Climate change and effectiveness of dams in flood mitigation in India

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India, the third-largest dam-building nation, highly relies on dams for irrigation, hydropower, and flood control. Observations show that dams both mitigated and triggered floods across Indian river basins. However, their effectiveness in mitigating floods under current and future climates remains unknown. Using in-situ and satellite observations and model simulations for 178 major dams, we show that flood mitigation depends more on antecedent reservoir storage than upstream rainfall. Downstream floods are more likely when reservoirs exceed 90% of their full capacity. The duration with reservoir storage exceeding 90% is projected to increase threefold at 3 °C warming compared to 1 °C. A substantial rise in compound events of high inflow and high antecedent reservoir storage is also projected from 0.55 ± 0.22 events/year at 1 °C warming to 1.1 ± 0.4 events/year at 3 °C warming. Our findings highlight the need for advanced approaches for dam operations (maintaining buffer storage) integrated with early warnings of extreme inflow in India.

India is the third-largest dam-building country, with over 6000 completed large dams serving multiple purposes including irrigation, flood control, hydroelectric power generation, drinking water supply, and fish production[1,2]. The number of large dams in India has increased significantly from 1106 in 1970 to over 6000 in the last 50 years. Notably, more than 2500 large dams were built in just two decades during 1971–1990 (NRLD, 2023), largely driven by the increasing irrigation water demands and hydropower production. The primary role of dams in India is to provide water for irrigation, which uses ~91% of available water[3]. Currently, there are 150 major irrigation projects with 16.33 million hectares of culturable command area[4]. At the same time, dam infrastructure has substantially contributed to hydropower production, which accounts for the second-largest share (13%) of the total energy produced in India[5]. Irrigation requires water storage and release aligned with crop growth cycles, while hydropower favors continuous flow for maximum power production, resulting in conflicting operational objectives. In addition to irrigation and hydropower, dams are also expected to mitigate floods, which demands maintaining low reservoir levels during the summer monsoon season to accommodate high inflows. Although the role of dams for irrigation water supply and hydropower generation has been well acknowledged, their effectiveness for flood control remains debatable[6]. This raises critical question about whether dams, originally designed with specific climatic and hydrologic assumptions, can be reliable for flood control under the warming climate.

Dams are one of the several stressors affecting river flow during different seasons[7]. For instance, dams store water during the water surplus season and release water during the dry season[8]. Therefore, dams can considerably influence streamflow variability and are among the most effective measures to mitigate the impacts of droughts[9]. In addition, dams control floods in downstream regions by attenuating high inflows. Water release from the dams in a controlled manner can help in reducing the downstream peak flow and mitigate the flood risk[10,11] by lowering the flood peak and delaying the time to peak[12,13]. Palmer et al.[14] reported that dam-impacted basins are more likely to require management interventions such as sediment management, dam retrofitting or removal, and floodplain and ecosystem restoration to mitigate the impacts of climate change compared to free-flowing river basins. This concern is particularly relevant in India due to its extensive dam infrastructure. Poor decision-making under critical conditions associated with high inflow and high reservoir storage can exacerbate flood events[15]. The dam-stimulated floods are more sudden and intense, leaving a more disastrous impact on lives and properties[16]. Several regions in India faced dam-stimulated floods in the recent past—for example, sudden releases from Pandoh (Himachal Pradesh), Kaddam (Telangana), and Sardar Sarovar (Gujarat) dams caused severe downstream flooding in 2023[17]. These events highlight a disconnect between existing reservoir operation protocols and the increasing hydrological extremes intensified by climate change.

Despite the mitigation measures such as constructing flood control infrastructures, implementing land use regulations, and enhancing early warning systems, the losses that occurred from floods have increased during the past few decades[18]. The increased inflow variability under the warming climate makes dam operations and decision-making more complex and

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challenging. Examining the impacts of streamflow variability on dam storage is crucial for making informed decisions. While dams play a crucial role in regulating river flows and mitigating downstream flooding, their effectiveness is increasingly being challenged by climate change-induced alterations in hydrology[19]. Previous global-scale studies have provided broad insights into future flood exposure[20] and flood nonstationarity[21]. However, they largely focus on global or continental scales, treat reservoir regulation in a generalized manner, and offer limited coverage of Indian river basins. The role of antecedent reservoir storage and inflow has not been examined in the current and projected future climate for the major reservoirs in India. The vast network of large dams in India holds great potential to control and alter the flow in downstream. However, there remains a critical gap in understanding how the warming climate will impact dam storage dynamics and the effectiveness of dams to attenuate extreme inflows. Understanding the inflow and reservoir storage conditions is essential for improving flood risk management strategies, optimizing reservoir operations, and supporting climate-resilient water infrastructure planning in India. To address these gaps, we investigate the following key questions: 1) How do dams influence high-flow downstream of reservoirs during the summer monsoon season in India? 2) To what extent precipitation in upstream catchments of dams and antecedent reservoir storage affect high-flow variability downstream of the dams? and 3) How will the effectiveness of dams in reducing flood risk change under projected future climate scenarios? To address these questions, we use the H08[22] land-surface model combined with the CaMa-Flood[23] hydrodynamic model to simulate the historical and future dam dynamics in India and their role in floods in downstream regions.

Results
Influence of dams on floods in India
First, we examined the role of dams in flooding in the downstream regions based on the observational datasets. Dams play a crucial role in either mitigating or intensifying downstream flooding (Fig. 1). For instance, the Tehri Dam on the Ganga River reduced flooding in the downstream in 2010, 2011, and 2013[24,25]. Several large dams, including Nagarjuna Sagar, Krishna Raja Sagar, and Ukai played a major role in reducing the flood risk in the downstream regions[26–28]. During August 2019 flood in the Sutlej River, the Bhakra Dam attenuated 82.33% of the inflow, while the Pong Dam maintained zero outflow throughout the event[29]. However, during the August 2023 floods in Punjab, sudden water release from the Bhakra and Pong dams, both of which had already exceeded their full reservoir levels, contributed to the flooding in the downstream regions[30]. In addition to large water release, a high reservoir level prior to extreme high inflow conditions can exacerbate downstream flooding. For example, during September 2023, Sardar Sarovar Dam's storage level remained close to the full reservoir level despite forecasts of high inflows and extreme rainfall in the upstream catchment[31]. This resulted in a high outflow from the dam, leading to flooding in Bharuch city. Similarly, in 2015, a high discharge from the Chembarambakkam Dam into the Adyar River led to severe flooding in Chennai. In contrast, proactive dam management significantly reduced storage levels ahead of widespread rainfall in 2023, effectively preventing a similar disaster[32] (Fig. 1). However, implementing such anticipatory operations faces multiple policy and technical barriers, including fragmented data systems, limited forecasting capacity, and lack of institutional coordination[33,34].

Next, we use the model simulations to examine the influence of dams on the frequency of high-flows (>99th percentile streamflow) in their downstream regions under the two scenarios: natural conditions (NAT) without considering the role of dams and with considering the role of dams (DAM) on streamflow. We estimated the total frequency of high-flows under the NAT and DAM scenarios in the 30-year (1991–2020) period (Fig. 2A, B). In the NAT scenario, the high-flow frequency is notably higher for the dams located in central and southern India than in northern India (Fig. 2A). More than 60% of the dams across India show a total high-flow
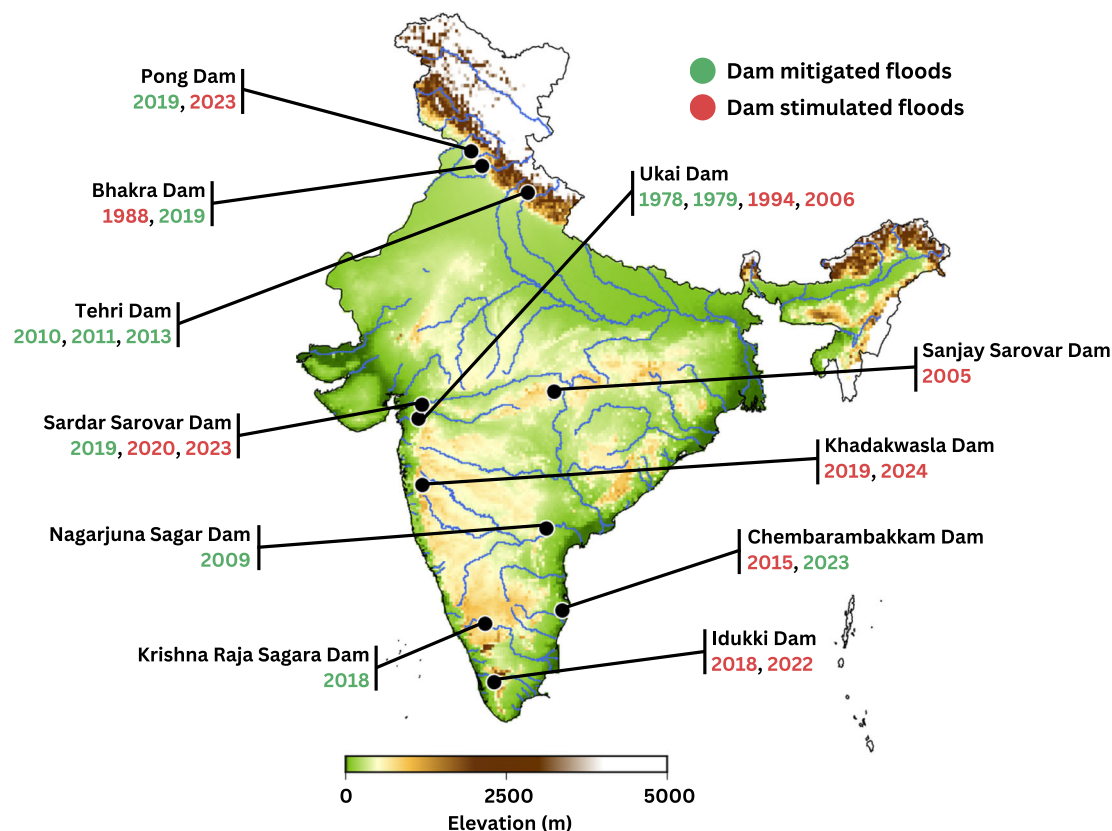

Fig. 1 | Reported cases highlighting the dual role of dams in flood events. Map illustrating the reported cases where dams played a major role in either mitigating or stimulating floods
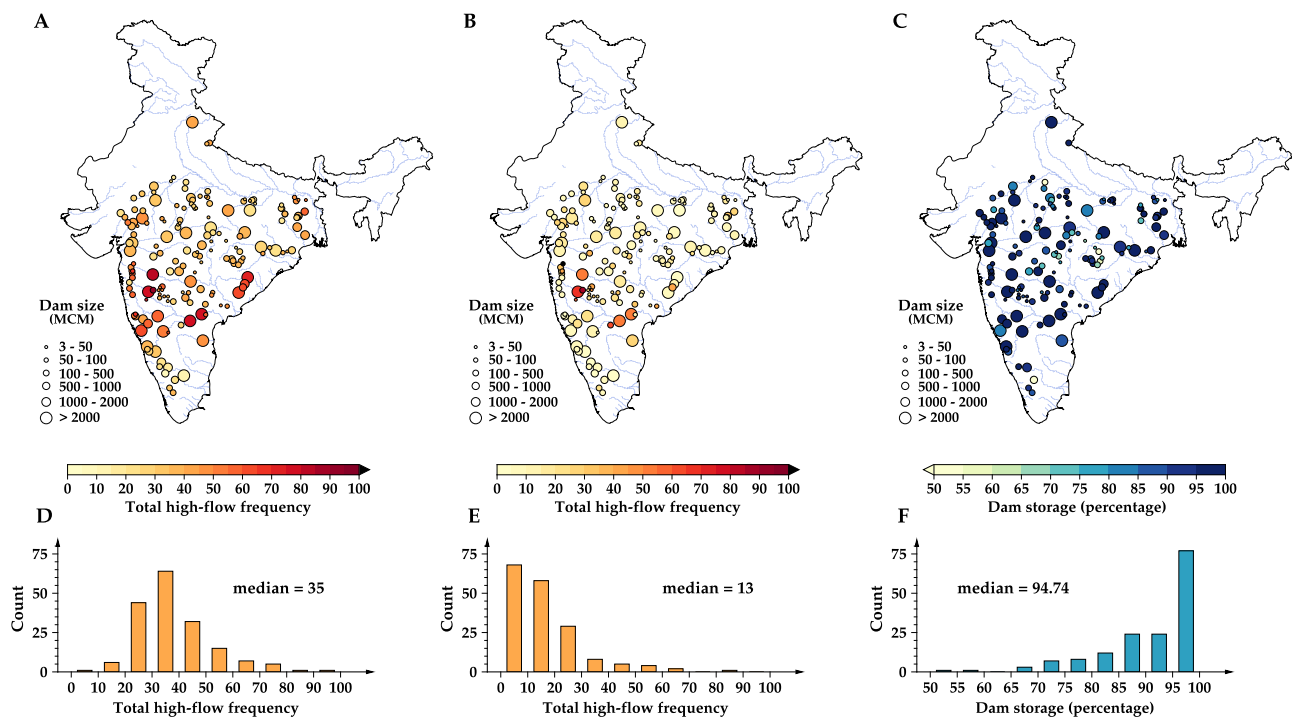
Fig. 2 | Changes in high-flow frequency and antecedent dam storage. A Total frequency of high-flows in the downstream of the dams under the NAT scenario for the 30-year period (1991–2020). **B** Total frequency of high-flows in the downstream of the dams under the DAM scenario for the 30-year period (1991–2020). **C** Corresponding antecedent dam storage one day before high-flow events in the DAM scenario. **D** Distribution of high-flow frequency under the NAT scenario. **E** Distribution of high-flow frequency under the DAM scenario. **F** Distribution of the antecedent dam storage one day before high-flow events in the DAM scenario.

frequency between 20 and 40, with median frequency of 35 during the 30-year period (Fig. 2D). However, under the DAM scenario, dams effectively reduce the total high-flow frequency compared to the NAT scenario (Fig. 2A, B). For instance, the total frequency of high-flows is less than 30 for more than 80% of the dams across India, with a median of 13 high-flow events/30-year under the DAM scenario (Fig. 2E). The effectiveness of dams to capture high inflows and reduce downstream flooding depends on the available reservoir storage capacity of the dams[35]. Thus, we analyzed the mean dam storage one day prior to the high-flow event for each dam, calculated across all the flood events under the DAM scenario to examine the antecedent reservoir storage (Fig. 2C). The median value across all the dams shows high antecedent reservoir storage (median 94%) [Fig. 2F] prior to high-flows, suggesting that when floods occur downstream of dams, most reservoirs are already near their full capacity, limiting their ability to mitigate floods. The difference in the frequency of high flows under the NAT and DAM scenarios highlights that dams considerably attenuate floods in the downstream region. However, the high antecedent reservoir storage levels before high-flow events remain the key driver in limiting the dam's ability in mitigating floods in the downstream regions.

Floods in India predominantly occur during the summer monsoon season (June–September)[36]. Therefore, we examine the changes in the high-flow magnitude (exceeding the 99th percentile) downstream of the dams under the DAM and NAT scenarios during the summer monsoon (Fig. S1A). We find that all the dams are effective in reducing high-flows during the summer monsoon. Dams with lesser reservoir storage capacity (<1000 MCM) can attenuate high-flows up to 30–43% (median change), whereas dams with larger reservoirs (>1000 MCM) can reduce the magnitude of high-flows by 47–59% (median change). Further, we examined the intra-seasonal variability in high-flow attenuation within the monsoon season (Fig. S1B–E). We hypothesize that the influence of dams in modulating high-flow is higher during the early monsoon season (June and July) due to lower initial dam storage. Our results show that the highest reduction in high-flow magnitude occurs in July (Fig. S1C), aligning with the period when dams begin to reach higher storage levels. The high-flow attenuation

persists through August and September (Fig. S1D, E) but with relatively lower reductions compared to July. Only a few dams considerably attenuate high-flow in June (Fig. S1B), whereas from July onwards, nearly all the dams play a role in regulating downstream flows.

We estimated changes in the flows using three different thresholds (exceeding 90th, 95th, and 99.9th percentiles) during the summer monsoon season individually (Fig. S2). The majority of dams do not experience extremely high flows exceeding the 99.9th percentile in June (Fig. S2L), as major floods in India occur mostly in August and September[37]. June being the onset month of the Indian summer monsoon, the frequency and intensity of extreme precipitation is relatively lower[38]. In addition, the absence of wet antecedent conditions does not create favorable conditions for riverine floods in June[39]. Lowering the threshold for high-flow conditions (from the 99.9th to the 90th percentile) increased the sample size of high-flow events, even during the June–July period (Fig. S2). As a result, several dams attenuate high-flows exceeding the 90th and 95th percentiles in June, while their influence reduces during August–September. This suggests that low antecedent dam storage leads to greater modulation of high-flow events in the early monsoon season. Moreover, large dams are more effective than small dams in reducing high-flow peaks during the onset period (Fig. S1B).

Linkage of catchment rainfall and antecedent reservoir storage with dam-induced changes

We examined the relationship of changes in high-flows with annual precipitation in the upstream catchment and antecedent dam storage for all the dams to understand how upstream hydrology influences downstream flow regulation (Fig. 3A, B). From the relationship between change (%) in the high-flow and antecedent dam storage (Fig. S3) for the four dams (Rengali, Mettur, Konar, and Sriram Sagar) located in different climatic and geographical settings, the median decrease in the high-flows due to dams was less in the years when higher rainfall in the upstream catchment was recorded. In addition, we note a considerable role of the antecedent reservoir storage on the downstream flow (Fig. S3B). High-flows show minimal change (less than 10%) in magnitude (orange points) when dam storage was
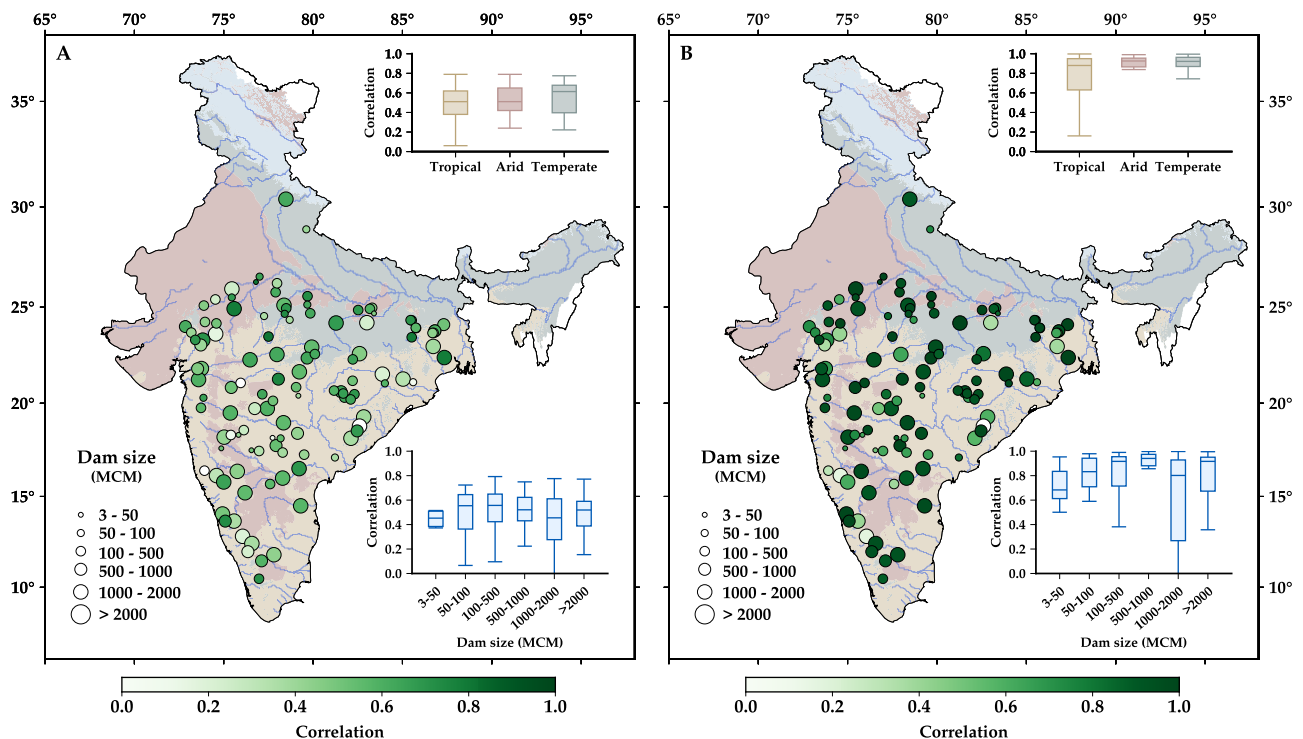
Fig. 3 | Linkage of catchment rainfall and antecedent reservoir storage with dam-induced changes. **A** Correlation between annual precipitation and the median decrease in high-flows for that year within different climate zones. **B** Correlation between antecedent dam storage and the decrease in high-flows.

above 90% of total capacity, with most flow reductions over 10% (blue points) occurring in July and August, as dams typically reached full capacity by August or September (Fig. S3C, D). Therefore, the relationship (based on correlation coefficient) was estimated only for instances where a decrease in flow greater than 10% was observed. We find a high correlation between the change in high-flows with antecedent dam storage than annual precipitation in the upstream catchment for all the dams (Fig. 3). The median correlation for all the dams exceeds 0.4 when correlated with both antecedent reservoir storage and annual upstream precipitation. However, dams located in arid and temperate climate zones exhibit a stronger relationship with antecedent reservoir storage, with a median correlation exceeding 0.9. This can be attributed to the relatively lower precipitation in such regions, which leads to greater reliance on controlled releases from reservoirs to manage downstream flows[40,41]. Moreover, because precipitation events in arid and temperate zones tend to be more episodic compared to tropical climates, operators in these zones often maintain substantial buffer storage, thereby allowing antecedent storage levels to more strongly determine high-flow attenuation[42]. In contrast, the correlation between annual upstream precipitation and the median decrease in high-flows is observed to be more than 0.5 for 57% of dams. Overall, our results highlight that the antecedent reservoir storage plays a more important role than precipitation variability in the catchments upstream of the dams. Therefore, maintaining the buffer reservoir storage that can accommodate high inflow is critical for the mitigation of flooding in the downstream regions.

Influence of dams in reducing future flood risk

We estimated the projected change in the number of days when dams remain above 90% of their live storage capacity under different global warming scenarios (1.0–3.0 °C) compared to the historical period (1995–2014) [Fig. 4]. We selected the 90% storage threshold based on the observation that dams lead to minimal change in the high-flow in the downstream regions highlighting their ineffectiveness in mitigating floods (Fig. S3). An increase in the number of days when dams remain near their full capacity is projected in the future at all the warming levels. Moreover, the duration in which dams can be ineffective increases with the increase in the

global warming level. The distribution shows a threefold increase in the median number of days, from 4.7 ± 6.7 (median ± 1 std) days at 1.0 °C warming to 14.6 ± 15.11 days at 3.0 °C warming (Fig. 4F). This trend suggests that climate change-induced shifts in hydrology will likely lead to more prolonged high-storage conditions in dams, increasing the flood risk in downstream areas.

Next, we estimated the changes in the projected frequency of compound extremes, defined here as the simultaneous occurrence of high inflow (exceeding the 99th percentile) and nearly full reservoir storage (>90%) [Fig. 5]. The frequency of the compound events is projected to rise across many dams under the warming climate. For instance, the median frequency across India remains relatively low at 0.55 ± 0.22 (median ± 1 std) per year at 1.0 °C global warming level but projected to increase by twofold (1.1 ± 0.4) per year at 3.0 °C warming (Fig. 5F). This suggests that under the higher global warming levels, dams will likely experience more frequent compound events of high inflow and high antecedent storage. These findings highlight a pressing need for adaptive dam management strategies to accommodate extreme inflows and mitigate downstream flooding.

Discussion

Globally, India is among the largely affected areas under the impact of dams[43]. The country's extensive network of dams plays a crucial role in water and flood management[44]. Several studies have examined the role of dams on the downstream hydrological regime on a regional or global scale[20,45]. We investigated the influence of dams in India on downstream river discharge, analyzing the changes induced in floods causing high-flows. Our results show that dams potentially reduce the high-flows during the onset of the summer monsoon period owing to the dam filling, and the attenuation capacity decreases as the monsoon progresses. The storage capacity of a dam before the occurrence of extreme weather events plays a critical role in determining its ability to mitigate flood risks[46]. The reduction of downstream high-flows by dams shows a strong linkage with antecedent dam storage and a moderate to strong correlation between peak flow reduction and rainfall in the upstream catchment. For instance, Zhou reported a
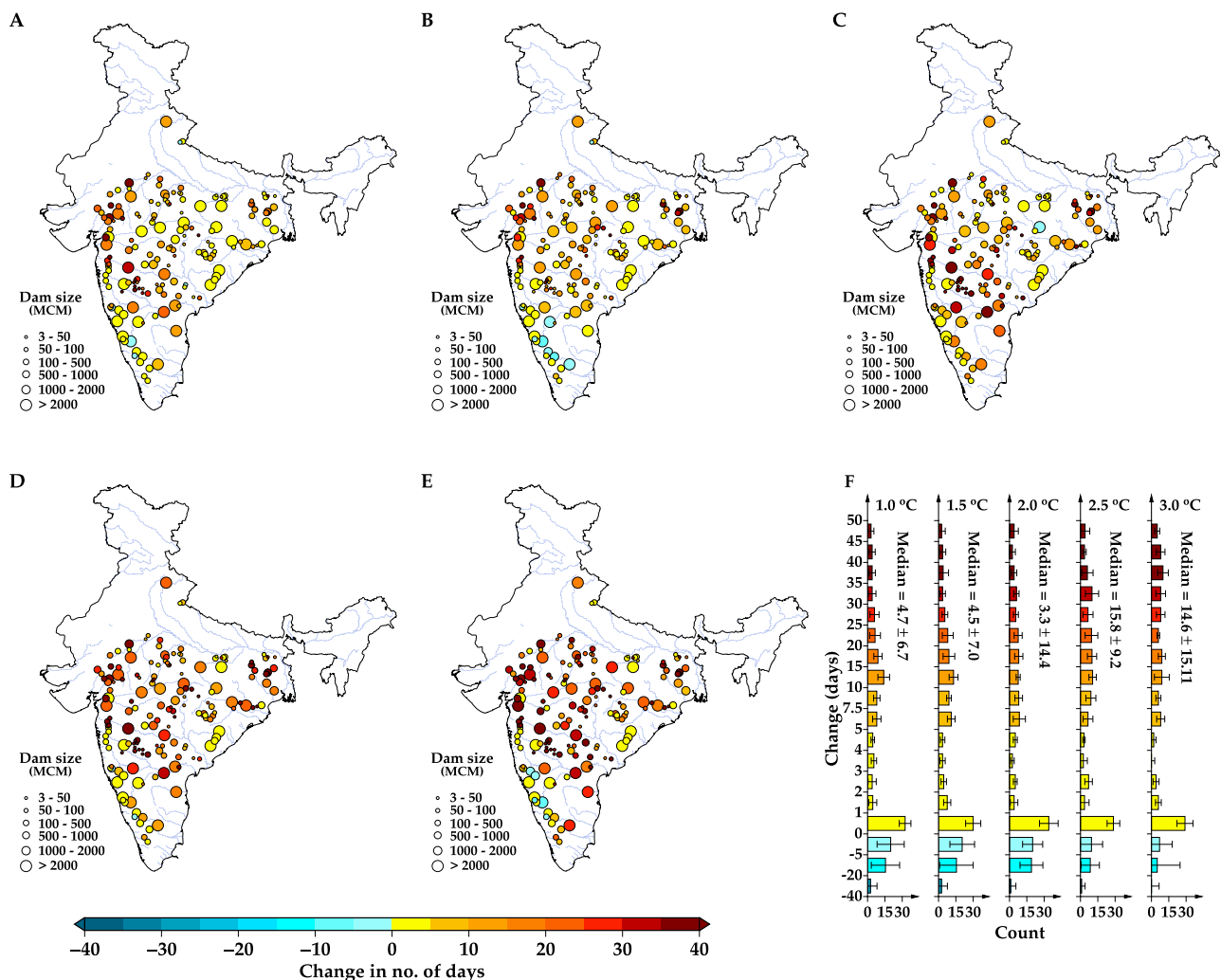
Fig. 4 | Change in days with high dam storage levels under a warming climate. Change in the number of days when dam storage remains full more than 90% of their live storage capacity for the selected global warming levels (**A** 1.0 °C, **B** 1.5 °C, **C** 2.0 °C, **D** 2.5 °C, **E** 3.0 °C). The change is computed against the historical reference period (1995–2014). **F** Distribution of change in the number of days when dam storage remains full more than 90% of their live storage capacity for the global warming levels shown through (**A–E**). The median ± standard deviation is calculated across all GCMs.

strong association between the decrease in flood risk and the flood control capacity of dams[21].

We find a significant increase in the frequency of high flows under a warming climate in the dam downstream when dams are ineffective in reducing the magnitude attributed to the full antecedent dam storage conditions. Under the warming climate, downstream regions of dams are projected to experience increased flooding attributed to prolonged high storage levels and increased high-flow frequency. Dams are projected to experience high storage levels for a prolonged period. Non-availability of adequate buffer storage in reservoirs during the summer monsoon season results in an increased risk of flooding in the downstream[47]. For instance, Lee and You[48] estimated the risk of dam overtopping under climate change for Shihmen Reservoir in Taiwan and found an increasing trend.

Our findings highlight the crucial role of antecedent reservoir storage in determining the effectiveness of dams in flood mitigation under the current and future climate. For instance, during the 2024 summer monsoon season, Krishna Raja Sagar dam on Cauvery River remained full for a record 172 days[49]. Furthermore, the dams are projected to receive highly variable and extreme inflows attributed to the precipitation changes under the warming climate. The projected increase in the magnitude and variability of inflow has been reported for different dams across the world[50–52]. The combination of extreme inflow and high storage level conditions is likely to result in more intense downstream flooding[53]. Globally (excluding dams in

China), approximately one-tenth of large dams are partially dedicated to flood mitigation, while another one-tenth are fully devoted to flood mitigation (mainly in US)[54]. In an agriculture-dominant country like India, dams primarily designed for irrigation and hydropower production can also be used for efficient flood mitigation. Lempérière[54] reported that climate change can significantly increase the need for flood mitigation in many countries, necessitating the repurposing of existing or new dams for flood control. In recent years, the operational flexibility of dams has demonstrated positive impacts under extreme climate scenarios[55]. Furthermore, dam inflow forecast plays a major role in maintaining a safe storage level during the summer monsoon period to prevent flooding downstream and meet the required demand during the dry period[56]. Effective reservoir management, incorporating advanced inflow forecasting and adaptive operational strategies, is crucial to mitigating downstream flood risks under a warming climate, especially in highly vulnerable regions like India.

We introduced a large-scale analysis incorporating 178 major dams across India using a consistent hydrological-hydrodynamic modeling framework, enabling a country-wide assessment of dam impacts under a warming climate. The combined modeling framework based on the H08-CaMa Flood model was used to estimate the dam-induced hydrological changes downstream. The hydrological modeling framework performed well against the observed flow and dam storage. The role of 178 major dams was considered in simulating the dam dynamics for historical and future
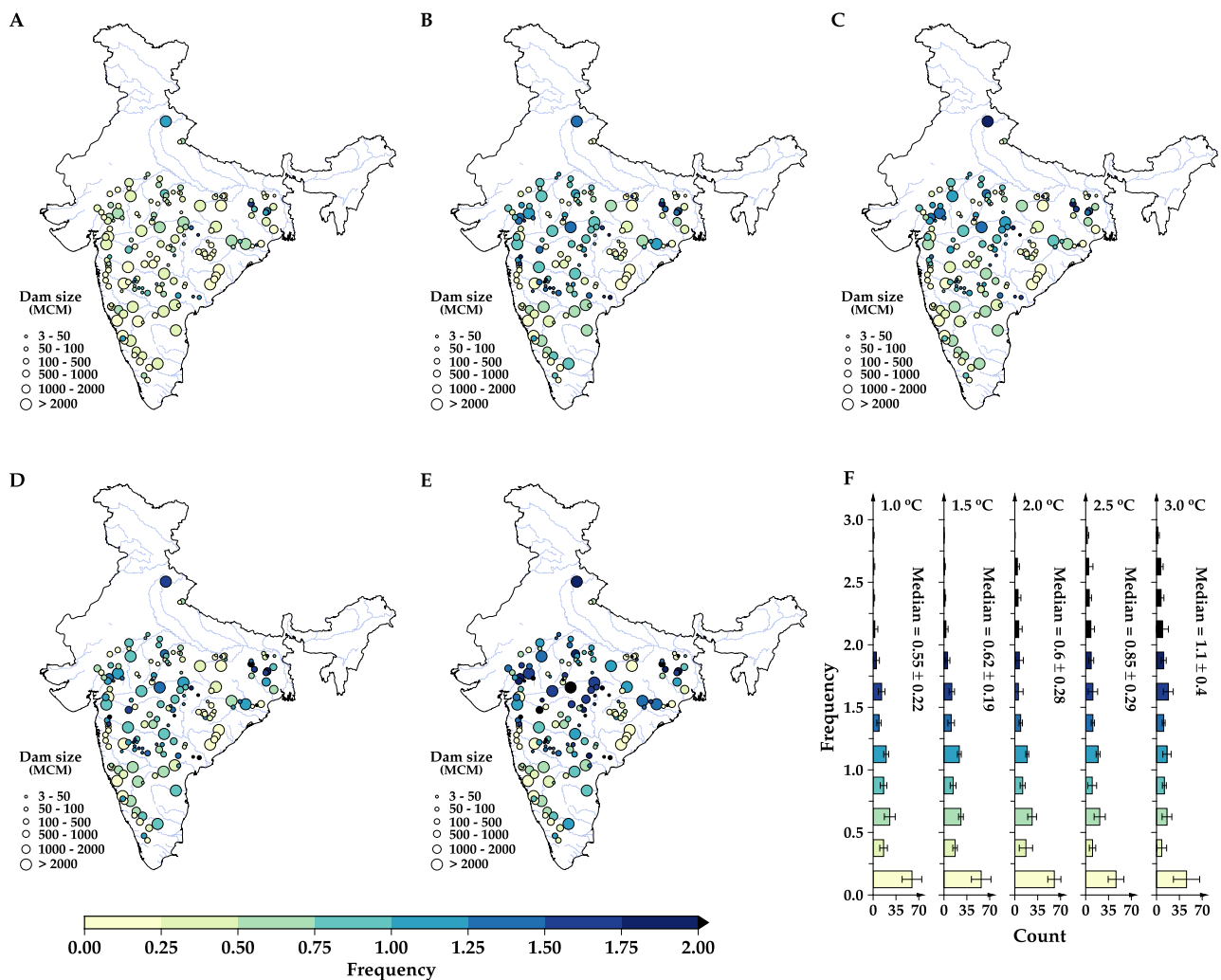
Fig. 5 | Frequency of the compound events of high inflow and nearly full dam storage under a warming climate. Frequency of high inflow events when dam storage is more than 90% of total live storage for the selected global warming levels (**A** 1.0 °C, **B** 1.5 °C, **C** 2.0 °C, **D** 2.5 °C, **E** 3.0 °C). **F** Distribution of frequency of the compound event for the global warming levels shown through (**A**–**E**). The median ± standard deviation is calculated across all GCMs.

climate. The CaMa-Flood model uses a generic dam operation scheme that does not incorporate site-specific operational rules or real-time management decisions. Dam releases are influenced by a range of factors such as reservoir purpose, inflow forecasts, socio-political priorities, and operational constraints. The absence of site-specific operational rules in the model means that certain release decisions, such as pre-releasing water in anticipation of extreme inflows, are not adequately captured. Shin et al.[45] discussed the drawbacks of relying on the generic reservoir scheme, such as limiting the model's ability to fully capture the complex dynamics of real-world reservoir operation. While we used the combination of high inflow and storage levels exceeding 90% to indicate elevated overtopping risk, estimates of Probable Maximum Flood (PMF) and dam-specific spillway design standards, and overtopping risk can further assist in quantifying the overall effectiveness of dams in flood mitigation under the current and projected future climate in India. These limitations may lead to an over- or underestimation of a dams' effectiveness in mitigating floods. The unavailability of operational rule curves and design flood hydrographs limits the accuracy of reservoir representation in the model.

Although most Indian dams are multi-purpose, incorporating dam-specific purposes and operational rules would provide a more realistic representation of release strategies. These modeling constraints need to be considered when drawing policy conclusions, as real-world operational flexibility could alter outcomes under future climate scenarios. Zhou et al.[57]

used design flood hydrographs to optimize cascade reservoir operations in the Upper Yangtze River Basin, which highlights the need to consider the operations of multiple dams for flood mitigation. In addition, structural issues such as gate failures, reduced storage capacity due to sedimentation, and delayed operational response can compromise the effectiveness of dams during high-flow events, which can lead to increased downstream flood risk are often not fully captured in model-based assessments. The use of daily time-step modeling, due to the unavailability of sub-daily meteorological observations, may underestimate the occurrence and magnitude of flash floods, which typically occur over sub-daily timescales. Additionally, we have not examined the role of dam operations over multi-day windows, which may be relevant for large reservoirs where storage and release decisions unfold over longer durations. Projected increase in inflow can further reduce the storage capacity due to sedimentation, which not only reduces the life span of the dam but also potentially increases the overtopping risk[58]. Dams in India experience a 0.72%/year sedimentation rate against the global average of 0.96%/year[59]. The loss of storage capacity due to sedimentation adds to the challenges associated with reducing flood risk under climate change.

Methods
Data
We used gridded precipitation[60] and temperature[61] observations from the India Meteorological Department (IMD) for the period 1901–2020. We

regridded the 1° gridded temperature data to 0.25° using bilinear interpolation, accounting for the lapse rate, to ensure consistency with the gridded precipitation data. Gridded daily precipitation and temperatures datasets from IMD have been widely used for hydrological modeling applications in India[62–64]. IMD's observational network only covers the Indian region, therefore, meteorological data for the region outside India were obtained from Princeton University[65]. Gridded datasets from Sheffield et al. show a good agreement with IMD observations and have been used in hydrological applications in India[62,63,65,66]. The additional meteorological forcing input variables (shortwave and longwave radiation, surface pressure and specific humidity) for the H08 land-surface model were obtained from Kushwaha et al. [67].

We obtained observed daily streamflow and dam storage from India Water Resources Information System (India-WRIS). For transboundary river basins, where daily streamflow data is not publicly available from India-WRIS, we used daily streamflow data from the Global Runoff Data Centre[68]. In addition, we used the monthly dam storage estimates from the Global Reservoir Storage (GRS) dataset[69]. The GRS dataset is prepared using multi-source satellite data to estimate storage variations of 7245 global reservoirs from 1999 to 2018. Li et al.[69] validated the performance of the GRS dataset against in situ measurements for 22 Indian dams and reported that the storage capacity values from the Global Reservoir and Dam database (GRanD) were significantly larger than those from the India-WRIS. This discrepancy can lead to overestimation of storage values, particularly for reservoirs lacking accurate capacity information. To minimize this issue, we only used GRS data for reservoirs where observed storage data from India-WRIS were unavailable. While this may still introduce some uncertainty, it enabled us to include key reservoirs that would otherwise be excluded due to data gaps. The information regarding other dam-related parameters was obtained from the National Register of Large Dams (NRLD).

We used daily precipitation, maximum and minimum temperatures from five general circulation models (GCMs; BCC-CSM2-MR, INM-CM5-0, MIROC6, NorESM2-MM, and TaiESM1) that were part of the Coupled Model Intercomparison Project (CMIP)-6 to examine the changes in the inflow and dam storage under the projected future climate. The selected GCMs effectively reproduce the observed seasonal variations in temperature and precipitation across the Indian monsoon region[5,70]. We used three scenarios: historical climate (1951–2014), and two shared socioeconomic pathways consisting of a low-emission scenario (SSP1-2.6; 2015–2100) and a high-emission scenario (SSP5-8.5) considering radiative forcing of 2.6 and 8.5 W/m², respectively by the end of 21st century. We selected these two scenarios as SSP1-2.6 represents a sustainable future, whereas SSP5-8.5 represents the most aggressive scenario because of fossil-fueled development. SSP5-8.5 also reflects a trajectory with high energy demand and continued dependence on fossil fuels[71], which remains a significant component of India's current energy sources[72]. We bias-corrected the CMIP6 projections for the five GCMs using the trend-preserving bias correction approach[73], ensuring the removal of bias while preserving the long-term climate signal. The bias-correction was performed against the observed precipitation and temperature datasets.

Hydrological and hydrodynamic models

We used the H08 land surface model[22,74] and the CaMa-Flood hydrodynamic model[23] to simulate streamflow and dam storage. The H08 model uses daily precipitation, air temperature, short and longwave radiations, wind speed, surface pressure, and specific humidity as input meteorological forcing to calculate runoff based on saturation excess non-linear flow[74]. Soil parameters (Soil Depth, Field capacity, Wilting point, Gamma, Tau) for the H08 model were obtained from the Harmonized World Soil Database (HWSD). Additionally, albedo and soil type datasets are taken from the Global Soil Wetness Project (GSWP)[75]. We ran the H08 model at 0.25° spatial and daily temporal resolution from 1901 to 2020. We considered five years as the model's spin-up period and the final run for 1901–2020 was started after the model spin-up was over. The runoff generated from the H08

model at 0.25° is used in the CaMa-Flood model to rout streamflow at 0.05° spatial resolution.

The CaMa-Flood is a hydrodynamic model, which simulates the river-floodplain dynamics[23,76]. Globally, the CaMa-Flood model has been extensively used for simulating streamflow[77,78]. The CaMa-Flood simulates river floodplain dynamics by solving shallow water equations of open channel flow while explicitly accounting for backwater effects using the local inertial approximation. The model offers a reservoir operation scheme, which has been used in many global and regional studies[45,64,79–81]. The CaMa-Flood model has been previously used to examine the hydrological changes caused by dams in various basins[82,83]. The dam module of the CaMa-Flood has also been extensively used for several other purposes such as flood dynamics downstream of dams and analyzing long-term hydrological changes[84–86]. We incorporated the influence of 178 major dams (>3 MCM storage) in India within the CaMa-Flood model based on the availability of observed reservoir storage. However, the exclusion of smaller dams and those lacking consistent observed data, including some on transboundary rivers, represents a limitation and may lead to an underestimation of localized hydrological impacts. Previous studies reported that small reservoirs, despite their individual scale, can collectively have substantial effects on stream discharge[87]. However, the collective impact of small reservoirs in a basin is often difficult to quantify due to limited data of reservoir parameters and operational activities. The model simulations were performed for the two scenarios: natural conditions (NAT) without considering the role of dams on streamflow and with considering the role of dams (DAM) on streamflow.

We manually calibrated the H08 model by adjusting the four parameters (single-layer soil depth, gamma, bulk transfer coefficient, and tau) against the daily streamflow observations at gauge stations[74,88,89] [Fig. S4]. We considered 60 gauge stations across 18 river basins to calibrate and evaluate the model. For the three transboundary river basins (Indus, Ganga, and Brahmaputra), where daily observed streamflow data were unavailable, we used observed monthly streamflow for calibration. We used the coefficient of determination (R^2), Nash-Sutcliffe efficiency (NSE)[90] and Kling-Gupta Efficiency (KGE)[91] to determine the performance of the model. Most gauge stations showed R^2, NSE, and KGE above 0.5 (Fig. S4A–C). In addition, we evaluated the model's performance in simulating annual maximum flow at different locations using bias in high-flow peaks and timing error (Fig. S4D, E). However, we did not perform this analysis for the transboundary rivers (Ganga, Brahmaputra, and Indus) due to the unavailability of daily streamflow observations. While most gauge stations exhibited moderate bias, a few stations in the Cauvery, Sabarmati, Krishna, and Mahi River basins showed a notable dry bias in the simulated mean annual maximum flow. The poor performance of the model at a few gauge stations can be attributed to the limited availability of long-term observations and the considerable influence of human interventions including irrigation, dam storage, and water diversions. Additionally, daily flow observations can be affected by measurement errors, changes in gauge location, and inconsistencies in data recording practices[92]. The mean timing error between the simulated and observed peak streamflow is less than two days at more than 80% of the gauge stations and less than three days for all the stations. Timing errors in the simulated peak flow can largely be attributed to errors in model structure, parameters, and initial conditions[93], which can be improved through data assimilation[94].

We examined the performance of the models to simulate reservoir storage. Over 70 dams exhibited NSE above 0.5, while more than 95 dams showed KGE above 0.5 in simulating live reservoir storage (Fig. S5A, C). The dams calibrated against the observations from India-WRIS exhibited better skills than those calibrated against the GRS dataset (Fig. S5B, D). Li et al. reported a large bias in the GRS dataset for a few Indian dams, which can be attributed to uncertainties such as reservoir sedimentation, reservoir geometry approximation, input data inconsistencies, water area representation, and overestimation[69]. The reservoir operation scheme may vary from one dam to another based on several factors, such as purpose, water demand, and dam location. These operation rules are altered based on the variations in inflow patterns and they highly influence the release from the dams[95].

This study used the generic dam operation scheme available within the CaMa-Flood dam module, as the actual dam operation scheme is not available.

Effect of dams and its linkage with catchment precipitation and antecedent dam storage

We examined the influence of dams on high-flows in the downstream regions by estimating the changes in the frequency of high-flow events considering the influence of dams. To do this, we calculated the frequency of high-flows exceeding the 99th percentile threshold over a 30-year period (1991–2020) under the NAT and DAM scenarios. The 99th percentile threshold was determined based on the long-term (1901–2020) streamflow time series under the NAT scenario at each location. Furthermore, we calculated the mean antecedent dam storage one day before a high-flow event in the downstream of a dam under the DAM scenario to assess the ability of dams to reduce the number of high-flow events and to determine the antecedent storage conditions when dams fail to mitigate high-flows. In addition, we analyzed the changes in the magnitude of high-flows under the DAM scenario compared to NAT scenario. For each dam, we estimated the change in downstream and reduction in the number of high-flow events. Additionally, we calculated the changes in high-flow magnitudes exceeding 90, 95 and 99.9th percentile thresholds. We accounted for different thresholds to examine how dams influence high-flow events of varying intensity. We also examined the linkage of dam-induced changes in river flows with the precipitation in the upstream catchment and antecedent dam storage.

We examined the projected change in duration (number of days) during which dams remain full under different global warming levels. In addition, we estimated the change in the frequency of compound events where high inflow events (>99th percentile) occur when dam storage exceeds 90% of their capacity, which indicates the number of instances when dams may become ineffective in mitigating downstream floods under different global warming levels. To simulate future dam dynamics under changing climate conditions, we use bias-corrected climate projections from the GCMs to run the H08 and CaMa-Flood models.

Data availability

The data used in this study are properly cited in the relevant sections. All data used for analysis are from publicly available sources. IMD data can be downloaded from the IMD website (https://imdpune.gov.in/cmpg/Griddata/Rainfall_25_NetCDF.html). The Princeton Global Forcing datasets are available from the online repository (https://hydrology.soton.ac.uk/data/pgf/). Streamflow data can be accessed from the India Water Resources Information System (I-WRIS) website (https://indiawris.gov.in/wris/#/timeseriesdata). The Global Reservoir Storage (GRS) dataset is available from the Zenodo repository (https://zenodo.org/records/7855477). The CMIP6 climate projections datasets are available from the CEDA archive (https://data.ceda.ac.uk/badc/cmip6/data/CMIP6). The codes that support the findings of this study are available from the author on request.

References

1. NRLD, C. National register of large dams. Central Water Commission. Ministry of Water Resources, Government of India (2019).
2. Pradhan, A. & Srinivasan, V. Do dams improve water security in India? A review of post facto assessments. *Water Secur.* **15**, 100112 (2022).
3. FAO. AQUASTAT Country Profile – India (2015).
4. IWRIS. command_area_development_programme — INDIA WRIS WIKI (2021).
5. Chuphal, D. S. & Mishra, V. Increased hydropower but with an elevated risk of reservoir operations in India under the warming climate. *iScience* **26**, 105986 (2023).
6. Abraham, M. How dams can control floods. *The Hindu* (2018).
7. Best, J. Anthropogenic stresses on the world's big rivers. *Nat. Geosci.* **12**, 7–21 (2019).
8. Ho, M. et al. The future role of dams in the United States of America. *Water Resour. Res.* **53**, 982–998 (2017).
9. Singh, R. & Mishra, V. Enhanced modulation of streamflow flash droughts by reservoir operations in India. *Water Resour. Res.* **60**, e2024WR037036 (2024).
10. Jia, B., Simonovic, S. P., Zhong, P. & Yu, Z. A multi-objective best compromise decision model for real-time flood mitigation operations of multi-reservoir system. *Water Resour. Manag.* **30**, 3363–3387 (2016).
11. Liu, X., Yang, M., Meng, X., Wen, F. & Sun, G. Assessing the impact of reservoir parameters on runoff in the Yalong River Basin using the SWAT model. *Water* **11**, 643 (2019).
12. Dey, P., Swarnkar, S. & Mujumdar, P. Dam operation affects the evolution and propagation of hydrological extremes. *Hydrol. Sci. J.* **69**, 294–308 (2024).
13. Jain, S. K., Shilpa, L. S., Rani, D. & Sudheer, K. P. State-of-the-art review: operation of multi-purpose reservoirs during flood season. *J. Hydrol.* **618**, 129165 (2023).
14. Palmer, M. A. et al. Climate change and the world's river basins: anticipating management options. *Front. Ecol. Environ.* **6**, 81–89 (2008).
15. Acreman, M. et al. Managed flood releases from reservoirs: issues and guidance. *Rep. DFID World Comm. Dams Cent. Ecol. Hydrol. Wallingford UK* **2000**, p86 (2000).
16. Pathak, S. Comparing floods in Kerala and the Himalaya. *Econ. Polit. Wkly.* **55**, 26–32 (2020).
17. SANDRP. 2023: Incidents of Dam Induced Floods in India. *SANDRP* https://sandrp.in/2024/01/02/2023-incidents-of-dam-induced-floods-in-india/ (2024).
18. Jongman, B. Effective adaptation to rising flood risk. *Nat. Commun.* **9**, 1986 (2018).
19. Phy, S. R. et al. Understanding climate change, dam impact, and flood management in the Mekong River Basin. In *The Mekong Delta Environmental Research Guidebook* (eds. Park, E., Loc, H. H. & Tran, D. D.) 19–41 https://doi.org/10.1016/B978-0-443-23673-0.00002-7 (Elsevier, 2025).
20. Boulange, J., Hanasaki, N., Yamazaki, D. & Pokhrel, Y. Role of dams in reducing global flood exposure under climate change. *Nat. Commun.* **12**, 417 (2021).
21. Zhou, Y. Exploring multidecadal changes in climate and reservoir storage for assessing nonstationarity in flood peaks and risks worldwide by an integrated frequency analysis approach. *Water Res.* **185**, 116265 (2020).
22. Hanasaki, N., Yoshikawa, S., Pokhrel, Y. & Kanae, S. A global hydrological simulation to specify the sources of water used by humans. *Hydrol. Earth Syst. Sci.* **22**, 789–817 (2018).
23. Yamazaki, D., Kanae, S., Kim, H. & Oki, T. A physically based description of floodplain inundation dynamics in a global river routing model. *Water Resour. Res.* **47**, (2011).
24. Singh, A. K., Mani, M. & Vishnoi, R. Tehri dam–a savior from climate change led extreme events. *INCOLD J. Half Yrly. Tech. J. Indian Comm. Large Dams* **11**, 29–35 (2022).
25. Singhal, G. D., Gottumukkala, S. & Sharma, N. Review of climate change impacts on dam safety and flood mitigation issues in India. *Water Energy Int.* **62**, 60–66 (2019).
26. Kar, S. On the reliability of medium-range probabilistic rainfall predictions over river basins in India. *Mausam* **70**, 215–232 (2019).
27. Mavalankar, D. V. Lessons from massive floods of 2006 in Surat City: a framework for application of MS/OR techniques to improve dam management to prevent flood (2008).
28. Prasad, E., Joy, K., Paranjape, S. & Vispute, S. *Agony of Floods: Flood Induced Water Conflicts in India* (Forum for Policy Dialogue on Water Conflicts in India Pune, 2012).

29. Sharma, D. & Gupta, R. Role of dams in mitigating the Impacts of climate change. *Water Energy Int.* **65**, 17–24 (2022).

30. SANDRP. No dispute about role of Pong and Bhakra dams in Punjab Aug 2023 floods. *SANDRP* https://sandrp.in/2023/08/21/no-dispute-about-role-of-pong-and-bhakra-dams-in-punjab-aug-2023-floods/ (2023).

31. SANDRP. Unaccountable Sardar Sarovar operators again bring avoidable floods in downstream Gujarat. *SANDRP* https://sandrp.in/2023/09/17/unaccountable-sardar-sarovar-operators-again-bring-avoidable-floods-in-downstream-gujarat/ (2023).

32. Chidambaram, V. Flood management at Chembarambakkam: An important lesson learnt from 2015 deluge. *The News Minute* https://www.thenewsminute.com/tamil-nadu/flood-management-at-chembarambakkam-an-important-lesson-learnt-from-2015-deluge (2023).

33. Jain, S. et al. Protecting ancient water harvesting technologies in India: strategies for climate adaptation and sustainable development with global lessons. *Front. Water* **6**, 1441365 (2024).

34. Jain, S. K. et al. Hydrology and water management in the Anthropocene: challenges and opportunities with particular reference to India. *Curr. Sci.* **128**, 353 (2025).

35. Richter, B. D. & Thomas, G. A. Restoring environmental flows by modifying dam operations. *Ecol. Soc.* **12**, (2007).

36. Nanditha, J. S. & Mishra, V. On the need of ensemble flood forecast in India. *Water Secur.* **12**, 100086 (2021).

37. Nanditha, J. S. & Mishra, V. Multiday precipitation is a prominent driver of floods in Indian River Basins. *Water Resour. Res.* **58**, e2022WR032723 (2022).

38. Pattanaik, D. R. & Rajeevan, M. Variability of extreme rainfall events over India during southwest monsoon season. *Meteorol. Appl.* **17**, 88–104 (2010).

39. Nanditha, J. S. & Mishra, V. Wet antecedent conditions and high baseflow trigger widespread floods in Indian Sub-continental River Basins. *Authorea Prepr.* (2023).

40. Lehner, B. et al. High-resolution mapping of the world's reservoirs and dams for sustainable river-flow management. *Front. Ecol. Environ.* **9**, 494–502 (2011).

41. Grill, G. et al. Mapping the world's free-flowing rivers. *Nature* **569**, 215–221 (2019).

42. Veldkamp, T. I. E., Wada, Y., Aerts, J. C. J. H. & Ward, P. J. Towards a global water scarcity risk assessment framework: incorporation of probability distributions and hydro-climatic variability. *Environ. Res. Lett.* **11**, 024006 (2016).

43. Döll, P. & Fiedler, K. Global-scale modeling of groundwater recharge. *Hydrol. Earth Syst. Sci.* **12**, 863–885 (2008).

44. Narayan, P. & Bueno, I. E. The role of dams in India's water crisis. **1**, 42 (2024).

45. Shin, S. et al. High resolution modeling of river-floodplain-reservoir inundation dynamics in the Mekong River Basin. *Water Resour. Res.* **56**, e2019WR026449 (2020).

46. Kwak, J. A study for the target water level of the dam for flood control. *J. Korea Water Resour. Assoc.* **54**, 545–552 (2021).

47. Li, X., Guo, S., Liu, P. & Chen, G. Dynamic control of flood limited water level for reservoir operation by considering inflow uncertainty. *J. Hydrol.* **391**, 124–132 (2010).

48. Lee, B.-S. & You, G. J.-Y. An assessment of long-term overtopping risk and optimal termination time of dam under climate change. *J. Environ. Manage.* **121**, 57–71 (2013).

49. Shilpa, S. KRS dam water level: full for record 172 days, water level at Krishna Raja Sagar dam starts depleting. *Deccan Herald* (2025).

50. Chernet, H. H., Alfredsen, K. & Midttømme, G. H. Safety of hydropower dams in a changing climate. *J. Hydrol. Eng.* **19**, 569–582 (2014).

51. Kang, B., Lee, S.-J., Kang, D.-H. & Kim, Y.-O. A flood risk projection for Yongdam dam against future climate change. *J. Hydro-Environ. Res.* **1**, 118–125 (2007).

52. Qin, P. et al. Projected impacts of climate change on major dams in the Upper Yangtze River Basin. *Clim. Change* **170**, 8 (2022).

53. Devi, D., Baruah, A. & Sarma, A. K. Characterization of dam-impacted flood hydrograph and its degree of severity as a potential hazard. *Nat. Hazards* **112**, 1989–2011 (2022).

54. Lempérière, F. Dams and floods. *Engineering* **3**, 144–149 (2017).

55. Watts, R. J., Richter, B. D., Opperman, J. J. & Bowmer, K. H. Dam reoperation in an era of climate change. *Mar. Freshw. Res.* **62**, 321–327 (2011).

56. Sankarasubramanian, A., Lall, U., Devineni, N. & Espinueva, S. The role of monthly updated climate forecasts in improving intraseasonal water allocation. *J. Appl. Meteorol. Climatol.* **48**, 1464–1482 (2009).

57. Zhou, C. et al. Optimal operation of cascade reservoirs for flood control of multiple areas downstream: a case study in the Upper Yangtze River Basin. *Water* **10**, 1250 (2018).

58. Abdul Rahman, S. S., Che Ros, F., Abdul Razad, A. Z. & Engku Mohamed, E. A. K. A. Reservoir sedimentation and storage capacity reduction: case study of high-risk flood mitigation dam in Malaysia. in *Proceedings of the 2nd International Conference on Dam Safety Management and Engineering* (eds. Mohd Sidek, L., Salih, G. H. A., Ahmed, A. N., Escuder-Bueno, I. & Basri, H.) 537–550 https://doi.org/10.1007/978-981-99-3708-0_36 (Springer Nature, 2023).

59. CIGB, I. *Sedimentation and Sustainable Use of Reservoirs and River Systems/Sédimentation et Utilisation Durable Des Réservoirs et Systèmes Fluviaux* (CRC Press, 2023).

60. Pai, D. et al. Development of a new high spatial resolution (0.25° × 0.25°) long period (1901–2010) daily gridded rainfall data set over India and its comparison with existing data sets over the region. *Mausam* **65**, 1–18 (2014).

61. Srivastava, A. K., Rajeevan, M. & Kshirsagar, S. R. Development of a high resolution daily gridded temperature data set (1969–2005) for the Indian region. *Atmos. Sci. Lett.* **10**, 249–254 (2009).

62. Chuphal, D. S. & Mishra, V. Reconstructed streamflow for Indian sub-continental river basins, 1951–2021. Zenodo https://doi.org/10.5281/zenodo.8004633 (2023).

63. Shah, H. L. & Mishra, V. Uncertainty and bias in satellite-based precipitation estimates over Indian subcontinental basins: Implications for real-time streamflow simulation and flood prediction. *J. Hydrometeorol.* **17**, 615–636 (2016).

64. Vegad, U., Pokhrel, Y. & Mishra, V. Flood risk assessment for Indian sub-continental river basins. *Hydrol. Earth Syst. Sci.* **28**, 1107–1126 (2024).

65. Sheffield, J., Goteti, G. & Wood, E. F. Development of a 50-year high-resolution global dataset of meteorological forcings for land surface modeling. *J. Clim.* **19**, 3088–3111 (2006).

66. Shah, H. L. & Mishra, V. Hydrologic Changes in Indian Subcontinental River Basins (1901–2012). *J. Hydrometeorol.* **17**, 2667–2687 (2016).

67. Kushwaha, A. P. et al. Multimodel assessment of water budget in Indian sub-continental river basins. *J. Hydrol.* **603** (2021).

68. GRDC. *The Global Runoff Data Centre*, 56068 Koblenz, Germany.

69. Li, Y., Zhao, G., Allen, G. H. & Gao, H. Diminishing storage returns of reservoir construction. *Nat. Commun.* **14**, 3203 (2023).

70. Aadhar, S. & Mishra, V. On the projected decline in droughts over South Asia in CMIP6 multimodel ensemble. *J. Geophys. Res. Atmos.* **125**, (2020).

71. O'Neill, B. C. et al. The Scenario Model Intercomparison Project (ScenarioMIP) for CMIP6. *Geosci. Model Dev.* **9**, 3461–3482 (2016).

72. Climate Action Tracker - India. https://climateactiontracker.org/countries/india/ (2024).

73. Hempel, S., Frieler, K., Warszawski, L., Schewe, J. & Piontek, F. A trend-preserving bias correction & the ISI-MIP approach. *Earth Syst. Dyn.* **4**, 219–236 (2013).

74. Hanasaki, N. et al. An integrated model for the assessment of global water resources – Part 1: model description and input meteorological forcing. *Hydrol Earth Syst Sci* **12**, 1007–1025 (2008).

75. Dirmeyer, P. A. et al. GSWP-2: multimodel analysis and implications for our perception of the land surface. *Bull. Am. Meteorol. Soc.* **87**, 1381–1398 (2006).

76. Yamazaki, D., Almeida, G. A. M. D. & Bates, P. D. Improving computational efficiency in global river models by implementing the local inertial flow equation and a vector-based river network map. *Water Resour. Res.* **49**, 7221–7235 (2013).

77. Koirala, S., Hirabayashi, Y., Mahendran, R. & Kanae, S. Global assessment of agreement among streamflow projections using CMIP5 model outputs. *Environ. Res. Lett.* **9**, 064017 (2014).

78. Zhao, F. et al. The critical role of the routing scheme in simulating peak river discharge in global hydrological models. *Environ. Res. Lett*. **12**, 075003 (2017).

79. Hanazaki, R., Yamazaki, D. & Yoshimura, K. Development of a reservoir flood control scheme for global flood models. *J. Adv. Model. Earth Syst.* **14**, e2021MS002944 (2022).

80. Mateo, C. M. et al. Assessing the impacts of reservoir operation to floodplain inundation by combining hydrological, reservoir management, and hydrodynamic models. *Water Resour. Res.* **50**, 7245–7266 (2014).

81. Singh, R. & Mishra, V. Atmospheric and land drivers of streamflow flash droughts in India. *J. Geophys. Res. Atmos.* **129**, e2023JD040257 (2024).

82. Dang, H. et al. Hydrologic balance and inundation dynamics of Southeast Asia's largest inland lake altered by hydropower dams in the Mekong River basin. *Sci. Total Environ.* **831**, 154833 (2022).

83. Shin, S. *Investigating the Impact of Manmade Reservoirs on Large-Scale Hydrology and Water Resources Using High-Resolution Modeling* (Michigan State University, 2019).

84. Huang, S. & Hattermann, F. F. Coupling a global hydrodynamic algorithm and a regional hydrological model for large-scale flood inundation simulations. *Hydrol. Res.* **49**, 438–449 (2018).

85. Marthews, T. R. et al. Inundation prediction in tropical wetlands from JULES-CaMa-Flood global land surface simulations. *Hydrol. Earth Syst. Sci.* **26**, 3151–3175 (2022).

86. Stelly, J. et al. Reconstruction of long-term hydrologic change and typhoon-induced flood events over the entire island of Taiwan. *J. Hydrol. Reg. Stud.* **53**, 101806 (2024).

87. Habets, F., Molénat, J., Carluer, N., Douez, O. & Leenhardt, D. The cumulative impacts of small reservoirs on hydrology: A review. *Sci. Total Environ.* **643**, 850–867 (2018).

88. Dangar, S. & Mishra, V. Natural and anthropogenic drivers of the lost groundwater from the Ganga River basin. *Environ. Res. Lett.* **16**, 114009 (2021).

89. Raghav, P. & Eldho, T. I. Investigations on the hydrological impacts of climate change on a river basin using macroscale model H08. *J. Earth Syst. Sci.* **132**, 87 (2023).

90. Nash, J. E. & Sutcliffe, J. V. River flow forecasting through conceptual models part I — a discussion of principles. *J. Hydrol.* **10**, 282–290 (1970).

91. Gupta, H. V., Kling, H., Yilmaz, K. K. & Martinez, G. F. Decomposition of the mean squared error and NSE performance criteria: Implications for improving hydrological modelling. *J. Hydrol.* **377**, 80–91 (2009).

92. Walker, D., Forsythe, N., Parkin, G. & Gowing, J. Filling the observational void: Scientific value and quantitative validation of hydrometeorological data from a community-based monitoring programme. *J. Hydrol.* **538**, 713–725 (2016).

93. Ajami, N. K., Hornberger, G. M. & Sunding, D. L. Sustainable water resource management under hydrological uncertainty. *Water Resour. Res.* **44**, (2008).

94. Prakash, V. & Mishra, V. Soil moisture and streamflow data assimilation for streamflow prediction in the Narmada River Basin. *J. Hydrometeorol.* **24**, 1377–1392 (2023).

95. Feng, M. et al. Identifying changing patterns of reservoir operating rules under various inflow alteration scenarios. *Adv. Water Resour.* **104**, 23–36 (2017).

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V.M. designed the study. U.V. performed the analysis and wrote the initial draft. V.M. and U.V. finalized the draft.

Competing interests
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