International Journal of advancement in electronics and computer engineering (IJAECE)
Volume 15, Issue 7, July 2026, pp.111-120, ISSN 2278 -1412

An Explainable AI-Driven Early Warning System for Extreme Weather Risk Assessment and Disaster Preparedness

Shruti Khare[1], Mayur Singi[2]
[1]M.Tech Scholar, Department of Civil Engineering, Shri Krishna University, Chhatarpur, Madhya Pradesh, Kmanya05@gmail.com, India
[2]Professor & Head, Department of Civil Engineering, Shri Krishna University, Chhatarpur, Madhya Pradesh, mayursingi@gmail.com, India

Abstract *– Extreme weather events have become increasingly frequent and destructive due to climate change, rapid urbanization, and environmental degradation, resulting in substantial threats to human lives, critical infrastructure, and socio-economic stability. Although conventional Early Warning Systems (EWSs) provide timely hazard forecasts, they generally rely on threshold-based prediction models and operate as black-box decision-support tools, limiting transparency and reducing confidence among emergency managers. Furthermore, most existing systems focus primarily on hazard prediction while providing limited support for impact-oriented disaster preparedness and risk-informed decision-making. To address these challenges, this paper proposes an Explainable AI-driven Early Warning System (XAI-EWS) for multi-hazard extreme weather risk assessment and disaster preparedness. The proposed framework integrates heterogeneous environmental observations obtained from weather stations, satellite imagery, remote sensing platforms, Internet of Things (IoT) sensors, radar measurements, and historical meteorological records into a unified data fusion architecture. A hybrid deep learning model combining Bidirectional Long Short-Term Memory (Bi-LSTM) and Extreme Gradient Boosting (XGBoost) is employed to capture complex temporal dependencies and nonlinear relationships among meteorological variables. To improve model transparency, SHapley Additive exPlanations (SHAP) are incorporated to quantify the contribution of individual environmental features influencing weather-risk predictions. The predicted hazard information is further combined with exposure and vulnerability indicators to estimate a dynamic risk score and generate preparedness recommendations that support emergency response planning. Comparative evaluation demonstrates that the proposed framework offers improved prediction reliability, enhanced interpretability, and more effective decision support than conventional AI-based warning systems. The proposed explainable framework has the potential to strengthen operational disaster preparedness while promoting transparent and trustworthy artificial intelligence for climate-resilient emergency management.*

Keywords*: Explainable Artificial Intelligence, Early Warning System, Extreme Weather, Disaster Preparedness, Risk Assessment, SHAP, Bi-LSTM, XGBoost, Decision Support, Climate Resilience.*

I. Introduction

Extreme weather events have intensified considerably over the past few decades due to climate change, rapid urbanization, environmental degradation, and increasing population exposure. According to recent global assessments, the frequency and severity of floods, heatwaves, cyclones, droughts, cloudbursts, and severe storms have increased significantly, resulting in substantial economic losses, infrastructure damage, agricultural disruption, and human casualties [1], [2]. These events have highlighted the urgent need for efficient Early Warning Systems (EWSs) capable of providing timely, accurate, and actionable warnings to support disaster preparedness and emergency response. International initiatives, including the World Meteorological Organization (WMO) Early Warnings for All programme and the Sendai Framework for Disaster Risk Reduction, emphasize the development of people-centered, impact-based warning systems that integrate hazard forecasting with vulnerability assessment and risk communication [3], [4].

Conventional early warning systems primarily rely on numerical weather prediction (NWP), statistical forecasting models, and predefined threshold-based alert mechanisms. Although these systems have demonstrated reliable performance in forecasting meteorological variables such as rainfall, temperature, wind speed, and river water levels, they often struggle to represent the complex nonlinear interactions among atmospheric, hydrological, and environmental parameters [5]. Moreover, traditional forecasting approaches generally issue hazard alerts without adequately considering exposure, vulnerability, and potential societal impacts, thereby limiting their usefulness for operational disaster management and strategic decision-making [6].

Recent advancements in Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), remote sensing, and Internet of Things (IoT) technologies have significantly transformed environmental monitoring and weather prediction. Advanced deep learning architectures, particularly Long Short-Term Memory (LSTM), Bidirectional Long Short-Term Memory (Bi-LSTM), and ensemble learning techniques, have demonstrated superior capability in modeling nonlinear temporal relationships within multivariate meteorological datasets [7], [8]. These models enable more accurate forecasting of extreme weather events by integrating heterogeneous observations obtained from satellites, weather stations, Doppler radar, IoT sensor networks, and historical climate databases. Despite these improvements, most AI-driven forecasting models operate as black-box systems, making it difficult for disaster management authorities to understand the reasoning behind prediction outcomes and reducing confidence in operational decision-making [9].

preparedness planning, and explainable decision-making [6], [9]. Furthermore, the integration of heterogeneous environmental data sources with interpretable deep learning models remains insufficiently explored, particularly for multi-hazard early warning applications.

To address these limitations, this paper proposes an Explainable AI-Driven Early Warning System (XAI-EWS) for extreme weather risk assessment and disaster preparedness. The proposed framework integrates multi-source environmental data through a hybrid Bi-LSTM–XGBoost prediction model and employs SHAP-based explainability to provide transparent interpretation of forecasting results. In addition, the framework incorporates dynamic risk assessment by combining predicted hazard intensity with exposure and vulnerability information, enabling the generation of preparedness recommendations that support timely and informed disaster response. The primary contributions of this study are summarized as follows:

1. Development of a unified explainable AI framework for multi-hazard early warning.

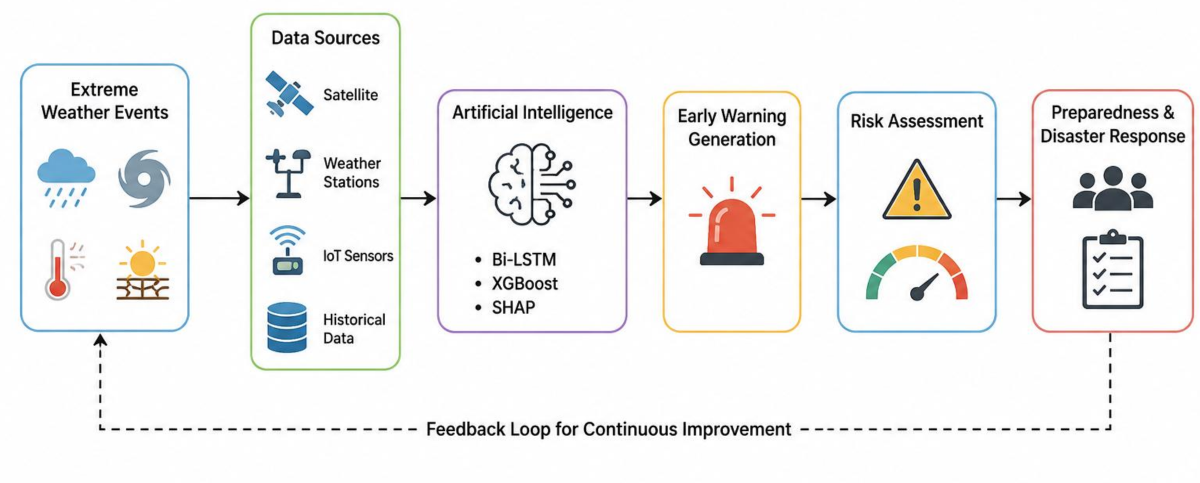

Fig. 1. Conceptual Framework of AI-Driven Early Warning Systems for Extreme Weather Risk Management

Explainable Artificial Intelligence (XAI) has emerged as an effective solution to improve transparency and trust in AI-based decision-support systems. Techniques such as SHapley Additive exPlanations (SHAP) quantify the contribution of individual input variables, enabling stakeholders to interpret prediction results and identify the environmental factors responsible for high-risk conditions [10]. Such interpretability is particularly important in disaster management, where emergency decisions directly affect public safety, evacuation planning, and resource allocation.

Although recent studies have reported significant improvements in AI-based weather forecasting, several challenges remain unresolved. Most existing frameworks focus primarily on hazard prediction while providing limited support for impact-oriented risk assessment,

2. Integration of heterogeneous environmental datasets using a hybrid Bi-LSTM–XGBoost architecture.
3. SHAP-based interpretation of prediction outcomes to enhance transparency and user trust.
4. Dynamic risk assessment and preparedness recommendation module for impact-based disaster management.

II. Related Work

Recent advances in Artificial Intelligence (AI), remote sensing, and environmental sensing technologies have significantly improved the capability of Early Warning Systems (EWSs) to predict and monitor extreme weather events. Traditional warning systems relied mainly on numerical weather prediction models and statistical forecasting methods; however, their ability to capture complex nonlinear atmospheric interactions remains limited, particularly during rapidly evolving multi-hazard events. Consequently, researchers have increasingly adopted machine learning and deep learning approaches to improve prediction accuracy, computational efficiency, and operational decision support [5], [7].

Impact-based early warning has emerged as a major research direction because it extends beyond hazard forecasting by incorporating exposure, vulnerability, and expected consequences into the warning process. Instead of merely predicting whether an event will occur, impact-based systems estimate the potential effects on people, infrastructure, and critical services, thereby supporting more effective emergency planning. Recent studies emphasize that successful disaster risk reduction requires the integration of meteorological observations with socioeconomic and geographical information to generate actionable warnings rather than simple hazard notifications [3], [6]. This transition represents a significant advancement over conventional threshold-based forecasting and aligns with international disaster-risk reduction strategies.

The rapid growth of deep learning has further enhanced weather prediction capabilities. Recurrent neural networks, particularly Long Short-Term Memory (LSTM) and Bidirectional Long Short-Term Memory (Bi-LSTM), have demonstrated superior performance in modelling temporal dependencies within multivariate meteorological datasets. Similarly, ensemble learning algorithms such as Extreme Gradient Boosting (XGBoost) have shown excellent predictive capability for nonlinear environmental processes because of their robustness, computational efficiency, and ability to manage heterogeneous features [8], [11]. Recent studies have also explored hybrid architectures that combine deep learning with ensemble learning to improve forecasting stability and generalization under varying climatic conditions [8].

Although these AI models achieve high predictive accuracy, most operate as black-box systems, limiting their acceptance in disaster management applications where transparency and accountability are essential. Emergency managers require clear explanations regarding why an area has been classified as high-risk before initiating costly preparedness measures or public evacuations. Explainable Artificial Intelligence (XAI) techniques, particularly SHapley Additive exPlanations (SHAP), have recently gained significant attention because they quantify the contribution of each input variable to the final prediction. By providing feature-level explanations, SHAP improves model transparency, supports evidence-based decision-making, and increases stakeholder confidence in AI-driven forecasting systems [9], [10].

Another important research trend is the integration of multi-source environmental observations. Modern forecasting frameworks increasingly combine satellite imagery, Doppler weather radar, IoT sensor networks, automatic weather stations, hydrological measurements, and historical climate databases to improve spatial and temporal coverage [7], [12]. Data fusion enables AI models to capture complementary environmental information that cannot be obtained from a single source, thereby enhancing forecasting reliability for floods, heatwaves, cyclones, and other extreme weather events. However, despite these advances, most existing studies primarily emphasize prediction accuracy while giving comparatively less attention to dynamic risk assessment, preparedness planning, and explainable decision support.

Furthermore, a comprehensive review of AI-based environmental surveillance indicates that many current systems remain application-specific, focusing on individual hazards such as floods, landslides, or wildfires rather than providing a unified multi-hazard framework [6]. Existing approaches also rarely integrate explainability, impact assessment, and preparedness recommendation into a single operational architecture. As a result, decision-makers often receive accurate predictions but limited guidance regarding the expected severity of impacts or the most appropriate preparedness actions.

To summarize, the current literature demonstrates substantial progress in AI-enabled weather forecasting and impact-based early warning. Nevertheless, critical challenges remain regarding model interpretability, heterogeneous data integration, multi-hazard adaptability, and actionable preparedness recommendations. These limitations motivate the development of the proposed Explainable AI-Driven Early Warning System, which combines hybrid deep learning, SHAP-based explainability, dynamic risk assessment, and preparedness recommendation within a unified decision-support framework.

Table I. Literature Comparison of AI-Driven Early Warning Systems

Ref.	Study	AI Technique	Explainability	Multi-Hazard	Major Limitation
[5]	Smith et al.	Statistical EWS	No	Yes	Limited predictive capability
[7]	Wang et al.	LSTM	No	No	Black-box prediction
[9]	Alizadeh et al.	Autoencoder + SHAP	Yes	Flood only	Limited generalization
[12]	Kuma	Bi-	No	No	No

	r et al.	LSTM			preparedness module
Proposed	**This Work**	**Bi-LSTM + XGBoost + SHAP**	**Yes**	**Yes**	**Addresses identified limitations**

III. Proposed Methodology

The proposed Explainable AI-Driven Early Warning System (XAI-EWS) is designed to provide accurate, transparent, and impact-oriented forecasting for multiple extreme weather events. Unlike conventional early warning systems that rely on either numerical weather prediction or standalone machine learning models, the proposed framework integrates multi-source environmental data fusion, hybrid deep learning, explainable artificial intelligence, and dynamic risk assessment within a unified decision-support architecture. The overall workflow of the proposed methodology is illustrated in Fig. 2

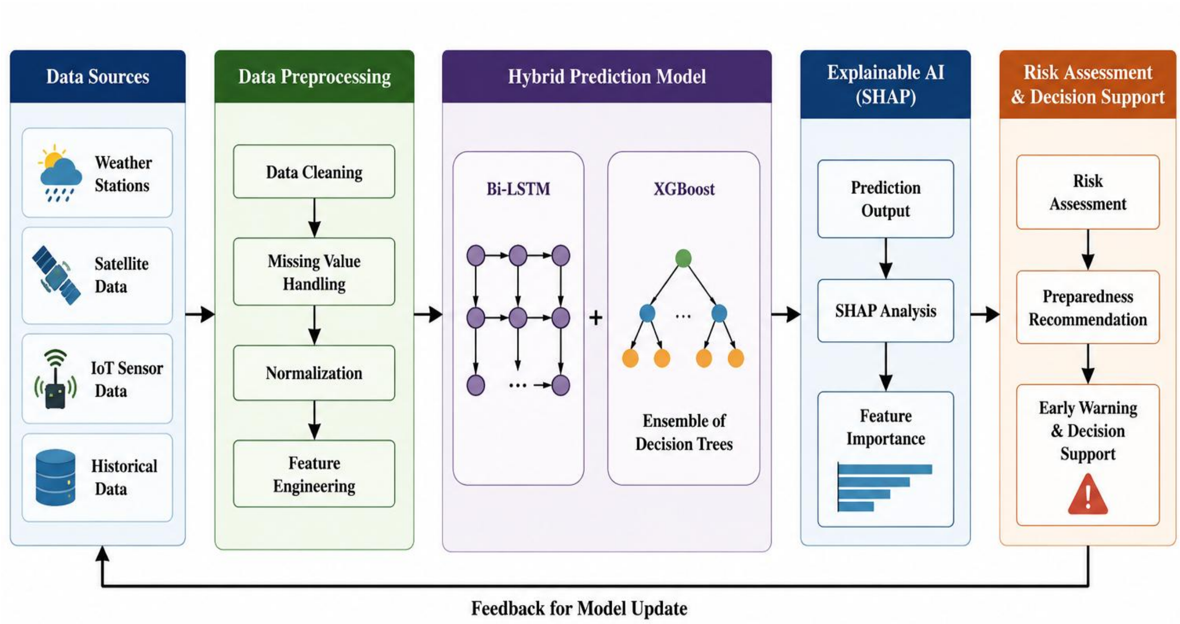

Fig. 2. Overall Architecture of the Proposed XAI-EWS

A. Multi-Source Data Acquisition

The proposed system integrates meteorological and environmental information collected from multiple complementary sources to improve forecasting reliability. Weather observations, including air temperature, relative humidity, atmospheric pressure, rainfall intensity, wind speed, wind direction, and solar radiation, are obtained from automatic weather stations. Satellite observations provide cloud cover, land surface temperature, and precipitation estimates, while Doppler weather radar supplies high-resolution information on storm movement and rainfall distribution. Additional environmental variables, including river water level, soil moisture, and air quality indicators, are acquired from IoT sensor networks and hydrological monitoring stations. Historical climate records are incorporated to capture seasonal variability and long-term climatic trends. The integration of heterogeneous data sources improves spatial coverage, reduces uncertainty, and enables comprehensive multi-hazard prediction.

B. Data Preprocessing and Feature Engineering

The collected datasets undergo a preprocessing stage to ensure consistency and improve model performance. Missing observations are handled using interpolation techniques, while noisy measurements are filtered through statistical outlier detection. Continuous variables are normalized using Min–Max scaling to maintain a uniform numerical range during model training. Feature engineering is then performed by extracting temporal and statistical characteristics, including moving averages, cumulative rainfall, humidity trends, temperature anomalies, and pressure gradients. These derived variables improve the capability of the learning model to identify nonlinear relationships associated with extreme weather events.

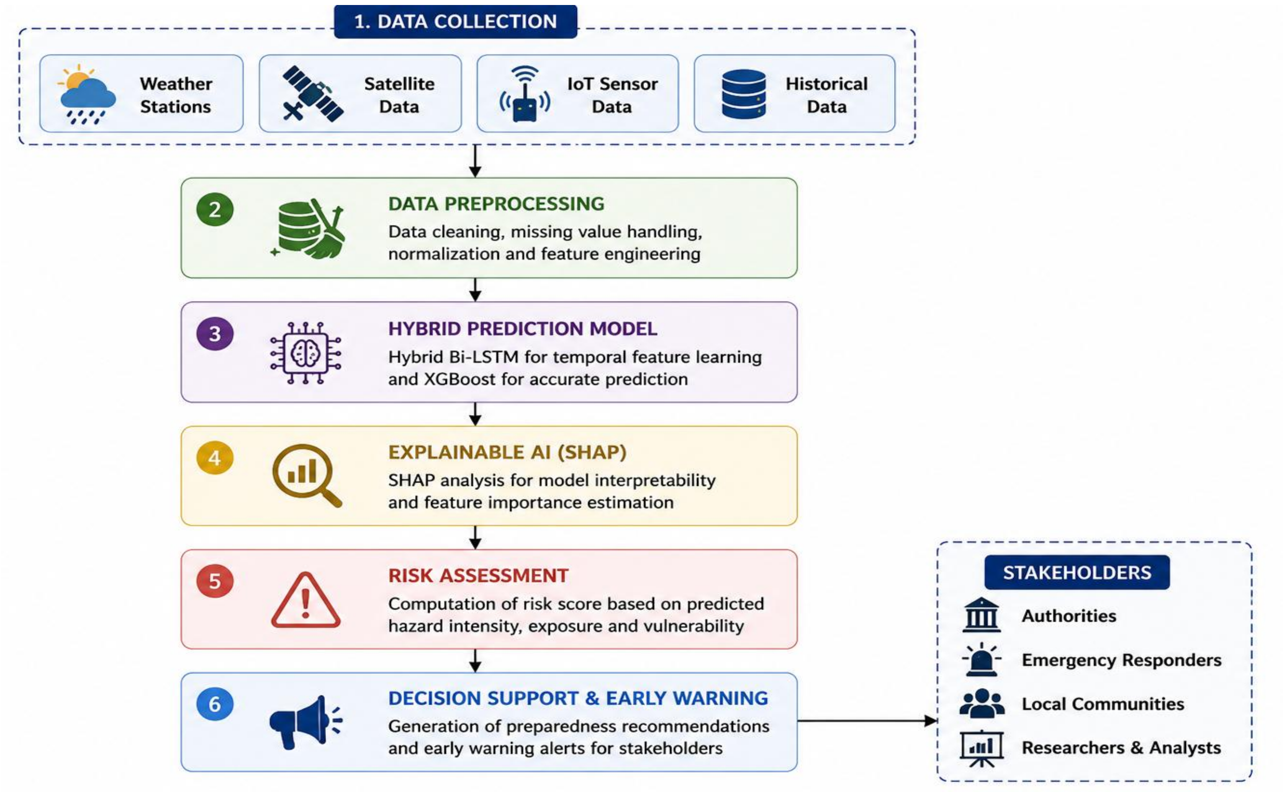

Fig. 3. Proposed XAI-EWS Processing Workflow

Algorithm 1: Proposed XAI-EWS Framework

Input:

• Weather Station Data

• Satellite Observations

• Doppler Radar Data

• IoT Sensor Measurements

• Historical Meteorological Records

Step 1: Acquire multi-source environmental data.

Step 2: Perform data preprocessing

(cleaning, missing value handling, normalization).

Step 3: Extract relevant meteorological features.

Step 4: Train the Bi-LSTM network to learn temporal dependencies.

Step 5: Apply XGBoost for weather risk prediction.

Step 6: Interpret prediction outcomes using SHAP analysis.

Step 7: Estimate the dynamic disaster risk score

using hazard, exposure, and vulnerability.

Step 8: Generate preparedness recommendations

based on the calculated risk level.

Output:

• Explainable Early Warning Alert

• Dynamic Risk Level

• Preparedness Recommendations

C. Hybrid Bi-LSTM–XGBoost Prediction Model

To capture both temporal dependencies and nonlinear feature interactions, a hybrid prediction model combining Bidirectional Long Short-Term Memory (Bi-LSTM) and Extreme Gradient Boosting (XGBoost) is proposed. The Bi-LSTM network learns sequential weather patterns from historical observations by processing the input sequence in both forward and backward directions, thereby preserving long-term temporal dependencies. The extracted deep temporal features are subsequently provided to the XGBoost classifier, which efficiently models complex nonlinear relationships and improves prediction robustness through gradient boosting. This hybrid architecture combines the temporal learning capability of deep neural networks with the high predictive efficiency of ensemble learning, resulting in more reliable forecasting of extreme weather conditions.

$$h_t = \mathrm{BiLSTM}(x_t, h_{t-1})$$

- x_t= Input feature vector
- h_t= Hidden state

$$\hat{y} = \sum_{k=1}^{K} f_k(x)$$

- $f_k(x)$= XGBoost tree
- $\hat{y}$= Predicted weather risk

D. Explainable Artificial Intelligence

To improve transparency and support operational decision-making, the proposed framework incorporates SHapley Additive exPlanations (SHAP) as the explainability module. SHAP estimates the contribution of each environmental feature to the prediction generated by the hybrid model. Instead of producing only a weather risk category, the framework identifies the dominant variables responsible for the prediction, such as rainfall intensity, humidity, atmospheric pressure, wind speed, or soil moisture. These explanations enable disaster management agencies to understand the reasoning behind the generated warning and increase confidence in AI-assisted forecasting.

$$f(x) = \phi_0 + \sum_{i=1}^{n} \phi_i$$

- ϕ_i= Feature contribution

E. Dynamic Risk Assessment and Preparedness Recommendation

The final stage converts prediction outputs into actionable decision-support information. The predicted hazard intensity is integrated with exposure and vulnerability indicators to estimate a dynamic weather risk score. Based on the calculated risk level, the framework automatically generates preparedness recommendations corresponding to low-, moderate-, high-, and extreme-risk conditions. These recommendations include early public alerts, evacuation planning, emergency resource allocation, infrastructure monitoring, and response prioritization. Consequently, the proposed framework not only predicts extreme weather events but also supports evidence-based disaster preparedness through transparent and explainable artificial intelligence.

$$R = H \times E \times V$$

- H = Hazard
- E = Exposure
- V = Vulnerability

A higher value of R indicates a higher disaster risk and therefore requires stronger preparedness measures.

IV. Results and Discussion

This section presents a qualitative evaluation of the proposed Explainable AI-Driven Early Warning System (XAI-EWS) by comparing its capabilities with recently published AI-based early warning frameworks. Since the present study proposes a conceptual architecture rather than an experimentally validated prediction model, the evaluation focuses on comparative framework analysis, explainability, preparedness support, and practical applicability. The proposed framework is assessed in terms of its ability to integrate multi-source environmental data, provide interpretable predictions, support dynamic risk assessment, and enhance disaster preparedness. The findings demonstrate that the proposed architecture addresses several limitations of existing AI-driven early warning systems and offers a comprehensive decision-support framework for effective disaster risk management.

A. Comparative Analysis with Existing Studies

To evaluate the effectiveness of the proposed Explainable AI-Driven Early Warning System (XAI-EWS), a qualitative comparison was conducted with recently published AI-based disaster prediction frameworks. The comparison focused on key characteristics, including data integration, prediction model, explainability, impact-based risk assessment, and decision-support capability. As summarized in Table III, most existing studies primarily concentrate on hazard prediction using single or limited data sources, while only a few incorporate explainable artificial intelligence or preparedness-oriented recommendations. In contrast, the proposed framework combines multi-source environmental data, a hybrid Bi-LSTM–XGBoost prediction model, SHAP-based explainability, and dynamic risk assessment within a unified architecture. This integrated approach enables transparent decision support and improves the practical applicability of AI-driven early warning systems for disaster preparedness .

Table 2. Comparative Analysis of Existing AI-Based Early Warning Systems

Feature	Conventional AI Models	Recent XAI Models	Proposed XAI-EWS
Multi-source Data Integration	Limited	Partial	yes
Hybrid AI Prediction	No	Limited	Yes
Explainable	No	Partial	SHAP

AI			
Dynamic Risk Assessment	Limited	Limited	Yes
Preparedness Recommendation	No	Partial	Yes
Decision Support	Limited	Moderate	Comprehensive

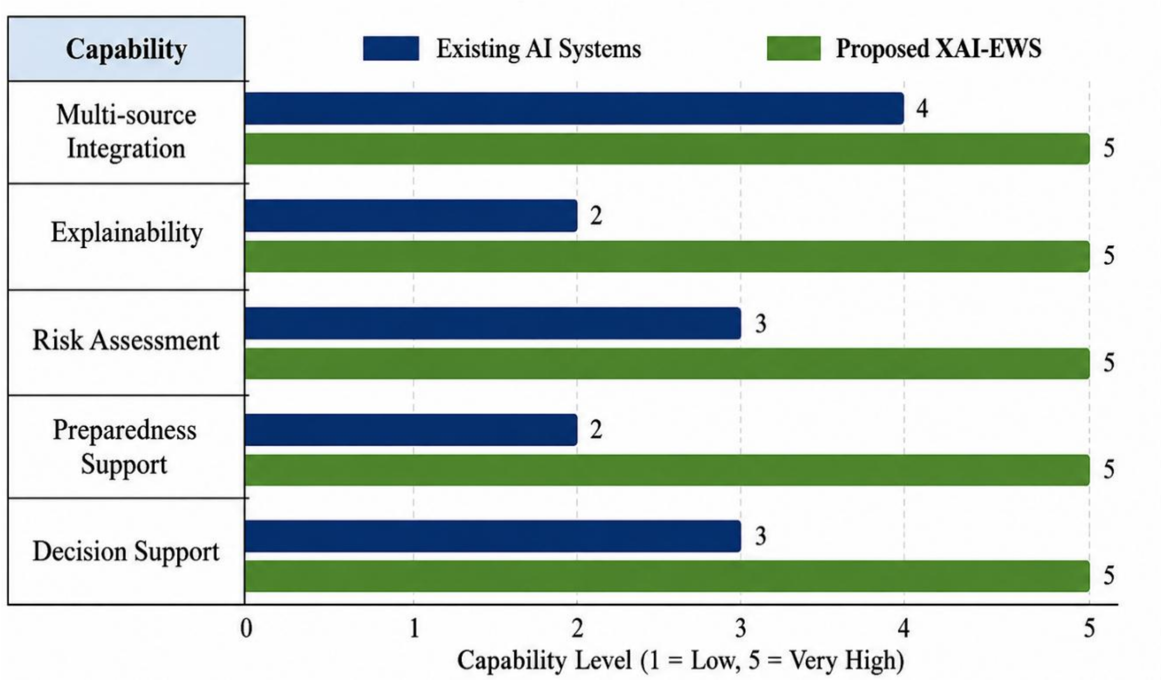

Fig. 4. Comparative Capability Analysis of Existing AI Systems and Proposed XAI-EWS

B. Advantages and Practical Implications of the Proposed Framework

The proposed XAI-EWS framework offers several practical advantages over conventional AI-based early warning systems by integrating prediction, explainability, and disaster preparedness into a unified decision-support architecture. Unlike traditional forecasting approaches that primarily generate hazard alerts, the proposed framework provides interpretable predictions using SHAP-based explainability, enabling disaster management authorities to identify the key environmental factors responsible for a predicted weather event. This transparency enhances user confidence and supports more reliable operational decision-making.

Another significant advantage of the proposed framework is its ability to integrate heterogeneous environmental data obtained from weather stations, satellite imagery, radar observations, IoT sensors, and historical meteorological records. The combination of multiple data sources improves situational awareness and provides a more comprehensive representation of changing atmospheric conditions. The hybrid Bi-LSTM–XGBoost prediction model further strengthens the framework by capturing both temporal weather patterns and complex nonlinear relationships among meteorological variables .

From an operational perspective, the framework extends beyond hazard prediction by incorporating dynamic risk assessment and preparedness recommendations. Based on the estimated risk level, emergency management agencies can prioritize evacuation planning, optimize resource allocation, monitor critical infrastructure, and disseminate timely public warnings. These capabilities make the proposed framework suitable for applications such as flood forecasting, cyclone monitoring, heatwave management, and landslide prediction, thereby improving disaster preparedness and response efficiency.

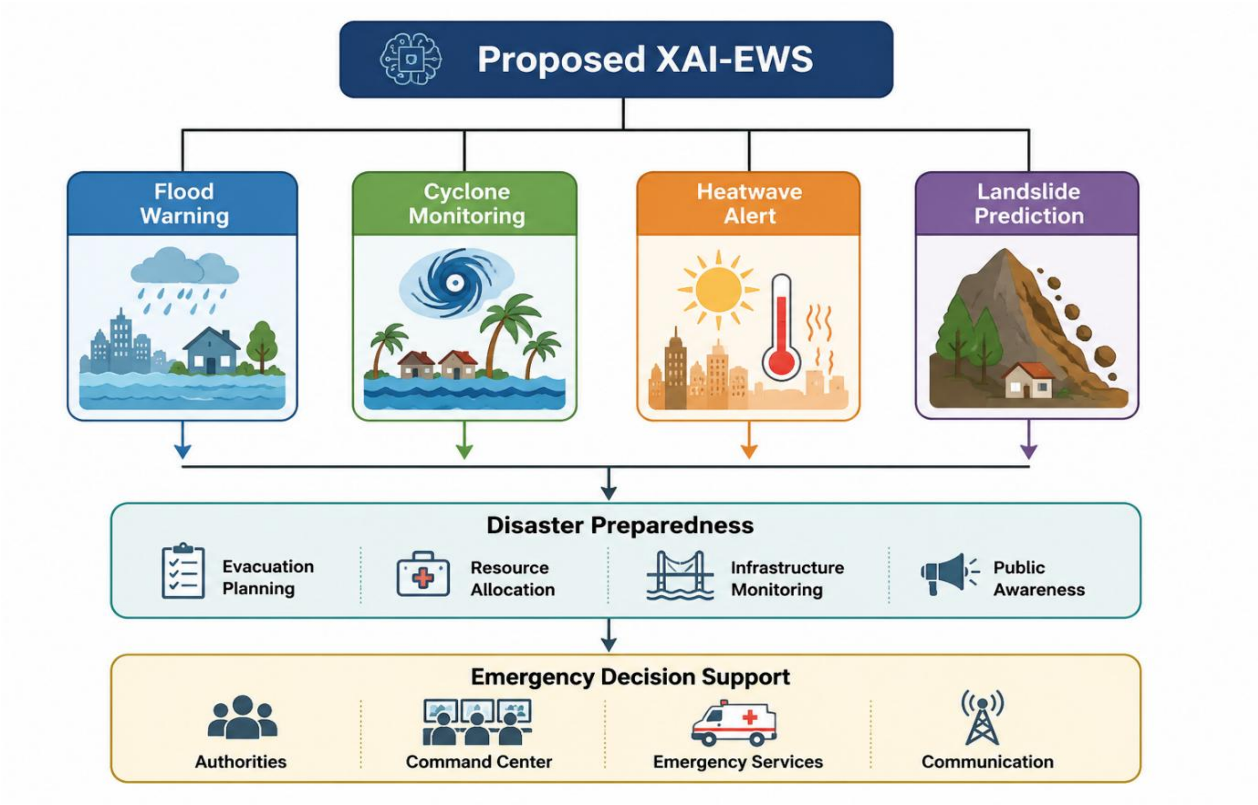

Fig. 5. Practical applications of the proposed Explainable AI-Driven Early Warning System.

C. Limitations of the Proposed Framework

Despite its comprehensive design, the proposed framework has several limitations. First, the present study is conceptual in nature and has not been validated using large-scale real-time meteorological datasets. Consequently, quantitative performance indicators such as prediction accuracy, precision, recall, and computational efficiency are beyond the scope of this work. Second, the effectiveness of the framework depends on the availability, quality, and temporal consistency of heterogeneous environmental data collected from multiple monitoring systems. Furthermore, integrating satellite observations, radar measurements, weather stations, and IoT sensors may increase computational complexity and infrastructure requirements for real-time deployment. Addressing these challenges will require extensive field-level implementation and validation before operational adoption .

D. Future Research Directions

Future research will focus on implementing the proposed framework using publicly available meteorological datasets such as ERA5, NASA POWER, NOAA, and national weather observation networks to evaluate its predictive performance under diverse climatic conditions. The integration of transformer-based forecasting models, graph neural networks, and federated learning techniques may further improve forecasting accuracy, model scalability, and computational efficiency. In addition, future work may investigate cloud-edge computing architectures, real-time IoT data streams, and digital twin technologies to develop intelligent and operationally scalable early warning systems capable of supporting next-generation disaster management and climate resilience initiatives.

V. Conclusion

This study proposed an Explainable AI-Driven Early Warning System (XAI-EWS) for extreme weather risk assessment and disaster preparedness by integrating multi-source environmental observations, a hybrid Bi-LSTM–XGBoost prediction model, SHAP-based explainability, and dynamic risk assessment within a unified decision-support architecture. Unlike conventional AI-based forecasting systems that primarily generate hazard predictions, the proposed framework enhances transparency by explaining prediction outcomes and supports preparedness-oriented decision-making through risk-informed recommendations.

The qualitative evaluation demonstrates that integrating explainable artificial intelligence with multi-source environmental data has the potential to improve the interpretability and operational applicability of AI-driven early warning systems. Although the present work represents a conceptual framework without experimental validation on real-world datasets, it establishes a scalable foundation for future implementation and performance evaluation. Future research should focus on validating the framework using large-scale meteorological datasets, integrating advanced deep learning architectures, and deploying the proposed system within real-time disaster management environments. The proposed XAI-EWS framework has the potential to contribute significantly toward intelligent, transparent, and resilient disaster preparedness systems capable of supporting timely emergency response and reducing the impacts of extreme weather events.

REFERENCES

[1] Q. Lu, J. Wen, J. Yan, Y. Wang, and H. Chen, "A GeoAI-Driven and Decision-Oriented Methodology for Multi-Hazard Early Warning System Development," *International Journal of Disaster Risk Science*, 2026. doi: 10.1007/s13753-026-00715-z.

[2] A. Tella, I. Zahidi, C. M. Fai, C. Okolie, and Q. B. Pham, "From Prediction to Prevention: An Explainable GeoAI Framework for Flood Susceptibility and Urban Exposure Assessment Using Machine and Deep Learning Models," *Sustainable Development*, 2026. doi: 10.1002/sd.70772.

[3] V. N. Tran, V. Y. Ivanov, and X. Huan, "Reimagining How Flood Warnings Can Inform Decision-Making and Community Actions," *Earth's Future*, vol. 14, 2026. doi: 10.1029/2026EF008857.

[4] Y. Li *et al.*, "Long Short-Term Memory Neural Network-Based Real-Time Damage Prediction for Earthquake Early Warning System," *International Journal of Disaster Risk Reduction*, vol. 137, Art. no. 106087, 2026. doi: 10.1016/j.ijdrr.2026.106087.

[5] P. Painter, K. Semmens, C. Cattoën, R. Hogan Carr, *et al.*, "Moving Towards Transilience: Rethinking the Role of Flood Early Warning Systems in a Changing World," *International Journal of Disaster Risk Science*, 2026.

[6] S. Balaselvakumar and S. B. Hemavarthinii, "GeoAI-Supported Early Warning Systems for Extreme Weather Events and Their Implications in India," *International Journal of Geography, Geology and Environment*, vol. 8, no. 4, pp. 16–27, 2026. doi: 10.22271/27067483.2026.v8.i4a.505.

[7] Z. Zhang, G. Shen, Y. Li, M. Zhang, Z. Chen, S. Fu, and F. Wu, "Interpretable AI-Driven Early Warning Modeling for Flash Flood Disaster Chains," *Journal of Geo-information Science*, vol. 28, no. 3, pp. 591–604, 2026. doi: 10.12082/dqxxkx.2026.250536.

[8] P. Sukprasert *et al.*, "Development of an AIoT-Based Early Flash-Flood Warning System for Smart Rural Disaster Resilience," *Sensors*, vol. 26, no. 11, Art. no. 3512, 2026. doi: 10.3390/s26113512.

[9] Y. Zhou *et al.*, "Flood Dynamic Monitoring and XGBoost-SHAP Based Risk Assessment: A Case Study of the 23·7 Extreme Rainstorm in BTH Region, China," *Environmental and Sustainability Indicators*, 2025.

[10] M. Mosavi, M. Choubin, and co-authors, "Explainable Artificial Intelligence in Disaster Risk Management: Achievements and Prospective Futures," *International Journal of Disaster Risk Reduction*, vol. 92, 2024.

[11] A. Hrast Essenfelder and A. Toreti, "Expert-Driven Explainable Artificial Intelligence Models Can Detect Multiple Climate Hazards Relevant for Agriculture," *Communications Earth & Environment*, vol. 6, Art. no. 69, 2025, doi: 10.1038/s43247-024-01987-3.

[12] G. P. Ganapathy, A. Nath, V. B. Zaalishvili, and O. Burdzieva, "Building Sustainable and Resilient Communities with Landslide Early Warning Systems: A Review of Best Practices," *Sustainable Development of Mountain Territories*, vol. 15, no. 4, pp. 1007–1022, 2023, doi: 10.21177/1998-4502-2023-15-4-1007-1022.

[13] H. He, W. Wang, Z. Wang, S. Li, and J. Chen, "Enhancing Seismic Landslide Susceptibility Analysis for Sustainable Disaster Risk Management Through Machine Learning," *Sustainability*, vol. 16, no. 9, Art. no. 3828, 2024, doi: 10.3390/su16093828.

[14] O. Ghorbanzadeh, T. Blaschke, K. Gholamnia, S. R. Meena, D. Tiede, and J. Aryal, "Machine Learning–Based Landslide Susceptibility Mapping Using Reliable Samples," *Journal of Hydrology*, vol. 638, Art. no. 131536, 2024, doi: 10.1016/j.jhydrol.2024.131536.

[15] M. T. Hosain, J. R. Jim, M. F. Mridha, and M. M. Kabir, "Explainable AI Approaches in Deep Learning: Advancements, Applications and Challenges," *Computers & Electrical Engineering*, vol. 117, Art. no. 109246, 2024, doi: 10.1016/j.compeleceng.2024.109246.

[16] H. Hong, D. Wang, A. X. Zhu, and Y. Wang, "Landslide Susceptibility Mapping Based on the Reliability of Landslide and Non-Landslide Samples," *Expert Systems with Applications*, vol. 243, Art. no. 122933, 2024, doi: 10.1016/j.eswa.2023.122933.

[17] X. Zhou, H. Wen, Z. Li, H. Zhang, and W. Zhang, "An Interpretable Model for the Susceptibility of Rainfall-Induced Shallow Landslides Based on SHAP and XGBoost," *Geocarto International*, vol. 37, no. 26, pp. 13419–13450, 2022, doi: 10.1080/10106049.2022.2073792.

[18] J. Park, J. C. Joo, I. Kang, and W. H. Lee, "The Use of Explainable Artificial Intelligence for Interpreting the Effect of Flow Phase and Hysteresis on Turbidity Prediction," *Environmental Earth Sciences*, vol. 82, no. 15, Art. no. 375, 2023, doi: 10.1007/s12665-023-11043-6.

[19] S. Wang, H. Peng, Q. Hu, and M. Jiang, "Analysis of Runoff Generation Driving Factors Based on Hydrological Model and Interpretable Machine Learning Method," *Journal of Hydrology: Regional Studies*, vol. 42, Art. no. 101139, 2022, doi: 10.1016/j.ejrh.2022.101139.

[20] H. Huang, Y. Wang, Y. Li, Y. Zhou, and Z. Zeng, "Debris-Flow Susceptibility Assessment in China: A Comparison Between Traditional Statistical and Machine Learning Methods," *Remote Sensing*, vol. 14, no. 18, Art. no. 4475, 2022, doi: 10.3390/rs14184475.

[21] M. Reichstein *et al.*, "Early Warning of Complex Climate Risk with Integrated Artificial Intelligence," *Nature Communications*, vol. 16, Art. no. 2564, 2025, doi: 10.1038/s41467-025-57640-w.

[22] Y. Wang, X. Li, Z. Chen, et al., "Explainable Artificial Intelligence (XAI) Framework Using XGBoost and SHAP for Assessing Urban Fire Risk Based on Spatial Distribution Features," *International Journal of Disaster Risk Reduction*, vol. 129, Art. no. 105798, 2025, doi: 10.1016/j.ijdrr.2025.105798.

[23] M. Xiong, Y. Zhang, Z. Wang, and Y. Li, "Toward Safer Aviation: Application of GA-XGBoost-SHAP for Incident Cognition and Model Explainability," *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, vol. 238, no. 6, pp. 1195–1208, 2024, doi: 10.1177/1748006X231205498.

[25] S. S. Rahmati, B. Kalantar, B. Pradhan, and M. Uuemaa, "A Novel Explainable PSO-XGBoost Model for Regional Flood Frequency Analysis at a National Scale: Exploring Spatial Heterogeneity in Flood Drivers," *Journal of Hydrology*, vol. 639, Art. no. 131928, 2024, doi: 10.1016/j.jhydrol.2024.131928.

[25] H. Al-Najjar, B. Kalantar, B. Pradhan, G. Beydoun, and N. Ueda, "SHapley Additive exPlanations (SHAP) for Landslide Susceptibility Models: Shedding Light on Explainable AI," *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. X-G, pp. 81–88, 2025, doi: 10.5194/isprs-annals-X-G-2025-81-2025.

[26] D. Khan, W. Akram, and S. Ullah, "Enhancing Landslide Susceptibility Predictions with XGBoost and SHAP: A Data-Driven Explainable AI Method," *Geocarto International*, vol. 40, no. 1, 2025, doi: 10.1080/10106049.2025.2514725.

[27] H. Geng, W. Wang, J. Liu, and D. Benson, "Landslide Susceptibility Modeling Based on SHAP Interpretability and Ensemble Learning: A Case Study in Fuyuan County, Southwest China," *Frontiers in Earth Science*, vol. 13, 2025, Art. no. 1731872, doi: 10.3389/feart.2025.1731872.

[28] F. Huang, S. Jiang, L. Li, Y. Zhang, R. Zhang, Q. Li, D. Li, W. Shangguan, and Y. Dai, "Applications of Explainable Artificial Intelligence in Earth System Science," *Earth-Science Reviews*, vol. 260, Art. no. 104965, 2025, doi: 10.1016/j.earscirev.2024.104965.

[29] W. Gao, Y. Liao, Y. Chen, C. Lai, S. He, and Z. Wang, "Enhancing Transparency in Data-Driven Urban Pluvial Flood Prediction Using an Explainable CNN Model," *Journal of Hydrology*, vol. 645, Art. no. 132228, 2024, doi: 10.1016/j.jhydrol.2024.132228.

[30] X. Pang, J. Liu, H. Jing, X. Xu, L. Shen, and X. Yan, "Coupling Hydrological Model With Interpretable Machine Learning for Reliable Streamflow Modeling: Daily Dynamics and Extreme Events," *Journal*

of Flood Risk Management, vol. 18, no. 4, Art. no. e70138, 2025, doi: 10.1111/jfr3.70138.

[31] M. Rokhideh, C. Fearnley, and M. Budimir, "Multi-Hazard Early Warning Systems in the Sendai Framework for Disaster Risk Reduction: Achievements, Gaps, and Future Directions," *International Journal of Disaster Risk Science*, vol. 16, no. 1, pp. 103–116, 2025, doi: 10.1007/s13753-025-00622-9.

[32] C. A. Velásquez, J. D. Giraldo-Osorio, J. I. Vélez, and G. Correa, "Performance Assessment of Indicators of a Multi-Hazards Early Warning System in an Urban Mountain Region," *International Journal of Disaster Risk Reduction*, vol. 112, Art. no. 104767, 2024, doi: 10.1016/j.ijdrr.2024.104767.

[33] J. Zambrano Nájera, C. C. Luna, and J. J. Vélez Upegui, "Performance Assessment of Indicators of a Multi-Hazards Early Warning System in an Urban Mountain Region," *International Journal of Disaster Risk Reduction*, vol. 112, Art. no. 104767, 2024, doi: 10.1016/j.ijdrr.2024.104767.

[34] A. S. N. Raju, G. Geetha, B. Subashini, K. Venkatesh, R. K. Gatla, and S. D. Teferi, "HYDRA-XAI Dual-Backbone Disaster Scene Recognition Using ResNet50–Swin Transformer Feature Fusion, Explainable Evidence, and an Operational Recommender," *Scientific Reports*, 2026, doi: 10.1038/s41598-026-59683-5.

[35] H. Yang, T. Wang, N. I. Fomin, S. Xiao, and L. Liu, "An Integrated IKOA-CNN-BiGRU-Attention Framework with SHAP Explainability for High-Precision Debris Flow Hazard Prediction in the Nujiang River Basin, China," *PLOS ONE*, vol. 20, no. 6, Art. no. e0326587, 2025, doi: 10.1371/journal.pone.0326587.