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Assessing climate vulnerability across districts of Odisha, India: A multidimensional index-based approach

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ABSTRACT

Climate change-induced environmental degradation necessitates adaptive and sustainable resource-use planning. However, uneven development, socio-economic inequality, and increasing climate variability have intensified vulnerability worldwide. To address these challenges, this study develops a Composite Vulnerability Index (CVI) based on the Intergovernmental Panel on Climate Change framework, integrating exposure, sensitivity, and adaptive capacity across four domains: social, economic, physical, and environmental. The analysis covers 30 districts of Odisha, a disaster-prone state in eastern India, using 37 carefully selected indicators. Principal Component Analysis (PCA) was employed to derive indicator weights to generate domain-specific sub-indices, which were subsequently aggregated into the overall CVI. Spatial patterns of vulnerability were mapped using QGIS, while robustness was assessed through alternative weighting techniques and spatial statistical validation. Results reveal strong regional disparities, with Mayurbhanj, Koraput, and Balangir districts exhibiting high vulnerability (CVI 0.92–1.00), driven by poor healthcare access, inadequate housing, land degradation, low forest cover, groundwater depletion and high socio-economic sensitivity. In contrast, Jharsuguda, Khordha, and Angul districts exhibit relatively low vulnerability (CVI 0.16–0.29), reflecting stronger adaptive capacity through better infrastructure, irrigation coverage, connectivity, higher district incomes, and improved human development outcomes. Spatial autocorrelation analysis confirms significant clustering of vulnerability across districts, highlighting the existence of regional vulnerability hotspots. Environmental and physical dimensions emerge as the dominant contributors to overall vulnerability, highlighting the need for targeted adaptation focused on ecological restoration and infrastructure strengthening.

1. Introduction

Climate change is one of the most formidable global challenges of this century, exerting profound and far-reaching impacts on both the human and natural environments [1]. Extreme climate events such as floods, heatwaves, droughts, and tropical cyclones are no longer rare occurrences; they have become the new normal, disrupting lives and ecosystems with increasing frequency and intensity [2]. Between 2000 and 2022, the world experienced 9416 major natural disasters, affecting over 4.3 billion people, claiming 1.38 million lives, and causing economic losses exceeding USD 3.5 trillion (Centre for Research on the Epidemiology of Disasters [[3]). The intensity of such events is projected to increase under future climate scenarios [4]. However, their impacts are not uniformly distributed across countries and populations, reflecting varying levels of exposure, sensitivity, and adaptive capacity [5]. Understanding these heterogeneous patterns of vulnerability will provide a scientific foundation for identifying the regions at risk and designing evidence-based policy responses to strengthen the resilience capacity.

On a global scale, South Asian countries experience the highest levels of physical and human losses from natural disasters, with India ranking at the top [6]. According to the Adil et al. [7], India ranks 5th among 191 countries in terms of disaster risk [8]. Its diverse socio-economic and climatic features, high dependence on climate-sensitive sectors, dense population, and environmental degradation intensify vulnerability to natural disasters [4]. In this context, it is imperative to assess

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vulnerability across spatial scales to inform effective national and sub-national adaptation and mitigation strategies. The concept of vulnerability, however, remains inherently complex, multidimensional, and interdisciplinary [9]. Scholars have approached it through various frameworks, including the risk-hazard [10], political economy [11], and resilience [12] perspectives. Wisner and Wisner [13] integrated these views in the Pressure and Release model, which conceptualized risk as a function of hazard and vulnerability. According to them, vulnerability is driven by root causes (political and economic systems), dynamic pressures (lack of institutional support and training), and unsafe conditions (poor livelihoods and inadequate infrastructure). The integrated socio-economic and biophysical approach, widely adopted in climate change studies [14,15], underpins the IPCC framework, which defines vulnerability in terms of exposure, sensitivity, and adaptive capacity [16].

Building on these foundations, indicator-based methods gained a widely accepted approach for assessing vulnerability at various scales [17–19], with recent studies incorporating hydraulic and hydrological indicators [20]. Balica and Wright [21] evaluated vulnerability across social, economic, physical and environmental domains in coastal cities worldwide. From a methodological perspective, Abdrabo et al. [22] applied Principal Component Analysis (PCA) and Analytic Hierarchy Process (AHP) to develop a more robust Flood Vulnerability Index (FVI) for Alexandria, Egypt. Similarly, Fernandez and Ahmed [23] employed cluster analysis (CA) to enhance the sensitivity of vulnerability classification. Some notable efforts have sought to quantify vulnerability through integrated approaches at national and sub-national levels ([24]; and [25]). Integrating biophysical and socio-economic indicators across diverse Indian geographies, Sharma and Patwardhan [26] assessed vulnerability in coastal peninsular districts; Sehgal et al. [27] in the Indo-Gangetic Plain; Beluru Jana and Hegde [28] in coastal Karnataka; Chakraborty and Joshi [18] across all Indian districts; Tripathi [19] in Uttar Pradesh; Jha and Gundimeda [29] in northern Bihar; Balaganesh et al. [30] in drought-prone Tamil Nadu; Shah and Malakar [31] in the Himalayan region are some of the recent contributions. Collectively, these studies highlight the multifaceted impacts of climate extremes across various geographical scales, encompassing economic losses, environmental degradation, and threats to human well-being.

In India, the state of Odisha exemplifies the intersection of climate exposure and socio-economic fragility [32]. Odisha is ranked as the 3rd most vulnerable state [33] and is often referred to as the “disaster capital” of India [34]. Odisha faces recurrent climate extremes compounded by high poverty, population pressure, food insecurity and dependence on climate-sensitive agriculture [35]. Despite progressive initiatives such as the “Climate Change Action Plan” and “Disaster Preparedness Action Plan”, challenges persist in translating these frameworks into effective local interventions [36]. Existing studies remain fragmented, addressing hazard zonation [37], waterlogging [38], sectoral vulnerabilities [39], or examining socio-economic institutional mechanisms [40]. The district-level vulnerability assessments, which systematically integrate the social, economic, physical, and environmental domains within a unified framework [41,42], often overlook domain-specific insights and limit their scope to identify the structural drivers of vulnerability and inform effective localized adaptation strategies. Therefore, by addressing these gaps, the present study adopted a multidimensional approach to assess the domain-specific vulnerability (social, economic, physical, and environmental), which can yield more nuanced insights to identify the potential drivers of regional disparities and the institutional pathways to inform spatially targeted, evidence-based adaptation strategies aligned with India's Sustainable Development Goals (SDGs) for 2030.

Building on the frameworks of the IPCC [43] and Balica et al. [5], this study addresses the existing knowledge gaps by posing the following research questions:

(i) How can multidimensional vulnerability to climate-induced disasters be quantified at the district level in Odisha using an integrated framework?
(ii) What are the spatial patterns and domain-specific drivers of vulnerability at the district level to guide localized interventions to reduce vulnerability?

To address these questions, the study aims to

(i) develop an integrated composite index to empirically assess the vulnerability for all districts of Odisha; and
(ii) map the spatial distribution and identify the vulnerability hotspots that exhibit similar or dissimilar vulnerability patterns across districts.

Adopting a multidimensional framework, the present study develops a Composite Vulnerability Index (CVI) to assess district-level vulnerability across Odisha. By integrating deductive and inductive methods and adopting a Principal Component Analysis (PCA)-based weighting approach, the study develops a replicable framework for evaluating climate vulnerability at subnational scales. The results revealed significant regional disparities, which were explained by the complex interaction of socio-economic, physical, and environmental factors. The findings provide evidence for designing domain-specific adaptation strategies by uncovering spatial heterogeneity in the state of Odisha. The multidimensional assessment of vulnerability validated through alternative aggregation techniques provides a replicable model for evaluating vulnerability and offers lessons relevant to other developing regions confronting similar climate challenges. Districts are selected as the unit of analysis due to their critical role in disaster management, response planning, and the implementation of resilience strategies at the local level.

The rest of the paper is organized as follows: Section 2 provides a brief profile of the study area; Section 3 outlines the conceptual framework and methodology; Section 4 discusses the results; and Section 5 concludes with policy implications.

2. Profile of the study area

Odisha, located in the eastern part of India, adjacent to the Bay of Bengal (BoB), has a coastline of 574.71 km in length [44]. Geographically, the state is situated between 17° 49′ N to 22° 34′ N latitude and 81° 29′ E to 87° 29′ E longitude, and shares borders with West Bengal in the north, Jharkhand in the northwest, Chhattisgarh in the west, and Andhra Pradesh in the south (Fig. 1). The state's total geographical area is 155,707 sq. km, and it is home to 46.3 million people, with agriculture being the primary source of livelihood for over 65% of the population [45,46]. Furthermore, the state's topographic diversity makes it prone to natural disasters, the most common of which are cyclones and floods in the eastern regions and droughts in the southern and western regions [47].

The state consists of 30 districts, with 14 identified as cyclone-prone, including six coastal districts (*Ganjam, Puri, Jagatsinghpur, Kendrapara, Bhadrak, and Balasore*) and eight non-coastal districts (*Khurda, Mayurbhanj, Jajpur, Keonjhar, Dhenkanal, Cuttack, Nayagarh, and Gajapati*) [41]. Tropical cyclones originating over the Bay of Bengal, accompanied by monsoon-season floods, severely affect the low-lying delta regions of major river systems, including the Mahanadi, Brahmani, Baitarani, Rushikulya, and Subarnarekha, thereby increasing the vulnerability of local inhabitants [48]. Since 1860, over 398 cyclonic storms have affected Odisha, with the 1999 super cyclone being a major event. Other significant cyclones include Phailin (2013), Fani (2019), Yaas (2021), and Dana (2024), which have caused widespread damage and destruction in the state [49]. On the other hand, the southern and western districts of the state have historically been prone to drought [50]. The erratic rainfall pattern, characterized by annual rainfall below



Fig. 1. Map indicating the study districts in Odisha state, India.

800 mm, high temperatures, and limited irrigation coverage, makes agriculture highly sensitive to climate variability [51]. Crop failure and seasonal migration are common consequences of these events in the regions [52]. According to the SDG Index (2023), the state is ranked below the national average, indicating its backwardness in the health, infrastructure, and education sectors [53]. The state's literacy rate is 72.87%, which is close to the national average of 72.98%. The population density of the state is 293 persons per square kilometre. Approximately 40% of the state's population belongs to the Scheduled Castes (17.13%) and the Scheduled Tribes (22.85%) [45].

3. Conceptual framework and methodology

The study has adopted the IPCC [43] and Balica et al. [5] framework to assess the vulnerability to climate-related hazards in the study regions. According to these frameworks, vulnerability is a function of three components viz., (i) *exposure:* the presence of people, assets, or ecosystems that could be adversely affected by climate extreme events; (ii) *sensitivity*: the degree to which a system is affected (ii) *adaptive capacity*: the ability of a system to withstand potential damage. Building on this conceptual foundation, the multidimensional nature of vulnerability was captured using the methodological framework proposed by Balica and Wright [21], which categorises vulnerability indicators into four thematic dimensions: social, economic, physical, and environmental. The following sections of the paper provide a detailed description of these areas, along with their respective indicators.

Indices represent a statistical approach that enables the indirect quantification of the vulnerability of complex systems in simplified terms [54]. The index-based method is widely accepted across various domains, including research on soil quality assessment [55], quality-of-life assessment [56], and vulnerability assessment to different hazards [21,57]. These studies collectively demonstrate the flexibility and robustness of index methods in simplifying complex phenomena and elucidating the interrelationship among indicators and their

contributions to overall vulnerability [58].

Following Balica and Wright [21], this study adopts an indicator-based approach to construct district-wise, domain-specific and composite vulnerability indices. This facilitates the identification, assessment, and ranking of districts based on their relative vulnerability levels to support targeted interventions. The proposed methodological framework involves the following steps: indicator selection, data collection, statistical analysis and normalization, weight assignment using PCA, indicator aggregation, construction of the domain-specific and composite vulnerability index, and vulnerability mapping (Fig. 2).

3.1. Indicator selection and data sources

Indicator selection is a critical stage in vulnerability analysis, as it requires careful consideration of the local context, the relevance and availability of data, and the overall scope of the assessment [58]. In such an analysis, indicators should reflect socio-economic characteristics, environmental attributes, and hazard-specific factors that collectively influence a community's vulnerability. However, obtaining appropriate datasets from diverse domains remains a challenge in developing vulnerability indices [59,60]. To address this, Kelly and Adger [61] proposed the use of proxy indicators as a practical means of quantifying vulnerability under changing global conditions. After a comprehensive review of publicly available data sources—including the Census of India [45,46], the District Statistical Handbook [62], Odisha Agriculture Statistics [63], Odisha Agriculture Statistics Report [64], Bhuban Portal, Water Resources Information System (WRIS), and reports from the Directorate of Economics and Statistics and the Department of Water Resources, as well as the Annual Natural Calamities Report (district-wise, 1960–2023) and the NCDS Policy Brief—a total of 55 indicators across social, economic, physical, and environmental domains were initially identified. A systematic screening procedure was applied independently within each of the four domains to address potential indicator redundancy. Pairwise Pearson correlation matrices were computed separately for each domain (social, economic, physical, and environmental) from the preliminary set of indicators (Supplementary 1). Indicators with a high correlation coefficient (above +70) were considered redundant. In each flagged pair of highly correlated

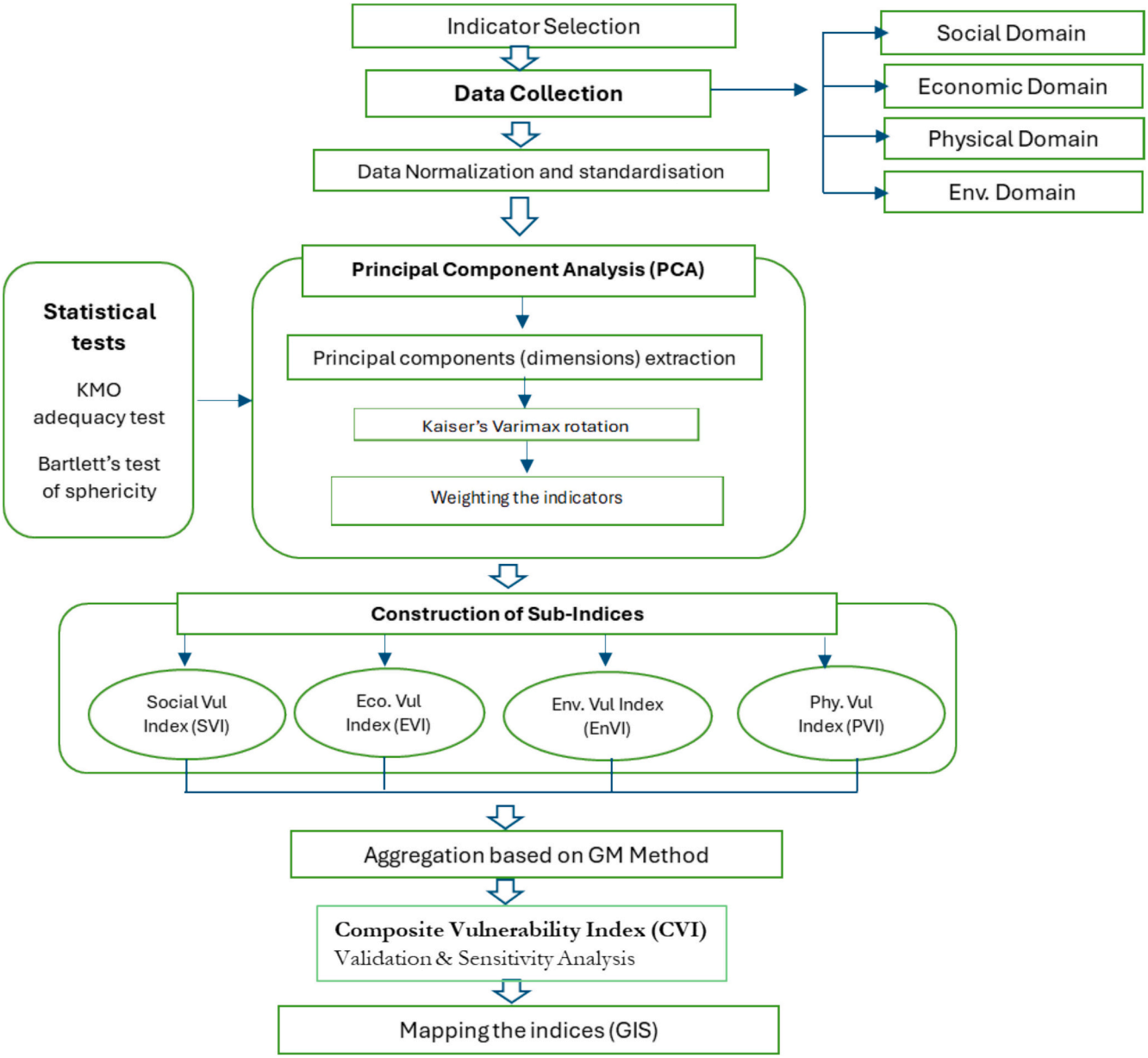


Fig. 2. Methodological framework of vulnerability assessment.

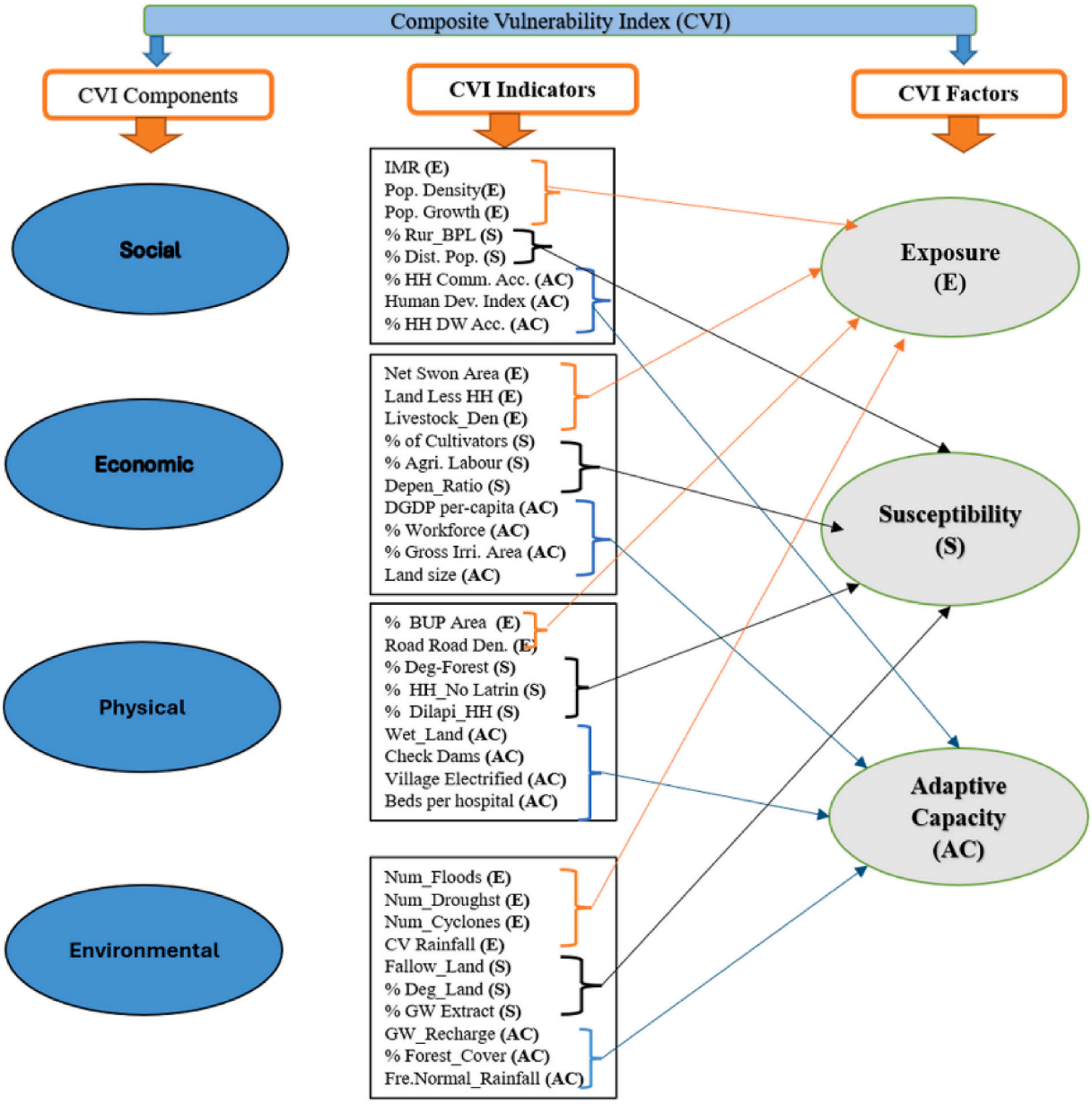


Fig. 3. Structured classification of CVI Indicators.

indicators, the indicator with lower theoretical grounding or weaker representativeness of the specific vulnerability context was excluded. This process reduced the initial sets from 14 to 8 in the social domain, 15 to 10 in the economic domain, 13 to 9 in the physical domain, and 13 to 10 in the environmental domain, resulting in a final set of 37 indicators across all domains (see Supplementary 2). The proxy indicators were selected in line with Birkmann [65], ensuring their applicability, feasibility, justification, and representativeness of the vulnerability context in the study regions. The correlations among retained indicators within each domain remained below 0.70. After the initial screening, Principal Component Analysis (PCA) was performed not only to weight the indicators but also as a dimensionality-reduction technique, transforming the retained correlated indicators into orthogonal principal components, thereby further addressing residual multicollinearity in the data set. The Kaiser-Meyer-Olkin (KMO) statistic and Bartlett test of sphericity, reported for each domain, were used to confirm that each domain indicator set possessed a correlation structure appropriate for this transformation (KMO ranging from 0.63 to 0.67 across the four domains; Supplementary Material 3). Following Balica and Wright [21], the selected proxy indicators were systematically categorised into three vulnerability factors, viz., exposure, sensitivity, and adaptive capacity, and four thematic components or domains, i.e., social, economic, physical, and environmental (Fig. 3). This framework enabled the construction of domain-specific vulnerability indices and an overall composite vulnerability index for assessing district-level susceptibility to natural disasters. The details of relevant proxies, including their definition, unit of measurement, data sources, and functional relationship to the vulnerability factor across the domain, are presented in Supplementary M*aterial 2.*

3.2. *Normalization of the indicators*

Normalization is a technique that transforms variables measured in different units into a common scale (0–1), thereby making them dimensionless and comparable [66]. Following Das et al. [57], the selected indicators were normalized using a modified linear min–max scaling technique (S_i). While the conventional min–max approach rescales values to the range [0,1], this study uses [0.1, 1] to avoid zero

values in the dataset. The presence of zero values can cause instability in subsequent aggregation, particularly in multiplicative frameworks, where a zero value may disproportionately distort or nullify the composite index. Indicators exhibiting both positive and negative functional relationships with vulnerability were normalized using the formula presented below:

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

(for a positive functional relationship)

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

(for a negative functional relationship)

where x_i, $x_{\min}$ and $x_{\max}$ represent the observed, minimum, and maximum values of the ith indicator, respectively. This transformation preserves the relative differences among observations as it is a linear rescaling of the original data, while ensuring computational stability in index construction. Although normalization choices can influence the magnitude of index values, previous studies suggest that linear transformations generally maintain the relative ranking of units. In this study, the robustness of results has been further verified through sensitivity analysis, confirming that the vulnerability rankings are not significantly affected by methodological choices, including normalization. Further, a robustness analysis was undertaken by recalculating each domain-specific index using alternative minimum normalization values of 0.01, 0.05, 0.10 (original specification), and 0.20. The PCA-derived indicator weights remained unchanged across all scenarios so that the analysis isolated the effect of varying the normalization floor. District rankings obtained under each specification were compared with the original rankings using Spearman's rank correlation coefficients.

3.3. Weighting using principal component analysis (PCA)

After normalising the indicators and following Wu [67], the present study employed PCA to assign weights to the indicators to construct the vulnerability index. While Principal Component Analysis (PCA) is used to derive indicator weights, it assigns weights based on the data's variance structure rather than on the causal or normative importance of indicators. Consequently, indicators with higher variability may receive larger weights, which do not necessarily reflect their policy significance. However, in the absence of prior information about the relative importance of indicators, PCA provides a data-driven, objective weighting mechanism that minimises subjectivity and addresses multicollinearity by transforming correlated variables into orthogonal components. Furthermore, alternative weighting approaches such as equal weighting, expert-based methods (e.g., AHP), and participatory techniques have their own limitations, including assumptions of equal importance, subjectivity, or feasibility constraints [68]. Therefore, to ensure methodological consistency, PCA was applied separately within each domain (social, economic, physical, and environmental), thereby avoiding direct comparison between indicators with different physical meanings. In addition, the robustness of PCA-based weights was evaluated through sensitivity analysis using alternative weighting schemes, and the results indicate strong consistency in vulnerability rankings.

Various methods are used to determine the number of principal components to retain. A common rule of thumb, proposed by Kaiser [69], is to retain only components with eigenvalues greater than 1. Before extracting principal components, several statistical tests are performed to assess the suitability of the data for PCA. The Kaiser-Meyer-Olkin (KMO) test measures sampling adequacy, with values ranging from 0 to 1; a KMO score > 0.60 indicates that the data are suitable for PCA [70]. Bartlett's test of sphericity is performed to assess redundancy among variables, and a p-value <0.5 supports the applicability of PCA [58]. Scree plot analysis and Varimax rotation are alternative approaches for identifying the optimal number of components to retain [71]. Based on these criteria, datasets with a KMO value greater than 0.60 and a significant Bartlett's test were retained for PCA. Following Wu [67] this study assigned weights based on the factor loadings of the indicators extracted from the PCA with eigenvalues greater than 1. After extracting the principal components, the weights, which reflect their relative contributions to the composite index, were calculated. The intermediate vulnerability indicators (IVI_{ji}) corresponding to each principal component j were then computed through a weighted aggregation of the normalized indicator values, as expressed in the following equation:

$$\boldsymbol{IVI_{ji}} = \sum_{k=1}^{k=n} \boldsymbol{w_{kj} I_{kj}} \quad (3)$$

Where, IVI_{ji} represent the intermediate vulnerability indicator for the component j and track i indicates the dimension of the vulnerability index. w_{kj} is the weight of the indicator k corresponding to the component j, I_{kj} is the normalized value of the indicator k for track i. The weights w_{kj} of each indicator based on the factor loading was estimated based on the following equation:

$$\boldsymbol{w_{kj}} = \frac{\left(\boldsymbol{factor_loading_{kj}}\right)^2}{\boldsymbol{eigenvalue_j}} \quad (4)$$

Where w_{kj}: weight of the indicators k in the component j; factor loading$_{kj}$ is the value of the factor loading of the indicator k in the principal component j, and the $eigenvalue_j$ is the eigenvalue of jth principal component. This weighting formula (Equ 4) has a clear mathematical justification: the squared factor loading divided by the eigenvalue gives the proportion of variance in the principal component attributable to indicator k. This directly measures the relative contribution of each indicator to the latent vulnerability dimension represented by that component. Indicators with higher factor loadings on a component contribute more to explaining the variance in that latent dimension and are accordingly assigned higher weights. The heterogeneous assignment of weights enables the determination of the individual contributions of indicators and provides a more realistic picture of local conditions. PCA was performed using SPSS (IBM, Statistical Package for the Social Sciences) and Q-GIS to map the domain-specific index spatially. In the social, physical, and environmental domains, three principal components were extracted from each, cumulatively explaining 76.36%, 68.16%, and 65.70% of the total variance, respectively. In the economic domain, four components were considered, accounting for 77.36% of the total variance. Considering that each indicator across the domains has a different physical meaning, each domain (social, economic, physical, environmental) is treated as a separate unit of analysis: PCA is applied independently within each domain, and domain-specific indices are computed separately. The detailed PCA results, including eigenvalues, factor loadings, and indicator weights, are provided in *Supplementary Material 4*.

3.4. Construction of Sub-Indices and Composite Index

After assigning the weights to each indicator, the domain-specific vulnerability indices were developed following the IPCC [43] framework:

$$\boldsymbol{VI_i} = \frac{\boldsymbol{Exposure_i} \times \boldsymbol{Sensitivity_i}}{\boldsymbol{Adaptive\ Capcity_i}} \quad (5)$$

Where VI_i=Vulnerability index of the domain i.

$Exposure_i = \sum_{J=1}^{J_E} IVI_{ji}^{(E)}$

$Sensitivity_i = \sum_{J=1}^{J_S} IVI_{ji}^{(S)}$

$Adaptive\ Capacity_i = \sum_{J=1}^{J_A} IVI_{ji}^{(A)}$

J_E, J_S, J_A is the number of principal components retained for exposure, sensitivity, and adaptive capacity, respectively. $IVI_{ji}^{(E)}$, $IVI_{ji}^{(S)}$, $IVI_{ji}^{(A)}$ are the intermediate vulnerability indicators for each component j under each domain of i (social, economic, physical and environmental domains).

The vulnerability index for each domain i was calculated based on the following equation:

$$\boldsymbol{VI_i} = \frac{\left(\sum_{J=1}^{J_E} \boldsymbol{IVI_{ji}^{(E)}}\right) \times \left(\sum_{J=1}^{J_S} \boldsymbol{IVI_{ji}^{(S)}}\right)}{\left(\sum_{J=1}^{J_A} \boldsymbol{IVI_{ji}^{(A)}}\right)} \quad (6)$$

According to Balica et al. [5], the above vulnerability index (VI) method links each indicator's values to vulnerability factors and domains. Both exposure and sensitivity are placed in the numerator, as they increase vulnerability, while adaptive capacity is in the denominator, as it reduces it.

After the estimation of domain-specific vulnerability indices, the composite vulnerability index $CVI_{(total)}$ was computed using the fourth root of the product of four sub-indices (social, economic, physical, and environmental), as expressed in eq. 7.

$$\mathbf{CVI_{(total)}} = \sqrt[4]{\mathbf{VI_{(social)}} \cdot \mathbf{VI_{(economic)}} \cdot \mathbf{VI_{(physical)}} \cdot \mathbf{VI_{(environmental)}}} \quad (7)$$

The use of the geometric mean ensures that the domain-specific sub-indices contribute proportionally to the composite vulnerability index (CVI). The multiplicative structure of the above equation captures the compound and interactive nature of vulnerability across domains. An advantage of this approach is to minimize the influence of extreme values in any single domain while preserving the relative ranking of districts. The resulting vulnerability index was classified into five categories: 0.00 to 0.20 (least vulnerable), 0.21 to 0.40 (low vulnerable), 0.41 to 0.60 (moderately vulnerable), 0.61 to 0.80 (highly vulnerable), and 0.81 to 1.00 (very highly vulnerable). Based on this classification, both domain-specific and composite vulnerability indices were mapped in QGIS to represent their spatial distribution across the districts of Odisha. Such spatial mapping of vulnerability enables policymakers to identify priority domains and regions for targeted disaster risk reduction interventions [72].

4. Results and discussion

4.1. Spatial distribution of sub-indices

To capture the multidimensional nature of vulnerability at the district level, this section explains the disaggregated vulnerability assessment across four domains: social, economic, physical, and environmental. Each domain captures a distinct aspect of exposure, sensitivity, and adaptive capacity, offering insights into the structural and contextual factors that influence vulnerability. The subsequent section presents the results of the domain-specific vulnerability assessment, which can be used to inform targeted policy interventions. Classification of the domain specific and composite vulnerability indices are given in Supplementary 3.

4.1.1. Social domain

The backwardness and persistent underdevelopment, as exemplified by poor health outcomes, demographic pressure, high poverty levels, and inadequate communication, heighten disaster risk (Table 1). These patterns are clearly reflected in the indicator-level data, where districts with higher exposure (IMR, population growth) and sensitivity (BPL, disability) have higher vulnerability scores.

The high Infant Moratlity Rates (IMR) in Malkangiri, Nabarangapur, Nuapada, and Rayagada districts, ranging from 51 to 61 per 1000 live births, compared to the state average of 36/1000 live births, indicate a neglect of maternal and child health services. Apart from that, these districts reflect low adaptive capacity, particularly in terms of HDI (as low as 0.447 in Nabarangapur and 0.502 in Malkangiri) and access to drinking water (as low as 5.7%), highlighting the linkage between health outcomes and adaptive capacity. Further, high rural poverty (average BPL of 76.47% versus a state average of 67.1%) and poor sanitation coverage (88% of households in these districts without

Table 1
Vulnerability index (Social Domain).

Districts	Exposure	Susceptibility	Resilience	Vul_Index	Std_Index	Rank
Angul	0.363	0.276	0.516	0.194	0.104	28
Balasore	0.619	0.438	0.604	0.449	0.241	15
Bargarh	0.370	0.400	0.582	0.254	0.136	24
Bhadrak	0.599	0.377	0.632	0.357	0.191	17
Balangir	0.465	0.479	0.341	0.653	0.350	11
Boudh	0.488	0.557	0.288	0.944	0.506	10
Cuttack	0.467	0.282	0.635	0.207	0.111	26
Deograh	0.398	0.579	0.359	0.642	0.344	12
Dhenkanal	0.414	0.349	0.529	0.273	0.146	21
Gajapati	0.496	0.642	0.214	1.488	0.797	5
Ganjam	0.451	0.306	0.476	0.290	0.155	20
Jagatsinghpur	0.528	0.264	0.690	0.202	0.108	27
Jajpur	0.619	0.370	0.606	0.378	0.203	16
Jharsuguda	0.250	0.389	0.547	0.178	0.095	29
Kalahandi	0.506	0.502	0.244	1.041	0.558	8
Kandhamal	0.481	0.835	0.320	1.255	0.673	7
Kendrapara	0.551	0.369	0.625	0.325	0.174	18
Keonjhar	0.499	0.581	0.453	0.640	0.343	13
Khordha	0.446	0.191	0.766	0.111	0.060	30
Koraput	0.555	0.595	0.250	1.321	0.708	6
Malkangiri	0.732	0.696	0.273	1.866	1.000	1
Mayurbhanj	0.521	0.696	0.360	1.007	0.540	9
Nabarangapur	0.683	0.728	0.294	1.691	0.906	2
Nayagarh	0.385	0.289	0.415	0.268	0.144	23
Nuapada	0.513	0.700	0.223	1.610	0.863	3
Puri	0.427	0.366	0.630	0.248	0.133	25
Rayagada	0.645	0.755	0.322	1.512	0.810	4
Sambalpur	0.247	0.509	0.461	0.273	0.146	22
Subarnapur	0.447	0.442	0.384	0.515	0.276	14
Sundargarh	0.309	0.481	0.511	0.291	0.156	19

latrines) undermine the capacity to withstand climate extreme events [45]. Adeagbo et al. [73] study confirms the positive association between poor health outcomes and disaster-related mortality.

In addition, demographic pressure plays an important role in shaping exposure. Districts, namely Malkangiri (21.6%), Nabarangapur (19%), and Nuapada (15%), exhibit significantly higher population growth rates than others, indicating greater strain on local resources and infrastructure [45]. Access to proper communication facilities in Gajapati, Malkangiri, and Kandhamal districts is extremely low (6.6%–7.7%), directly constraining information flow and disaster preparedness mechanisms. On the other hand, districts such as Khordha (33.8%) and Cuttack (23.5%) demonstrate significantly higher communication access, contributing to lower vulnerability rankings [74].

Despite the implementation of various watershed projects under the Atal Bhujal Yojana and the Jal Jivan Mission, these persistent gaps reflect systemic exclusion and hinder the inclusive development of these districts. Such persistent underdevelopment has future implications for human development and overall regional well-being [75].

Similar structural disadvantages are also evident in the districts of Koraput, Gajapati, and Kandhamal, which rank them high in the vulnerable category in the social domain. These districts show a combination of high sensitivity (BPL above 75% in Koraput and Kandhamal) and weak resilience (HDI below 0.57), indicating a compounded vulnerability structure rather than a single-factor effect. However, the districts of Kalahandi, Boudh, and Mayurbhanj exhibit mixed patterns [45,74].

Though the deprivation indicators still pose challenges like the prevalence of high poverty levels (65% on average of rural BPL) and population growth rates (ranging between 13 and 18%), the better HDI score (ranging between 0.509 and 0.623), and improved access to drinking water and communication facilities keep these districts in the transitional stages. This suggests that incremental improvements in resilience indicators can partially offset high exposure and sensitivity, highlighting the importance of balanced development.

Districts, namely, Balangir, Subarnapur, Deogarh, Keonjhar, Jajpur, and Balasore, are identified as being in the low-vulnerability category. These districts benefit from improved resilience indicators, a higher HDI (average: 0.694), better communication (average: 14.2%), and access to drinking water facilities (average: 39.4%) [74]. Although some of these districts still exhibit moderate exposure (e.g., high population density in Balasore), their stronger adaptive capacities reduce overall vulnerability.

Finally, the least vulnerable districts, such as Bargarh, Sambalpur, Jharsuguda, Sundargarh, Angul, Nayagarh, Ganjam, Khordha, Puri, Cuttack, Jagatsinghpur, Kendrapara, Bhadrak, and Dhenkanal, are characterized by high resilience capacity, low exposure, and low sensitivity score. The high resilience capacity of the districts is explained by relatively better HDI scores (ranging from 0.809 to 0.853), higher access to communication facilities (an average of 33.8%), and improved access to drinking water (an average of 41.7%). For instance, Khordha, the least vulnerable district (Rank 30), combines relatively moderate exposure with the highest resilience indicators in the dataset, including HDI (0.853), communication access (33.8%), and drinking water availability (47.2%), clearly illustrating how strong adaptive capacity can offset exposure risks [74]. The regions are also observed to have a moderate level of rural poverty and demographic pressure, along with a stable IMR, reflecting a sound health status. These patterns mirror global evidence that human development and infrastructure significantly reduce social vulnerability [76]. The high level of poverty, demographic stress, and disparities in human development are the major determinants of social vulnerability. Policy interventions must prioritize southern and western Odisha by focusing on poverty reduction, improving health services, and enhancing access to basic amenities to strengthen social resilience **(**Fig. 4**a).**

4.1.2. *Economic domain*

The results of the economic vulnerability analysis reveal a distinct spatial pattern, with the western and southern districts (namely

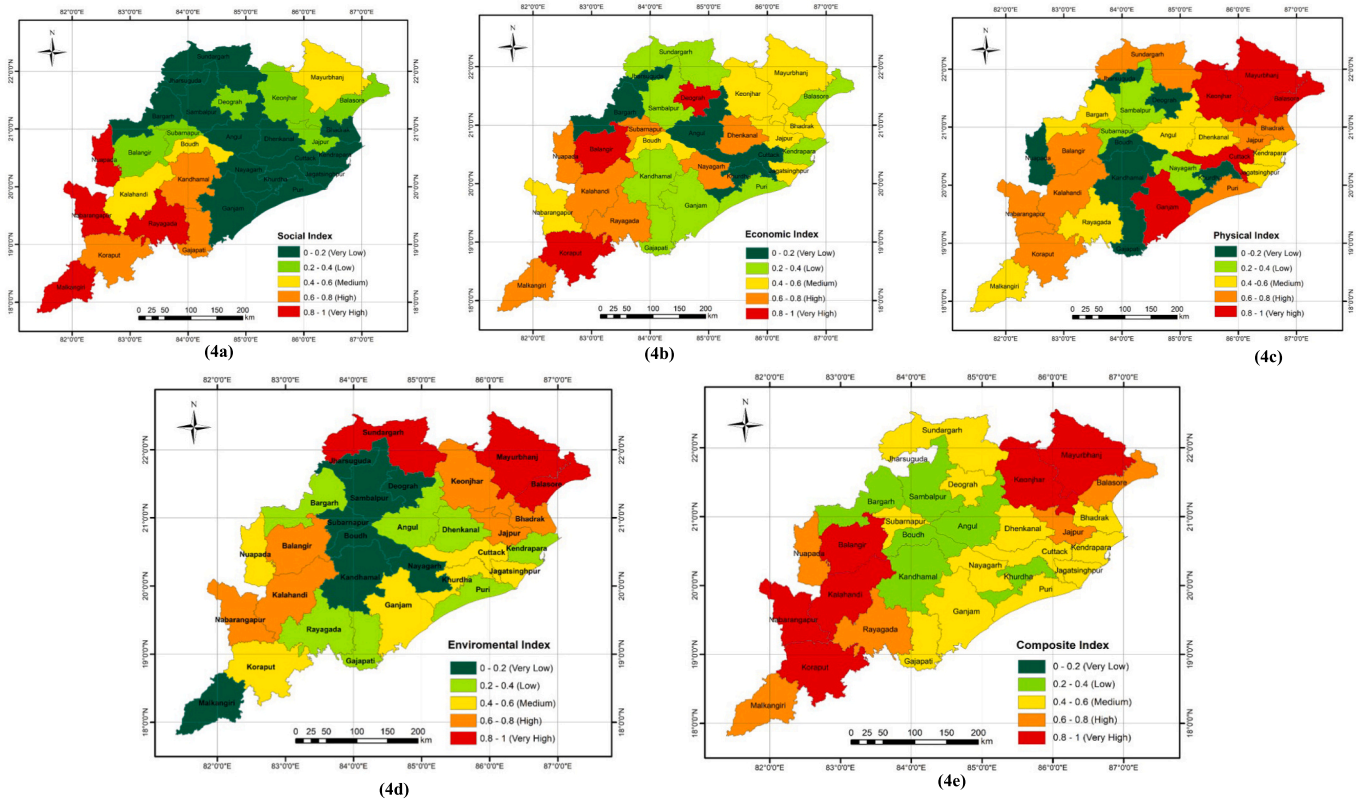


Fig. 4. Spatial Mapping of Domain-Specific and Composite Vulnerability Indices in Odisha.

Koraput, Balangir, and Deogarh) identified as the most economically vulnerable (Table 2). The predominance of agriculture characterized by extensive net-sown areas with limited irrigation coverage indicates a heavy reliance on rainfall, undermining agricultural productivity and making it sensitive to climatic fluctuations. For instance, the high net sown area (263,000 ha) and high dependency rate (43%) in the Koraput district indicate heavy reliance on agriculture and low adaptive capacity. Furthermore, high agricultural workforces (38–50%) and low per-capita DGDP (average of Rs. 125,000) weaken their resilience capacity to combat the impacts of climate-induced natural disasters [77]. This finding again aligns with Bahinipati [41], who argued that the prevalence of high poverty weakens the economic capacity of the western and southern districts, making them highly vulnerable to climate shocks. Similarly, Malkangiri, Rayagada, Kalahandi, Nuapada, Subarnapur, Nayagarh, and Dhenkanal fall under the highly vulnerable category (2nd category). These districts account for an average of 360,000 ha of net sown area, 58% agricultural workers, and a per-capita DGDP of only Rs 2,10,000, confirming that sensitivity factors, including high agricultural dependence and low resilience capacity, are the primary drivers of vulnerability in these regions.

Although the moderately vulnerable districts (Nabarangpur, Kendujhar, Mayurbhanj, Bhadrak, Jajpur, and Jagatsinghpur), with their persistent agricultural dependence, have high coverage of irrigation areas (an average of 0.218 million hectares) and DGDP (an average of Rs 215,000), these factors provide some buffer against shocks. Furthermore, the coastal districts, namely Bhadrak and Jagatsinghpur, benefit from improved access to markets and irrigation infrastructure, which demonstrates their greater resilience.

Furthermore, the small landholdings among farmers (averaging 0.95 ha) reduce their bargaining power in agricultural markets, limiting access to quality seeds, modern technology, and mechanization, thereby lowering agricultural productivity [78]. The fragmentation of landholding is primarily driven by generational subdivision and the absence of effective land consolidation policies. This is evident in the districts of Balangir (0.75 ha) and Cuttack (0.63 ha), where smaller landholding sizes constrain economies of scale, whereas comparatively larger holdings in districts like Koraput (1.36 ha) and Sambalpur (1.39 ha) provide better production potential, though still constrained by other factors. In the absence of alternative livelihood options, the high dependency rate in these districts (average 43.5%) imposes a considerable burden on the working-age population, undermining per capita productivity and constraining long-term economic growth [79]. This is observed in the districts of Keonjhar (dependency ratio: 63.61) and Malkangiri (45.23), where economic pressure on the working population remains high, reducing savings and investment capacity.

On the other hand, the moderate exposure and strong resilience capacity of the Gajapati, Ganjam, Kandhamal, Sambalpur, Sundargarh, Balasore, Kendrapara, and Puri districts place them in the low-vulnerability category. For example, the improved irrigation coverage (averaging 299,000 ha) and better DGDP (Rs. 28,000–35,000) demonstrate the robust economic base of these districts. Furthermore, the integrated irrigation projects and climate-resilient agriculture programs in Odisha strengthened the resilience of these districts by promoting options for crop diversification and water-use efficiency [32].

The greater options for economic diversification and the infrastructural strength of the Jharsuguda, Angul, Cuttack, and Khordha districts make them the least vulnerable to climatic shocks. These districts are characterized by relatively lower agricultural dependence (e.g., Jharsuguda: 22.93% agricultural workers) and significantly higher DGDP, reflecting diversified economic structures. Although the Barghargh district is referred to as the rice bowl of Odisha, improved irrigation coverage from the Hirakud Dams enables farmers to cultivate three crops per year, compensating for losses they may incur in other seasons due to natural shocks [80]. Further, the high per capita GDP, driven by high industrial activity in the coal and power sectors in the Jharsuguda and Angul districts, reflects their economic strength and affluence [81]. The strong economic base of these regions has the potential to provide a better standard of living for their populations, fostering overall development, resilience, and renewal in response to various climatic shocks. These districts also reflect a high workforce participation rate (15 to 59 years of age), suggesting wider participation in productive activities and a strong local economic base. For instance,

Table 2
Vulnerability index (Economic Domain)

Districts	Exposure	Susceptibility	Resilience	Eco_Index_N	Std_Index	Rank
Angul	0.043	0.375	0.099	0.163	0.108	28
Balasore	0.161	0.339	0.194	0.281	0.187	23
Bargarh	0.417	0.292	0.543	0.224	0.149	26
Bhadrak	0.221	0.386	0.211	0.404	0.269	17
Balangir	0.687	0.454	0.210	1.485	0.989	2
Boudh	0.223	0.585	0.253	0.516	0.343	12
Cuttack	0.583	0.121	0.420	0.168	0.112	27
Deograh	0.087	0.330	0.022	1.305	0.869	3
Dhenkanal	0.334	0.513	0.271	0.632	0.421	10
Gajapati	0.056	0.391	0.072	0.304	0.203	21
Ganjam	0.657	0.226	0.554	0.268	0.179	24
Jagatsinghpur	0.301	0.428	0.295	0.437	0.291	15
Jajpur	0.522	0.348	0.427	0.425	0.283	16
Jharsuguda	0.124	0.415	0.333	0.155	0.103	30
Kalahandi	0.699	0.491	0.489	0.702	0.468	7
Kandhamal	0.135	0.420	0.151	0.375	0.250	18
Kendrapara	0.141	0.409	0.199	0.290	0.193	22
Keonjhar	0.450	0.556	0.431	0.581	0.387	11
Khordha	0.062	0.440	0.169	0.161	0.108	29
Koraput	0.188	0.535	0.067	1.501	1.000	1
Malkangiri	0.888	0.532	0.485	0.974	0.649	4
Mayurbhanj	0.430	0.690	0.660	0.450	0.299	14
Nabarangapur	0.292	0.436	0.247	0.515	0.343	13
Nayagarh	0.219	0.516	0.124	0.911	0.607	5
Nuapada	0.255	0.369	0.135	0.697	0.464	8
Puri	0.724	0.285	0.651	0.317	0.211	20
Rayagada	0.287	0.448	0.198	0.649	0.433	9
Sambalpur	0.244	0.227	0.214	0.259	0.172	25
Subarnapur	0.266	0.665	0.233	0.759	0.506	6
Sundargarh	0.122	0.606	0.199	0.372	0.247	19

districts, namely Deogarh (52.9%) and Gajapati (50.9%), were found to have higher workforce participation, indicating stronger engagement in economic activities, which contributes to resilience despite other vulnerabilities. Despite its low irrigation coverage, Khordha benefits from its proximity to the state capital, Bhubaneswar. This urban advantage facilitates better connectivity, access to services, and diverse employment opportunities, resulting in reducing out-migration pressure and supporting the local economy. This result is in line with global findings indicating that economic diversification significantly reduces vulnerability [76]. The spatial vulnerability map for the Economic domain is presented in Fig. 4b.

4.1.3. Physical domain

Mayurbhanj and Keonjhar districts are found to be highly vulnerable in the physical domain due to their infrastructural limitations and environmental stressors (Table 3). The expansion of urban built-up areas in the Mayurbhanj (619.13 km^2) and Keonjhar (393.15 km^2) districts, in the absence of adequate drainage systems and green cover, exacerbates the risk of urban flooding and undermines water quality. As noted by Miller and Hutchins [82], unplanned urbanization and ageing infrastructure intensify flood risk. In this context, Camorani et al. [83] opined that urbanization increases interaction between human society and the ecological environment, leading to various social, environmental, and ecological problems. The vulnerability in Keonjhar district is further intensified by its higher rural road density (0.28%), which enhances the likelihood of infrastructural damage during floods and cyclones. Such damages hinder community mobility, slow evacuation, and delay post-disaster relief and recovery efforts [84]. At the same time, high levels of environmental sensitivity are evident in these regions. For instance, Mayurbhanj (97.72 thousand ha) and Keonjhar (87.67 thousand ha) exhibit substantial degraded forest cover, while districts such as Rayagada (168.69 thousand ha) and Sundargarh (148.96 thousand ha) show even higher ecological degradation, indicating broader environmental stress that amplifies physical vulnerability.

The housing conditions in these districts remain a major concern, with a higher proportion of kutcha houses and thatched roofs (15.8% in Mayurbhanj and 18.5% in Keonjhar), made of wood, polyethene, plastics, thatch, and other materials. This reflects the lack of structural strength in these houses to withstand extreme climatic events, such as high rainfall, floods, and cyclones. [85]. Apart from this, a high proportion of households (81.4%) and (84.9%) in the Mayurbhanj and Keonjhar districts, respectively, lack private latrine facilities. Similar patterns are also observed in districts such as Nabarangapur (90.7%) and Malkangiri (90.7%), indicating a widespread sanitation deficit that increases health risks during disasters. The absence of such adequate sanitation facilities disproportionately affects the vulnerable communities, including women, children, the elderly, and people with disabilities, by increasing health risks and social insecurity, during and after the disaster, with long term implication of overall development of the regions.

Furthermore, the limited presence of structural water management infrastructure (296 and 365 check dams in Mayurbhanj and Keonjhar, respectively) results in rapid surface runoff, soil erosion, and land degradation. These factors potentially reduced agricultural productivity and threatened rural livelihoods. Although districts, namely Kalahandi (620) and Sundargarh (402) exhibit higher numbers of check dams, the uneven spatial distribution and limited integration with watershed management reduce their overall effectiveness in mitigating vulnerability.

Additionally, studies highlight the importance of check dams in landscape stabilization, reducing soil erosion, storing floodwater, replenishing groundwater, and enhancing the overall ecosystem to support rural livelihoods [86]. In contrast, districts such as Jharsuguda, Gajapati, Boudh, Deogarh, and Khurda are found to be the least physically vulnerable to extreme climate events. These districts are characterized by low exposure (limited built-up area), moderate sensitivity, and strong resilience indicators, particularly in infrastructure and service availability. For instance, the minimal urban build-up areas in Jharsuguda (5089 ha), Gajapati (1066 ha), Boudh (3453 ha), and Deogarh (5026 ha) reduce the risk of urban flooding and infrastructure damage during the monsoon. Although Khurda claims a higher urban footprint (14,812 ha), it compensates with lower land degradation

Table 3
Vulnerability index (Physical Domain).

Districts	Exposure	Susceptibility	Resilience	Eco_Index_N	Std_Index	Rank
Angul	0.227	0.521	0.771	0.154	0.276	20
Balasore	0.854	0.306	0.622	0.420	0.756	3
Bargarh	0.251	0.455	0.715	0.160	0.287	17
Bhadrak	0.601	0.286	0.837	0.205	0.369	12
Balangir	0.307	0.563	0.696	0.248	0.446	8
Boudh	0.175	0.334	0.849	0.069	0.124	28
Cuttack	0.604	0.235	0.352	0.403	0.725	4
Deograh	0.137	0.501	0.937	0.073	0.131	27
Dhenkanal	0.263	0.477	0.790	0.159	0.286	18
Gajapati	0.162	0.359	0.869	0.067	0.120	29
Ganjam	0.353	0.493	0.490	0.355	0.639	5
Jagatsinghpur	0.647	0.228	0.841	0.176	0.316	14
Jajpur	0.533	0.382	0.792	0.257	0.462	6
Jharsuguda	0.145	0.284	0.958	0.043	0.077	30
Kalahandi	0.234	0.611	0.574	0.249	0.448	7
Kandhamal	0.137	0.517	0.751	0.094	0.169	24
Kendrapara	0.519	0.273	0.812	0.175	0.314	15
Keonjhar	0.531	0.670	0.654	0.544	0.978	2
Khordha	0.405	0.159	0.749	0.086	0.154	26
Koraput	0.298	0.566	0.749	0.225	0.405	10
Malkangiri	0.248	0.562	0.888	0.157	0.282	19
Mayurbhanj	0.541	0.540	0.526	0.556	1.000	1
Nabarangapur	0.477	0.364	0.798	0.217	0.391	11
Nayagarh	0.215	0.463	0.721	0.138	0.248	21
Nuapada	0.208	0.363	0.825	0.091	0.164	25
Puri	0.534	0.304	0.796	0.204	0.366	13
Rayagada	0.225	0.496	0.683	0.164	0.294	16
Sambalpur	0.180	0.489	0.652	0.135	0.243	22
Subarnapur	0.278	0.369	0.865	0.119	0.214	23
Sundargarh	0.266	0.551	0.636	0.231	0.415	9

(40,975 ha vs the state average of 54,000 ha), suggesting better soil conservation and land-use practices. The better housing conditions in these districts, with a lower proportion of kutcha houses, Boudh (4.7%), Jharsuguda (5.8%), Gajapati (5.8%), and Khurda (4.3%), indicate stronger structural resilience to flood and cyclonic events. Improved physical infrastructure, such as road connectivity and reliable electrification, further facilitates emergency response and communication. Khurda, the state's administrative hub, benefits from well-connected transportation networks, while Jharsuguda's industrial profile has spurred improvements in rural infrastructure. The higher availability of hospital beds (899) in Khurda enables timely medical care and communication during disasters. The spatial vulnerability map for the Physical domain is presented in Fig. 4c.

4.1.4. Environmental domain

Balasore and Sundargarh were observed to be highly vulnerable in the environmental domain (Table 4). Between 1990 and 2024, Balasore recorded 23 disaster events (11 floods, 5 droughts, and 7 cyclones) while Sundargarh experienced 16 disaster events (including 5 floods, 6 droughts, and 5 cyclones) during the same period. This high frequency of such hydro-meteorological extremes reflects higher exposure to climate-induced disasters. Furthermore, the intensity of vulnerability is accentuated by significant rainfall variability, 17.8% in Balasore and 16.3% in Sundargarh, aligned with Maharana [87] projections on increased rainfall events and seasonality due to climate change, which threatens agriculture and water security in Odisha

The high fallow land (538.41 ha) and degraded forest area (14,896,000 ha) in Sundargarh indicate the severe ecological stress of the district. Similarly, Balasore exhibits considerable stress, with high fallow land (248.11) combined with low forest cover, reflecting unsustainable land use and declining productivity.

Furthermore, groundwater extraction rates of 53.08% in Balasore and 48.78% in Sundargarh, compared to the state average of 46.24%, indicate acute water stress and a reduced natural buffering capacity. Over-extraction, combined with declining groundwater recharge rates, undermines the state's long-term water sustainability [88]. Furthermore, the lowest forest cover, at 9.48% in Balasore and 18.35% in Sundargarh, undermines the ecological resilience of these regions to extreme climate events. Forests play a vital role in regulating the water cycle, conserving biodiversity, and mitigating climate extreme events [89]. High land degradation, low forest cover, and high groundwater extraction contribute to ecological fragility and an increased risk of extreme climate events in these regions.

In contrast, districts such as Boudh, Kandhamal, Jharsuguda, and Deogarh are found to be less environmentally vulnerable. These districts are characterized by relatively lower ecological stress and better natural resource conditions, which strengthen their capacity to withstand climatic shocks. The current fallow land in Boudh (4.63 million hectares), Kandhamal (3.62 million hectares), and Deogarh (6.32 million hectares) is well below the state average of 17.30 million hectares, indicating better land utilization and lower land degradation. Similarly, the minimal degradation of forest land in Boudh (2.95 million hectares), Deogarh (2.62 million hectares), and Jharsuguda (2.29 million hectares), compared to the state average of 5.63 million hectares, reflects their improved ecological strength. Extensive forest cover areas, notably in Kandhamal (73.06%), Deogarh (54.79%), and Malkangiri (61.16%), enhance carbon sequestration, biodiversity conservation, and ecosystem services, contributing to environmental resilience capacity. The stable groundwater and rainfall patterns in these districts further reduce environmental stress and help maintain the ecological equilibrium. In Subarnapur, the relatively small wetland area of 129 ha restricts water retention, reducing the chance of persistent waterlogging and flood risks, thereby strengthening its resilience to climate-related disasters. These findings align with the IPCC [2], which emphasizes that environmental resilience improves when natural systems are preserved and resource use stays within regenerative limits. The environmental vulnerability pattern reflects a clear contrast between districts experiencing intense ecological pressure and those maintaining relatively stable natural systems, highlighting the critical role of land, water, and forest resources in determining vulnerability outcomes. The spatial vulnerability map for the environmental domain is presented in Fig. 4d.

Table 4
Vulnerability index (Environmental Domain).

Districts	Exposure	Susceptibility	Resilience	Env_Index	Std_Index	Rank
Angul	0.277	0.312	0.496	0.174	0.301	20
Balasore	0.296	0.402	0.205	0.579	1.000	1
Bargarh	0.235	0.384	0.509	0.177	0.306	19
Bhadrak	0.384	0.321	0.391	0.315	0.544	6
Balangir	0.297	0.520	0.499	0.310	0.535	8
Boudh	0.143	0.214	0.622	0.049	0.085	30
Cuttack	0.307	0.249	0.323	0.237	0.410	13
Deogarh	0.236	0.253	0.699	0.085	0.147	27
Dhenkanal	0.298	0.254	0.483	0.157	0.271	22
Gajapati	0.315	0.303	0.577	0.166	0.286	21
Ganjam	0.236	0.323	0.296	0.258	0.445	10
Jagatsinghpur	0.345	0.307	0.443	0.239	0.413	12
Jajpur	0.420	0.393	0.407	0.405	0.700	4
Jharsuguda	0.146	0.298	0.631	0.069	0.119	28
Kalahandi	0.376	0.408	0.529	0.291	0.502	9
Kandhamal	0.157	0.269	0.696	0.061	0.105	29
Kendrapara	0.331	0.356	0.620	0.190	0.328	17
Keonjhar	0.297	0.442	0.359	0.366	0.632	5
Khordha	0.318	0.336	0.456	0.234	0.405	14
Koraput	0.171	0.439	0.355	0.212	0.366	15
Malkanagiri	0.160	0.335	0.597	0.090	0.155	25
Mayurbhanj	0.350	0.466	0.373	0.437	0.756	3
Nabarangpur	0.268	0.518	0.442	0.314	0.542	7
Nayagarh	0.221	0.217	0.550	0.087	0.151	26
Nuapada	0.307	0.437	0.561	0.239	0.413	11
Puri	0.281	0.370	0.509	0.204	0.353	16
Rayagada	0.244	0.398	0.528	0.184	0.317	18
Sambalpur	0.235	0.255	0.572	0.105	0.181	23
Subarnapur	0.269	0.230	0.662	0.094	0.162	24
Sundargarh	0.225	0.773	0.328	0.531	0.917	2

4.1.5. Composite vulnerability index (CVI)

Integrating the social, economic, physical, and environmental dimensions, the composite vulnerability index (CVI) presents the multidimensional nature of vulnerability to climate extreme events and regional disparities at the district level in Odisha (Table 5). The CVI highlights significant regional disparities, with Mayurbhanj, Koraput, and Balangir districts appeared as the most vulnerable, while Jharsuguda, Khordha, and Angul rank as less vulnerable. Notably, none of the districts falls into the least or very low vulnerability category in the composite index. This diverse pattern of vulnerability reflects the compounding effects of multiple factors, in which high exposure and sensitivity in one or more domains elevate overall vulnerability. For example, the moderate economic vulnerability of Mayurbhanj is significantly undermined by its social, physical, and environmental deprivation, which collectively push it into the highly vulnerable category. The multidimensional poverty rate in Mayurbhanj district is 44.90%, nearly three times the national average of 14.95% (NITI [90]). The absence of education beyond primary school among the vulnerable tribal group in the district further leads to a critical deficit in access to information and to critical infrastructure such as healthcare, drinking water, roads, and electricity [88,91].

Similarly, the moderate vulnerability of Koraput in environmental domains is offset by deprivation in social and physical domains. The district reported having a high multidimensional poverty rate (51.4%) and a low literacy rate (35.7%) compared with the state average, ranking first in Head Count Ratio and second in Poverty Gap Index among all districts of Odisha (NITI [90,92]). The district was further designated as an Aspirational District, confirming its chronic structural underdevelopment, limited institutional support, and high reliance on agriculture, accompanied by recurrent exposure to drought and floods [93]. Further, the historically high poverty rate in Balangir (61.01%) combined with minimal irrigation (about 3% of cultivated land) indicates a drought-prone regime with marginal droughts occurring every 2–4 years and severe droughts every 24–48 years across its blocks [94,95]. This aligns closely with Balangir's CVI ranking (Rank 3rd), where high economic and social vulnerability contribute significantly to its overall position. The four-month hydrological drought in Nuapada district (July–October 2021) threatened food security, prompted distress asset sales, and reduced income [96]. Similarly, Nuapada (Rank 10th) and adjacent districts such as Kalahandi (Rank 6th) and Nabarangapur (Rank 5th) are identified as highly vulnerable in the CVI, reflecting the KBK region's broader drought-prone nature. At the basin scale, the Tel River basin—covering Nabarangpur, Kalahandi, Balangir, Boudh, and Kandhamal—experienced about 18% moderate, 10% severe, and 5% extreme drought incidence. A study of the broader KBK region reports that 45% of households migrate distressfully and a multidimensional poverty rate is 44%, nearly three times the state average, illustrating the proliferation of vulnerability in the region [97].

On the other hand, Jharsuguda, Khordha, and Angul demonstrate strong resilience in social, economic, and physical domains. Their low composite vulnerability, supported by their high adaptive capacity, is characterized by greater irrigation coverage, improved infrastructure, higher district GDP, and a higher HDI score. Jhrasuguda district reported as the highest per capita income (Rs. 54,148) with a literacy rate of 78.86% — well above the state average of 72.87% [45,98]. The major industrial units, namely Vedanta Alumina, Aditya Birla Group, Reliance Energy, and the Ib Thermal Power Station, which operates under the Odisha Power Generation Corporation, anchor the district's strong economic base [81]. Khordha, on the other hand, is reported as the 2nd lowest vulnerable district (ranked 29th). The districts contribute 7.72% of Odisha's total State Domestic Product and are primarily concentrated in government administration, information technology, education, and healthcare infrastructure around the state capital, Bhubaneswar. Interestingly, while Khordha exhibits moderate vulnerability in the environmental domain, it is significantly offset by the low vulnerability of the other domains, which balance the overall ranking and place it among the least vulnerable districts. Similarly, the strong industrial base in coal and power of Angul, which is considered the home to the major public sector units of National Aluminium Company Limited (NALCO), National Thermal Power Corporation (NTPC), and Mahanadi Coalfields

Table 5
Composite vulnerability index.

Districts	Soc_Index	Eco_Index_N	Phy_Index	Env_Index	Compo_Index	Std_Index	Rank
Angul	0.194	0.163	0.154	0.174	0.171	0.296	28
Balasore	0.449	0.281	0.420	0.579	0.419	0.727	7
Bargarh	0.254	0.224	0.160	0.177	0.200	0.348	26
Bhadrak	0.357	0.404	0.205	0.315	0.311	0.539	13
Balangir	0.653	1.485	0.248	0.310	0.522	0.907	3
Boudh	0.944	0.516	0.069	0.049	0.201	0.350	25
Cuttack	0.207	0.168	0.403	0.237	0.240	0.417	20
Deograh	0.642	1.305	0.073	0.085	0.269	0.467	15
Dhenkanal	0.273	0.632	0.159	0.157	0.256	0.445	18
Gajapati	1.488	0.304	0.067	0.166	0.266	0.462	16
Ganjam	0.290	0.268	0.355	0.258	0.290	0.504	14
Jagatsinghpur	0.202	0.437	0.176	0.239	0.247	0.428	19
Jajpur	0.378	0.425	0.257	0.405	0.360	0.624	11
Jharsuguda	0.178	0.155	0.043	0.069	0.095	0.165	30
Kalahandi	1.041	0.702	0.249	0.291	0.480	0.833	6
Kandhamal	1.255	0.375	0.094	0.061	0.228	0.395	24
Kendrapara	0.325	0.290	0.175	0.190	0.236	0.410	22
Keonjhar	0.640	0.581	0.544	0.366	0.521	0.905	4
Khordha	0.111	0.161	0.086	0.234	0.138	0.239	29
Koraput	1.321	1.501	0.225	0.212	0.555	0.963	2
Malkangiri	1.866	0.974	0.157	0.090	0.400	0.694	9
Mayurbhanj	1.007	0.450	0.556	0.437	0.576	1.000	1
Nabarangapur	1.691	0.515	0.217	0.314	0.494	0.857	5
Nayagarh	0.268	0.911	0.138	0.087	0.233	0.404	23
Nuapada	1.610	0.697	0.091	0.239	0.396	0.687	10
Puri	0.248	0.317	0.204	0.204	0.239	0.415	21
Rayagada	1.512	0.649	0.164	0.184	0.414	0.719	8
Sambalpur	0.273	0.259	0.135	0.105	0.178	0.308	27
Subarnapur	0.515	0.759	0.119	0.094	0.257	0.446	17
Sundargarh	0.291	0.372	0.231	0.531	0.339	0.589	12

Source: Author's own computation.

Limited (MCL), along with private sector enterprises, namely Jindal Steel and Power Limited (JSPL) makes the district as an industrial hub of the state and third-largest coal-producing district of India [99]. This benefits the district with the highest per capita income and workforce participation rate as compared to the other districts placed in one of the 3rd lowest vulnerable districts [81].

The CVI also reveals the convergence and divergence in vulnerability patterns across the districts. Some districts consistently rank high or low across all domains, while others exhibit a mixed pattern. For instance, Deogarh identified as economically vulnerable, but its better performance in environmental domains placed it in the moderately vulnerable category in the composite index. This indicates a complex interplay among multiple dimensions of vulnerability, highlighting the importance of multidimensional assessments in informing adaptive strategies. Further, by capturing both overlaps and contrasts across domains, the CVI emphasized the need for integrated planning that addresses not only sectoral deficits but also cross-cutting issues that influence a district's overall capacity to withstand and recover from climate-induced shocks **(**Fig. 4e**).**

4.2. *Robustness check of vulnerability indices*

4.2.1. *Sensitivity analysis*

To assess the robustness of the vulnerability index to methodological choices, both sensitivity and uncertainty analyses were performed. First, a sensitivity analysis was conducted by comparing the results from PCA-based weighting with an alternative equal-weighting scheme in which all indicators were given equal weight, assuming they are equally important. These new rankings were then compared with those from PCA-based weighting. A scatter diagram comparing PCA-based and equal-weight rankings for the social domain (Fig. 5a), the economic domain (Fig. 5b), the physical domain (Fig. 5c) and the environmental domain (Fig. 5d) as below.

The scatter plot indicates a strong alignment between PCA-based and equal-weight ranks across all the domains. However, for environmental domains, a slight deviation was observed for a few districts. Using equal weights enhances the credibility of the vulnerability assessment and offers a more balanced basis for policymaking and resource distribution.

Spearman's and Kendall's rank correlations were computed to assess the robustness of the weighting methods used to develop the vulnerability sub-indices. The Spearman rho value of 0.98 ($p < 0.001$) and the Kendall's tau-a and tau-b values, each at 0.9310 for the social index, indicate that the districts' ranking is independent of the different

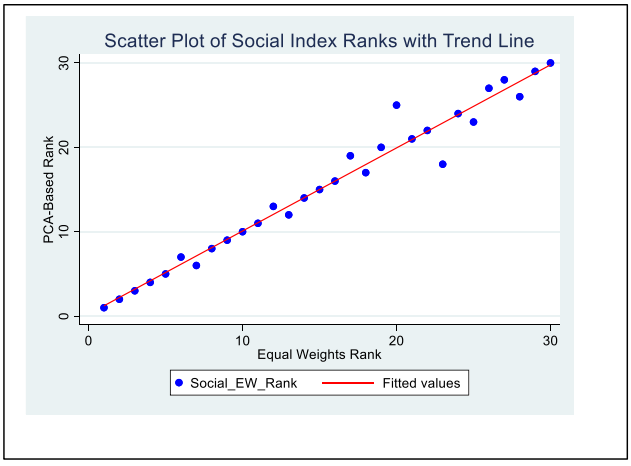


Fig: 5a

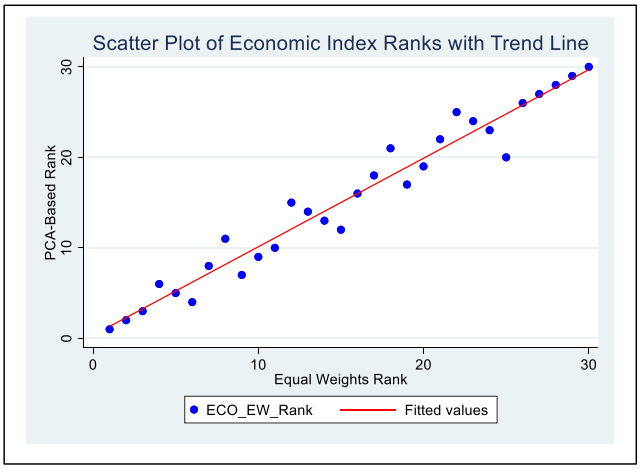


Fig:5b

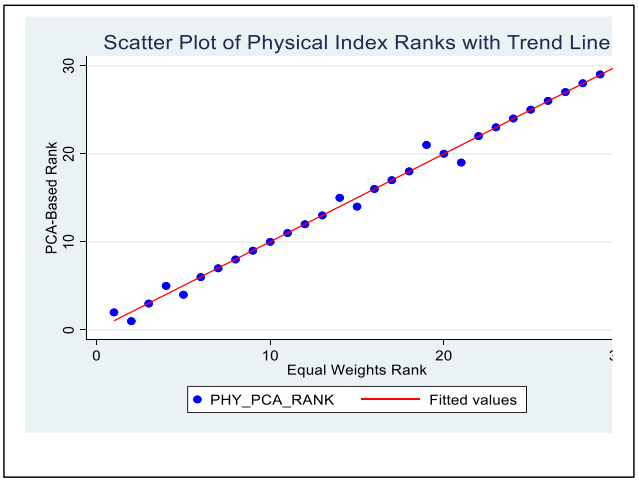


Fig: 5c

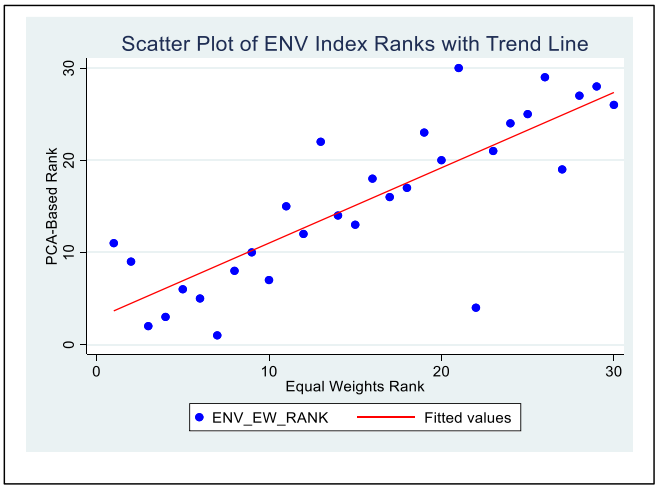


Fig: 5d

Fig. 5. Comparison of district-level vulnerability rankings: original vs. equal weights.

weighting systems and is strongly positively associated between the district rank produced by the PCA weights and the equal weighting system. Similarly, Spearman's rho for the economic index is 0.9786 ($p < 0.001$), and Kendall's tau-a and tau-b, each at 0.88, reject the hypothesis of independence between district rankings and the weighting systems (PCA and equal weights). The physical index also reported the robustness and internal consistency of the district rankings (Spearman's rho: 0.9969; Kendall's tau: 0.9724). A nearly perfect alignment was observed from the scatter plot of the environmental index with respect to the PCA and equal weighting methods. Spearman's rho at 0.8171 and Kendall's tau at 0.6506 with a significant probability value reject the independence of the weighting system. These findings suggest that the vulnerability patterns are not sensitive to the choice of weighting scheme.

4.2.2. Sensitivity analysis of district ranking under alternative normalization floors and alternative vulnerability index formulation

Based on the alterative normalization floor (0.01, 0.05, 0.20), we obtained the results which indicate that the district rankings are highly robust to changes in the normalization floor across all vulnerability domains. Correlation coefficients between the original rankings and those obtained under alternative floors ranged from 0.956 to 0.968 for the social domain (Supplementary Table 5a, 5b), 0.944–0.966 for the economic domain (Supplementary Table 6a, 6b) and 0.940–0.952 for the physical domain (Supplementary Table 7a, 7b) and 0.932–0.954 for the environmental domain (Supplementary Table 8a, 8b). These consistently high correlations demonstrate that the relative ranking of districts remains largely unchanged despite variations in the normalization floor, indicating that the vulnerability indices are not unduly sensitive to the treatment of low adaptive capacity values. Overall, the findings confirm the methodological robustness and reliability of the proposed PCA-based vulnerability assessment framework (Supplementary Table 9).

To examine whether the study's findings were influenced by this modelling choice, we estimated an alternative additive vulnerability index, $VI_A = (E + S + (1 - AC))/3$, in which adaptive capacity is incorporated as its complement rather than in the denominator. This formulation eliminates the possibility of inflated index values arising from very small adaptive-capacity scores while retaining the same conceptual dimensions of vulnerability. District rankings derived from the alternative formulation were then compared with those obtained from the original multiplicative formulation using Spearman's rank correlation coefficient. The results showed very high agreement between the two formulations across all domains, with correlation coefficients of 0.988 (social), 0.890 (economic), 0.979 (physical), and 0.981 (environmental), all statistically significant at $p < 0.001$ (Table 6). These findings indicate that the identification and relative ranking of vulnerable districts remain highly consistent irrespective of whether adaptive capacity is incorporated in the denominator or as a complementary component. Therefore, the conclusions of the study are not driven by the denominator-based treatment of adaptive capacity but are robust to an alternative and widely used additive formulation (refer Supplementary Table 10).

Table 6
Spearman's rank correlation between the original and alternative vulnerability index formulations across vulnerability domains.

Vulnerability Domain	Spearman's Rank Correlation	Significance
Social	0.988	*** ($p < 0.001$)
Economic	0.895	*** ($p < 0.001$)
Physical	0.979	*** ($p < 0.001$)
Environmental	0.981	*** ($p < 0.001$)

Note: Spearman's rank correlation coefficients (ρ) compare district rankings obtained from the original vulnerability index formulation, $VI = (E \times S)/AC$, with those derived from the alternative additive formulation, $VI_A = (E + S + (1 - AC))/3$, where E, S, and ACdenote the normalized exposure, sensitivity, and adaptive capacity indices, respectively. The alternative formulation incorporates adaptive capacity as its complement rather than in the denominator, thereby avoiding inflated vulnerability values that may arise from very small adaptive-capacity scores. All correlations are statistically significant at the 0.1% level (**$p < 0.001$**).

4.2.3. Robustness analysis of PCA based weighting method

To evaluate the robustness of the principal component analysis (PCA), multiple diagnostic procedures were employed. Bartlett's test of sphericity was statistically significant ($p < 0.001$), confirming sufficient intercorrelation among the indicators, while Kaiser–Meyer–Olkin (KMO) values ranged from 0.63 to 0.67 across the four vulnerability domains, indicating acceptable sampling adequacy for PCA [100,101]. Horn's Parallel Analysis further supported the number of retained principal components. In addition, a bootstrap analysis with 1000 replications was conducted to evaluate the reproducibility of the estimated component loadings. Indicator reliability was assessed using the Bootstrap Ratio (BSR), calculated as the absolute value of the rotated component loading divided by its bootstrap standard error (|Loading|/Bootstrap SE). Following McIntosh and Lobaugh [102] and Krishnan et al. [103], BSR values were interpreted analogously to z-statistics, with absolute values of 1.96 or greater indicating statistically reliable loadings. Across the environmental, social, physical, and economic vulnerability domains, most indicators exhibited absolute BSR values of 1.96 or greater, while the remaining indicators produced values between 1.90 and 1.99, which are very close to this reference value. Overall, these results indicate that the estimated component loadings were reproducible across bootstrap samples and support the robustness of the PCA-derived weighting scheme. Detailed bootstrap results are presented in Supplementary Tables 11–14.

4.2.4. Uncertainty analysis: Monte Carlo simulation

To account for uncertainty arising from data variability and potential measurement errors, a simulation-based uncertainty analysis was conducted using a Monte Carlo–type approach. Small random perturbations (±5%) were applied to the domain-level indices (social, economic, physical, and environmental) using normally distributed with zero mean and standard deviation 0.05. The perturbed indices were then used to recompute the Composite Vulnerability Index (CVI) using the same aggregation framework. The resulting rankings were compared with the original rankings using Spearman rank correlation (Table 7).

The results show an extremely high correlation coefficient ($\rho = 0.9969$) between original and simulated rankings, indicating that the vulnerability rankings are highly stable and insensitive to minor variations in input values. This confirms that the findings are robust to uncertainty in the data and methodological assumptions, thereby enhancing the reliability of the composite vulnerability assessment.

4.2.5. Uncertainty analysis: bootstrap resampling

In addition to the Monte Carlo–based uncertainty analysis, a bootstrap resampling approach was employed to further assess the statistical stability of the Composite Vulnerability Index (CVI). The bootstrap procedure involved 500 replications, in which the dataset was resampled with replacement and the mean CVI was recalculated for each sample. The results indicate a small standard error (0.0226) and a

Table 7
Sensitivity analysis of CVI rankings under Monte Carlo simulation.

Analysis Type	Method Applied	Correlation Coefficient (Spearman ρ)	Interpretation
Original vs Simulated CVI Ranking	Monte Carlo Simulation (±5% perturbation)	0.9969	Very strong correlation (high robustness)

Source: Author's own computation.

relatively narrow 95% confidence interval (0.2734–0.3621), suggesting that the CVI estimates are stable and not sensitive to sampling variability (Table 8). These findings provide additional evidence that the constructed vulnerability index is statistically robust and reliable.

Overall, the combination of sensitivity analysis (equal-weight comparison), Monte Carlo simulation, and bootstrap resampling provides strong evidence that the vulnerability rankings are robust to variations in weighting schemes, data uncertainty, and sampling variability.

4.2.6. Spatial pattern and statistical validation of vulnerability

To verify whether the spatial pattern of vulnerability across Odisha's districts follows a genuine geographical pattern rather than being random, we used Global Moran's I and Local Indicators of Spatial Association (LISA) with a Queen contiguity spatial weights matrix, standardised by row to account for variation in the number of neighbouring districts [104,105].

The findings indicate that the distribution of the composite vulnerability index is not random but shows significant positive spatial autocorrelation (Moran's $I = 0.5303$, $z = 4.84$, $p = 0.001$) (Table 9). This suggests that districts with similar vulnerability levels tend to cluster geographically: high-vulnerability districts are located near other high-vulnerability districts, and low-vulnerability districts near low-vulnerability districts. Among the domain-specific indices, social vulnerability displays the strongest clustering ($I = 0.5695$, $p = 0.001$), followed by physical ($I = 0.3305$, $p = 0.008$), environmental ($I = 0.2769$, $p = 0.007$), and economic vulnerability ($I = 0.1794$, $p = 0.052$).

Additionally, the LISA analysis reveals local clusters: High–High clusters in Mayurbhanj and Balasore in the northeast, and Koraput, Kalahandi, and Nabarangapur in the southwest; Low-Low clusters in Sambalpur, Cuttack, Nayagarh, and Ganjam in the central-eastern region (Fig. 6).

No significant High-Low or Low-High outliers were identified, indicating no district's vulnerability sharply contradicts that of its neighbours. High–Low districts represent localized vulnerability hotspots that remain highly vulnerable despite being surrounded by comparatively less vulnerable neighbours. This suggests that district-specific environmental degradation, infrastructure deficits, or socioeconomic constraints contribute disproportionately to their vulnerability. In contrast, Low–High districts show comparatively lower vulnerability despite being located within otherwise vulnerable regions. This indicates localized resilience, defined by stronger governance, improved infrastructure, or more effective resource management. Further, this highlights the significance of local drivers of vulnerability and resilience capacity, which are not captured by the broader regional trend. The remaining 21 districts are in the non-significant category, which is expected given the moderate sample size and the conservative nature of local significance tests [104]. Overall, these results statistically confirm that the vulnerability patterns are spatially structured and regionally interconnected, validating the GIS-based mapping.

4.2.7. External validation using observed disaster outcomes

To further assess the empirical validity of the Composite Vulnerability Index (CVI), historical disaster outcome records were examined for the five most vulnerable and five least vulnerable districts in Odisha.

Table 8
Bootstrap estimates of the composite vulnerability index (CVI).

Statistic	Value
Observations	30
Replications	500
Mean CVI	0.3177
Std. Error	0.0226
95% CI	0.2734–0.3621

Source: Author's own computation.

Table 9
Global Moran's I results.

Index	Moran's I	Z Score	*p*-value	Interpretation
Composite	0.53	3.42	0.001	Significant Clustering
Social	0.57	3.68	0.001	Significant Clustering
Economic	0.17	1.94	0.052	Marginal Clustering
Physical	0.33	2.65	0.002	Significant Clustering
Environmental	0.27	2.69	0.001	Significant Clustering

Source: Author's own computation.

Unlike spatial autocorrelation analysis, which tests whether vulnerability values are geographically clustered, this validation exercise compares CVI rankings with independent observed outcomes, including disaster frequency, affected population, crop damage, housing loss, livestock loss, and human casualties.

The results reveal a distinct contrast between the two groups. The five most vulnerable districts, namely Mayurbhanj (CVI = 1.000), Koraput (0.963), Balangir (0.907), Keonjhar (0.905), and Nabarangapur (0.857), exhibited substantially higher multidimensional poverty (average MPI = 0.222) and experienced recurrent floods, droughts, cyclones, and fire incidents over the last two decades. These districts recorded extensive losses in terms of affected population, agricultural land, housing, livestock, and human lives. For example, Mayurbhanj experienced 17 flood events affecting approximately 1.84 million people and reported 329,457 ha of drought-affected crop area. Similarly, Balangir recorded 14 drought events affecting nearly 1.65 million people and resulting in crop losses exceeding 124,792 ha. Keonjhar experienced cyclone impacts affecting more than 1.80 million people, while Nabarangapur reported 245,786 drought-affected people and more than 24,112 ha of cyclone-related crop damage. Koraput also experienced repeated floods, droughts, cyclones, and landslides, causing significant housing, livestock, and agricultural losses (Supplementary Table 15).

In contrast, the five least vulnerable districts, namely Jharsuguda, Khordha, Angul, Sambalpur, and Bargarh, exhibited a considerably lower average CVI (0.271) and MPI (0.094). Although some of these districts experienced climatic hazards, the magnitude and persistence of impacts were generally lower (Supplementary tables 16 to 18). For instance, Jharsuguda reported approximately 46,506 drought-affected persons, substantially lower than the drought impacts observed in Balangir and Nabarangapur. Angul recorded no major flood, drought, or cyclone impacts during the assessment period, with only localized fire incidents being reported. While Khordha experienced severe cyclonic events such as Phailin, Fani, and Jawad, its relatively low vulnerability and poverty levels suggest stronger adaptive capacity, improved infrastructure, and better institutional preparedness.

These findings indicate that Moran's I and LISA should be interpreted as spatial statistical validation, whereas comparison with observed disaster outcomes provides external empirical validation of the CVI. The broad agreement between high CVI rankings and higher observed disaster impacts supports the validity of the index as a meaningful representation of real-world vulnerability. At the same time, the case of Khordha highlights that disaster exposure alone does not determine vulnerability; rather, impacts are mediated by socioeconomic conditions, livelihood resilience, infrastructure, and institutional adaptive capacity.

5. Conclusions and policy implications

Grounded on the IPCC (AR4) framework and Balic and Wright (2012) domain-specific approach, this study presents a multidimensional vulnerability assessment across the districts of Odisha. Both the deductive and inductive approaches were employed for indicator selection, ensuring methodological rigour and contextual relevance. Principal Component Analysis (PCA) was used for weighting, and QGIS-based spatial mapping was utilized. A composite index was developed

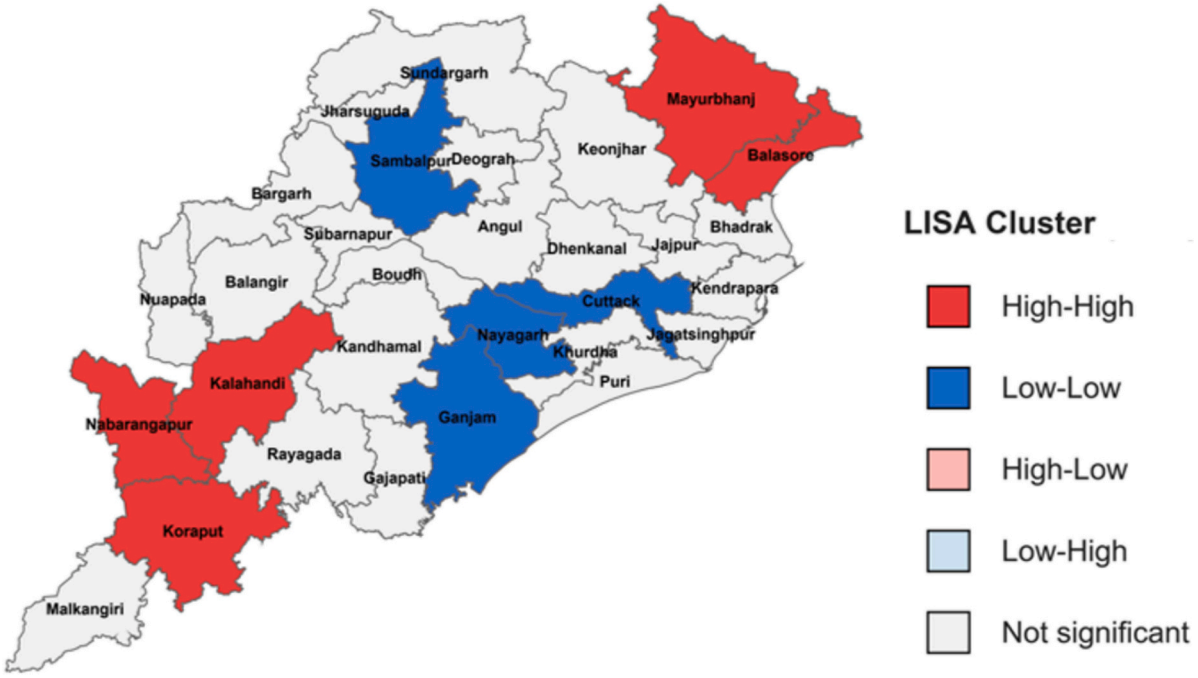


Fig. 6. Local indicators of spatial association (LISA) map for composite vulnerability index.

based on domain-specific sub-indices to capture the spatial and structural complexity of climate vulnerability. Furthermore, Kernel–Thomas weighting, equal weighting, and scatter plot methods were employed to assess the robustness and credibility of the weight assignments used in developing the index. Further, spatial statistical validation using Global Moran's I and Local Indicators of Spatial Association (LISA) confirmed that the observed vulnerability patterns are not random but exhibit significant spatial clustering, thereby strengthening the reliability of the model outputs.

The CVI results reveal stark regional disparities. The southern and western districts, namely Mayurbhanj, Koraput, and Balangir, appear highly vulnerable in CVI rankings, primarily due to their high exposure to recurrent droughts and rainfall deficits, infrastructural and socio-economic sensitivity, and limited adaptive capacity. These findings are further supported by independent empirical evidence, including documented drought frequency, high poverty levels, and livelihood stress in the KBK region, as well as socio-economic and ecological constraints in districts such as Mayurbhanj and Koraput, confirming the consistency between model-based results and real-world conditions. In contrast, districts like Jharsuguda, Khordha, and Angul have relatively strong resilience bases, supported by higher per capita GDP, improved HDI, better irrigation, and infrastructure, placing them in the low vulnerable rank in the composite index. Districts such as Deogarh exhibit mixed profiles, economic fragility offset by environmental strength, highlighting the complex interactions within their domains. The domain-specific vulnerability analysis indicates that physical and environmental factors are major contributors to overall vulnerability. Districts like Kendrapara, Bhadrak, Koraput, and Balangir face challenges including low literacy rates, high dependency ratios, inadequate income security, and limited institutional support. Physical vulnerability is prominent in Mayurbhanj and Keonjhar, where poor housing and inadequate drainage increase flood and cyclone risks. Environmental stress peaks in Balasore and Sundargarh, driven by frequent hydro-meteorological events, deforestation, and high groundwater extraction.

Vulnerability reduction efforts should target the most affected domains instead of blanket strategies, which risk inefficient resource allocation. For example, districts with high social and physical vulnerabilities need focused investments in education, healthcare, and resilient infrastructure. Ecologically fragile districts should prioritize forest regeneration, sustainable water management, and disaster preparedness. Strengthening governance, institutional support, and social safety nets is vital to enhancing adaptive capacity and building resilience. Incorporating district-level vulnerability profiles into disaster risk reduction and climate adaptation plans will promote more equitable, effective, and context-sensitive resilience in Odisha and similar regions. Integrating multidimensional vulnerability assessments into state and national disaster management planning can enhance precision and prevent resource misallocation, ensuring that the most vulnerable regions receive adequate institutional support. Moreover, the study framework can be replicated to assess vulnerability in other developing-country contexts that are frequently affected by extreme climate events, offering a practical guideline for mainstreaming vulnerability assessment within national adaptation and disaster risk management frameworks. Strengthening data systems and cross-sectoral coordination will be critical for sustaining these efforts. Ultimately, embedding multidimensional vulnerability metrics into policy design can help move adaptation planning from reactive crisis management toward proactive resilience building.

Declaration of generative AI in scientific writing

During the preparation of this work, the author(s) used ChatGPT 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.

CRediT authorship contribution statement

Niranjan Padhan: Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **K.H. Anantha:** Writing – original draft, Supervision, Methodology, Conceptualization. **S. Madheswaran:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Kaushal K. Garg:** Writing – review & editing, Methodology. **Venkata Radha Akuraju:** Writing – review & editing, Methodology. **Ramesh Singh:** Writing – review & editing.

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Ethics approval and consent to participate

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The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.pdisas.2026.100704.

Data availability

The data used in this study are publicly available from government and institutional sources, including the Census of India, climate datasets, and socio-economic indicators. Detailed information on data sources and processing is provided in the manuscript.

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