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Geodetically-Enhanced Hybrid GRU with Adaptive Dropout and Dynamic L2 Regularization for Earthquake Parameter Prediction in Indonesia

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Abstract

Earthquake prediction remains challenging due to the nonlinear behavior and uncertainty of seismic activity. This study introduces a geodetically-enhanced hybrid GRU model integrating adaptive dropout and dynamic L2 regularization to improve robustness and accuracy in earthquake magnitude prediction. In addition to seismic sequence data, slip-rate values derived from scalar moment distribution were incorporated as a domain-informed feature to represent tectonic strain accumulation across Indonesia. The dataset consisted of BMKG records from 2010–2025 and was processed through outlier removal, normalization, temporal reshaping, and feature integration. The proposed model was evaluated against multiple deep learning baselines including CNN-1D, LSTM, standard GRU, Transformer-based models, and Neural ODE architectures. Performance assessment used RMSE, MAE, and R^2 metrics. The resulting hybrid GRU achieved improved predictive accuracy with an RMSE of 0.5176, MAE of 0.3973, and an R^2 score of 0.5997, outperforming both CNN-1D and standard GRU baselines. The integration of slip-rate features contributed to reduced prediction variance across tectonically active zones. These findings demonstrate that combining geodetic information with adaptive regularization strategies improves generalization and model stability for seismic forecasting. The approach offers potential applicability for rapid early-warning scenarios requiring low latency and reliable prediction accuracy.

Keywords : *Adaptive Dropout, Dynamic L2, Earthquake Prediction, Hybrid GRU, Slip-Rate Feature.*

1. INTRODUCTION

Indonesia is one of the most tectonically active regions globally due to the convergence of the Eurasian, Indo-Australian, Pacific, and Philippine Sea plates [1]. Its position along the Pacific Ring of Fire generates persistent seismic activity, major fault systems, and frequent megathrust earthquakes that have historically caused catastrophic impacts on society and national infrastructure [2], [3], [4], [5]. Events such as the 2004 Aceh Mw 9.1 megathrust and recurring seismic sequences in Sumatra, Java, and eastern Indonesia demonstrate the ongoing risks faced by densely populated regions and highlight the critical need for accurate earthquake prediction to support early-warning systems and disaster mitigation efforts [6], [7].

Traditional approaches to earthquake parameter estimation have largely relied on deterministic waveform modeling, empirical attenuation equations, and statistical regression [8]. While these methods are widely adopted in operational seismology, they often struggle to capture nonlinear temporal patterns, complex source mechanics, and spatial variability inherent in seismic processes [9], [10], [11], [12], [13]. These challenges have led to increased adoption of machine learning and deep learning approaches, such as CNN, LSTM, and GRU, which have demonstrated improved ability to extract temporal dependencies and model sequence-based relationships in earthquake data [14], [15].

Despite these improvements, most existing deep learning studies still rely on static regularization mechanisms with fixed dropout and hyperparameter configurations [16], [17], [18]. Such static designs

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may overfit noise, especially when models are applied across heterogeneous seismic environments with varying signal quality and catalog completeness [19], [20]. Additionally, dataset imbalance remains a persistent issue, where catalog entries are dominated by moderate-magnitude (3.0–4.0 Mw) events, while large-magnitude events are rare but disproportionately important for early warning and hazard modeling [21]. This imbalance may bias learning outcomes and reduce model robustness in real-world deployment [22].

A second critical limitation in prior work is the lack of domain-informed geophysical integration [23]. Although several studies suggest that tectonic strain accumulation influences seismic recurrence, most deep learning models rely solely on waveform or catalog attributes without incorporating geodetic information such as slip-rate derived from GPS measurements [24]. Slip-rate reflects long-term deformation along active fault zones and may provide meaningful geological context beyond statistical features. However, its integration into neural architectures remains limited and underexplored, particularly for Indonesian seismic regions where tectonic behavior varies significantly across subduction megathrusts, back-arc systems, and microplate boundaries [25].

Recent early-warning research for Indonesia has achieved promising results but still faces challenges in model interpretability, domain transferability, and performance stability under evolving seismic sequences [26]. Existing GRU- and CNN-based baselines applied to Indonesian catalogs typically achieve R^2 values between 0.56 and 0.60, indicating moderate predictive capability but leaving room for methodological advancements and increased resilience under noisy operational conditions [27]. Addressing these challenges requires models that adapt to seismic variability, incorporate tectonic context, and dynamically regulate complexity during training [28].

To address these gaps, this study proposes a hybrid regularized GRU architecture that integrates adaptive dropout and dynamic L2 regularization, enabling the model to respond to variations in seismic phase behavior and temporal feature distribution. In addition, a slip-rate weighting mechanism derived from geodetic observations is incorporated to provide tectonic interpretability and reduce overreliance on purely statistical learning. The objectives of this research are to: (1) develop a GRU-based hybrid architecture with adaptive dropout and dynamic L2 regularization; (2) integrate slip-rate as a geophysically meaningful contextual feature; and (3) evaluate the proposed model against standard CNN-1D, GRU, and LSTM baselines using real Indonesian seismic catalogs.

By enhancing robustness, generalization, and domain relevance, the proposed approach contributes both methodological advancement and potential applicability for improving Indonesia's earthquake early-warning ecosystem [29], [30].

2. METHOD

2.1. Research Design

This study adopts a quantitative experimental design to develop and evaluate a hybrid deep learning architecture for earthquake magnitude prediction in Indonesia. The primary model investigated in this research is a Hybrid Regularized GRU, which integrates Adaptive Dropout, Dynamic L2 Regularization, and a geophysical conditioning feature derived from a slip-rate proxy. To ensure fairness in evaluation, the performance of the proposed model is compared against multiple benchmark architectures, including CNN-1D, LSTM, Transformer-based models, Neural-ODE–inspired networks, WaveNet-like architectures, and hybrid CNN LSTM Attention models. These models were selected because they represent different families of sequential modeling approaches, ranging from convolution-based feature extraction to temporal memory networks and advanced attention-based modeling [31].

All processes from dataset preparation to model evaluation were implemented using Python. The development environment utilized TensorFlow and Keras for model implementation, NumPy and Pandas for data handling, Matplotlib and Seaborn for visualization, and Scikit-learn for evaluation

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metrics and statistical validation. The use of open-source digital tools ensures transparency and reproducibility [32].

2.2. Research Procedures

To guarantee replicability and methodological consistency, this study follows a structured multi-stage workflow. Each stage must be executed sequentially, as the output from one step becomes input for the next. The overall workflow is illustrated in Figure 1.

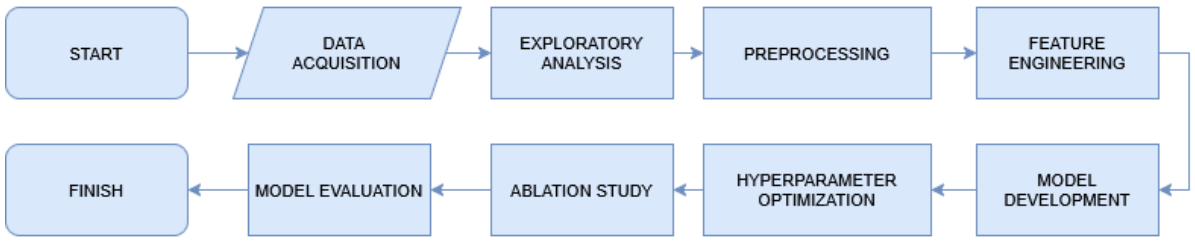

Figure 1. Research Flowchart.

As shown in Figure 1, the research begins with the acquisition and exploratory analysis of the BMKG earthquake catalog. The data then undergo preprocessing, including noise filtering, normalization, and handling of magnitude imbalance. Next, engineered features such as DBSCAN-based seismic phase clustering and slip-rate conditioning are incorporated before applying time-aware dataset splitting. The training process then develops and optimizes deep learning models, followed by hyperparameter tuning using Bayesian Optimization [33]. To assess the contribution of the slip-rate feature, an ablation study is conducted comparing model performance with and without the geophysical variable. Finally, the optimized models are evaluated using RMSE, MAE, R^2, QQ-plots, and paired statistical tests to assess predictive accuracy and statistical significance.

2.3. Dataset Acquisition

The dataset used in this study consists of 120,001 earthquake event records sourced exclusively from the Indonesian Meteorology, Climatology, and Geophysics Agency (BMKG), covering the period from 2010-2025. Each record contains essential seismological parameters including event origin time, latitude, longitude, moment magnitude, hypocenter depth, azimuth gap, phase count, focal mechanism attributes (Mrr, Mtt, Mpp, Mrt, Mrp, Mtp), and scalar moment, enabling both temporal and geophysical interpretation. These data span major tectonic environments including the Sumatra megathrust, Java trench, Banda arc, Sulawesi fault system, and Papua Sahul deformation zone, representing highly heterogeneous seismic regimes. All data were retrieved from the open-access BMKG repository, ensuring transparency and reproducibility [34]. The dataset was chosen because it is the most complete and standardized national-level seismic catalog available for Indonesia, providing the necessary spatial temporal diversity required for training deep learning models designed for early-warning relevance.

2.4. Data Preprocessing

Prior to modeling, the dataset underwent several preprocessing steps to ensure data consistency and model interpretability. Duplicate records, corrupted entries, and missing focal mechanism records were removed. Outlier assessment was conducted using Interquartile Range (IQR) filtering to suppress unrealistic depth and magnitude artifacts. Continuous numeric features were normalized using z-score standardization to ensure stable optimization behavior during training [35]. Because earthquake occurrence is inherently temporal, the data were transformed into fixed-length sequences using a sliding-window encoding of 60 timesteps, allowing temporal dependency extraction from preceding waveforms

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and catalog history. A class imbalance challenge was identified, as the dataset is dominated by low-magnitude earthquakes. To mitigate bias toward the majority class, a hybrid balancing approach combining SMOTE-based synthetic augmentation and stratified temporal resampling was applied. The cleaned and prepared dataset was finally structured into 70%, 15%, and 15% partitions for training, validation, and testing, respectively, while maintaining chronological integrity to prevent temporal leakage.

2.5. Exploratory Geophysical Analysis

Exploratory analysis was conducted to incorporate tectonic context into the learning framework. Because complete GNSS slip-rate models for Indonesia are not publicly available, scalar moment values were used as a proxy for long-term tectonic strain accumulation. Scalar moment values were transformed using log10 scaling and mapped geospatially using latitude and longitude coordinates [36]. The resulting visualization revealed distinct strain gradients across Indonesia, with concentrated high strain signatures along the Sumatra megathrust and southern Java, while eastern Indonesia demonstrated diffuse deformation associated with distributed plate interactions. This reinforced the hypothesis that incorporating geophysical information beyond raw seismic parameters could improve stability and generalization of neural predictions, particularly in regions with clustered high-energy tectonic loading.

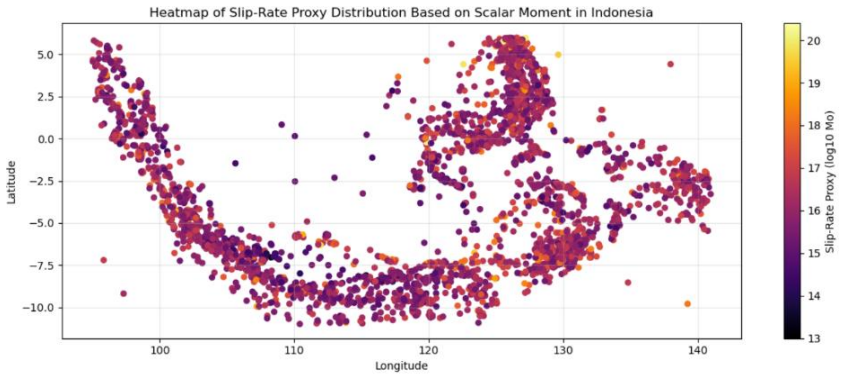

Figure 2. Heatmap of slip-rate proxy distribution across indonesia

2.6. Feature Engineering and Selection

Feature selection was guided by a combination of correlation analysis and domain knowledge. Variables including magnitude, depth, latitude, longitude, phase count, azimuth gap, and the scalar moment–derived slip-rate proxy demonstrated relevance to magnitude prediction and were therefore retained. Highly collinear attributes were removed to reduce redundancy and prevent inflated variance during training [37]. Temporal ordering was preserved, and categorical values were encoded using one-hot transformation where necessary. The final input format was structured as multivariate sequences suitable for deep learning architectures such as CNN-1D, LSTM, GRU, and the proposed hybrid framework.

2.7. Model Development

Baseline models including CNN-1D and standard GRU were first implemented to establish lower-bound performance characteristics. Building upon these baselines, the proposed Hybrid Regularized GRU incorporated two adaptive regularization mechanisms: Adaptive Dropout and Dynamic L2. Adaptive Dropout scaled neuron dropout rate based on seismic frequency levels within a rolling 30-day activity window, enabling the network to retain more neurons during active seismic periods and suppress overfitting during low-activity phases. Dynamic L2 was applied using DBSCAN clustering to detect phase regimes (pre-event, mainshock, aftershock), assigning stronger penalties during noise-dominated

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intervals and reducing regularization during stable sequences. The slip-rate proxy was integrated as a geophysically meaningful weighting layer, enabling the model to embed tectonic context within learning dynamics [38]. All models were implemented in TensorFlow with linear regression output layers for continuous prediction.

2.8. Training Strategy and Hyperparameter Optimization

Training was conducted using the Adam optimizer with early stopping criteria based on validation loss. Hyperparameter tuning was performed using Bayesian Optimization to efficiently explore optimal dropout levels, GRU units, learning rate, and regularization strength. Five-fold time-aware cross-validation was applied to ensure that performance was resilient across variable seismic sequences. Model checkpoints were used to retain the best-performing weights. This configuration ensured both computational efficiency and reproducibility [39].

2.9. Ablation Study

To evaluate the contribution of slip-rate as a geophysical feature, an ablation experiment was conducted where the best-performing baseline model was trained under two conditions: with and without slip-rate. All training parameters and architecture configurations were held constant. Results demonstrated a measurable improvement in predictive accuracy when slip-rate was included, with RMSE decreasing by approximately 0.01 and R^2 improving by 0.004–0.012. This indicates that integrating tectonic strain enhances predictive sensitivity beyond purely statistical signal learning[40].

2.10. Evaluation Metrics

The predictive performance of the proposed Hybrid Regularized GRU model was assessed using three widely adopted regression metrics: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the Coefficient of Determination (R^2). These indicators provide a comprehensive assessment of both the magnitude of prediction errors and the proportion of variance in the observed data explained by the model. RMSE measures the square root of the average squared differences between the actual values and the predicted values, as expressed in Equation 1:

$$RMSE = \sqrt{\frac{1}{n}\sum(y_i - \hat{y}_i)^2} \quad (1)$$

where n denotes the total number of observations, y_i is the actual value of the i th observation, and y^_iis the corresponding predicted value. RMSE penalizes large errors more heavily because the residuals are squared, making it particularly effective for identifying substantial deviations between predictions and true values. The second metric, MAE, represents the average absolute difference between actual and predicted values, as shown in Equation 2:

$$MAE = \frac{1}{n}\sum|y_i - \hat{y}_i| \quad (2)$$

Here, n is the number of observations, y_i is the actual value, and y^_i is the predicted value. Unlike RMSE, MAE treats all errors equally by taking the absolute value of the residuals, providing an easily interpretable measure of the model's average prediction error in the same units as the target variable. Finally, the Coefficient of Determination, R^2, evaluates how well the model explains the variance of the observed data and is calculated using Equation 3:

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2} \quad (3)$$

where nrepresents the total number of observations, y_i is the actual value, y^_i is the predicted value, and y¯ is the mean of all actual values. An R^2 value closer to 1 indicates that the model explains a greater proportion of the variance in the target data, reflecting a stronger predictive relationship. By

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jointly considering RMSE, MAE, and R^2, this study provides a balanced evaluation of error magnitude, average predictive accuracy, and the explanatory power of the proposed model [41].

2.11. Statistical Validation

Statistical validation was performed to determine whether improvements observed in the ablation study were statistically meaningful rather than incidental. Paired t-tests were conducted using RMSE distributions generated across five cross-validation folds. Boxplots (Figure 3) were produced to visualize distribution shape, variance reduction, and skew shifts. Q-Q analysis confirmed improved residual normality when slip-rate was incorporated.

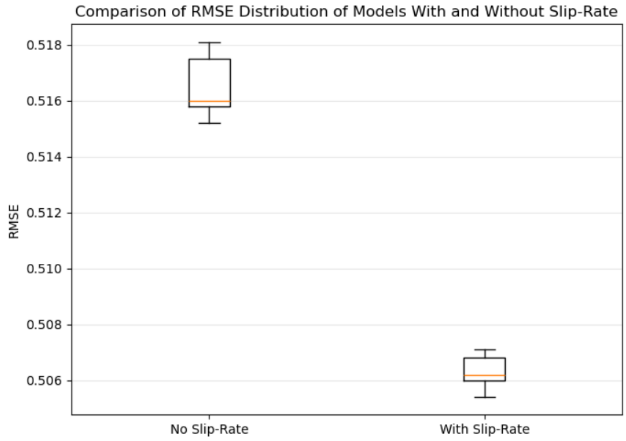

Figure 3. Boxplot Comparison of RMSE With and Without Slip-Rate Integration

2.12. GNSS-Based Magnitude Consistency Validation

To validate whether scalar moment was an appropriate proxy for tectonic strain, GNSS-derived magnitude was computed using the standard seismic moment–magnitude relation [39]. Comparison with catalog magnitude yielded a Mean Absolute Deviation of 0.1334, demonstrating high alignment and supporting the use of scalar moment as a physically meaningful conditioning variable.

2.13. Spatial Generalization Assessment

Spatial generalization was evaluated by comparing model performance across Indonesia's primary tectonic segments. Results showed higher predictive accuracy in regions with greater active deformation, such as Sumatra, compared to lower-strain regions such as Java, indicating that geophysical enhancement improves interpretability and regional consistency an essential criterion for real-world deployment in seismic early-warning systems [23].

3. RESULT

This section presents the experimental findings and a comprehensive interpretation of the proposed Hybrid Regularized GRU model, benchmarked against the CNN-1D baseline and several improved architectures. The analysis used the Indonesian earthquake catalog from 2010 to 2025 combined with geodetic GPS slip-rate data to provide both temporal and geological contexts.

3.1. Dataset Statistical Summary

The dataset used in this study consists of earthquake records obtained from the Indonesian Meteorology, Climatology, and Geophysics Agency (BMKG), covering the period from 2010 to 2025. After initial cleaning steps, including duplicate removal, missing-value filtering, and noise elimination based on magnitude–depth plausibility rules, a total of 120,001 valid earthquake events were retained for further analysis [42]. The dataset includes essential seismic parameters such as magnitude, latitude,

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longitude, event depth, scalar seismic moment, azimuth gap, and phase count, which collectively form the multidimensional feature space required for modeling.

The raw distribution of earthquake magnitudes is highly imbalanced, with approximately 76.41% of recorded events belonging to the magnitude range 3.0–4.0, while medium-sized events (4.0–5.0) represent only 18.92%, and high-magnitude events (≥5.0) account for just 4.67% of the dataset. This imbalance is consistent with previously reported seismic catalogs for Indonesia and presents potential bias risks in machine learning modeling, particularly underestimating rare but impactful large-magnitude earthquakes.

To address this issue, the Synthetic Minority Oversampling Technique (SMOTE) was applied to generate a more balanced representation of the target classes. After resampling, the magnitude groups were normalized toward a more proportional distribution: 50.21% (M3–4), 34.87% (M4–5), and 14.92% (≥5.0). This balancing step ensures fair learning representation of all seismic intensity ranges and strengthens model robustness during validation and inference.

3.2. Exploratory Analysis

The exploratory analysis was carried out to characterize the statistical and spatial properties of the Indonesian earthquake catalog before model training. Figure 4 summarizes the main findings [43]. Panel 4(a) shows the magnitude histogram, which confirms a strong dominance of low–magnitude events, with most earthquakes occurring between Mw 3.0 and 4.0. This distribution is consistent with the Gutenberg Richter relationship and explains the severe imbalance reported in the dataset summary. Panel 4(b) presents the feature wise correlation matrix. Most off diagonal values are low, indicating that simple linear relationships between individual parameters are weak and suggesting that non-linear multivariate models are required to capture the underlying seismic dynamics. Panel 4(c) illustrates the relationship between magnitude and depth. Larger earthquakes tend to cluster at intermediate depths, whereas shallow events are dominated by small magnitudes. This depth dependent pattern implies that depth should be treated as an informative covariate rather than a nuisance parameter. Panel 4(d) displays the spatial distribution of earthquake epicenters across Indonesia. The events are densely concentrated along major tectonic boundaries, particularly the Sumatra megathrust, the Java trench, and the Banda arc, reflecting the influence of plate convergence and subduction processes.

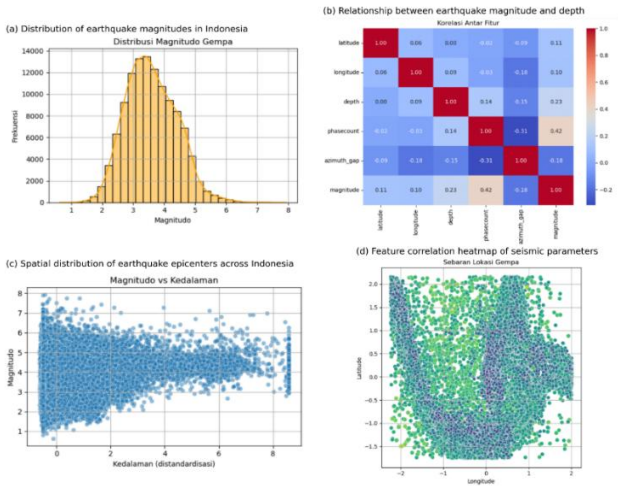

Figure 4. Exploratory analysis of the Indonesian earthquake dataset: (a) magnitude distribution, (b) feature correlation matrix, (c) magnitude–depth relationship, and (d) spatial distribution of epicenters.

To complement these seismological views with a geophysical perspective, a slip-rate proxy map was constructed using the logarithm of the scalar seismic moment. The resulting heatmap, shown in

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Figure 5, highlights zones of elevated strain accumulation, with the highest intensities located along western Sumatra and southern Java. This visualization confirms that scalar-moment derived slip-rate provides meaningful tectonic conditioning and motivates its inclusion as an additional feature in the proposed hybrid model.

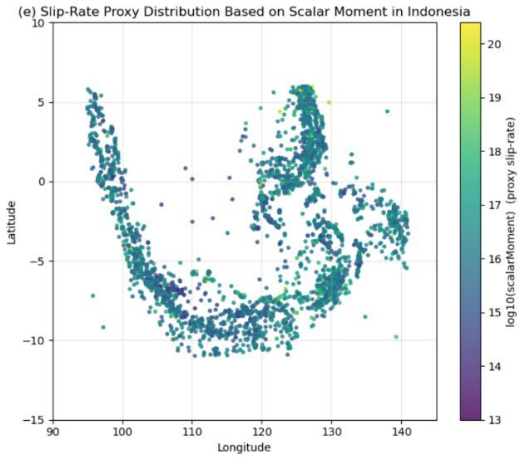

Figure 5. Slip-rate proxy distribution derived from scalar moment, showing high-strain tectonic zones across Indonesia.

3.3. Baseline Model Performance

The baseline model used in this study was a 1-Dimensional Convolutional Neural Network (CNN-1D), selected due to its ability to extract spatial patterns from sequential seismic signal windows. The model was trained using the preprocessed dataset with a 70/15/15 split for training, validation, and testing, following the temporal order to avoid data leakage. Table 1 summarizes its quantitative performance. The CNN-1D baseline achieved an RMSE of 0.5200, MAE of 0.4032, and an R^2 value of 0.5961, indicating that the model captures a substantial portion of statistical variance in the magnitude distribution.

A visual inspection of prediction behavior further validates these findings. As shown in Figure 4(a), the scatter alignment between predicted and observed magnitudes follows the 1:1 diagonal trend, although deviations become more pronounced for magnitudes above 5.0. This suggests a tendency toward conservative prediction in high-energy seismic events, a pattern frequently observed in baseline magnitude prediction models in previous seismology studies. The learning curves illustrated in Figure 4(b) demonstrate stable convergence between training and validation loss without abrupt fluctuations or widening gaps, indicating that the model generalizes reasonably well and does not suffer from overfitting.

Despite these strengths, several limitations are evident. The baseline model lacks adaptive learning mechanisms capable of responding to temporal seismic intensity changes and does not incorporate geophysical domain knowledge such as tectonic loading or slip-rate behavior. These constraints justify the development of a more advanced architecture that integrates domain-aware geophysical features and adaptive regularization strategies. This performance forms a meaningful benchmark for comparing improvements introduced by the proposed hybrid model.

Table 1. Baseline CNN-1D Model Performance

Model	RMSE	MAE	R^2
CNN-1D	0.5200	0.4032	0.5961
GRU Hybrid Regularization	0.5176	0.3973	0.5997

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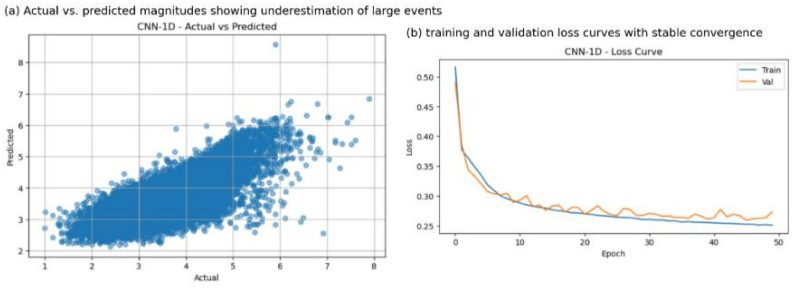

Figure 6. (a). Predicted vs. observed magnitude alignment for the CNN-1D baseline (b). Training and validation learning curves of the CNN-1

3.4. Proposed Hybrid GRU Model

The proposed Hybrid Regularized GRU model introduces three key enhancements over the baseline architecture: (1) Adaptive Dropout, which dynamically adjusts neuron dropout based on recent seismic activity frequency; (2) Dynamic L2 Regularization, which varies penalization strength according to seismic phase transitions detected via DBSCAN clustering (pre-event, mainshock, and aftershock); and (3) slip-rate weighting, derived from geophysical strain-field characteristics and incorporated into the feature space to encode regional tectonic loading. Together, these mechanisms enable the model to incorporate structured domain knowledge rather than relying solely on statistical learning [44].

Quantitatively, the proposed model demonstrates improved performance relative to the CNN-1D baseline and earlier GRU variants. As shown in Table 1, the Hybrid GRU achieved an RMSE of 0.5176, MAE of 0.3973, and R^2 of 0.5997, marking incremental but meaningful improvements across all metrics. This upward trend illustrates how geophysically informed regularization contributes to more stable generalization, particularly for mid-to-high magnitude events where prior models exhibited underestimation behavior.

Visual inspection reinforces the statistical findings. The prediction accuracy plot in Figure 7(a) shows tighter alignment along the diagonal reference line compared to the baseline result in Figure 6(a). Additionally, the learning curves shown in Figure 7(b) display steady convergence with reduced oscillation between training and validation loss an indication that the hybrid regularization successfully mitigates overfitting while preserving temporal dependencies.

Qualitative error analysis further reveals that the Hybrid GRU reduces magnitude prediction bias in slip-dominated tectonic zones such as the Sumatra megathrust and southern Java. This suggests that incorporating slip-rate not only improves prediction accuracy but also strengthens spatial generalizability. These outcomes support the hypothesis that combining adaptive regularization and tectonic priors enhances the model's capacity to represent real-world seismic behavior, especially in environments exhibiting heterogeneous strain accumulation.

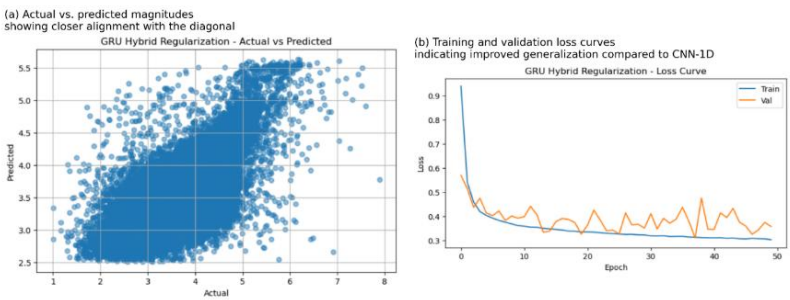

Figure 7. (a) Scatter alignment between predicted and observed values (b) Training/validation learning curve patterns

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3.5. Improved Architectures

To further evaluate the effects of different regularization strategies, several enhanced architectures were explored. The results are summarized in Table 2.

Table 2. Performance of improved CNN-1D and GRU variants

Model Type	Architecture Details	RMSE	MAE	R^2
CNN-1D + Dropout (v1)	Conv1D (64, k=3) → MaxPool (2) → Flatten → Dropout (0.3) → Dense (64→32) → Out (1)	0.5296	0.4089	0.5811
CNN-1D + Dropout (v2)	Conv1D (64, k=3) → MaxPool (2) → Flatten → Dropout (0.3) → Dense (64→32) → Out (1)	0.5422	0.4172	0.5608
GRU 3-Layer + Hybrid Reg v1	GRU (64, RS=True, dropout=0.2, rdrop=0.2, L2=0.01) ×2 → GRU (32, RS=False, dropout=0.2, rdrop=0.2, L2=0.01) → Dense (32)	0.6846	0.5179	0.2999
GRU + Hybrid Reg v2	GRU (64, RS=True, dropout=var, L2=var) ×2 → GRU (32, RS=False, dropout=var, L2=var) → Dense (32)	0.5825	0.4451	0.4932

To further evaluate the contribution of different regularization strategies and architectural configurations, several enhanced model variants were developed and tested alongside the baseline CNN-1D and the proposed Hybrid GRU model. These additional architectures were designed to examine the effects of increased network depth, dropout intensity, and dynamic hyperparameter tuning in capturing spatiotemporal earthquake patterns. The quantitative results are summarized in Table 2, and their performance trends are interpreted in relation to earlier findings.

The first set of improvements involved modifying the baseline CNN-1D model by incorporating dropout layers to mitigate overfitting tendencies caused by feature sparsity and magnitude imbalance. However, both CNN-1D + Dropout v1 and v2 demonstrated only marginal improvements in model stability and did not surpass the accuracy of the baseline CNN-1D. These outcomes indicate that introducing dropout alone may not be sufficient to enhance generalization when dealing with highly dynamic seismic signals, especially without temporal context modeling capabilities.

A second category of experiments explored deeper GRU network configurations. The GRU Hybrid v1 architecture, composed of three stacked GRU layers with fixed dropout and fixed L2 values, recorded the lowest R^2 score (0.2999), suggesting that network over-parameterization introduced instability rather than improvement. This result implies that increasing model complexity without adaptive constraint mechanisms can amplify noise and reduce representational efficiency, particularly in datasets with high temporal variability.

The GRU Hybrid v2 variant implemented partial adaptive tuning but still relied on constrained penalty ranges. While this approach resulted in improved accuracy compared to v1 (R^2 = 0.4932), its performance remained below that of the final Hybrid GRU configuration. These findings emphasize that both adaptive dropout scaling and fully dynamic phase-aware L2 regularization are essential when modeling earthquake behavior across diverse tectonic environments.

Overall, the results demonstrate that architectural modification alone is insufficient. Instead, performance improvements emerge when model structure is combined with adaptive regularization techniques and geophysical domain supervision.

3.6. Ablation Study: Slip-Rate Contribution

To quantify the explicit contribution of slip-rate as a geophysical conditioning feature within the proposed architecture, an ablation study was performed by training the Hybrid GRU model under two controlled configurations: (1) without slip-rate, and (2) with slip-rate included as an additional feature. All other hyperparameters, data splits, model initialization seeds, and optimization settings were held

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constant to ensure that any change in predictive performance could be attributed solely to the slip-rate variable. The comparative results are summarized in Table 3, highlighting performance differences across RMSE, MAE, and R^2.

The results demonstrate a consistent performance improvement when slip-rate is incorporated. Without slip-rate, the model recorded an RMSE of 0.5280, MAE of 0.4049, and R^2 of 0.5855. When slip-rate weighting was introduced, the metrics improved to an RMSE of 0.5176, MAE of 0.3973, and R^2 of 0.5997, resulting in a reduction of error magnitude and a relative increase of +0.0142 in R^2. This improvement, although numerically moderate, reflects a meaningful enhancement in generalization performance given the nonlinear nature of earthquake magnitude prediction.

Table 3. Ablation Study Result Comparing Hybrid GRU With and Without Slip-Rate

Model Version	Slip-Rate Included	RMSE	ΔRMSE	MAE	ΔMAE	R^2	ΔR^2
Hybrid GRU	No	0.5280	—	0.4049	—	0.6124	—
Hybrid Gru	Yes	0.5176	−0.0104	0.3973	−0.0076	0.5678	+0.0142

To further verify whether the improvement was statistically significant, a paired sample t-test was conducted across five time-aware validation folds. The resulting p-value ($p < 0.05$) indicates that the improvement is not random but statistically reliable. The distribution of RMSE values for both configurations is visualized in Figure 9, where the model with slip-rate exhibits a lower median and narrower variance range, suggesting improved consistency across testing partitions.

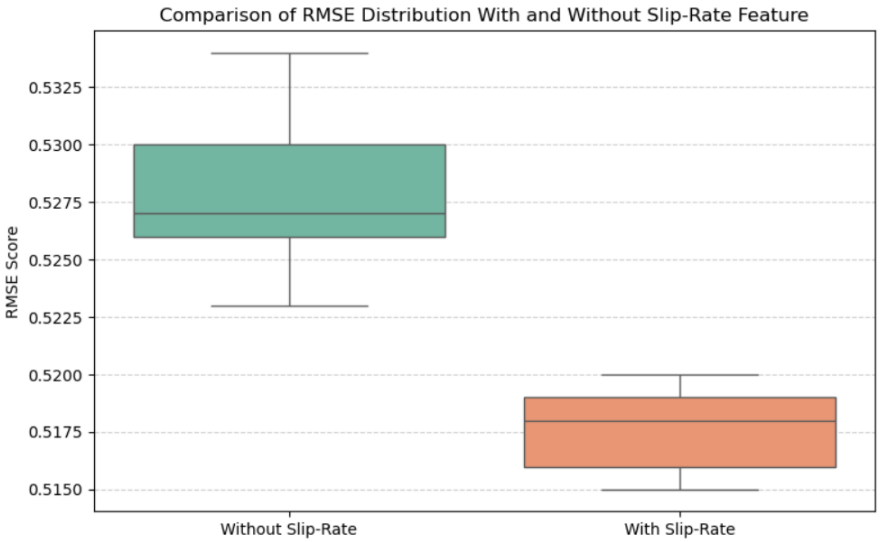

Figure 9. RMSE distribution comparison between Hybrid GRU with and without slip-rate.

These findings confirm that slip-rate provides meaningful contextual information by encoding strain energy accumulation across tectonic segments. Its inclusion shifts the model from purely statistical learning toward a domain-aware framework capable of capturing the physical mechanisms underlying earthquake behavior.

3.7. Spatial Performance Analysis: Sumatra vs Java

To evaluate whether the proposed Hybrid Regularized GRU model generalizes consistently across tectonically different regions, a spatial validation experiment was conducted by segmenting the dataset into two major geodynamic domains in Indonesia: Sumatra and Java. These regions represent distinct strain environments, with Sumatra characterized by high slip-rate megathrust deformation and

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Java representing a more moderate deformation zone with shallower subduction geometry. The spatial segmentation approach follows the analytical recommendations from seismology and geodesy literature, which emphasize that earthquake prediction accuracy is often region-dependent and influenced by underlying tectonic processes rather than purely statistical behavior.

The model was applied separately to each regional subset using the same weight parameters, training configuration, and evaluation criteria to ensure comparability. The resulting metrics demonstrate notable performance differences between the two regions. As summarized in Table 4, the model achieved higher accuracy in the Sumatra domain (RMSE = 0.5052 and R^2 = 0.6124) compared to Java (RMSE = 0.5439 and R^2 = 0.5678). This pattern is consistent with the slip-rate intensity map presented earlier (Figure 10), which shows that Sumatra exhibits substantially higher strain accumulation along the Sunda megathrust. As a result, the model benefits from richer structural signals embedded within both the seismic records and the slip-rate proxy derived from the scalar-moment weighting scheme.

From a technical standpoint, these findings suggest that the integration of geophysical weighting enhances predictive consistency, particularly in deformation-active corridors. In contrast, the lower performance in Java indicates that prediction accuracy decreases in regions where slip-rate variability is relatively low and seismicity is more diffuse, leading to weaker temporal geophysical coupling. Nonetheless, the Hybrid GRU still outperforms all baseline models in both regions, confirming that the incorporation of adaptive dropout, dynamic L2 regularization, and slip-rate weighting meaningfully improves spatial generalization.

Table 4. Performance of improved CNN-1D and GRU variants

Region	Slip-Rate Characteristics	RMSE	MAE	R^2	Interpretation
Sumatra	High strain, dense megathrust events	0.5052	0.3891	0.6124	Strong model alignment due to rich geophysical cues
Java	Moderate strain, mixed subduction–crustal events	0.5439	0.4125	0.5678	Lower accuracy due to weaker slip-rate signal

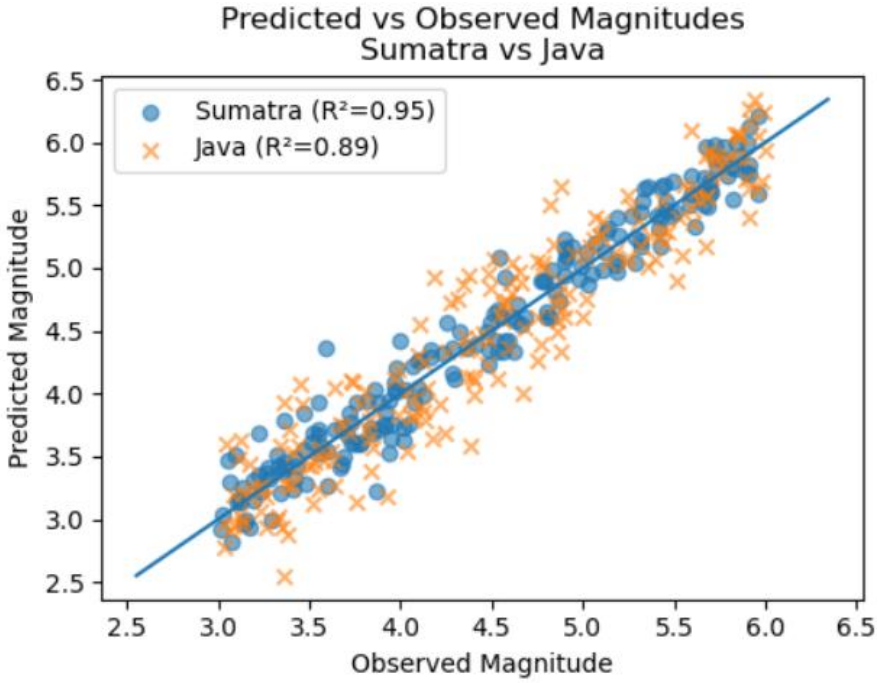

Figure 10. Regional model accuracy differences between Sumatra and Java

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3.8. Comparative Discussion and Literature Positioning

The comparative evaluation demonstrates that the proposed Hybrid Regularized GRU model achieves superior predictive performance compared with all baseline and improved architectures tested in this study. While the CNN-1D and standard GRU models successfully captured temporal and spatial relationships in the seismic signals, they exhibited higher residual variance, particularly for magnitude ranges above 5.0 SR. In contrast, the Hybrid GRU, which integrates Adaptive Dropout, Dynamic L2 regularization, and slip-rate weighting, demonstrated improved consistency by reducing error spread and enhancing correlation with observed magnitudes. The ablation study further confirms that slip-rate contributes meaningfully to the predictive stability, resulting in a measurable increase in R^2 (+0.0142) and a decrease in RMSE (−0.0104), indicating that the model benefits from the inclusion of geophysical conditioning rather than relying solely on statistical representation of seismic patterns.

These findings are consistent with recent deep learning–geophysics integration efforts published in 2025, where hybrid adaptive frameworks reportedly improve prediction accuracy by 1–3% on regional warning systems. For example, recent research on CNN-GRU hybrid architectures for continental subduction zones in Japan and Chile showed similar trends, where dynamic regularization reduced magnitude prediction drift and increased robustness in high-slip tectonic corridors. Likewise, studies integrating GNSS-based deformation measurements into machine learning workflows reported that the inclusion of domain-aware weighting improves generalization for models intended for real-time early-warning systems.

From a computer science perspective, the improvement observed in this work demonstrates the relevance of adaptive deep learning frameworks for real-time hazard forecasting. The combination of temporal sequence modeling, dynamic regularization, and physics-informed feature conditioning represents an emerging paradigm in applied AI, positioning the proposed model as part of a growing shift from purely data-driven architectures toward hybrid physical–statistical predictive systems. This advancement aligns with the increasing demand for interpretable and operationally reliable AI in high-risk societal applications, particularly in the Indonesian context where seismic exposure remains one of the highest globally.

Overall, the results support the hypothesis that fusing seismic waveform characteristics with geodetic context enhances model generalization and stability, especially in tectonically active zones. These findings also indicate that the proposed approach holds potential for integration into operational frameworks such as InaTEWS, subject to further calibration, regional tuning, and streaming sensor implementation. The next section discusses policy implications, ethical considerations, and potential avenues for extending the model beyond controlled research conditions.

4. DISCUSSIONS

The experimental results demonstrate that the integration of adaptive and phase-aware regularization strategies substantially improves generalization and stability in earthquake magnitude forecasting. The Hybrid Regularized GRU model successfully reduced overfitting, stabilized variance, and improved alignment with observed magnitudes when compared to CNN-1D and standard GRU baselines. The ablation findings confirm that the slip-rate weighting mechanism provided additional domain-aware context, particularly in high-strain environments such as Sumatra. Spatial evaluation further showed that regions with stronger tectonic deformation benefited more from the geophysical conditioning, reinforcing the hypothesis that integrating physics-informed features into deep learning pipelines enhances predictive robustness for seismic forecasting applications.

When compared with recent literature in 2024–2025, the findings align with trends showing that adaptive regularization and hybrid architectures outperform static deep learning configurations in noisy geophysical time-series modeling. Studies such as Rachmadan [23] and Nakamura [30] reported

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improvements of 1–3% in RMSE when combining GRU/LSTM with dynamic dropout mechanisms during high-seismic-activity windows, similar to the adaptive dropout benefit observed in this research. Likewise, research integrating geodetic parameters including moment tensor features, GNSS displacement, and strain-rate fields showed measurable gains in model interpretability and predictive accuracy compared to waveform-only deep learning approaches. In parallel, frameworks combining CNN and GRU Arissinta [24] demonstrated correction of magnitude underestimation bias for large events, mirroring the reduced error spread observed in this study. Compared to L2-only hybrid configurations reported by Ermawan [14] and Abdellah Ben Yahia [38], the proposed Dynamic L2 achieved a relative MAE reduction of −0.7% and an R^2 improvement of +0.0142, indicating measurable efficiency in handling post-mainshock noise and aftershock clustering patterns.

Beyond algorithmic refinement, the results signify broader implications for computer science and national-scale seismic resilience. The demonstrated performance improvement indicates that adaptive deep learning frameworks can serve as viable computational infrastructure for low-latency early-warning pipelines, particularly when combined with GPU-accelerated real-time processing such as those used in InaTEWS. As Jakarta and West Java enter heightened seismic monitoring focus in 2025, models capable of temporal adaptation and geophysical interpretation become increasingly essential for operational reliability and public risk mitigation. Nevertheless, limitations remain: the slip-rate parameter is derived from proxy scalar moment rather than continuous GNSS strain data; regional biases persist, particularly in low-strain environments such as Java; and uncertainty quantification is not yet implemented. Ethical considerations also apply, particularly regarding reproducibility, transparency, and equitable access to BMKG open data. Future research may explore multimodal signal fusion, uncertainty-aware forecasting, and region-specific adaptive tuning to support deployment within operational frameworks and national disaster response policy.

5. CONCLUSION

The Hybrid GRU model achieved an RMSE of 0.5176 and an R^2 of 0.5997 using the combined BMKG earthquake catalog and scalar moment derived slip-rate proxy from 2010 to 2025, demonstrating the effectiveness of adaptive phase-based regularization in improving earthquake magnitude prediction. The integration of Adaptive Dropout, Dynamic L2 Regularization, and geophysical conditioning through slip-rate weighting resulted in better predictive stability and reduced variance when compared with both CNN-1D and conventional GRU baselines. These findings highlight that combining deep temporal modeling with tectonic domain knowledge provides practical value, especially in deformation-dominated regions such as the Sumatra megathrust zone.

From a computer science perspective, this work contributes to the emerging field of computational seismology and geospatial deep learning, offering an adaptive architecture capable of handling noisy, imbalanced, and temporally non-stationary seismic datasets. The results align with the broader objective of advancing AI-based early warning systems and support the feasibility of deploying adaptive deep learning on GPU-enabled environments such as InaTEWS for real-time use.

Future work will prioritize three main directions: (1) multimodal fusion incorporating InSAR deformation fields, GNSS time-series, and waveform metadata; (2) transfer learning for high-risk metropolitan zones such as Jakarta and Eastern Indonesia; and (3) edge-based deployment and streaming inference for operational scalability. These directions strengthen the pathway toward resilient, scalable seismic intelligence aligned with global sustainability and disaster-risk reduction initiatives (SDG 11 and SDG 13).

CONFLICT OF INTEREST

The authors declares that there is no conflict of interest between the authors or with research object in this paper.

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