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Human development and disaster mortality: evidence from India

Rituparna Kaushik [1✉], Yashobanta Parida [1] & Ravikiran Naik [1]

Natural disasters present substantial dangers to both human life and physical infrastructure. Although the human development index (HDI) is recognized for its pivotal role in mitigating mortality resulting from natural disasters, the exact extent of its impact on fatalities remains unclear. In this study, we investigate the relationship between HDI and fatalities resulting from floods and cyclones using panel data for 19 states of India spanning from 1983 to 2011. Employing Fixed Effects Poisson and Negative Binomial estimates, we establish a causal-effect relationship between HDI and disaster-related fatalities. Additionally, we utilize the Instrumental Variable Poisson (IV) model to address the endogeneity between HDI and fatalities. Our empirical findings indicate that states with higher HDI levels experience lower fatalities due to natural disasters. Furthermore, our results underscore the importance of critical policy discussions regarding the role of inequality-adjusted HDI, government responsiveness, and human capital development in disaster risk reduction strategies.

[1] FLAME University, Pune, India. ✉email: rituparna.kaushik@flame.edu.in

Introduction

In environmental economics, natural disasters are seen as events that disrupt economic activities, causing significant harm to assets, production, employment, and consumption patterns. Examples include earthquakes, storms, hurricanes, precipitation extremes, droughts, heatwaves, cold snaps, and lightning storms. The economic perspective on disasters suggests that natural disasters consistently harm a nation's economy. Moreover, they impact Human development Index (HDI) by destroying public and private infrastructures and people's livelihood thereby reducing income and increasing poverty. Natural disasters, owing to their capacity to inflict damage on assets and deplete savings, have the potential to push households into "poverty traps." Research indicates that such events can exert enduring effects on psychological well-being (Norris (2006)) and impede the developmental trajectories of children (Alderman et al., 2006). In their study of children in Bangladesh, Ethiopia, and Malawi; Yamauchi et al. (2009) concluded that individuals with greater biological human capital exhibit reduced vulnerability to the detrimental impacts of flooding.

Several studies suggest that developed countries with higher per capita income (PCI) have successfully reduced deaths due to natural disasters (Parida, 2020; Kahn, 2005; Stromberg, 2007; Toya and Skidmore, 2007). In addition to income and better governance, developed countries benefit from superior disaster management practices, advanced warning systems, resilient infrastructure, and robust institutional frameworks (Fankhauser and McDermott, 2014; Parida, 2020; Raschky, 2008; Kahn, 2005; Anbarci et al., 2005). On the other hand, the mortality rate resulting from disasters tends to be notably higher in developing countries compared to their developed counterparts, primarily due to their higher susceptibility to the devastating impacts of natural calamities and their limited capacity to cope with such events. Between 1970 and 2019, developing countries bore the brunt of 71 percent of natural disasters fatalities, while developed countries, including those in economic transition, accounted for the remaining 29 percent. Among developing nations, ~91 percent of fatalities are attributable to natural disasters, starkly contrasting with the 9 percent in developed countries[1]. Significantly, natural disasters inflicted 38 percent of economic losses in developing nations, with the remaining 62 percent attributed to developed countries. However, when considering economic losses as a proportion of GDP, despite enduring lesser economic losses compared to developed countries, developing nations experienced overall losses ten times higher than their developed counterparts (Douris and Kim, 2021; UNDRR GAR, 2022). According to the United Nations Development Programme (UNDP), countries with low levels of HDI accounted for over half of all reported casualties in the past two decades, despite comprising only one-tenth of the population exposed to natural disasters. Moreover, ~85% of individuals exposed to natural disasters reside in countries with medium to low levels of human development. Regions with lower HDI are more susceptible to natural hazards due to the prevalence of impoverished communities characterized by low income, education, and life expectancy. This vulnerability arises from two primary factors. Firstly, areas prone to risks may attract settlement due to the presence of inexpensive agricultural lands, low living costs, access to natural resources, and better land productivity (Hallegatte, 2012). As HDI levels rise, individuals gain greater capacity and resources to relocate to areas with lower susceptibility to natural disasters. Consequently, a prevalent trend observed in many developing nations is the migration of wealthier individuals away from regions prone to repeated disasters (Hallegatte et. al, 2016). Secondly, people and households with lower incomes experience diminished benefits from hazard protection primarily due to inadequate infrastructure and investments. In low-income countries, particularly those with a GDP per capita below $5000 in purchasing power parity and low attainment in health and education, individuals are less safeguarded compared to their counterparts in wealthier nations (Hallegatte et al., 2016). This disparity persists within countries, where investments, including those in disaster risk reduction, are often channeled towards relatively affluent areas at the expense of impoverished regions. This phenomenon may be attributed to decision-making frameworks of flood management policies that prioritize higher-value assets over less productive ones. Moreover, developing countries often grapple with inadequate disaster management plans, deficient infrastructure resilience, and heightened socioeconomic vulnerability. Contributing factors include higher population density, rapid population growth, reliance on the agricultural sector, elevated poverty rates, unplanned urbanization, and low PCI (Thomas and López, 2015). Hence, overall, allocating resources towards improving HDI to mitigate disaster risk has the potential to yield growth and benefits that extend beyond preventing human casualties and physical infrastructure damage.

India, like many other developing nations, faces significant challenges and dangers to both human life and infrastructure from natural disasters. Over the decades, India has grappled with the devastating consequences of such events. Every year, the country grapple with severe floods, cyclones, droughts, and landslides. Official data reveals that the country has incurred losses amounting to ~0.46% to 2% of its gross state domestic product due to recurrent floods and cyclones, thereby adversely impacting its economic progress (Parida and Dash, 2020). India also ranked 3rd in terms of human mortality due to extreme weather events between 2000 and 2019 (Eckstein et al., 2021). Moreover, the agricultural sector, a crucial sector of India's economy, has been severely affected by periodic floods across various states, resulting in diminished employment opportunities and wages (Parida and Chowdhury, 2021; Chowdhury et al., 2022). Between 1983 and 2011, India experienced a total of 190 floods and 54 cyclones, with a significant proportion originating in the Bay of Bengal and Arabian Sea regions and striking the eastern and western coastline, leading to substantial economic repercussions (India Meteorological Department[2]). In addition to economic losses, frequent floods and cyclones have resulted in significant loss of life in India. Between 1980 and 2011, floods claimed ~60,919 lives, with 1.22 billion people affected. Similarly, during the same period, cyclones led to the deaths of 20,360 individuals, with 56 million people affected. India's geo-climatic and socioeconomic conditions play a significant role in the escalating fatalities and infrastructure-related damages caused by severe floods and cyclones. (Government of India (2011)[3]).

In recent times, there has been a notable shift in focus towards identifying strategies to minimize human losses resulting from disasters. Alongside efforts to construct more resilient infrastructure, policymakers are increasingly prioritizing the elevation of PCI to enhance initiatives aimed at reducing disaster-related fatalities. However, solely emphasizing the improvement in PCI as a means to minimize disaster fatalities, particularly in developing nations like India, proves ineffective due to PCI's inability to accurately reflect the country's true economic development. Alternatively, the focus should pivot towards a more holistic approach to development, which entails examining the combined impacts of higher per capita income, improved health conditions, and expanded educational opportunities—all of which collectively denote the country's genuine progress in economic development. Therefore, our study employs HDI as a proxy for gauging the overall development of states in India.

Current study. Drawing inspiration from both theoretical and empirical evidence within the context of India's natural disaster impacts, this study delves into the understanding of the impact of an enhanced HDI on the aggregate deaths resulting from natural disasters. The motivation behind this study stems from the recognition that solely relying on PCI as a proxy for economic development may not sufficiently mitigate the death rate resulting from disasters. This inadequacy is particularly pronounced in developing countries, where increases in PCI often fail to translate into tangible improvements in living standards. Moreover, PCI alone does not adequately capture the multifaceted dimensions of economic development in countries like India.

Considering these limitations, the study argues for the adoption of composite human development indicators, which encompass not only higher PCI but also includes factors such as improved health and educational infrastructure. Such holistic indicators offer a more accurate reflection of inclusive development and are instrumental in minimizing the impact of disasters in terms of human life loss. Utilizing panel data spanning Indian states over the period 1983–2011, this study aims to enrich the extant literature on the economics of natural disasters through several key contributions. Primarily, we investigate the influence of HDI at time 't' on flood-related fatalities in subsequent time periods $(t+1)$, $(t+2)$, and $(t+3)$, thereby discerning the recurring impact of HDI over time on overall flood mortality. Secondly, we extend our analysis to cyclone-related deaths across the same time horizons as stated above. Furthermore, we also delved into the combined impact of HDI at time 't' on fatalities attributable to both floods and cyclones during same time periods, providing a comprehensive understanding of the joint effects of these calamities. Additionally, we construct indicators for disaster occurrences across various time intervals, such as cyclones occurring in periods $t+1$, $t+2$, *and* $t+3$, and areas affected by floods in $t+1$, $t+2$, *and* $t+3$. Lastly, we employ an innovative econometric methodology, namely the Instrumental Variable Poisson (IV-Poisson) model utilizing a control function approach, to mitigate potential endogeneity concerns between HDI and fatalities stemming from cyclones and floods.

The findings of this study reveal important insights into the relationship between HDI and natural disaster-induced mortality. Our results indicate a notable reduction in the likelihood of deaths caused by natural disasters following an increase in HDI. Specifically, we observe a decline of expected fatalities by 109 individuals in the first, 182 in the second, and 236 in the third year, respectively, for every one-unit rise in HDI. Moreover, the analysis demonstrates a corresponding decrease in flood-related expected fatalities by 85 individuals in the first, 141 in the second, and 173 in the third year respectively, as HDI increases. Similarly, fatalities attributed to cyclones exhibit expected declines by 12 individuals in the first year, 6 in the second, and 12 in the third year, respectively, for an increase in HDI. Furthermore, employing Control Function estimation reinforces the negative association between HDI and disaster fatalities. Additionally, our examination underscores the significance of ecological and institutional factors in shaping disaster outcomes.

The subsequent sections of this paper are organized as follows: "Theoretical Context" discusses theoretical context of the study, "Review of Literature" presents the review of literature, "Data and Descriptive Statistics" presents data, variables, and descriptive statistics, "Identification and Methodology" elaborates on the identification strategy and methodology, "Empirical Results and Discussions" presents the results derived from our analysis and finally, "Conclusions and Policy Discussions" concludes the study and discusses policy recommendations based on the findings.

Theoretical context

Scholars like Pelling (2003), Lindell and Prater (2003), Cochrane (2004), Rose (2004), and others have contributed to understanding disaster impacts, often categorizing them as direct and or indirect losses[4]. Within the category of direct impacts of disasters, which are conspicuous and severe, losses stemming from disasters are categorized commonly into two principal types: direct market losses and direct non-market losses, the latter also occasionally referred to as intangible losses, despite the fact that non-market losses are not necessarily intangible (Hallegatte and Przyluski, (2010); Rogers et al., (2019)). Market losses encompass the devaluation of goods and services traded within established markets, where prices are readily observable. Direct market losses resulting from most disasters (e.g., earthquakes, floods, etc.) primarily involve the destruction or impairment of agricultural output, infrastructure, and overall economic output. These losses are typically quantified in terms of the costs associated with repairing or replacing the damaged assets. On the other hand, Non-market direct losses encompass all forms of damage that cannot be rectified or substituted through transactions within a market setting. Unlike market losses, there exists no readily observable price to gauge the extent of these losses. This holds true for various instances, including but not limited to health impacts, loss of life, damage to natural assets and ecosystems, etc. Given the nature of the disaster-driven losses, our study aligns with the theoretical framework of addressing non-market direct losses resulting from disasters through investment in improving HDI[5]. HDI is a composite statistical measure used to assess and compare the level of development and well-being of countries around the world[6]. It provides a more holistic and comprehensive assessment of development emphasizing the importance of investing in health, education, and living standards to improve overall human well-being.

Given the low HDI attainment, poor regions or countries have limited physical and human resources to combat the impact of disasters and its aftermath. In cases where communities experience frequent disruptions from disasters, the interval between successive events may be insufficient for comprehensive rebuilding efforts. Consequently, they may become ensnared in a perpetual cycle of reconstruction, allocating all available resources towards repair activities rather than investing in the development of new infrastructure and equipment. Such kind of severe destruction and difficulties of capital accumulation leads to slow and failure to build disaster resilient infrastructure (Hallegatte et al., 2020). In most cases, government bodies taking advantage of low income and education levels of the people residing nearby the disaster-prone areas would drive away the investment funds to more productive and richer areas (Hallegatte et al., 2020). Hence, in this context, investment in all components of HDI would ensure that when the income, health, and the education the people living in the disaster-prone area would improve, they would naturally demand for more disaster resilient infrastructures form government as well as they themselves can invest in bulling better disaster resilient homes minimizing the extent of devastations. Hallegatte et al. (2007) demonstrate that the GDP impact of natural disasters can vary significantly. In instances where reconstruction capacity is constrained, particularly prevalent in certain least developed countries, the GDP impact can be substantial. Furthermore, beyond empirical evidence, certain theoretical models, such as intermediate models combining features of input-output (IO)[7] models with the flexibility demonstrated in Hallegatte (2008), computable general equilibrium (CGE)[8] models featuring reduced substitution elasticity as seen in Rose (2004), or IO-CGE hybrid models with bottom-up characteristics like those presented by Horridge et al. (2005), underscore the significance of infrastructure and investment in mitigating the losses incurred from disasters (see, for instance, Jiang and Haimes (2004)).

In India, where large glacial-fed rivers intersect with the Bay of Bengal, Arabian Sea and Indian Ocean, a significant portion of the population resides in close proximity to these water bodies, with the majority residing in rural areas. Consequently, these communities are highly vulnerable to floods and cyclones, lacking the necessary infrastructure to mitigate the impact of disasters triggered by glacier-fed rivers and recurrent cyclones. Furthermore, governmental allocation of funds often favor wealthier regions and cities, neglecting the development of disaster-resilient infrastructure in impoverished areas, thereby exacerbating the risk faced by vulnerable households. Additionally, in many developing countries, including India, coverage of disaster-related social protection programs remains limited, rendering them insufficient to adequately support affected populations. The Asian Disaster Reduction Centre (A.D.R.C.)[9] highlights that Asian countries with higher levels of human development find it comparatively easier to implement disaster mitigation, allocate financial assistance, preparedness planning, and management strategies in the aftermath of disasters. Enhancing human development indicators such as literacy rates, life expectancy, education levels, and PCI can significantly diminish the adverse effects of natural disasters (Noy, 2009). Therefore, it is reasonable to anticipate that higher levels of investments in education and health and increased income per capita will result in a reduction in fatalities caused by natural disasters.

While previous studies have extensively examined the impact of natural disasters on HDI, there is a dearth of research exploring the reverse causality—specifically, how improvements in HDI can mitigate direct non-market losses resulting from natural disasters and a broader discussion of the channels through which these reductions take place. Given India's significant economic and social diversity, our study aims to investigate how enhancements in HDI within each Indian state could potentially reduce direct non-market losses triggered by natural disasters. To quantify these losses, we focus on human fatalities resulting from floods and cyclones in India.

Review of literature

This study delves into the crucial role of achievements in the HDI in reducing fatalities from floods and cyclones. Recognizing the inadequacy of PCI as a measure of disaster resilience, it highlights the significance of composite human development indicators like health and education infrastructure in mitigating loss of life during natural disasters.

The existing literature on the intersection of natural disasters, economic growth development, and human development sheds light on the multifaceted dynamics influencing disaster mitigation and its impact on societies. Overall, the economics of natural disasters is a multifaceted and complex field. One branch of scholars such as Ratti (2017) and Hallegatte (2010) offer insights into understanding losses from disasters. Whereas the other branches, such as Kunreuther (2006) and Botzen et al. (2019) explore the economic impact of disasters, Kellenberg, Mobarak (2008) and Yu et al. (2017) discuss disaster vulnerability of countries and importance of disaster mitigation strategies, and Noy et al. (2018) surveys economic vulnerability and resilience.

Research consistently shows that higher PCI is associated with reduced human loss in the event of natural disasters (Primantia et al., (2018); Ji et al., 2013). However, this relationship is not straightforward, as income inequality does not necessarily lead to higher rates of death and injury from disasters (Graham, 2021). The impact of disasters is particularly severe in low and middle-income countries, where they can lead to significant economic and human losses (Poundrik, 2010; Anttila-Hughes and Hsiang (2013)). The relationship between rising income and disaster risk is complex, with some studies suggesting that disaster risk increases with income up to a certain level before decreasing (Kellenberg and Mobarak, (2008)). The consequences of disasters extend beyond immediate physical damages, with post-disaster losses including unearned income and excess infant mortality (Anttila-Hughes and Hsiang (2013)). Disasters have a major impact on living conditions, economic performance, and environmental assets, with developing countries being particularly vulnerable due to the lack of effective early warning and evacuation systems (Bradshaw, 2003).

In the context of vulnerability to disasters, it is linked to developmental aspects such as low income, health concerns, and lack of education (Nirupama, 2012). Higher economic development is associated with lower disaster losses, particularly in terms of deaths (Zhou et al., (2014); Toya and Skidmore, 2007). Disasters can also have long-lasting and far-reaching effects on human capital, including education and health (Baez et al. (2010)). Moreover, HDI emerges as a significant determinant of disaster resilience, as evidenced by Chowdhury et al., 2021, Padli and Habibullah (2008), and Haque et al. (2012). The reduction of fatalities from natural disasters is closely linked to human development, particularly in developing countries. Blum (1991) highlights the importance of addressing the social determinants of health, such as poverty and education, to reduce child mortality. A range of studies have explored the relationship between the Human HDI and disaster casualties. Feng et al. (2014) and Prasojo et al. (2021) both found that higher HDI is associated with lower casualties, with Prasojo specifically noting a negative correlation between HDI and human losses from disasters. This is further supported by Baradan et al. (2019), who found an inverse relationship between HDI and fatality rates in construction. Raschky (2008) underscores the importance of institutional quality in lessening the effects of disasters, drawing attention to a non-linear correlation between economic growth and disaster damages. Noy (2009) adds to this by pinpointing crucial elements like literacy rates, institutional robustness, and governmental expenditure, which strengthen resilience and inhibit the domino effects following a disaster. Hence, effective administration and investments in education and infrastructure are vital parts of holistic strategies for disaster risk reduction. In the same context, Kellenberg and Mobarak (2008) adds another layer of complexity by pointing out that the twin objectives of preventing disaster risk and promoting economic growth might not always align for all types of natural disasters.

However, the relationship between development and disaster outcomes is nuanced, as Ferreira et al., 2013 suggests, and may be influenced by various factors including income disparities and governance efficiency. For example, the distribution of disaster impacts across income groups can be influenced by pre-existing vulnerabilities and the poorest often bear the heaviest burden of these effects (Masozera et al., (2007)). Anbarci et al. (2005) establishes a crucial link between income inequality and the severity of damages incurred during natural disasters, underscoring how societal divisions impede collective action for mitigation efforts. For example, Natural disasters have a gendered impact on life expectancy, with women being more vulnerable due to social and economic factors (Neumayer and Plümper (2007)). This suggests that affluent populations may resort to self-insurance, leaving the marginalized more vulnerable. Such disparities in disaster response and recovery highlight the critical need for inclusive policies and equitable resource allocation to address the root causes of vulnerability. Schumacher and Strobl (2011) further explore the trajectory of losses in low-risk countries undergoing economic development, revealing an initial rise followed by a decline, indicative of evolving resilience capacities. However, this positive trend can be offset by increasing inequality, as evidenced by the findings of Cappelli et al. (2021), suggesting the existence of a destructive cycle perpetuating the disasters-inequality trap. Along with socio-economic conditions, empirical research consistently shows that government expenditure on quality infrastructure can significantly reduce the damages from natural disasters (Taghizadeh-Hesary et al. (2019); Taghizadeh-Hesary et al., (2021)). Social infrastructure, such as community centers and parks, also plays a key role in mitigating the impact of disasters (Aldrich 2023). However, the importance of public investment in physical infrastructure, such as roads and bridges, should not be overlooked (Aschauer (1990)).

A review of the literature on poverty and disasters reveals a complex interplay between the two phenomena. Due to factors like exposure, vulnerability, and socio-economic resilience, poor individuals are more susceptible to disasters, which in turn exacerbate poverty, creating a destructive cycle (Hallegatte et al., 2020; Fothergill and Peek (2004)). The macro-level nexus between natural disasters and poverty underscores the need for complementary approaches from markets, governments, and communities (Sawada and Takasaki (2017)). Theories of poverty, including individual deficiencies, cultural beliefs, and economic distortions, provide a framework for understanding the root causes of poverty (Addae-Korankye (2019)). The long-term impacts of disasters on poverty, particularly in low-income countries, highlight the need for resilience-building measures (Rentschler, 2013). The poverty-environmental degradation nexus further complicates this relationship, with institutional and market failures contributing to both poverty and environmental issues (Duraiappah (1998)). The re-emergence of working poverty in advanced economies underscores the need for a more nuanced understanding of poverty and its various forms (Crettaz, 2013).

Data and descriptive statistics

For the empirical analysis, we compiled socioeconomic and disaster fatalities data for 19 states of India from 1983 to 2011[10]. Data on deaths due to floods and cyclones data are obtained from annual reports of "Accidental Deaths & Suicides in India (ADSI)", Government of India (GoI). We have collected data on areas affected by floods from the "Central Water Commission (CWC)" reports, GoI. Our primary variable of interest is HDI. We have compiled state-wise HDI data from Mukherjee et al. (2016) paper. The HDI consists of three development indicators such as PCI, health, and educational attainments indexes. The advantage of using HDI is that it is a better and more comprehensive measure of human and economic development in the Indian states.

The HDI data is available in different periods, such as 1983, 1987, 1993, 1999, 2004, 2009, and 2011. First, we construct the outcome variables, such as flood and cyclone fatalities, based on the HDI data available in different years. To mitigate the potential endogeneity issues, we take lag values of HDI. For 1983's HDI, we use the value of the outcome variable of the year 1984; for 1987's HDI, we use the value of the outcome variable for the year 1988. Similarly, we match our outcome variable with HDI values in the rest of the sample.

Flood and cyclone fatalities data are matched with the HDI at different time points; that is, we calculated the averages of flood and cyclone fatalities to the respective years for which HDI data is available in the particular states. For example, for HDI, in 1983, we estimated the average flood fatalities from 1984 to 1986. For the next HDI year, i.e., 1987, we follow the similar method for taking average of flood mortality between 1988 and1992 and so forth for the next HDI years. A similar method is used to match the data on cyclone fatalities with the HDI data estimated at different time points. For our main control variables, forest cover data is taken from 'Land Use Statistics at A Glance', GoI. The 'India Meteorological Department (IMD)', Pune provides the annual rainfall.

On the other hand, information on state-wise severity of floods and cyclones has been compiled from the Disastrous Weather Events reports of the IMD, Pune. Information on state-wise credit deposit ratio has been compiled from the Economic and Political Weekly database. The state government security and calamity spending has been compiled by the Reserve Bank of India. Population data has been extracted from the census years, mainly 1981, 1991, 2001, and 2011. However, due to the nature of census data, which is collected every 10 years, we linearly interpolate state-wise population data to fill up the remaining years' population. We have utilized the data on drought-prone areas as reported in Parida (2020).

Table A5 provides a comprehensive overview of summary statistics. Figures 1, 2 visually represent scatter plots, which affirm a negative correlation between HDI and fatalities stemming from floods and cyclones. This implies that states in India with higher HDI levels tend to experience fewer disaster-related deaths. On average, floods claim the lives of 47 individuals each year, while cyclones result in 11 fatalities. The average HDI across the states is calculated at 0.36. Notably, the government's annual allocation towards social and calamity expenditure stands at ~Rs. 137, indicating a relatively modest budgetary commitment to disaster mitigation efforts. Forest coverage in India spans nearly 22 percent of the land, with around 4 million hectares identified as drought-prone areas by various state governments.

Figure 3 illustrates that cyclones have resulted in a higher number of fatalities across Indian states. Additionally, frequent floods have led to loss of human life, particularly in coastal and landlocked states of India with glacial-fed rivers (refer to Fig. 4). However, even within these states, those with higher HDI levels have experienced lower disaster-related fatalities. For instance, states like Uttar Pradesh (UP) and Bihar, which record the lowest HDI figures in the country, have witnessed a significant number of flood-related deaths (indicated by darker shades of green in Fig. 4). Conversely, in terms of cyclone-related deaths, Odisha, characterized by a low HDI, has reported the highest number of disaster-related fatalities (refer to Fig. 3).

Identification and methodology

We identify our model by establishing a cause-effect relationship between HDI and disaster fatalities using Panel Fixed Effects Poisson, Negative Binomial Models, and Instrumental Variable Method (or Control Function Approach). In the following sections, we discuss these estimation methods and empirical strategies in detail.

Fixed effects Poisson estimation. In our analysis, the outcome variables are flood fatalities, cyclone fatalities, and total fatalities (both cyclones and floods). These variables, by nature, are non-negative count variables. Hence, to analyze the impact of HDI (inequality-adjusted) on flood fatalities, cyclone fatalities, and total fatalities, we estimate Eqs. (1), (2), and (3), respectively, using two key approaches. We adopt Fixed Effects (FE) negative binomial and FE Poisson models for estimation purposes. Since we find the conditional variance of the dependent variables is higher than the conditional mean, the data on fatalities are overdispersed, violating the equal mean and variance assumption of Poisson distribution (See Appendix Table A5). However, the presence of overdispersion does not make FE negative binomial a better estimator (Ferreira et al., 2013). Moreover, in a panel

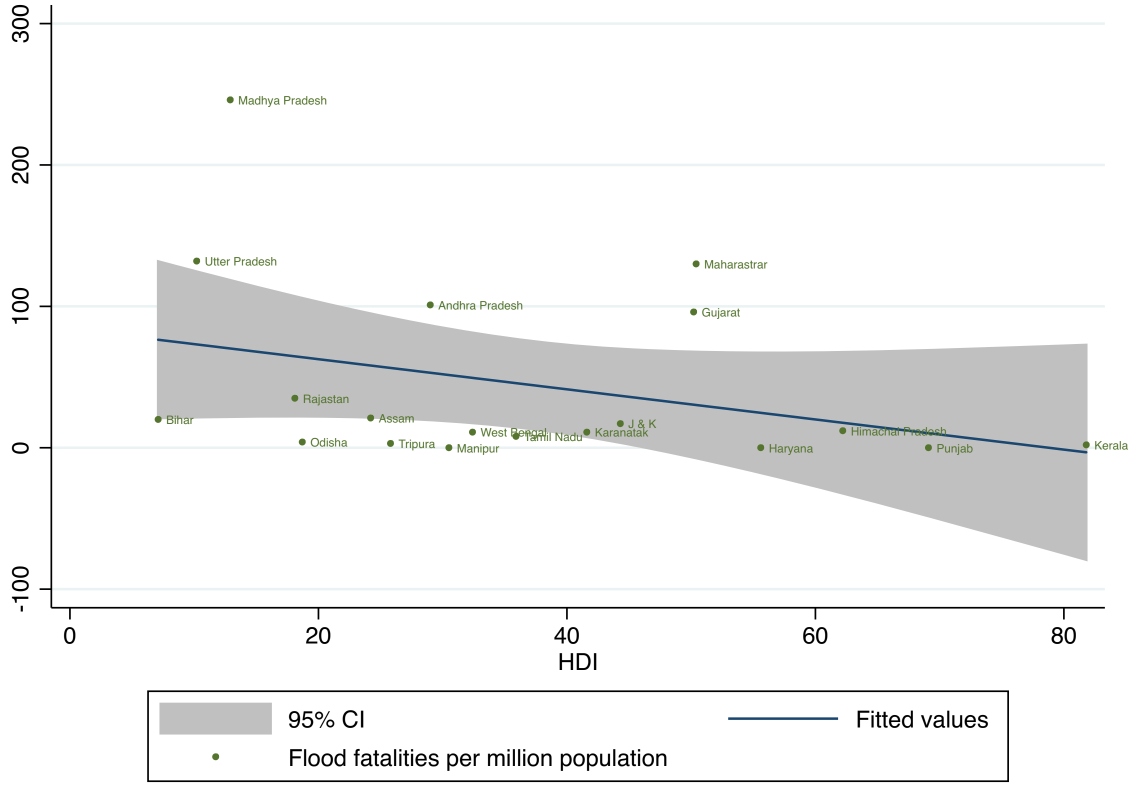

Fig. 1 Plot diagram of average HDI and flood fatalities. The figure shows relationship between HDI and flood fatalities for Indian states. The realtionship is negative, indicating reduction in fatalities as HDI increases. Each green dots indicates states.

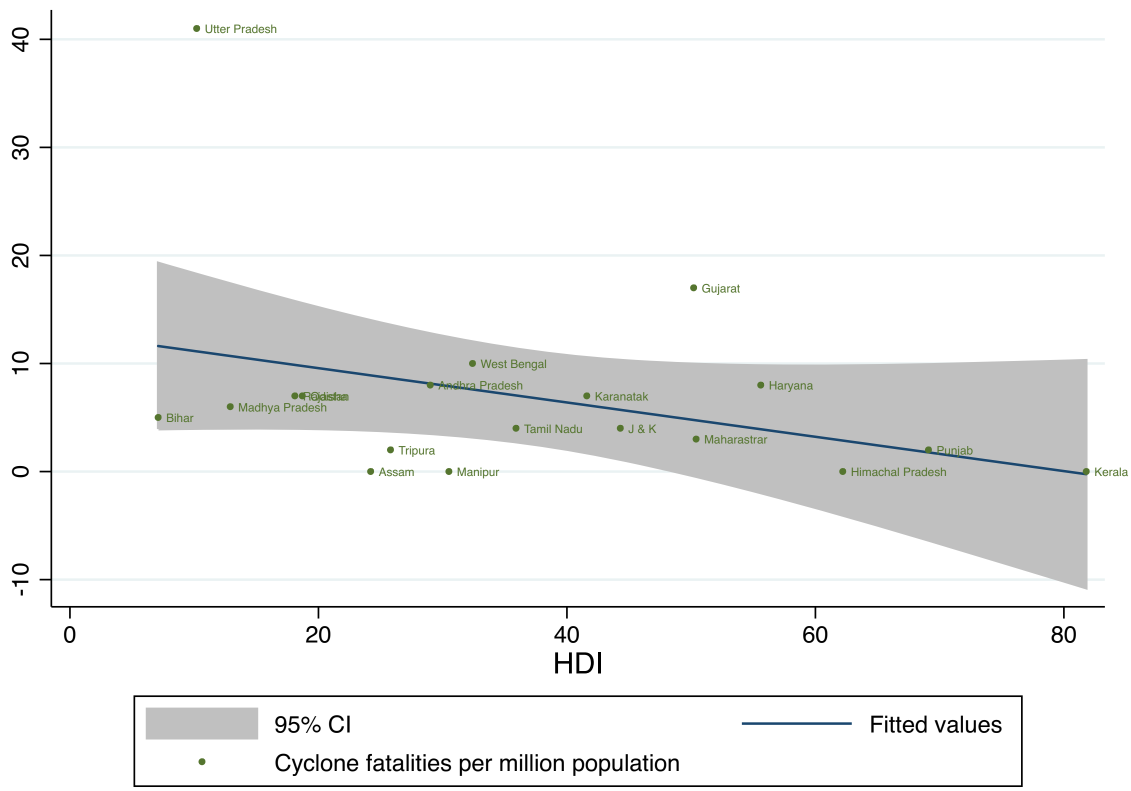

Fig. 2 Plot diagram of average HDI and cyclone fatalities. The figure shows relationship between HDI and cyclone fatalities for Indian states. The realtionship is negative, indicating reduction in fatalities as HDI increases. Each green dots indicates states.

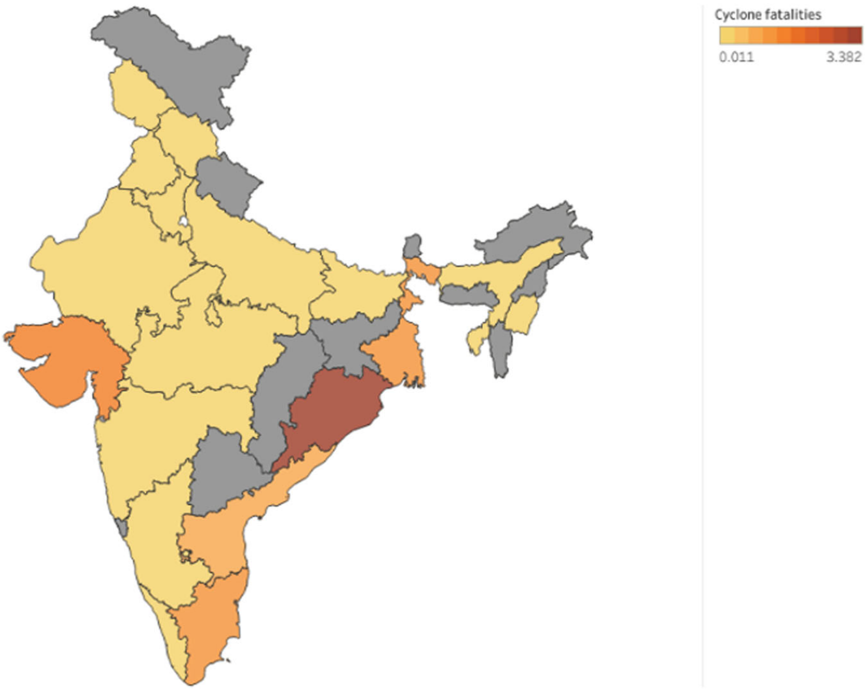

Fig. 3 State-wise average cyclone fatalities. The figure indicates that darker the shade of the colour orange, higher is the fatalities from cyclone.

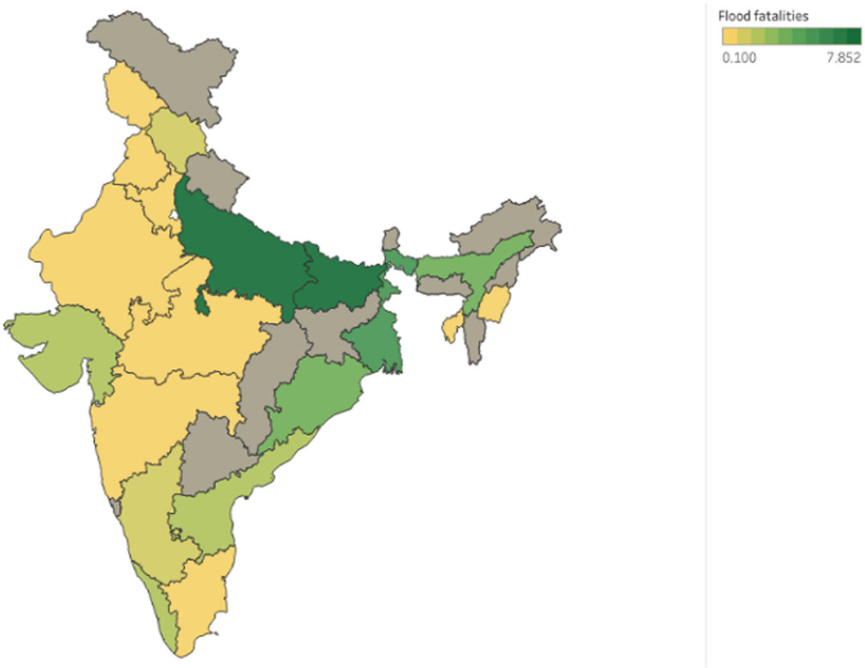

Fig. 4 State-wise average flood fatalities. The figure indicates that darker the shade of the colour green, higher is the fatalities from flood.

setting, the FE negative binomial model does not robustly control for unobserved region effects (Ferreira et al., 2013). On the contrary, the FE Poisson estimator generates consistent estimates even when data are over-dispersed. Therefore, we follow the Cameron and Trivedi (2010, 575) test to determine the appropriate methodology for our analysis. The Cameron and Trivedi (2010, 575) test results indicated that the FE Poisson is appropriate for our dataset[11]. However, to make our results more robust, we also apply FE negative binomial as an additional mechanism to check robustness.

Standard errors are calculated based on a sandwich estimator for the FE Poisson estimation, which allows for deviation from the Poisson distribution, including overdispersion and zero observations (Wooldridge, 2002:674–676; Ferreira et al., 2013). It is important to note that the sandwich estimator controls the consequences of overdispersion rather than assuming a negative binomial distribution to model overdispersion (Greene, 2006). Sufficiently enough, the FE Poisson model also controls for unobserved region effects, which cause overdispersion in the data (Wooldridge, 2002:674–676). Following the arguments in the literature, we define our econometric model as follows;

$$FF_{it+1} = exp\,exp\{\beta HDI_{it} + \beta_1 CR_{it-1} + \beta_2 FC_{it-1} + \beta_3 PCSCE_{it} + \beta_4 Z_{it} + \partial_r + \lambda_t\} + \mu_{it} \quad (1)$$

$$CF_{it+1} = exp\,exp\{\beta HDI_{it} + \beta_1 CR_{it-1} + \beta_2 FC_{it-1} + \beta_3 PCSCE_{it} + \beta_4 Z_{it} + \partial_r + \lambda_t\} + \mu_{it} \quad (2)$$

$$TF_{it+1} = exp\,exp\{\beta HDI_{it} + \beta_1 BC_{it-1} + \beta_2 FC_{it-1} + \beta_3 PCSCE_{it} + \beta_4 Z_{it} + \partial_r + \lambda_t\} + \mu_{it} \quad (3)$$

In Eqs. (1), (2), and (3), FF_{it+1}, CF_{it+1}, and, TF_{it+1} denote the number of persons killed in state i due to floods and cyclones, respectively, in year t. Our primary variable of interest in each specification is HDI_{it}, the inequality-adjusted HDI for each state in various years[12] considered in our study. To control the impact of financial development, we include the lag of the bank credit ratio, CR_{it-1}. Moreover, the availability and ease of bank credit can help to mitigate deaths caused by natural disasters. One of the primary purposes of financial credit is to allocate credit to build housing infrastructure, which can safeguard against unforeseen natural calamities, thereby protecting families residing in the house and reducing the number of deaths. However, on the contrary, higher occurrences of disasters incentivized banks to provide loans in the aftermath of disasters as the demand for credit increases, primarily to repair housing and other infrastructure damage. This also puts a strain on banks to supply credit and meet the demand. Hence, to address this potential endogeneity issue, we include a one-period lag of credit ratio in our analysis. This lag ensures that the impact of credit is appropriately captured as it takes some time for financial development to take place and then yield its impact on overall physical infrastructure, thereby reducing deaths due to natural disasters.

Forest coverage is an important factor in not just improving ecological resilience but also mitigating natural disasters. Dense forest cover and forest ecosystems control the adverse effects of floods and cyclones, prevent landslides, and help to control environmental degradation. The higher the forest coverage of the state, the higher the resilience toward natural disasters. For example, states in Northeast India have comparatively higher forest coverage than other states of India. These states are generally more resilient to natural disasters than other states of India, with less forest coverage. Hence, to account for ecological resilience, we control the lag of forest coverage in every state of the country (FC_{it-1}).

The quality and effectiveness of government institutions also play an important role in mitigating the immediate effects of natural disasters. Public investment in social welfare and timely disbursement of natural disaster relief can help the affected population cope with natural disasters' impacts. Hence, the government's spending mainly on building disaster-resilient infrastructures is essential for preventing natural disasters. On the other hand, the government's spending on social security and welfare can act as a safety net against deaths caused by natural disasters (Parida, 2020; Chowdhury et al., 2021). Hence, the quality of institutions in our analysis is proxied by the natural logarithm of a lag of per capita government expenditure for social security and welfare, calamity relief, and expenditure directed toward better disaster management. The variable is indicated by $\ln PCSCE_{it-1}$.

Other variables, such as the severity of floods and cyclones, average rainfall, and state-wise population, are included as controls in Z_{it}. However, their inclusion is also context driven; for example, in Eq. (1), we include the severity of floods, whereas in Eq. (2), we include the severity of cyclones. ∂_r is the unobserved region fixed-effects that do not vary over time, λ_t is the year fixed-effects to control for time-varying factors, and μ_{it} is the error term. Given the significant geographical, ecological, and cultural diversity of each state of India, we argue that the unobserved time-invariant region effects, such as geo-climatic conditions of the states and other cultural factors, could be correlated with the outcome variables, the variable of interest (HDI), and other control variables incorporated in our model. To resolve this issue, we control region-fixed effects. This identification strategy eliminates the confounding effects generated due to time-invariant structural differences between regions by including the region-fixed effects. Some studies argue that controlling the time-invariant unobserved region effects is more important instead of unobserved state effects while using state-wise panel data (Parida et al., 2018; Parida, 2020). In addition, our models also control for time-variant unobserved factors that are correlated with both outcome and explanatory variables. For example, the central government's disaster management policies, minimum agricultural wage laws, and social security measures change over time; however, they are implemented in all states or regions of India. Year dummies allow us to control for such effects, and they are also included in our empirical model.

Instrumental variable model (control function approach). The FE model produces biased results if the time-varying variables omitted are correlated with the explanatory variables included in the model (Wooldridge, 2013:512). Moreover, the FE model does not adequately control the endogeneity problem resulting from reverse causality between variables. We predict the presence of reverse causality between HDI and mortality. Existing literature has also identified evidence of reverse causality between PCI and the damages and fatalities resulting from disasters (Parida, 2020; Parida et al., 2021; Kahn, 2005; Stromberg, 2007). Previous research contends that reverse causality exists between HDI and mortality. The state-wise HDI is estimated by Mukherjee et al. (2016), encompassing factors such as PCI, educational attainment, and health achievement. Prior studies argue that PCI is an endogenous variable. Consequently, we posit that HDI is also an endogenous variable due to its inclusion of PCI. To address this endogeneity issue in our econometric model, we employ the Control Function approach. For instance, states ranking low in human development achievements suffer a larger number of flood-related deaths. For example, the state of Bihar has one of the low HDI scores and has a poor infrastructure to tackle deaths due to floods. Hence, every year, Bihar experiences a large number of flood-related deaths. Furthermore, higher flood fatalities can adversely affect all components of human development, GDP per capita, education, and health. This relationship makes the HDI an endogenous variable.

We argue that the instrument and the HDI are inversely associated. For instance, states with a relatively larger drought-prone area are also likely to experience lower human development. A larger proportion of the total area marked as "drought-prone" can adversely affect per capita consumption expenditure[13], educational attainment, and health attainments leading to a decline in the overall HDI score of all states in India. In the case of Ethiopia, Dercon et al. (2005) found that droughts were linked to reduced levels of per capita consumption in households between 1999 and 2004. Parida (2020) has also used "state-wise drought-prone area" as an instrument for PCI to address endogeneity issues of the model using a state-wise flood fatalities dataset for India. Hence, following literature, we use "state-wise drought-prone area (SDPA)" as an instrument for HDI. In the first stage equation, we estimate the impact of SDPA as an instrument on HDI while controlling for socio-political and other explanatory variables. The first stage equations are as follows:

$$IHDI_{it} = \pi_i SDPA_i + \delta_1 CR_{it-1} + \delta_2 FC_{it-1} + \delta_3 PCSCE_{it} + \delta_4 Z_{it} + \gamma_r + \vartheta_t + \epsilon_{it} \quad (4)$$

$$FF_{it} = exp\,exp\left\{\alpha\widehat{HDI}_{it} + \beta_1 CR_{it-1} + \beta_3 FC_{it-1} + \beta_4 PCSCE_{it} + \beta_4 Z_{it} + \partial_r + \lambda_t\right\} + \mu_{it} \quad (5)$$

HDI_{it} is the inequality-adjusted HDI for state i at time t and $SDPA_i$ is the state-wise liable to the drought-prone area for state i. We estimate Eqs. (2) and (3) by applying a control function (CF) approach. It allows the endogenous regressors to be continuous (in our estimation HDI is a continuous variable). Wooldridge (2015) argues that the CF approach to estimation is an instrumental variable method, where the structural equation contains at least one endogenous explanatory variable. The CF approach corrects the bias resulting from the correlation between HDI and the error term. In the first stage of Eq. (2), we regress the endogenous variable (HDI) on the instrumental variable (SDPA) and other control variables and estimate the reduced form residuals. After estimating control functions in the first stage, the endogenous explanatory variable becomes exogenous in the second stage regression (Wooldridge, 2015). The final model (Eq. (5)) is estimated using the control function approach by incorporating estimated residuals as an additional regressor. A proxy variable is generated in the estimation process that allows us to condition on the part of HDI that depends on the error term. This helps us to isolate the remaining variation in the endogenous variable that is independent of the error, producing consistent results (Petrin and Train (2010)). We argue that the instrument only affects disaster fatalities through its influence on human development. In CF estimation (the first stage regression in Eq. (4)), the negative sign and significance of state-wise drought-prone areas show the validity of the instrument (Tables 5, 6). In addition, the significance of coefficients of the estimated residuals as an additional regressor in the final models (ρ) shows that the HDI is an endogenous variable (Tables 5, 6). In the next section, we describe the empirical results with the instrumental variables empirical strategy and the fixed effects model as evidence of robust analysis.

Empirical results and discussions

HDI and human life due to flood. The Poisson results are presented in columns C1–C3 of Table and the outcome variable is flood mortality. The coefficient of HDI is negative and significant, showing that the expected flood fatalities declined by 2.2 percent after one year, 3 percent in the second year, and 4 percent in the third year, respectively, with a one-unit increase in HDI.

The empirical findings suggest that better human development helps to prevent flood fatalities over the long run. This result is consistent with existing literature[14], which showed that PCI is inadequate for minimizing deaths from floods in the districts of Odisha, India (Parida et al., 2021). Substantial investments in social sector development help states minimize deaths from floods. Indian states that are highly populated, such as Bihar and UP, have experienced higher flood fatalities as a result of lower achievements in human development[15]. Our findings are similar to Feng et al. (2014) and Prasojo et al. (2021). Both found that higher HDI is associated with lower casualties, with Prasojo specifically noting a negative correlation between HDI and human losses from disasters. This is further supported by Baradan et al. (2019).

It is observed that an increase in government expenditure on building flood-resilient infrastructure, such as the construction and renovation of river embankments, also helps reduce deaths caused by floods. This effect of government expenditure on social and calamity-proof infrastructure is also visible in our results. As expected, the estimated results yield a negative sign, but it is only significant in the FE Poisson estimation. On the other hand, financial development, as indicated by the credit ratio, shows how bank credit can help mitigate deaths caused by natural disasters. Our results indicate that higher credit availability can help reduce flood-related fatalities by offering more financial help to build robust flood-resilient infrastructure. Our findings echo those of previous research, emphasizing the crucial role of increased government expenditure on quality infrastructure in mitigating the damages from natural disasters, particularly in disaster-prone countries like the Philippines (Taghizadeh-Hesary et al. (2019); Taghizadeh-Hesary et al. (2021), Aldrich, 2023, Aschauer (1990)). The average marginal effects (AME) are presented in Appendix Table A1. Our estimates show that one-unit increase in HDI leads to a fall in the expected number of flood fatalities by 85 in the first year, 141 in the second, and 173 in the third year, respectively. For robustness analysis, we use Negative binomial estimates, and the results are presented in Table 1 (C4–C6). The Negative binomial estimates produce similar results to that of the Poisson estimations (see C4–C6, Table A1).

HDI and cyclone fatalities. A range of studies have found that human development, particularly in the form of strong institutions and effective governance, can lead to a reduction in cyclone fatalities (Tennant, Gilmore (2020), Noy and Yonson 2018). We observe a similar level of impact of HDI when compared with disaster driven fatalities. Overall, our results suggest that improvement in HDI score leads to a reduction in cyclone fatalities. The first three columns (C1-C3) of Table 2 show the FE Poisson estimates. Similar to the results obtained for flood fatalities, the coefficient of HDI is negative and significant for cyclone fatalities. This indicates that a one-unit increase in HDI leads to a decline in the average cyclone fatalities by 1 percent after one year, 0.7 percent in the second year, and ultimately a sharp fall in deaths by 5 percent in the third year, respectively. In the third year, a sharp fall is observed for cyclone fatalities compared to floods, and only in the third year does the impact of HDI become highly significant.

On the one hand, the empirical findings underline the importance of other important control variables. One of them is the government expenditure on social sector development and calamity relief, which measures the government's effort to reduce the adverse impact of natural disasters. It is observed that similar to flood fatalities, an increase in government expenditure on building disaster-resilient infrastructure leads to a reduction in cyclone-related fatalities in all three subsequent years. The variable is significant in the first and third years. On the other hand, financial development, as indicated by the credit ratio, shows that higher credit availability helps reduce cyclone-related fatalities by offering more financial assistance to build a robust cyclone-resilient infrastructure. However, Indian states with a higher population density have experienced a relatively larger number of cyclone-related deaths. Moreover, as expected, as the severity of cyclones increases, fatalities tend to increase. To check the robustness of our analysis, we also estimate AME, shown in Appendix Table A.2. Our estimate shows that with a one-unit increase in HDI, the expected number of fatalities caused by cyclones declines by 12 in the first year, 6 in the second year, and 69 in the third year, respectively due to a one-unit increase in the HDI. We also perform an exact estimation using FE negative binomial estimation to validate our findings (see columns C4–C6, Table 2). Our results in the Negative binomial estimates are similar and comparable to those

Table 1 HDI and flood fatalities.

	Poisson estimate			Negative Binomial		
Dependent variable	**Flood Fatalities$_{it+1}$**	**Flood Fatalities$_{it+2}$**	**Flood Fatalities$_{it+3}$**	**Flood Fatalities$_{it+1}$**	**Flood Fatalities$_{it+2}$**	**Flood Fatalities$_{it+3}$**
Independent variables	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**
HDI	−0.022**	−0.037***	−0.049***	−0.037 ***	−0.046 ***	−0.044 ***
	(0.009)	(0.011)	(0.011)	(0.009)	(0.009)	(0.008)
Per capita social and calamity	−0.026	−0.362	−0.461***	−.0059	−0.211	−0.424
Expenditure$_{it-2}$	(0.212)	(0.231)	(0.178)	(0.236)	(0.296)	(0.267)
Credit ratio$_{it-2}$	−0.003	0.001	−0.009	−0.012	−0.018**	−0.022***
	(0.009)	(0.008)	(0.010)	(0.008)	(0.008)	(0.007)
ln (Rainfall)	0.182	0.384	0.525**	0.360	0.531**	0.417**
	(0.224)	(0.263)	(0.255)	(0.224)	(0.269)	(0.210)
ln (Population)	0.447	0.383	0.137	0.731**	0.650**	0.494
	(0.370)	(0.307)	(0.261)	(0.315)	(0.290)	(0.344)
Area affected by flood Dummy$_{it+1}$	0.284			0.824***		
	(0.283)			(0.275)		
Area affected by flood Dummy$_{it+2}$		0.257			0.229	
		(0.259)			(0.322)	
Area affected by flood Dummy$_{it+3}$			0.522**			0.823***
			(0.238)			(0.306)
Forest cover$_{it-2}$	1.77	0.333	0.251	0.399	−1.074	0.810
	(1.5)	(1.57)	(1.195)	(1.70)	(1.421)	(1.558)
Constant	−0.0608	1.418	3.837	−0.658	−2.743	2.815
	(2.311)	(2.417)	(2.390)	(2.729)	(3.358)	(0.139)
Observations	133	133	133	133	133	133
No of States	20	20	20	20	20	20

Robust standard errors in parentheses. Significant at *** $p < 0.01$, ** $p < 0.05$. We include year and region fixed effects.

Table 2 HDI and cyclone fatalities.

	FE Poisson			FE Negative Binomial		
Dependent variable	**Cyclone Fatalities$_{it+1}$**	**Cyclone Fatalities$_{it+2}$**	**Cyclone Fatalities$_{it+3}$**	**Cyclone Fatalities$_{it+1}$**	**Cyclone Fatalities$_{it+2}$**	**Cyclone Fatalities$_{it+3}$**
Independent variables	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**
Human development index	−0.010	−0.007	−0.052 ***	−0.028***	−0.023***	−0.042 ***
	(0.011)	(0.008)	(0.019)	(0.009)	(0.008)	(0.009)
Per capita social and	−0.783**	−0.033	−1.221***	−0.896***	−0.010	−0.800**
calamity expenditure$_{it-2}$	(0.315)	(0.219)	(0.454)	(0.317)	(0.231)	(0.336)
Credit ratio$_{it-2}$	−0.092***	−0.012	−0.045**	−0.040***	−0.017	−0.002
	(0.013)	(0.010)	(0.021)	(0.010)	(0.008)	(0.009)
ln (Population)	1.468***	1.331***	0.859	1.112***	0.800***	0.151
	(0.440)	(0.423)	(0.608)	(0.318)	(0.298)	(0.364)
Severe cyclone dummy$_{it+1}$	3.780***			2.996***		
	(0.428)			(0.461)		
Severe cyclone dummy$_{it+2}$		1.15***			0.925**	
		(0.363)			(0.380)	
Severe cyclone dummy$_{it+3}$			2.670***			2.600***
			(0.493)			(0.585)
Forest cover$_{it-2}$	2.152	−0.034	2.163	0.363	−0.825	−2.90*
	(2.091)	(2.092)	(2.483)	(1.627)	(1.761)	(1.629)
Constant	2.257	−6.970**	6.463	2.315	−3.819	4.918
	(3.457)	(3.293)	(4.984)	(2.923)	(2.724)	(3.528)
Observations	133	133	133	133	133	133
No of States	20	20	20	20	20	20

Robust standard errors in parentheses. Significant at *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. We include year and region fixed effects.

obtained in the Poisson estimates. However, the coefficients (shown in Table 2) and the marginal effects vary marginally (see C4–C6, Table A.2). Hence, overall, it is observed from this analysis that higher achievements in HDI cause a reduction in cyclone-related deaths.

Impact of HDI on total fatalities (floods and cyclones). We analyze the effects of HDI on total fatalities caused by both floods and cyclones. It can be observed from Table 3 that the HDI is negative and highly significant in both specifications, i.e., FE Poison (columns C1–C3) and FE Negative Binomial (columns

Table 3 HDI and total fatalities (floods and cyclones).

	FE Poisson			FE Negative Binomial		
Dependent variable	**Cyclone & flood fatalities$_{it+1}$**	**Cyclone & flood fatalities$_{it+2}$**	**Cyclone & Flood fatalities$_{it+3}$**	**Cyclone & flood fatalities$_{it+1}$**	**Cyclone & flood fatalities$_{it+2}$**	**Cyclone & Flood fatalities$_{it+3}$**
Independent variables	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**
Human development index	−0. 022**	−0.281***	−0.052 ***	−0. 035***	−0.038***	−0.042 ***
	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.007)
Per capita social and calamity expenditure$_{it-2}$	−0.049	−0.275	−0.806***	−0.199	0.251	−0.511**
	(0.184)	(0.199)	(0.212)	(0.211)	(0.243)	(0.239)
Credit ratio$_{it-2}$	−0.017	0.0007	−0.005	−0.018**	−0.013*	−0.020***
	(0.011)	(0.008)	(0.010)	(0.008)	(0.007)	(0.006)
ln (Population)	0.534*	0.538*	0.224	0.716***	0.689***	0.389
	(0.313)	(0.290)	(0.293)	(0.271)	(0.260)	(0.325)
ln (Rainfall)	0.412**	0.287	0.323*	0.570***	0.343	0.380**
	(0.192)	(0.219)	(0.189)	(0.178)	(0.226)	(0.180)
Area affected by flood dummy$_{it+1}$	0.373			0.744***		
	(0.249)			(0.237)		
Area affected by flood dummy$_{it+2}$		0.204			−0.021	
		(0.253)			(0.247)	
Area affected by flood dummy$_{it+3}$			0.755***			0. 879***
			(0.273)			(0.271)
Severe cyclone dummy$_{it+1}$	1.127***			1.250***		
	(0.358)			(0.445)		
Severe cyclone dummy$_{it+2}$		0.117			0.389	
		(0.345)			(0.321)	
Severe cyclone dummy$_{it+3}$			0.841***			0.882**
			(0.260)			(0.360)
Forest cover$_{it-2}$	1.805	0.138	1.163	0.244	−1.059	0.465
	(1.366)	(1.45)	(1.173)	(1.415)	(1.305)	(1.510)
Constant	−1.105	0.351	5.486**	−0.977	−2.487	4.015
	(2.377)	(2.151)	(2.723)	(2.513)	(2.714)	(2.810)
Observations	133	133	133	133	133	133
No of States	20	20	20	20	20	20

Robust standard errors in parentheses. Significant at *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. We include year and region fixed effects.

C4–C6). This result again confirms that HDI improvement has significantly decreased the fatalities caused by natural disasters like floods and cyclones, to which India is highly vulnerable. However, for our major control variables, i.e., social and calamity expenditure, we see a similar sign and pattern in terms of significance and magnitude. An overall increase in government expenditure on building calamities-proof infrastructure reduces deaths caused by natural disasters. However, the impact becomes stronger only in the third year. In addition, the credit ratio is negative in the FE Poison estimation, but the coefficient is insignificant. However, it is negative and significant in all specifications of the FE Negative Binomial. This implies that financial development helps reduce the adverse effects of natural disasters.

Similar to previous sections, we also estimate the AME, shown in Appendix Table A3, to check the robustness of our analysis. The FE Poison estimates show that with a one-unit increase in HDI, the expected number of disaster fatalities declines by 109 in the first year, 183 in the second year, and 247 in the third year, respectively (see columns C1–C3, Table A3). However, using the FE Negative Binomial approach, with a one-unit increase in HDI, the expected number of fatalities caused by natural disasters declines by 220 in the first year, 193 in the second year, and 222 in the third year, respectively due to a one-unit increase in the HDI (see columns C4–C6, Table A3). For the robustness exercise, we employed Poisson and Negative binomial estimates, and results are presented in Table 4. The results confirm that better HDI helps to reduce flood and cyclone fatalities. The AME shows the expected number of disaster fatalities declines by 106 in the first year, 62 in the second year, and 169 in the third year, respectively from floods and cyclones due to a one-unit increase in the HDI (see Appendix Table A4). Furthermore, increased forest cover, enhanced financial development, and greater government expenditure on social and calamity relief efforts contribute to mitigating the impact of disasters. Collectively, these findings validate our hypothesis that improvements in HDI can lead to a reduction in deaths resulting from natural disasters. Consequently, these results underscore the urgency for government action in investing resources to uplift the socioeconomic conditions of impoverished regions and populations highly susceptible to damage inflicted by natural disasters.

Instrumental variable approach. As discussed in "methodology section", we argue that endogeneity exists in our model due to the simultaneity between HDI and disaster fatalities. To correct for the endogeneity problem, we use "state-wise drought-prone area" as an instrument for HDI. We argue that 'drought-prone area' and HDI are negatively related, which suggests that the state with a higher 'drought-prone area' experiences a lower achievement in HDI. In the first stage equation, our results suggest that drought-prone areas are negatively associated with HDI, which confirms that lower HDI results from higher drought-prone states. The significance of ρ shows that HDI is an endogenous variable (see C1-C6, Table 5).

The CFA's final stage equation shows that the HDI coefficient is negative and significant (C1 of Table 5). Still, HDI remains

Table 4 HDI and average fatalities.

Dependent variable	Average Flood Fatalities$_{it+1}$		Average Cyclone Fatalities$_{it+1}$		Average Cyclone & Flood Fatalities$_{it+1}$	
	FE Poison	FE Negative Binomial	FE Poison	FE Negative Binomial	FE Poison	FE Negative Binomial
Independent variables	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**
Human development index	−0.022***	−0.031***	−0.056 ***	−0.049 ***	−0.029***	−0.036***
	(0.005)	(0.006)	(0.012)	(0.007)	(0.005)	(0.005)
ln Per capita social and calamity expenditure$_{it-1}$	−0.488**	−0.222	−0.893**	−0.741**	−0.483**	−0.295
	(0.203)	(0.267)	(0.361)	(0.242)	(0.201)	(0.248)
Credit ratio$_{it-1}$	0.007	−0.009	−0.039***	−0.010	0.001	−0.012*
	(0.005)	(0.006)	(0.009)	(0.008)	(0.007)	(0.006)
Severe flood dummy$_{it+1}$	0.005	0.337			−0.030	0.365
	(0.224)	(0.245)			(0.236)	(0.265)
Severe cyclone dummy$_{it+1}$			2.137***	1.593***	0.159	0.463*
			(0.380)	(0.351)	(0.224)	(0.265)
Forest cover$_{it-2}$	−0.019*	−0.035***	0.0008	−0.022**	−0.017*	−1.029**
	(0.010)	(0.012)	(0.021)	(0.010)	(0.010)	(0.010)
Constant	4.180***	5.356***	8.534***	6.637***	5.665***	6.264***
	(0.613)	(0.879)	(1.115)	(0.907)	(0.682)	(0.875)

Robust standard errors in parentheses. Significant at *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. We include year and region fixed effects.

Table 5 HDI and fatalities; FE IV Poisson model (CF Approach).

	Flood Fatalities $_{(it)}$		Cyclone Fatalities $_{(it)}$		Cyclone & Flood Fatalities $_{(it)}$	
Independent Variables	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**
Human development index	−0.068***	−0.046 ***	−0.027	−0.048***	−0.064***	−0.048***
	(0.016)	(0.022)	(0.019)	(0.024)	(0.013)	(0.018)
Per capita social and calamity expenditure$_{it-1}$		−0.284 ***		−0.891**		−0.387**
		(0.391)		(0.385)		(0.275)
Credit ratio$_{it-1}$		−0.005		−0.010		−0.002
		(0.009)		(0.010)		(0.008)
ln (Population)		−0.121		1.010***		0.159
		(0.485)		(0.478)		(0.339)
Area affected by flood dummy		1.176***				0.995***
		(0.425)				(0.351)
Severe cyclone dummy				2.118***		0.807**
				(0.516)		(0.337)
Forest cover$_{it-1}$		−3.055		−0.870		−2.257
		(2.409)		(2.965)		(2.115)
Observations	133	133	133	133	133	133
No of States	20	20	20	20	20	20
First stage regression: The dependent variable is Human Development Index (HDI)						
ln (Drought prone area)	−10.830***	−9.470***	−10.830***	−10.165***	−10.830***	−9.455***
	(1.364)	(1.623)	(1.364)	(1.672)	(1.364)	(1.642)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
ρ	0.047**	0.025	0.046**	0.047*	0.0337**	0.014*
	(0.019)	(0.024)	(0.021)	(0.026)	(0.016)	(0.019)

Significant at *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors in parentheses. We include year and region fixed effects. The dependent variable is fatalities from floods and cyclones. *Instrument*: ln (drought-prone area) as an instrument for HDI. In the first stage regression, the dependent variable is HDI. We regressed HDI on drought-prone area and other control variables and also controlled region and year-fixed effects. The significance of ρ shows that HDI is an endogenous variable.

negative and significant even after considering the other variables (C2 of Table 5). In addition, better HDI helps minimize deaths from natural disasters (i.e., cyclones; and floods and cyclones combined) (C3–C6 of Table 5). The results also suggest that credit ratio and satisfactory forest coverage help to reduce human life loss from natural disasters. Moreover, as robustness checks, we also construct the outcome variable 'flood and cyclone fatalities' by taking the average of two HDI rounds[16]. The CF estimates are consistent with our earlier results after changing the outcome variable, as shown in Table 6.

Overall, our empirical finding confirms the hypothesis that improvement in the HDI leads to a reduction in the fatalities caused by natural disasters like floods and cyclones. Specifically, looking at the state-level differences in the Indian context, it is observed that states that have higher HDI tend to manage deaths from natural disasters better compared to other states. However, we should also be careful to note that not just simply HDI, other important socioeconomic factors, such as the availability of credit and government spending on building calamity-proof infrastructure, also provide protection against deaths from disasters.

Table 6 Impact of human development on average fatalities from flood and cyclones; IV Poisson model (CF Approach).

	Average Flood Fatalities$_{it}$		Average Cyclone Fatalities$_{it}$		Average Flood & Cyclone Fatalities$_{it}$	
Independent Variables	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**
Human development index	−0.064***	−0.055***	−0.072***	−0.041***	−0.067***	−0.054***
	(0.013)	(0.012)	(0.013)	(0.013)	(0.011)	(0.010)
Per capita social and calamity expenditure$_{it-1}$		0.103		−1.081***		−0.061
		(0.295)		(0.353)		(0.258)
Credit ratio$_{it-1}$		−0.013**		0.008		−0.013**
		(0.006)		(0.011)		(0.006)
Severe flood dummy		0.297				0.347
		(0.261)				(0.234)
Severe cyclone dummy				1.984***		0.431
				(0.359)		(0.273)
Forest cover$_{it-1}$		−0.040**		−0.033**		−0.031**
		(0.018)		(0.013)		(0.014)
Observations	133	133	133	133	133	133
No of States	19	19	19	19	19	19
First stage regression: The dependent variable is Human Development Index (HDI)						
ln (Drought prone area)	−10.830***	−11.730***	−10.830***	−11.752***	−10.830***	−1.728***
	(1.364)	(1.484)	(1.364)	(1.479)	(1.364)	(1.502)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
ρ	0.042**	0.038**	0.019	−0.028**	0.039***	0.030**
	(0.015)	(0.015)	(0.014)	(0.013)	(0.012)	(0.012)

Significant at *** $p < 0.01$, ** $p < 0.05$. Robust standard errors in parentheses. *Instrument*: ln (drought-prone area) as an instrument for HDI. In the first stage regression, the dependent variable is HDI. We regressed HDI on drought-prone areas and other control variables and also controlled region and year fixed effect. The value of ρ confirm that HDI is endogenous. We include year and region fixed effects.

Conclusions and policy discussions

This paper explores the relationship between higher levels of human development and reduced flood and cyclone fatalities. It highlights the significance of investing in human capital development as a crucial aspect of comprehensive disaster risk management strategies. This emphasizes the importance of adopting a holistic approach to disaster risk reduction, which not only addresses underlying vulnerabilities but also promotes sustainable development pathways. Floods and cyclones have inflicted substantial damage on physical infrastructure and led to loss of human life in India. In this study, we examine the impact of HDI on two types of natural disaster fatalities, i.e., floods and cyclones, using panel data for 19 states of India from 1983 to 2011. The use of inequality-adjusted HDI helped us capture the impact of overall development on mitigating the impact of disasters by reducing human life loss due to floods and cyclones. Overall results of the study suggest that disaster fatalities are lower in Indian states with better HDI scores. Our results confirm that a one-point increase in HDI leads to 85 less human fatalities occurring due to floods after 1 year, 141 after 2 years, and 173 after 3 years, respectively (see Appendix Table A1). In addition, we find that expected fatalities from cyclones decrease by 12 individuals in the first year, then by 6 in the second year, and by 69 in the third year, respectively due to an increase in HDI by one point (see Appendix Table A2).

Overall we can conclude that deaths from floods and cyclones have largely reduced for Indian states with a better level of human development while controlling the degree of severity of floods and cyclones. In addition, government responsiveness proxied by social and calamity expenditure and financial development is currently inadequate to prevent disaster deaths and mitigate the impacts of disasters. For robust analysis, we apply the Negative Binomial method to examine the effects of HDI on natural disaster deaths. The estimated results remain closely identical to FE Poisson estimates.

Our results have opened up the scope for critical policy discussion over the importance of understanding the role of inequality-adjusted HDI and government responsiveness in preventing deaths due to natural disasters. In light of the observed relationship between higher levels of human development and diminished flood and cyclone fatalities, it becomes imperative for the government to place a paramount emphasis on investments in human capital development. Such endeavors should encompass targeted initiatives aimed at enhancing education, healthcare, and overall living standards throughout the nation. Moreover, facilitating improved public health services and broadening access to educational opportunities across all strata of society can bolster community resilience and readiness in response to disasters. In addition to enhancing human development across Indian states, the government should increase ex-ante budgetary allocation for disaster prevention and mitigation purposes. Furthermore, the government should devise a long-term disaster management policy to improve the flood and cyclone warning systems, build flood and cyclone-resilient infrastructure, and improve flood forecasting using advanced technology. In addition to disaster-related mesures, increasing forest coverage, better public health provision, access to educational opportunities for all, and a better financial market can help prepare the long-term action plan for disaster preparedness. Finally, we believe that employing comprehensive disaster risk management strategies that address immediate vulnerabilities while promoting sustainable development pathways can enhance resilience and preparedness at the community level, ultimately preventing losses across all fronts.

Data availability

The data used in this study are publicly available and have been compiled from various sources, as detailed in the data section of the paper. The final data file utilized in this study is provided as supplementary material.

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Notes

1 See https://www.worldbank.org/en/topic/disasterriskmanagement/overview.
2 https://rsmcnewdelhi.imd.gov.in/uploads/climatology/landfallingcd.pdf.
3 https://www.thehindubusinessline.com/opinion/centre-state-coordination-is-key-in-mitigating-impact-of-cyclones/article31721920.ece https://www.thehindubusinessline.com/opinion/centre-state-coordination-is-key-in-mitigating-impact-of-cyclones/article31721920.ece.
4 Indirect losses (also labeled "higher-order losses" in Rose, 2004) include all losses that are not provoked by the disaster itself, but by its consequences.
5 The HDI is calculated based on three key dimensions of human development: health, education, and standard of living reflected by Gross National Income (GNI) per capita, adjusted for purchasing power parity (PPP).
6 It was introduced by the United Nations Development Programme (UNDP) in 1990 as an alternative to traditional economic indicators such as Gross Domestic Product (GDP) per capita, which only provide a narrow perspective on a country's development.
7 Based on the principles of general equilibrium theory and economic production theory, the I-O model draws focus to the differentiation between direct economic losses and the subsequent ripple effects within a multi-industry framework resulting from disruptions.
8 The CGE model is leveraged to calculate the indirect economic impacts, fed with information on transportation disruptions generated by explicit transportation network models through a series of well-built model linkages.
9 Annual Report 2009: Asian Disaster Reduction Center(ADRC).
10 We chose the time period 1983–2011 because HDI data is available in various rounds of the National Sample Survey Office (NSSO) data.
11 Results are available upon request.
12 The IHDI data is available in six different periods, such as 1983, 1987, 1993, 1999, 2004, 2009, and 2011.
13 A proxy of GDP per capita.
14 Padli and Habibullah, 2008, Kellenberg, 2008, Ferreira, 2010.
15 Population density figures from the recent census of 2011 showed that states like UP, Bihar, and West Bengal have higher population density than the national average and other states. See https://censusindia.gov.in/census.website/data/data-visualizations for details. High flood fatalities are recorded in these states, as can be seen in Fig. 4. In 2011, out of 28 states in India, the rank of UP and Bihar with respect to their HDI scores were 28 and 25, respectively (Mukherjee et. al., 2016).
16 A detailed discussion on the construction of the outcome variable is presented in "Data and Descriptive Statistics".

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Rituparna Kaushik (CA): Conceptualization and Validation, Introduction and Methodology, Yashobanta Parida: Data curation and Formal analysis, Ravikiran Naik: Theoretical context, Literature review, and Formal analysis.

Competing interests
The authors declare no competing interests.

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Ethical approval was not required as the study did not involve human participants.

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Correspondence and requests for materials should be addressed to Rituparna Kaushik.

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