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SafeCast – Integrated Disaster Management System

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Abstract: *Disaster risk emerges from the interaction of hazardous processes with exposed and vulnerable communities, infrastructure, and ecosystems. Operational systems therefore require more than isolated weather forecasts or static hazard maps. This paper proposes SafeCast, an AI-driven, multi-source framework that integrates spatio-temporal data fusion, hazard-specific machine learning, exposure and vulnerability modelling, GeoAI risk mapping, uncertainty estimation, and confidence-aware early warning. Environmental observations, IoT measurements, satellite products, terrain and land-use information, historical events, infrastructure layers, and population indicators are harmonized on a common spatial-temporal grid. Hazard models generate calibrated probabilities or severity estimates, which are combined with exposure, vulnerability, and temporal context through a Dynamic Disaster Risk Index. A geospatial reasoning layer transforms these estimates into interpretable risk surfaces and identifies hotspots and critical assets. The warning engine considers risk magnitude, confidence, persistence, and source quality before escalation. The paper defines a reproducible experimental protocol using spatial and event-based validation, calibration metrics, latency, false-alarm burden, robustness testing, and ablation studies. Since this work proposes an independent framework rather than reporting a completed field trial, no fabricated accuracy values are presented. The design provides a research foundation for transparent multi-hazard intelligence and people-centred early warning*

Keywords: artificial intelligence, disaster risk, GeoAI, GIS, early warning, multi-hazard assessment, spatio-temporal fusion, uncertainty

I. INTRODUCTION

Climate-related and geophysical hazards produce consequences that vary sharply across space and time. The same rainfall intensity can generate limited impact in one catchment and severe flooding in another because drainage, topography, antecedent moisture, land cover, settlement density, and infrastructure differ. This makes disaster risk a compound inference problem rather than a single-variable forecasting task.

Contemporary monitoring environments provide large volumes of heterogeneous data. Weather stations and numerical forecasts describe atmospheric conditions; satellites observe land, clouds, water, vegetation, and damage; IoT sensors can measure local rainfall, river stage, soil moisture, temperature, or air quality; geographic databases describe terrain, roads, buildings, hospitals, schools, and utilities; historical inventories provide event context. The scientific challenge is to align these sources and convert them into information that supports decisions.

Artificial intelligence can model nonlinear relationships across these variables, while GIS can preserve the geographical meaning of predictions. However, an operational early-warning system must also communicate uncertainty, distinguish hazard from societal risk, avoid spatial leakage during validation, remain useful when data sources fail, and translate model outputs into warning states that humans can understand.

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SafeCast is proposed as an independent research framework addressing these requirements. Instead of binding the system to one hazard or algorithm, it defines common interfaces for data quality, hazard probability, exposure, vulnerability, uncertainty, geospatial reasoning, and warning decisions. This design enables a flood model, heat-risk model, landslide model, or other hazard model to share the same downstream risk and warning infrastructure.

A. Main Contributions

First, the framework separates hazard probability from exposure and vulnerability, preventing a high hazard score from automatically being interpreted as high societal impact.Second, it introduces source quality, data age, and predictive uncertainty as explicit variables in the decision chain.Third, it proposes spatially aware validation and event-held-out testing to reduce optimistic performance estimates caused by geographic autocorrelation.Fourth, it links calibrated model outputs with a Dynamic Disaster Risk Index, GeoAI risk surfaces, and confidence-aware warning states.Fifth, it defines evaluation criteria extending beyond accuracy to calibration, false alarms, alert latency, robustness

II. LITERATURE REVIEW

AI and machine learning have become prominent in disaster-risk research because they can integrate high-dimensional environmental and geographic variables. AI-powered GIS has been investigated for flood susceptibility, landslide mapping, risk visualization, monitoring, and early-warning applications [1]. These studies demonstrate that spatial context is not merely a presentation layer; it is a core analytical dimension because terrain, proximity, connectivity, and neighborhood effects influence risk.

Early-warning research increasingly emphasizes the complete warning chain. Tiggeloven et al. discuss AI across risk knowledge, detection and forecasting, dissemination, and preparedness [2]. This perspective is important because an accurate prediction does not guarantee an effective warning. Communication channels, timing, interpretability, trust, and preparedness determine whether technical information becomes useful action.

Trustworthy AI is another growing concern. Disaster applications may operate under distribution shift, sensor failure, incomplete labels, and extreme events that are rare in training data [3]. Consequently, confidence calibration, uncertainty reporting, auditability, and human oversight are necessary. A model that returns a probability without information about data freshness or uncertainty can create false precision.

Multi-hazard research extends beyond single-event prediction by combining several environmental and social dimensions. Recent geospatial work applies machine learning to multi-hazard susceptibility and integrates climatic, topographic, hydrologic, environmental, anthropogenic, and socioeconomic variables [4], [5]. These approaches motivate a common risk layer that can receive hazard-specific outputs without forcing every hazard into the same predictive model.

Flood prediction remains one of the most studied AI disaster applications. Literature reviews show widespread use of neural networks, support-vector methods, decision trees, ensembles, and hybrid approaches [9], [10]. Yet reported performance can be difficult to compare because datasets, horizons, spatial scales, event definitions, and validation protocols differ. SafeCast therefore treats evaluation design as part of the framework rather than as an afterthought.

A. Research Gap

The literature suggests a gap between powerful hazard-specific models and integrated operational risk intelligence. Four issues are particularly relevant: heterogeneous data are frequently fused without preserving source quality; exposure and vulnerability are sometimes mixed directly into prediction labels; geographic validation may permit spatial leakage; and warning performance is often represented only through model accuracy. SafeCast addresses these issues by separating layers and by requiring predictive, spatial, calibration, and operational evaluation.

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B. Comparative Positioning

Approach	Primary Strength	Typical Limitation	SafeCast Response
Hazard-only ML	Strong prediction	Impact not explicit	Adds exposure/vulnerability
Static GIS overlay	Interpretability	Limited temporal dynamics	Continuous updates
Single-source EWS	Simple pipeline	Source failure sensitivity	Multi-source fusion
Black-box deep model	Complex pattern learning	Weak interpretability	Confidence + audit trail
SafeCast	Integrated risk chain	Needs regional calibration	Modular validation

TABLE I. Conceptual comparison of disaster-risk system approaches.

III. PROBLEM DEFINITION AND SYSTEM MODEL

Let the geographical study region be partitioned into cells $l \in L$ and the monitoring period into time intervals $t \in T$. At every cell-time pair, the system receives observations from K heterogeneous sources. The raw observation vector can be written as $X(l,t) = \{x1, x2, \ldots, xK\}$. Each observation is associated with metadata describing timestamp, spatial resolution, provenance, and quality.

The framework estimates four latent components. $H(l,t)$ represents hazard likelihood or intensity; $E(l,t)$ represents exposed population, infrastructure, and assets; $V(l,t)$ represents susceptibility and coping limitations; $C(l,t)$ captures temporal and contextual modifiers such as antecedent rainfall, seasonality, recent events, and data freshness.

$$DRI(l,t) = \sigma [\alpha H(l,t) + \beta E(l,t) + \gamma V(l,t) + \delta C(l,t)]$$

DRI is the Dynamic Disaster Risk Index, σ is a bounded transformation, and α, β, γ, and δ are region- and hazard-specific parameters. These parameters are not assumed to be universal. They should be calibrated from historical impacts, expert elicitation, or multi-objective optimization.

A. Source Reliability Model

Data quality influences the confidence of downstream predictions. For source k, SafeCast defines a quality factor qk based on completeness, freshness, spatial representativeness, and historical reliability. A fused observation can therefore weight measurements by both relevance and quality.

$$\hat{x}(l,t) = [\Sigma_k \; q_k(l,t) \; x_k(l,t)] / [\Sigma_k \; q_k(l,t) + \varepsilon]$$

The quality factor does not imply that all variables can be numerically averaged. The equation represents continuous measurements with comparable semantics. Categorical, image, and vector sources require variable-specific fusion operators.

B. Risk-State Representation

For communication, the continuous DRI can be mapped to operational states such as Low, Moderate, High, and Critical. Thresholds should be learned or expert-calibrated using historical consequences and acceptable false-alarm rates. The same numerical threshold should not be assumed across different hazards or districts.

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IV. PROPOSED ARCHITECTURE

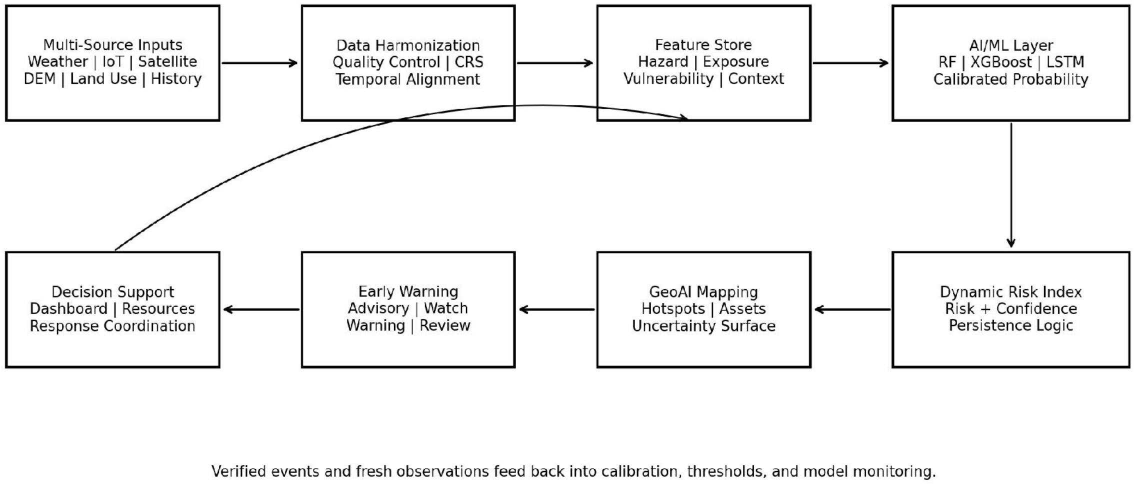

Fig. 1. SafeCast multi-source AI/GeoAI disaster-risk architecture.

The architecture contains eight interacting layers. Multi-source inputs are first harmonized and quality checked. A feature store organizes hazard, exposure, vulnerability, and context features. Hazard-specific AI models produce calibrated estimates. The dynamic risk engine combines these estimates with consequence-related information. GeoAI transforms risk into spatial products, and the warning engine applies persistence and confidence rules before decision-support outputs are delivered.

V. MULTI-SOURCE DATA FUSION AND FEATURE ENGINEERING

A. Environmental and IoT Data

Environmental inputs may include precipitation intensity and accumulation, temperature, humidity, wind, pressure, river stage, soil moisture, and forecast variables. IoT sensors can provide high-frequency local observations but may suffer from drift, outages, and inconsistent maintenance. SafeCast therefore stores sensor health indicators and time since last valid observation alongside the measurement.

B. Remote Sensing and Terrain

Satellite imagery can provide rainfall proxies, cloud properties, surface water, vegetation indices, land-surface temperature, burn scars, and post-event change information. Terrain derivatives from a digital elevation model include elevation, slope, curvature, flow accumulation, topographic wetness, and drainage proximity. These features are especially relevant for flood and landslide applications.

C. Exposure and Vulnerability

Exposure describes what may be affected. Candidate layers include gridded population, building footprints, road length, bridges, hospitals, schools, power facilities, water systems, and economic assets. Vulnerability describes susceptibility or limited coping capacity and may include building type, access constraints, demographic indicators, historical damage ratios, and distance to emergency services. Sensitive attributes should be used only when justified, protected, and governed.

D. Temporal Features

Risk often depends on accumulated conditions rather than a single timestamp. The feature store can calculate rolling rainfall totals, temperature anomalies, rate of river rise, consecutive hot days, antecedent soil moisture, time since previous event, and seasonal indicators. Lag features must be computed without using future information.

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E. Data Harmonization

All spatial layers are transformed to a common coordinate system and analysis grid. Continuous variables use appropriate interpolation or resampling; categorical layers preserve class identity; vector infrastructure is summarized by count, density, length, or proximity. Every transformation is recorded to support reproducibility.

Data Group	Example Variables	Update Pattern	Key Quality Risk
Weather	Rain, temperature, wind	Minutes-hours	Missing/stale observations
IoT	River level, soil moisture	Seconds-minutes	Sensor drift/outage
Satellite	Water, vegetation, LST	Hours-days	Cloud/temporal gaps
Terrain	Slope, elevation	Static	Resolution
Exposure	Population, assets	Months-years	Outdated inventories
History	Past events/damage	Event based	Reporting bias

TABLE II. Representative SafeCast data groups and quality considerations.

VI. AI/ML HAZARD MODELLING

The AI layer is intentionally model-agnostic. Random Forest and gradient boosting provide interpretable baselines for mixed tabular features. XGBoost-style models can capture nonlinear interactions and missingness patterns. Recurrent, convolutional, or transformer-based temporal models can be evaluated when long sequences are available. Satellite imagery may require convolutional or vision-transformer encoders.

A. Probabilistic Ensemble

$$P_h(l,t) = \Sigma_m \lambda_m P_m(h \mid X(l,t)), \qquad \Sigma_m \lambda_m = 1$$

The ensemble combines M candidate models. Weights λm are selected using validation data or stacking and must be fixed before final testing. The ensemble should be compared with each component model to demonstrate whether complexity produces measurable benefit.

B. Probability Calibration

A warning system requires probabilities that correspond to observed frequencies. A model can have strong discrimination while remaining poorly calibrated. Reliability diagrams, Brier score, expected calibration error, Platt scaling, or isotonic calibration can therefore be used. Calibration must be performed only on validation data.

$$\text{Brier} = (1/N)\, \Sigma_i (p_i - y_i)^2$$

C. Uncertainty Estimation

Uncertainty arises from model disagreement, sparse training examples, missing inputs, and distribution shift. SafeCast can estimate uncertainty using ensemble variance, bootstrap models, Monte Carlo dropout, conformal methods, or source-quality indicators. The chosen method depends on the predictive model and available data.

$$R^*(l,t) = \text{DRI}(l,t) \cdot [1 - \kappa U(l,t)]$$

R^* is a confidence-adjusted decision score, U is normalized uncertainty, and κ controls the adjustment. Operational deployments may alternatively keep the original DRI and use U to determine whether human verification is required.

D. Explainability

Feature attribution can help analysts understand why risk increased. Tree models can use permutation importance or SHAP-style explanations; image models can use spatial attribution maps. Explanations should be treated as model diagnostics rather than causal evidence. The interface should distinguish observed measurements, model predictions, and explanatory indicators.

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VII. GEOAI RISK MAPPING

GeoAI converts model outputs into risk surfaces while preserving spatial context. Each update cycle produces cell-level hazard probability, exposure, vulnerability, final risk, and confidence layers. Spatial clustering can identify contiguous hotspots, while overlays can identify hospitals, roads, substations, shelters, and other critical assets inside high-risk zones.

A useful map should communicate uncertainty and data age as clearly as risk. Cells with stale observations can be hatched or marked as low-confidence rather than shown with the same visual certainty as recently observed cells. Time-enabled layers can display hotspot growth, movement, and decay.

VIII. EARLY-WARNING AND DECISION LOGIC

SafeCast separates analytical risk from public warning. An alert decision considers risk magnitude, predictive confidence, persistence across update cycles, source corroboration, and hazard-specific escalation policy. This design reduces the chance that a single noisy sensor creates an unstable public warning.

State	Trigger Concept	System Behaviour	Human Role
Normal	Low risk	Routine monitoring	None required
Advisory	Elevated/persistent	Dashboard notice	Observe
Watch	High or rapidly rising	Notify operators	Prepare response
Warning	High/critical + confidence	Issue location alert	Coordinate action
Review	High risk + weak confidence	Hold/escalate internally	Verify sources

TABLE III. Example operational warning-state design.

A. Persistence and Hysteresis

If risk fluctuates around a threshold, repeated warning changes can reduce trust. SafeCast therefore supports persistence rules and hysteresis. Escalation may require the threshold to remain exceeded for n update cycles, while de-escalation can require a lower release threshold. The exact values must be validated for each hazard because excessive persistence can delay urgent warnings.

B. Alert Content

An alert should identify the hazard, affected area, issue time, expected time window, severity or risk state, confidence where appropriate, and recommended authoritative action. Messages should be concise, multilingual where required, and accessible. SafeCast is intended to support—not replace—official warning authorities.

C. Decision-Support Dashboard

The analyst dashboard can present a map, time series, current risk state, model confidence, data freshness, exposed critical assets, active alerts, and source status. An audit panel records which model version, data snapshot, and thresholds produced each decision.

IX. EXPERIMENTAL DESIGN

A publishable empirical evaluation should use event inventories and region-specific datasets that are independent of the model-development process. The experimental design should define the prediction target, lead time, spatial resolution, event criteria, study period, missing-data policy, and train-validation-test split before reporting results.

A. Leakage-Resistant Validation

Randomly splitting neighbouring grid cells can inflate performance because nearby cells share terrain and environmental conditions. SafeCast therefore recommends spatial block cross-validation, leave-one-region-out testing, and leave-one-event-out testing. For time-dependent forecasting, training data must precede validation and test periods.

B. Metrics

$$\text{Precision} = TP/(TP+FP), \quad \text{Recall} = TP/(TP+FN)$$
$$F1 = 2 \cdot \text{Precision} \cdot \text{Recall}/(\text{Precision}+\text{Recall})$$

For multi-class risk, macro-F1 and per-class recall are preferable to accuracy alone when severe classes are rare. PR-AUC is informative for imbalanced event detection. Continuous forecasts can use MAE and RMSE. Probabilistic predictions should include Brier score and calibration curves.

C. Operational Metrics

End-to-end evaluation should measure ingestion delay, inference time, map-generation time, notification delay, uptime, data freshness, false alerts per event or month, missed-event rate, and time-to-detection. These quantities determine whether a statistically strong model is operationally useful.

D. Ablation Experiments

Ablation studies remove one component at a time: satellite features, IoT data, historical context, exposure, vulnerability, source-quality weighting, or uncertainty calibration. The resulting performance change reveals which components add genuine value and which merely increase system complexity.

X. PROPOSED EXPERIMENTAL SCENARIOS

A. Flood Risk Scenario

For flood assessment, hazard features may include current and accumulated rainfall, upstream water level, flow accumulation, elevation, slope, drainage density, soil moisture, land cover, and distance to rivers. Exposure can include population, roads, buildings, hospitals, and power assets. The target can be observed inundation or verified flood-event labels. Spatially held-out catchments should be included in the final test.

B. Heat-Risk Scenario

A heat-risk model may combine maximum temperature, nighttime temperature, humidity, land-surface temperature, vegetation, built-up density, population, age-sensitive exposure proxies, and access to cooling or health facilities where ethically and legally appropriate. Because heat impacts can lag meteorological peaks, temporal context is important.

C. Landslide Scenario

Landslide susceptibility can use rainfall, slope, lithology, land cover, soil properties, drainage proximity, road cuts, and historical landslide inventories. Event-based testing is essential because random spatial sampling may allow the model to memorize local terrain patterns.

D. Multi-Hazard Interaction

The first implementation can model hazards independently and combine their standardized risk layers. More advanced research can model dependencies explicitly. For example, extreme rainfall may simultaneously increase flood and landslide risk, while a cyclone may create wind, rainfall, storm-surge, and infrastructure-failure cascades. Graph-based or probabilistic dependency models can represent these interactions.

XI. RESULTS AND DISCUSSION

The proposed SafeCast framework is designed to evaluate disaster risk through multiple interconnected dimensions rather than relying only on the predictive accuracy of an individual machine learning model. Since the framework has not yet been subjected to a complete regional field implementation, this paper does not present fabricated numerical accuracy, F1-score, AUC, or latency values. The evaluation of SafeCast can be organized into four major groups.

The first group focuses on comparing different hazard prediction models under identical training, validation, and testing conditions. Models such as Random Forest, XGBoost, LSTM, and other suitable learning approaches can be compared using Precision, Recall, F1-score, PR-AUC, and related performance measures. Such comparison can help determine whether additional model complexity provides a meaningful improvement in hazard prediction.

The second group evaluates probability calibration and predictive uncertainty. In disaster management, a model should not only identify hazardous conditions but should also provide reliable confidence estimates. Calibration analysis can therefore determine whether predicted probabilities correspond appropriately to observed event frequencies. Uncertainty information can further help distinguish reliable high-risk predictions from cases that require additional verification.

The third group examines the contribution of exposure and vulnerability information to spatial risk prioritization. Two geographical locations may have similar hazard probabilities but substantially different overall disaster risks because of differences in population density, infrastructure, accessibility, and vulnerability. Integrating these factors with hazard predictions is expected to produce more meaningful GeoAI-based risk maps and improve the identification of priority areas for emergency response.

The fourth group evaluates the complete early-warning chain using operational indicators such as data-ingestion delay, model-inference time, alert latency, false alarms, missed events, source availability, and system robustness. This evaluation is important because high predictive performance alone does not guarantee an effective real-time disaster warning system.

Experiment	Primary Question	Recommended Evidence
Model comparison	Which predictor generalizes?	Macro-F1, PR-AUC, calibration
Spatial transfer	Does it work elsewhere?	Held-out-region metrics
Fusion ablation	Which sources add value?	ΔF1/ΔBrier/robustness
Risk composition	Does impact context matter?	Hotspot/exposure comparison
Alert simulation	Are warnings timely/stable?	Latency, misses, false alerts
Failure test	Does system degrade safely?	Source-outage experiments

TABLE IV. Recommended empirical evaluation matrix.

XIV. FUTURE SCOPE

Future research should implement the framework using an openly documented case study and publish the preprocessing pipeline, spatial partitions, model configurations, calibration procedure, and alert simulation. Promising extensions include physics-informed machine learning, graph neural networks for infrastructure dependencies, multimodal foundation models for satellite and text reports, conformal prediction, federated sensing, multilingual warning generation, route optimization, and digital-twin simulation. Longitudinal studies should examine whether calibration and false-alarm burden remain stable as climate and land-use conditions change.

XV. CONCLUSION

SafeCast provides a structured research architecture for converting heterogeneous disaster data into hazard estimates, consequence-aware risk, geospatial intelligence, and confidence-aware warnings. The framework separates prediction from exposure and vulnerability, preserves source quality and uncertainty, supports multiple AI model families, and requires spatially rigorous validation. Its evaluation plan extends beyond classification accuracy to calibration, transferability, latency, false alarms, robustness, and system reliability. The next research step is empirical implementation with region-specific datasets and transparent benchmarking. This approach can support more interpretable and operationally meaningful disaster-risk intelligence while preserving the role of authoritative agencies and human decision makers.

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