

Physically Consistent Peak Ground Acceleration Prediction in Bali Using Ensemble Machine Learning

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Abstract

Bali faced significant seismic risks from the Java Trench and back-arc thrust faults, making accurate Peak Ground Acceleration (PGA) prediction crucial. While traditional empirical models struggled with complex, non-linear site effects, machine learning offered a robust alternative. This study aimed to develop and compare Random Forest and XGBoost algorithms, utilizing moment magnitude (M_w), hypocentral distance (R_{hypo}), and local site conditions (Vs₃₀) as primary inputs, to predict PGA in the Bali region. The research utilized 1,000 strong-motion records from 287 earthquakes ($M_w > 4.0$) recorded between 2018 and 2025. Following rigorous quality control, we applied logarithmic transformations and hyperparameter optimization via Randomized Search with 3-fold cross-validation. Expanding upon our preliminary model evaluations, this comprehensive analysis demonstrated that the Random Forest architecture outperformed XGBoost by maintaining superior predictive stability, yielding a Coefficient of Determination of 0.741, a Mean Absolute Error of 0.340, and a highly constrained residual standard deviation of 0.434. Furthermore, feature importance analysis revealed that Random Forest was physically consistent with seismological principles. It correctly identified hypocentral distance as the dominant ground-motion attenuation predictor, whereas XGBoost exhibited an overfitted bias toward local site conditions. Ultimately, the Random Forest algorithm provided a highly reliable model for PGA prediction, effectively supporting the development of Probabilistic Seismic Hazard Analysis maps and rapid real-time ShakeMaps in Indonesia.

Keywords: Attenuation relationship; Ensemble learning; Hyperparameter tuning; Seismic hazard assessment; Strong-motion records.

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Introduction

Bali is a major tourism destination in Indonesia that faces high seismic risks from the Java Trench subduction zone and northern back-arc thrust faults. Accurate prediction of Peak Ground Acceleration (PGA) is essential for seismic hazard assessment because it estimates the maximum ground shaking during an earthquake. These predictions, which fundamentally depend on the rapid determination of initial earthquake parameters (Hielmy et al., 2025a), are vital for comprehensive seismic hazard assessments and rapid ShakeMap

generation (Monterrubio-Velasco et al., 2024), which have traditionally relied on standard empirical Ground Motion Prediction Equations (Hielmy & Rajagukguk, 2025; Khosravikia & Clayton, 2021; Parker et al., 2022) to model regional site effects.

However, traditional GMPEs often struggle to capture complex, non-linear site effects without requiring extensive regional calibration. Recent studies show that GMPEs fail to model non-linear seismic wave attenuation, which drives the shift toward machine learning architectures like Support Vector Machines and tree-based

ensembles (Bojórquez et al., 2025; Zhu et al., 2023). Tree-based models, such as Random Forests, perform better on global datasets by capturing multidimensional predictors and overcoming the rigid assumptions of GMPEs (Somala et al., 2024; Ziar & Basari, 2025). Furthermore, compared to Support Vector Machines and the opaque nature of Artificial Neural Networks, ensemble tree architectures like Random Forest and XGBoost were specifically selected for this study because they offer superior robustness against overfitting on skewed tabular data and provide transparent feature importance metrics essential for physical validation. Therefore, Machine Learning (ML) has emerged as a powerful, data-driven alternative for modeling ground motion (Khosravikia & Clayton, 2021; Kubo et al., 2020).

Recent applications in active subduction zones, like southern Sumatra, show that ensemble algorithms can extract non-linear patterns from historical records to improve predictive accuracy (Lisa et al., 2026). Globally, tree-based ensemble models also show better performance in ground motion prediction compared to classical numerical simulations (Sun et al., 2023). Similar studies in West Java have proven the potential of ML to support early warning systems (Rachmadan et al., 2025). Despite this progress, there is still a lack of comparative studies evaluating the physical consistency and precision of algorithms like Random Forest and XGBoost for the unique site conditions (Vs30) in Bali.

Evaluating these ML algorithms against physical attenuation laws can provide a robust approach to fill this research gap. Building significantly upon our preliminary extended abstract (Hielmy & Muzli, 2026), this comprehensive manuscript introduces rigorous cross-validation and evaluates the models' strict adherence to physical wave attenuation principles. Therefore, this study aims to develop and compare Random

Forest and XGBoost models to accurately predict PGA in the Bali region. The research uses 1,000 strong-motion records partitioned into a 70:30 training-testing split, applying data preprocessing, logarithmic transformations, and hyperparameter tuning; evaluating a search space of 100 to 1,000 estimators and maximum tree depths from 10 to 50 (including no limit); with a 3-fold cross-validation method. Ultimately, this study offers a reliable and physically consistent model for PGA prediction, which supports better seismic hazard assessment and resilient infrastructure planning in Indonesia.

Materials and Methods

Study Area and Geological Setting

The research area encompasses Bali and its surrounding regions, which are characterized by a highly active and complex tectonic framework. A robust understanding of this local setting is essential for accurate ground motion modeling, similar to studies on the Sumedang and Baribis faults in West Java or the Palu-Koro fault in Sulawesi (Muzli et al., 2026). Bali is highly susceptible to seismic activity driven primarily by the Java Trench subduction zone to the south, where the Indo-Australian plate subducts beneath the Eurasian plate. Additionally, the region is continually affected by back-arc thrust faulting located to the north of the island.

Figure 1 illustrates the spatial distribution of earthquake epicenters and strong-motion sensor stations, focusing specifically on the Bali region delineated by the red bounding box. The map explicitly displays the seismicity profile, where earthquake epicenters are scaled by magnitude and color-coded by hypocentral depth. As observed, shallow earthquakes (red to yellow circles, < 50 km depth) are predominantly concentrated along the Java Trench and local thrust faults. In contrast,

deeper earthquakes (green to blue circles) are distributed further north, and their ground motions are captured by 17 well-

distributed accelerometer stations marked as purple triangles.

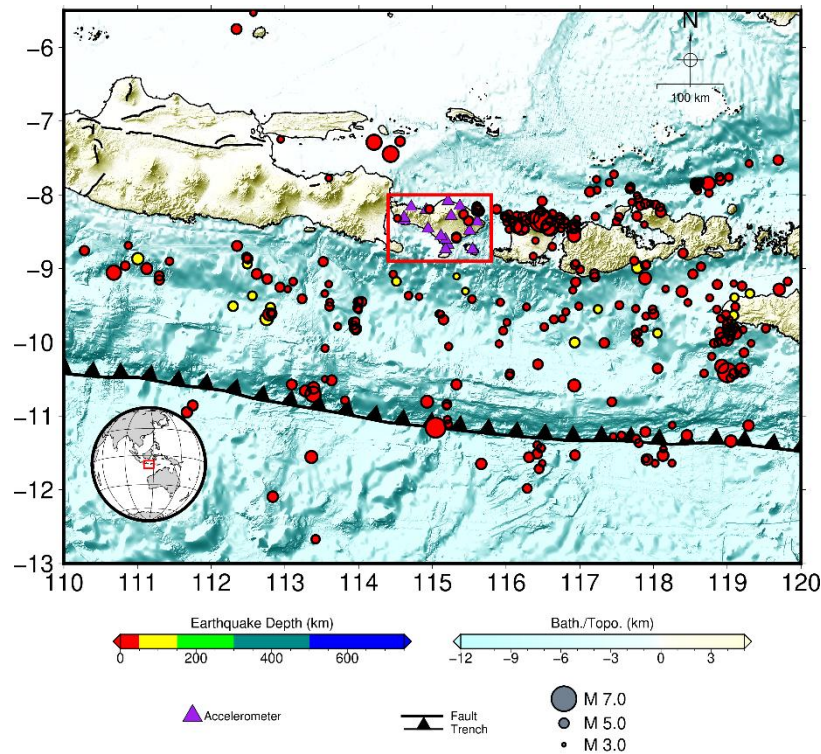


Figure 1. Map of the study area showing earthquake epicenters and sensor stations distributed across Bali and nearby regions. The map is projected using the WGS 84 coordinate reference system. The spatial distribution reveals a high concentration of shallow seismic events (depth < 50 km) dominating the Java Trench and northern back-arc thrust faults, which are comprehensively captured by the localized accelerometer network.

Dataset and Quality Control

This study utilized a strong-motion dataset comprising 1,000 earthquake records obtained from the Agency for Meteorology, Climatology, and Geophysics (BMKG). The collected data covered the period from 2018 to 2025, recording 287 distinct earthquake events across 17 regional seismic stations. To ensure data homogeneity, all recorded earthquake magnitudes were standardized and converted to Moment Magnitude (M_w). This standardization adhered to the guidelines of the 2024 National Center for Earthquake Studies (PuSGeN, 2024) and the framework by the Team for Revision of Seismic Hazard Maps of Indonesia (Irsyam et al., 2010).

Prior to extracting the PGA values, the raw waveforms underwent uniform baseline correction and bandpass filtering to

eliminate instrumental noise, after which only quality-controlled events with a magnitude of $M_w > 4.0$ and a hypocentral distance (R_{hypo}) of less than 500 km were retained for modeling. Furthermore, for stations where local measurements were unavailable, the time-averaged shear-wave velocity (V_{s30}) was estimated using a global model based on topographic slope (Allen & Wald, 2009; Heath et al., 2020; Thompson et al., 2014; Wald & Allen, 2007), though we explicitly acknowledge that this proxy introduces inherent uncertainties and potential biases in regions where surface topography does not fully capture complex local geological anomalies. The resulting earthquake frequency distribution is presented in Figure 2, while Figure 3 depicts the spatial distribution of the 17 seismic stations categorized by their site class conditions (Badan Standardisasi Nasional, 2019).

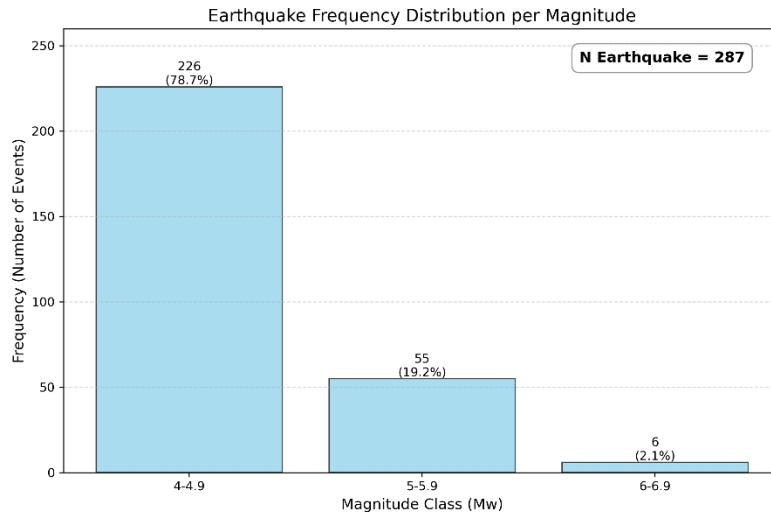


Figure 2. Earthquake frequency distribution per magnitude class (Mw). The dataset is heavily dominated by moderate seismic events (Mw 4.0–4.9), which account for nearly 79% of the catalog, highlighting the highly skewed distribution of the regional seismicity.

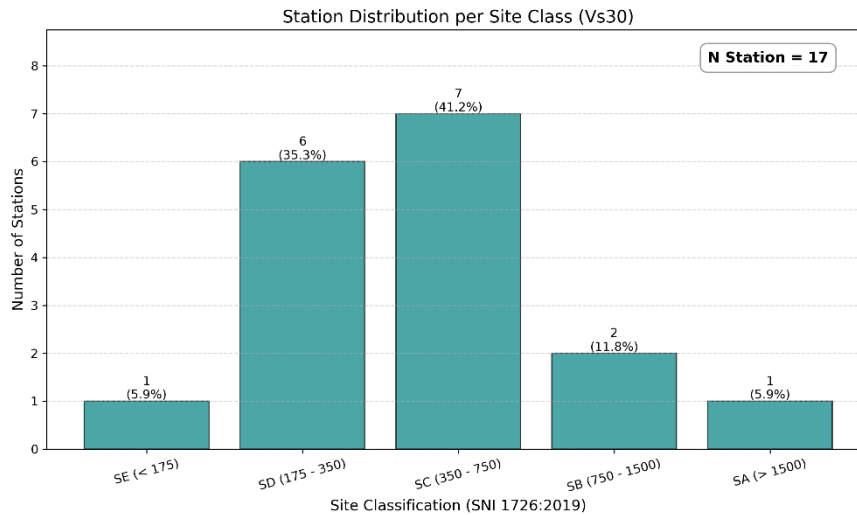


Figure 3. Station distribution per site classification (Vs30). The majority of the recording stations are situated on medium to stiff soil classes (SD and SC), which fundamentally influence the non-linear local ground motion amplification.

Exploratory Data Analysis (EDA)

Before training the models, Exploratory Data Analysis (EDA) was conducted to evaluate the data distribution and feature relationships. This analysis revealed significant non-linear relationships between the target variable and the input predictors. As a result, a Base-10 Logarithmic (Log10) transformation was applied to the Peak Ground Acceleration (PGA), hypocentral distance (Rhypo), magnitude (Mw), and site class conditions (Vs30). This logarithmic transformation is a fundamental procedure in ground motion modeling because it stabilizes residual

variance and perfectly matches the log-normal attenuation behavior of seismic waves (Baumann & Dalguer, 2014).

The resulting feature correlation heatmap (Figure 4) shows that Log10_PGA has a strong inverse correlation with logarithmic hypocentral distance (-0.5657) and a positive correlation with magnitude (0.3016). Conversely, the local site condition (Vs30) demonstrates a relatively weak negative correlation (-0.1054) with the target variable. Furthermore, the empirical attenuation behavior is clearly visualized in the hexbin distribution plot of PGA against hypocentral distance (Figure

5). This plot of 1,000 data points reveals a distinct physical trend where ground acceleration exponentially decays as

distance increases, with the highest concentration of events occurring beyond 100 km.

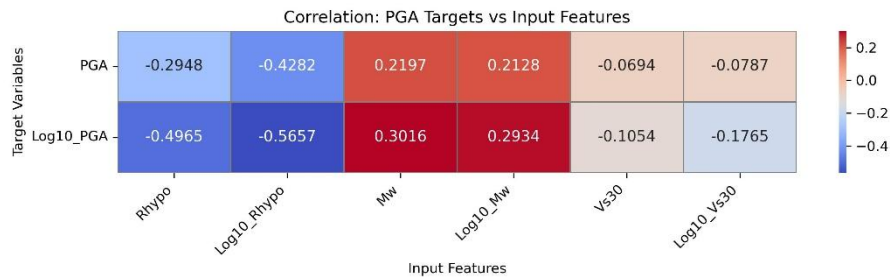


Figure 4. Correlation heatmap showing the relationships between predictor variables and target variables. Positive values indicate direct correlations, whereas negative values indicate inverse relationships. The analysis reveals that logarithmic hypocentral distance (Log10_Rhypo) has the strongest inverse correlation (-0.5657) with ground motion intensity, establishing it as the most critical predictor.

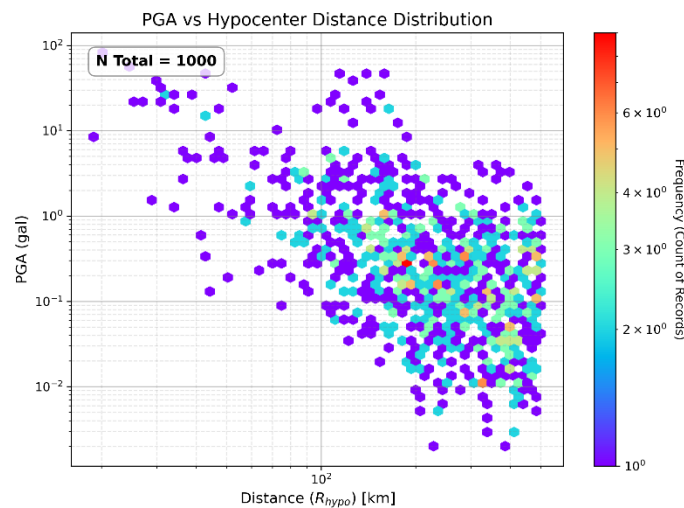


Figure 5. Distribution of Peak Ground Acceleration (PGA) against hypocentral distance (Rhypo). The data concentration clearly visualizes the physical principle of empirical attenuation, demonstrating that ground shaking intensity decays exponentially as distance from the seismic source increases.

Machine Learning Approach

To predict PGA, two distinct ensemble machine learning algorithms were implemented and compared: Random Forest and XGBoost. Random Forest is a bagging method that builds multiple decision trees during training and averages their outputs to reduce variance and prevent overfitting (Probst et al., 2019). This algorithm outperforms conventional linear regression methods in geospatial sciences, especially when handling complex spatial datasets with uncertainties (Apriliansyah et al., 2026). Additionally, random forest architectures are highly recommended for modern seismological tasks due to their strong resilience against overfitting on

complex earthquake records (Kong et al., 2019; Mousavi & Beroza, 2022).

Conversely, XGBoost (eXtreme Gradient Boosting) is a highly scalable sequential tree boosting system that iteratively minimizes residual errors (Chen & Guestrin, 2016). Gradient boosting machines are proficient at modeling non-linear relationships in sparse data, making them effective for rapid and physics-consistent peak acceleration estimations (Feng et al., 2025; Ramadan et al., 2026). The conceptual comparison of these methodologies is illustrated in Figure 6, which highlights the architectural differences between the two models. As

depicted, Random Forest uses a parallel approach to train independent trees using bootstrap samples, whereas XGBoost uses a sequential mechanism where each new tree corrects the residual errors of the previous one.

The complete analytical workflow proceeded sequentially: (1) data preprocessing including Log10 transformations, (2) model training via data partitioning, (3) hyperparameter optimization using Randomized Search, and (4) robust model validation. To ensure optimal predictive performance, hyperparameter optimization was conducted using Randomized Search

(Moon et al., 2024). As detailed in the optimization module of Figure 6, the dataset was initially partitioned into a 70% training set and a 30% testing set, with the training portion paired with a 3-fold cross-validation strategy. This approach was deliberately chosen over 5-fold or 10-fold methods to iteratively evaluate hyperparameter combinations while ensuring each validation fold retained a statistically robust sample (~233 records) of the highly skewed ground motion distribution. The search space ranged from 100 to 1000 for the number of estimators and from None to 50 for the maximum tree depth, ensuring both models successfully avoided data overfitting.

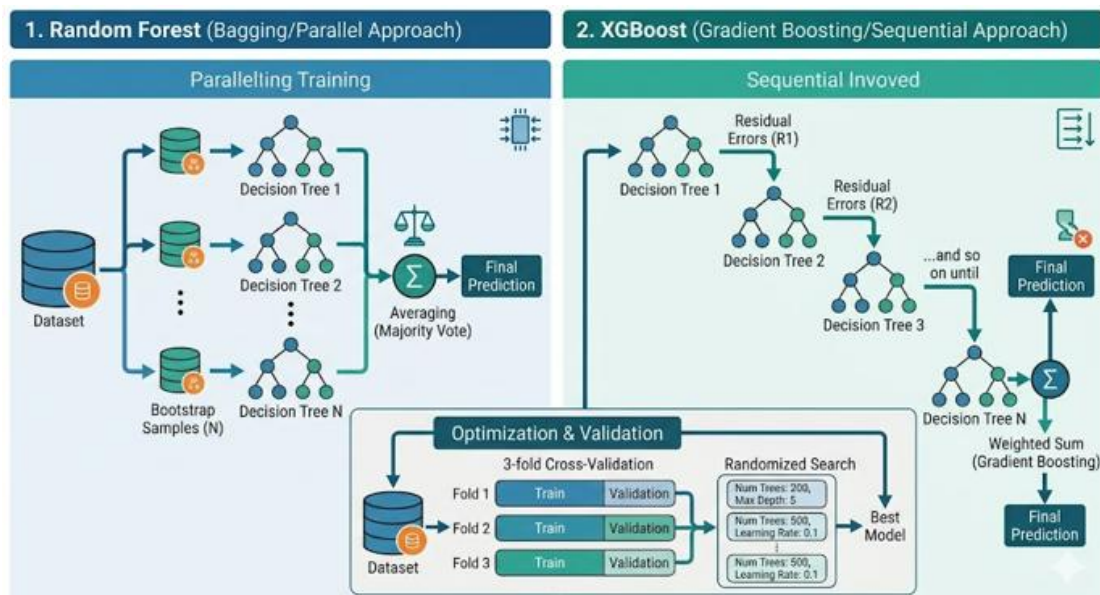


Figure 6. The sequential analytical workflow, illustrating the parallel training of Random Forest, the sequential approach of XGBoost, and the progression from initial data handling through to the hyperparameter optimization process. This rigorous cross-validation strategy ensures optimal model tuning while effectively preventing data overfitting (Adapted from Khan et al., 2021; Mohammadi et al., 2023).

Results and Discussion

Predictive Performance Metrics

The two machine learning models were evaluated based on their ability to accurately predict Peak Ground Acceleration (PGA) after rigorous hyperparameter tuning. The Random Forest model achieved its best performance using 1000 trees ($n_{\text{estimators}} = 1000$) with a maximum depth of 10. In contrast, the XGBoost model reached its optimal setup

with 500 trees ($n_{\text{estimators}} = 500$) and no maximum depth limit. Quantitative evaluation showed that Random Forest outperformed XGBoost across all key metrics, as summarized in the bar chart comparison (Figure 7).

Specifically, Random Forest achieved a higher Coefficient of Determination (R^2) of 0.741 and a lower Mean Absolute Error (MAE) of 0.340, whereas XGBoost yielded a slightly lower R^2 of 0.715 and an MAE of

0.344. Although the numerical difference in the aggregate MAE appears modest, this performance gain is structurally significant due to Random Forest's significantly tighter error variance; it effectively minimizes extreme prediction outliers and yields a noticeably lower residual standard deviation (0.434) compared to XGBoost

(0.456). Figure 8 illustrates the observed versus predicted Log10 PGA values for both of these tuned models. The scatter plots show that Random Forest predictions (Figure 8a) tightly follow the ideal 1:1 reference line, whereas XGBoost predictions (Figure 8b) display a wider dispersion with noticeable errors.

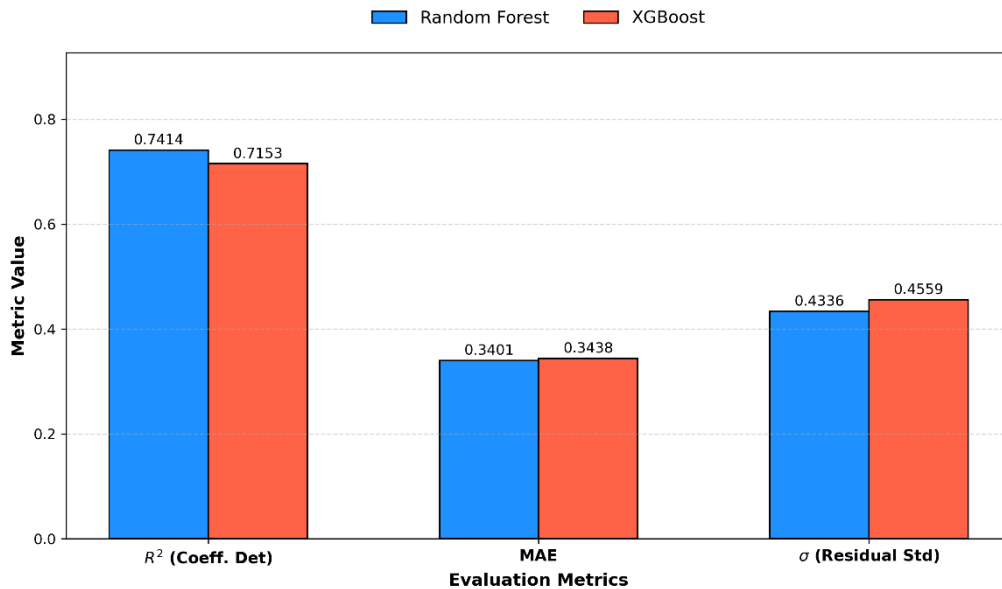


Figure 7. Quantitative performance comparison between the machine learning models. Random Forest consistently outperforms XGBoost across all metrics, achieving a higher Coefficient of Determination ($R^2=0.741$) and a lower residual standard deviation ($\sigma = 0.434$), which demonstrates its superior predictive stability.

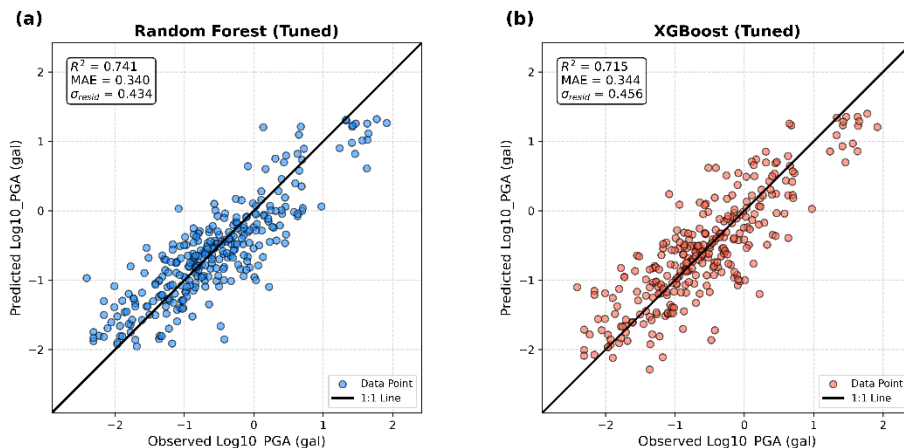


Figure 8. Comparison of observed versus predicted PGA values for (a) Random Forest and (b) XGBoost. The Random Forest predictions (a) cluster more tightly along the ideal 1:1 reference line, indicating higher precision and fewer extreme prediction outliers compared to the wider error dispersion seen in the XGBoost model (b).

Residual Analysis

To further evaluate model precision, we conducted a comprehensive residual analysis. The results showed that the residual standard deviation for Random Forest was 0.434. This value was

noticeably lower than the standard deviation of 0.456 recorded for the XGBoost model. This clear difference in error variance between the two models is visually depicted in the residual distribution density plot (Figure 9).

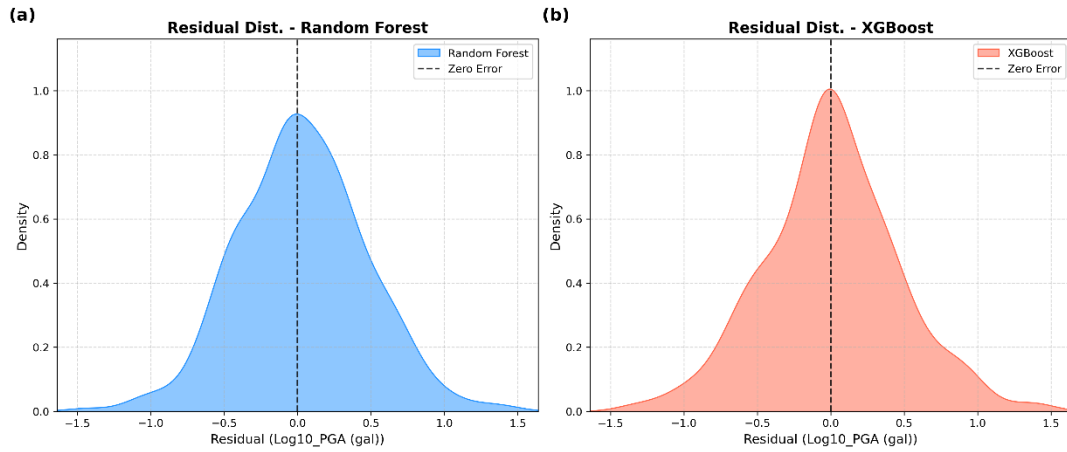


Figure 9. Residual distribution density plot for (a) Random Forest and (b) XGBoost. The Random Forest model produces a highly constrained, symmetrical error distribution, whereas XGBoost exhibits wider tails associated with higher prediction uncertainty and extreme outliers.

The plot reveals that while XGBoost residuals (Figure 9b) are slightly denser at the zero-error line, they exhibit wider tails that indicate more extreme prediction errors. In contrast, the Random Forest model (Figure 9a) forms a more proportional bell curve with narrower tails and fewer extreme outliers. To further investigate this behavior across key earthquake parameters, the prediction residuals were plotted against hypocentral distance (Figures 10a and 10b), local site conditions or Vs30 (Figures 11a and 11b), and moment magnitude or Mw (Figures 12a and 12b). These scatter plots demonstrate that both models, particularly Random

Forest (Figures 10a, 11a, and 12a), maintain a well-distributed and unbiased error variance across the entire parameter space, with the majority of data points falling within the ± 1 standard deviation threshold and showing no systemic distance, site, or magnitude-dependent trends. This statistical behavior proves that Random Forest provides higher precision and stability across varying earthquake distances and magnitudes. This stability is consistent with recent comparative studies, which emphasize the adaptive learning capacity and robust residual patterns of Random Forest across diverse site conditions (Taya et al., 2026).

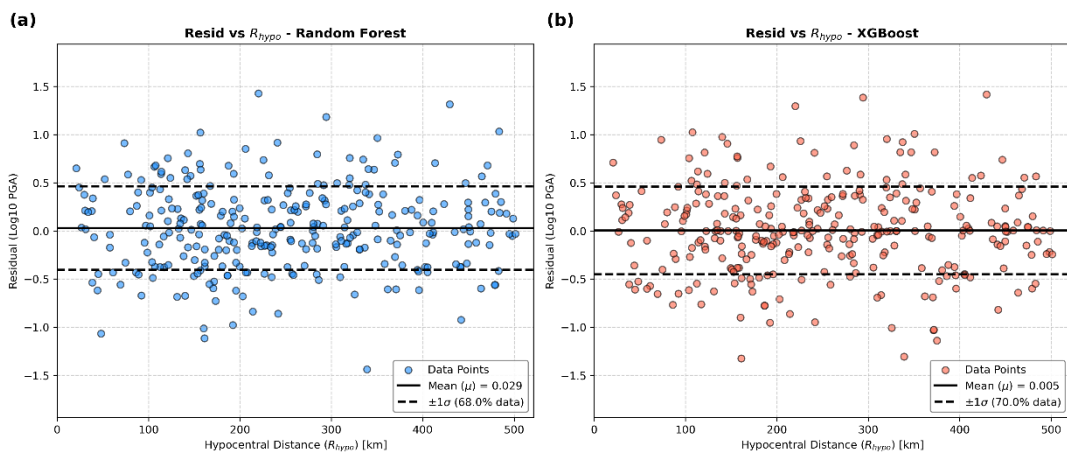


Figure 10. Scatter plots of prediction residuals against hypocentral distance (R_{hypo}) for (a) Random Forest and (b) XGBoost, highlighting the ± 1 standard deviation error bounds. Both models maintain stable error variances across varying distances without systemic bias, proving their robustness in capturing regional attenuation.

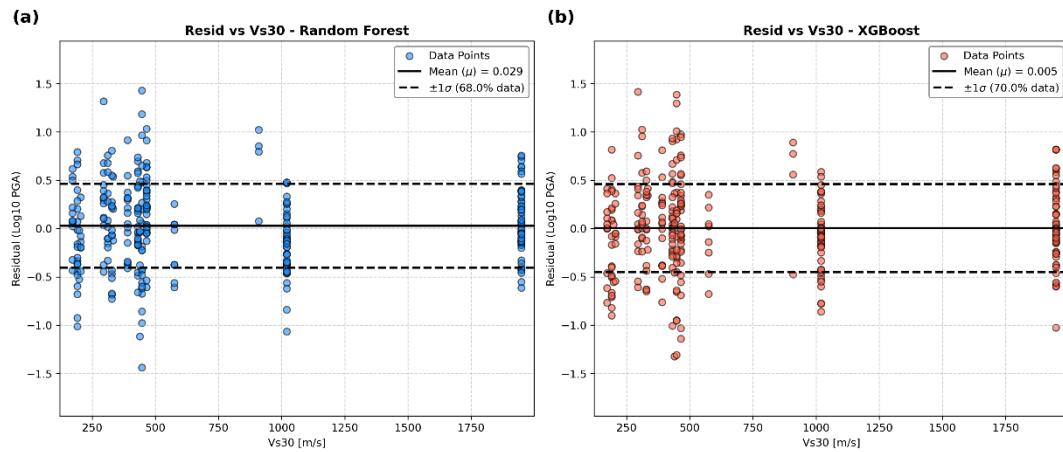


Figure 11. Scatter plots of prediction residuals against time-averaged shear-wave velocity (V_{s30}) for (a) Random Forest and (b) XGBoost. The Random Forest model demonstrates robust stability across diverse site classifications without overfitting to localized ground responses.

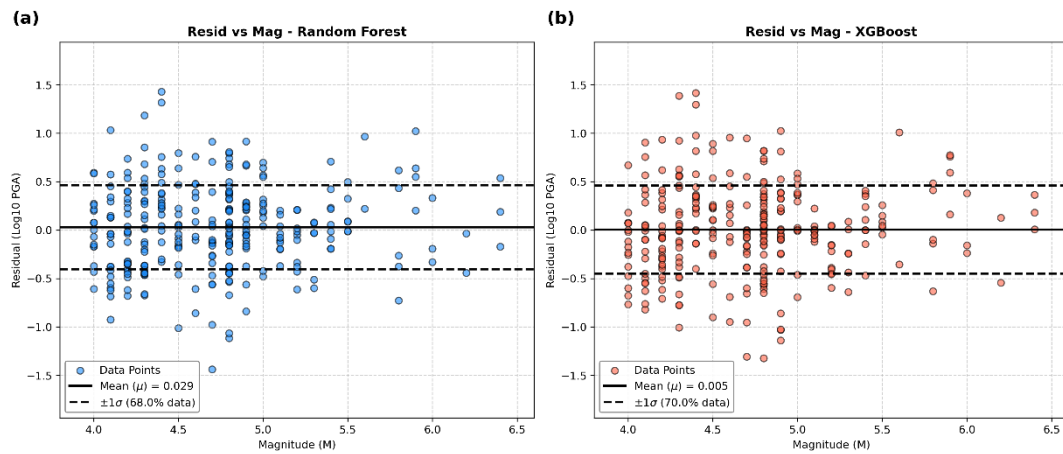


Figure 12. Scatter plots of prediction residuals against moment magnitude (M_w) for (a) Random Forest and (b) XGBoost. The uniform spread of residuals confirms an unbiased error distribution irrespective of earthquake size, validating the models' reliability for both moderate and large events.

Feature Importance and Physical Consistency

A critical aspect of modeling ground motion is ensuring that data-driven algorithms follow established seismological principles. Feature importance metrics were extracted from both models to quantitatively understand which input variables drove the predictions. The Random Forest model (Figure 13a) correctly identified Hypocentral Distance ($\text{Log}_{10_R_{\text{hypo}}}$) as the dominant predictor with a relative importance of 0.533, followed by Magnitude (0.237) and local site conditions ($\text{Log}_{10_V_{s30}}$) at 0.230. This hierarchical order perfectly aligns with standard physical attenuation laws, where distance is the primary factor of shaking decay.

Recent machine learning evaluations strongly support this finding, showing that distance is a highly reliable predictor for regional co-seismic impacts (Shi et al., 2024). Conversely, the XGBoost model (Figure 13b) exhibited an unexpected and physically incorrect bias. It assigned the highest relative importance to local site conditions ($\text{Log}_{10_V_{s30}}$) at 0.427. At the same time, it reduced Magnitude (0.291) and Hypocentral Distance (0.282) to secondary and tertiary roles. This prioritization fundamentally violates the established seismological principle of exponential decay, wherein seismic energy dissipates primarily as a function of geometric spreading and anelastic attenuation over distance. While local site conditions (V_{s30}) certainly contribute to localized amplification, the overarching

decay of ground motion is unequivocally driven by source-to-site distance, rendering XGBoost's feature hierarchy physically

inconsistent with empirical attenuation laws.

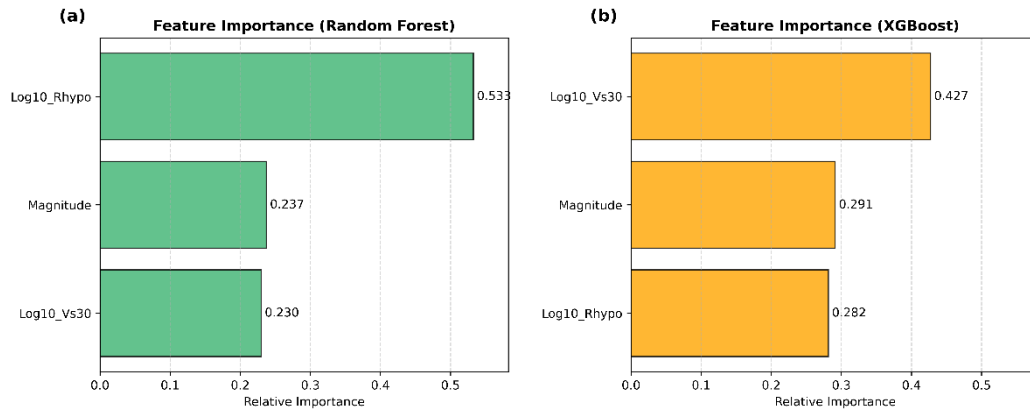


Figure 13. Feature importance chart showing (a) hypocentral distance as the dominant predictor for Random Forest, whereas (b) XGBoost prioritizes site class (Vs30). The feature hierarchy of Random Forest is physically consistent with established empirical attenuation laws, unlike the physically counterintuitive, localized overfitting observed in the XGBoost model.

Discussion

The results of this study clearly demonstrate that Random Forest provides a more accurate, precise, and physically consistent model for predicting PGA in Bali compared to XGBoost. The superiority of Random Forest is attributed to its parallel bagging architecture, which is robust against noise and prevents overfitting on complex geological data (Probst et al., 2019). However, it is important to acknowledge that XGBoost remains a highly potent algorithm in different seismological contexts. While its sequential gradient boosting approach was susceptible to overfitting the localized site conditions in our specific regional dataset, XGBoost typically excels when applied to massive, high-dimensional global catalogs (such as the NGA-West2 database). In such large-scale environments, its ability to iteratively minimize complex residual errors allows it to capture highly intricate, non-linear feature interactions more effectively than Random Forest, provided that extensive regularization is employed. Most importantly, the feature importance analysis reveals that Random Forest aligns seamlessly with empirical ground-motion attenuation laws. In traditional seismology, ground shaking intensity decreases mainly

as a function of distance from the seismic source due to geometric spreading and anelastic attenuation.

The combined effect of geometric spreading and anelastic damping dictates that hypocentral distance fundamentally controls the decay of seismic waves (Kramer & Stewart, 2024). By prioritizing hypocentral distance over site conditions, Random Forest successfully captures these physical attenuation principles. On the other hand, XGBoost tends to prioritize Vs30, which indicates potential overfitting to local site responses at the expense of regional attenuation behavior. These overall findings represent a significant step forward from traditional Ground Motion Prediction Equations (GMPEs).

As noted in previous studies, traditional GMPEs deployed in Bali often struggle to handle the non-linear effects of local geology without extensive calibration (Hielmy, 2024; Hielmy, et al., 2026; Hielmy & Rajagukguk, 2025). The Random Forest model in this study overcomes this limitation by learning complex interactions directly from recent strong-motion records to produce a robust localized model. The ability of ensemble models to capture complex seismic

relationships addresses the limitations of empirical equations and earlier neural network designs (Leema et al., 2025). Once optimized, these data-driven approaches provide well-calibrated predictions that can be directly evaluated against engineering thresholds to assess structural damage risks (Shokrgozar-Yatimdar & Chen, 2025).

The application of such advanced algorithms has proven effective in solving complex seismological problems, from aftershock decay estimation to ground motion prediction (Withers et al., 2020). This success aligns with recent advancements in neighboring areas like West Java, where ML has successfully enhanced predictive capabilities (Rachmadan et al., 2025). The implementation of this highly accurate Random Forest model has substantial practical applications for disaster mitigation. For long-term planning, a reliable PGA model is crucial to develop Probabilistic Seismic Hazard Analysis (PSHA) maps, which dictate national building codes in vulnerable areas like Bali.

Such robust hazard mapping is essential for regional earthquake mitigation, similar to vulnerability assessments used to identify high-risk zones across Indonesia (Ningrum et al., 2022). Translating these technical models into community preparedness is also vital, as shown by school mitigation simulations that rely on accurate seismic risk data (Hielmy et al., 2026; Hielmy et al., 2025b). For rapid response, integrating ML algorithms into seismic networks significantly improves the generation of real-time ShakeMaps by BMKG (Jozinović et al., 2020). Recent deployments of such hybrid workflows have demonstrated reduced prediction errors and significant lead time gains, which strengthen the overall effectiveness of early warning systems (Zhang et al., 2026).

Conclusion

This study successfully evaluated and compared the predictive capabilities of Random Forest and XGBoost algorithms for estimating Peak Ground Acceleration in the highly seismic region of Bali. The results demonstrated that the parallel bagging architecture of Random Forest provides a more accurate and stable prediction model than the sequential boosting approach of XGBoost. This statistical superiority is clearly evidenced by a higher Coefficient of Determination and significantly lower overall error metrics. Beyond pure statistical performance, a major advantage of the Random Forest model is its strong adherence to physical consistency.

The model successfully captured geometric spreading and anelastic attenuation by correctly identifying hypocentral distance as the primary driver of ground shaking. By prioritizing distance, the model effectively avoided the overfitting to local site conditions that was observed in XGBoost. Although constrained by the available training data, this data-driven approach overcomes the limitations of traditional empirical equations in modeling non-linear site effects. Ultimately, this accurate model establishes a fundamental precedent for developing Probabilistic Seismic Hazard Analysis maps, enhancing real-time ShakeMaps, and supporting proactive structural risk mitigation in Indonesia (Nemutlu et al., 2025).

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Author Contribution

Rayhan Irfan Hielmy: Conceptualization, Methodology, Software, Formal analysis, Visualization, Writing - Original Draft. Muzli Muzli: Supervision, Validation, Writing - Review & Editing.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

- Allen, T. I., & Wald, D. J. (2009). On the Use of High-Resolution Topographic Data as a Proxy for Seismic Site Conditions (VS30). *Bulletin of the Seismological Society of America*, 99(2A), 935–943. <https://doi.org/10.1785/0120080255>
- Apriliansyah, F., Nuha, M. U., Atmojo, A. T., Setiawan, K. T., & Syafnur, A. (2026). Comparative Accuracy of Satellite-Derived Bathymetry Using Random Forest, Multiple Linear Regression, and Van Hengel and Spitzer Algorithm. *Jurnal Geoelebes*, 48–68. <https://doi.org/10.70561/geoelebes.v10i1.43582>
- Badan Standardisasi Nasional. (2019). *SNI 1726:2019: Tata Cara Perencanaan Ketahanan Gempa untuk Struktur Bangunan Gedung dan Nongedung*. Badan Standardisasi Nasional. <https://sitaba.pu.go.id/publikasi/6977fb4f-d02f-4fd0-a857-65219c38f24e>
- Baumann, C., & Dalgner, L. A. (2014). Evaluating the Compatibility of Dynamic Rupture-Based Synthetic Ground Motion with Empirical Ground-Motion Prediction Equation. *Bulletin of the Seismological Society of America*, 104(2), 634–652. <https://doi.org/10.1785/0120130077>
- Bojórquez, E., Payán-Serrano, O., Bojórquez, J., Rodríguez-Castellanos, A., Ruiz, S. E., Reyes-Salazar, A., & Velarde, F. (2025). Support Vector Machines to Propose a Ground Motion Prediction Equation for the Particular Case of the Bojórquez Intensity Measure INp. *AI*, 6(10), 254. <https://doi.org/10.3390/ai6100254>
- Chen, T., & Guestrin, C. (2016). XGBoost: A Scalable Tree Boosting System. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 785–794. <https://doi.org/10.1145/2939672.2939785>
- Feng, Y., Li, Y., Wang, F., & Yang, L. (2025). Hybrid CNN-GRU-Attention-XGBoost Model for Rapid and Accurate Prediction of Peak Acceleration and Trigger Time in Dam Safety Monitoring. In *2025 5th International Conference on Artificial Intelligence, Big Data and Algorithms (CAIBDA)*, 1245–1251. <https://doi.org/10.1109/CAIBDA65784.2025.11183451>
- Heath, D. C., Wald, D. J., Worden, C. B., Thompson, E. M., & Smoczyk, G. M. (2020). A global hybrid VS30 map with a topographic slope-based default and regional map insets. *Earthquake Spectra*, 36(3), 1570–1584. <https://doi.org/10.1177/8755293020911137>
- Hielmy, R. I. (2024). Perbandingan Metode Davenport, Milne, dan McGuire dalam Penentuan Nilai Percepatan Tanah Maksimum di Pulau Bali. *Buletin Meteorologi, Klimatologi Dan Geofisika*, 4(5), 9–16. https://balai2bmkg.id/index.php/buletin_mkg/article/view/133
- Hielmy, R. I., Pranata, B., Wijayanto, & Daryono. (2025a). Performance Evaluation of Automated and Manual Seismic Phase Picking for Rapid Earthquake Parameter. *Jurnal Meteorologi Dan Geofisika*, 26(2), 89–107. <https://doi.org/10.31172/jmg.v26i2.11>

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Hielmy, R. I., Aritonang, B. H., Sijabat, N. A., An-nizami, M. S., Setyowati, P. R., Wijaya, A., Adzan, M. A., Aji, T. W., Kristianto, A., Rachmawardani, A., & Sianipar, D. S. J. (2025b). Sosialisasi Mitigasi Bencana Gempa Bumi , Tsunami, dan Hidrometeorologi di SMAN 6. *To Maega | Jurnal Pengabdian Masyarakat*, 8(3), 607–616.
<https://doi.org/10.35914/hk0rn065>
- Hielmy, R. I., Kean, F. A. C., Gosi, M. F. Al, Syifa, F., Daraman, M. A., Lala, R. Y., Sianipar, D. S. J., Justicea, A. A., Suardi, I., Muzli, Karyono, Harahap, D., Adi, S. P., Wandono, & Peera, F. (2026). Evaluasi Efektivitas Simulasi Mitigasi Bencana Gempa Bumi di Sekolah An-Nisaa' Izada, Tangerang Selatan. *To Maega | Jurnal Pengabdian Masyarakat*, 9(1), 1–12.
<https://doi.org/10.35914/4gqdg87>
- Hielmy, R. I., & Muzli, M. (2026). Comparative Analysis of Random Forest and XGBoost for Peak Ground Acceleration Prediction in Bali, Indonesia. *Proceedings of the 8th Asia Pacific Meeting on Near Surface Geoscience & Engineering*, 2026(1), 1–4. European Association of Geoscientists & Engineers.
<https://www.earthdoc.org/content/papers/10.3997/2214-4609.202671070>
- Hielmy, R. I., & Rajagukguk, M. L. (2025). Analisis Probabilistik Bahaya Seismik di Denpasar dan Sekitarnya Berdasarkan Pendekatan PSHA. *Journal Online of Physics*, 11(1), 21–28.
<https://doi.org/10.22437/jop.v11i1.47825>
- Hielmy, R. I., Santoso, E., Muzli, M., Pramono, S., & Prayোধhie, S. (2026). Machine learning-based ground motion prediction models for Indonesia: A performance evaluation of XGBoost and Random Forest against conventional GMPE. *Jurnal Meteorologi dan Geofisika*, 27(1), 51–67.
<https://doi.org/10.31172/jmg.v27i1.1233>
- Irsyam, M., Sengara, W., Aldiamar, F., Widiyantoro, S., Triyoso, W., Hilman, D., Kertapati, E., Meilano, I., Suhardjono, Asrurifak, M., & Ridwan, M. (2010). *Ringkasan Hasil Studi Tim Revisi Peta Gempa Indonesia 2010*. Kementerian Pekerjaan Umum Republik Indonesia.
- Jozinović, D., Lomax, A., Štajduhar, I., & Michelini, A. (2020). Rapid Prediction of Earthquake Ground Shaking Intensity Using Raw Waveform Data and a Convolutional Neural Network. *Geophysical Journal International*, 222(2), 1379–1389.
<https://doi.org/10.1093/gji/ggaa233>
- Khan, M. Y., Qayoom, A., Nizami, M. S., Siddiqui, M. S., Wasi, S., & Raazi, S. M. K.-u.-R. (2021). Automated Prediction of Good Dictionary EXamples (GDEX): A Comprehensive Experiment with Distant Supervision, Machine Learning, and Word Embedding-Based Deep Learning Techniques. *Complexity*, 2021(1), 2553199.
<https://doi.org/10.1155/2021/2553199>
- Khosravikia, F., & Clayton, P. (2021). Machine learning in ground motion prediction. *Computers and Geosciences*, 148, 104700.
<https://doi.org/10.1016/j.cageo.2021.104700>
- Kong, Q., Trugman, D. T., Ross, Z. E., Bianco, J., Meade, B. J., & Gerstoft, P. (2019). Machine Learning in Seismology: Turning Data into Insights. *Seismological Research Letters*, 90(1), 3–14.
<https://doi.org/10.1785/0220180259>
- Kramer, S. L., & Stewart, J. P. (2024). *Geotechnical Earthquake Engineering*. CRC Press.
<https://doi.org/10.1201/9781003512011>
- Kubo, H., Kunugi, T., Suzuki, W., Suzuki, S., & Aoi, S. (2020). Hybrid predictor

- for ground-motion intensity with machine learning and conventional ground motion prediction equation. *Scientific Reports*, 10(1), 1–12. <https://doi.org/10.1038/s41598-020-68630-x>
- Leema, A., Balakrishnan, P., Kiruba, G. G., Rajarajan, G., Goel, S., & Aggarwal, P. (2025). SeismoQuakeGNN: A Hybrid Framework for Spatio-Temporal Earthquake Prediction with Transformer-Enhanced Models. *Frontiers in Artificial Intelligence*, 8, 1690476. <https://doi.org/10.3389/frai.2025.1690476>
- Lisa, A., Refrizon, R., & Samdara, R. (2026). The Earthquake Prediction in the Southern Part of Sumatra Using Deep Learning (Long Short-Term Memory) Models. *Jurnal Geoelebes*, 1–11. <https://doi.org/10.70561/geoelebes.v10i1.42958>
- Mohammadi, A., Karimzadeh, S., Banimahd, S. A., Ozsarac, V., & Lourenço, P. B. (2023). The potential of region-specific machine-learning-based ground motion models: Application to Turkey. *Soil Dynamics and Earthquake Engineering*, 172, 108008. <https://doi.org/10.1016/j.soildyn.2023.108008>
- Monterrubio-Velasco, M., Callaghan, S., Modesto, D., Carrasco, J. C., Badia, R. M., Pallares, P., Vázquez-Novoa, F., Quintana-Ortí, E. S., Pienowska, M., & de la Puente, J. (2024). A machine learning estimator trained on synthetic data for real-time earthquake ground-shaking predictions in Southern California. *Communications Earth & Environment*, 5(1), 258. <https://doi.org/10.1038/s43247-024-01436-1>
- Moon, Y., Lee, Y., Hwang, Y., & Jeong, J. (2024). Long Short-Term Memory Autoencoder and Extreme Gradient Boosting-Based Factory Energy Management Framework for Power Consumption Forecasting. *Energies*, 17(15), 3666. <https://doi.org/10.3390/en17153666>
- Mousavi, S. M., & Beroza, G. C. (2022). Deep-learning Seismology. *Science*, 377(6607), eabm4470. <https://doi.org/10.1126/science.abm4470>
- Muzli, M., Lythgoe, K. H., Hielmy, R. I., Triyono, R., & Wei, S. (2026). Aftershock Characteristics of the 2018 Palu Earthquake: Implications for Supershear Rupture Segment. *Indonesian Physical Review*, 9(2), 374–385. <https://doi.org/10.29303/ipr.v9i2.666>
- Nemutlu, Ö. F., Özçelik, S. T. A., & Freeshah, M. (2025). A Machine Learning Framework for Regional Damage Assessment Using Multi-Station Seismic Parameters: Insights from the 2023 Kahramanmaraş Earthquakes. *Buildings*, 15(18), 3326. <https://doi.org/10.3390/buildings15183326>
- Ningrum, R. W., Amelia, R. N., Taib, S., Achmad, R., & Aswan, M. (2022). Pemetaan Potensi Kerentanan Seismik sebagai Mitigasi Bencana Gempa di Morotai Selatan. *Jurnal Geoelebes*, 37–46. <https://doi.org/10.20956/geoelebes.v6i1.19150>
- Parker, G. A., Stewart, J. P., Boore, D. M., Atkinson, G. M., & Hassani, B. (2022). NGA-subduction global ground motion models with regional adjustment factors. *Earthquake Spectra*, 38(1), 456–493. <https://doi.org/10.1177/87552930211034889>
- Probst, P., Wright, M. N., & Boulesteix, A.-L. (2019). Hyperparameters and tuning strategies for random forest. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, 9(3), e1301. <https://doi.org/10.1002/widm.1301>
- PuSGeN. (2024). *Buku Peta Sumber dan*

- Bahaya Gempa Indonesia Tahun 2024*. Kementerian Pekerjaan Umum Republik Indonesia. https://ciptakarya.pu.go.id/admin/assets/upload/galeri/gempa/2026/02/10/887359_0.%20Final_BUKU_PETA_SUMBER_DAN_BAHAYA_GEMPA_2024_Publish.pdf
- Rachmadan, A., Koeshidayatullah, A., & Kaka, S. L. I. (2025). Developing ground motion prediction models for West Java: A machine learning approach to support Indonesia's earthquake early warning system. *Applied Computing and Geosciences*, 25, 100212. <https://doi.org/10.1016/j.acags.2024.100212>
- Ramadan, F., Nissen-Meyer, T., Koelemeijer, P., & Fry, B. (2026). PGVnet: a Machine Learning Framework for the Generation of Rapid, Physics-Consistent PGV Maps. *Geophysical Journal International*, 244(3), 1–14. <https://doi.org/10.1093/gji/ggag008>
- Shi, Y., Zhang, Z., Xue, C., & Feng, Y. (2024). Machine Learning Prediction of Co-Seismic Landslide with Distance and Azimuth Instead of Peak Ground Acceleration. *Sustainability*, 16(19), 8332. <https://doi.org/10.3390/su16198332>
- Shokrgozar-Yatimdar, E., & Chen, P. (2025). Explainable Deep Learning for Real-Time Prediction of Uniform Hazard Spectral Acceleration for On-Site Earthquake Early Warning. *Geophysical Journal International*, 243(2), 1–18. <https://doi.org/10.1093/gji/ggaf345>
- Somala, S. N., Chanda, S., Alhamaydeh, M., & Mangalathu, S. (2024). Explainable XGBoost–SHAP Machine-Learning Model for Prediction of Ground Motion Duration in New Zealand. *Natural Hazards Review*, 25(2), 4024005. <https://doi.org/10.1061/NHREFO.NHENG-1837>
- Sun, R., Qi, W., Zheng, T., & Qi, J. (2023). Explainable Machine-Learning Predictions for Peak Ground Acceleration. *Applied Sciences*, 13(7), 4530. <https://doi.org/10.3390/app13074530>
- Taya, R., Mittal, H., Saini, A., & Kumar, R. (2026). Comparative Evaluation of Machine-Learning Models and Recalibrated GMPEs for Ground-Motion Prediction. *EGU General Assembly 2026*, Vienna, Austria, 3–8 May 2026, EGU26-17735, <https://doi.org/10.5194/egusphere-egu26-17735>
- Thompson, E. M., Wald, D. J., & Worden, C. B. (2014). A V_{S30} Map for California with Geologic and Topographic Constraints. *Bulletin of the Seismological Society of America*, 104(5), 2313–2321. <https://doi.org/10.1785/0120130312>
- Wald, D. J., & Allen, T. I. (2007). Topographic slope as a proxy for seismic site conditions and amplification. *Bulletin of the Seismological Society of America*, 97(5), 1379–1395. <https://doi.org/10.1785/0120060267>
- Withers, K. B., Moschetti, M. P., & Thompson, E. M. (2020). A machine learning approach to developing ground motion models from simulated ground motions. *Geophysical Research Letters*, 47(6), e2019GL086690. <https://doi.org/10.1029/2019GL086690>
- Zhang, H., Liu, Q., Jin, X., Cai, H., Chen, Z., & Wang, S. (2026). Hybrid Approach of Real-Time Ground Motion Prediction for Earthquake Early Warning. *Seismica*, 5(1), 1–18. <https://doi.org/10.26443/seismica.v5i1.2194>
- Zhu, C., Cotton, F., Kawase, H., & Nakano, K. (2023). How Well Can We Predict Earthquake Site Response So Far? Machine Learning vs Physics-Based Modeling. *Earthquake Spectra*, 39(1),

478–504.

<https://doi.org/10.1177/87552930221116399>

Ziar, A., & Basari, E. (2025). Accurate Prediction of Peak Ground Acceleration Using Random Forests: A Data-Driven Approach with PEER Updated NGA-WEST2 Ground Motion Records. *Archives of Advanced Engineering Science*, 0(0), 1–9.
<https://doi.org/10.47852/bonviewAAES52026930>