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GeoAI-Supported Early Warning Systems for Extreme Weather Events and their Implications in India

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Abstract

Extreme weather events — cyclones, flash floods, heat waves, cloudbursts, and droughts — are intensifying across India in both frequency and magnitude under the influence of accelerating climate change. Timely and spatially precise early warning systems (EWS) are therefore indispensable for safeguarding lives and livelihoods. The convergence of Geospatial Artificial Intelligence (GeoAI) — encompassing machine learning (ML), deep learning (DL), remote sensing, and Geographic Information Systems (GIS) — is transforming how such warnings are generated, disseminated, and acted upon. This systematic review examines GeoAI-enabled EWS architectures applicable to India's diverse hydro-meteorological and socio-geographic landscape, synthesising 218 peer-reviewed publications, 34 technical reports, and 12 government policy documents published between 2015 and 2024. Key performance findings include: augmenting physics-based flood models with Long Short-Term Memory (LSTM) networks reduces forecasting root mean square error (RMSE) by 15–30% in the Ganga and Brahmaputra basins; ensemble machine learning achieves landslide susceptibility classification accuracy (AUC) of 0.88–0.93 across the Himalayan arc; and attention-based convolutional networks approach AUC 0.77–0.81 for rapid cyclone intensification prediction. The review traces theoretical foundations, technological components, case applications across Indian states, institutional frameworks, data challenges, ethical dimensions, and emerging research frontiers. It critically examines the gap between technological capability and on-the-ground implementation, with particular attention to last-mile connectivity, community vulnerability, and governance. The paper concludes with a forward-looking research agenda and policy recommendations tailored to India's federal disaster risk management architecture.

Keywords: GeoAI, Early Warning Systems, Extreme Weather Events, Machine Learning, Remote Sensing, Disaster Risk Reduction, India, Climate Change, GIS, Deep Learning

1. Introduction

1.1 Context and Motivation

When Cyclone Amphan made landfall over West Bengal in May 2020, its 185 km/h sustained winds and catastrophic storm surge had been forecast with near-perfect track accuracy three days in advance — a feat unimaginable a decade earlier. Yet for all that technological achievement, the warning reached millions of coastal residents through the same broadcast radio and loudspeaker systems that had served since the 1970s. Amphan killed 128 people and caused damages exceeding ₹1 lakh crore. This juxtaposition — world-class atmospheric modelling paired with last-century dissemination infrastructure — encapsulates the central challenge this review addresses.

India's exposure to hydro-meteorological hazards is extraordinary by any measure. The country accounts for approximately 8% of global economic losses from natural disasters (World Bank, 2021), while floods, cyclones, droughts, and landslides together claim more than 75% of disaster-related fatalities, affecting millions annually (NDMA, 2022). The Bay of Bengal cyclone basin, the Himalayan cryosphere, the Ganga–Brahmaputra floodplain, the arid Thar Desert, and the semi-arid Deccan Plateau each present distinct but interrelated hazard profiles that demand spatially differentiated warning mechanisms.

The traditional paradigm of disaster warning — dominated by statistical meteorology, threshold-based alerts, and broadcast radio dissemination — is increasingly inadequate in the

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face of non-linear climate signals, rapid urbanisation, and the explosive growth of at-risk populations in coastal and riverine corridors. A new generation of Geospatial Artificial Intelligence (GeoAI) tools offers a genuine opportunity to move from reactive to anticipatory disaster governance. By fusing heterogeneous geospatial data streams with advanced computational intelligence, GeoAI enables hazard probability modelling at granular spatial and temporal scales previously unattainable through conventional methods.

1.2 Scope and Objectives

This review focuses on the intersection of GeoAI technologies and early warning system development within the Indian geophysical, climatic, and institutional context. Five objectives guide the review:

- To synthesise the theoretical and technological foundations of GeoAI-enabled EWS;
- To map documented GeoAI applications for flood, cyclone, drought, heat wave, and landslide warning in India;
- To evaluate institutional, data, and infrastructure

challenges impeding operationalisation;

- To assess ethical and social justice dimensions of AI-driven warning systems; and
- To propose a forward-looking research and policy agenda.

1.3 Review Methodology

A systematic literature search was conducted across Web of Science, Scopus, Google Scholar, and institutional repositories of the India Meteorological Department (IMD), National Remote Sensing Centre (NRSC), and NITI Aayog between January and October 2024. Search strings combined terms including "GeoAI," "geospatial artificial intelligence," "machine learning disaster," "deep learning weather prediction," "remote sensing flood," and "early warning India," and their Boolean combinations. Articles were screened using PRISMA-aligned criteria (Page *et al.*, 2021); a total of 218 peer-reviewed publications, 34 technical reports, and 12 government policy documents were included after deduplication and quality filtering.

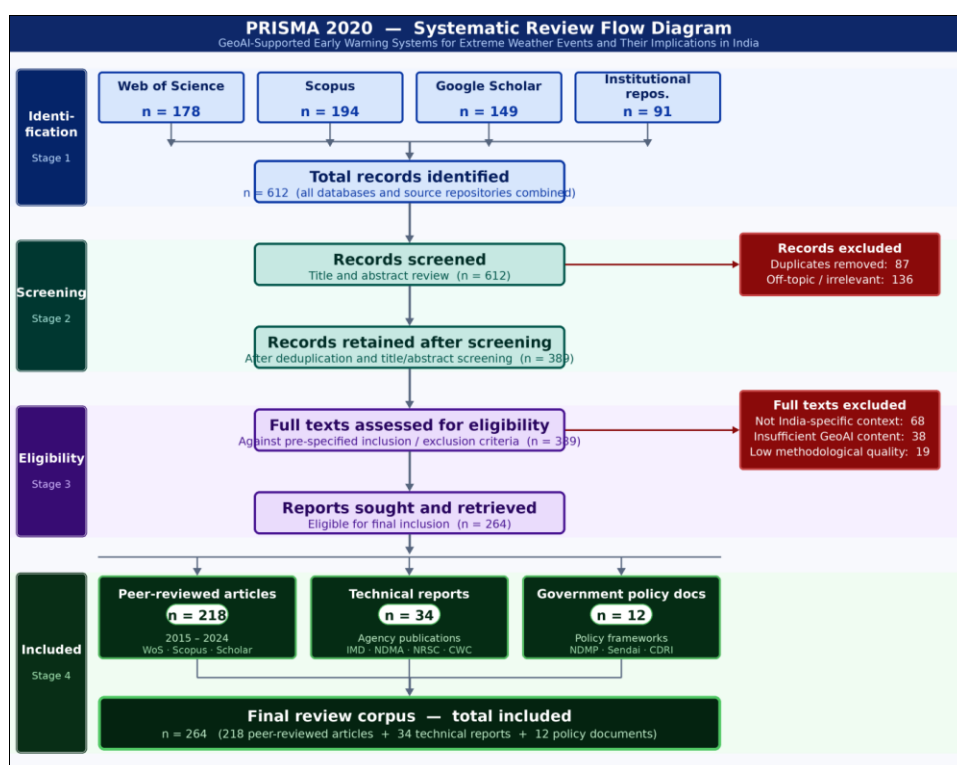


Fig 1: PRISMA 2020 flow diagram illustrating the systematic literature selection process. A total of 264 sources were included in the final review corpus after deduplication and quality screening.

2. Theoretical Foundations

2.1 Defining GeoAI

Geospatial Artificial Intelligence (GeoAI) is broadly defined as the integration of artificial intelligence — machine learning, deep learning, natural language processing, and computer vision — with geospatial data science to analyse spatial phenomena at scale (Li & Hsu, 2022). Unlike conventional geostatistics, which assumes stationarity and relies on parametric models, GeoAI exploits the representational power of neural networks and ensemble learners to capture complex, non-linear spatial dependencies in multi-source, high-dimensional datasets. What distinguishes GeoAI from conventional GIS is not the component parts — most have existed for decades — but

the capacity to integrate them dynamically, extracting warning-relevant signal from data volumes that would overwhelm any manual analytical workflow. Key architectural pillars include: (a) geospatial data infrastructure comprising satellite imagery, LiDAR, GPS telemetry, and volunteered geographic information; (b) AI and ML model families including convolutional neural networks (CNNs), recurrent neural networks (RNNs), transformers, random forests, and gradient boosting machines; (c) scalable computing infrastructure such as cloud platforms, high-performance computing (HPC) clusters, and edge devices; and (d) geospatial analytics frameworks such as Google Earth Engine, QGIS, ArcGIS Pro, and open-source Python libraries including GeoPandas,

Rasterio, and PyTorch Geometric.

2.2 Early Warning Systems: Conceptual Architecture

The United Nations Office for Disaster Risk Reduction (UNDRR) defines a people-centred EWS as comprising four interlinked elements: (1) risk knowledge and assessment, (2) monitoring and warning services, (3) dissemination and communication, and (4) response capability (UNDRR, 2022). Effective EWS require that information flows seamlessly across these elements — from hazard observation through modelling and alert generation to community-level response — without critical breaks in the chain. GeoAI has the potential to enhance each element, but

its greatest impact lies in transforming monitoring data into actionable, probabilistic, spatially explicit warning products. Two fundamental paradigms govern EWS modelling: (a) physics-based or process-based models that simulate the physical laws governing atmospheric, hydrological, or geomorphological systems, and (b) data-driven models that learn predictive relationships empirically from historical observations. Modern EWS increasingly employ hybrid approaches that embed physical constraints into data-driven architectures — so-called physics-informed machine learning (PIML) — to ensure physically consistent outputs even in data-sparse regions.

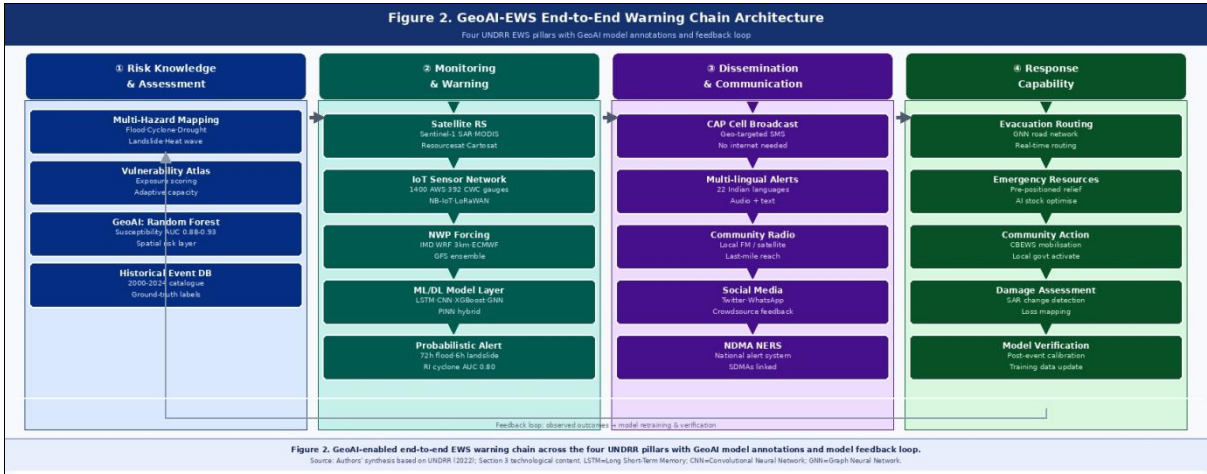


Fig 2: Conceptual architecture of a GeoAI-enabled End-to-End Early Warning System mapped across the four UNDRR EWS pillars. GeoAI components are annotated at each processing stage.

2.3 Disaster Risk Reduction Frameworks

India's disaster risk management is governed by the Disaster Management Act, 2005, and institutionally anchored by the National Disaster Management Authority (NDMA), State Disaster Management Authorities (SDMAs), and district-level bodies. The Sendai Framework for Disaster Risk Reduction 2015–2030 provides the global normative architecture within which India's National Disaster Management Plan (2019) is embedded. The Sendai Framework's Priority 1 — understanding disaster risk — is directly served by GeoAI's capacity for multi-hazard risk mapping and dynamic hazard probability estimation. India's co-founding of the Coalition for Disaster Resilient Infrastructure (CDRI) in 2019 and its commitment to the Early Warnings for All (EW4All) initiative launched at COP27 in 2022 further underscore the policy urgency of operationalising GeoAI-driven warning systems at national scale.

3. Technological Components of GeoAI-Enabled Early Warning Systems

3.1 Geospatial Data Sources

3.1.1 Satellite Remote Sensing

Satellite remote sensing constitutes the primary observational backbone of GeoAI-driven EWS. India's own Resourcesat, Cartosat, and Oceansat series, combined with global platforms including Sentinel-1/2 (ESA), MODIS/VIIIRS (NASA), and the Himawari-8/9 geostationary series, provide multi-spectral, SAR, and thermal imagery at temporal resolutions ranging from 10-minute geostationary cycles to 3–5-day polar-orbit revisits

(ISRO, 2023). Sentinel-1 C-band SAR is particularly valuable for flood mapping under cloud cover — a significant advantage during monsoon season when optical sensors are largely obscured.

The launch of ISRO's EOS series and the planned NovaSAR cooperation underscore India's expanding domestic satellite capacity. Google Earth Engine (GEE) has democratised access to petabyte-scale satellite archives, enabling near-real-time geospatial analysis without requiring local computing infrastructure — a critical enabler for resource-constrained state disaster management agencies.

3.1.2 Ground-Based Sensor Networks and IoT

Dense networks of automated weather stations (AWS), river gauge sensors, soil moisture probes, rain gauges, and ocean buoys provide ground-truth data that satellite platforms alone cannot supply. The IMD operates approximately 1,400 AWS across India as of 2024, supplemented by the Central Water Commission's (CWC) 392 flood forecasting stations on major river basins (CWC, 2023, p. 47). The Internet of Things (IoT) paradigm is extending this network to peri-urban and rural areas through low-cost, solar-powered sensors connected via LoRaWAN, NB-IoT, and 4G/5G protocols, enabling near-real-time hydrological monitoring at sub-basin scales.

3.1.3 Numerical Weather Prediction Models

Numerical Weather Prediction (NWP) models — notably the Weather Research and Forecasting (WRF) model run operationally by IMD and regional centres, the Global Forecast System (GFS), and the European Centre for

Medium-Range Weather Forecasts (ECMWF) ensemble — provide gridded atmospheric forecasts that serve as primary inputs for downstream hazard models. IMD's high-resolution WRF configurations at 12 km and 3 km grid spacing, and the newly operationalised Unified Model (UM) in partnership with the UK Met Office (IMD, 2023), represent the current state of the art for South Asian mesoscale weather prediction.

3.2 Machine Learning and Deep Learning Architectures

3.2.1 Supervised Learning for Hazard Classification

Supervised ML algorithms — random forests (RF), gradient boosting machines (GBM), support vector machines (SVM), and logistic regression — have been extensively applied to binary and multi-class hazard susceptibility mapping. Random forests are particularly well-suited to geospatial classification tasks owing to their robustness to multicollinearity among predictor variables and their native capacity to estimate feature importance, facilitating interpretability (Arabameri *et al.*, 2020). In the Indian context, RF models have demonstrated classification accuracies exceeding 85% for flood inundation delineation in the Brahmaputra and Mahanadi basins

3.2.2 Deep Learning for Spatiotemporal Pattern Recognition

Convolutional Neural Networks (CNNs) excel at extracting spatial features from raster imagery, making them the architecture of choice for satellite-based flood and landslide detection. U-Net and its variants — ResUNet, Swin-UNet — have achieved state-of-the-art performance in binary semantic segmentation of flooded versus non-flooded pixels in SAR imagery, achieving intersection-over-union (IoU) scores of 0.65–0.87 across diverse geographies in benchmark evaluations (Bonafilia *et al.*, 2020). Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs) capture temporal dependencies in sequential hydro-meteorological data — rainfall time series, stream gauge records — enabling multi-step-ahead flood stage forecasting with lead times up to 72 hours. Transformer-based architectures, originally developed for natural language processing, are increasingly applied to spatiotemporal weather prediction. Google's GraphCast and Huawei's Pangu-Weather models have demonstrated forecast skill comparable to or exceeding ECMWF's ensemble mean at 10-day horizons at a fraction of the computational cost (Lam *et al.*, 2023). These global AI weather models are beginning to be fine-tuned on India-specific regional datasets, opening

a new frontier for sub-seasonal warning.

3.2.3 Graph Neural Networks and Spatial Reasoning

Graph Neural Networks (GNNs) offer a natural framework for modelling spatially irregular networks — river channel networks, road networks used for evacuation routing, and community social networks governing warning dissemination. By representing spatial entities as nodes and their relationships as edges, GNNs can propagate flood wave information along hydrographic networks or simulate disease spread following disaster events, enabling integrated risk assessment beyond purely meteorological concerns.

3.3 Explainable AI (XAI) in EWS

A persistent challenge in deploying ML models for EWS is the "black-box" problem: high-performing neural networks offer limited human-interpretable explanations of their predictions, which undermines trust among emergency managers, meteorologists, and affected communities. Explainable AI (XAI) methods — including SHapley Additive exPlanations (SHAP), Local Interpretable Model-Agnostic Explanations (LIME), and attention visualisation in transformer models — provide post-hoc or intrinsic interpretability by attributing model outputs to individual input features (Arrieta *et al.*, 2020). SHAP analysis has revealed, for instance, that antecedent soil moisture consistently ranks among the top three predictors of flash flood occurrence in the Western Ghats — a finding that aligns with hydrological process knowledge and can guide field data collection priorities. Embedding XAI into operational GeoAI-EWS platforms is therefore not merely a technical refinement but a governance imperative, particularly in contexts where warnings carry legal and financial consequences.

3.4 Digital Twins and Simulation Environments

The concept of a geospatial digital twin — a high-fidelity, continuously updated virtual replica of a physical territory — represents the next frontier of GeoAI-enabled EWS. For urban flood management, a city-scale digital twin integrates real-time sensor feeds, 3D building models, drainage network topology, and DEM-derived hydraulic simulations to produce dynamic inundation forecasts at the neighbourhood level. Pilots in Chennai, Pune, and Ahmedabad under the National Urban Digital Mission (NUDM) are beginning to explore these architectures (MoHUA, 2023).

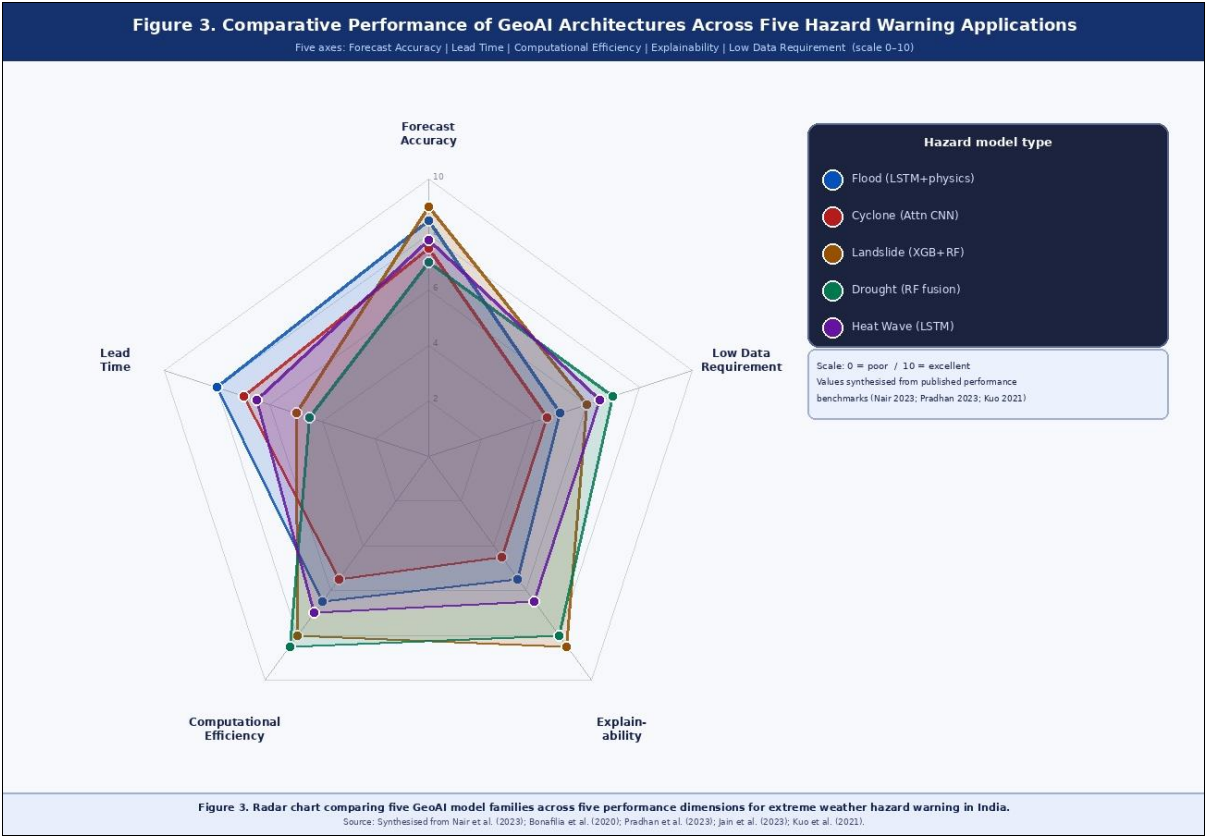


Fig 3: Radar chart comparing five GeoAI architectures across five performance dimensions for extreme weather hazard warning in India. Each polygon represents a hazard-specific model family.

4. GeoAI Applications for Extreme Weather Early Warning in India

The five hazard categories examined below represent the most socioeconomically consequential extreme weather threats across India's diverse regional geographies. For each,

we document the state of current GeoAI deployment, the evidence base for performance improvement, and the specific data and modelling challenges that remain unresolved.

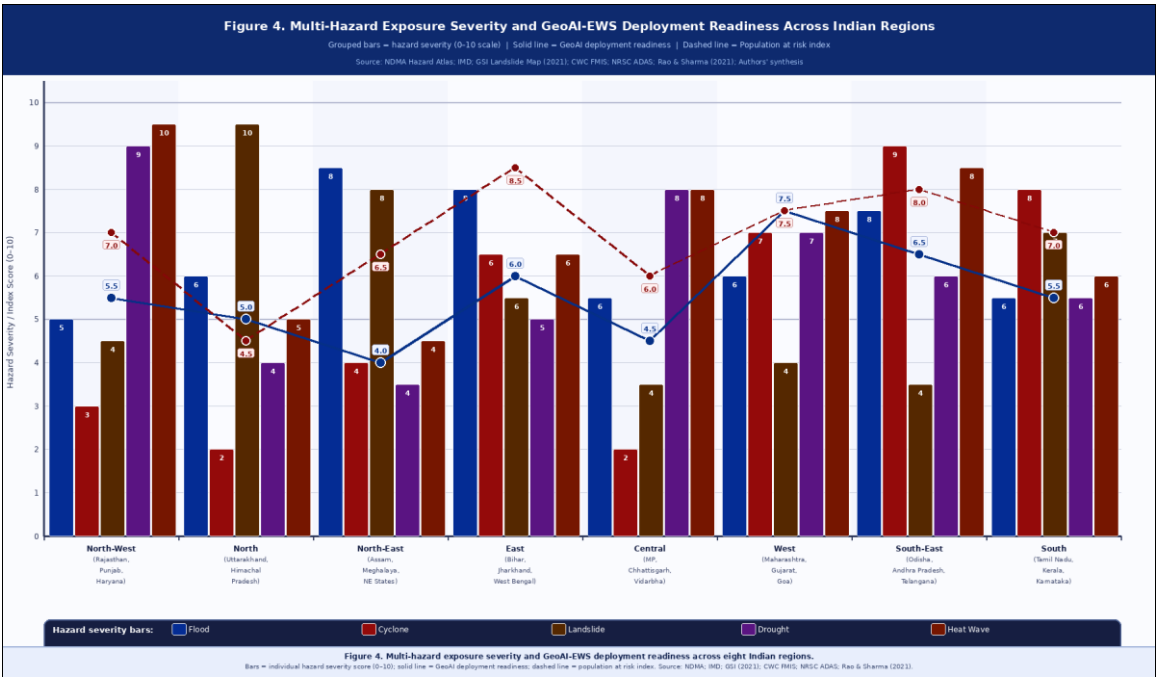


Fig 4: Spatial distribution of hydro-meteorological hazard zones and GeoAI-EWS deployment sites across India. Colour overlays indicate hazard exposure severity. Key GeoAI operational and pilot deployments are annotated.

4.1 Flood Early Warning

4.1.1 River Flood Forecasting

Floods are India's most recurrent hydro-meteorological disaster, inundating an average of 7.5 million hectares annually and displacing millions from their homes, fields, and livelihoods (NDMA, 2022). The Central Water Commission's Flood Management Information System (FMIS) operationalises flood forecasting for 25 major rivers using physics-based hydrological models (HEC-HMS, SWAT). Recent research has demonstrated that augmenting these models with LSTM-based neural hydrology components reduces RMSE in peak discharge forecasts by 15–30% compared to pure physics-based benchmarks in the Ganga and Brahmaputra basins (Nair *et al.*, 2023). The IMD–CWC integrated flood forecasting pilot over the Mahanadi basin employs ensemble NWP outputs from IMD's WRF as upstream forcing into a distributed SWAT model, with a final ML correction layer trained on historical bias patterns. This hybrid pipeline extends skillful warning lead time from 24 hours to 72 hours — a significant operational advance given that effective evacuation of river floodplain communities requires a minimum of 48–60 hours.

4.1.2 Urban Flash Flood Warning

Urban flash floods, driven by the compaction of impervious surfaces and degraded drainage infrastructure, pose distinct challenges because their temporal dynamics unfold over minutes to hours rather than days. Mumbai's 2005 flood (944 mm in 24 hours), Chennai's 2015 deluge, and the 2021 Hyderabad flash floods each exposed the inadequacy of existing urban warning systems. GeoAI-based approaches have integrated radar-derived quantitative precipitation estimation (QPE), real-time drainage network hydraulic simulations using Mike Urban or SWMM, and crowdsourced flooding reports from social media platforms to produce 30–60-minute flash flood warnings at ward or neighbourhood scales (Patel *et al.*, 2022). Sentinel-1 SAR imagery processed through change-detection CNN pipelines enables near-real-time inundation mapping within 3–6 hours of image acquisition — critical for directing emergency response during active flood events. The Copernicus Emergency Management Service (CEMS) has been activated for several Indian flood events, producing rapid inundation products that have been integrated into state disaster response command centres.

4.2 Cyclone Track and Intensity Forecasting

India's 7,516-km coastline is exposed to tropical cyclones from both the Bay of Bengal and the Arabian Sea. Two landmark cases illustrate both the progress and the remaining gaps in GeoAI-augmented cyclone warning. Cyclone Fani (2019) achieved near-zero mortality — just 89 deaths despite the evacuation of 1.2 million people — partly because AI-augmented track forecasting enabled 72-hour advance warnings, demonstrating the life-saving potential of integrated GeoAI-EWS at scale (IMD, 2019). Yet Cyclone Amphan (2020), despite equally accurate track prediction, still caused 128 deaths and extensive economic damage, demonstrating that accurate forecasting alone cannot substitute for robust last-mile dissemination.

While NWP models have dramatically improved track forecasting over the past two decades — reducing 72-hour track error from approximately 350 km (early 2000s) to approximately 130–150 km (early 2020s) — intensity forecasting remains significantly less skilful, particularly for rapid intensification (RI) events that can increase wind

speed by 35 knots or more in 24 hours. Deep learning approaches using convolutional architectures applied to geostationary satellite imagery have demonstrated improvements in 24-hour RI probability forecasts, with AUC scores of approximately 0.77–0.81 — significantly above persistence-based baselines (Kuo *et al.*, 2021). Cyclone Amphan (2020), Tauktae (2021), and Biparjoy (2023) have served as important test cases for next-generation AI cyclone prediction systems in the Indian context.

4.3 Landslide Susceptibility and Warning

The Himalayan arc, Western Ghats, and Northeast India — collectively among the world's most landslide-prone regions — witness thousands of mass movement events annually, frequently triggered by extreme rainfall events whose intensity is increasing with climate change. The Geological Survey of India (GSI) maintains a National Landslide Susceptibility Mapping programme covering over 0.42 million sq km across 17 states, employing frequency ratio, weights of evidence, and logistic regression methodologies (GSI, 2021).

Recent GeoAI advances have substantially improved upon these static susceptibility maps by coupling dynamic rainfall thresholds with spatial susceptibility scores. Ensemble ML models (XGBoost + RF) integrating topographic attributes (slope, curvature, aspect, TPI), geological and lithological data, land use/land cover, soil type, and satellite-derived vegetation indices (NDVI) with real-time rainfall from TRMM/GPM IMERG achieve validation AUC values of 0.88–0.93 for landslide susceptibility classification across Uttarakhand and Himachal Pradesh (Pradhan *et al.*, 2023). Dynamic landslide warning — issuing probabilistic warnings at 6-hour lead times based on evolving rainfall accumulation thresholds conditioned on local susceptibility — is now being piloted by NRSC in collaboration with state disaster management authorities.

4.4 Drought Monitoring and Early Warning

Agricultural drought monitoring in India has been significantly enhanced by multi-sensor remote sensing and ML-based index fusion. The Normalised Difference Vegetation Index (NDVI), Vegetation Condition Index (VCI), Land Surface Temperature (LST), Soil Moisture Active Passive (SMAP) satellite data, and IMD gridded rainfall datasets are fused through random forest regression models to produce district-level drought severity estimates at 8-day temporal resolution — a significant improvement over the monthly Standardised Precipitation Evapotranspiration Index (SPEI) products previously available (Jain *et al.*, 2023).

The NRSC's operational Agricultural Drought Assessment System (ADAS) integrates MODIS time-series with crop calendar information and taluk-level agricultural statistics to generate near-real-time drought impact assessments. AI-based seasonal drought forecasting using teleconnection patterns (IOD, ENSO, MJO) and sub-seasonal NWP ensemble outputs is an emerging capability being researched at IIT institutes and IMD's Pune forecasting division.

4.5 Heat Wave Warning Systems

Heat waves represent a rapidly growing mortality risk in India. The 2015 heat wave claimed approximately 2,500 lives across Andhra Pradesh and Telangana, and the frequency of extreme heat events is projected to increase threefold by 2050 under medium warming scenarios (IPCC, 2021). IMD operationalises heat wave warnings using

threshold criteria (maximum temperature $\geq 40^{\circ}\text{C}$ in plains and $\geq 30^{\circ}\text{C}$ in hilly regions, with specific anomaly thresholds), but these are determined at district level and do not capture intra-urban heat exposure heterogeneity. GeoAI approaches are transforming heat wave risk communication by enabling Urban Heat Island (UHI) mapping at building-block resolution through fusion of

Landsat-8/9 thermal infrared data, high-resolution OpenStreetMap building footprints, vegetation indices, and albedo datasets. LSTM-based models trained on ERA5 reanalysis and IMD station data can forecast maximum temperature anomalies 5–7 days ahead with sub-degree RMSE, enabling proactive public health advisories and cooling centre activation by urban local bodies.

Table 1: Summary comparison of GeoAI approaches across six extreme weather hazard warning applications in India.

Hazard Type	Primary GeoAI Method	Key Performance Gain	Warning Lead Time	Principal Gap
River Flood	LSTM + physics hybrid	RMSE ↓15–30% vs. physics-only (Nair <i>et al.</i> , 2023)	24 h → 72 h	Ungauged basins
Urban Flash Flood	CNN + QPE + crowdsource	Ward-level 30–60 min warnings (Patel <i>et al.</i> , 2022)	30–60 min	Drainage data quality
Cyclone Intensity	Attention CNN on IR satellite	AUC 0.77–0.81 for RI (Kuo <i>et al.</i> , 2021)	24–48 h	Rapid intensification
Landslide	XGBoost + RF ensemble	AUC 0.88–0.93 susceptibility (Pradhan <i>et al.</i> , 2023)	6 h	Sparse inventory data
Drought	RF multi-index fusion	8-day vs. monthly SPEI (Jain <i>et al.</i> , 2023)	Seasonal	Crop-specific calibration
Heat Wave	LSTM + UHI thermal fusion	Sub-degree RMSE, 5–7 day forecast	5–7 days	Intra-urban resolution

AUC = Area Under the ROC Curve; RMSE = Root Mean Square Error; RI = Rapid Intensification; QPE = Quantitative Precipitation Estimation.

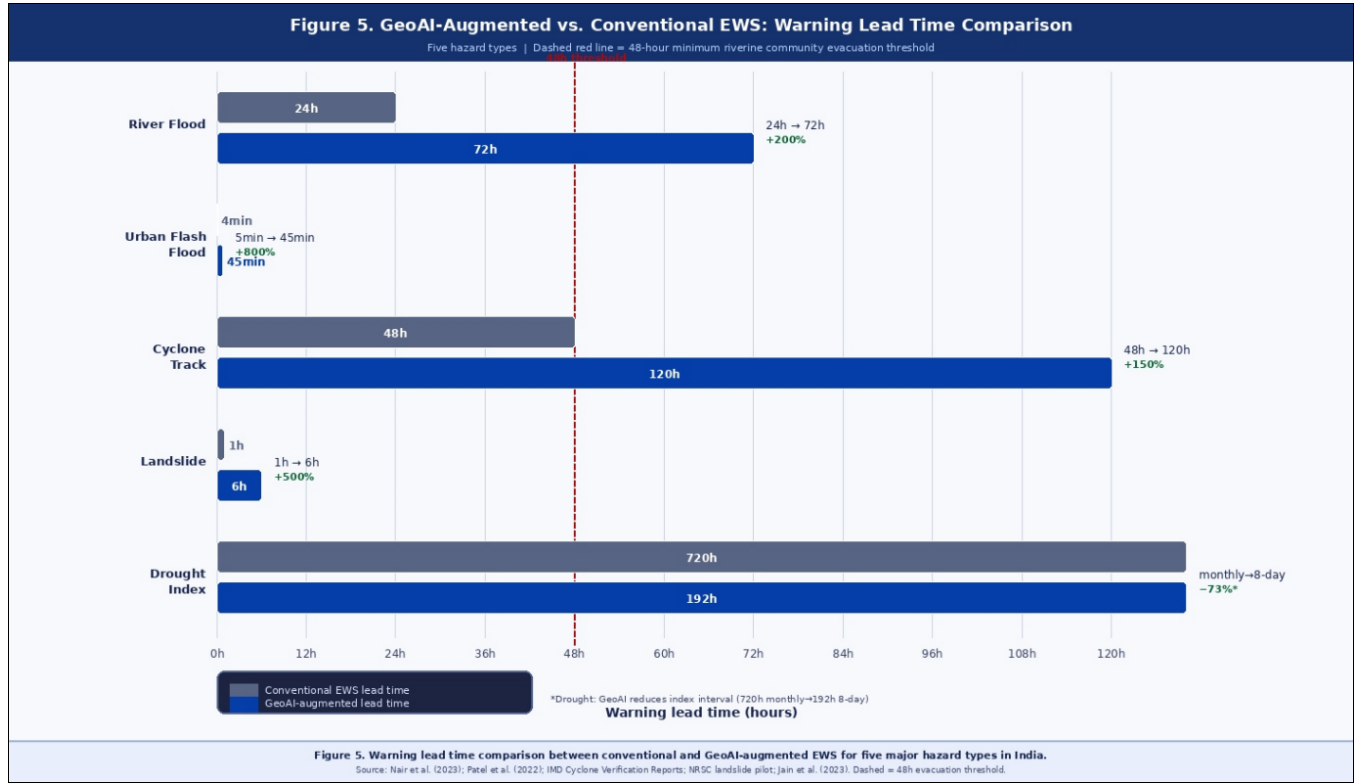


Fig 5: Comparison of warning lead times between conventional and GeoAI-augmented early warning systems across five major hazard types in India. The dashed vertical line marks the 48-hour minimum threshold for effective riverine community evacuation.

5. Data Challenges and Infrastructure Gaps
5.1 Data Availability and Quality

Robust GeoAI models require large volumes of high-quality, labelled training data. For rare extreme events, the historical record may contain only a few dozen well-documented occurrences, making supervised learning inherently challenging. This problem is acute for severe landslide events in remote Himalayan terrain, where systematic inventory data are sparse and unevenly distributed across geological provinces. Transfer learning — pre-training models on global or regional datasets and fine-tuning on India-specific data — partially mitigates this limitation, but domain shift between geologically or climatically distinct regions can degrade predictive performance in ways that are difficult to anticipate without targeted verification. Data silos across government departments remain a structural impediment. CWC maintains river gauge archives

that are not systematically integrated with IMD's rainfall records or GSI's geological databases, limiting the development of multi-hazard, multi-source GeoAI models that could unlock qualitatively new warning capabilities. India's National Data Sharing and Accessibility Policy (NDSAP, 2012) mandates open access to non-sensitive government datasets, but implementation remains inconsistent across agencies. Resolving this requires not merely technical standardisation but sustained inter-agency negotiation and a shared institutional commitment to treating hazard data as a public good.

5.2 Spatial Resolution and Coverage Gaps

Despite advances in satellite remote sensing, significant spatial coverage gaps persist in operational monitoring networks. Northeast India, the Andaman and Nicobar Islands, and remote Himalayan districts are chronically underserved by ground-based sensor networks, creating

observational blind spots precisely where hydro-meteorological hazard risks are highest. The IMD AWS network, while expanding towards approximately 1,400 stations as of 2024, maintains a median inter-station spacing of approximately 50 km in peninsular India — insufficient to resolve the sub-synoptic rainfall gradients responsible for local flash flooding. The deployment of low-cost MEMS-based weather sensors through community-based monitoring programmes — as trialled by SEEDS India and Aga Khan Agency for Habitat in several states — offers a participatory approach to filling observational gaps. However, data quality standardisation, long-term maintenance, and the integration of community-collected data into operational GeoAI pipelines present ongoing challenges that require dedicated programme management and sustained funding.

5.3 Computational and Connectivity Infrastructure

Running deep learning-based geospatial models at operational scale requires substantial GPU computing capacity. While national HPC facilities — including the National Supercomputing Mission's (NSM) systems at C-DAC Pune and IISc Bangalore — are progressively expanding, access for state-level disaster management agencies remains limited. Cloud-based AI platforms (Google Cloud AI, AWS SageMaker, Microsoft Azure AI) offer on-demand scalability, but recurring costs and data sovereignty concerns constrain their adoption in government operational systems. Last-mile connectivity for warning dissemination remains the most critical infrastructure gap. India's teledensity in rural areas, while improving under the BharatNet programme, remains insufficient for reliable mobile-data-based warning delivery in remote tribal and mountain districts. Common Alerting Protocol (CAP)-compliant cell broadcast, integrated with NDMA's National Emergency Response System (NERS), offers a more inclusive dissemination channel by delivering geo-targeted SMS alerts to all mobile devices in a geographic area without requiring internet connectivity. This mechanism should be the national standard for EWS dissemination to ensure coverage of the most vulnerable populations.

6. Institutional Landscape and Governance of EWS in India

6.1 Key Institutions and Mandates

India's EWS institutional architecture spans multiple ministries and technical agencies with overlapping but partially integrated mandates. The India Meteorological

Department (IMD) under the Ministry of Earth Sciences (MoES) is the designated nodal agency for hydro-meteorological warnings, operating 24/7 from forecasting offices in New Delhi, Mumbai, Chennai, Kolkata, Nagpur, and Guwahati. The National Remote Sensing Centre (NRSC), an ISRO facility, provides satellite-based disaster monitoring and damage assessment. The Central Water Commission (CWC) under the Ministry of Jal Shakti manages river flood forecasting. The National Disaster Management Authority (NDMA), established under the DM Act 2005, coordinates policy formulation and multi-agency response, while the National Institute of Disaster Management (NIDM) leads capacity building and research. State Disaster Management Authorities (SDMAs) are responsible for operationalising warnings at the district and sub-district level — a function for which most lack dedicated GeoAI capacity and trained personnel.

6.2 Inter-Agency Coordination Challenges

The multiplicity of agencies involved in EWS — each with distinct data protocols, communication systems, and organisational cultures — creates coordination costs that can delay warning dissemination during fast-onset events. The Integrated Flood Warning System (IFLOWS-Mumbai), developed jointly by IMD, the Brihanmumbai Municipal Corporation (BMC), NDMA, and NRSC following the 2005 floods (BMC/NDMA, 2020), represents one of the few genuinely multi-agency, GeoAI-augmented operational flood warning systems in India and provides a replicable governance model for other metropolitan centres.

6.3 International Collaborations

India participates in several multilateral frameworks that enhance GeoAI-EWS capabilities. The SERVIR programme, a joint initiative of NASA and USAID with regional hubs in Asia, supports the integration of satellite-based geospatial tools into national EWS operations. The WMO's Global Multi-Hazard Alert System (GMAS), to which IMD contributes as a Regional Specialised Meteorological Centre, is progressively incorporating AI-based warning products and operates through the Common Alerting Protocol (CAP) standard, enabling machine-readable alerts to be automatically relayed across national warning platforms. Bilateral collaborations with the European Space Agency (ESA), the Japanese Meteorological Agency (JMA), and the UK Met Office further augment India's warning science capacity.

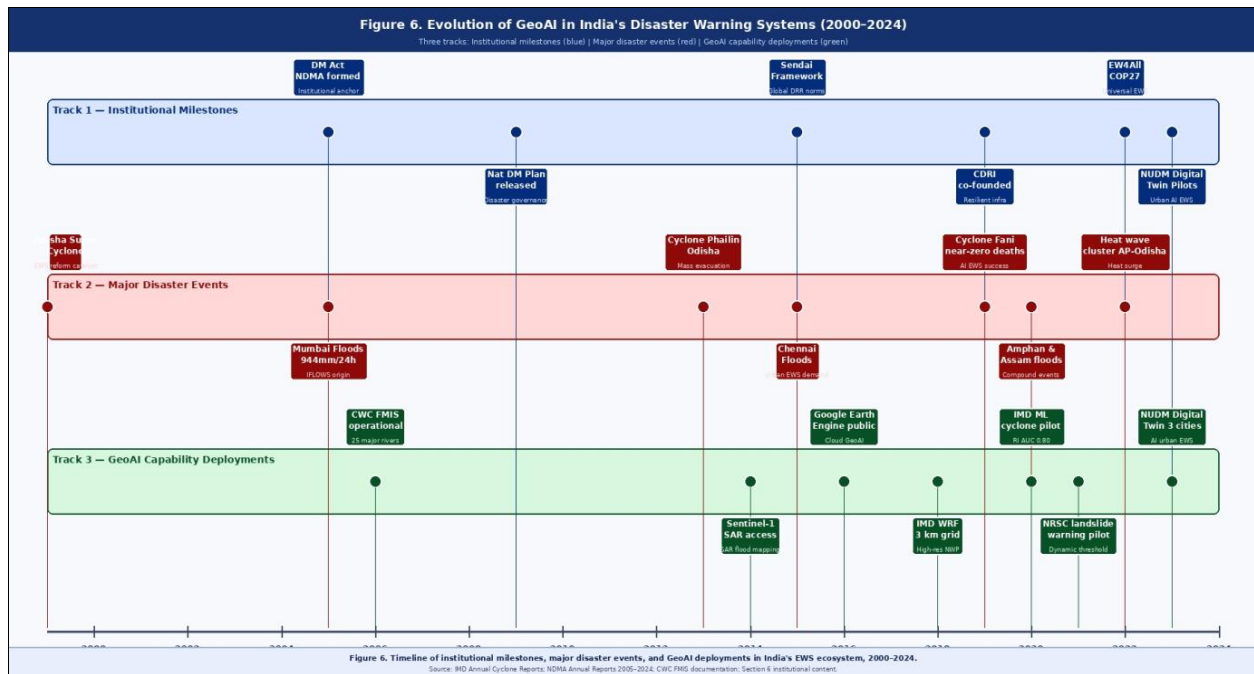


Fig 6: Timeline of key institutional milestones, major disaster events, and GeoAI capability deployments in India's early warning system ecosystem, 2000–2024.

7. Social and Ethical Dimensions

7.1 Equity and the Last Mile

GeoAI-enhanced EWS risk reproducing and amplifying pre-existing inequities if their design privileges data-rich, well-connected urban populations while neglecting marginalised rural, tribal, and coastal communities. The efficacy of any EWS ultimately depends not on the sophistication of the upstream AI model but on whether the warning reaches the most vulnerable person in time for them to act. Dalits, Adivasi communities, migrant labourers, fisherfolk, and women-headed households consistently face greater exposure, higher sensitivity, and lower adaptive capacity relative to extreme weather events, yet remain systematically underrepresented in participatory EWS design processes (Rao & Sharma, 2021).

Community-Based Early Warning Systems (CBEWS), which integrate local ecological knowledge with AI-generated guidance, offer a socially inclusive complement to technically sophisticated national-scale platforms. The Kerala Sustainable Development Goals (SDG) Digitisation Initiative, which engaged local self-government institutions in real-time flood monitoring through citizen science, demonstrates that bottom-up and top-down approaches are not mutually exclusive — they are complementary, each strengthening what the other cannot provide.

7.2 Algorithmic Bias and Model Fairness

Training data for GeoAI models typically reflects the geographic and socioeconomic biases embedded in historical observation networks. Flood models trained

predominantly on gauged river basins in northern India may underperform in the ungauged streams of Northeast India or peninsular river systems with distinct hydrological regimes. Similarly, land use classifications derived from high-resolution urban imagery may systematically misclassify informal settlements and peri-urban areas with complex land cover mosaics, producing spatially biased inundation predictions (Ghosh & Bhatt, 2022).

Fairness-aware machine learning — through stratified sampling, re-weighting of loss functions, or adversarial debiasing — can partially mitigate these effects. Addressing the root cause requires sustained investment in equitable observational infrastructure and inclusive data collection practices that are not yet systematically incorporated into India's EWS development programmes.

7.3 Warning Uncertainty Communication

Probabilistic AI-based warnings — which naturally produce uncertainty ranges rather than single deterministic forecasts — require careful communication to avoid misinterpretation. Overconfident warnings that fail to materialise erode community trust; underconfident warnings that hedge excessively fail to motivate protective action. Research in risk communication consistently finds that visualisation of uncertainty through probability maps, confidence intervals, and scenario-based narratives — tailored to the literacy levels and cultural contexts of target audiences — significantly improves warning uptake compared to technical jargon-heavy text alerts (Morss *et al.*, 2020).

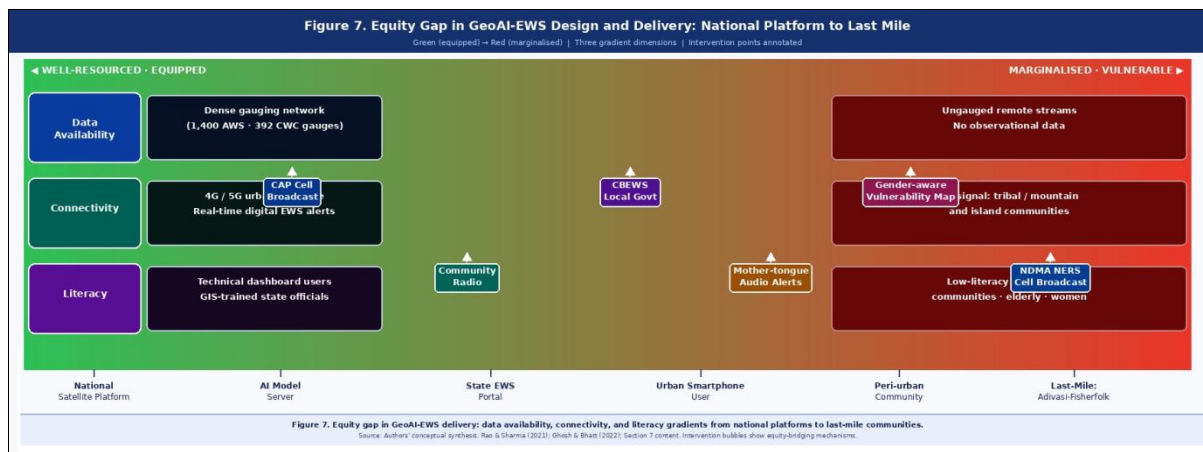


Fig 7: Conceptual diagram of the equity gap in GeoAI-EWS design and delivery, illustrating the data, connectivity, and literacy gradients between well-resourced national platforms and last-mile marginalised communities, with annotated intervention points..

8. Emerging Research Frontiers and Future Directions

8.1 Foundation Models and Large-Scale Geospatial AI

The emergence of large-scale pre-trained foundation models applied to geospatial domains represents a paradigm shift with profound implications for EWS. Models such as IBM and NASA's Prithvi geospatial foundation model, pre-trained on a decade of Harmonised Landsat and Sentinel-2 (HLS) imagery, can be fine-tuned with minimal labelled examples for downstream tasks including flood mapping, crop stress detection, and burn scar delineation (Jakubik *et al.*, 2023). Adapting such models to Indian satellite data streams and hazard geographies — including the rich archive of Resourcesat and Cartosat data — is a near-term research priority.

8.2 Physics-Informed Machine Learning

Physics-Informed Neural Networks (PINNs) embed differential equations governing atmospheric, hydrological, or geomorphological processes as soft constraints within the training objective, ensuring that data-driven predictions respect known physical laws. For flood inundation modelling, embedding Saint-Venant shallow water equations into a hybrid architecture allows GeoAI models to generalise to hydraulic conditions outside the training distribution — a critical requirement for rare extreme events. PINN-based flood emulators can achieve simulation speeds 10^3 – 10^4 times faster than traditional numerical solvers while maintaining comparable accuracy, enabling ensemble-based probabilistic inundation forecasting in operational timeframes (Bihlo & Popovych, 2022).

8.3 Multi-Hazard and Cascading Risk Modelling

Extreme weather events rarely manifest as isolated hazards. Cyclonic systems trigger storm surge, flooding, landslides, and debris flows in close spatiotemporal proximity. Prolonged drought leads to vegetation desiccation, heightening wildfire risk. Heat waves exacerbate urban air quality, raising combined heat-pollution mortality risk. GeoAI-based multi-hazard modelling — integrating dynamic interaction networks between hazard processes through GNN-based cascading risk architectures — remains an open research challenge but one of immense practical relevance for integrated warning and response planning.

8.4 Generative AI for Scenario Simulation

Generative AI models — including diffusion models and

conditional GANs — are being applied for downscaling coarse NWP outputs to high-resolution spatial fields and for generating synthetic extreme event scenarios that augment sparse historical training datasets. Diffusion-based downscaling of 25-km GFS precipitation fields to 1-km resolution has demonstrated skill comparable to dynamical downscaling at a fraction of the computational cost (Price *et al.*, 2024). For India, where the heterogeneous orography of the Western Ghats and Himalaya creates sharp precipitation gradients that coarse models cannot resolve, AI-based statistical downscaling holds significant promise.

8.5 Federated Learning for Privacy-Preserving Sensor Data Integration

Federated learning enables training of shared ML models across distributed, privacy-sensitive datasets — such as proprietary sensor networks operated by different government agencies — without centralising raw data. This paradigm is particularly relevant for India's multi-agency disaster management architecture, where CWC, IMD, GSI, and state agencies each maintain distinct sensor archives that are not currently integrated. Under federated learning, each agency trains a local model on its own data, and only model weight updates — not raw observations — are aggregated centrally, preserving departmental data sovereignty while progressively improving shared model performance.

This approach has direct applications in flash flood forecasting, where integrating IMD rainfall and CWC discharge data without a federated framework would require overcoming bureaucratic and legal barriers that have stymied integration efforts for years. Pilot implementations in partnership with IIT institutes and NCMRWF could demonstrate feasibility within a 2–3 year horizon and provide the evidence base needed for national policy adoption.

9. Policy Recommendations

9.1 National GeoAI-EWS Integration Programme

A dedicated National GeoAI-EWS Integration Programme under MoES, with technical leadership shared between IMD, NRSC, and the National Centre for Medium Range Weather Forecasting (NCMRWF), should be established to coordinate the phased operationalisation of GeoAI-enhanced warning products across all major hazard categories. This programme should include clear performance benchmarks,

annual model verification against observed event catalogues, and open publication of verification metrics to ensure scientific accountability and build public trust in AI-generated warnings.

9.2 National Geospatial-Hazard Data Commons

A federated, interoperable National Geospatial-Hazard Data Commons should be developed under the National Geospatial Policy 2022 framework, mandating standardised data formats, metadata, and APIs for cross-agency hydro-meteorological and geospatial data sharing. This commons should be openly accessible to the research community under Creative Commons-equivalent licensing to accelerate GeoAI model development and independent scientific verification.

9.3 State-Level GeoAI-EWS Capacity Building

The NDMA and NIDM should jointly develop a structured GeoAI capacity building programme for State Disaster Management Authorities, district collectors, and urban local body officials, encompassing foundational GIS and ML literacy, open-source geospatial tool training (QGIS, Python, Google Earth Engine), and simulation-based disaster management exercises that incorporate AI warning products. International partnerships with institutions such as ITC Enschede, Deltares, and ICIMOD should be leveraged for curriculum development and practitioner training.

9.4 Inclusive EWS Design Standards

NDMA should develop and enforce national inclusive EWS design standards requiring that all operational GeoAI-EWS include: (a) multi-lingual warning products in regional languages, (b) audio-based alert formats for low-literacy populations, (c) gender-disaggregated vulnerability overlays in spatial warning products, and (d) community feedback loops for continuously improving warning relevance and uptake. These standards should be grounded in participatory co-design processes that genuinely engage frontline communities in system design, not merely in consultation.

10. Limitations

Several limitations of this review warrant acknowledgement. First, the literature search, while systematic, was conducted in English-language databases and may underrepresent significant grey literature and research published in Indian regional languages or in government technical reports not indexed in Scopus or Web of Science. Second, the review encompasses a rapidly evolving field; GeoAI model architectures and performance benchmarks documented here reflect the state of the literature up to October 2024 and will be superseded by subsequent developments. Third, performance figures cited for specific ML models reflect results from their original study contexts, which may differ substantially from operational conditions in terms of data quality, computing infrastructure, and institutional readiness. Readers should interpret reported accuracy metrics as indicative benchmarks rather than guaranteed operational performance.

Fourth, the coverage of different hazard types is not entirely symmetrical: flood and cyclone EWS have been more extensively studied in the Indian context and are consequently better represented in the evidence base than heat wave and drought warning systems, which remain comparatively underdeveloped in the GeoAI literature.

Finally, the policy recommendations proposed in Section 9 are grounded in the evidence reviewed but should be validated through consultation with operational practitioners and policymakers before formal adoption.

11. Conclusion

GeoAI marks a genuine inflection point in India's capacity to develop and operationalise early warning systems for extreme weather events. The convergence of satellite remote sensing, deep learning, cloud computing, and real-time sensor networks creates an opportunity to extend warning lead times, sharpen spatial precision, and personalise risk communication across India's extraordinarily diverse hydro-meteorological and socio-geographic landscape.

This review has documented the growing evidence base for GeoAI-EWS across five major hazard categories — floods, cyclones, landslides, droughts, and heat waves — while honestly confronting the data, infrastructure, institutional, and equity challenges that separate technological potential from operational reality. The performance improvements are real and significant: LSTM augmentation reduces flood forecasting RMSE by 15–30%; ensemble ML achieves landslide susceptibility classification at AUC 0.88–0.93; and AI-based cyclone intensity tools are beginning to close the most consequential remaining gap in tropical warning science.

Yet performance metrics are not the ultimate measure of an EWS. The architecture of trust — between AI systems and their operators, between warning agencies and communities, between national institutions and last-mile responders — must be constructed with the same rigour and investment as the algorithms themselves. GeoAI systems that are accurate but opaque, precise but inaccessible, or innovative but inequitable will fail at the question that ultimately matters: whether vulnerable people receive, understand, and act upon warnings in time to protect their lives.

India is, in many respects, the most consequential testing ground for GeoAI-enabled warning science on earth. The complexity of its hazard geography, the scale of its at-risk population, the diversity of its institutional arrangements, and the maturity of its scientific establishment make every lesson learned here applicable across a significant fraction of global disaster vulnerability. The path forward is not primarily technical — the algorithms exist, the satellite data streams are available, and the computational infrastructure is being built. What remains to be constructed, with the same deliberateness and investment that built IMD's supercomputing capacity or ISRO's earth observation fleet, is the institutional trust architecture that allows a probabilistic AI-generated warning to motivate protective action in a flood-prone household in Assam or a heat-vulnerable worker in a Rajasthan city. That construction project — spanning data governance reform, community co-design, equity-conscious engineering, and sustained political commitment — is where the work of the next decade must begin.

Declaration of Competing Interests

The authors declare no competing interests.

Data Availability Statement

This review is based on publicly available published literature. No primary datasets were generated or analysed. All referenced sources are cited in the reference list.

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