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Does development reduce damage risk from climate extremes? Empirical evidence for floods in India

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Abstract

Using a dataset on reported loss and damage (L&D) from flood-affected Indian states between 1953 and 2011, this paper inquires whether development makes states become flood resilient. Although the disaster-specific and the generic adaptation measures have been largely researched, there are limited empirical studies, particularly those that conducted an analysis at the sub-national level and used a dataset of more than 50 years. Considering human development and different loss and damage indicators is another advantage. Employing zero-inflated negative binomial and fixed effects models, this study produces three major findings. First, an increasing trend is observed for the reported loss and damage indicators across the states. Second, both human development and income are mostly found as statistically insignificant, indicating that the states are not becoming flood-resilient with respect to the present development. Third, there is a lack of evidence of learning effect, however, disaster risk management programme mitigates risk. Therefore, the paper suggests that the ongoing development strategies must take into account climate risk and address the persistent adaptation deficit. These findings could have larger policy implications since Indian states are likely to encounter such events frequently, and they also provide inputs to several states' action plans on climate change.

Keywords: Floods; Human development; Income; Indian states; Loss and damage; Resilience

Highlights

- Use of a dataset of more than 50 years that covers all flood-affected Indian states which was not previously analysed.
- Investigating the relationship between human development and L&D outcomes.
- Examination of the repercussions on various L&D outcomes, such as people affected, loss of crops, houses damaged, destruction of public property and economic L&Ds.

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Introduction

An entity's exposure to risk is determined by a combination of social, economic and political factors as per the natural disasters' discourse (Wisner *et al.*, 2003). These factors largely represent the notion of adaptive capacity, i.e., the ability of a household to resist the impacts of extreme events (Wisner *et al.*, 2003). As nation/states continue on a growth trajectory over the years, economic development is contemplated to reduce loss and damages (L&Ds) from climatic extremes in two ways. First, richer nations could make the appropriate investment in disaster mitigation options, e.g., building codes, multi-purpose cyclone and flood shelters, early warning system, evacuation preparedness, etc., and, as a consequence, incur less impact (Ferreira *et al.*, 2013; Skidmore & Toya, 2013). Second, development may lead to better quality of institutions and enhance schooling facilities and access to health care, which could enhance households' overall capacity to withstand various risks including climatic ones (Kellenberg & Mobarak, 2008; Patnaik *et al.*, 2017). In sum, the poor suffer more from natural disasters as compared to the rich as they have a lack of access to resources, assets, income, etc. (Wisner *et al.*, 2003).

Nations have been addressing these issues through targeted developmental interventions and disaster-specific mitigation measures from time to time, with the objective being the improvement in households' standard of living at the micro-level and the promotion of economic growth at a macro-scale. Albeit, an important research question emerging from the above is, whether economic development matters, particularly in the context of economies in transition, reduce L&Ds from natural disasters. Evidence shows fewer disaster-related deaths being reported in the developed nations, while events on a similar scale cause huge fatalities in the developing and poorest nations (Stromberg, 2007; Skidmore & Toya, 2013). For instance, approximately 0.9 million people were killed in low-income countries from 1980 to 2004, compared to 75.43 thousand in high-income countries (Stromberg, 2007). Also, according to the IPCC (2012), between 2001 and 2006, the developing nations have lost 1% of their gross domestic product due to climate extremes, and is less than 0.1% for high-income nations. Further, Stromberg (2007) asserts that high-income nations are likely to experience 70% lower fatalities than low-income nations from a disaster with similar intensity. These examples reflect the possibility of an encouraging role played by economic development but warrant empirical research at the macro-scale to investigate the linkages between development and impact from climate extremes, especially in developing nations. On the other hand, disaster-specific measures also play a significant role in mitigating impacts from natural disasters, for example, a disaster risk management programme reducing the impact from cyclones and floods and heat stress in Odisha, India (Das & Smith, 2012; Bahinipati & Patnaik, 2015).

During the last two to three decades, a significant number of studies have emerged to empirically demonstrate the causal relationship between development per se and impacts from several natural disasters. We can divide the studies into four strands, i.e., negative relationship, non-linearity (inverted U-shape), the role of risk and exposure (either U-shape or inverted U-shape) and insignificant association. Based on a cross-country sample, several studies depict an inverse relationship between economic development/income and L&Ds, particularly death tolls, from natural disasters (e.g., Anbarci *et al.*, 2005; Kahn, 2005; Stromberg, 2007; Toya & Skidmore, 2007; Skidmore & Toya, 2013; Bahinipati & Patnaik, 2015; Parida, 2020). Investigating the non-linear relationship between development and a natural disaster's impact, Kellenberg & Mobarak (2008) find an inverse U-shape for income and lives lost. The turning point was found to be around US$ 4,500–5,500, implying that deaths from natural disasters increase for countries having per-capita income less than US$ 4,500 and start declining once those countries' income crosses the turning point (Kellenberg & Mobarak, 2008). Schumacher & Strobl (2011), however, indicate that such causal association is linked to geographical location; for instance, an inverted U-shape is reported for low-risk countries, whereas a U-shape is obtained for high-risk countries. Ferreira *et al*. (2013) noted an insignificant association between income and flood fatalities. Although the causal association between development, particularly income, better institutions, good governance, etc., and disasters' impacts are being widely studied, the findings contrast with each other, apparently at the country level. In addition, there are limited studies at the regional level, particularly with reference to the developing nations like India (Parida, 2020). We extend the analysis by covering flood-prone states of the country as well, for the period 1953 to 2011.

As the backdrop of these findings, the paper aims to investigate the ramifications of development on L&Ds due to the incidence of floods in India; which, in fact, contributes the most to the annual average economic L&Ds from disasters in India (Tripati, 2015). Two major proxies are taken to capture development in the present study context: income and human development indices. While the former has been extensively studied and is considered as a standard measure of development, there is scant literature with reference to the latter although, indeed, it is a well-known yardstick of human well-being and in turn captures overall development (Klugman *et al*., 2011). The findings could contribute to the international policy debate on mainstreaming climate change in development planning and policies. It is timely and relevant since global warming is expected to increase the frequency and intensity of floods in India in the near future (Dubash & Jogesh, 2014). The findings could be more robust if we consider indicators associated with governance, institution, social capital, etc.; however, such variables are not considered due to paucity of information for such a long period and, in fact, for flood-affected states. Moreover, this study contributes to the existing literature in four ways: (i) it reconfirms the existing findings with a dataset at sub-national level; (ii) use of a dataset of more than 50 years that covers all flood-affected Indian states which have not been previously analysed, as far as we know; (iii) investigating whether there is any relationship between human development and L&D outcomes, while the previous studies have mostly looked at the association with income; and (iv) examination of the repercussions on various L&D outcomes, such as people affected, loss of crops, houses damaged, destruction of public properties and economic L&Ds; several previous studies have specifically focused on the death tolls (Kahn, 2005). This paper is structured as follows: L&Ds from floods in India, data and methods, results and discussions, and concluding remarks with policy suggestions.

Loss and damages from floods in India

L&Ds refer to the residual impact of climate extremes that cannot be mitigated through adaptation measures (Warner & van der Geest, 2013). Based on the data collected from the Central Water Commission (CWC) of the Government of India[1] on L&D indicators, this section briefly explains the impact of floods not only in India but also across the states.

According to Bahinipati *et al*. (2016), a large chunk of L&Ds was attributed to the incidence of floods and cyclonic storms. India has encountered 302 flood events (47%) out of 649 disasters that hit between 1915 and 2015 (Tripati, 2015). On average, there are three floods per year, and around half of them are a riverine flood (Tripati, 2015). Table 1 outlines the summary of L&Ds from floods between 1953 and

[1] State-wise Flood Damage Statistics, published by the Central Water Commission, Government of India, New Delhi (Vide Letter No. 3/38/2011 FFM/2200-2291 dated: 27 November 2012).

Table 1. Summary of L&Ds from floods in India (1953–2011).

Sl. no.	L&D indicators	Unit	Mean	SD	Min	Max
1	Area affected	Million ha	7.22	3.43	1.10	17.50
2	People affected	Million	32.43	16.80	3.61	70.45
3	Crop area affected	Million ha	3.79	2.34	0.27	12.30
4	Crop loss	INR in billion	11.15	14.76	0.06	73.07
5	Houses affected	Million	1.25	0.84	0.11	3.51
6	Houses damaged	INR in billion	5.57	14.85	0.002	108.09
7	No. of cattle lost	Thousand	96.59	117.25	4.57	618.25
8	Number of lives lost	Thousand	1.65	1.61	0.04	11.32
9	Public property damaged	INR in billion	18.68	34.88	0.01	175.09
10	Reported economic L&Ds	INR in billion	35.40	58.46	0.07	325.52

INR, Indian rupee; SD, standard deviation; Min, minimum; Max, maximum.
Source: Authors' estimation.

2011 in India. One general concern is that some of the L&D indicators are not reported, and hence, missing from this dataset. Given the caveats, on average, 32.43 million people were affected (3% of India's total population, as of the 2011 Census), and around 1.65 thousand people were killed per year. While agriculture absorbs half of the households in rural India, around 0.03% of the total net sown area (3.79 million ha) was destroyed per year, corresponding to a monetary loss to the tune of INR[2] (Indian rupee) 11.15 billion. The mean value of reported economic L&Ds was INR 35.4 billion, and of this, the damage to public property accounts for 53%. With regard to the temporal scale, an increasing trend has been noticed for economic L&Ds (Figure 1).

The state-wise occurrence of a total number of flood years and mean people affected and average economic L&Ds for the same period are presented in Figures 2–4. It is observed that around 17 states have experienced floods for more than 40 years during the study period (see Figure 2). The states where floods occur almost every year are Bihar (59 flood years), West Bengal (58 flood years), Assam (57 flood years) and Uttar Pradesh (56 flood years). A higher number of people per year were affected in the following states: Uttar Pradesh (6.85 million), Bihar (6.56 million), West Bengal (3.79 million), Assam (2.77 million) and Odisha (2.52 million) (see Figure 3). With respect to mean of reported economic L&Ds, Karnataka is in first position (INR 14.58 billion), followed by Andhra Pradesh (INR 9.45 billion), Uttar Pradesh (INR 3.01 billion), West Bengal (INR 2.76 billion), Bihar (INR 2.30 billion) and Odisha (INR 2.22 billion) (see Figure 4). Higher economic L&Ds indicate the occurrence of high intensity of floods, and it is, henceforth, expected to get a similarly larger value for other L&D indicators, e.g., people affected. The irony is that Karnataka is in first position in terms of economic L&Ds, while it is in 15th position in the case of people affected. This reveals the fact that development may not mitigate L&Ds occurring in the different sectors in a similar manner. For instance, over recent years, development along with better preparedness has reduced human casualties to a large extent across the Indian states, however, the mitigation potential in the case of other L&D indicators is limited. Therefore, it is imperative to establish the causal association between development and several L&D indicators, as previous studies were mostly focused on the human death toll. Appendix 1

[2] US$ 1 = INR 74 approximately during September 2020.

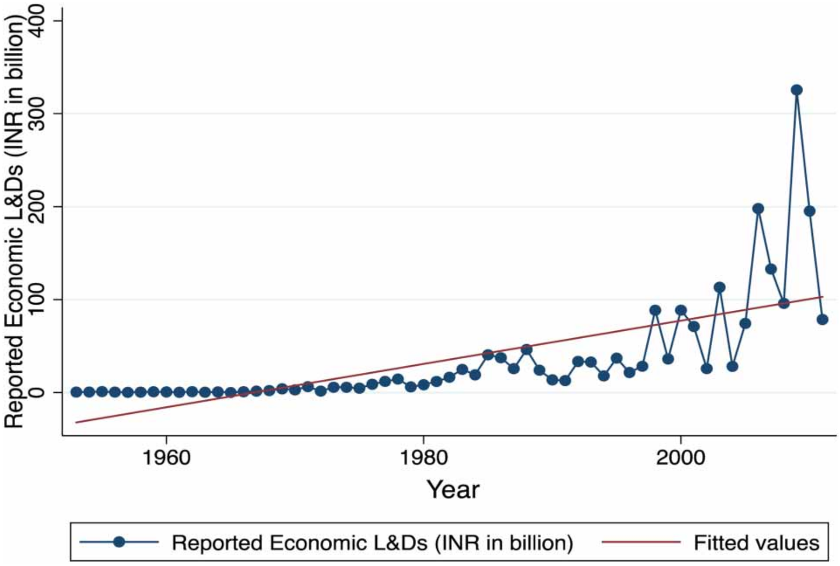

Fig. 1. Year-wise reported economic L&Ds from floods in India (1953–2011).

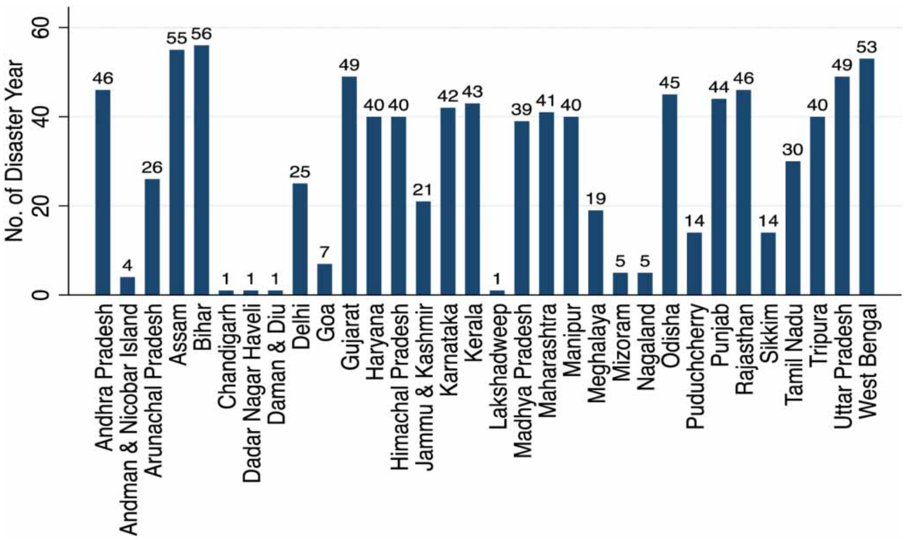

Fig. 2. State-wise total number of flood years during 1953 and 2011.

(Supplementary Material) outlines the year-wise reported economic L&Ds across the Indian states. While an increasing trend has been found for all the states, a relatively higher steeper slope is observed for states like Andhra Pradesh, Assam, Bihar, Himachal Pradesh, Kerala, Maharashtra, Manipur, Odisha, Tripura and Uttar Pradesh. In sum, results reveal that economic L&Ds have been increasing over the years in India as well as across the states.

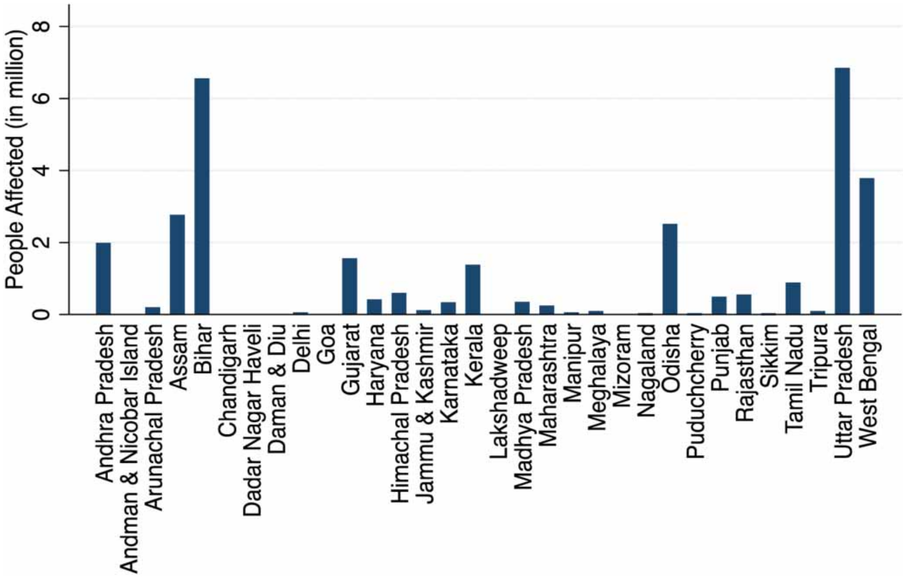

Fig. 3. State-wise average people affected during 1953 and 2011 (in million).

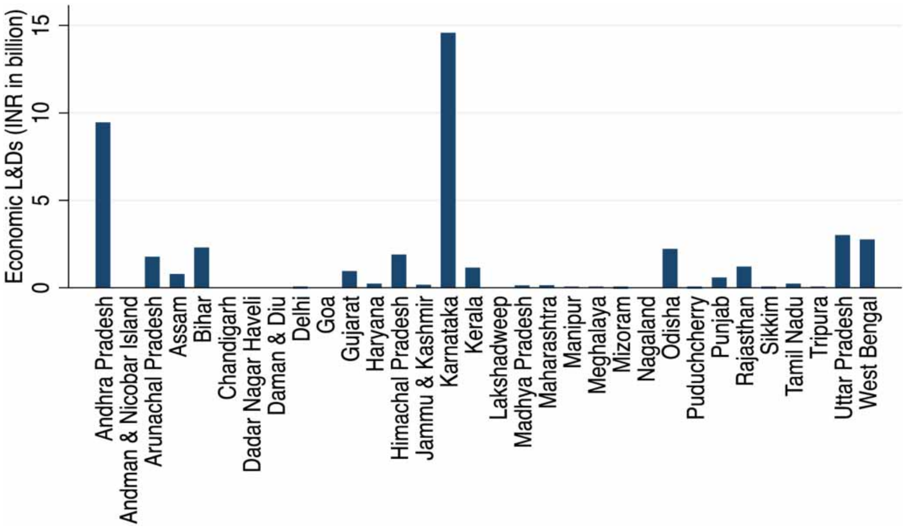

Fig. 4. State-wise average economic L&Ds during 1953 and 2011 (INR in million).

Materials and methods

In this study, the outcome of a flood is represented in terms of immediate *ex-post* physical impacts, e.g., people affected, crop loss, houses damaged, damage to public property, economic L&Ds. The people affected variable is presented in countable number, and the rest of the indicators are depicted in Indian rupee terms at the current price. The extent to which a state is affected depends on socio-economic characteristics, level of development and inherent levels of natural disaster risk, i.e., a mix of natural hazards and human action (Wisner *et al.*, 2003). Following the recent assessment report of IPCC, this study models the impact of floods (i.e., risk) as a function of hazard, exposure and vulnerability (IPCC, 2014). According to this report, the hazard is defined as a potential occurrence of extreme events that may foster L&Ds. While exposure refers to the presence of people and resources that could be adversely affected, vulnerability infers a lack of capacity to adapt (IPCC, 2014).

A number of proxies are used to represent these broad variables. The unit of analysis states and the data for each proxy are collected for the years between 1953 and 2011 for 21 flood-affected states[3] in India, from various secondary sources which are described in Supplementary Material, Appendix 2. It should be noted that L&D figures are inadequately recorded, and there is a high likelihood of non-reporting for the early years. While the state-wise population and literacy rate figures are available for different census years (e.g., 1951, 1961, 1971, 1981, 1991, 2001 and 2011), the data for NSDP and IMR are also missing for some years, mostly during the 1950s and 1960s, across the states, especially north-eastern states. We have adopted a linear interpolation method to fill the information for the non-reported and not available years. The model includes variables consisting of L&D indicators, development, hazard risk and disaster risk reduction measures. Table 2 displays the definition of the variables employed in the model and descriptive statistics. In general, the number of observations in the present study context are 1,239, covering 21 states. Using per-capita net state domestic product (PCNSDPC)[4] at constant price as one of the confounders, the number of observations is reduced to 1,003, covering 17 states due to the non-availability of data.

Five outcomes are employed to capture the state's risk from floods: (i) people affected, (ii) crop loss, (iii) houses damaged, (iv) damage to public properties and (v) reported economic L&Ds. In general, these indicators are calculated by the affected state in order to receive aid from national and donor agencies, although, in fact, the disaster reports do not give clear guidelines for estimation of these indicators. It is observed from Supplementary Material, Appendix 3 that these variables are over-dispersed as their standard deviations are higher than the corresponding means while also depicting a positive skewness. Several indicators have been used to capture an entity's development in the literature, e.g., income, inequality, institution, democracy, trade openness, etc. (Bahinipati & Patnaik, 2015). Given the onus of this study, variables like human development index (HDI) and income are used to represent the state's development status. The HDI[5] is a well-known yardstick of human well-being and development, and previous studies completely overlooked it. Following various state-wise human development reports, we use three indicators to construct the HDI: per-capita income at the current price, literacy rate and infant mortality rate (IMR)[6]. HDI is calculated as an arithmetic average of normalization of these three indices. UNDP (2004) reports that human development contributes to a significant reduction in disaster risk, and this

[3] Defined as a state that experienced at least ten flood years during the study period, i.e., 1953 to 2011. Apart from this, we have excluded union territories such as Delhi and Goa as they have experienced floods for more than ten years. The state Sikkim has been dropped from the empirical analysis due to lack of information related to socio-economic variables. The states considered for the empirical analysis are: Andhra Pradesh, Arunachal Pradesh, Assam, Bihar, Gujarat, Haryana, Himachal Pradesh, Jammu and Kashmir, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Manipur, Meghalaya, Odisha, Punjab, Rajasthan, Tamil Nadu, Tripura, Uttar Pradesh, and West Bengal.

[4] The values for each year have been estimated by taking the base year as 1999/2000.

[5] It is a composite index of three basic dimensions: to have a long and healthy life, to acquire knowledge and to have access to resources needed for a decent standard of living (Klugman *et al.*, 2011).

[6] In general, these indicators are mostly used to construct national level HDI such as per-capita income, literacy rate/gross enrollment ratio and life-expectancy (see Klugman *et al.*, 2011). The indicators used in this study are based on the indicators considered in the different state-level human development reports in India.

Table 2. Definition of the variables and descriptive statistics.

Variable	Description	Mean (SD)
Dependent variables		
NPOP	Reported people affected (in million)	1.53 (3.48)
LCROP	Loss of crops(ln)	10.97 (8.92)
DHOUSE	Damage to house(ln)	9.64 (8.38)
DPP	Damage to public property(ln)	10.38 (8.84)
TELD	Reported total economic loss and damages(ln)	12.98 (8.76)
Independent variables		
Development indicators		
HDI	Human development index	0.382 (0.12)
$(HDI)^2$	Square of human development index	0.159 (0.091)
PCNSDPC	Ln (Per-capita net state domestic product at constant price)	9.19 (0.62)
$(PCNSDPC)^2$	Ln (Square of per-capita net state domestic product at constant price)	18.38 (1.25)
Hazard and risk		
ARAIN	Mean of rainfall	1,064.09 (704.63)
AAREA	Average area affected by flood	0.03 (0.07)
Disaster-specific adaptation measures		
NFY	Number of flood years in the past three years	2.04 (1.10)
DRR	Dummy = 1 if the state is covered under the DRR programme; 0 otherwise	0.06 (0.24)

Note: The number of observations is 1,003 for PCNSDPC variable and it is 1,239 for the remaining dependent and independent variables.
SD, Standard deviation.
Source: Authors' computation.

study, therefore, anticipates a negative coefficient value for HDI. Further, per-capita NSDP at constant price is taken as a proxy to capture income. As outlined earlier, both macro- and micro-level studies have depicted a negative relationship (Parida, 2020). Similar to previous studies (Kellenberg & Mobarak, 2008; Ferreira *et al*., 2013), the square term of the variables like HDI and PCNSDPC are also considered in the model to look into the non-linearity relationship.

The hazard of a region is crucial in determining the risk outcome and it is being captured here through two indicators: rainfall and average area affected by the flood. Both the confounders represent flood intensity, and therefore, are likely to increase L&Ds from floods. It is anticipated that households may learn from previous disasters and rectify their mistakes during the next event, so L&Ds can be minimized. A similar approach could have been applied at community and state levels. There is also the possibility of cross-learning among the entities. The effect of learning varies across the L&D indicators. In the case of protecting tangible assets at both micro- and macro-levels, it mostly depends on past experience and wealth. To account for the learning effect from previous and ongoing disaster-specific adaptation measures, this study uses incidence of floods in the previous three years (NFY) as one of the independent variables along the lines of Yamamura (2010).

It is being argued that the affected entity learns the lessons from previous disasters and applies those learning experiences to mitigate L&Ds from future disasters. For instance, the coastal households in Odisha were reluctant to evacuate during the 1999 super-cyclonic storms, but an overwhelming response was observed during the subsequent cyclones that occurred during the last one and a half decades. Indeed, both the communities and the administration in Odisha are better organized in the recent past years in terms of providing early warning and carrying out quick evacuation (Dash, 2013, 2016).

Further, it is observed that the demand for crop insurance is significantly increased following a disaster year. Also, the flood-affected states have taken up several policy initiatives such as structural and non-structural measures, especially at district and village levels, in order to mitigate recurrent L&Ds. These examples reflect evidence of learning effect, and Yamamura (2010) and Bahinipati & Patnaik (2015) empirically established an inverse relationship between learning effect and vulnerability. Based on this, a negative association is being expected in the present study context. There is also the chance of getting positive coefficient value, if the state does not have sufficient wealth to utilize the previous experience, i.e., to undertake required precautionary measures.

The variable DRR represents a state where the disaster risk management programme (DRM) of the UNDP was implemented during specific time periods. The states where the programme was enforced are Gujarat, Odisha, Bihar, Assam, West Bengal, Meghalaya, Sikkim, Uttaranchal, Delhi, Maharashtra, Tamil Nadu and Uttar Pradesh. The proposed cost for this programme was approximately US$ 27 million; while US$ 7 million was given by the UNDP, the additional US$ 20 million was borne by the Government of India[7]. One can anticipate that the L&Ds from disasters could have been reduced in these states in the recent past years. For instance, the dissemination of effective early warning alerts during the recent past severe cyclonic storms 'Phailin' (2013) and 'Hudhud' (2014) helped in effective evacuation in the state of Odisha (Dash, 2013, 2016). As a consequence, zero casualties were reported in the case of the former cyclonic storm (Dash, 2013). Likewise, a remarkable reduction of cyclone and flood-induced death tolls has been noticed over the years in Indian states like Andhra Pradesh and Odisha (Raghavan & Rajesh, 2003; Bahinipati & Venkatachalam, 2016). We, therefore, hypothesize that both the learning effect and DRM programme would bear a negative sign. Based on the examples from Odisha and Andhra Pradesh, it is evident that both the learning effect and the DRM programme played an vital role in reducing death tolls and the number of people affected, and not with respect to damage to both private and public property. The geographical location of an entity significantly matters for the likelihood of experiencing a natural disaster as well as its potential consequences (Kahn, 2005; Kellenberg & Mobarak, 2011). For instance, states such as Assam, Bihar, Uttar Pradesh, West Bengal and Odisha are geographically exposed to floods. There is either inclusion of state-specific dummies or adoption of fixed effects regression to account for the other unobserved and time-invariant characteristics of the individual states. Further, time dummies are included to capture common time-varying unobserved impact.

Among the L&D indicators, the number of people affected is a non-negative count variable, and the appropriate suitable econometric models that could be used for estimation are Poisson, negative binomial (NB), zero-inflated Poisson (ZIP) and zero-inflated negative binomial (ZINB). If the count data are over-dispersed with excess zeros[8], the ZINB model is appropriate (Kahn, 2005). In the context of other L&D indicators, those that are reported in monetary terms (i.e., damage to crops, houses and

[7] http://www.ndmindia.nic.in/EQProjects/goiundp2.0.pdf; accessed 24 July 2016.

[8] The reported information is over-dispersed (see Supplementary Material, Appendix 3) and also has a greater number of zero observations (i.e., 41%); the latter occurs due to either non-occurrence of floods in that particular year or non-reporting. Hence, zero-inflated models are preferred that provide a way of modelling dispersion and the excess zeros by changing the mean structure to allow the zero to be generated by two distinct processes (Zaninotto & Falaschetti, 2011). The first one is the group of zeros, and the second is the group of non-zero; while the first one is modelled with logit/probit, the second is either a Poisson or NB model. Vuong statistics and likelihood ratio were calculated to choose between ZIP, ZINB and NB, and the results were found to be significant (see Table 3), suggesting the ZINB model.

public property and total economic L&Ds), we have adopted an ordinary least square fixed effects model.

In the present study context, the estimated equation for the ZINB model takes the following form (Yamamura, 2010):

$$(NPoP)_{it} = \alpha_0 + \alpha_1 HDI_{it} + \alpha_2 (HDI)^2_{it} + \alpha_3 AARAIN_{it} + \alpha_4 AAREA_{it} + \alpha_5 NFY_{it} + \alpha_6 DRR_{it} + \nu_t + \varepsilon_i + \omega_{it} \ldots\ldots \tag{1}$$

$$(NPoP)_{it} = \alpha_0 + \alpha_1 PCNSDPC_{it} + \alpha_2 (PCNSDPC)^2_{it} + \alpha_3 AARAIN_{it} + \alpha_4 AAREA_{it} + \alpha_5 NFY_{it} + \alpha_6 DRR_{it} + \nu_t + \varepsilon_i + \omega_{it} \ldots\ldots \tag{2}$$

Further, the OLS fixed effects model is:

$$(LD)_{it} = \alpha_0 + \alpha_1 HDI_{it} + \alpha_2 (HDI)^2_{it} + \alpha_3 AARAIN_{it} + \alpha_4 AAREA_{it} + \alpha_5 NFY_{it} + \alpha_6 DRR_{it} + \nu_t + \varepsilon_i + \omega_{it} \ldots\ldots \tag{3}$$

$$(LD)_{it} = \alpha_0 + \alpha_1 PCNSDPC_{it} + \alpha_2 (PCNSDPC)^2_{it} + \alpha_3 AARAIN_{it} + \alpha_4 AAREA_{it} + \alpha_5 NFY_{it} + \alpha_6 DRR_{it} + \nu_t + \varepsilon_i + \omega_{it} \ldots\ldots \tag{4}$$

where $(NPoP)_{it}$ shows the number of people affected, and $(LD)_{it}$ represents other L&D indicators like reported loss of crops, houses damaged, damage to public property and reported total economic L&Ds, in state $'i'$ and time $'t'$. The $\alpha' s$ indicates the regression parameter. ν_t exemplifies the unobservable specific effects of year 't' (a fixed-effect time vector). ε_i represents time-invariant state-specific unobservable effects, and ω_{it} shows the error terms.

Results and discussion

Human development, income and flood risks in India

It is plausible that high-income countries are likely to be less vulnerable compared to the low-income nations on encountering an event with similar intensity (Wisner *et al.*, 2003; Noy, 2009). As spelled out earlier, richer nations exhibit lower sensitivity to climate extremes due to spectacular performance in several socio-economic indicators, and hence, are likely to devote greater resources to disaster-specific mitigation measures (Skidmore & Toya, 2013). In contrast, having a large percentage of poor households and a lack of resources could impose restrictions on developing nations/states to undertake several disaster-specific interventions. Further, these countries also have a higher Gini coefficient which further amplifies the scale and scope of damage risks from natural disasters (Anbarci *et al.*, 2005). Over the years, it has been observed that increasing informal settlements in urban areas and marginalized communities in rural areas are forced to stay in low elevation disaster-prone regions, and as a result, they are relatively more vulnerable to various natural disasters; historically lower socio-economic development could be the major reason (Wisner *et al*., 2003). UNDP (2004) found that only 11% of people exposed to natural disasters live in low human development nations, while these nations together account for 53% of the total fatalities. Similarly, at the micro-level, a richer household could demand safety mechanisms, and also invest in different precautionary measures, e.g., earthquake/flood/cyclone-resistant houses, insurance, income diversification, etc., to reduce damage risks (Toya & Skidmore, 2007). During the *ex-post* period, richer households can easily access resources and credit, and therefore, the impact is far less severe for them in comparison to the poor (Wisner *et al*., 2003). We anticipate the existence of a causal relationship between the development status and impacts from climate extremes.

Previous studies have shown an inverse relationship between economic development, particularly income, and L&Ds (most often lives lost being considered as an outcome variable) caused by natural disasters (Anbarci *et al*., 2005; Kahn, 2005; Kellenberg & Mobarak, 2008; Schumacher & Strobl, 2011; Kellenberg & Mobarak, 2011; Skidmore & Toya, 2013; Bahinipati & Patnaik, 2015). The stakeholders and individual households always encounter a trade-off between only development and integration of development and disaster mitigation. A poor entity may initially prefer development-based activities and could demand disaster mitigation measures with increasing income (Kellenberg & Mobarak, 2008). In line with this, Kellenberg & Mobarak (2008) find the relationship between income and death tolls as inverted U-shape, and such an association is found to be even stronger in the case of floods, landslides and windstorms as human behaviour could shift exposure of building code, embankment, selection of location, etc. Schumacher & Strobl (2011), in contrast, find that exposure plays a major role in deriving the association between wealth and disasters, and hence, this study reveals the relationship as either U-shape or inverted-U shape. With regard to Indian states, it is observed that better governance and institutions ameliorate the evacuation process, leading to fewer casualties due to extreme events. However, the relationship between development and other L&D indicators, e.g., people affected, loss of agricultural crops, damage to private and public properties, and reported economic L&Ds, is still largely unexplored. Access to opportunities and resources are not equally distributed across the social groups living in a nation/state. Therefore, macro-level development while exhibiting high skewness with respect to social, economic and political factors may not reduce vulnerability to a large extent (Wisner *et al*., 2003). Moreover, it is being recognized that not all adaptation would alleviate poverty and not all poverty reduction could subsidize vulnerability (Sherman *et al*., 2016). Appropriate development policies are required to reduce potential risks from climate extremes.

Figure 5 examines the relationship between the number of people affected and the HDI[9], and Figure 6 plots the average of the ratio of reported economic L&Ds to NSDP at a current price against the average of HDI for the 21 flood-affected Indian states. Based on previous literature (e.g., UNDP, 2004), we anticipate that increasing human development enhances a state's resilience capacity and, in turn, reduces vulnerability. Supporting this, a declining trend is observed for both people affected and economic L&Ds, and this asserts that for states with higher HDI, people affected are less and economic L&Ds are lower (see Figures 5 and 6)[10]. Households living in states exhibiting high HDI score are expected to alter their behaviour in terms of adopting various strategies to reduce their exposure to floods, while

[9] State-wise HDI was calculated based on three indicators: literacy rate, infant mortality rate and per-capita net state domestic product at current price.

[10] In both the figures, position of states like Arunachal Pradesh and Himachal Pradesh could be deemed as outliers, and perhaps, the shape of the trend line could be influenced by the values of these states. For robustness check, we have redrawn the graph without these states (see Supplementary Material, Appendices 4 and 5) and observe similar results.

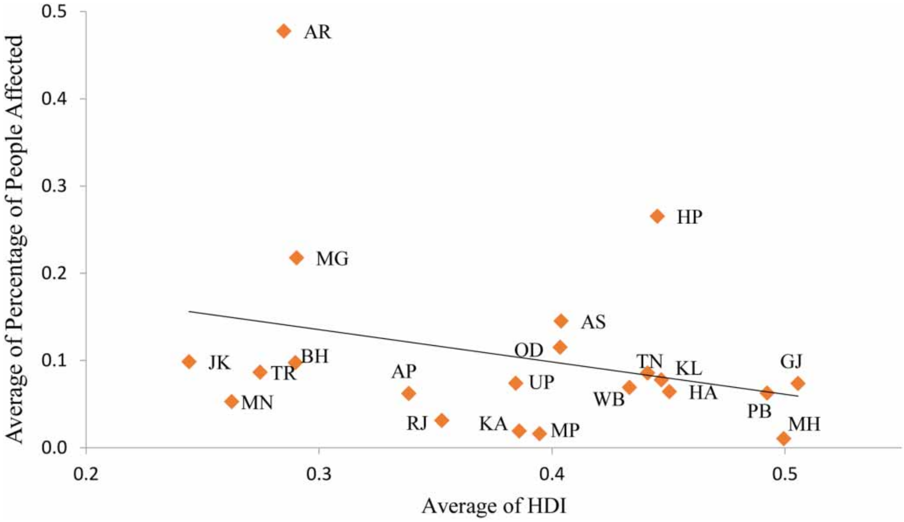

Fig. 5. Relationship between people affected and HDI. *Note*: AP, Andhra Pradesh; AR, Arunachal Pradesh; AS, Assam; BH, Bihar; GJ, Gujarat; HA, Haryana; HP, Himachal Pradesh; JK, Jammu and Kashmir; KA, Karnataka; KL, Kerala; MP, Madhya Pradesh; MH, Maharashtra; MN, Manipur; MG, Meghalaya; OD, Odisha; PB, Punjab; RJ, Rajasthan; TN, Tamil Nadu; TR, Tripura; UP, Uttar Pradesh; WB, West Bengal.

the governments in these states are also anticipated to facilitate disaster risk reduction measures and planning. Evidence does suggest that richer households are indeed taking precautionary measures for shielding themselves and their tangible resources (e.g., agricultural crops, houses and public property) from cyclones and floods (Bahinipati & Patnaik, 2015). Figures 7 and 8 display the cross-state relationship between each state's average percentages of people affected and the ratio of reported economic L&Ds to NSDP at the current price and its per-capita income. A moderate increasing trend is found for people affected while, more or less, no change is observed in the case of reported economic L&Ds[11]. This confirms that richer states are not in a better position compared to the poorer states in the context of managing disaster risks.

Empirical analysis

Tables 3 and 4 present the results of the ZINB and OLS fixed effects' estimations[12]. In the ZINB model, columns (1) and (3) report results of NB regression, and columns (2) and 4) demonstrate the results of the logit model (see Table 3). Vuong statistics are found as significant in both the models, suggesting the appropriateness of using the ZINB model. Again, the significant likelihood ratio value supports the ZINB over the ZIP. We had controlled both time- and state-specific effects by taking time and state dummy variables. The *wald* χ^2 values are observed as significant, indicating that the

[11] In similar way to footnote 4, we have redrawn these graphs without the possible outliers, and in the present case, it is Himachal Pradesh (see Supplementary Material, Appendices 6 and 7). While there are similar results in the case of people affected, the trend line is marginally declining for the ratio of reported economic L&Ds to NSDP at current price.

[12] For robustness check, we have also done similar analysis with employing random effects model and the results are reported in Supplementary Material, Appendix 8. Out of the eight models, Hausman test supports fixed effects for five models.

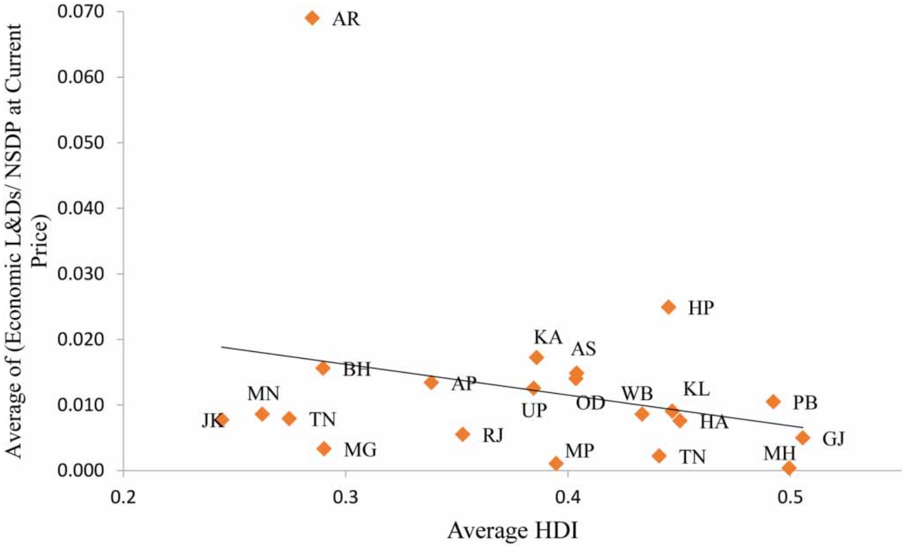

Fig. 6. Relationship between reported economic L&Ds and HDI. *Note*: Refer to Figure 5 for abbreviations; NSDP, net state domestic product.

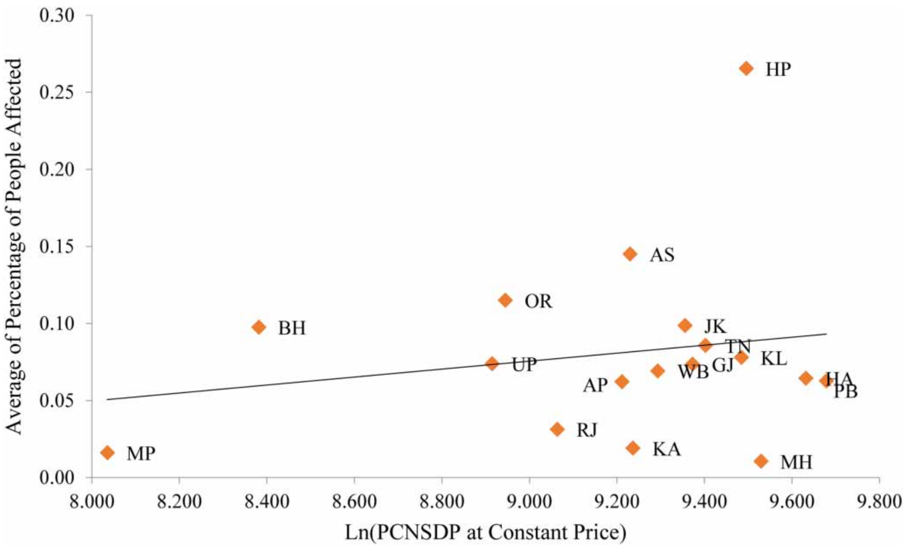

Fig. 7. Relationship between people affected and NSDP. *Note*: Refer to Figure 5 for abbreviations.

independent variables taken as a group are quite significant in explaining the L&Ds from floods. In Table 4, the results of four outcome variables – crop loss, houses damaged, damage to public property and total economic L&Ds – are presented in sequence. Columns (1), (3), (5) and (7) show the results when HDI is used as a confounder. Columns (2), (4), (6) and (8) demonstrate the results when PCNSDPC is separately considered as an independent variable. Fixed effects model was employed to capture the state-specific effects, and further, year dummies were taken to capture time-variant

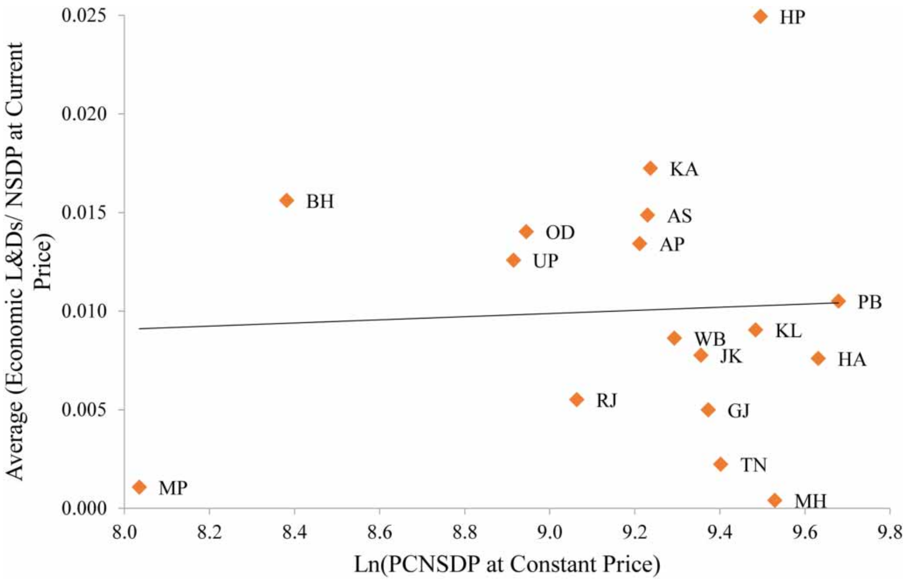

Fig. 8. Relationship between economic L&Ds and NSDP. Note: Refer to Figure 5 for abbreviations; NSDP, net state domestic product.

essences. In the logit model reported in columns (2) and (4) in Table 3, one variable is found as statistically significant, learning effect, i.e., number of flood years in the past three years. Previous studies have shown the evidence of a learning effect (Yamamura, 2010; Bahinipati & Patnaik, 2015), while this study finds a negative sign for NFY variables, indicating the absence of a learning process.

The results of the NB and OLS fixed effects are discussed in this and the following paragraphs as well. The coefficients of HDI are anticipated to be negative and statistically significant (UNDP, 2004). However, we find a positive coefficient value for all the L&D indicators (column (1) of Table 3 and columns (1), (5) and (7) of Table 4) except for one variable, damage to house (column (3) of Table 4). None of them are, in fact, statistically significant. The coefficients of HDI^2 are found to be the opposite sign (i.e., mostly negative), suggesting an inverted-U shape relationship. Growing economic development accumulates more tangible assets and higher population density, and thus, a higher number of people, private houses and public infrastructure could be affected, if various disaster specific adaptation measures are not in place. In a similar vein, normalization studies report that socioeconomic factors have played a major role in enhancing L&Ds in recent years in India (Bahinipati & Venkatachalam, 2016; Bahinipati *et al*., 2016). On the other hand, several cross-country studies have found economic development is one of the major determinants to minimize L&Ds from natural disasters (Anbarci *et al*., 2005; Kahn, 2005; Toya & Skidmore, 2007; Kellenberg & Mobarak, 2008; Yamamura, 2010, 2012; Skidmore & Toya, 2013; Bahinipati & Patnaik, 2015). Toya & Skidmore (2007) and Ferreira *et al*. (2013), in contrast, detect an insignificant coefficient for income proxy, and the latter study finds it to be positive. We observed mixed results for per-capita income, i.e., positive in the case of people affected, damage to public properties and economic L&Ds, and negative for crop loss and damage to houses. When income increases, the population density also surges, and at the same time, expands both public and private properties. Given this, there is a high likelihood of more people affected and economic L&Ds if the state encounters floods. The negative association in the case of crop loss and

Table 3. Determinants of number of people affected (zero-inflated negative binomial model).

	Number of people affected			
Variable	NB model (1)	Logit model (2)	NB model (3)	Logit model (4)
Development indicators				
HDI	2.70 (2.85)	2.26 (4.69)	–	–
$(\mathrm{HDI})^2$	−3.10 (3.49)	−0.69 (5.45)	–	–
Ln(PCNSDPC)	–	–	11.11 (13.55)	1.03 (25.09)
$\mathrm{Ln(PCNSDPC)}^2$	–	–	−5.91 (6.78)	−0.34 (12.55)
Hazard and risk				
ARAIN	0.001*** (0.0002)	–	0.001***	
(0.0002)	-			
AAREA	9.08*** (1.19)	–	9.32***	
(1.27)	-			
Disaster-specific adaptation measures				
NFY	0.004 (0.062)	−0.66*** (0.09)	0.006 (0.07)	−0.41*** (0.11)
DRR	0.05 (0.24)	0.79 (0.41)	−0.06 (0.30)	0.45 (0.46)
Constant	13.12*** (0.63)	1.34 (1.12)	19.98*** (3.33)	−1.05 (4.50)
State effects	Y	Y	Y	Y
Time effects	Y	Y	Y	Y
$Ln\ \alpha$	0.2*** (0.05)		0.204*** (0.050)	
α	1.22 (0.06)		1.23 (0.06)	
No. of samples	1,239		1,003	
No. of non-zero samples	748		633	
No. of states	21		17	
Wald χ^2	2054.85***		890.98***	
Log pseudo likelihood	− 11724.43		− 10,102.11	
Vuong test	26.61***		26.70***	

Note: This model has two equations. Columns 2 and 4 report the logit model estimates of the probability that nobody in a given state in a given year reports loss and damage from floods. Columns 1 and 3 report results from the negative binomial model. Robust standard errors are presented in parentheses. In the case of Vuong test, z-value is reported. Likelihood ratio (LR) test is significant in all the models, indicating that zero-inflated negative binomial is better than zero-inflated Poisson regression. Absence of serial correlation as p-value of Wooldridge test for autocorrelation is insignificant. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Authors' computation.

damage to houses reflects the evidence of undertaking adaptive measures by richer states to protect them. Similar to HDI, none of the coefficients are statistically significant except for the damage to public properties variable.

It is expected that the Indian states are supposed to take various precautionary measures to minimize flood risks with increasing income and human development. Three possible reasons for such contrasting findings in the present study context are: (i) the undertaken adaptation options might not be sufficient to make the states as flood resilient, i.e., lack transformation from development to resilience; (ii) they may not have reached the turning point which cross-country empirical studies estimate (e.g., US$ 4,500–5,500 according to Kellenberg & Mobarak, 2008); and (iii) persisting high inequality in terms of income and access to resources across the Indian states leads to a large chunk of households in lower income strata, and therefore, a relatively advanced state is also not able to undertake various precautionary options

Table 4. Determinants of loss and damage indicators from floods (fixed effects model).

	Ln(1 + LCROP)		Ln(1 + DHOUSE)		Ln(1 + DPP)		Ln(1 + TELD)	
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Development indicators								
HDI	17.03 (18.48)	–	−10.54 (19.38)	–	0.839 (18.69)	–	8.32 (19.35)	–
$(HDI)^2$	−27.75 (24.50)	–	7.70 (24.66)	–	−6.02 (25.75)	–	−12.51 (26.05)	–
Ln(PCNSDPC)	–	−1.3 (1.43)	–	−0.38 (1.57)	–	3.17* (1.69)	–	1.45 (1.55)
$Ln(PCNSDPC)^2$	–	0.00 (0.00)	–	−0.00 (0.00)	–	−0.00 (0.00)	–	−0.00 (0.00)
Hazard and risk								
ARAIN	0.004** (0.002)	0.003** (0.002)	0.005*** (0.002)	0.005** (0.002)	0.006*** (0.001)	0.006*** (0.002)	0.006*** (0.001)	0.006*** (0.002)
AAREA	25.62*** (7.10)	23.97*** (6.87)	20.61** (7.36)	18.70** (7.11)	25.08*** (6.45)	22.81*** (5.94)	21.98*** (6.15)	21.09*** (6.04)
Disaster-specific adaptation measures								
NFY	1.96*** (0.40)	1.42** (0.54)	1.85*** (0.31)	1.61*** (0.48)	1.83*** (0.43)	1.23** (0.52)	2.4*** (0.35)	1.79*** (0.34)
DRR	−3.37* (1.92)	−1.4 (2.21)	−1.28 (1.79)	−0.11 (2.02)	−1.26 (2.38)	0.97 (2.65)	−1.59 (1.90)	0.28 (1.88)
Constant	−2.51 (3.90)	13.08 (12.64)	−0.41 (4.25)	2.41 (13.99)	−2.98 (3.65)	−28.75* (14.78)	−3.74 (3.87)	−12.44 (13.79)
Time effects	Y	Y	Y	Y	Y	Y	Y	Y
R^2 (overall)	0.297	0.301	0.229	0.267	0.229	0.240	0.225	0.247
No. of observations	1,239	1,003	1,239	1,003	1,239	1,003	1,239	1,003
No. of states	21	17	21	17	21	17	21	17
Model	OLS(FE)	OLS(FE)	OLS(FE)	OLS(FE)	OLS(FE)	OLS(FE)	OLS(FE)	OLS(FE)

Note: Cluster robust standard errors in parentheses; FE, fixed effects; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Authors' computation.

while a richer household can do (see Anbarci *et al.*, 2005). According to Wisner *et al.* (2003), the impacts of a hazard are derived from the distribution of assets, income, access to resources, and allocation of social protection programme. This proves the hypothesis that all development cannot lead to a reduction of damage from floods. Further, it also indicates that only development at the aggregate level may not reduce damage risks, and hence, there is a need to enhance accessibility capacity of lower quintiles. It is, therefore, imperative to integrate climate change in development planning and policies to avoid the possibility of mal-adaptation in the foreseeable future and also address the persistent adaptation deficit. However, such finding does not categorically roll out the role of development in mitigating L&Ds from natural disasters. While only income can enhance an individual household's resilience capacity, distribution of income matters at the state and country levels. This needs further empirical investigation, but, we are unable to do this in this study due to the paucity of information.

The variables representing hazard and risk components are found as positive across the models. Such findings are a priori expected and supported by studies such as those of Kahn (2005), Sharma & Patwardhan (2008), Kellenberg & Mobarak (2008), Ferreira *et al.* (2013) and Bahinipati & Patnaik

(2015). This reveals that higher L&Ds are likely to be reported with the increasing intensity of floods. As mentioned in a previous section, we have taken two proxy variables to capture the effects of disaster-specific adaptation measures. With respect to learning effect (i.e., NFY), we observe mostly a positive sign and also most of the coefficients are statistically significant (see Tables 3 and 4). While earlier studies have shown evidence regarding the presence of a learning effect (Yamamura, 2010; Bahinipati & Patnaik, 2015), we did not do so in the present case. It seems flood vulnerability has not changed over the years, with regions being vulnerable in the past continuing to exhibit a similar trend. In effect, the growth and economic development accruing over the years have not been effective in dealing with the idiosyncratic risks faced at a micro-level and rather may have worked in the opposite way due to the intensification of existing inequities. In contrast, with regards to several disaster-specific adaptation measures taken up across these states to minimize disaster impacts, we find evidence of a positive payoff. These activities have reduced L&Ds from flood events, as also observed by Das & Smith (2012) and Bahinipati & Patnaik (2015), i.e., the states with DRM in place are likely to be less affected. Such interventions are large scale in nature and often targeted to reduce the covariate risks associated with extreme events across geographically vulnerable regions.

Summary and conclusions

Previous studies have clearly established the relationship between development and L&Ds from natural disasters. Over the years, a few cross-country studies have also emerged that examine the effects of development (captured in terms of income, education, governance, institution, corruption, etc.) on L&Ds from disasters, especially human casualties. However, there is a dearth of literature with respect to effects at a regional level, particularly in the case of developing nations like India and which the present study has attempted to investigate. Moreover, no previous studies have examined the role of human development in mitigating a disaster's impact and the causal relationship between development and several L&D indicators, which is the key contribution of this paper. However, some key limitations do exist: first, the findings could be affected by a reporting bias, as the present dataset encounters non-reported L&D figures in the flood years with the possibility of either under- and overestimation of reported L&D figures; second, there is also a lack of availability of long-term socio-economic indicators across Indian states, negating the scope of inclusion of other possible confounders, e.g., forest area, governance, institution, inequality, etc.

Nevertheless, based on the analysis and subject to data limitations, we conclude the following. First, an increasing trend is observed for the reported loss and damage indicators not only at the aggregate all-India level but also across the flood-affected states. An increasing trend is clearly visible for states like Andhra Pradesh, Assam, Bihar, Himachal Pradesh, Kerala, Manipur, Odisha, Rajasthan, Tripura, Uttar Pradesh, etc. This confirms that the impact from flood is rising over the years and could significantly affect an individual household's well-being and the state's macroeconomic health. We posit that this could simply be due to an increase in the exposure of assets at risk as a consequence of the economic growth trajectories of the states in question. Second, human development and income do not significantly reduce a flood's impact; this implies the present level of human development and income does not necessarily translate to the states becoming resilient towards floods. While several micro-level and macro-studies with cross-country analysis observed that income can significantly reduce L&Ds, the contrasting finding could be because of the disproportionate distribution of resources among the strata. Meanwhile, Parida (2020) observed a negative relationship between economic development and flood fatalities and damages based on the analysis carried out with the same dataset used in this study, and data considered for the analysis is between 1980 and 2011. Third, although we do not find the evidence of learning effect in mitigating floods' impact, disaster risk mitigation programmes deployed at a macro-level are effective in reducing L&Ds from extreme events like floods, suggesting that they could be a potent instrument to deal with risks at a covariate level. Bahinipati & Patnaik (2015) find evidence of learning effect in the case of Odisha with respect to cyclone and flood. This study suggests for a continuation and extension of the DRM programmes to other vulnerable regions across the Indian states to reduce potential L&Ds from floods.

From the policy perspective, this study urges that the ongoing development policies and planning must take into account climatic risks and address the persistent adaptation deficit. Until the middle of the last decade, issues related to the impacts of climate change were mostly discussed at the international negotiation level, and not part of the development planning at national and state levels (Dubash & Jogesh, 2014). However, in the recent past, climate change action plan reports have been drafted both at national and state levels, and even disaster management plan documents have been prepared for some of the Indian states. However, the main lacuna is the lack of integration between the development planning and state action plan for climate change, and on the other hand, non-inclusion of all developmental issues in the latter report (Dubash & Jogesh, 2014). For example, although most of the Indian states have suffered from various disasters, it is surprising to see that none of the state level human development reports has a separate chapter on natural disaster except the state of Odisha, even when climate change appears as a major theme in an international human development report of 2007. Instead of drafting a separate action plan, we urge integrating climate in all development planning processes, so all the development projects can be climate-friendly and compatible. Further, we should focus on enhancing the performance of several socio-economic indicators across the lower income strata households, as only higher development with a skewed distribution of resources does not assist the state to reduce flood impacts. This finding is more relevant in the present context as all the Indian states are currently initiating a process to draft a second state action plan on climate change.

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Data availability statement

Data cannot be made publicly available; readers should contact the corresponding author for details.

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