Ambio 2019, 48:192–212
https://doi.org/10.1007/s13280-018-1061-8

KUNGL. VETENSKAPS- AKADEMIEN
THE ROYAL SWEDISH ACADEMY OF SCIENCES

RESEARCH ARTICLE

Framework for mapping the drivers of coastal vulnerability and spatial decision making for climate-change adaptation: A case study from Maharashtra, India

Pandian Krishnan, Pachampalayam Shanmugam Ananthan, Ramachandran Purvaja, Jeyapaul Joyson Joe Jeevamani, John Amali Infantina, Cherukumalli Srinivasa Rao, Arur Anand, Ranganalli Somashekharappa Mahendra, Iyyapa Sekar, Kalakada Kareemulla, Amit Biswas, Regulagedda Kalpana Sastry, Ramachandran Ramesh

Received: 28 September 2017 / Revised: 3 April 2018 / Accepted: 8 May 2018 / Published online: 31 May 2018

Abstract The impacts of climate change are of particular concern to the coastal region of tropical countries like India, which are exposed to cyclones, floods, tsunami, seawater intrusion, etc. Climate-change adaptation presupposes comprehensive assessment of vulnerability status. Studies so far relied either on remote sensing-based spatial mapping of physical vulnerability or on certain socio-economic aspects with limited scope for upscaling or replication. The current study is an attempt to develop a holistic and robust framework to assess the vulnerability of coastal India at different levels. We propose and estimate cumulative vulnerability index (CVI) as a function of exposure, sensitivity and adaptive capacity, at the village level, using nationally comparable and credible datasets. The exposure index (EI) was determined at the village level by decomposing the spatial multi-hazard maps, while sensitivity (SI) and adaptive capacity indices (ACI) were estimated using 23 indicators, covering social and economic aspects. The indicators were identified through the literature review, expert consultations, opinion survey, and were further validated through statistical tests. The socio-economic vulnerability index (SEVI) was constructed as a function of sensitivity and adaptive capacity for planning grassroot-level interventions and adaptation strategies. The framework was piloted in Sindhudurg, a coastal district in Maharashtra, India. It comprises 317 villages, spread across three taluks viz., Devgad, Malvan and Vengurla. The villages in Sindhudurg were ranked based on this multi-criteria approach. Based on CVI values, 92 villages (30%) in Sindhudurg were identified as highly vulnerable. We propose a decision tool for identifying villages vulnerable to changing climate, based on their level of sensitivity and adaptive capacity in a two-dimensional matrix, thus aiding in planning location-specific interventions. Here, vulnerability indicators are classified and designated as ‘drivers’ (indicators with significantly high values and intervention priority) and ‘buffers’ (indicators with low-to-moderate values) at the village level. The framework provides for aggregation or decomposition of CVI and other sub-indices, in order to plan spatial contingency plans and enable swift action for climate adaptation.

Keywords Adaptive capacity · Climate change · Exposure · Multi-hazard map · Sensitivity · Socio-economic

INTRODUCTION

Climate change is the most complex and challenging environmental problem confronted by the world today (Ojwang’ et al. 2010). Tropical ecosystems are more vulnerable to climate change (Eguiguren-Velepucha et al. 2016), and the impacts are well pronounced in low-latitude tropical and subtropical coastlines, particularly in areas inhabited significantly by lower income populations (McCarthy et al. 2001). The coastal stretches are susceptible to erosion, inundation, storm surge flooding, saltwater intrusion and sea level rise (Amadore et al. 1996), thereby threatening the existing infrastructure, property, houses, agricultural fields and lives (IPCC 2014; Srinivasa Rao 2016). India ranks fifth among the tropical countries in the world and sixth among the Asian countries, in terms of the length of its coastline (Central Intelligence Agency 2018). About 35% of Indian population lives within 100 km of the

Electronic supplementary material The online version of this article (https://doi.org/10.1007/s13280-018-1061-8) contains supplementary material, which is available to authorized users.

country's coast line measuring 8000+ km, including those of island territories (ISRO-SAC 2015).

Adapting to the changing climate has been the central theme of most Climate Change Action Plans. Developed countries have committed to mobilize US$ 100 thousand million by 2020 (Smith et al. 2011) in assisting the developing countries to prepare for climate-change adaptation. Under this scenario, a framework for systematic vulnerability assessment that aids in preparing location-specific interventions (IPCC 2007; Cutter 2009), and arms the agencies/local bodies with spatial tools for decision making, would help to channel such funds effectively and swiftly for adaptation action. Vulnerability is a function of exposure, sensitivity to stimuli and the ability of a system to cope with the adverse effects (IPCC 2007). Wide range of indicators have been used for vulnerability assessment, globally and also in India (Moss et al. 2001; Kumar et al. 2007; Patnaik and Narayanan 2009; Rao et al. 2013; Sehgal et al. 2013).

India has a long coastline stretching along nine states and four union territories including the island territories. The Indian Network of Climate Change Assessment (INCCA) considered the coastal region as one of the four climate-sensitive regions of India (INCCA 2010). There are various studies to assess vulnerability of different coastal landscapes, such as discrete coastal parts, coastal belts and entire coast of India (Hegde and Reju 2007; Dwarakish et al. 2009; Rao et al. 2009; INCOIS 2012; Chandrasekar et al. 2013; Murali et al. 2013). Most coastal-vulnerability assessments in India are based on remote sensing and GIS methods (Rani et al. 2015), and have largely understated, if not ignored, the importance of social and economic factors in either accentuating the physical vulnerability or strengthening the adaptive capacity to climate change.

Development economics interprets vulnerability as the inclination of the entity to face the negative externalities in terms of poverty, food insecurity or welfare loss (Rao et al. 2013). Vulnerability assessments are subjective and vary between regions and hazards. However, inclusion of contributing factors into the vulnerability-assessment framework depends on data availability and context of the study (Sehgal et al. 2017). Some studies have focused on the socio-economic dimension of vulnerability in the context of changing climate over the last decade (Table 1), as they constitute the core areas of intervention towards building resilience.

Spatial distribution of factors which contribute to the vulnerability of community/region to climate change are to be clearly understood for planning appropriate actions for climate adaptation (Lee et al. 2015). The vulnerability studies in India, thus far, have been undertaken at district and state levels in order, thus, to provide a macro-picture of vulnerable areas. However, following the implementation of the 73rd and 74th Constitutional Amendment Acts, 1992, which gave constitutional status to Panchayati Raj institutions and urban local bodies, respectively (Planning Commission 2005), the interventions for adaptation and building resilience among vulnerable communities are required to be planned at village or Panchayat level, the smallest unit of local governance. Further, although exposure, sensitivity and adaptive capacity are usually recognized as constituent parts of vulnerability, studies integrating all the three into a single spatial representation of vulnerability are scanty (Weis et al. 2016).

The present study was undertaken in order to bridge these crucial gaps, with the key objectives as follows: (i) to develop a conceptual framework for assessing coastal vulnerability, integrating all its components into a spatial representation at the village level, and (ii) to demonstrate the utility of the framework so developed, in quantifying vulnerability and its contributing factors at the village level and identifying the indicators of concern for appropriate adaptive action. It may also help establishing a baseline for long-term monitoring and evaluation of interventions and assess the outcome in relation to the objectives.

The Sindhudurg District in Maharashtra, on western coast of India and one of the disaster-prone districts with frequent landslides, floods and cyclones, was chosen for implementing the framework. It has been estimated that 1 km^2 area would be lost along the Sindhudurg District, owing to climate change and resultant sea level rise (ICOR 2015), thus impacting the coastal community significantly. Apart from climate change, the stressors to the district include tourism, pollution from maritime traffic and unsustainable fishing practices. In the current study, the vulnerability profile of 317 villages in Sindhudurg, spread across three taluks, has been mapped, highlighting the key contributing factors to help initiate location-specific interventions to ameliorate the socio-economic vulnerability.

Our approach provides for building a multi-layered spatial decision-making framework for vulnerability assessment and intervention planning. The resultant indices can be scaled up to different levels (taluk, district, state, or national) by appropriate aggregation or decomposition of the spatial index data, in order to address the issues pertaining to climate adaptation in the coastal regions of India.

MATERIALS AND METHODS

Study area

The framework was piloted in the Sindhudurg District (latitude 15°45′ and 16°30′, longitude 73°15′ and 73°45′), a coastal district in west coast of India. Of the eight talukas

Table 1 Various studies related to assessment of socio-economic vulnerability index

Name of the index	Author and year	Study area	Key point
Social vulnerability index (SoVI)	Cutter et al. (2003)	Counties in US	Focused on context specific and place specific data
Social vulnerability index (SVI)	Vincent (2004)	Africa	Index based on different sub-indices across multiple countries with the help of country specific secondary data
Social vulnerability index (SVI)	Fekete (2009)	Counties in Germany	Development and validation of a social vulnerability map of population characteristics towards river-floods
Household social vulnerability index (HSVI)	Vincent and Cull (2010)	Maangani in South Africa	To evaluate the performance of adaptation projects in developing countries
Coastal vulnerability index (CVI)	Yin et al. (2012)	China	Characterized the vulnerability of China's coastal damage due to sea level rise using both oceanic and terrestrial variables
Social vulnerability index (SVI)	Ge et al. (2013)	Yangtze River Delta in China	Developed index in response to the natural hazards considering few economic indicators
Social vulnerability index (SVI)	Maiti et al. (2015)	Eastern coastal states of India	Assessed the social vulnerability to climate change in the eastern states of India by using socio-economic and biophysical factors
Social vulnerability	Lee (2014)	Chiayi in Taiwan	Study based on variables with direct/positive relation to vulnerability, on account of single hazard—flood
Socioeconomic vulnerability index (SeVI)	Ahsan and Jeroen (2014)	South-western coastal Bangladesh	Captured the vulnerability scenario of coastal communities considering spatial variation and climate-change impacts

in Sindhudurg, three taluks viz., Devgad, Malvan and Vengurla (Fig. 1) located along the coast were studied. The sampling unit in the study was village/town in the three coastal taluks, totalling to 317 units, viz., 98 villages in Devgad Taluk, 134 villages and 1 town in Malvan Taluk, and 83 villages and 1 town in Vengurla Taluk. One uninhabited village (Bhandarwada) in Malvan Taluk was not considered in our study.

The Sindhudurg District is located in the agro-climatic zone of 'western coast plains and ghat region' of India with hot moist, sub-humid to humid climate. With normal annual rainfall of 3598 mm spread over 103 rainy days (mainly between June and October), it falls under high rainfall zone in the country. Of the total geographical area of 504 000 ha, almost 33% each are cultivable and uncultivable lands. The district is divided into eight administrative tehsils/blocks (having 748 villages and 8 towns) of which three blocks (315 villages and 2 towns) namely Devgad, Malvan and Vengurla are coastal taluks and form the study areas.

In the predominantly agriculture-based district (60% depend on it), rice (78 700 ha), cashew (60 600 ha), mango (27 100 ha) and coconut (16 600 ha) are the major crops cultivated. Marine capture fisheries in the most important non-crop based economic activity especially along the 121 km coastal stretch. Dotted with greenery, numerous rivers, creeks and pristine beaches, temples, historical forts and folk arts, tourism is emerging as an important source of revenue. In fact, the entire district has been declared a Tourism district by the State Government of Maharashtra (a first of its kind in the country).

As per 2011 Census, Sindhudurg's population was 849 651 with female-to-male sex ratio of 1036 (higher than state average) due partly to job-oriented male outmigration to cities such as Mumbai and Pune and partly due to the absence of any discrimination towards girl child. Also, unlike rest of the state, the population growth has declined by 2% between 2001 and 2011. The district is predominantly *rural* with 88% people living in rural areas as against the state average of 45%. For a coastal region, the population density (PD) is relatively less at 163/km^2. The district fares better in terms of higher literacy rate (87%) as against the overall state (76%). It has slightly less proportion of workers (41% as against 44% for state) indicating relatively higher dependency ratio. During 2010–2011, the annual net per capita income (current prices) in the district was estimated as Rs. 69 552 (approx. US $1000) which is about 20% less than the Maharashtra State average. According to the National Family Health Survey (2015–2016), in Sindhudurg, almost all households have electricity (98%), 75% have access to improved drinking-water source as well as improved sanitation facility, but only 38% use clean fuel for cooking and 10% are covered by health scheme or insurance. About 26% of children under 5 years are stunted (height-for-age) as against state average of 34%, while about 20% of children under 5 years

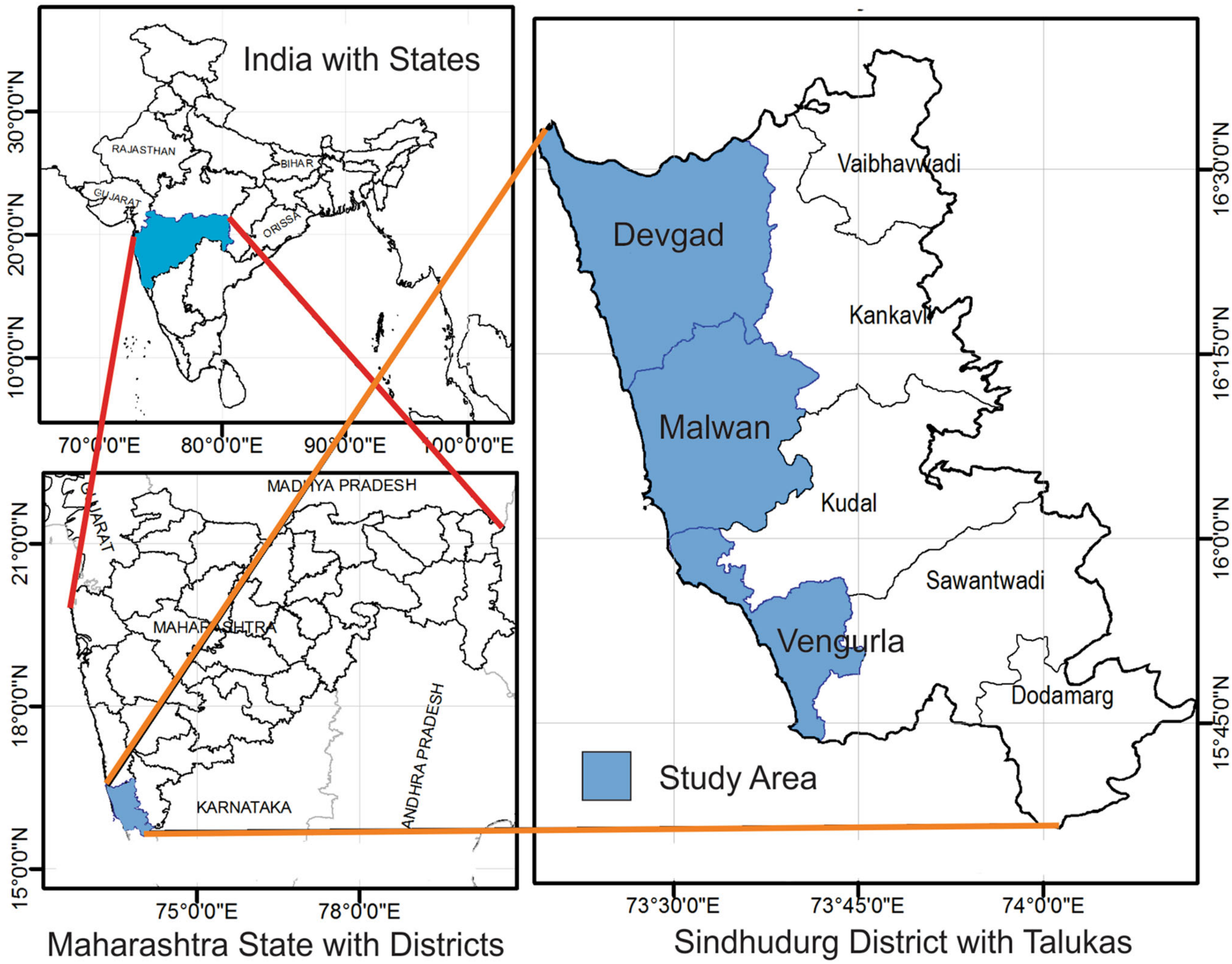


Fig. 1 Study area showing the three taluks in the Sindhudurg District, Maharashtra

are wasted (weight-for-height) as against state average of 26% indicating *relatively* better health status. Detailed information on the Sindhudurg District of Maharashtra is given in Supplementary material.

Exposure index (EI)

The spatial multi-hazard map prepared for the entire country by Indian National Centre for Ocean Information Services (INCOIS), Hyderabad was used as the base for preparing the spatial exposure profile at the village level.

Multi-hazard mapping

The coastal physical vulnerability due to inundation by oceanogenic disasters was estimated following Mahendra et al. (2010, 2011). The flood line mapping was carried out based on sea level trend, shoreline change rate, contours, extreme water level and their return periods in 100 years. The data on extreme water levels were extracted from the adjoining tide gauging stations viz., Mumbai and Marmagoa and added with those of future sea level (after 100 years) based on the sea level trend calculated using the Permanent Service for Mean Sea Level (MSL) with monthly mean sea level data pertaining to Mumbai and Marmagoa. The data on astronomical tides were removed by calculating the predicted values estimated using Sea Level Processing (SLPR2) software, developed by University of Hawaii Sea Level Center and National Oceanographic Data Center. The inundation level for Sindhudurg was calculated by interpolating the values thus obtained from the tide gauge stations in Mumbai and Marmagoa. The highest water level recorded from tide gauge and historical events was 3.11 m, while the estimated flood level including future (100 years) sea level was 3.48 m. The estimated inundation level for Sindhudurg Coast was 4 m with reference to MSL and the corresponding 4 m contour line derived from Cartosat-1 digital elevation model (DEM) was selected as the flood line ($\sim$ 10–15 cm), following Dube et al. (2009). Further, the future shoreline position was calculated by projections made using the shoreline change rate calculated for 1972–2000 period, which in turn were combined with flooding areas. The resultant area is delineated and mapped spatially as multi-hazard vulnerability line (MHVL).

Village-level profiling of exposure index (EI)

A slope map was generated from the Cartosat-1 DEM (NRSC 2014), which was found to be the DEM with the best spatial resolution of 1/3 arc second ($\sim$ 10 m) in the study area, in comparison to the global DEMs, i.e. the NASA Shuttle Radar Topographic Mission (SRTM) global DEM (NASA JPL 2013) and Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global DEM (NASA METI 2011), which have a pixel size of 1 arc second ($\sim$ 30 m). The vertical accuracy of Cartosat-1 DEM is 8 m, while those for SRTM (Rodríguez et al. 2006) and ASTER DEM (NASA METI 2011) are estimated to be < 16 and 17.01 m, respectively. The geospatial shape file of MHVL was used to generate parallel buffers at 500, 1000 and 1500 m distances, and a slope map was used to consider only the low-lying areas falling within the buffer areas (NRSC 2011). An aggregated slope mask (low-lying area mask) was generated by merging the slope categories up to 10% slope. The GIS layers of MHVL buffer and the slope mask were intersected to create a MHVL buffer (with 500, 1000 and 1500 m) of low-lying areas, for identifying the villages within each of the buffer zones. Along the buffer zones, the slope of the land would determine the presumed vulnerability beyond MHVL (lower the slope, the vulnerability would extend more toward inland and vice versa).

The extent of village(s) that fell within the MHVL were considered as Zone-1, while those within the 500, > 500 to ≤ 1000 and > 1000 to ≤ 1500 m from MHVL were considered as Zones-2, -3 and -4, respectively. Area beyond the 1500-m buffer distance was considered as Zone-5. The spatial extent (%) of village(s) under these five different zones was determined using Arc-GIS software. The weighted ('1' for Zone-1, '0.75' for Zone-2, '0.5' for Zone-3, '0.25' for Zone-4 and '0' for Zone-5) sums of scores were normalized and expressed as EI for each village (range 0–1). A five-point ordered scale was used to rank from very low (0–0.2), to very high (0.8–1.0) for EI. Census villages (Census 2011), for which corresponding maps were not available with ISRO-NRSC spatial database (NRSC 2011), [Bandegaon and Wadaker Poi in Devgad Taluk, Karlachavhal and Katta in Malvan Taluk, Deosu, Pimpalgaon and Satvayangani in Vengurla Taluk], EI were not spatially represented.

Socio-economic vulnerability indicators

Development of indicators and assigning weights

The indicators for socio-economic vulnerability were collated through extensive review of published literature (listed in Table 2; Rao et al. 2013; Sehgal et al. 2013, 2017; and others) and shortlisted based on visual procedure, series of expert consultations, statistical validation and expert judgment (Mayer and Butler 1993; Table S1). The indicators thus identified were assessed for their appropriateness and relative weightage through an online expert survey (n = 45) and measured on a five-point Likert scale. The results of the expert opinion survey were analysed using weighted sum model (WSM) following Smith and Theberge (1987). The criterion scores were normalized to be comparable and were multiplied by their respective weights. The weighted scores were summed up over all criteria, yielding a priority score for each of the indicators (Table S2). The indicators, with priority scores of > 10, were subjected to analysis using analytic hierarchy process (AHP; Saaty 1990; Ramasubramanian et al. 2014), a tool used to transform a multi-dimensional scaling problem to a unidimensional scaling problem (Saaty 2001). WSM was used as a first stage in AHP to screen some of the shortlisted indicators based on review.

$$A_i^{\text{WSM}-\text{score}} = \sum_{j=1}^{n} w_j a_{ij}, \quad \text{for } i = 1,\ 2,\ 3, \ldots, m,$$

where w_j denotes the relative weight of importance of the criterion (indicator) C_j, and a_{ij} is the performance value of alternative A_i when it is evaluated in terms of criterion C_j.

WSM and AHP were used to prioritise the final set of indicators (first level of hierarchy) along with their weights (Fig. S1) that constitute sensitivity index (SI) and adaptive capacity index (ACI) which in turn contributed to building the socio-economic vulnerability index (SEVI) and cumulative vulnerability index (CVI). The weights (Fig. 2) indicated their respective proportionate weightages in respect of building the sub-indices for four intermediate dimensions that form the second level of hierarchy. However, *equal weightage* was assumed for *social* and *economic* dimensions in terms of building both SI and ACI.

Data collection and transformation

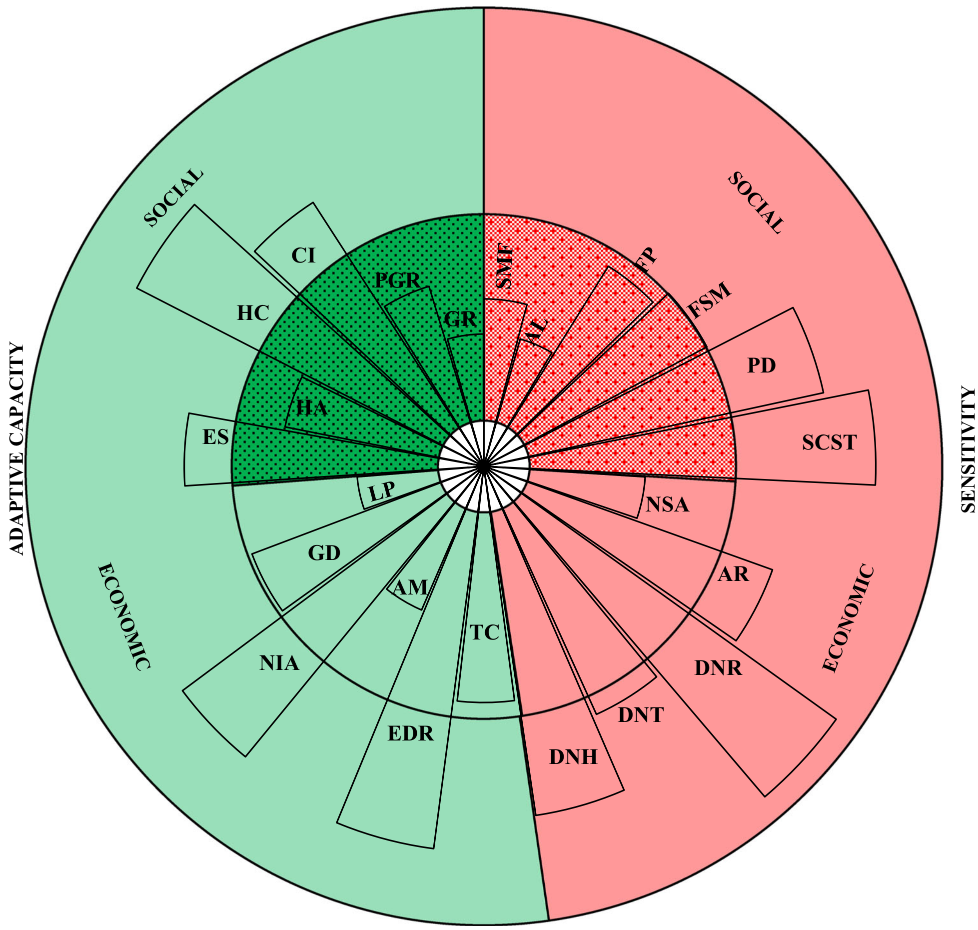
The data sources were chosen based on their accuracy, credibility and availability at the village level, to enable aggregation at the state and country levels. Census of India (2011 and 2001) data were used for measuring 17 indicators, while the Marine Fisheries Census (2010), the

Table 2 Details of selected indicators in the framework for assessment of socio-economic vulnerability index

Indicators	Definition/measurement	Refs.	Data sources
Sensitivity (social)			
(1) Small and marginal farm(ers) (SMF)	Extent of farm area owned by small and marginal farmers in relation to total sown area (%)	1	A
(2) Agriculture labourers (AL)	Proportion of agricultural labourers (main + marginal) in total workers' population (%)	1	B
(3) Fishers population (FP)	Proportion of total fisher population in relation to total population in village (%) plus proportion of full time fisher population in relation to total fisher population in fishing village (%)	P	C
(4) Malnutrition (FSM)	Measure of food (in)sufficiency; proportion of underweight children (weight–age) in the age cohort of 1–14 years	P	D
(5) Population density (PD)	Average number of people living in a unit area, expressed as no. of people per km^2 of village area	1, 2	B
(6) SC/ST population (SCST)	Proportion of SC and ST population in relation to the total population in village (%)	1	B
Sensitivity (economic)			
(7) Net sown area (NSA)	Extent of net sown area in relation to total geographical area of village (%)	1, 2	B
(8) Annual rainfall (AR)	Average annual rainfall (mm) for 2011–2012 at taluk/block level	1	E
(9) Dependence on natural resource (DNR)	Extent of area (ha) under CPRs: 'forests, pastures', 'misc. tree crops' and 'tanks & lakes' in relation to total geographical area (%)	P	B
(10) Distance to nearest town (DNT)	Distance from village to nearest town. A four-point scale as per Census distance classes used (if town-1, < 5 km-2, 5–10 km-3, > 10 km-4)	P	B
(11) Distance to nearest hospital (DNH)	Distance from village to nearest health facility. A four-point scale as per Census distance classes used (within village-1, < 5 km-2, 5–10 km-3, > 10 km-4)	P	B
Adaptive capacity (social)			
(1) Education status (ES)	Combined measure of (a) proportion of literate population and (b) proportion of literate female population (%)	1, P	B
(2) Household amenities (HA)	Combined measure of (%) (i) HHs with access to drinking water, (ii) HHs with access to sanitation, (iii) HHs having electricity and (iv) HHs having clean fuel	P	B
(3) Housing condition (HC)	Combined measure of (%) (i) housing ownership, (ii) no. of rooms, (iii) household type and (iv) housing material type	P	B
(4) Community infrastructure (CI)	Data entered in numbers for (i) schools, (ii) colleges, (iii) hospitals (govt., non-govt.), (iv) community halls	P	B
(5) Population growth rate (PGR)	Decadal growth rate in total population between 2011 and 2001 (%)	P	B, F
(6) Gender ratio (GR)	Ratio of number of females to 1000 males; in cases where ratio is > 1.2 or < 0.8, '0' is given as they are least desirable scenarios	1*	B
Adaptive capacity (economic)			
(7) Transport and communication (TC)	Combined measure of (%) (i) HHs with access to communication assets, and (ii) HHs wit transport facilities	P	B
(8) Economic dependency ratio (EDR)	Ratio of non-working (age group < 14 and > 60+ *non-workers*' *population in working age group of* 15–59) to working population in age group 15–59 years	P	B
(9) Access to market (AM)	Distance from village to nearest market. A four-point scale as per Census distance classes used (within-4, < 5 km-3, 5–10 km-2, > 10 km-1)	1	B
(10) Net irrigated area (NIA)	Proportion of net sown area having access to irrigation (%)	1, 2	B
(11) Groundwater development (GD)	Draft (extent of extraction) of groundwater in relation to availability during 2011–2012 (%)	1	E
(12) Livestock population (LP)	Population of all types of livestock accounted in the livestock census (LSE or %)	1, 2	G

1 Rao et al. (2013), *2* Sehgal et al. (2013), *P* present study, *A* Agricultural Census 2010–2011, *B* Census 2011, *C* Marine Fisheries Census 2010, *D* National Family Health Survey 2015–2016, *E* CSDA/CGWB, 2014 (data 2011–2012), *F* Census 2001, *G* Livestock Census 2012, *Data type* except distance to nearest town/hospital (ordinal) and transport and communication (%) all indicators have cardinal values, *Weightage* except for transport and communication [for Communication: Radio (5%), TV (15%), Internet (25%), No internet (10%), Landline (10%), Mobile (10%), Mobile + Landline (25%); for transport: Car (60%), Bike (30%), Cycle (10%)] and fisher population (67% for total fishers, 33% for full-time fishers), all other indicators were assigned equal weightage (100%)

*Modified from source



SMF-Small and Marginal Farmers, **AL**-Agricultural Labourers, **FP**-Fisher Population, **FSM**-Food Sufficiency/ Malnutrition, **PD**-Population Density, **SCST**-Schedule Castes/Schedule Tribes Population, **NSA**- Net Sown Area, **AR**-Annual Rainfall, **DNR**-Dependence on Natural Resources, **DNT**-Distance to Nearest Town, **DNH**-Distance to Nearest Hospital, **TC**-Transport and Communication, **EDR**-Economic Dependency Ratio, **AM**-Access to Market, **NIA**-Net Irrigated Area, **GD**-Groundwater Development, **LP**-Livestock Population, **ES**-Education Status, **HA**-Household Amenities, **HC**-Housing Condition, **CI**-Community Infrastructure, **PGR**-Population Growth Rate, **GR**-Gender Ratio

Fig. 2 Framework for assessment of socio-economic vulnerability depicting the prioritised indicators based on their weightages for SEVI (%)

Livestock Census (2012), the Agricultural Census (2010–2011), and reports of the Central Ground Water Board (2011–2012) and the National Family Health Survey (2015–2016) were relied upon for measuring the remaining six indicators. Village-level datasets were available and used for 19 indicators. In case of four indicators, for which, village-level datasets were not available, but were considered essential for measuring socio-economic vulnerability, taluk-level (three indicators) and district-level (one indicator) data were used. The list of indicators with their definitions and data sources are provided in Table 2, while the detailed explanations for all indicators, including their measurement, rationale, direction of association (direct/ inverse) with the socio-economic vulnerability, data sources and data type are provided in Table S3.

Data available from the identified sources were of both cardinal and ordinal types. Census data available as distance intervals were converted into ordinal data by assigning scale values. Data sets, which were available in percentages [household amenities (HAs), housing condition (HC), transport and communication (TC)] and discrete numbers [community infrastructure (CI) and livestock population (LP)] were considered directly, while for some indicators [agriculture labourers (ALs), fishers population (FP), SC/ST population (SCST), net sown area (NSA), dependence on natural resource (DNR), education status (ES), and net irrigated area (NIA)], raw data were converted into percentages. Scale values were used for population growth rate (PGR) indicator based on decadal population growth between 2001 and 2011.

Normalization of data

Data ranges and scales used were different among the indicators and in order to compare and perform arithmetical operations on them, they were normalized (Gómez-Limón and Sanchez-Fernandez 2010) during their integration into aggregate vulnerability index within a dimensionless range (0–1). Normalization was carried out for each indicator depending on the relationship with the broad categories as follows:

$$Z_i = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}}, \tag{1}$$

$$Z_i = \frac{X_{\max} - X_i}{X_{\max} - X_{\min}}. \tag{2}$$

Equations 1 and 2 were applied for directly and inversely related indicators, respectively. Z_i is normalized value of ith village with respect to the indicator X, and X_i is the value of the indicator in original units for the ith village. $X_{\min}$ and $X_{\max}$ denoted the universal minimum and maximum values, respectively. An *absolute scale* was used against a relative scale, so as to enable a national-level comparison of indices.

Indicators having multiple variables were normalized at each variable level and averaged after applying the weightage, to determine the normalized indicator value, and in case of data gaps, the medians of the normalized values were used for imputation.

Sensitivity indices (SI) and adaptive capacity indices (ACIs)

Village-wise indices for each dimension, i.e. social sensitivity, economic sensitivity, social adaptive capacity and economic adaptive capacity, were determined by taking the average of the normalized indicators assigned for each dimension. Socio-economic SI/ACIs for villages were constructed by taking the averages of social and economic SI/ACIs, respectively.

SI and ACIs at taluk level were estimated as under:

$$\text{Socio-economic sensitivity index for taluk} = \sum_{i=1}^{I} (\mathrm{WP}_i * \mathrm{SI}_i),$$

$$\text{Socio-economic adaptive capacity index for taluk} = \sum_{i=1}^{I} (\mathrm{WP}_i * \mathrm{ACI}_i),$$

where i denotes the individual villages in respective taluks, I denotes the total number of villages in the taluk, WP_i is the proportion of ith village population to the taluk's total population, SI_i and ACI_i denote the socio-economic SI and ACIs of ith village in the taluk, respectively. Similarly, socio-economic SI and socio-economic ACI at district level were estimated as under:

$$\text{Socio-economic sensitivity index for Sindhudurg District} = \sum_{t=1}^{T} (\mathrm{WP}_t * \mathrm{SI}_t),$$

$$\text{Socio-economic adaptive capacity index for Sindhudurg District} = \sum_{t=1}^{T} (\mathrm{WP}_t * \mathrm{ACI}_t),$$

where t denotes the individual taluk, T denotes the total number of taluks in the Sindhudurg District (i.e. Devgad, Malvan and Vengurla), WP_t is the proportion of tth taluk's population to the total population of the three taluks, SI_t and ACI_t denote the socio-economic SI and ACIs of the tth taluk, respectively.

Cumulative vulnerability index (CVI)

Cumulative vulnerability index (CVI) in this study was determined as the positive function of EI and SI, but negative function of ACI following Li et al. (2015), as under:

$$\begin{aligned}\text{Cumulative vulnerability} &= \text{f (exposure, sensitivity, adaptive capacity)}\\ &= (\text{exposure x sensitivity})/\text{adaptive capacity},\end{aligned}$$

$$\mathrm{CVI} = (\mathrm{EI} * \mathrm{SI})/\mathrm{ACI}.$$

Overall vulnerability level of a system can be determined using the CVI value in which higher values indicate higher degree of vulnerability. It provides a consolidated measure of vulnerability to understand the relative position of one geo-socio-economic unit (village/taluk/district/state/country) in relation to another unit, and prepare appropriate interventions.

Framework for village-level intervention planning

Rescaling of indices

In order to discern greater variability to enable grassroot-level (villages/blocks) planning and interventions, SI, ACI and SEVI were rescaled on a relative basis, keeping observed minimum and maximum as $X_{\min}$ and $X_{\max}$ values (unlike universal minimum and maximum as stated in 2.3.3). For all indices, viz., SI, ACI and SEVI, five-point ordered scale was used to rank from very low (0–0.2) to very high (0.81–1.0), according to their functional relationships with vulnerability (Sehgal et al. 2017).

Computation of SEVI

SEVI values for all villages, taluks and the Sindhudurg District were constructed from the rescaled socio-economic sensitivity (SI-R) and socio-economic adaptive capacity (ACI-R) indices using the following formula:

$$\mathrm{SEVI} = \frac{\text{Socio-economic sensitivity index}}{1 + \text{Socio-economic adaptive capacity index}}.$$

SI and ACIs were considered *equally important* in constituting the overall SEVI.

SEVI decision matrix

A decision matrix was developed by plotting SI-R against ACI-R for villages in each taluk to identify socio-economically vulnerable areas and aid in planning appropriate interventions. Villages in the quadrant with SI-R ≤ 0.50 and ACI-R > 0.50 were recognized as those with low vulnerability. Villages in the quadrant with SI-R > 0.50 and ACI-R ≤ 0.50 were classified as villages with high socio-economic vulnerability. The sub-indicators (23 no.) in such villages were further analysed to identify the *drivers* (> 0.50 for sensitivity indicators, ≤ 0.50 for adaptive capacity indicators) and *buffers* (≤ 0.50 for sensitivity indicators, > 0.50 for adaptive capacity indicators) of coastal vulnerability.

Village-level spatial mapping of indices

The geo-spatial village administrative boundaries in three talukas were prepared from published maps and village cadastral maps (NRSC 2011). The indices, EI, SI, ACI, and CVI, were linked with the spatial village maps using the village name as the common link attribute using Arc-GIS software. The attributes (indices) were then displayed in the 0.1–1.0 scale as thematic maps for the particular index. The multi-hazard vulnerability polygon was also overlaid on the indices maps to show the physical extent of hazard zone, while the EI shows the village-level exposure, derived from MHV maps.

Statistical validation of indicators

Spearman rank correlation was used to measure the correlation among the indicators in each category (Gibbons and Chakraborti 2003). Indicators of same category showing high correlation between them indicated their over-representation within the index. Exploratory factor analysis was done to identify the variables which give rise to an underlying factor, that can be called an index of certain phenomenon (Long 1983). *Cronbach's* reliability coefficient was used to measure internal consistency among the variables representing a particular indicator (Cronbach 1951). Confirmatory factor analysis was undertaken (Long 1983) to check the goodness of fit for the proposed model. Non-parametric tests were applied since the normalized index values were non-normally distributed. Kruskal–Wallis ANOVA test was applied to test the significance of variation between the indices. All statistical analyses were performed with OriginPro 8 SR0 (v8.0724).

RESULTS AND DISCUSSION

Multilevel hazard mapping and exposure index (EI)

The cumulative areas of flooding and erosion as depicted in the multi-hazard vulnerability map (MHVM; Fig. 3a), represent the probable coastal areas that could get inundated at least once in 100 years, in which the actual settlements (urban/rural dwellings in a village) and cropland/forest areas are also depicted. The settlements within or adjacent to MHVL were in direct threat to estimated hazard, which would contribute to the cumulative vulnerability of the respective coastal villages. Though the figure provides the pattern of settlement, for the purpose of vulnerability assessment, the village boundary as a whole was considered for estimating the EI. The biophysical vulnerability has been determined based on sea level trend, shoreline change rate, elevation, extreme water level and their return periods in 100 years. The data sources for each of these parameters are not uniformly distributed along the coast of India (e.g. tide gauging stations) and hence the hazard predictions are to be taken as a geographically normalized representation of the estimated multi-hazard.

The study showed that spatially, 7% of the Sindhudurg District fell within the MHVL, and this proportion ranged between 3% (Vengurla) and 8% in Malvan (Fig. 3b). 32% of the coastal villages (99 villages) in the Sindhudurg District were found to be with high or very high EI (EI ≥ 0.6), with Vengurla (21%; 17 villages) and Malvan (39%; 52 villages), registering the minimum and maximum, respectively.

Socio-economic vulnerability indicators

Vulnerabilities, that make human societies and communities prone to damage from external hazards and due to the internal characteristics of the human system, have been referred to as social vulnerability (Adger 1999; Adger and Kelly 1999). Factors like social inequality, poverty, inadequate access to essential facilities such as education, health care, housing, other essential infrastructure, etc., generally determine social vulnerability (Blaikie et al. 1994; Adger and Kelly 1999; Cross 2001). Esteves et al.

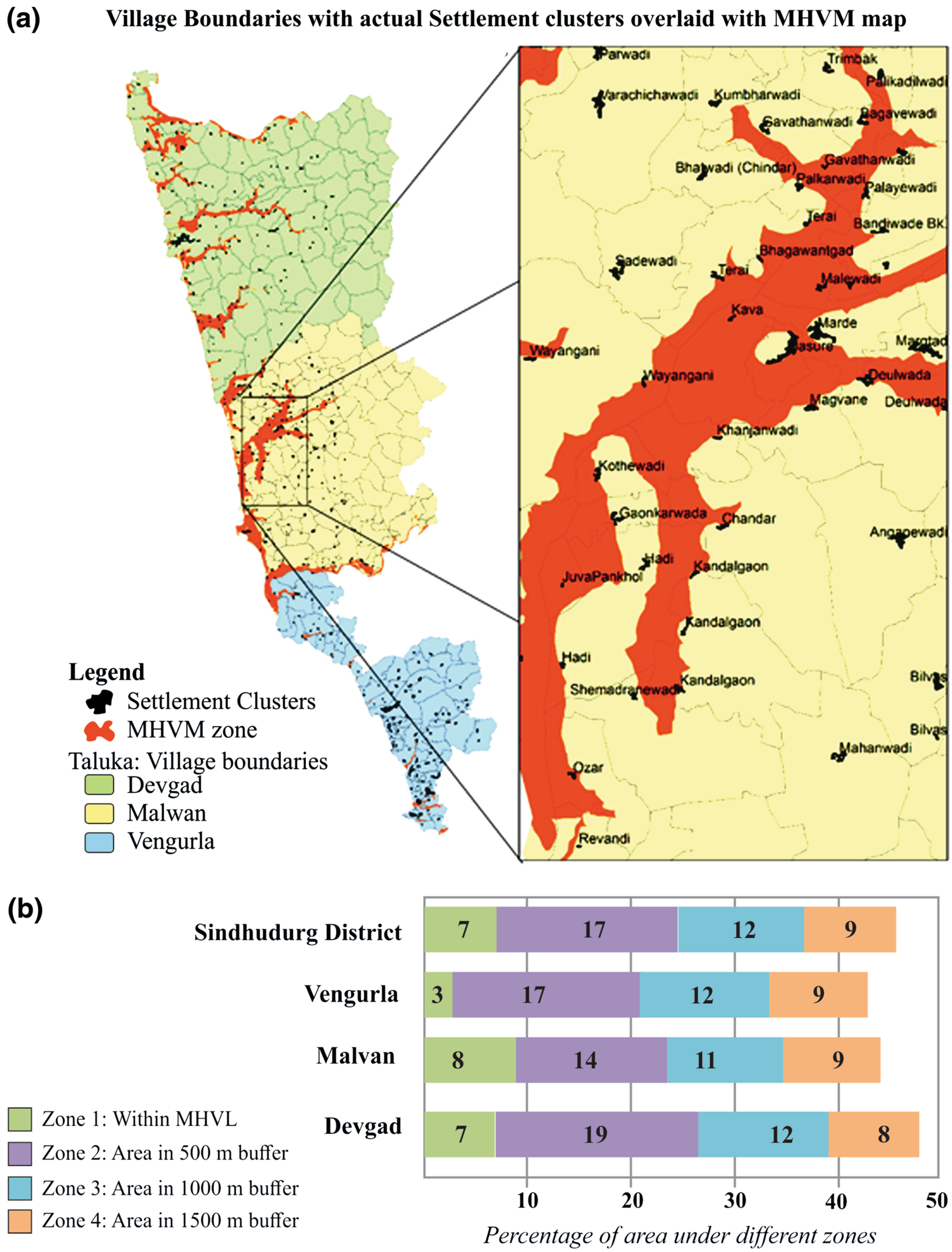


Fig. 3 Multi-hazard vulnerability map (MHVM) and buffer zones. **a** Village-wise settlements and cropland/forest areas overlaid with MHVM, and **b** extent of coastal taluks under MHV line and different buffer zones

(2016) assessed the socio-economic vulnerability in inland districts of Karnataka State. Two approaches are highlighted, in general, for vulnerability assessments: top-down and bottom-up approaches (Satapathy et al. 2014). Top-down approach deals with analysis of climate change and its impacts and is usually preferred at global, national and regional levels. Bottom-up approach focuses on analysis of population affected due to climate change and is usually preferred at the local level, such as, households, villages and communities (Satapathy et al. 2014). In the current framework, bottom-up approach has been used to assess the socio-economic vulnerability status of the study area.

The indicators for assessing socio-economic vulnerability were collated based on review and expert consultation (Dale and Beyeler 2001; Zhen and Routray 2003) and 30 indicators were shortlisted based on their appropriateness as *measurable* indicators, *relevance* in Indian context and possible *data* availability. Six indicators (*mortality rate*, *women headed households*, *aquaculture activity*, *road connectivity*, *fertilizer consumption*, *and share of agriculture in district domestic product*) were dropped from further analysis and inclusion in vulnerability index, based on the results of online expert survey, while one indicator ‘degraded and waste lands’ was dropped due to high degree of collinearity with ‘net sown area’. Thus, finally 23 indicators were included in the SEVI framework. The experts opined that categorisation of sensitivity/adaptive capacity indicators, further as ‘social’ and ‘economical’, are not to be treated rigidly as many encompass both aspects, while also collectively measuring the same, but rather felt as a useful classificatory tool. Two indicators under adaptive capacity, *economic dependency ratio*, and *TC*, were shifted from ‘social’ to ‘economical’ as overwhelming majority of experts suggested.

The *Cronbach*’*s* value calculated for indicators, grouped under the indices, were below 0.5 (unacceptable). However, this could be an underestimate due to non-normally distributed data and small sample size (317 subjects), and with larger samples ($\geq$ 1000) it may get rectified (Sheng and Sheng 2012). Thus, all the 23 selected indicators were retained in our framework for vulnerability assessment (Fig. 2).

Correlation analysis exhibited no strong correlation ($-0.7 \geq r_s \leq 0.7$) between any two indicators, except in one case, in either of the categories (Table S4), thus revealing their relative independence from each other and justifying the need for all identified indicators for inclusion in computing indices. Among the indicators identified for SI, NSA and total wasteland area (DWA) showed high but negative correlation ($r_s = -0.68$), and hence DWA was dropped from analysis. Also, NSA and DNR showed moderate positive correlation ($r_s = 0.54$) between them. Among adaptive capacity indicators, moderate positive correlation ($r_s = 0.55$) was observed between ES and TC, as well as, between CI and LP ($r_s = 0.55$), while correlations in all other cases were between each other.

Socio-economic sensitivity index (SI)

Socio-economic SI for villages in the Sindhudurg District ranged between 0.321 and 0.573, with the median value of 0.442, indicating *moderate* socio-economic sensitivity. Interestingly, all three taluks in the Sindhudurg District viz., Devgad (0.452), Malvan (0.435) and Vengurla (0.437) had moderate sensitivity. Among all villages, only 8% of villages had low level (> 0.2 to 0.4) of socio-economic sensitivity, while most of the villages (92%) had moderate socio-economic sensitivity (> 0.4 to 0.6) raising some concerns if not serious threat. Of the 317 villages studied, sensitivity was relatively high for Khalchikar Village in Vengurla Taluk due to very high PD (10 667 persons/km^2) and lack of natural resources cover (0%) along with farther distance from the nearest town and hospitals. This is uniformly the case with villages having relatively high sensitivity. In contrast, Math Village of Vengurla Taluk had the lowest sensitivity among all, as a result of less SC/ST population (9%), less NSA (15%), high natural resources cover (61%) and its closeness to town.

Except for few indicators of sensitivity namely NSA, DNR, proportion of agriculture labour and to some extent proximity to town/hospital, the variability among villages in all the three taluks was low, i.e. they were homogenous on many indicators (Fig. 4). Hence, the SE-sensitivity levels in Devgad, Malvan and Vengurla villages were almost in similar ranges. It ranged between 0.336 (Baparde) and 0.536 (Kunkeshwar) in Devgad, between 0.328 (Chauke) and 0.557 (Devbag) in Malvan, and between 0.321 (Math) and 0.573 (Khalchikar) in Vengurla. Also, the proportion of villages with low sensitivity was 10% in Devgad, 7% in Malvan and 6% in Vengurla, while the rest of villages (90–94%) of the three taluks had moderate sensitivity.

The decomposed social-sensitivity and economic-sensitivity indices provide more useful insights. The Sindhudurg District exhibited *higher economic sensitivity* (range = 0.480–0.905, median = 0.785) but very low social sensitivity (range 0.087 and 0.393, median = 0.135) with significant difference between these two dimensions ($\chi^2 = 474.75$, $p < 0.05$). Similar characteristics were exhibited in all the three taluks. Higher economic sensitivity was mainly due to the influence of relatively poor access to urban areas, medical services and lower extent of natural resources (Fig. 4). On the other hand, low PD, less share of SC/ST and FP contributed significantly to low social sensitivity indicating relatively favourable demographic and social conditions (Fig. 4). The variations in social SIs ($\chi^2 = 1.496$, $p = 0.473$), as well as, economic SIs

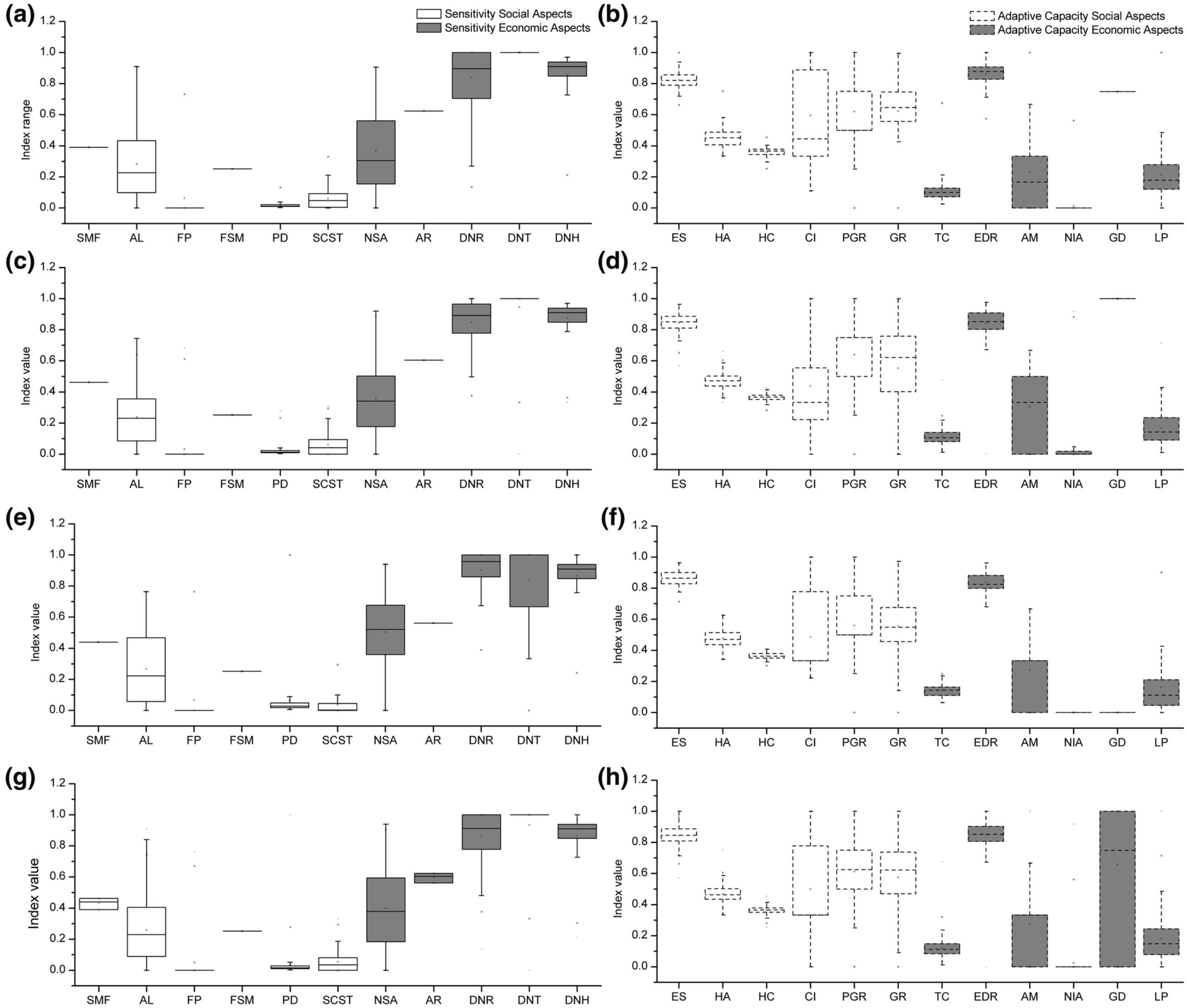


Fig. 4 Estimated indices for all indicators used for social and economic dimensions of both sensitivity and adaptive capacity components for the three coastal taluks. **a**, **b** Devgad, **c**, **d** Malvan, **e**, **f** Vengurla and **g**, **h** Sindhudurg District. Boxes indicate the 25th to 75th percentile range, band in the middle represent the median value, lower and upper bands indicate minimum and maximum values respectively, bottom and top × symbol indicate 1st and 99th percentile respectively, square inside the box displays arithmetic mean. *SMF* small and marginal farmers, *AL* agricultural labourers, *FP* fishers' population, *FSM* food sufficiency/ malnutrition, *PD* population density, *SC/ST* schedule castes/schedule tribes population, *NSA* net sown area, *AR* annual rainfall, *DNR* dependence on natural resources, *DNT* distance to nearest town, *DNH* distance to nearest hospital, *TC* transport and communication, *EDR* economic dependency ratio, *AM* access to market, *NIA-Net* irrigated area, *GD* groundwater development, *LP* livestock population, *ES* education status, *HA* household amenities, *HC* housing condition, *CI* community infrastructure, *PGR* population growth rate, *GR* gender ratio

of villages (χ^2 = 0.811, p = 0.666) among the three taluks, were not significant. Given that most of sensitivity indicators are malleable for short term interventions, they rather provide broader, and *limiting*, socio-economic context within which strategies based on ACI scores shall be addressed.

Socio-economic adaptive capacity index (ACI)

The adaptive capacity of the coastal Sindhudurg District as a whole was moderate (0.491) with ACI values ranging between 0.333 and 0.639. Among the three taluks, Vengurla Taluk had the lowest ACI (0.431) as compared to

Devgad (0.506) and Malvan (0.521). Majority of villages (88%) had moderate adaptive capacity, with the rest (11%) suffered from lower capacity to adapt. Of all villages, Hirlewadi Village in Malvan Taluk had the highest ACI score (0.639) due to various factors viz., higher proportion of literate population (91%) including females (89%), declining PGR (− 1.58), favourable gender ratio (1.19) and relatively low economic dependency ratio (0.97). Conversely, Warchiwadi Village in Vengurla Taluk scored poorly on many indicators of adaptive capacity especially TC assets, distance to market, irrigated areas (0%) and LP (355 animals, mainly composed of backyard poultry) with the lowest ACI value (0.333).

Adaptive capacity in Devgad villages ranged between 0.405 (Malpewadi) and 0.596 (Hindale). ACI values for Malvan and Vengurla Taluks were between 0.358 (Mahan) and 0.639 (Hirlewadi), and between 0.333 (Warchiwadi) and 0.491 (Tulas), respectively. All the 98 villages in Devgad Taluk had moderate adaptive capacity, while as much as 97% of 135 villages in Malvan Taluk also had moderate adaptive capacity. However, of the 84 villages in Vengurla Taluk, only 60% of villages had moderate ACI and the remaining 40% of villages fared poorly on ACI.

The ACIs among the three taluks varied significantly (χ^2 = 142.80, $p < 0.05$) with mean rank of 57.9 for Vengurla, 182.4 for Devgad and 204.9 for Malvan. The social dimension of adaptive capacity (AC-S) of coastal Sindhudurg ranged between 0.360 and 0.729, whereas the economic dimension of adaptive capacity (AC-E) ranged from 0.218 to 0.685. The coastal Sindhudurg exhibited significantly (χ^2 = 392.68, $p < 0.05$) higher AC-S (median = 0.550) than AC-E (median = 0.407). Similar characteristics were exhibited in all the three taluks. There were significant differences between AC-S (χ^2 = 10.51, $p < 0.05$) and AC-E (χ^2 = 223.01, $p < 0.05$) among the three taluks. The major contributing factors for higher AC-S were high literacy rate, higher sex ratio and low PGR (Fig. 4). Lower AC-E could be attributed to low economic strength depicted by lack of adequate TC assets, relatively poor access to markets, near absence of irrigated agriculture and very less LP (Fig. 4).

Cumulative vulnerability index (CVI)

CVI was estimated as a function of three main components, i.e. exposure, sensitivity and adaptive capacity. *Exposure* together with *sensitivity* represents the propensity and predisposition of the system to be adversely affected by climate change, whereas *adaptive capacity* reduces these effects (Nelson et al. 2010). A very high positive correlation existed between EI and CVI (r = 0.97, $p < 0.05$). The correlation of SI with CVI was positive but weak (r = 0.20, $p < 0.05$). ACI had a very weak negative correlation with CVI ($r = -0.03$, $p > 0.05$). Thus, as could only be expected, the exposure component had a greater influence in assessing the vulnerability status than either sensitivity or adaptive capacity. As explained earlier, this is partly due to relative homogeneity of villages, except for few in Vengurla, in the Konkan Coast on which Sindhudurg lies. Furthermore, correlation among the three main components were found to be weak ($r_{\mathrm{EI\ vs.\ SI}} = 0.12$, $r_{\mathrm{EI\ vs.\ ACI}} = 0.14$, $r_{\mathrm{SI\ vs.\ ACI}} = -0.25$) suggesting that the three components occur *independently*, which Li et al. (2015) have also observed while assessing agricultural vulnerability due to climate change in the Chinese Loess Plateau.

In the study, based on CVI values, 92 villages (30%) in the Sindhudurg District were identified as *highly vulnerable* with 33 among them falling in very high vulnerability category. Regions closer to the coast line were the highly vulnerable regions (Fig. 5) due to high EI (median 0.754), moderate SI (median 0.474) and ACI (median 0.475) indices. A total of 51 villages (16%) in the study area showed moderate vulnerability, which had moderate exposure (median 0.489), SI (median 0.459) and ACI (median 0.478) indices. However, little more than half of the villages (167) were found to have *low vulnerability*, which was explained by the very low EI (median 0.003), moderate SI (median 0.455) and ACIs (median 0.471). It further substantiates the fact that exposure component influences far more the overall cumulative vulnerability in the Sindhudurg District.

SEVI: Village-level intervention planning

In order to discern the variations in the components of SEVI and to get farther insights on relative statuses of villages/taluks in a *within-district* perspective, the indices were rescaled by normalizing them with observed minimum and maximum values (as against universal min–max values). Assuming greater homogeneity among neighbouring villages/taluks, this will help magnify otherwise hidden heterogeneity, in terms of key socio-economic vulnerability indicators, thereby providing pointers for more specific and customised interventions. The detailed list of SEVI with the ranking of various indices is provided in Table S5.

The SEVI for the Sindhudurg District, calculated from rescaled SI and ACI, was rated as low (0.316). Vengurla Taluk had relatively higher SEVI (0.347) than Devgad (0.332) and Malvan (0.280) Taluks. There were significant differences (χ^2 = 28.9, $p < 0.05$) in SEVI among the three taluks with mean SEVI rank of 203.98 for Vengurla, 151.05 for Devgad and 136.78 for Malvan. Nearly one-third (32%) of villages in the study area, were identified as socio-economically *high vulnerable*, 41% as *moderately vulnerable* and remaining 27% as *low vulnerable*. The

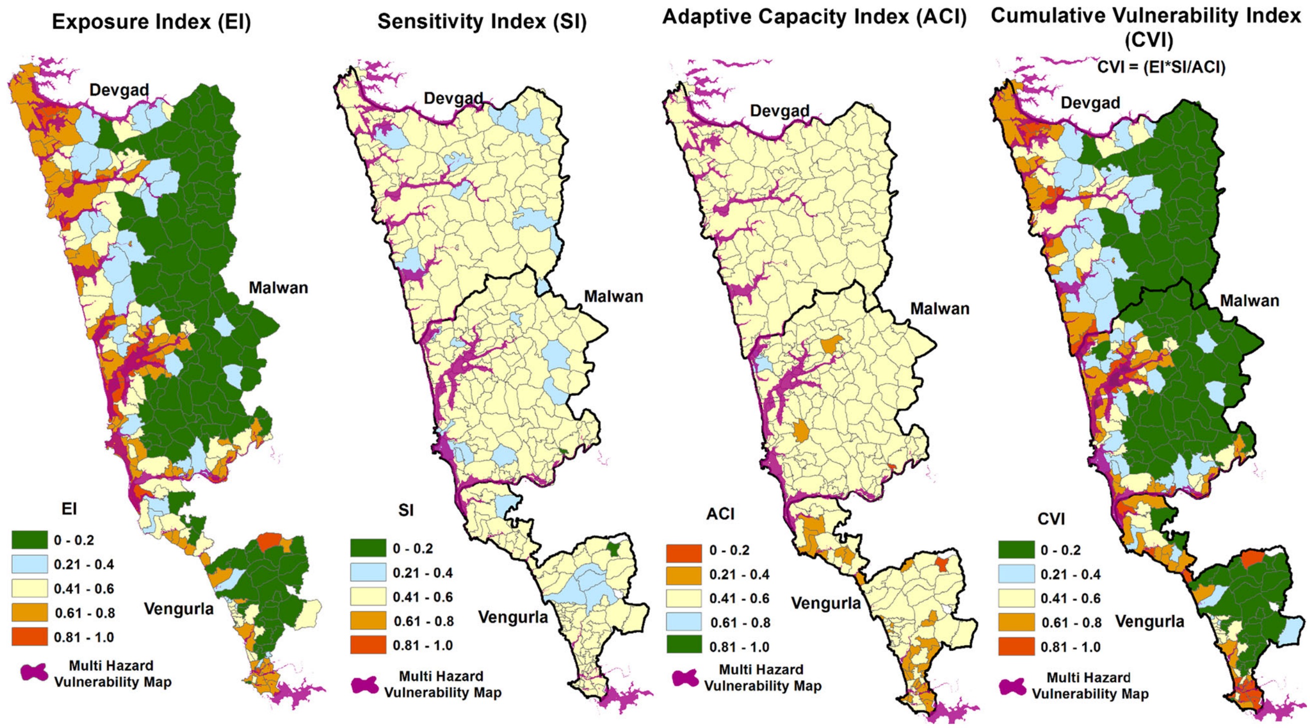


Fig. 5 Spatial representation of village-wise exposure, sensitivity, adaptive capacity and cumulative vulnerability indices for the Sindhudurg District

levels of socio-economic vulnerability among all 317 study villages in the Sindhudurg District are shown in Fig. 6. The study showed that as many as 15 of 20 most vulnerable (southern and northern regions), as also a few of the least vulnerable villages (middle region) were from Vengurla Taluk (Table 3), indicating greater socio-economic differentiation (can also be read as less equitable) among villages in Vengurla Taluk.

Intervention planning using SEVI decision matrix

The socio-economic SI and ACIs of all villages in each taluk were plotted in a two-dimensional decision matrix tool (Fig. 7). It was observed that almost 43% (136) of villages in Sindhudurg were in third quadrant (highly vulnerable). At taluk level, highly vulnerable villages accounted for 35% (34) in Devgad, 32% (43) in Malvan and 70% (59) in Vengurla Taluks (Fig. 7), indicating areas where the foci of location-specific interventions need to be located within the district. Though the overall SEVI of Sindhudurg District was low, this framework along with decision matrix tool helped to identify villages with high sensitivity and low adaptive capacity, by adequately highlighting the existing inequity in terms of key socio-economic indicators at intra-district level (Fig. 7). The results corroborated well with the earlier observations of TERI (2014) on the vulnerability of Sindhudurg to climate change. The Sindhudurg District ranked 493rd position among the 573 districts in India based on agriculture vulnerability to climate change (Rao et al. 2013).

Drivers and buffers of vulnerability

In the identified highly vulnerable regions, certain indicators were found to *push up* the vulnerability levels due to either high sensitivity and or low adaptive capacity which we designate as *drivers*. Conversely, variables that *pull down* vulnerability levels due to either high adaptive capacity and or low sensitivity in a given area were considered as *buffers*. Five *drivers*, influencing high sensitivity in Sindhudurg, were distance to the nearest town (DNT), distance to the nearest hospital (DNH), NSA, proportion of small and marginal farm(ers) (SMFs) and ALs. It was clear from representative villages (Fig. 7) that high vulnerability is structural to an extent due to predominantly agrarian economy with relatively smaller farm size and sizeable population of agricultural labour, which is exacerbated by hilly terrain leading to distant location (> 10 km) of town and health facilities. The status of contributing factors for a representative village in Devgad Taluk is illustrated in a Sunburst plot in Fig. 8 for intervention planning.

The key *buffers*, which stabilised 'sensitivity', were DNR, FP, PD, SC/ST population (SCST) and malnutrition (FSM). High proportion of common property natural resources such as forests, permanent pastures,

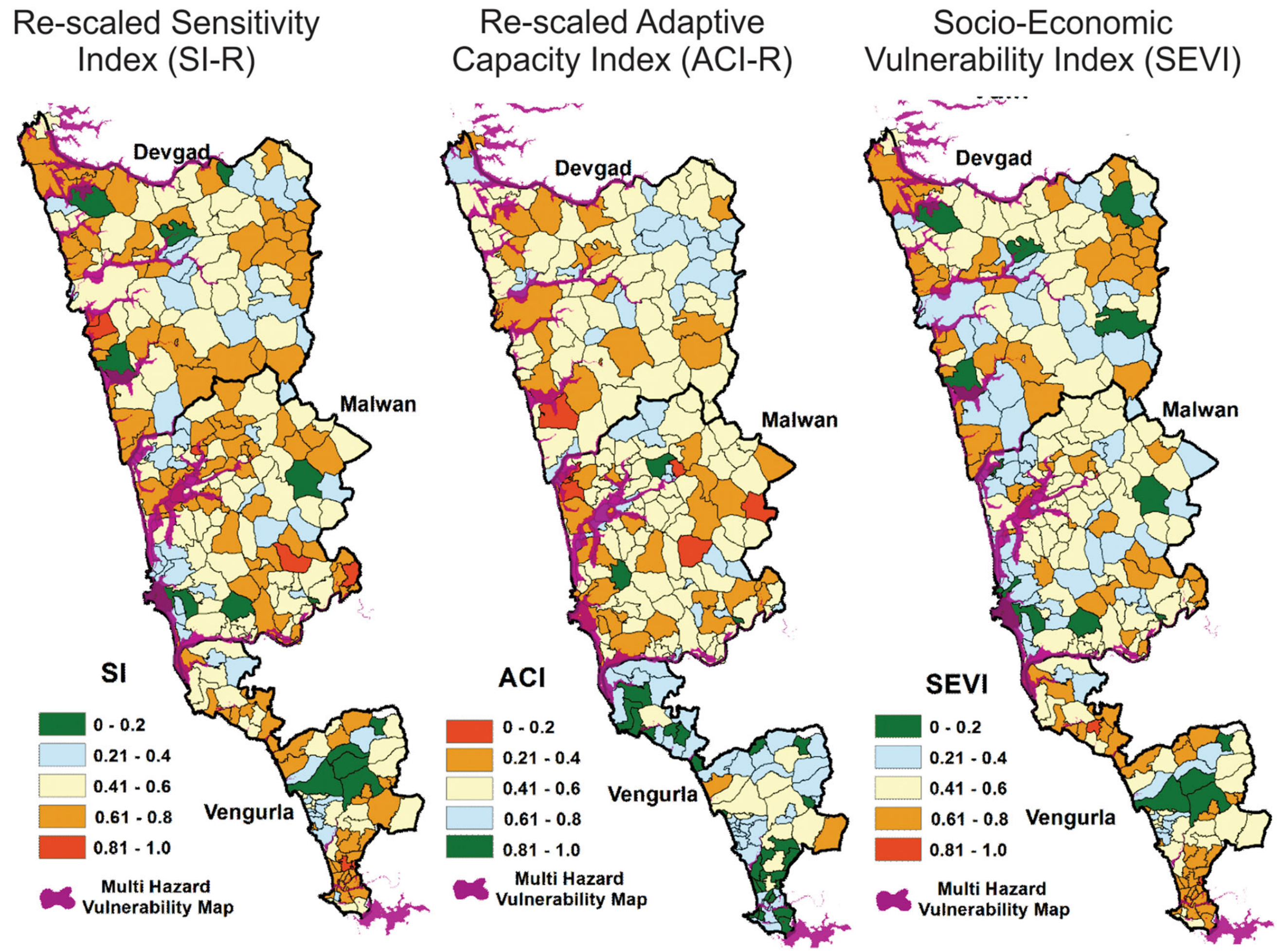


Fig. 6 Spatial representation of SE-sensitivity (SI-R), SE-adaptive capacity (ACI-R) and socio-economic vulnerability index (SEVI) for the Sindhudurg District

miscellaneous tree crops and tanks/lakes on which community depends provides a cushion against climate shocks and natural calamities. Similarly, the main *drivers* that lowered adaptive capacity were found to be NIA, TC, LP, access to market (AM), CI and economic dependency ratio (EDR). The *buffers*, which contributed to enhance adaptive capacity were ES, groundwater development (GD), gender ratio and HAs.

The low value for FP indicator could be attributed to the data constraint pertaining to the indicator (data for FP were available for only 52 coastal villages). Very low value for PD could be due to the influence of extremely high PD observed in Khalchikar Village in Vengurla Taluk (10 667 person/km^2). A detailed account on the descriptive statistics for each indicator has been provided in Table S6.

Implications for national policy

Recognizing the significance of the coasts and their vulnerability to changing climate, the Government of India has launched the National Coastal Mission (NCM) as a sub-mission under the National Action Plan to Climate Change (NAPCC) to ensure that adaptive responses are appropriately built in so as to deal with newer threats of climate change (NCM 2016). The Mission has been organised into three key components: (i) assessment of current coastal vulnerability, (ii) response strategies to climate change through *adaptation* and *mitigation*, and (iii) capacity building as a cross cutting activity, which in turn include five key activities (Fig. 9). Thus, scientific assessment of coastal vulnerability is central to the implementation of the national interventions for adaptation to climate change. The framework developed and demonstrated is unique in terms of (i) scale of operation—the implementation unit is a village, which is the functional administrative unit as per the prevailing laws, (ii) comprehensive socio-economic indicators—the final indicators, which have been tested for consistency and scalability, would capture social and economic dimensions of all contributing factors (sensitivity/adaptive capacity), (iii) data

Table 3 Ranking of top 20 villages in the Sindhudurg District based on their SEVI values

Taluks	Villages	SEVI	Rank based on		
			SEVI	SI-R	ACI-R
Vengurla	Khalchikar		1	1	37
Vengurla	Bandh		2	3	2
Vengurla	Kurlewadi		3	22	7
Vengurla	Khalchiwadi		4	11	22
Malvan	Devbag		5	2	244
Vengurla	Parabgaon		6	30	18
Vengurla	Temb		7	25	26
Devgad	Kunkeshwar		8	4	114
Vengurla	Bagayat		9	43	16
Vengurla	Josoli		10	47	15
Vengurla	Muth		11	10	62
Vengurla	Kelus		12	23	38
Devgad	Mithmumbari		13	5	126
Devgad	Wadaker Poi		14	35	48
Vengurla	Sagartirtha		15	88	4
Vengurla	Mhapan		16	24	66
Vengurla	Shriramwadi		17	80	9
Vengurla	Arawali		18	8	129
Vengurla	Sakhelekhol		19	76	20
Malvan	Sayyad Juva		20	52	47

Length of bar in each cell represents the SEVI value. Low rank values for SEVI, SI-R, ACI-R indicates higher socio-economic vulnerability, higher socio-economic sensitivity and lower adaptive capacity, respectively and vice versa on relative basis. Rankings for all villages in the Sindhudurg District are provided in Table S5

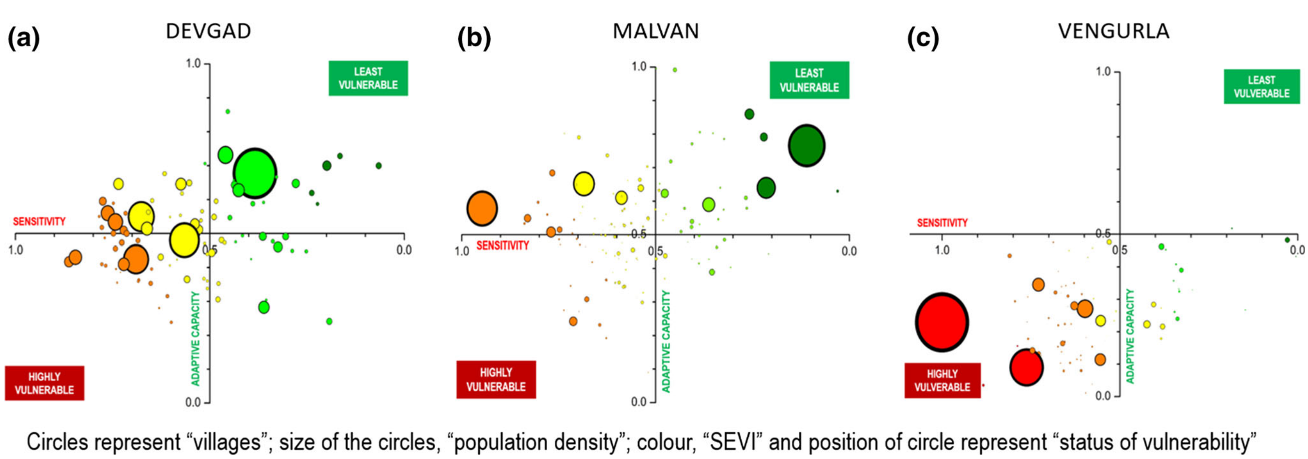


Fig. 7 Decision matrix for villages in **a** Devgad, **b** Malvan and **c** Vengurla Taluks in Sindhudurg by plotting SE-sensitivity indices (SI-R) against SE-adaptive capacity indices (ACI-R)

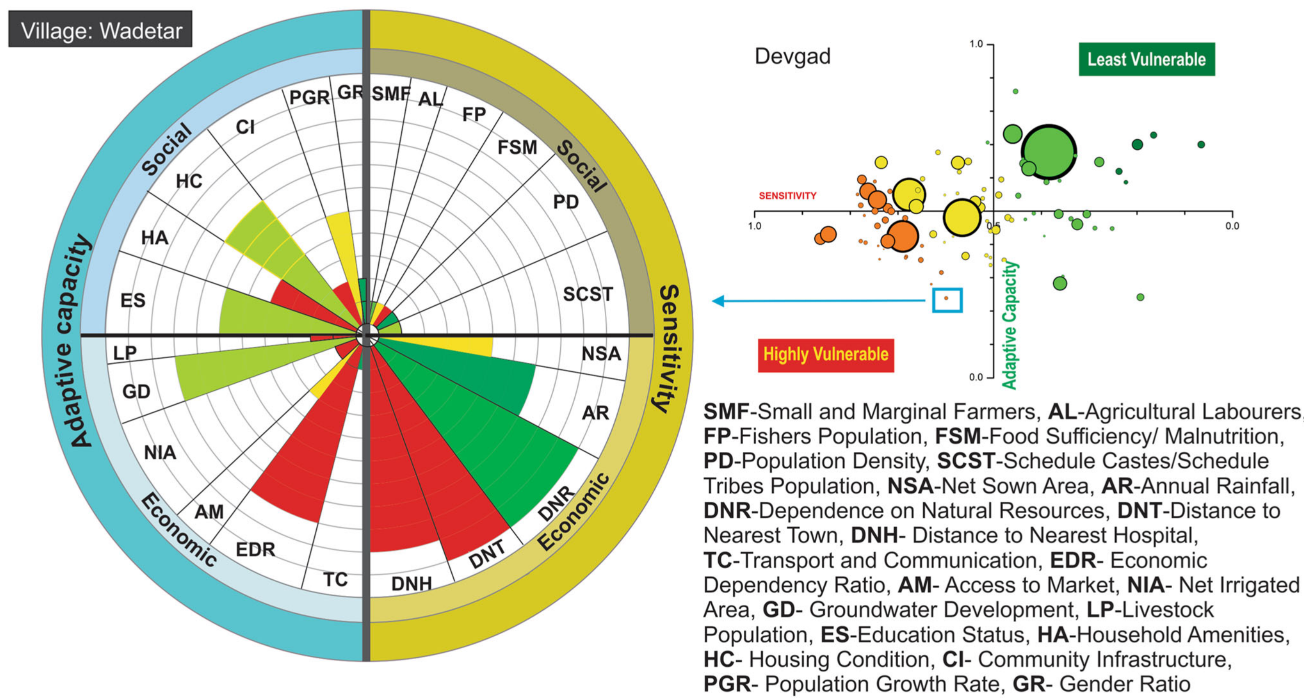


Fig. 8 Illustration of status of contributing factors for a representative village in Devgad for intervention planning (*red* most important, *green* least important)

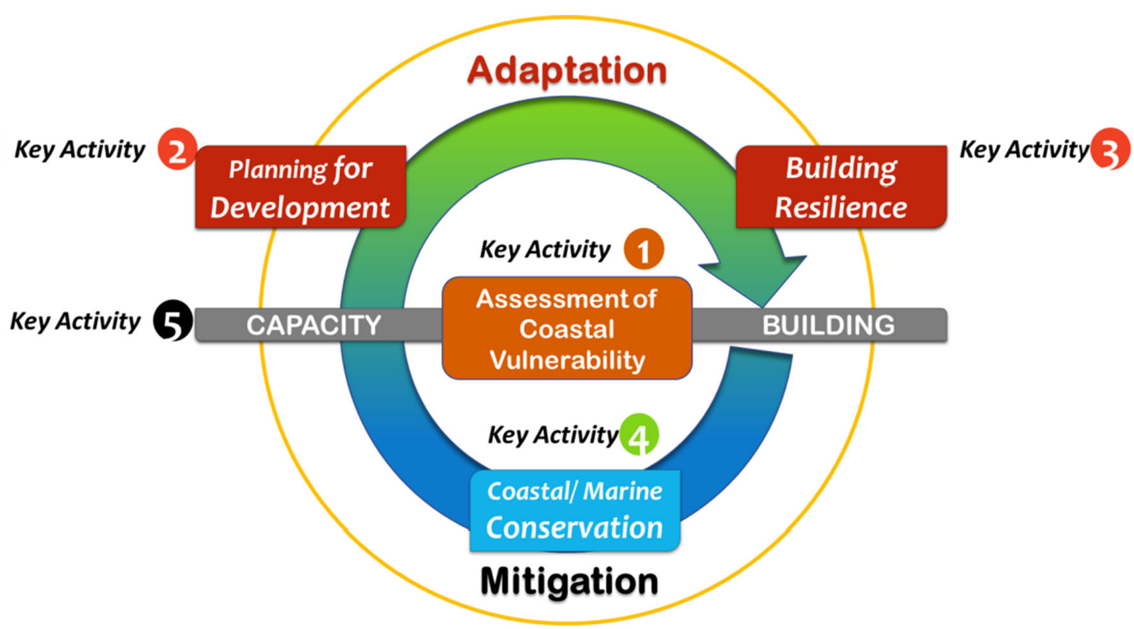


Fig. 9 Conceptual framework of the National Coastal Mission with focus on climate-change adaptation and mitigation (adopted from the National Coastal Mission, MoEFCC, GoI)

availability—most of the datasets are sourced from national data repositories and thus are reliable and scalable for the entire country; it also highlights the need to institutionalize collection of village-level data for a few indicators, for which currently the data are available at district level only, and (iv) cross-sectoral utility—though the framework is developed for the coastal region in India with special reference to climate-change impacts, the SEVI approach advocated in this paper can be appropriately used, for assessment of coastal vulnerability to factors other than climate change as well (*hazard-neutral*) and to plan location-specific interventions at the smallest administrative unit in India, i.e. the village/*gram Panchayat*.

The results of this study indicated that the current framework–developed with specific indicators for which datasets are available with the state and there exists an established institutional mechanism for periodic update—can be applied to capture the variation in the indicators at the village level. Thus, it is envisaged that the framework for assessing village-level socio-economic vulnerability can be scaled up to the entire coastal region of India and effectively integrated into the NCM, which has made vulnerability assessment as central to planning mitigation and adaptation strategies.

CONCLUSION

Coastal areas are vulnerable to development pressures as well as to climate-change impacts, exposing both human populations and ecosystems to climate-change impacts. As vulnerability is not static (Satapathy et al. 2014), there is a need to institutionalize its periodical assessment in the level of the spatial unit, at which interventions are planned, and also to strengthen the profile of indicators. The current study provides a framework for assessing the sensitivity and adaptive capacity of the coastal community to coastal hazards, which would help in identifying the most vulnerable community, for prioritized attention. Further, it also aids in identifying the contributing factors to the current status of vulnerability, designated in this study as “drivers” and “buffers”—the former being the areas for prioritized intervention for any adaptation action.

The current framework would provide the policy makers to prioritize target areas for intervention, plan appropriate interventions based on need, and thus aid in strengthening the implementation of the NCM launched by the Government of India as a sub-mission of NAPCC, which has made scientific assessment of coastal vulnerability, a prerequisite for adaptation and mitigation planning. The study demonstrates the feasibility of developing a national decision-making support system with the spatial maps and datasets available with the states, which are periodically updated and with the existing institutional mechanism in place in order to scale up this approach for the entire country and beyond.

Acknowledgements The framework developed in this study for assessment of coastal vulnerability was benefitted by the insights of Sh. V. Rajagopalan, the Former Secretary to Govt. of India, Ministry of Environment, Forests and Climate Change; Dr. Rabikumar, Secretary, National Biodiversity Authority, Government of India and Dr. S. Senthil Kumar, Indira Gandhi National Forest Academy, Dehradun. The study was funded by the Mangrove Cell of Maharashtra, under the UNDP’s Program, “Mainstreaming Coastal and Marine Biodiversity Conservation into Production Sectors in Sindhudurg Coast in Maharashtra”. The authors thank Professor Ramachandra Bhatta, Emeritus Professor, Indian Council of Agricultural Research, New Delhi; Dr. R. Soundararajan, MoEFCC-NCSCM, Chennai; Dr. B. Ganesh Kumar, ICAR-NAARM, Hyderabad; Dr. P.C. Mohanty, INCOIS, Hyderabad and S.P. Subash, ICAR-NCAP, New Delhi for their valuable inputs.

REFERENCES

Adger, W.N. 1999. Social Vulnerability to Climate Change and Extremes in Coastal Vietnam. *World Development* 27: 249–269.

Adger, W.N., and P.M. Kelly. 1999. Social vulnerability to climate change and the architecture of entitlements. *Mitigation and Adaptation Strategies for Global Change* 4: 253–266.

Ahsan, N.Md., and W. Jeroen. 2014. The socioeconomic vulnerability index: A pragmatic approach for assessing climate change led risks—A case study in the south-western coastal Bangladesh. *International Journal of Disaster Risk Reduction* 8: 32–49.

Amadore, L., W.C. Bolhofer, R.V. Cruz, R.B. Feir, C.A. Freysinger, S. Guill, K.F. Jalal, A. Iglesias, et al. 1996. Climate change vulnerability and adaptation in Asia and the Pacific: Workshop Summary. *Water, Air, and Soil Pollution* 94: 1–12.

Babanrao, N.D. 2011. Cashew cultivation in south Konkan of Maharashtra: A geographical analysis. PhD Thesis, Shivaju University, Kolhapur.

Blaikie, P., T. Cannon, I. Davis, and B. Wisner. 1994. *At Risk: Natural Hazards, People’s Vulnerability, and Disasters*. London: Routledge.

Bos, M.G., H. Van den Bosch, H. Diemont, H. Van Keulen, J. Lahr, G. Meijerink, and A. Verhagen. 2007. Quantifying the sustainability of agriculture. *Irrigation and Drainage Systems* 21: 1–15.

Central Intelligence Agency. 2018. *The World Factbook 2018*. Washington, DC: Central Intelligence Agency. https://www.cia.gov/library/publications/the-world-factbook/fields/2060.html. Accessed 8 September 2017.

Chandrasekar, N., V. Joevivek, and S. Saravanan. 2013. Coastal vulnerability and shoreline changes for southern tip of India—Remote sensing and GIS approach. *Journal of Earth Science and Climate Change* 4: 144.

CMIS Online. 2017. *Coastal Mgmt Info System*. https://mahammb.maharashtra.gov.in/1155/Geographic-Information-System-Portal. Accessed 2 Aug 2017.

Cronbach, L.J. 1951. Coefficient alpha and the internal structure of tests. *Psychometrika* 16: 297–334.

Cross, J.A. 2001. Megacities and small towns: Different perspectives on hazard vulnerability. *Environmental Hazards* 3: 63–80.

Cutter, S.L., B.J. Boruff, and W.L. Shirley. 2003. Social vulnerability to environmental hazards. *Social Science Quarterly* 84: 242–261.

Dale, V.H., and S.C. Beyeler. 2001. Challenges in the development and use of ecological indicators. *Ecological Indicators* 1: 3–10.

Dube, S.K., I. Jain, A.D. Rao, and T.S. Murty. 2009. Storm surge modelling for the Bay of Bengal and Arabian Sea. *Natural Hazards* 51: 3–27.

Dwarakish, G.S., S.A. Vinay, U. Natesan, T. Asano, T. Kakinuma, K. Venkataraman, J. Pai, and M.K. Babita. 2009. Coastal vulnerability assessment of the future sea level rise in Udupi Coastal Zone of Karnataka State, west coast of India. *Ocean and Coastal Management* 52: 467–478.

Esteves, T., D. Ravindranath, S. Beddamatta, K.V. Raju, J. Sharma, G. Bala, and I.K. Murthy. 2016. Multi-scale vulnerability assessment for adaptation planning. *Current Science* 110: 1225–1239.

Eguiguren-Velepucha, P.A., J.A.M. Chamba, N.A.A. Mendoza, T.L. Ojeda-Luna, N.S. Samaniego-Rojas, M.J. Furniss, C. Howe, and Z.H.A. Mendoza. 2016. Tropical ecosystems vulnerability to climate change in southern Ecuador. In *Tropical Conservation Science*, 1–17.

Fekete, A. 2009. Validation of a social vulnerability index in context to river-floods in Germany. *Natural Hazards and Earth System Sciences* 9: 393–403.

Ge, Y., W. Dou, Z. Gu, X. Qian, J. Wang, W. Xu, P. Shi, X. Ming, et al. 2013. Assessment of social vulnerability to natural hazards in the Yangtze River Delta, China. *Stochastic Environmental Research and Risk Assessment* 27: 1899–1908.

Gibbons, J.D., and S. Chakraborti. 2003. *Nonparametric statistical inference*. New York: Marcel Dekker, Inc.

Gómez-Limón, J.A., and G. Sanchez-Fernandez. 2010. Empirical evaluation of agricultural sustainability using composite indicators. *Ecological Economics* 69: 1062–1075.

Goswami, R. 2011. What Census 2011 reveals about our growers and their land. http://www.macroscan.org/anl/jun13/Census_2011.pdf. Accessed 22 July 2017.

Hegde, A.V., and V.R. Reju. 2007. Development of coastal vulnerability index for Mangalore Coast, India. *Journal of Coastal Research* 23: 1106–1111.

Hwang, C., and K. Yoon. 1981. *Multiple attribute decision making: Methods and Applications a state-of-the-art survey*. Berlin: Springer.

ICOR. 2015. *Report on the conference on climate change, coastal ecology and fisheries resources and livelihood in Maharashtra*. Mumbai: Institute of Community Organisation Research.

INCCA. 2010. *Climate change and India: A 4 × 4 Assessment—A sectoral and regional analysis for 2030s*. INCCA: Indian Network for Climate Change Assessment, Ministry of Environment and Forests, Government of India.

INCOIS. 2012. *Coastal vulnerability Atlas of India*. Hyderabad: Indian National Centre for Ocean Information Services.

IPCC. 2007. *Climate change (2007): Impacts, adaptation and vulnerability*. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge: Cambridge University Press.

IPCC. 2014. *Climate change 2014: Impacts, adaptation and vulnerability. Part A: Global and sectoral aspects*. Contribution of Working Groups I and II of the Intergovernmental Panel on Climate Change. Cambridge: Cambridge University Press.

Kumar, K.K.S., R.J.T. Klein, C. Ionescu, J. Hinkel, and R. Klein. 2007. *Vulnerability to poverty and vulnerability to climate change: Conceptual framework, measurement and synergies in policy*. Working Paper 19/2007. Chennai: Madras School of Economics.

Kumar, K.K., S.K. Patwardhan, A. Kulkarni, K. Kamala, K.K. Rao, and R. Jones. 2011. Simulated projections for summer monsoon climate over India by a high-resolution regional climate model (PRECIS). *Current Science* 101: 312–326.

Lee, Y.J. 2014. Social vulnerability indicators as a sustainable planning tool. *Environment Impact Assessment Review* 44: 31–42.

Lee, J.R., R. Maggini, M.F.J. Taylor, and R.A. Fuller. 2015. Mapping the drivers of climate change vulnerability for Australia's threatened species. *PLoS ONE*. https://doi.org/10.1371/journal.pone.0124766.

Li, X., J. Philp, R. Cremades, A. Roberts, L. He, L. Li, and Q. Yu. 2015. Agricultural vulnerability over the Chinese Loess Plateau in response to climate change: Exposure, sensitivity, and adaptive capacity. *Ambio* 45: 350–360. https://doi.org/10.1007/s13280-015-0727-8.

Livestock Census. 2012. Report on 19th Livestock Census-2012. Commissionerate of Animal Husbandry. http://farmer.gov.in/livestockcensus.aspx?Scode=11. Accessed 18 May 2017.

Long, S.J. 1983. *Confirmatory factor analysis: A preface to LISREL*. Sage University Paper series on quantitative applications in the social sciences, series no. 07-033. Thousand Oaks, CA: Sage Publications, Inc.

Mahendra, R.S., P.C. Mohanty, S.T. Kumar, S.S.C. Shenoi, and S. Nayak. 2010. Coastal multi-hazard vulnerability mapping: A case study along the Coast of the Nellore District, Andhra Pradesh, East Coast of India. *Italian Journal of Remote Sensing* 42: 67–76.

Mahendra, R.S., P.C. Mohanty, H. Bisoyi, S.T. Kumar, and S. Nayak. 2011. Assessment and management of coastal multi-hazard vulnerability along the Cuddalore–Villupuram, East Coast of India using geospatial techniques. *Ocean and Coastal Management* 54: 302–311.

Maiti, S., S.K. Jha, S. Garai, A. Nag, R. Chakravarty, K.S. Kadian, B.S. Chandel, K.K. Datta, et al. 2015. Assessment of social vulnerability to climate change in the eastern coast of India. *Climatic Change* 131: 287–306.

Marine Fisheries Census. 2010. Marine Fisheries Census 2010: Maharashtra. Part II (9). Kochi: Central Marine Fisheries Research Institute.

Mayer, D.G., and D.G. Butler. 1993. Statistical validation. *Ecological Modelling* 68: 21–32.

McCarthy, J.J., O.F. Canziani, N.A. Leary, D.J. Dokken, and K.S. White. 2001. *Climate change 2001: Impacts, adaptation, and vulnerability*. Cambridge: Cambridge University Press.

Moss, R.H., A.L. Brenkert, and E.L. Malone. 2001. *Vulnerability to climate change: A quantitative approach*. Oak Ridge: United States Department of Energy under Contract DE-AC06-76RLO 1830.

Murali, R.M., M. Ankita, S. Amrita, and P. Vethamony. 2013. Coastal vulnerability assessment of Puducherry Coast, India, using analytical hierarchical process. *Natural Hazards and Earth System Sciences* 13: 3291–3311.

NCM. 2016. *National Coastal Mission*. New Delhi: Ministry of Environment, Forest and Climate Change, Government of India.

Nijkamp, P., P. Rietveld, and H. Voogd. 1990. *Multicriteria evaluation in physical planning*. Amsterdam: Elsevier Science Publishers B.V.

NASA METI. 2011. Routine ASTER global digital elevation model. *NASA EOSDIS Land Processes DAAC*. https://doi.org/10.5067/aster/astgtm.002.

NASA JPL. 2013. NASA Shuttle Radar Topography Mission Global 1 arc second (Data set). *NASA EOSDIS Land Processes DAAC*. https://doi.org/10.5067/measures/srtm/srtmgl1.003.

Office of the Registrar General and Census Commissioner, India. 2001. *Census of India*. Office of the Registrar General and Census Commissioner, India, Ministry of Home Affairs, Government of India.

Office of the Registrar General and Census Commissioner, India. 2011. *Census of India*. Office of the Registrar General and Census Commissioner, India, Ministry of Home Affairs, Government of India.

NRSC. 2011. *Space based information support for decentralized planning (SIS-DP): Preparation of geo spatial layers using high resolution (Cartosat-1 Pan + LISS-IVMx) orthorectified satellite imagery, remote sensing and GIS applications area*. Hyderabad: National Remote Sensing Centre, Indian Space Research Organisation (ISRO), Department of Space, Government of India.

NRSC. 2014. *CartoDEM: A national digital elevation model from Cartosat 1 stereo data*. Hyderabad: National Remote Sensing Centre, Indian Space Research Organisation (ISRO), Department of Space, Government of India. http://www.http://bhuvan.nrsc.gov.in/data/download/tools/document/cartodem_bro_final.pdf. Accessed 7 Sep 2017.

O'Brien, K., S. Eriksen, A. Schjolden, and L.P. Nygaard. 2004. *What's in a word? Conflicting interpretations of vulnerability in climate change research*. CICERO Working Paper 2004:04. Oslo: Centre for International Climate and Environmental Research.

Ojwang', G.O., J. Agatsiva, and C. Situma. 2010. *Analysis of climate change and variability risks in the smallholder sector: Case studies of the Laikipia and Narok Districts representing major agro-ecological zones in Kenya*. Rome: Food and Agriculture Organization of the United Nations.

Palanisami, K., C. Ranganathan, S. Senthilnathan, and C. Umetsu. 2008. *Developing the composite vulnerability index relating to climate change for the different agro climatic regions of Tamilnadu*. FY2007 FR1 Project Report. Inter-University Research Institute Corporation, National Institutes for the Humanities, Research Institute for Humanity and Nature, Japan.

Patnaik, U., and K. Narayanan. 2009. *Vulnerability and climate change: An analysis of the eastern coastal districts of India*. Paper No. 22062. Munich Personal RePEc Archive, Germany.

Pelling, M., and J.I. Uitto. 2001. Small island developing states: Natural disaster vulnerability and global change. *Environmental Hazards* 3: 49–62.

Planning Commission. 2005. *Mid-term Appraisal of the Tenth Five Year Plan (2002–2007)*. New Delhi: Government of India. http://planningcommission.nic.in/plans/mta/midterm/english-pdf/chapter-17.pdf. Accessed 22 September 2017.

Ramasubramanian, V., A. Kumar, P. Bishop, P. Ramasundaram, and C.J. Jeeva. 2014. Applications of quantitative techniques in technology forecasting: Some case studies. In *Role of applied statistics in forestry research*, ed. H. Chandra, and G. Chandra. Dehradun: Indian Council of Forestry Research and Education.

Rani, S.N.N.V., A.N.V. Satyanarayana, and P.K. Bhaskaran. 2015. Coastal vulnerability assessment studies over India: A review. *Natural Hazards* 77: 405–428.

Rao, R.C.A., B.M.K. Raju, S.A.V.M. Rao, K.V. Rao, V.U.M. Rao, K. Ramachandran, B. Venkateswarlu, and A.K. Sikka. 2013. *Atlas on vulnerability of Indian agriculture to climate change*. Hyderabad: Central Research Institute for Dryland Agriculture.

Rao, N.K., P. Subraelu, V.T. Rao, B.H. Malini, R. Ratheesh, S. Bhattacharya, and A.S. Rajawat. 2009. Sea-level rise and coastal vulnerability: An assessment of Andhra Pradesh Coast, India through remote sensing and GIS. *Journal of Coastal Conservation* 12: 195–207.

Ravindranath, N.H., S. Rao, N. Sharma, M. Nair, R. Gopalakrishnan, A.S. Rao, S. Malaviya, R. Tiwari, et al. 2011. Climate change vulnerability profiles for North East India. *Current Science* 101: 384–394.

Rodríguez, E., C.S. Morris, and J.E. Belz. 2006. A global assessment of the SRTM performance. *Photogrammetric Engineering and Remote Sensing* 72: 249–260.

SAC-ISRO. 2012. *Coastal zones of India*. http://www.moef.nic.in/sites/default/files/Coastal_Zones_of_India.pdf. Accessed 25 May 2017.

Satapathy, S., I. Porsché, D. Rolker, S. Bhatt, S. Tomar, and S. Nair. 2014. *A framework for climate change vulnerability assessments*. Project on Climate Change Adaptation in Rural Areas of India (CCA RAI), New Delhi, India.

Saaty, T.L. 1990. *Multi-criteria decision making: The analytic hierarchy process*. Pittsburgh, PA: RWS Publications.

Saaty, T.L. 2001. The seven pillars of the analytic hierarchy process. In *Multiple criteria decision making in the new millennium: Lecture notes in economics and mathematical systems*, ed. M. Köksalan, and S. Zionts. Berlin: Springer.

Sehgal, V.K., M.R. Singh, A. Chaudhary, N. Jain, and H. Pathak. 2013. *Vulnerability of agriculture to climate change: District level assessment in the Indo-Gangetic Plains*. New Delhi: Indian Agricultural Research Institute.

Sehgal, V.K., M.R. Singh, N. Jain, and H. Pathak. 2017. Climate change and variability: Mapping vulnerability of agriculture using Geospatial Technologies. In *Agriculture under Climate Change: Threats, Strategies and Policies*, ed. V.V. Belavadi, N.N. Karaba, and N.R. Gangadharappa, 74–79. Allied Publishers Pvt. Ltd.

Sheng, Y., and Z. Sheng. 2012. Is coefficient alpha robust to non-normal data? *Frontier in Psychology* 3: 34.

Smith, P.G.R., and J.B. Theberge. 1987. Evaluating natural areas using multiple criteria: Theory and practice. *Environmental Management* 11: 447–460.

Sullivan, C., and J. Meigh. 2005. Targeting attention on local vulnerabilities using an integrated index approach: The example of the climate vulnerability index. *Water Science Technology* 51: 69–78.

TERI. 2003. *Coping with global change: Vulnerability and adaptation in Indian agriculture*. New Delhi: The Energy and Resource Institute.

TERI. 2014. *Assessing Climate Change vulnerability and adaptation strategies for Maharashtra: Maharashtra State Adaptation Action Plan on Climate Change (MSAAPC)*. Report 2010GW01. New Delhi: The Energy and Resources Institute Project.

Thornton, P.K., P.G. Jones, T. Owiyo, R.L. Kruska, M. Herrero, P. Kristjanson, A. Notenbaert, N. Bekele, et al. 2006. *Mapping climate vulnerability and poverty in Africa*. Nairobi: Report to the Department for International Development, ILRI.

Tran, L.T., R.V. O'Neill, and E.R. Smith. 2010. Spatial pattern of environmental vulnerability in the Mid-Atlantic region, USA. *Applied Geography* 30: 191–202.

Vincent, K. 2004. *Creating an index of social vulnerability for Africa*. Working Paper 56. Norwich: Tyndall Center for CC Research, University of East Anglia.

Vincent, K. and T. Cull. 2010. A household Social Vulnerability Index (HSVI) for evaluating adaptation projects in developing countries. In *Proceedings of PEGNet conference 2010: Policies to foster and sustain equitable development in times of crises*, Midrand.

Weis, S.W.M., V.N. Agostini, L.M. Roth, B. Gilmer, S.R. Schill, J.E. Knowles, and R. Blyther. 2016. Assessing vulnerability: An integrated approach for mapping adaptive capacity, sensitivity and exposure. *Climate Change* 136: 615–629.

Yin, J., Z. Yin, J. Wang, and S. Xu. 2012. National assessment of coastal vulnerability to sea-level rise for the Chinese coast. *Journal of Coastal Conservation* 16: 123–133.

Yusuf, A.A. and H. Francisco. 2009. *Climate change vulnerability mapping for Southeast Asia*. Economy and Environment Program for Southeast Asia (EEPSEA), Singapore.

Zhen, L., and J.K. Routray. 2003. Operational indicators for measuring agricultural sustainability in developing countries. *Environmental Management* 32: 34–46.

AUTHOR BIOGRAPHIES

Pandian Krishnan (✉) is a Principal Scientist in Research Systems Management and has undertaken research studies on diverse aspects *viz.*, coastal bio-resource conservation, coastal community-based resource management, conservation planning and policy, fisheries resource management and aquatic environment management.
Address: ICAR-National Academy for Agricultural Research Management (NAARM), Rajendra Nagar, Hyderabad, Telangana 500 030, India.
e-mail: krishnanars@yahoo.com

Pachampalayam Shanmugam Ananthan is a Social Scientist working in fisheries sector with multi-disciplinary research interests in fishers livelihoods, fisheries development and policy, extension systems, and ICT applications.
Address: ICAR-Central Institute of Fisheries Education (CIFE), Versova, Mumbai, Maharashtra 400 061, India.
e-mail: ananthanps@gmail.com

Ramachandran Purvaja leads the Futuristic Research Division at the National Centre for Sustainable Coastal Management. She is a Marine Biologist and Bio-geochemist by training and has undertaken extensive researches related to coastal zone management, climate change, nutrient modelling, ecosystem modelling, conservation planning, environmental-impact assessment and natural resource management.
Address: National Centre for Sustainable Coastal Management (NCSCM), Ministry of Environment Forest and Climate Change, Govt. of India, Anna University Campus, Guindy, Chennai 600 025, India.
e-mail: purvaja.ramachandran@gmail.com

Jeyapaul Joyson Joe Jeevamani is a Marine Biologist by training and serves as a Project Scientist at the National Centre for Sustainable Coastal Management (NCSCM). His core expertise includes coastal resource management, evidence-based conservation planning, and community-based resource management.
Address: National Centre for Sustainable Coastal Management (NCSCM), Ministry of Environment Forest and Climate Change, Govt. of India, Anna University Campus, Guindy, Chennai 600 025, India.
e-mail: joyjoejee87@yahoo.com

John Amali Infantina is a Doctorate in Fisheries Economics and serves as a Project Scientist at the National Centre for Sustainable Coastal Management (NCSCM). She has done research on socio-economic status of the coastal fishers, alternative livelihood management for the coastal community and resource management.
Address: National Centre for Sustainable Coastal Management (NCSCM), Ministry of Environment Forest and Climate Change, Govt. of India, Anna University Campus, Guindy, Chennai 600 025, India.
e-mail: amaliinfantina@gmail.com

Cherukumalli Srinivasa Rao is the Director of ICAR-National Academy for Agricultural Research Management. His research interests are climate change, contingency planning, soil carbon sequestration, rainwater management, climate-resilient villages, rainfed mission development and climate-and-conservation policy.
Address: ICAR-National Academy for Agricultural Research Management (NAARM), Rajendra Nagar, Hyderabad, Telangana 500 030, India.
e-mail: cherukumalli2011@gmail.com

Arur Anand is a Fishery Biologist by training and an Expert in GIS and Remote Sensing. He serves as a Scientist in the Laboratory of Indian Space Research Organization (ISRO). His research interests include fisheries resource management, spatial planning, decision-support systems and conservation planning.
Address: Regional Remote Sensing Centre (NRSC-RRSC), Indian Space Research Organization (ISRO), Nagpur 440 010, India.
e-mail: anand_isro@rediffmail.com

Ranganalli Somashekharappa Mahendra serves as a Scientist at INCOIS and is an Expert in Marine Geology and Geo-informatics. His research interests include coastal geospatial applications pertaining to coastal zone and oceanography with special reference to coastal multi-hazard vulnerability, mapping coastal resources like coral reef and mangroves and shoreline change assessment.
Address: Indian National Centre for Ocean Information Services (INCOIS), Ministry of Earth Sciences, Govt. of India, Hyderabad 500 090, India.
e-mail: mahendra@incois.gov.in

Iyyapa Sekar is a Principal Scientist in Agricultural Economics and Heads the Division of Research Systems Management at ICAR-NAARM. His core expertise pertains to micro-economics, natural resource management and impact assessment, agricultural technology and policy research, and research systems management.
Address: ICAR-National Academy for Agricultural Research Management (NAARM), Rajendra Nagar, Hyderabad, Telangana 500 030, India.
e-mail: sekariyyapa@naarm.org.in

Kalakada Kareemulla is a Principal Scientist in Agricultural Economics and serves in the Division of Research Systems Management at ICAR-NAARM. His core research interests are project management, agricultural finance, agribusiness management, natural resource economics, policy and institutional analysis, impact assessment and watershed development.
Address: ICAR-National Academy for Agricultural Research Management (NAARM), Rajendra Nagar, Hyderabad, Telangana 500 030, India.
e-mail: kalakareem@gmail.com

Amit Biswas is a Statistician by training and serves as a Professor in the Indian Statistical Institute. He offers courses in M.Stat. Program and his core expertise is in applied statistics, mathematics and operational research. He is an Expert in Mathematic and Statistical Modelling.
Address: Indian Statistical Institute-Chennai Centre, Ministry of Statistics and Programme Implementation, Government of India, Chennai 600 029, India.
e-mail: amit_biswas@hotmail.com

Regulagedda Kalpana Sastry is the Joint Director of the ICAR-National Academy for Agricultural Research Management. Her research interests include agricultural innovations, intellectual property and technology management systems; policy issues in agricultural research management and capacity building.
Address: ICAR-National Academy for Agricultural Research Management (NAARM), Rajendra Nagar, Hyderabad, Telangana 500 030, India.
e-mail: kalpanas.regulagedda@gmail.com

Ramachandran Ramesh is the Director at the National Centre for Sustainable Coastal Management and also serves as Chair, Global Partnership on Nutrition Management (GPNM). He has undertaken various trans-disciplinary research studies for national and international agencies on areas spanning coastal vulnerability, socio-economic development, coastal/marine conservation, spatial planning, land-based pollution, island management, integrated coastal zone management and climate change.
Address: National Centre for Sustainable Coastal Management (NCSCM), Ministry of Environment Forest and Climate Change, Govt. of India, Anna University Campus, Guindy, Chennai 600 025, India.
e-mail: rramesh_au@yahoo.com