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Multi-Criteria Seismic Vulnerability and Healthcare Accessibility Assessment Using Fuzzy C-Means Clustering in Cox's Bazar, Bangladesh

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Abstract

Systematic spatial prioritization of critical lifelines like healthcare facility, incorporating seismic vulnerability and accessibility to healthcare in the coastal areas of South Asia has not been adequately explored. A multi-criteria seismic vulnerability and accessibility towards healthcare facilities study have been conducted for 184 healthcare facilities of Cox's Bazar district in Bangladesh using the Fuzzy C-Means (FCM) clustering techniques in GIS. Three seismic hazard scenarios were considered: (i) mean M6.5 event (based on Peak Ground Acceleration (PGA)); (ii) 475-year return period (M7.0, 10% probability of exceedance in 50 years); and (iii) 975-year return period (M7.5, 5% probability of exceedance in 50 years). In every scenario, average travel time (ATT) generated by the network, population covered in the 5km buffer and the importance factor for the network as per Bangladesh National Building Code (BNBC 2020) were taken into account. All the variables were scaled between 0 and 1 (min-max scaling). The optimal number of clusters ($c = 2-15$) were determined using the Xie–Beni validity index. In all the analysis, $c = 4$ was the best solution in all the cases and $XB = 0.204 - 0.212$ was the reasonable compactness of the clusters. Within facility-level cluster consistency, the results indicate that there is stability across the three seismic scenarios for the four vulnerability archetypes (98.9%). The most vulnerable cluster is occupied constantly by the facilities of Cox's Bazar Sadar hospital class, which is due to the coincidence of the primary surge-capacity demand and the peak seismic hazard. Critically, the multi-criteria analysis shows Rank inversion that is not evident in hazard-only-based analysis: facilities serving mean catchment populations of 167,371 persons including 900,000 Rohingya camp residents are ranked with the highest Capacity Mismatch risk, yet they are located in the least seismically hazardous area in the district. The broad spatial patterns are similar across normalization strategies and the membership of clusters vary slightly across scenarios.

Keywords: Fuzzy C-Means, GeoAI, GIS, Healthcare Accessibility, Seismic Vulnerability, Cox's Bazar

1 Introduction

Bangladesh is one of the most seismically active countries in south Asia. The Bengal Basin and Chittagong Hill tracts are located in the region where the Indian and Asian and Burma tectonic plates meet, and with complicated fault systems have the potential to produce moderate to large magnitude earthquakes (Samm-A et al. 2025).

Among these the most vulnerable region is the south-eastern coastal district of Cox's Bazar that is near Indo-Burma subduction interface (Barua et al. 2023). The historical seismicity record, the existence of the traces of active faults and thick Quaternary sediments with low shear wave velocity (V_{s30}) contribute to enhance the ground motion (Safayet et al. 2025). The Arakan earthquake of 1762 with an estimated moment magnitude (M) of 8.5-8.8 indicates that very large earthquakes have happened in the past in this region (Mondal 2018).

In addition, Cox's Bazar houses the world's largest refugee camp, resulting in a strain on the already weak healthcare system (Reza et al. 2025). Healthcare infrastructure plays a major role in post disaster response in this context. The BNBC 2020 has given the highest importance to hospitals - 1.5 followed by community clinic (1-1.25) depending on proximity to population centers and capacity. Earthquakes produce a double crisis, in the form of human deaths due to collapse and the inability of emergency medical services to function (Muttaqin et al. 2025).

Healthcare facilities are the backbone of any disaster management system especially for post-disaster response and rehabilitation, and they are also among those assets that are most vulnerable to seismic events. Earthquake-affected areas provide evidence that when hospitals sustain damage or are made inaccessible, mortality and morbidity became significantly worse because the increased need for emergency care at the time of the earthquake happens at exactly the time that the facilities that are best equipped to provide emergency care are most damaged (Cimellaro et al. 2010; Khazai et al. 2014). However, Seismic risk alone is not sufficient to prioritize investment in healthcare infrastructure. Structurally vulnerable facilities in low demand areas may have lower systemic risk than structurally strong facilities in high capacity areas, where catchment population is high, but network travel time is not a problem (Wang 2012; Rahman et al. 2019). Accessibility and capacity dimensions thus should be included in any meaningful framework of vulnerability alongside hazard intensity (Shang et al. 2022).

The traditional vulnerability assessments are deterministic and rely on information about structural properties that is often not available in resource constrained settings. Numerous disaster risk assessment researches in South and Southeast Asian countries have employed GIS-based clustering approach, most of which adopted deterministic approaches such as K-means or DBSCAN, which did not take accessibility and population exposure, and structural importance simultaneously into consideration (Nakasu and Amrapala 2023; Tocchi et al. 2025). Because of the cross-over of features in the input dataset like PGA, travel time, and population, hard assignment suffers from overshooting and undershooting the clusters and generates vulnerability maps that are sensitive to the changes in the initialization (Reza et al. 2025). The Fuzzy C-Means (FCM) algorithm introduced by (Bezdek 1981) assigns partial membership value to clusters which allows modelling of seismic vulnerability as a continuous phenomenon and not as a discrete one as proposed by (Dunn 1973). FCM generally outperforms K-Means in handling data uncertainty (Rajagukguk et al. 2024), as each facility is assigned a grade of membership across all of the clusters at once and preserves the transitional risk character of facilities that fall in between vulnerability archetypes rather than forcing a binary classification (Bezdek 1981; Pal and Bezdek 1995).

There are few studies that evaluate the robustness of the Fuzzy C-Means (FCM) results in different Seismic Hazard scenarios and normalization methods in the same framework of healthcare accessibility (Song et al. 2023). Multi-criteria spatial analysis in a GIS framework can detect relative vulnerability and spatial hotspots even without a complete structural inventory (Giovinazzi et al. 2015). GIS integrates seismic hazard, healthcare access, population exposure, and facility features to create a spatially explicit framework to assess the interaction between these factors to determine the vulnerability of the healthcare system. In the GeoAI paradigm, multi-dimensional spatial datasets can be combined with unsupervised learning algorithms like FCM to identify spatial vulnerability patterns that are not necessarily attainable with traditional hard clustering algorithms (Panahi et al. 2014). The combination of spatial analysis and fuzzy clustering provides an effective way of assisting in evidence-based prioritization of health care facilities in situations where detailed structural data is not readily available (Valluzzi et al. 2023; Mangir 2023).

Although there have been new applications of GIS-based clustering for disaster risk assessment, most of the studies have so far been carried out in either seismic hazard or healthcare accessibility separately (Yang et al. 2025; Ansari et al. 2025). There are few studies that combine seismic hazard, healthcare facility criticality, population exposure, and healthcare system in a single fuzzy clustering framework and no study has explored the Cox's Bazar healthcare system under various earthquake scenarios, applying large-scale sensitivity analysis (SA) to assess clustering stability (Kaur et al. 2026). This study is a spatial prioritization of 184 healthcare facilities for multi-scenario seismic hazard analysis, network-based accessibility metrics and fuzzy clustering stability analysis validated over 126 sensitivity runs.

Objectives:

To determine the seismic vulnerability of healthcare facilities in Cox's Bazar, Bangladesh, using Fuzzy C-Means (FCM) clustering based on a multi-criteria spatial analysis integrating seismic hazard, network-based accessibility, population exposure, and facility criticality.

Specific Objectives

- To apply FCM-based unsupervised learning to detect spatial patterns of seismic vulnerability and healthcare accessibility across Cox's Bazar district.
- To characterize the dominant vulnerability type of each cluster whether hazard-driven, accessibility-driven, or exposure-driven across multiple earthquake scenarios.
- To identify and rank vulnerable upazilas and healthcare facilities based on combined seismic hazard, population exposure, travel accessibility, and structural criticality.
- To deliver spatially-informed decision-support outputs that can assist in prioritization of health care facilities for seismic risk reduction and emergency preparedness planning.

2 Study Area

Cox's Bazar district is located in the Chittagong division of the south eastern part of Bangladesh, having an area of about 2491 km² between latitude 20.63°N – 21.91°N and longitude 91.85°E – 92.33°E. Geological diversity of the district. The coastal plain is mainly composed of soft coastal sediments ($V_{s30}=210-270$ m/s) and the higher relief land areas of the interior are characterized by Tertiary sediments ($V_{s30}=400-450$ m/s) (Ansary and Sharfuddin 2003). There are more than 2.6 million residents living in the district and an estimated 900,000 Rohingya refugees are in the vicinity of Ukhia and Teknaf (Reza et al. 2025). There is a total of 184 health infrastructure facilities, 114 of which are community clinics, 59 government hospitals, 4 NGO hospitals, 4 private hospitals, 2 diagnostic centers and 1 miscellaneous health service point.

3 Data and Methodology

3.1 Data Sources

Four primary datasets were integrated to construct the analytical framework.

3.1.1 Healthcare Facility Inventory

Healthcare facility locations were obtained from the Cox’s Bazar Development Authority (CBDA) as a georeferenced point dataset. After spatial clipping to the district boundary and quality control, 184 facilities were retained, including government hospitals, health complexes, union-level clinics, and NGO health posts.

3.1.2 Seismic and Geological Data

Probabilistic seismic hazard data were generated using the OpenQuake Engine. Site-specific geological conditions were defined using Vs30 values (210–450 m/s) derived from USGS geological classification. Active fault proximity was computed using Euclidean distance to mapped faults in the Chittagong–Myanmar belt.

Table 1. Vs30 site parameter assignments by geological unit (GLG code) used in PGA computation (Rahman et al. 2018)

GLG Code	Geological Description	Vs30 (m/s)	NEHRP Class
csd	Coastal deltaic sediments	210	D/E — soft soil
dm	Deltaic mud	190	E — very soft
dsd	Deltaic sandy deposits	240	D — stiff soil
asd	Alluvial sandy deposits	270	D — stiff soil
H2O	Water body / estuarine	270	D — default
QTdt	Quaternary terrace deposits	360	D — dense soil
Tt	Tertiary formations	400	C — soft rock
Tbb	Tertiary bedded formations	450	C — soft rock
DEFAULT	All unmapped units	270	D — conservative

120

3.1.3 Road Network Data

Road network data were extracted from OpenStreetMap (OSM) and converted into a weighted graph structure. Road segments were classified by highway type and assigned travel speeds based on functional hierarchy.

3.1.4 Population Data

Population distribution was derived from the WorldPop 2026 gridded dataset at 100 m resolution. This dataset captures recent demographic changes, including rapid population growth in refugee settlement areas of Ukhiya and Teknaf.

3.1.5 Administrative Boundary Data

The Cox’s Bazar district administrative boundary was used to define the study extent and to clip all spatial datasets. This ensured consistent spatial masking across vector and raster layers.

3.2 Feature Construction

The collected data were then processed to derive the 4 features provided to be used for clustering.

3.2.1 Peak Ground Acceleration (PGA)

PGA was computed using probabilistic seismic hazard analysis (PSHA) implemented in OpenQuake with the Boore and Atkinson (2008) ground motion model. Site response was defined using Vs30-based geological classification. Rupture distance was estimated using:

$$R_{rup} = \sqrt{R_{jb}^2 + d^2}$$

where $d=15$ km represents hypo central depth, R_{jb} = Euclidean distance of each facility from the nearest faultline. Three hazard scenarios were considered: M6.5 (serviceability), M7.0 (475-year return period design basis earthquake), and M7.5 (975-year maximum credible earthquake).

3.2.2 Healthcare Accessibility

Accessibility was computed using a weighted road network graph derived from OSM data. Edge weights were defined as travel time:

$$w(e) = \frac{s(e)}{d(e)} \times 60$$

Shortest path travel times were calculated using Dijkstra’s algorithm within a 30-minute threshold. The final feature represents the average travel time to reachable network nodes.

3.2.3 Population Catchment

Population served by each facility was estimated by aggregating WorldPop-2026 raster values within a 5 km Euclidean buffer. This reflects WHO/WFP guidance for primary healthcare accessibility in low-resource and humanitarian

149 contexts.(WorldPop 2024).This was chosen to consider the sharp rise of Rohingya refugees in the Ukhiya and Teknaf
150 regions. The refugee-augmented population context of Cox's Bazar, where the national standard of one community clinic
151 per 6,000–10,000 population is substantially exceeded, making population catchment a critical discriminating feature in
152 the clustering framework (WHO 2019).

153 3.2.4 BNBC 2020 Importance Factor

154 The BNBC 2020 Structural Importance Factor (SIF) was assigned based on facility type: 1.5 for hospitals and major
155 health complexes, and 1.0–1.25 for smaller clinics and health posts. This represents structural criticality under national
156 seismic design provisions (Ministry of Housing and Public Works 2020).

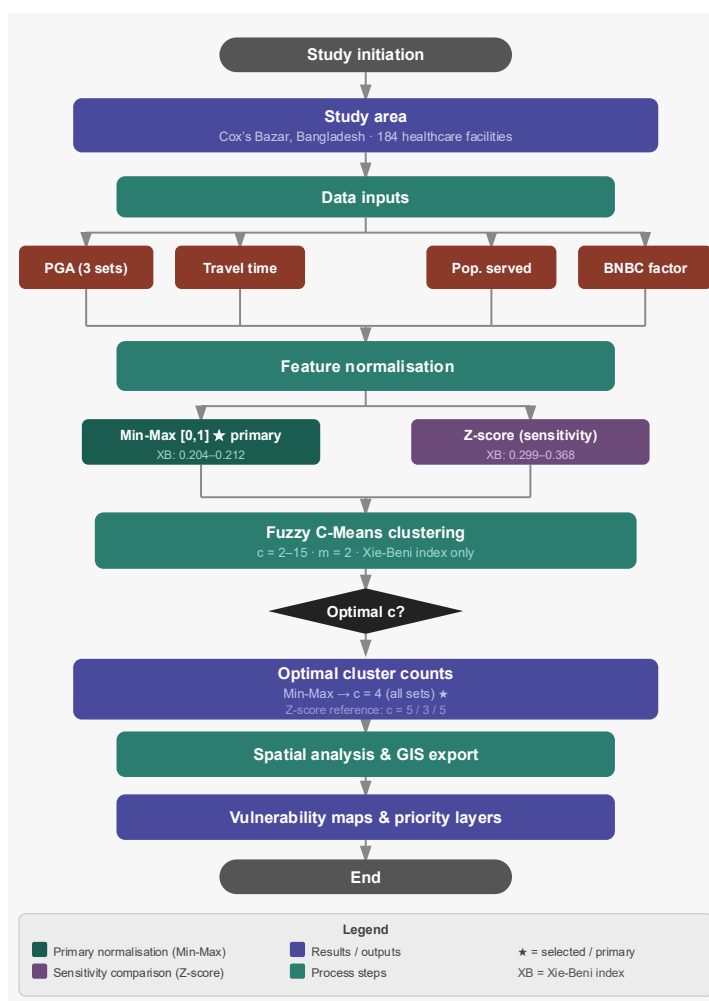


Fig. 1 Flowchart detailing the integration of spatial data inputs, multi-criteria feature engineering (seismic hazard, accessibility, exposure, and criticality), and cluster validation.

157 3.3 Feature Matrix Summary

158 All features were compiled into a standardized 184×4 matrix for Fuzzy C-Means clustering **Table 2**.

159 **Table 2.** Summary statistics of input features (N = 184)

Variable	Min	Max	Mean	SD	Units
PGA M6.5 (Mean Hazard)	0.0926	0.4108	0.1859	0.0410	g
PGA M7.0 (475yr, 10%/50yr)	0.1223	0.4517	0.2205	0.0420	g
PGA M7.5 (975yr, 5%/50yr)	0.1499	0.4682	0.2479	0.0415	g
Avg. Travel Time	0.34	23.60	18.28	4.06	min
Population Served	5,122	238,138	113,728	55,901	persons
BNBC Importance Factor	1.000	1.500	1.340	0.123	dimensionless

161 3.4 Feature Normalization

162 FCM is a distance-based algorithm; normalization is essential for equitable multi-criteria weighting. Min-Max scaling [0, 1] was selected as the normalization strategy:

164 **Min-Max Scaling [0, 1]:** All the features were scaled using min-max scaling to a [0, 1] range, to preserve the distribution and shapes providing equitable weighting across mixed-unit features. This method was chosen because it produced more consistent and superior cluster compactness compared to Z-score normalization.

167 3.5 Fuzzy C-Means Clustering Framework (FCM)

168 FCM (Bezdek 1981; Pal and Bezdek 1995) minimizes the objective function:

$$169 J_m(U, V) = \sum_i \sum_j u_{ij}^m \|x_j - v_i\|^2$$

170 where fuzzifier $m = 2$, convergence tolerance $\varepsilon = 10^{-6}$, maximum 1,000 iterations, and fixed random seed = 42 (skfuzzy v0.4.2). The full analysis comprises 42 FCM runs. The runs include 3 different seismic scenarios across 14 different values of c from 2 to 15.

173 3.6 Cluster Validity Analysis

174 The optimal cluster count (c^*) was determined by minimizing the Xie–Beni (XB) validity index (Xie and Beni 1991). Which quantifies the ratio of total fuzzy intra-cluster compactness to the minimum squared inter-centroid separation. Lower XB values indicate simultaneously more compact and better-separated clusters. The value of c^* was identified independently for each of the three seismic scenarios:

$$178 c^* = \operatorname{argmin} XB(c), c \in \{2, \dots, 15\}$$

179 Here argmin function finds the index of the lowest value for XB which is the optimum no of clusters represented by c^* .

180 3.7 GIS Integration and Spatial Export

181 Spatial operations data processing including proximity analysis, spatial joins, reprojection from WGS-84 (EPSG:4326) to UTM Zone 46N (EPSG:32646), and cartographic visualization was conducted in ArcGIS Pro 3.1 (Esri). FCM clustering, road network analysis, and vector output generation were performed in Python 3.13 via GeoPandas (version 1.1.3) and Shapely (version 2.1.2). Results were exported as three shapefiles and three CSVs (one per seismic scenario, Min-Max Scaling, $c = 4$), each containing cluster assignments, maximum fuzzy membership values, and full membership vectors.

187 4 Results

188 4.1 Cluster Validity Analysis and Optimal Cluster Selection

189 Min-Max [0, 1] was selected as the scaling method and Xie-Beni validation were considered as the primary validation method and Dunn index was used for sensitivity only as shown in **Fig. 1**.

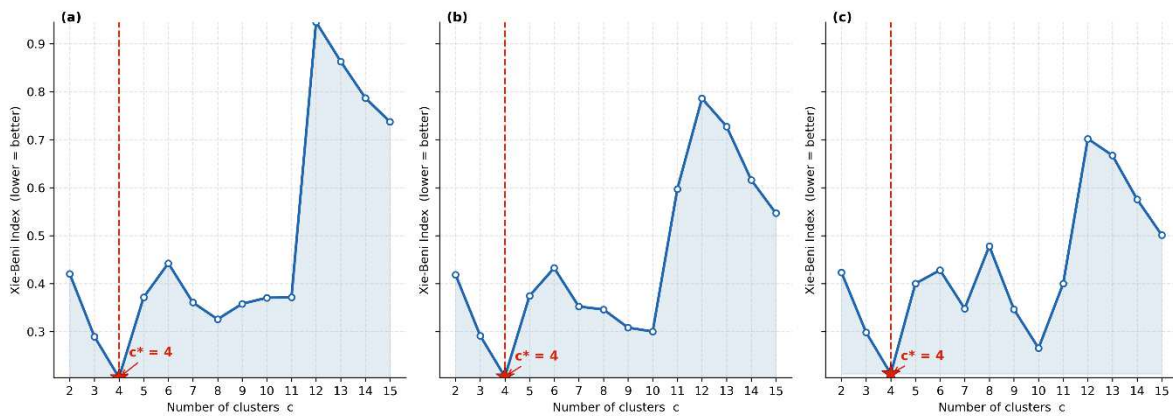


Fig. 2 Xie-Beni (XB) validity curves across seismic scenarios. The global minimum at $c^* = 4$ identifies the optimal number of clusters.

191 **Table 3.** Xie-Beni validity index at optimal cluster count using Min-Max scaling (c^* = Optimum no of Clusters)

Seismic hazard case	Normalization	c^*	Xie-Beni (XB) (Lower is better)	Dunn Index (Higher is better)	Cluster Sizes (C1/C2/C3/C4)
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Case 1 – M6.5 Mean Hazard	Min-Max [0, 1]	4	0.2044	0.0569	36 / 31 / 57 / 60
Case 2 – M7.0 (475yr RP)	Min-Max [0, 1]	4	0.2061	0.0335	36 / 31 / 56 / 61
Case 3 – M7.5 (975yr RP)	Min-Max [0, 1]	4	0.2121	0.0164	35 / 32 / 56 / 61

The Xie-Beni validity index curves for all three seismic scenarios ($c = 2-15$, Min-Max Scaling). All three scenarios despite showing a local minimum at $c=10/11$ it still shows a sharp, global minimum at $c = 4$, confirming that four clusters optimally partition the feature space under Min-Max scaling. The Xie-Beni index identifies $c = 4$ as the compact, well-separated solution across all three seismic scenarios and was cross validated using Dunn index as well (Table 3).

4.2 Cluster characteristics:

Fig. 3-(a-c), plots seismic hazard (PGA) against average travel time, with point size encoding the BNBC structural importance factor. Cluster 1 (purple) occupies the lower-right zone of each panel, combining the highest PGA values (0.24–0.42g under M6.5, extending to 0.47g under M7.5) with the shortest travel times (0.3–7 minutes), and is dominated by large symbols reflecting hospital-class BNBC factors of 1.5.

This spatial position in feature space identifies Cluster 1 as a dual-exposure concentration facilities simultaneously facing the greatest seismic demand and serving as the primary post-disaster response nodes. Cluster 4 (yellow) occupies the upper-left region, characterized by low PGA and long travel times exceeding 18 minutes, representing peripheral facilities with low structural criticality. Clusters 2 (blue) and 3 (green) fill the intermediate space with moderate PGA and moderate-to-high travel times, reflecting the transitional risk zones of Ramu, Chakaria and Maheshkhali upazilas. The cluster

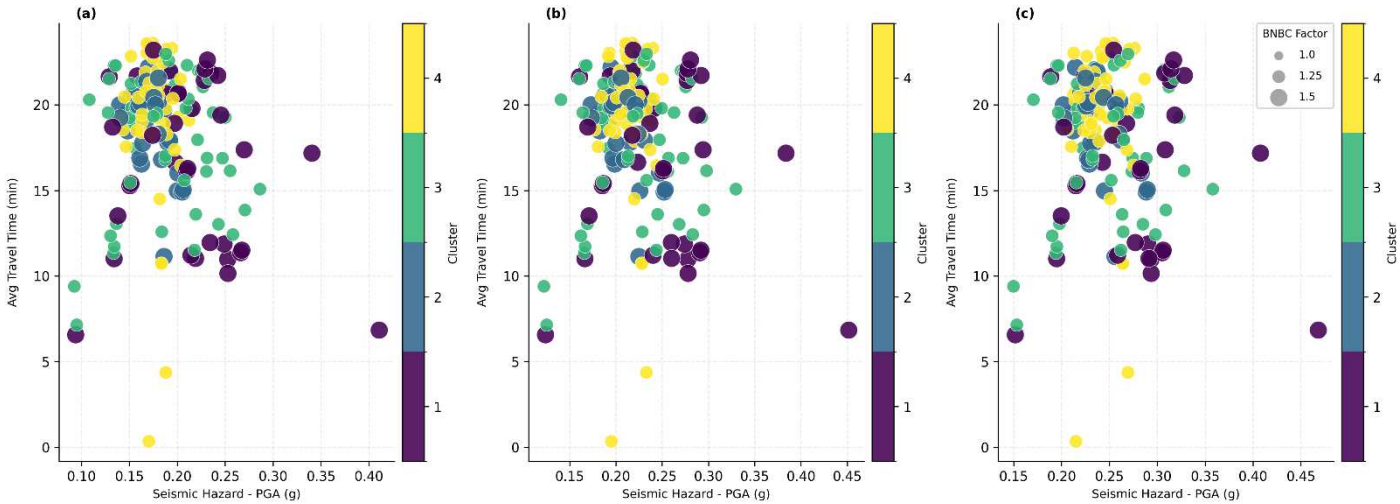


Fig. 3 Hazard vs Average travel time for different earthquake magnitudes (M) (a) M6.5, (b) M7.0, and (c) M7.5. Point sizes encode the structural importance factor.

boundaries remain visually consistent across all three seismic panels, with the primary cross-scenario difference being a rightward shift of the PGA axis as hazard intensity increases from M6.5 to M7.5, confirming that the four-cluster partition is stable across scenarios.

Fig. 4 plots average travel time against population served, with point size again encoding BNBC importance factor. Cluster 4 (yellow) is strongly differentiated along the population axis, concentrating facilities serving more than 140,000 people, at travel times between 10 and 20 minutes. These are the large-catchment facilities of Cox's Bazar Sadar and Ramu that combine high population exposure with moderate accessibility. Cluster 1 (purple) is tightly grouped at very low travel times (under 7 minutes) with high population served and large point sizes, reinforcing its identification as the highest-priority group hospital-class facilities that are both structurally critical and highly accessible, making them the primary surge-capacity nodes in any post-earthquake scenario. Clusters 2 (blue) and 3 (green) are distributed across the central portion of the plot at travel times of 10–22 minutes and moderate population catchments of 50,000–130,000, with Cluster 3 showing a notably lower BNBC factor distribution reflected in smaller point sizes. The relative positions of all four clusters are stable across the three seismic cases, confirming that population exposure and travel accessibility dimensions are not sensitive to the choice of hazard scenario.

Fig. 5 plots PGA against population served, with point size encoding average travel time. This projection most clearly reveals the exposure-hazard interaction. Cluster 4 (yellow) forms a vertically elongated band at moderate PGA values (0.15–0.25g) but spanning the full population range up to 238,000 persons, with predominantly large point sizes indicating long travel times.

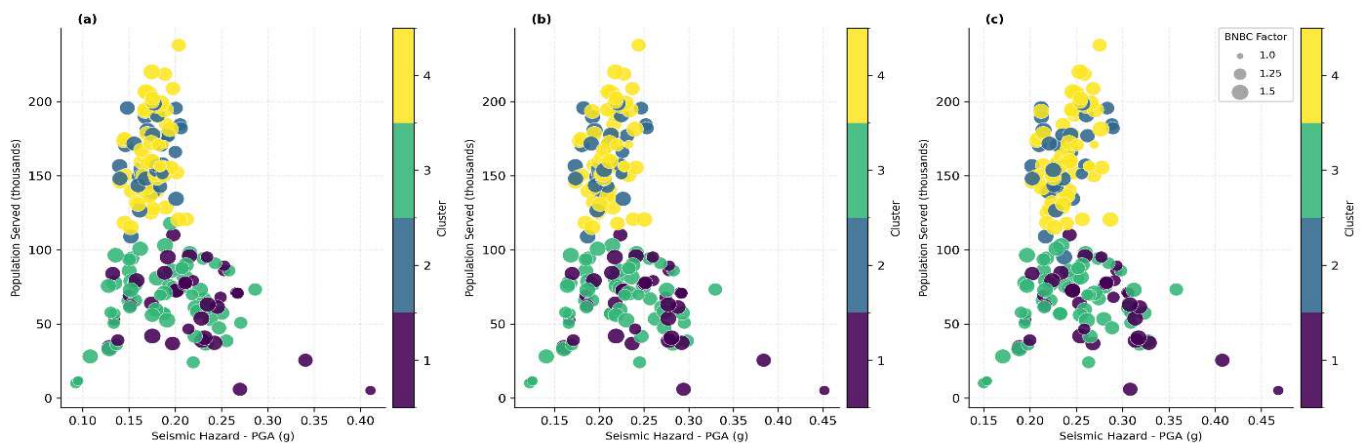


Fig. 4 Hazard vs Population Served for different earthquake magnitudes(M) (a) M6.5, (b) M7.0, and (c) M7.5. Point sizes encode the structural importance factor.

225 This confirms that Cluster 4 facilities face a compound vulnerability of high population pressure combined with poor
 226 post-disaster accessibility, despite moderate seismic hazard. Cluster 1 (purple) remains tightly bounded at high PGA and
 227 high population served with small point sizes, short travel times and distinguishing it as the group where hazard intensity,

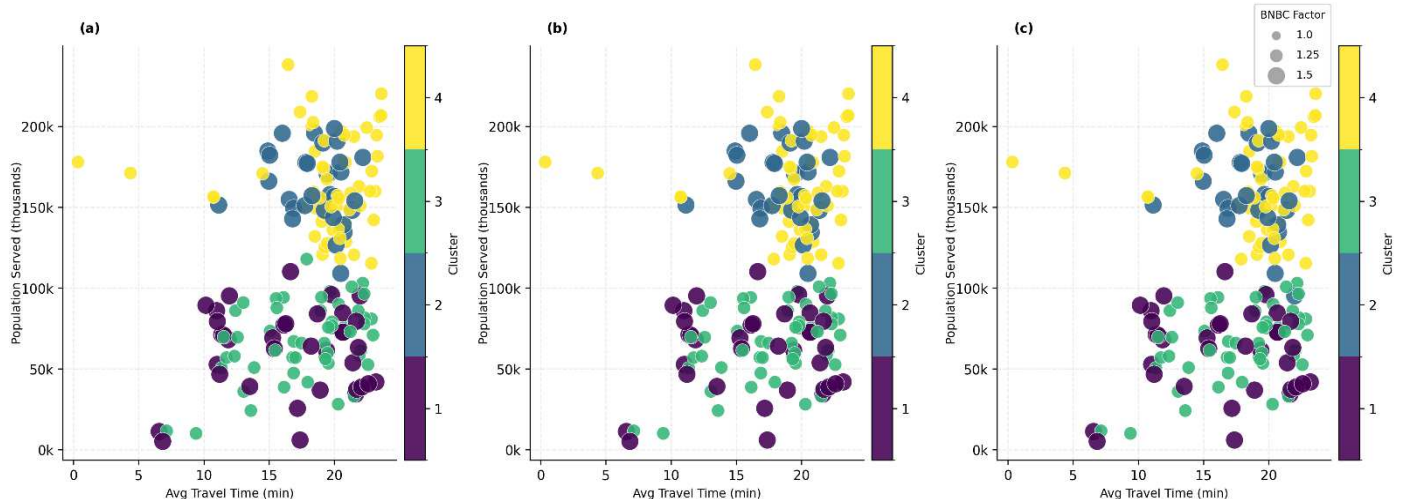


Fig. 5 Avg travel time vs Population Served for different earthquake magnitudes (M) (a) M6.5, (b) M7.0, and (c) M7.5. Point sizes encode the structural importance factor.

228 structural criticality, and demand converge simultaneously. Cluster 3 (green) is concentrated at low-to-moderate PGA and
 229 low population served, with mixed travel times, consistent with the interior upazila facilities of Chakaria and Pekua where
 230 hazard is lower but service catchments are small.

231 As in Fig. 3, Fig. 4, Fig. 5, the overall cluster geometry is preserved across all three seismic scenarios, with the M7.5
 232 panel showing only a modest rightward extension of the PGA axis without disrupting cluster membership, further
 233 supporting the robustness of the four-cluster solution.

234 **Table 4. Relative cluster characteristics and vulnerability interpretation (c = 4, all seismic scenarios)**

Cluster	PGA	Accessibility	Population Exposure	Facility Criticality	Vulnerability Type	Common Facility type
C1	Very High	Very High	Moderate	Very High	Seismic Risk	Large Public/private Hospitals
C2	Moderate	Moderate	Very High	High	Demand Overload	Government/Upa zila hospitals
C3	Low–Moderate	Low	Moderate	Moderate	Post-Disaster Isolation	Community Clinic
C4	Moderate	Low	High	Low	Capacity Mismatch	Rural Community Clinics

235 **Table 4** shows that Cluster 1 exhibited the highest PGA values (0.24–0.47 g across scenarios), shortest travel times (<7
236 min), and consisted predominantly of BNBC importance factor 1.5 hospitals. The four vulnerability archetypes are stable
237 across all three seismic scenarios: only two of 184 facilities changed cluster assignment between Case 1 and Case 3
238 (98.9% stability), confirming that the multi-criteria vulnerability structure is not sensitive to the choice of hazard intensity.

239 **Table 5. Upazila wise Hazards Hazards: Description and Analysis**

Upazila	Seismic Risk C1	Demand Overload C2	Post- Disaster Isolation C3	Capacity Mismatch C4	Total	Dominant Vulnerability Type
Chakaria	9	9	20	17	55	Post-Disaster Isolation
Cox's Bazar Sadar	1	6	1	9	17	Capacity Mismatch
Eidgaon	-	3	2	2	7	Demand Overload
Kutubdia	7	-	7	-	14	Seismic Risk
Maheshkhali	6	-	9	-	15	Post-Disaster Isolation
Pekua	1	4	3	5	13	Capacity Mismatch
Ramu	3	5	5	8	21	Capacity Mismatch
Teknaf	8	-	9	-	17	Post-Disaster Isolation
Ukhia	1	4	1	19	25	Capacity Mismatch

240 4.3 Spatial Distribution of Clusters

241 All 184 facilities are spatially projected across nine upazilas by FCM cluster classification **Fig. 6**. Capacity Mismatch
242 (C4, n = 60) and Post-Disaster Isolation (C3, n = 57) together account for 64% of facilities, confirming that service
243 disruption risk outweighs direct structural damage (C1, n = 36) as the dominant system-level vulnerability. The spatial
244 distribution of clusters across upazilas is detailed in **Fig. 6** and summarized in **Table 5**.

245 **Fig. 6** maps the hard cluster assignments of all 184 healthcare facilities across the nine upazilas of Cox's Bazar district
246 under Case 3 (M7.5, 975-year return period). This scenario is selected as the primary cartographic output as it represents
247 the maximum credible earthquake intensity considered in this study and constitutes the standard design basis event in
248 seismic risk assessment. The representativeness of **Fig. 6** for the full multi-scenario analysis is confirmed by the cross-
249 scenario stability result. Where 182 of 184 facilities (98.9%) retain identical cluster assignments across all three seismic
250 cases, with only Dhemusia UP Hospital (Chakaria, C1→C2) and Tetaiya Dailpara Community Clinic (Cox's Bazar Sadar,
251 C3→C4) changing cluster between Case 1 and Case 3.

252 The map reveals a spatially structured vulnerability pattern organized along the north-south coastal morphology of the
253 district. Three broad spatial zones are visually distinguishable. The northern zone, comprising Chakaria and Pekua, is
254 dominated by C3 (Post-Disaster Isolation) and C4 (Capacity Mismatch) points distributed across a large interior area with
255 limited road connectivity, reflecting the community clinic-dominated facility composition of these upazilas. The central
256 zone, comprising Cox's Bazar Sadar, Eidgaon, and Ramu, shows the highest density of C2 (Demand Overload) points
257 alongside C4, consistent with the concentration of large-catchment hospitals and high-population community clinics in
258 the urban core. The southern zone, comprising Teknaf and Ukhia, is characterized by a striking spatial dominance of C4
259 points in Ukhia 19 of 25 facilities (76%) and an exclusive mix of C1 (Seismic Risk) and C3 in Teknaf, with no C2 or C4
260 facilities present in either upazila.

261 Two island upazilas are spatially distinctive in **Fig. 6**. Kutubdia contains exclusively C1 (7 facilities) and C3 (7 facilities)
262 no demand-driven or capacity-mismatch types reflecting its combination of elevated PGA (mean 0.260g, max 0.341g
263 under M7.5) and complete dependence on sea or air transport for post-disaster accessibility. Maheshkhali shows an
264 identical pattern of C1 and C3 exclusivity (6 and 9 facilities respectively) for the same structural reason. The single facility
265 at the extreme southern tip of the district Saint Martin Govt. Hospital on Saint Martin Island is the highest-PGA facility
266 in the entire dataset (0.468g under M7.5) and appears as an isolated C1 point with no hospital-class facility within any
267 viable post-disaster travel radius. The spatial concentration of C4 in Ukhia is the most visually prominent pattern in Figure
268 6 and directly corresponds to the geographic footprint of the Rohingya refugee camp complex. The dense cluster of C4
269 points in Ukhia's northern portion, set within a moderate-low PGA zone, illustrates the rank inversion finding quantified
270 in Table 4 these facilities serve a mean catchment populations of 167,371 persons yet face the lowest seismic hazard of
271 any upazila in the district. The spatial mapping also shows a distinct north-to-south gradient where the lowest hazard
272 intensities align directly with the highest population exposures. For the island facilities categorized under C3, the baseline
273 network travel times strictly exceed 22 minutes prior to any simulated co-seismic road degradation. Additionally, the data
274 in Figure 6 shows nearly zero overlap between the demographic demand-driven clusters of the mainland and the hazard-
275 dominant clusters of the offshore upazilas.

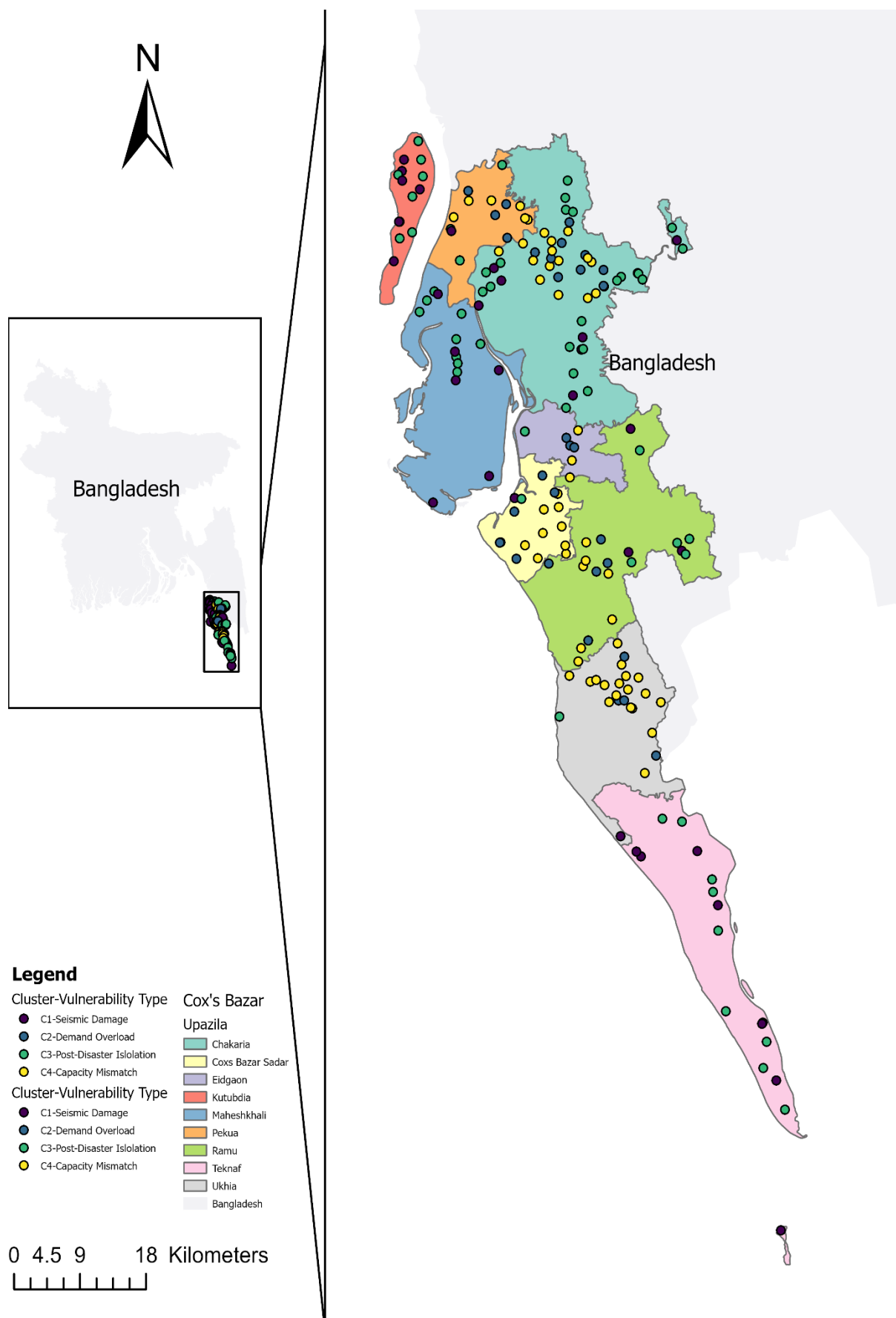


Fig. 6 Spatial distribution of the four FCM vulnerability archetypes ($c^* = 4$) across Cox's Bazar under a maximum credible M7.5 earthquake scenario.

5 Discussion

The consistently high-vulnerability cluster (C1) gathers facilities in the coastal-urban core of Cox's Bazar Sadar upazila, where soft Quaternary sediments ($V_{s30} = 210\text{--}270$ m/s) amplify ground motion and proximity to active fault structures elevates the base hazard level. These facilities are dual-exposure nodes: simultaneously facing the highest seismic demand in the district (PGA 0.24–0.47 g across scenarios) and likely to function as key post-disaster referral facilities given their hospital-class BNBC importance factors of 1.5 and the shortest travel times in the network (<7 minutes) (Fig. 3, Table 4). This duality means that a design-level earthquake event would damage the very facilities that would otherwise absorb the mass-casualty response load. Hazard-based assessments do not capture this functional vulnerability dimension, and the results confirm that large population concentrations represent high service disruption potential even at moderate PGA. The implication for emergency preparedness planning is that C1 facilities must be treated as both structural retrofit priorities and contingency planning anchors: their failure in a seismic event would cascade into demand overload at C2 facilities, compressing the entire district healthcare network simultaneously.

The most consequential methodological finding is the rank inversion revealed by the multi-criteria clustering. Ukhia's C4 cluster 19 of 25 facilities (76%) serves mean catchment populations of 167,371 persons yet faces the lowest seismic hazard of any upazila in the district (Table 5, Fig. 6). A conventional hazard-only vulnerability ranking would classify these facilities as the lowest priority in Cox's Bazar. The FCM result inverts this ranking entirely: Ukhia represents a Capacity Mismatch vulnerability driven by the mismatch between an outsized refugee-augmented demand (camp populations exceeding 900,000 persons) and a community clinic-level structural stock with BNBC importance factors of 1.0–1.25 and travel times of 10–20 minutes (Table 4). This finding directly supports calls in the literature for multi-dimensional healthcare vulnerability assessments that integrate accessibility and demand alongside hazard intensity. Similarly, the C2 Demand Overload cluster centered on Government and Upazila hospitals in Cox's Bazar Sadar, Eidgaon, and Ramu exhibits moderate PGA but very high population catchments (>140,000–178,000 persons), confirming that even a sub-design-level event could trigger service collapse through patient surge well before structural failure occurs (Fig. 4, Table 4).

It is important to recognize the study's key limitations. First, the Peak Ground Acceleration (PGA) values were computed based on probabilistic seismic hazard scenarios, not on recorded strong-motion observations, so the identified clusters are indicative of relative spatial vulnerability to earthquakes based on those scenarios, rather than predictions of damage from an actual earthquake. Second, it is assumed that there is no change in the road network after the earthquake, but an earthquake could potentially degrade the road network by causing bridges to collapse, landslides and obstructions to roads, especially in coastal and hilly areas, which would lead to worse accessibility after the earthquake than assumed. Third, there is still a lack of information on the age and structure of a large number of healthcare facilities due to the lack of building inventories. Fourth, population served was estimated using a 5 km Euclidean catchment buffer, which ignores the presence of topographic barriers, road geometry, ferry crossings and actual health care-seeking behavior. In upazilas in the northern mountainous areas like Chakaria and Pekua, effective catchment areas may be less than shown which could mean that population exposure at some facilities may be under-estimated while it may be over-estimated at others. Likewise, the spatial estimates of refugee populations from WorldPop 2026 might not align with the dynamic distribution of refugee populations in camps. Last, the choice of the fuzzification parameter (m) and the initialization of the model have an effect on the Fuzzy C-Means clustering. Despite the use of the conventional value $m = 2$ and the use of 126 sensitivity combinations based on earthquake scenario, normalization strategy and random seed, the sensitivity for the wider range of values for m (1.5 to 3.0) has not been extensively tested.

The Post-Disaster Isolation cluster (C3, $n = 57$) points to a separate level of operational vulnerability, which does not occur in normal structural vulnerability studies. The seismic hazard is generally lower at these facilities than at the C1 cluster, but their relatively long travel times make these facilities very vulnerable to becoming functionally isolated after an earthquake. Baseline travel time in normal road condition in Teknaf, Kutubdia and Maheshkhali is already more than 15–22 minutes (Figures 3, 4 and 6). Based on the empirical evidences, 30–60% of the capacity can be lost in a road network due to earthquake damage, with the travel time to those facilities being increased to 40–60 minutes or beyond in the event of an earthquake (Kaur et al. 2026). These delays could significantly affect access to emergency health services post-impact, even though the facilities have relatively smaller structural hazard (Chelariu et al. 2023). The road-network assumption was especially conservative for the island upazilas of Kutubdia and Maheshkhali where access will have been greatly reliant on sea or air travel rather than road access and so was not represented in the current network analysis. Furthermore, the humanitarian consequences are particularly high in Ukhia and Teknaf, home to over 900,000 Rohingya refugees. Many of the health facilities that serve these areas were still identified as being in the C3 or C4 vulnerability category (Table 5), which means that they have limited access or service capacity if a tsunami occurs. This is one of the biggest gaps identified in terms of earthquake preparedness at the district level regarding access to healthcare and the humanitarian needs. The spatial patterns are consistent in both seismic scenarios, supporting the pre-positioning of emergency medical supplies; upgrading of the satellite communication system; the marking of helicopter landing sites; and the development of alternate maritime evacuation and medical transport plans for these high-risk upazilas.

338 Even with these constraints, the current analysis indicates vulnerability of healthcare facilities is not only a function of
339 ground shaking intensity, but an interplay between seismic hazard, accessibility, facility criticality and population
340 demand. The multi-criteria assessment revealed a different vulnerability profile in each area of Cox's Bazar district,
341 indicating that a vulnerability-based approach to disaster preparedness and response would be fundamentally different
342 from one district to the other, depending on accessibility limitations and service demand. The results underscore the need
343 to consider functional and spatial aspects in addition to structural hazard, when performing vulnerability assessments for
344 health care facilities. The findings serve as a basis for effective seismic retrofit of critical hospitals, optimization of
345 emergency logistics to isolated facilities and placement of healthcare resources in areas with high demand, which
346 ultimately helps in more resilient healthcare planning in coastal earthquake prone areas.

347
348 To systematically assess the seismic vulnerability of the 184 healthcare facilities in Cox's Bazar, this study synthesized
349 these spatial findings and considered the seismic hazard, baseline accessibility, population exposure, and structural
350 criticality of the facilities in a single framework, using Fuzzy C-Means (FCM) clustering method. These four vulnerability
351 archetypes are consistently generated by the analysis for all three earthquake scenarios simulated. That this structural
352 constancy implies a high stability and a strong geographical and built environment anchoring of the overall spatial
353 vulnerability architecture of the district, that is, as opposed to a dynamic change as a function of varying earthquake
354 hazard intensities.

355 In conclusion, the above results show that the system vulnerability of the healthcare infrastructure cannot be evaluated
356 only based on the seismic hazard at the structure level. For hospital class facilities, exposure to high ground shaking and
357 high systemic critical importance is a primary constraint in the urban core of Cox's Bazar Sadar, whereas operational
358 constraints like accessibility and demand imbalance are major constraints in the peripheral areas. In particular, the
359 formalized recognition of mismatches in capacity and post-disaster isolation as separate vulnerability types underscores
360 the fact that the typical hazard-based assessment systematically underestimates the vulnerability of facilities that are an
361 integral part of the healthcare system during a mass-casualty event.

362 This multi-criteria assessment, therefore, offers empirical evidence that can serve as an action tool for the transition of
363 Cox's Bazar towards risk-informed disaster preparedness. Each vulnerability profile identified will have its own systemic
364 drivers, and thus require a uniquely targeted intervention strategy. They include the specific structural and seismic
365 strengthening of essential central hospitals, as well as the optimization of the positioning and logistics of emergency
366 health networks in geographically remote areas, and strategic resource allocation and surge protections in health networks
367 intensely used during humanitarian emergencies. The inclusion of hazard indices, road accessibility networks, and the
368 intrinsic structural features of the healthcare system in one single framework makes this study a much more
369 comprehensive and resilient approach for prioritizing regional emergency preparedness measures than traditional hazard-
370 only engineering-based approaches.

371 In the future, additional research can expand this foundation, taking into account the time-varying transportation network
372 effects that occur soon after an earthquake. The use of detailed and building-specific structural condition assessments,
373 along with empirical fragility data for local health facilities, would also eliminate reliance on generic assumptions as
374 made in building codes. Moreover, future versions should use sophisticated network-based health facility catchment
375 models based on observed utilization of health facilities instead of the Euclidean buffers. Finally, this multi-criteria
376 approach can be extended to assess alternative multi-hazard scenarios, expanded to other vulnerable coastal districts in
377 Bangladesh, and can be seamlessly integrated into broader regional healthcare-resilience plans.

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385 **7.3 Author Contributions**

386 All authors contributed to the study conception and design. Material preparation, data collection and analysis were
387 performed by the lead author. The first draft of the manuscript was written by the lead author and all authors commented
388 on previous versions of the manuscript. All authors read and approved the final manuscript. Below are the full author
389 contributions for each author.

- 390 • **Author 1 (Corresponding and First Author):** Conceptualization, literature review, study design and title
391 formulation, methodology development, data processing and coding, figure preparation, interpretation of
392 results, and manuscript drafting.

- **Author 2:** Supervision, Conceptualization, facilitation of healthcare data acquisition, methodological validation, and critical review of analytical procedures and results.
- **Author 3:** Supervision, validation of study design and findings, and critical review of the manuscript for accuracy, and quality assurance
- **Author 4:** Supervision, & final review of the manuscript for quality assurance.

7.4 Data Availability

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

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