ProSafeNet
The Global Hub for Safety, Security, Risk & Emergency Professionals & Scientists
www.prosafenet.com | Founder & Director

International Journal of Disaster Risk Management • Vol. 8. No. 2 • https://doi.org/10.66050/an82aj38

Publisher: Scientific-Professional Society for Disaster Risk Management

International Journal of Disaster Risk Management



Article

Cyclone Risk and Socioeconomic Vulnerability in Indian Coastal Districts

Ekanki Pathak[1*], Rajarshi Majumder[2]

[1] Department of Economics, University of Burdwan, Golapbag, Bardhaman - 713104, Purba Bardhaman, West Bengal, India; ekanki.pathak@gmail.com.

[2]Department of Economics, University of Burdwan, Golapbag, Bardhaman - 713104, Purba Bardhaman, West Bengal, India; rmajumder@eco.buruniv.ac.in.

* Correspondence: ekanki.pathak@gmail.com

Received: 25 August 2026; Revised: 5 November 2026; Accepted: 8 November 2026; Published: 17 November 2026.

ABSTRACT

Frequent exposure to natural hazards strips people of assets, breaks down physical infrastructure, and snips livelihood options. These have long-run consequences, including reduced human capital in affected populations through lower education and health standards and reduced income levels. Existing socioeconomic vulnerability compounds the impact of such disasters and traps people in a low level of human development across generations. Understanding the extent and severity of these vulnerabilities enables preventive and adaptive policy actions. Coastal India, with 251 million people, is exposed to one-tenth of the world's tropical cyclones and faces several such disasters each year. Cyclone risk management is therefore an emergent need for the region. This paper examines the trends in cyclone exposure, its interaction with development indicators, and how it overlaps existing socioeconomic weaknesses in the 99 coastal districts of India. A spatiotemporal approach is adopted, in which ANOVA, pooled regression, and spatial regression models are used across two time points of data, 2011 and 2023, to understand the association between cyclone exposure and development. Separate indices of cyclone exposure and socioeconomic vulnerability are constructed using PCA and then combined to yield a Coastal Vulnerability Index. Results indicate increasing exposure to cyclones but diminishing socioeconomic vulnerability. Coastal Vulnerability Index shows a mixed trend, with the distribution bulging at two ends and thinning in the middle. One standard deviation increase in cyclone exposure is associated with a 1 percentage point decrease in Literacy, a 2 per thousand increase in infant mortality, a 1.4 percentage point increase in the poverty head count ratio, and a 5 percent lower consumption level. Coastal vulnerability has increased for 20 districts during 2011-23, and the number of districts in the Extremely High vulnerability category has increased from 18 to 21, highlighting intensifying compound risks. The study identifies three sets of districts with distinct exposure and socioeconomic vulnerability mixes and suggests that cyclone risk management policy be grounded in the specific type of district. It bridges existing gaps by enabling targeted and evidence-based coastal resilience planning and would help in adopting

Academic Editor:
Prof. Dr. Vladimir M. Cvetković
Copyright: © 2026 by the authors.
e-ISSN2620-2786

Pathak, E., & Rajarshi Majumder. (2026). Cyclone Risk and Socioeconomic Vulnerability in Indian Coastal Districts. *International Journal of Disaster Risk Management*, 8(2), 373-400.

appropriate and distinct policies for climate adaptation, disaster risk management planning, and resilient regional development.

KEYWORDS

Tropical cyclone; socioeconomic vulnerability; coastal vulnerability; risk management; natural hazard; coastal districts; India.

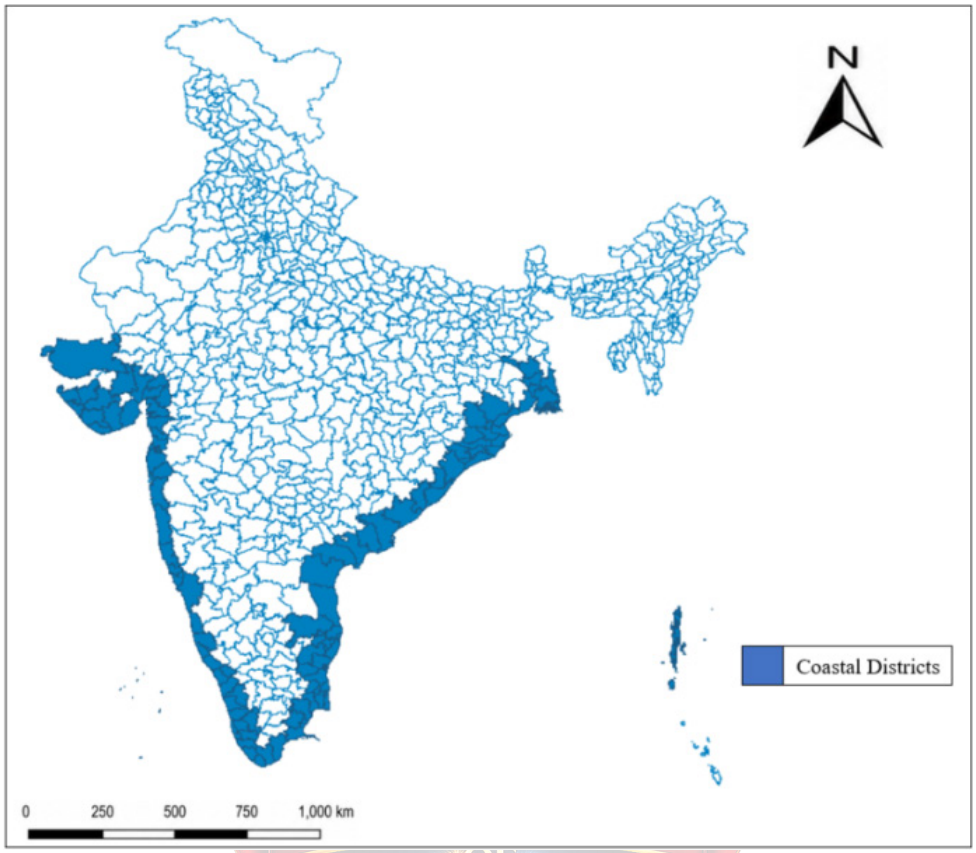
1. Introduction

Tropical cyclones originating in the North Indian Ocean frequently strike the coastline of India and Bangladesh regularly and bring compound extreme events of high-velocity winds, storm surge, unusually heavy rainfall, high seas, flooding, and land/mud-slides, causing massive destruction to property, people, and the economy of the region. The frequency and intensity of these storms also show an increasing long-term trend (Bandyopadhyay et al., 2018; Kabir et al., 2022; Rajeev & Mishra, 2023). Since India has a long coastline surrounded by the two branches of the North Indian Ocean – the Bay of Bengal in the east and the Arabian Sea in the west – its exposure to the hazards of tropical cyclones is also enormous. The Indian coastal region, comprising approximately 99 districts, is home to approximately 15.5 percent of the country's population, many of whom rely on the coastal ecosystem for their livelihood. The region is critical for sectors such as agriculture, fisheries, livestock rearing, tourism, etc., making it an economic hub. The coastal biosphere is also precious because of its ecological value. However, coastal regions and communities are becoming increasingly vulnerable to a range of challenges, including climate change and extreme weather events like cyclones and floods (IPCC,2007), and both the frequency and intensity of such hydrometeorological events are on the rise (Cvetković et al., 2025). The compound hazards associated with tropical cyclones lead to significant damage to infrastructure, property, human and animal lives, and to the productive and service sectors of the economy (IPCC, 2012). These damages are not only transient but have long-term socioeconomic impacts threatening sustainable development of the region by reducing people's standard of living (Akter & Mallick, 2013; Anttila-Hughes et al., 2013; Roy & Sharma, 2015; Barua & Banerjee, 2020; Hossain et al., 2021; Schleypen et al., 2024). Frequent cyclonic activities have also increased school dropout cases among children (Sharmin & Naznin, 2013). Moreover, damages across the Indian coastal districts are not uniform and create spatial inequality (Ali et al., 2020). It is also argued that ecosystems exposed to similar physical hazards may experience different levels of risk because of differences in their inherent resilience (Canete & Biñas, 2025). Two implications thus emerge from existing literature. First, vulnerability assessment, especially for coastal communities, is essentially multidimensional; and second, risk reduction policies therefore must weigh not only vulnerabilities resulting from exposure to the physical hazard of tropical cyclones but also the underlying socioeconomic vulnerabilities of the coastal region and its people. IPCC's Sixth Assessment Report also emphasizes that without targeted adaptation strategies, climate change will exacerbate both cyclone intensity and poverty (IPCC, 2022).

Against this background, this paper focuses on four objectives. First, it explores and quantifies the exposure of Indian coastal districts to cyclones. Second, it examines the relationship between exposure to tropical cyclones and the socioeconomic conditions of the people, specifically Education, health, and livelihood situations in the coastal districts of India. Third, it explores existing socioeconomic vulnerabilities of the coastal region by constructing a district-level Socioeconomic Vulnerability Index and classifying the coastal districts into low, moderate, high, very high, and extremely vulnerable categories. Fourth, it constructs a comprehensive Coastal Vulnerability Index (CVI) by combining both Cyclone Hazard and Socioeconomic Vulnerability. Such an exercise would help in targeting mitigation and adaptive policies and disaster management responses in the region based on the type and intensity of the vulnerabilities.

This paper contributes to existing literature by combining cyclone hazards and socioeconomic risks to assess coastal vulnerability in India. The findings reveal significant spatial variations across dis-

tricts, highlighting that both environmental threats and community vulnerabilities are unevenly distributed along the coast and mitigation strategies therefore must be targeted and location-specific.



Map 1. Coastal Districts of India. Source: Authors

INTERNATIONAL JOURNAL OF DISASTER RISK MANAGEMENT
IJDRM

2. Methods

The methodological workflow follows the four objectives – computation of the Cyclone Hazard Index, examining the relation between exposure to cyclone hazard and socioeconomic conditions, computation of a Socioeconomic Vulnerability Index, and finally computation of the comprehensive Coastal Vulnerability Index. However, we start with a short description of the study area and mention the data sources at the end of this section.

2.1. Description of the Study Area

Coastal India is one of the most vulnerable regions to extreme events like tropical cyclones. India has a 7516.6 km long coastline – 5422.6 km along the mainland and 2094 km in the island territories – spread over nine states and four union territories. 99 districts are designated as coastal districts, among which 69 touch the coastline, and 30 do not touch the coastline but are within 100 km from the coast (Map 1). While most of the existing studies focus on selected portions of the Indian coastline (Hegde & Raju, 2007; Kumar et al., 2010; Kumar & Kunte, 2025, for example), we focus on the entire coastline of India.

Indian subcontinent accounts for nearly 10 percent of the world's tropical cyclones and is one of the worst affected regions. The eastern coastal states of Odisha, Andhra Pradesh, and West Bengal mostly bear the brunt, having faced close to 300 cyclones between 1891 and 2022 (Mohapatra, 2023). Overall, the Indian coastline has seen 137 cyclones of severe and higher grades during the last fifty years, often more than twice a year (Table 1).

Table 1. Cyclonic Trends over NIO from 1970-2019

Period	Severe Cyclonic Storm (A)	Very Severe Cyclonic Storm (B)	Extremely Severe Cyclonic Storm (C)	Super Cyclonic Storm (D)	Very Severe Cyclonic Storm & above (B+C+D)	Severe Cyclonic Storm & above (A+B+C+D)
1970-79	14	19	10	1	30	44
1980-89	7	10	4	1	15	22
1990-99	8	8	8	3	19	27
2000-09	8	1	7	1	9	17
2010-19	5	12	9	1	22	27
Total	42	50	38	7	95	137

Note: Authors' computation from Mohapatra et al. (2012), Mohapatra (2023); Severe Cyclonic Storm (Wind speed - 48-63 knots), Very Severe Cyclonic Storm (Wind speed - 64-89 knots), Extremely Severe Cyclonic Storm (Wind speed - 90-119 knots) and Super Cyclonic Storm (Wind speed - 120 knots).

2.2. Construction of Cyclone Hazard Index

For cyclone hazard data, the study relies on Indian Meteorological Department (IMD) Reports (Mohapatra et al., 2012; Mohapatra, 2023). Using cumulative historical figures across five dimensions – Total number of cyclones (C_1), Number of severe cyclones (C_2), Maximum wind speed (C_3), Probable maximum storm surge (C_4), and Probable maximum precipitation (C_5) – IMD computed composite cyclone hazard categories of the coastal districts by the weighted average method for the years 2011 and 2023 and classified coastal districts into four groups of cyclone hazard – Very High, High, Moderate, and Low. Initially, we used these categories provided by IMD in our study. In addition, we aggregated the five raw indicators provided by IMD to construct our own composite Cyclone Hazard Score (CHS) for the districts at the two time points.

First, we normalize the raw scores in the following manner:

$$\text{Normalised Score} = C'_{ijt} = \frac{C_{ijt} - \text{Min}(C_{ijt})}{\text{Max}(C_{ijt}) - \text{Min}(C_{ijt})} * 100$$

$$i = 1,2,\ldots 99;\ j = 1,2,..5;\ t = 1,2$$

where C_{ijt} is the raw score provided by IMD corresponding to the i-th district in the j-th dimension for the t-th year. Min(Cijt) and Max(Cijt) are the minimum and maximum of Cijt across the districts over the two periods, i.e., the global minima; therefore varies from 0 to 100.

Thereafter, the Composite Cyclone Hazard Score of i^{th} district at t^{th} time is obtained as a weighted average of these normalized scores:

$$CHS_{it} = \sum w_j (C'_{ijt})$$

Where w_j are the weights suggested by IMD for each dimension of cyclone hazard (Table 2), CHSit therefore ranges from 0 to 100, with higher values indicating greater vulnerability.

Table 2. Weightage scheme for Cyclone Hazard Score

Variables	Weight
Annual Average Number of Severe Cyclones (C_1)	2
Annual Average Number of Cyclones (C_2)	1
Maximum Wind Speed (C_3)	3
Maximum Storm Surge (C_4)	5
Annual Mean Precipitation (C_5)	2

Source: Mohapatra et al. (2012), Mohapatra (2023)

A final Cyclone Hazard Index is computed using these scores by Z-transformation and scale and origin shift so that the mean becomes 50 and the standard deviation becomes 10:

$$\mathrm{CyHI_{it}} = 50 + \frac{[\mathrm{CHS_{it}} - \mathrm{Mean}(\mathrm{CHS_{it}})]}{\mathrm{Standard\ Deviation}(\mathrm{CHS_{it}})} * 10$$

Similar quantitative transformations, including min–max normalization and Z-transformation of composite scores, have been used by Cvetković et al. (2026). $\mathrm{CyHI_{it}}$ theoretically ranges from -∞ to +∞, but assuming that the hazard scores are normally distributed, the 99% interval for $\mathrm{CyHI_{it}}$ would be around 50±3σ, or 50±3*10, or between 20 and 80. The cyclone hazard score is employed as an independent variable in our study to understand the impact of cyclone hazard on education and livelihood, while the index is used for constructing the coastal vulnerability index.

2.3. Indicators of Education, Health and Livelihood

Education has been represented by three variables – Literacy Rate; Proportion of 5-9 year old children out of School (Primary level); and Proportion of 21-29 youth not in education, employment or training (NEET). Infant Mortality Rate (IMR) is used as an indicator of Health situation. Livelihood is represented by three variables: Head-Count Ratio (HCR) poverty measure (proportion of people below the national poverty line); proportion of households with vulnerable residences (earthen and semi-permanent); and Average Monthly Per Capita Consumption Expenditure (MPCE). The socioeconomic variables are not available for calendar years; hence, 2011-12 and 2023-24 data are used to correspond to the cyclone data for 2011 and 2023, respectively.

2.4. Examining impact of Cyclone Hazard on Education, Health and Livelihood

To examine how cyclone hazard affects the socioeconomic variables mentioned above, we start with a univariate one-way ANOVA model with Cyclone Hazard Category (CHC) as the categorical explanatory variable. We test whether there is any significant mean difference in the outcome variables across different categories of cyclone hazard (a similar one-way ANOVA is used by Cvetković et al., 2026a). Thereafter, we move to a regression framework with the Cyclone Hazard Score (CHS) as the explanatory variable, where we try to quantify the degree of association between cyclone hazard and the outcome variables. Several control factors have also been included in the regression models. These are: Education Infrastructure for the education outcome variables and Health Infrastructure for the IMR models. In addition, control factors like population density and rate of urbanization of the district have been tested. To represent unobserved state-specific effects, state dummies have also been included in the models. The model specifications are written below:

$$\text{ANOVA:} \qquad Y_{\{it\}} = f\left(CHC_{\{it\}}, X_{\{it\}}\right)$$

$$\text{Regression:} \qquad Y_{\{it\}} = \alpha + \beta_{\{2\}} CHS_{\{it\}} + \beta_{\{3\}} X_{\{it\}} + \varepsilon_{\{it\}}$$

Y_{it} is the outcome variable (Literacy Rate, Out-of-School Children, Youth-NEET, IMR, Poverty-HCR, Vulnerable-Residence, MPCE, as the case may be) of district i at time t; CHC_{it} is a categorical variable

representing the Cyclone Hazard Category of i^{th} district at time t as derived from the IMD report; CHS_{it} is the Cyclone Hazard Score of i^{th} district at time t computed in this study; X_{it} stands for covariates or control variables and state dummies as mentioned above. We have used Pooled OLS with year effects as our base model.

2.5. Spatial Regression

It can also be argued that the coastal districts are geographically connected, and neighboring districts share cyclone exposure, socioeconomic conditions, infrastructure, and coastal policies. Thus, there may be spatial association affecting the socioeconomic variables under scrutiny. To accommodate this, we extend our OLS model to a spatio-temporal model. First, we use individual, time-specific OLS models and examine residual spatial autocorrelation using a queen contiguity spatial weight matrix and computing Moran's I. We continue with OLS but report robust SEs for equations where spatial dependence is not detected. If spatial dependence is detected, we use SAR/SEM/SDM as indicated by the LM/RS and Robust LM / Adjusted Rao Score Tests following Anselin's classic decision tree (Anselin, 2005). The equations for this part of the study are:

Spatial Baseline Regression (Year-specific OLS):

$$Y_{it} = \alpha + \beta_{1it} CHS_{it} + \sum_{k=2}^{k} \beta_k X_{kit} + \sum_{s=1}^{s-1} \gamma_s D_{si} + \varepsilon_{it}$$

Spatial Autoregressive (SAR) Model:

$$Y_{it} = \alpha + \rho W Y_{it} + \beta_{1it} CHS_{it} + \sum_{k=2}^{k} \beta_k X_{kit} + \sum_{s=1}^{s-1} \gamma_s D_{si} + \varepsilon_{it}$$

Spatial Error (SEM) Model:

$$Y_{it} = \alpha + \beta_{1it} CHS_{it} + \sum_{k=2}^{k} \beta_k X_{kit} + \sum_{s=1}^{s-1} \gamma_s D_{si} + u_{it}, \text{ where } uit = \lambda W uit + \epsilon it$$

Y_{it} is the outcome variable for district i in year t (as mentioned in the previous section); CHS_{it} is the Cyclone Hazard Score of i^{th} district at time t; X_{it} stands for covariates or control variables; D_{si} represents state dummies; δ_t represents the year fixed effect; the error term εit captures unobserved factors; W refers to the spatial weight matrix; ϱ is spatial autocorrelation and measures the extent to which the outcome in one district is associated with outcomes in neighboring districts; λ measures the degree of spatial dependence in the unobserved disturbances. The coefficient $\beta 1$ is of our primary interest.

INTERNATIONAL JOURNAL OF DISASTER RISK MANAGEMENT
SCIENTIFIC-PROFESSIONAL SOCIETY FOR DISASTER RISK MANAGEMENT

Table 3. Variables used for constructing Socioeconomic Vulnerability Index

Dimension	Variables	Dimension Indices
Education	Out-of-school children (17-18) [X1]	Education Vulnerability Index (EduVI)
	Out-of-school children (19-21) [X2]	
	Percentage of Youth not in Education, Employment or Training (NEET) age 21-29 [X3]	
Health	Infant Mortality Rate [X4]	Health Vulnerability Index (HltVI)
	Percentage of HH not having Sanitation within premises [X5]	
	Percentage of HH without LPG/Electric Cooking fuel [X6]	
Economy	Poverty HCR (%) [X7]	Economic Vulnerability Index (EcoVI)
	Percentage of HH with Vulnerable Residence [X8]	
	Percentage of HH with Primary sector as main source of income [X9]	

Source: Authors' conceptualization

2.6. Construction of Socioeconomic Vulnerability Index

To construct the Socioeconomic Vulnerability Index (SEVI), we have used nine indicators representing three dimensions – Education, Health and Economic Condition (Table 3). Three dimension-specific indices – Education Vulnerability Index (EduVI), Health Vulnerability Index (HltVI), and Economic Vulnerability Index (EcoVI) – were first constructed using the Principal Component Method.

$$PCA_{\{education\}} = PCA\left(X_{\{1\}}, X_{\{2\}}, X_{\{3\}}\right)$$

$$PCA_{\{health\}} = PCA\left(X_{\{4\}}, X_{\{5\}}, X_{\{6\}}\right)$$

$$PCA_{\{economic\}} = PCA\left(X_{\{7\}}, X_{\{8\}}, X_{\{9\}}\right)$$

In all three cases, the first principal component was retained since it explained more than 50 percent of the total variance and had an eigenvalue greater than 1 (see Supplementary Table S1 for details). These three principal components have a mean of zero and a standard deviation of one. We rescale them by multiplying by 10 and adding 50. This gives the transformed index values a mean of 50 and a standard deviation of 10, in line with our earlier cyclone hazard index.

$$\text{Education Vulnerability Index} = EduVI = 50 + \left(PCA_{\{education\}} * 10\right)$$

$$\text{Health Vulnerability Index} = HltVI = 50 + \left(PCA_{\{health\}} * 10\right)$$

$$\text{Economic Vulnerability Index} = EcoVI = 50 + \left(PCA_{\{economic\}} * 10\right)$$

Socioeconomic Vulnerability Index (SEVI) is then prepared as an unweighted geometric mean of the three-dimensional indices:

$$\text{Socioeconomic Vulnerability Index} = \text{SEVI} = \sqrt[3]{(\text{EduVI} * \text{HltVI} * \text{EcoVI})}$$

2.7. Construction of Coastal Vulnerability Index

To explore the combined effect of cyclone hazard and socioeconomic vulnerabilities, we construct a Coastal Vulnerability Index (CVI) in line with existing literature (Gornitz, 1991; Thieler, 1999; Kumar, 2012). CVI is obtained as the geometric mean of the Cyclone Hazard Index and the Socioeconomic Vulnerability Index:

$$\text{CVI}_{\text{it}} = \sqrt{\text{CyHI}_{\text{it}} * \text{SEVI}_{\text{it}}}$$

This is akin to assigning equal weight to cyclone hazard and socioeconomic vulnerability, and we contend that vulnerability depends equally on exposure (to cyclones) and inherent socioeconomic weakness. However, we conducted a sensitivity analysis with alternative weighting schemes. Both Spearman Rank correlation and Jaccard similarity indices show that the baseline equal-weighting scheme is structurally robust, and highly vulnerable districts remain stable (Supplementary Table S2). Further, a variance-based optimization was explored that resulted in a sensitivity-based weighting scheme of 0.45 for the Socio-Economic Vulnerability Index (SEVI) and 0.55 for the Cyclone Vulnerability Index (CycHI) to achieve a perfect 50/50 variance contribution share. The marginal deviation (± 0.05) from our equal-weighting framework empirically justifies our choice, and the final Coastal Vulnerability Index is confirmed to be statistically robust, objective, and reliable for regional vulnerability mapping.

2.8. Categorization of districts according to indices

Once the various indices are constructed we have categorised the districts in terms of the indicators into five categories, Since our indices are standardised with mean roughly equal to 50 and Standard

Deviation of 10, we have used the cut-off points of ($\mu - \sigma$), ($\mu - 0.5*\sigma$), μ, and ($\mu + 0.5*\sigma$) respectively as the demarcating lines between Low Vulnerability (score < 40), Moderate Vulnerability (score between 40-45), High Vulnerability (score between 45-50), Very High Vulnerability (score between 50-55) and Extremely High Vulnerability (score > 55).

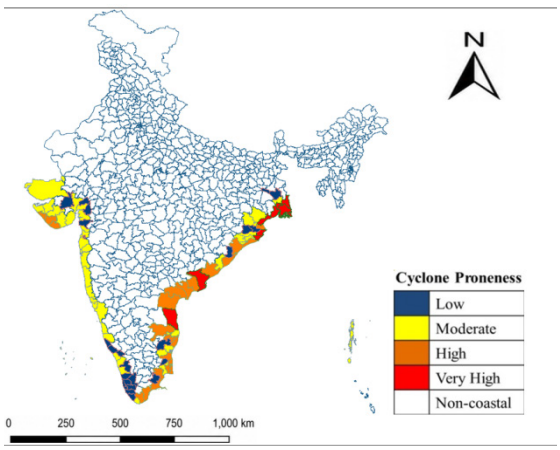
2.9. Data Sources

The cyclone hazard scores and index have been prepared using data from IMD (Mohapatra et al., 2012; Mohapatra, 2023). While the underlying definitions, observation periods, weighting scheme, and calculation procedures are identical in both IMD datasets, there have been some changes in the district boundaries between 2011 and 2023. We have clubbed the offspring districts of 2023 to get the mother districts in 2011, and our analysis is based on them. Additionally, for the spatial regression models, we have dropped the three island districts (in the Andaman and Lakshadweep) and the three metro districts (Chennai, Mumbai, and Kolkata) as their spatial associations are of a different nature. Data for the socioeconomic variables have been extracted from secondary data in the public domain. Literacy Rates, Out-of-school proportions, and youth NEET proportions are computed from the NSSO survey on Employment & Unemployment 2011-12 and the Periodic Labor Force Survey 2023-24 (GoI, 2011a, 2023a). Proportion of households without sanitation, without LPG/Electric cooking fuel, Incidence of vulnerable residence, HCR poverty rate, and MPCE are computed from NSSO surveys on Household Consumption Expenditure for 2011-12 and 2023-24 (GoI, 2011b, 2023b). Infant Mortality Rate was obtained from the Sample Registration System, 2011 and 2022 (GoI, 2011c, 2022). [For short model descriptives, refer to Supplementary Table S3].

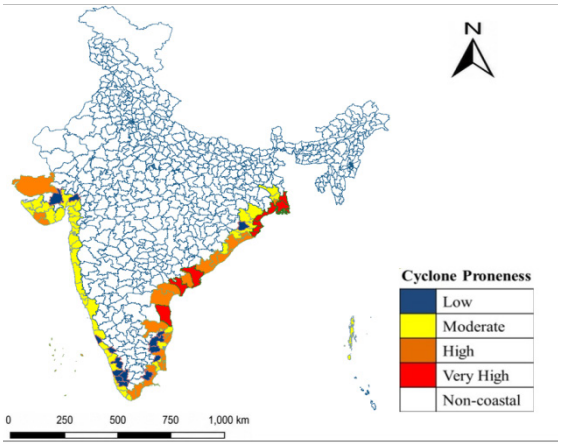
3. Results

3.1. Cyclone Hazard

As evident from maps 2a and 2b, created with IMD cyclone hazard data for 2011 and 2023, there are changes in cyclone intensity over the last decade and a half. It is also clearly visible that the eastern coast is much more exposed to tropical cyclones compared to the western coast. Most of the districts on the western side were moderately exposed in 2011, while eastern coastal districts were mostly in the high and very high cyclone exposure categories. A slightly different picture emerges for the eastern coast in 2023, while the same moderate situation continues on the western coast. Extreme cyclonic exposure continues for all the coastal districts of West Bengal and Odisha, along with a few districts in Andhra Pradesh and Tamil Nadu. All districts in Puducherry and most of the districts in Andhra Pradesh and Tamil Nadu have shifted to the High Hazard-prone classification in 2023 from the Very High group in 2011.



Map 2a: Cyclone Hazard across Coastal Districts in India 2011



Map 2b: Cyclone Hazard across Coastal Districts in India 2023

If we look at the values of the Cyclone Hazard Index computed by us, we find that the magnitude of hazard increased in 48 out of 99 coastal districts, indicating aggravated exposure in 2023. Among them, districts like Nagapattinam, Guntur, Prakasam, Malappuram, Palakkad, and South Goa experienced more than a 15-percentage-point increment in hazard score. According to our categorization, districts were mostly concentrated in the Low to Moderate hazard categories in 2011, whereas in 2023 they clustered more in the Very High to Extremely High hazard categories (Table 4).

Table 4. Distribution of Districts according to Cyclone Hazard Category

Cyclone Hazard Category	2011	2023
Low	28	13
Moderate	13	18
High	25	11
Very High	24	20
Extremely High	9	37
TOTAL	99	99

Source: Authors' calculation

There is also a significant jump in the number of districts in the Very High and Extremely High cyclone hazard category from 33 to 57 during this period. Cross-tabulating the results for 2011 and 2023 shows that the cyclone hazard category went up for 52 districts during 2011-23, while it came down for only 2 districts (Table 5). This is also reflected in the histogram of Cyclone Hazard Index across the two periods (Figure 1).

Table 5. Change in Cyclone Hazard Index - 2011 to 2023

Cyclone Hazard Index category		2023					
Low		**Moderate**	**High**	**Very High**	**Extremely High**	**ALL**	
2011	Low	12	10	2	3	1	22
	Moderate	8	-	2	3		13
	High	-	-	8	7	10	25
	Very High	1	-	1	8	14	24
	Extremely High	-	-	-	-	9	9
	ALL	13	18	11	20	37	93

Source: Authors' Calculation

Going into further detail, we find that 9 districts - Nellore (in Andhra Pradesh), Valsad (in Gujarat), Balasore, Bhadrak, Jagatsinghpur and Kendrapara (in Odisha), Ramanathapuram (in Tamil Nadu), Medinipur and South 24 Parganas (in West Bengal) remained in the Extremely High cyclone hazard category in both 2011 and 2023. On the other hand, 12 districts – Kheda (in Gujarat), Idukki, Kottayam, Palakkad, Pathanamthita, Wayand (in Kerala), Dhenkanal, Keonjhar (in Odisha), Ariyalur, Sivaganga, Tiruvannamalai (in Tamil Nadu), and Bardhaman (in West Bengal) remained in the Low cyclone hazard category throughout the decade.

How such spatially varied and time-varying cyclone hazard affects socioeconomic variables has been examined in the next sections using three methods – One-way ANOVA with IMD cyclone category as explanatory variable, Pooled OLS with Cyclone Hazard Score as explanatory variable, and year-specific spatial models with Cyclone Hazard Score as explanatory variable.

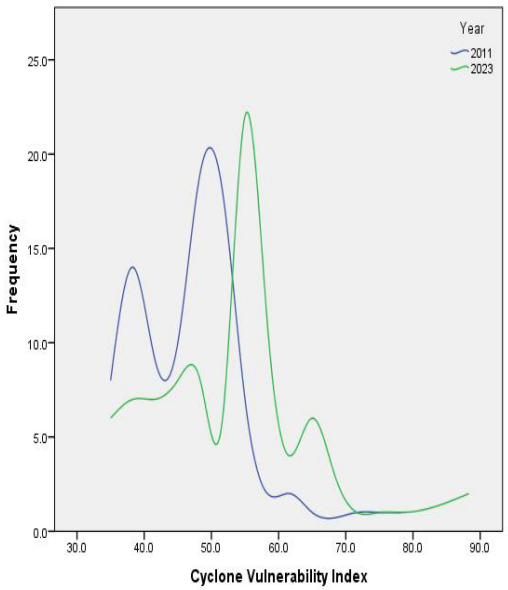


Figure 1. Density Curve of Cyclone Hazard Index in Indian coastal districts - 2011 and 2023

Table 6: Impact of Cyclone Hazard on Education – ANOVA Results

	Dependent Variable →	**Adult Literacy**		**Out-of-School Children (5-9 yrs)**		**Youth NEET**	
Variables	Year →	2011	2023	2011	2023	2011	**2023**
Constant	Coefficient	76.38	83.32	5.86	4.21	96.61	45.39
	p-val	.001	.001	.001	.001	.001	.001
	SE	2.42	1.43	2.25	1.61	1.31	2.38
Low	Coefficient	2.48	2.93	-1.68	-2.87	-1.10	-4.43
	p-val	.422	.229	0.510	0.160	.508	.277
	SE	3.08	2.42	2.56	2.04	1.66	4.05
Moderate	Coefficient	8.25	2.76	-1.41	-1.28	-3.46	-2.22
	p-val	.028	.268	0.550	0.450	.087	.593
	SE	3.70	2.48	2.38	1.71	2.00	4.14
High	Coefficient	0.63	5.80	-1.57	-1.63	-0.12	-3.13
	p-val	.832	.028	0.530	0.370	.942	.472
	SE	2.95	2.59	2.52	1.85	1.59	4.33
School Density per 100 sq km	Coefficient	0.00	0.04	-0.01	-0.01	-0.06	-0.01
	p-val	.98	.020	0.810	0.430	.001	.99
	SE	0.03	0.02	0.01	0.01	0.01	0.03
R sq		0.06	0.11	0.01	0.03	0.21	0.03
Adj R sq		0.02	0.07	0.04	0.02	0.18	0.02
F (Between)		1.806	2.021	0.16	0.70	1.141	0.776
p-val		.152	.117	.920	.550	.337	.511
Degrees of freedom		3,95	3,95	3,95	3,95	3,95	3,95
Sample size		99	99	99	99	99	99

Note: * p<0.05, ** p<0.01, ***p < 0.001

Source: Authors' calculation

3.2. Impact of Cyclone Hazard: ANOVA Results

3.2.1. Cyclone hazard and Education

The outcome variables for Univariate ANOVA are Adult Literacy Rate, Out-of-School Rate for Primary-grade-appropriate children, and Youth-NEET, while the explanatory variable is Cyclone Hazard Category recorded by IMD. Results show that higher degrees of cyclone hazard are adversely associated with lower literacy rates for both years (Table 6). On the other hand, the proportion of Out-of-School Children and Youth-NEET is lower for lower categories of cyclone hazard relative to the Very High category. School availability is also associated with lower school drop-out and youth-NEET.

Table 7. Impact of Cyclone Hazard on Health & Livelihood – ANOVA Results

	Dependent Variable →	**IMR**		**Poverty HCR**		**Vulnerable Residence**		**MPCE**	
Variables	Year →	2011	2023	**2011**	**2023**	**2011**	**2023**	**2011**	**2023**
Constant	Coefficient	28.92	-3.00	2.42	16.30*	71.83	-8.31	2043.40*	5200.54*
	p-val	0.044	0.902	0.510	0.000	0.000	0.502	0.000	0.000
	SE	14.18	24.22	3.67	1.91	16.18	12.33	291.63	656.84
Low	Coefficient	-2.03	-4.69	3.87	-5.88*	-0.71	-0.88	362.77	1863.18*
	p-val	0.254	0.080	0.370	0.020	0.724	0.517	0.290	0.030
	SE	1.77	2.65	4.37	2.52	2.02	1.35	347.61	864.87
Moderate	Coefficient	-2.87	-5.02	3.01	-5.62*	-3.35	-0.33	502.55	1750.35*
	p-val	0.179	0.070	0.460	0.000	0.168	0.813	0.120	0.010
	SE	2.12	2.74	4.09	2.12	2.41	1.39	324.5	726.83
High	Coefficient	-0.31	-3.37	5.97	-5.83*	-3.68	-4.90	58.38	1697.21*
	p-val	0.856	0.240	0.170	0.010	0.061	0.001	0.860	0.030
	SE	1.70	2.85	4.4	2.31	1.94	1.45	349.33	793.2
(ln) MPCE	Coefficient	-2.82	-1.56	-7.62	-17.98	-20.39	3.80		
	p-val	0.131	0.575	0.023	0.000	0.000	0.008		
	SE	1.85	2.77	3.29	0.84	2.11	1.41		
R sq		0.06	0.07	0.02	0.07	0.06	0.07	0.04	0.06
Adj R sq		0.02	0.03	-0.01	0.04	0.02	0.03	0.01	0.03
F (Between)		1.14	1.993	0.68	2.64	1.54	3.85	1.58	2.13
p-val		0.338	.121	-0.560	-0.050	0.209	0.012	0.190	0.100
Degrees of freedom		3,95	3,95	3,95	3,95	3,95	3,95	3,95	3,95
Sample Size		99	99	99	99	99	99	99	99

Note: Authors' calculation; * p<0.05, ** p<0.01, ***p < 0.001

3.2.2. Cyclone hazard and Health & Livelihood Situation

ANOVA results reveal that districts in Low, Moderate, and High cyclone hazard categories have lower Infant Mortality Rate, indicating that exposure to cyclone hazard is related to lower health

outcomes. Lower categories of cyclone exposure are also associated with lower incidence of vulnerable residence, lower Poverty-HCR, and higher MPCE levels, especially in 2023, compared to Very High cyclone hazard-prone districts (Table 7).

Table 8. Pooled Regression Results - Cyclone Hazard and Education

Dependent Variable → / **Independent Variables ↓**		**Adult Literacy**	**Out-of-School Children (5-9 yrs)**	**Youth NEET**
Intercept	Coefficient	76.25	1.99	98.87
	p-value	0.001	0.115	0.001
	SE	1.64	1.26	2.35
Cyclone Hazard Score	Coefficient	-0.08	0.01	0.05
	p-value	0.037	0.781	0.411
	SE	0.04	0.04	0.06
Schools per 100 sq km	Coefficient	0.04	0.00	-0.05
	p-value	0.001	0.502	0.069
	SE	0.01	0.01	0.03
Urbanisation Rate	Coefficient			-6.95
	p-value			0.085
	SE			4.01
State Dummies (control: Tamil Nadu)				
Andhra Pradesh	Coefficient	-13.20	1.34	-5.24
	p-value	0.000	0.132	0.062
	SE	2.07	0.88	2.79
Gujarat	Coefficient	-2.22	5.69	-7.89
	p-value	0.149	0.001	0.001
	SE	1.53	1.33	1.96
Karnataka	Coefficient	2.76	0.47	-3.15
	p-value	0.317	0.696	0.404
	SE	2.75	1.20	3.76
Kerala	Coefficient	11.75	-0.57	-1.49
	p-value	0.000	0.479	0.492
	SE	1.37	0.80	2.16
Maharashtra	Coefficient	2.52	2.44	-6.53
	p-value	0.042	0.112	0.039
	SE	1.23	1.53	3.14
Odisha	Coefficient	-8.01	4.38	4.78
	p-value	0.000	0.001	0.040
	SE	2.10	1.33	2.31
West Bengal	Coefficient	-6.08	2.89	0.11
	p-value	0.008	0.044	0.969
	SE	2.28	1.42	2.84
Year Effect (control: 2011)	Coefficient	8.12	-2.07	-47.29
	p-value	0.000	0.018	0.000
	SE	1.11	0.87	1.57
No of Obs		186	186	186
R Squared		0.58	0.20	0.88
Adj R Squared		0.56	0.15	0.87
F Statistic		24.6	4.2	104.0
p-value		0.000	0.000	0.000
Log Likelihood		-621.9	-574.2	-670.8

Note: Authors' calculation; * p<0.05, ** p<0.01, ***p < 0.001

Table 9. Pooled Regression Results - Cyclone Hazard and Health & Livelihood

Dependent Variable → / Independent Variables ↓		IMR	HCR Poverty	Vulnerable Residence	MPCE
Intercept	Coefficient	5.07	8.79	17.97	7.39
	p-value	.004	.001	.001	.001
	SE	1.75	1.94	1.14	0.07
Cyclone Hazard Score	Coefficient	0.02	0.14	0.03	-0.01
	p-value	0.107	0.006	0.055	0.661
	SE	0.01	0.05	0.02	0.00
Health Centers per 100 sq km	Coefficient	-0.15			
	p-value	0.148			
	SE	0.10			
Urbanisation Rate	Coefficient	9.48	-8.94	-9.39	0.75
	p-value	0.013	0.004	0.000	0.000
	SE	3.79	3.03	2.05	0.13
State Dummies (control: Tamil Nadu)					
West Bengal	Coefficient	0.69	7.20	0.14	0.11
	p-value	0.783	0.032	0.882	0.065
	SE	2.51	3.33	0.95	0.06
Odisha	Coefficient	1.10	3.52	-5.72	-0.04
	p-value	0.490	0.011	0.000	0.387
	SE	1.59	1.38	1.07	0.05
Andhra Pradesh	Coefficient	-1.88	-2.07	-7.25	0.25
	p-value	0.457	0.191	0.000	0.029
	SE	2.53	1.58	1.59	0.11
Kerala	Coefficient	-1.17	-3.36	-6.01	0.28
	p-value	0.443	0.006	0.000	0.001
	SE	1.52	1.21	0.96	0.08
Karnataka	Coefficient	-1.15	3.10	-5.82	0.06
	p-value	0.424	0.112	0.000	0.214
	SE	1.44	1.94	1.01	0.05
Maharashtra	Coefficient	7.28	9.58	5.44	-0.33
	p-value	0.020	0.000	0.000	0.000
	SE	3.10	2.23	1.13	0.07
Gujarat	Coefficient	-1.35	6.00	-1.72	-0.18
	p-value	0.508	0.000	0.369	0.014
	SE	2.04	1.63	1.91	0.07
Year Effect	Coefficient	0.91	6.37	9.56	1.08
	p-value	0.333	0.000	0.000	0.000
	SE	0.94	1.19	1.25	0.03
No of Obs		186	186	186	186
R Squared		0.16	0.33	0.57	0.90
Adj R Squared		0.10	0.29	0.54	0.89
F Statistic		2.7	7.8	20.8	141.1
p-value		0.003	0.000	0.000	0.000
Log Likelihood		-626.5	-652.1	-605.3	31.5

Note: Authors' calculations; * p<0.05, ** p<0.01, ***p < 0.001

3.3. Regression – Pooled OLS Results

3.3.1. Cyclone hazard and Education

We utilize the cyclone hazard score CHS as a causal variable in a pooled OLS regression framework with year effects. We observe a significant negative influence of cyclone hazard on the literacy rate of the coastal districts after controlling for urbanization, unobserved state-specific effects captured by state dummies, and year effects (Table 8). Each standard deviation rise in CHS reduces literacy rate by close to one percentage point. For both out-of-school children and youth-NEET, coefficients of CHS are positive, though insignificant. The weak association may be because disaster preparedness and educational resilience can facilitate rapid school reopening and temporary learning arrangements can substantially mitigate long-term educational losses. The year effect is significant, indicating an across-the-board increase in Literacy and a decline in school dropout and youth NEET between 2011 and 2023. Several state dummies are also significant, signaling regional variation in the educational situation.

3.3.2. Cyclone hazard and Health & Livelihood

It is observed from the pooled regression results (Table 9) that both health and livelihood are adversely affected by cyclone hazard – a rise in cyclone hazard score by one standard deviation is associated with about a 2 per thousand increase in IMR, a 1.4 percentage point rise in poverty-HCR, and a 5 percent decrease in consumption level (Table 9)

3.4. Regression with Spatial Dependence

Cyclone-related risks or damages are inherently spatial phenomena. In addition, spatial dependence among the coastal districts is possible, resulting in spatially correlated disturbances that may affect our OLS regression results. To account for this, we examine the effect of cyclone hazard score on socioeconomic situation in a spatial regression framework. We row-standardized a Queen contiguity matrix and used it as the spatial weight matrix. This assumes that two spatial entities are neighbors if their boundaries overlap or touch and is particularly suitable for irregular district boundaries. The previous OLS equations were first estimated separately for the two time points, and the residuals were tested using Moran's I. Of the 14 equations (7 equations × 2 time points), Moran's I of the residuals was insignificant for 9 equations, allowing us to proceed with OLS with Robust Standard Errors. For 4 other equations, the Spatial Error Model is indicated, and for one equation, OLS was indicated as LM/LR tests were inconclusive and OLS had the lowest AIC [see Supplementary Table S4]. We report the results below.

3.4.1. Cyclone hazard and Education

For all three education variables across both time points, OLS was indicated. Results suggest that the negative association between cyclone hazard and literacy, and the positive association between cyclone hazard and both school drop-out and youth-NEET, hold true even when examined separately for the two time points and spatial association is accounted for. The degree of association has strengthened in 2023 compared to 2011, and coefficients are significant when *Robust Standard Errors* are used (Table 10).

3.4.2. Cyclone hazard and Health & Livelihood

For IMR too, OLS was indicated for both 2011 and 2023. Results suggest that higher cyclone hazard is linked with higher IMR in both years (Table 10). Poverty-HCR and Incidence of Vulnerable residence are also positively associated with Cyclone hazard, though the strength of the association is

lower in 2023 compared to 2011. For MPCE, the relationship is very weak but negative, indicating that districts with higher cyclone hazard have lower average consumption level.

Table 10. Spatial Regression Results - Cyclone Hazard and Education

Dependent Variable →		Adult Literacy		Out-of-School Children (5-9 yrs)		Youth NEET	
Independent Variables ↓	Year	2011	2023	2011	2023	2011	2023
	Specification	**OLS**	**OLS**	**OLS**	**OLS**	**OLS**	**OLS**
Intercept	Coefficient	77.77	83.58	2.79	0.54	98.22	53.23
	p-value	0.000	0.000	0.195	0.051	0.000	0.000
	SE	3.02	1.77	2.13	0.27	2.11	3.70
Cyclone Hazard Score	Coefficient	-0.02	-0.09	0.06	0.06	0.01	0.10
	p-value	0.113	0.035	0.051	0.094	0.954	0.100
	SE	0.01	0.04	0.03	0.04	0.06	0.06
Schools per 100 sq km	Coefficient	0.03	0.04	0.00	0.00	-0.11	-0.05
	p-value	0.029	0.002	0.880	0.791	0.010	0.148
	SE	0.02	0.01	0.01	0.01	0.04	0.03
Urbanisation Rate	Coefficient					-3.58	-12.33
	p-value					0.321	0.113
	SE					3.58	7.70
Andhra Pradesh	Coefficient	-14.86	-11.37	2.56	-0.54	-1.09	-9.78
	p-value	0.000	0.001	0.088	0.737	0.655	0.045
	SE	2.95	3.31	1.48	1.61	2.42	4.81
Gujarat	Coefficient	-3.32	-1.19	6.57	4.46	-0.79	-16.17
	p-value	0.240	0.541	0.007	0.010	0.711	0.000
	SE	2.80	1.94	2.37	1.69	2.13	3.67
Karnataka	Coefficient	0.87	4.84	0.88	0.13	-0.31	-5.75
	p-value	0.860	0.013	0.725	0.906	0.891	0.471
	SE	4.91	1.90	2.49	1.07	2.29	7.94
Kerala	Coefficient	13.98	9.18	-1.38	0.18	-3.83	-0.54
	p-value	0.000	0.000	0.330	0.873	0.115	0.873
	SE	2.32	1.60	1.40	1.14	2.40	3.34
Maharashtra	Coefficient	2.35	2.87	4.77	0.18	-3.61	-9.57
	p-value	0.211	0.160	0.148	0.851	0.483	0.001
	SE	1.86	2.03	3.27	0.94	5.12	2.69
Odisha	Coefficient	-9.24	-6.83	4.71	3.83	4.57	5.07
	p-value	0.011	0.003	0.027	0.088	0.008	0.208
	SE	3.56	2.21	2.09	2.21	1.67	4.00
West Bengal	Coefficient	-5.35	-6.47	7.07	-0.83	4.65	-3.55
	p-value	0.133	0.008	0.016	0.512	0.155	0.382
	SE	3.53	2.38	2.88	1.25	3.24	4.04
No of Obs		93	93	93	93	93	93
OLS R Squared		0.53	0.53	0.22	0.20	0.34	0.38
OLS Adj R Sq		0.47	0.47	0.13	0.12	0.25	0.30
OLS baseline F Stat		10.24	10.21	2.57	2.33	3.78	4.55
F-stat p-value		0.001	0.001	0.009	0.018	0.001	0.001
AIC		664.81	603.88	610.35	568.07	600.72	720.15
Koenker BP p-val		0.06	0.331	0.06	0.018	0.10	0.234
Residual Moran's-I p-value		0.163	0.014	0.435	0.150	0.541	0.272

Note: Authors' calculations;SE are Robust Standard Errors; * p<0.05, ** p<0.01, ***p < 0.001

Table 11. Spatial Regression Results - Cyclone Hazard and Health & Livelihood

Dependent Variable →		IMR		Poverty-HCR		Vulnerable Residence		MPCE	
Independent Variables ↓	Year	2011	2023	2011	2023	2011	2023	2011	2023
	Specification	OLS	OLS	OLS	SEM	SEM	SEM	OLS	SEM
Intercept	Coefficient	6.57	5.19	7.57	15.40	20.90	21.99	7.27	8.53
	p-value	0.006	0.011	0.019	0.000	0.000	0.000	0.000	0.000
	SE	2.34	1.99	3.17	1.41	1.97	1.42	0.09	0.07
Cyclone Hazard Score	Coefficient	0.05	0.04	0.24	0.02	0.09	0.01	-0.01	-0.01
	p-value	0.081	0.141	0.018	0.415	0.010	0.104	0.603	0.949
	SE	0.03	0.03	0.10	0.03	0.03	0.01	0.00	0.00
Health Center per 100 sq km	Coefficient	0.01	-0.24						
	p-value	0.977	0.006						
	SE	0.14	0.09						
Urbanisation Rate	Coefficient	6.93	12.46	-6.22	-12.80	-15.12	2.57	0.70	0.84
	p-value	0.080	0.023	0.250	0.000	0.000	0.234	0.000	0.000
	SE	3.91	5.36	5.36	2.65	2.40	2.16	0.14	0.13
Andhra Pradesh	Coefficient	-1.07	2.54	13.17	0.32	-3.57	7.16	0.17	0.08
	p-value	0.597	0.566	0.070	0.847	0.155	0.000	0.019	0.364
	SE	2.01	4.40	7.18	1.64	2.51	1.82	0.07	0.09
Gujarat	Coefficient	-1.66	3.20	5.77	1.56	-8.48	-1.59	0.10	-0.17
	p-value	0.379	0.126	0.039	0.242	0.001	0.320	0.149	0.021
	SE	1.88	2.07	2.75	1.33	2.45	1.60	0.07	0.07
Karnataka	Coefficient	-0.09	-3.84	-0.10	-3.75	-5.80	-6.38	0.44	0.14
	p-value	0.977	0.204	0.950	0.074	0.081	0.007	0.009	0.207
	SE	3.02	3.00	1.50	2.09	3.33	2.36	0.16	0.11
Kerala	Coefficient	-1.30	-1.87	-3.28	-2.85	-7.90	-0.31	0.44	0.15
	p-value	0.574	0.282	0.050	0.050	0.000	0.842	0.000	0.051
	SE	2.29	1.73	1.65	1.45	2.05	1.54	0.10	0.08
Maharashtra	Coefficient	-0.71	-1.88	1.57	5.45	-8.41	-5.31	0.21	-0.07
	p-value	0.735	0.443	0.580	0.013	0.016	0.028	0.001	0.543
	SE	2.09	2.44	2.82	2.18	3.48	2.42	0.06	0.12
Odisha	Coefficient	9.73	4.51	11.18	7.65	12.39	0.57	-0.25	-0.39
	p-value	0.001	0.303	0.008	0.000	0.000	0.743	0.010	0.000
	SE	2.75	4.35	4.13	1.51	2.59	1.75	0.09	0.08
West Bengal	Coefficient	-1.08	-1.76	3.51	7.72	1.99	-0.78	-0.05	-0.29
	p-value	0.734	0.549	0.242	0.000	0.550	0.726	0.557	0.006
	SE	3.17	2.93	2.98	1.91	3.33	2.24	0.09	0.10
Lambda (SEM)	Coefficient				0.14	0.59	0.44		0.27
	p-value				0.224	0.000	0.000		0.012
	SE				0.12	0.08	0.09		0.11
No of Obs		93	93	93	93	93	93	93	93
OLS R Squared		0.30	0.19	0.25				0.66	
OLS Adj R Sq / SEM Pseudo R sq		0.21	0.08	0.16	0.69	0.89	0.60	0.62	0.72
OLS baseline F Stat		3.22	1.77	2.70	17.84	39.19	8.46	16.18	19.50
F-stat p-value		0.002	0.079	0.006	0.001	0.001	0.001	0.001	0.001
AIC		602.6	671.6	720.0	526.5	534.3	497.9	-1.2	-36.4
Koenker BP p-value		0.010	0.482	0.280	0.053	0.060	0.008	0.150	0.033
Residual Moran's-I p-value		0.124	0.988	0.863	0.016	0.001	0.001	0.030	0.001

Note: Authors' calculations; SE are Robust Standard Errors; * p<0.05, ** p<0.01, ***p < 0.001

3.5. Socioeconomic Vulnerability

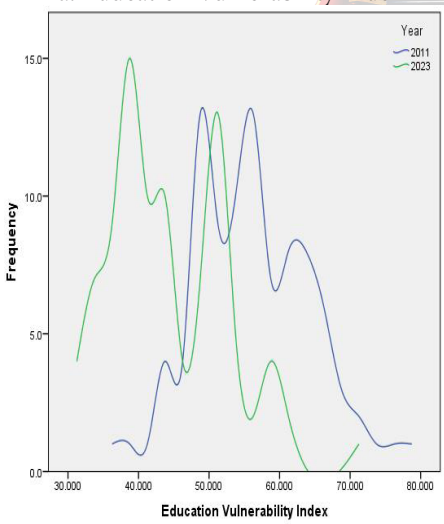
To explore the socioeconomic vulnerability, we have converted the dimension-specific vulnerability indices into categories as mentioned earlier. The number of districts in each category, by dimension of socioeconomic vulnerability, for the two time points is shown in Table 12. All the vulnerability dimensions exhibit noticeable shifts in the distribution of districts across categories between 2011 and 2023. There is a pronounced fall in the number of districts in the extremely high vulnerability category and a significant increase in the number of districts in the Low vulnerability category – indicating a declining socioeconomic vulnerability over time. This improvement is more pronounced for Economic vulnerability and less so for education and health vulnerabilities. These changes are reflected in the density plots presented in Figures 2. a – 2.d.

Table 12. Number of Districts according to Degrees of Vulnerability

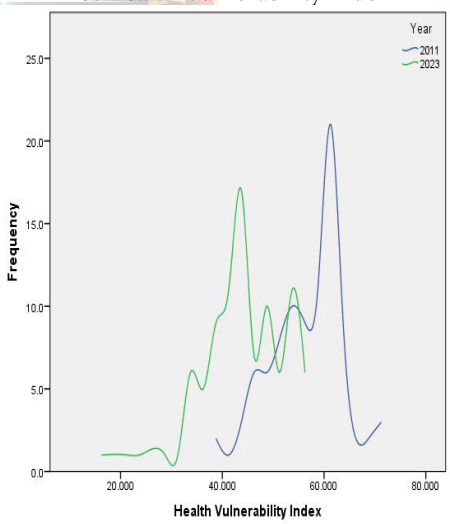
Categories	Education Vulnerability		Health Vulnerability		Economic Vulnerability		Socioeconomic Vulnerability	
	2011	***2023***	***2011***	***2023***	***2011***	***2023***	***2011***	***2023***
Low	2	35	2	25	6	29	5	35
Moderate	11	20	10	28	7	43	8	20
High	17	11	12	17	8	19	17	11
Very High	19	18	18	17	10	2	19	18
Extremely High	50	15	57	12	68	6	50	15
TOTAL	99	99	99	99	99	99	99	99

Source: Authors' Calculation

2a: Education Vulnerability Index



2b: Health Vulnerability Index



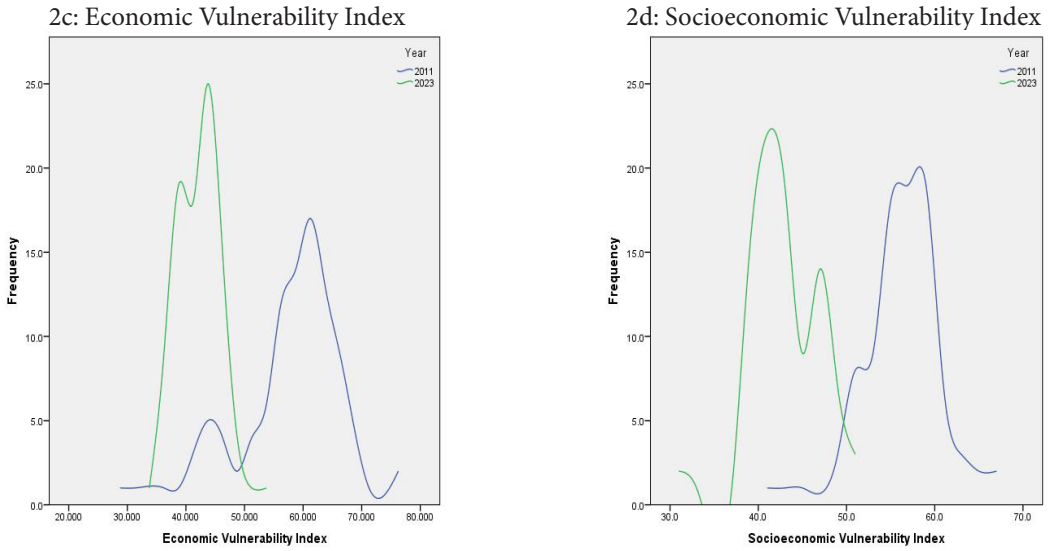


Figure 2. Density Plots of Vulnerability Indices of 2011 and 2023

3.6. Comprehensive Coastal Vulnerability

Our analysis shows some overlap between cyclone hazard and socioeconomic vulnerabilities in Indian coastal districts (Tables 13 and 14).

Table 13. Overlap between CyHI and SEVI - 2011

Low		Socio-Economic Vulnerability Index				
		Moderate	High	Very High & above	ALL	
Cyclone Hazard Index	Low	4	2	2	17	25
	Moderate	2	3	4	7	16
	High	0	2	5	18	25
	Very High & above	0	1	6	26	33
	ALL	6	8	17	68	99

Note: Authors' Calculation; Very High and Extremely High categories have been clubbed together

Table 14. Overlap between CyHI and SEVI - 2023

Low		Socio-Economic Vulnerability Index				
		Moderate	High	Very High & above	ALL	
Cyclone Hazard Index	Low	4	2	2	5	13
	Moderate	5	2	0	5	12
	High	7	2	4	1	14
	Very High & above	19	14	8	19	60
	ALL	35	20	14	30	99

Note: Authors' Calculation; Very High and Extremely High categories have been clubbed together

Close to 30-40 percent of districts in both years fall into similar categories for both Cyclone Hazard and Socioeconomic Vulnerability (Both Low, Both Moderate, Both High, or Both Very High and above). It also signals that the incidence of high cyclone vulnerability levels has increased, while that of socioeconomic vulnerability has declined over the decade. We explored the combined effect of cyclone hazard and socioeconomic vulnerability using the Coastal Vulnerability Index (CVI). Dis-

tricts were categorized into Low, Moderate, High, Very High, and Extremely High groups using the same demarcation points as for the previous indices. In 2011-12, 18 districts had an Extremely High Coastal Vulnerability Index, while 2 were in the Low category (Table 15). The largest concentration of districts was observed in the Very High category, followed by the High category. The distribution in 2023 continued to be driven by the Very High category. Overall, the middle has thinned while both extremes have thickened.

Table 15. Distribution of Districts according to Coastal Vulnerability Category

Coastal Vulnerability Category	2011-12	2023
Low	2	8
Moderate	9	18
High	30	21
Very High	40	31
Extremely High	18	21
TOTAL	99	99

Source: Authors' calculation

What is worrisome is the increase in vulnerability at the higher end, where the number of districts in the Extremely High category has increased from 18 to 21. This is observed from the density map as a small hump near the right-hand tail (Figure 3).

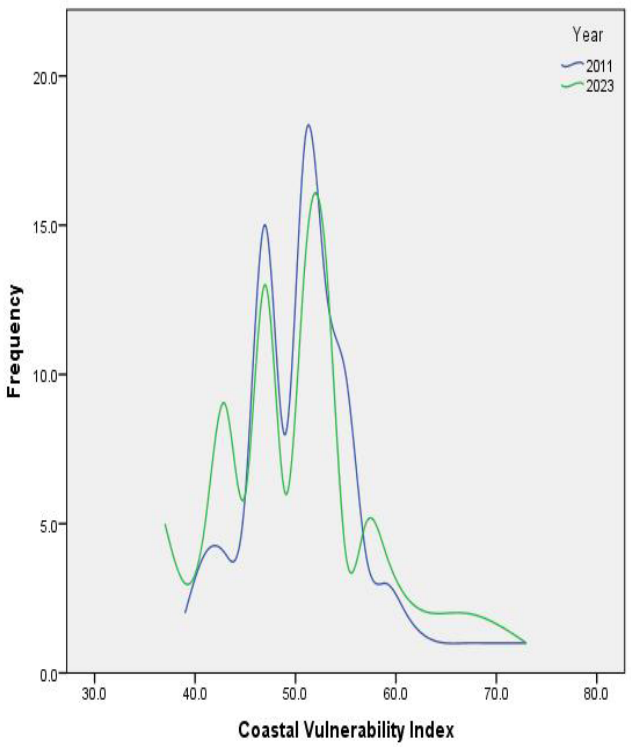


Figure 3. Coastal Vulnerability Index of 2011 and 2023

Cross-tabulating the CVI of 2011 and 2023 shows that vulnerability category has increased for 20 districts, decreased for 39 districts, and remained the same for 40 districts (Table 14). The absolute value of CVI has decreased for 63 districts and increased for 36 districts, driven mainly by a fall in SEVI.

Table 16. Overlap between CVI 2011 and CVI 2023

		Coastal Vulnerability Index 2023					
	Low	Moderate	High	Very High	Extremely High	ALL	
Coastal Vulnerability Index (2011).	Low	2	-	-	-	-	2
	Moderate	5	3	1	-	-	9
	High	1	10	7	9	3	30
	Very High	-	5	11	17	7	40
	Extremely High	-	-	2	5	11	18
	ALL	8	18	21	31	21	99

Note: Authors' Calculation;

We observe that eight districts – Valsad and Kheda in Gujarat, Purba and Paschim Bardhaman in West Bengal, Dhenkanal and Keonjhar in Odisha, Udupi in Karnataka, Mumbai Suburban in Maharashtra – experienced a fall in both cyclone hazard as well as socioeconomic vulnerability during 2011-23 (Table 15). On the other hand, 9 districts show significant deterioration in both dimensions. These are Jagatsinghapur in Odisha; Jamnagar and Navsari in Gujarat; Haora and South 24 Parganas in West Bengal; Idukki and Ernakulam in Kerala; and Nagapattinam and Chennai in Tamil Nadu. In Surat in Gujarat and the three island districts of the Andaman and Nicobar Islands and Lakshadweep, cyclone hazard has decreased, but socioeconomic vulnerability has increased. In the remaining districts, socioeconomic vulnerability has decreased, but cyclone vulnerability has increased.

Table 17. Change in Coastal Vulnerability 2011-2023

Decreased		Socioeconomic Vulnerability Increased	ALL	
Cyclone Hazard	Decreased	8	4	12
	Increased	78	9	87
	ALL	86	13	99

Source: Author's Calculation

INTERNATIONAL JOURNAL OF DISASTER RISK MANAGEMENT IJDRM SCIENTIFIC-PROFESSIONAL SOCIETY FOR DISASTER RISK MANAGEMENT

4. Discussion

Our results bring out three clear signals. First, cyclone hazard has increased in Indian coastal districts in recent decades. Second, exposure to higher cyclone hazard is associated with lower socioeconomic conditions across education, health, and livelihood dimensions. The association weakens for a few outcome variables and strengthens for others when spatial associations are accounted for, but remains consistent and valid in terms of direction. Third, while socioeconomic situation is improving during this period, there are mixed results on overall coastal vulnerability.

The rise in frequency, intensity, and physical impact of tropical cyclones along the Indian coastline is a geo-climatic phenomenon and stems from global anthropogenic factors. Mitigation and adaptation are, however, local, and our remaining results help in informed policymaking. Lower education, health, and livelihood outcomes in districts with higher cyclone exposure is in line with existing literature (Dercon, 2004; Carter et al., 2007; Jing et al, 2025; Wang, 2025; Guo et al, 2025) and may result from schools remaining closed for prolonged periods during and after cyclones resulting in fewer days of schooling and affecting academic performance (Esnard et al., 2017; Segarra-Alméstica et al., 2022). The decline in MPCE and rise in poverty and vulnerable residences in cyclone-prone districts likely reflect losses to assets and income during such extreme events. The impact on IMR reflects the long-term impact of climate-hazard-related deprivations on health and wellbeing, compounded by frequent destruction of health infrastructure, and supports existing literature (Jana et al., 2022; Wang et al., 2025; Guo et al., 2025). It thus comes out that the adverse impact of tropical cyclones extends

beyond immediate disruptions to infrastructure and public services, with measurable spill-over effects on long-term development indicators. These patterns point to a development gap in the coastal belt of India, where communities in higher cyclone-vulnerable areas shoulder a disproportionate burden of the damages.

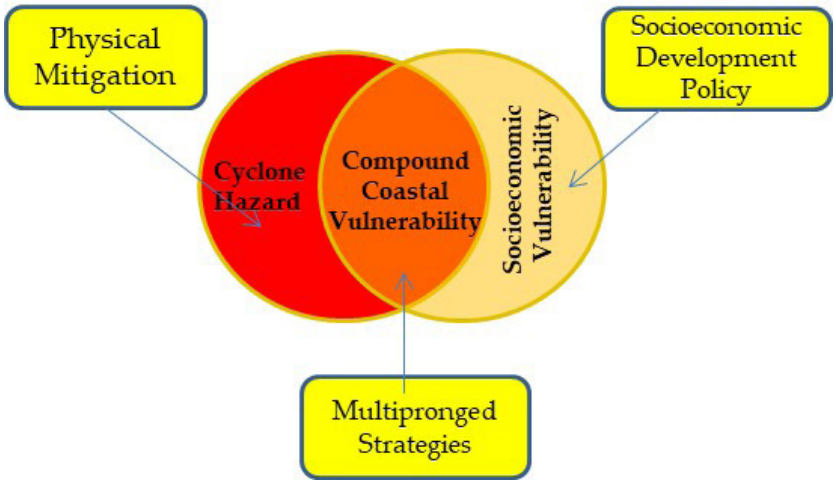


Figure 4: Coastal Policy Paradigm

4.1. Policy Relevance

One of the important inferences from our results is that there are three sets of coastal districts requiring attention – one where both cyclone hazard and inherent socioeconomic vulnerability juxtapose; and the other two where one of the situations is relatively better but the other is not (Figure 4). Our integrated yet decomposable analysis clearly identifies these locations so that policy-makers can adapt the policies to the type of vulnerability of the district (see Supplementary Table S5 for a complete list). Districts characterized primarily by physical exposure to cyclones but with robust socioeconomic patterns would benefit most from strengthening physical infrastructure, early warning systems, and evacuation preparedness. Conversely, districts with high socioeconomic vulnerability but low exposure should focus more on enhanced social infrastructure, livelihood support, broad-based development policies, and social protection to reduce long-term risk. The subset of districts facing both forms of vulnerability simultaneously poses more complex challenges for disaster risk management. For this latter category, policymakers should adopt multi-pronged interventions that integrate strengthening physical infrastructure to combat cyclones and social resilience strategies to increase the adaptive capabilities of the people. Enhanced evacuation preparedness, strengthened social protection measures, resilient housing, livelihood support, and fast post-event reinstatement should be incorporated into the regional planning strategies of these districts. Actions that address specific needs of each district would lead to effective disaster preparedness and management. Such a targeted and localized policy regime would become more effective if it taps into local community knowledge and participation, as there is ample evidence that community-based disaster risk reduction strategies are the key to preparedness and resilience (Cvetković, 2025). Lessons from Bangladesh, which also frequently faces cyclones, suggest combining formal institutional frameworks like the national, state, and district disaster management authorities with informal community practices for two-way learning (Salam et al., 2025). However, successful disaster management also relies on incorporating environmental concerns into the development policy of the coastal region, compliance with coastal zone regulations, and proactive mitigation, failing which catastrophes are waiting to happen, as highlighted by Goyal (2019) in the case of the Kerala floods. Fortunately, India has come a long way since then, and states like Odisha have been pioneers in proactive disaster management in spite of facing cyclones very frequently (Pradhan et al., 2025). Recent evidence also highlights the role of technology, especially AI-driven models for prediction, warning, and resource optimization (Hanspal & Behera, 2024). All these should be integrated into a dedicated district cyclone manage-

ment plan that is locally grounded but draws on global best practices rather than relying on an umbrella nationwide disaster management plan.

On the flip side, our study fails to overcome the constraints arising out of a lack of comparable data at an appropriate granular level for additional social and institutional variables that may influence the association between cyclone hazard and vulnerability in particular and human vulnerability in general. The presence of omitted variable bias is accepted, although the directions of associations do provide an idea of the necessary policies. In several cases, the statistical significance of the coefficient of cyclone exposure is poor, indicating that the association is weak. This may be because district-level relationships are also influenced by initial asset base, concentration of population and economic activities within the district but away from the vulnerable coastal part, labor market situation, and migration that can offset the link with direct cyclone exposure. A household-level disaggregated study may therefore provide more insight into the relationship between cyclone exposure and socioeconomic outcomes. Also, we have worked with aggregate district-level data, while most often the impact of disasters falls disproportionately on specific population groups like women, children & elderly, marginal socio-religious groups and the poor. Future research should therefore explore these issues.

5. Conclusion

Our objective was to provide an overview of the vulnerability of India's coastal districts to exposure to a natural hazard like tropical cyclones and how it is compounded because of socioeconomic vulnerabilities. We have shown that though development policies over the past decade have reduced socioeconomic vulnerabilities, the incidence of cyclone hazard has increased, as a result of which the number of both low-vulnerability and high-vulnerability areas has increased, with a thinning of the middle. This research adds value to the disaster risk management paradigm in India by classifying coastal districts into three broad groups and identifying specific sets of policies for each group. These insights should be incorporated into the regional planning strategies of the coastal districts for minimizing both short-term and long-term losses from tropical cyclones. Adopting appropriate, distinct yet integrated policies for climate adaptation, disaster risk management planning, and resilient regional development is the need of the hour.

Author Contributions: Both authors contributed to Conceptualization, Methodology, Data collection, Data cleaning and analysis, Visualization, Writing original draft, Writing revised draft & editing.

Funding: The author(s) received no financial support for the research, authorship, and/or publication of this article.

Data availability statement: All data used in this study are derived from open access secondary sources and are cited in the relevant sections of the manuscript.

Acknowledgments: The authors acknowledge the suggestions received from anonymous reviewers regarding methodology and presentation.

Conflicts of Interest: The authors declare no conflict of interest.

6. References

1. Akter, S., &Mallick, B. (2013). The poverty–vulnerability–resilience nexus: Evidence from Bangladesh. Ecological Economics, 96, 114–124. https://doi.org/10.1016/j.ecolecon.2013.10.008
2. Ali, S. A., Khatun, R., Ahmad, A., & Ahmad, S. N. (2020). Assessment of cyclone vulnerability, hazard evaluation and mitigation capacity for analyzing cyclone risk using GIS technique: A study on Sundarban Biosphere Reserve, India. Earth Systems and Environment, 4, 71–92. https://

doi.org/10.1007/s41748-019-00140-xAnselin, Luc. 2005. Exploring Spatial Data with Geoda: A Workbook. University of Illinois at Urbana, Champaign

3. Anttila-Hughes, J. K., & Hsiang, S. M. (2013). Destruction, disinvestment, and death: Economic and human losses following environmental disaster. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2220501
4. Bandyopadhyay, S., Dasgupta, S., Khan, Z., & Wheeler, D. (2018). Cyclonic storm landfalls in Bangladesh, West Bengal and Odisha, 1877–2016: A spatiotemporal analysis (Policy Research Working Paper No. 8316). World Bank. https://doi.org/10.1596/1813-9450-8316
5. Barua, S., & Banerjee, A. (2020). Impact of climatic shocks on household well-being: Evidence from rural Bangladesh. Asia-Pacific Journal of Rural Development, 30(1–2), 89–112. https://doi.org/10.1177/1018529120977246
6. Canete, R., &Biñas, R. "Rusty". (2025). Differential risk and the elements of resilience: A framework for advancing disaster risk reduction. International Journal of Disaster Risk Management, 7(2), 209–238. https://doi.org/10.18485/ijdrm.2025.7.2.12
7. Carter, M. R., Little, P. D., Mogues, T., &Negatu, W. (2007). Poverty traps and natural disasters in Ethiopia and Honduras. World Development, 35(5), 835–856. https://doi.org/10.1016/j.worlddev.2006.09.010
8. Cvetković, V. M., Aleksova, B., Renner, R., Gačić, J., Ivanov, A., &Milašinović, S. (2025). Community-Based Disaster Risk Reduction: Overcoming Barriers to Build Stronger Communities. International Journal of Disaster Risk Management, 7(2), 113-130. https://doi.org/10.18485/ijdrm.2025.7.2.7
9. Cvetković, V. M., Milenković, D., & Lukić, T. (2026). Measuring Community Disaster Resilience in Serbia Using an Adapted BRIC Framework Grounded in DROP: Index Construction and Regional Disparities. *Geosciences*, 16(4). https://doi.org/10.3390/geosciences16040135.
10. Cvetković, V. M., Milenković, D., Bašić, J., Lukić, T., & Renner, R. (2026a). Predictive Model of Community Disaster Resilience Across Serbia: A BRIC–DROP Composite Index and Spatial Patterns. Safety, 12(3), 59. https://doi.org/10.3390/safety12030059.
11. Cutter, S. L., Boruff, B. J., & Shirley, W. L. (2003). Social vulnerability to environmental hazards. Social Science Quarterly, 84(2), 242–261. https://doi.org/10.1111/1540-6237.8402002
12. Dercon, S. (2004). Growth and shocks: Evidence from rural Ethiopia. Journal of Development Economics, 74(2), 309–329. https://doi.org/10.1016/j.jdeveco.2004.01.001
13. Esnard, A. M., Lai, B. S., Wyczalkowski, C., Malmin, N., & Shah, H. J. (2017). School vulnerability to disaster: Examination of school closure, demographic, and Hazard factors in Hurricane Ike's wind swath. Natural Hazards, 90, 513–535. https://doi.org/10.1007/s11069-017-3057-2
14. GoI (2011a) Unit-level records on Employment and Unemployment Survey 2011-12, NSSO, Ministry of Statistics and Programme Implementation, Government of India [https://microdata.gov.in/NADA/index.php/catalog/127]
15. GoI (2011b) Unit level records on Household Consumption Expenditure Survey 2011-12, NSSO, Ministry of Statisitcs and Programme Implementation, Government of India [https://microdata.gov.in/NADA/index.php/catalog/1]
16. GoI (2011c) Sample Registration System Statistical Report 2011, Office of the Registrar General & Census Commissioner of India, Government of India [https://censusindia.gov.in/nada/index.php/catalog/34790]
17. GoI (2022) Sample Registration System Statistical Report 2022, Office of the Registrar General & Census Commissioner of India, Government of India, [https://censusindia.gov.in/nada/index.php/catalog/45570]
18. GoI (2023a) Unit level records on Periodic Labour Force Survey, NSSO, Ministry of Statistics and Programme Implementation, Government of India [https://microdata.gov.in/NADA/index.php/catalog/213]

19. GoI (2023b) Unit level records on Household Consumption Expenditure Survey 2023-24, NSSO, Ministry of Statisitcs and Programme Implementation, Government of India [https://microdata.gov.in/NADA/index.php/catalog/237]
20. Goyal, N. (2019). Disaster Governance and Community Resilience: The Law and the Role of SDMAs. *International Journal of Disaster Risk Management*, *1*(2), 61-75. https://doi.org/10.18485/ijdrm.2019.1.2.5
21. Guo, Y., Zhu, Y., He, C., Gao, Y., Zhou, L., Bachwenkizi, J., Kan, H.-D., & Chen, R. (2025). Cyclone exposure and mortality risk of children under 5 years old: An observational study in 34 low- and middle-income countries. PLOS Medicine, 22(9), e1004735. https://doi.org/10.1371/journal.pmed.1004735
22. Hanspal, M. S., & Bijayananda Behera. (2025). Disaster Management Laws in India: Past, Present, and Future Directions. International Journal of Disaster Risk Management, 7(1), 115-136. https://doi.org/10.18485/ijdrm.2025.7.1.7
23. Hegde AV, Raju VR (2007) Development of coastal vulnerability index for Mangalore coast, India. Journal of Coast Research, 23:1106–1111
24. Hossain, A., Ahmed, B., Rahman, T., Sammonds, P., Zaman, S., Benzadid, M. S., & Jakariya, M. (2021). Household food insecurity, income loss, and symptoms of psychological distress among adults following the Cyclone Amphan in coastal Bangladesh. PLOS ONE, 16(11), Article e0259098. https://doi.org/10.1371/journal.pone.0259098
25. Hotelling, H. (1933). Analysis of a complex of statistical variables into principal components. Journal of Educational Psychology, 24(6), 417–441. https://doi.org/10.1037/h0071325
26. IPCC (2007). Climate change 2007: Impacts, adaptation and vulnerability (M. L. Parry, O. F. Canziani, J. P. Palutikof, P. J. van der Linden, & C. E. Hanson, Eds. for Intergovernmental Panel on Climate Change). Cambridge University Press.
27. IPCC (2012). Managing the risks of extreme events and disasters to advance climate change adaptation. Intergovernmental Panel on Climate Change, Cambridge University Press.
28. IPCC. (2022). Summary for Policymakers. In Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press.
29. Jana, A., Shaw, S., &Chattopadhyay, A. (2022). Estimating cyclone vulnerability and its linkages with child mortality trajectories along the Bay of Bengal coast of India: A geospatial approach. GeoJournal, 88, 1–14. https://doi.org/10.1007/s10708-022-10717-1
30. Jing, R., Heft-Neal, S., Wang, Z., Che, J., Qiu, M., Opper, I. M., Wagner, Z., & Bendavid, E. (2025). Decreased likelihood of schooling as a consequence of tropical cyclones: Evidence from 13 low- and middle-income countries. PNAS Nexus. https://doi.org/10.1073/pnas.2413962122
31. Kabir, R., Ritchie, E. A., & Stark, C. (2022). Tropical cyclone Hazard in the North Indian Ocean. Atmosphere, 13(9), Article 1421. https://doi.org/10.3390/atmos13091421
32. Kumar, R., &Kunte, P. D. (2012). Coastal vulnerability assessment for Chennai, east coast of India using geospatial techniques. Natural Hazards, 64(1), 853–872. https://doi.org/10.1007/s11069-012-0276-4Kumar, T.S.; Mahendra, R.S.; Nayak, S.; Radhakrishnan, K., and Sahu, K.C., 2010. Coastal vulnerability assessment for Orissa State, east coast of India. Journal of Coastal Research, 26(3), 523–534.
33. Mohapatra, M. (2023). Cyclone hazard climatology. India Meteorological Department. https://rsmcnewdelhi.imd.gov.in/uploads/climatology/hazard.pdf
34. Mohapatra, M., Mandal, G. S., Bandyopadhyay, B. K., Tyagi, A., &Mohanty, U. C. (2012). Classification of cyclone hazard-prone districts of India. Natural Hazards, 63, 1601–1620. https://doi.org/10.1007/s11069-011-9891-8
35. Pradhan, B., Kumar, S., &Nayak , D. (2025). From Vulnerability to Resilience: A Systematic Review of Odisha's Integrated Approach to Disaster Risk Reduction. International Journal of Disaster Risk Management, 7(1), 519-532. https://doi.org/10.18485/ijdrm.2025.7.1.30

36. Rajeev, A., & Mishra, V. (2023). Increasing risk of compound wind and precipitation extremes due to tropical cyclones in India. Environmental Research: Climate, 2(2). https://doi.org/10.1088/2752-5295/accf2e
37. Roy, A., & Sharma, S. (2015). Perceptions and adaptations of the coastal community to the challenges of climate change: A case of Jamnagar City Region, Gujarat, India. Environment and Urbanization ASIA, 6(1), 71–91. https://doi.org/10.1177/0975425315585182
38. Salam, M. F., Hemel, M. B. U., Roni, A. H., Pandith, J. C., &NabilahMaeesha. (2025). Grassroots Disaster Governance in Bangladesh: The Roles of Union Parishads and Disaster Management Committees. International Journal of Disaster Risk Management, 7(2), 395-404. https://doi.org/10.18485/ijdrm.2025.7.2.21
39. Schleypen, J., Plinke, C., & Geiger, T. (2024). The impacts of multiple tropical cyclone events and associated precipitation on household income and expenditures. Economics of Disasters and Climate Change, 8(2), 197–233. https://doi.org/10.1007/s41885-024-00149-1
40. Segarra-Alméstica, E., Caraballo-Cueto, J., Cordero, Y., & Cordero, H. (2022). The effect of consecutive disasters on educational outcomes. International Journal of Disaster Risk Reduction, 83, Article 103398. https://doi.org/10.1016/j.ijdrr.2022.103398
41. Sharmin, S., &Naznin, S. (2013). Impacts of Cyclone Aila on educational institutions: A study of southwestern Bangladesh. In M. P. K. P. S. D. (Ed.), Climate change and disaster risk management (pp. 237–256). Springer. https://doi.org/10.1007/978-3-642-31110-9_15
42. Thieler, E. R., &Hammar-Klose, E. S. (1999). National assessment of coastal vulnerability to future sea-level rise: Preliminary results for the U.S. Atlantic Coast (Open-File Report 99-593). U.S. Geological Survey. https://doi.org/10.3133/ofr99593
43. Wang, Z., Jing, R., Heft-Neal, S., Clark-Ginsberg, A., Guha-Sapir, D., Bendavid, E., & Wagner, Z. (2025). The impact of tropical cyclone exposure on infant mortality in low- and middle-income countries. Science Advances, 11(21), https://doi.org/10.1126/sciadv.adt9640

Supplementary Materials

Table S1: PCA Diagnostics and Component Loadings

Dimension Indices	Component Variables	KMO & Bartlett's Measures	Eigen Value	% of variance explained	Component Loadings
Education Vulnerability Index (EduVI)	Out of school children (17-18 yrs) [X1]	K: 0.58 B: 93.8 p: (0.001)	1.747	58.2	0.833
	Out of school children (19-21yrs) [X2]				0.846
	Youth-NEET (21-29 yrs) [X3]				0.580
Health Vulnerability Index (HltVI)	Infant Mortality Rate [X4]	K: 0.56 B: 11.11 p: (0.011)	1.282	52.73	0.634
	HH without Sanitation [X5]				0.698
	HH without Clean Cooking fuel [X6]				0.627
Economic Vulnerability Index (EcoVI)	Poverty HCR (%) [X7]	K: 0.52 B: 22.13 p: (0.001)	1.361	55.38	0.613
	HH with Vulnerable Residence [X8]				0.789
	HH with Primary sector as main source of income [X9]				0.602

Note: K – KMO test for sample adequacy; B: Bartlett's test for sphericity χ^2 stat; p – p-value of Bartlett's χ^2

Table S2: Sensitivity Analysis for construction of CVI

Scenario ID	Weight for SEVI (w_1)	Weight for CyVI (w_2)	Spearman's Rho (ρ)	p-value	**Jaccard Index (Top 20% districts)**
Baseline	0.50	0.50	1.000	--	1.000
Scenario 1	0.30	0.70	0.885	*.001*	0.667
Scenario 2	0.40	0.60	0.966	*.001*	0.818
Scenario 3	0.60	0.40	0.959	*.001*	0.667
Scenario 4	0.70	0.30	0.860	*.001*	0.533

Note: All Spearman and Jaccard metrics are calculated relative to the Baseline configuration.

Table S3: Model Variables Descriptives

Variables	2011		2023	
	Mean	SD	Mean	SD
Cyclone Hazard Score	20.0	11.8	27.8	15.2
Cyclone Hazard Index	47.4	8.5	52.9	10.9
Adult Literacy %	78.3	11.2	86.9	8.1
Out of school children (5-9 yrs) %	4.7	6.5	2.7	5.1
Out of school children (17-18 yrs) %	41.9	23.2	28.8	22.5
Out of school children (19-21 yrs) %	70.4	23.9	53.8	24.6
Youth NEET (21-29 yrs) %	92.8	6.6	45.9	12.9
Infant Mortality Rate (per thousand)	8.1	6.5	8.9	8.7
Households without sanitation (%)	42.6	25.3	78.5	4.6
Households without clean fuel (%)	37.8	17.7	62.3	26.0
Poverty HCR (%)	6.3	11.8	11.7	6.4
Households with Vulnerable Residence (%)	14.2	10.6	24.1	4.7
Households with primary sector as main income source (%)	24.1	13.0	2.3	0.7
Schools per 100 sq km	55.0	45.5	53.8	49.8
Health Centres per 100 sq km	10.2	6.6	12.0	10.1
Urbanisation Rate (%)	36.8	0.2	40.0	0.2
Socioeconomic Vulnerability Index	56.3	4.3	43.1	3.8
Coastal Vulnerability Index	50.9	6.1	49.4	7.2

Source: Authors' calculations

SPS-DRM
INTERNATIONAL JOURNAL OF DISASTER RISK MANAGEMENT
IJDRM
SCIENTIFIC-PROFESSIONAL SOCIETY FOR DISASTER RISK MANAGEMENT

Table S4: Spatial Model Selection

Dependent Variable	Year	Moran's I on OLS Residuals		Robust LM Lag	Robust LM Error	Final Model	Remarks
		Statistics	**p-value**	**p-value**	**p-value**		**Selection Rule**
Adult Literacy	2011	0.980	0.163	-	-	OLS	Insig. Moran's-I
Adult Literacy	2023	2.191	0.142	-	-	OLS	Insig. Moran's-I
OOSC	2011	0.163	0.435	-	-	OLS	Insig. Moran's-I
OOSC	2023	1.035	0.150	-	-	OLS	Insig. Moran's-I
Youth-NEET	2011	0.086	0.465	-	-	OLS	Insig. Moran's-I
Youth-NEET	2023	0.608	0.271	-	-	OLS	Insig. Moran's-I
IMR	2011	1.153	0.124	-	-	OLS	Insig. Moran's-I
IMR	2023	-2.255	0.987	-	-	OLS	Insig. Moran's-I
Poverty-HCR	2011	-1.095	0.863	-	-	OLS	Insig. Moran's-I
Poverty-HCR	2023	2.142	0.016	0.061	0.0341	SEM	LM Error Sig
Vulnerable Residence	2011	6.449	0.001	0.081	0.078	SEM	Based on lowest AIC
Vulnerable Residence	2023	4.434	0.001	0.699	0.444	SEM	Based on lowest AIC
MPCE	2011	1.885	0.029	0.265	0.175	OLS	Based on lowest AIC
MPCE	2023	3.121	0.001	0.003	0.001	SEM	Based on lowest AIC

Source: Authors' calculations

Table S5: Policy Focus – Indian Coastal Districts

State	District	**State**	**District**
Top Priority - Twin strategy of Physical & Socioeconomic resilience building			
West Bengal	South 24 Parganas	Gujarat	Jamnagar
Odisha	Kendrapara	Gujarat	Amreli
Odisha	Baleshwar	Tamil Nadu	Kallakurichi
Odisha	Jagatsinghapur	Daman	Daman
Odisha	Bhadrak	Andhra Pr	Chittor
Odisha	Puri	Gujarat	Bharuch
West Bengal	Howrah	Puduchchery	Pudukkottai
Tamil Nadu	Nagapattinam	Odisha	Cuttack
West Bengal	North 24 Parganas	Gujarat	Surat
Gujarat	Porbandar	Gujarat	Anand
Odisha	Ganjam	Karnataka	Udupi
Gujarat	Bhavnagar	Gujarat	Vadodara
Gujarat	Rajkot	Lakshadweep	Lakshadweep
Gujarat	Navsari	Odisha	Gajapati
Gujarat	Valsad	A&N Island	North & Middle Andaman
Gujarat	Kachchh	A&N Island	South Andaman
Physical Resilience Building			
West Bengal	PurbaMedinipur	Gujarat	Ahmadabad
Andhra Pr	Krishna	Tamil Nadu	Tirunelveli

SPS-DRM INTERNATIONAL JOURNAL OF DISASTER RISK MANAGEMENT IJDRM SCIENTIFIC-PROFESSIONAL SOCIETY FOR DISASTER RISK MANAGEMENT

Andhra Pr	Nellore	Tamil Nadu	Thiruvallur
Andhra Pr	Guntur	Odisha	Khordha
Andhra Pr	East Godavari	Tamil Nadu	Viluppuram
Tamil Nadu	Ramanathapuram	Puduchchery	Puducherry
Andhra Pr	Prakasam	Andhra Pr	Vizianagaram
Andhra Pr	West Godavari	Maharashtra	Thane
Andhra Pr	Visakhapatnam	Tamil Nadu	Thoothukkudi
Gujarat	Junagadh	Karnataka	Dakshina Kannada
Diu	Diu	Maharashtra	Raigarh
West Bengal	Kolkata	Tamil Nadu	Chennai
Andhra Pr	Srikakulam	Maharashtra	Sindhudurg
Tamil Nadu	Thiruvarur	Goa	South Goa
Tamil Nadu	Cuddalore	Goa	North Goa
Puduchchery	Karaikal	Maharashtra	Ratnagiri
Puduchchery	Mahe	Karnataka	Uttara Kannada
Maharashtra	Mumbai suburban	Kerala	Kozhikode
Tamil Nadu	Ranipet	Kerala	Malappuram
Tamil Nadu	Kanchipuram	Kerala	Kannur
Tamil Nadu	Thanjavur	Kerala	Thrissur
State	**District**	**State**	**District**
		Socioeconomic Development Policy	
Dadra &Nagar	Dadra & Nagar Haveli	West Bengal	PaschimBardhaman
West Bengal	Hooghly	Odisha	Keonjhar
Odisha	Nayagarh	Gujarat	Kheda
Odisha	Jajpur	Kerala	Idukki
Gujarat	Surendra Nagar	Tamil Nadu	Tiruvannamalai
West Bengal	Bardhaman	Odisha	Dhenkanal
		Watch & Develop	
Kerala	Kasaragod	Kerala	Palakkad
Kerala	Alappuzha	Kerala	Wayanad
Kerala	Ernakulum	Tamil Nadu	Ariyalur
Kerala	Thiruvananthapuram	Kerala	Pathanamthita
Kerala	Kollam	Tamil Nadu	Sivaganga
Odisha	Mayurbhanj	Kerala	Kottayam
Tamil Nadu	Kanniyakumari		

Source: Authors' calculations

SPS-DRM INTERNATIONAL JOURNAL OF DISASTER RISK MANAGEMENT IJDRM SCIENTIFIC-PROFESSIONAL SOCIETY FOR DISASTER RISK MANAGEMENT