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ARTIFICIAL INTELLIGENCE MODELS FOR EARTHQUAKE PREDICTION AND SEISMIC HAZARD ASSESSMENT

Saad Ullah

Riphah Institute of Systems Engineering

saadullahali687@gmail.com

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Saad Ullah

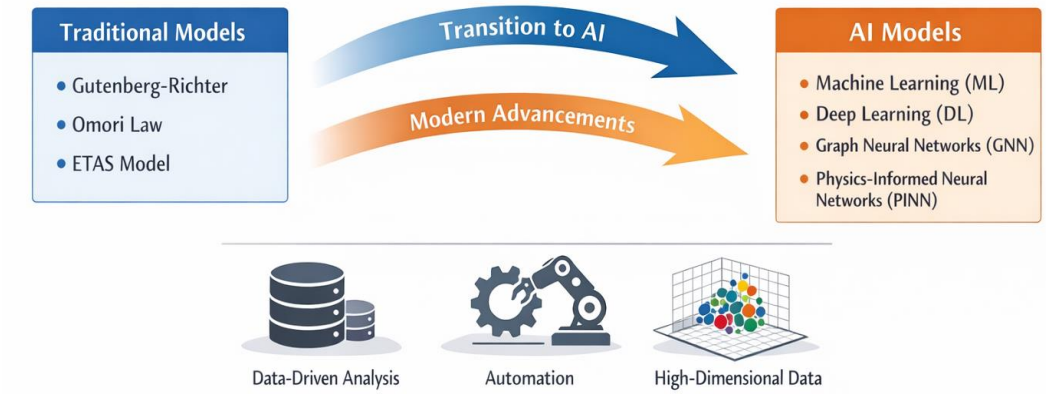
Abstract
Earthquake prediction and seismic hazard assessment remain among the most challenging problems in geophysics due to the complex, non-linear, and multi-scale nature of lithospheric dynamics. Traditional statistical models (Gutenberg-Richter law, ETAS) provide valuable long-term probabilistic insights but struggle with short-term forecasting and subtle precursory signals hidden in massive, noisy datasets. Artificial intelligence encompassing supervised learning (SVM, Random Forest, XGBoost), deep learning (LSTM, CNN, TCN), graph neural networks (GNNs), and physics-informed neural networks (PINNs) has emerged as a transformative paradigm, enabling automated catalog development (increasing detected events by up to 10×), high-resolution spatiotemporal modeling, and improved ground-motion prediction. Hybrid frameworks like SeismoQuakeGNN integrate graph-based spatial dependencies with Transformer attention for long-range temporal patterns, while PINNs embed physical laws (wave equation, Eikonal) directly into the loss function for mesh-free simulations and physics-consistent predictions. Multimodal foundation models (SeisModal) fuse waveforms, catalogs, GNSS, ionospheric TEC, geochemical (radon, methane), and satellite data for comprehensive event understanding. Performance benchmarks show LSTM and hybrid models achieving superior RMSE/MAE in magnitude prediction, with SHAP-based explainable AI enhancing interpretability and trust. Regional applications (Western Turkey, Yunnan-Sichuan, Pakistan-Hindukush) demonstrate strong regional generalization when properly tuned. Persistent challenges include spectral bias in PINNs, long training times limiting real-time early warning, dataset quality, modifiable areal unit problem (MAUP), and the need for robust validation against physical baselines. Future directions emphasize multimodal foundation models, integration with IoT/drones/satellites, federated learning, and hybrid physics-AI systems to bridge the gap between data-driven pattern recognition and mechanistic understanding paving the way for more reliable probabilistic hazard assessment and actionable short-term forecasting to enhance societal resilience.

1. INTRODUCTION

The historical progression of seismology has reached a critical juncture where the integration of advanced computational paradigms is no longer an auxiliary luxury but a fundamental necessity (Plevris, 2024). The inherent complexity

of the Earth's lithosphere, characterized by its non-linear dynamics, multiscale interactions, and pervasive heterogeneity, has long challenged the limits of traditional physics-based and statistical modeling (Eaton et al., 2024). Conventional approaches, rooted in the foundational laws of the 20th century, such as the Gutenberg-Richter relationship and Omori's law, provide invaluable long-term averages and statistical frameworks for understanding seismicity (Smirnov et al., 2019). However, these methods often falter when tasked with high-resolution forecasting or the identification of subtle precursory signals that exist within massive, noisy datasets (Jiao & Alavi, 2020). The emergence of Artificial Intelligence (AI), encompassing Machine Learning (ML) and Deep Learning (DL), represents a transformative leap toward data-driven insights that can navigate these complexities with unprecedented precision (Dikshit et al., 2024). To better illustrate the transition from classical to modern approaches, a conceptual comparison is presented in figure 1. The figure highlights how artificial intelligence frameworks extend beyond traditional statistical limitations by leveraging high-dimensional data and automated learning.

FIGURE 1: Conceptual Evolution from Traditional Seismology to AI-Driven Frameworks



2. The Paradigm Shift in Seismological Analysis

The transition from classical statistical models to AI-driven frameworks is motivated by the exponential growth of seismic and geodetic data. Global monitoring networks now produce data at a volume, variety, and velocity that exceed the processing capacity of manual interpretation and traditional computational tools (Dervisi et al., 2025). While traditional methods are hindered by the interpretive constraints of the human mind and the ability to process only limited fractions of available information, machine learning is designed specifically to perform well on large-scale and complex datasets (Al Banna et al., 2020). This paradigm shift allows for the identification of latent relationships between geophysical indicators such as magnitude, depth, and geographic coordinates and historical seismic activity that were previously obscured (Al Banna et al., 2021).

A cornerstone of this evolution is the ability of AI to automate the development of earthquake catalogs, which are essential for any subsequent forecasting or hazard assessment. Machine learning-based methods have demonstrated the capacity to increase the number of detected events in catalogs by tenfold compared to conventional automatic processing (Ma & Chen,

2022). This is achieved by detecting small, hidden earthquakes that often dominate earthquake catalogs but are typically missed by standard algorithms. The resulting high-resolution catalogs provide a far more detailed picture of earthquake sequences and fault structures, laying the groundwork for more accurate predictive modeling (Mancini et al., 2022).

Table 1: Comparison of Methodological Paradigms in Seismology

Feature	Traditional Statistical Approaches	Artificial Intelligence & Machine Learning
Foundation	Analytical formulas and empirical laws (Gutenberg & Richter, 1954).	Data-driven patterns and neural architectures (Al Banna et al., 2021).
Feature Extraction	Expert-designed rules and manual picking (Tan et al., 2021).	Automated feature learning from raw data (Tan et al., 2021).
Data Requirements	Tabular data and historical averages (Al Banna et al., 2021).	High-dimensional waveforms, imagery, and text (Munikoti & Stewart, 2026).
Real-time Feasibility	Computationally expensive simulations (e.g., ETAS) (Dervisi et al., 2025).	Near-instantaneous inference post-training (Dervisi et al., 2025; Ravanelli et al., 2024).
Model Transparency	High; based on clear physical equations (Dervisi et al., 2025).	Variable; often requires Explainable AI (XAI) (Singh & Roy, 2025).

3. Foundational Machine Learning Architectures in Earthquake Prediction

The application of machine learning to earthquake prediction involves a diverse array of supervised, unsupervised, and reinforcement learning models, with supervised learning being the most utilized methodology in recent years (Gutenberg & Richter, 1954). These models are tasked with various challenges, including classifying seismic zones, predicting impending magnitudes, and estimating time-to-failure for specific faults (Chen et al., 2025).

3.1 Supervised Learning and Ensemble

Supervised learning techniques such as Support Vector Machines (SVM), Random Forest (RF), and XGBoost have become standard tools for seismic forecasting (Li & Gao, 2024). These models are trained on historical datasets where the input features (e.g., seismic indicators) are paired with known labels (e.g., subsequent earthquake magnitude) (Akyol et al., 2020). Random Forest, in particular, has demonstrated exceptional performance in regional studies. By generating an ensemble of decision trees, each trained on different subsets of features, RF can capture the inherent variability and uncertainty of the data (Akinci et al., 2022). For instance, in the North Zagros region and Western Turkey, ensemble learning methods have shown superior skills in predicting significant seismic events and weekly earthquake magnitudes compared to simpler linear models (Yavas et al., 2026).

The efficacy of these models is often tied to the selection of seismicity characteristic parameters. Researchers have identified eight key indicators including seismic frequency (N), mean magnitude (M_mean), and the slope of the G-R relation (b), which are frequently used as inputs for neural networks to predict the maximum magnitude over a subsequent period (Alarifi et al., 2012). These indicators are derived from historical catalogs and reflect the state of stress and accumulation of energy within the crust (Baveja and Singh, 2023).

3.2 Deep Learning and Sequential Modeling Methods

Deep Learning (DL) represents a more advanced branch of Artificial Intelligence (AI) that utilizes multilayered neural networks to learn hierarchical representations of data. The Multilayer Perceptron (MLP) serves as a foundational neural network architecture, consisting of an input layer, multiple hidden layers, and an output layer, in which all neurons are fully connected (Tan et al., 2021). The training process involves optimizing the network

weights to minimize a loss function using gradient descent and the backpropagation algorithm. The weight update rule is expressed as:

$$w_{\text{new}} = w_{\text{old}} - \eta \frac{\partial L}{\partial w}$$

where η (eta) represents the learning rate, L denotes the loss function, and ∂L/∂w is the gradient of the loss with respect to the weight parameter. While the Multilayer Perceptron is effective for tabular and structured datasets, it is often outperformed by specialized architectures designed to capture the temporal and spatial characteristics of seismic data, such as Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) (Kaftan, 2025).

Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, are specifically engineered to process sequential data by maintaining an internal memory state that captures dependencies over time (Panakkat and Adeli, 2007). This capability makes LSTM networks particularly suitable for modeling earthquake sequences as time-series problems. In comparative studies conducted in Western Turkey, LSTM-based models achieved the lowest error rates in earthquake magnitude prediction, demonstrating a strong ability to capture the complex temporal patterns that often precede seismic events (Panakkat and Adeli, 2007).

Table 2: Performance Benchmarks for Magnitude Prediction (Western Turkey 1975-2024)

Model Architecture	RMSE	MAE	MSE	MAPE (%)
Long Short-Term Memory (LSTM)	0.1391	0.1046	0.0193	3.0631
1D-Convolutional Neural Network (CNN)	0.1609	0.1277	0.0259	3.6695
Adaptive Neuro-Fuzzy Inference (ANFIS)	(Higher)	(Higher)	(Higher)	(Higher)
Decision Tree (DT)	(Higher)	(Higher)	(Higher)	(Higher)

4. Advanced Spatiotemporal Modeling and Graph Neural Networks

A significant limitation of standard ML and DL models is their difficulty in capturing the intricate spatiotemporal relationships that define seismic activity. Earthquakes are not isolated events; they are part of a broader system of interactions across tectonic faults (Sadhukhan, 2025). To address this, researchers have proposed hybrid frameworks that integrate spatial and temporal learning (Baveja and Singh, 2023).

4.1 SeismoQuakeGNN and Graph Architectures

SeismoQuakeGNN is a novel hybrid framework that combines Graph Neural Networks (GNN) with Transformer-based attention mechanisms. In this architecture, seismic prediction zones or stations are represented as nodes in a graph, and the interdependencies between them are modeled as edges (Liu et al., 2024). Unlike traditional CNNs that operate on grid-like data, GNNs can dynamically learn the irregular spatial relationships between fault segments (Singh & Roy, 2025). When coupled with a Transformer driven by attention modules, the system can capture long-range temporal correlations, allowing for improved transferability to different seismic regions (Ommi & Hashemi, 2024).

4.2 Temporal Convolutional Networks (TCN) in Hazard Risk

Temporal Convolutional Networks (TCN) have emerged as an alternative to RNNs for modeling seismic triggers, such as earthquake-induced landslides. TCNs leverage dilated causal convolutions to efficiently model long-range temporal dependencies without the vanishing gradient problems often associated with LSTMs (Mallouhy et al., 2019). In studies of the Sichuan Province in China, TCN models outperformed both GRU and RF in assessing seismic landslide risks, highlighting the importance of capturing the dynamic triggers such as antecedent rainfall

and ground shaking that occur across various timescales (Godoy & Vargas Jiménez, 2025).

5. Physics-Informed Neural Networks (PINNs) and Seismic Simulations

One of the most promising frontiers in seismological AI is the development of Physics-Informed Neural Networks (PINNs). These models represent a synthesis of data-driven learning and physical principles, embedding governing partial differential equations (PDEs) directly into the network's loss function (Wang et al., 2025). By minimizing the residuals of equations such as the wave equation or the Eikonal equation, PINNs ensure that their predictions are physically consistent (Raissi et al., 2019).

5.1 Architecture and Loss Formulation in PINNs

The total loss function of a Physics-Informed Neural Network (PINN) typically consists of two primary components: a data-fitting term and a physics-informed term. The overall loss function is defined as:

$$L_{\text{total}} = L_d + \lambda L_p$$

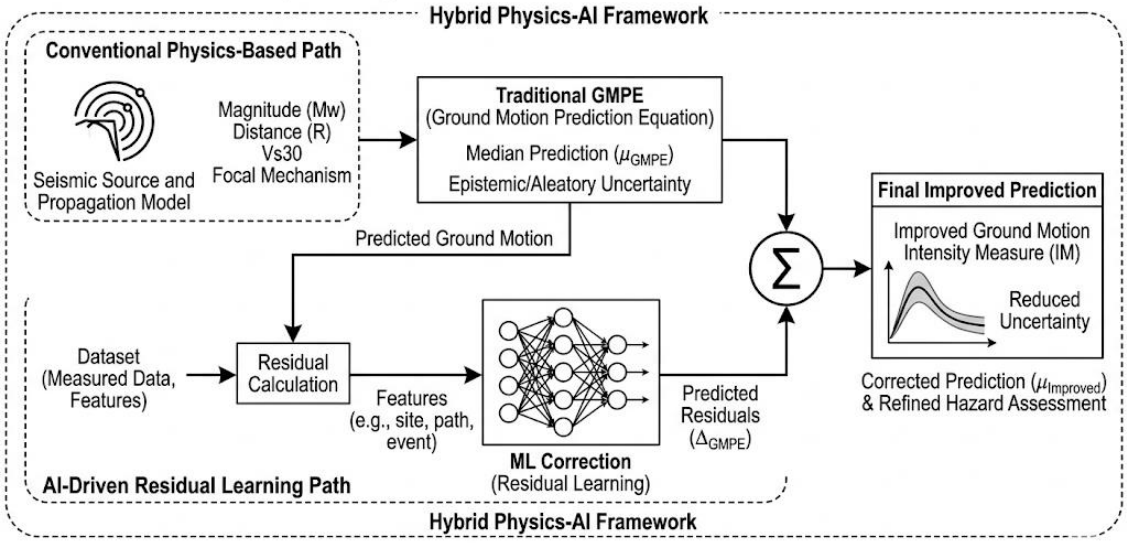
where λ (lambda) is a weighting parameter that controls the balance between the data-driven objective and the physics-based constraint. The data-fitting term ensures that the model predictions align with observed data, while the physics-informed term enforces consistency with governing physical laws.

In the context of seismic site response analysis (SRA), the physics-informed component incorporates the governing equations of motion and relevant material properties. This integration enables the model to solve differential equations directly without requiring a discretized computational mesh (Ommi & Hashemi, 2024). The mesh-free characteristic of Physics-Informed Neural Networks is particularly advantageous for modeling high-frequency wave propagation in complex geological media with sharp material contrasts, where traditional numerical methods may face stability and computational challenges (Wolbes, 2025).

5.2 Operational Feasibility and the Timing Barrier

Despite their theoretical appeal, the practical application of PINNs to tasks like Earthquake Early Warning (EEW) is currently constrained by computational limitations. Traditional EEW systems, such as ShakeAlert, are designed to characterize a source within seconds of detecting P-waves (Kohler et al., 2020). However, training a PINN model can take over 1,000 seconds (approximately 20 minutes) far exceeding the arrival time of destructive S-waves (Cui et al., 2024). Furthermore, PINNs often suffer from "spectral bias," where they preferentially learn low-frequency components and struggle to capture the high-frequency signals that are critical for seismic phase picking (Rahaman et al., 2019). Figure 2 demonstrates the hybrid approach combining physics-based models with machine learning corrections. This integration significantly enhances prediction accuracy while maintaining physical interpretability.

FIGURE 2: Hybrid Physics-AI Framework for Ground Motion Prediction



A significant breakthrough in this area involves using neural networks to learn what physics cannot easily predict (Bergen et al., 2019). Models that focus on predicting Ground Motion Prediction Equation (GMPE) residuals essentially the regional corrections to established physical models have achieved intensity correlations of r = 0.943 (Trugman, 2024). This hybrid approach resolves the contradiction between the limitations of pure PINNs and the operational requirements of early warning systems (Okazaki et al., 2024).

Table 3: PINN Application Comparison for Seismic Tasks

Application	Physical Governing Equation	Primary Advantage	Main Challenge
Wave Propagation	Wave Equation (Time/Freq Domain) (Wolbes, 2025).	Mesh-free; handles complex media (Wolbes, 2025).	Point-source singularity (Wolbes, 2025).
Site Response (SRA)	1D/3D Equations of Motion.	Comparable to numerical methods.	Spectral bias in high frequency (Raissi et al., 2019; Wolbes, 2025).
Early Warning (EEW)	Wave equation soft constraints (Raissi et al., 2019).	Learned regional corrections (Raissi et al., 2019).	Training time is too long for real-time (Raissi et al., 2019).
Inversion (FWI)	Eikonal or Wave Equations (Wolbes, 2025).	High-resolution subsurface estimates (Wolbes, 2025).	Surface observation constraints (Raissi et al., 2019).

6. Seismic Hazard Assessment and Probabilistic Analysis

Probabilistic Seismic Hazard Analysis (PSHA) is the standard framework for estimating the likelihood of ground shaking levels being exceeded at a specific site. Traditionally, PSHA has relied on deterministic equations and stochastic approximations, but the integration of machine learning is ushering in a more robust hybrid approach (Kaftan, 2025).

6.1 Evolution of Ground-Motion Prediction Models (GMMs)

Machine learning algorithms are increasingly used to develop data-driven Ground-Motion Models (GMMs) that predict Peak Ground Acceleration (PGA) with higher accuracy than traditional parametric regressions (Ji et al., 2023). For instance, Random Forest models trained on datasets of over 10,000 records have significantly outperformed linear and polynomial regressions in predicting PGA from variables like moment magnitude (M_w), hypocentral distance, and average shear wave velocity (V_S30) (Karpatne et al., 2017). By leveraging a hybrid ensemble of systems, PSHA can better capture the variability inherent in ground motion records and the uncertainties of earthquake occurrence (Wang et al., 2022).

6.2 Building Fragility and Damage Detection

AI models are also applied to the structural engineering aspects of seismic hazard assessment. Convolutional Neural Networks (CNNs) have been used to identify pulse-like ground motions and generate artificial, spectrum-compatible ground motions for structural testing (Karniadakis et al., 2021). Additionally, machine learning facilitates the evaluation of building damage post-event. In studies following major earthquakes, models like Random Forest and XGBoost have classified building damage states based on ground motion intensity and structural characteristics with remarkable precision (Beyer, 2025). To increase the resilience of existing infrastructure, retrofitting buildings with RC jacketing and fiber-reinforced polymer (FRP) wrapping can increase ultimate capacity by over 180% (Sindhushree et al., 2025). Using explainable AI techniques like SHAP, researchers have even identified which building features such as height, material type, and population density are the most critical drivers of structural failure (Singh & Roy, 2025).

7. Crustal Deformation and GNSS-Based Monitoring

Global Navigation Satellite System (GNSS) data provides a unique window into the slow accumulation of strain that precedes earthquakes. Analyzing geodetic data related to crustal deformation is essential for estimating fault slip rates and long-term hazard analysis (Tan et al., 2021).

7.1 GNSS Velocity Accuracy Prediction

Machine learning algorithms, such as Support Vector Machines and Multiple Linear Regression (MLR), are used to model the relationship between GNSS position and velocity accuracies. These models help geophysicists determine the optimal observation durations and intervals needed to achieve the high precision required for fault slip rate estimation, where slip rates may be as low as a few millimeters per year. AI-assisted methods have also been used to estimate horizontal GNSS velocities in active tectonic regions, achieving accuracies lower than 0.4 mm/year.

7.2 Ionospheric Seismology and Tsunami Warning

A novel application of GNSS data involves monitoring the ionosphere's response to seismic waves and tsunamis. Traveling Ionospheric Disturbances (TIDs) can be detected through GNSS-derived Total Electron Content (TEC) observations (Meng et al., 2023). Deep learning frameworks utilizing CNNs have achieved high performance (F1 score of 91%) in detecting these perturbations, offering a promising avenue for improving Tsunami Early Warning Systems (TEWS) (Ravanelli et al., 2024). By analyzing how the ionosphere responds to natural hazards, researchers can assess the genesis of a tsunami in real-time, even in remote open-ocean regions where traditional sensors are absent (Uyeda et al., 2024).

8. Multimodal AI and Foundation Models in Seismology

The future of AI in earthquake research is moving toward "foundation models" that are built from inception to understand scientific concepts rather than just performing specific tasks. These models are characterized by their ability to integrate diverse data streams a property

known as multimodality (Munikoti & Stewart, 2026).

8.1 SeisModal and the Steel Thread Project

SeisModal is an AI foundation model developed by a consortium of national laboratories to explore fundamental questions in seismology. Unlike traditional models that might only process waveforms or catalogs, SeisModal integrates intensity data, location, timing, waveform details, text descriptions, and even imagery/video of seismic events (Sheng et al., 2023). This multimodal approach creates a comprehensive picture of each event, allowing the model to draw firm conclusions even when certain data points are missing. Such models are designed to be "trustworthy," with a heavy focus on the origin and security of training data to ensure scientific validity (Mousavi et al., 2019).

8.2 The Role of IoT, Drones, and Satellites

Modern detection systems are increasingly incorporating unconventional data sources. Drones equipped with repositionable geophones and satellites monitoring environmental surveillance are being coordinated with machine learning to enhance detection versatility (Ajayi & Ikemefuna, 2025). For example, the incorporation of satellite data allows for the analysis of perturbations in the total electron content of the atmosphere, which may serve as an early indicator of seismic activity (Manfreda et al., 2018). By shifting focus from quick detection to advanced prediction, these integrated technologies aim to allot more time for preparation and risk mitigation (Bowie State University, 2024).

9. Earthquake Precursors and Short-Term Forecasting

Short-term earthquake forecasting predicting an event within a window of weeks, days, or hours remains a core goal of seismology. While inherently more difficult than long-term assessment, research into geochemical, atmospheric, and electromagnetic precursors has shown promising results when analyzed through the lens of AI (Godoy & Vargas Jiménez, 2025).

9.1 Geochemical Indicators: Radon and Methane

Radon gas (^{222}Rn) has long been investigated as a potential earthquake precursor due to its sensitivity to crustal strain variations. Changes in subsurface stress and deformation can alter the permeability of geological formations, leading to measurable fluctuations in radon concentration prior to seismic events. Artificial Intelligence (AI) models, including the Empirical Mode Decomposition–Long Short-Term Memory (EMD–LSTM) framework, have been successfully applied to identify potential radon anomalies associated with significant earthquakes (Li et al., 2022). In Yogyakarta, Indonesia, Monte Carlo simulation techniques were integrated with machine learning algorithms to address the limitations associated with small precursor datasets. This hybrid approach improved the robustness of predictive modeling and enabled effective estimation of earthquake-related parameters within a radius of approximately 300–400 km from monitoring stations (Abadi et al., 2021).

In the Black Sea region, researchers have identified methane seepage as a site-specific precursor. Satellite remote sensing has detected coastal water jets originating from gas seeps that increase in area and discharge four days before significant offshore earthquakes (Ginzburg et al., 2020). These findings suggest that the tectonic stress preceding an event influences the properties of fluids in the Earth's crust, providing a measurable signal for forecasting (Martinelli, 2020).

9.2 Lithosphere-Atmosphere-Ionosphere Coupling (LAIC)

The LAIC model proposes that physical irregularities such as electromagnetic field disturbances, radon fluctuations, and surface temperature alterations are interconnected before a major earthquake (Dogan et al., 2023). Analysis of Swarm satellite data has allowed researchers to investigate over 50 different anomalies simultaneously. By applying Mamdani fuzzy inference systems to these time-series datasets, studies have suggested that powerful

earthquakes could be predicted between one and nine days before they occur, based on the cumulative increase in seismo-LAI anomalies (Sklyarenko et al., 2024)

Table 4: Summary of Potential Seismic Precursors

Precursor Type	Indicator/Variable	Monitoring Method	Forecast Window
Geochemical	Radon concentration; Methane discharge.	Ground stations; Satellite remote sensing.	Hours to weeks.
Ionospheric	Electron density (N_e); TEC perturbations (Ravanelli et al., 2024).	Swarm satellites; GNSS-TEC analysis (Ravanelli et al., 2024).	1-9 days.
Atmospheric	CO, CH_4, CO_2$, water vapor, aerosols (Godoy & Vargas Jiménez, 2025).	Sentinel-5P; Aqua-AIRS (Godoy & Vargas Jiménez, 2025).	2-5 months (Godoy & Vargas Jiménez, 2025).
Geodetic	Tilt; irregular surface deformations.	GNSS networks; Tiltmeters.	Weeks to hours.
Thermal	Surface temperature; outgoing long waves.	Satellite thermal infrared sensors.	Weeks to days.

10. Explainable AI (XAI) and Model Interpretability

One of the primary barriers to the widespread adoption of AI in seismology is the lack of transparency in "black-box" models. Explainable AI (XAI) addresses this by providing insights into the decision-making processes of neural networks (Singh & Roy, 2025).

10.1 SHAP Analysis and Feature Evaluation

The SHAP (Shapley Additive Explanations) framework is used to interpret the outputs of complex models by calculating the contribution of each feature to a specific prediction. In magnitude prediction models, SHAP has been used to validate hybrid modeling efforts that combine ML with physical properties, such as energy-depth interactions (Spivak et al., 2022). For example, SHAP provided definitive proof that a new "energy variable" became the dominant predictor in a model, thereby confirming the efficacy of engineered features derived from domain knowledge (Eppelbaum, 2021).

XAI also aids in identifying redundant features, which can improve model accuracy and simplify the operational framework for real-time applications. By revealing non-linear thresholds and interaction effects, XAI generates deeper mechanistic insights that traditional statistical systems cannot provide, fostering trust among stakeholders and first responders (Adi et al., 2024).

11. Regional Case Studies and Global Comparisons

The effectiveness of AI models often depends on regional geological and tectonic settings. Case studies from across the globe highlight both the potential and the limitations of current methodologies (Xie et al., 2023).

11.1 Yunnan and Sichuan, China

The Yunnan and Sichuan regions are among the most seismically active areas on the southeastern margin of the Tibetan Plateau. Research in Yunnan has focused on "seismic prediction zoning," using 15 delineated zones to enhance machine learning performance (Chen et al., 2025). Stacking ensemble methods have demonstrated high robustness in predicting the annual maximum earthquake magnitude in this region. Meanwhile, in Sichuan, advanced AI techniques like TCN and GRU have been applied to assess landslide risks, leveraging inventory data from over 3,000 landslides triggered by earthquakes (Godoy & Vargas Jiménez, 2025).

11.2 Pakistan and the Hindukush Region

In Pakistan, researchers have used Decision Trees and Support Vector Machines to classify earthquake-prone zones based on historical and geological data. Their work emphasizes the importance of regional model tuning, noting that models perform best when adapted to local tectonic behavior. Similarly, in the Hindukush region, ensemble classifiers have been applied to predict destructive earthquakes (M\ge 5.5) using eight mathematically calculated seismicity indicators (Chen et al., 2025).

11.3 The ETAS Debate in California

In California, the use of Fully Convolutional Networks (FCN) for long-term forecasting has sparked a debate over whether AI genuinely offers a breakthrough. Comparisons with the ETAS (Epidemic-Type Aftershock Sequence) model show that both model types perform similarly in forecasting earthquakes of magnitude 3.0 or higher (Dervisi et al., 2025). However, critics argue that many AI models lack a proper baseline comparison, with many studies failing to compare their results against established statistical null hypotheses like the Poisson model (Woith, 2015)

12. Challenges and Future Trajectories

Despite the remarkable progress, several obstacles remain in the quest for reliable AI-driven earthquake prediction. Data quality is a major concern, as seismic recordings can be noisy or incomplete (Al Banna et al., 2020). Achieving low-uncertainty warnings remains a challenge, particularly in the short-term forecasting domain where direct links between observations and impending events are difficult to establish (Cicerone et al., 2009).

12.1 Spatiotemporal Generalization and MAUP

The way continuous spatial phenomena are discretized known as the modifiable areal unit problem (MAUP) can significantly impact model performance. Models that work well in one region may struggle to generalize to another due to differences in geological scale and tectonic settings (Sadhukhan, 2025). Future research must focus on developing spatially explicit models that can handle the complex, non-linear interconnections between influencing factors while avoiding overfitting on limited regional data (Jeevanandam, 2025).

12.2 Trust and Accountability in High-Stakes Scenarios

As AI is integrated into decision-making frameworks for disaster response, ensuring the accountability and reliability of these models is paramount. The goal is not merely to achieve high accuracy but to provide results that are actionable and understandable for emergency managers and policymakers (Munikoti & Stewart, 2026). The ongoing development of multimodal foundation models like SeisModal, coupled with the insights of XAI, represents a path toward more transparent and effective seismic hazard mitigation (Singh & Roy, 2025).

The union of AI and ML with seismology is one of the greatest steps forward in the field. As more data from GNSS, satellites, and IoT sensors becomes available, the accuracy and timeliness of earthquake forecasts will continue to improve (Banna et al., 2021). While the physical mechanisms of earthquake genesis have yet to be fully determined, the application of machine learning offers a promising solution for uncovering the hidden laws of seismic activity and protecting communities from future catastrophic events (Panakkat and Adeli, 2007).

Conclusion

Artificial intelligence has ushered in a new era in seismology, moving beyond the limitations of traditional statistical and physics-based models to deliver data-driven insights capable of processing vast, heterogeneous datasets and uncovering hidden patterns in seismic activity. From supervised ensemble methods and recurrent architectures (LSTM) for magnitude and time-series forecasting, to graph neural networks and temporal convolutional networks for spatiotemporal modeling, and physics-informed neural networks for embedding governing equations into learning, AI approaches consistently demonstrate improved catalog

completeness, higher predictive skill, and better handling of uncertainty compared to conventional techniques. Multimodal foundation models that integrate waveforms, GNSS deformation, ionospheric perturbations, geochemical precursors (radon, methane), and satellite observations represent the frontier, enabling holistic event characterization and potential short-term forecasting. Explainable AI techniques (SHAP, attention visualization) are critical for building scientific trust and operational adoption by revealing feature importance and mechanistic links. Regional case studies confirm that properly tuned models achieve strong performance, yet challenges remain: spectral bias and computational cost in PINNs, generalization across tectonic regimes, data quality issues, and the inherent difficulty of short-term prediction in complex non-linear systems. Hybrid physics-AI frameworks that leverage learned corrections to established physical models (e.g., GMPE residuals) offer a promising path to balance accuracy, physical consistency, and real-time feasibility for earthquake early warning. Continued progress requires high-quality, openly accessible multimodal datasets, rigorous benchmarking against physical baselines, interdisciplinary collaboration, and transparent validation frameworks. As seismic monitoring networks and computational capabilities expand, AI-driven models will play an increasingly central role in probabilistic seismic hazard assessment, rapid post-event damage evaluation, and ultimately in saving lives through more timely and reliable risk mitigation strategies in earthquake-prone regions worldwide.

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