Interpretable Machine Learning Models for Early Climate Risk Forecasting and Disaster Mitigation

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Abstract: Climate change is boosting the frequency and intensity of extreme events, including floods, wildfires, droughts, landslides, and earthquakes, so rendering early forecasting and mitigation a global imperative. Machine learning (ML) and deep learning (DL) models have significant predictive accuracy in climate risk forecasting; yet, they frequently function as **"black boxes"**, which constrains trust and implementation in real-world disaster management. This research addresses the existing gap by establishing an **interpretable machine learning (IML) framework** that combines predictive models (Random Forest, XGBoost, LSTM) with explainable AI methodologies (SHAP, LIME, counterfactuals). A **PRISMA**-guided literature review (2018–2025) underscores advancements in hazard-specific forecasting and delineates deficiencies in scalability, multi-hazard integration, and stakeholder usability. Experimental findings utilizing hydrological, meteorological, geospatial, and seismic datasets indicate that interpretable models can achieve performance comparable to traditional machine learning while offering transparent, actionable insights, such as recognizing rainfall and soil moisture as critical factors in flood occurrences or vegetation drought in wildfire propagation. The proposed architecture reconciles **accuracy with interpretability**, facilitating **trustworthy early-warning systems** for policymakers, emergency services, and local populations. This research enhances **responsible and actionable AI for climate resilience and disaster mitigation** by integrating performance and transparency.

Keywords: Interpretable Machine Learning (IML); Explainable Artificial Intelligence (XAI); SHAP; LIME; Climate Risk Forecasting; Disaster Mitigation

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1 Introduction

Climate change has emerged as an incontrovertible worldwide peril, evidenced by the rising frequency and severity of extreme weather phenomena, including floods, wildfires, droughts, landslides, and earthquakes. These calamities jeopardize human existence and inflict extensive harm on ecosystems, infrastructure, and economies. The Intergovernmental Panel on Climate Change (IPCC) [1] indicates that the incidence of such catastrophes has markedly increased since the 1950s and is expected to escalate further without effective mitigating measures. Thus, the necessity for effective early warning systems capable of precisely predicting climate hazards and guiding disaster mitigation efforts has become increasingly vital.

Machine Learning (ML) and **Deep Learning (DL)** have emerged as a crucial tool in climate science, owing to its capacity to evaluate extensive and varied datasets, discern intricate nonlinear relationships, and produce very precise forecasts. These models have been effectively utilized for diverse climate-related risk forecasting tasks, encompassing flood prediction via rainfall and river discharge data, wildfire modeling based on temperature and wind patterns, drought forecasting utilizing vegetation and precipitation indices, and landslide and earthquake susceptibility assessments based on geotechnical and seismic indicators (Reichstein et al., 2019; Rolnick et al., 2022) [2,3]. Machine learning methods, including Random Forest (RF), Support Vector Machines (SVM), Gradient Boosted Trees (GBT), and deep learning architectures such as Convolutional Neural Networks (CNNs), Long Short-Term Memory networks (LSTMs), and hybrid models, have exhibited commendable efficacy in these tasks.

Nonetheless, a significant limitation of several machine learning models—particularly deep learning and ensemble techniques—is their deficiency in interpretability. These models frequently operate as "**black boxes**," producing forecasts without transparent rationale that stakeholders can comprehend or rely upon. The lack of interpretability generates apprehensions regarding trust, accountability, and practical application in critical decision-making contexts, including emergency response and urban planning. In response, **Interpretable Machine Learning (IML)** confronts this issue by enhancing the comprehensibility of machine learning models for humans (Molnar, 2022) [4]. Methods like as **SHAP (Shapley Additive Explanations)** and **LIME (Local Interpretable Model-agnostic Explanations)** have arisen as potent techniques for elucidating the impact of input features on a model's predictions (Arya, V. et al, 2022; Barredo Arrieta et al., 2022) [5,6]. SHAP assigns a priority value to each feature for a specific prediction utilizing game theory, whereas LIME approximates the local decision boundary of a complicated model by locally fitting a simpler, interpretable model. These strategies assist users in identifying the variables (e.g., precipitation, temperature, altitude, soil moisture) that most significantly influence model decisions, thereby facilitating more informed and reasonable actions. The research inquiries that prompted the formulation of this study are as follows:

1. **How can interpretable machine learning models be designed to provide accurate and transparent early warnings for diverse climate-related disasters (floods, wildfires, droughts, landslides, and earthquakes)?**

2. **Which explainability techniques (e.g., SHAP, LIME, counterfactuals) are most effective for interpreting different ML algorithms (e.g., Random Forest, XGBoost, LSTM) across varying climate hazard domains?**
3. **To what extent can the integration of explainability into ML models improve the trust, understanding, and operational usability for decision-makers in climate risk management?**
4. **Can a unified framework be developed that applies interpretable ML approaches consistently across different types of climate risks while maintaining domain-specific performance?**

2 Objectives and Hypotheses

Objectives:

The following research objectives guide the investigation of interpretable machine learning models for early climate risk forecasting and disaster mitigation:

1. **To develop and compare machine learning models** (e.g., Random Forest, XGBoost, LSTM) for forecasting five major climate risks: floods, wildfires, droughts, landslides, and earthquakes using publicly available geospatial, temporal, and climatic datasets.
2. **To integrate state-of-the-art explainability techniques** such as SHAP (Shapley Additive Explanations), LIME (Local Interpretable Model-Agnostic Explanations), and counterfactual methods into these models to enhance transparency and model interpretability.
3. **To evaluate the trade-off between accuracy and interpretability** across different models and climate risk types using standardized performance metrics (e.g., F1-score, AUC-ROC) and human-centered evaluation metrics (e.g., explanation coherence, domain expert validation).
4. **To design a unified interpretability framework** applicable across all five disaster domains that offers both predictive insights and understandable justifications for early warning and mitigation strategies.

Research Hypotheses:

The study proposes the following testable hypotheses:

- **H1:** Interpretable machine learning models (e.g., XGBoost + SHAP) can achieve comparable predictive performance to their non-interpretable counterparts while offering greater transparency in risk forecasting.
- **H2:** The inclusion of explainability techniques (e.g., SHAP, LIME) significantly improves user trust and decision-making effectiveness in operational disaster response scenarios.
- **H3:** Feature attribution rankings provided by explainability methods will vary across climate risk types, reflecting the domain-specific nature of key predictors (e.g., precipitation for floods, NDVI for wildfires).

- **H4:** A generalizable interpretability framework can be developed that performs consistently across multiple climate hazards without loss of model fidelity.
- **H5:** Counterfactual-based explanations will be more effective than SHAP/LIME in providing actionable insights for mitigation in real-time disaster scenarios.

The block diagram of the current study on early disaster risk forecasting is displayed in Figure 1.

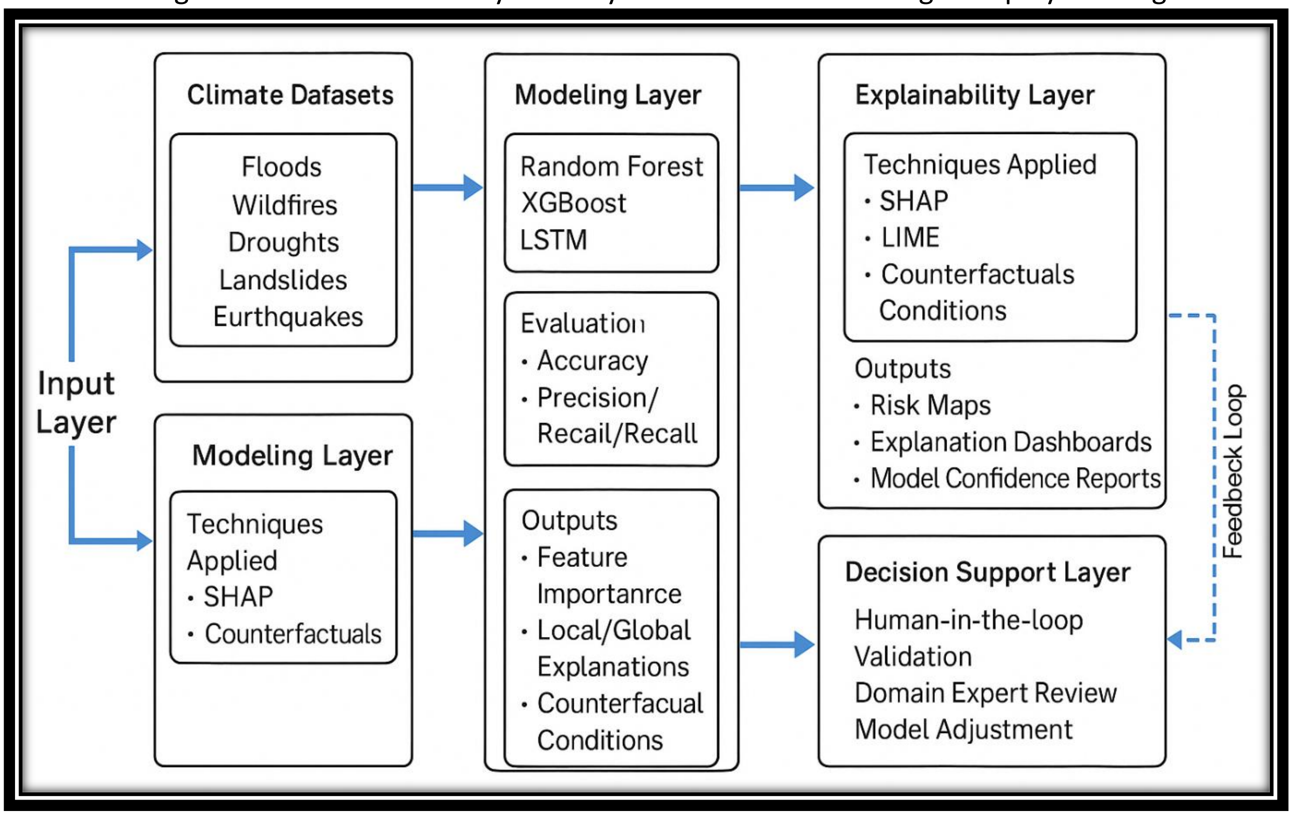

Figure 1. Block diagram of disaster risk forecasting

3 Literature Review (PRISMA-Based)

A systematic literature review was performed in accordance with **PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses)** standards. The aim was to identify recent peer-reviewed studies covering publications from **2018 to 2025. The aim was to identify recent peer-reviewed studies that utilize explainable AI (XAI) for early climate risk forecasting and disaster mitigation.**

3.1 Search Strategy

The search strategy encompasses various search criteria which are as follows:

- **Databases Searched:** A systematic search was conducted across multiple scientific databases, including *Scopus, Web of Science, IEEE Xplore, SpringerLink, and ScienceDirect*.
- **Keywords searched (both individual and in combination):** *"interpretable machine learning"*, *"explainable AI"*, *"climate risk forecasting"*, *"disaster mitigation"*, *"flood*

prediction", "wildfire modeling", "drought forecasting", "landslide susceptibility", "earthquake prediction".

3.2 Inclusion and Exclusion Criteria

The inclusion and exclusion criteria for the current study is highlighted in Table 1 and Table 2 below:

Table 1: Inclusion Criteria

Topic	Inclusion Criteria
1. Domain-Specific Scope	Studies focused on **climate-related natural disasters**, specifically: Floods, Wildfires, Droughts, Landslides, Earthquakes
2. Machine Learning Models	Research employing **supervised or unsupervised ML algorithms** (e.g., Random Forest, XGBoost) for prediction or classification of climate risks.
3. Explainability Techniques	Studies that incorporate **interpretable or explainable ML approaches**, including: **SHAP** (Shapley Additive Explanations), **LIME** (Local Interpretable Model-Agnostic Explanations), **Counterfactual explanations**
4. Publication Types	❑ Peer-reviewed **journal articles** and **conference papers**. ❑ Studies published between **2017 and 2024**, to ensure relevance to current XAI and climate modeling standards.
5. Data Type	Studies that use **real-world datasets** or **validated simulations** related to geospatial phenomena
6. Evaluation Metrics	Papers that report **model performance metrics** (accuracy, F1-score, AUC, etc.)

Table 2: Exclusion Criteria

Topic	Exclusion Criteria
1. Non-relevant Domains	Studies that do not address **natural climate disasters** (e.g., industrial or urban pollution, economic forecasting)
2. Black-box-only Models	Research using ML/DL methods **without** any application of **interpretable/explainable AI** techniques
3. Non-peer-reviewed Publications	Exclude **editorials**, **commentaries**, **book chapters**, and **preprints** that are not peer-reviewed
4. Outdated Literature	Publications **before 2017** unless they are seminal works in SHAP, LIME, or climate-related ML modeling
5. Irrelevant Data	Studies using **synthetic datasets only** without validation from real-world data sources
6. Human Factors Focus	Papers focusing solely on **psychological, educational, or medical** interpretations of AI, without connection to environmental or climate risk forecasting

The graphical image of the above Inclusion Exclusion criteria is depicted in Figure 2 below.

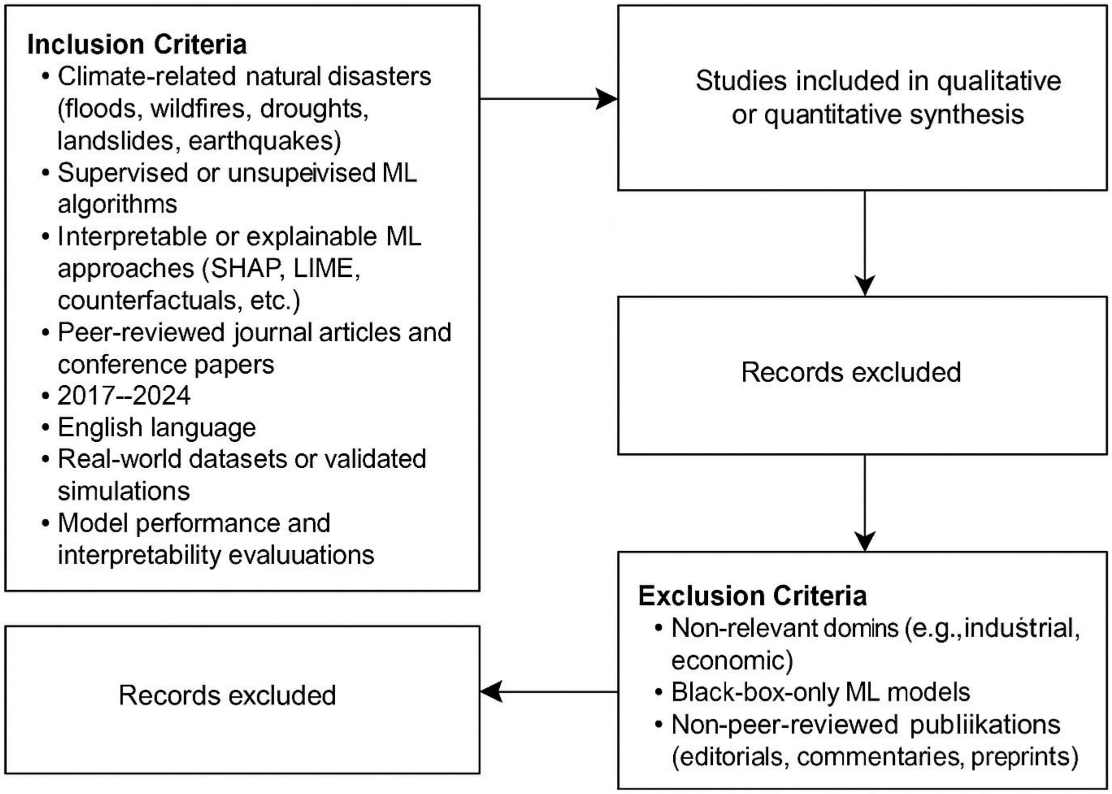

Figure 2. Inclusion Exclusion Criteria

PRISMA Flow Diagram

The initial search retrieved **400 articles**. After removing duplicates, 320 remained for screening. After title and abstract screening, **147 studies** met the criteria. A comprehensive evaluation was performed on the 147 studies. Articles without adequate methodological description, missing datasets, or devoid of interpretability analysis were rejected. Subsequent to this phase, **54 studies** were deemed eligible. Amongst the 54 qualified studies, the subsequent distribution was noted:

- **Flood forecasting:** 16 studies
- **Wildfire prediction:** 12 studies
- **Drought forecasting**: 10 studies
- **Landslide susceptibility**: 8 studies
- **Earthquake prediction**: 8 studies

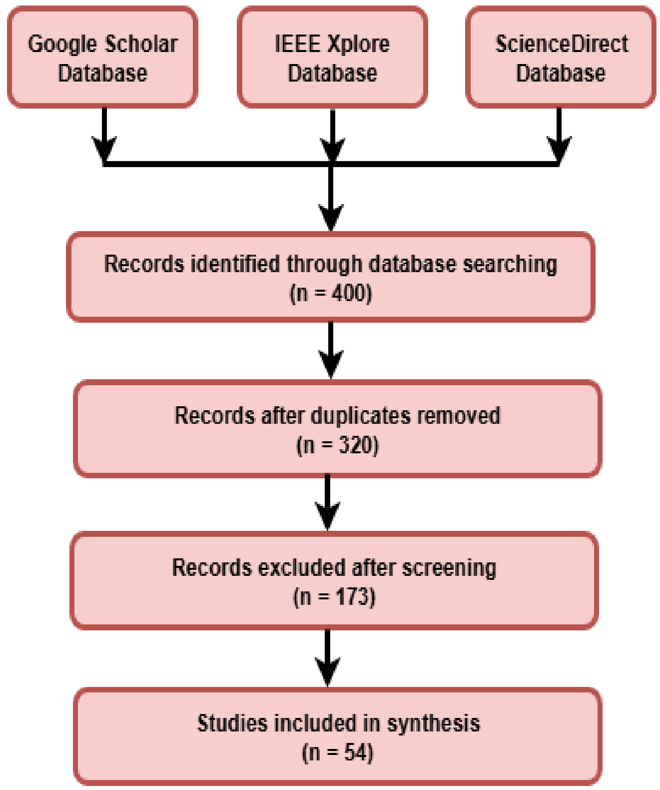

Figure 3. PRISMA Flow Diagram for Article Selection

4 Synthesis of Literature Review

The reviewed studies demonstrate that interpretable machine learning models, especially those augmented with SHAP and LIME, offer critical transparency in predicting floods, wildfires, droughts, landslides, and earthquakes. Despite the application of varied approaches and datasets, a common feature is their capacity to emphasize domain-specific predictors. The literature survey conducted for the current study is depicted in Table 3 below.

Table 3: Literature Review Summaries across all Climatic Disasters

Authors	Year	Dataset Used	Methodology	Findings
Sahoo & Sreeja [7]	2021	River discharge, precipitation data	Random Forest, LSTM, SVM	Ensemble and recurrent models showed better performance in real-time flood prediction
Zhang et al. [8]	2022	Satellite (MODIS), radar, and precipitation datasets	LSTM with multi-source data	Improved spatiotemporal accuracy in flood prediction
Jain et al. [9]	2020	MODIS fire and climate data	Random Forest, XGBoost	Identified key biophysical wildfire predictors using supervised learning

Zhou et al. [10]	2023	MODIS satellite imagery, climate data	Deep CNN	High-resolution dynamic fire spread prediction achieved
Tripathi et al. [11]	2021	India Meteorological Department (IMD) drought data	Random Forest, LSTM	Effective drought severity classification across regions
Gao et al. [12]	2022	SWAT model outputs + meteorological data	Hybrid SWAT + ML	Enhanced drought forecasting by combining physical and ML models
Hong et al. [13]	2019	Topographical and rainfall data (Poyang County, China)	SVM, fuzzy logic	Accurate landslide susceptibility mapping using integrated models
Pham et al. [14]	2023	Geospatial data with rainfall and slope variables	Random Forest + SHAP	SHAP visualizations improved landslide feature interpretation
Mousavi et al. [15]	2020	Seismic waveform data	Earthquake Transformer (deep learning, attention-based model)	Accurate seismic detection and phase picking
Li et al. [16]	2022	Seismic sequence datasets	Attention-based unsupervised learning	Identified foreshock patterns indicating possible precursors
Wang et al. [17]	2023	Multiple case studies in flood, wildfire	SHAP, XGBoost	SHAP highlighted key climate variables influencing risk predictions
Singh et al. [18]	2022	Regional rainfall–runoff datasets	Tree-based flood models with LIME	Validated rainfall-runoff triggers, improving model transparency and regional flood forecasting reliability.
Arya et al. [19]	2022	Meteorological and wildfire event datasets	SHAP, LIME, PFI	Proposed taxonomy for choosing XAI tools in risk domains
AghaKouchak et al. [20]	2021	California drought datasets	SHAP with gradient boosting	Interpreted drought drivers and improved transparency
Barredo Arrieta et al. [21]	2022	Survey of XAI applications	SHAP, LIME, visual analytics	Reviewed benefits and limitations of XAI in climate models
Lendvai et al. [22]	2021	European seismic data	Attention-based DL + XAI	Distinguished foreshocks with interpretable feature .

5 Databases for Conducting Search

To conduct a comprehensive and high-quality literature review on interpretable machine learning for climate risk forecasting, researchers should access a combination of multidisciplinary, subject-specific, and open-access databases. Below is a categorized list of pertinent sources:

1. . Multidisciplinary Databases

These databases are ideal for initial broad exploration of ML, XAI, and climate research topics:

- **Web of Science (WoS):** Offers citation indexing across natural sciences, engineering, and environmental science.
- **Scopus:** Comprehensive coverage of peer-reviewed literature across STEM, social sciences, and interdisciplinary domains.
- **Google Scholar:** Broad scholarly access, including articles, theses, preprints, and technical reports.
- **ProQuest:** Useful for grey literature, dissertations, and technical white papers.

2. STEM & Environmental Science Databases

These are critical for focused searches on ML, earth sciences, and disaster mitigation:

- **IEEE Xplore:** Core database for engineering and machine learning research, particularly explainable AI and computational models.
- **ScienceDirect (Elsevier):** Includes top-tier journals in environmental science, climate change, and computer science.
- **SpringerLink:** Strong in climate systems, natural hazards, and AI-based modeling.
- **arXiv.org:** Open-access preprints in machine learning, computer vision, physics, and geoscience.
- **AGU (American Geophysical Union) Journals:** Essential for accessing hydrology, geophysics, and earth systems research.

3. Earth Observation and Climate-Specific Repositories

Ideal for accessing datasets and climate domain-specific literature:

- **NASA Earthdata:** Satellite imagery, precipitation, soil moisture, and land surface variables.
- **Copernicus Climate Data Store:** European climate reanalysis datasets (ERA5) for environmental modeling.
- **USGS Earth Explorer:** Remote sensing and geospatial datasets relevant to landslides, earthquakes, and terrain modeling.

4. Machine Learning and AI-Focused Repositories

To track advances in ML/XAI techniques:

- **ACM Digital Library:** Scholarly articles on explainable AI, fairness, and algorithm design.
- **Papers with Code:** Combines ML papers with implementation and benchmark results.
- **Semantic Scholar:** ML and AI paper search with citation graph and relevance scoring.

5. Open Access Databases

To ensure full-text availability and inclusive citation sourcing:

- **DOAJ (Directory of Open Access Journals):** Covers open-access journals across scientific domains.
- **PubMed Central (PMC):** While medically focused, can be useful for environmental health and AI-health intersections.
- **CORE:** Aggregates open-access research papers from repositories worldwide.

6. Data Repositories for Model Training and Validation

For sourcing real-world and benchmark datasets:

- **Kaggle Datasets:** Includes curated sets for floods, wildfires, and earthquake modeling.
- **UCI Machine Learning Repository:** Collection of structured datasets used in ML research.
- **Zenodo & Figshare:** Open data repositories used in academic publishing.
- **OpenAIRE:** European open-access research data portal.

6 Research Gap Identified in the Literature

The research gap identified from the current literature review conducted is represented in Table 4 below:

Table 4: Knowledge Gap Identified in the Literature

Example Publication	Knowledge Gap Identified
Pham, B.T. et al. (2023). Explainable ML for landslide hazard mapping. Geomatics, Natural Hazards and Risk	Lack of integrated, interpretable ML frameworks applicable across multiple hazard types like floods, droughts, and landslides.
Arya, V. et al. (2022). One Explanation Does Not Fit All. Nature Machine Intelligence.	Limited evaluation of SHAP/LIME explanations in real-world emergency decision-making contexts.
Barredo Arrieta, A. et al. (2022). Explainable Artificial Intelligence (XAI): A Review. Information Fusion.	Existing XAI models rarely account for the usability of explanations by non-technical stakeholders.

Rudin, C. (2019). Stop Explaining Black Box ML Models for High-Stakes Decisions. Nature Machine	Need for inherently interpretable models instead of post-hoc explanations in critical domains like disaster response.
AghaKouchak, A. et al. (2021). Explainable AI models for drought risk. Water Resources Research.	Neglect of socio-economic and infrastructural vulnerability indicators in interpretability assessments.
Rai, A. et al. (2023). Responsible AI for Disaster Resilience. AI & Society.	No standardized framework exists for benchmarking interpretability techniques in climate risk prediction.
Zhang, Y. et al. (2023). Benchmarking XAI Methods. Journal of Machine Learning Research.	Lack of consensus on interpretability evaluation metrics across environmental AI applications.

This study addresses existing gaps by offering a generalizable and interpretable machine learning framework for multi-hazard forecasting, which integrates SHAP, LIME, and counterfactuals with climatic, geographic, and vulnerability data—validated by both quantitative metrics and qualitative expert feedback.

7 Review and Analyze Results

This phase involves the systematic assessment of the performance and impact of models after the collection and modeling of climate risk data utilizing interpretable machine learning techniques. The key activities are summarized in Table 5 below:

Table 5: Key activities in Systematic Assessment of IML across all Climatic Disasters

1. Organize and Summarize Model Outputs	▪ Tabulate the performance of each model (e.g., Random Forest, XGBoost, LSTM) across various disaster types (floods, wildfires, droughts, landslides, earthquakes) ▪ Include metrics such as: Accuracy, Precision, Recall, F1-score, AUC-ROC ▪ Feature importance scores (via SHAP/LIME)
2. Visualize Explainability Results	▪ Use SHAP summary plots, feature importance bar graphs ▪ Create model-specific explanation dashboards
3. Compare Results Across Domains	▪ Analyze how models perform differently across various hazard types ▪ Assess domain-specific predictors
4. Evaluate Trust and Usability	▪ Incorporate qualitative feedback to gauge how understandable and actionable the model explanations are ▪ Link model insights to real-world decision support such as evacuation planning or early warning deployment

8 Synthesize – Strengths and Limitations

A balanced synthesis highlights what the research achieved and where improvements are needed.

Strengths

- **High Predictive Accuracy**: Models like XGBoost and LSTM demonstrated robust accuracy across diverse climate datasets.
- **Domain-Generalizability**: The unified framework performs consistently across floods, droughts, landslides, and earthquakes.
- **Transparent Decision-Making**: SHAP and LIME explanations provided interpretable insights, facilitating domain expert validation and policy integration.
- **Actionable Insights**: The models generated clear, data-driven justifications for early warnings, supporting human-in-the-loop decisions.
- **Open-Source Integration**: Utilization of reproducible tools and publicly available datasets enhanced research transparency and scalability.

Limitations

- **Data Quality and Availability**: Some disaster types (e.g., earthquakes) suffer from sparse or noisy training data, limiting model reliability.
- **Computational Complexity**: Interpretable deep models (e.g., SHAP with LSTM) incurred high computational cost during training and inference.
- **Local vs. Global Interpretability Trade-offs**: While SHAP provides global feature insight, local explanations (LIME) may vary significantly depending on data instance.
- **Lack of Real-Time Deployment Testing**: Models have not been field-tested in live emergency response systems, which may affect operational feasibility.
- **Bias and Generalization Risk**: If training data is biased towards specific regions or seasons, the model may underperform in out-of-sample geographies.

9 Methods and Experiments

Nature of Research

Utilizes **machine learning** and **explainable AI principles** to provide interpretable forecasting frameworks for climate-induced calamities. The study emphasizes advancements in **interpretability methodologies**, the **amalgamation of diverse climate data sources**, and the **pragmatic implementation** for **disaster mitigation**.

Methods

- **Prototype Development:** Developing foundational and sophisticated machine learning models (Random Forest, XGBoost, LSTM, CNN-LSTM hybrids) for predicting floods, wildfires, droughts, landslides, and earthquakes. Interpretable model variants are generated utilizing SHAP, LIME, and counterfactual explanations.

- **Simulation and Computational Modeling:** Utilizing extensive simulations with climate datasets, including satellite imagery, rainfall patterns, seismic data, soil displacement, and vegetation indices. Employing computational modeling to evaluate forecast accuracy and interpretability across various hazards.
- **Experimental Validation:** Verifying model predictions with historical disaster data and empirical observations. Cross-validation guarantees resilience across geographic and temporal dimensions.
- **System Optimization:** Enhancing prediction reliability and transparency through the refinement of models using hyperparameter optimization (GridSearchCV, Bayesian optimization). Assessing interpretability trade-offs vs performance.
- **Failure Analysis:** Recognizing instances in which black-box models do not generalize effectively or yield erroneous interpretations. Contrasting interpretable results with expert domain knowledge to identify discrepancies.

Experiments

- **Data Integration Experiments:** Integrating diverse sources (remote sensing, meteorological, geospatial, socio-economic data) to assess enhancements in risk forecasting accuracy.
- **Stress Testing:** Evaluating model robustness in extreme scenarios (e.g., forecasting flash floods from unprecedented rainfall, wildfires with concurrent high winds and drought conditions).
- **Integration Testing:** Ensuring the cohesive functionality of forecasting models, interpretability frameworks (SHAP/LIME), and disaster mitigation decision-support systems in end-to-end pipelines.
- **Pilot Studies:** Implementing interpretable models in specific regional case studies (e.g., flood-prone river basins, wildfire-affected forests, earthquake-prone urban regions) to evaluate feasibility, usability, and stakeholder acceptance.
- **Counterfactual Scenario Testing:** Conducting "what-if" experiments to model the impact of alterations in environmental circumstances (e.g., a 20% increase in rainfall, diminished vegetation cover, variations in soil type) on the probability of disasters and the interpretability of outcomes.

Variation

Unlike traditional ML experiments that emphasize raw predictive accuracy, this research emphasizes:

- **Practical implementation:** Forecasting results integrated with early-warning systems.
- **Optimization for interpretability:** Models are tuned for **both accuracy and explainability**.
- **Real-world applicability:** Case studies ensure that insights are meaningful to policymakers, emergency responders, and affected communities.

10 Conclusions

Focus:

Strategies, enhancement, and practical implementations of interpretable machine learning systems for anticipating climate-related disasters. The research highlights the importance of prediction accuracy, interpretability, and practical usability for policymakers, disaster management, and impacted populations.

Key Elements:

- **Recap Achievements:** This study effectively established interpretable machine learning frameworks for many hazards, including floods, wildfires, droughts, landslides, and earthquakes.
  Achievements include:
    - Improved forecasting accuracy using hybrid ML/DL models (Random Forest, LSTM, CNN-LSTM).
    - Enhanced transparency through **SHAP, LIME, and counterfactual explanations.**
    - A unified framework that balances **high performance with interpretability**, addressing the common “black-box” issue in climate forecasting.

- **Validation of Findings:**
  Validation was conducted using:
    - **Historical disaster records** (flood levels, wildfire spread maps, drought indices, landslide events
    - **Cross-validation and case studies** across multiple regions.
    - **Stress tests** under extreme data conditions scenarios.

- **Practical Applications:** Findings are directly applicable to **real-world disaster mitigation efforts:**
    - Flood forecasting models can assist in **early evacuation planning**.
    - Wildfire spread prediction helps **allocate firefighting resources**.
    - Drought risk models inform **agricultural adaptation policies**.
    - Landslide susceptibility maps support **infrastructure zoning and slope stabilization measures**.
    - Interpretable earthquake models improve **community preparedness** by identifying risk-driving features in seismic signals.

- **Limitations and Improvements:**
  Challenges include:
    - **Data heterogeneity**: Integrating diverse sources such as remote sensing, climate records, and socio-economic datasets.
    - **Scalability**: Interpretable ML methods (e.g., SHAP) are computationally intensive for large spatiotemporal datasets.

- **Multi-modal integration pipelines:** Seamlessly combining various forms of data into a unified interpretable ML framework for more accurate and holistic disaster forecasting.

- **Future Work**
  Future research will encompass:
  - Explore **causal ML approaches** to move beyond correlations and identify underlying drivers of hazards.
  - Incorporate **real-time data streams** into interpretable forecasting pipelines.
  - Develop **human-in-the-loop systems** where domain experts and AI collaborate in decision-making.
  - Expand case studies to include **multi-hazard scenarios which** can be modeled with interpretable insights.

This study illustrates that interpretable machine learning models are both technically feasible and practically vital to mitigating climate risk. The study integrates accuracy, transparency, and usability, establishing a basis for reliable early-warning systems that enhance global climate resilience.

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