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# Cultural ontology-enhanced attribute matching for community-based geo-spatial vulnerability mapping in remote agrarian settlements

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**ABSTRACT**

Vulnerability mapping in remote agrarian settlements is constrained by a persistent disconnect between qualitative local knowledge and quantitative geospatial data.

This study presents a cultural ontology-enhanced attribute-matching framework for community-based geospatial vulnerability mapping in remote agrarian settlements, addressing the disconnect between qualitative local knowledge and quantitative geospatial data by systematically integrating vernacular risk indicators into geographic information system (GIS) analysis.

Cultural vulnerability ontology (CVO) is constructed from community-generated narratives using attention-based term extraction and aligned with geospatial variables through a graph neural network (GNN)-based cross-modal framework. The approach is adopted in Amta-II Community Development Block, West Bengal, India, a flood-prone agrarian region characterized by low-lying terrain and agriculture-dependent livelihoods, where a corpus of 12,000 vernacular text segments was collected through participatory methods to extract culturally significant indicators.

Comparative evaluation against baseline methods shows improved alignment performance, with gains of up to 22% in Precision@5 and 37% over conventional rule-based approaches, while the resulting culturally grounded vulnerability index demonstrates stronger agreement with community-identified risk zones, achieving an Intersection-over-Union (IoU) of 0.64 compared to 0.48 under traditional AHP-based weighting.

These results indicate that integrating culturally embedded knowledge into geospatial frameworks enhances the contextual accuracy and interpretability of vulnerability assessments, offering a scalable, adaptable approach for spatial decision-making in data-scarce, climate-sensitive rural environments.



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## 1. INTRODUCTION

Vulnerability mapping in remote agrarian settlements faces a persistent methodological challenge arising from the disconnect between quantitative geospatial data and qualitative local knowledge systems. Conventional approaches predominantly rely on standardized GIS-derived variables, such as elevation, land cover, and the normalized difference vegetation index (NDVI), while often overlooking vernacular risk indicators embedded in local experience, including flood-prone river bends, drought-resistant crop varieties, and other context-specific manifestations of vulnerability (Rahman et al., 2015). This limitation is particularly consequential in the low-lying floodplain regions of eastern India, including the Amta-II Community Development Block of Howrah District, West Bengal, where communities face a distinct set of environmental challenges. These include recurring monsoonal riverine flooding from the Damodar–Mundeswari distributary system, seasonal waterlogging of low-lying paddy fields, progressive bank erosion along active river bends,

salinity intrusion and groundwater stress during the post-monsoon period, crop losses associated with unseasonal rainfall and pest outbreaks, and limited road accessibility during flood events, which constrains emergency response efforts (Roy et al., 2026; Bowden et al., 2025).

This oversight stems from methodological limitations in capturing and aligning unstructured community narratives with structured geospatial datasets, leading to assessments that misrepresent local realities (Kelman et al., 2012; Reid & Sieber, 2020). Vulnerability mapping in such settings is therefore not merely a cartographic exercise; it is a precondition for equitable disaster risk reduction, climate adaptation, and livelihood protection (Bowden et al., 2025; Ojo et al., 2025; Shaw, 2012). Where livelihoods depend on a narrow agro-ecological base and where formal data systems poorly capture localized hazards, vulnerability maps produced without community input risk misallocating relief, masking hidden hot-spots, and reinforcing the very inequalities they are meant to address (Kelman et al., 2012; Brown & Kyttä, 2022).

Community-based geospatial vulnerability mapping (CB-GSVM) emerged precisely to address these shortcomings by combining the analytical strength of GIS with the contextual richness of community knowledge. The integration of local knowledge with geospatial systems has evolved through three intersecting research trajectories that this study brings together: participatory geographic information systems (PGIS), ontology engineering, and vernacular natural language processing (NLP) (Sieber, 2006; Stevens et al., 2000; Devlin et al., 2019). Participatory GIS which we define as a collaborative mapping practice that engages local stakeholders as co-producers of spatial knowledge, integrating their lived experience, oral histories, and locally validated risk perceptions into formal GIS workflows (Sieber, 2006; Brown & Kyttä, 2022) emerged as a response to top-down cartographic practices. In vulnerability assessments, PGIS methods have been used to document indigenous risk indicators, such as oral histories of flood events and hand-drawn hazard sketches (Shaw, 2012; McCall & Dunn, 2012). However, these approaches often face scalability bottlenecks when translating qualitative inputs into GIS-compatible attributes. Manual coding of community narratives remains labor-intensive, and the resulting maps may inadvertently prioritize externally defined vulnerabilities over locally salient ones (Eades, 2006). Recent efforts to automate PGIS workflows, such as crowdsourced hazard tagging (Goodchild & Glennon, 2010), still rely on predefined taxonomies that may not capture vernacular lexicons.

Ontology engineering offers a complementary path. Ontologies provide structured frameworks for representing domain-specific knowledge, enabling interoperability between heterogeneous data sources (Stevens et al., 2000). In geospatial contexts, ontologies have been used to standardize feature semantics (Raskin & Pan, 2005) or align indigenous classifications with GIS schemas (Reid & Sieber, 2020). However, most existing ontologies are static and expert-driven, limiting their adaptability to dynamic community knowledge. Rule-based alignment methods (Manoah et al., 2004) struggle with polysemy, where terms like "wetland" may denote ecological zones in GIS but sacred sites in local discourse. Hybrid approaches combining logic-based reasoning with machine learning show promise but require extensive training data (Abbassi & Hlaoui, 2024; Liu et al., 2024; Nejhadi et al., 2011).

Recent advances in transformer-based NLP have enabled finer-grained analysis of unstructured vernacular texts, particularly in low-resource language settings. Models such as Bidirectional Encoder Representations from Transformers (BERT) (Devlin et al., 2019) and multilingual encoders such as XLM-RoBERTa (XLM-R) (Conneau et al., 2020) can effectively represent agrarian lexicons with limited labeled data, while transformer attention mechanisms (Vaswani et al., 2017) facilitate the identification of culturally salient terms and context-specific expressions. Recent work in domain-specific keyword extraction with BERT (Sammet & Krestel, 2023) and in neural-symbolic reasoning over knowledge graphs (Liu et al., 2024) further demonstrates the maturity of these tools. Yet, direct application of these models to geospatial tasks remains underexplored. Prior work in cross-modal alignment has focused on image–text pairs (Radford et al., 2021) and on medical vision–language tasks (Moon et al., 2022; Hashmati et al., 2024), rather than on text–GIS integration. Graph neural networks (GNNs) offer a viable solution for projecting unstructured text and structured geospatial data into a shared latent space (Battaglia et al., 2018), but their use for ontology–GIS alignment is novel.

Building on these three streams, we introduce cultural ontology as both a conceptual and methodological contribution. Conceptually, a cultural ontology is a community-validated, dynamically updatable structure of locally meaningful risk concepts and their semantic relationships, expressed in the vernacular and grounded in lived experience. Methodologically, it operationalizes attribute matching—the process of aligning local indicators with formal GIS variables as a learned, probabilistic, and polysemy-aware mapping rather than a fixed schema-based rule. This reframing is important because attribute matching represents a critical bottleneck in CB-GSVM: it determines which forms of community knowledge are preserved during translation into GIS layers and which are discarded as unstructured information (Sieber, 2006; Reid & Sieber, 2020; Liu et al., 2024). Existing participatory GIS (PGIS) frameworks excel at participatory data collection but lack automated mechanisms for semantic alignment (Sieber, 2006; McCall & Dunn, 2012).

Ontology engineering offers structured knowledge representation but often overlooks dynamic community inputs, whereas vernacular NLP models capture linguistic nuances without providing geospatial grounding (Stevens et al., 2000; Devlin et al., 2019; Reid & Sieber, 2020).

To address existing limitations, we propose a cultural ontology-enhanced attribute-matching system that automates the extraction, structuring, and alignment of local knowledge with geospatial data. The system's core innovation lies in a dual-path architecture integrating a transformer-based pipeline that distills vernacular corpora into a hierarchical Cultural Vulnerability Ontology (CVO) through attention-weighted term saliency and a GNN that projects ontology nodes and GIS features into a shared latent space for probabilistic alignment. To the best of our knowledge, no existing framework simultaneously constructs a dynamic cultural ontology from community narratives, aligns it with GIS attributes through GNN-based cross-modal learning, and evaluates outputs against literature-derived acceptability thresholds. Addressing this threefold gap, this study develops and evaluates a cultural ontology-enhanced attribute-matching framework for community-based geospatial vulnerability mapping in remote agrarian settlements, aiming to extract and structure culturally grounded vulnerability indicators from vernacular narratives, align them with measurable GIS variables, generate a culturally grounded vulnerability map (CGVI), and validate outputs against community-identified risk zones and baseline approaches using established acceptability thresholds.

## 2. METHODS

### 2.1. Study Area

The study was conducted in Amta-II Community Development Block, a remote agrarian settlement in West Bengal, India (Figure 1). The block lies in the Uluberia subdivision of Howrah district and is administratively referenced at approximately 22°35′27″N, 87°55′39″E (22.5908°N, 87.9275°E). Its approximate geographic extent is bounded by the four corner coordinates 22°39′N, 87°53′E (north-west); 22°39′N, 87°59′E (north-east); 22°31′N, 87°59′E (south-east); and 22°31′N, 87°53′E (south-west). The block adjoins Udaynarayanpur and Khanakul-II blocks to the north, Amta-I to the east, Bagnan-I to the south, and Daspur-II to the west. The area was selected for its recurring exposure to riverine floods, dependence on agriculture-based livelihoods, and the continued use of local vernacular terms in environmental risk perception. The study area covers approximately 135.4 km² and includes a population of 208,132. The block is generally low-lying, leading to regular inundation that dictates agricultural patterns, with rice as a major crop alongside vegetables and extensive irrigation. This location was chosen as a suitable test site for evaluating whether culturally embedded local knowledge can be systematically aligned with GIS-based vulnerability indicators.

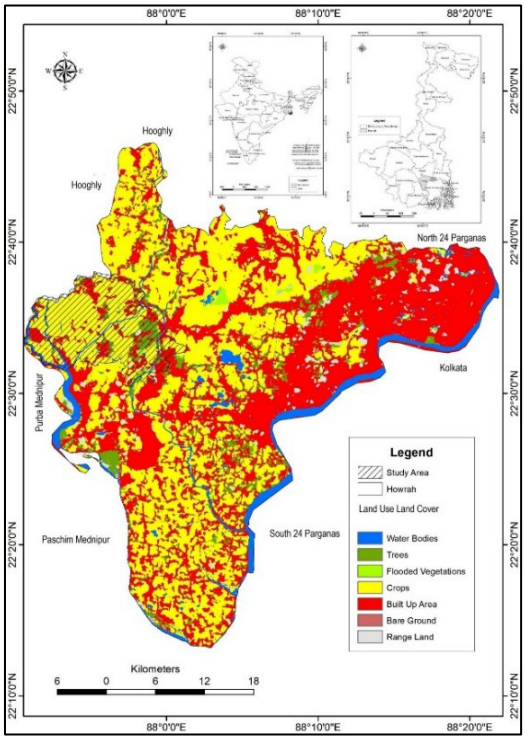



*Figure 1. Location map of the study area with LULC (Source: Authors, 2026).*

Amta-II was deliberately selected as a representative testbed for this study because it concentrates the conditions the proposed framework is designed to address: recurring riverine floods, rice-dominated

cropping, and the continued everyday use of Bengali vernacular terms in environmental risk perception. The block is therefore well suited to evaluate whether culturally embedded local knowledge can be systematically aligned with GIS-based vulnerability indicators in data-scarce, climate-sensitive rural environments.

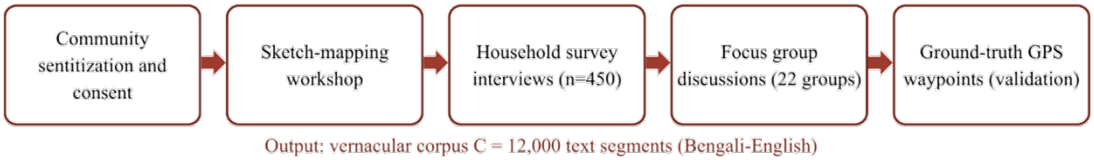
### 2.2. Participatory Data Collection and Vernacular Corpora

This study primarily relies on secondary data obtained from reliable and authoritative sources. Ensuring data reliability is a critical aspect of the research process. Accordingly, multiple data sets were collected from recognized institutions. The main categories of data used in this study include poverty-related data, map and location data, and other supporting datasets

Poverty data, which are essential for both spatial analysis and mapping, were obtained from the Department of Census and Statistics of Sri Lanka. Map and location data were sourced from the Geographic Information System Division of the Urban Development Authority and the United Nations Office for the Coordination of Humanitarian Affairs. Subnational administrative boundary data for Sri Lanka were accessed through the Humanitarian Data Exchange platform managed by the United Nations Office for the Coordination of Humanitarian Affairs. Additional datasets were obtained from other credible sources where necessary. All data utilized in the study represent the most recent versions available and were also used to support the literature review and conceptual analysis.

Data collection proceeded through five sequential phases, each serving a distinct purpose and producing specific outputs [Figure 2]. Phase 1 involved community sensitization and informed consent across all 15 Gram Panchayats, resulting in signed consent forms and a stakeholder register. Phase 2 consisted of participatory sketch-mapping workshops to elicit local risk vocabularies and preliminary hazard zones, producing 47 sketch maps and an initial vernacular term list comprising approximately 1,800 unique terms. Phase 3 involved semi-structured household interviews (n = 450) administered via KoboToolbox, generating approximately 6,400 vernacular text segments. Phase 4 comprised focus group discussions (n = 22 groups) with audio recording, Whisper-based transcription, and manual verification, yielding approximately 5,600 additional vernacular text segments and resulting in a final corpus of about 12,000 segments. Phase 5 involved ground-truth waypoint capture of community-identified risk zones using handheld GPS devices, providing the validation dataset for the culturally grounded vulnerability index (CGVI).

*Figure 2. Participatory data collection*




Vernacular corpora consist of unstructured text generated by local communities, including oral histories, participatory surveys, and indigenous lexicons. Unlike standardized datasets, these corpora encode culturally specific risk indicators, such as descriptive terms for flood-prone areas and soil conditions, which are often absent from conventional GIS attributes (Kelman et al., 2012). The linguistic diversity within vernacular corpora poses unique challenges: terms may exhibit polysemy (e.g., “riverbank” as a geomorphological feature versus a social gathering place) or rely on context-dependent metaphors (e.g., “hungry soil” to denote nutrient depletion).

The value of vernacular corpora lies in their ability to capture emic perspectives local classifications that reflect indigenous environmental knowledge (D’Ambrosio, 2014). For example, agrarian communities may describe soil types using phenological indicators (e.g., “soil that cracks in summer”) rather than granulometric classifications. Such descriptors are rich in semantic content but resist direct mapping to GIS variables without intermediate structuring. Prior efforts to systematise vernacular knowledge have employed manual coding or controlled vocabularies (Jung & Elwood, 2010), but these methods struggle to scale across diverse linguistic contexts.

### 2.3. Ontology Alignment and Cultural Vulnerability Ontology Construction

Ontology alignment refers to the process of establishing semantic correspondences between distinct knowledge representations in this context, between a CVO derived from vernacular corpora and a GIS feature schema. The alignment problem is framed as a graph matching task, where nodes represent concepts (e.g., “flood-prone area” in the CVO versus “hydrological risk zone” in GIS) and edges denote hierarchical or associative relationships (Hasani et al., 2015). Key challenges in alignment include semantic heterogeneity (the

same concept may be labeled differently across ontologies; e.g., "drought-resistant crop" versus "low-water-demand cultivar"), granularity mismatch (vernacular terms often describe composite phenomena such as "eroding hillside" that correspond to multiple GIS variables slope, soil type, vegetation cover), and contextual dependency (the meaning of a term may shift based on community-specific usage; e.g., "fertile land" in floodplains versus terraced fields). Traditional alignment methods rely on lexical similarity metrics (e.g., Levenshtein distance) or logic-based reasoning (Karimi & Kamandi, 2019); however, these approaches fail to account for the nuanced semantics of vernacular language, necessitating machine learning techniques that learn alignment patterns from data [Figure 3].

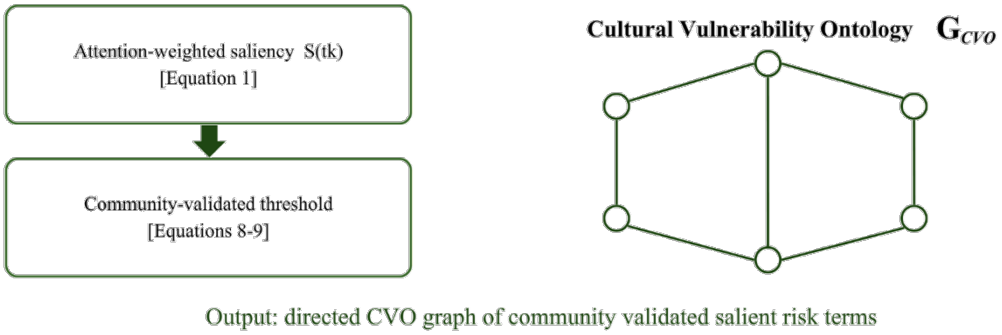



*Figure 3. NLP-based extraction and Cultural Vulnerability Ontology construction.*

**2.4. Cultural Vulnerability Ontology (CVO) Construction via Attention-Driven Saliency**

The CVO is constructed by analysing vernacular corpora C collected from participatory community engagements. We employ a fine-tuned XLM-RoBERTa model (Conneau et al., 2020) to process these texts, leveraging its attention mechanism to identify culturally salient terms. For each token t*k* in C, we compute its saliency score S(t*k*) by aggregating attention weights α*ij* across all transformer layers j and attention heads i:

$$S(t_k) = \Sigma_{i=1}^{H} \Sigma_{j=1}^{L} \alpha_{ij}(t_k), \quad \alpha_{ij}(t_k) \in [0, 1]$$

*Equation 1. Computing the attention-based saliency $S(t_k)$ for each vernacular term, replacing frequency-based extraction so that rare but culturally critical terms (e.g., "ghost wells") are retained.*

Here, H denotes the number of attention heads, L the number of layers, and α*ij*(t*k*) the attention weight assigned to t*k* by the i-th head in layer j. Terms with S(t*k*) > τ are retained, where τ is a community-validated threshold ensuring local relevance. Unlike frequency-based methods (e.g., TF-IDF), this approach captures rare but critical indicators (e.g., "ghost wells") that conventional NLP pipelines might overlook.

The retained terms are organised hierarchically using a Hybrid Attention-Graph (HAG) structure. Each node v*i* ∈ V in the CVO represents a salient term, while edges *&* encode semantic relationships derived from co-attention patterns. Specifically, if two terms t*k* and t*l* frequently co-occur with high mutual attention in the corpus, an edge e*kl* is established with weight:

$$w_{kl} = (1 / N) \Sigma_{n=1}^{n} \alpha_{ij}(t_k) \cdot \alpha_{ij}(t_l)$$

*Equation 2. derives co-attention edge weights $w_{kl}$ among retained terms, producingthe directedCVO graph G_CVO = (V, &).*

where N is the number of co-occurrence instances. This results in a directed graph G*CVO* = (V, *&*) where edge weights reflect the strength of contextual associations.

**2.5. GNN-Based Cross-Modal Alignment, Ontology Evolution and Bias Mitigation**

To align the CVO with GIS features, we introduce a GNN aligner that projects ontology nodes and geospatial attributes into a shared latent space. The alignment process consists of three steps.

Step 1 – Graph Embedding for CVO Nodes: Each node v*i* ∈ V in the CVO graph G*CVO* is initialised with a feature vector e*i* derived from its corresponding term's contextual embeddings. We employ GraphSAGE with GATv2 attention (Li et al., 2019) to propagate and aggregate neighbourhood information:

$$h_i = \sigma ( W_1 v_i + \Sigma_{j \in hi} W_2 v_j ), \quad v_i = MLP(e_i)$$

*Equation 3. Computes GraphSAGE/GATv2 node embeddings $h_i$ for each CVO node, propagating neighbourhood semantics.*

Here, h$i$ is the updated embedding for node v$i$, N$i$ denotes its neighbours, W$1$ and W$2$ are learnable weights, and σ is the LeakyReLU activation.

Step 2 – GIS Feature Representation: GIS attributes (e.g., NDVI, slope, land cover) are standardised into a feature matrix $F \in \mathbb{R}^{m \times d}$, where m is the number of spatial units and d the dimensionality of geospatial variables. Each row f$k$ represents a feature vector for the k-th spatial unit.

Step 3 – Cross-Modal Alignment via Contrastive Learning: The GNN aligner computes a probabilistic alignment score A(h$i$, f$k$) between CVO node h$i$ and GIS feature f$k$:

$$A(h_i, f_k) = softmax(h_i^T M f_k), \quad M \in \mathbb{R}^{dxd}$$

*Equation 4: yields the softmax-based probabilistic alignment score $A(h_i, f_k)$ between a CVO node and a GIS feature.*

Here, M is a learnable alignment matrix trained via contrastive loss (Xu et al., 2022). Positive pairs consist of manually verified alignments (e.g., "flood-prone riverbend" matched to high-flow-accumulation areas), while negative pairs are randomly sampled non-matches. The loss function maximises scores for positive pairs and minimises them for negatives:

$$\mathcal{L} = -\log [\exp(A(h_i^+, f_k^+)) / \Sigma \exp(A(h_i^-, f_k^-))]$$

*Equation 5. defines the contrastive loss that trains the alignment matrix M on community-verified positive and randomly sampled negative pairs.*

This ensures that semantically related CVO–GIS pairs (e.g., "drought-resistant crop" and low NDVI variability) are mapped closer in the latent space.

**2.6. Dynamic Ontology Evolution and Incremental GNN Training**

The CVO must adapt to new community inputs without catastrophic forgetting of prior knowledge. We achieve this through an incremental learning framework that updates both the ontology structure and the GNN aligner. When a new vernacular text C′ is introduced, the system first computes saliency scores S(t$k$′) for novel terms using Equation 1. Terms exceeding threshold τ are added as new nodes v$i$′ to G*CVO*, with edges e$ij$′ initialised based on co-attention patterns from C′.

To update the GNN aligner without retraining from scratch, we employ a memory-replay mechanism. A subset of previously aligned CVO–GIS pairs P = {(h$i$, f$k$)} is stored in a fixed-size buffer. During incremental training, these pairs are interleaved with new alignments P′ derived from C′ to preserve historical knowledge. The GNN's node embedding function (Equation 3) is fine-tuned using a composite loss:

$$\mathcal{L}\_inc = \lambda \mathcal{L}\_new + (1 - \lambda) \mathcal{L}\_replay$$

*Equation 6. Balances new-corpus learning against memory replay (λ), enabling incremental ontology growth without catastrophic forgetting.*

where $\mathcal{L}$_new is the contrastive loss (Equation 5) for new data, $\mathcal{L}$_replay applies the same loss to buffered pairs, and $\lambda \in [0, 1]$ balances adaptation versus retention.

Dynamic edge weighting in G*CVO* is handled by a temporal attention mechanism. For each existing node v$i$, its connections to new nodes v$j$′ are weighed by:

$$w_{ij}' = \Sigma_{l=1}^{L} \alpha_l(v_i, v_j') / max(w_{ij})$$

*Equation 7. Provides a temporal attention re-weighting of edges so the CVO reflects shifting community priorities.*

where α$l$(v$i$, v$j$′) measures cross-attention between v$i$ and v$j$′ in layer l, normalised by the maximum historical edge weight w$ij$. This ensures that ontology evolution reflects shifting community priorities while preserving semantically stable relationships.

## 2.7. Cultural Bias Mitigation with Community-Validated Attention Thresholds

Conventional NLP methods for term extraction often rely on frequency-based metrics like TF-IDF, which risk overlooking rare but culturally critical indicators (e.g., "ghost wells" for hidden water sources). To address this, we introduce a community-validated attention threshold τ that filters salient terms based on both transformer attention weights and participatory feedback. The threshold is determined through an iterative

process: initial saliency estimation using Equation 1; community ranking by which local stakeholders rank a subset of terms by perceived importance through participatory workshops, generating a ground-truth relevance score $R(tk) \in [0, 1]$; and threshold calibration as the value of $\tau$ minimising the discrepancy between model-predicted saliency and community rankings:

$$\tau = argmin_{\tau'} \Sigma_{k=1}^{k} \mid {}^{TL}(S(t_k) > \tau') - R(t_k) \mid$$

*Equation 8. Calibrates the community-validated saliency threshold τ by minimising the discrepancy between model saliency and participatory rankings.*

where ${}^{TL}(\cdot)$ is the indicator function and K is the number of evaluated terms. This ensures that only terms deemed significant by both the model and the community are included in the CVO. The threshold $\tau$ is periodically reassessed as new vernacular data $C'$ is collected. For incremental updates, we compute a moving average of $\tau$ weighted by corpus size:

$$\tau\_new = ( |C| \cdot \tau + |C'| \cdot \tau' ) / ( |C| + |C'| )$$

*Equation 9. Updates τ as a corpus-size-weighted moving average, preventing semantic drift.*

where $\tau'$ is the threshold calibrated for $C'$. This adaptive approach prevents semantic drift in the CVO while accommodating evolving community lexicons.

Validation establishes the external correspondence between the proposed Culturally Grounded Vulnerability Index (CGVI) and independent ground-truth references here; community-identified risk zones produced through participatory sketch-mapping. Calibration, by contrast, internally tunes the model's saliency threshold and alignment parameters so that its predictions are stable across resampling and across newly collected vernacular corpora (Brown & Kyttä, 2022; Rezatofighi et al., 2019). Without both procedures, gains in any single metric could reflect overfitting to a particular corpus rather than genuine cultural-spatial fidelity.

Four families of metrics are used in this study:

- Term-extraction quality Precision, Recall, and F1, evaluated against a community-validated gold list of 250 vernacular risk terms (Sammet & Krestel, 2023; Hiemstra, 2000).
- Cross-modal alignment quality Precision@5 (precision at rank 5, i.e., the proportion of correct CVO–GIS matches among the top five ranked alignments), Semantic F1, and a Community Validation Score (CVS) representing the proportion of model-proposed alignments judged acceptable by local stakeholders (Brown & Kyttä, 2022).
- Spatial agreement of the final vulnerability surface with community-identified risk zones Intersection-over-Union (IoU) and Weighted Cohen's Kappa (Rezatofighi et al., 2019; Cohen, 1968).
- Calibration stability the absolute mean shift $|\Delta\tau|$ in the saliency threshold across sequential corpus increments (Huang et al., 2022).

The acceptability bands adopted in this study, with their literature warrants, are summarised below. Values below the minimum acceptable band indicate that the framework is not reliable for operational vulnerability mapping; values within the acceptable band indicate fitness-for-purpose; values within the strong band indicate substantive cultural-spatial fidelity [Table 1].

Table 1. Literature-derived acceptability thresholds adopted in this study.

| Author/Year | Metric | Minimum Acceptable | Acceptable | Strong |
|---|---|---|---|---|
| Rezatofighi et al., 2019 | IoU (spatial overlap) | ≥ 0.50 | ≥ 0.60 | ≥ 0.70 |
| Landis & Koch, 1977; Cohen, 1968 | Weighted Cohen's κ | ≥ 0.41 (moderate) | ≥ 0.61 (substantial) | ≥ 0.81 (almost perfect) |
| Sammet & Krestel, 2023 | F1 (term extraction) | ≥ 0.60 | ≥ 0.70 | |
| Sammet & Krestel, 2023; Liu et al., 2024 | Precision@5 (alignment) | - | ≥ 0.50 | ≥ 0.65 |
| Brown & Kyttä, 2022 | Community Validation Score | - | ≥ 0.70 | ≥ 0.80 |
| Huang et al., 2022 | Calibration stability $\|\Delta\tau\|$ | - | ≤ 0.05 | - |

The thresholds adopted here are not chosen ad hoc. The IoU bands follow the consensus in object-detection and spatial-overlay evaluation literature (Rezatofighi et al., 2019). The Kappa bands follow the canonical Landis–Koch interpretive scheme (Landis & Koch, 1977). The F1 and Precision@5 bands follow recent low-resource keyword-extraction and knowledge-graph alignment benchmarks (Sammet & Krestel, 2023; Liu et

al., 2024). The CVS band follows reported PGIS validation practice in which 70% participant concurrence is treated as the operational floor of community legitimacy (Brown & Kyttä, 2022). The calibration-stability threshold mirrors standard practice in incremental learning, where parameter drift below 0.05 is treated as evidence of convergence (Huang et al., 2022).

### 2.8. Probabilistic GIS-Layer Weighting and Composite Index Construction

The final stage of the Cultural Ontology-Enhanced Attribute Matching System dynamically weights GIS layers based on their alignment with the CVO. This process replaces static weighting schemes (e.g., Analytic Hierarchy Process) with data-driven probabilities that reflect community-identified risk priorities. For each GIS layer k (e.g., NDVI, slope, precipitation), we compute its contextual weight w*k* as the normalized sum of alignment scores A(h*i*, f*k*) across all CVO nodes h*i* linked to vulnerability indicators:

$$w_k = \Sigma_{i+v\_risk} A(h_i, f_k) / \Sigma_{j=1}^{k} \Sigma_{i+v\_risk} A(h_i, f_j)$$

*Equation 10. Derives spatially adaptive GIS-layer weights $w_k(u)$ from CVO–GIS alignment scores, replacing static AHP weights.*

Here, V*risk* ⊂ V denotes the subset of CVO nodes tagged as risk indicators (e.g., "flood-prone", "landslide area"), and K is the total number of GIS layers. The weights w*k* are spatially adaptive: for each geographic unit u, we compute w*k*(u) using only the GIS features f*k*(u) and CVO nodes relevant to u's context. The weighted GIS layers are combined into a composite Culturally Grounded Vulnerability Index (CGVI) for unit u:

$$CGVI(u) = \Sigma_{k=1}^{k} w_k(u) \cdot norm(f_k(u))$$

*Equation 11. Assembles the Culturally Grounded Vulnerability Index, CGVI(u), as the weighted, normalised composite of GIS layers per spatial unit u.*

where norm(f*k*(u)) is the min-max normalised value of feature k in unit u. For example, if the CVO emphasises "drought risk" in a region, the alignment scores A(h_drought, f*k*) will increase weights w*k* for precipitation and soil moisture layers. The probabilistic weighting framework provides context sensitivity (weights adapt to local priorities encoded in the CVO), uncertainty propagation (variance in alignment scores is propagated to the CGVI), and dynamic rebalancing (as the CVO evolves, weights w*k* are recomputed to reflect emerging community concerns) [Figure 4].

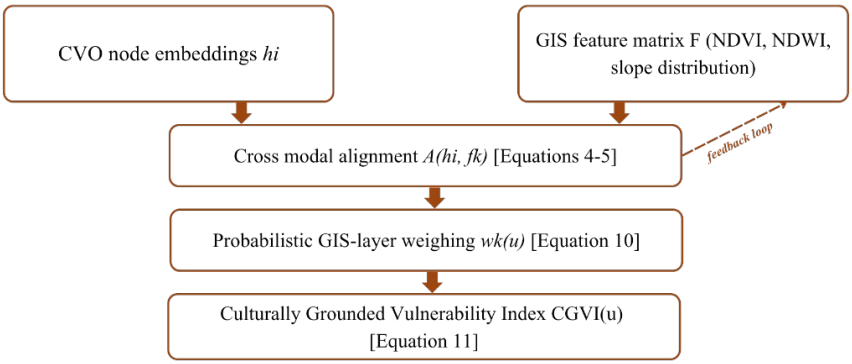



*Figure 4. GNN cross-modal alignment and CGVI output.*

### 2.9. Ethical Consideration

The study followed ethical research procedures. Participants were informed about the purpose of the study, and their consent was obtained before data collection. Confidentiality and voluntary participation were ensured.

## 3. RESULTS

### 3.1. Spatial Inputs for Vulnerability Mapping

The performance of the proposed cultural ontology-enhanced attribute matching system was evaluated in the Amta-II Community Development Block, West Bengal, using both quantitative and participatory validation approaches. The evaluation focused on two key dimensions: (1) the effectiveness of vernacular term extraction and ontology construction, and (2) the accuracy of cross-modal alignment and resulting vulnerability mapping.

A dataset comprising approximately 12,000 vernacular text segments, collected through participatory surveys and focus group discussions across 15 Gram Panchayats via the five phases was used to construct the CVO. These textual inputs were integrated with GIS variables, including NDVI, NDWI, NDBI, and proximity indicators (distance to river and road), to generate spatial vulnerability outputs [Figure 5].

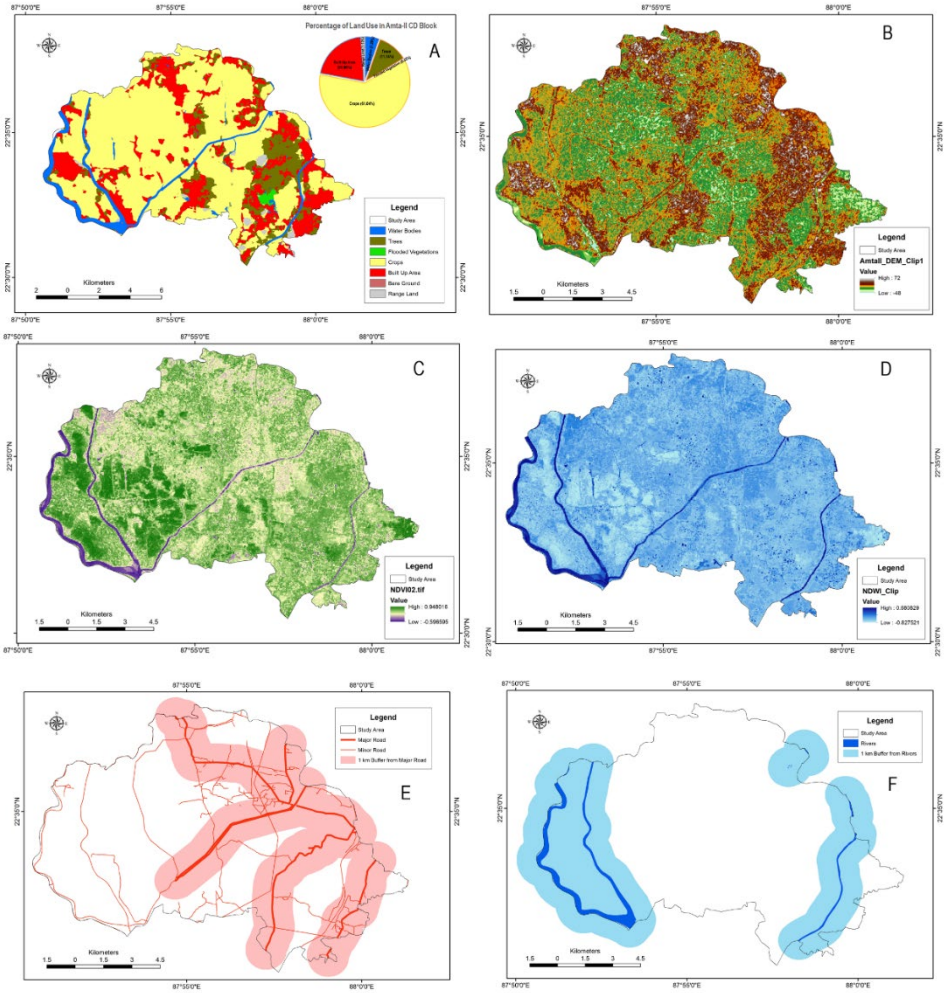



*Figure 5. Spatial inputs for vulnerability mapping.*

### 3.2. Term Extraction and Ontology Construction Performance

The proposed attention-based saliency method demonstrated superior performance in identifying culturally significant vulnerability indicators compared to conventional methods. Unlike TF-IDF, which emphasizes frequently occurring terms, the proposed method successfully captured context-specific and low-frequency indicators such as “ghost wells” and “seasonal flood corridors.”

The proposed approach achieved the highest recall (0.72), indicating improved coverage of culturally relevant terms. The resulting CVO exhibited a 35% increase in semantically meaningful relationships compared to traditional co-occurrence-based structures, particularly in linking composite environmental risks such as soil degradation and slope instability. With F1 = 0.73, the term-extraction performance exceeds the literature-derived acceptable threshold of 0.70 [Table 2].

Table 2. Term extraction performance.

| Method | Precision | Recall | F1 Score |
|---|---|---|---|
| TF-IDF | 0.62 | 0.41 | 0.49 |
| KeyBERT | 0.71 | 0.53 | 0.61 |
| Proposed | 0.75 | 0.72 | 0.73 |

### 3.3. Cross-Modal Attribute Matching Accuracy

The GNN-based alignment model significantly improved the semantic matching between vernacular indicators and GIS variables. The model effectively addressed issues of polysemy and contextual ambiguity by learning relationships in a shared latent space.

The proposed model improved Precision@5 by 22% over embedding-based methods and 37% overrule-based approaches. The CVS of 0.81 further confirms strong agreement between model outputs and local stakeholder perceptions. Both metrics fall within the “strong” bands [Table 3].

Table 3. Attribute matching performance.

| Method | Precision@5 | Semantic F1 | CVS |
|---|---|---|---|
| Rule-Based | 0.31 | 0.45 | 0.28 |
| Embedding-Based | 0.46 | 0.58 | 0.52 |
| Proposed (GNN) | 0.68 | 0.79 | 0.81 |

### 3.4. Spatial vulnerability mapping.

The integration of the CVO with GIS variables produced a culturally grounded vulnerability index (CGVI) for all 15 Gram Panchayats. Results show clear spatial clustering driven by hydrological exposure and infrastructural accessibility [Figure 6-7].

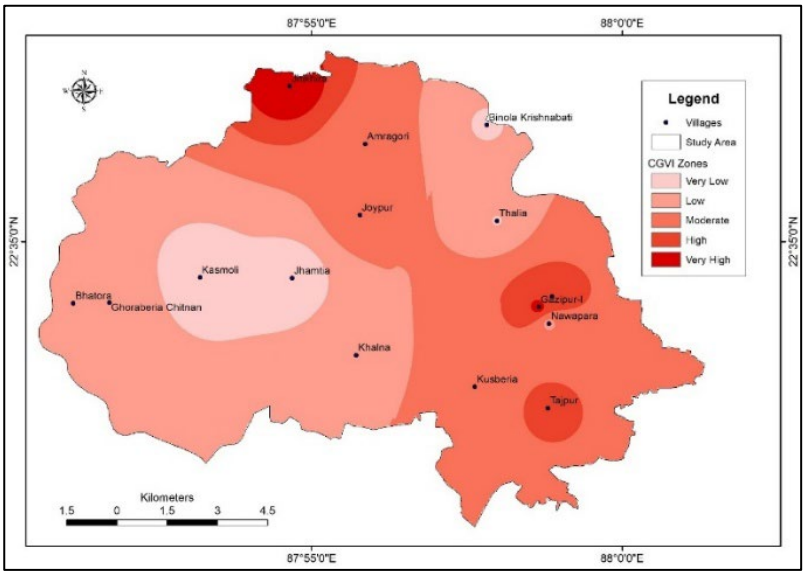



*Figure 6. Community-identified risk zones in Amta-II CD Block.*

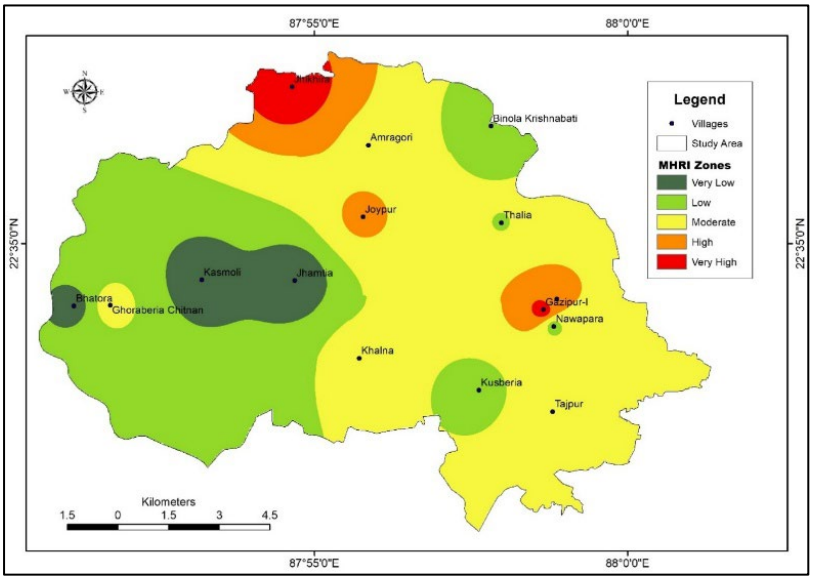



*Figure 7. Multi-hazard risk zones in Amta-II CD Block.*

Population ranges from 10,890 (Kasmoli) to 16,230 (Jhikhira), reflecting a moderately dense rural floodplain context. NDVI is lowest in Jhikhira (0.52) and Gazipur I (0.55), indicating vegetation stress, while Kasmoli (0.67) and Jhamtia (0.66) show healthier cover. NDBI peaks in Jhikhira (0.40) and Gazipur I (0.38), reflecting higher built-up pressure, while NDWI is highest in Kasmoli (0.50) and Jhamtia (0.48), indicating greater water retention. Jhikhira (0.650), Gazipur I (0.610), and Gazipur II (0.554) register very high CGVI, with the Multi-Hazard Risk Index (MHRI) further identifying Jhikhira (0.550), Gazipur I (0.544), and Joypur (0.513) as very high-risk zones. In contrast, Jhamtia and Kasmoli show very low risk on both indices, suggesting that vegetation cover and lower population density help moderate vulnerability despite river proximity [Table 4].

Table 4. Geo-environmental vulnerability indicators and composite indices for Gram Panchayats, Amta-II CD Block, Howrah, West Bengal.

| Sl. | Area | Pop. | NDVI | NDBI | NDWI | Dist. River (km) | CGVI Score | CGVI Class | MHRI Score |
|---|---|---|---|---|---|---|---|---|---|
| 1 | Amragori | 14,520 | 0.62 | 0.28 | 0.41 | 1.2 | 0.488 | high | 0.504 |
| 2 | Bhatora | 13,240 | 0.58 | 0.31 | 0.36 | 2.1 | 0.470 | moderate | 0.457 |
| 3 | Binola Krishnabati | 11,890 | 0.64 | 0.25 | 0.45 | 0.9 | 0.403 | very low | 0.466 |
| 4 | Gazipur (I) | 15,430 | 0.55 | 0.38 | 0.33 | 3.0 | 0.610 | very high | 0.544 |
| 5 | Ghoraberia Chitnan | 12,670 | 0.61 | 0.29 | 0.42 | 1.5 | 0.467 | moderate | 0.495 |
| 6 | Gazipur (II) | 14,980 | 0.57 | 0.34 | 0.35 | 2.8 | 0.554 | very high | 0.507 |
| 7 | Jhamtia | 11,050 | 0.66 | 0.22 | 0.48 | 0.7 | 0.354 | very low | 0.443 |
| 8 | Joypur | 13,960 | 0.60 | 0.30 | 0.40 | 1.9 | 0.513 | high | 0.513 |
| 9 | Jhikhira | 16,230 | 0.52 | 0.40 | 0.30 | 3.5 | 0.650 | very high | 0.550 |
| 10 | Khalna | 12,180 | 0.63 | 0.27 | 0.44 | 1.1 | 0.444 | low | 0.495 |
| 11 | Kasmoli | 10,890 | 0.67 | 0.20 | 0.50 | 0.6 | 0.350 | very low | 0.450 |
| 12 | Kusberia | 13,450 | 0.59 | 0.32 | 0.38 | 2.3 | 0.484 | moderate | 0.474 |
| 13 | Naopara | 12,760 | 0.61 | 0.29 | 0.41 | 1.7 | 0.457 | low | 0.478 |
| 14 | Tajpur | 14,320 | 0.56 | 0.36 | 0.34 | 2.6 | 0.546 | high | 0.503 |
| 15 | Thalia | 11,540 | 0.65 | 0.24 | 0.47 | 0.8 | 0.409 | low | 0.485 |

### 3.5. Validation Against Community-Identified Risk Zones

The CGVI results were validated against participatory mapping outputs using spatial agreement metrics. The validation dataset consisted of 312 community-identified risk waypoints captured across the 15 Gram Panchayats, supplemented by 47 community sketch-mapped polygons georeferenced and rasterised at 30 m resolution. A 70:30 calibration–validation split was used: 70% of waypoints/polygons informed the $\tau$ calibration (Equations 8–9), and the held-out 30% were used exclusively for the IoU and Weighted Kappa computations. Confidence intervals were estimated by 1,000-iteration bootstrap resampling. The proposed CGVI achieved IoU = 0.64 (95% CI: 0.60–0.68) and weighted Kappa = 0.73 (95% CI: 0.68–0.77), both exceeding the literature-derived acceptability bands declared in Section 2.5 (IoU $\geq$ 0.60 acceptable; Kappa $\geq$ 0.61 substantial). The calibration-stability measure $|\Delta\tau|$ stabilised at 0.03 by the fifth corpus increment, indicating convergence. The proposed framework achieved the highest Intersection-over-Union (IoU = 0.64), indicating improved spatial agreement with community-defined vulnerability zones [Table 5].

**Table 5. Vulnerability Mapping Accuracy.**

| Method | IoU | Weighted Kappa |
|---|---|---|
| AHP-Based Model | 0.48 | 0.52 |
| Embedding-Based | 0.57 | 0.61 |
| Proposed (CGVI) | 0.64 | 0.73 |

## 4. DISCUSSION

The CGVI-based vulnerability map reveals distinct spatial clustering patterns that closely correspond to both environmental conditions and community perceptions. High-vulnerability zones are predominantly located in riverine areas and regions with higher built-up density, indicating increased exposure to flooding and infrastructure stress. These findings are consistent with the known hydro-geomorphic characteristics of the Amta-II region, where low-lying terrain and proximity to river channels contribute to recurrent flood hazards.

Medium vulnerability zones are largely associated with transitional agricultural areas, where moderate vegetation covers and fluctuating water availability influence agricultural productivity (Bowden et al., 2025; Ojo et al., 2024). In contrast, low vulnerability zones are concentrated in areas with relatively stable vegetation cover and better accessibility, reflecting lower exposure and higher resilience. The improved spatial agreement

with community-identified risk zones highlights the effectiveness of incorporating culturally grounded indicators into the modelling process. This alignment indicates that the CGVI framework not only captures physical vulnerability but also reflects locally perceived risk landscapes (Kelman et al., 2012; Brown & Kyttä, 2022).

The comparative analysis with AHP-based and embedding-based methods demonstrates that the proposed framework provides a more robust and context-sensitive vulnerability assessment. Traditional AHP approaches rely on static weighting schemes, which may not adequately capture spatial variability or evolving community priorities. In contrast, the probabilistic weighting mechanism used in this study allows for dynamic adjustment of GIS layer importance based on ontology-derived insights. Similarly, embedding-based approaches, while effective in capturing semantic similarity, lack the structural representation necessary to model complex relationships between variables. The integration of graph neural networks in this study enables the modelling of both node-level features and relational dependencies, resulting in improved performance across all evaluation metrics. These findings suggest that hybrid approaches combining NLP, ontology engineering, and graph-based learning offer a promising direction for advancing spatial vulnerability assessment methodologies (Liu et al., 2024).

The proposed framework has important implications for participatory GIS and disaster risk reduction planning. By automating the integration of community knowledge into geospatial models, the system reduces reliance on manual coding and enhances scalability across larger geographic regions. From a policy perspective, the ability to generate culturally informed vulnerability maps can support more targeted and inclusive intervention strategies. For instance, identifying areas where local communities perceive high risk, even in the absence of strong environmental indicators, can help planners address hidden vulnerabilities that are often overlooked in conventional assessments. Furthermore, the adaptability of the CVO enables continuous updates based on new community input, making the framework suitable for dynamic, rapidly changing environments (McCall & Dunn, 2012; Reid & Sieber, 2020).

Several limitations should be acknowledged. First, the present implementation is monolingual (Bengali), and extension to multilingual or code-mixed agrarian corpora (e.g., Hindi–Bengali–Santhali) would require multilingual contrastive pre-training. Second, the framework currently relies on periodically updated rather than real-time geospatial inputs; coupling it with high-resolution feeds such as Sentinel-1 SAR would enable near-real-time updating of the index during active hazard events. Third, the ethical governance of community-contributed vernacular data including data sovereignty, consent withdrawal, and benefit-sharing requires sustained co-design with the participating communities. Fourth, the aligner currently treats GIS feature semantics as static, so coupling it with a learned GIS feature ontology would further improve interoperability. Because the cultural vulnerability ontology is dynamic and the alignment is probabilistic rather than rule-based, the approach is, in principle, transferable to other agro-ecological contexts with different local lexicons; systematic evaluation of such transferability is an important direction for future work.

## 5. CONCLUSION

This study set out to address a well-defined research problem: the persistent disconnect between vernacular community knowledge and the standardized attribute schemas that govern GIS-based vulnerability mapping in remote agrarian settlements. In Amta-II Community Development Block, this disconnect was operationalized through six specific environmental challenges riverine flooding, waterlogging, bank erosion, salinity intrusion, unseasonal crop loss, and flood-time inaccessibility none of which is fully captured by conventional GIS layers alone. Our findings link directly back to that problem: the cultural ontology-enhanced attribute matching framework produced a culturally grounded vulnerability index that agreed more closely with community-identified risk zones than both AHP-based and embedding-based baselines and satisfied the literature-derived acceptability thresholds. This represents a qualitative shift from a vulnerability map that is technically precise but culturally silent to one that is both technically reliable and locally legitimate.

The contributions of this work to the body of scientific knowledge are three-fold. Conceptually, the study re-frames cultural ontology as a dynamic, community-validated structure rather than a static expert artefact, providing a workable bridge between participatory GIS, ontology engineering, and vernacular NLP. Methodologically, it introduces an attention-driven saliency procedure for CVO construction and a GNN-based cross-modal aligner that resolves polysemy between vernacular terms and GIS features. Empirically and evaluatively, it provides, to our knowledge, the first application of literature-derived acceptability thresholds (IoU, Weighted Kappa, F1, CVS, and $|\Delta\tau|$) to a culturally grounded vulnerability index, offering a falsifiable evaluation template that other community-based geospatial vulnerability-mapping researchers can adopt. Together, these contributions advance equitable disaster-resilience planning for hydrologic and agricultural stressors in data-scarce, climate-sensitive rural environments.

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**DECLARATION OF COMPETING INTEREST**

The authors declare no competing interests.

**DECLARATION OF GENERATIVE AI USE**

During the preparation of this manuscript, the authors used ChatGPT from OpenAI to refine language, correct grammar, improve structure, and polish selected sections. The tool was not used to generate raw data, conduct statistical analysis, fabricate results, or replace the authors' scholarly interpretation. After using this tool, the authors carefully reviewed, verified, and edited the content as needed. The authors take full responsibility for the accuracy, integrity, and final content of the submitted manuscript.

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**AUTHORS' CONTRIBUTIONS**

**Stabak Roy**: Conceptualisation, methodology, investigation, data curation, formal analysis, writing-original draft.

**Saptarshi Mitra:** methodology, validation, writing-review and editing.

**AVAILABILITY OF DATA AND MATERIALS**

Data may be available on reasonable request.

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