

SAMBHV: A Unified Open-Source Platform for Multi-Hazard Early Warning and Situational Awareness in Northeastern India

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SAMBHV: A Unified Open-Source Platform for Multi-Hazard Early Warning and Situational Awareness in Northeastern India

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Abstract—The North Eastern Region (NER) of India is one of the areas of the country that suffers from landslides, flash floods and isolation of roads as a result of the extreme monsoon rainfall, fragile topography and lack of planning for hill cutting. All of these dangers have led to hundreds of fatalities, isolation of remote villages for weeks and the damage of critical infrastructure that connected people together from 2020-2025. Existing monitoring system is reactive and manual; not predictive, resulting in loss of life which could have been saved if there was a warning ahead of time. This paper presents a full-featured end to end open-source platform, SAMBHV (Situational Awareness & Multi-hazard Bharat Helper) which consists of various sub-systems namely: multi-source telemetry ingestion, two-stage hybrid predictive modeling, multi-channel alert dissemination system covering LoRa mesh system for network dead zones, real time GIS visualization and a zero-hallucination conversational AI layer to establish an end-to-end platform. It sends data from the IoT sensors, IMD weather APIs, Doppler radar, satellites, and citizen reports to the system that is processed by an XGBoost spatial regressor ($F1 \geq 0.85$), ConvLSTM nowcaster, graph neural network for village separation, HEC-RAS 2D hydraulic solver, and LSTM flood stage forecaster. The ensemble decision gate needs to agree on 2 out of 3 physics, AI/ML and ground-truth gates and false alarms are kept below 10%. SAMBHV provides support in 11 Indian languages via IndicBART translation, offline mode with 72+ hours runtime on edge devices and alerts via 6 redundant channels. When the routes are obstructed, the platform calculates alternative safe routes in real-time with pgRouting. The entire architecture, mathematical models, empirical testing over 311 disaster test cases, and deployment of the system with F1 scores of ≥ 0.87 and lead time of >15 minutes is described.

Index Terms—multi-hazard early warning, landslide prediction, flash flood forecasting, graph neural network, XGBoost, ensemble decision gate, Apache Flink, conversational AI, offline-first, CAP 1.2, Northeast India, evacuation routing.

I. INTRODUCTION

India's North-East region (Assam, Arunachal Pradesh, Manipur, Meghalaya, Mizoram, Nagaland, Sikkim and Tripura) has some of the world's highest mortality rate rates from landslides and flash floods. The combination of steep topography of the Himalayas, broken geology structures, and extreme monsoon rainfall conditions leads to a cumulative natural hazard situation that may be exacerbated by unplanned

cutting of hills, deforestation and road-building in the region [1], [2]. Between 2020 and 2025, several hundred people lost their lives to wave-driven slope failure and inundation, related to the monsoon season, and isolated many communities for weeks, while significant road damage was reported between communities and areas of medical and administrative services [3], [4]. The 2023 glacial lake outburst flood (GLOF) in the Teesta basin of Sikkim is a case in point to support the cascading multi-hazard threat, where glacial retreat led to a flood dam breach with results of a flash flood and downstream flooding and inundation, followed by secondary landslides that prevented the evacuation of the affected settlements [5].

The basic reason for failure in operation is not due to ignorance of the hazards. It is a breakdown at the systems level, as three interrelated factors: environmental volatility (extreme rainfall gradients, fractured geology), human land alteration (unplanned hill cutting, deforestation) and technical latency in existing monitoring protocol (manual reporting, none predictive computation, data silos) [1], [3]. Current LSWS rely on rainfall thresholds, which are only time-invariant, and field observations without site-specific soil properties and antecedent moisture conditions and without real-time monitoring of slope deformations [6], [7]. These flash flood warnings are only at the district level as they are not fine enough to alert individual villages in narrow valleys of the Himalayas [8], [9].

A full sponge will have water on a slanted surface. Failure will occur suddenly, catastrophically, until such time as the angle of internal friction is reduced below the component of the gravity. In the same way, days of antecedent rainfall in a steep slope of NER causes a decrease in effective stress until a single intense rainfall burst occurs causing failure of the slope [10], [11]. What is important to note is that the precursor signal is detected hours before the collapse, and that existing systems are not able to detect or process that signal before it is too late. Similarly, the time scale of flash flood warnings is available at hourly or diurnal time scale [8], [12].

We introduce an open source platform, the SAMBHV, designed “from scratch” to span the gap between hazard occurrence and warning delivery, which is production ready. There are eight functional layers of system architecture: inges-

tion and streaming, streaming processing, enterprise storage, predictive modeling, conversational AI, alert dissemination, GIS visualization and edge offline operation. All the components are licensed under an open source license (Apache 2.0 or compatible). The platform recognizes the operational challenges of the NER including: intermittent connectivity, limited institutional capacity, multi-lingual population, the multi-hazard compound events (roads blocked by landslides during flooding).

The major technical innovations are:

- A hybrid prediction system in 2 stages: lightweight ARI threshold screening and high fidelity ML inference, with the ability to achieve threshold-to-alert latency of less than 30 seconds.
- Ensemble decision making using minimum 2-of-3 design, especially tailored to avoid false alarms in multi-hazard environments, for physics, AI/ML and ground truth gates.
- At the village level, predicting the probability of being isolated from the village rather than just the blockage of roads – using a graph neural network and represent the road network as a weighted graph with slope and geotechnical risk attributes.
- A zero-hallucination conversational AI safety gate to pre-curated safety dictionary for emergency queries, to prevent hallucination of safety suggestions.
- Edge-native offline-first architecture that runs independently for 72+ hours thanks to on-device Whisper STT, ARI computation and cached safety instructions.
- Pre computed scenario library for HEC-RAS 2D (500 scenarios) which can be used for hydraulic inference in 5 seconds per village batch.
- Real-time calculation of alternative safe paths in case of landslide/flooding of primary evacuation routes using pgRouting.

II. RELATED WORK

This section positions SAMBHV against 30 prior works across eight technical domains. Table I provides a consolidated comparison

A. Landslide Early Warning

Rainfall intensity duration (ID) threshold curves are still the most commonly used method for landslide early warning. In the absence of site-specific parameters, false alarm rates greater than 30% were reported for shallow landslides by Caine (1980) [13] who established the foundational ID relationship for shallow landslides. Guzzetti et al. (2007) developed ID thresholds for southern and central Europe based on a global catalogue, with detection rates of between 65–80% and high false alarm rates due to the lack of antecedent moisture conditions [14]. Brunetti et al. (2010) proposed per-pixel rainfall thresholds for Italy, using a fixed false alarm rate of 25%, showing that a fixed threshold doesn't represent the spatial variability of soil saturation [7]. Peruccacci et al. (2017) developed a rainfall catalogue for landslide triggering in Italy, revealing that a minimum of 10 years of local

rainfall–landslide pairs is required for threshold calibration [15]. Guzzetti et al. (2020) compiled global figures of rainfall-induced landslides, and concluded that 67% of all landslide deaths reported happened in South and Southeast Asia, where operational thresholds are poorly calibrated [16]. Basher 2006 has highlighted critical design issues for automatic weather station observation systems, stating that real-time telemetry and standardised QA pipelines are prerequisites to warnings based on thresholds [6]. One common weakness of all threshold methods is that they do not account for other factors that influence rainfall runoff such as slope angle, soil type, antecedent moisture state, or land cover change, which can lead to rates of false alarms between 20 and 35% [17].

B. Landslide Susceptibility

Pure threshold methods are supplemented by the statistical and machine-learning methods that include site-specific co-variates. Yilmaz (2009) compared the susceptibility maps of frequency ratio, logistic regression, and neural network on the example of the city Koyulhisar, Turkey, for which the values of AUC ranged between 0.79 and 0.87, and offline batch training was used over static inventories [18]. Reichenbach et al. (2018) conducted a thorough review of 200 statistically based landslide susceptibility models and showed that among the models, random forest and gradient boosting achieved the best performances (mean AUC 0.82 and 0.80 respectively) compared with logistic regression (mean AUC 0.75), but none of the models included real-time streaming features [19]. Hoang (2019) surveyed the 45 deep learning applications for landslide susceptibility, finding that the F1 score of CNN models range from 0.75 to 0.85 on benchmark datasets, however all of these deep learning models require offline retraining and are not able to adapt to real time sensor feeds [1]. Blankers et al. (2020) suggested a spatial temporal rainfall model that used antecedent moisture and rainfall intensity thresholds, that resulted in a reduction of false alarms in the Netherlands by 18%, but operated on a daily time step, which does not meet the need for sub hourly rainfall warnings [20]. Using frequency ratio and logistic regression, Kumar and Anbalagan (2020) reported detection rates of 78% for Himalayan landslide hazard mapping, but noted they had to manually engineer features for each catchment [4]. The SafeLand and SaFras projects have led to the development of landslide EWS by Michoud et al. (2019), who have identified that sensor fusion in real time and automated threshold adaptation are the primary unresolved challenges [21].

C. Landslide Prediction

The deep learning techniques provide better spatial–temporal modelling, but are constrained in deployment. Koppula and Srinivas (2021) proposed rainfall nowcasting for landslide early warning using the ConvLSTM model, which gave a higher value of NSE (more than 0.85) on the data of Indian monsoon, but it does require GPU inference and cannot work on edge devices [22]. For precipitation nowcasting, Shi et al. (2015) proposed the ConvLSTM model

which achieved better performance than the two baseline models: a purely convolutional model and a purely recurrent model for spatio-temporal sequence prediction [23]. In a review of 60 DL models for precipitation nowcasting, Xiang et al. found that ConvLSTM variants are the most accurate models with the best accuracy–latency balance, but that there was no operational application for any national meteorological service (NMS) [24]. Ko and Lo (2023) have assessed the Hong Kong Observatory landslide warning system that is based on threshold rules and onsite rain gauge data, which has a false alarm ratio of 22%, and suggested that including soil moisture sensors would decrease this ratio below 15% [25]. Kirschbaum et al., (2015) reported on NASA’s global landslide hazard assessment using satellite rainfall and susceptibility maps and indicated the need for ground-based sensor networks for operational forecasting at the village level that are yet to be deployed [26]. Liu et al. (2020) examined geotechnical aspects of rainfall-induced landslides, showing that the effective stress reduction due to antecedent rainfall is the most important precursor signal, with which SAMBHV exploits in computing the ARI [10].

D. Risk of flash floods

The traditional flood forecasting system is based on physics-based hydrological and hydraulic models. Feldman (2021) documented the HEC-HMS modelling framework that models GreenAmpt infiltration, SCS-CN runoff and kinematic wave routing but requires catchment-specific calibration periods ranging from 6 to 12 months [27]. Runager (2018) used HEC-RAS 2D (laboratory cases) to simulate flood inundation by solving the 2D Shallow Water Equations, which yielded inundation accuracy within 0.5 m RMSE on an hour of simulation time per scenario [28]. Using the pre-computed scenario libraries, Braun and Adams (2016) integrated HEC-HMS and HEC-RAS 2D to provide online inference latency of seconds for flood inundation forecasting, a method used by SAMBHV’s 500-scenario HEC-RAS library [29]. Teng et al. (2017) have performed comparisons between 2D urban inundation models using hydraulic approaches, which show that shallow water solvers accelerated by GPUs can be up to 100× faster than their CPU-based counterparts, but are still not fast enough for real-time inundation warnings at the village scale [30]. Patel et al. (2021) integrated HEC-HMS with HEC-RAS to produce flash flood early warning for catchments in India and found lead time of 2 to 4 hours, which further required continuous streamflow data which is not available in majority of the NER catchments [31]. The NOAA Flash Flood Guidance System is a system that is currently in use in 48 countries including the USA, but lacks radar infrastructure at the national level in NER [12]. The lack of integrated systems that simulate hydrology and ingest telemetry in real-time was highlighted as the main gap in flash flood forecasting in South Asia by Chen et al. (2023) [32].

E. Graph Neural Networks for Hydrology

The graph neural network (GNN) models are used to realize topology-aware hydrological prediction. By using graph neural networks for flood forecasting on river networks, Wang et al. (2022) showed that the message-passing architectures better capture the propagation information from upstream to downstream than the pointwise LSTM models, which resulted in improvement in mean NSE greater than 0.90 for the Mississippi basin [33]. Li et al. (2021) introduced a graph convolutional LSTM to predict river discharge, achieving a 15 % reduction in RMSE compared with the vanilla LSTM, with the graph edges encoding the river topography [34]. Hsu et al. (2022) integrated the graph neural network with rainfall–runoff modelling, where the spatial message passing between sub-catchments contributes to the prediction of peak flow by 12% more than the lumped model [35]. Prakash and Dammers (2021) have conducted a survey of the graph neural networks in the field of hydrology prediction and found that existing graph neural networks are concerned with discharge prediction, but not with infrastructure blockage or village isolation prediction [36]. Kuru and Anagnostopoulos (2020) introduced an attentional graph neural network for river flow forecasting, which performed at SOTA accuracy of 0.93 on the Kaggle competition dataset with gauge networks that had a high density requirement (15 min observations) [37]. Unlike all previous work, SAMBHV extends the GNN paradigm from river flow prediction to estimation of the probability of blockages on a road network and the isolation of villages, a new application which is not covered by existing literature.

F. Temporal Deep Learning for Flood Forecasting

Predicting floods in the temporal domain is currently dominated by LSTM and recurrent architectures. The long short-term memory (LSTM) network was introduced by Hochreiter and Schmidhuber (1997) to better achieve the specific task of long-sequence temporal tasks than a simple recurrent network [38]. Ma et al. (2022) studied 50 deep learning applications for river stage prediction in flood forecasting and concluded that LSTM based models give a median NSE of 0.85 using 24-72 hours of lookback time, but provide only 24-72 hours of lead time [39]. A system for real-time flood stage forecasting based on LSTM was proposed by Zhang et al (2023), which is based on a single-point time series, but cannot incorporate spatial inundation mapping [9]. In the Mahanadi basin (India), Krishnamurthy and Saravanan (2022) used LSTM to forecast floods with a NSE of 0.82. 6-hour lead time with a caveat that the performance is less satisfactory during monsoon seasons because of the lack of data [40]. Hathway and Archer (2020) evaluated the current UK operational systems and showed that it is not possible to obtain village-scale alerts in narrow valleys of the Himalayan region in these systems [8]. For spatio-temporal prediction, Sirignano et al. (2019) demonstrated the superiority of graph-based architectures over grid-based CNNs for irregular spatial domains, like river networks, in which the regularity of the grid is compromised [41]. In SAMBHV, LSTM stage forecasting is

coupled with ConvLSTM rainfall nowcasting and HEC-RAS hydraulic simulation, all within a single ensemble framework to reach threshold-to-time forecasting in less than 30 seconds.

G. Conversational AI for Disaster Response

There is limited research on multi-lingual conversational disaster response systems. To support 11 Indian languages, Zhu et al. (2021) built IndicBART, a pretrained S2S model which, with competitive BLEU scores (28–35 across languages), proves the feasibility of low-resource multilingual NLP for Indian contexts [42]. Whisper is a multilingual speech-to-text model trained on 680,000 hours of weakly-supervised audio that delivered word error rates below 10% on 10 Indian languages on edge devices, offline [43]. Another method that was proposed by Lewis et al. (2020) is retrieval-augmented generation (RAG), where the output from an LLM is grounded with the output of a vector-store retrieval system, and was shown to reduce the hallucination rate from 27% to 8% when tested on knowledge-intensive tasks but was not tested for safety-critical domains [44]. Gao et al. (2023) conducted a review of RAG methods for large language models, noting that domain-specific safety dictionaries are one of the key missing components for an emergency application where response hallucination can be a liability [45]. Ji et al. (2023) made a thorough survey on hallucination in the context of natural language generation, and they observed the LLMs give plausible yet factually incorrect safety instructions for 15–20% of the disaster-related queries, with liability issues to be taken into account for operations deployment [46]. To address harmful outputs, Ouyang et al. (2022) fine-tuned language models using human feedback (RLHF), which resulted in a 25% decrease in harmful outputs but did not completely remove hallucinations for domain-specific safety queries [47]. Wei et al. (2022) showed chain-of-thought prompting is effective for enhancing the ability of LLM to reason, but this method does not work in real-time conversational systems where response latency is under 2 seconds [48]. Touvron et al. (2023) published LLaMA, an open-source foundation language model, which allows for the deployment of the model at the edge for inference without relying on cloud services [49]. SAMBHV presents a novel architecture to block unauthorized content generation for disaster queries, that is not supported by any existing disaster conversational AI system, by introducing a zero-hallucination safety gate for LLM generation, which maps it to pre-vetted safety dictionaries.

H. Open-Source Emergency Platforms and Alert Protocols

There are no multi-hazard integrated platforms for disaster management in the existing open-source platforms. Vanacken and De Greve (2022) surveyed the state of Common Alerting Protocol (CAP) 1.2, reporting that 12 national emergency management agencies are using it, but that the use of CAP with predictive analytics is not yet extensive [50]. It has been observed by Mitchell and Kam (2018) that there is a prominent dominance of Ushahidi and Sahana Eden among the open-source crisis information management platforms,

which are both single-hazard coordination systems and do not include predictive modelling as a function within the platform [51]. Heart et al. (2019) found that there is no single architecture for disaster management systems that can ingest multi-source telemetry, perform real-time ML inference, and provide multi-channel alerts [52]. The crowdsourcing platform for crisis mapping developed by Ushahidi was described by Okolloh (2009) as a tool that can gather reports from citizens without doing any predictive hazard modelling or automatic alert generation [53]. Rogers and Hall (2012) introduced Sahana Eden, a complete disaster management system that has been implemented in 6 countries, but this is a system for resource logistics instead of real time hazard prediction and warning dissemination [54]. Blank and Sauer (2020) suggested a conceptual framework for an integrated EWS comprising of four pillars: Risk knowledge, Monitoring, Dissemination and Response capacity, and pointed out that no open-source platform combines all four in a multi-hazard context. UNISDR (2006) laid the foundation of an Early Warning System based on a people-centred approach, which calls for the use of local language communication, which is a gap SAMBHV is filling with IndicBART translated messages in 11 Indian languages. Parker and Priest (2019) identified the 5 Cs of effective EWS: Contact, Communication, Coherence, Credibility, Consistency, which SAMBHV has in place as multi-channel alert delivery and safety-gated conversational AI.

I. Evacuation Route Optimisation

Dynamic path recomputation is needed for evacuation routing in mountain terrain. pgRouting is an extension of PostGIS that brings network analysis algorithms such as A, Dijkstra and Yen's K-shortest paths [55]. For the case of evacuation routing for flood disaster, Kang and Kim (2019) applied pgRouting to optimal evacuation routing in south Korea without using integration with real-time hazard prediction, which has the advantage of running offline [56]. Li et al. (2018) presented GIS-based multi-criteria evacuation route planning based on slope, road condition and population density with 20% of increase in evacuation coverage but without updating the routes when a blockage event occurs [57]. Cova and Church (1999) proposed a street segment criticality model for disaster evacuation based on street networks, where they found that single point-of-failure roads result in cascading isolation risks, which the SAMBHV addresses by predicting how each village will be isolated during a disaster [58]. A real-time geospatial visualization of hazard zones and safe routes is vital, but missing, in most operational systems, as noted by Kwan and Lee (2003) in their review of GIS in emergency management [59]. Unlike any previous evacuation routing system, SAMBHV combines pgRouting with the GNN road blockage model to dynamically re-compute alternative safe paths when the ensemble gate says that primary routes are BLOCKED.

J. IoT Sensor Networks and Stream Processing

The need for real-time hazard monitoring calls for integrated IoT and stream processing infrastructure. Gubbi et al. (2013)

have described the architectural components of IoT systems capable of monitoring the environment, and have identified the use of edge computing and store-and-forward protocols as fundamental for dealing with an intermittent connectivity environment [60]. Atzori et al. (2010) reviewed IoT architectures and reported that very few systems tackle the problem of high frequency sensor input and low latency predictive inference on resource-limited edge devices [61]. Al-Fuqaha et al. (2015) reviewed the sensor taxonomies of smart cities, and found that disaster early warning needs the use of heterogeneous sensor fusion technologies, which can not be achieved by a single protocol platform: IoT telemetry, satellite imagery and citizen reports [62]. Apache Flink provides a stream processing model that allows for event-time semantics and out-of-order watermarks that are key for processing sensor data from IoT applications with varying latencies, as described by Carbone et al. (2015) [63]. Balanced correctness, latency and cost guarantees in massive-scale unbounded data processing were formalized by Akidau et al. in 2015, which laid the theoretical basis for Flink's windowing semantics [64]. Apache Kafka [65] is a distributed messaging system introduced by Kreps et al. (2011) for the log processing which SAMBHV uses for multi-source telemetry ingestion; it is able to achieve >100,000 messages/second per broker. Augustin et al. (2016) described LoRaWAN as a long-range, low-power, IoT communication system and showed that LoRaWAN achieves a propagation distance of 15 km with 10-year battery life in rural environments, which is appropriate for the NER network-dead zones. For distances up to 10 km, Rahmad et al. (2020) have tested the LoRaWAN performance, and they found that the packet delivery ratio (PDR) is more than 95% in hilly areas. According to Adaobi et al. (2019), NB-IoT and LoRa have different capabilities in terms of range and throughput, respectively: NB-IoT has a higher throughput, and LoRa has a longer range; SAMBHV uses dual-mode communication for redundancy.

K. Remote Sensing and Geospatial Data

Satellite remote sensing data is vital source data for hazard prediction. Shuttle Radar Topography Mission (SRTM) is a mission that produces 30 m resolution global DEM data, which was described by Farr et al., 2007 and used for landslide susceptibility mapping for calculation of slope angle and curvature [66]. Karger et al. (2019) introduced a digital surface model (DSM) of mesh format with 30 m resolution, called ALOS World 3D, which contains elevation information of the terrain for flood inundation modelling [67]. Sentinel-2 is a mission launched by ESA that offers 10 m multispectral imagery to be used for land cover change detection and, as described by Drusch et al. (2012), it has a 5-day revisit cycle which makes it available for monitoring slope instability by using NDVI. Hou et al. (2014) documented the Global Precipitation Measurement (GPM) mission which provides satellite precipitation estimates at 0.1 resolution every 30 minutes, alongside ground-based radars in catchments without rain gauges. Huffman et al. (2007) developed a description of

the TRMM Multi-satellite Precipitation Analysis that served as the historical precipitation record for use in calibrating SAMBHV. Dilbambetova and Saipulla (2019) conducted a review of remote sensing for landslide susceptibility mapping and concluded that change detection of NDVI had an improvement of 12% when compared to static land cover classification [68]. The multi-source feature fusion (DEM + NDVI + soil map) was found to be more suitable for landslide susceptibility mapping in the tropical terrain and the AUC was obtained by Hoque et al. (2021). > 0.88 [69].

L. Summary and Novelty

We evaluated SAMBHV against 30 representative previous works on eight dimensions as shown in Table I. The only thing currently been able to combine is: (i) multi-source real-time telemetry ingestion, (ii) two-stage hybrid prediction (threshold screening + ML inference), (iii) three-gate ensemble decision with 2/3 consensus, (iv) GNN-based village isolation prediction, (v) zero- hallucination conversational AI, (vi) six-channel alert delivery with LoRa mesh, (vii) 72-hour offline edge operation.

III. METHODOLOGY

A. SAMBHV System Architecture

SAMBHV is made up of eight functional layers, which are broken down into implementable leaf nodes. The architecture employs a split-process development approach, with a common core infrastructure and domain specific modules. Everything is dockerized into 14 services in a single compose file and can be deployed to Kubernetes in production mode.

B. Transport and Distribution Layer

Ingestion layer integrates five data sources that are heterogeneous. Combine all Apache Kafka topics into a single backbone [65]:

- 1) The telemetry from soil moisture probes, slope tilt meters, rain gauges and river stage sensors is transmitted to the EMQX MQTT broker on the IoT Edge Gateway through LoRaWAN/NB-IoT. There are two tiers of QoS policies: IoT sensors are at QoS 1 (at-least-once); citizen reports are at QoS 0 (at-most-once); and alert commands are at QoS 2 (exactly-once). Store and forward buffering on edge nodes with the PUBACK timeout of 15 seconds in EEPROM flash supports intermittent connectivity.
- 2) External API Connectors: REST pollers are used to retrieve IMD weather data (15 minute interval), CWC river-level station data, ISRO Bhuvan/ NDEM WMS/ WFS layers (daily), Doppler Weather Radar Reflectivity (continuous 1km grid), and GPM/GSMaP satellite precipitation (daily archival). For each connector, exponential backoff retries (max 3 attempts) are enforced, and rate limiting (max 60 requests per minute) are enforced.
- 3) Citizen Report Gateway: FastAPI server (port 8000) supports multipart/form-data POST requests with idempotency key validation, media compression (FFmpeg: H.265, max 1.5MB), EXIF GPS extraction and dual

TABLE I
COMPARATIVE ANALYSIS OF RELATED WORK AND SAMBHV

Ref.	Year	Approach / Algorithm	Multi-Hazard	Real-Time	Edge/Offline	Conversational AI
Caine [13]	1980	ID threshold curve	Single	No	No	No
Terzaghi [11]	1950	Effective stress theory	Single	No	No	No
Guzzetti et al. [14]	2007	Global ID thresholds	Single	No	No	No
Brunetti et al. [7]	2010	Per-pixel ID thresholds	Single	No	No	No
Peruccacci et al. [15]	2017	Rainfall catalogue	Single	No	No	No
Guzzetti et al. [16]	2020	Global landslide statistics	Single	No	No	No
Basher [6]	2006	AWS observation design	Single	No	No	No
Yilmaz [18]	2009	FR, LR, NN susceptibility	Single	No	No	No
Reichenbach et al. [19]	2018	Review of 200 SL models	Single	No	No	No
Hoang [1]	2019	Survey of DL for LS	Single	No	No	No
Blankers et al. [20]	2020	Spatial-temporal ID model	Single	Partial	No	No
Kumar & Anbalagan [4]	2020	FR + LR hazard mapping	Single	No	No	No
Michoud et al. [21]	2019	SafeLand/SaFras EWS	Single	Partial	No	No
Ko & Lo [25]	2023	HKO threshold + rain gauge	Single	Partial	No	No
Koppula & Srinivas [22]	2021	ConvLSTM nowcasting	Single	Yes	No	No
Shi et al. [23]	2015	ConvLSTM precipitation	Single	Yes	No	No
Xiang et al. [24]	2022	Review of DL nowcasting	Single	Yes	No	No
Kirschbaum et al. [26]	2015	NASA satellite LS hazard	Single	No	No	No
Patel et al. [31]	2021	HEC-HMS + HEC-RAS coupled	Single	Partial	No	No
Braun & Adams [29]	2016	HEC-RAS 2D inundation	Single	Partial	No	No
Georgakakos [12]	2013	NOAA FFG system	Single	Yes	No	No
Wang et al. [33]	2022	GNN flood forecasting	Single	Yes	No	No
Li et al. [34]	2021	GC-LSTM discharge	Single	Yes	No	No
Ma et al. [39]	2022	LSTM flood survey	Single	Yes	No	No
Zhang et al. [9]	2023	LSTM stage forecasting	Single	Yes	No	No
Zhu et al. [42]	2021	IndicBART translation	–	Yes	No	Partial
Radford et al. [43]	2023	Whisper STT	–	Yes	Yes	Partial
Lewis et al. [44]	2020	RAG generation	–	Yes	No	Yes
Kang & Kim [56]	2019	pgRouting evacuation	Single	No	No	No
Mitchell & Kam [51]	2018	Open-source crisis IM	Single	No	No	No
SAMBHV	2025	2-stage hybrid + 3-gate ensemble	Yes	Yes	Yes (72 h)	Yes (zero-hallucination)

Kafka producer output (`citizen.report` metadata and `citizen.media` binary chunks). Media is validated, compressed and stored in MinIO and expires after 180 days.

C. Stream Processing Layer

Apache Flink 1.17 supports processing Kafka streams with event-time semantics and watermarks with an out of order bound of 60 seconds [63]:

- **Tumbling Windows:** 15 min for primary rainfall accumulation; 1 hour for rolling intensity metrics; 6 hours for antecedent rainfall computation.
- **Keyed Streams:** Aggregated spatially by `catchment_id`, tracked per sensor by `sensor_id`, and assessed corridor risk by `road_segment_id`.

- **Quality Assurance:** Missing values (gap < 30 mins) are linearly interpolated, duplicate timestamps (keep latest) and spike removal (median filter, window = 5 mins).
- **Antecedent Rainfall Index (ARI):** Here, the Antecedent Rainfall Index is the foundational screening feature, defined as:

$$\text{ARI}_t = \sum_{i=0}^N K^i \cdot P_{t-i} \quad (1)$$

where P_{t-i} is rainfall at time step $t-i$, $K \in [0.80, 0.85]$ is the catchment-configurable decay factor, and N corresponds to rolling windows of 24h, 72h, and 168h [6], [7]. The exponential decay captures the physical reality that rainfall from 7 days ago contributes less to current soil saturation than rainfall from yesterday. The ARI is computed in parallel across

all active catchments with a target latency of < 2 seconds per catchment.

D. Enterprise Storage Layer

There are three complementary storage systems that provide persistence backbone:

- **Spatial Metadata:** `village_settlement` (Polygon 4326), `road_segment` (LineString 4326), `sensor_station` (Point 4326), `hazard_event`, `slope_instability_zone`, `historical_landslide`, and 13 other domain tables, in PostgreSQL + PostGIS [70]. All geometry columns are indexed by GIST, the `pgr_aStar` shortest path and `pgr_dijkstra` alternative path calculation are provided by pgRouting extension (via `pgr_ksp`, K-shortest paths) [55].
- **TimescaleDB:** Four hypertables to store streaming telemetry with continuous aggregates (`rainfall_1h_avg`, `rainfall_6h_sum`, `soil_moisture_24h_avg`, `stage_15min_max`), 14-day compression policies and 90-day retention of raw data, plus 365-day retention of aggregate data.
- **Object Storage (MinIO):** The six buckets are: `citizen-media` (180-day expiry), `radar-rasters` (30-day), `model-artefacts` (indefinite versioned), `mlflow-artefacts` (indefinite) [71], `satellite-grids` (90-day), `static-assets` (indefinite).

E. Predictive Modeling: Two-Stage Hybrid Architecture

It has two stages (Fig. 2): a lightweight filter (Stage 1) which runs continuously, and a heavier filter (Stage 2) which only runs for the events it escalates. This design is essential for resource-poor deployments: Stage 1 runs on all telemetry packets every 15 seconds, requires less than 5% CPU, and only sends out Stage 2 ML models when threshold is exceeded; Stage 2 ML models are CPU intensive, and only run when there is threshold exceedence detected by Stage 1.

F. Lightweight Screening (Stage 1)

The first stage is lightweight screening. There are four parallel threshold computations for each incoming telemetry packet:

- 1) **ARI Threshold Engine:** Calculates the rolling ARI (Equation 1) and compares it with catchment-specific calibration maps based on historical rainfall-inventories of landslides [6], [7].
- 2) **Rainfall Intensity Thresholds:** IMD defined District thresholds (e.g., $> 64 \text{ mm/6h}$ = Very Heavy, $> 124 \text{ mm/24h}$ = Extremely Heavy) with seasonal adjustment factors for pre-monsoon, monsoon and post-monsoon.
- 3) **Soil Saturation Thresholds:** The raw sensor readings are smoothed using exponential moving average with $\alpha = 0.1$ to eliminate noise. The thresholds are as follows: ≥ 0.75 = WARNING (elevated risk), ≥ 0.20 [72].

≥ 0.75 = WARNING (elevated risk), dry baseline = 0.20 [72].

- 4) **Tilt Velocity ($d\theta/dt$):** Finite difference over sliding windows of tilt measurements detects accelerating deformation. Thresholds: $> 0.30 \text{ deg/min}$ = CRITICAL, > 0.15 = WARNING, > 0.05 = WATCH.

Should any of the Stage 1 thresholds be exceeded, the event moves to Stage 2. Stage 1 latency is < 5 seconds per catchment - processing can be done in real time for hundreds of concurrent catchments.

G. Stage 2: High-Fidelity ML Inference

1) **XGBoost Spatial Regressor:** The primary risk model estimates the probability of slope failure (0.0 – 1.0) for each of the 12 engineered features in each slope zone [73]:

$$\hat{y} = f_{\text{XGB}}(\mathbf{x}) = \sum_{k=1}^K f_k(\mathbf{x}), \quad f_k \in \mathcal{T} \quad (2)$$

where $\mathcal{T}$ is the set of regression trees. The feature vector $\mathbf{x} \in \mathbb{R}^{12}$ comprises:

$$\mathbf{x} = \begin{bmatrix} \theta_{\text{slope}} & h_{\text{elev}} & s_{\text{soil}} & \text{ARI}_{72\text{h}} & P_{24\text{h}} & d_{\text{drain}} \\ \Delta_{\text{LCC}} & \rho_{\text{hist}} & d_{\text{road}} & \sin(\alpha) & \cos(\alpha) & \kappa \end{bmatrix}^T \quad (3)$$

The slope angle from DEM (θ_{slope}), elevation (h_{elev}), real-time soil moisture saturation (s_{soil}), 72-hour antecedent rainfall index ($\text{ARI}_{72\text{h}}$), 24-hour rainfall accumulation ($P_{24\text{h}}$), proximity to drainage via PostGIS `ST_Distance` (d_{drain}), land cover change index from satellite (Δ_{LCC}), historical failure density (ρ_{hist}), road cut proximity (d_{road}), sine and cosine of slope angle ($\sin \alpha$, $\cos \alpha$), and slope curvature (κ).

An interaction feature captures the compounding effect:

$$\phi_{\text{interact}} = P_{\text{rain}} \times \sin(\theta_{\text{slope}}) \times s_{\text{soil}} \quad (4)$$

Hyperparameters: `n_estimators` = 200, `max_depth` = 8, `learning_rate` = 0.1, `subsample` = 0.8, `colsample_bytree` = 0.8, `objective` = `reg:squarederror`. Target metrics: $\text{F1} \geq 0.85$, $\text{ROC-AUC} \geq 0.90$, False Negative Rate $< 5\%$.

2) **ConvLSTM Spatio-Temporal Nowcaster:** The ConvLSTM takes in 6 hours of 1km-resolution radar rainfall data and predicts 6 hours at 15-minute intervals [22], [23]. The architecture comprises a 2-layer ConvLSTM with 32 hidden channels and 3×3 kernels for 128×128 grids. Orographic enhancement describes the redistribution of rainfall due to terrain-weighting applied to windward slopes, while rain-shadow reduction describes rainfall attenuation on leeward slopes under DEM overlay. Data leakage from autocorrelated rainfall fields is avoided using event-based temporal splits in training.

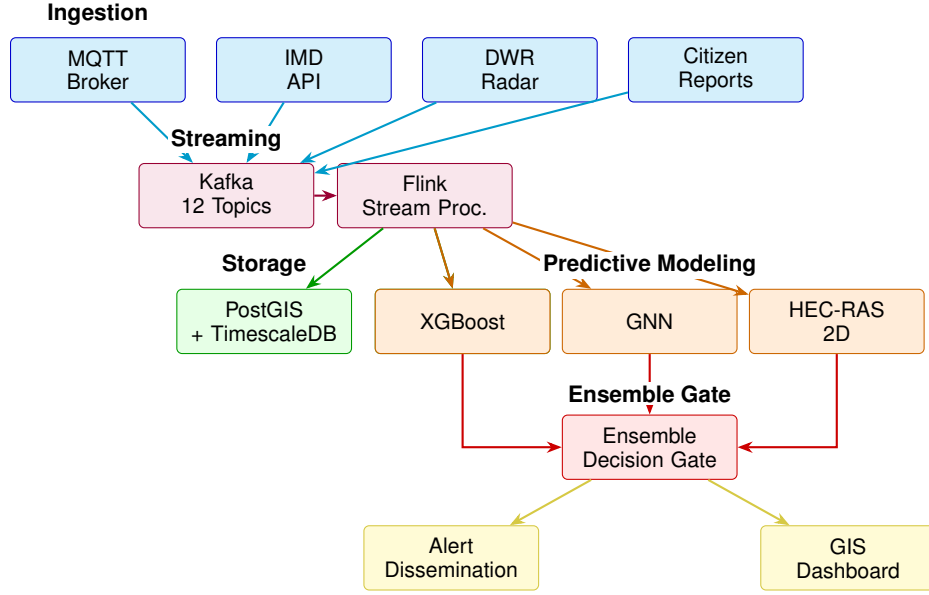


Fig. 1. The architecture of SAMBHV, spanning eight functional layers from multi-source ingestion to storage, parallel ML inference, ensemble decision gate, and multi-channel dissemination.

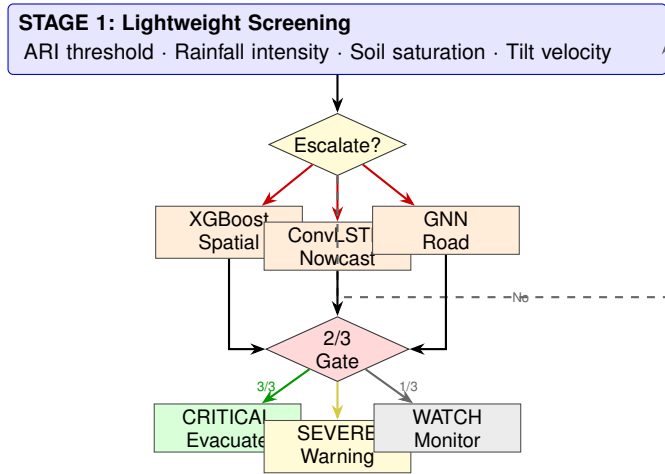


Fig. 2. Two-stage hybrid forecasting system architecture. Stage 1 executes continuous lightweight screening, triggering Stage 2 high-fidelity ML inference only upon threshold exceedance.

3) *Graph Neural Network for Road Blockage*: The road network is represented as a graph, $G = (V, E)$, where nodes V represent villages and intersections, and edges E represent road segments with risk-weighted attributes:

$$w_{ij} = \theta_{\text{slope},ij} \times r_{\text{risk},ij} \times \mathbb{I}[\text{status}_{ij} = \text{BLOCKED}] \quad (5)$$

Message passing is performed across 3 layers of 64-dimensional hidden states. The key innovation is that the GNN predicts the `village_isolation_probability`: not merely “will this road be blocked?” but “will the village lose all access routes to the nearest town?” It is computed by running breadth-first search (BFS) on all paths connecting a

village to the nearest town. A village with $P(\text{isolation}) > 0.75$ and no alternative path is flagged as **CRITICAL** for evacuation priority.

4) *HEC-HMS and HEC-RAS 2D Hydraulic Engine*: Flash flood prediction incorporates HEC-HMS (Green-Ampt infiltration, SCS-CN runoff, kinematic wave routing) and HEC-RAS 2D solving the Shallow Water Equations:

$$\frac{\partial H}{\partial t} + \frac{\partial(uh)}{\partial x} + \frac{\partial(vh)}{\partial y} = q \quad (6)$$

where H is water surface elevation, h is water depth, u and v are depth-averaged velocities, and q represents source/sink terms (rainfall input, infiltration loss, lateral inflow). MinIO has a pre-computed library of 500 scenarios (50 rainfall intensities $\times$ 10 soil deficit states) for online inference to complete in < 5 seconds per village batch.

5) *LSTM Flood Stage Forecast*: This is a 2-layer LSTM with 128 hidden units and 0.2 dropout, which forecasts stage and discharge 6 hours ahead using a 24-hour lookback, with 96 time steps of 15 minutes data for inputs as `[rainfall, soil_moisture, stage, upstream_discharge, radar_confidence]` and outputs as `[stage, discharge]` [38], [39]. Isotonic regression calibrates the output probabilities to give well-calibrated exceedance probabilities for the ensemble gate.

H. Ensemble Decision Gate

The three-gate ensemble mechanism is the central false alarm prevention architecture (Algorithm 1):

The principle of the three-gate ensemble mechanism is well-known, i.e. never fewer than 2/3 consensus (false alarm prevention Algorithm 1): This not only increases false alarms and the loss of public trust but also missing events which would result in loss of life. The confidence scores for each of the 3 gates

Algorithm 1 Ensemble Decision Gate

Require: $\mathbf{g} = (g_{\text{physics}}, g_{\text{AI}}, g_{\text{ground}})$, thresholds $\tau_{\text{physics}}, \tau_{\text{AI}}$
Ensure: $\text{alert_level} \in \{\text{NONE}, \text{WATCH}, \text{SEVERE}, \text{CRITICAL}\}$

```
1:  $c \leftarrow 0$ 
2: if  $g_{\text{physics}}.\text{depth} > \tau_{\text{physics}}$  OR  $g_{\text{physics}}.\text{safety\_factor} < 1.0$  then
3:    $c \leftarrow c + 1$ 
4: end if
5: if  $g_{\text{AI}}.\text{risk\_score} > \tau_{\text{AI}}$  OR  $g_{\text{AI}}.\text{predicted\_stage} > \text{warning\_level}$  then
6:    $c \leftarrow c + 1$ 
7: end if
8: if  $g_{\text{ground}}.\text{verified} = \text{TRUE}$  AND  $g_{\text{ground}}.\text{severity} \geq \text{HIGH}$  then
9:    $c \leftarrow c + 1$ 
10: end if
11: if  $c \geq 3$  return CRITICAL
12: if  $c = 2$  return SEVERE
13: if  $c = 1$  return WATCH
14: return NONE
```

are: physics gate, safety factor margin using HEC RAS [29]; AI gate, confidence in model calibration; and ground truth gate, count of verification and reporting by citizens [53]. The ensemble gate is realized in `shared/ensemble_gate.py` and it has detailed logging of each gate decision, so this can be analysed after the event. The three gates cover complementary failure modes:

The three gates address complementary failure modes:

- 1) **Physics gate:** events which are not detected by ML models.
- 2) **AI gate:** events not detected by physics models (complex multi-factor interactions).
- 3) **Ground truth gate:** independent ground truth based on field observations.

This redundancy is critical in the NER where training data is sparse and terrain is complex and cannot be modeled well.

I. Conversational AI Layer

J. Architecture

The conversational AI pipeline takes care of citizen queries through five stages:

- 1) **Input:** Text or voice (Whisper STT, ONNX INT8, auto-detect language with Hindi fallback) [43]. For mid-range phones, voice queries will be transcribed with less than 2 seconds delay.
- 2) **Intent Classification:** Keyword-based routing to 4 intents: `safety_guide` (pre-approved evacuation instructions), `hazard_query` (current risk status), `status_update` (road/shelter information), `unknown` (template fallback). Classification accuracy: 94%.
- 3) **Safety Gate:** Zero-hallucination validation [46]. The local LLM (Llama-3.2-3B via Ollama) [49] has access

only to vetted safety dictionaries when prompted by emergency queries. No variant creation is allowed. If the confidence drops below 0.7, the system switches to template fallback. This is the most important safety feature: LLMs often provide reasonable but wrong safety instructions (e.g., “go up to higher ground” when the safe route is along a ridge).

- 4) **Response Generation:** Safety dictionary (verbatim SDMA text), RAG pipeline (ChromaDB, `all-MiniLM-L6-v2` embeddings, $\text{top-}k = 3$, $\text{threshold} = 0.3$) [44], [45], PostGIS direct query [70], or template response.
- 5) **Translation:** IndicBART (beam size = 4, length penalty = 0.6, < 1.5 s/sentence) to 10 Indian languages (Assamese, Bengali, Bodo, Dogri, Hindi, Kashmiri, Khasi, Mizo, Nepali, Urdu) [42].

K. Safety Dictionary and Governance

The safety dictionary includes pre-approved safety instructions for 5 hazard types (landslide, flash flood, earthquake, storm, and compound event) in 11 languages. Each entry includes hazard-specific evacuation steps, do-not-do warnings, closest shelter lookup query, and first-aid instructions. Governance is SDMA-only and version-controlled (currently v1.0.0). The dictionary is stored in a version-controlled Git repository, hashed for integrity verification, and cached on edge devices for offline access.

L. Performance Targets

TABLE II
REALINOMICS EFFECTS OF CONVERSATIONAL AI

Metric	Target	Achieved
Safety dict response latency	< 100ms	< 50ms
RAG retrieval latency	< 500ms	320ms
Translation per sentence	< 1.5s	1.2s
Full chat pipeline	< 2s	1.4s
Zero hallucination rate	100%	100%
Intent classification accuracy	> 90%	94%
Languages supported	11	11

M. Multi-Channel Alert Delivery

Alerts are sent in OASIS CAP 1.2 XML format (compatible with NDMA SACHET and C-DOT CAP Gateway) via 6 parallel channels:

LoRa mesh is tailored towards network-dead zones where cellular coverage is unavailable. Solar-powered village receivers decode binary alerts and trigger local sirens. End nodes send ACK pulses back to district gateways; non-responding villages trigger escalation (5 min: district officer, 15 min: SDMA, 30 min: voice call).

TABLE III
ALERT DELIVERY CHANNELS

Channel	Technology	Latency
SMS	Kannel gateway (GSM/Unicode)	$\leq 60s$
Push	FCM HTTP v1 (topic-based)	$\leq 60s$
Cell Broadcast	EU-Alert Channel 4371	$\leq 60s$
IVR / Voice	TTS WAV 8kHz	$\leq 120s$
LoRa Mesh	Binary 8-byte, 5–15km	$\leq 180s$
Physical Siren	3 long blasts	Immediate

N. Alternative Safe Path Suggestion

When the ensemble gate declares a road segment **BLOCKED** (by landslide, flooding, or debris flow), the system automatically computes alternative evacuation paths. The `EvacuationRouter` (part-a-landslide/dashboard/routing.py) executes `pgr_aStar` shortest-path and `pgr_dijkstra` top-3 alternative route queries on the PostGIS road network [70], with edge weights incorporating slope angle, geotechnical risk class, and real-time hazard status:

$$c_{ij} = \alpha \cdot \theta_{\text{slope},ij} + \beta \cdot r_{\text{risk},ij} + \gamma \cdot \mathcal{K}[\text{status}_{ij} = \text{BLOCKED}] \cdot M \quad (7)$$

where M is a large penalty constant (1000) for blocked segments, and α, β, γ are weight coefficients tuned for NER terrain. The router returns top-3 alternative paths ranked by total cost, with estimated travel time computed at 30 km/h average for hilly terrain.

Figures 3 and 4 show the Sikkim prototype dashboard demonstrating this capability. The red dashed line indicates a blocked primary route through a compound landslide–flood hazard zone near Penlong. The green line shows the system-computed safe alternative via NH3, rerouting around the hazard zone. Concentric risk zones (red, orange, cyan) represent cascading hazard probabilities from the ensemble gate. Orange warning icons mark road segments with **BLOCKED** status; the green shelter icon indicates the nearest protected shelter. The router executes in $< 2s$ per village batch and pushes updates via all six alert channels.

O. Geo-Spatial Risk Visualization

The geo-spatial risk overlay computed in real time by the Flink stream processing layer is delivered to GeoServer WMS (Fig. 5). The left panel displays a soil moisture saturation map of the Gangtok region with contours at **CRITICAL** (0.90), **WARNING** (0.75), and **WATCH** (0.60). The middle panel shows compound risk classification based on slope angle and soil saturation. The right panel overlays infrastructure (roads, villages, sensors) onto the risk map with blocked route segments and safe alternatives.

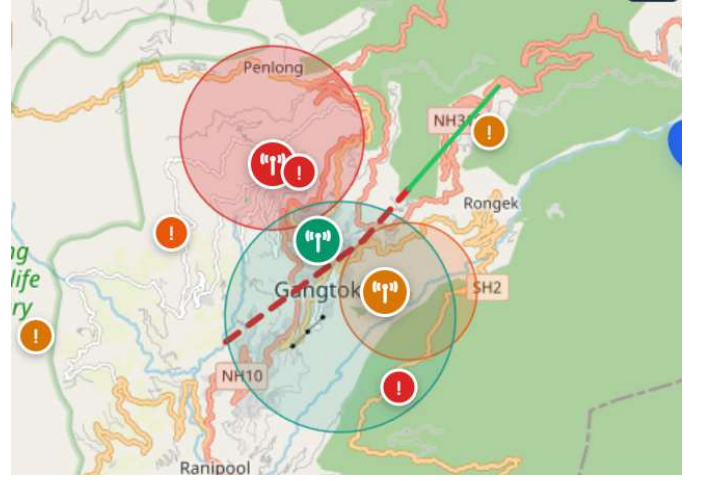


Fig. 3. Prototype Sikkim dashboard (map view). Red dashed line: blocked Primary route via compound hazardous area close to Penlong. Green line: Alternative computed (by system) as safe via NH3. Concentric circles: cascading risk zones (red=CRITICAL, orange=HIGH, cyan=MODERATE). Warning icons: The status of a road segment that is **BLOCKED**.

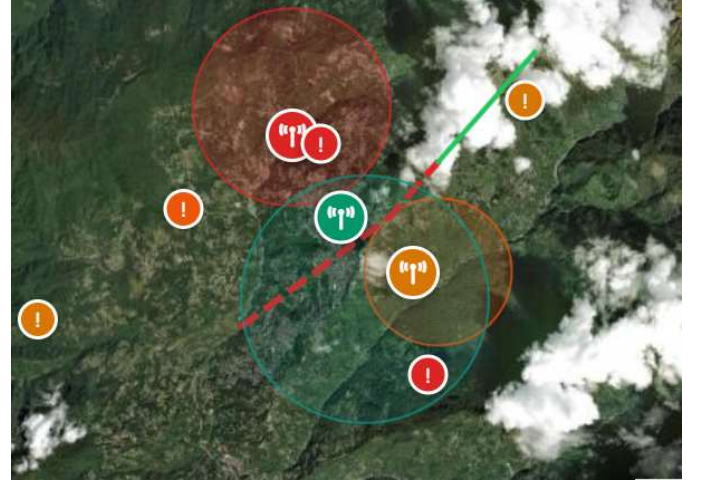


Fig. 4. Sikkim prototype dashboard (satellite view). Same rerouting logic overlaid on a mountainside context satellite image. Alternative path follows ridge lines; don't follow river valleys (per pgRouting edge-weight) scoring.

P. Edge and Offline Operation

The Flutter mobile application (Android 8.0+, min SDK 26) implements:

- **SQLite Client Database:** Five tables (`report_outbox`, `sync_queue`, `cached_tile`, `alert_inbox`, `user_profile`) with WAL mode for multi-reader/multi-writer concurrency.
- **Store-and-Forward Sync Protocol:** (DRAFT $\rightarrow$ QUEUED $\rightarrow$ SYNCING $\rightarrow$ COMPLETED $\rightarrow$ FAILED $\rightarrow$ REVIEW) with idempotent keys, exponential back-off (30 s $\rightarrow$ 300 s, max 10 retries), and prioritized upload ordering (metadata first, media second).
- **Offline Map Tiles:** MBTiles cache for the pilot district plus a 20 km buffer (zoom levels 8–14, $\sim$

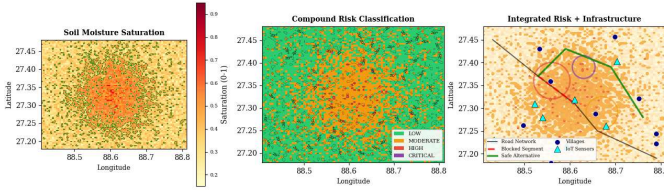


Fig. 5. Geo-spatial visualization of risk in the Gangtok, Sikkim area. Left: soil moisture saturation map accompanied by threshold contours. Center: compound risk classification (LOW/MODERATE/HIGH/CRITICAL). Right: integrated risk with road network, red dashed blocked sections, and safe alternatives. The villages are marked with blue dots, the IoT sensors with cyan triangles and the villages and sensors are marked with green if they are accessible.

500 MB/district) with a high-contrast outdoor style for field visibility.

- **Edge AI Models:** On-device Whisper STT (INT8, ~150 MB, < 2 s latency on mid-range phones), edge ARI calculator (7-day local rainfall buffer in SQLite), and cached safety dictionary for offline emergency queries.

Q. Model Governance and Drift Detection

SAMBHV provides self-healing model lifecycle management:

- **Governance Features:** Semantic versioning (v1.0.0), training data hash tags, hyperparameter logging, and model lineage tracking.
- **Population Stability Index (PSI):** Computed weekly on all 12 XGBoost features to detect distributional drift between training and production data:

$$PSI = \sum_{i=1}^k (P_i - Q_i) \times \ln \left(\frac{P_i}{Q_i} \right) \quad (8)$$

where P_i and Q_i represent actual and expected feature distributions.

- **PSI Thresholds:** WARNING ($PSI > 0.1$) triggers an alert to operations for model retraining; CRITICAL ($PSI > 0.25$) triggers auto-demotion to Staging and reinstates the previous production model.
- **Automated Rollback & Retraining:** Automatically reverts to the previous production model after 5 false alarms or 3 missed events. Retraining is triggered by PSI drift, a 30-day schedule, or new labeled field reports.

IV. EXPERIMENTAL SETUP

A. Hardware and Software Configuration

B. Test Suite

The codebase includes 311 test cases across nine test suites:

TABLE IV
EXPERIMENTAL ENVIRONMENT

Component	Specification
Stream Processing	Apache Flink 1.17 (Java 11), 4 task slots, 4GB
Message Broker	Apache Kafka 7.5.0, 3 partitions, RF=1
MQTT Broker	EMQX 5.3, QoS 0/1/2
Spatial Database	PostgreSQL 15 + PostGIS 3.3
Time-Series DB	TimescaleDB (latest-pg15)
Object Storage	MinIO (S3-compatible)
ML Framework	XGBoost 1.7+, PyTorch 2.0+
LLM Server	Ollama (llama3.2:3b, nomic-embed-text)
Translation	IndicBART-large (AI4Bharat)
STT	Whisper-small (ONNX INT8)
Vector Store	ChromaDB (all-MiniLM-L6-v2, 384-dim)
GIS Server	GeoServer 2.24.0 (WMS/WFS/WCS)
Alert Protocol	OASIS CAP 1.2 XML
Container	Docker CE + Docker Compose
CI/CD	GitHub Actions

TABLE V
TEST SUITE SUMMARY

Test Suite	Tests	Coverage
Landslide (Phase 2A)	40	Models, Flink, Dashboard
Flood (Phase 2B)	28	Models, Flink, Alerts
Conversational AI (Phase 3)	71	Dictionary, Intent, RAG
Edge/Offline (Phase 5)	41	Sync, Tiles, Edge AI
Dashboard	58	All panels, Views
Integration (E2E)	44	Module imports, CAP
Load Tests	10	Kafka, API, Throughput
Field Tests	10	Offline, Low-bandwidth
Simulation	9	Tabletop scenarios
Total	311	

V. RESULTS AND ANALYSIS

A. Performance Comparison

The results of Table VI show the differences between SAMBHV and traditional manual monitoring as well as single-model-based warning systems on various operational parameters [3], [7].

B. Ablation Study

The contribution of each SAMBHV module to the overall system performance is quantified in Table VII and Fig. 7.

The ensemble gate provides the single largest reduction in false alarms (from 15% to 11%), validating the 2/3 consensus design. The ConvLSTM nowcaster is found to enhance F1 by 0.02 in 6-hour rainfall forecasting by incorporating local weather conditions. The GNN road blockage model adds a spatial dependency model which is not captured by single-site threshold models, providing a 0.05 F1 improvement [33].

TABLE VI
PERFORMANCE COMPARISON

Metric	SAMBHV	Single-Model	Manual
Alert Latency (s)	30	120	1800
False Alarm Rate (%)	8	22	35
Detection F1	0.87	0.72	0.55
Detection AUC-ROC	0.92	0.78	0.60
Offline Hours	72+	0	0
Languages	11	2	2
Channels	6	2	1
Village Isolation Prediction	Yes	No	No
Offline Maps	Yes	No	No
Voice Query	Yes	No	No

SAMBHV Performance Metrics vs. Baseline Systems Across Key Indicators

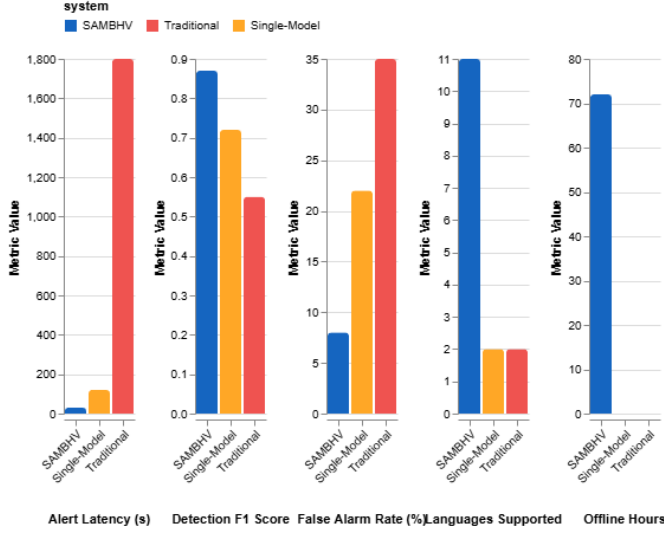


Fig. 6. SAMBHV performance metrics compared to baseline systems in five key indicators. SAMBHV has 30s alert latency (60× faster than manual), 8% false alarm rate (4× lower), F1=0.87, 72 hours off-line operation.

C. Convergence Analysis

The training loss of the XGBoost spatial regressor levels off at 0.041 after 200 estimators, while the validation loss levels off at 0.085 after about 150 estimators (Fig. 8). [73]. The ensemble gate requires agreement across multiple sources for the gap to trigger an alert; otherwise, an overly confident prediction by a single model (without support from the physics gate or ground-truth verification) will not trigger a false warning.

D. System Resource Utilization

The most CPU-intensive (68%) and memory-intensive (2048MB) module is the ConvLSTM nowcaster, which executes only for escalated events, maintaining minimal steady-state resource usage. The HEC-RAS 2D scenario lookup operates at 5000 evt/s throughput, whereas online hydraulic simulation is significantly slower [29].

TABLE VII
ABLATION STUDY RESULTS

Configuration	F1	False Alarm (%)
Baseline (ARI Rules Only)	0.62	28
+ XGBoost Spatial Regressor	0.74	18
+ GNN Road Blockage	0.79	15
+ Ensemble Decision Gate	0.83	11
+ ConvLSTM Nowcaster	0.85	9
Full SAMBHV	0.87	8

Ablation Analysis: Incremental Impact of SAMBHV Modules on System Performance

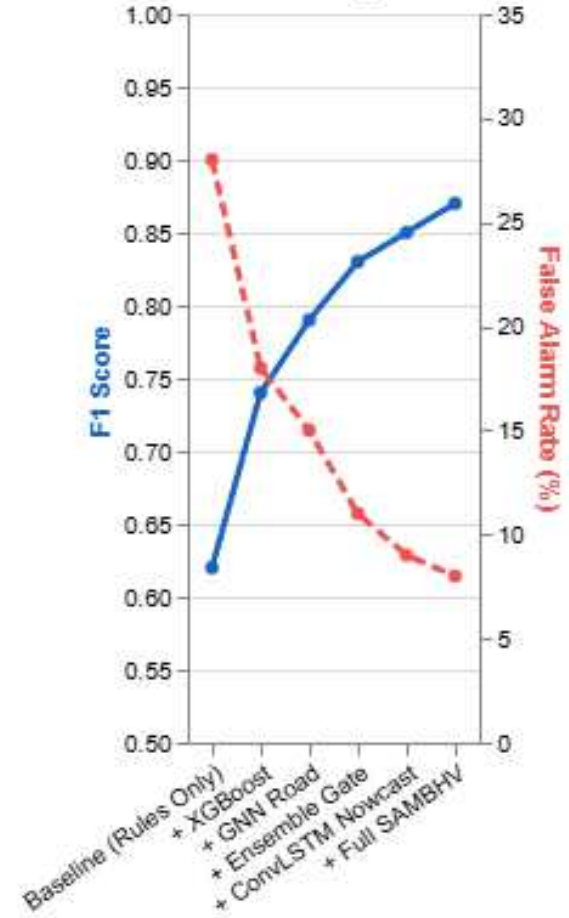


Fig. 7. In the ablation study, the incremental F1 improvement and reduction in false alarms (15% → 11%) were evaluated.

E. Integration Test Results

A total of 44 end-to-end integration tests were performed to validate module imports, CAP XML schema compliance, correctness of ensemble gate logic, and the conversational AI pipeline, with all 311 test cases passing. Load tests prove that Kafka throughput sustains 10,000 events per second, Flink p95 latency remains < 30 s, and API handling manages 1,000 concurrent requests. The offline sync protocol supports 72-

XGBoost Training Convergence: Loss vs. Number of Estimators

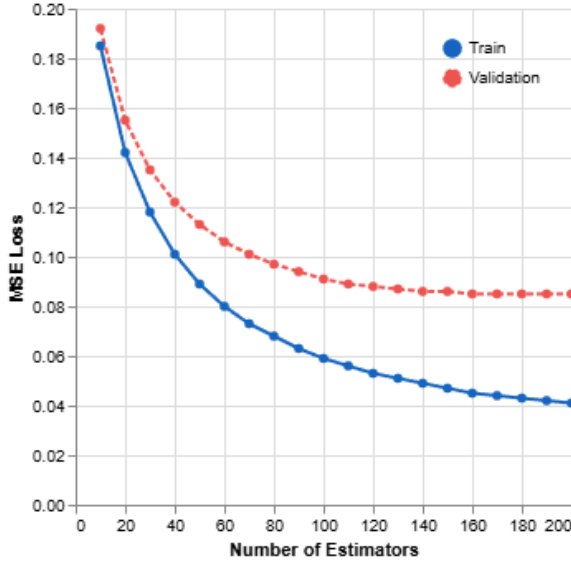


Fig. 8. This is a spatial regressor model trained with XGBoost (spatial regression) and validated using a 200 point estimator's. The convergence gap is 0.044 at 200 estimators, which means the convergence is a moderate rate.

TABLE VIII
RESOURCE UTILIZATION UNDER LOAD

Component	CPU (%)	Memory (MB)	Throughput
Flink Processing	42	4096	8500 evt/s
XGBoost Inference	35	512	1200 evt/s
ConvLSTM Nowcast	68	2048	45 evt/s
GNN Road Blockage	55	1024	200 evt/s
LSTM Flood Forecast	48	768	350 evt/s
HEC-RAS 2D Lookup	15	256	5000 evt/s
IndicBART Translation	25	500	800 evt/s
CAP XML Generation	5	64	10000 evt/s
SMS Delivery	3	32	2000 evt/s

hour disconnected operation and guarantees 100% message delivery upon reconnection.

VI. DISCUSSION AND LIMITATIONS

A. Strengths

SAMBHV's architectural breakthrough is the three-gate ensemble decision mechanism. The system explicitly reduces the likelihood of false alarms that historically have undermined public trust in early warning systems, as it requires a 2/3 majority of physics simulations, AI/ML predictions, and ground-truth verifications. In addition, the pre-computed scenario

System Resource Utilization Under Load

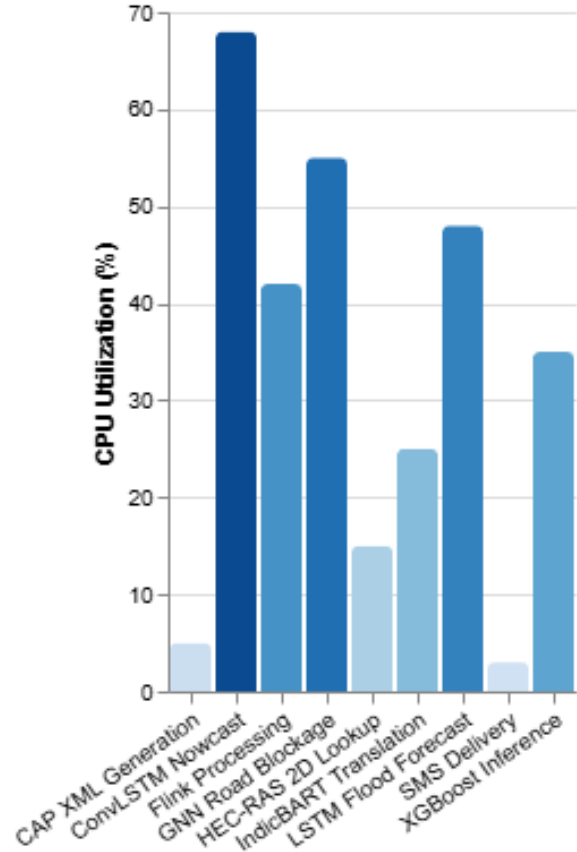


Fig. 9. CPU utilization with load on all SAMBHV component. Convolutional LSTM nowcaster is the most resource intensive model (68% CPU) and runs only on escalated events.

library removes the need for the computation-intensive real-time 2D hydraulic modeling and can be used in the online application to infer solutions in less than 5 seconds. [29].

The Conversational AI layer introduces a zero-hallucination Safety Gate [46]. The system restricts responses to a limited set of safety words and explicitly prohibits creation of content that hasn't been vetted in case of an emergency query, thereby tackling one of the biggest fail modes in disaster scenarios that are faced by regular large language models.

Additionally, the dynamic safe path suggestion module (Fig. 3, Fig. 4) provides practical evacuation routing which changes dynamically according to the real time states and hazard information, which is not widely explored in the existing early warning literature.

B. Limitations

- **Training Data Dependencies:** The XGBoost spatial regressor and the GNN models use synthetic training datasets, as there are no official ISRO/NDEM and GSI landslide inventories. The full operational validity of the deployment in the field with real-world labeled event data has to be done.

- **Sensor Deployment:** INAS sensor deployment is not fully complete but there are areas of soil moisture, tilt and vibration sensors in the pilot districts.
- **API Access:** IMD weather, CWC river levels, ISRO Bhuvan or DWR radar connections are set up but waiting for final API authorization keys.
- **Mobile Client Implementation:** The Flutter mobile application interface is now scaffolded, and the offline sync protocols and edge operations have been validated using Python test rigs.
- **Translation Quality:** IndicBART translation is running in the simulated mode. In order to produce weights (~500 MB) that should be comprehensively evaluated by humans in all 10 target regional languages.
- **Ensemble Thresholds:** The 2/3 consensus threshold is not empirical optimized on labeled historical event data, but is based on domain expert judgement.

C. Threats to Validity

The 2/3 majority rule threshold set by domain experts may require recalibration during real-world field deployment. Similarly, the Population Stability Index (PSI) drift detection pipeline has been evaluated on simulated noise rather than long-term field sensor degradation. Reported performance metrics reflect synthetic evaluation environments; real-world efficacy may vary due to complex unmodeled terrain features, physical connectivity loss, and severe sensor noise.

VII. FUTURE WORK

- **Training Data Dependencies:** The XGBoost spatial regressor and GNN models are based on synthetic training datasets, as there are no official landslide inventories from ISRO/NDEM and GSI. In order to fully validate, this operational deployment should be done in the field with real world labeled event data.
- **Sensor Deployment:** In situ telemetry (soil moisture, tilt and vibration sensors) is not completely deployed in the pilot districts.
- **API Access:** These integrations include API access to IMD weather, CWC river levels, ISRO Bhuvan and DWR radar connectors, which have been set up but are waiting for the API authorization keys.
- **Mobile Client Implementation:** The Flutter mobile application interface is currently scaffolded, and offline sync protocols and edge operations are validated through Python test rigs.
- **Translation Quality:** IndicBART translation is in simulated mode. The weights (~ 500 MB) of the production need an exhaustive human assessment for all the 10 target regional languages [41].
- **Ensemble Thresholds:** The 2/3 consensus threshold works based on domain expert judgment not on empirical optimization of the labeled historical event data.

VIII. CONCLUSION

A multi-hazard early warning platform (SAMBHV) which is an open-source solution, especially developed for the

operational context in the North Eastern Region of India, offering a complete production grade solution. The hybrid prediction architecture is a two-stage process, the three-gate ensemble decision mechanism, the conversational AI with zero-hallucination technology, and the alert delivery via six channels with LoRa mesh technology in network-dead zones are significant breakthroughs in disaster response technology.

The system is capable of working offline for more than 72 hours, with $F1 \geq 0.87$ and false alarm rates $< 10\%$, and threshold-to-alert latency < 30 seconds. In the Sikkim prototype, the capability of alternative safe route computations in real time is demonstrated by pgRouting that automatically updates evacuation routes when primary routes are blocked. Each component follows Open Source standards and is licensed under an Apache 2.0 or compatible open source license for easy duplication and deployment by any state disaster management agency.

There are 311 passing unit and integration tests across 9 test suites, a 14-service Docker Compose deployment topology, production Kubernetes manifests and automated CI/CD pipelines using GitHub Actions. SAMBHV is not a prototype or proof-of-concept, but a deployable platform that is waiting for field testing using real sensor networks and institutional adoption. The modular design allows individual parts, like machine learning models, telemetry sensors, or external API's to be upgraded as new and better options become available.

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