

Socioeconomic and infrastructural vulnerability indices for cyclones in the eastern coastal states of India

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Abstract Numerous disasters over the past several years have revealed the differential impacts due to social structure, economic conditions and level of infrastructure. This study investigates the vulnerability of eastern coastal states of India from potential cyclones. In this regard, a method is proposed for quantifying the socio-economic and infrastructural vulnerability to potential cyclone in the districts of the eastern coastal states. The variables included in the study are extracted from Census of India (2011) at district level administrative unit. In the analysis, a large number of variables are reduced to a smaller number of factors by using factor analysis, specifically principal component analysis that represents the socioeconomic and infrastructural vulnerability to potential cyclone. Subsequently, the factor scores have been mapped for spatial analysis using Jenk's natural break technique. Utilizing socioeconomic and infrastructural vulnerability indices, the highly vulnerable districts are demonstrated, which are expected to face substantial amount of challenges in coping with cyclones. The highly vulnerable districts require strategies to address the various aspects of socioeconomic and infrastructural vulnerability. The indices and maps produced in this paper could not only be incorporated for multi-level governance but also to integrate it with the real-time weather forecasts to identify the predictive areas of vulnerability.

Keywords Coastal vulnerability · Principal component analysis · Socioeconomic vulnerability index · Infrastructural vulnerability index · Cyclone · India

1 Introduction

The history of coastal disaster around the globe due to nature's fury has provided powerful reminders of the vulnerability of coastal regions. The recent decade has witnessed not only an increase in the frequency but also the intensity and duration of cyclones (IPCC 2012).

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The economic damage associated with the global natural disasters has dramatically increased, especially in the coastal regions (Weinkle et al. 2012). The coastal areas are densely populated and growing rapidly due to their economic importance (Mcgranahan et al. 2007; Murali et al. 2013; Small and Nicholls 2003). The extent to which communities are susceptible to hazards is not only dependent on proximity to the potential source of the threat but also on socioeconomic (Birkenholtz 2012; Boruff et al. 2005) and infrastructural factors (Adger et al. 2004; Balica et al. 2012; Borden et al. 2007).

In this paper, two fundamental questions are addressed: (a) who are vulnerable to the hazard? and (b) why they are vulnerable to the hazard? An attempt has been made in this study to address these objectives by identifying the districts of the Eastern Coastal States (ECS) of India, which are highly vulnerable to hazard events, particularly cyclones. According to a report published by the National Disaster Management Authority (NDMA) of India, 80 % of the coastal areas are vulnerable to cyclones specifically the ECS of India (NDMA 2008). The topographic characteristics being exposed to Bay of Bengal and the bathymetry of the eastern coast make the ECS a naturally vulnerable zone (Dube et al. 1997, 2000). The impact of a hazard on a societal system is determined by the degree of resilience of that system. The higher the resilience, the lower the vulnerability to hazard and vice versa. However, in reality there is a tendency of hazard event to transcend the threshold of precautionary measures. Implausible and unexpected events do occur. The inability of the potentially vulnerable communities due to socioeconomic inequalities, their proximity to the hazardous event, high population density, the degree of awareness and understanding, and poor infrastructure often turns a hazard into a disaster.

To answer the above questions, it is required to identify the socioeconomic and infrastructural vulnerability of the districts of the ECS, which needs close attention for preparedness against any potential cyclone. This study is motivated by the “hazard-of-place” concept initially formulated by Cutter (1996). This was further elaborated to inspect the “place-based” community resilience to natural hazards (Cutter and Finch 2008). The contribution of the application of the hazard-of-place model is the detailed demarcations of exposure to a hazard and their association with the sensitivities of the population, at various levels of administrative units (Cutter et al. 2009). The methodology as proposed by Cutter et al. (2003) was implemented in the counties of USA. Later on it was adopted by several researchers and applied at different scales in various countries. The detail of their work is briefly described in Sect. 3.

Quantification of vulnerability is a complex task because it contains a mixture of individualities that regulates the degree to which it affects someone’s everyday life, earning possibilities, etc. Since, it is a multidimensional phenomenon; no unique approach has yet been standardized for measuring vulnerability. Nonetheless, Cutter et al. (2003) have established a methodology that is widely used for quantifying factors influencing the vulnerability of a place. A similar approach has been used in this study for the districts of the ECS relating to potential cyclones. The vulnerable aspects were divided into two parts: (1) Socioeconomic Vulnerability Index (SVI) and (2) Infrastructure Vulnerability Index (InVI). The main motive behind analyzing SVI and InVI separately is the nature of their representation in the vulnerability assessment. Most of the variables in SVI represent the exposure due to lack of social (marginalized and aged population, illiteracy etc.) and economic (agricultural workers, household workers etc.) status. Similarly, variables in InVI signify the exposure due to lack of physical infrastructure like the quality of houses, access to basic infrastructure services (sanitation, health and education) the density of built environment, etc. This is an inclusive attempt to assess the vulnerability of all the districts of the ECS based on such indices (SVI and InVI). Further, this incorporates variables like

illiterates, houseless population, radio communication, etc. (see Table 1 for detail) in the comprehensive vulnerability analysis of the ECS of India. The scale of this paper is based on the analysis of the district level administrative unit (as defined by Census of India). Local level analysis of vulnerability has not been attempted in this study.

The first section of this article introduces the vulnerability and associated concepts, vulnerability to hazard context, previous studies conducted on vulnerability to hazard in coastal India and an analysis of past cyclones. The next section demonstrates results from the principal component analysis. Furthermore, the final scores for the indices were plotted on GIS maps to study the district level variances in socioeconomic and infrastructural vulnerability. The discussion and concluding sections highlight the efficacy of this study by utilizing the existing available data from the Census. Thereafter, some implications of the outcome of this research have been discussed.

2 Vulnerability and associated concepts

The five fundamental terms central to this paper are hazard, disaster, risk, preparedness and vulnerability. These terms were discussed extensively by several researchers who have related them to hazard studies (see Adger 2006; Cutter 1996; Hinkel 2011; Winsor et al. 1994). In this paper, these terms are explained briefly to highlight their importance. *Hazard* is a potential threat to a system emerging from endogenic or exogenous forces like cyclone, earthquake, tsunami, landslide etc. *Disaster* is a function of hazard and degree of exposure of a system. The degree of exposure depends on social, political, economic and environmental factors. For example, if a cyclone hits a barren land along the coast, it will not be considered as a disaster, unless it affects a human settlement causing damage to life and property. *The Risk* is the probability of a hazard event that adversely affects life and property. *Preparedness* is the action taken by any individual, community, and administrative bodies to reduce the loss of life and property occurred due to hazard event by facilitating early warning system, rescue, relief, rehabilitation, etc. Finally, *vulnerability* may be defined as the susceptibility of a system or community to be harmed by any adverse impact induced either naturally or anthropologically. As such there is no universally accepted definition of vulnerability (Cutter 1996). However, vulnerability is a dynamic concept as the magnitude of exposure and resilience vary from time to time. The probability of being vulnerable at a place depends on its social, economic and infrastructural characteristics. The degree of vulnerability makes a place more prone to potential hazard and influences the recovery process of that place. The socioeconomic factors are those which create either obstacle or empower an individual's or place's potential to respond or recover from a catastrophe; the infrastructural factors are those which either intensify or reduce the impact of such catastrophe (Borden et al. 2007).

Vulnerability has been seen as one of the answers to understand disaster, as it seems highly associated with the deprived, previous damages, and prone to future impact from a hazard (Chakraborty et al. 2005; Cutter 1996; Montz and Tobin 2011). Vulnerability manifests itself in different ways at different places signifying a necessity for place-based understanding of vulnerability to potential hazards (Cutter 1996; Cutter et al. 2003; Pelling 1997). Socioeconomic and infrastructural inequalities often defined by age, literacy, occupation, health, access to basic services, etc., which are believed to be the major causes of people's vulnerability to a potential hazard. Most of the empirical studies on vulnerability show indicator-based research that relies on available sources of data such as census,

surveys conducted by government organizations, etc. It is difficult to measure vulnerability since it is not an obvious phenomenon. The use of indicator-based indices is important in order to make vulnerability operational as an observable concept (Birkmann 2006; Hinkel 2011). Hence, such indices represent the operational phenomenon of a place vulnerability and eminence of a system.

3 Vulnerability to hazard context

In the late 1920s and 1930s, many prominent environmental extremes occurred in the USA. The natural hazards besides the great economic depression during this period assumed catastrophic proportions that resulted in social hardships (Macdonald et al. 2012). The philosophical change in the political perspective transformed the approach to disaster reduction. During that period, the substantial changes in the field of vulnerability to natural hazard research were pioneered by the landmark work of Gilbert White. His study showed that the severity of natural hazard was more of a function of socioeconomic characteristics than the hazard itself (White 1936, 1945). Subsequent contribution to the increasing vulnerability to hazard study was done by Starr (1969). In his study, he addressed the question “How safe is safe enough?” by establishing the major determinants of risk and benefit and creating a balance between the two. Refocusing on the concept of human drivers of vulnerability during 1970s it was argued that increasing hazard vulnerability was a product of political and economic struggles (O’Keefe et al. 1976).

During the 1990s many literatures on vulnerability emphasized on the importance of incorporating social and economic assets together with physical and biophysical aspects of vulnerability to natural hazards (Adger 1998; Capobianco 1999; Cutter et al. 2000; Riebsame et al. 1986; Winsor et al. 1994). In this regard, Cutter (1996) considered the ‘biophysical’ and the ‘social’ aspects of vulnerability as independent parameters. Klein and Nicholls (1999) conceptualized ‘natural vulnerability’ as one of the determining factor of ‘socioeconomic vulnerability’. The vulnerability concept has been continuously widening including susceptibility, exposure, coping capacity and adaptive capacity, as well as different thematic areas, such as physical, social, economic, environmental and institutional vulnerability (Birkmann 2007). Some of the initial applications of the vulnerability models focused on unfolding the geophysical risk factor of a place. Gornitz et al. (1994) first formulated the Coastal Vulnerability Index (CVI) for southeast USA based on thirteen variables (elevation, geology, landform, local subsidence, historical shoreline erosion, tide range, wave height, tropical storm and hurricane probabilities of occurrence, hurricane strike frequency-intensity index, tropical cyclone forward velocities, mean annual number of extra-tropical cyclones, and mean hurricane surge height). These variables were grouped into three categories using factor analysis to identify the coastal areas at risk to erosion, permanent inundation, and episodic flooding. Although the work of Gornitz et al. (1994) did not consider the socioeconomic data in CVI, however, it is one of the widely used physical vulnerability assessment method adopted around the globe (see Boruff et al. 2005; Hegde and Reju 2007; Kumar et al. 2010; Murali et al. 2013). The importance of socioeconomic aspects in hazard studies got its momentum during the mid-1990 (see Cutter 1996; Klein et al. 1998; Pelling 1997) by subsequent advancement to CVI with the addition of socioeconomic variables to form a composite index of vulnerability. Boruff et al. (2005) combined the Social Vulnerability Index (SoVI) (Cutter et al. 2003) with the CVI to form the Coastal Social Vulnerability Index (CSoVI). Boruff’s method has been

widely used for comprehensive study of coastal hazard vulnerability. Furthermore, this study used the “hazard-of-place model” to develop the Place Vulnerability Index (PVI) for each of the counties in the USA (Cutter 1996). The PVI was the resultant of aggregation of CVI and CSoVI scores. Construction of vulnerability indices at sub-national level is a comprehensive approach that has been widely applied in countries like the USA (Cutter et al. 2000; Rygel et al. 2006). Chakraborty et al. (2005) used the similar method developed by Cutter et al. (2000) to develop the Social Vulnerability for Evacuation Assistance Index (SVEAD). It examined the spatial variability in evacuation assistance needs related to hurricane hazard. Two quantitative indicators were developed: (a) geophysical risk index, based on National Hurricane Center and National Flood Insurance Program data, and (b) social vulnerability index, based on census information. The resultant values indicate overall evacuation assistance need. Another approach adopted by Cardona (2005) considered more indicators of vulnerability that aimed to provide an inclusive and disaggregated view. This method included four main indices: the Disaster Deficit Index (DDI), the Local Disaster Index (LDI), the Prevalent Vulnerability Index (PVI) and the Risk Management Index (RMI) (Cardona 2005). These indices were applied to twelve Latin American and the Caribbean countries. Holand et al. (2011) and Holand and Lujala (2012) used the approach of Cutter et al. (2003) and applied to the municipalities of Norway. In most of the cases, usage of the same conceptual framework and methodology resulted in many variations in the progress of social vulnerability indices. Those variations are either in terms of giving weight to the factors or conceptualizing vulnerability framework in place context.

A common critique of hazard-of-place model is that place-specific detail confines the model to generalize the outcomes in other areas. However, this criticism is deemed to be significant, as the vulnerability is “place” specific and the nature of vulnerability is crucial in defining what exactly influences the vulnerability of those areas from potential hazards.

4 Vulnerability of coastal states in India

The Indian vulnerability to hazard scenario is changing rapidly since the last three decades, with the increasing intensity of cyclones. Even though the number of cyclones hitting the Indian coasts is less in comparison to other coasts in the world, the impact is relatively very high and devastating, particularly when it strike the Bay of Bengal coast (SAARC 2008; WMO 2012). The frequency of cyclones in the North Indian Ocean (NIO) basin is bimodal, which is specific to this region (Dube et al. 2000). The ratio of cyclones forming in the Bay of Bengal to that in the Arabian sea is 4:1 (Dube et al. 2000). A frequency analysis of cyclones (based on Indian Meteorological Department (IMD) data during 1912–2012) shows that nearly 405 cyclones (out of which 191 were severe) affected the ECS, whereas 94 cyclones (out of which 40 were severe) affected the western coast of India (Fig. 1). The probability of developing Severe Cyclonic Storm (SCS) and Cyclonic Storm (CS) from depression (D) is 60–70 % in the Bay of Bengal and 40–50 % in the Arabian Sea during pre and post-monsoon months of May and November, respectively. Hence, it is evident that the high SCS and CS increase the chances of high vulnerability of Bay of Bengal from the cyclonic storm. Thus, the natural vulnerability of the Bay of Bengal reveals the severity of the ECS from the cyclones. However, the impact of cyclones hitting the coasts reveals its socioeconomic and infrastructural resilience.

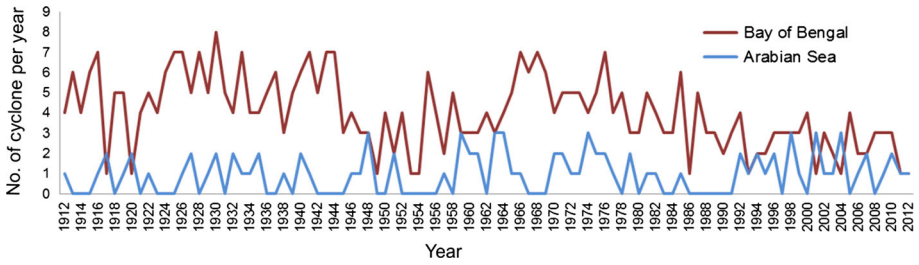


Fig. 1 Annual frequency of cyclones in Bay of Bengal and Arabian Sea (1912–2012)

Several vulnerability studies have been taken into account for the eastern and western coasts of India for sea-level rise using physical variables as an input to the coastal vulnerability index (Murali et al. 2013). The initial CVI was developed by Hegde and Reju (2007) for the coast of Mangalore in Karnataka. It was based on the work of Gornitz et al. (1994). Similar work has also been done by various researchers for the coast of Odisha and Chennai (Kumar and Kunte 2012; Kumar et al. 2010). In the earlier studies, researchers put more emphasis on the physical factors of vulnerability in CVI, where there was very little scope for social factors in estimating the index. In this regard, limited work has been done with the consideration of the socioeconomic indicators (see Hegde and Reju 2007; Murali et al. 2013; Rao et al. 2007; Sharma and Patwardhan 2008). Das (2012) had pointed out some of these important variables in her study to represent the vulnerability of villages of Kendrapara district in Odisha. However, there are some limitations in the coastal vulnerability studies where most of the socioeconomic factors were represented by a fewer variables like population density, total population, etc. but other characteristics of the population were ignored. In India, where there are vast differences in income, access to information, access to basic amenities, etc., the resilience of the population is expected to vary based on these factors. Hence, selecting a considerable number of variables might help to specify the probable contributors of vulnerability. Another gap in the previous studies in the Indian context is that, none of the vulnerability studies provides separate categories to measure socioeconomic and infrastructural vulnerability for all the districts of the ECS. Nevertheless, such studies have important implications for the society and development of government policies, but there is a need for a common methodology for evaluating the vulnerability of a place from the potential cyclones. This issue has been addressed here so that the SVI and InVI could be used as a model for assessing vulnerability to potential cyclones.

5 Methodology

5.1 Data

The focus of this study is on the districts of the ECS of India, which shares a common coastline with the Bay of Bengal. The four ECS are West Bengal, Odisha, Andhra Pradesh, Tamil Nadu and a union territory of Puducherry (Fig. 2). The ECS comprises total 107 districts out of which 42 are the coastal districts. The selection of the study area was based on the degree of the proneness of these states from the cyclones during the last 100 years (1912–2012). The data representing socioeconomic and infrastructural vulnerability were

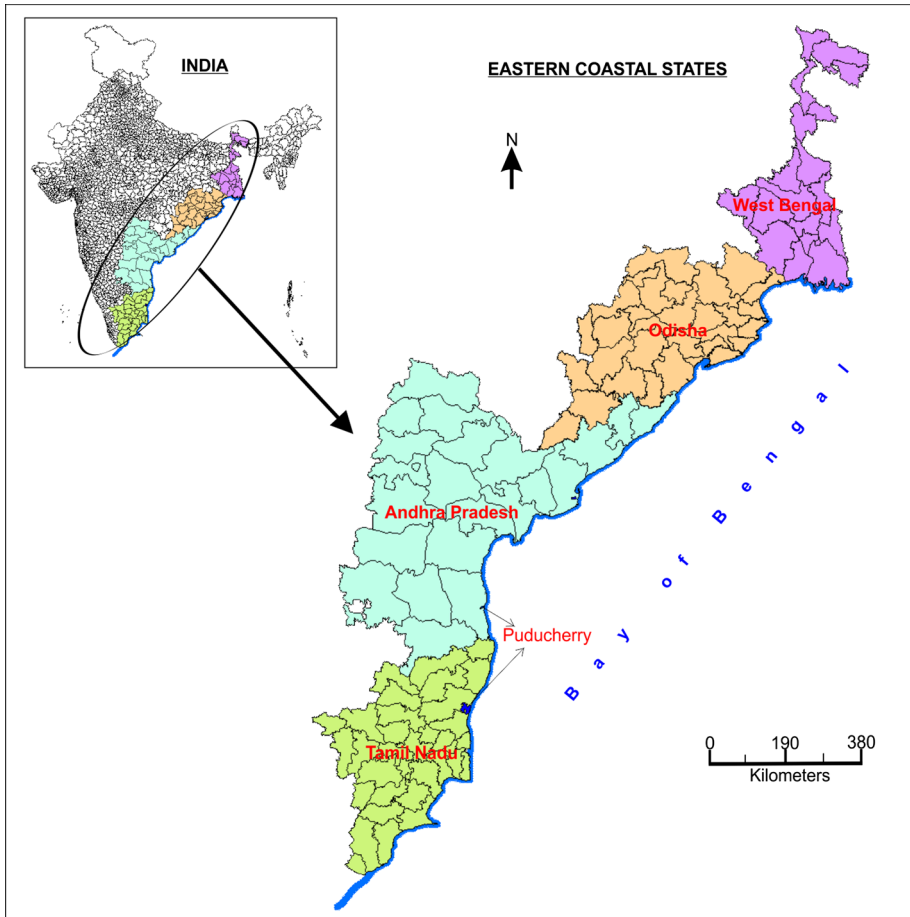


Fig. 2 Location of eastern coastal states of India

obtained from Census of India, 2011. These data were collected for all the 107 districts of the ECS excluding the district of Mahe, lying on the western coast of India.

The theoretical concepts of vulnerability contributing to this study identified primarily through a review of the literature. Based on these concepts and availability of data, variables were selected, which best represent the socioeconomic and infrastructural vulnerability. However, there are certain limitations in acquiring data, their coverage, and its depiction. Some datasets had good spatial resolution, and some are less. Considering this limitation, the most reliable source of data recognized by the government of India has been used in this paper to highlight the vulnerability of the districts of the ECS.

5.2 Method

Factor analysis is the primary method used for the reduction of large set of variables, specifically principal component analysis (PCA), developed by Hotelling in 1933. PCA has been previously used in a number of studies (see Armaş and Gavriş 2013; Borden et al. 2007; Cutter et al. 2003; Fekete 2009; Schmidtlein et al. 2008; Tate 2012). Due to the

consistency and reliability of factor analysis method, it is the most suitable technique often used to reduce raw data into robust and dependable factors (Borden et al. 2007; Cutter et al. 2003). Thus, it helps in the better understanding of the principal factors of vulnerability.

Initially a large number of datasets were selected for the analysis from the literature, which influences the socioeconomic and infrastructural vulnerability. In the pre-processing stage of factor analysis, the data were normalized into density function, percentage, per capita etc. Log transformation was applied to the variables in order to reduce the skewness and kurtosis. A final set of 15 variables for SVI and 19 variables for InVI were selected for PCA after testing the multi-collinearity of the variables (Table 1). In PCA, a number of steps need to be followed like any other multivariate analyses that are outlined in Fig. 3 and discussed below.

5.2.1 Steps for factor analysis

- a. At first, *Bartlett's test of Sphericity* was applied to test whether the correlation matrix is an Identity Matrix, where all the diagonals are 1 and the off-diagonals are 0 which follows a Chi-square distribution (Walker and Maddan 2008). This signifies that none of the variables are correlated in the matrix. The Bartlett's test should be significant to the application of factor analysis.
- b. Secondly, it was important to analyze the *anti-image correlation matrix*. This matrix indicates whether a low degree of correlation exists between the variables when the other variables are constant. The off-diagonal values (majority of the values are close to zero) in the matrix are examined to assess the adequacy of variables to be included in the factor analysis (Sarstedt and Mooi 2014).
- c. Thirdly, the *Kaiser–Meyer–Olkin (KMO)* Measure of Sampling Adequacy (developed by Kaiser in 1974) was used to compare the observed correlation coefficients with the partial correlation coefficients. A KMO value below 0.50 is unacceptable for factorial reduction (Walker and Maddan 2008).
- d. Thereafter, the principal component analysis (PCA) was used for factor extraction. The objective of PCA is to find the linear combination of variables that account for the greatest amount of common variance. Factors having eigenvalue >1 were retained. Eigenvalue is used to establish a cut-off of factor. It is similar to R^2 in regression, representing the strength of a factor.
- e. Finally, *varimax rotation* was used to make the data orthogonal by increasing the interpretability of the factors. This technique minimizes the number of variables that have high loading on a single factor. The outcome of the rotated factors contributing to increased or decreased vulnerability was conceptually determined. If the rotated factors represent variables that might contribute to decrease vulnerability, the loading values for those variables would be positive. The positive loading values correspond to a high frequency of the variables in a place, when multiplied by -1 , is defined as the final dimension (Borden et al. 2007). In this manner, substituting a factor with its negative allowed the final dimension to subtract from SVI and InVI, since it represents the variables that contributed to decreased vulnerability in a place (Borden et al. 2007).

Based on Eq. 1 scores of the first component extracted using PCA:

$$C_1 = \beta_{11}f_1 + \beta_{12}f_2 + \dots + \beta_{1p}f_p \quad (1)$$

where, C_1 = the subject's score on principal component 1; β_{1p} = the regression coefficient (or weight) for observed variable p ; f_p = the subject's score on observed variable p .

Likewise, scores of consecutive factors are calculated.

Table 1 Selected variables for SVI and InVI

Concept	Proxy variables selected	Description	Sources
SVI variables			
Density	Population density	High-density areas are likely to complicate the evacuation measures and increase the risk of fatalities	(Balica et al. 2012; Chakraborty et al. 2005)
Houseless*	% Houseless households	In India it is difficult to identify the houseless population due to their scattered location in a region. Hence, at the time of cyclonic event, they are likely to be one of the most vulnerable	EM-DAT: the OFDA/CRED international disaster database
	% Houseless child population (0–6 years)		Authors
	Houseless sex ratio		Authors
	% Houseless main worker cultivators and agriculture		EM-DAT: the OFDA/CRED international disaster database
Age	% Population above 60 years	Extreme age and disability may have constraints in mobility, increasing the liability of care at the time of cyclone	(Adger et al. 2004; Cutter et al. 2003; Holand et al. 2011; Rød et al. 2012)
Disabled	% Disabled population		(Adger et al. 2004; Cutter et al. 2003)
Population growth	Decadal growth rate of population	Rapid growth of population put pressure on housing stock, quality of life, basic services etc. High decadal growth in developing countries like Indian states is highly vulnerable at the time of cyclone	(Cardona 2005; Cutter et al. 2003)
Marginalized population	% Scheduled tribe population	Scheduled tribe population is one of the most marginalized groups of community that needs special attention at the time of cyclone	Authors
Education level	% Illiterate population	Illiterate population put liability to the system due to inefficiency in understanding cyclone warning system	Authors
Occupational structure and economically active population	% Economically active population	Occupation is the means of earning that defines the ability to recover after the disaster. Economically active population has higher tendency to recover faster than those who are not	(Adger et al. 2004)
	% Total main worker—cultivators and agriculture		(Cutter et al. 2009)
	% Total main worker in household industries		(Cannon 2008)
	% Total marginal workers cultivators and agriculture		(Das 2012)
	% Total marginal worker in household industries		(Armaş and Gavriş 2013)

Table 1 continued

Concept	Proxy variables selected	Description	Sources
InVI variables			
Built density	Residential density	Higher density of built environment is more vulnerable at the time of cyclonic event because it increases the damage potential of houses in dense areas and increases the risk of high mortality	(Borden et al. 2007; Cutter et al. 2000)
	Commercial density		(Cutter et al. 2003; Rød et al. 2012)
Institutional infrastructure	Educational infrastructure (per thousand population)	Educational and health infrastructure indicates the levels of resilience of a society. It contributes to the betterment of a society. In other way, schools, colleges etc. are used as a shelter during the time of disaster	(Adger et al. 2004; Cutter et al. 2000; Sharma and Patwardhan 2008)
	Health infrastructure (per thousand population)		(Birkmann 2006; Füssel 2007)
Housing infrastructure	% Floor Kutcha**	Non-masonry or Kutcha houses are easily blown away at the time of cyclone	Authors
	% Roof Kutcha**		
	% Wall Kutcha**		
Critical infrastructure	% House dilapidated	Dilapidated buildings are always in the verge of damage during severe cyclonic storm	EM-DAT: The OFDA/CRED International Disaster Database
Access to basic services	% Household having access to electricity	Access to basic services helps in recovering after disaster	(Adger et al. 2004)
	% Household having access to portable drinking water		(Colle et al. 2008)
	% Household having untreated water		World bank, EM-DAT: the OFDA/CRED international disaster database
Sanitation	% Household with open drainage	Poor drainage system increases the risk of flooding and water-borne diseases	(Adger et al. 2004)
	% Household with no drainage		
Banking facilities	% Household having access to banking facilities	Banks provides financial assistance at post-cyclonic event to those who are in need through loans and other financial assistance	(Borden et al. 2007)
Communication	% Household having access to radio communication	It helps in disseminating early warning system at the time of cyclonic event	(Joerin et al. 2012; Penning-Rowsell et al. 2013)
	% Household having access to television		(Joerin et al. 2012)
	% Household having access to mobile phones		(Acosta-Michlik et al. 2008; Joerin et al. 2012)

Table 1 continued

Concept	Proxy variables selected	Description	Sources
Vehicle ownership	% Household having access to 2,3 and 4 wheeler	The rationale of vehicle ownership is to provide a source of basic transport especially for the elderly and the disabled population at the time of evacuation	Authors
No asset	% Household having no asset	Households possessed no assets have difficulties in relocation	Authors

* In Census of India the term ‘Houseless’ is used instead of Homeless

** As per Census of India ‘Kutchha’ houses are the temporary structure houses made with non-masonry materials

6 Reliability of principal components

The performing PCA on the selected variables (Table 1) produced four factors of each SVI and InVI (Table 2), explaining 74.63 and 82.33 % of the variance, respectively. The Bartlett’s test of sphericity and KMO show an acceptable range for PCA (SVI = 0.657 and InVI = 0.872). Percentage of variance explained by each component for the rotated factor solution is shown in Table 2. Most of the variables that clustered on factor 1 are associated with houseless and marginalized population for SVI and assets-and-access to basic services for InVI. These factors have accounted for 37.21 and 56.61 % of the total variance for SVI and InVI, respectively. Similarly, the other components explain the remaining percentage of the variance.

In addition, the graphical representation of increasing variance described by each factor is shown in Scree plot (Fig. 4). This plot indicates the number of factors incorporated in the PCA. The distinct break in the Scree plot is referred to as the “elbow.” It is recommended to retain all the factors above this break, as they explain most of the variance in the dataset. Hence, four-factor solutions are deemed appropriate for SVI and InVI.

7 Mapping vulnerability

For mapping vulnerability, factor scores were used which has been generated in the PCA process (produced in SPSS software module), which are equivalent to coefficients in multiple regression analysis for SVI and InVI. ArcGIS software was used for spatial mapping using Choropleth mapping technique and Jenk’s natural break classification (Burns 2007; Rød et al. 2012). The purpose of using this technique is to minimize differences between data values within the same class and to maximize the differences between the classes (Rød et al. 2012). Spatial mapping adds to the visual representation of the vulnerability indices across space.

8 Results

8.1 Linking SVI and InVI factors of vulnerability to cyclones

The four extracted components of SVI and InVI for the all the districts of the ECS are shown in Table 2. Each of these components is described below:

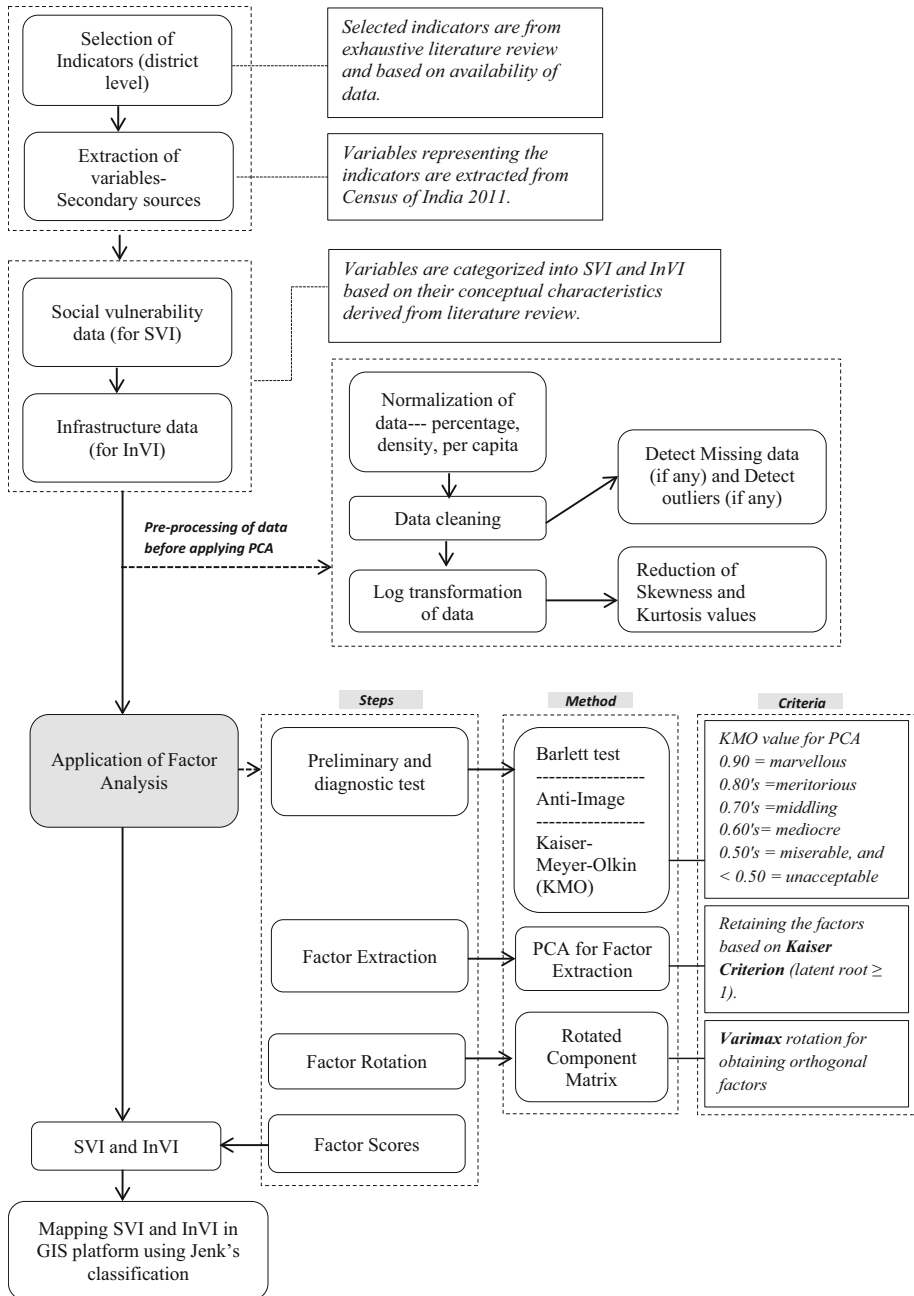


Fig. 3 Steps for performing PCA

8.1.1 Houseless and marginalized population

Population under this category is socioeconomically weaker and has limited access to economic means to cope with the disaster situation (Cutter et al. 2003; Holand and Lujala

Table 2 Extracted factors after rotation

Components	Description	% Variance explained	Functional relationship with vulnerability
SVI			
SVI-1	Houseless and marginalized population	37.211	+
SVI-2	Illiteracy rate and primary sector occupation	18.498	+
SVI-3	Condition of workers	10.080	+
SVI-4	Aged and decadal growth of population	8.842	+
InVI			
InVI-1	Assets and access to basic services	56.613	–
InVI-2	Density of built environment	13.682	+
InVI-3	Health and sanitation	6.879	+
InVI-4	Radio communication	5.161	–

Rotated component matrix. Extraction Method: principal component analysis. Rotation Method: Varimax with Kaiser Normalization. Rotation converged in 5 iterations for SVI and 9 iterations for InVI. For the method, variables, and definitions, see the text. Sign adjustment: negative (-) or positive (+)

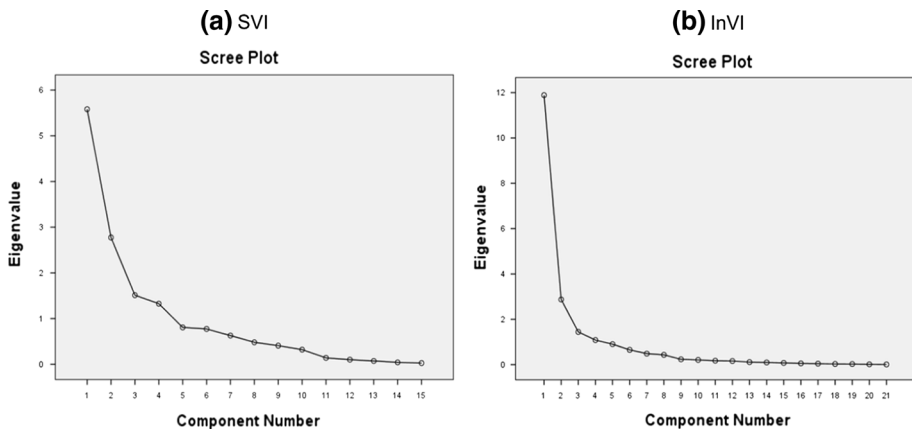


Fig. 4 Scree plot for factor extraction (SVI and InVI)

2012). Marginalized population is those who are largely dependent on government’s welfare services for their subsistence. It is quite difficult to identify them as they are inexplicably affected at the time of cyclones. Because of their indiscernibility in a society, they are often ignored during pre- and post-disaster period (Cutter et al. 2003). To measure the presence of disadvantaged population, the percentages of the differently abled population, tribal household and houseless population has been included. Thus, districts having a high score on this factor are likely to be the most vulnerable ones. It explains 37.21 % of the total variance in SVI and has a positive functional relationship with vulnerability.

8.1.2 Illiteracy rate and primary sector occupation

Education is linked to socioeconomic status. Decent income is the resultant of higher educational attainment. Literate people are expected to be better informed and capable of taking precautionary measures at the time of disaster (Das 2012). The illiteracy among the general population constraints the ability to understand warning and recovery information provided by the government organization or other responsible agencies at the time of cyclone (Cutter et al. 2003). Hence, it is suggested that illiteracy rate is directly proportional to vulnerability.

Loss of agricultural land at the time of cyclones directly affects the workers of the primary sector due to their economic dependency on agriculture and allied activities. Therefore, a higher percentage of workers in this category imply higher vulnerability. This factor explains 18.50 % of the total variance in SVI. It has a positive functional relationship with vulnerability.

8.1.3 Household workers

Household workers (main and marginal) are directly affected by cyclonic events. The income from household industries is not enough to support the post-disaster recovery. Moreover, the workers involved in these industries are either daily wage earners or survive in a very low sustenance cost. Therefore, this factor determines high vulnerability and has a positive relationship with it. This component explains 10.08 % of the total variance in SVI.

8.1.4 Aged and decadal growth of population

Percentage of the population above 60 years of age is considered to be the most vulnerable in the community. Along with the age factor, it is often realized that they are sometimes suffering from some health problems. Therefore, they need special care during and after a cyclonic event.

The growth of population has both direct and indirect effects on vulnerability. The direct effect is represented by the percentage of population exposed to cyclonic events, while the indirect effect is associated with the increase in pressure on land, basic amenities, employment, etc. This indirect effect stratifies the population based on education, income, and land ownership. Thus, it intensifies the vulnerability both directly as well as indirectly. The districts having high loading on this factor are likely to be more vulnerable than other districts. A positive sign has been assigned this factor, and it explains 8.84 % of the total variance in SVI.

8.1.5 Assets and access to basic services

Basic assets (television, mobile phones etc.) are used as a means to disseminate cyclone warning through news and push messaging system (Birkmann 2007; Cardona 2005). The percentage of population having access to these assets is likely to be less affected and hence reduces the vulnerability.

Until the entitlement of access to basic services and quality of life are ensured for the entire population, it is unlikely to have community-based structural mitigation action (Revi 2008). Assets and access to basic amenities improve living conditions as well as create awareness. Therefore, the districts scoring high on this factor are less vulnerable to

cyclonic events. Hence, this factor has negative loading on vulnerability and explains 56.63 % of the total variance in InVI.

8.1.6 Density of built environment

It is measured by the density of residential units and commercial establishments in a given geographical area. Those districts having a high score on this factor are likely to be more vulnerable. There is a general tendency that core areas of urban districts are contributing to high developmental activities and they consist of high density of built forms. It increases the vulnerability at the time of cyclonic event. Therefore, the districts having high loading on this factor are considered more vulnerable. It has a positive functional relationship with vulnerability. This factor explains 13.69 % of the total variance in InVI.

8.1.7 Health and sanitation

Cyclonic events are accompanied by heavy rain and windstorm. Under such circumstances, poor sanitation increases the chance of flooding and hence affecting the health of the people (mostly by water-borne diseases) in a region. On the other hand, poor health infrastructure limits the capability of a region to tackle any epidemics and fatalities caused at the time of a cyclonic event. Thus, districts that score high on this factor are more vulnerable and have been assigned a positive sign. This component accounts for 6.9 % of the total variance explained in InVI.

8.1.8 Radio communication

Radio is one of the oldest and most widely used means of communication. It is one of the most far-reaching modes of disseminating early warning messages especially in rural areas of India. Due to its remote access and live updates of weather forecasting, it is considered to be one of the vital means of spreading information. Hence, it has a negative impact on vulnerability. It explains about 5 % of the total variance in InVI.

8.2 Identifying highly vulnerable districts

The spatial distribution of SVI and InVI has been obtained by applying the Jenk's natural break classification in GIS framework (Fig. 5). It is classified into five categories, where districts with a negative score (very low vulnerability) are shown with the lightest shade of yellow, and those with a positive score (very highly vulnerable) are in classes of darkest brown. The spatial mapping of SVI and InVI shows that there is a strong regional difference in the socioeconomic and infrastructural vulnerability across the districts of the ECS. In this analysis, it has been shown that a vast majority of the districts in Odisha have a high level of social vulnerability followed by Andhra Pradesh, West Bengal, and Tamil Nadu (Fig. 5a). Infrastructural vulnerability is found to be very high in districts of the eastern part of West Bengal as compared to other states (Fig. 5b). It is followed by a cluster of highly vulnerable districts in the southern part of coastal Odisha and northern Andhra Pradesh (Fig. 5b).

The factor wise break-up of SVI (Fig. 6) shows that houseless and marginalized population (factor-1) dominate the vulnerability scenario in the districts of Odisha, whereas illiteracy rate and primary sector occupation (factor-2) are the highest in Andhra Pradesh,

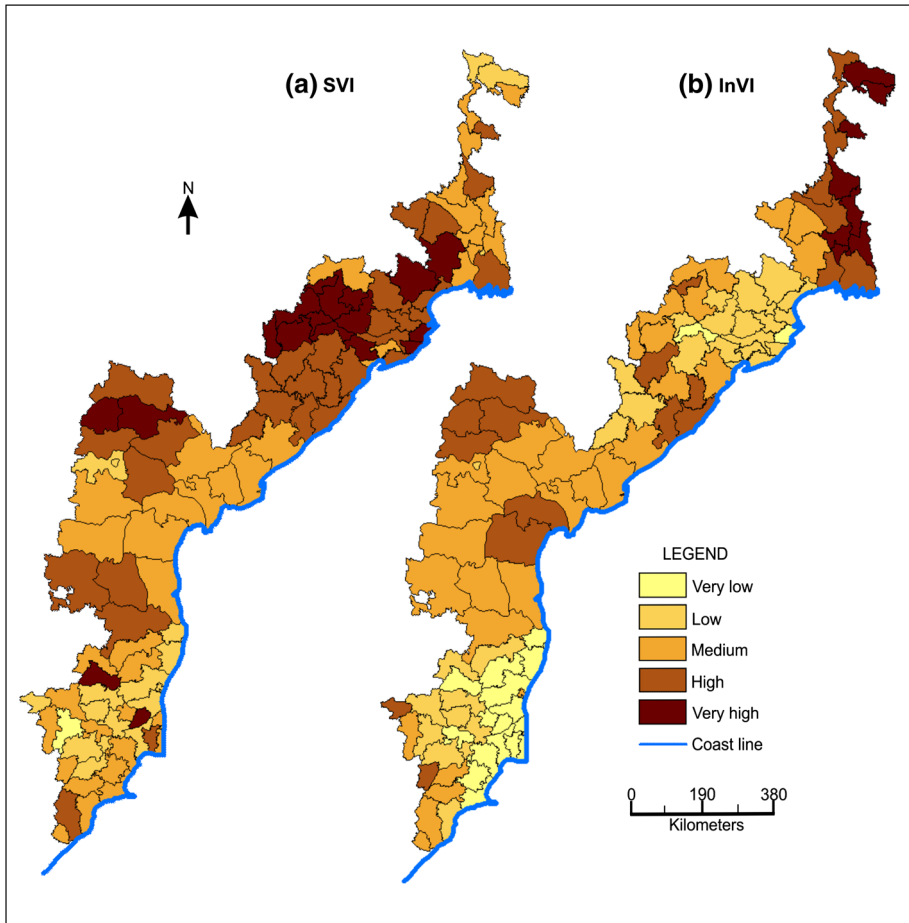


Fig. 5 Socio-economic vulnerability (SVI) and Infrastructure vulnerability (InVI) map of eastern coastal states of India (for location refer Fig. 2)

while the condition of workers (factor-3) is the highest in West Bengal. The aged and decadal growth of population (factor-4) is scattered across the ECS with higher concentration in the districts of Tamil Nadu followed by Odisha, Andhra Pradesh, and West Bengal. The factor wise break-up of InVI (Fig. 7) indicates that assets and access to basic services (factor-1) and density of built environment (factor-2) contribute to very high vulnerability in West Bengal, while health and sanitation (factor-3) vulnerability clustered mostly in the northern and coastal Andhra Pradesh followed by western part of Tamil Nadu and eastern districts of West Bengal. Radio communication (factor-4) vulnerability dominates the coastal districts of Odisha and Andhra Pradesh (Fig. 7).

A vast majority of the districts covering 43 % of the population for SVI and 32 % of the population for InVI are in the category of medium level of vulnerability (Table 3). It is worth mentioning that a large proportion of the population is subjected to a high level of vulnerability in both SVI and InVI. Apparently, the socioeconomic vulnerability is more alarming than the infrastructural vulnerability in the ECS (Fig. 8). The major urban districts that are located in the coastal areas have a low socioeconomic vulnerability (Kolkata

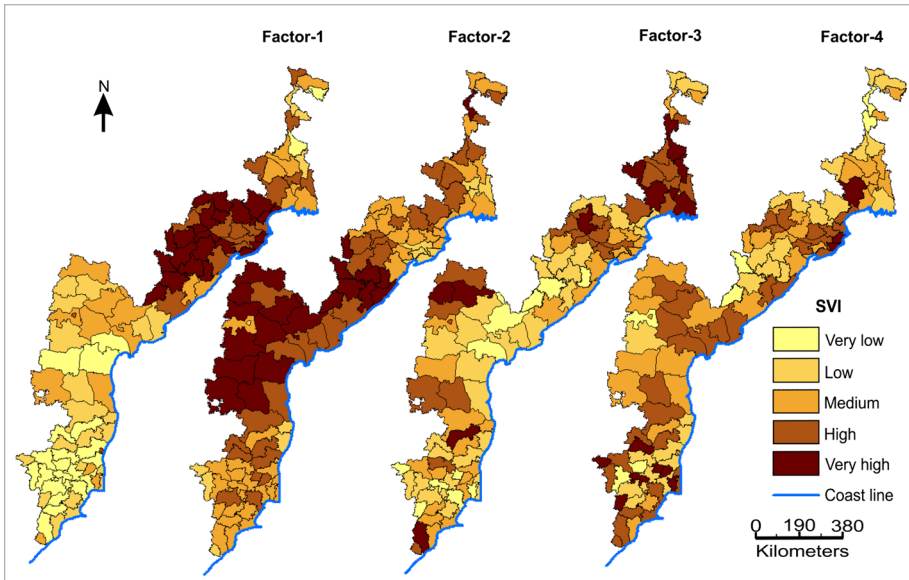


Fig. 6 Factors of socio-economic vulnerability: 1 houseless and marginalized population, 2 illiteracy rate and primary sector occupation, 3 condition of workers and 4 aged and decadal growth of population

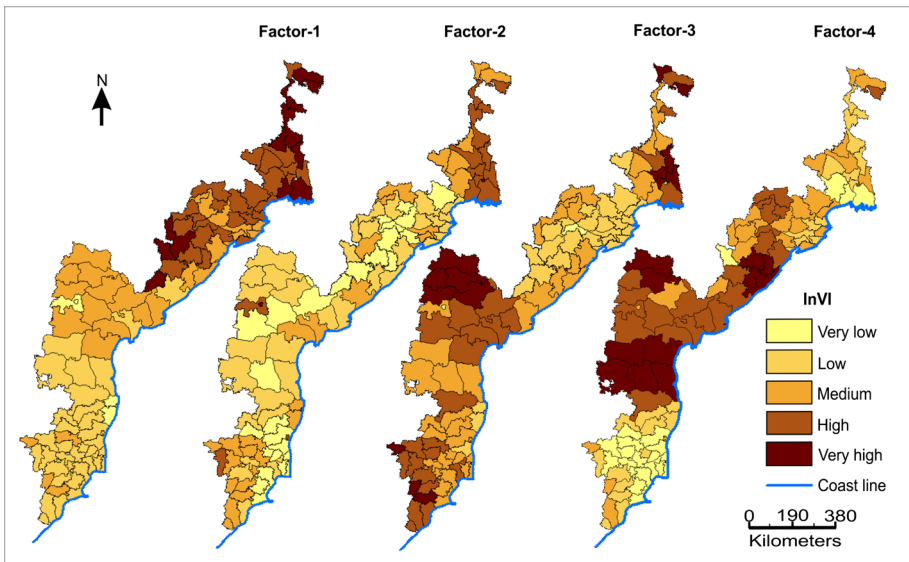


Fig. 7 Factors of infrastructural vulnerability: 1 assets and access to basic services, 2 density of built environment, 3 health and sanitation and 4 radio communication

and Haora). This is probably due to the reason that urban areas have a tendency to attract educated working-class population with good income. However, the infrastructural vulnerability does exist in some of the urban district of Kolkata and Haora in West Bengal as well as Yanam in Puducherry.

Among the coastal districts of the ECS, 23 districts have high SVI and InVI representing 27 % of the total coastal district population. The coastal districts of the ECS those are highly vulnerable in terms of SVI and InVI are shown in Table 4. It is evident from this analysis that most of the districts are socioeconomically vulnerable in the ECS (Fig. 8). The major contributing factors are the homeless population, illiteracy and higher dependency on primary sector. On the contrary, major factors contributing to the infrastructural vulnerability are access to basic services and density of built environment.

9 Discussion

Several concepts have been developed by various researchers for establishing the relation between vulnerability of people and places (Adger 2006; Adrianto and Matsuda 2002; Birkmann 2006; Turner et al. 2003). These conceptual frameworks provide multi-

Table 3 Distribution of levels of vulnerability

Type of vulnerability	Level of vulnerability	No. of districts	% Share of population
SVI	Very high	15	11
	High	35	27
	Medium	36	43
	Low	19	19
	Very low	2	1
InVI	Very high	17	16
	High	29	21
	Medium	30	32
	Low	20	19
	Very low	11	12

Total no. of districts (n) = 107, % share of population is calculated by dividing no. of population in each level divided by total population of 107 districts in eastern coastal states of India

Fig. 8 Difference in SVI and InVI

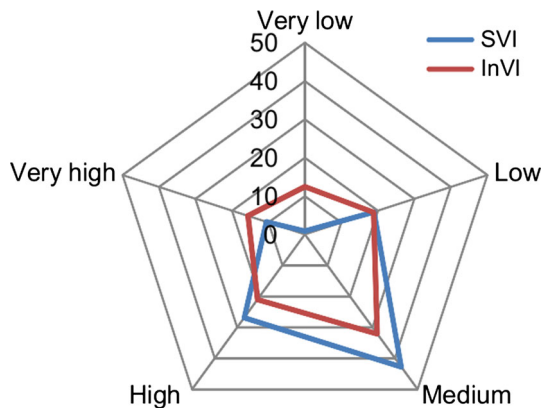


Table 4 Vulnerability of coastal districts

Sr. No.	SVI	InVI	SVI + InVI
1	West Medinipur	East Medinipur	South twenty-four Parganas
2	Baleshwar	Kolkata	Gajapati
3	Bhadrak	North twenty-four Parganas	Srikakulam
4	Kendrapara	Hugli	Vizianagaram
5	Jagatsinghapur	Haora	
6	Cuttack	Prakasam	
7	Jajapur	Yanam	
8	Puri		
9	Ganjam		
10	Chittoor		
11	Thiruvarur		
12	Tirunelveli		

dimensional aspects of vulnerability. However, the application of these concepts in decision-making process provides partial assistance for identifying location-specific vulnerability and its driving factors. In Indian context, most of the studies have been focused on physical exposure of vulnerability contributed to the construction of Coastal Vulnerability Index (CVI) (Kumar and Kunte 2012). Murali et al. (2013) have used analytical hierarchical process (AHP) for assessing the vulnerability of the Puducherry coast. In their study, limited number of social variables was included along with the indicators of biophysical vulnerability. Sharma and Patwardhan (2008) identified the hotspots of vulnerability by applying cluster analysis method. Similar recent attempts made by various researchers included social aspects along with the physical dimension of vulnerability at different scales of administrative units. The methodological framework presented here for assessing vulnerability to hazard addresses two major issues: (1) identifying the highly vulnerable areas in the ECS and (2) identifying the factors responsible for the vulnerability in those areas.

The present approach to the study of vulnerability assessment has been replicated in a number of case studies at various regional settings and periods (Borden et al. 2007; Cutter et al. 2000; Rød et al. 2012). Undoubtedly, the applied method is more advanced than the simple numerical index and has been acknowledged as one of the best algorithms for measuring vulnerability (Schmidtlein et al. 2008). In this study, the first question was addressed by identifying the districts of the ECS, which are highly vulnerable to potential cyclone. In an attempt to answer the question of why those districts are vulnerable, PCA algorithm was used to find out the contributing factors of vulnerability in the ECS. This approach empathize the priorities when it comes to addressing vulnerability and increasing the resilience of the district population from cyclone. The results are summarized as:

- a. There are significant differences in the social and infrastructural vulnerability among the districts considered within the ECS.
- b. Social factors are the important determinants of vulnerability in the ECS, but infrastructural vulnerability dominates in the urban districts of ECS.

The choice of indicators used in this exploratory research has been determined by the limited availability of explicit datasets for all the districts of ECS. The indicators of socioeconomic and infrastructural vulnerability such as livestock, agricultural land under

crop area, per capita income, etc. can be further analyzed to encompass the economic aspects of vulnerability in the ECS. The result might vary by the inclusion of these variables in the vulnerability index. However, the maximum number of variables available from Census of India, 2011, was used at the time of this research.

PCA-based approach indicates diverse spatial patterns of relative vulnerability relating to the spatially co-occurrences of individual drivers of vulnerability. Therefore, it could be argued that the application of PCA for aggregating vulnerability indices would not be of much importance where a specific factor of vulnerability is already known. However, it is still possible to weigh the resulting vulnerability components based on the knowledge of policymakers assuming that each factor of vulnerability could be connected to one of the components of vulnerability. For example, in the SVI analysis houseless and marginalized population (SVI-1) may be judged as a more vital issue than subsequent vulnerability (SVI-2) while relating to funding and support based on appropriate assessment.

The results presented here suggest that the use of PCA to derive multiple independent indices of SVI and InVI will be of considerable use in the broad-scale mapping of socioeconomic and infrastructural vulnerability. It provides more detailed information than mere representation of vulnerable districts. For example, two districts (X and Y) could have the same SVI score but district X might have scored higher on factor-1 while district Y on factor-3. In this case, the place vulnerability of both the districts is a function of different factor score. Hence, through this analysis not only the factor scores were compared within each vulnerability index but also it can disaggregate the scores of SVI and InVI to comprehend what is the most contributing factor toward vulnerability of that particular district from the potential cyclone. This study clearly justifies that places matter in the context of vulnerability, validating the 'hazard-of-place model'.

Moreover, findings from this analysis provide a picture of spatial variations in district level vulnerability and the drivers influencing it. The spatial mapping of SVI and InVI provides a "snapshot" description of vulnerability at a particular point in time. As conditions change, new vulnerability maps are required to reflect changes in place vulnerability. For such reasons, care must be taken while interpreting factors contributing to the vulnerability of a place. The SVI and InVI should be used as a quick tool for the policymakers to consider a set of mitigation and preparedness measures rather than applying 'one size fit all' approach to reducing vulnerability to potential cyclone in the ECS. Both the indices of vulnerability could be useful to policymakers and development aid donors, particularly when it comes to identifying hotspots of highly vulnerable areas at a glance. The maps presented in this paper should not be considered as a final product for assessing vulnerability; rather it would be reasonable to use them as a visualizing tool for the disaster planners and policy makers.

10 Conclusion

Within the social science community, there is no definite answer to the determinants of vulnerability. The human interface with potential hazard needs deliberate consideration of social, economic and infrastructural systems that give rise to the vulnerable situation. Additionally, it is to understand the susceptibility to hazard within a particular geographical setting. Using the framework of hazard-of-place model (Cutter et al. 2003), the socioeconomic and infrastructural vulnerability to potential cyclone in the districts of ECS has been explored in this study. The outcomes from this analysis contributed to the vulnerability studies in following ways.

1. This is a first comprehensive effort to measure district level vulnerability to potential cyclone in ECS of India using PCA algorithm.
2. Further, vulnerabilities arising from socioeconomic and infrastructural factors have been dealt separately in Indian scenario in this paper. The SVI and InVI provide a better understanding of the spatial dimensions of vulnerability in diverse settings.

It is essential to identify the areas that are not able to cope with and recover from the hazard events, in order to improve the emergency preparedness before and after the catastrophe. In this regard, this study provides a tool to assess the most vulnerable districts in the ECS. The delineation of vulnerable areas could be helpful for taking up case studies at block or village level to identify the local drivers of vulnerability thereby increasing the resilience of that region. Although this paper has analyzed the data of a single year, the same approach could be further used with real-time cyclone data on a time-based scenario. Such temporal and spatial analysis will enable to identify the changes in vulnerability of a place over time and space.

Simple analytical tool will not be sufficient to do effective vulnerability management in the present dynamic and unpredictable World. The methodological construction and conceptualization of SVI and InVI illustrated in this study is not to anticipate an explanation of vulnerability. Rather it provides an overview of the status of each district and further aids in determining the probability of being affected by a cyclonic event. The spatial variation analyzed in this study also reveals that the socioeconomic and infrastructure vulnerability are distinct with a few exceptions. Hence, the issue of vulnerability should be addressed separately for effective governance, policy implementation, and capacity building, thereby increasing resilience and reducing vulnerability to hazard events.

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