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ADAPTATION TO RAINFALL EXTREMES: ROLE OF DAMS IN INDIA

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Abstract

Can large dams keep the floods at bay? In the last twenty years, major flood events in India have wreaked widespread destruction on people's lives and livelihoods. With a threefold increase in extreme rainfall event in these years, severe flood damages are likely to increase without proper risk management. The increasing trend in constructing dams necessitates careful assessment of the effectiveness of these projects as a flood adaptation measure. The study employs a state-level dataset of India for 1969-2009 on flood damages, monthly average rainfall, and concentration of types of dams in each state taking 2001 census defined state borders. The analysis uses Feasible Generalized Least Squares for estimation, while employing panel corrected standard errors to correct for contemporaneous correlation in the dataset. Controlling for population density, dam concentration and unobserved regional heterogeneity, the study finds significant adverse impact of extreme rainfall on population during the South-West and North-East monsoon periods. The results highlight that large dams built for irrigation and hydroelectric power generation have historically exacerbated flood damages, whereas multipurpose dams have reduced such damages marginally. As the frequency and intensity of extreme rainfall events and floods are likely to increase under climate change conditions, the potential of mitigation measures such as Dam Safety Act 2021 and Flood Early Warning System (FLEWS) in averting flood damages assumes significance.

Keywords: *Rainfall Extremes; Dams; Adaptation; Development*
JEL Codes: *Q54; O13; O10*

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INTRODUCTION

In recent years, the world has experienced several unprecedented floods due to climate change (Huber and Gulledge, 2011), much of which is concentrated in South and South East Asia. These events are often related to cyclones, cloudburst, and high tides, or a combination thereof, which hamper economic activities (Davenport *et. al.*, 2021; Paprotny *et. al.*, 2018; Tazen *et. al.*, 2018; Chen *et. al.*, 2020; Yan *et. al.*, 2021). India is no different with a projected increase in flood events in future (Ali *et. al.*, 2019). Goswami *et. al.* (2006) found strong influence of sea surface temperature anomalies over the tropical Indian Ocean on the coefficient of variability of daily precipitation during summer monsoon season. Linking this increasing trend to erratic precipitation patterns, Chaudhuri *et. al.* (2010) and Chowdary *et. al.* (2019) among others, found out that Indian summer monsoon rainfall and circulation has become anomalous. Needless to say, the consequences translate to significant unplanned costs on various economic agents leading to loss of welfare. Significant human and economic impact of extreme weather events like floods is well documented in India (see, Parida, 2020; Parida *et. al.*, 2021).

The capacity to undertake adaptation measures by different stakeholders is often determined by their income, social institutions they live in, cognitive abilities, etc. Simultaneously, mitigation and adaptation of large scale disasters fall under the scope of national governments and international organizations. These measures, which may include large or small scale interventions, provide better results when not left in the hands of private sectors (Patt *et. al.*, 2010). Government intervention and programs have often ignored their long run impacts in view of short term gains (Cimato and Mullan, 2010). One such policy measure that was implemented worldwide during the second half of last century is construction of Dams. Developing countries have used dam as a multifaceted tool to address welfare issues like poverty alleviation through irrigation and flood control. Dams were viewed as a vehicle of development and the Multi-purpose River Valley Development (MPRVD) projects gained significant momentum in India around the time of its independence. Construction of Dams in India had found its origin in the Keynesian fiscal stimulus approach in the context of the US macro-economic planning to stave off economic depression like situations (D'Souza, 2003). Institutions like World Bank believed that the answer to poverty alleviation of developing countries lie in the power to tame the gorging rivers which led them to undertake investments making them the largest financier of large dam construction in the early 1970s (Goodland, 2010). Dam construction helped in bringing more cropland under irrigation, harnessing “cheap” power and facilitating a growth path. However, these interventions ignored the consequences of water salinity, erosion of watersheds, mass displacement of people, devastating changes in ecosystems, and drastic modification of geographical terrain. In spite of these adverse effects associated with dams, India has seen a large increase in dam construction since 1971. As of 2017, India had 5264 Large dams with 437 additional dams under construction (National Register of Large Dams, 2018). Once constructed, dams are irreversible investments. While weather extremes, particularly rainfall variability and extremes were not a policy concern in 1980s, constructed dams now pose threats when exposed to the increased variability in precipitation and rainfall extremes. Given the precipitation anomalies in recent decades, it is important to evaluate whether dams mitigate flood risks or not, especially in the emergence of climate change and associated unpredictable risks. A recent assessment of large Indian dams (Central Water Commission, 2020) has shown higher than design rate of sedimentation in the dams on east flowing rivers of India, and on the rivers of Indo-Gangetic plains. Higher sedimentation rate translates to loss of live storage capacity of reservoirs. This increases the probability of a flood in the catchment area and release of debris downstream.

In the last six decades, India has lost approximately Rs. 4.7 trillion (in current prices) and 1695 lives on an average to flood (CWC, 2019). According to the Jal Shakti Ministry of India, India has suffered a loss of Rs. 95,736 crore in 2018 floods – a three-fold increase to the financial loss due to floods in 2017. In the last two decades, extreme rainfall events have increased steadily in North, North East, and South India due to possible rise in sea surface temperature leading to floods (Mukherjee *et. al.*, 2018). With a rise in flood intensity, flood damages have also increased. Chennai floods in 2002, 2005, and 2015, the Mumbai floods of 2005 and 2021, 2013 Kedarnath flood, and 2018 Kerala flood are some of the notorious flood events in the recent history of India. In 2020, India faced three deadly flooding events – one in West Bengal and Jharkhand due to Cyclone Amphan, one in Assam and Meghalaya due to extreme rainfall, and one in Bihar due to sudden downpour in Nepal. Fortunately, with technological development, losses can be prevented with early warning systems (Perera *et. al.*, 2019). However, India is still in the early stages of implementation of automated Flood Early Warning Systems (FLEWS), developed jointly by The Energy and Resources Institute (TERI) and National Disaster Management Authority (NDMA). If the existing and under construction dams are more likely to facilitate flooding events as argued above, then a case can be made for speedier implementation of early warning systems and other technological solutions for reducing the flood induced losses.

This study empirically estimates the flood damage function and examines the role dams have historically played as an adaptation measure to extreme rainfall induced floods in India. The study assesses flood vulnerability in relation to summer monsoon (June-September) rainfall variability, and winter monsoon (October-December) rainfall variability separately. The study relies on a state-level panel dataset from 1969 to 2009 which combines flood damages data for 25 states, monthly precipitation data for each state, number of dams in the states, and other control variables including typology of dams and region-specific characteristics. Rest of the paper is organized as follows. The next section discusses the relation between floods, extreme rainfall events, and dams which is followed by description of the data employed in this study. In the sections that follow, methodology along with variable construction is discussed, which is followed by the results. The last section discusses the limitations along with the findings and policy implications of the study and provides conclusions.

Rainfall Shocks, Flood Damages and Dams

Floods cause damage through impact on houses, infrastructure, agricultural produce, human lives, livestock, or through its impact on livelihoods due to migration, or via impact on ecological conditions like soil composition, quality of watershed, groundwater recharge capacity, etc. India has suffered from floods owing to the complex river system that crosses its geographical area, coupled with extreme rainfall events, and environment-endangering human activities.

Assessment of flood induced damages depends on the nature of damage. In addition to the often accounted direct impacts such as loss of property, damage to infrastructure, crop losses, and human and livestock losses, floods can also cause indirect impacts. Such indirect impacts due to floods can be either permanent or temporary. Affected residents might have to move out and seek shelter till the flood water recedes, leading to temporary migration which reduces the intensity of economic activities in flooded regions and generates pressure in regions to which the population migrates (Wamer and Afifi, 2014). Short term migration due to flood can act as a social stressor through potential unemployment, lack of entitlements, and a burden for future sustenance (Carleton and Hsiang, 2016). Further, flood damages can induce permanent loss such as psychological trauma, leading to loss of standard of living and mental health, endangering the factors of production.

Increased variability in rainfall and/or extreme weather patterns along with tropical storms have often been associated with consequent landslides, loss of business, loss of lives and livelihoods and irreparable ecosystem damages. Rainfall anomalies therefore posit randomness in risk structure making risks unpredictable and forecasting exercise erroneous. Available response strategies also provide limited options to hedge against such risks completely. Available evidence suggests that the forecasting of extreme precipitation events is still imprecise in India (Shastri *et. al.*, 2017). In case of consequent floods, forecasting gets further complicated due to the complex local environmental feedback system.

Although dams could act as an adaptive measure against rainfall induced floods, they may also exacerbate vulnerabilities during extreme rainfall events (Thakkar, 2018). In terms of irrigation benefits, Duflo and Pande (2007) assessed the distributional effects of dams across Indian districts for 1971 to 1999. The results clearly showed that while the downstream regions reap the benefits from large irrigation dams, upstream regions bear the cost of watershed erosion, water turbidity, and other similar social costs. During extreme rainfall, a dam may put both upstream and downstream regions vulnerable to flood. As of 2017, India had 5254 dams with another 447 dams under construction. These dams are often managed by different authorities, bringing on board lack of communication and coordination on managing them. Water surge from extreme rainfall transcend both state and national administrative boundaries. Coordination failure aggravates the cascading effect of dam failure due to jurisdiction red tapes (Pathak, 2020). According to the CAG report submitted to the parliament in 2017, only 7 percent of the constructed dams have emergency plans (CAG, 2017). In the last two decades, severe floods were often associated with dam failures and breached embankments (Thakkar, 2018). Against this backdrop, it is pertinent to explore whether construction of more dams makes a region more susceptible to disaster risk, and reassess the role of dams in enhancing adaptive capacity besides serving as development investment. Despite being a contentious topic in the policy arena (Damle, 2021), there has been relatively less empirical evidence on the role played by the dams in the event of extreme rainfall. The present study focuses on this aspect and employs statistical analysis to gain insight on interlinkages between flood damages, rainfall, and presence of dams in India.

Data

The objective of the study is two pronged – to assess whether extreme rainfall shocks caused floods, and, to analyse if dams helped in reducing the corresponding flood damages. The study focuses on 25 Indian states over the time period 1969-2009. The data used for analysis can be categorized as outcome data on flood damages, weather data on precipitation, and covariate data on dams and state-wise population.

Outcome Data

The flood damages data for every state over the period 1969-2009 has been gathered from Central Water Commission (2018) report on Flood Statistics from 1953-2016. It reports 10 different statistics for flood damages including, area affected (Million Hectares), population affected (Millions), damages to crops (Rs. in crore), value of house damage (Rs. in crore), human lives lost, cattle lost, number of house damaged, damage to public utilities (Rs. in crore) and also total damages for each year (Rs. in crore). After India's independence, the Indian state administrative boundaries have undergone periodic changes until 1966-67 which involved transfer of several sub-regions of one state to another. With a two-year transition period for all administrative records and databases, the collected flood statistics at the state level after 1969 can be considered consistent. Hence 1969 was treated as the starting period for the study's analysis. Data for the states of Jharkhand, Chhattisgarh, and Uttarakhand, carved out in 2000-01, were merged with their corresponding parent states.

Weather Data (Precipitation)

Precipitation data have been sourced from India Meteorological Department (IMD). The data is given as total precipitation (in mm) per month for each month of each year from 1969-2009.

Dams Data

The dams data have been compiled from the National Register of Large Dams (NRLD) which includes all dams in each state with names, year of completion, geographical attributes and several dam specific attributes like gross storage capacity, effective storage capacity, volume, height, designed spillway capacity, etc. According to the International Commission on Large Dams (ICOLD), "a large dam is classified as one with a maximum height of more than 15 metres from its deepest foundation to the crest." Other dams with heights between 10 to 15 metres have also been included in the classification of a large dam provided the dam satisfies certain conditions. The candidate dam should have either a length of crest of the dam which is not less than 500 metres; or, capacity of the reservoir formed by the dam is not less than one million cubic meters; or, the maximum flood discharge dealt with by the dam is not less than 2000 cubic meters per second; or, the dam has special difficult foundation problems; or, the dam is of unusual design (CWC, 2018). Dams construction in India since 2000 has slowed down significantly.[1] Keeping this in view and the long gestation period pertaining to dams construction, the first decade of the 21st century was included for the analysis.

State-Wise Population Data

State-wise total population data was sourced from Handbook of Statistics on Indian States 2018-2019 (RBI, 2019) which tabulates the census data of population for the Census years of 1951, 1961, 1971, 1981, 1991, 2001, 2011. The population data for the non-Census years was assessed through linear interpolation.

METHODOLOGY

Variables Construction

To assess the effect of rainfall on floods damages the study takes into account two types of weather variables – rainfall anomalies and extreme rainfall events. Rainfall anomalies are defined as deviation of each rainfall realization from its long-term average. Let x_{it} be the observed rainfall (in

[1] During 2000-2009 a total of 664 dams have been completed, compared to almost eight times higher number between the period 1969-2000.

mm) during South-West (henceforth JJAS, referring to the months June, July, August, and September), or North-East (henceforth OND, referring to the months October, November, and December) legs of monsoon for *i*th state in *t*th year. Let $\bar{x}_i$ denote the long term (41 year) rainfall average for *i*th state. Then rainfall anomaly is defined as $(x_{it} - \bar{x}_i)$. The standard deviation of rainfall for *i*th state, σ_i, captures the variability in rainfall and is used to standardize the rainfall anomaly. The standardized rainfall anomaly denoted by SA_{it} is then defined as:

$$SA_{it} = \frac{x_{it} - \bar{x}_i}{\sigma_i}$$

The extreme rainfall variable takes into account the extremities of the observed rainfall for each month of the year. The variable is defined as a binary variable. Let $\bar{x}_t$ be the national monthly average for year *t* and σ_t be the standard deviation of national rainfall for that month of year *t*. Let R_{it} denote the monthly extreme rainfall event observed. Then,

$$\begin{aligned} R_{it} &= 1, \qquad if\ x_{it} > \bar{x}_t + \sigma_t \\ R_{it} &= 0, \qquad if\ x_{it} \leq \bar{x}_t + \sigma_t \end{aligned}$$

Therefore, a state records extreme rainfall event in a month if the recorded rainfall in that state during the month is more than one standard deviation of the national average for the month under consideration in year *t*.

The study uses flood affected population as its outcome variable. Through their effect on population, floods affect drivers of the economic activities of a state, indirectly harming and halting businesses, organizations, livelihood and standard of living. Limited number of studies use population affected data in econometric modeling of flood damages assessment due to its unreliability on account of poor reporting of such events and the role played by socio-political factors. The alternative is to use assessed value of damages in monetary terms. Central Water

Commission (CWC) of India collects damage assessment reports from state governments and several disaster management agencies. As centralized process of data collection becomes riddled with uncertainty due to temporary population movement, reliability of the monetary damage estimates may be questioned. Total damages, value of crop damages, value of damages to public utilities as reported by CWC (2018) are expressed in monetary terms where the money metric, the price, remains in blur. Moreover, these estimates do not always rely on surveys of the affected population since transaction costs to conduct surveys tend to be high. Further, in a decentralized setup, individuals reporting their own damage during a survey may also inflate their reported estimates. However, such measurement errors may be systematically upward biased and may not interfere with the damage distribution and damage function estimation. Given this background, the statistic on flood affected population is used as the relevant outcome variable for its relative superiority over the other damage statistics reported by CWC (2018).

Base analysis of the study uses natural log of flood affected population. The study further uses the statistic on flood affected population to construct two new variables, namely proportion of population affected and mean absolute deviation of affected population from the long-term average. Let z_{it} and P_{it} denote the flood affected population and total population respectively, for *i*th state in *t*th year. Proportion of population affected by occurrence of flood is defined as $PP_{it} = \frac{z_{it}}{P_{it}}$. The mean of absolute deviation of population affected is defined as $PAA_{it} = \frac{\sum_{t=1}^{41} |z_{it} - \bar{z}_i|}{41}$, where $\bar{z}_i$ is the long-term average of population affected for *i*th state, and the denominator captures the number of years over which the data is used.

Early warning systems often play a key role in minimizing the population affected due to floods. However, due to unavailability of state-specific early warning system information the study could not include the controls for the same.

As dams could be viewed as an instrument for adaptation to rainfall extremes, number of dams could capture the capacity of a state to adapt to rainfall shocks. As a country develops, developmental infrastructures like dams will accumulate in a region. Therefore, the dam variable, defined as the number of large dams in a state, increases over time. The dam variables have been constructed from NRLD Report 2018 (CWC, 2018) based on the total number of dams in each state constructed for Irrigation, Hydroelectric Power Generation and Multipurpose. Multipurpose subsumes all the categories barring irrigation and hydel power, that is, it includes water supply dams, flood control dams, fishery reservoirs and a combination of two or more purposes. It may be noted that dams considered for the analysis are large dams and, therefore, do not include small dams or dykes. Dam variables used in the econometric models include the number of each type of dams whose construction was completed in a given year for a given state and the total number of dams; (i.e., an aggregate of the three categories), for each year in each state.

The study introduces population density to control for increasing population in a region which, over time, becomes vulnerable to calamities like floods. Population density for a state is defined as the ratio of population for that state in t^{th} year and the geographical area of the state.

As flood is a geographical phenomenon, it could be correlated with a number of unobserved spatial heterogeneous factors at a regional level rather than at state level. Including region fixed effects is therefore justified instead of state fixed effects. Regional dummy variables are constructed based on the region the state belongs to. Adhering to administrative boundaries, India can be classified into six regions, namely, North, East, West, South, Central and North-East (see Table 1).

Table 1: Classified Regions and Corresponding States

Regions	North	North-East	South	Central	East	West
States	Jammu and Kashmir, Punjab, Haryana, Uttar Pradesh (including Uttarakhand) Himachal Pradesh.	Arunachal Pradesh, Assam, Tripura, Meghalaya, Mizoram, Manipur, Nagaland, Sikkim.	Andhra Pradesh, Karnataka, Tamil Nadu, Kerala	Madhya Pradesh (including Chhattisgar) Maharashtra.	West Bengal Bihar (including Jharkhand) Odisha.	Gujarat, Rajasthan, Goa.

The descriptive statistics of the variables used for analysis are presented in Table 2. The variable column lists the names of each variable along with their respective names in parentheses as used in the result tables hereafter. The total sample size of the pooled dataset is 1025. Natural logarithm of flood affected population has only 595 observations compared to two other outcome variables – mean absolute deviation of affected population and proportion of population affected. Moreover, the natural logarithm of the population affected has a highly skewed distribution. Relatively, the other two outcome variables are more centered. The JJAS and OND anomalies are observed to be highly varying across regions due to their path of movement over India. Standardization of these two anomalies reduces skewness and centers them around their mean as is evident from Table 2.

The maximum number of dams variable shows the maximum number of the dam registered in a state. A large number of irrigation dams are located in places that record lower rainfall than the national average. For instance, in 2009, Maharashtra had a total of 1967 dams, 1856 of which are for irrigation purposes.

Table 2: Descriptive Statistics

Variables	N	Mean	Std. Dev.	Min	Max
Flood Damage Variable					
Natural Log of Population Affected (popaffl)	595	-0.633	2.292	-6.908	3.413
Population affected anomaly (md_popaff)	1025	1.426	1.625	0.003	6.101
Proportion of Population Affected (prop_pop)	804	0.0701	0.1816	0.000	3.35
Rainfall Variables					
Mean Deviation of JJAS rainfall (md_jjas)	995	-0.000153	353.452	-1711.72	4374.68
Mean Deviation of OND rainfall (md_ond)	1000	7.64e-07	100.298	-333.798	1144.10
Standardized JJAS anomaly (a_jjas)	995	6.31e-08	0.988	-2.782	3.942
Standardized OND Anomaly (a_ond)	1000	7.36e-09	0.988	-2.311	4.910
January Extreme	1025	0.144	0.352	0	1
February Extreme	1025	0.159	0.366	0	1
March Extreme	1025	0.189	0.392	0	1
April Extreme	1025	0.187	0.390	0	1
May Extreme	1025	0.187	0.390	0	1
June Extreme	1025	0.153	0.360	0	1
July Extreme	1025	0.140	0.348	0	1
August Extreme	1025	0.136	0.343	0	1
September Extreme	1025	0.164	0.370	0	1
October Extreme	1025	0.161	0.368	0	1
November Extreme	1025	0.145	0.353	0	1
December Extreme	1025	0.131	0.337	0	1

Dam Variables					
Irrigation Dam (irr)	1014	122.1	288.953	0	1856
Hydroelectric Dam (hydel)	1014	3.686	7.641	0	33
Multipurpose Dam (multi)	1014	7.352	13.949	0	97
Total Dams (total)	1025	131.709	301.186	0	1967
Control Variable					
Population Density (popden)	1025	0.000251	0.00021	0.0000053	0.001

Source: Authors' own calculations

Note: The variable column lists the names of each variable along with their respective names in parentheses as used in estimates' tables hereafter. Population density (popden) is the number of people per square kilometer.

Arid and semi-arid regions like Madhya Pradesh, Gujarat, and Rajasthan, in the same year, had 1087, 596 and 187 irrigation dams, respectively. States with higher altitude and steep gradients are not suitable for irrigation dams. Water stored in hydroelectric dams or multipurpose dams are often channelized through canals for irrigation purposes. Given heavy incidence of rainfall in mountain and hill states and choice of crops cultivated in these regions, irrigation dams are not needed. Thus, as of 2009, states like Himachal Pradesh, Haryana, Punjab, Arunachal Pradesh, Assam, Meghalaya, Mizoram, Nagaland, Sikkim, and Tripura had no irrigation dams. Tamil Nadu, surprisingly, has the largest number of Hydel Power Dams; 33 in total as of 2009. Despite being completely dependent on hydroelectricity, Arunachal Pradesh has 3 large pure hydel dams and 11 multipurpose dams. This signifies an overlap in the dam categorization used in the study.

Model Specification

The paper adopts the following general specification given in Eq. (1):

$$Z_{it} = \alpha_0 + \alpha_1 W_{it} + \alpha_2 D_{it} + \sum_{k=3}^{7} \alpha_k H_k + \alpha_8 \ln(PD)_{it} + u_{it} \qquad (1)$$

where, Z denotes one of the three flood damage (outcome) variables referred above, W is the vector of rainfall variables of interest, D is the dam variable of interest, H is the categorical variable for regions, and PD is the population density. The error term given by u_{it} is assumed to be *i.i.d.* normally distributed with mean 0 and variance σ^2. States, the unit of analysis, are denoted with i and years are denoted with t. The coefficients are interpreted as the estimated effect of a marginal increase in explanatory variable(s) on the dependent variable.

Choice of Estimation Method

Estimates of a panel fixed effects model with a large number of time units, and few cross-sectional units are likely to be biased and inconsistent due to presence of panel heteroskedasticity, autocorrelation, and cross-sectional dependence. The panel dataset used in this study suffers from all the three issues. To overcome these issues, either Feasible Generalized Least Squares (FGLS), or Panel Corrected Standard Error (PCSE) model can be adopted. Given the finite sample properties of the FGLS method, both estimation procedures are used to evaluate rainfall and dam impacts on flood affected population. Moreover, standard errors of PCSE estimators are efficient with moderately higher time units compared to cross-sectional units (41 compared to 25 in the present case).

With natural log of population affected (popaffl) as the dependent variable, Equation (1) is estimated using FGLS method. For the estimations based on PCSE method, to ensure a moderately large sample, the analysis uses proportion of flood affected population, given by PP_{it} (as defined in the 'Variables Construction' sub-section) as the outcome variable of interest. The rainfall variable correspondingly changes to standardized rainfall anomaly SA_{it}. In this case, population density is not included as a control because the dependent variable accounts for the state population. While assessing the role played by the dams in the presence of extreme rainfall variables (RA_{it}), deviations of flood affected population from long term mean (PAA_i) are used as the relevant dependent variable. The rest of the model specification remains the same. Region and year fixed effects are subsequently introduced in the PCSE models.

RESULTS

GLS Estimates

Table 3 presents the FGLS estimates of the effects of rainfall anomalies on natural logarithm of flood affected population. While Cols 1-2 report estimates based on model specification that takes into account total number of dams, estimates reported in Cols. 3-4 consider different types of dams. Under each model specification, the estimated coefficients are reported with and without accounting for time fixed-effects. Unobserved regional heterogeneity has been taken into account under all specifications in Table 3. As expected, higher the population density implies more flood affected population. Estimated coefficients for absolute deviations of JJAS rainfall remain positive and significant across the variants of both models, while that of OND rainfall are negative and insignificant. Marginal increase in the deviations of JJAS by 1 mm will affect approximately 10000 additional people, holding other variables constant. Estimates which account for the types of dams (Cols. 3-4) suggest that, hydel power dams significantly reduce flood damages; construction of one more hydel power dams significantly reduces flood damages on approximately 0.6 million people (see Col. (4)), holding other variables fixed. Total number of dams in a state significantly reduces flood affected population (Cols. 1-2). Construction of one more dam helps in reducing population affected approximately by 8250 people, ceteris paribus.

Table 3: FGLS Estimates for Rainfall Anomaly

VARIABLES	(1)	(2)	(3)	(4)
md_jjas	**0.000999*** **	**0.000776*** **	**0.00137*** **	**0.00127*** **
	(0.00017)	**(0.00019)**	**(0.00019)**	**(0.00021)**
md_ond	-0.00068	-0.00084	-0.00061	-0.00097
	(0.00066)	(0.00077)	(0.00068)	(0.00079)
irr			0.000216	9.94E-05
			(0.0007)	(0.00081)
hydel			**-0.0700*** **	**-0.0639*** **
			(0.0208)	**(0.0204)**
multi			-0.174	-0.0166
			(0.0174)	(0.0192)
total	**-0.000826***	**-0.00114** **		
	(0.00046)	**(0.00053)**		
popdenl	**0.291** **	**0.281** **	**0.302** **	**0.311** **
	(0.128)	**(0.14)**	**(0.139)**	**(0.156)**
Constant	1.848	1.198	**2.135***	1.956
	(1.137)	(1.299)	**(1.242)**	(1.444)
Observations	589	589	585	585
Time Effects	N	Y	N	Y
Region Effects	Y	Y	Y	Y

Note: Dependent variable is natural log of population affected (popaffl). Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 4 showcases the GLS estimates of impacts of rainfall extremes. The model specifications are similar to those reported in Table 3. Effects of extreme rainfall events for the month of January are estimated to be positive and significant implying an increase in flood affected population owing to extreme January month rainfall. Extreme rainfall events in July are negatively associated with flood damages, while June remains positive throughout. This indicates that extreme rainfall at the onset of the Monsoon (June-September) season may have different effect compared to their effect later during the Monsoon season. Historically higher rainfall experienced during the July month may also aid in lowering the extreme rainfall induced flood affected population. On the contrary, as discussed above, post-monsoon extreme rainfall during the winter month of January increases flood affected population.

Table 4: FGLS Estimates for Rainfall Extremes

VARIABLES	(1)	(2)	(3)	(4)
january extreme	**0.665****	**0.632****	**0.646****	**0.653****
	(0.278)	**(0.282)**	**(0.278)**	**(0.283)**
february extreme	-0.0436	0.05	-0.104	-0.009
	(0.232)	(0.24)	(0.235)	(0.243)
march extreme	-0.137	-0.0499	-0.0485	0.0241
	(0.213)	(0.223)	(0.212)	(0.225)
april extreme	-0.118	-0.189	-0.0931	-0.141
	(0.203)	(0.216)	(0.206)	(0.217)
may extreme	-0.0698	-0.0884	-0.14	-0.154
	(0.210)	(0.227)	(0.211)	(0.228)
june extreme	0.279	0.266	**0.584****	**0.518***
	(0.263)	(0.27)	**(0.276)**	**(0.28)**
july extreme	**-0.661****	**-0.561***	**-0.543***	-0.452
	(0.299)	**(0.301)**	**(0.296)**	(0.305)
august extreme	0.208	0.0946	0.245	0.156
	(0.244)	(0.25)	(0.243)	(0.25)
september extreme	0.188	0.205	0.0621	0.0958
	(0.190)	(0.188)	(0.19)	(0.189)
october extreme	0.249	0.0221	0.281	0.0854
	(0.233)	(0.236)	(0.237)	(0.240)
november extreme	-0.0305	-0.0864	0.147	0.0731
	(0.253)	(0.262)	(0.258)	(0.270)
december extreme	0.0825	0.106	0.115	0.135
	(0.264)	(0.261)	(0.257)	(0.259)
total	-0.00071	-0.00071		
	(0.000517)	(0.000533)		
irr			-2.12e-05	0.00053
			(0.00101)	(0.00097)
hydel			**-0.0875*****	**-0.0803*****
			(0.0221)	**(0.0227)**
multi			-0.00823	-0.00462
			(0.0227)	(0.0229)
popdenl	0.503	**0.729***	**0.348****	**0.445****
	(0.443)	**(0.436)**	**(0.156)**	**(0.171)**
Constant	1.659	1.894	**2.336***	**2.961***
	(1.172)	(1.353)	**(1.307)**	**(1.535)**
Observations	595	595	591	591
Time Effects	N	Y	N	Y
Region Effects	Y	Y	Y	Y

Note: Dependent variable is natural log of population affected (popaffl). Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

PCSE Estimates

Since there are relatively large number of time periods compared to the cross-sectional units, there is a possibility that the pooled dataset used for the analysis has cross-sectional dependence. If so, the error terms will violate the assumptions for OLS estimation. The study employs Pesaran's test to check for violation (Pesaran, 2004; De Hoyos and Sarafidis, 2006). The test concludes that the models under fixed effect specifications are indeed cross-sectionally dependent. Correcting for panel heteroskedasticity and correlated errors, the study incorporates panel level first order autoregressive error structure to account for panel-level autocorrelation.

The direction of impacts of standardized weather anomalies (reported in Table 5), for both JJAS and OND, remain same across all model variants. While the magnitude of JJAS anomaly remains similar throughout specifications, i.e., with or without panel specific correlation, the estimated standard errors are found consistently smaller for the PCSE estimations. Due to unbalanced panel structure, the model could not incorporate year fixed effects as including them makes the variance-covariance matrix singular. Under this model specification, dams appear to reduce the proportion of flood affected population. There is weak evidence that irrigation dams and multipurpose dams could reduce adverse effects of floods. Introduction of region fixed effects significantly reduce the impact magnitude of total number of dams making them statistically insignificant but does not change the sign of the coefficient. This suggests that at the regional scale factors other than the total number of dams could play an important role in reducing proportion of flood affected population.

Table 5: Estimates of Models with Standardized Rainfall Anomalies

VARIABLES (PP_{it})	(1)	(2)	(3)	(4)	(5)	(6)
a_jjas	**0.0225*** **	**0.0220*** **	**0.0233*** **	**0.0238*** **	**0.0233*** **	**0.0251*** **
	(0.00658)	**(0.00585)**	**(0.00604)**	**(0.00680)**	**(0.00598)**	**(0.00615)**
a_ond	-0.00473	-0.00149	-0.00174	-0.00397	-0.000926	-0.00138
	(0.00596)	(0.00494)	(0.00498)	(0.00608)	(0.00504)	(0.00507)
Irr				-1.96e-05	**-7.16e-05** **	4.71e-05
				(2.81e-05)	**(3.18e-05)**	(3.20e-05)
hydel				-0.000552	-0.000287	0.000977
				(0.000546)	(0.00154)	(0.00202)
multi				-0.00108	-0.000419	**-0.00156***
				(0.000704)	(0.000872)	**(0.000888)**
total	**-6.45e-05*** **	**-8.08e-05*** **	-3.84e-06			
	(1.01e-05)	**(2.52e-05)**	(1.03e-05)			
Constant	**0.0791*** **	**0.0899*** **	**0.122*** **	**0.0840*** **	**0.0933*** **	**0.124*** **
	(0.00744)	**(0.0142)**	**(0.0375)**	**(0.00781)**	**(0.0128)**	**(0.0341)**
Observations	796	796	796	790	790	790
R-squared	0.030	0.049	0.064	0.034	0.053	0.068
Autocorrelation		PS	PS		PS	PS
Region FE			YES			YES

Note: Dependent variable is Proportion of population affected (PP_{it}). Standard errors in parentheses. PS is Panel Specific AR (1). *** p<0.01, ** p<0.05, * p<0.1

Table 6: Estimates of Models with Rainfall Extremes

VARIABLES(*PAA$_i$*)	1	2	3	4
january ext.	**0.261****	0.0975	0.134	**0.0748*****
	(0.127)	(0.133)	(0.135)	**(0.0172)**
february ext.	-0.114	-0.172	-0.102	**0.0537*****
	(0.111)	(0.106)	(0.105)	**(0.0183)**
march ext.	**-0.211*****	**-0.194*****	**-0.163****	-0.00985
	(0.0757)	**(0.0658)**	**(0.0659)**	(0.0165)
april ext.	-0.0183	**0.245*****	**0.255*****	**-0.0423*****
	(0.0805)	**(0.0855)**	**(0.0836)**	**(0.0130)**
may ext.	**-0.139***	0.0318	-0.00152	**-0.0315****
	(0.0761)	(0.0766)	(0.0739)	**(0.0135)**
june ext.	**-0.777*****	**-0.499*****	**-0.510*****	-0.0250
	(0.127)	**(0.0903)**	**(0.0932)**	(0.0158)
july ext.	**-0.430*****	**-0.273*****	**-0.266*****	**-0.0408****
	(0.109)	**(0.0755)**	**(0.0800)**	**(0.0164)**
august ext.	0.0658	-0.0208	-0.0328	**-0.0172***
	(0.110)	(0.0868)	(0.0901)	**(0.0101)**
september ext.	0.161	0.00668	-0.000379	**-0.0205****
	(0.102)	(0.0794)	(0.0828)	**(0.00909)**
october ext.	**-0.150***	**-0.130****	**-0.170*****	**-0.0214***
	(0.0870)	**(0.0549)**	**(0.0572)**	**(0.0121)**
november ext.	**-0.247*****	**-0.0472**	**-0.167****	-0.000262
	(0.0945)	(0.0765)	(0.0792)	(0.0153)
december ext.	-0.0768	**-0.110****	**-0.115***	**0.0336****
	(0.0762)	**(0.0555)**	**(0.0589)**	**(0.0135)**
total	**-0.0005*****	**0.000797*****	**0.00131*****	**0.000318*****
	(4.52e-05)	**(0.000160)**	**(0.000160)**	**(7.65e-05)**
popden	**4,768*****	**2,966*****	**3,700*****	**3,170*****
	(195.5)	**(195.9)**	**(155.9)**	**(112.9)**
Constant	**0.562*****	**0.309*****	**0.792*****	**0.233*****
	(0.0522)	**(0.0499)**	**(0.0508)**	**(0.0186)**
Observations	1,025	1,025	1,025	1,025
R-squared	0.475	0.580	0.605	0.702
Region FE		Yes	Yes	
Year FE			Yes	
Autocorrelation				PS

Note: Dependent variable is mean of absolute deviation of population affected (PAA$_i$). Standard errors in parentheses. PS is Panel Specific AR (1). *** p<0.01, ** p<0.05, * p<0.1

Table 6 reports the impact of monthly extreme weather events on anomalies in the population affected by floods. The table has 4 columns each corresponding to different combinations of region and year fixed effects, and panel specific correlation. A quick glance across shows that including region and year fixed effects has increased the precision of estimates for total number of dams. Extreme rainfall events in January (Column 1 and 4), February (Column 4), April (Column 2 and 3), and December (Column 4) positively influence the anomaly of population affected relative to their longer-term average. The effects of rainfall extremes during the other months, in contrast, is negatively associated with the reported flood damages. Thus, the results suggest that off-season extreme rainfall increases the prospects for flood induced damages. This is because there is very little or no seasonal rain during the off-season. In such times extreme rain may come as a surprise allowing little or no preparedness by the population. On the contrary, rainfall during monsoon season is generally much higher compared to off-season rainfall. Hence, extreme rainfall during monsoon months that occur over and above the monsoon rainfall leads to less adverse impact due to relatively more preparedness of the affected population.

The variable of interest, total number of dams, positively impacts flood damages even after controlling for population density. Moreover, a steady declining standard error (Columns 2 to 4) with inclusion of region fixed effects or correction of panel dependence verifies presence of unobserved spatial heterogeneity in damages which are related to dams. Increase in total number of dams increases the anomaly of the population affected as compared to its longer-term trends (Columns 2 and 3), raising suspicion on the role of dams in the presence of rainfall extremes. This indicates that rather than acting as a flood protection mechanism, presence of more dams on average has contributed to the increases in flood damages in the country.

The estimates with different types of dams included in the model specification along with monthly extreme rainfall events reiterates that the off-season extreme rainfall positively influences the anomaly of population affected. The number of large dams for irrigation tend to adversely influence the flood impacts due to rainfall extremes, whereas the dams for hydroelectric power generation and multipurpose dams tend to reduce the flood affected population moderately.

Limitations and Conclusions

This study assesses the impacts of floods on state population in India induced by extreme rainfall in the presence of dams and answers whether or not large dams make their neighborhood more vulnerable. The study uses the FGLS method for estimating the effects of rainfall extremes on flood damages while assessing the role of dams in modulating these damages. The PCSE approach has been employed to correct for contemporaneous correlations and cross-sectional dependence. Results suggest that dams have influence on the affected population during a flood event. Irrigation dams do not necessarily increase the flood affected population due to extreme rainfall events. However, such projects may help in reducing the proportion of population affected due to floods. Dams for hydroelectric power generation and multipurpose dams are also likely to reduce affected population at margins. Dams for hydroelectric power may help in reducing the population affected due to extreme rainfall, whereas other types of dams do not have such effects. The results also suggest that while dams may have proved useful in averting the normal rainfall induced floods, their role in averting extreme rainfall induced floods is limited. In fact, under extreme rainfall situations dams, unless regulated effectively, may further exacerbate the flood impacts.

Due to non-availability of disaggregated data in damage and rainfall at a finer spatial and temporal scale, the study potentially falls short in completely isolating the effect of rainfall anomaly from other confounding variables affecting damages. Therefore, the reported estimates may not be causal in nature. The model specification used assumes that the effect of precipitation is regionally immediate and bounded by state boundaries. In case of the precipitation data, monthly averages mollify the effects of outliers which are likely the extreme events. For simplicity, the cascading effects of floods in event of dam failure are completely ignored. The model also assumes in some stages a first order autoregressive structure of autocorrelation in flood damages. The choice of order, in this case, is heuristic at best.

Developed countries in North America and Europe stopped building large dams in the early 1980s as the associated social and environmental costs became unacceptable (Moran *et. al.*, 2018). India should carefully assess its strategy on large dams in face of increased risk from climate change. The new Dam Safety Bill passed in 2019 is a promising way ahead (Mishra and Kaur, 2019). It necessitates setting up two national bodies and two state bodies to resolve, monitor, provide technical assistance, and maintain the dams. Any failure or breach needs to be reported to the national bodies for further investigation. The bill also mandates pre and post monsoon inspection of dams along with inspections before and after earthquakes, floods, or any distress, annually. The dam owners (states, central public sector undertakings, and private sectors) are to chalk out emergency action plan for every dam including an inundation map. However, as things stand, 93 percent of Indian dams lack such plans (CAG, 2017). In addition to legislative regulations, early warnings and forecasting should be made available to the vulnerable population to facilitate adequate precautionary measures to be undertaken at micro level. Flood risks due to dam failures can also be mitigated by automatic calibration of sluice gate operations between and across the dammed rivers. In sum, one must recognize that large dams are not purely engineering phenomenon, especially in the era of climate change. It seems pertinent for India to establish expert committees that deliberate on the need for large dams in future along with their design features, and facilitate establishment of a flexible water governance regime in the country.

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