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

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

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

We use the H08 (Hanasaki et al., 2018) global hydrological model combined with the CaMa-Flood (Yamazaki et al., 2011) model for the sub-basin level flood risk assessment in India considering the role of reservoirs. The CaMa-Flood model combined with the H08 model has been used for several river basins globally (Boulange et al., 2021; C. M. R. Mateo et al., 2013). The CaMa-Flood model performs well in simulating flood dynamics

(Chaudhari and Pokhrel, 2022; H. Dang et al., 2022; Gaur & Gaur, 2018; Hirabayashi et al., 2013, 2021; Yamazaki et al., 2018; Yang et al., 2019). The CaMa-Flood model takes runoff as input simulated from any hydrological model and can simulate flood depth and inundation. In India, almost all the major rivers are influenced by reservoirs (Lehner et al., 2011). Therefore, the major scientific questions that we address are: 1) How does the flood risk vary at the sub-basin scale in India for the observed worst floods that occurred during the 1901-2020 period? 2) Which are the sub-basins where the presence of reservoirs considerably influences the flood risk? To address these questions, we use long-term observations (1901-2020) from India Meteorological Department (IMD) along with a hydrological modelling framework.

2. Data and Methods

2.1 Datasets

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

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

2.2 H08-CaMa-Flood combined model

We used the H08 (Hanasaki et al., 2018) global hydrological model to simulate hydrological variables. The H08 is a distributed global water resources model comprising six sub-models: land surface hydrology, river routing, reservoir operation, crop growth, environmental flow, and water abstraction. The model estimates baseflow using a leaky bucket method, while runoff is calculated based on saturation excess non-linear flow (Hanasaki et al., 2008). The H08 model can be run separately or combined with any hydrodynamic model to perform flow routing. The H08 model uses precipitation, air temperature, short and longwave radiations, wind speed, surface pressure, and specific humidity as input meteorological forcing. Soil parameters for the H08 model were obtained from Harmonized World Soil Database (HWSD). We forced the H08 model with the input meteorological forcing at 0.25° spatial and daily temporal resolution. We combined the H08 land surface model with the CaMa-Flood model. The CaMa-Flood model has been previously combined with the H08 model to obtain flood inundation estimates (C. M. Mateo et al., 2014).

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

We manually calibrated the H08 model by adjusting four parameters for each river basin, which include single-layer soil depth, gamma, bulk transfer coefficient, and tau (Hanasaki et al., 2008). We evaluated the model performance using the coefficient of determination (R^2) and Nash-Sutcliffe Efficiency (NSE) for daily streamflow and reservoir live storage. In addition, we compared the simulated and satellite-based observed flood occurrences. The satellite-based flood occurrence is calculated using the Global Surface Water (GSW) dataset (Pekel et al., 2016), available for the 1984-2020 period. We forced the well-calibrated combined (H08 and CaMa-Flood) models with observed meteorological forcing from India Meteorological Department (IMD) at 0.25° spatial resolution to conduct simulations from 1901 to 2020. The H08 model simulated runoff is used in CaMa-Flood to rout flood dynamics at six arc-minutes (0.1 degrees). We generated the flood depth maps for the historical worst flood at the sub-basin level. The worst flood is based on the highest magnitude of river flow observed at the subbasin outlet. The generated flood depths at 6 arc-minutes (0.1°) were further downscaled to 1 arc-minute (~0.185 km) resolution using the downscaling module available within the CaMa-Flood.

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

2.3 Risk assessment

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

$$Risk = Vulnerability * Exposure * Hazard \quad \ldots\ldots (1)$$

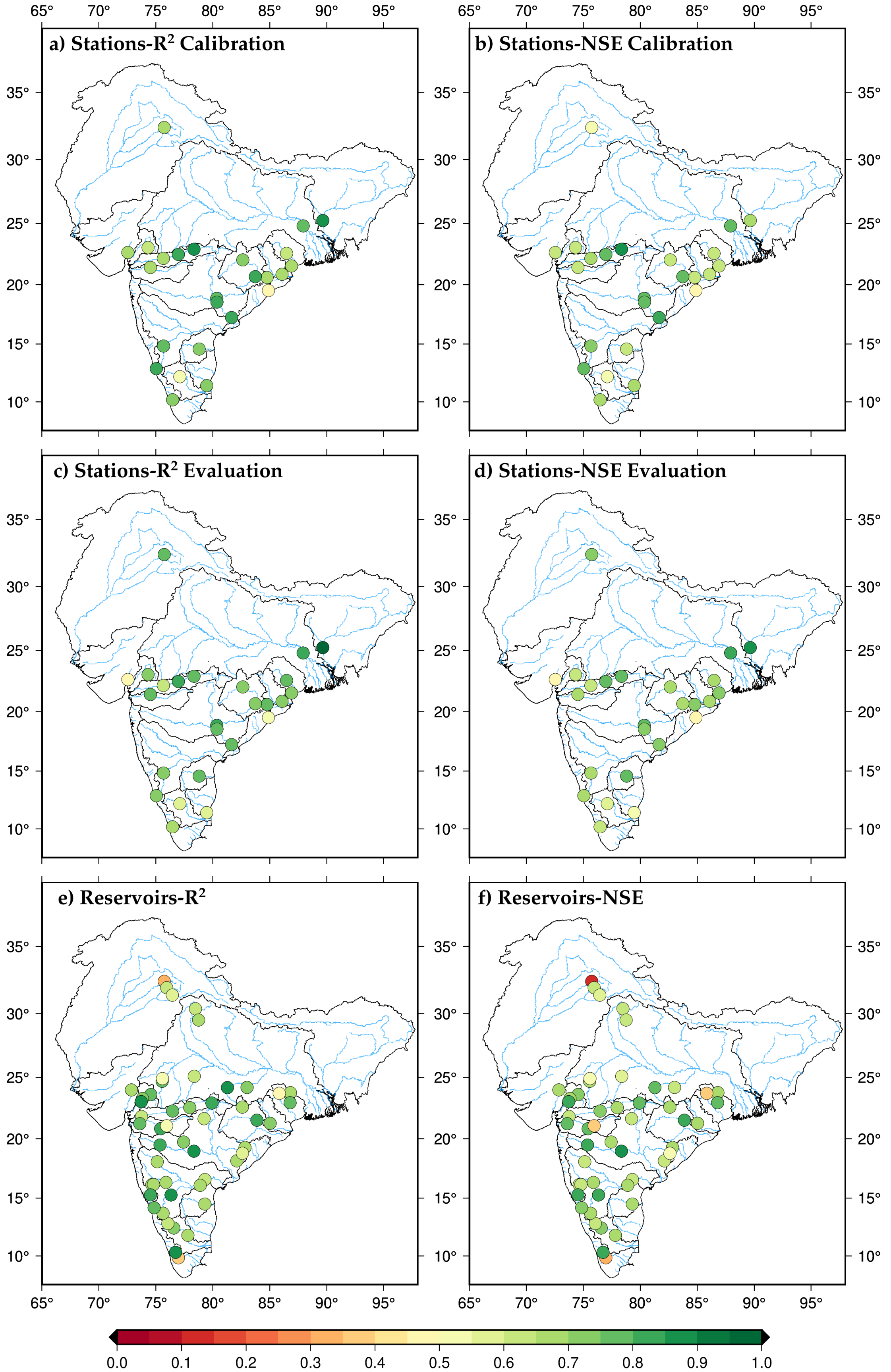
The flood risk assessment can help identify the hotspots and prioritize climate adaptation (de Moel et al., 2015). Among the three components, vulnerability is a degree of damage to a particular object at flood risk with a specified amount and present on a scale from 0 to 1. We obtained the vulnerability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

3. Results

3.1 Calibration and evaluation of hydrological models

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

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



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

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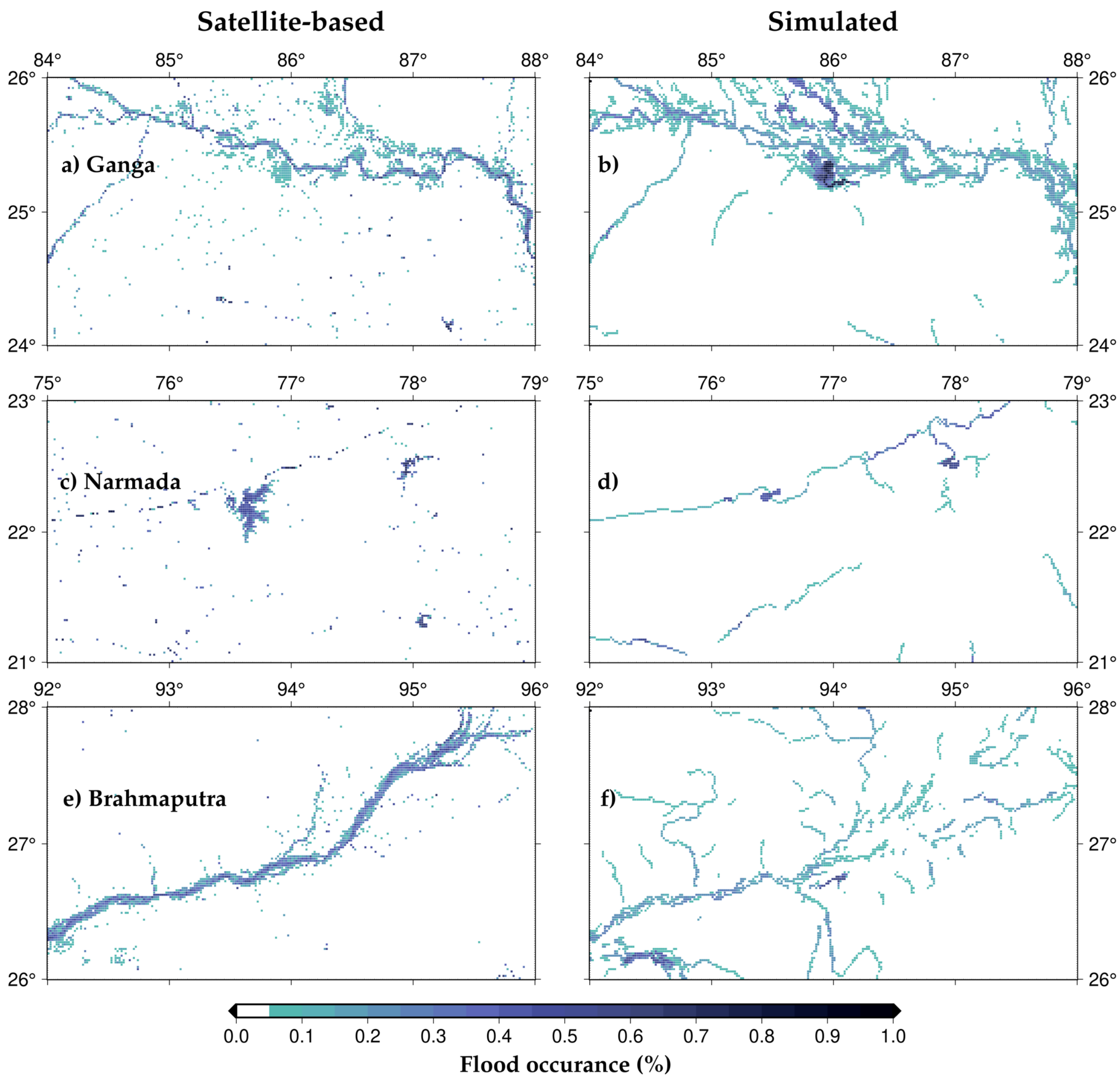

222 **Figure 2: Simulated flood occurrences compared with satellite-based flood occurrence for different**
223 **regions in Ganga, Narmada and Brahmaputra River basin.**

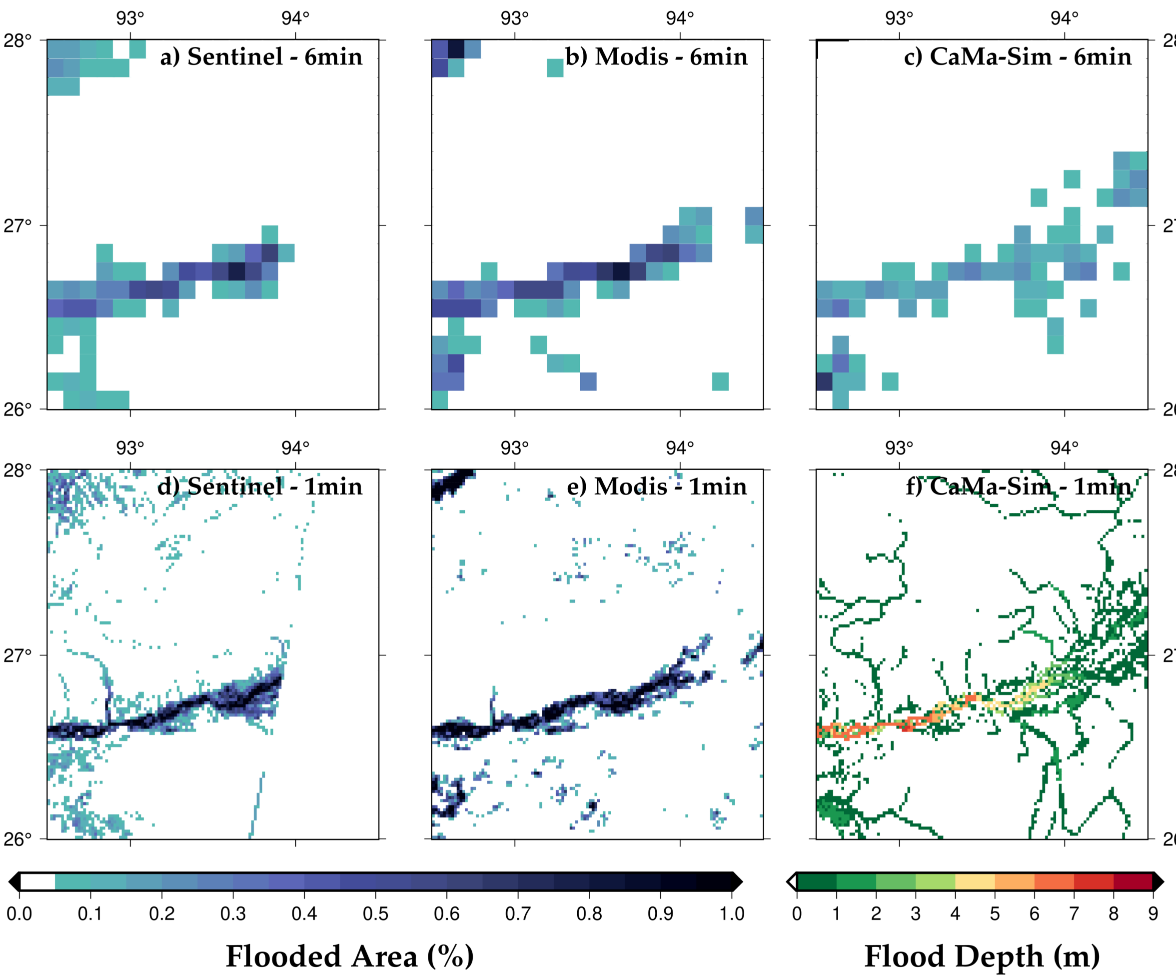

Figure 3: Simulated flood extent compared with Sentinel-1 SAR and MODIS satellite-based flood extent for the 2016 flood event in the Brahmaputra river

3.2 Estimation of the observed flood extent

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

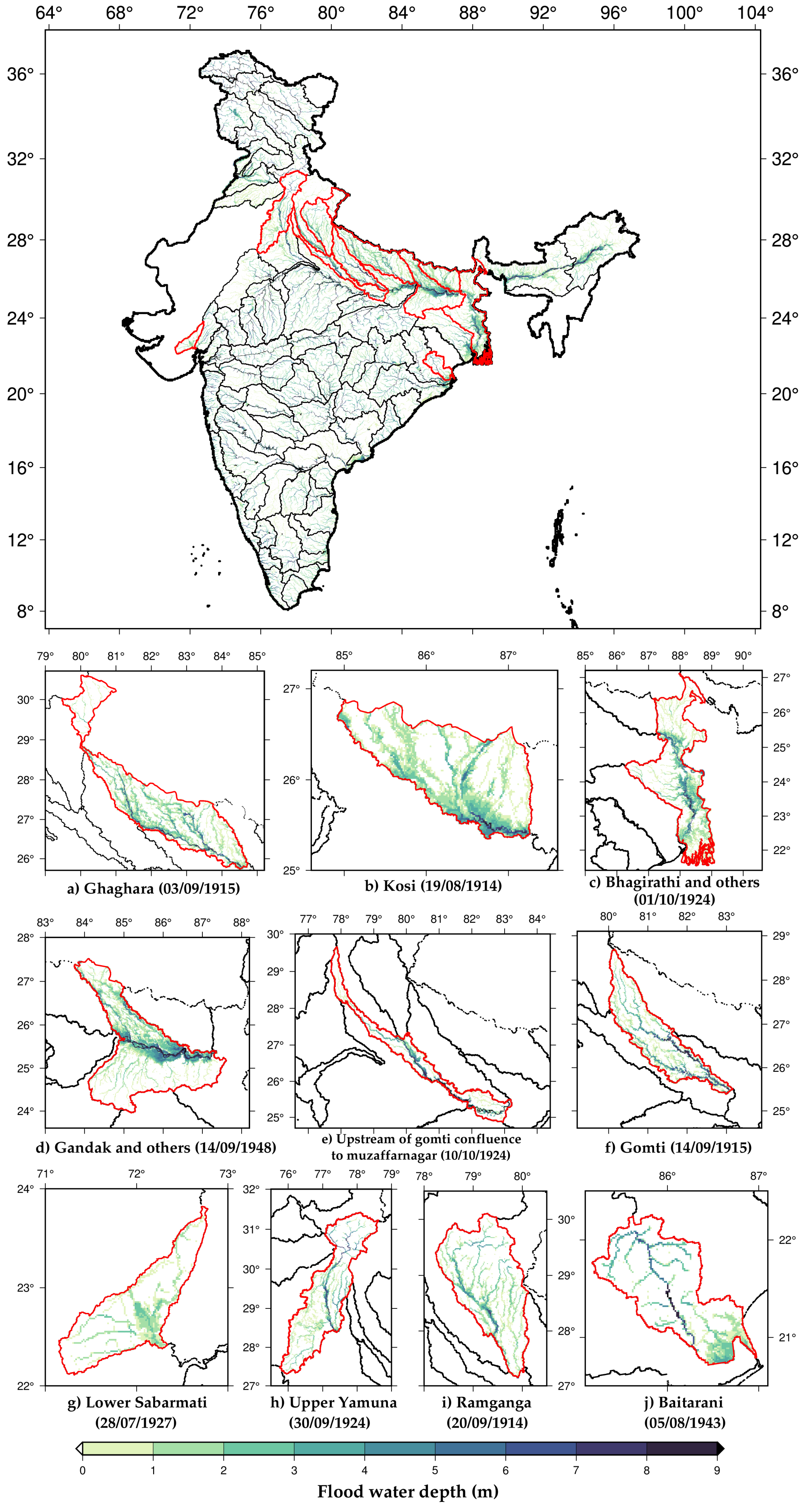
a) Ghaghara (03/09/1915)
b) Kosi (19/08/1914)
c) Bhagirathi and others (01/10/1924)
d) Gandak and others (14/09/1948)
e) Upstream of gomti confluence to muzaffarnagar (10/10/1924)
f) Gomti (14/09/1915)
g) Lower Sabarmati (28/07/1927)
h) Upper Yamuna (30/09/1924)
i) Ramganga (20/09/1914)
j) Baitarani (05/08/1943)
0
1
2
3
4
5
6
7
8
9
Flood water depth (m)

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

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

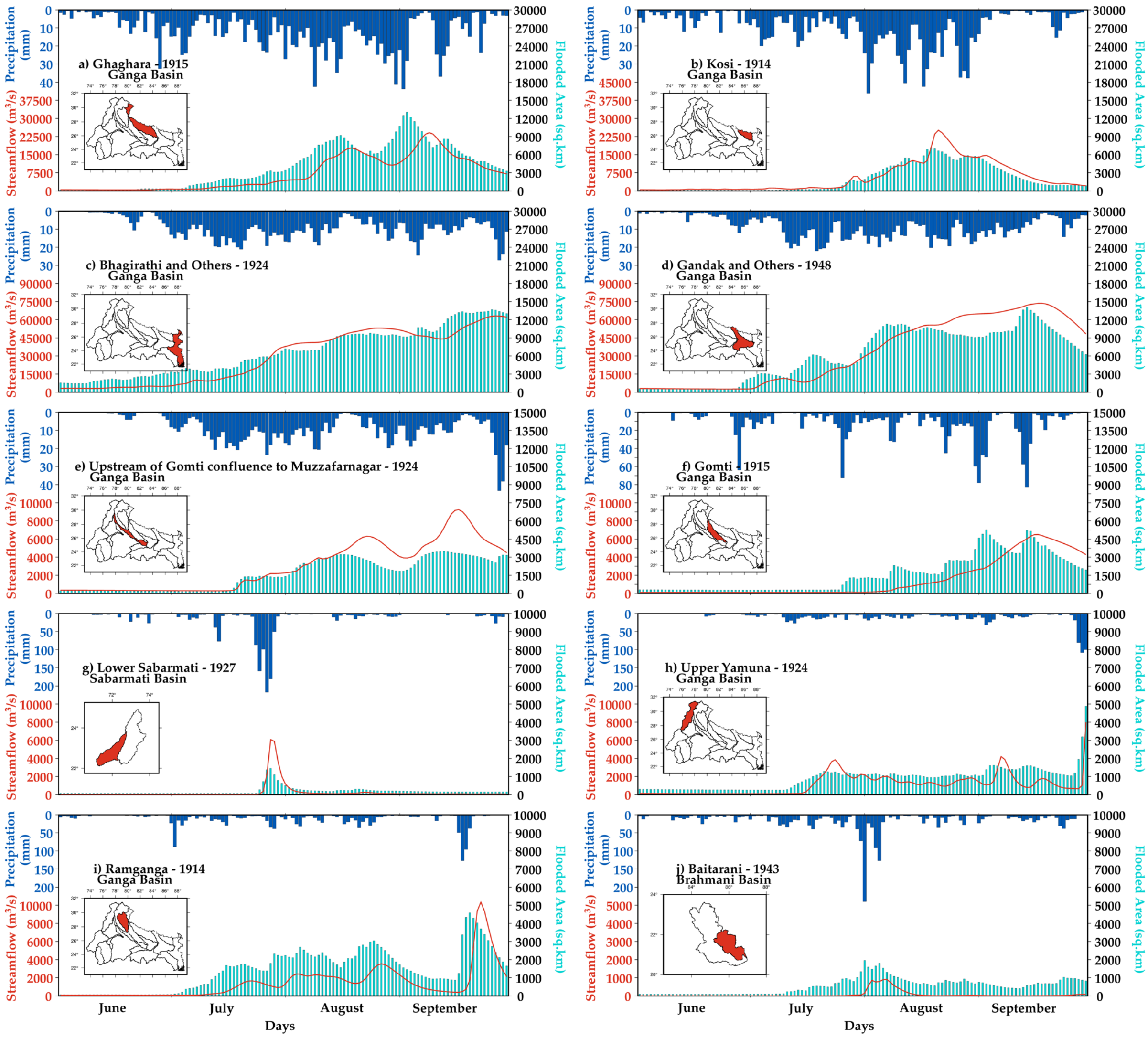

Figure 5: Daily upstream precipitation (mm, blue), the H08 model simulated streamflow (red) at the sub-basin outlet (m3/s), and flooded area (km2, green) for the summer monsoon (June-September) period of the corresponding worst flood year. (a) Ghaghara - Ganga River basin (b) Kosi - Ganga River basin (c) Bhagirathi and others - Ganga River basin (d) Gandak and others - Ganga River basin (e) Upstream of Gomti confluence to Muzzafarnagar - Ganga River basin (f) Gomti - Ganga River basin (g) Lower Sabarmati – Sabarmati River basin (h) Upper Yamuna – Ganga River basin (i) Ramganga – Ganga River basin (j) Baitarani – Brahmani River basin

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

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

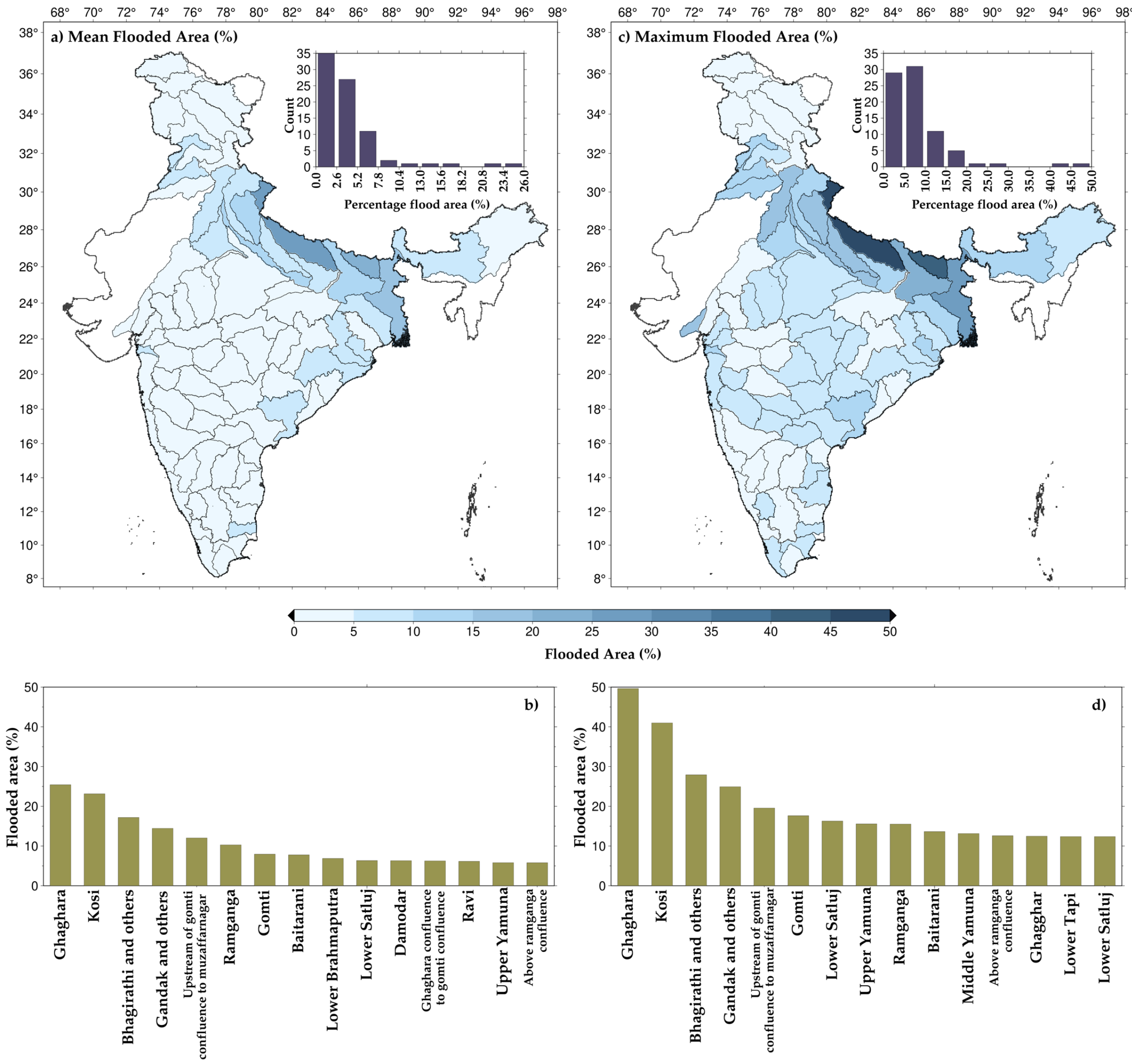

Figure 6: (a) Mean of annual maximum flooded area (percentage) between 1901-2020 and the overall distribution (b) highlighting the top fifteen sub-basin. (c) Historical maximum flooded area (percentage) and the overall distribution (d) highlighting the top fifteen sub-basin.

3.3 Influence of reservoirs on flood extent

We selected and considered 51 major reservoirs to examine their influence on flood risk based on the availability of the observed storage data. We estimated C-ratio for each sub-basin considering the river flow at the outlet to investigate the impact of reservoirs on streamflow. C-ratio can vary between zero to infinity, and higher values indicate the prominent effect of dams on river flow. We identified sub-basins with a greater influence on dams based on the C-ratio. We find that Beas, Brahmani, upper Satluj, Upper Godavari, Middle and Lower Krishna, and Vashishti are among the most influenced by the dams. Beas sub-basin has the highest C-ratio (4.16) among all the sub-basin in the Indian sub-continent (Figure 7a). Out of the 80 sub-basins, only eleven have C-ratio greater 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 reservoirs in our analysis. However, there are several major and minor dams for which observed data is unavailable. Therefore, the influence of reservoirs based on the C-ratio might need to be considered. However, our analysis indicates that dams in a few sub-basins can significantly alter the river flow and flood risk. For instance, dams effectively alter extreme flow's timing, duration, and frequency (Mittal et al., 2016). C-ratio alone may not effectively capture the influence of dams on floods; therefore, we multiplied the fractional area affected by floods and the C-ratio for each sub-basins. For instance, if a sub-basin is considerably affected by dams and has a large flood extent, the value of the multiplied ratio will be higher. The multiplier ratio can effectively identify the sub-basins with high flood-affected areas and flow regulated by the reservoirs. We find that Beas, Brahmani, Ravi, and Lower Satluj are among the highly influenced by floods and the presence of reservoirs. Overall, the sub-basins with higher C ratio and the highest flood-affected area are across the Indian subcontinent. Central India has sub-basins that are relatively less affected by floods and the presence of dams.

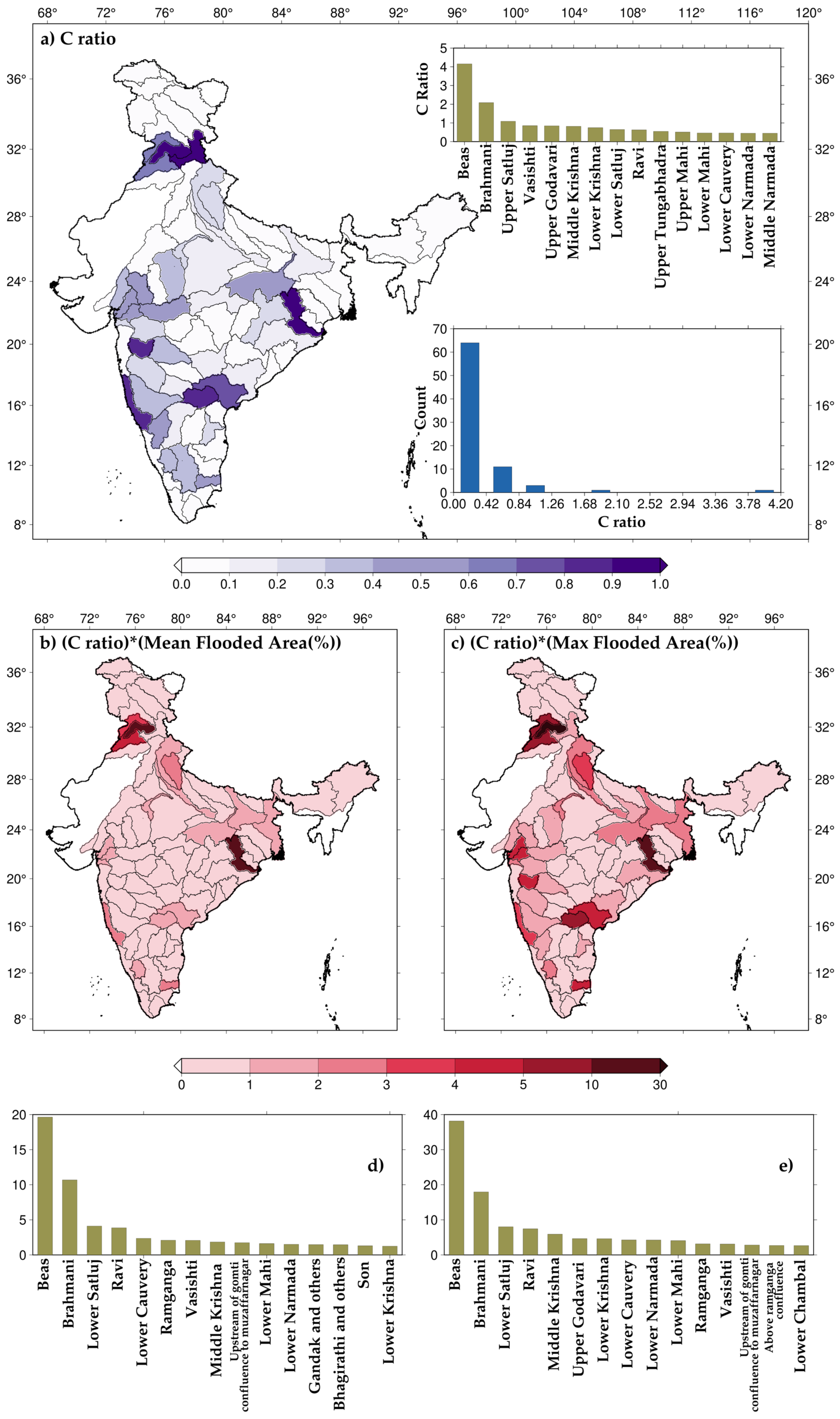
a) C ratio
C Ratio
Beas
Brahmani
Upper Satluj
Vasishti
Upper Godavari
Middle Krishna
Lower Krishna
Lower Satluj
Ravi
Upper Tungabhadra
Upper Mahi
Lower Mahi
Lower Cauvery
Lower Narmada
Middle Narmada
Count
C ratio
0.00 0.42 0.84 1.26 1.68 2.10 2.52 2.94 3.36 3.78 4.20
0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0
b) (C ratio)*(Mean Flooded Area(%))
c) (C ratio)*(Max Flooded Area(%))
0 1 2 3 4 5 10 30
d)
Beas
Brahmani
Lower Satluj
Ravi
Lower Cauvery
Ramganga
Vasishti
Middle Krishna
Upstream of gomti confluence to muzaffarnagar
Lower Mahi
Lower Narmada
Gandak and others
Bhagirathi and others
Son
Lower Krishna
e)
Beas
Brahmani
Lower Satluj
Ravi
Middle Krishna
Upper Godavari
Lower Krishna
Lower Cauvery
Lower Narmada
Lower Mahi
Ramganga
Vasishti
Upstream of gomti confluence to muzaffarnagar
Above ramganga confluence
Lower Chambal

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

3.4 Sub-basin level flood risk assessment

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

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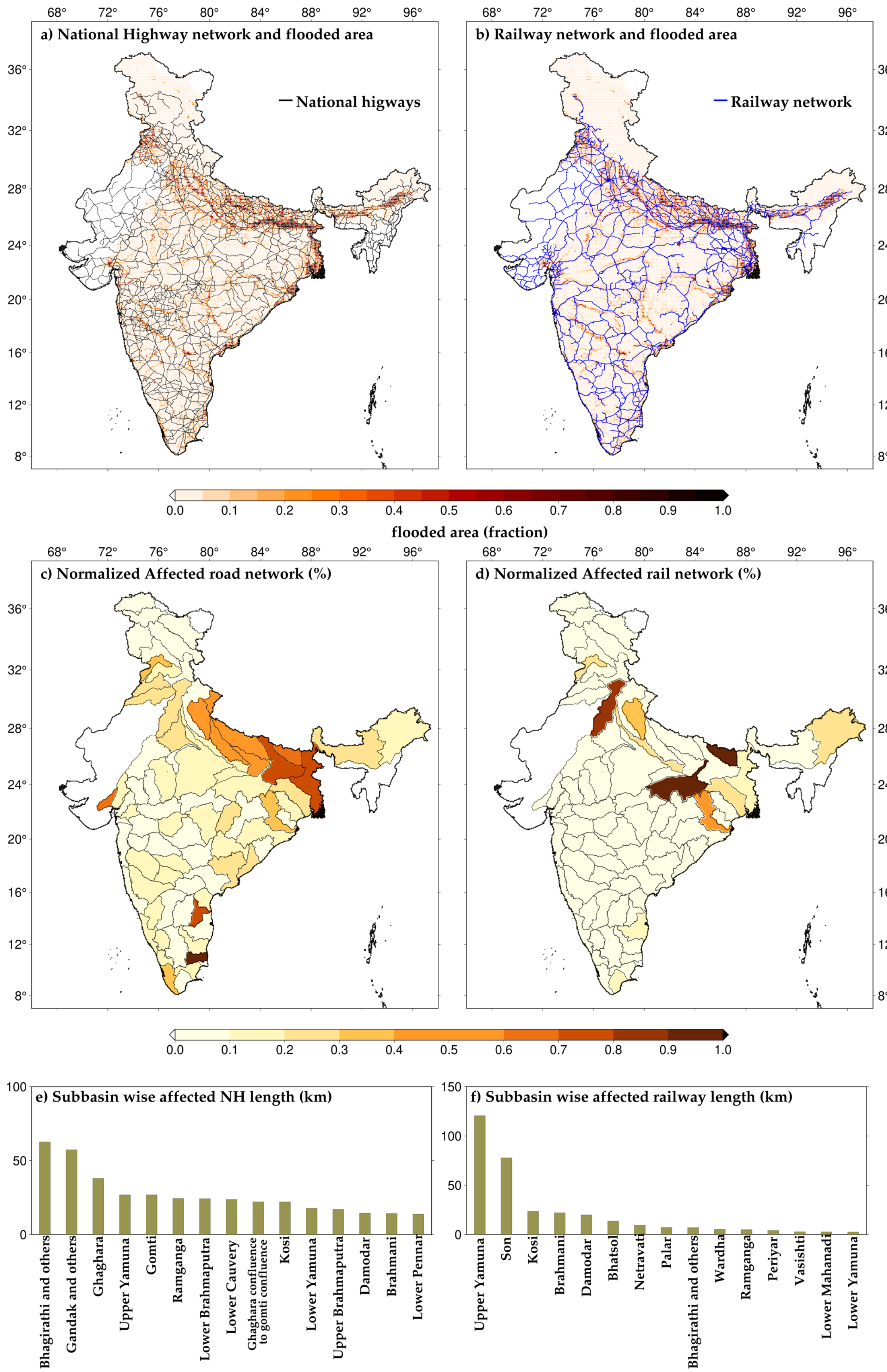

a) National Highway network and flooded area
National higways
b) Railway network and flooded area
Railway network
flooded area (fraction)
c) Normalized Affected road network (%)
d) Normalized Affected rail network (%)
e) Subbasin wise affected NH length (km)
Bhagirathi and others
Gandak and others
Ghaghara
Upper Yamuna
Gomti
Ramganga
Lower Brahmaputra
Lower Cauvery
Ghaghara confluence to gomti confluence
Kosi
Lower Yamuna
Upper Brahmaputra
Damodar
Brahmani
Lower Pennar
f) Subbasin wise affected railway length (km)
Upper Yamuna
Son
Kosi
Brahmani
Damodar
Bhatsol
Netravati
Palar
Bhagirathi and others
Wardha
Ramganga
Periyar
Vasishti
Lower Mahanadi
Lower Yamuna

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

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

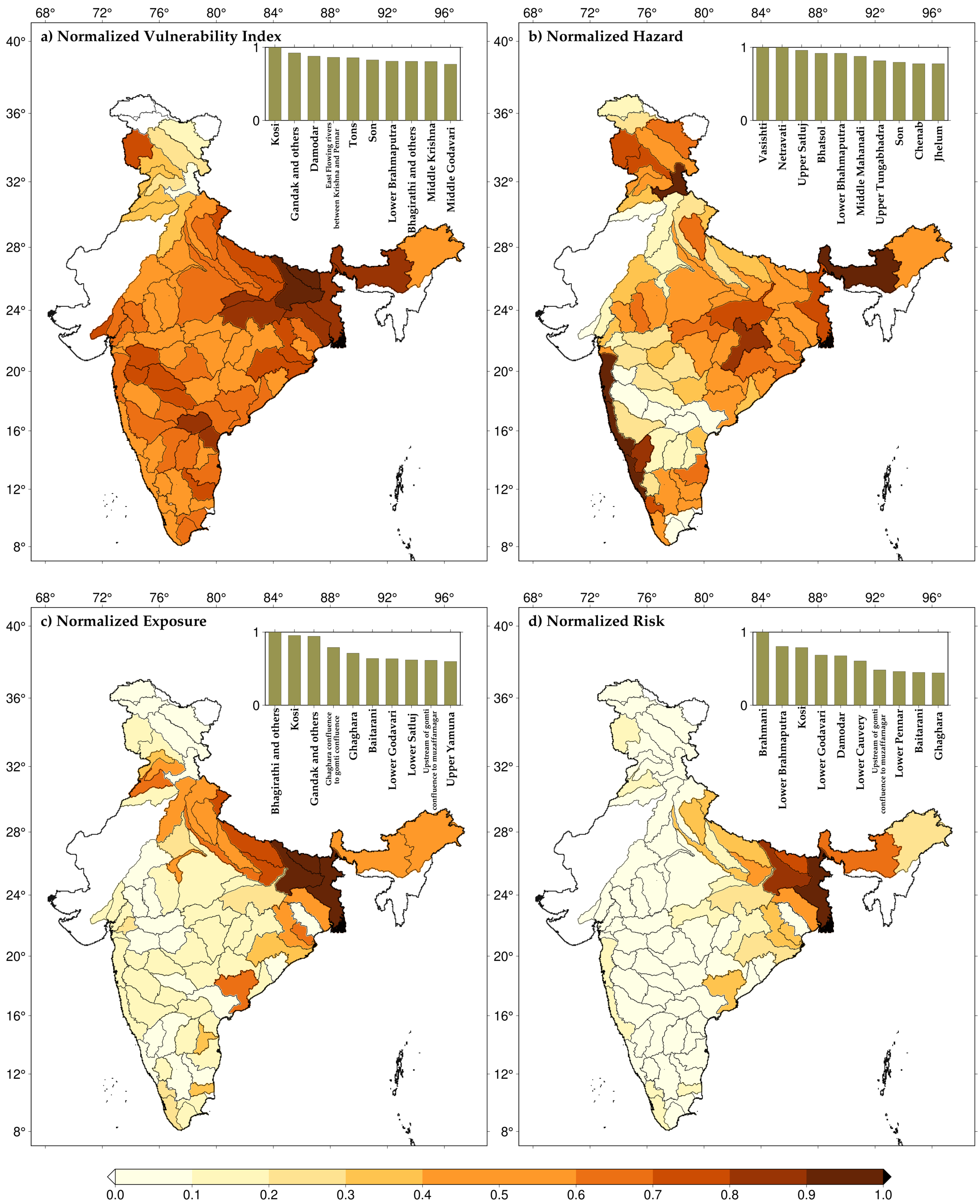

Figure 9: Sub-basin level (a) Normalized vulnerability index (b) Normalized hazard (c) Normalized exposure (d) Normalized risk. The top 10 sub-basins are highlighted as bars in panels inside the figures.

We estimated the flood risk for each sub-basin, a collective representation of vulnerability, hazard, and exposure. As expected, the flood risk is higher in the Ganga and Brahmaputra river basins compared to other parts of the country. The higher flood risk in these basins can be attributed to higher vulnerability, hazard probability, and exposure. For instance, Bhagirathi, Gandak, Kosi, lower Brahmaputra, and Ghaghra are the sub-basins with the highest flood risk in India (Figure 9d). Despite the higher hazard probability in the sub-basins of the Indus and west coast river basins, the overall flood-risk is considerably lower than the sub-basins of the Ganga and Brahmaputra river basins primarily due to less vulnerability and exposure. Our results show that flood risk in some of the sub-basins of the Ganga and Brahmaputra river basins can be reduced by reducing the vulnerability.

4. Discussion and conclusions

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

While mapping the flood risk at appropriate spatial resolution is complex and challenging, it is vital for disaster risk reduction. Flood inundation mapping that provides the spatial extent of flooding is crucial as the first responders use it during a flood emergency (Apel et al., 2009). There are several approaches to mapping flood inundation (Teng et al., 2017). We used hydrodynamic modelling to develop long-term flood inundation maps for the Indian sub-basins. Creating high-resolution flood inundation maps based on hydrodynamic modelling is computationally expensive (Dottori et al., 2016) for a large domain like India. In addition, higher-resolution flood risk mapping that can be used at the local scale for decision-making requires accurate terrain information and river cross-section datasets that are not available. For instance, freely available digital elevation models (DEM) can be too coarse to resolve the flood inundation and depth variability at a local scale (Cook & Merwade, 2009; Dey et al., 2022). The uncertainties within hydrologic outputs can primarily arise due to inaccuracies in both input data and model parameterization (Poulin et al., 2011). Inaccuracies in input meteorological data may stem from disparate sources, leading to errors in spatial and temporal interpolation (Brown & Heuvelink, 2005). Similarly, model parameterization errors, which involve assigning values to parameters governing diverse hydrological processes, can emerge during the calibration process (Laiolo et al., 2015). Moreover, there are uncertainties originating from utilizing long-term flood occurrence data to assess flood mapping capabilities. Our modelling framework that considers the influence of reservoirs provides sub-basin scale flood inundation extent as our aim was to provide a long-term assessment of flood extent in at the country scale. Additionally, downscaling of flood depths introduces biases as coarse-scale information is translated to the local scale (He et al., 2021), which might have considerable deviations from the actual observed flood extent. Given these limitations, our findings provide valuable information based on the long-term record developed using model simulations that can be used for the regional scale policy development for flood mitigation. Cloud cover during the summer monsoon, when most floods occur in India (Nanditha et al., 2022), hinders the utility of satellite data for flood inundation mapping. We calibrated and evaluated our H08-CaMa flood modelling framework using the observed flow, reservoir storage, and satellite-based inundation. However, all these datasets available from the in-situ network or satellites are prone to errors and uncertainty (Di Baldassarre & Montanari, 2009; Stephens et al., 2012; Teng et al., 2017). We used C-ratio as an indicator to quantify the influence of dams on streamflow. However, C-ratio may not fully capture the complexities and variations in the impacts of reservoir operations. Furthermore, in case of run-of-the-river (RoR) dams, the C-ratio may over-estimate the downstream hydrological impacts. Therefore, C-ratio may not solely capture the downstream hydrological effects resulting from dams. Nevertheless, it provides preliminary information on the potential dam influence on the downstream flow.

India has implemented several flood risk mitigation measures at multiple government levels. The construction of embankments along rivers is a common flood risk mitigation measure in India. These embankments help contain the floodwaters within the river channels and protect nearby areas from inundation (NDMA, 2016). The CWC in India operates a network of flood forecasting stations that collect real-time data on rainfall and water levels to forecast floods and issue warnings to vulnerable communities. Notwithstanding the considerable investments and flood-control measures, India has witnessed substantial mortality, human migration, and economic loss. Flood mortality has increased mainly because of increased frequency, not necessarily due to increased flood intensity (Hu et al., 2018). About 3% of the total geographical area of India is affected by floods every year that cause damage to agriculture and infrastructure. The top ten floods that occurred during 1985-2015 caused the mortality of more than 1000 people while more than 35 million people were displaced due to floods between 2000-2004 (Dartmouth Flood Observatory). The recent riverine floods in Uttarakhand and Kerala highlighted the growing flood risk in India, which warrants the need for flood mitigation. The recent flood in August 2022 in Pakistan caused an estimated loss of $30 billion. Both structural and non-structural measures are required for flood mitigation (Nanditha & Mishra, 2021). Our risk assessment provides policy implications towards reducing vulnerability to reduce the flood risk. Moreover, a sub-basin level ensemble forecast is needed to be used for early flood warnings in the sub-basins with higher flood risk.

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

- The coupled hydrological and hydrodynamic modelling framework based on the H08-CaMa Flood model was used to estimate the flood risk assessment in India. The hydrological modelling framework performed well against the observed flow, reservoir storage, and satellite-based flood inundation. The role of 51 major reservoirs was considered in flood risk assessment based on the long-term simulations for the 1901-2020 period.
- The sub-basins in the Ganga and Brahmaputra river basins experienced the most significant flood extent during the worst flood in 1901-2020. Similarly, the mean annual maximum flood extent is higher for the sub-basins in the two major transboundary river basins (e.g., Ganga and Brahmaputra). The worst flood affected different sub-basins on the two main flood-affected river basins in different years. Major floods in the flood-prone sub-basins of the Ganga and Brahmaputra basins occur during the summer monsoon season, especially during the August-September period.
- The sub-basins with a more prominent influence of dams based on the C-ratio were identified. Beas, Brahmani, upper Satluj, Upper Godavari, Middle and Lower Krishna, and Vashishti sub-basins are

among the most influenced by the dams. Moreover, Beas, Brahmani, Ravi, and Lower Satluj are among the most affected by floods and the presence of reservoirs.

- Flood risk is higher in the Ganga and Brahmaputra river basins compared to other parts of the country. The higher flood risk in the two transboundary river basins can be attributed to higher vulnerability, hazard probability, and exposure. Bhagirathi, Gandak, Kosi, lower Brahmaputra, and Ghaghra are India's sub-basins with the highest flood risk.

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

Competing interest: Authors declare no competing interest.

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

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