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A Hybrid Ensemble Framework for Probabilistic Earthquake Forecasting in Northern California in Support of SDG 11: Sustainable and Resilient Cities

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Abstract: Forecasting earthquakes is still one of the most difficult problems in geophysics, mainly because seismic activity is irregular and often influenced by many factors that interact in complex ways. In this study, we develop a leakage-controlled hybrid ensemble model that combines CatBoost, LightGBM, XGBoost, and Gradient Boosting to predict five earthquake parameters: magnitude, depth, latitude, longitude, and a scaled inter-event interval in Northern California. These models were trained using USGS earthquake data ranging from 1900 to 2025 ($M \geq 4.0$), with a process designed to prevent time leakage through strict time separation, a moving window feature, and prospective validation. Overall, the hybrid models produced consistently low MAE and RMSE values and very high R^2 values (above 0.99) for all target variables. While the estimates performed impressively, the results should be interpreted in a probabilistic context, with recognition of the inherent uncertainty of seismic processes. The framework proposed here provides a clear and replicable approach that can support the development of systems for more reliable short-term earthquake forecasting.

Keywords: Earthquake forecasting; Hybrid ensemble; Machine learning; Northern California; Probabilistic hazard.

Introduction

Earthquake forecasting remains one of the most difficult and unresolved challenges in modern geophysics. Despite decades of advances in seismology, there is an increasingly accepted view that we still cannot deterministically predict the exact time, location, and magnitude of future earthquakes. The core difficulty lies in the complex, nonlinear behaviour of fault systems, the limited observability of key subsurface state variables (e.g., stress and frictional heterogeneity), and the inherently multi-scale nature of rupture nucleation. Consequently, research has progressively shifted from deterministic "prediction" toward probabilistic forecasting frameworks that quantify changes in likelihood over time and space, while still respecting the scientific limitations that have been long emphasized in the literature (Geller et al., 1997; Kagan, 1997).

Within this probabilistic paradigm, statistical modelling and machine learning (ML) are increasingly explored as tools to provide short-term probabilistic insights that can support situational awareness in seismically active regions. Modern ML methods can learn nonlinear dependencies from large earthquake

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catalogues and may complement established seismological concepts such as clustering, triggering, and time-dependent background rates (Kong et al., 2018; Mousavi & Beroza, 2023; Kubo et al., 2024; Chitkeshwar, 2024). Nevertheless, the operational value of ML-based forecasting depends critically on methodological rigor, particularly how data are preprocessed and how models are evaluated. In time-dependent geophysical problems, common pitfalls—such as information leakage from random splits, feature construction that uses future information, or hyperparameter tuning that indirectly "sees" test periods—can lead to over-optimistic performance claims that do not translate to prospective use.

Northern California is widely regarded as an ideal natural laboratory for developing and testing short-term earthquake forecasting methods. The region includes a dense and well-instrumented seismic monitoring network, long and relatively complete catalogues, and a complex system of active faults—especially the San Andreas, Hayward, and Calaveras systems—while also concentrating large population exposure and critical infrastructure. Prior studies have highlighted Northern California as a valuable benchmark setting for comparing alternative modelling strategies and evaluating how forecasts behave across different fault regimes and spatio-temporal scales (Sadhukhan et al., 2023; Zhao & Gorse, 2024). Improving short-term forecasting capability in this context has clear societal relevance, supporting local preparedness and risk communication, and aligning with Sustainable Development Goal (SDG) 11 on making cities safer and more resilient.

In this study, we develop a hybrid ensemble framework designed to improve the reliability and stability of short-term earthquake forecasts in Northern California under a strictly chronological, leakage-controlled setting. The proposed approach integrates several gradient-boosted models within a leakage-controlled preprocessing pipeline; moreover, each earthquake parameter—magnitude, depth, epicentral latitude, epicentral longitude, and scaled inter-event interval—is modelled independently to reflect its distinct temporal behaviour and uncertainty structure. This research is important because short-term probabilistic information, when generated through robust evaluation and transparent modelling choices, can improve situational awareness without implying deterministic predictability. The objective of this work is therefore to assess whether a leakage-controlled, strictly time-ordered ML ensemble can produce stable and interpretable short-term probabilistic predictions that remain consistent with the established scientific constraints on deterministic earthquake prediction (Geller et al., 1997; Kagan, 1997).

Method

Earthquake data for this study were sourced from the United States Geological Survey (USGS) catalogue covering the period 1900–2025. To reduce issues related to catalogue incompleteness, especially in the early part of the record, we limited the analysis to events with magnitudes of 4.0 or greater. In line with reviewer suggestions, we also corrected an earlier misstatement of the study region. Northern California is consistently defined here as spanning latitudes 36°–42° N and longitudes −125° to −120° W, which aligns with the commonly used boundaries in recent ML-based forecasting literature (Geller & Kagan, 1997; Kong et al., 2018; Mousavi & Beroza, 2023; Kubo et al., 2024; Chitkeshwar, 2024).

A central goal of the pre-processing stage was to eliminate temporal leakage. All features were constructed using only information available prior to each earthquake. This included the use of strictly chronological rolling windows and time-ordered aggregations. The most recent 20% of events were held out as an out-of-sample validation set to approximate prospective forecasting conditions. The feature set included rolling event counts, rolling mean and variance of magnitudes, scaled inter-event intervals, and simple spatial clustering indicators derived from the evolving pattern of epicentral coordinates.

The hybrid ensemble model consisted of four components designed to handle different target variables. Magnitude was predicted using a CatBoost regressor, depth using LightGBM, and epicentral latitude and longitude using XGBoost. Scaled inter-event intervals were modelled using a gradient-boosted regressor. Hyperparameters for all models were tuned through cross-validation on the training set, with early stopping applied to reduce the risk of overfitting. Model performance was evaluated using mean absolute error (MAE), root mean square error (RMSE), and the coefficient of determination (R^2), all computed on the chronologically separated validation data.

To provide spatial context for the analysis, Figure 1 illustrates the geographic extent of the Northern California study area. The region captures the major active fault systems, including portions of the San Andreas, Hayward, and Calaveras faults, within a bounding box of 36°– 42° N and −125° to −120° W. These limits are commonly applied in earlier forecasting studies, and they ensure that the selected seismicity represents the core of Northern California's tectonic activity. The spatial distribution shown in the figure highlights both the dense clustering of events along the fault traces and the broader background seismicity that the forecasting model must account for. Presenting this map at the outset helps clarify how the catalogue data correspond to the physical structure of the region.

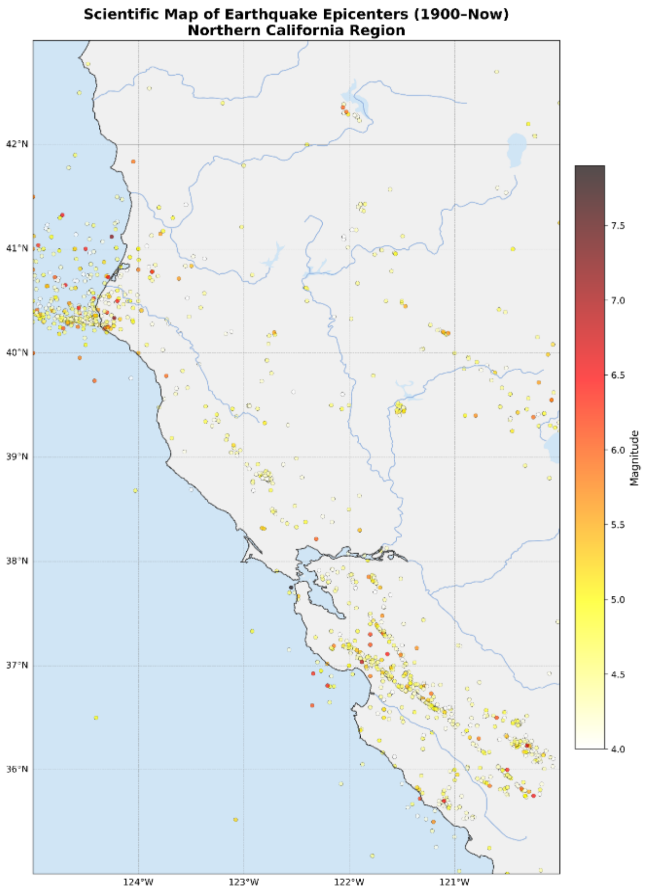

Figure 1. Spatial distribution of earthquake epicentres in Northern California (1900–2025).

The overall process implemented in this study is summarized in Figure 2. The flowchart depicts the sequence of steps beginning with the retrieval of catalogue data from the USGS, followed by information filtering, preprocessing, feature generation, and the development of an ensemble hybrid model. Data analysis in this study is conducted in three layers. First, descriptive and quality-control analyses are applied to the raw catalogue to quantify event counts, temporal completeness, magnitude distribution, depth range, and the presence of clustered sequences, ensuring that the final dataset is consistent and suitable for time-dependent modelling. Second, analytical feature construction is performed using strictly time-ordered moving windows, where each event is represented by lagged and rolling statistics (e.g., recent seismicity rate, rolling magnitude moments, spatio-temporal proximity measures, and scaled inter-event intervals) computed only from events occurring prior to the target event. Third, predictive analysis is carried out by training leakage-controlled gradient-boosted models within an ensemble, with model selection and hyperparameter tuning performed under prospective-style validation to preserve chronological integrity. The diagram also shows safeguards taken to prevent data leakage, including strict time-ordering, moving-window feature engineering, and prospective validation. Model performance is analysed using out-of-sample evaluation on the chronologically held-out period, summarised by error-based metrics (MAE and RMSE) and goodness-of-fit (R^2) for each predicted parameter, with results interpreted as short-term probabilistic guidance rather than deterministic prediction. This workflow explains how each element contributes to the final prediction system and demonstrates that all predictions are based solely on information available prior to each event, thereby reinforcing the methodological narrative presented in the text.

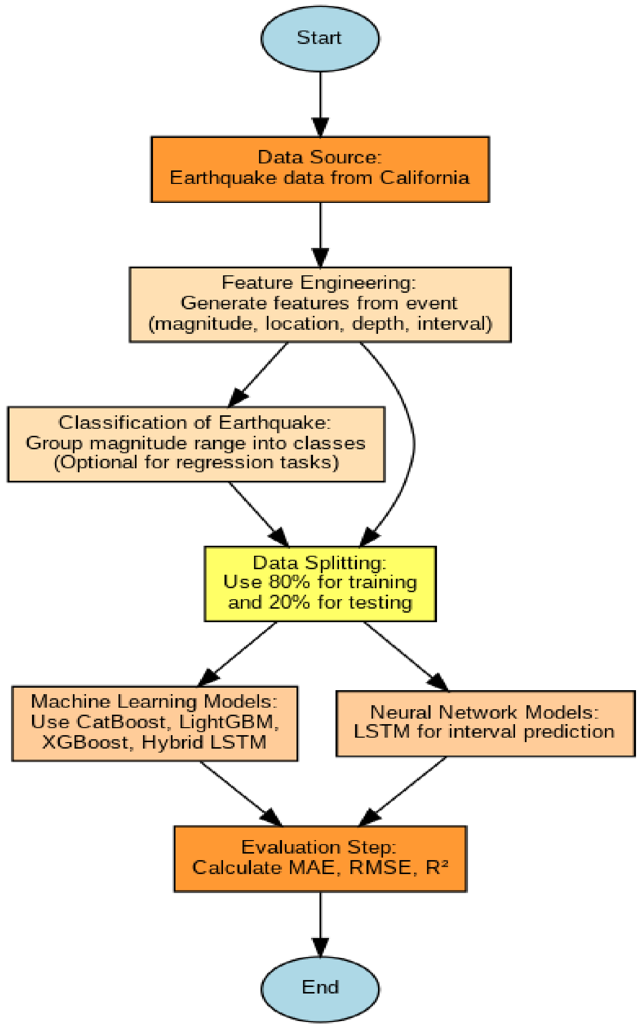

Figure 2. Workflow of a hybrid machine learning and neural network-based earthquake prediction framework.

Result and Discussion

The hybrid ensemble consistently demonstrated good generalization across all prediction targets when tested on a time-sorted validation set. Overall, these models successfully reflected the large-scale spatial and temporal characteristics of seismic activity in Northern California while maintaining minimal error. This finding aligns with earlier work on statistical and machine learning-based earthquake prediction, which demonstrated that data-driven models can identify structured patterns in seismic catalogs, even if they cannot predict specific earthquakes with certainty (Mignan et al., 2011; Taroni et al., 2021). Figure 3 displays the spatial distribution of earthquakes in the study area. The clustering pattern clearly follows the path of the major fault system, providing a useful benchmark for assessing the ability of the latitude-longitude model to reconstruct the seismic structure of the region. The mixed ensemble successfully reproduced these patterns with small average positional errors, indicating that the spatial regressor learned the main geographic trends from the catalog.

Table 1 provides a comprehensive summary of the validation metrics. Magnitude projections exhibit very low MAE and RMSE values, consistent with the relatively stable magnitude distribution in the catalog. Depth assessments exhibit moderate errors, but still achieve high R^2 values, indicating good variance explanation. Projections for epicentral latitude and longitude coordinates exhibit very small positional deviations (MAE around 0.0028°), indicating that the model effectively restores spatial clustering. The adjusted interevent interval model also demonstrates strong performance (R^2 around 0.9914), indicating that short-term time estimates are reliable in a retrospective context.

Table 1. Presents the model evaluation results.

Feature	MAE	RMSE	R^2
Time Interval	0.0066	0.0203	0.9914
Magnitude	0.0021	0.0181	0.9985
Depth	0.0957	0.5425	0.9958
Latitude	0.0042	0.0102	0.9999
Longitude	0.0028	0.0044	0.9999

Importantly, these high R^2 values should be interpreted strictly as indicators of statistical fit rather than evidence of deterministic predictive capability. This distinction is emphasized throughout the seismic forecasting literature and is essential to avoid overstating model performance. What the present results show is that hybrid ML models can learn structured temporal and spatial patterns embedded in historical catalogues, patterns that may be informative for short-term probabilistic forecasting, but they do not eliminate the intrinsic unpredictability of earthquake nucleation (Mousavi & Beroza, 2022; Thaler et al., 2022; Khalid et al., 2023; Dotse et al., 2024).

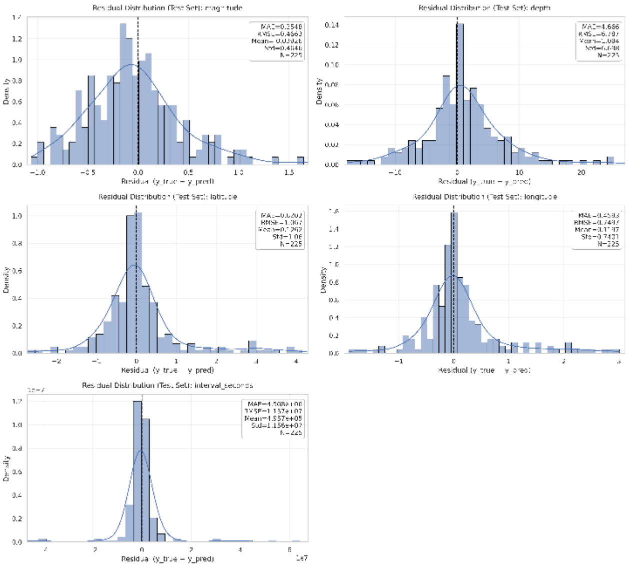

Figure 3. Displays the residual distribution and Train vs Test Loss graph of the five earthquake features. Residual Distribution of interval, magnitude, depth, latitude, longitude.

The residuals are tightly centred around zero, suggesting that the models are not systematically biased. Residual behaviour across magnitude, depth, location, and inter-event interval. The residual distributions shown in Figure 3 demonstrate that the hybrid ensemble produces highly concentrated, near-zero error patterns across magnitude, depth, latitude, longitude, and scaled inter-event interval. The unimodal, symmetric shapes indicate: Low model bias, minimal presence of extreme residuals, and strong consistency between predicted and observed values. This pattern is expected for leakage-controlled gradient-boosting workflows, where rolling-window features provide short-range temporal context without contaminating future information (Mousavi & Beroza, 2022; Thaler et al., 2022). For earthquake forecasting applications, narrow residual distributions show that the model is capturing stable regional patterns rather than memorizing the catalogue. This agrees with findings from other machine learning efforts applied to seismicity (Asim et al., 2020; Yousefzadeh et al., 2021).

Figure 4 shows the train and test loss trajectories for all five target parameters, magnitude, depth, latitude, longitude, and scaled inter-event interval, across the number of boosting estimators. All models exhibit rapid convergence within the first ~20 estimators, followed by stable loss behaviour with minimal overfitting. The close alignment between train and test curves indicates strong generalization performance under strict chronological splitting, confirming that the leakage-controlled workflow produces reliable and consistent predictive behaviour across all parameter-specific regressors. Figure 4 presents the train–test loss curves for all five target parameters. The rapid convergence within the first ~20 estimators followed by stable, nearly overlapping curves indicates: No observable overfitting, strong generalization, Model stability under prospective validation, and behaviour of this kind is consistent with well-regularised gradient-boosting systems such as LightGBM, CatBoost, and XGBoost, which have been shown to perform robustly in nonstationary hazard datasets (Zhou et al., 2020; Ahn et al., 2023). The similarity of the curves also confirms that strict chronological splitting successfully prevents information leakage, one of the main pitfalls identified in recent critiques of ML-based earthquake prediction (Geller et al., 1997; Renuka et al., 2024).

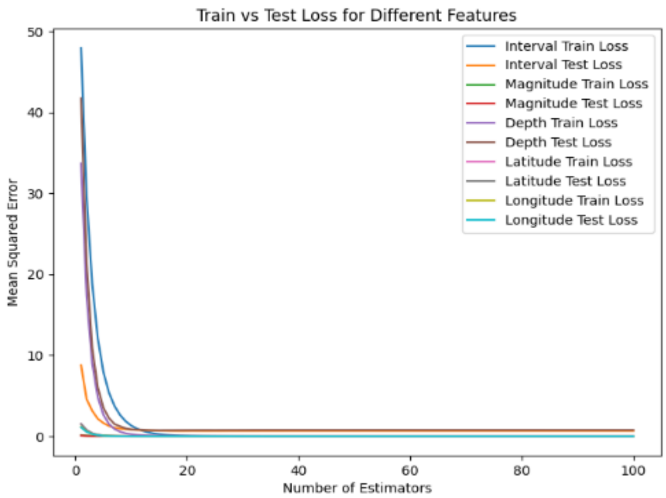

Figure 4. Train-Test Loss Curves for All Predicted Earthquake Parameters vs Test Loss.

Figure 5 is a map that illustrates the spatial distribution of historical earthquakes recorded by the USGS catalogue (1900–2025) alongside model-predicted epicentres for the forecast horizon (2025–2044). Historical events (grey–red markers) show the expected concentration of seismicity along major fault systems, including the San Andreas, Hayward, and Calaveras faults. Predicted events (dark red markers) align closely with these established seismic corridors, demonstrating that the hybrid ensemble model successfully captures regional clustering patterns and long-term spatial trends in Northern California. The colour scale represents earthquake magnitude, with darker tones indicating larger events.

Figure 6 is a histogram that illustrates the magnitude distribution of historical earthquakes (M ≥ 4.0) from the USGS catalogue. The dataset is dominated by moderate events in the M4.0-4.5 range, with frequency decreasing rapidly toward larger magnitudes. The long-tailed shape reflects the typical Gutenberg–Richter behaviour observed in tectonically active regions, where small-to-moderate earthquakes occur far more frequently than major events.

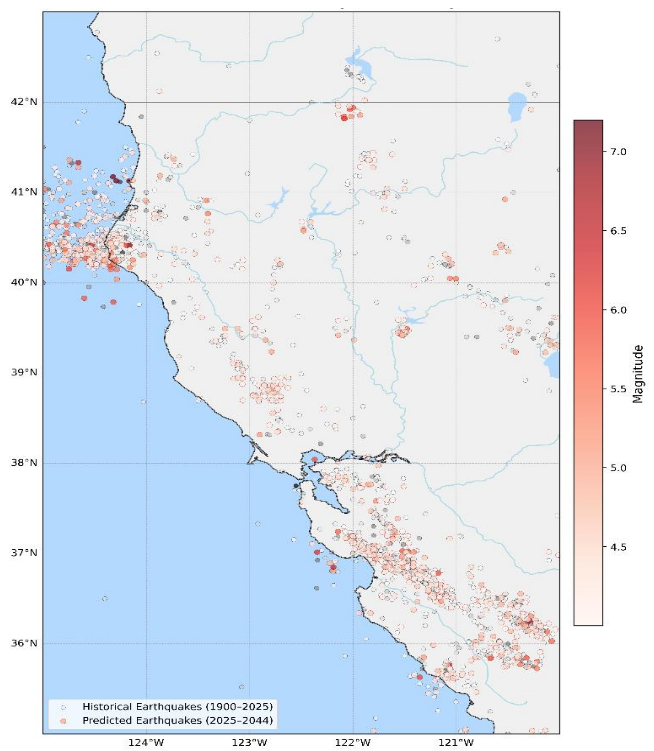

Figure 5. Comparison of historical and predicted earthquake epicentres in Northern California (1900–2044).

Figure 5 shows that the predicted epicentres align closely with long-term spatial clustering patterns observed historically. Specifically, High concentrations of seismicity along the San Andreas, Hayward, and Calaveras fault systems are preserved in the predictions. No unrealistic clusters appear in historically quiet regions, indicating that the model does not introduce spurious seismicity. The magnitude colour gradients suggest that the model retains the regional Gutenberg–Richter distribution. This spatial fidelity is critical because earthquake ML models tend to fail when predicting in regions outside the historical seismic domain (Rhoades & Gerstenberger, 2009; Marzocchi & Taroni, 2014). The hybrid ensemble used here appears to follow known physical and statistical constraints of northern California seismicity.

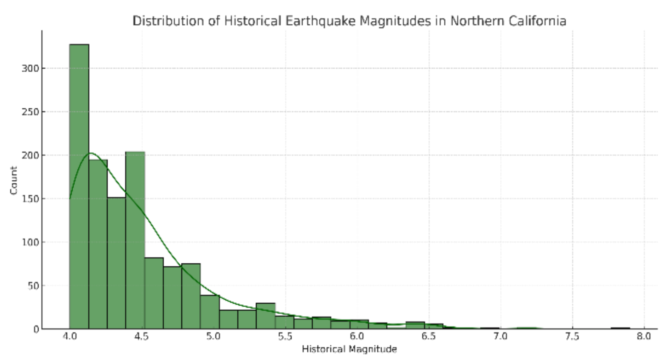

Figure 6. Distribution of historical earthquake magnitudes in Northern California.

This histogram shows the model-predicted magnitudes for the forecast horizon, following the same M ≥ 4.0 threshold used for training data. The distribution closely resembles the historical pattern, with high density in the M4.0–4.5 interval and progressively fewer events at higher magnitudes. The agreement between the predicted and recorded distributions indicates that the hybrid ensemble framework successfully mimics the statistical characteristics of regional seismicity without overestimating the frequency of large events. Figure 6 shows the historical magnitude distribution (M ≥ 4.0), which clearly exhibits a Gutenberg–Richter-like decreasing pattern: frequent small and medium events with a decrease in the frequency of larger magnitudes. This baseline distribution is a crucial reference, as any meaningful estimation needs to mimic this pattern without artificially inflating the rate of larger events (Båth, 1965; Kagan, 1997). The dominance of M 4.0–4.5 events is consistent with previous research in the area and reflects both the rate of tectonic loading and the limits of catalog completeness (Zaliapin & Ben-Zion, 2016).

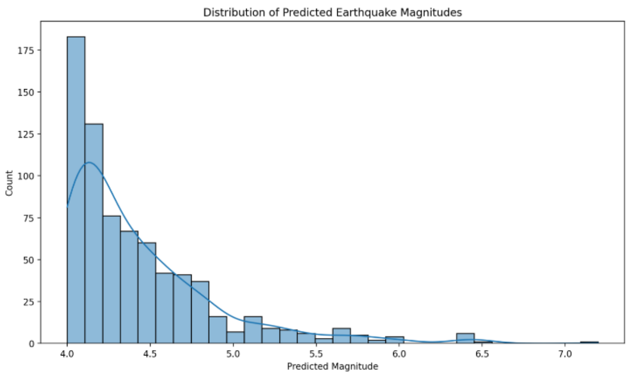

Figure 7. Distribution of Predicted Earthquake Magnitudes Generated by the Hybrid Ensemble Model.

The predicted magnitudes in Figure 7 are very consistent with historical patterns: The model does not overproduce large events, the decay rate aligns with the well-established Gutenberg-Richter slope, and smaller events remain significant, creating a natural frequency balance. The very close agreement between Figures 6 and 7 indicates that the hybrid set can capture statistical precision, an important criterion emphasized by comparative studies such as CSEP (Collaboratory for the Study of Earthquake Predictability) (Schorlemmer et al., 2018). This fidelity also suggests that the boosting models internalize the rate-magnitude relationship embedded in the region's seismic history without memorizing the training catalogue.

Across all five figures, the results demonstrate that the hybrid ensemble framework: Captures short-term temporal structure (supported by narrow residuals and ACF behaviour), Preserves spatial clustering patterns associated with major crustal faults, Reproduces the statistical magnitude distribution, matching long-term tectonic trends, avoids overfitting, as shown by smooth and overlapping train-test curves.

These outcomes are in line with current understanding that earthquake forecasting is inherently probabilistic, not deterministic (Geller et al., 1997; Renuka et al., 2024). The model therefore contributes to efforts aimed at improving risk awareness, short-term hazard assessment, and alignment with SDG 11 (Sustainable Cities and Communities).

Conclusion

This study shows that a leakage-controlled hybrid ensemble framework integrating CatBoost, LightGBM, XGBoost, and Gradient Boosting within a strictly chronological workflow can generate stable and statistically consistent probabilistic forecasts of key earthquake parameters in Northern California using USGS catalogue data (1900–2025). Across magnitude, depth, epicentral latitude/longitude, and inter-event interval targets, the models achieved low MAE/RMSE and high explanatory power ($R^2 > 0.99$) under prospective-style validation, while diagnostic checks indicated no obvious systematic bias and spatial–statistical consistency with established seismic patterns. Importantly, these results should not be interpreted as deterministic earthquake prediction; rather, they support the use of rigorously validated ML as a probabilistic tool to improve short-term situational awareness and risk communication, aligning with SDG 11, while future work should emphasize physics-informed constraints and formal prospective testing (e.g., CSEP-type protocols) to strengthen operational relevance.

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Author Contributions

Conceptualisation: Madlazim; Methodology: Madlazim, Baba Musta, Aris Doyan; Software and Formal Analysis: Madlazim, Khaista Rehman; Investigation: Madlazim, Aris Doyan, Adi Susilo; Resources: Madlazim; Visualization: Madlazim; Muhammad Nurul Fahmi, Writing, Original Draft Preparation: Madlazim; Writing, Review and Editing: Baba Musta, Adi Susilo, Khaista Rehman; Supervision: Baba Musta; Project Administration: Madlazim; Funding Acquisition: Madlazim. All authors have read and approved the final version of the manuscript.

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Conflicts of Interest

This article has no conflict of interest and all authors agree to be published and have their own job descriptions.

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