



Assessing vulnerability to cyclones in coastal Odisha using fuzzy logic integrated AHP: towards effective risk management

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Abstract

The frequency of tropical cyclones has increased across the globe due to climate change in recent years. The eastern coastal plains of India have witnessed significant rise in frequency and severity of tropical cyclones during past decades, making it essential to do a comprehensive vulnerability assessment and implement effective risk reduction measures. Therefore, this study seeks to analyse the spatial vulnerability of tropical cyclones in coastal Odisha using geospatial techniques and fuzzy analytical hierarchy process. Seventeen spatial criteria within physical, social, and mitigation aspects has been used to assess the vulnerability to tropical cyclones. Result shows that Baleswar and parts of Bhadrak and Kendrapara districts are the most vulnerable regions to tropical cyclones. In terms of physical and social vulnerabilities, about 40% area of Odisha falls under high and very highly vulnerable zones to tropical cyclones. Overall, about 41% of the area comes under high and very high vulnerability without mitigation capacity, but integration of mitigation capacity may reduce it to 21%, which emphasize the significance of mitigation measures in reducing vulnerability to cyclones. The results may be helpful in spatial planning for effective cyclone risk management and implementing mitigation measures to improve cyclone resilience in the region.

Keywords Cyclone events · Fuzzy-AHP · Physical coastal vulnerability · Social vulnerability · Mitigation capacity

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1 Introduction

Tropical cyclones, considered the most perilous hydro-meteorological threat on a global scale, unleash destruction through their powerful winds, intense rainfall, and devastating storm surges [1]. These natural disasters leave behind a trail of destruction, causing human casualties, widespread property damage, and communication network outages [2–4]. Every year, the various cyclone basins around the world produce an average of 90 tropical cyclones [5, 6]. Coastal communities around the world live in the path of these cyclones and have experienced their devastating effects, with estimated global losses of about 1965 billion USD between 1970 and 2019 [7, 8]. The exposure of coastal population and their assets to the damaging effects of tropical cyclones is rapidly increasing and is a matter of concern among the planners and policy makers [9, 10]. Moreover, sea level rise due to the changing climate have further exacerbated the vulnerability of coastal population to tropical cyclones and other hazards [2, 11].

India is a country that has faced the wrath of nature in the form of devastating cyclones, especially along the eastern

coastline. These natural disasters have caused immense destruction and loss of human and animal life [2, 12]. With the Indian Ocean to its south, the Bay of Bengal to its east, and the Arabian Sea to its west, India is surrounded by water on three sides, making it susceptible to cyclones [13]. The Bay of Bengal, in particular, is a hotspot for the formation of these deadly storms [14, 15]. A study conducted recently has revealed that the potential for the destruction caused by these cyclones has increased, as indicated by the Power Dissipation Index [16, 17]. India's vulnerability to these events along its eastern coastline is most pronounced during the monsoon season, especially during the southwest monsoon spanning from June to September and northeast monsoon occurring from October to December [18]. The Bay of Bengal witnesses the formation of about 12–14 cyclones each year, with 5–6 intensifying into full-blown tropical cyclones [19, 20]. These cyclones have often made landfall in the coastal regions of Odisha, causing widespread damage and loss of life [2, 13]. The 1999 Super Cyclone in Odisha is a testament to the devastating impact of these storms, with nearly 10,000 people losing their lives and over 3.5 lakh people displaced. Cyclone Fani in 2018 and Hudhud in 2014 were other catastrophic events that caused widespread damage. The 2013 Cyclone Phailin was no different, resulting in 50 deaths, over 10,000 homeless, and over 4.26 billion US dollars in damage [21–24]. Despite the destruction, there is a silver lining. The Indian National Centre for Ocean Information Services (INCOIS), operating under the Ministry of Earth Sciences, Government of India, established a real-time storm surge warning system, leading to the successful evacuation efforts during the occurrences of Phailin and Hudhud. Thanks to these endeavours, numerous lives were saved, and the storm's impact was significantly reduced.

The damaging impact of deadly tropical cyclones can be minimized by employing proper mitigation strategies [25, 26]. A comprehensive assessment of tropical cyclone vulnerability provides valuable information for effective mitigation efforts [27, 28]. Vulnerability encompasses the aspects of risk exposure, susceptibility, and resilience [29, 30]. One effective method to evaluate tropical cyclone vulnerability is through the integration of remote sensing data and spatial analysis [2, 25]. To comprehend the criteria used to determine tropical cyclone vulnerability, a substantial amount of both spatial and non-spatial data is necessary. Geospatial tools and various mapping methodologies have been applied to obtain spatial tropical cyclone vulnerability [2, 27]. The best mapping techniques are those that factor in multiple criteria, providing detailed information on the spatial vulnerability of damage from tropical cyclones [25]. The fuzzy analytical hierarchy process (FAHP) is widely used method in the literature for geographical multi-criteria evaluation [31, 32]. In recent times, researchers use different machine learning and statistical models such as clustering methods like K-means or density-based

spatial clustering of applications with noise (DBSCAN), which can help in identify vulnerable areas by grouping regions with similar characteristics e.g. neural networks (NN) models like convolutional neural networks (CNNs), recurrent neural networks (RNNs), decision trees (DTs) models, including random forests (RFs) and gradient boosted trees (GBTs), are very useful for predicting vulnerability for better results [33, 34]. For tracking and predicting the evolution of vulnerability over time; time series models like autoregressive integrated moving average (ARIMA) and Exponential Smoothing may be employed [35].

Despite the high susceptibility of severe tropical cyclone in the India's eastern coast, there is less research on investigating the vulnerability of tropical cyclone in these coastal regions. Previous studies have explored various aspects of cyclone such as sensitivity, risk, and adaptability to cyclones [10, 36, 37]. Jaman et al. [27] used a multi-criteria approach to examine the impact of the Phailin and Titli cyclones on social vulnerability at the district level. Similarly, Das and Dsouza [24] described the resilience factors during the Hudhud and Phailin cyclones. Further, Saravanan et al. [36] conducted an assessment of the physical vulnerability of the Cuddalore coast utilizing the weighted sum model (WSM). Sahoo and Bhaskaran [2] examined the coastal vulnerability to multiple hazards posed by tropical cyclones, considering both physical and social factors related to storm surge events. Jana et al. [38] investigated the relationship social vulnerability and cyclone vulnerability along the Bay of Bengal coast, with a focus on the child mortality. However, their study did not incorporate any mitigation criteria. To date, no research has mapped the spatial tropical cyclone vulnerability using a multi-criterion (Physical, Social, and Mitigation) evaluation that covers all relevant aspects of vulnerability in the entire coastal district of Odisha, India.

The objective of the current research is to make a tropical cyclone vulnerability zone using physical, social, and mitigating parameters. The approach we took in this study is to look at how spatial tropical cyclone vulnerability is distributed across the coastal region of Odisha, India. Two distinct goals are the main focus of this analysis: (1) to prepare the physical and social vulnerability with the mitigation capacity for tropical cyclones utilizing different types of factors using FAHP. (2) Combining all these physical, social, and mitigating elements to determine the spatial tropical vulnerability zone.

2 Methods and materials

2.1 Study area

This research delves into the vulnerability of the eastern coastal regions of India, specifically the six coastal districts

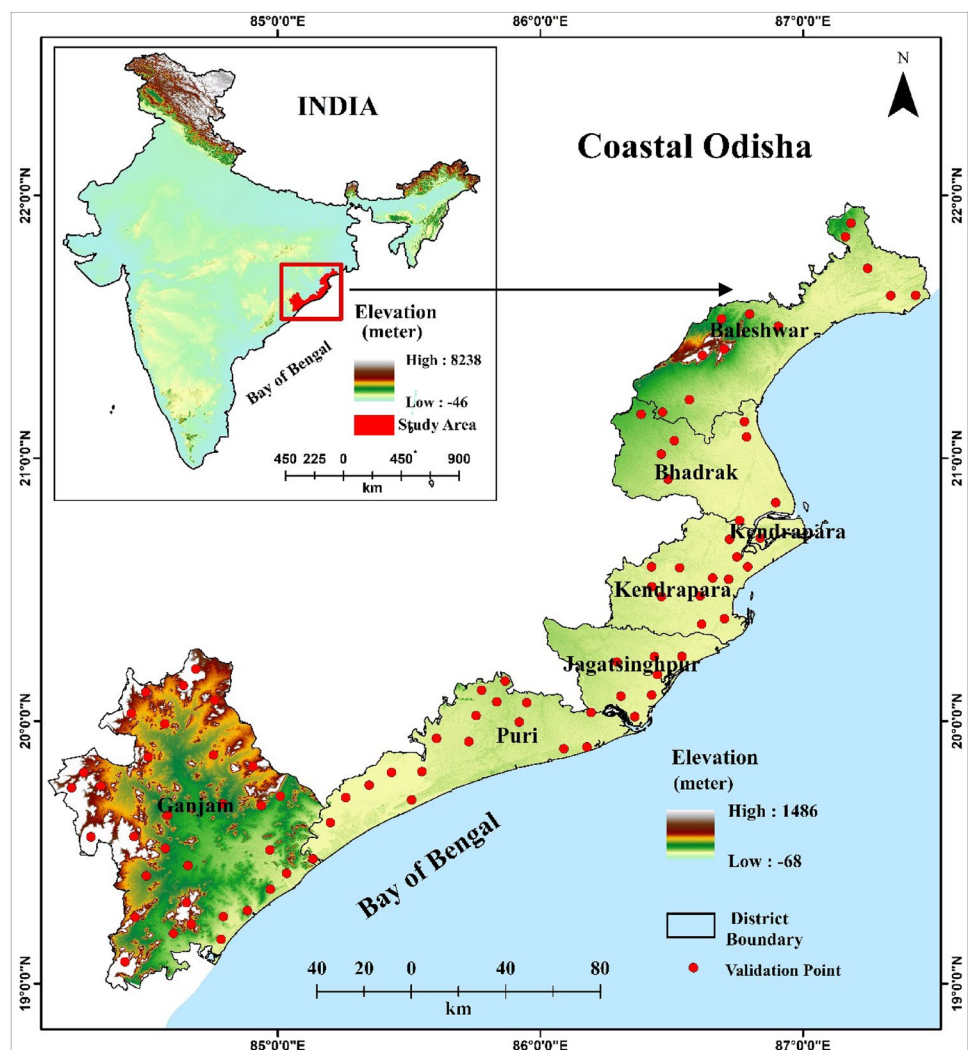
of Odisha. Situated between $18^{\circ} 58' - 21^{\circ} 43' N$ latitude and $84^{\circ} 22' - 87^{\circ} 28' E$ longitude. This particular area, distinguished by a humid and hot climate, with an average annual precipitation of 200 cm, has unfortunately become a hot-spot for severe tropical cyclones. Home to over 11.9 million residents, with a density of population 560 person/km^2 as reported by the 2011 Census, this coastal plain is a mosaic of delta formations from major rivers and boasts lagoons and estuaries. Despite the presence of the southwestern part of the Eastern Ghats Mountain range as a barrier, this area has witnessed 52 major tropical cyclones making landfall between 1971 and 2021. The 1999 super cyclone was the most devastating event in this region, claiming over 10,000 lives. In recent years, the Odisha coast has been frequently pummelled by Phailin (2013), Hudhud (2014), Titli (2018), Fani (2019), Yass (2021), and Jawad (2021), leaving a trail of destruction in its wake. These events have resulted in millions of people being affected, over 800 lives being lost, and billions of dollars in damages. Thus, the current study focuses on these six coastal districts, which have been

severely impacted by tropical cyclones in the past. Although the effects of these cyclones may spread beyond the research area, we aim to map the spatial tropical cyclone vulnerability through a combination of physical, social, and mitigating parameters using the FAHP method. Our goal is to provide a comprehensive analysis of the vulnerability zone, considering all relevant aspects and thus, help in better preparation for any future cyclones (Fig. 1).

2.2 Method

In order to integrate physical, social, and mitigation capacities for analysing vulnerability to tropical cyclones, a multi-criteria assessment approach relying on the FAHP technique was employed (Fig. 2). To determine the vulnerability of natural hazards, several equations have been published in the scientific literature [39]. Based on our literature review, we employed Eq. 1 to calculate the vulnerability of tropical cyclones [31, 40].

Fig. 1 Location map of the study area



$$V = \frac{P * S}{M} \tag{1}$$

where V represents vulnerability, P represents physical vulnerability, S represents social vulnerability, and M represents mitigation capacity.

2.3 Database and sources

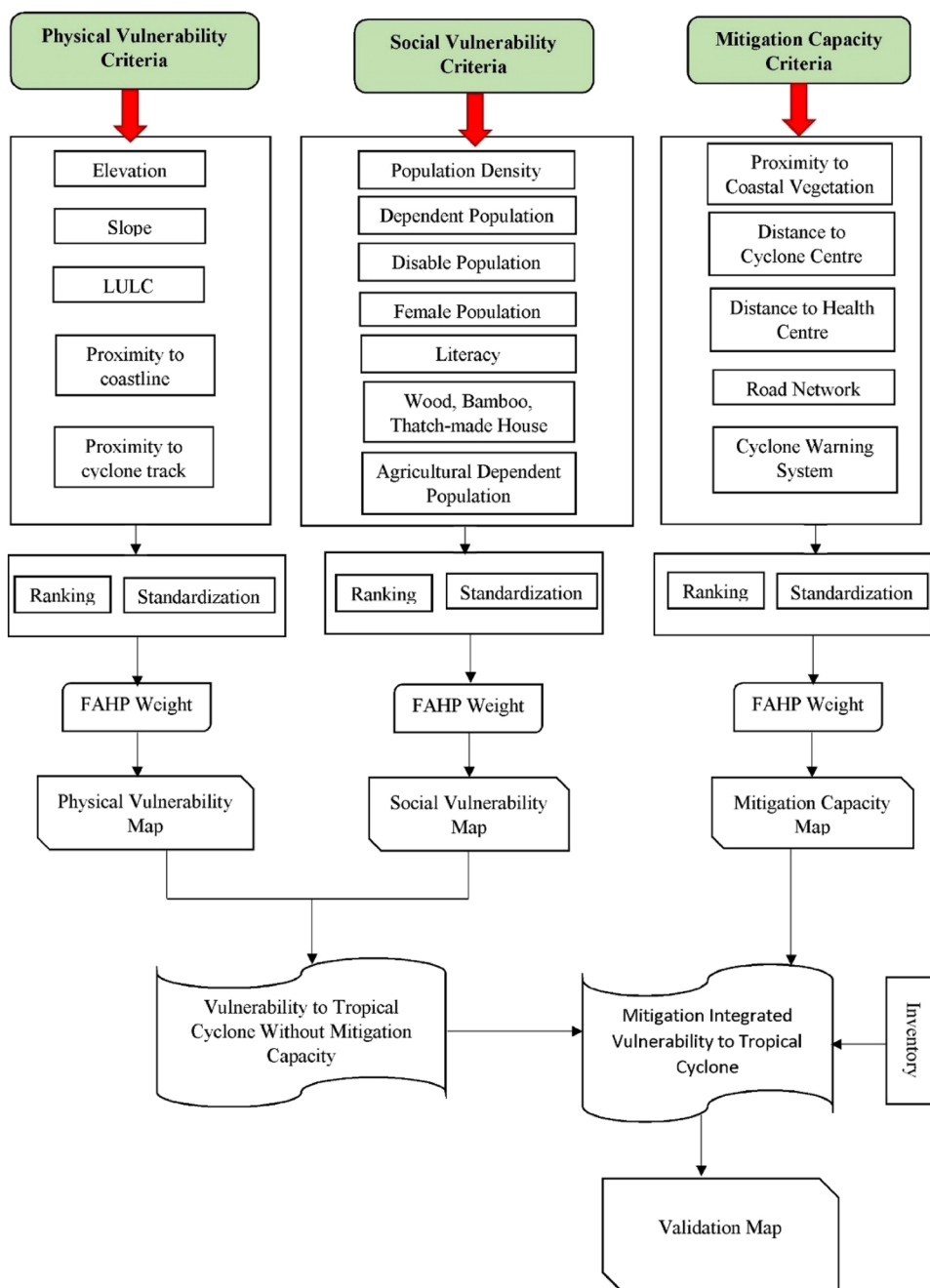
This study developed physical, social, and mitigating criteria for assessing tropical cyclone vulnerability using multiple

types of data from different sources. Geospatial methods were employed to produce the spatial data that served as the basis for the criteria evaluation. International, national, and the state of Odisha's official website are among the data sources. Table 1 below provides specifics regarding the data sources, time frame, and intended usage.

2.4 Vulnerability assessment criteria

Under three main criteria, physical, social, and mitigating factors, we selected 17 sub-criteria based on

Fig. 2 Methodological framework of the study



literature reviews and their impact on vulnerability to tropical cyclones. We then created 17 criteria layers with a spatial resolution of 30×30 m using QGIS, ArcGIS, and MS Excel. The classification of the maps was performed utilizing the natural break classification method, which effectively illustrates the spatial pattern of vulnerability. Table 2 depicts the ranking system of the parameters based on relative importance of tropical cyclone vulnerability. The mapping process

and the significance of the selected criteria are explained in detail in the following sections.

2.4.1 Physical vulnerability criteria

In our study, five key physical elements were identified as affecting tropical cyclone vulnerability: elevation, slope, coastal proximity, cyclone tracks, and Land Use/Land Cover

Table 1 Details of the datasets and their characteristics

Data type	Sources	Year and month	Output
Landsat 8	United States Geological Survey (USGS) Earth Explorer	March, 2022	LULC and coastal vegetation
Digital elevation model (DEM) at 30 m spatial resolution	United States Geological Survey (USGS) Earth Explorer	2018	Elevation and Slope
Population data	Census of India	2011	Population density, dependent population, female population, disable population, literacy, wood, bamboo, and thatch made houses, and agricultural dependent population
Cyclone track	International Best Track Archive for Climate Stewardship (IBTrACS)	1971–2021	Proximity to cyclone track
Cyclone shelter, Health Centre, Cyclone warning system	Odisha state Govt. official website (cmrfodisha.gov.in and osdma.org/state-hazard), Census of India	2022, 2011	Distance to cyclone shelter, distance to health centre, cyclone warning system
Road	Bhukosh (Bhukosh.gsi.gov.in)	2018	Road network

Table 2 Ranking system for the sub-criteria based on the relative importance of tropical cyclone vulnerability

Component	Criteria	Ranking (based on vulnerability)				
		Very low (1)	Low (2)	Moderate (3)	High (4)	Very High (5)
Physical vulnerability	Elevation (m)	> 536	100–536	40–100	5–40	< 5
	Slope (%)	> 6.9	4.41–6.9	2.12–4.4	0.6–2.1	< 0.6
	Distance to cyclone track (km)	> 8	6–8	4–6	2–4	< 2
	Distance to coastline (km)	> 8	6–8	4–6	2–4	< 2
	LULC	Water bodies, sand bar	Fallow land	Vegetation	Agriculture	Built up
Social vulnerability	Population density (sq. km)	< 480	481–530	531–590	591–630	> 630
	Dependent population (%)	< 28.86	28.86–29.27	29.28–29.77	29.78–30.08	> 30.08
	Disabled population (%)	< 2.82	2.82–2.92	2.93–3.04	3.05–3.08	> 3.08
	Female population (%)	< 49.15	49.15–49.4	49.5–49.66	49.67–49.91	> 49.91
	Literacy rate (%)	> 85.2	82.83–85.2	79.79–82.82	74.1–79.78	< 74.1
	Wooden, bamboo, and thatch house (%)	< 4.94	4.94–9.09	9.091–9.12	9.13–10.31	> 10.31
	Agriculture dependent population (%)	< 32.68	32.68–33.01	33.02–37.20	37.21–38.37	> 38.37
Mitigation capacity	Proximity to coastal vegetation (km)	< 5	5–7	7–9	9–11	> 11
	Distance to cyclone shelter (km)	< 2	2–4	4–6	6–8	> 8
	Distance to health centre (km)	< 2	2–4	4–6	6–8	> 8
	Road network (km)	< 1	1–2	2–3	3–4	> 4
	Cyclone warning system		Effective	Moderate	Ineffective	

[27, 31]. The power of a cyclone can be greatly diminished by topographical barriers such as hills and mountains, making high elevation and steep slopes advantageous in reducing vulnerability [41]. Low-lying areas with a high vulnerability risk are less equipped to withstand the force of a cyclone, compared to elevated and sloped regions. To map out these crucial elements, the shuttle radar topography mission (SRTM) DEM was employed, using a spatial resolution of 30 m, bringing us one step closer to understanding the intricate relationship between geography and tropical cyclone vulnerability.

A highly vulnerable area for tropical cyclones is the region located beneath the path of previous storms and close to the coast [2]. Physical vulnerability to these storms was evaluated based on factors such as the proximity of the storm's track (Fig. 3c). Data from the International Best Track Archive for Climate Stewardship (IBTrACS) was utilized to construct buffers and differentiate them from storm tracks [3]. In the research area, 52 spatial storm tracks were identified from 1971 to 2021, ranging from category 1 to 5. These tracks were used for proximity analysis. The distance from the study area's coastline was calculated using the Euclidean distance tool in ArcGIS and converted into raster layers (Fig. 3c).

Tropical cyclones pose a threat to various types of land covers. To create the land use/land cover (LULC) map (Fig. 3e), we utilized four Landsat 8 images. First, we performed preliminary procedures that included adjustments for radiometric, geometric, and atmospheric factors [42]. Then, we applied the Random Forest algorithm, a supervised machine learning approach, to classify the LULC classes. Random Forest is built on decision trees [43]. We

identified six LULC classes including water bodies, vegetation, built-up areas, agricultural land, fallow land, and sand bars. To assess the precision of the LULC map, we generated roughly 1400 random points from high-resolution Google Earth images and assessed the accuracy using the literature as a reference [42, 43]. Our results showed that the overall accuracy and kappa coefficients were 86.46% and 87.66%, respectively.

2.4.2 Social vulnerability criteria

In this study, we selected several social factors that impact tropical cyclone vulnerability. There are seven factors: population density, the disabled population, the dependent population, literacy, the female population, homes made of wood, bamboo, and thatch, and an agricultural-dependent population (Fig. 4). We utilized 2011 Census data for all criteria. Using ArcGIS software, we obtained the data and created raster layers for each criterion. As the world grows, so does the threat of disaster, especially in coastal regions. The swell of population and urbanization intensifies the vulnerability to tropical cyclones, making it a matter of global concern. Figure 4a showcases the spatial distribution of population density and its impact on a location's vulnerability to tropical storms. It's evident that densely populated areas, such as Jagatsinghpur in Odisha's coastal district, face a higher risk than less populated areas like Bhadrak. The threat posed by tropical cyclones only grows with each passing day, making it imperative to understand and address the risk factors.

Groups that are dependent, such as children and the elderly (Fig. 4b), are particularly vulnerable during tropical cyclones as they may not be able to effectively follow

Fig. 3 Physical vulnerability criteria: **a** Elevation, **b** Slope, **c** Proximity to cyclone track, **d** Proximity to coastline, **e** LULC

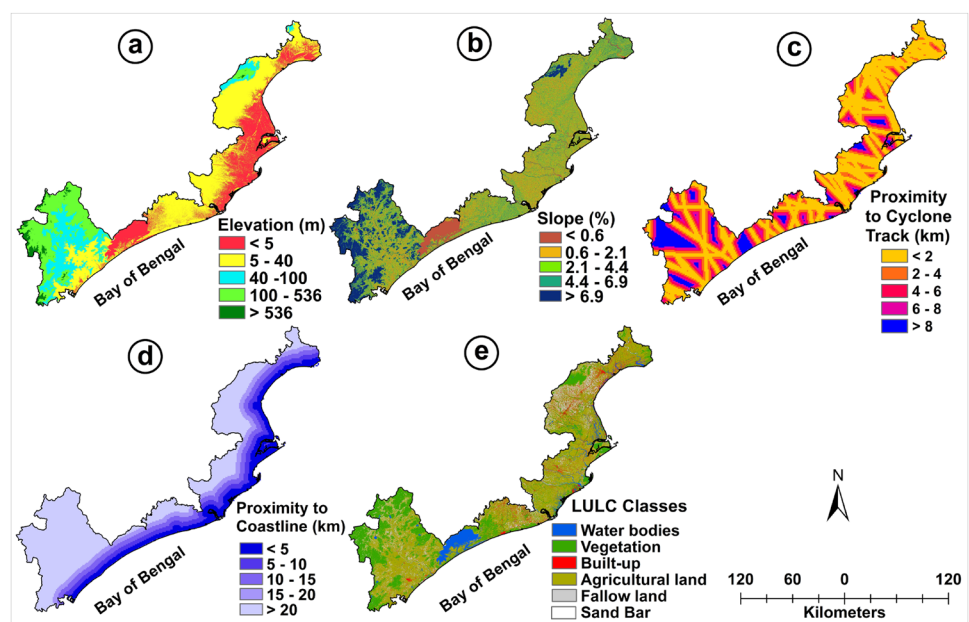
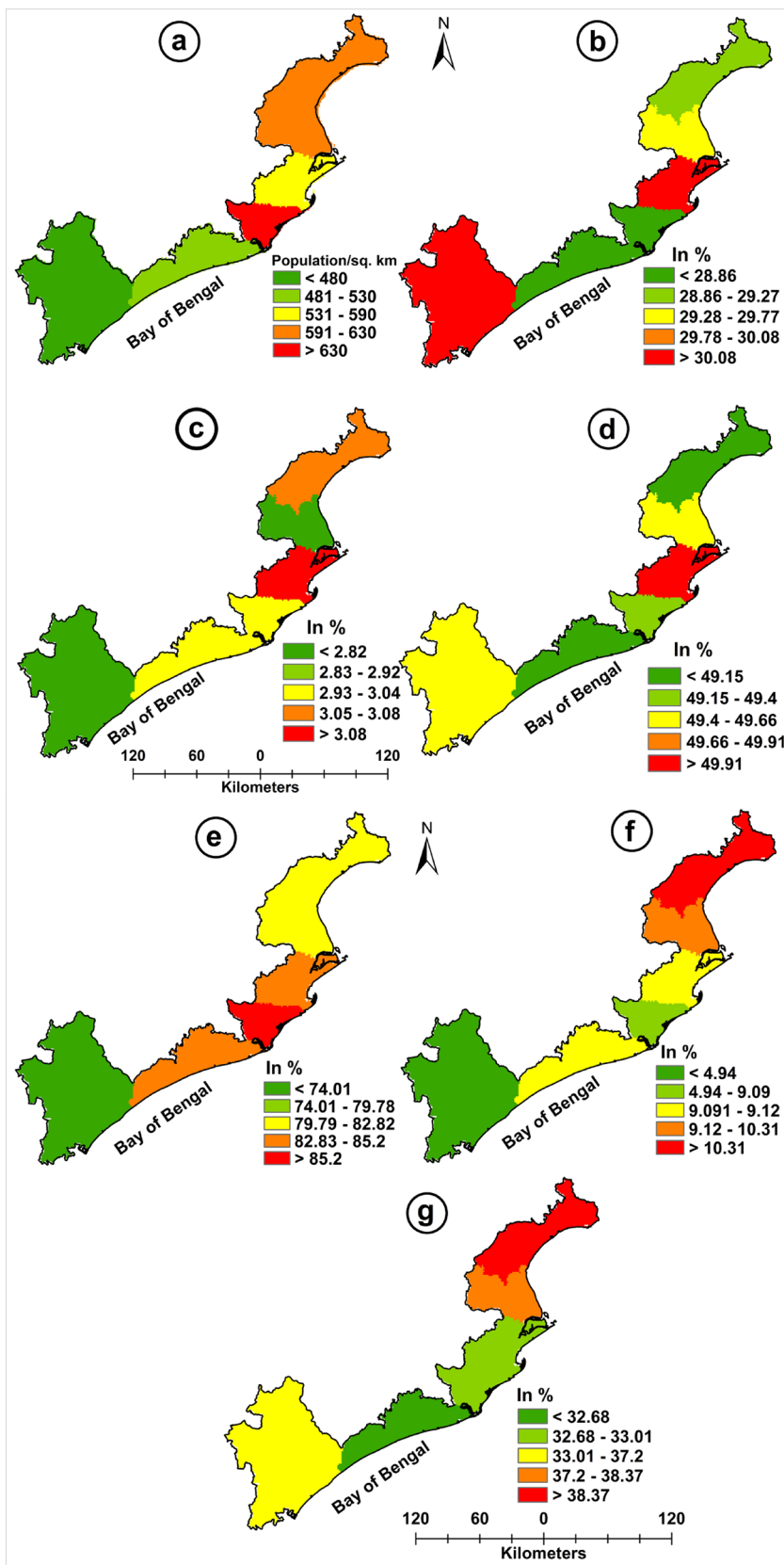


Fig. 4 Social vulnerability criteria: **a** Population density, **b** Dependent population, **c** Disabled population, **d** Female population, **e** Literacy, **f** Wood, bamboo, and thatch houses, **g** Agricultural dependent population



emergency measures and evacuate on their own. These vulnerable groups are particularly susceptible to the risk of tropical cyclones, mainly because they have a limited capacity to cope effectively with such situations in times of disaster [27, 44]. In the context of the dependent population, the highest percentage was found in the Kendrapara district, followed by Ganjam, making these areas more vulnerable. Tropical cyclones can pose a significant threat to disabled individuals, who often struggle to evacuate without aid. During disaster emergencies, they may be left without support or access to early warning systems [2]. In India, the disparity in literacy rates between men and women makes the latter particularly vulnerable to the devastating effects of cyclones. This lack of knowledge and limited mobility can lead to limited access to resources and information during these events.

Determining social vulnerability in the aftermath of a cyclone catastrophe requires a crucial indicator: literacy [38]. Literate individuals tend to be more diligent in following evacuation procedures and taking other preparedness actions to mitigate the effects of cyclones, as they are more cognizant of their impact. In this study, we utilized literacy data from the 2011 Census to create a raster layer. The impact of any disaster on a home is mainly determined by the materials used in construction. Brick houses are much more resilient and less vulnerable than those made of mud, wood, bamboo, or thatch. As a result, areas, where many homes are built from these materials, are more susceptible to damage from wind, heavy rain, and storm surges during tropical cyclones. According to Census 2011 data, statistics on homes made of wood, bamboo, and thatch were collected district by district. Results showed that residents living in homes made of these materials were far more exposed to risk. Thus, building homes using wood, bamboo, and thatch is considered to be a more dangerous option.

In coastal areas, tropical cyclones have a significant impact on agricultural land. Storm surges, heavy rainfall, and high-speed winds can damage crops, resulting in significant financial losses for farmers [39]. At times, salt water can intrude into the mainland due to high storm surges, causing the fertility of the agricultural land to be lost. This saline water also affects fishing farms, leading to a substantial loss for those who rely on agriculture for their livelihood. Using data from the Census of India, 2011, we created a spatial layer that shows the dependency rates on agriculture using a five-category classification. This information highlights the areas and population most impacted by the effects of tropical cyclones on agriculture.

2.4.3 Mitigation capacity criteria

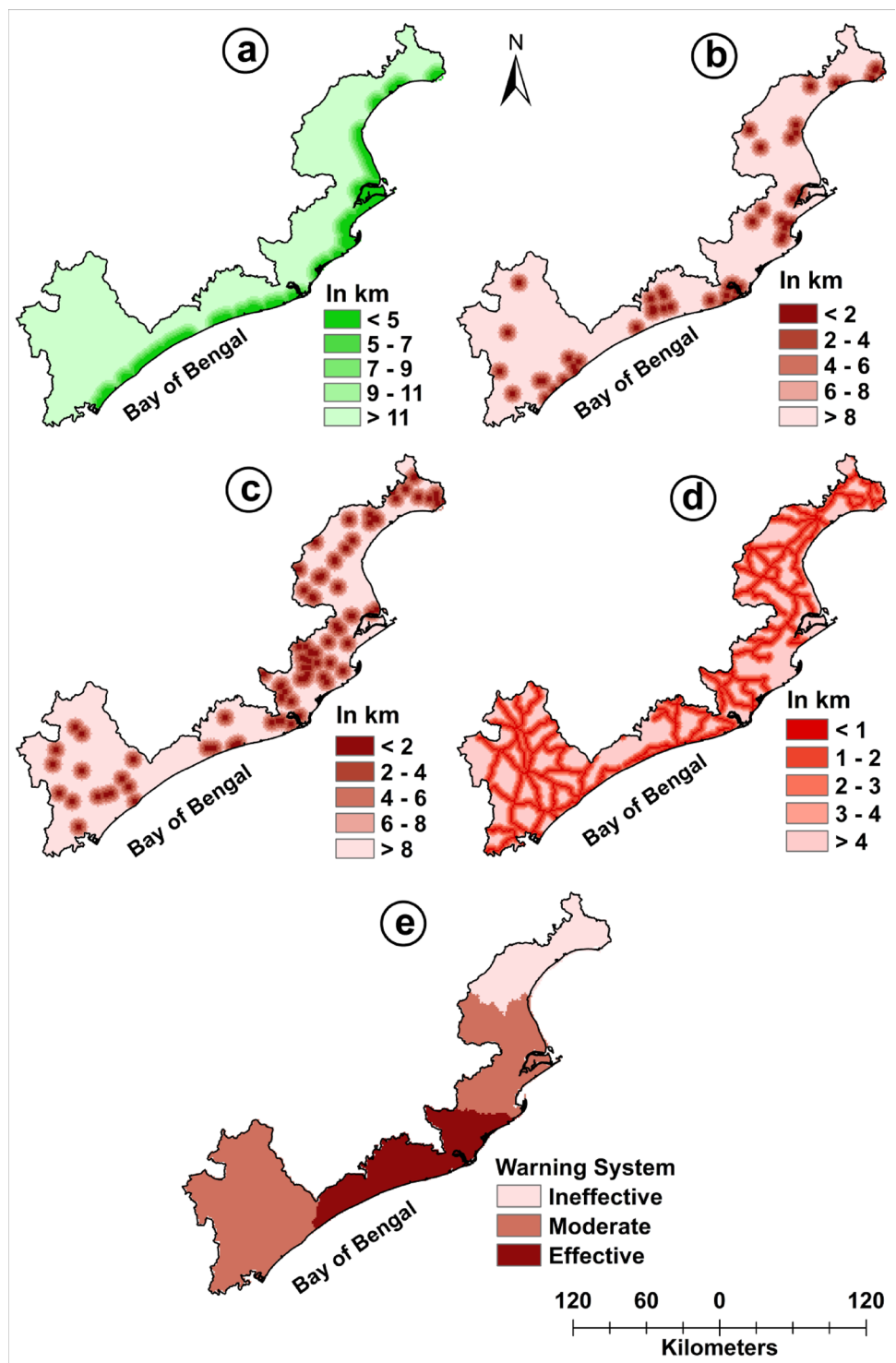
Reducing the potential harm from any unfavourable event is referred to as mitigation. The key strategy, along with both structural and non-structural approaches, to minimize

the effects of tropical cyclones is reflected in the ability to mitigate those risks. For structural mitigation, we selected four parameters as criteria for mitigation: proximity to coastal vegetation, distance from a health centre, distance from a cyclone shelter, and distance to the road network. For non-structural mitigation, we chose to implement a cyclone warning system. The fundamental structure of a cyclone shelter is a sturdy, raised building that offers protection against cyclones and the ensuing storm surges. The foundations are constructed in such a way that they dissipate energy from impending riverine or sea-based cyclonic storm surges [45]. Cyclone shelters are important pieces of infrastructure that are required to provide shelter for marooned individuals during cyclones. We gathered the information for this research from the official website of the Odisha state government. Then we utilized ArcGIS's Euclidean distance tools to create a raster layer representing the distance to the cyclone shelter (Fig. 5b).

Health centres have a crucial role in saving lives and alleviating the pain of those impacted by disasters. An increased number of health centres can reduce the number of casualties and lower the vulnerability to tropical cyclones. A spatial layer was created utilizing the Euclidean tool in ArcGIS, using data from the official website of the state government. Coastal vegetation utilizes its roots, husks, and leaves to obstruct water flow during cyclones to safeguard against storm surges. The protection offered by coastal vegetation reduces the impact of tropical cyclones on people, assets, and the surrounding ecosystem [25]. It functions as a barrier to the cyclone, effectively lowering wind speed and withstanding the initial impact of the storm. By using NDVI, we can extract information on coastal vegetation from Landsat 8 images. The Euclidean distance method was employed to calculate the proximity to coastal vegetation.

A cyclone warning system issues warning about strong winds and potential threats to infrastructure. This system also provides improved tracking and forecasting of cyclones, which helps to minimize economic and human losses. In our study, we utilized district-wise data from various sources such as radio, television, mobile, and the internet, as well as local-level warning system data obtained from the state Government's official website. We then calculated the weight of different parameters, such as television, radio, and internet, using weighted linear composite (WLC) techniques. Finally, with the help of a raster calculator in ArcGIS, we generated the final spatial layer for the cyclone warning system (Fig. 5e) and categorized it into three groups: effective, moderate, and ineffective. When disaster strikes, road structures such as bridges, culverts, and flood ways become indispensable as they play a pivotal role in the rescue, recovery, and reconstruction efforts as well as the community's ability to bounce back. To accurately depict the road network, we

Fig. 5 Mitigation capacity criteria: **a** Proximity to coastal vegetation, **b** Distance to cyclone shelter, **c** Distance to health centre, **d** Road network, **e** Cyclone warning system



obtained primary data from the Bhukosh website (Bhukosh.gsi.gov.in), and expertly generated the spatial layer illustrating road distances (Fig. 5d) using the Euclidean distance technique in ArcGIS.

2.5 Ranking sub-factors

We used two classification methods, natural breaks and manual classification, to categorize each criterion and rank

the subfactors. We then assigned each sub-factor a hazard level from 1 to 5, with rank 1 representing low hazard and rank 5 representing extremely high hazard. This approach assumed that higher scores correspond to higher levels of vulnerability. To ensure consistency with the physical factors, we converted the district-level social criteria data into a grid format. Raster levels with a resolution of 30 m were created for each spatial criterion. These raster criterion levels were then normalized to align their values using Eq. 2.

$$P = (X - \min) / (\min - \max) \tag{2}$$

where P denotes normalized score, min, max, and X denote the minimum, maximum, and cell value in each spatial raster layer related to each dataset respectively.

2.6 FAHP and criteria weighting

FAHP stands for "Fuzzy Analytic Hierarchy Process." It is a method used in decision-making that considers multiple criteria, allowing for imprecision, uncertainty, and partial information. The process involves evaluating different alternatives and criteria and weighing each criterion according to its importance. Zadeh [46] proposed the concept of fuzzy set theory, which offers a modeling approach to replicate complex systems that are difficult to comprehend using precise numerical values. The entry of unclear, inaccurate, and vague information is permitted by fuzzy logic [47]. Fuzzy logic is often used in decision making to represent spatial elements on a map using fuzzy membership functions. While classical set theory categorizes objects as either belonging or not belonging to a set, fuzzy set theory allows

membership values between 0 and 1 to indicate the degree of membership. In this study, the FAHP (Fuzzy Analytic Hierarchy Process) was used to assign weights to the criteria. Unlike other researchers who have used different FAHP strategies, we adopted the integrated FAHP methodology proposed by Chang in 1996. This approach simplifies pairwise comparisons using triangular fuzzy numbers (TFNs), thus eliminating the complexity of the comparison process. The FAHP methodology used in this study included five stages to determine the criteria weights.

In Phase 1, the relevant standards for classifying vulnerabilities to tropical cyclones were selected.

In Phase 2, is the process of pairwise comparison and determination of weights. In this phase, the decision-maker assesses the relative importance or priorities of the criteria and alternatives by making pairwise comparisons. The judgments are captured using linguistic variables (such as "more important," "equally important," or "slightly more important") and are then converted into numerical values using fuzzy linguistic scales. These numerical values are used to calculate the weights of criteria and alternatives, which are essential for the subsequent analysis and decision-making. In this research, the relative importance of the chosen criteria was established by constructing pairwise comparison matrices based on the input from five experts. Fuzzy set theory and fuzzy membership functions (FMF) are instrumental in representing data that contains ambiguity and uncertainty. They serve a crucial role in capturing and representing imprecise information. A fuzzy set is a collection of objects defined by a function that assigns a membership grade to each item, ranging from 0 to 1 and vice versa. The relationship between quantitative values and linguistic variables is depicted in Table 3.

$$F = (a, b, c), N = 1, 2, \dots, N (F = \text{triangular fuzzy member} \ \& \ N = \text{no. of DMs}) \tag{3}$$

$$\text{where } a = (a_1 * a_2 * a_3 \dots * a_N)^{1/N}, b = (b_1 * b_2 * b_3 \dots * b_N)^{1/N}, c = (c_1 * c_2 * c_3 \dots * c_N)^{1/N}.$$

Table 3 Membership function of linguistic scale

Linguistic variable	Crisp numbers	Triangular fuzzy numbers	Reciprocal triangular fuzzy numbers
Equally strong	1	(1, 1, 1)	(1, 1, 1)
Moderately strong	3	(2, 3, 4)	(1/4, 1/3, 1/2)
Strong	5	(4, 5, 6)	(1/6, 1/5, 1/4)
Very strong	7	(6, 7, 8)	(1/8, 1/7, 1/6)
Extremely strong	9	(9, 9, 9)	(1/9, 1/9, 1/9)
Intermediate	2	(1, 2, 3)	(1/3, 1/2, 1)
	4	(3, 4, 5)	(1/5, 1/4, 1/3)
	6	(5, 6, 7)	(1/7, 1/6, 1/5)
	8	(7, 8, 9)	(1/9, 1/8, 1/7)

In phase 3, involves aggregating the pairwise comparison judgments and calculating the overall weights for the criteria and alternatives. This phase is also known as the aggregation phase. The aggregated judgments are combined using mathematical operations like the weighted average method or the geometric mean method to determine the final weights. In this research we employed geometric mean method. These weights are then used for further analysis and decision-making in the FAHP framework.

In phase 4, the maximal eigenvector or relative weights and λmax were calculated to ensure consistency in the order of items. The relative weights for each parameter under different criteria have been depicted in Table 4. In order to

Table 4 Criteria weights from pairwise comparison matrices

Component	Criteria	Weight
Physical vulnerability	Elevation (m)	0.197
	Slope	0.198
	Distance to cyclone track (km)	0.19
	Distance to coastline (km)	0.177
	LULU	0.245
Social vulnerability	Population density (sq. km)	0.191
	Dependent population (%)	0.162
	Disabled population (%)	0.15
	Female population (%)	0.158
	Literacy rate (%)	0.112
	Wooden, bamboo, and thatch-made house (%)	0.12
	Agriculture dependent population (%)	0.107
Mitigation capacity	Distance from coastal vegetation (km)	0.28
	Distance from cyclone centre (km)	0.2
	Distance from health centre (km)	0.22
	Distance from road (km)	0.12
	Cyclone warning system	0.18

complement the expert evaluations in the pairwise matrices, the calculation of the consistency index (CI) was conducted utilizing Eq. 4. The consistency ratio (CR) was calculated as well, following Eq. 5, with a value of 0.1 or below indicating accurate judgment [48]. The equation for CR was as follows:

$$CI = (\lambda_{max} - n)/(n - 1) \tag{4}$$

$$CR = (CI/RI) \tag{5}$$

Within this context, 'n' signifies the count of items in the matrix under comparison, 'λ_{max}' denotes the maximum eigenvalue, and 'RI' represents a random index derived from numerous simulations runs, which relies on the matrix order.

2.7 Vulnerability assessment

To develop the indices for physical, social, and mitigation capability, the relevant spatial layers and their weights were used in individual overlay analysis. This resulted in a map of physical, social, and mitigation capability vulnerability, each divided into five zones ranging from very high to very low. The physical and social vulnerability indices were multiplied to create a vulnerability map without considering mitigation capacity. However, by using Eq. 1, an integrated

vulnerability index that incorporated mitigation capacity was created. The vulnerability indexes (both with and without mitigation) were standardized to a common scale of 0 to 1 and then divided into five categories: very high, high, moderate, low, and very low.

2.8 Validation of cyclone vulnerability assessment

In this study, the cyclone vulnerability model was validated using the receiver operating characteristics (ROC) curve. ROC is a graphical representation of the performance of a binary classifier as the discrimination threshold is varied [49, 50]. The formula for the ROC curve is as follows:

$$\text{True Positive Rate (TPR)} = \text{True Positives}/(\text{True Positives} + \text{False Negatives})$$

$$\text{False Positive Rate (FPR)} = \text{False Positives}/(\text{False Positives} + \text{True Negatives})$$

The area Under the Curve (AUC) is a single number that summarizes the performance of a binary classifier. AUC represents the probability that a randomly selected positive example will have a higher score than a randomly selected negative example. The formula for AUC is as follows:

$$AUC = (1/m) * \sum ((i/m) - (j/n)) * y [j] \quad \text{for } i = 0 \text{ to } m - 1 \text{ and } j = 0 \text{ to } n - 1 \tag{6}$$

here 'm' stands for the number of positive examples and 'n' for the number of negative examples. Within the formula, 'y[j]' stands for the true designation of the jth negative example. Additionally, we received opinions from 102 locals in the research area. We also made comprehensive personal observations by determining the precise levels of various locations on the map and confirming the actual vulnerability of tropical cyclones. Based on the locals' perceptions and the overlaid parameters for creating the inventory map, 120 validation points were used. Using this inventory map as a reference, we extract values from the generated cyclone vulnerability map at their corresponding points. Thereafter, using the software R Studio (Version 4.2.0), ROC curve was constructed for the study.

3 Results and discussion

3.1 Evaluation of the spatial pattern of physical vulnerability

Five parameters have been used to assess the physical vulnerability to tropical cyclones in the coastal Odisha (Fig. 3). The contribution of each parameter to physical vulnerability is shown in Table 5 and Fig. 3. In order to categorise physical vulnerability to tropical cyclones, the region has been divided into five classes i.e. very low, low, moderate, high and very high. The results show that approximately 40% of the region falls under high to very high vulnerability zone, while the remaining area is distributed among the moderate, low and very low vulnerability categories, accounting for 21.58%, 22.07% and 17.70% respectively. The zones with high to very high physical vulnerability is mainly concentrated along the coastal areas of the region, particularly in Bhadrak, Baleshwar, Kendrapara and Jagatsingpur districts. These areas are characterized by low elevation, shallow slopes, frequent cyclones, close proximity to the sea coast and hazardous land use classifications. Conversely, the southern and northeastern parts of the study area, particularly in the Baleshwar and Ganjam districts have low to very

low levels of vulnerability to cyclone activity because these areas are characterized by comparatively high elevation, and low frequency of cyclone tracks as well as these areas are located at a significant distance from the coast. The western and central parts of the Baleshwar, Puri, and Ganjam districts make up the moderately vulnerable zone (Fig. 6).

3.2 Evaluation of the spatial pattern of social vulnerability

The social vulnerability to tropical storms in a given area is shown in Fig. 7. The social vulnerability mapping has been done using seven parameters, including population density, dependency, disability and female population, literacy rate, type of housing made of wood, bamboo, and thatch, and agricultural dependency. The districts of Baleshwar, Kendrapara, and Bhadrak have comparatively high socially vulnerability as these districts have comparatively higher dependency, agriculture-dependent population, poor housing conditions, and low literacy rates. Overall, nearly 39% of the total area of coastal Odisha has been categorized under high to very high levels of social vulnerability. While, nearly 21% of the total area of region has been classified under moderately vulnerable in terms of social vulnerability. The central part of the region, particularly Jagatsinghpur and Puri districts, shows comparatively low social vulnerability than other parts. This is because this part has less dependent population, lower number of people with disabilities, low agricultural dependency, and higher literacy rate.

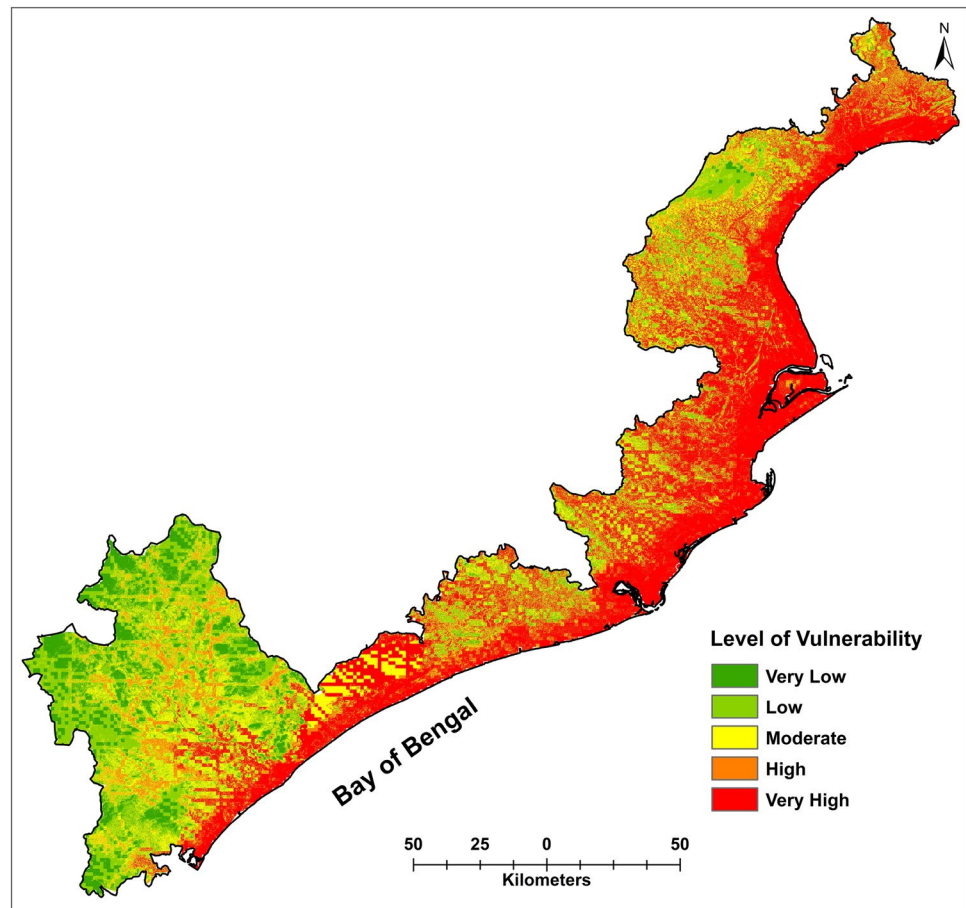
3.3 Evaluation of spatial pattern of mitigation capacity

The result shows that coastal Odisha have significant prospects for enhancing the mitigation capacity. The analysis of mitigation capacity has been done using five indicators which describes that about 12,150.6 sq. km (> 55%) area of coastal Odisha have high to very high level of mitigation capacity. This is due to the abundance cyclone shelters, the

Table 5 Area computation of vulnerability

CClass	Physical vulnerability		Social vulnerability		Mitigation capacity		Vulnerability without mitigation		Vulnerability with mitigation	
	Area (sq. km)	% of area	Area (sq. km)	% of area	Area (sq. km)	% of area	Area (sq. km)	% of area	Area (sq. km)	% of area
Very low	3910.43	17.70	3402.44	15.40	3406.59	15.42	2865.12	12.97	4771.87	21.60
Low	4874.98	22.07	1651.99	7.48	1983.86	8.98	3819.71	17.29	7776.38	35.2
Moderate	4767.45	21.58	8268.98	37.43	4749.78	21.5	6243.2	28.26	4880.12	22.09
High	4401.96	19.93	2378.98	10.77	5810.20	26.3	4201.82	19.36	3108.34	14.07
Very high	4137.17	18.73	6389.62	28.92	6141.58	27.8	4886.72	22.12	1555.28	7.04

Fig. 6 Spatial distribution of physical vulnerability to tropical cyclones



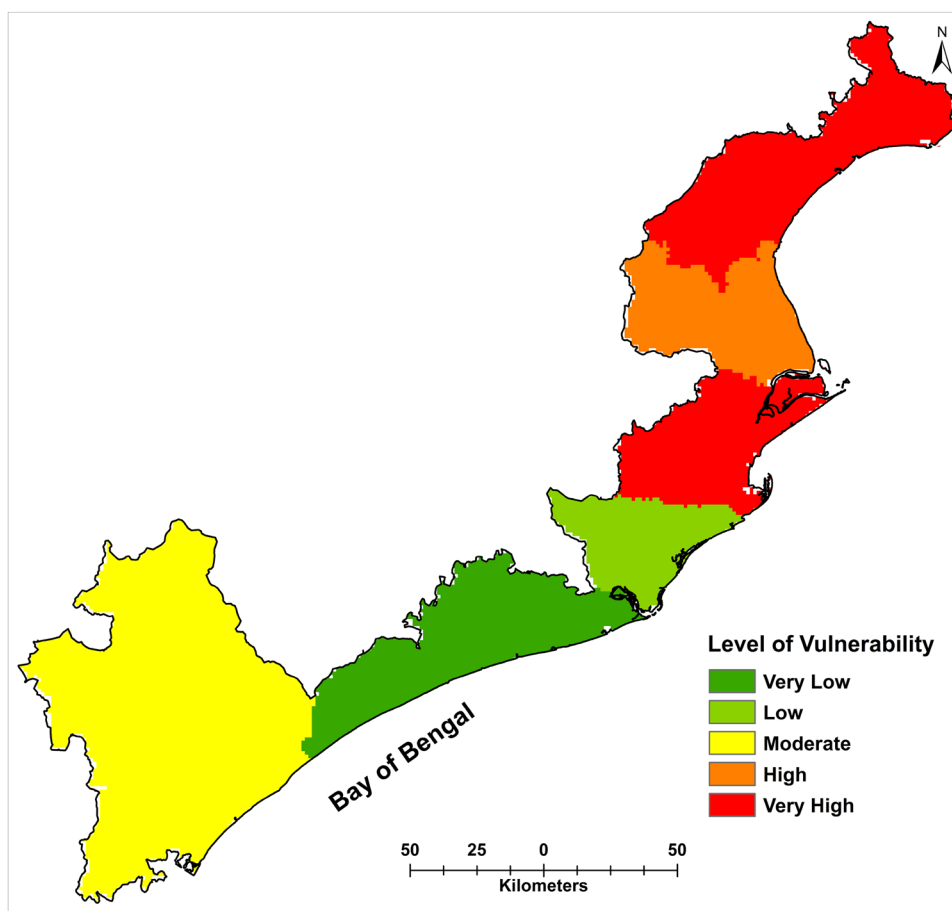
presence of well-equipped health centres, the effectiveness of the cyclone warning system and the well-developed road networks in the coastal districts. Additionally, the study shows that nearly 9% area of the coastal Odisha have moderate mitigation capacity, mainly in the northern parts of the Ganjam district as well as parts of Puri and Bhadrak districts. At the same time, about 25% of the region have low to very low mitigation capacity which includes a zone spanning 5,390 sq. km. in Baleshwar and Bhadrak districts as well as parts of the Ganjam district. The Baleshwar district has the lowest mitigation capacity due to a lack of cyclone shelters, limited coastal vegetation cover, and a weak cyclone warning system. Moreover, the mountainous areas particularly in Ganjam district are relatively inaccessible and thus have low mitigation capacity (Fig. 8).

3.4 Evaluation of the spatial distribution of vulnerability without mitigation capacity

The analysis of vulnerability to tropical cyclones without considering mitigation capacity shows that the northeastern parts of the coastal Odisha have higher vulnerability in

contrast to the southwestern region (Fig. 9). The districts like Baleshwar, Bhadrak, and Kendrapara have been found to be more vulnerable, while Puri and Ganjam were less vulnerable. The high to very highly vulnerable zone, which covers approximately 9100 sq. km area, makes up over 40% of the land area (Table 5). This zone includes most of the Baleshwar, Bhadrak, and Kendrapara districts, as well as the coastal part of the Jagatsinghpur district. A small area near the coastline of the Ganjam district is also located in this zone. The high vulnerability in this area is due to factors like low elevation, flat terrain, proximity to the coast, frequent cyclone occurrences, and underdeveloped socioeconomic conditions. In contrast, Puri and northern parts of the Ganjam districts have mostly low to very low vulnerability to tropical cyclones which covers an area of about 6684 sq. km (29% area of the region). This is because, this part of coastal Odisha is characterized by steep slope, high elevation, distance from the coast, fewer cyclones, and well-organized and developed socioeconomic conditions. Finally, the moderately vulnerable area, which encompasses 28.26% of the region, is predominantly located in the northern and western portions of Jagatsinghpur district, the southern area of Puri, and the central region of Ganjam district.

Fig. 7 Spatial distribution of social vulnerability to tropical cyclones



3.5 Evaluation of the spatial distribution of mitigation capacity integrated vulnerability

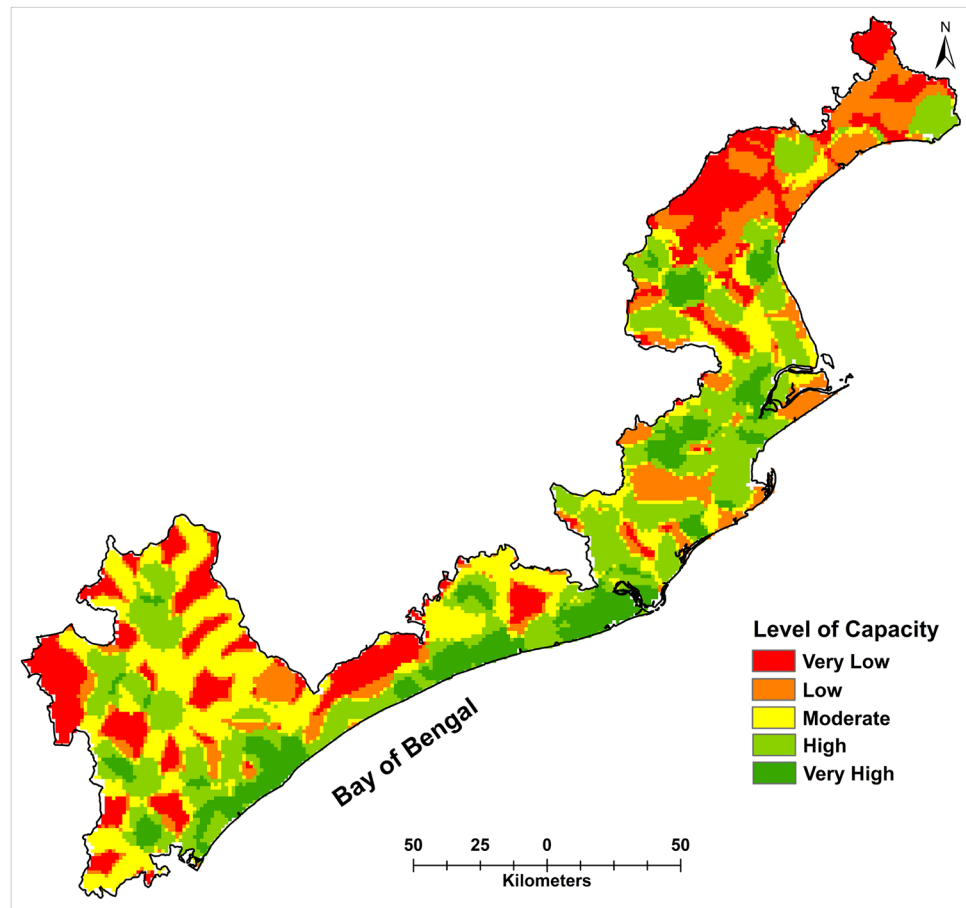
The analysis of vulnerability to tropical cyclone by considering mitigation capacity has been presented in Fig. 10. Mitigation capability, which encompasses the community's assets, strengths, and resources, is a critical factor in determining a region's level of vulnerability. The result shows that about 4664 sq. km area (nearly 21% area of the coastal Odisha) is under high-vulnerability zone while considering mitigation capacity in the analysis, majority of which is located in the Baleswar district. Parts of Baleswar district, middle and coastal parts of the Bhadrak district, the eastern coastal part of the Kendrapara district, and some areas of the Ganjam district, have been found under high to extremely high vulnerability zones. Further, the moderate vulnerability zone encompasses nearly 4480 sq. km area (22%) of the coastal Odisha which includes the eastern parts of the Bhadrak district, most of the Jagatsingpur district, and some parts of the Ganjam district. On the other hand, low and very low vulnerability zones cover nearly 56% of the region. Most of the low and very low vulnerability zones are located in Puri, Ganjam, parts of the Jagatsingpur district, and the eastern parts of the Kendrapara and Bhadrak districts.

The analysis of vulnerability to tropical cyclones without integrating mitigating capacity shows that districts like Baleswar, Bhadrak, and Kendrapara are entirely under high to very highly vulnerable zones. Similarly, the coastal parts of the Ganjam district are in a highly vulnerable zone, and most parts of the Ganjam and Puri districts are moderately vulnerable. However, when mitigation capacity is integrated into the analysis of vulnerability to tropical cyclones, the results show that the most of these areas come under either low or moderate vulnerability zones. For instance, most parts of Bhadrak and Kendrapara, as well as the central and eastern portions of the Baleswar district, shift from high vulnerability to moderate and low vulnerability while considering the mitigation capacity in the analysis. In addition, the Puri and Ganjam districts, which were high to moderately vulnerable without mitigation capacity, are found under very low to low vulnerability zone while considering the mitigation capacity.

3.6 Validation of the cyclone vulnerability assessment

In this research, the employed models were validated using the ROC curve. As stated by Das and Pal [50], the AUC

Fig. 8 Spatial pattern of mitigation capacity to tropical cyclones



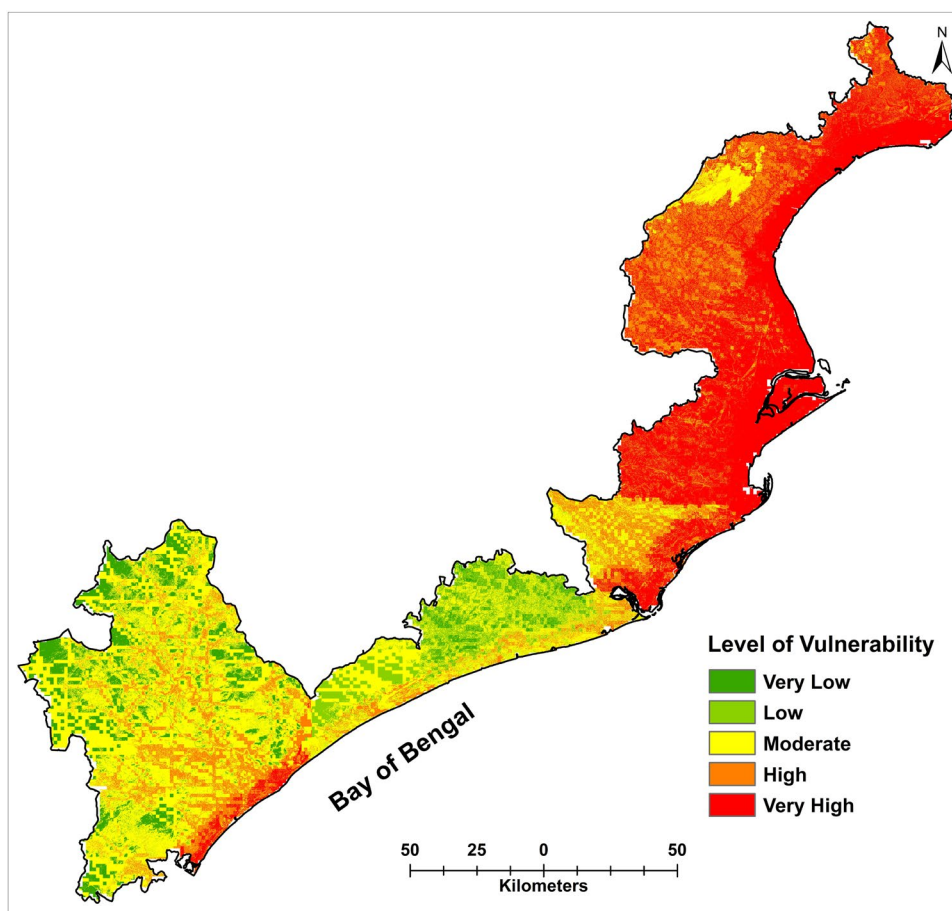
value ranges from 0.5 to 1, with higher values closer to 1 indicating increased accuracy. Typically, an AUC value of 0.80 or higher is regarded as a reliable performance threshold [51], signifying the model's ability to make precise predictions. The vulnerability model without mitigation yielded an AUC of 0.866, while the integrated vulnerability model with mitigation achieved an AUC of 0.902. These results indicate that the model has performed satisfactorily and may be used in further studies for this kind of analysis. It is noteworthy that the vulnerability model without mitigation would not capture the ground reality, suggesting that mitigation should be incorporated in vulnerability modeling [52, 53]. Without mitigation, it is not possible to accurately assess the vulnerability to a hazard. For example, if a place is exposed to frequent cyclone events, it does not necessarily mean that the place is truly vulnerable because residents may have proper infrastructure and mitigation capacity to cope with the vulnerability. Conversely, a place with less mitigation capacity is more exposed to events, making it necessary to include mitigation in vulnerability modeling [54] (Fig. 11).

4 Potential practical implications and management policies

The eastern coast of India witnesses tropical cyclones at least twice each year which causes devastating damage to the economy, society, and environment. Hence, it is important for the National and State Government disaster management agencies as well as local communities to prioritize highly vulnerable regions for deploying emergency response teams, pre-positioning relief supplies, and constructing resilient infrastructure such as cyclone shelters and health centres. As this study already shows that the by considering mitigation capacity, the area under very high and high vulnerability to tropical cyclones is low, therefore, the focus may be given towards developing mitigation capacity in the region. For this, high-risk areas may be pinpointed, and evacuation routes may be established accordingly. Understanding vulnerability patterns enhances the effectiveness of early warning systems, enabling authorities to issue timely and targeted alerts to populations in high-risk areas, thus empowering people to prepare and evacuate ahead of cyclones.

The districts like Baleswar, Bhadrak, and Kendrapara may be given special attention by the disaster management

Fig. 9 Spatial distribution and level of vulnerability without mitigation capacity to tropical cyclones



agencies to develop mitigation capacity in these districts as they have low mitigation capacity and high vulnerability to tropical cyclones. For this, government and disaster management agencies may look for deploying emergency response teams in these districts on one hand while also ensuring the development of cyclone shelters, health infrastructures, cyclone warning system, and cyclone resilient infrastructures on the other hand. Moreover, the policy makers may also focus on increasing the mangrove vegetation as it has been seen that the mangroves in coastal regions act as a protective shield against cyclones by diminishing the force of winds and surges as they traverse through and hence, they reduce the impact of tropical cyclones on people, society, and economy. The mangrove vegetation will not only reduce the vulnerability to tropical cyclones, but may also improve the local environment and provide livelihood the people in coastal areas.

5 Conclusion

Among east coastal states of India, Odisha witnesses' maximum number of tropical cyclones, surpassing other states such as West Bengal, Andhra Pradesh, and Tamil Nadu.

Hence, the current study carries out a comprehensive analysis of tropical cyclone vulnerability in the coastal plains of Odisha, considering seventeen parameters from three aspects i.e. physical, social and mitigation aspects. The study shows that approximately 38% of the total area falls into the high to very high physical vulnerability zone, while roughly 40% of the area is classified as high to very high vulnerability in terms of social vulnerability. The spatial pattern of physical vulnerability shows high vulnerability in the northern part of Baleswar, almost the entire Bhadrak, Kendrapara, and Jagatsinghpur districts, as well as the southern parts of the Ganjam district. Social vulnerability is notably high in most of the parts of Baleswar, Bhadrak, and Kendrapara districts. The study also shows a strong mitigation capacity in the coastal Odisha, with nearly 51% of the total area demonstrating high mitigation capacity. The analysis of vulnerability without considering mitigation capacity shows very high area under very high and high vulnerability (> 40%) to the tropical cyclones. While when mitigation capacity is integrated in the vulnerability assessment, the coverage of area under high and very high vulnerability zones is reduced to about half (about 21%) of area under vulnerability without mitigation capacity and 56% is found under low vulnerability to tropical cyclones. Study shows that Baleswar district is

Fig. 10 Spatial distribution and level of vulnerability with mitigation capacity to tropical cyclones

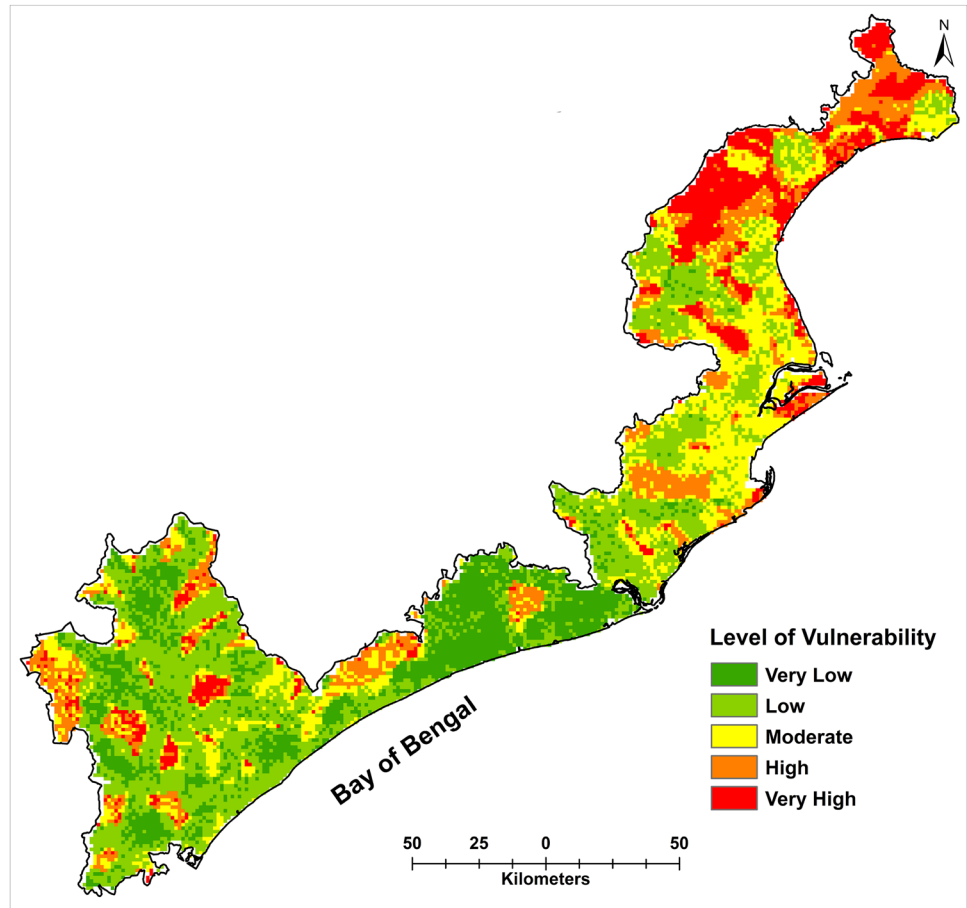
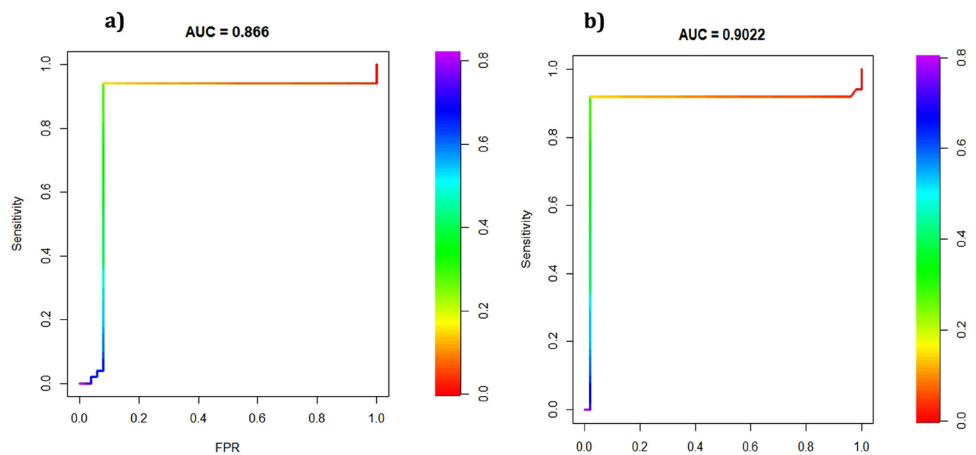


Fig. 11 Model validation through ROC curve: **a** ROC curve for vulnerability without mitigation capacity, **b** ROC curve for vulnerability integrated mitigation capacity



the most vulnerable district to tropical cyclones along with eastern and south-eastern parts of Kendrapara district and central parts of Bhadrak district. Despite some limitations, this research is crucial for the development of a management strategy for the highly vulnerable area, both for government agencies and coastal authorities.

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Author contributions T.D: Methodology, Data curation, Software and Writing—original draft. S.T: Visualization, Software, and

Writing—original draft. Shahfahad: Software, Formal analysis and Writing—review and editing. M.R.I.B: Data curation, Visualization. H.T.H: Methodology and Software. A.M.S: conceptualization and Visualization. A.R: Conceptualization, Project administration, Writing—review and editing.

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Data availability The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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