



Random forest-based peak ground acceleration prediction for shallow crustal earthquakes in Northern Sumatra: A comparison of hyperparameter optimization methods

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ARTICLE INFO

Keywords:

Peak ground acceleration;
Random Forest;
Hyperparameter optimization;
Bayesian Optimization;
Shallow crustal earthquakes;
Northern Sumatra.

ABSTRACT

Reliable prediction of peak ground acceleration (PGA) is essential for seismic hazard assessment in tectonically active regions such as northern Sumatra, where shallow crustal earthquakes are associated with complex source, propagation-path, and site effects. This study evaluates three hyperparameter optimization strategies—Grid Search, Randomized Search, and Bayesian Optimization—for improving Random Forest-based PGA prediction. The dataset consists of 2,509 PGA records from 453 shallow crustal earthquakes recorded in northern Sumatra during 2017–2023. Moment magnitude, epicentral distance, hypocentral depth, dominant soil period, and altitude were used as predictor variables, while PGA was transformed to its natural logarithm before model development. Model configurations were optimized using five-fold cross-validation and evaluated using mean squared error (MSE), root mean squared error (RMSE), and the coefficient of determination (R^2). Bayesian Optimization yielded the lowest cross-validation MSE of 0.9847, compared with 0.9855 for Randomized Search and 0.9857 for Grid Search, indicating only marginal differences in predictive accuracy among the three approaches. Randomized Search was computationally most efficient, requiring 754.2 s, compared with 1,353.6 s for Bayesian Optimization and 1,677.7 s for Grid Search. The optimized Random Forest model achieved a test MSE of 0.9851, RMSE of 0.9925, and (R^2) of 0.6078. These results indicate that Bayesian Optimization provides a slight advantage in predictive accuracy, whereas Randomized Search offers a more favorable trade-off between accuracy and computational efficiency. The findings highlight the importance of hyperparameter optimization strategy in developing data-driven ground-motion models for shallow crustal earthquakes in northern Sumatra.

1. Introduction

Northern Sumatra is one of the most seismically active regions in Indonesia, reflecting the interaction between the Indo-Australian and Eurasian plates together with the presence of numerous active faults across Sumatra. This tectonic configuration produces earthquake sources with diverse characteristics, including shallow crustal earthquakes associated with onshore fault systems. Because these events occur relatively close to the surface and, in many cases, near populated areas, they may generate strong ground shaking over comparatively short source-to-site distances. Consequently, understanding and predicting ground motion from shallow crustal earthquakes is

important for earthquake-hazard evaluation and disaster-risk reduction in northern Sumatra [1, 2].

Peak ground acceleration (PGA) is widely used to characterize earthquake-induced ground shaking and constitutes an important parameter in seismic-hazard assessment, engineering design, and evaluation of earthquake risk. PGA is controlled by several interacting factors, including earthquake magnitude, source-to-site distance, focal depth, and local site conditions. In the dataset considered in this study, site characteristics are represented by the dominant soil period and altitude. The relationship between these variables and PGA is not necessarily linear, particularly in tectonically complex regions where earthquake sources and propagation paths vary substantially [3–5].

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Ground-motion prediction equations (GMPEs) are commonly used to estimate earthquake ground motion by relating source, path, and site parameters to measures such as PGA. Although these empirical approaches provide an interpretable mathematical framework, their predictive capability depends strongly on the selected functional form and regression coefficients. In a complex tectonic environment such as northern Sumatra, where earthquake sources and fault characteristics vary spatially, the relationship between explanatory variables and observed ground motion may involve nonlinear interactions that are difficult to represent using a single predefined empirical function. This motivates the evaluation of more flexible data-driven approaches for regional PGA prediction [6, 7].

Machine-learning methods have increasingly been applied to ground-motion modeling because they can identify nonlinear relationships among multiple predictor variables without requiring a predetermined functional form. Previous studies have demonstrated the applicability of algorithms such as Random Forest, Artificial Neural Networks, Kernel-Ridge Regression, and Support Vector Regression for ground-motion prediction. Research conducted in Indonesia has also shown that machine-learning approaches can be used to model PGA under different tectonic settings and has emphasized the importance of earthquake magnitude and source-to-site distance as major explanatory variables. These developments suggest that machine learning can complement conventional empirical ground-motion modeling, particularly where sufficiently large observational datasets are available [8–10].

Among these approaches, Random Forest is attractive because it combines predictions from multiple decision trees and can represent complex nonlinear relationships while maintaining relatively high robustness to noisy and heterogeneous datasets. However, Random Forest performance depends strongly on its hyperparameter configuration, including the number of trees, maximum tree depth, minimum samples required for node splitting, minimum samples per terminal leaf, and the number of features considered during splitting. Inappropriate hyperparameter selection may reduce predictive performance or lead to excessive model complexity and poor generalization. Therefore, hyperparameter optimization is a critical component of Random Forest model development [3, 11].

Several strategies are commonly employed for hyperparameter optimization. Grid Search evaluates all combinations within a predefined parameter grid but becomes computationally expensive as the search space increases. Randomized Search evaluates a limited number of randomly sampled parameter combinations and can substantially reduce computational cost. Bayesian Optimization uses information obtained from previous trials to guide subsequent evaluations toward potentially better regions of the hyperparameter space. Because these methods differ in both search efficiency and computational demand, their practical performance should be evaluated not only in terms of prediction error but also in terms of the computational resources required to obtain the optimized model [12, 13].

Despite the growing application of machine learning to earthquake ground-motion prediction, the relative performance of different hyperparameter optimization strategies for Random Forest-based PGA prediction has not been sufficiently evaluated for shallow crustal earthquakes in northern Sumatra. Moreover, an optimization method that produces the lowest prediction error may not necessarily provide the best balance between predictive performance and computational efficiency. This distinction is particularly relevant when multiple optimization strategies yield only small differences in prediction accuracy [6, 14, 15].

Accordingly, this study compares Grid Search, Randomized Search, and Bayesian Optimization for tuning a Random Forest regression model used to predict PGA from shallow crustal

earthquakes in northern Sumatra. The analysis is based on 2,509 PGA records from 453 earthquake events during 2017–2023, using moment magnitude, epicentral distance, hypocentral depth, dominant soil period, and altitude as predictor variables. The specific objectives are to: (1) compare the predictive performance of the three optimization strategies, (2) evaluate their computational efficiency, and (3) identify an appropriate balance between prediction accuracy and computational cost for Random Forest-based ground-motion modeling. Rather than assuming that one optimization strategy is universally superior, this study evaluates their relative advantages within the characteristics of the northern Sumatra shallow-crustal earthquake dataset.

2. Method

2.1. Study area and earthquake dataset

This study focuses on shallow crustal earthquakes in northern Sumatra, Indonesia, within approximately 0° – 6° N and 94° – 102° E. Earthquake and ground-motion data were obtained from the Agency for Meteorology, Climatology, and Geophysics of Indonesia (BMKG) for the period 2017–2023. A total of 453 earthquake events classified as shallow crustal earthquakes were included in the analysis, producing 2,509 earthquake–station PGA records. Events with focal depths of up to 50 km were retained in the dataset.

Table 1

Example structure of the PGA dataset used for machine-learning analysis

Variable	Description
Time	Earthquake origin time
R_{epi}	Epicentral distance
PGA	Observed peak ground acceleration
M_w	Earthquake magnitude
Depth	Hypocentral depth
T_0	Dominant soil period
Altitude	Station elevation

For each earthquake–station record, five predictor variables were used: moment magnitude (M_w), epicentral distance (R_{epi}), hypocentral depth, dominant soil period (T_0), and station altitude. The response variable was Peak Ground Acceleration (PGA). To reduce positive skewness in the PGA distribution and improve numerical stability during model training, PGA was transformed using the natural logarithm: [6, 14, 15].

$$y = \ln PGA \quad \dots (1)$$

Thus, all model-training and primary error metrics reported in this study refer to the logarithmic PGA domain unless otherwise stated. The dataset covers magnitudes of approximately 3.0–6.1, focal depths of up to 50 km, and epicentral distances of approximately 11–518 km. The distribution of the input variables and transformed target is presented in Fig. 1. Table 1 summarizes representative records from the dataset.

2.2. Data partitioning and validation strategy

To reduce the risk of information leakage between the training and testing datasets, data partitioning was performed at the earthquake-event level rather than at the individual record level. Because a single earthquake may generate multiple PGA records at different seismic stations, randomly splitting individual records could result in observations from the same earthquake being included in both the training and testing datasets. Such overlap may lead to an overly optimistic estimate of model performance because the model would be evaluated using records that share the same source characteristics as events already

encountered during training.

Accordingly, all PGA records associated with a given earthquake event were assigned exclusively to either the training or testing subset. Approximately 80% of the earthquake events were allocated to the training dataset, while the remaining 20% were retained as an independent testing dataset. The testing data were excluded from all stages of model training, hyperparameter optimization, and model selection, and were used only for the final evaluation of predictive performance.

Hyperparameter optimization was conducted exclusively within the training dataset using grouped five-fold cross-validation. Earthquake event identification was used as the grouping variable so that all records originating from the same earthquake remained within the same fold. In each iteration, four folds were used for model training and the remaining fold was used for validation. This procedure was repeated until each fold had served once as the validation subset. The same grouped cross-validation partitions were applied consistently to Grid Search, Randomized Search, and Bayesian Optimization to ensure a fair comparison among the three tuning strategies.

This event-based validation framework was adopted to evaluate the ability of the Random Forest model to generalize to earthquake events that were not represented during model development. By preventing records from the same earthquake from being distributed across training and validation or testing subsets, the procedure provides a more stringent and realistic assessment of model performance for previously unseen shallow crustal earthquakes in northern Sumatra.

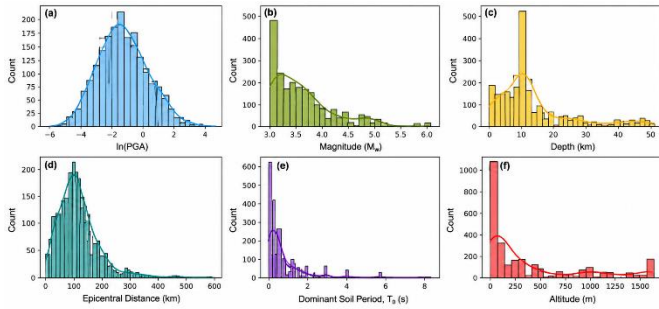


Fig. 1. Distribution of the predictor variables and transformed target used for Random Forest-based peak ground acceleration modeling in northern Sumatra: (a) natural logarithm of PGA, $\ln(\text{PGA})$; (b) earthquake magnitude, (M_w); (c) hypocentral depth; (d) epicentral distance, (R_{epi}); (e) dominant soil period, (T_0); and (f) station altitude. The dataset comprises 2,509 PGA records from 453 shallow crustal earthquake events recorded during 2017–2023.

2.3. Random Forest regression model

Random Forest regression was employed to model the nonlinear relationship between earthquake-source parameters, site-related variables, and $\ln(\text{PGA})$. Random Forest is an ensemble-learning method that combines predictions from multiple decision trees generated using bootstrap samples and randomized feature subsets. The aggregation of multiple trees generally improves predictive stability and reduces the sensitivity of the model to individual noisy observations [4, 16].

Five principal hyperparameters were considered:

- `n_estimators`, the number of decision trees in the forest;
- `max_depth`, the maximum depth permitted for each tree;
- `min_samples_split`, the minimum number of samples required to split an internal node;
- `min_samples_leaf`, the minimum number of samples permitted in a terminal leaf; and
- `max_features`, the number of predictor variables considered when determining the best split.

2.4. Hyperparameter optimization strategies

Three hyperparameter optimization strategies were evaluated: Grid Search, Randomized Search, and Bayesian Optimization. Grid Search evaluates all combinations within a predefined discrete parameter grid. Although exhaustive within the specified grid, its computational demand increases rapidly with the number of hyperparameters and candidate values. Randomized Search evaluates randomly sampled combinations from predefined parameter distributions. This strategy may substantially reduce computational cost because only a subset of the full parameter space is evaluated [17, 18].

Bayesian Optimization sequentially evaluates candidate configurations by using information obtained from previous trials to identify promising regions of the hyperparameter space. This adaptive strategy seeks to reduce the number of unnecessary model evaluations while approaching configurations associated with lower validation error. The hyperparameter search spaces used in the original analysis are summarized in Table 2.

Table 2

Hyperparameter search spaces used for Random Forest optimization

Hyperparameter	Grid Search	Randomized Search	Bayesian Optimization
<code>n_estimators</code>	100, 200, 300, 400, 500	100–500	100–500
<code>max_depth</code>	5, 10, 15	5–15	5–15
<code>min_samples_split</code>	10, 12, 13, 15	10–15	10–15
<code>min_samples_leaf</code>	10, 12, 13, 15	10–15	10–15
<code>max_features</code>	sqrt, log2	sqrt, log2	sqrt, log2

2.5. Cross-validation and optimization objective

Five-fold cross-validation was used within the training dataset to evaluate candidate hyperparameter configurations. For each candidate configuration, the Random Forest model was fitted repeatedly using four folds for training and the remaining fold for validation. This process was repeated until each fold had served once as validation data [19–21]. The optimization objective was to minimize Mean Squared Error (MSE) in the logarithmic PGA domain:

$$MSE = \frac{1}{n} \sum_{i=1}^n [\ln(PGA_{obs,i}) - \ln(PGA_{pred,i})]^2 \quad \dots (1)$$

where (n) is the number of validation records, ($PGA_{obs,i}$) is the observed PGA, and ($PGA_{pred,i}$) is the model prediction. For the improved analysis, the same cross-validation folds should be used for all three optimization strategies to ensure a fair comparison. [14, 22, 23].

2.6. Computational-efficiency assessment

Computational efficiency was evaluated together with predictive performance because the three hyperparameter optimization strategies differ substantially in the way they explore the search space. For each tuning method, the total optimization time, number of candidate hyperparameter configurations, and total number of Random Forest model fits were considered as indicators of computational cost. All three methods were evaluated using the same training dataset and the same grouped five-fold cross-validation structure to ensure that differences in computational performance were attributable primarily to the optimization strategy rather than to inconsistencies in the validation procedure [14, 22, 23].

For Grid Search, the predefined parameter grid consisted of five values for `n_estimators`, three values for `max_depth`, four values for `min_samples_split`, four values for `min_samples_leaf`, and two values for `max_features`, resulting in a total of:

$$5 \times 3 \times 4 \times 4 \times 2 = 480$$

candidate hyperparameter combinations. With five-fold cross-validation, this corresponds to approximately 2,400 Random Forest model fits.

Randomized Search evaluated a fixed number of randomly sampled hyperparameter combinations from the predefined search space, while Bayesian Optimization sequentially explored the parameter space by using information obtained from previous evaluations to identify promising candidate configurations. In the present analysis, Bayesian Optimization was conducted for 200 iterations. To allow a fair comparison, the number of iterations used for Randomized Search should be explicitly reported together with the total number of model evaluations.

The total computation times reported in the original analysis were 1,677.7 s for Grid Search, 754.2 s for Randomized Search, and 1,353.6 s for Bayesian Optimization. These values were used to compare the computational efficiency of the optimization strategies in addition to their predictive performance. Because computation time is affected by hardware configuration, software implementation, degree of parallelization, and random initialization, the computational environment should also be reported, including processor specifications, software versions, random seed, and the number of parallel jobs used during optimization.

Overall, computational efficiency was interpreted jointly with validation error rather than as an independent criterion. A tuning strategy was therefore considered favorable when it achieved competitive predictive performance while requiring fewer model evaluations and lower computational cost [6, 14, 15].

2.7. Model evaluation

After hyperparameter optimization, the optimal Random Forest configuration obtained from each search method was retrained using the complete training dataset and subsequently evaluated once against the independent test dataset [8]. Three primary metrics were used:

$$\text{Mean Squared Error (MSE)} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad \dots (2)$$

$$\text{Root Mean Squared Error (RMSE)} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad \dots (3)$$

$$\text{Coefficient of determination (R}^2\text{)} = 1 - \frac{\frac{1}{n} \sum_{i=1}^n (y_i - \bar{y})^2}{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad \dots (4)$$

where $y_i = \ln(PGA_{obs,i})$, $\hat{y}_i = \ln(PGA_{pred,i})$, and $\bar{y}$ is the mean observed logarithmic PGA. Lower MSE and RMSE values indicate smaller prediction errors, whereas an (R^2) value approaching unity indicates that a greater fraction of the observed $\ln(PGA)$ variance is explained by the model [6, 14, 15].

3. Results and discussion

3.1. Characteristics of the earthquake and ground-motion dataset

A total of 2,509 PGA records associated with 453 shallow crustal earthquake events recorded in northern Sumatra during 2017–2023 were used in the analysis. The predictor variables consisted of earthquake magnitude, hypocentral depth, epicentral distance (R_{epi}), dominant soil period (T_0), and station altitude, while the response variable was transformed to $\ln(PGA)$. The earthquake magnitudes range from approximately 3.0 to 6.1, focal depths extend to about 50 km, and epicentral distances range from approximately 11 to 518 km. Most earthquake–station observations are concentrated at epicentral distances of approximately 50–110 km.

The distributions of the predictor variables and transformed target are shown in Fig. 1. The magnitude distribution is dominated by small-to-moderate events, whereas relatively few observations are available at the upper end of the magnitude range. Epicentral distance, dominant soil period, and altitude exhibit positively skewed distributions with comparatively long upper tails. In contrast, the $\ln(PGA)$ distribution is more approximately unimodal after logarithmic transformation. These characteristics are important because strongly unbalanced

predictor distributions may cause machine-learning performance to be dominated by densely sampled portions of the parameter space.

The concentration of observations at lower magnitudes and moderate source-to-site distances should be considered when interpreting model performance. A Random Forest model can interpolate effectively within densely sampled predictor ranges, but its reliability may decrease for combinations that are poorly represented in the training data. Consequently, global metrics such as MSE and (R^2) should not be interpreted as evidence of uniform predictive skill across the entire magnitude and distance domains.

3.2. Comparison of hyperparameter optimization strategies

The performances of Grid Search, Randomized Search, and Bayesian Optimization were compared using the cross-validation MSE and total computational time. The results are summarized in Table 3. Bayesian Optimization produced the lowest validation MSE of 0.9847, followed by Randomized Search with 0.9855 and Grid Search with 0.9857.

Table 3

Comparison of hyperparameter optimization strategies

Optimization method	Computation time (s)	Validation MSE
Grid Search	1,677.7	0.9857
Randomized Search	754.2	0.9855
Bayesian Optimization	1,353.6	0.9847

Although Bayesian Optimization yielded the minimum MSE, its improvement over the other methods was very small. Relative to Randomized Search, the MSE reduction was only approximately 0.08%, while the improvement relative to Grid Search was approximately 0.10%. Therefore, the results do not indicate a substantial predictive advantage of Bayesian Optimization. Instead, the three tuning strategies produced nearly equivalent validation errors within the tested hyperparameter space.

A much clearer distinction is observed in computational efficiency. Randomized Search required only 754.2 s, compared with 1,353.6 s for Bayesian Optimization and 1,677.7 s for Grid Search. Thus, Randomized Search reduced computation time by approximately 44% relative to Bayesian Optimization and approximately 55% relative to Grid Search. These results indicate that Randomized Search provides a favorable accuracy–efficiency trade-off, particularly when computational resources are limited.

Grid Search required the greatest computational effort because it exhaustively evaluated all predefined hyperparameter combinations. Based on the adopted parameter grid, 480 unique combinations were possible, corresponding to approximately 2,400 model fits under five-fold cross-validation. Bayesian Optimization, in contrast, sequentially searched the parameter space using information from previous trials and was conducted for 200 iterations in the original analysis.

The comparison therefore suggests that identifying the “best” optimization method depends on the evaluation criterion. Bayesian Optimization achieved the numerically lowest validation error, whereas Randomized Search offered substantially greater computational efficiency with almost identical predictive performance. For this reason, the superiority of Bayesian Optimization should be interpreted as marginal rather than absolute.

3.3. Optimal random forest hyperparameters

Bayesian Optimization identified the hyperparameter configuration associated with the lowest validation MSE. The optimal configuration consisted of 162 trees, a maximum tree depth of 13, a minimum of 13 samples required to split an internal node, a minimum of 10 samples per terminal leaf, and the square root of the number of predictors as the feature-selection strategy at each split.

The selected value of $n_{estimators}$ indicates that a moderately large ensemble of decision trees was required to obtain stable

predictions. Increasing the number of trees generally reduces variance in the ensemble prediction, although the marginal improvement decreases once a sufficiently large forest has been generated. The maximum depth of 13 allows the individual trees to capture relatively complex nonlinear relationships among the earthquake and site variables.

Table 4

Optimal random forest hyperparameters obtained using bayesian optimization

Hyperparameter	Optimal value
n_estimators	162
max_depth	13
min_samples_split	13
min_samples_leaf	10
max_features	sqrt

The relatively large values of `min_samples_split` and `min_samples_leaf` act as constraints on tree complexity. Rather than controlling model “weights,” these parameters prevent excessively specific node partitions by requiring a minimum number of observations before a split can occur and within terminal leaves. This reduces the tendency of individual trees to fit small subsets of observations and contributes to better generalization.

However, the physical interpretation of these hyperparameters should remain limited. Hyperparameter values characterize the statistical architecture of the fitted Random Forest and should not be interpreted directly as indicators of earthquake-source or site processes [24].

3.4. Predictive performance of the optimized random forest

The optimized Random Forest produced a testing MSE of 0.9851, an RMSE of 0.9925, and a coefficient of determination of ($R^2 = 0.6078$). Because the target variable was transformed to $\ln(\text{PGA})$, the MSE and RMSE values represent prediction errors in logarithmic PGA space rather than in the original physical units of PGA.

An (R^2) value of 0.6078 indicates that approximately 60.78% of the variance in the observed $\ln(\text{PGA})$ values is explained by the five predictor variables included in the model. The remaining approximately 39.22% of the variance is not explained by the present predictor set. This represents moderate predictive performance and indicates that the Random Forest captures a substantial portion, but not all, of the ground-motion variability.

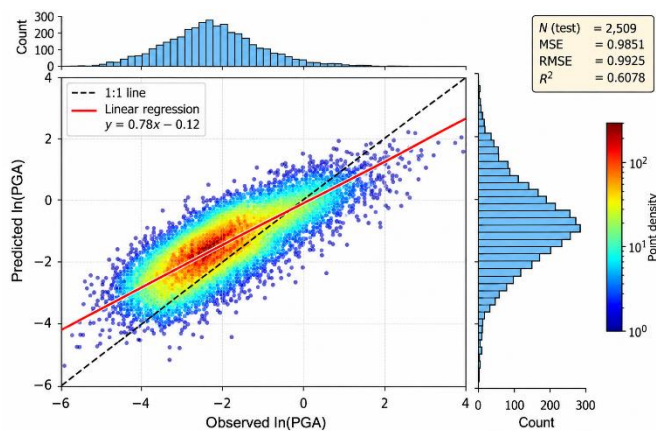


Fig. 2. Comparison between observed and Random Forest-predicted $\ln(\text{PGA})$ values for the test dataset. The dashed black line represents the ideal 1:1 relationship, whereas the solid red line denotes the fitted linear regression; marginal histograms show the distributions of observed and predicted $\ln(\text{PGA})$, and the color scale indicates point density. The optimized model achieved an MSE of 0.9851, RMSE of 0.9925, and (R^2) of 0.6078.

The unexplained component may reflect physical processes that are not explicitly represented in the current model. These potentially include faulting mechanism, rupture geometry, directivity, source stress characteristics, path attenuation, near-surface velocity structure, basin effects, and other site-response parameters such as V_{S30} . Consequently, the present model should be interpreted as a regional data-driven predictor based on the available variables rather than as a complete representation of ground-motion physics. Comparison between observed and Random Forest-predicted $\ln(\text{PGA})$ values for the test dataset can be seen in Fig 2.

3.5. Training and testing performance

Comparison between training and testing performance provides information on model generalization. The training dataset produced an MSE of 0.7109, an RMSE of 0.8432, and ($R^2 = 0.7280$), whereas the corresponding testing metrics were 0.9851, 0.9925, and 0.6078, respectively.

Table 5

Performance of the optimized Random Forest on training and testing datasets

Dataset	MSE	RMSE	(R^2)
Training	0.7109	0.8432	0.7280
Testing	0.9851	0.9925	0.6078

The decrease in (R^2) from 0.7280 during training to 0.6078 during testing and the corresponding increase in RMSE indicate some degradation in performance when the model is applied to unseen data. This difference does not necessarily indicate severe overfitting, but it is sufficiently large that the model should not be described as showing “no significant overfitting” without additional evidence [25].

The use of event-based data partitioning and grouped cross-validation, as proposed in the revised methodology, will provide a more stringent assessment of this generalization gap because earthquake records from the same event will no longer be distributed across training and testing subsets. Therefore, the final numerical values in Table 5 should be recalculated after applying the revised validation strategy.

3.6. Accuracy–efficiency trade-off among optimization methods

The present comparison demonstrates that optimization performance should not be judged solely by the minimum validation error. Bayesian Optimization produced the lowest MSE, but Randomized Search achieved almost identical predictive performance in approximately half the computational time required by Grid Search.

This result is particularly relevant for regional ground-motion modeling, where model development may involve repeated training under alternative predictor sets, validation strategies, or earthquake subsets. In such applications, modest reductions in computational cost can become important when thousands of model fits are required [26].

Grid Search is useful when the hyperparameter space is relatively small and exhaustive exploration is desirable. However, its computational cost increases rapidly as additional parameters or candidate values are introduced. Randomized Search is more scalable because it samples only a subset of the parameter space, while Bayesian Optimization offers a more directed search by concentrating evaluations in promising regions [28].

The results therefore suggest two practical choices. If the primary objective is to minimize validation error regardless of computational cost, Bayesian Optimization is marginally preferable. If computational efficiency is also an important criterion, Randomized Search provides a stronger trade-off because its validation MSE differs from Bayesian Optimization by only 0.0008 while requiring substantially less processing time [27–29].

3.7. Implications for PGA prediction in northern Sumatra

The results indicate that Random Forest can represent nonlinear relationships among earthquake magnitude, source-to-site distance, focal depth, dominant soil period, altitude, and PGA. However, the moderate test (R^2) demonstrates that these variables alone do not fully explain the observed variability of shallow-crustal ground motion in northern Sumatra.

The value of the machine-learning approach lies primarily in its ability to model complex interactions without imposing a predetermined functional form. Nevertheless, high predictive flexibility should not be confused with physical completeness. Conventional GMPEs incorporate physically motivated scaling with magnitude, distance, and site condition, whereas Random Forest derives relationships directly from the empirical distribution of the training data.

Accordingly, the optimized Random Forest should be evaluated against an appropriate conventional ground-motion model before claiming superiority for seismic-hazard applications. Such comparison would clarify whether the additional model complexity provides meaningful improvement over established empirical approaches.

4. Conclusion

This study evaluated Grid Search, Randomized Search, and Bayesian Optimization for tuning a Random Forest model to predict peak ground acceleration from shallow crustal earthquakes in northern Sumatra. Using 2,509 PGA records from 453 earthquake events, the model incorporated earthquake magnitude, epicentral distance, hypocentral depth, dominant soil period, and altitude as predictor variables, with PGA modeled in the natural-logarithmic domain.

Among the three optimization strategies, Bayesian Optimization produced the lowest validation MSE of 0.9847, followed closely by Randomized Search at 0.9855 and Grid Search at 0.9857. The differences in predictive accuracy were therefore marginal. In contrast, computational efficiency differed substantially, with Randomized Search requiring 754.2 s, compared with 1,353.6 s for Bayesian Optimization and 1,677.7 s for Grid Search. These results indicate that Bayesian Optimization provides a slight advantage in prediction error, whereas Randomized Search offers a more favorable balance between predictive performance and computational cost.

The optimized Random Forest achieved a test MSE of 0.9851, RMSE of 0.9925, and (R^2) of 0.6078, indicating moderate capability in explaining the observed variability of $\ln(\text{PGA})$. The remaining unexplained variance suggests that additional source, path, and site parameters may be needed to improve model performance.

Overall, the results show that hyperparameter optimization is an important component of Random Forest-based ground-motion modeling, but the choice of tuning strategy should consider both predictive accuracy and computational efficiency. Further improvement of the model should include event-based validation, residual analysis, feature-importance assessment, and comparison with conventional ground-motion prediction equations before the model is applied to regional seismic-hazard analysis in northern Sumatra.

CRedit authorship contribution statement

Raka Syahfaqih Silalahi: Writing – review & editing, Writing – original draft, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Data curation. **Lailatul Husna Lubis:** Writing – review & editing, Writing – original draft, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Data curation. **Russell Ong:** Writing – review & editing, Investigation. **Angga Wijaya:** Writing – review & editing, Writing – original draft, Supervision, Software, Resources, Methodology.

Declaration of Competing 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.

Data availability

Data will be made available on request.

Acknowledgment

The authors gratefully acknowledge the Agency for Meteorology, Climatology, and Geophysics of Indonesia (BMKG) for providing the earthquake and peak ground acceleration data used in this study. The authors also thank the Department of Physics, Faculty of Science and Technology, Universitas Islam Negeri Sumatera Utara, for academic and institutional support during the development of this research. Appreciation is extended to all colleagues who contributed through technical discussions, data preparation, and constructive suggestions that supported the completion of this study.

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