western Ghats, and a few sub-basins of the Indus river basin (Figure 9b). For instance,  
352 upper Satluj, Chenab, and Jhelum sub-basins of the Indus river have higher hazard probability. Other than the  
353 Western Ghats, most sub-basins in Peninsular India have relatively lesser hazard probability. Exposure, which  
354 represents the fraction of the population affected by flood under the worst flood scenario, is higher in the Indo-  
355 Gangetic Plain. Apart from the sub-basins of the Ganga River basin, the lower Brahmaputra, lower Godavari, and  
356 Baitarani sub-basin show higher exposure. Therefore, Ganga and Brahmaputra Rivers basins are the highest flood-  
357 prone river basins and have high flood exposure. Rentschler et al. (2022) also reported that the highest population  
358 exposure due to floods is in Uttar Pradesh, Bihar, and West Bengal, which is part of the Ganga river basin.



359

360 **Figure 9: Sub-basin level (a) Normalized vulnerability index (b) Normalized hazard (c) Normalized**  
 361 **exposure (d) Normalized risk. The top 10 sub-basins are highlighted as bars in panels inside the figures.**

362 We estimated the flood risk for each sub-basin, a collective representation of vulnerability, hazard, and exposure.  
 363 As expected, the flood risk is higher in the Ganga and Brahmaputra river basins compared to other parts of the  
 364 country. The higher flood risk in these basins can be attributed to higher vulnerability, hazard probability, and  
 365 exposure. For instance, Bhagirathi, Gandak, Kosi, lower Brahmaputra, and Ghaghra are the sub-basins with the  
 366 highest flood risk in India (Figure 9d). Despite the higher hazard probability in the sub-basins of the Indus and

367 west coast river basins, the overall flood-risk is considerably lower than the sub-basins of the Ganga and  
368 Brahmaputra river basins primarily due to less vulnerability and exposure. Our results show that flood risk in  
369 some of the sub-basins of the Ganga and Brahmaputra river basins can be reduced by reducing the vulnerability.

#### 370 **4. Discussion and conclusions**

371 Flood risk mapping is essential for risk reduction and developing mitigation measures. The flood risk will likely  
372 increase due to increased hazard probability and exposure (Ali et al., 2019). Hirabayashi et al. (2013) showed that  
373 a warmer climate would increase the risk of floods on a global scale. In India also, floods are expected to become  
374 more likely under warming climate. For instance, Ali et al. (2019) reported that multi-day floods are projected to  
375 rise faster than single-day flood events. The projected rise in the flood frequency in India can be attributed to  
376 increased extreme precipitation under warming climate (Mukherjee et al., 2018). Observational studies have also  
377 concluded that there has been a considerable rise in extreme precipitation in India during the summer monsoon  
378 season (Roxy et al., 2017), which is linked to warming climate. While the warming climate is directly linked to  
379 the increased frequency of extreme precipitation, its association with riverine floods is not straightforward. For  
380 instance, Nanditha & Mishra (2021, 2022) reported that multi-day precipitation on the wet antecedent condition  
381 is the most favourable conditions for riverine floods in India.

382 While mapping the flood risk at appropriate spatial resolution is complex and challenging, it is vital for disaster  
383 risk reduction. Flood inundation mapping that provides the spatial extent of flooding is crucial as the first  
384 responders use it during a flood emergency (Apel et al., 2009). There are several approaches to mapping flood  
385 inundation (Teng et al., 2017). Various hydrological models have been employed for conducting flood risk  
386 assessments at a global scale (Dottori et al., 2018; Gu et al., 2020; Tabari et al., 2021). For instance, Dottori et al.  
387 (2018) used the H08 model combined with CaMa-Flood model to estimate losses resulting from river flooding at  
388 the country level. Additionally, the LISFLOOD model (van der Knijff et al., 2010) at 5 km spatial resolution was  
389 used to estimate the river flood risk in Europe (Alfieri et al., 2018). Flood risk assessment at relatively larger  
390 scales are conducted using the coarse resolution land surface hydrological models. The objective of these large  
391 scale flood risk assessment is to identify regions that are flood-prone (Dottori et al., 2018; Gu et al., 2020; Tabari  
392 et al., 2021). On the other hand, high resolution flood inundation mapping is needed to understand the local flood  
393 risk and damage caused to infrastructure. For the analysis of flood inundation during a particular flood at a local  
394 scale, high-resolution models such as HEC-RAS and Mike FLOOD can be employed (Khalaj et al., 2021; Nguyen  
395 et al., 2016). High resolution flood risk mapping requires comprehensive information of high-resolution  
396 topography, cross-sections of channels, and data associated to structural measures of flood protection. However,  
397 the smallest subbasin considered in our study has more than 5000 km<sup>2</sup> area (Fig S7), while most subbasins have  
398 area between 10,000 and 50,000 km<sup>2</sup>, with Lower Yamuna being the largest subbasin, with an area of 124,867.19  
399 km<sup>2</sup>. Therefore, the performance of our modelling framework against the satellite and other observations can be  
400 considered satisfactory to provide a sub-basin scale flood risk assessment. Moreover, we used hydrodynamic  
401 modelling to develop long-term flood inundation maps for the Indian sub-basins. The long-term data (1901-2020)  
402 provides us a record of several floods, which can help in robust estimates of flood risk in different sub-basins.

403

404 While high-resolution models are suitable for event-specific finer-level flood assessments, their feasibility  
405 diminishes in studies involving large-scale flood inundation over longer durations (Yamazaki et al., 2018b).  
406 Creating high-resolution flood inundation maps based on hydrodynamic modelling is computationally expensive  
407 (Dottori et al., 2016) for a large domain like India. In addition, higher-resolution flood risk mapping that can be  
408 used at the local scale for decision-making requires accurate terrain information and river cross-section datasets  
409 that are not available. For instance, freely available digital elevation models (DEM) can be too coarse to resolve  
410 the flood inundation and depth variability at a local scale (Cook & Merwade, 2009; Dey et al., 2022). The  
411 uncertainties within hydrologic outputs can primarily arise due to inaccuracies in both input data and model  
412 parameterization (Poulin et al., 2011). Inaccuracies in input meteorological data may stem from disparate sources,  
413 leading to errors in spatial and temporal interpolation (Brown & Heuvelink, 2005). Similarly, model  
414 parameterization errors, which involve assigning values to parameters governing diverse hydrological processes,  
415 can emerge during the calibration process (Laiolo et al., 2015). Moreover, there are uncertainties originating from  
416 utilizing long-term flood occurrence data to assess flood mapping capabilities. Our modelling framework that  
417 considers the influence of reservoirs provides sub-basin scale flood inundation extent as our aim was to provide a  
418 long-term assessment of flood extent in at the country scale. Additionally, downscaling of flood depths introduces  
419 biases as coarse-scale information is translated to the local scale (He et al., 2021), which might have considerable  
420 deviations from the actual observed flood extent. Given these limitations, our findings provide valuable  
421 information based on the long-term record developed using model simulations that can be used for the regional  
422 scale policy development for flood mitigation. Cloud cover during the summer monsoon, when most floods occur  
423 in India (Nanditha et al., 2022), hinders the utility of satellite data for flood inundation mapping. We calibrated  
424 and evaluated our H08-CaMa flood modelling framework using the observed flow, reservoir storage, and satellite-  
425 based inundation. However, all these datasets available from the in-situ network or satellites are prone to errors  
426 and uncertainty (Di Baldassarre & Montanari, 2009; Stephens et al., 2012; Teng et al., 2017). We used C-ratio as  
427 an indicator to quantify the influence of dams on streamflow. However, C-ratio may not fully capture the  
428 complexities and variations in the impacts of reservoir operations. Furthermore, in case of run-of-the-river (RoR)  
429 dams, the C-ratio may over-estimate the downstream hydrological impacts. Therefore, C-ratio may not solely  
430 capture the downstream hydrological effects resulting from dams. Nevertheless, it provides preliminary  
431 information on the potential dam influence on the downstream flow.

432 India has implemented several flood risk mitigation measures at multiple government levels. The construction of  
433 embankments along rivers is a common flood risk mitigation measure in India. These embankments help contain  
434 the floodwaters within the river channels and protect nearby areas from inundation (NDMA, 2016). The CWC in  
435 India operates a network of flood forecasting stations that collect real-time data on rainfall and water levels to  
436 forecast floods and issue warnings to vulnerable communities. Notwithstanding the considerable investments and  
437 flood-control measures, India has witnessed substantial mortality, human migration, and economic loss. Flood  
438 mortality has increased mainly because of increased frequency, not necessarily due to increased flood intensity  
439 (Hu et al., 2018). About 3% of the total geographical area of India is affected by floods every year that cause  
440 damage to agriculture and infrastructure. The top ten floods that occurred during 1985-2015 caused the mortality  
441 of more than 1000 people while more than 35 million people were displaced due to floods between 2000-2004  
442 (Dartmouth Flood Observatory). The recent riverine floods in Uttarakhand and Kerala highlighted the growing  
443 flood risk in India, which warrants the need for flood mitigation. The recent flood in August 2022 in Pakistan

444 caused an estimated loss of \$30 billion. Both structural and non-structural measures are required for flood  
445 mitigation (Nanditha & Mishra, 2021). Our risk assessment provides policy implications towards reducing  
446 vulnerability to reduce the flood risk. Moreover, a sub-basin level ensemble forecast is needed to be used for early  
447 flood warnings in the sub-basins with higher flood risk.

448 Based on our findings, the following conclusions can be made:

- 449 • The coupled hydrological and hydrodynamic modelling framework based on the H08-CaMa Flood model  
450 was used to estimate the flood risk assessment in India. The hydrological modelling framework  
451 performed well against the observed flow, reservoir storage, and satellite-based flood inundation. The  
452 role of 51 major reservoirs was considered in flood risk assessment based on the long-term simulations  
453 for the 1901-2020 period.
- 454 • The sub-basins in the Ganga and Brahmaputra river basins experienced the most significant flood extent  
455 during the worst flood in 1901-2020. Similarly, the mean annual maximum flood extent is higher for the  
456 sub-basins in the two major transboundary river basins (e.g., Ganga and Brahmaputra). The worst flood  
457 affected different sub-basins on the two main flood-affected river basins in different years. Major floods  
458 in the flood-prone sub-basins of the Ganga and Brahmaputra basins occur during the summer monsoon  
459 season, especially during the August-September period.
- 460 • The sub-basins with a more prominent influence of dams based on the C-ratio were identified. Beas,  
461 Brahmani, upper Satluj, Upper Godavari, Middle and Lower Krishna, and Vashishti sub-basins are  
462 among the most influenced by the dams. Moreover, Beas, Brahmani, Ravi, and Lower Satluj are among  
463 the most affected by floods and the presence of reservoirs.
- 464 • Flood risk is higher in the Ganga and Brahmaputra river basins compared to other parts of the country.  
465 The higher flood risk in the two transboundary river basins can be attributed to higher vulnerability,  
466 hazard probability, and exposure. Bhagirathi, Gandak, Kosi, lower Brahmaputra, and Ghaghra are India's  
467 sub-basins with the highest flood risk.

468 **Data availability:** All the datasets used in this study can be obtained from the corresponding author.

469 **Competing interest:** Authors declare no competing interest.

470 **Author contributions:** VM designed the study. UV conducted the analysis and wrote the first draft. All the  
471 authors contributed in the writing and discussion.

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475 <http://floodobservatory.colorado.edu>, population data from GHSL:

476 <https://sedac.ciesin.columbia.edu/data/set/ghsl-population-built-up-estimates-degree-urban-smod>, vulnerability  
477 assessment data from DST: HYPERLINK

478 "<https://dst.gov.in/sites/default/files/Full%20Report%20%281%29.pdf>"[https://dst.gov.in/sites/default/files/Full%20Report%20%281%29](https://dst.gov.in/sites/default/files/Full%20Report%20%281%29.pdf)  
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