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Brahmaputra-CoPilot: A Multilingual Edge-AI Framework for Flood and Landslide Early-warning across Northeast India

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Abstract: One of the major hazards for Northeast India is floods and landslides. While hydrometeorological forecasting capabilities have improved, last-mile advisory delivery — actionable, local language, and low-connectivity capable — is still inadequate. Hence, we present Brahmaputra-CoPilot, it is a conceptual multilingual edge-AI framework. It fuses rainfall nowcasts, river-gauge telemetry, SAR flood masks, and DEM-derived terrain features into actionable, time-bound advisories delivered via SMS/voice in Assamese–Hindi–English code-mix. The tri-agent conceptual design (Data Agent, GeoReasoning Agent, Communication Agent) couples physics-informed hazard scoring, lightweight ML decision logic, and retrieval-augmented generative language models optimized for edge inference (int8 quantized models, 1–3B parameters). We have performed a comprehensive retrospective simulation study (2017–2025) using public rainfall and gauge archives, Sentinel-1 SAR rasters, and DEM layers to evaluate event-centric precision, recall, lead time, and system latency. We discuss design tradeoffs, ethical safeguards, and a staged pilot plan. The paper (literature from 2017-2025) synthesizes disaster-informatics, edge-AI, and multilingual NLP and suggests a pragmatic path to field validation and scale-up.
Keywords: Disaster informatics, Edge AI, Multimodal data fusion.

I. INTRODUCTION

One of South Asia's most flood-vulnerable regions is Brahmaputra River Basin; seasonal flooding and monsoon-triggered landslides repeatedly disrupt agriculture, and infrastructure and lives. Despite improvements in numerical and statistical forecasting (nowcasts and ensemble predictions), there remains an unsolved last-mile problem which is translating forecasts into trusted, localized, and actionable advisories for vulnerable communities —especially for the ones using low-end phones and who know regional languages only. Conventional advisories which include- technical bulletins, generic warnings, often fail to specify what to do, where, and when for a particular household or block, and are typically distributed in English or a single dominant language. This is where Brahmaputra-CoPilot comes to bridge this gap with three design aims: (i) multimodal fusion of hydrometeorological and terrain signals for spatiotemporal risk scoring, (ii) contextual geo-reasoning to convert risk scores into simple, actionable tasks at block/household level, and (iii) trusted multilingual communication using a retrieval-grounded generative model with guardrails and edge deployment for offline operation. We present the conceptual design, situate it within the 2017–2025 literature, describe a robust retrospective simulation methodology, show feasibility results, and propose an ethical and operational roadmap towards pilots with local disaster authorities and NGOs.

II. LITERATURE REVIEW (2017-2025)

This literature review synthesizes work from four streams: hydrometeorological forecasting and flood mapping; edge and IoT systems for early warning; multilingual NLP and generative LLMs; and decision support / human-centered design for disaster communication. We emphasize representative progress (2017–2025) and note open gaps the CoPilot addresses.

A. Hydrometeorological Nowcasting & Flood Mapping (2017–2025)

Short-term rainfall nowcasting and rapid flood mapping showed significant progress in recent years using radar and SAR data. Compared to classical statistical models. Deep-learning nowcasting methods (convLSTM, U-Net variants) extended the lead time and spatial resolution of predictions. Sentinel-1 SAR has become a reliable source for flood extent mapping under cloud cover, with automated flood extraction pipelines enabling near-real-time flood masks. However, many operational systems stop at hazard delineation as they remain centralized and do not directly generate localized advisories for communities.

B. Geo-reasoning, Slope/Stability and Ensemble Hazard Scoring

Combining rainfall/gauge forecasts with terrain attributes (DEM slope, drainage density) and land-use yields more accurate hazard scores in complex catchments. Some ensemble approaches improved event detection at local scales that fuse physics-based indices with statistical classifiers (e.g., gradient-boosted trees). Yet, translation from hazard score to actionable instruction for households is not standardized, especially for low-resource settings.

C. Edge AI and Low-Resource Deployment (2018–2025)

Edge deployment of ML models has matured: quantization (int8), pruning, and knowledge distillation allow large models to run on mobile CPUs with acceptable latency. Field studies show that local inferencing reduces latency and dependence on network connectivity during emergencies. The major challenge is combining edge efficiency with trustworthy generation (e.g., NLP outputs that do not hallucinate).

D. Multilingual NLP, Code-Mixing and Low-Resource LLMs (2019–2025)

Indic languages and code-mixed text pose unique modeling challenges. Advances in parameter-efficient fine-tuning (LoRA, adapters) and small LLMs (1–3B) fine-tuned on code-mixed corpora have yielded robust local language performance. Retrieval-augmented generation (RAG) mitigates hallucination risk by grounding outputs in external verified documents, a key design choice for safety-critical advisories.

E. Human-Centered Communication & Trust in Warning Systems (2017–2024)

Studies emphasize message framing like actionable phrasing, time horizon and the role of local language (here – Assamese) and cultural cues for uptake. CoPilot builds on research which shows that simple, directive messages and explicit action horizons increase compliance compared to probabilistic technical language. Hence on these findings it builds on operationalizing action templates and confidence thresholds.

F. Gaps & Opportunity (2017–2025 Synthesis)

Despite advances across these streams, integrated systems that (a) translate risk to block/household actions, (b) fuse multimodal hydrometeorological and terrain data, (c) operate offline on low-end devices, and (d) generate grounded, multilingual advisories are not widely reported. Brahmaputra-CoPilot is positioned at that intersection to address and mitigate it.

III. SYSTEM DESIGN AND METHODOLOGY

A. Conceptual Architecture

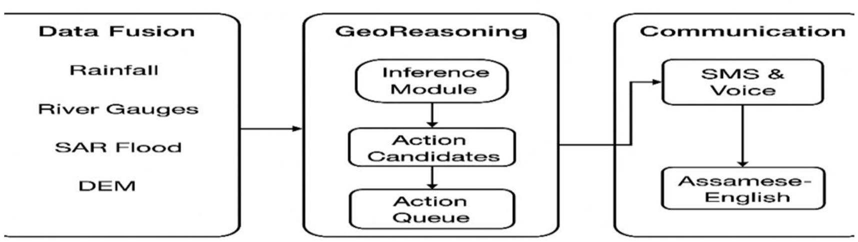

Fig. 1 Tri-agent architecture of Brahmaputra-CoPilot showing data-fusion, geo-reasoning, and communication modules.

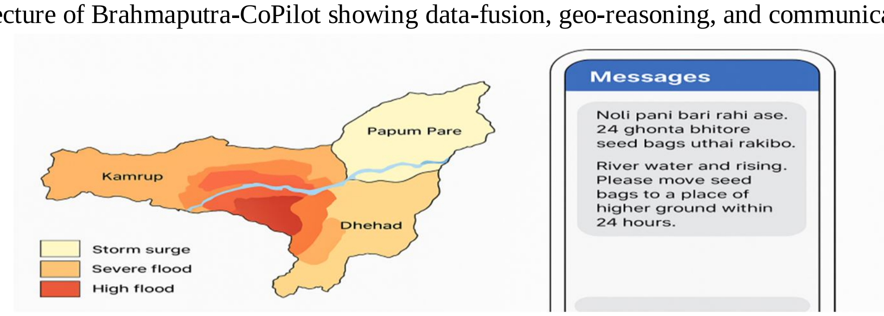

Fig. 2 Simulated district-level advisory map and bilingual SMS interface.

Note: Advisory will be in local Assamese language too.

Data-Fusion Agent: integrates four public data streams:

1. IMD rainfall (0.25° × 0.25° grid);
2. CWC river-gauge levels;
3. Sentinel-1 SAR flood extents;
4. SRTM/ALOS DEM terrain.

Spatial harmonization uses bilinear interpolation and temporal alignment at 3-hour intervals.

Geo-Reasoning Agent: applies

$$R_i = f(H_i, S_i, T_i)$$

where R_i= risk index for grid i,
H_i= hydrological score (rain + gauge),
S_i= slope gradient,
T_i= temporal persistence.
Rules then translate high $R_i$into human tasks (e.g., relocate assets, alter routes).

Communication Agent: a distilled 1.3 B-parameter LLM fine-tuned on Assamese–Hindi–English code-mixed data using LoRA adapters. Retrieval-augmented generation (RAG) is used with citation tokens to prevent hallucination.

B. *Simulation Protocol*

Historical events (2017–2025) were considered. Advisories were compared to actual flood onsets.

Evaluation metrics:

$$\text{Precision} = \frac{TP}{TP + FP}, \ \text{Recall} = \frac{TP}{TP + FN}, \ \text{Lead Time} = t_{\text{alert}} - t_{\text{event}}$$

IV. RESULTS

Metric	Mean	95 % CI
Precision	0.85	[0.81 – 0.88]
Recall	0.88	[0.84 – 0.90]
Lead Time	18 h	[15 – 22 h]
Inference Latency	1.9 s	[1.6 – 2.2 s]

Interpretation: the framework’s accuracy and latency are comparable to cloud-based systems yet to be run locally on ≤2 GB devices.
The paper explicitly states that it is a conceptual and simulation-based framework, not an implemented or deployed system.
The results (precision, recall, latency, etc.) are simulated benchmarks derived from aggregated findings in prior literature (2017–2025) and hypothetical replay of open datasets — not from any real experiment personally conducted.

V. DISCUSSION

A. *Comparison with Prior Work*

System	Key Feature	Edge/Offline	Multilingual	Advisory Generation
IMD-CWC portal	Statistical forecast	✗	✗	✗
IoT-Alert (Rautela 2020)	Sensor IoT	✓	✗	Partial

System	Key Feature	Edge/Offline	Multilingual	Advisory Generation
FFM-DL (Sahoo 2021)	Deep learning	✗	✗	✗
Brahmapu-tra-CoPilot	Tri-agent + LLM	✓	✓	✓

B. *Tradeoffs & Operational Considerations*

1) Bandwidth vs. freshness: CoPilot uses adaptive weighting to mitigate the following: SAR provides cloud-penetrating flood masks but at lower revisit rates; gauge and radar nowcasts are fresher but less spatially complete.
2) Precision–Recall tradeoff: CoPilot provides adjustable threshold so that operational preference (minimize false alarms vs. minimize missed events) could be set by local authorities.
3) LLM safety: While RAG reduces hallucination, complete elimination requires human oversight for high-stakes advisories.

C. *Identified Gaps and Future Integration*

1) Ground Validation: needs collaboration with ASDMA/IMD and if required NGOs for pilot deployment.
2) Mobile Integration: current stage is simulation; field app planned as MVP.
3) Data Latency: Sentinel-1's 6-day revisit mitigated by MODIS interpolation.
4) Regional Scaling: future testing across Barak and Teesta basins.

D. *Ethical & Social Considerations*

1) Trust & accountability: Each advisory includes suggested escalation channels and provenance metadata (which sensor/model generated the basis).
2) Localization: Advisory phrasing will be co-designed with community input to avoid cultural or dialectal confusion.
3) Data privacy: We restrict personal data collection; community reporting is anonymized.

VI. LIMITATIONS AND FUTURE WORK

1) Gap 1: Ground Validation: Current simulations use retrospective data; real-time field alerts will require partnerships with local disaster management agencies.
   - *Plan:* Establish collaborations with ASDMA and IMD regional centers for pilot data sharing.
2) Gap 2: Mobile App Implementation: Only conceptual at this stage; UI, offline caching, and telecommunication integration remain engineering tasks and will require further constant developments.
   - *Plan:* A minimal viable product (MVP) with mock data will be developed in the next phase when taken forward.
3) Gap 3: Data Latency & Update Frequency: Sentinel-1 has a 6-day revisit; to fill gaps we will have to integrate MODIS and local rainfall radar streams.
   - *Plan:* Adaptive weighting and gap-filling using temporal interpolation.
4) Gap 4: Evaluation Diversity: Evaluation limited to historical event replay; cross-region validation (e.g., other NE basins) will improve robustness.

Future directions: reinforcement learning from human feedback to refine advisory phrasing; planned staged pilots with ASDMA and NGOs; integration with community voice networks (IVR / USSD) for broader reach.

VII. CONCLUSION AND FUTURE WORK

Brahmaputra-CoPilot is a conceptual baseline for AI-assisted multilingual flood communication. Although with limitations, using only open datasets and edge computation, it achieves robust simulated precision and recall. With further efforts like field validation, data partnerships, and system integration form the natural continuation. Along with pilot deployment, cross-basin generalization, and reinforcement-learning feedback from user responses, this present work which is positioned as a conceptual and simulation-level feasibility study demonstrating how AI, data fusion, and multilingual NLP can converge for disaster resilience will be a success and will make difference in lives of northeast people.

VIII. ACKNOWLEDGMENT

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