Theoretical and Applied Climatology (2025) 156:409
https://doi.org/10.1007/s00704-025-05623-8

RESEARCH

Assessment of climate change vulnerability of agriculture in coastal districts of India using principal component analysis and entropy-based methods

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Received: 26 February 2025 / Accepted: 18 June 2025 / Published online: 5 July 2025

Abstract

Agricultural communities are facing a higher level of vulnerability as a result of the emerging challenges posed by climate change. Climate change-related stressors are adversely impacting agricultural production and food security. Developing region-specific climate-smart strategies demands an integrated climate change vulnerability assessment in agriculture considering regional disparities. This study aimed to evaluate climate change vulnerability of agriculture in the coastal districts of India. A comprehensive set of district-wise 30 indicators concerning sensitivity, exposure, and adaptive capacity indicators was systematically gathered for this region. The indicators were normalized using a linear scoring technique and their relative weights were determined using both entropy and principal component analysis (PCA). Subsequently, the normalized indicators were multiplied by their respective weights, resulting in the computation of sensitivity, exposure, and adaptive capacity indices which were, in turn, used for the vulnerability index calculation for each district. Entropy and PCA methods are completely data-driven and do not require additional inputs beyond the dataset itself making the analysis free from expert opinion bias. The results indicated that entropy is a better method for weight assignment as compared to PCA as it dynamically adjusts weights based on the distribution and uncertainty of the data, ensuring that indicators with significant variations receive more importance. So, this method was more sensitive to regional variations, making it a preferred approach for differentiating vulnerabilities among the districts. Based on entropy analysis, Kachchh (0.3183) is found to be the most vulnerable, whereas Uttara Kannada (0.0263) is the least vulnerable district of coastal India. The average vulnerability for the entire coastal region of India is calculated at 0.1148. PCA analysis too, ranked Kachchh (0.2146) as the most vulnerable district and Ganjam (0.0506) as the lowest vulnerable district with a mean vulnerability of 0.1311 for the entire coastal region. These findings can be used for targeted strategies and development activities in climate-vulnerable areas to facilitate effective adaptation measures.

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1 Introduction

Climate change is significantly impacting the global economy and food security. Global surface temperature has already increased by 1.1 °C and is projected rise between 1.4 and 4.4 °C by 2100 according to the various shared socio-economic pathways (SSPs) (IPCC 2022, 2023). Consequently, mean sea levels are expected to rise between 0.28 and 1.88 m by 2100 relative to 1995–2014 (IPCC 2022). The frequency and intensity of extreme weather events are also supposed to increase (Mishra et al. 2011). Coastal regions rank among the most densely populated areas worldwide, housing approximately 37% of the global population at a density that is twice the global average (Kummu et al. 2016) and play a crucial role in fostering sustainability and driving a nation's economy (Hauer et al. 2019). India has a coastline of about 7500 km which hosts approximately 40% of its population within a range of 100 km (Rehman et al. 2021). However, these regions are highly vulnerable to multiple hazards like droughts, cyclones, floods, storm surges, salinity intrusion, changes in rainfall patterns, sea surface temperature and rising sea levels (Mondal et al. 2020, 2024, 2025). India already faces nearly 10% of the world's tropical cyclones and nearly 340 million individuals are annually impacted by the severity of cyclonic events (Pelli et al. 2023). Various studies have reported a rise in the frequency of tropical cyclones in the Bay of Bengal due to rise in sea surface temperature caused by global warming over the past five decades causing substantial economic and human losses (Hirano 2021; Mishra et al. 2023, 2024). The anticipated rise in such extreme events coupled with heat and water stress, will negatively impact agriculture and allied sectors thereby impacting the livelihood of coastal communities (IPCC et al. 2023; Baraj et al. 2024). Sea-level rise leads to coastal erosion and saline water intrusion making the soil as well as groundwater saline leading to soil degradation (Hossain et al. 2022). Future climate change may further shrink coastal area thus area under food production leading to disparities in food availability and elevated undernourishment levels (Shukla et al. 2018; Maja and Ayano 2021; Singh et al. 2023).

Vulnerability assessment serves as a vital tool for recognizing, measuring, and ranking the vulnerability of a system which refers to the propensity or predisposition to be adversely affected by climate change (IPCC 2022). Measuring agricultural vulnerability to climate change requires quantifying exposure, sensitivity, and adaptation indicators (Wiréhn et al. 2015; Li et al. 2016). Exposure refers to the nature and degree to which a system is subjected to climatic variations and extremes, such as temperature and precipitation changes, and extreme weather events (IPCC 2022). Studies have shown that regions with high exposure to these climatic factors face significant risks to crop yields and agricultural productivity (Lobell and Gourdji 2012). Sensitivity is assessing the degree to which a system is affected by climate change or variability (IPCC 2001, 2007, 2022). Adaptation refers to the process of adjustment to actual climatic conditions and its impact (IPCC 2022). Quantifying these indicators requires integrating biophysical measures such as rainfall, drought, soil organic carbon content, groundwater availability land degradation etc. and socioeconomic measures such as illiteracy, population density, rural road connectivity and human development index (Wiréhn et al. 2015).

Various approaches like index-based methods, indicator-based approaches, GIS-based decision support systems and dynamic computer models-based methods have been used to evaluate climate change vulnerability (Ramieri et al. 2011). Sehgal et al. (2013) mapped agricultural vulnerability for the 161 districts in the Indo-Gangetic Plains (IGP) using the analytical hierarchy process (AHP) indicating higher vulnerability of eastern and southern parts of Uttar Pradesh and Bihar as compared to Punjab and Haryana. Principal component analysis (PCA) is another well-received approach used for socio-ecological vulnerability mapping under climate change (Abson et al. 2012; Maiti et al. 2017). PCA integrated with expert opinions has also been used in analyzing sector-wise (agriculture, forest, and water) vulnerability at the district level in North East India (Ravindranath et al. 2011). Similarly, Kumar et al. (2016) developed a district-level vulnerability index of Karnataka state using environmental and socio-economic indicators. Rao et al. (2016) assessed the district-wise vulnerability on a much larger scale (India level) using 38 indicators (2001 census data) with weights assigned by experts. Their results highlighted that Rajasthan, Gujarat, Uttar Pradesh, Madhya Pradesh, Karnataka and Maharashtra were having the majority of the districts with high vulnerability. Brown et al. (2018) employed a vulnerability-focused and decision-centric framework to assess the future vulnerability of coastal areas in response to storm occurrences. Kumar et al. (2010) mapped the vulnerability of coastal areas of Orissa using risk variables derived from satellite data and numerical models.

Adopting an integrated approach to agricultural vulnerability assessment is essential in a nation like India, which is marked by high susceptibility and inadequate adaptation capacity in the face of climate change concerns (Panda 2009). Though climate change is a global phenomenon, its manifestations and consequences vary locally. Therefore, it is crucial to develop mitigation and adaptation strategies tailored to the specific needs and priorities of local communities. So, there is a necessity for a comprehensive assessment of agriculture vulnerability to climate change, with a specific focus on the Indian coastal region, to facilitate the formulation of effective mitigation and adaptation strategies. Prior research has predominantly relied on subjective expert opinions for indicator weights assignment. This method has several limitations, including dependence on expert availability and bias, variable count, and time for obtaining responses (Sendhil et al. 2018). The novelty of the current study is that we have compared two data-driven weight assignment methods namely PAC and entropy for regional vulnerability analysis. Further, soil health indicators such as soil organic carbon content, soil erosion, and land degradation which are very important for agriculture yet underrepresented in previous literature is another key novelty of this study. Therefore, the aims of the current study were (i) to compare PCA and entropy based objective approach for assigning weights to 30 diverse indicators related to exposure, sensitivity, and adaptation in order to create a composite vulnerability index for coastal districts of India, (ii) to identify most vulnerable coastal districts to climate change and (iii) to facilitate the development of efficient mitigation and adaptation strategies customized to the specific needs and priorities of Indian coastal region. The major contributions of the current study may be the balanced representation of 30 indicators covering important climatic, demographic, soil and socioeconomic determinants of vulnerability with comparative analysis of two objective weighting techniques i.e. PCA and entropy, addressing inconsistencies in previous studies that relied on subjective approaches. The district-level vulnerability map will enable location-specific resource allocation and planning of adaptation and mitigation strategies, which are often lacking in broader regional or state-level analyses.

2 Materials and methods

2.1 Study area

The mainland coastline of India encompasses nine coastal states that extend along the Arabian Sea and the Bay of Bengal. Gujarat, Maharashtra, Goa, Karnataka, and Kerala reside on the western coast while the eastern side is home to West Bengal, Odisha, Andhra Pradesh, and Tamil Nadu. The east and west coasts of India exhibit distinct physiographic, climatic, and ecological differences. Bordering the Bay of Bengal, the east coast primarily has flat terrain with fertile soil made of large deltas formed by rivers such as Ganga, Mahanadi, Godavari, and Krishna, hence highly suitable for agriculture. It receives rainfall from both southwest and northeast monsoons and experiences more frequent cyclones. In comparison, the west coast along the Arabian Sea, has more rugged and rocky terrain with several estuaries and lagoons intersected by the Western Ghats. Though it has a more stable climate with lower cyclone frequency, the west coast experiences heavy rainfall from the southwest monsoon leading to loss of fertile soil through erosion. These variations in structure, fertility, and climatic factors create the unique agricultural, economic, and environmental characteristics of the two regions. This study took into account 61 coastal districts directly bordering the sea in all these nine states of India. The local population sustains their livelihoods through agriculture, fishing as well as activities related to shipping.

2.2 Vulnerability analysis

In this study, we adopted an indicator-based approach by meticulously selecting 30 indicators for each category of exposure, sensitivity, and adaptive capacity. These selections were made following an extensive review of published research reports (O'Brien et al. 2004; Brooks et al. 2005; Gbetibouo and Ringler 2009; Ravindranath et al. 2011; Abson et al. 2012; Hiremath and Shiyani 2013; Sehgal et al. 2013; Monterroso et al. 2014; Newton and Weichselgartner 2014; Rao et al. 2016), expert consultations, and data availability. The indicators were selected to represent multiple dimensions of vulnerability, including climatic, socio-economic, and agricultural factors.

2.2.1 Exposure indicators

A total of eleven exposure indicators were considered in the vulnerability assessment of Indian coastal districts based on primary meteorological factors, including precipitation and temperature extremes, and critical hazards such as cyclones and drought, as key indicators (Table 1). The temperature and rainfall related parameters were calculated using India Meteorological Department (IMD) daily gridded temperature ($1 \times 1°$) and rainfall ($0.25 \times 0.25°$) data for the period 1951–2018 and 1901–2018, respectively (Srivastava et al. 2009; Pai et al. 2014). The daily data was converted to monthly data using mean and sum for temperature and rainfall, respectively. The average monthly minimum and maximum temperature for the months June, July, August and September was designated as *kharif* season while the mean of November, December, January, February and March months were designated as *rabi* season. Non-parametric Sen's slope estimator was used to calculate the rate of change in maximum and minimum temperature during *kharif* and *rabi* seasons. The daily rainfall data was used to calculate the frequency of very heavy and extremely heavy rainy days while frequency of excess rainfall, moderate and severe drought years were computed based on mean annual rainfall data. The information on number of cyclones

Table 1 List of sensitivity, exposure and adaptive capacity indicators

Sr. No.	Indicators	Unit	Functional relationship	Data source
Exposure Indicators				
1.	Rate of change in maximum temperature during *kharif*	°C per year	+ve	India Meteorological Department (IMD)
2.	Rate of change in maximum temperature during *rabi*	°C per year	+ve	IMD
3.	Rate of change in minimum temperature during *kharif*	°C per year	+ve	IMD
4.	Rate of change in minimum temperature during *rabi*	°C per year	+ve	IMD
5.	Frequency of very heavy rainy days	Total number of days receiving rainfall between 124.5 to 244.5 mm during 1901–2018	+ve	IMD
6.	Frequency of extremely heavy rainy days	Total number of days receiving rainfall greater than 244.5 mm during 1901–2018	+ve	IMD
7.	Frequency of excess rainfall years	Total number of years receiving annual rainfall $\geq$ 120% of normal rainfall	+ve	IMD
8.	Frequency of moderate drought years	Total number of years receiving annual rainfall between 26–50% of normal rainfall	+ve	IMD
9.	Frequency of severe drought years	Total number of years receiving annual rainfall $<$ 50% of normal rainfall	+ve	IMD
10.	Variability in annual rainfall	Coefficient of variation of annual rainfall (%)	+ve	IMD
11.	Number of cyclones	Number of cyclones reaching coastal districts	+ve	Mohapatra et al. (2015) and reported cases
Sensitivity indicators				
12.	Human density	Persons km^{-2}	+ve	Population Census Reports 2011
13.	Illiterate population	Percentage of illiterate population	+ve	Population Census Reports 2011
14.	Organic C content of soil (SOC)	$g\ kg^{-1}$	-ve	Food and Agriculture Organization (FAO) soil map
15.	Water holding capacity of soil (TAWC)	$cm\ m^{-1}$	-ve	FAO soil map
16.	Groundwater availability	ha-m	-ve	Central Ground Water Board (CGWB)
17.	Groundwater development stage	% annual draft over the annual recharge	-ve	CGWB
18.	Soil erosion	$kg\ ha^{-1}\ yr^{-1}$	+ve	National Bureau of Soil Survey & Land Use Planning
19.	Land degradation	000 ha	+ve	Maji et al. (2010)
20.	Food grain yield	$kg\ ha^{-1}$	-ve	Directorate of Economics and Statistics (DES) Respective State Reports
Adaptive capacity indicators				
21.	Livestock density	Number of livestock per km^2	-ve	Livestock Census 2012
22.	Forest cover	% of total geographical area (TGA)	-ve	Forest Survey of India (2012–2013)
23.	Frequency of years with normal rainy days	Number of years having rainy days between 81–119% of yearly normal rainy days	-ve	IMD
24.	Fertilizer (NPK) consumption	$kg\ ha^{-1}$	-ve	DES Respective State Reports
25.	Net irrigated area	% of TGA	-ve	DES Respective State Reports
26.	Net sown area	000 ha	-ve	DES Respective State Reports
27.	Cropping intensity	(GCA/NSA) × 100%	-ve	DES Respective State Reports
28.	Rural road connectivity	% of Habitations	-ve	District Census Hand Book 2011
29.	Villages electrified	% of Habitations	-ve	District Census Hand Book 2011
30.	Human development index	0–1	-ve	UNDP

between 1891 and 2021 was collected from (Mohapatra et al. 2015) and reported cases.

2.2.2 Sensitivity indicators

We considered both short-term and long-term variables affecting agricultural vulnerability. The study selected a total of nine parameters, which directly or indirectly influence agriculture and thereby food security. These parameters include soil health, water availability, crop yields, human density and illiterate population (Table 1).

2.2.3 Adaptive capacity indicators

The parameters representing the social, ecological, and infrastructural status of the coastal region influencing agriculture directly or indirectly are regarded as indicators of adaptive capacity. A total of ten indicators of adaptation including livestock density, forest cover, fertilizer consumption, human development index, net irrigated area, rural road connectivity, villages electrified, cropping intensity, net sown area and frequency of years with normal rainy days were selected in the study (Table 1). Data on sensitivity, exposure and adaptive capacity indicators were collected for coastal districts of India. The details of the indicators namely their units, functional relationship and the source are provided in Table 1.

2.2.4 Data normalization

The indicators were normalized using linear scoring technique (Si). Normalization makes the values for each parameter to range between 0.1 and 1 and thus making them scale independent. For positive and negative functional relationship of indicators with vulnerability, the formula presented in Eqs. 1 and 2 were utilized for data normalization.

$$S_i = 0.1 + \frac{(x_i - x_{min})}{(x_{max} - x_{min})} \times 0.9 \tag{1}$$

(for positive functional relationship)

$$S_i = 1.1 - 0.1 - \frac{(x_i - x_{min})}{(x_{max} - x_{min})} \times 0.9 \tag{2}$$

(for negative functional relationship)

where x_i, x_{min} and x_{max} are the actual, minimum and maximum values of ith parameter, respectively. In case of min-max normalization, the values vary between 0 and 1. To avoid 0 indicator values, we have used scaled min-max normalization in our study.

2.2.5 Weight calculation

The indicators were weighted using two methods namely entropy-based method and principal component analysis (PCA) (Fig. 1). In entropy-based method, the weights for the individual indicators were calculated based on Shannon's entropy. The steps for calculation of Shannon's entropy weights are given below-.

The indicators were made scale independent by

$$p_{ij} = \frac{x_{ij}}{\sum_{j=1}^{m} x_{ij}} \tag{3}$$

where j = 1, 2,…, m alternatives i.e. districts and i = 1, 2,…, n indicators.

Shannon entropy was computed as

$$e_i = -\frac{1}{\ln(m)} \sum_{j=1}^{m} p_{ij} \ln p_{ij} \tag{4}$$

where $p_{ij} \ln p_{ij}$ is defined as 0 if $p_{ij} = 0$. The weights (W_i) of each indicator were calculated as

$$W_i = \frac{1 - e_i}{\sum_{i=1}^{n} (1 - e_i)} \tag{5}$$

For the PCA-based method, the weights (Wi) for individual indicators were calculated as the ratio of individual communality to cumulative communality, derived from the PCA ran using all 30 indicators as input. PCA and entropy methods were used in the current study to calculate weights as these methods are completely data-driven and do not require additional inputs beyond the dataset itself. The weights were then multiplied to the normalized parameters ($S_i \times W_i$). Subsequently, the product ($S_i \times W_i$) for all the parameters under respective indicators were summed up ($\sum S_i \times W_i$) to calculate sensitivity, exposure and adaptive capacity indices. The vulnerability index for each coastal district was calculated using Eq. 7 (Balaganesh et al. 2020; Rehman et al. 2021). The overall methodology adopted in the current study is presented in Fig. 1.

$$\begin{aligned} &\text{VulnerabilityIndex} = \\ &\text{ExposureIndex} + \text{SensitivityIndex} - \text{AdaptiveCapacityIndex} \end{aligned} \tag{6}$$

.

Fig. 1 Methodology flowchart for vulnerability assessment

3 Results

3.1 Entropy vs. PCA derived weight

The weights assigned to various indicators exhibited higher variability for the entropy method compared to the PCA method (Fig. 2). The weights were found to be highly variable ranging between 0 for electrified villages to 0.1193 for extremely heavy rainy days for entropy-based method. The indicators which may affect the vulnerability of agriculture to climate change got more weight through the entropy method. Parameters such as very heavy rainy days, drought, cyclones, land degradation, and soil erosion, which directly impact on agriculture, were assigned high weightage (>0.05), consistent with findings from previous studies (Rao et al. 2016; Hoque et al. 2019; Thirumurthy et al. 2022). Parameters with limited impacts on agriculture, such as total available water capacity (TAWC), frequency of years with normal rainy days, electrified villages, human development index, and rural road connectivity, were assigned lower weightage (w<0.01). In contrast, all the parameters were assigned weights within the range of 0.0213 to 0.0389 through PCA thereby limiting the difference in their importance to a very narrow range.

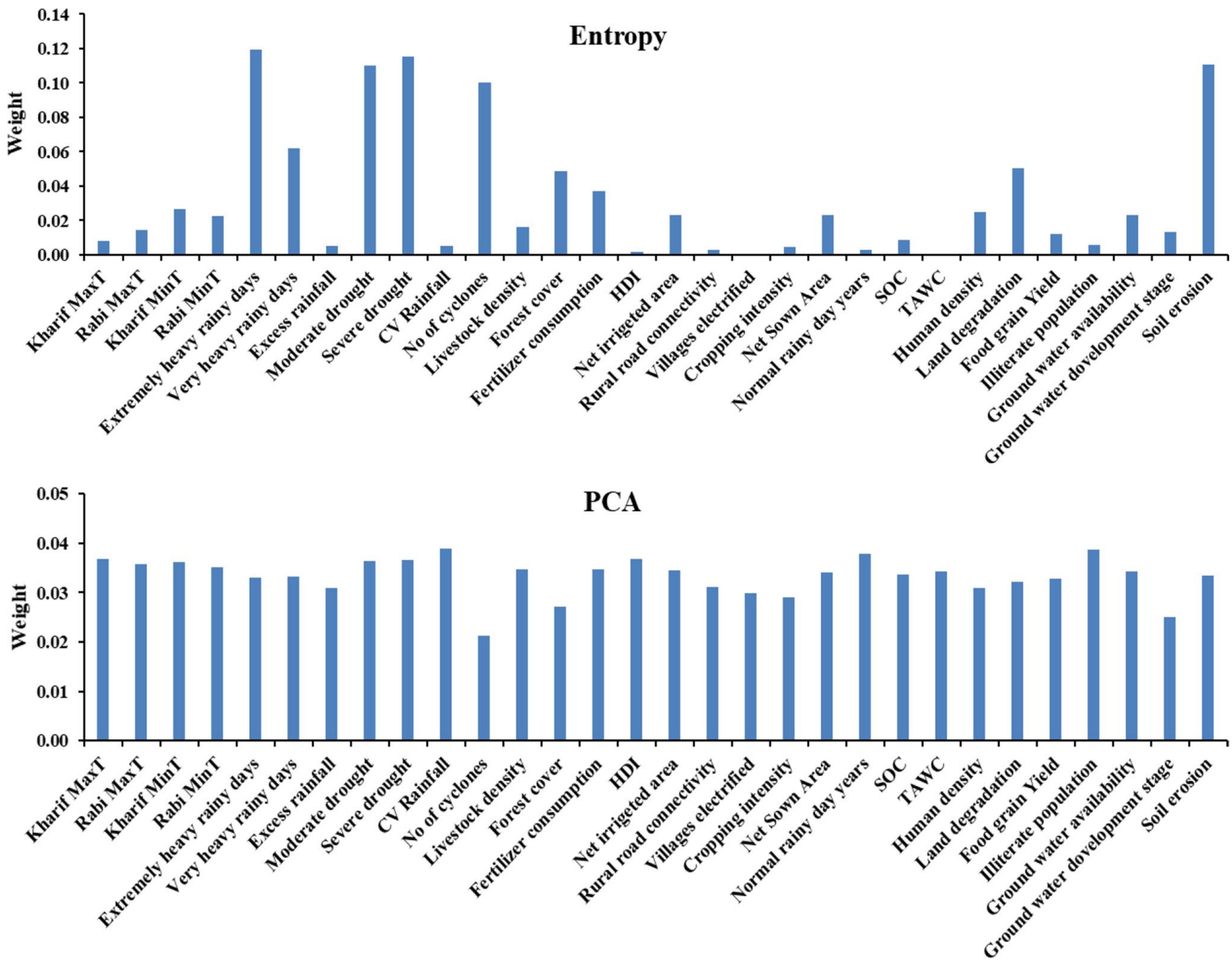

Fig. 2 Indicator weights calculated using entropy and PCA

3.2 Exposure

The exposure indicators used for PCA and entropy-based methods for coastal districts of India is presented in Fig. 3. The mean rate of change in maximum temperature during *kharif* and *rabi* were higher on the east coast (0.0148 and 0.0154 °C per year, respectively) than the west coast (0.0143 and 0.0148 °C per year, respectively) of India. On the east coast, the highest rate of change in maximum temperature during *kharif* and *rabi* season was observed in Thoothukudi (0.0232 °C per year) and Thiruvarur (0.0218 °C per year) districts of Tamil Nadu whereas on the west coast, it was observed in Thiruvananthapuram (0.0228 °C per year) and Udupi (0.0239 °C per year).

districts, respectively. Contrary to maximum temperature, the mean rate of change in minimum temperature during *kharif* and *rabi* was higher for the west coast (0.0073 and 0.0082 °C per year, respectively) than the east coast (0.0035 and 0.0062 °C per year, respectively). Junagadh showed the highest rate of change in minimum temperature during both the *kharif* and *rabi* seasons on the west coast. Conversely, Pudukkottai (0.0078 °C per year) and North 24 Parganas (0.0101 °C per year) districts on the east coast demonstrated the highest rate of change in minimum temperature during the *kharif* and *rabi* seasons, respectively.

The rainfall trends from 1901 to 2018 demonstrated that the west coast experienced significantly more very heavy rainy (124.5 to 244.5 mm) and extremely heavy rainy (>244.5 mm) days as compared to the east coast. Eight districts on the west coast received rainfall between 124.5 and 244.5 mm for more than 100 days compared to east coast where maximum number of very heavy rainy days was 64. The total number of very heavy and extremely heavy rainy days was the highest in Raigarh (341) and Navsari (8), respectively on the west coast. On the east coast, Nagapattinam accounted for the highest number of both extremely heavy (7) and very heavy (64) rainy days. During the period of 118 years (1901–2018), frequency of excess rainfall years

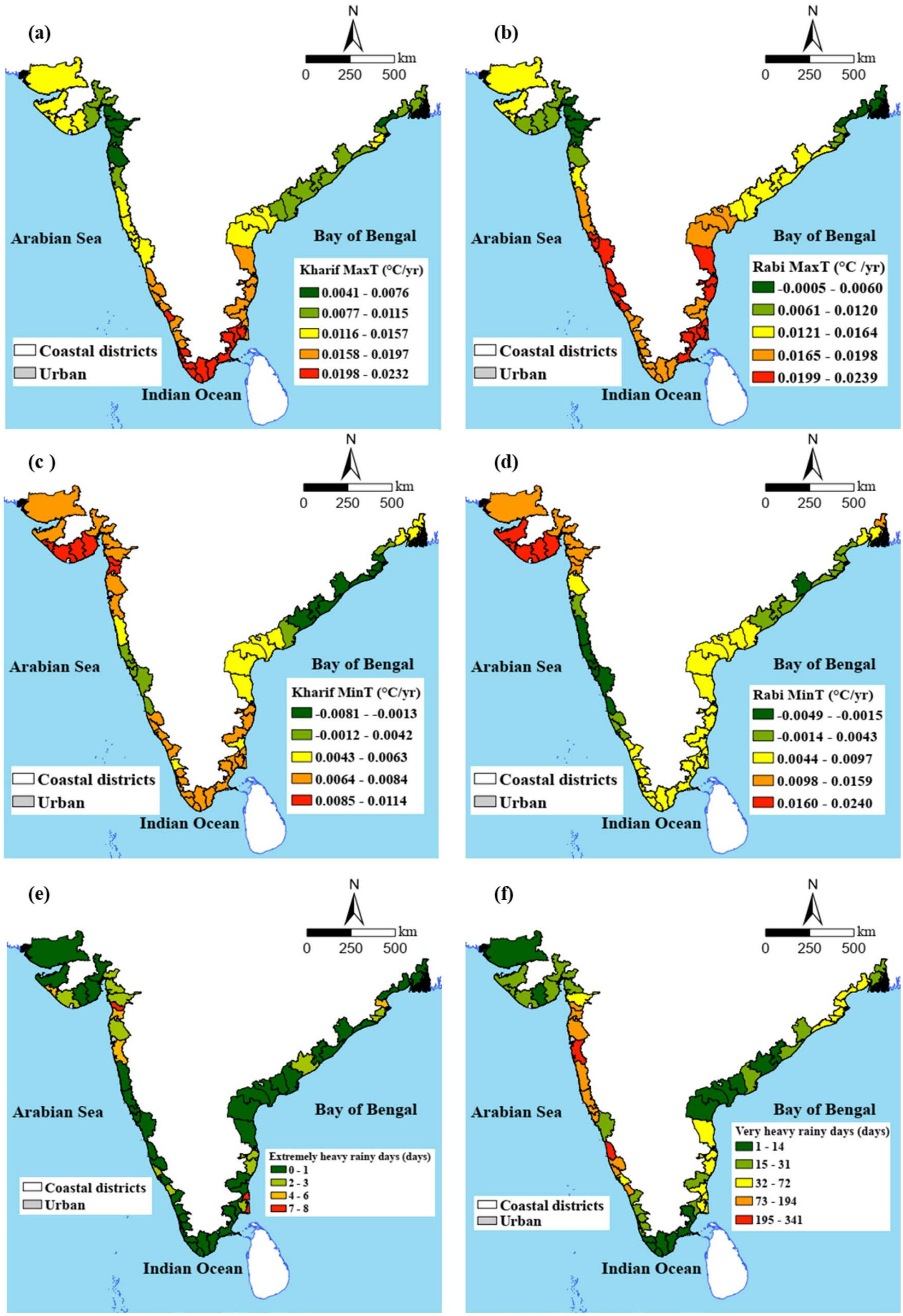

Fig. 3 District-wise exposure indicators for coastal region of India (**a**) Rate of change in maximum temperature during kharif, (**b**) Rate of change in maximum temperature during rabi, (**c**) Rate of change in minimum temperature during kharif, (**d**) Rate of change in minimum temperature during rabi, (**e**) Frequency of extremely heavy rainy days, (**f**) Frequency of very heavy rainy days, (**g**) Frequency of excess rainfall years, (**h**) Frequency of moderate drought years, (**i**) Frequency of severe drought years, (**j**) Variability in annual rainfall and (**k**) Number of cyclones

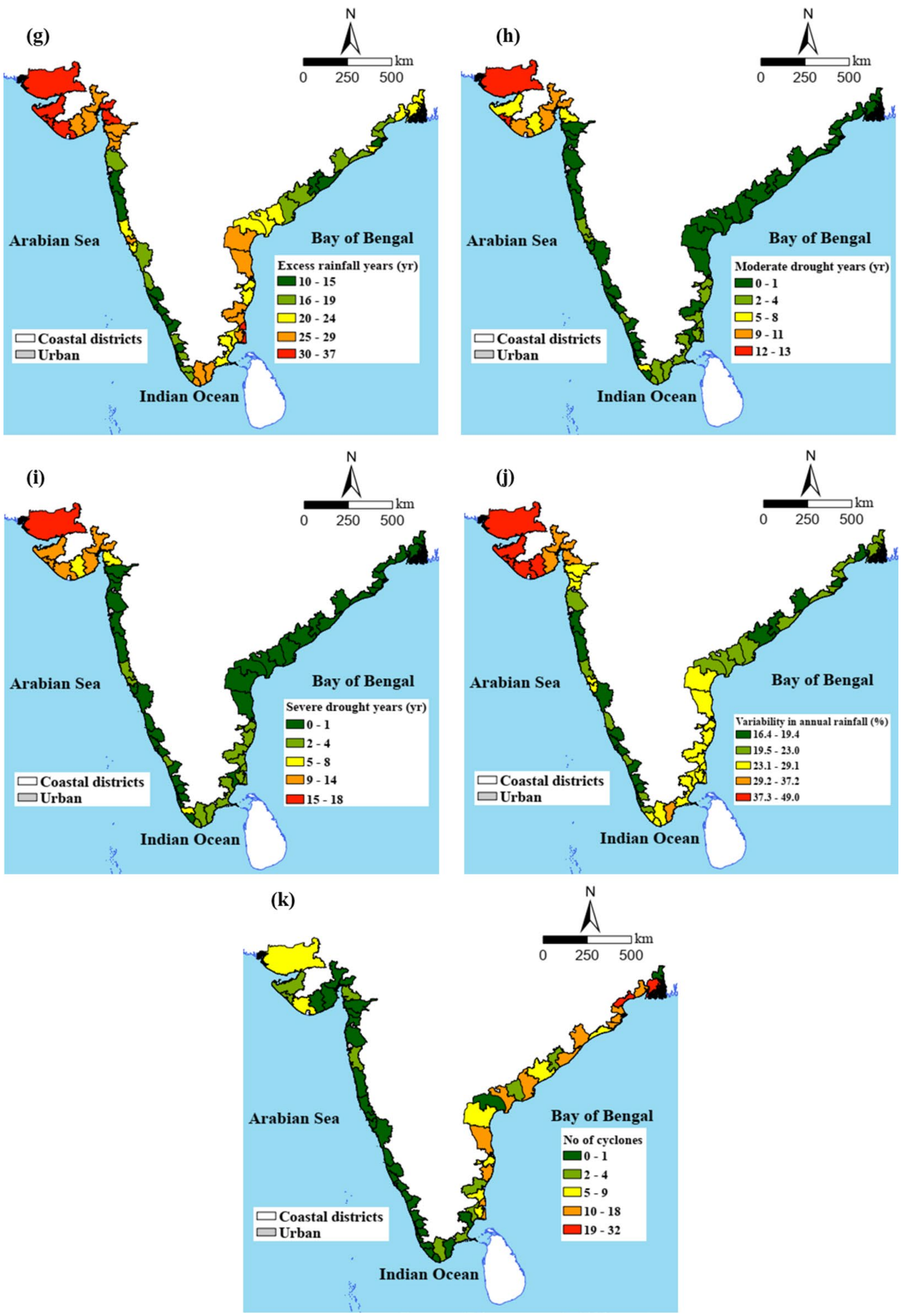

Fig. 3 (continued)

was the highest in Kachchh (37) district of Gujarat and Nagapattinam (31) district of Tamil Nadu on the west and east coast, respectively. This is due to the fact that Kachchh was having very less normal annual rainfall (402.3 mm) and in 37 years out of 118 years the annual rainfall was > 482.9 mm (i.e., 120% of 402.3 mm).

The analysis of rainfall patterns was also employed to examine drought trends, indicating that the west coast experiences a greater average number of moderate (3.6) and severe (4) drought years compared to the east coast (1.1 and 1.2, respectively). Kachchh district on the west coast faced the highest number of moderate (13) and severe drought (18) years, whereas, on the east coast, districts like Cuddalore, Nagapattinam and Thoothukudi in Tamil Nadu witnessed the highest number of moderate (4) and severe drought (4) years. The variability in annual rainfall was also higher on the west coast (26.70%) compared to the east coast (23.33%). In the western coast, Kachchh (49.01%) experienced the highest variability in annual rainfall, while Thoothukudi (32.55%) reported the highest variability in the eastern coast. In contrast to the above trends, the average number of cyclones between 1891 and 2021 was much higher on the east coast (09) as compared to the west coast (01). Along the east coast, thirteen districts experienced more than 10 cyclones with South 24 Parganas of West Bengal possessing the highest proneness to cyclone with the landfall of 32 cyclones during the period. On the west coast, only few districts were found as cyclone-prone, with Junagadh reporting the highest number (9) of cyclones.

The combination of these parameters was used to create an exposure map employing both entropy and PCA methods (Figs. 4 and 5). As per the entropy-based method, the average exposure of the entire Indian coastal belt was found to be 0.1440 with a standard deviation of 0.0849. Porbandar showed the highest exposure (0.3702) whereas Udupi (0.0367) showed the lowest exposure, both on the west coast. All districts in Gujarat exhibited very high exposure levels except for Surat which registered moderate exposure (0.1444). The remaining states along the west coast, namely Maharashtra, Goa, Karnataka, and Kerala displayed low to very low exposure of agriculture to climate change except Thane district of Maharashtra showing moderate exposure (0.1446). On the east coast, districts of Tamil Nadu showed the highest exposure ranging between moderate and very high (0.3035 − 0.1349). In Andhra Pradesh, four districts fell into the low category, four into moderate, and one into high exposure. In Odisha, the exposure ranged between low and high for two and four coastal districts, respectively. In West Bengal, two districts showed moderate exposure, whereas one district showed high exposure.

The PCA based analysis indicated that Porbandar was the highest (0.2652) and Vizianagaram was the lowest exposed (0.0886) district. The average and standard deviation of exposure for the entire coastal belt of India were 0.1583 and 0.0386, respectively. Similar to the entropy-based method, the districts of Gujarat demonstrated the highest exposure levels, with eight districts displaying very high exposure and one district showing high exposure levels. In Maharashtra, Goa and Karnataka, the exposure mainly remained between low and very low levels except for Sindhudurg (high exposure), North Goa and Dakshina Kannada districts (moderate exposure). In Kerala, the exposure varied between low and very high levels with two districts lying in high, six in moderate and one each in low and high exposure categories. On the east coast, the PCA method marked the districts of Tamil Nadu with higher exposure. All districts in Tamil Nadu, except for Kanniyakumari, fell into the high to very high exposure category. Prakasam and Nellore districts of Andhra Pradesh showed moderate exposure. Rest of the districts in all remaining states along the east coast-namely Andhra Pradesh, Odisha and West Bengal showed low to very low exposure levels.

3.3 Sensitivity

Sensitivity indicators used for PCA and entropy-based methods for coastal districts of India is presented in Fig. 6. The analysis of sensitivity parameters showed that the average human density was higher on the west coast (649.61 person km^{-2}) compared to the east coast (606.33 person km^{-2}). However, their distribution among districts varies greatly with the highest coastal human density found in North 24 Parganas (2500 person km^{-2}) on the eastern coast and the lowest in Kachchh (46 person km^{-2}) on the western coast. Nine districts on the west coast and only three districts on the east coast have higher human density (> 1000 person km^{-2}). The average percentage of the illiterate population in the coastal region (26.97%) is very close to the national average of 26% (Census of India, 2011). The percentage of the illiterate population was higher on the east coast (30.58%) than on the west coast (23.48%). Among the coastal states, Kerala had the lowest illiteracy rate at 15.27%, while Andhra Pradesh had the highest at 39.53%. The average soil organic carbon content (SOC) was slightly higher on the east coast (16.67 g kg^{-1}) compared to the west coast (13.91 g kg^{-1}) of India. Alappuzha and Kachchh showed the highest (48.15 g kg^{-1}) and lowest (6.57 g kg^{-1}) SOC values on the west coast, whereas, on the east coast, North 24 Parganas and Puri recorded the highest (30.1 g kg^{-1}) and lowest (8.73 g kg^{-1}) SOC values, respectively. The total available water content (TAWC) for the entire coastal region was 15.33 cm m^{-1} with both the east (15.41 cm m^{-1}) and west (15.25 cm m^{-1}) coasts having nearly similar TAWC.

The average groundwater availability on the east coast (101,995.56 ha-m) was nearly double that of the west coast (51,130.22 ha-m). The maximum and minimum groundwater availability were found in Prakasam (202389 ha-m) and South Goa (5989 ha-m) districts, respectively. The ground water development stage was higher on the east coast (58.83%) compared to the west coast (47.23%). The highest groundwater development was observed in Kanyakumari (119%) on the east coast, while the lowest was

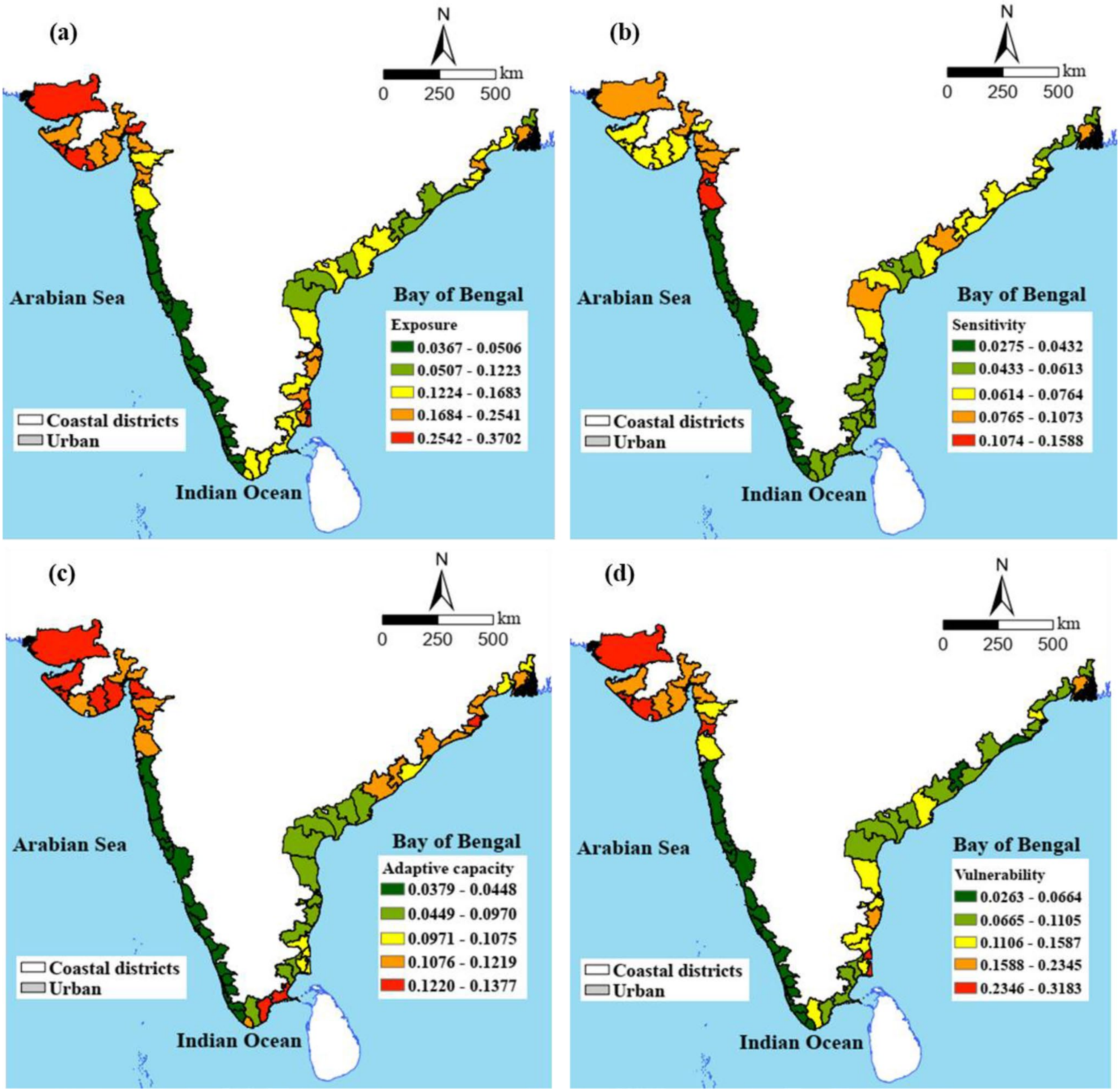

Fig. 4 (**a**) Exposure, (**b**) sensitivity, (**c**) adaptive capacity and (**d**) vulnerability of coastal districts of India obtained from entropy-based weights

found in Ratnagiri (11%) on the west coast. The average rate of soil erosion was found to be more than double on the west (322.70 kg ha^{-1} yr^{-1}) coast than that of the east coast (129.70 kg ha^{-1} yr^{-1}). Soil erosion exhibited a wide range, especially on the west coast where maximum and minimum values of soil erosion were 2621.09 and 9.56 kg ha^{-1} yr^{-1} in Raigarh and Kachchh districts, respectively. On the east coast, soil erosion varied between 16.77 kg ha^{-1} yr^{-1} (Puri) and 624.95 kg ha^{-1} yr^{-1} (Vizianagaram). Land degradation was also found to be higher on the west coast (208.35 thousand ha) than east coast (138.44 thousand ha). Raigarh exhibited the highest coastal land degradation on the west coast (615 thousand ha), while on the east coast, Prakasam had the highest land degradation (590 thousand ha). The average food grain yield was higher in the west (2345 kg ha^{-1}) coast in comparison to the east coast (2069 kg ha^{-1}). The highest and lowest coastal food grain yield was found in the eastern coastal districts of Thoothukudi (4945 kg ha^{-1}) and Visakhapatnam (258 kg ha^{-1}), respectively. On west coast, the highest and lowest food grain yield was found in Junagadh (3554 kg ha^{-1}) and Kachchh (1094 kg ha^{-1}) districts of Gujarat, respectively. All of these parameters were

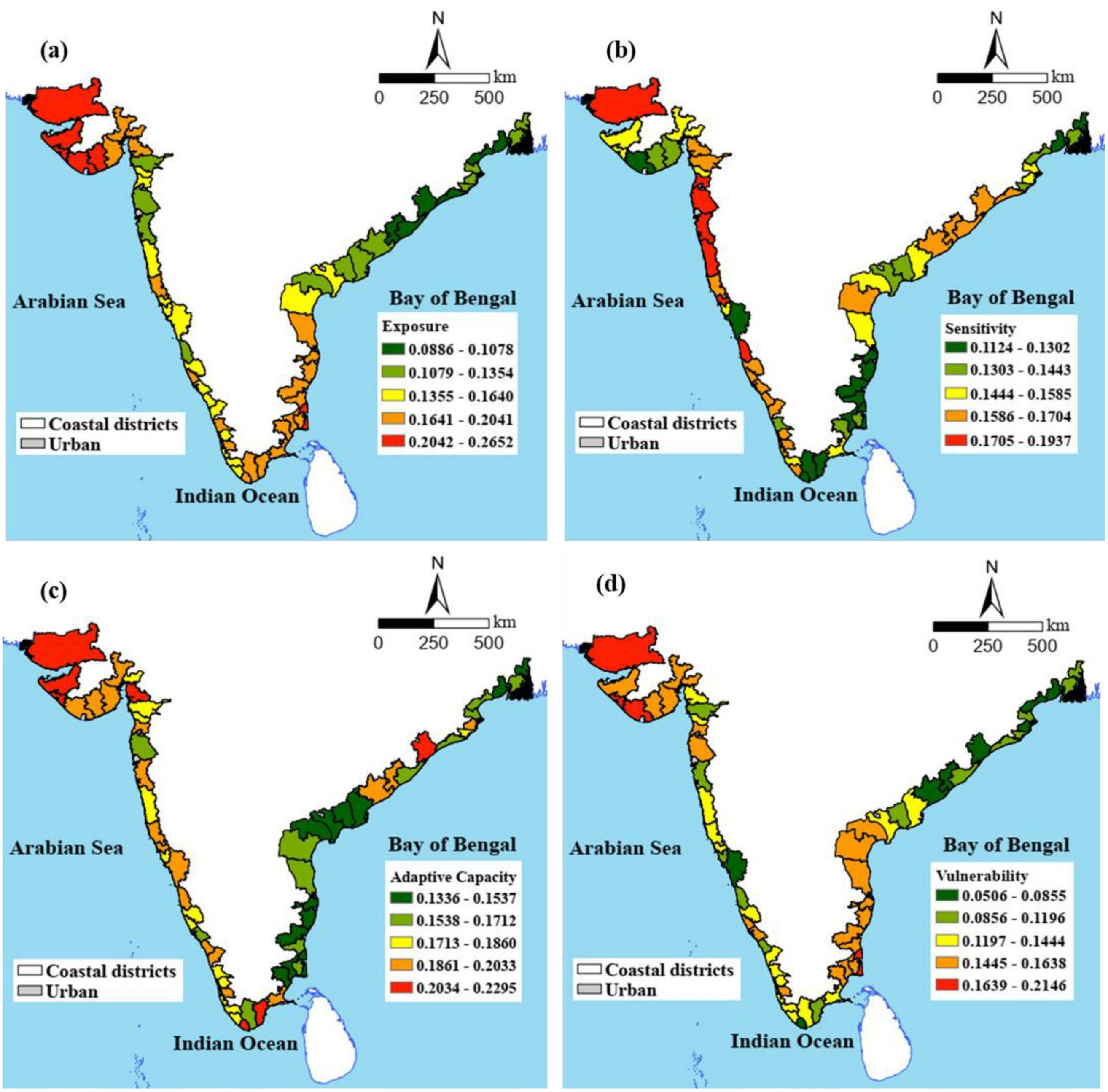

Fig. 5 (**a**) Exposure, (**b**) sensitivity, (**c**) adaptive capacity and (**d**) vulnerability of coastal districts of India obtained from PCA analysis

combined to create the sensitivity maps presented in Figs. 4 and 5.

According to the entropy-based method, the average sensitivity for coastal districts of India was found to be 0.0609 with a standard deviation of 0.0242. The districts of Gujarat on the west coast showed relatively higher sensitivity to climate change. Valsad district exhibited the highest (0.1588), while Uttara Kannada showed the least (0.0275) sensitivity within the Indian coastal region (Fig. 4). All other districts in the remaining states on the west coast, except for Thane, exhibited low to very low sensitivity, with values ranging from 0.0275 to 0.0432. On the east coast, the majority of Andhra Pradesh and Odisha districts registered relatively higher sensitivity to climate change than the districts of Tamil Nadu which has low to moderate sensitivity (0.0482–0.0606). In Andhra Pradesh, four districts were categorized under high sensitivity, three districts as very high sensitivity, and one each under low and moderate sensitivity, respectively. In Odisha, all districts have moderate to high sensitivity except Baleshwar which demonstrated low sensitivity. In West Bengal, East Midnapore and North 24 Parganas

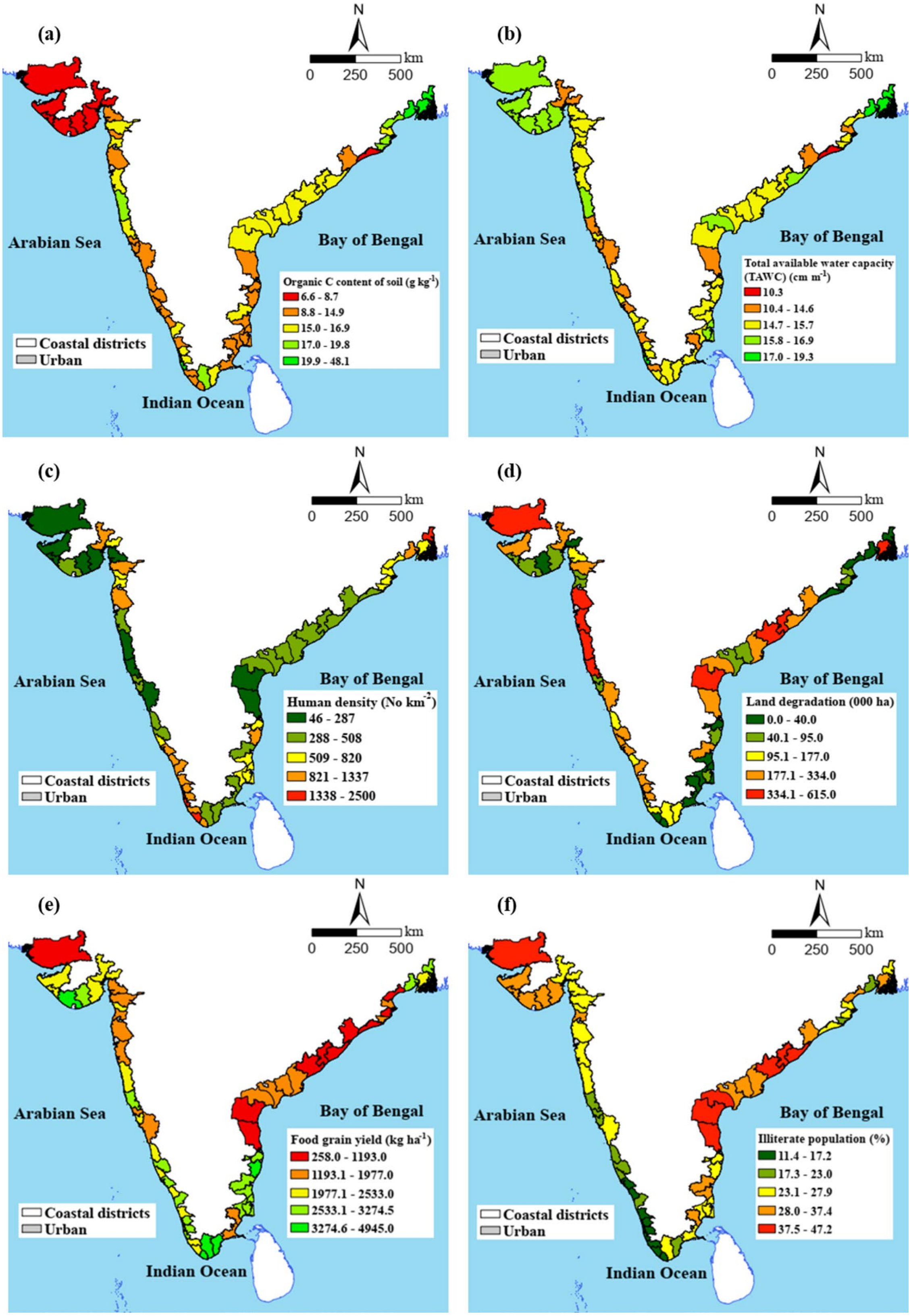

Fig. 6 District-wise sensitivity indicators for coastal region of India (**a**) Organic C content of soil (SOC), (**b**) Total available water capacity (TAWC), (**c**) Human density, (**d**) Land degradation, (**e**) Food grain yield, (**f**) Illiterate population, (**g**) Groundwater availability, (**h**) Groundwater development stage and (**i**) Soil erosion

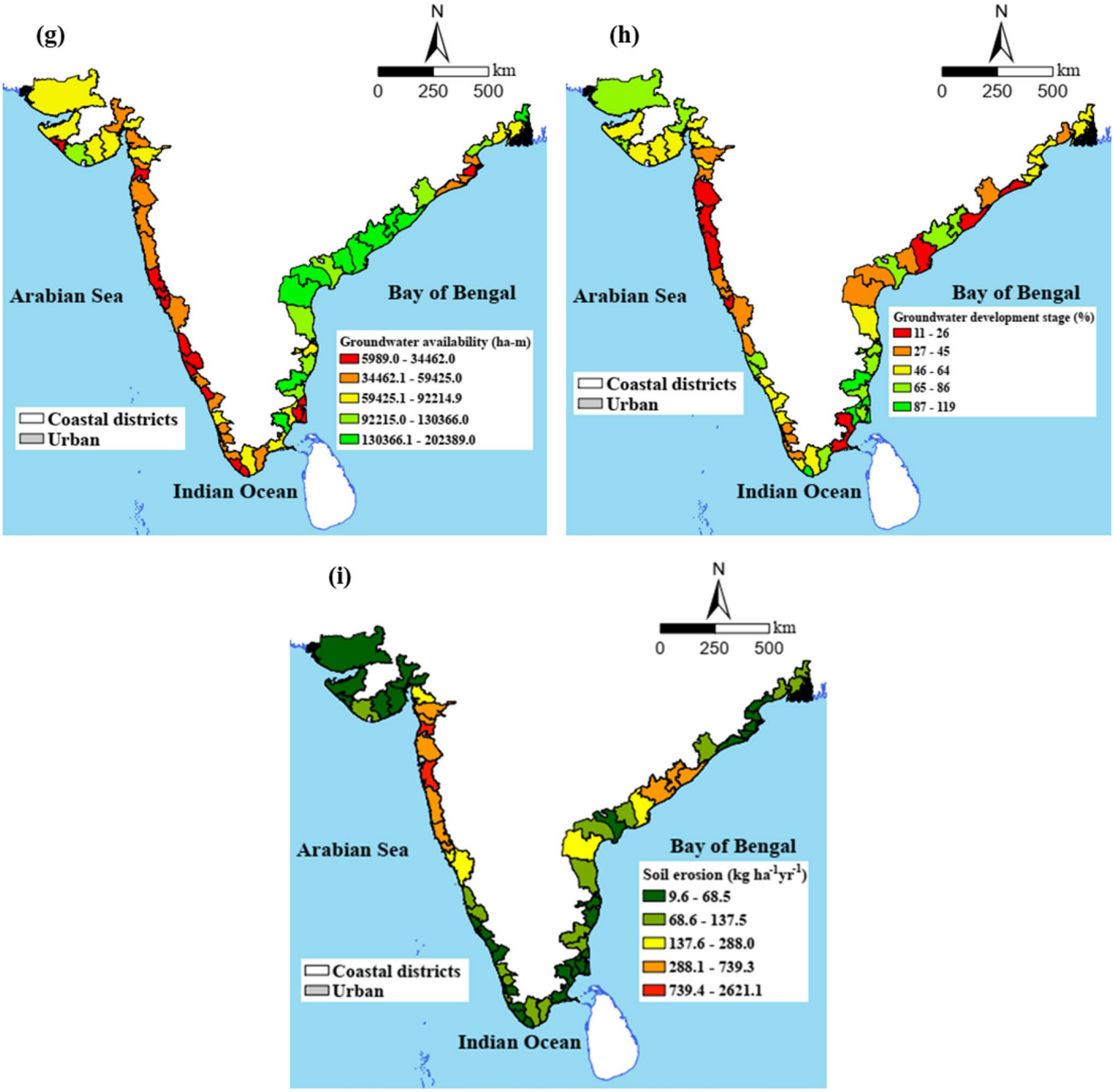

Fig. 6 (continued)

showed moderate sensitivity, whereas, South 24 Parganas district showed very high sensitivity to climate change.

PCA based analysis indicated that the districts on the west coast were more sensitive (0.1613) than the east coast (0.1406) with a mean sensitivity of 0.1511 and a standard deviation of 0.0194 for the entire coastal region. The highest and lowest sensitivity was observed for Raigarh (0.1937) and Kanyakumari (0.1124), respectively (Fig. 5). The state of Maharashtra showed the highest sensitivity to climate change compared to all other coastal states with all its districts falling into very high sensitivity category. Maharashtra was followed by Kerala, where all the districts exhibited moderate to very high sensitivity levels except Thrissur district with low sensitivity. Karnataka, exhibited three different sensitivity levels i.e. very low, high and very high. For Goa, the sensitivity level varied between moderate and very high. In Gujarat, all the sensitivity levels were represented except very low with two districts categorized as very high, two as high, four as moderate, and four as low. All three districts of West Bengal were categorized under low or very low sensitivity. Similarly, except for Ramanathapuram, all other districts of Tamil Nadu also exhibited either low or very low sensitivity levels. In Andhra Pradesh, sensitivity varied from low to very high levels with four districts in moderate, two districts each in low and high, one in very high category. In Odisha on the east coast, the sensitivity levels varied from low to very high with two districts each in very high, moderate and low sensitivity categories.

3.4 Adaptive capacity

The district-wise adaptive capacity indicators of coastal India used for vulnerability analysis is presented in Fig. 7. On the east coast, adaptive capacity parameters like average livestock density (196.27 livestock km^{-2}), fertilizer consumption (173.78 kg ha^{-1}), net irrigated area (61.60%), cropping intensity (141.01%) were significantly higher than west coast (93.94 livestock km^{-2}, 70.17 kg ha^{-1}, 29.55% and 114.59%, respectively). The west coast has higher forest cover (29.23%), rural road connectivity (96.80%) and HDI (0.66) than the east coast (12.28%, 73.13% and 0.61, respectively). The remaining parameter averages were similar in magnitude on both the east and west coast. However, most of the adaptive capacity parameters exhibited a wide range of variation across eastern and western coastal districts.

On the west coast, average livestock density was the highest in Anand (243 livestock km^{-2}) district of Gujarat and lowest in North Goa (37 livestock km^{-2}). Except for Anand, all other districts on the west coast had an average livestock density of less than 200 livestock km^{-2}. On the east coast, the highest livestock density was in North 24 Parganas (332 livestock km^{-2}) with ten other districts having livestock density greater than 200 livestock km^{-2}. Even the lowest livestock density in the east coast was higher than 100 livestock km^{-2} (106 livestock km^{-2}). The lowest forest cover on both coasts was found in Ahmedabad (1.65%) district of Gujarat and Thiruvarur (1.1%) district of Tamil Nadu. The district with the highest forest cover in the western and eastern coast showed significant difference with Sindhudurg registering 88% forest cover in the west coast compared to Kanyakumari in the east coast reporting only 38.72% forest cover. Eight districts on the west coast had a forest cover higher than 40%. Normal rainy days were the lowest in Kachchh (41) and highest in Udupi (116) districts on the west coast, whereas on the east coast, the lowest and highest were recorded in Thoothukudi (72) and South 24 Parganas (105) districts, respectively. On the west coast, the fertilizer consumption rate was the lowest in Jamnagar (10.16 kg ha^{-1}) district of Gujarat. Several other districts in Gujarat also had lower fertilizer consumption rates. On the east coast, Kendrapara (24.55 kg ha^{-1}) district of Odisha had the lowest fertilizer consumption rate. The net irrigated area was the highest in Anand (99%) on the west coast and Thiruvarur (96%) on the east coast of India. On the west coast, eight districts (four each in Maharashtra and Kerala) had a net irrigated area of less than 10% with Sindhudurg and Kasargod recording the lowest net irrigated area. On the east coast, the lowest net irrigated area was found in Thoothukudi (24%). The net sown area exhibited a wide range of variability in the west coast region, with Kachchh reporting the highest (631,000 ha) and South Goa (54,000 ha) reporting the lowest net sown area. Similarly, in the eastern coastal region, Guntur showed the highest (6,18,000 ha) and Jagatsinghpur showed the lowest (69000 ha) net sown area. Cropping intensity was found to be the lowest in South Goa (100.51%) and Ramanathapuram (100%) whereas it was the highest in Kannur (142%) and North 24 Parganas (215%) on the west and east coast, respectively.

HDI was the highest in Ernakulam (0.80) and Kanchipuram (0.71) whereas it was the lowest in Kachchh (0.46) and Vizianagaram (0.40) on the west and east coast, respectively. On the west coast, rural road connectivity was greater than 90% for most of the districts except Uttara Kannada (83%) and Porbandar (88%). On the east coast, except for five districts, all other districts have less than 90% rural road connectivity. Most of the Indian coastal districts have 100% villages electrified. The least electrified villages were found to be in Uttara Kannada (98.6%) and Ganjam (93.4%) districts on the west and east coast, respectively.

The entropy-based method integrated these parameters to quantify the average adaptive capacity for coastal districts of India at 0.0900 with a standard deviation of 0.0337. Porbandar (0.1377) and Kannur (0.0379) were marked as districts with the highest and lowest adaptive capacity, respectively (Fig. 4). Among all the states of coastal India, Gujarat registered the highest adaptive capacity with all of its districts lying in either the high or very high category (0.1119–0.1377). All other districts in western coastal states except Thane (0.1166) of Maharashtra showed low to very low adaptive capacity (0.0379–0.0448). Odisha, located on the east coast, demonstrated relatively higher adaptive capacity, ranging from moderate to very high levels, compared to other states on the east coast. In Tamil Nadu and Andhra Pradesh, most of the districts marked moderate to low levels of adaptive capacity except Ramanathapuram, Thoothukudi, Kanyakumari, Visakhapatnam and Vizianagaram (0.0837–0.1320). In West Bengal, East Midnapore and North 24 Parganas districts showed low adaptive capacity while South 24 Parganas had high adaptive capacity.

The PCA-based method quantified the average adaptive capacity of the entire coastal belt of India as 0.1784 with a standard deviation of 0.0230. The analysis also showed that the east coast of India, in general, has a relatively lower adaptive capacity (0.1906) compared to the west coast (0.1657). The analysis also revealed that Porbandar had the highest

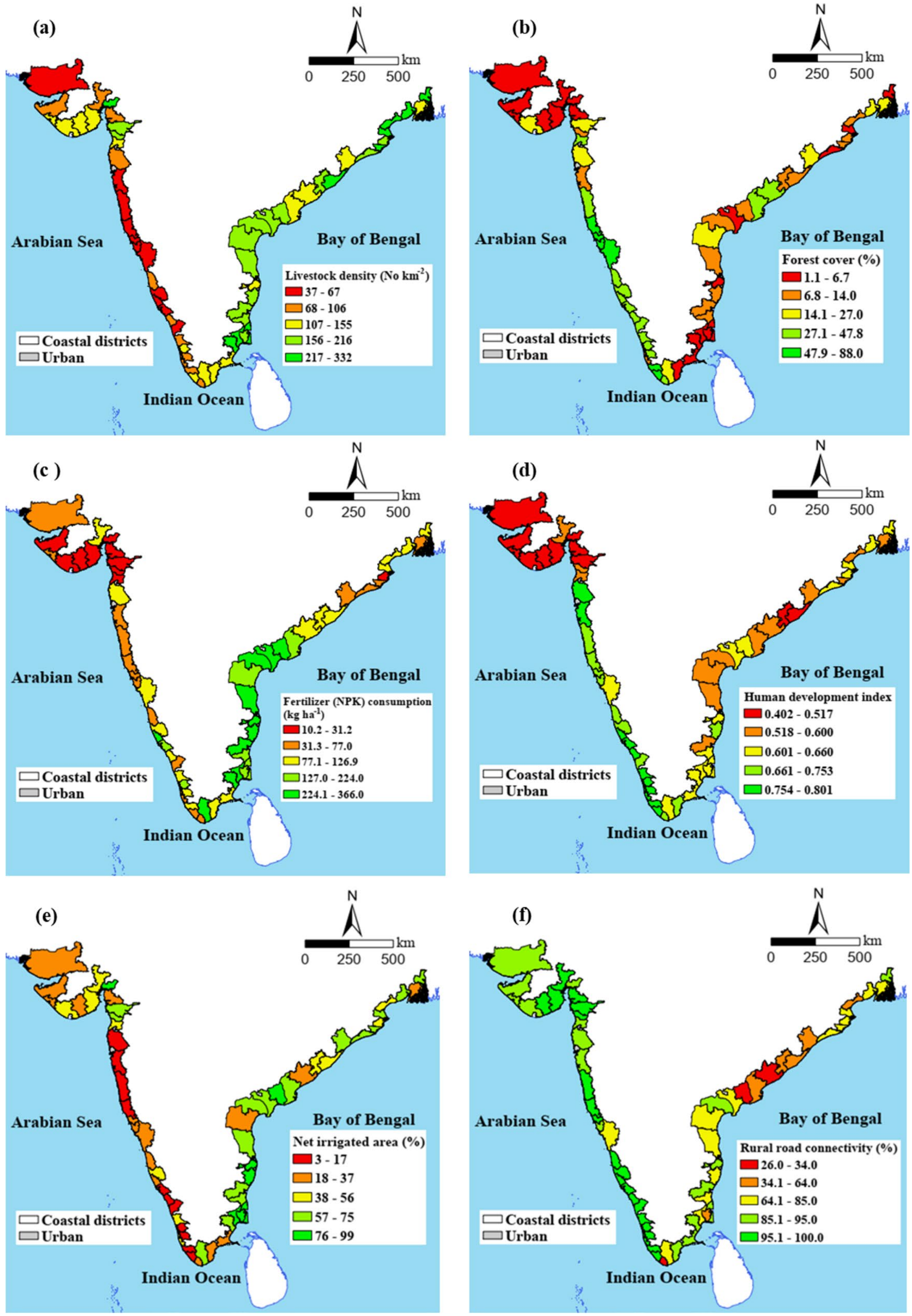

Fig. 7 District-wise adaptive capacity indicators for coastal region of India (**a**) Livestock density, (**b**) Forest cover, (**c**) Fertilizer (NPK) consumption, (**d**) Human development index, (e) Net irrigated area, (**f**) Rural road connectivity, (**g**) Villages electrified, (**h**) Cropping intensity, (**i**) Net sown area and (**j**) Frequency of years with normal rainy days

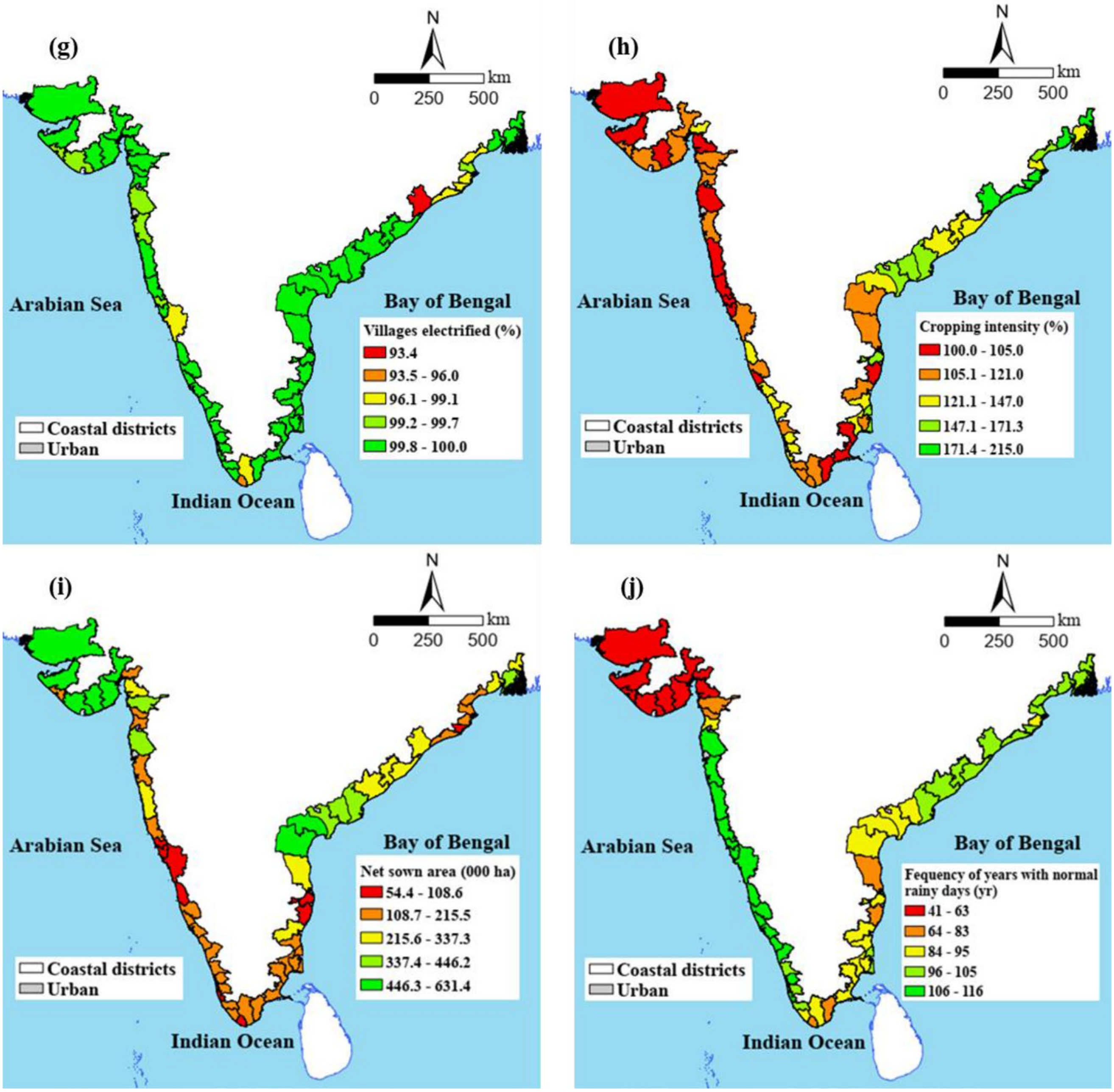

Fig. 7 (continued)

adaptive capacity (0.2295) on the west coast whereas, North 24 Parganas showed the lowest adaptive capacity (0.1336) (Fig. 5). The districts in Gujarat showed the highest adaptive capacity with the majority of its districts within moderate to very high levels. Only two districts on the west coast registered low adaptive capacity with one each in Maharashtra (Thane) and Kerala (Kannur). All other districts of the west coast had moderate to high adaptive capacity category. Out of 30 coastal districts in the eastern belt, 22 districts fall into either low or very low category. Only three districts in Odisha, two in Andhra Pradesh, and three in Tamil Nadu have moderate to very high adaptive capacity.

3.5 Vulnerability

The entropy-based method estimated the average vulnerability for entire coastal region of India at 0.1148 with a standard deviation of 0.0744. As per the analysis, Kachchh (0.3183) was the most vulnerable, whereas Uttara Kannada (0.0263) was the least vulnerable district of coastal India. The districts of Gujarat showed higher vulnerability to climate change in the entire coastal belt of India exhibiting either high or very high vulnerability. In contrast, apart from Thane, all other districts in the western coastal states of Maharashtra, Goa, Karnataka, and Kerala were found to have either low or very low vulnerability (Fig. 4). On the east coast, districts of Tamil Nadu showed higher vulnerability where all districts fall between low and very high vulnerability levels. In Andhra Pradesh and Odisha, the vulnerability level varied from low to high. Two districts of Andhra Pradesh were found to be highly vulnerable, five as moderately vulnerable and two as less vulnerable. In Odisha, one district showed high vulnerability, whereas, three and two districts showed moderate and low vulnerability, respectively. In West Bengal, one district was found to be very highly vulnerable, one as moderately vulnerable and one as low vulnerable.

According to the PCA-based analysis, mean vulnerability of coastal region of India was 0.1311 with standard deviation of 0.0349. As per the analysis, the west coast (0.1422) was more vulnerable to climate change than east coast (0.1196). Kachchh (0.2146) was the highest vulnerable district in the entire coastal region of India, whereas Ganjam had the lowest vulnerability (0.0506) (Fig. 5). Among the west coastal districts, Uttara Kanada (0.0750) showed very low vulnerability while Bharuch, Surat, Raigarh, South Goa, Udupi, Kozhikode and Kollam districts were having low vulnerability. The low vulnerability of coastal Karnataka districts is in line with previous studies (Kumar et al. 2016a, b; Shivakumara and Murthy 2019). On the other hand, high to very high vulnerability in coastal districts of Gujarat and Tamil Nadu was also reported by (Rao et al. 2016, 2025). The rest of the districts on the west coast of India showed moderate to very high vulnerability. The maximum vulnerability to climate change in the west coast of India was shown by the districts of Gujarat and Kerala. In the eastern coastal region of India, Tamil Nadu showed the highest vulnerability where except two districts, all other districts showed moderate to very high vulnerability (0.1360–0.2112). In Andhra Pradesh, vulnerability levels varied from very low to very high with three districts in very low, two in low, two in high and one each in moderate and very high vulnerability categories. All the districts of Odisha and West Bengal showed low to very low vulnerability (0.0506–0.1126).

4 Discussion

4.1 Comparison of entropy-based weighting and PCA-derived weighting

In the context of assessing agricultural vulnerability to climate change, the approach used to determine indicator weights has a significant impact on the results. In this study, entropy-based and principal component analysis (PCA)-based weighting were compared for vulnerability analysis of Indian coastal districts. The weights assigned to various indicators exhibited higher variability in the entropy method compared to the PCA method. Entropy-based weighting is based on Shannon's entropy to assign weights to indicators. This method measures the amount of disorder or uncertainty in the dataset, thereby assigns higher weights to indicators with more variability across the study area. This results in a detailed differentiation of vulnerability levels, especially for indicators like rainfall patterns and temperature variations that have a direct impact on agriculture. The entropy-based weighting by assigning higher weights to the parameters like extreme rainfall events, droughts, cyclone and soil erosion while assigning lower weights to other parameters, helped to frame targeted policy recommendations. Higher weights assigned to droughts and cyclones are in accordance with previous studies (Rao et al. 2025). In contrast, the weights in PCA are derived from the communality of each indicator, which is the proportion of each indicator's variance that can be explained by the principal components. The PCA method by focusing on overall variance tends to distribute weights more evenly among indicators. This approach is beneficial for identifying broader patterns of vulnerability but may underemphasize specific critical factors affecting agriculture. Thus, in the present study, PCA based weight assignment method was less useful for targeted policy recommendation. In the current study, the range of vulnerability index for coastal region of India varied between 0.0263 and 0.3183 for entropy-based method while for PCA-based method, it ranged from 0.0506 to 0.2146. This highlighted more variability in the vulnerability scores across districts through entropy-based compared to PCA-based method. The correlation between weights computed using entropy and PCA was non-significant (ρ = -0.110; p-value = 0.562) indicating that the two methods are quite different. However, the correlation of vulnerabilities calculated using these two methods was significant (ρ = 0.498; p-value = 0.000). This suggests that despite producing widely different weights, both methods yielded comparable vulnerability patterns across the coastal districts, highlighting their effectiveness in capturing underlying vulnerability. The choice between entropy-based weighting and PCA-derived weighting should be guided by the specific goals of the vulnerability assessment. The entropy-based method is more sensitive to the variability of each indicator, providing a detailed understanding of vulnerability. On the other hand, it is computationally intensive and sensitive to outlier data points, which may affect reliability in data-scarce regions. The PCA method, while less variable in its weighting, might still be preferable under these circumstances. Analytic hierarchy process (AHP) which requires expert opinion based pairwise comparison may also be used under less data availability.

4.2 Determents of vulnerability

The study examined patterns in a range of environmental and socioeconomic factors indicative agricultural vulnerability to climate change for Indian coastal region. The rate of change in maximum temperature (higher on the east coast) and minimum temperature (higher on the west coast) per year during both *kharif* and *rabi* seasons highlighted the differential impact of climate change on temperature across the coasts. The west coast has become more susceptible to extreme weather events, with a notable rise in very/extremely heavy rainfall compared to the east coast (Maharana et al. 2021; Samantray and Gouda 2023). This might be linked to increased instability, warming of the Arabian Sea, and a stronger monsoon over western India which are expected to persist due to climate forcing (Maharana et al. 2021). The higher variability in annual rainfall on the west coast, particularly in the districts of Gujarat, further emphasizes the region's climatic instability and vulnerability. Water is crucial for successful crop growth, however, both extremes of water stress, whether it is drought or heavy rainfall, have significant impacts on agriculture. Drought can impede crop growth and lead to complete crop failure or reduced crop yields, particularly in rainfed regions of the country (Swain and Swain 2011; Balaganesh et al. 2020; Guria et al. 2025). Gujarat is the most exposed state on the west coast, with most of the districts experiencing droughts as well as extreme rainfall events throughout the season. These changing patterns can be attributed to microclimatic changes triggered by local climate change drivers such as land-use change, deforestation, and encroachments upon wetlands and water bodies. Tamil Nadu was also routinely impacted by high/extreme rainfall and drought events making it the highest-exposed state on the east coast. In future due to global warming, there will an increase in duration, magnitude and severity of drought as reported in many previous studies (Jehanzaib et al. 2020; Vicente-Serrano et al. 2020; Santos et al. 2021).

The markedly higher cyclone activity on the east coast necessitates robust cyclone preparedness and mitigation measures, especially for highly susceptible districts such as South 24 Parganas in West Bengal. Cyclones, characterized by strong winds and heavy rainfall, lead to crop lodging and waterlogging in poorly drained fields, ultimately causing complete crop failure. Coastal states like Andhra Pradesh, Odisha, West Bengal and Tamil Nadu are highly susceptible to cyclone impacts (Bahinipati 2014; Sudha Rani et al. 2015; Sahoo and Bhaskaran 2018; Reddy et al. 2020; Abijith et al. 2021).

Sensitivity analysis offered a comprehensive insight into the regional variations and specific vulnerabilities to climate change within Indian coastal region. SOC is considered as keystone of soil quality as it positively impacts almost all soil physical, chemical and biological properties. SOC improves soil structural stability and aggregation thereby helps in soil aeration. It enhances the cation exchange capacity and water-holding capacity of soil (Sehgal et al. 2013). SOC is negatively related to vulnerability i.e., as the SOC content increases, vulnerability decreases. Both the east and west coasts were having high SOC. TAWC, which has a direct impact on agricultural productivity and the ability to withstand drought, was also found to be adequate. Higher TAWC of soil helps to combat water-deficit stress thereby reducing the chance of crop failure due to dry spells or droughts. So, TAWC is inversely related related to vulnerability. The implications of higher human density are universally applicable to various disruptions, including those related to climate. Higher human density in certain districts such as North 24 Parganas can exacerbate the pressure on natural resources, increase competition for water and land, and exacerbate vulnerability to climate impacts. Districts with dense populations may also face greater challenges during extreme weather events due to limited evacuation options and overcrowded infrastructure. Human Development Index (HDI) and illiteracy rates reflect the level of social and economic development of a region. Therefore, states demonstrating a higher HDI and lower illiteracy rates such as Kerela exhibit an increased capacity to manage and adapt to climate-related stressors. It also increases the ability to adopt modern agricultural practices or diversify livelihoods. The increased sensitivity of the west coast (especially Gujarat) is attributed to higher land degradation, greater soil erosion (double that of the east coast), lower groundwater availability (almost one-half of the east coast) and the stage of groundwater development. Soil erosion specially in coastal region leads to the loss of inhabitable land, mangroves, agricultural land, and other natural and man-made resources (Mondal et al. 2020; Hossain et al. 2022). High land degradation and soil erosion often result in reduced soil fertility, loss of arable land, and crop productivity leading to increased vulnerability of agriculture to climate change.

The comparative evaluation of adaptive capacity highlights significant differences in parameters between the east and west coasts and their implications for regional resilience. The higher livestock density, net irrigated area, and cropping intensity suggest robust agricultural practices and resource availability on the east coast. Higher livestock density can reduce agriculture-related economic vulnerability and pressure. Increased cropping intensity entails cultivating a greater number of crops within a specific area. Both higher cropping intensity and greater livestock density not only boost the self-sufficiency and nutritional security of a system but also fortify the system's resilience against the impacts of climate change, thereby reducing its vulnerability. Proper fertilizer use can help maintain soil fertility over time, making agricultural systems more sustainable and can act as a buffer against the negative impacts of climate variability. The higher cropping intensity is generally closely linked to the greater availability of groundwater and net irrigated area. Therefore, the districts with higher areas under irrigation such as Anand and Thiruvarur will be less vulnerable to climatic vagaries. Despite these strengths, the east coast showed lower forest cover and rural road connectivity, which may limit ecological sustainability and infrastructure development, respectively. The higher forest cover provides significant ecological benefits, including carbon sequestration and biodiversity preservation (Endreny et al. 2017; Prăvălie 2018; Anees et al. 2024). Districts such as Sindhudurg which has a greater proportion of area under forest cover are expected to experience fewer impacts from climate change-associated disasters. Additionally, superior rural road connectivity and a higher HDI indicate better infrastructure and overall human development as observed on the west coast. Improved connectivity of rural roads facilitates the smoother transportation of both individuals and agricultural goods, allowing for the movement from more susceptible regions to less vulnerable ones or from surplus to deficit areas, consequently minimizing overall vulnerability. An increased frequency of years with normal rainfall and regular rainy days correlates with favourable agricultural yields. Consequently, improved agricultural production contributes to enhancing the adaptive capacity of the population.

4.3 Adaptation and mitigation measures

Agricultural sustainability and food security depend on reducing vulnerability by minimizing the effects of extreme weather events on agriculture. It can be achieved by identifying issues that are unique to a given location and putting tailored adaptation and mitigation strategies in place. For instance, regions prone to drought, such as Kachchh in Gujarat and Cuddalore, Nagapattinam and Thoothukudi in Tamil Nadu should implement integrated water resource management strategies, including rainwater harvesting and the enhancement of water storage structures to ensure supply during droughts (Chauhan et al. 2010). More efficient irrigation methods, agroforestry, and soil moisture conservation can help in mitigating drought impact. Encouraging the adoption of water use efficient and water-saving technologies like recycling can significantly reduce overall water demand in these areas. Initiatives for ecosystem restoration, including afforestation, reforestation, and sustainable land management practices, are crucial components in maintaining sustainable water availability and land rehabilitation (Jat et al. 2016; Mehmood et al. 2025). Additionally, effective water management practices that ensure equitable distribution, facilitated through collaboration among neighbouring catchments and basins, contribute to a more resilient and sustainable water resource management system (Srivastava and Maity 2023). Likewise, in regions where temperature extremes pose a primary challenge, contributing to the vulnerability of the area, strategies such as modifying the sowing time can minimize exposure to extreme temperatures during critical growth stages. Installing shade nets over crops or incorporating agroforestry practices for natural shade may also help in mitigating direct exposure to intense heat. Utilizing soil moisture conservation methods, such as mulching and cover cropping, will aid in retaining soil moisture when temperatures are high (Gupta et al. 2007; Bijay-Singh et al. 2008; Balwinder-Singh et al. 2011; IPCC 2022). Additionally, implementing efficient irrigation systems like drip or precision irrigation may optimize water usage and mitigate heat stress on crops.

In cyclone-prone areas, like coastal states of Andhra Pradesh, Odisha, West Bengal and Tamil Nadu, enhancing windbreaks and shelter belts can protect crops from strong winds accompanying cyclones by serving as sturdy structures thereby also preventing soil erosion. Cyclone shelters should also be established and maintained in vulnerable areas to ensure secure refuge for communities during cyclonic events. Cyclones are also associated with excess rainfall and flood-like situations, during which proper drainage facilities should be ensured to prevent waterlogging and soil erosion. Planting cover crops during non-growing seasons will aid in safeguarding soil structure, reduce erosion, and improve water absorption. In hilly terrains, contour ploughing and terracing should be adopted to reduce surface runoff. Raised beds can mitigate crop damage during floods by elevating them above floodwaters (Humphreys et al. 2005; Choudhury et al. 2007). Small-scale water storage facilities, such as ponds or reservoirs, should also be constructed to capture excess rainfall to be used during later dry periods (Altieri and Nicholls 2017).

Apart from these specific measures, there are some general measures which may be undertaken, such as promoting climate resilient and tolerant crop varieties (drought, flood and heat tolerant), strengthening early warning systems for extreme weather events to enhance preparedness, conducting capacity building and training programs for farmers, investing in infrastructure development, implementing supportive policies like subsidies for climate-resilient inputs and financial assistance for recovery, etc. (Lobell et al. 2008; Fedoroff et al. 2010; Jat et al. 2016). Diversification of livelihood and crops can also reduce dependency and help to mitigate the risk of complete loss (Behera et al. 2007; Philpott et al. 2008; Rosset et al. 2011). Encouraging farmers for crop insurance also helps in recovering their losses incurred due to damage from extreme weather events, providing a safety net for their livelihoods. Implementing a combination of these measures can significantly enhance the resilience of agriculture to droughts, temperature extremes, excess rainfall, floods, and cyclones, contributing to reduced vulnerability and sustainable agriculture.

4.4 Sources of uncertainties

The entropy technique assigned higher weights to indicators exhibiting greater variability. So, small changes in the weights may influence indicators having higher weights, thereby potentially modify district-level vulnerability classifications. Alternative weighting schemes such as equal weighting, AHP, or hybrid methods should be assessed to test the robustness of the findings reported in the current study. Secondary datasets were used for vulnerability analysis may have intrinsic errors. Temporal mismatches among the parameters collected for vulnerability analysis could also introduce errors in the analysis. The selection of 30 indicators reflects a comprehensive approach, but it implicitly assumes that these indicators fully capture agricultural vulnerability. Excluding other potential factors like market access, per-capita income, institutional support introduces model uncertainty. Combining diverse indicators into composite indices involves subjective decisions about functional relationships with vulnerability which was assumed to be linear in this study. These assumptions can propagate uncertainty into the final vulnerability index due to the presence of nonlinear relationships.

4.5 Limitation and future perspectives

The main limitations of the study are (i) some indicators like human density, illiterate population, land degradation etc. relied on older datasets, which may not reflect current conditions. (ii) The vulnerability analysis was carried out for coastal districts of India which may not be generalizable to other regions or inland areas. (iii) Though 30 indicators were used in the current study, inclusion of other relevant factors could improve the vulnerability analysis. In future, vulnerability analysis may be performed at finer spatial scales (block/taluka/village level) for more targeted interventions including additional socioeconomic indicators like income inequality, access to credit, and market connectivity. Hybrid weighting approaches combining entropy, PCA and expert opinions or machine learning techniques for vulnerability assessment may be tested for improvement of the results. Further, future studies may include participatory approaches and local knowledge to validate and refine the findings of the current study.

5 Conclusion

The current study evaluated the degree of agricultural vulnerability to climate change among coastal districts of India using principal component analysis (PCA) and entropy-based method. During the analysis, the magnitude of exposure and sensitivity along with the potential location-specific adaptive capacity were assessed using 30 different indicators. The entropy-based method was found better for agricultural vulnerability mapping compared to PCA based method. Coastal districts of Gujarat, Tamil Nadu, Odisha and West Bengal showed very high to high vulnerability to climate change due to droughts, extreme rainfall events leading to floods, cyclone and land degradation. The major adaptation and mitigation strategies in drought prone areas like Gujarat should be on integrated water management with soil moisture conservation techniques, expanding micro-irrigation systems like drip and sprinklers, promoting rainwater harvesting and utilising of drought-tolerant crops like millets and pulses. Tamil Nadu, Odisha and West Bengal, on the other hand, requires policies that prioritise cyclone preparedness, coastal resilience, and flood mitigation. This includes improving early warning systems for cyclones and extreme weather events, restoration of mangrove to provide natural barriers to storm, and developing cyclone-resistant constructions. Policymakers can utilize the district-level vulnerability maps to prioritize resource allocation and infrastructure development in highly vulnerable districts identified in this study.

Acknowledgements The India Meteorological Department is duly acknowledged for providing gridded weather data. This work was supported by the Indian Council of Agricultural Research under Institute project at ICAR-Central Coastal Agricultural Research Institute, Old Goa, Goa, India.

Author contributions B.D. Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Data Analysis; S.S. Writing – original draft, Writing – review & editing, Data Analysis; K.V.R. Data Collection, Data Analysis; S.J.B. Data Collection, Data Analysis; S.D. Data Collection, Data Analysis; G.M. Writing – review & editing, Data Analysis; P.R. Writing – review & editing; S.S. Writing – review & editing; U.A.R. Writing – review & editing; V.K.S. Conceptualization, Methodology; R.N.S. Data Analysis, Writing – review & editing; D.A.S. Methodology.

Data availability No datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate Not applicable.

Consent for publication Not applicable.

Declaration of generative AI in scientific writing During the preparation of this work the author(s) used ChatGPT only in the writing process to improve the readability and language of the manuscript. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Competing interests The authors declare no competing interests.

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