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DECODING THE SPATIAL VARIATION OF CLIMATE VULNERABILITY IN ODISHA, INDIA

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Abstract

Coastal states in India face various climate-related challenges, including cyclones, floods, rising sea levels, heat waves, droughts, and changing precipitation patterns, which pose a significant barrier to alleviating poverty, improving health, and advancing development. In the Indian context, various studies have explored such issues by assessing vulnerability, but only limited studies have downscaled to micro-spatial units. This paper constructs a district-level climate vulnerability index and maps the spatial heterogeneity for Odisha, India. Using the site-specific indicators, the composite vulnerability index reflecting sensitivity, exposure, and adaptive capacity is framed for each spatial unit. The aggregate vulnerability index varies from 0 to 1, denoting lower to higher vulnerability. The southern and central districts are naturally vulnerable due to their spatial dimensions, but higher sensitivity and lower adaptation capacity make the situation worse for these districts. Districts like Baleshwar and Bhadrak with high exposure to climate vulnerability can be addressed by enhancing the adaptive capacity indices like forest area, television satellite connections, and concrete houses, and reducing the sensitivity due to population density, muddy houses, and non-working population. Results highlight the inter-district variations among components of vulnerability, indicating the importance of local-scale policy-making for better management of climate-induced vulnerability.

Keywords: Spatial variation; Vulnerability; Exposure; Adaptive capacity; Sensitivity; Climate Change

1. Introduction

Natural disasters are significant events that can wreak havoc on populations and economies. They can hinder development regardless of whether a country is developed or developing. India is often referred to as one of the most disaster-prone countries in the world and faces numerous challenges due to its vast population and limited landmass (GoI, 2014). India has experienced frequent calamities and has 40 million hectares of land vulnerable to floods, a long coastline prone to cyclones, and 68% of its agricultural land susceptible to drought (Patel et al., 2020). India is subject to many natural and artificial disasters, which can happen differently; over 40 million hectares are at risk of flooding and river erosion; of the 7,516 km of coastline, close to 5,700 km are at risk of cyclones and tsunamis; 68% of the land that can be farmed is at risk of drought, and hilly areas are at risk of landslides and avalanches (GoI, 2014). More than 3 out of 10 of the world's poor live in India; 70% of its population works in agriculture; 40 million ha are at risk from flooding; 68% of its agricultural land is at risk from drought; the country's coastal regions are vulnerable to cyclones; and the country's annual mean temperature is rising, making it one of the most vulnerable nations in the world (Radhakrishnan et al., 2017).

Natural catastrophes frequently hit Odisha due to its location and climatic conditions, hence it is considered as the most disaster-prone state in India. The state is frequently hit by cyclones and has a tropical climate with heavy monsoon rains, leading to frequent flooding. Low-lying coastal plains and hilly regions are susceptible to floods, storm surges, and landslides (Sharma, 2016). Among the natural calamities that strike and devastate the state, occurrences of floods, droughts, cyclones, and heatwaves are almost a regular feature, befalling more than once in some years, and those of hailstorms, whirlwinds, tornadoes, and landslides are occasional (OES, 2015). The environment of Odisha can be described as tropical, with warm temperatures and high humidity year-round, moderate to heavy rainfall, and pleasant winters. Odisha has been hit by extreme weather fluctuations that have had devastating consequences on agricultural output, raising the dangers of food insecurity and malnutrition. Odisha is one of India's most risky states regarding climate change and the frequency with which natural disasters like floods, cyclones, droughts, and heatwaves occur (Patel, 2019). These disasters, in particular, and climate change, in general, negatively influence agriculture and other economic sub-sectors; therefore, appropriate action needs to be taken in response to this problem (OES, 2015).

The state is frequently plagued by floods, which impede development, and occasionally hit by cyclones, which, while less common than floods, threaten public safety and property, particularly in the state's coastal regions (SDMP, 2013). Heatwaves have become more frequent and severe due to the structure of economic activity in Odisha, negatively influencing the quality of life of many people, particularly those whose jobs require them to work outside (Patel et al., 2019). Each year, the industrial sector and coal-fired plants release 164 million tonnes of carbon gases, comparable to 3% of the expected growth in human greenhouse gases globally. They are therefore blamed for the rising temperature and intensity of heatwaves in Odisha. Deforestation rates in mining areas have risen over time, and the industry has exacerbated this trend. Moreover, this has also added to the disruption of irregular rainfall patterns and rising temperatures that impact Odisha's coastal agricultural production (D. Mishra & Sahu, 2014). According to Das (2016), Odisha is a fascinating example of natural disaster-led underdevelopment due to its frequent and repeated calamities and economic backwardness.

Climate change-related natural disasters and meteorological disruptions threaten most coastal regions. The impact of recurrent exposure events on the socioeconomic characteristics of the population in the coastal system creates vulnerability, which varies depending on coping capacity (Yadav & Barve, 2017). Demographic, socioeconomic, and hazardous physical and environmental surroundings are the leading causes of vulnerability, according to Wisner et al. (2003). Vulnerability affects different populations' resource distribution, livelihood possibilities, social rights, and institutional access. The people or communities waiting for aid to re-establish their livelihoods after a disaster are equally vulnerable to subsequent calamities. Cutter et al., (2003) classify vulnerability as exposure, social condition, integration of prospective directions, and societal resilience, focusing on places or regions. The IPCC, (2007) defines vulnerability holistically, covering economic, social, and environmental variables of an area or population at risk. Communities in rural areas with low infrastructure, social systems, illiteracy, and unemployment are more prone to frequent disasters and fewer preventive actions.

According to Cutter et al. (2003), vulnerability is closely linked to a household or community's socioeconomic condition, and their contribution must be measured to minimize their negative impact and identify appropriate actions. Such an assessment can explain why specific communities suffer more from hazard events. Cutter et al. (2003) found social vulnerability variables like resource scarcity, political power, representation, social capital, social networks and relationships, beliefs and conventions, and infrastructure and lifeline density. Birkmann (2013) believed that social vulnerability should include income, age, and gender inequality. According to Brouwer et al. (2007), households with lower incomes and fewer natural assets are more vulnerable to disasters. Balica et al. (2012) stated that socioeconomic parameters strongly influence a human system's crisis response. Recurrent hazards, insufficient adaptive capacity, and weak institutional backing are the leading causes of social vulnerability (Chakraborty et al., 2005). Demography, agriculture, and economic capability increase socioeconomic vulnerability (Bahinipati, 2014).

IPCC, (2007) outlines vulnerability as “the degree to which a system is susceptible to or is unable to cope with adverse effects of climate change including climate variability and extremes, and it is the function of the character, magnitude, and rate of climate variation to which a system is exposed, its sensitivity and adaptive capacity.” So, the IPCC, (2007) categorized vulnerability into three dimensions: Adaptive capacity, exposure, and sensitivity. Vulnerability, thus, results from the interaction of socioeconomic status, physical condition, and exposure to potential danger. When these factors are considered, regional vulnerability can be assessed. Numerous global vulnerability assessments have focused on areas and communities most at risk from natural disasters (Acharya & Das, 2020). Despite its considerable exposure to weather-related disasters, India scores poorly in susceptibility estimates using socioeconomic indicators. Analysis of vulnerability in Indian context studies has typically focused on physical characteristics rather than social markers (Mazumdar & Paul, 2016).

Climate change and climate-related disasters pose a significant barrier to alleviating poverty (Jain & Jain,2016), improving health, and advancing development in many developing countries, including India. Odisha’s geological position on the eastern coast of India and its meteorological situation have caused the state to be highly susceptible to climate change and many disasters, especially cyclones, floods, and droughts. Therefore, assessing all dimensions of vulnerabilities and their spatial distribution across the state is crucial to prioritizing climate risk reduction strategies for the state. So, the present study aims to assess climate-induced vulnerability by constructing a composite vulnerability index based on the IPCC (2007) framework to address Odisha's vulnerability progression due to climate change.

2. Data and Methodology

The study is based on secondary data district statistical handbook, statistical abstract reports of the Government of Odisha, the census of India, and the annual report on natural catastrophes of Odisha database. Since the census data is required for a secondary vulnerability analysis, this study is based on 2011 data for all 30 districts. Microsoft Excel and SPSS-25 (Statistical Package for Social Sciences) have been used for data analysis, and QGIS (Quantum Geographic Information System) software for spatial analysis.

2.1 Study Site

Odisha has been split into five distinct morphological regions based on factors such as geographic location, degree of continuity, and degree of homogeneity. The Odisha Coastal Range in the east, the Central Mountainous and Highlands Area, the Central plateaus, the western undulating uplands, and the significant flood plains comprise this region's topographical features. Odisha has been divided into three revenue divisions known as the Central region (Puri, Cuttack, Jajapur, Jagatsinghapur, Kendrapara, Bhadrak, Baleshwar, Khordha, Nayagarh, and Mayurbhanj), Northern region (Anugul, Sambalpur, Jharsuguda, Kendujhar, Dhenkanal, Debagarh, Bargarh, Balangir, Subarnapur, and Sundergarh) and Southern region (Baudh, Nuapada, Gajapati, Ganjam, Kalahandi, Kandhamal, Rayagada, Nabarangpur, Koraput, and Malkangiri). This study uses the three revenue divisions.

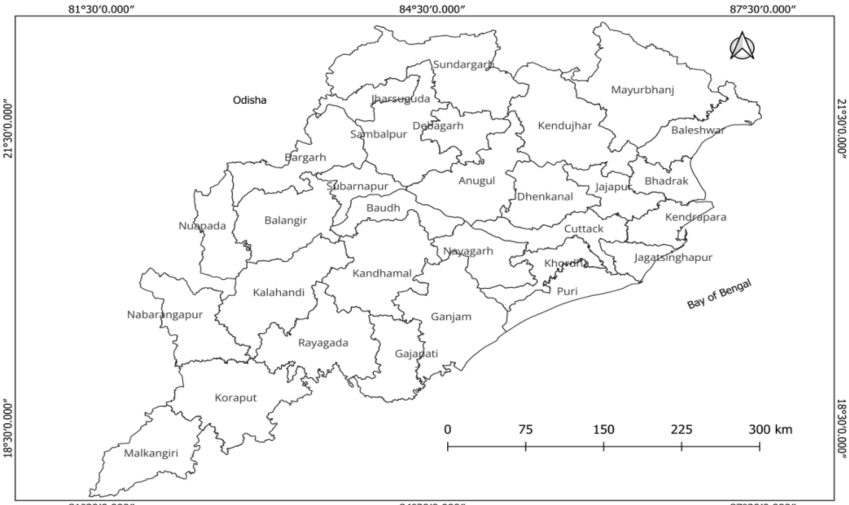

Fig. 1 Study Area (Odisha) with district administrative boundaries

2.2 Components of Vulnerability

To capture the three components of the vulnerability index, exposure, sensitivity, and adaptive capacity, 27 indicators have been selected.

Table 1. Major Components of Vulnerability Index and its Indicators.

Components	Indicators	Rational	References
Exposure	Number of cyclones in the last decades (C)	The greater the number of storms, the greater the risk.	(Rehman et al., 2021; Yadav & Barve, 2017)
	Number of floods in the last ten years (F)	High occurrence of floods leads to exposure.	(Rehman et al., 2021)
	Annual average rainfall in the last ten years (R)	Higher rainfall leads to exposure.	(Rehman et al., 2021)
	Occurrence of heatwave in the last ten years (H)	Heat waves can exacerbate existing vulnerabilities.	(Patel et al.,2019)
	Number of droughts in the last ten years (D)	Droughts can increase vulnerability.	(Patel et al., 2019)
Sensitivity	Illiterate population (IL) (%)	The consequences of catastrophes are more on these people.	(Yadav & Barve, 2017)
	Female population (FP) (%)	Natural disasters have a longer-term impact on women.	(Rehman et al., 2021)
	Decadal population growth (GR) (%)	More people mean more pressure.	(Rehman et al., 2021)
	Population Density (PD) (%)	High-population cities may take longer to escape and cause significant damage in natural catastrophes.	(Rehman et al., 2021)
	Scheduled castes and Scheduled tribes (SC & ST) (%)	They represent society's most deprived group.	(Rehman et al., 2017)
	Dependent Population (DP) (%)	Higher children and elderly people mean more vulnerability to catastrophes.	(Mazumdar & Paul, 2016)
	Agricultural laborer to Main workers (AL) (%)	Workers in the agricultural sector who are paid daily to perform tasks on other people's farms are not guaranteed a stable income.	(Yadav & Barve, 2017)

	Cultivators (CV) (%)	Farmers are more vulnerable due to hazards.	(Paltasingh & Goyari, 2015)
	Non-Worker (NW) (%)	Non-working populations are more vulnerable.	(Mudasser et al., 2020)
	Marginal worker (MW) (%)	Marginal workers are vulnerable due to seasonal hazards.	(Mudasser et al., 2020)
	Dilapidated house (DH) (%)	These homes are more likely to be damaged by natural disasters.	(Rehman et al., 2021)
	Muddy houses (MH) (%)	These homes are more likely to be damaged by natural disasters.	(Rehman et al., 2021)
Adaption	Forest percentage of GA (FA) (%)	Well-established forestry may help provide some physical protection against the effects of natural disasters.	(Rehman et al., 2021)
	Female Literacy (FL) (%)	Women who are educated and able to read and write can help raise disaster awareness.	(Rehman et al., 2021)
	Mean Road density (RD)	Emergency evacuation may be faster with better road infrastructure.	(Rehman et al., 2021)
	Literacy Rate (LR) (%)	Literate people may be more aware of and equipped for climate change adjustments.	(Yadav & Brave, 2017)
	Concrete house (CH) (%)	These homes will be less likely to be damaged or destroyed.	(Ahsan & Warner, 2014)
	Electricity facility (EF) (%)	Electricity may improve adaptability.	(Mazumdar & Paul, 2016)
	Drinking water facility (DW) (%)	Clean drinking water may improve adaptability.	(Mazumdar & Paul, 2016)
	Television connection (TV) (%)	Areas with communication may have better adaptability.	(Yadav & Brave, 2017)
	Main Worker (Ma.W) (%)	Higher percentage of workers means high adaptive capacity.	(Mudasser et al., 2020)
	Banking facility (BF) (%)	Money saved can be used to offset disaster losses.	(Yadav & Barve, 2017)

2.3 Measurements of Composite Vulnerability Index

A combined indicator-based approach has been used to develop the Composite Vulnerability Index (CVI); its primary characteristics are adaptability, exposure, and sensitivity (Ahsan & Waner, 2014). Given that each indicator has been measured using a unique unit of measurement, a normalizing approach can be used to derive a single, non-unit-specific value, as demonstrated by the equation (I) below

$$(\text{Index } X_i)i = \frac{(X_i - Min\ X)}{\text{Max } X_i - \text{Min } X_i} \quad \text{(I)}$$

Where (Index X_i)i represents the normalized indicator score of District I, and the value of the normalized indicators lies between 0 and 1. X_i is the value of the i^{th} indicator. Min X_i and Max X_i stand for the minimum and maximum value of the i^{th} indicator among all the districts.

After standardizing each indicator, average the indicators using the equation below to calculating the final components.

$$M_i = \sum_{j=1}^{n} Index\ X_i \ / \ n \quad \text{(II)}$$

Where M_i shows the three major components of district i, the major components comprise sensitivity, exposure, and adaptive capacity. N represents the number of indicators for a particular major component used in this study. The CVI was then determined using the composite indicator structure technique.

$$CVI_i = \frac{(\text{Exposure})i + (\text{Sensitivity})i + (1 - \text{Adaptive capacity})i}{3} \quad \text{(III)}$$

Here, CVI_i (Table 5) represents the Composite vulnerability index of the i^{th} district, ‘1- Adaptive capacity’ shows lack of adaptive capacity.

After analysing exposure, sensitivity, and lack of adaptive capacity components and composite vulnerability, spatial variability has been depicted through mapping.

3. Results and Discussion

3.1 Exposure

Extreme weather occurrences are becoming more common and severe, which depicts the exposure components' vulnerability. As a result of climate change, communities worldwide have adapted coping mechanisms towards extreme weather events (Table 2) such as hurricanes, cyclones, heatwaves, and droughts. Due to rising sea levels, homes, livelihoods, and entire civilizations are in danger of submersion in coastal locations. Floods or parched landscapes caused by unpredictable rainfall threaten agricultural output and water supply in inland regions. Hence, to find out the level of exposure of all 30 districts, we considered five indicators.

Baleshwar, Bhadrak, Cuttack, and Kendrapara are among the districts with higher exposure to floods, and Debagarh, Jharsuguda, Koraput, Malkangiri, Nuapada, and Sundargarh have lower exposure scores (Table 5). Baleshwar, Bhadrak, Ganjam, Kendrapara, and Puri are among the districts with higher exposure to cyclones due to frequent cyclones. Cuttack, Mayurbhanj, and Kendrapara are among the districts with the highest exposure to heavy rainfall, and Bolangir and Kendujhar exhibit relatively lower exposure. Districts like Anugul, Sambalpur, and Sundargarh have relatively higher exposure, and Baudh, Gajapati, Koraput, Malkangiri, Nabarangapur, and Nuapada have lower heatwaves. Exposure to droughts also varies among the districts; Malkangiri, Nabarangapur, and Rayagada exhibit higher exposure, and Baudh, Jajapur, Kalahandi, and Nuapada have relatively lower exposure to droughts.

Table 2. Indicator values of exposure components

Districts	Heatwave	Droughts	Rainfalls	Floods	Cyclones
Anugul	0.60	0.40	0.76	0.47	0.00
Baleshwar	0.40	0.30	0.95	0.93	0.67
Bargarh	0.53	0.40	0.70	0.27	0.00
Bhadrak	0.40	0.30	0.82	0.93	0.60
Bolangir	0.33	0.40	0.76	0.53	0.00
Baudh	0.07	0.30	0.80	0.47	0.00
Cuttack	0.40	0.30	0.99	0.67	0.13
Debagarh	0.13	0.40	0.68	0.13	0.00
Dhenkanal	0.53	0.40	0.76	0.20	0.00
Gajapati	0.07	0.30	0.71	0.60	0.13
Ganjam	0.53	0.50	0.71	0.33	0.47
Jagatsinghapur	0.53	0.40	0.84	0.67	0.40
Jajapur	0.27	0.20	0.90	0.93	0.13
Jharsuguda	0.40	0.50	0.74	0.13	0.00
Kalahandi	0.20	0.40	0.97	0.47	0.00
Kandhamal	0.13	0.30	0.99	0.47	0.00
Kendrapara	0.40	0.40	0.87	0.93	0.53
Kendujhar	0.40	0.20	0.78	0.33	0.00
Khordha	0.47	0.20	0.80	0.67	0.20
Koraput	0.07	0.30	0.80	0.33	0.00
Malkangiri	0.07	0.50	0.83	0.20	0.00
Mayurbhanj	0.40	0.40	0.84	0.47	0.07
Nabarangapur	0.07	0.50	0.98	0.33	0.00
Nayagarh	0.40	0.20	0.82	0.60	0.13
Nuapada	0.20	0.40	0.63	0.33	0.00
Puri	0.27	0.30	0.87	0.67	0.60
Rayagada	0.13	0.40	0.75	0.60	0.00
Sambalpur	0.60	0.40	0.85	0.40	0.00
Subarnapur	0.27	0.30	0.79	0.47	0.00
Sundargarh	0.53	0.50	0.71	0.27	0.00

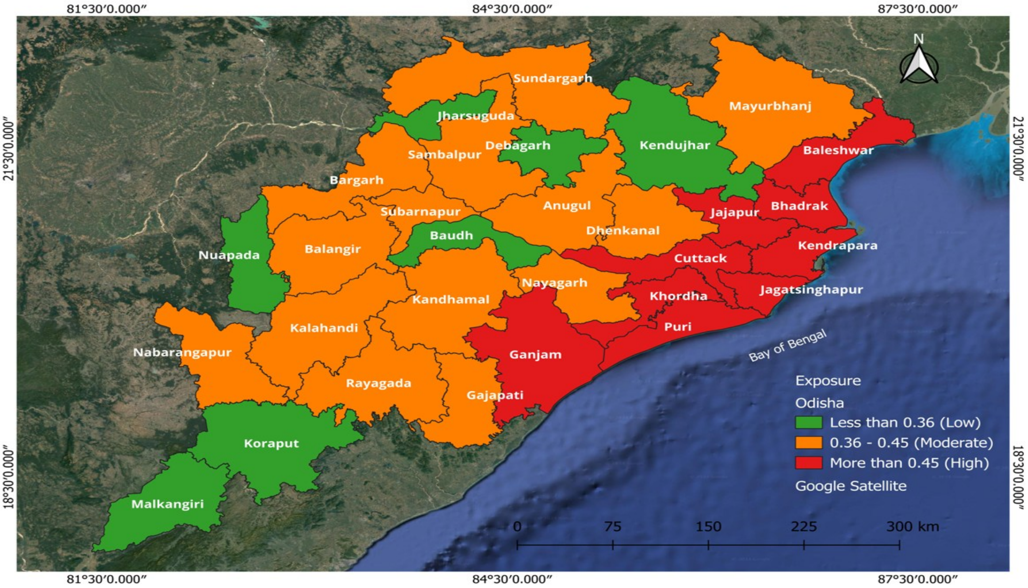

Fig. 2 Spatial Variation in Exposure Map of Different Districts of Odisha

Higher exposure scores (Fig.2 & Fig.5) are witnessed in districts like Baleshwar, Bhadrak, Kendrapara, Puri, Jagatsinghapur, Cuttack, and Ganjam because these districts face different types of natural hazards like cyclones and floods. Also, these districts face drought due to unpredictable rainfalls (Table 4). Southern and Northern region districts have lower exposure scores like Koraput, Kandhamal, Debagarh, Sundargarh, Jharsuguda, and Kendujhar because these districts face only heatwaves, droughts, and floods in some regions.

3.2 Sensitivity

Sensitivity assesses the extent to which districts are affected by climate change, making it an essential factor in vulnerability assessments because it indicates tolerance within a social structure. Hence, the sensitivity aspects of 30 districts are evaluated by taking 12 indicators into account to ascertain the level of vulnerability. Analysing the decadal population growth proves valuable in assessing the population-related stress across various districts. Factors such as the percentage of the prevalence of dilapidated houses and the extent of agricultural land play a pivotal role in gauging the sensitivity of different districts. A higher proportion of dilapidated houses signifies increased vulnerability. Those involved in agrarian pursuits face heightened susceptibility to the impacts of disasters. Notably, the female population, as well as the Scheduled Caste (SC) and Scheduled Tribe (ST) populations, emerge as the most vulnerable and sensitive groups to disasters.

Population density is critical in central districts like Khordha, Cuttack, Jagatsinghapur, Jajapur, and Baleshwar, making them sensitive to natural hazards.

Districts like Bolangir, Malkangiri, and Rayagada experience rapid population increases. Illiteracy rates were higher in the southern and northern regions, making these region more sensitive. Housing conditions of the southern and northern regions districts like Debagarh, Koraput, Malkangiri, Gajapati, Rayagada, Nabarangapur, Kalahandi, and Mayurbhanj have made them sensitive to different types of hazards, in terms of more muddy and dilapidated houses. Southern districts like Malkangiri, Nabarangapur, Kandhamal, Koraput, Nuapada, and Rayagada are more sensitive due to the higher percentage of non-working and dependent populations (Table 3).

Table 3. Indicator values of Sensitivity components

Districts	IL	FP	GR	PD	SC&ST	DP	AL	CV	NW	MW	DH	MH
Anugul	0.23	0.49	0.12	0.2	0.33	0.37	0.33	0.2	0.59	0.4	0.19	0.49
Baleshwar	0.2	0.49	0.15	0.61	0.33	0.38	0.38	0.31	0.6	0.34	0.14	0.6
Bargarh	0.25	0.49	0.1	0.25	0.39	0.36	0.47	0.28	0.49	0.38	0.11	0.67
Bhadrak	0.17	0.5	0.13	0.6	0.24	0.38	0.48	0.33	0.69	0.44	0.11	0.68
Bolangir	0.35	0.5	0.23	0.25	0.39	0.4	0.32	0.23	0.56	0.3	0.09	0.55
Baudh	0.28	0.5	0.18	0.14	0.36	0.42	0.45	0.29	0.5	0.44	0.07	0.73
Cuttack	0.15	0.48	0.12	0.67	0.23	0.35	0.27	0.15	0.64	0.26	0.14	0.34
Debagarh	0.27	0.49	0.14	0.11	0.52	0.39	0.5	0.26	0.47	0.5	0.2	0.39
Dhenkanal	0.21	0.49	0.12	0.27	0.33	0.37	0.38	0.16	0.64	0.36	0.16	0.58
Gajapati	0.47	0.51	0.11	0.13	0.61	0.42	0.52	0.22	0.49	0.42	0.08	0.35
Ganjam	0.29	0.5	0.12	0.43	0.23	0.38	0.38	0.19	0.57	0.4	0.13	0.25
Jagatsinghapur	0.13	0.49	0.08	0.68	0.23	0.35	0.27	0.28	0.65	0.28	0.08	0.36
Jajapur	0.2	0.49	0.13	0.63	0.32	0.37	0.34	0.22	0.7	0.26	0.2	0.52
Jharsuguda	0.21	0.49	0.13	0.27	0.49	0.35	0.23	0.17	0.57	0.31	0.09	0.62
Kalahandi	0.41	0.5	0.18	0.2	0.47	0.41	0.58	0.19	0.52	0.5	0.1	0.41
Kandhamal	0.36	0.51	0.13	0.09	0.69	0.43	0.46	0.22	0.52	0.53	0.09	0.44
Kendrapara	0.15	0.5	0.11	0.55	0.22	0.35	0.31	0.32	0.68	0.31	0.1	0.65
Kendujhar	0.32	0.5	0.15	0.22	0.57	0.39	0.41	0.26	0.58	0.42	0.1	0.68
Khordha	0.13	0.48	0.2	0.8	0.18	0.34	0.15	0.12	0.65	0.2	0.1	0.34
Koraput	0.51	0.51	0.17	0.16	0.65	0.43	0.42	0.3	0.5	0.43	0.07	0.57
Malkangiri	0.52	0.5	0.22	0.11	0.8	0.45	0.34	0.49	0.49	0.42	0.09	0.54
Mayurbhanj	0.37	0.5	0.13	0.24	0.66	0.4	0.47	0.2	0.51	0.55	0.13	0.68
Nabarangapur	0.54	0.5	0.19	0.23	0.7	0.44	0.54	0.28	0.5	0.54	0.06	0.68
Nayagarh	0.2	0.48	0.11	0.25	0.2	0.38	0.35	0.24	0.64	0.33	0.17	0.39
Nuapada	0.43	0.51	0.15	0.16	0.47	0.43	0.49	0.31	0.5	0.5	0.06	0.58
Puri	0.15	0.49	0.13	0.49	0.2	0.36	0.26	0.28	0.63	0.28	0.16	0.44
Rayagada	0.5	0.51	0.17	0.14	0.7	0.42	0.53	0.21	0.52	0.51	0.08	0.48
Sambalpur	0.24	0.49	0.12	0.16	0.53	0.36	0.32	0.17	0.51	0.33	0.1	0.56
Subarnapur	0.26	0.49	0.13	0.28	0.35	0.38	0.49	0.26	0.53	0.41	0.09	0.71
Sundargarh	0.27	0.49	0.14	0.21	0.6	0.37	0.29	0.21	0.58	0.39	0.08	0.5

Thus, the sensitivity component (Fig. 3 & Fig. 5) of the southern districts of the state is relatively higher than the others, such as Nabarangapur, Rayagada, Koraput, Malkangiri, Rayagada, Nuapada, and Kandhamal, as they are mostly Schedule Caste and

Schedule Tribe dominated, and also, they have a higher percentage of illiterate populations (Table 3). These also have higher decadal population growth and muddy or dilapidated houses. The sensitivity component scores of the central and northern regions of the state sensitivity scores are mostly the same.

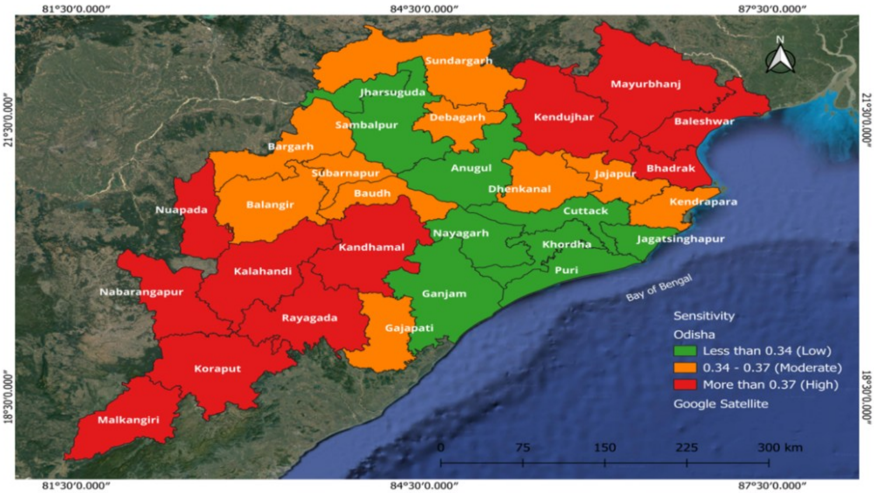

Fig. 3 Spatial Variation in Sensitivity Map of Different Districts of Odisha

3.3 Lack of Adaptive Capacity

Adaptation refers to the human capacity to adjust to disasters induced by climate change. It aligns with individuals' ability to respond and acclimate to such catastrophic events. Communities having access to facilities such as potable water, electricity, paved roads, mobile connectivity, and cement houses have a greater ability for adaptation. Literacy rates, particularly among females, act as useful community readiness and resilience measures. In estimating the composite vulnerability index, the lack of adaptive capacity is used instead of adaptive capacity. Therefore, a lower value means higher adaptive capacity and vice versa. Initially, adaptive capacity measures were defined using ten indicators.

Districts like Khordha, Jagatsinghapur, Cuttack, Kendrapara, and Puri demonstrate higher adaptive capacities that can respond effectively to various environmental and socio-economic challenges. These districts are primarily coastal districts. Factors like female literacy, household access to electricity, mean road density, and availability of banking facilities increase their adaptive capacity (Table 4). Southern region districts of the state have low scores in adaptive capacity (Fig.4 and Fig.5), which means these districts lack adaptive capacity. Districts like Nabarangapur, Koraput, Kandhamal, Malkangiri, Rayagada, Kalahandi, and Nuapada lack adaptive capacity due to lower literacy rates, lower female literacy, availability of electricity, banking facilities, and mean road density (Table 4). Dhenkanal, Debagarh, Bolangir, Mayurbhanj, and Subarnapur lack adaptive capacity compared to other northern districts. However, Sambalpur and Bargarh districts have high adaptive capacity because these districts have high literacy rates, banking facilities, and mean road density (Table 4).

Table 4. Indicator values of Adaptive capacity components

Districts	FA	FL	EF	BF	TV	DW	RD	Ma.W	LR	CH
Anugul	0.42	0.69	0.45	0.37	0.15	0.94	0.26	0.60	0.78	0.01
Baleshwar	0.08	0.72	0.56	0.38	0.21	0.96	0.40	0.66	0.80	0.01
Bargarh	0.15	0.65	0.45	0.26	0.20	0.98	0.27	0.62	0.75	0.03
Bhadrak	0.01	0.76	0.53	0.32	0.16	0.98	0.54	0.56	0.83	0.01
Bolangir	0.14	0.54	0.29	0.28	0.15	0.96	0.11	0.70	0.65	0.04
Baudh	0.41	0.60	0.18	0.36	0.07	0.97	0.37	0.56	0.72	0.00
Cuttack	0.17	0.80	0.62	0.43	0.27	0.98	0.33	0.74	0.86	0.01
Debagarh	0.46	0.63	0.03	0.34	0.08	0.94	0.31	0.50	0.73	0.00
Dhenkanal	0.30	0.71	0.42	0.29	0.11	0.93	0.24	0.64	0.79	0.00
Gajapati	0.58	0.43	0.49	0.44	0.22	0.89	0.30	0.58	0.54	0.02
Ganjam	0.24	0.61	0.54	0.38	0.19	0.95	0.33	0.60	0.71	0.01
Jagatsinghapur	0.01	0.81	0.53	0.50	0.23	0.97	0.43	0.72	0.87	0.01
Jajapur	0.09	0.73	0.47	0.31	0.12	0.94	0.42	0.74	0.80	0.00
Jharsuguda	0.14	0.71	0.61	0.47	0.34	0.98	0.43	0.69	0.79	0.02
Kalahandi	0.29	0.47	0.23	0.26	0.12	0.95	0.37	0.50	0.59	0.02
Kandhamal	0.07	0.52	0.17	0.52	0.09	0.81	0.23	0.47	0.64	0.01
Kendrapara	0.39	0.79	0.53	0.51	0.18	0.99	0.37	0.69	0.85	0.00
Kendujhar	0.68	0.58	0.30	0.44	0.17	0.89	0.15	0.58	0.68	0.01
Khordha	0.14	0.82	0.72	0.38	0.37	0.98	0.45	0.80	0.87	0.02
Koraput	0.19	0.39	0.25	0.33	0.17	0.88	0.20	0.57	0.49	0.01
Malkangiri	0.38	0.38	0.18	0.39	0.22	0.91	0.18	0.58	0.49	0.01
Mayurbhanj	0.38	0.53	0.24	0.48	0.16	0.94	0.27	0.45	0.63	0.01
Nabarangapur	0.32	0.36	0.13	0.28	0.12	0.97	0.23	0.46	0.46	0.01
Nayagarh	0.22	0.72	0.54	0.26	0.13	0.97	0.26	0.67	0.80	0.01
Nuapada	0.43	0.45	0.28	0.26	0.26	0.95	0.34	0.50	0.57	0.01
Puri	0.03	0.78	0.55	0.38	0.20	0.93	0.63	0.72	0.85	0.01
Rayagada	0.44	0.39	0.27	0.43	0.16	0.91	0.23	0.49	0.50	0.01
Sambalpur	0.50	0.68	0.51	0.42	0.32	0.96	0.33	0.67	0.76	0.04
Subarnapur	0.14	0.64	0.33	0.28	0.13	0.96	0.34	0.59	0.74	0.02
Sundargarh	0.42	0.66	0.47	0.52	0.37	0.96	0.28	0.61	0.73	0.02

3.4 Composite Vulnerability Index

The overall vulnerability (Fig.6) shows that some central districts, like Baleshwar, Bhadrak, Jagatsinghapur, Jajapur, Mayurbhanj, and Kendrapara, are highly vulnerable because of the high exposure to natural hazards and climate change. But districts like Puri, Cuttack, and Nayagarh are moderately vulnerable because of lower sensitivity and better adaptive capacity. Southern districts like Ganjam, Nabarangapur, Rayagada, Kandhamal, and Kalahandi are highly vulnerable because these districts are comparatively higher in sensitivity components and lack adaptive capacity but are low on exposure. However, the southern districts like Malkangiri and Koraput were moderately vulnerable even if they have more sensitivity (Fig.2) and less adaptive capacity (Fig.3) because these districts have lower exposure components in terms of natural hazards. Northern districts like Bargarh, Subarnapur, Anugul, and Kendujhar are moderately vulnerable because of the average score in three components of the vulnerability index. However, Bolangir district is highly vulnerable due to higher sensitivity and lack of adaptive capacity. However, northern districts like Sambalpur, Jharsuguda, Sundargarh, and Baudh are less vulnerable because of less exposure.

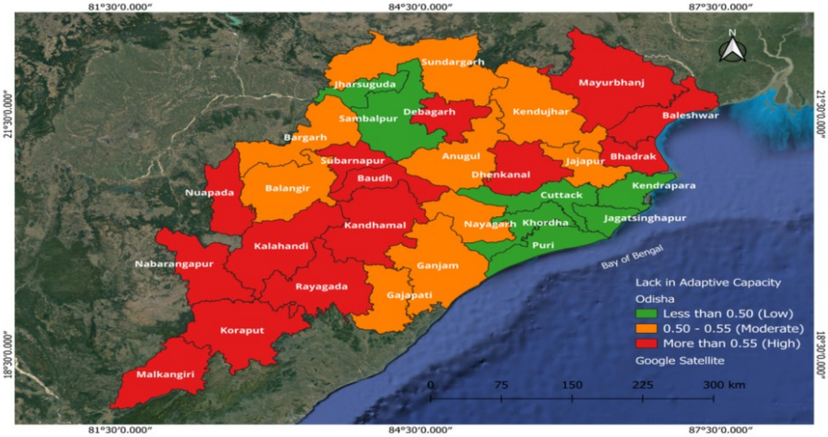

Fig. 4 Spatial Variation in Lack of Adaptive Capacity Map of Different Districts of Odisha

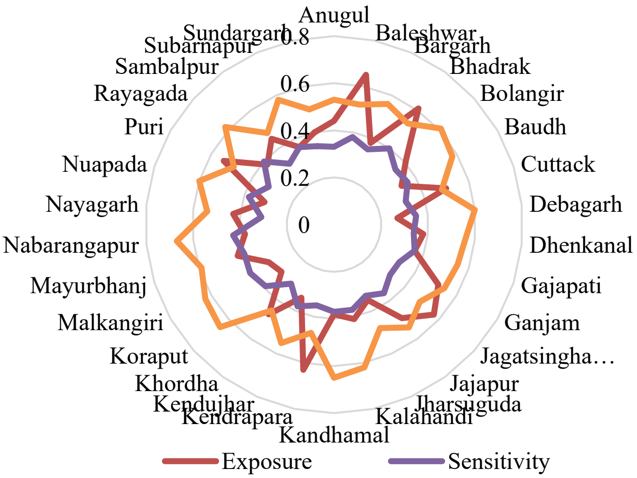

Fig. 5 Three Components Score of Vulnerability Index

Table 5. Components score of Vulnerability index

Districts	Exposure	Sensitivity	Adaptive capacity	1-Adaptive capacity	CVI
Anugul	0.44	0.33	0.47	0.53	0.44
Baleshwar	0.65	0.38	0.48	0.52	0.52
Bargarh	0.38	0.35	0.44	0.56	0.43
Bhadrak	0.61	0.40	0.47	0.53	0.51
Bolangir	0.41	0.35	0.39	0.61	0.46
Baudh	0.33	0.36	0.42	0.58	0.42
Cuttack	0.50	0.32	0.52	0.48	0.43
Debagarh	0.27	0.35	0.40	0.60	0.41
Dhenkanal	0.38	0.34	0.44	0.56	0.42
Gajapati	0.36	0.36	0.45	0.55	0.43
Ganjam	0.51	0.32	0.46	0.54	0.46
Jagatsinghapur	0.57	0.32	0.51	0.49	0.46
Jajapur	0.49	0.36	0.46	0.54	0.46
Jharsuguda	0.35	0.33	0.52	0.48	0.39
Kalahandi	0.41	0.37	0.38	0.62	0.47
Kandhamal	0.38	0.37	0.35	0.65	0.47
Kendrapara	0.63	0.35	0.53	0.47	0.48
Kendujhar	0.34	0.38	0.45	0.55	0.43
Khordha	0.47	0.31	0.55	0.45	0.41
Koraput	0.30	0.39	0.35	0.65	0.45
Malkangiri	0.32	0.41	0.37	0.63	0.45
Mayurbhanj	0.43	0.40	0.41	0.59	0.48
Nabarangapur	0.38	0.43	0.33	0.67	0.49
Nayagarh	0.43	0.31	0.46	0.54	0.43
Nuapada	0.31	0.38	0.40	0.60	0.43
Puri	0.54	0.32	0.51	0.49	0.45
Rayagada	0.38	0.40	0.38	0.62	0.46
Sambalpur	0.45	0.32	0.52	0.48	0.42
Subarnapur	0.36	0.36	0.42	0.58	0.44
Sundargarh	0.40	0.34	0.50	0.50	0.41
Coefficient of Variation (C.V.)	23.26	9.17	13.38	10.70	6.84

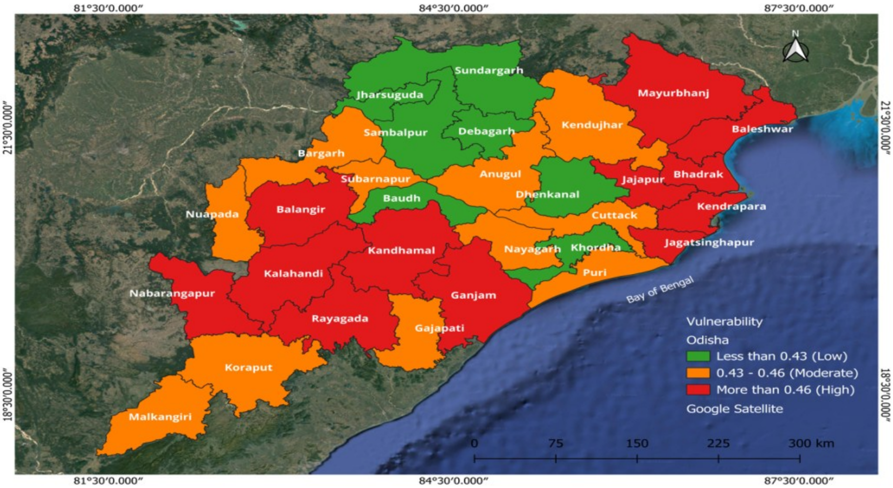

Fig. 6 Spatial Variation in Vulnerability Map of Different Districts of Odisha

4. Conclusion

The composite vulnerability index has been evaluated for 30 districts in Odisha by evaluating three components: exposure, sensitivity, and adaptive capacity, incorporating 27 indicators. A very high degree of exposure was found in Odisha's central districts because these districts face different types of natural hazards due to climate change; cyclones and floods are the most critical disasters affecting coastal districts, making them more sensitive due to these hazards, even if their adaptive capacity is higher than other state districts. Thus, the central districts like Baleshwar, Bhadrak, Jagatsinghapur, Jajapur, Mayurbhanj, and Kendrapara are highly vulnerable due to high exposure and sensitivity coupled with inadequate adaptive capacity. The southern part of the state has more backward districts with poor adaptive capacity and high sensitivity components. So, southern districts like Ganjam, Nabarangapur, Rayagada, Kandhamal, and Kalahandi are also highly vulnerable due to their high sensitivity and lack of adaptive capacity despite having lower exposure to natural hazards. The Northern region of the state is relatively less vulnerable because these regions have lower exposure scores to climate disasters and are moderate in sensitivity and adaptive components.

The research reveals that reducing vulnerability would require working on sensitivity and adaptive capacity components, as exposure is natural and cannot be reduced. Reforms in education, improving housing conditions, and offering employment can help reduce sensitivity and adaptive components. Educational institutions, local businesses, and transportation infrastructure can turn rural places into semi-urban hubs to decrease vulnerability in the central districts. Drinking water, power, toilets, and a low-interest credit facility for building permanent housing should be provided to increase the adaptive capacity in the backward districts of the state. The inter-district spatial variations on vulnerability components indicate the importance of local-scale policy-making for better management of climate-induced vulnerability.

References

1. Acharya, A., & Das, A. K. (2020). District-level analysis of climate vulnerability and household nutrition status among rural communities in Odisha, India. International Journal of Population Studies, 6(1). https://doi.org/10.18063/ijps.v6i1.1069
2. Ahsan, M. N., & Warner, J. (2014). The socioeconomic vulnerability index: A pragmatic approach for assessing climate change led risks-A case study in the south-western coastal Bangladesh. International Journal of Disaster Risk Reduction, 8, 32–49. https://doi.org/10.1016/j.ijdrr.2013.12.009
3. Bahinipati, S. C. (2014). Assessment of vulnerability to cyclones and floods in Odisha, India: A District-level analysis Economic loss and damage assessment to diamond and textile industries in Surat due to Floods View project Will climate change adaptation enhance farm productivity? A study of Micro-Irrigation Systems (MIS) in Gujarat, India View project. https://www.researchgate.net/publication/265459164
4. Balica, S. F., Wright, N. G., & van der Meulen, F. (2012). A flood vulnerability index for coastal cities and its use in assessing climate change impacts. Natural Hazards, 64(1), 73–105. https://doi.org/10.1007/s11069-012-0234-1
5. Birkmann, J. (2013). Measuring vulnerability to natural hazards: Towards disaster resilient societies (second edition). https://collections.unu.edu/eserv/UNU:2880/n9789280812022_text.pdf
6. Brouwer, R., Akter, S., Brander, L., & Haque, E. (2007). Socioeconomic vulnerability and adaptation to environmental risk: A case study of climate change and flooding in Bangladesh. Risk Analysis, 27(2), 313–326. https://doi.org/10.1111/j.1539-6924.2007.00884.x
7. Chakraborty, J., Tobin, G. A., & Montz, B. E. (2005). Population Evacuation: Assessing Spatial Variability in Geophysical Risk and Social Vulnerability to Natural Hazards. Natural Hazards Review, 6(1), 23–33. https://doi.org/10.1061/(asce)1527-6988(2005)6:1(23)
8. Cutter, S. L., Boruff, B. J., & Shirley, W. L. (2003). Social Vulnerability to Environmental Hazards n. Social Science Quarterly, 84(2), 242–261. https://doi.org/10.1111/1540-6237.8402002
9. Das, S. (2016). Economics of Natural Disasters in Odisha. In the Economy of Odisha (pp. 266–300). Oxford University Press. https://doi.org/10.1093/acprof:oso/9780199464784.003.0009
10. GoI. (2014). Disaster Management in India. Under the GOI-UNDP Project on Disaster Risk Reduction Program (2009-2012). https://ndmindia.mha.gov.in/goi-undp-projects
11. IPCC. (2007). Climate change 2007: the physical science basis: contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press. https://www.ipcc.ch/report/ar4/wg2/
12. Jain & Jain (2016). Quenching Thirst by Stealing Livelihood. Economic and Political Weekly. Vol. LI No.46.

13. Mazumdar, J., & Paul, S. K. (2016). Socioeconomic and infrastructural vulnerability indices for cyclones in the eastern coastal states of India. Natural Hazards, 82(3), 1621–1643. https://doi.org/10.1007/s11069-016-2261-9
14. Mishra, D., & Sahu, N. C. (2014). Economic Impact of Climate Change on Agriculture Sector of Coastal Odisha. APCBEE Procedia, 10, 241–245. https://doi.org/10.1016/j.apcbee.2014.10.046
15. Mudasser, M., Hossain, Md. Z., Rahaman, K. R., & Ha-Mim, N. M. (2020). Investigating the Climate-Induced Livelihood Vulnerability Index in Coastal Areas of Bangladesh. World, 1(2), 149–170. https://doi.org/10.3390/world1020012
16. OES. (2015). Government of Odisha ODISHA ECONOMIC SURVEY 2014-15 Rising Trend of Per capita Income at Market Prices at Current Price of Odisha Planning and Coordination Department Government of Odisha. https://pc.odisha.gov.in/sites/default/files/2020-03/Economic_Survey_2014-15.pdf
17. Paltasingh, K. R., & Goyari, P. (2015). Climatic Risks and Household Vulnerability Assessment: A Case of Paddy Growers in Odisha. Agricultural Economics Research Review, 28(conf), 199. https://doi.org/10.5958/0974-0279.2015.00035.x
18. Patel, S. K., Mathew, B., Nanda, A., Mohanty, B., & Saggurti, N. (2020). Voices of rural people: Community-level assessment of effects and resilience to natural disasters in Odisha, India. International Journal of Population Studies, 6(1). https://doi.org/10.18063/ijps.v6i1.1042
19. Patel, S. K., Mathew, B., Nanda, A., Pati, S., & Nayak, H. (2019). A review on extreme weather events and livelihood in Odisha, India. In MAUSAM (Vol. 70, Issue 3).
20. Radhakrishnan, K., Sivaraman, I., Jena, S. K., Sarkar, S., & Adhikari, S. (2017). A Climate Trend Analysis of Temperature and Rainfall in India. Climate Change and Environmental Sustainability, 5(2), 146. https://doi.org/10.5958/2320-642x.2017.00014.x
21. Rehman, S., Sahana, M., Kumar, P., Ahmed, R., & Sajjad, H. (2021). Assessing hazards induced vulnerability in coastal districts of India using site-specific indicators: an integrated approach. GeoJournal, 86(5), 2245–2266. https://doi.org/10.1007/s10708-020-10187-3
22. SDMP. (2013). Observations Regarding Preparation of Disaster Management Plan of Works Department. In 2013.
23. Sharma, R. (2016). Impact of Climate Induced Natural Disasters in Costal Odisha Focused on Socio-Economic Vulnerability. MOJ Cell Science & Report, 3(5). https://doi.org/10.15406/mojcsr.2016.03.00073
24. Wisner, B., Blaikie, P., Cannon, T., & Davis, I. (2003). At Risk: natural hazards, people’s vulnerability and disasters Second edition 2003.
25. Yadav, D. K., & Barve, A. (2017). Analysis of socioeconomic vulnerability for cyclone-affected communities in coastal Odisha, India. International Journal of Disaster Risk Reduction, 22, 387–396. https://doi.org/10.1016/j.ijdrr.2017.02.003