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Determination of Ground Motion Prediction Equations of New Zealand Region Using Multilinear Regression Analysis

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Abstract - *Seismic hazard assessment requires reliable estimation of ground motion parameters in earthquake-prone regions. New Zealand is located along the active tectonic boundary between the Pacific Plate and the Australian Plate and frequently experiences moderate to strong earthquakes. This study aims to develop a region-specific Ground Motion Prediction Equation (GMPE) using recorded strong-motion data from 23 earthquake events with moment magnitudes ranging from Mw 6.0 to Mw 9.0. A total of 927 strong-motion records were analyzed considering parameters such as hypocentral distance, earthquake magnitude, site classification, and fault mechanism. Multilinear regression analysis was applied to derive empirical relationships for predicting peak ground acceleration (PGA). In addition, several machine learning techniques including Linear Regression, Support Vector Machine (SVM), k-Nearest Neighbors (KNN), Random Forest Regression, and Artificial Neural Networks (ANN) were implemented to enhance prediction accuracy. Model performance was evaluated using statistical metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Squared Error (MSE), and coefficient of determination (R^2). Results indicate that nonlinear models, particularly ANN, provide improved prediction accuracy compared to conventional regression approaches.*

***Key Words*: Ground motion Prediction Equation (GMPE), Peak Ground Acceleration (PGA), Earthquake Magnitude, Hypocentral Distance, Machine Learning.**

1. INTRODUCTION

Ground Motion Prediction Equations (GMPEs) are fundamental tools in seismic hazard assessment and earthquake-resistant structural design. Over the past two decades, significant advancements have been made in the development of empirical and semi-empirical ground motion models for active crustal and subduction regions [1–5]. Large collaborative projects such as NGA-West2 have contributed to improved prediction equations for peak ground acceleration (PGA), peak ground velocity (PGV), and spectral acceleration, incorporating magnitude scaling, distance attenuation, and site response effects [4,5]. These global models have been widely adopted; however, their direct application to specific regions may not adequately capture local tectonic and attenuation characteristics. Several researchers have emphasized the importance of region-specific GMPE development to improve prediction reliability [6–8]. Studies focusing on New Zealand seismicity have demonstrated that local tectonic conditions, including crustal faulting and subduction interface events, significantly influence ground motion behavior [6,7]. Near-source attenuation characteristics and site amplification effects further complicate prediction accuracy [9,10]. In addition, recent investigations have explored advanced modeling approaches, including simulation-based techniques and time–frequency analysis, to better understand ground motion characteristics [11–14]. Recent research has also highlighted the importance of seismic hazard disaggregation and probabilistic analysis for regional hazard evaluation [8,15]. These studies demonstrate that dominant magnitude–distance scenarios vary geographically, reinforcing the need for locally calibrated prediction models.

Despite substantial global progress in GMPE development, limited studies have integrated both traditional regression approaches and advanced data-driven techniques within the New Zealand context. Therefore, the present study aims to develop a region-specific GMPE using strong-motion records and to evaluate its performance using both multilinear regression and machine learning techniques. This approach contributes toward improving seismic hazard assessment and ground motion prediction reliability for New Zealand.

2. LITERATURE SURVEY

Updated seismic hazard modeling studies following major earthquake sequences have emphasized the importance of incorporating newly recorded strong-motion data and revised site response parameters into hazard assessment frameworks [16]. Evaluation of empirical ground motion models for New Zealand has identified systematic prediction biases and recommended refinement of logic-tree weighting factors to enhance national seismic hazard models [17]. Improvements in earthquake catalogue preparation, including declustering techniques and magnitude consistency analysis, have significantly strengthened the reliability of probabilistic seismic hazard estimation [18]. Probabilistic seismic hazard assessments conducted in other tectonically active regions further demonstrated the importance of integrating comprehensive historical and instrumental earthquake catalogs for accurate hazard evaluation [19]. Development of predictive models for cumulative absolute velocity (CAV), Arias Intensity (AI), and significant duration has expanded understanding of energy-based ground motion parameters beyond conventional peak ground acceleration (PGA) [20]. Engineering seismological investigations incorporating advanced fault-source characterization and hazard disaggregation methods have improved regional seismic design criteria [21]. Updated earthquake source models and refined methodologies have contributed to enhanced hazard reliability for Canterbury and surrounding regions [22]. Foundational probabilistic hazard studies highlighted the spatial variation of seismic demand across New Zealand and reinforced the need for region-specific modeling approaches [23]. Extension of probabilistic frameworks to volcanic hazard assessment demonstrated the applicability of multi-hazard methodologies in tectonically complex environments [24]. Hybrid modeling techniques integrating artificial neural networks with optimization algorithms have shown improved predictive performance compared to conventional regression models [25]. Detailed geotechnical characterization of strong-motion stations has reduced uncertainty associated with site amplification effects and strengthened GMPE calibration procedures [26]. Additional probabilistic evaluations of regional seismicity and attenuation behavior have improved understanding of magnitude–distance relationships and regional ground motion characteristics [27,28]. Advanced ground motion simulation, time–frequency analysis, and region-specific GMPE development in other tectonic regions have further demonstrated the importance of local calibration for reliable seismic hazard prediction [29].

Although substantial progress has been made in probabilistic hazard assessment and GMPE development for New Zealand, limited studies have systematically integrated updated strong-motion datasets with both classical multilinear regression and advanced machine learning techniques. Moreover, comprehensive comparative evaluation of predictive performance across multiple algorithms remains insufficient within the New Zealand seismic context. Therefore, the present study addresses this research gap by developing a region-specific GMPE and evaluating its performance using both empirical regression and modern data-driven approaches to enhance prediction reliability and seismic hazard assessment accuracy.

3. RESEARCH AIM

The primary aim of this study is to develop a region-specific Ground Motion Prediction Equation (GMPE) for the New Zealand seismic region using recorded strong-motion data. The research establishes empirical relationships between peak ground acceleration (PGA), earthquake magnitude, hypocentral distance, site classification, and fault mechanism. A multilinear regression framework is adopted to model attenuation characteristics, while advanced machine learning techniques are implemented to enhance predictive performance. The overall goal is to improve the reliability and regional applicability of ground motion estimation for seismic hazard assessment and earthquake-resistant structural design in New Zealand.

3.1 Objectives of the Study

The main objectives of this research are:

1. To collect and process strong-motion records from moderate to strong earthquakes in the New Zealand region.
2. To develop a New Zealand-specific GMPE using multilinear regression analysis considering magnitude, hypocentral distance, site class, and fault mechanism.
3. To investigate the attenuation behavior of peak ground acceleration with respect to seismic parameters.
4. To implement and compare machine learning models, including Linear Regression, Support Vector Machine, k-Nearest Neighbors, Random Forest Regression, and Artificial Neural Networks, for ground motion prediction.

To evaluate model performance using statistical indicators such as RMSE, MAE, MSE, and R^2 to determine the most reliable predictive approach.

4. NUMERICAL MODELLING AND ANALYSIS

4.1 Strong Motion Dataset and Study Area

The strong-motion data used in this study were obtained from the GeoNet seismic monitoring network of New Zealand, which provides high-quality earthquake recordings across the region. A total of 927 strong-motion records corresponding to 23 moderate to strong earthquake events that occurred between 2000 and 2021 were used for the analysis. The selected earthquakes have moment magnitudes ranging from Mw 6.0 to Mw 8.1, with focal depths varying between 5 km and 241 km. For the development of the predictive models, hypocentral distances ranging from 5 km to 300 km were considered.

The earthquake events are spatially distributed across different seismically active regions of New Zealand, covering latitudes from −45.770° to −29.245° and longitudes from −177.929° to 178.537°. The number of recording stations associated with each event varies depending on the spatial distribution of seismic stations and the intensity of the earthquake, ranging from 1 to 51 stations. The dataset includes several significant earthquakes such as the 2003 Fiordland earthquake (Mw 7.1), 2009 Fiordland earthquake (Mw 7.8), 2010 Darfield earthquake (Mw 7.2), 2013 Cook

Strait earthquake sequence (Mw 6.5), 2016 Kaikōura earthquake sequence, and the 2021 Kermadec Islands earthquake (Mw 8.1).

Each ground motion record contains three orthogonal components of acceleration, namely East–West (EW), North–South (NS), and Up–Down (UP). For every record, important seismological parameters such as moment magnitude (Mw), hypocentral distance (R), site classification (S), and fault mechanism (F) were compiled. Site classification was represented using a dummy variable where 0 indicates rock sites and 1 indicates soil sites, while the fault mechanism was categorized as strike-slip (0) or dip-slip (1). These parameters were used as input variables for developing the Ground Motion Prediction Equation (GMPE) and for training the machine learning models.

The spatial distribution map presented in Figure 1 was developed using QGIS software by plotting the geographic coordinates of selected earthquake epicenters and strong-motion recording stations obtained from the GeoNet seismic database. The figure illustrates the coverage of the dataset and the regional distribution of seismic events across New Zealand.

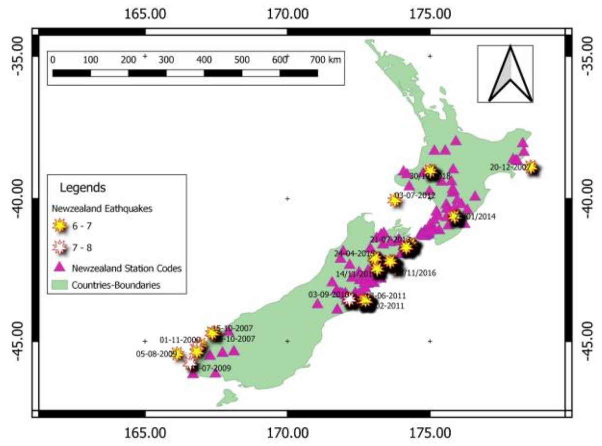

Fig -1: Spatial distribution of selected earthquake events (Mw 6.0–8.1) used in the study across New Zealand.

4.2 Methodological Framework

The overall framework adopted for the development and evaluation of the Ground Motion Prediction Equation (GMPE) is illustrated in Figure 2. The methodology consists of systematic stages beginning with strong-motion data acquisition and ending with model validation and performance comparison. Initially, earthquake event information and corresponding strong-motion recordings were obtained from the GeoNet database. The raw acceleration time histories were processed using SeismoSignal software to extract key ground motion parameters such as Peak Ground Acceleration (PGA), Peak Ground Velocity (PGV), and Peak Ground Displacement (PGD). Signal processing included baseline correction and filtering to ensure data consistency and reliability.

Subsequently, relevant seismic predictor variables including moment magnitude (Mw), hypocentral distance (R), site classification, and fault mechanism were compiled for each record. These parameters were structured into a numerical dataset for regression and machine learning modeling. The processed dataset was then divided appropriately for model development and evaluation. Multilinear regression analysis was applied to derive the empirical GMPE coefficients.

In parallel, machine learning algorithms were implemented to capture nonlinear relationships within the seismic data. Finally, model performance was assessed using statistical indicators such as RMSE, MAE, MSE, and R^2 to determine the most reliable predictive approach.

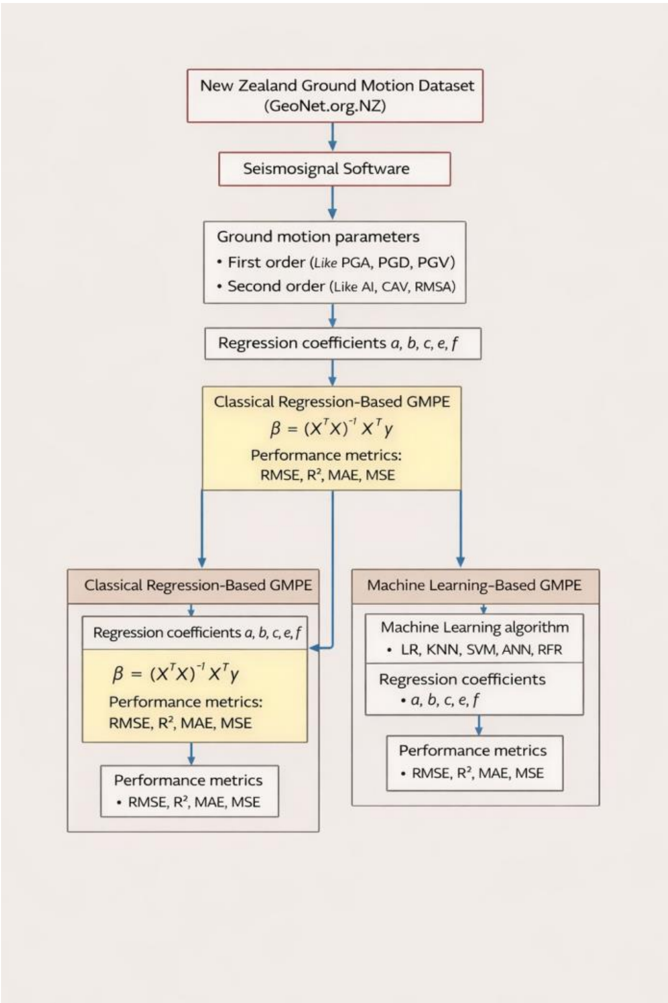

Fig -2: Methodological framework for development and evaluation of regression-based and machine learning-based GMPE models.

4.3 Functional Form of the GMPE

The functional form adopted in this study is based on widely accepted empirical attenuation relationships used in probabilistic seismic hazard assessment. Several previous studies have expressed ground motion intensity measures as a function of earthquake magnitude, source-to-site distance, site classification, and fault mechanism effects [5], [6], [8]. These models commonly utilize a logarithmic transformation of peak ground acceleration (PGA) to linearize the regression relationship and reduce variability in residuals.

Consistent with established attenuation modelling approaches [5], [28], the magnitude term accounts for amplitude scaling, while the distance term represents geometric spreading and energy dissipation during wave propagation. To avoid singularity at small distances, a fictitious depth parameter is incorporated within the distance function. Site classification and fault mechanism are introduced as categorical (dummy) variables to capture local amplification and tectonic influences specific to the New Zealand seismic environment.

The adopted functional form of the GMPE is expressed as:

$$\log_{10}(Y) = a + bM + c\log_{10}\left(\sqrt{R^2 + h^2}\right) + eS + fF \pm \sigma$$

where:

- Y = Peak Ground Acceleration (PGA)
- M = Moment magnitude
- R = Hypocentral distance (km)
- S = Site classification
- F = Fault mechanism
- a, b, c, e, f = Regression coefficients
- h = Fictitious depth parameter
- σ = Standard deviation

Although the structural form of the equation follows standard empirical GMPE formulations reported in the literature [5], [6], [28], the regression coefficients were derived exclusively from the strong-motion dataset considered in this study using multilinear least-squares regression analysis. Therefore, the calibrated model represents a region-specific ground motion relationship for the New Zealand seismic region.

4.4 Estimation of Regression Coefficients and Model Evaluation

The regression coefficients of the proposed Ground Motion Prediction Equation (GMPE) were estimated using multilinear least-squares regression analysis. A total of 927 strong-motion records corresponding to 23 earthquake events were used for model calibration. The dependent variable was defined as:

$$Y = \log_{10}(PGA)$$

where PGA represents the peak ground acceleration recorded at each station.

The independent variables considered in the regression model include moment magnitude (M), the distance attenuation term $\log_{10}(\sqrt{R^2 + h^2})$, site classification (S), and fault mechanism (F). The regression coefficients were determined by minimizing the sum of squared residuals between observed and predicted logarithmic PGA values.

For the East–West (EW) component, the developed empirical GMPE is expressed as:

$$\log_{10}(Y) = -0.6163 + 0.3226M - 1.0465\log_{10}\left(\sqrt{R^2 + h^2}\right) + 0.2065S - 0.2370F \pm 0.175$$

The positive magnitude coefficient indicates that ground motion amplitude increases with increasing earthquake magnitude. The negative coefficient associated with the distance term confirms attenuation of seismic waves as the source-to-site distance increases. The site and fault coefficients reflect the influence of local geological conditions and tectonic characteristics on ground motion behavior.

The same regression procedure was independently applied to the North–South (NS) and Up–Down (UP) components of ground motion. For each component, identical predictor variables and the same least-squares optimization approach were used to estimate component-specific regression coefficients. This component-wise modeling ensures that directional variations in seismic wave propagation and attenuation characteristics are properly captured within the developed GMPE framework.

Residuals were computed to evaluate model accuracy and dispersion:

$$\text{Residual} = \log_{10}\left(\frac{Y_{observed}}{Y_{predicted}}\right)$$

Residual analysis was performed to verify the absence of systematic trends with respect to magnitude and distance, thereby confirming the stability and reliability of the regression model.

In addition to classical regression modeling, supervised machine learning algorithms including Linear Regression (LR), Support Vector Machine (SVM), k-Nearest Neighbors (KNN), Random Forest Regression (RFR), and Artificial Neural Networks (ANN) were implemented to enhance predictive capability and capture potential nonlinear relationships within the dataset.

Model performance was evaluated using the following statistical indicators:

- Mean Absolute Error (MAE): Represents the average absolute difference between predicted and observed values.

$$\mathrm{MAE} = \frac{1}{N}\sum \mid y_i - \hat{y}_i \mid$$

- Mean Squared Error (MSE): Indicates the square root of the average squared prediction errors.

$$\mathrm{MSE} = \frac{1}{N}\sum (y_i - \hat{y}_i)^2$$

- Root Mean Square Error (RMSE): Indicates the square root of the average squared prediction errors.

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

- Coefficient of Determination (R^2): Shows how well the model explains the variability of the response data.

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

These statistical measures were used to compare regression-based and machine learning-based GMPE models and to identify the most reliable predictive framework for seismic hazard assessment in the New Zealand region.

5. RESULTS AND DISCUSSIONS

5.1 Regression-Based GMPE Results

The multilinear regression analysis produced component-specific Ground Motion Prediction Equations (GMPEs) for the East–West (EW), North–South (NS), and Up–Down (UP) components. The estimated regression coefficients for all three components are presented in Table 1.

Table -1: Regression Coefficients (EW, NS, UP)

Regression coefficients	EW	NS	UP
a	-0.6163	-0.5346	-0.7635
b	0.3226	0.3173	0.3781
c	-1.0465	-1.0467	-1.2534
e	0.2065	0.1651	0.1383
f	-0.237	-0.2480	-0.2105

Table 1 presents the regression coefficients obtained from the multilinear regression analysis for the East–West (EW), North–South (NS), and Up–Down (UP) components of ground motion. Separate sets of coefficients were determined for each component to capture directional differences in seismic response characteristics. The variation in coefficient values reflects differences in magnitude scaling and attenuation behavior between the horizontal and vertical components. These estimated parameters form the basis of the developed Ground Motion Prediction Equations (GMPEs) and are used for reliable prediction of peak ground acceleration in the study region.

The variation of PGA with hypocentral distance for EW, NS, and UP components is illustrated in Charts 1(a)–1(c).

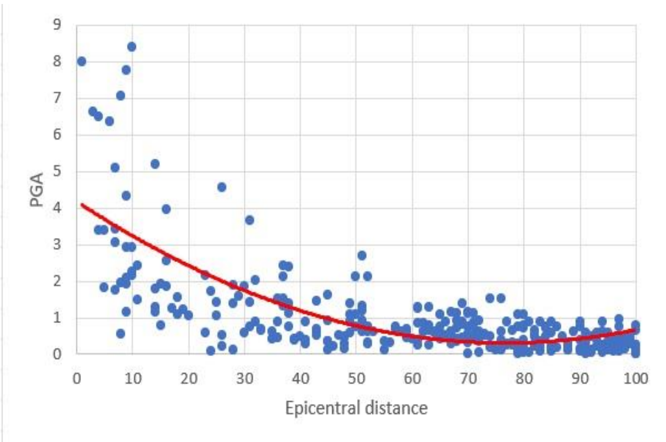

Chart -1(a): Attenuation of PGA with Epicentral Distance for EW Component

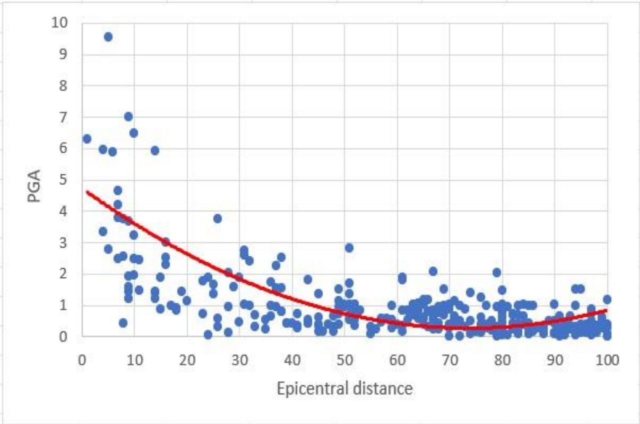

Chart -1(b): Attenuation of PGA with Epicentral Distance for NS Component

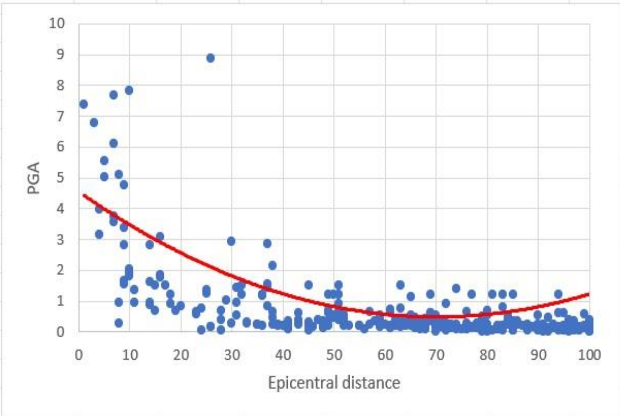

Chart -1(C): Attenuation of PGA with Epicentral Distance for UP Component

Charts 1(a–c) present the variation of PGA with epicentral distance for the EW, NS, and UP components. Each dot represents an individual recorded PGA value from a specific earthquake–station pair. The plots show a general reduction in ground acceleration as distance increases, reflecting seismic energy attenuation. The fitted regression curves follow the overall decay trend, indicating satisfactory model representation for all three components.

5.2 Residual Analysis

Residual analysis was performed to evaluate model stability and potential bias. The log residuals plotted against epicentral distance for EW, NS, and UP components are shown in Charts 2(a)–2(c).

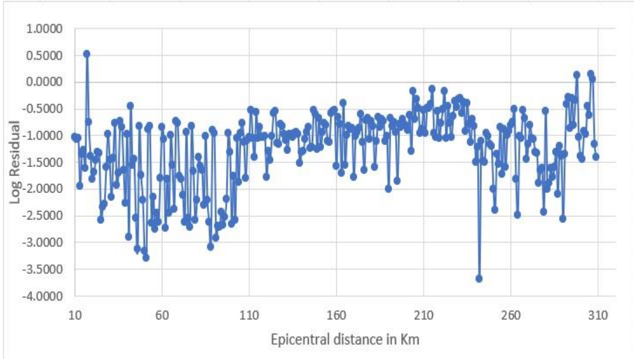

Chart -2(a): : Log Residuals vs Epicentral Distance for EW Component

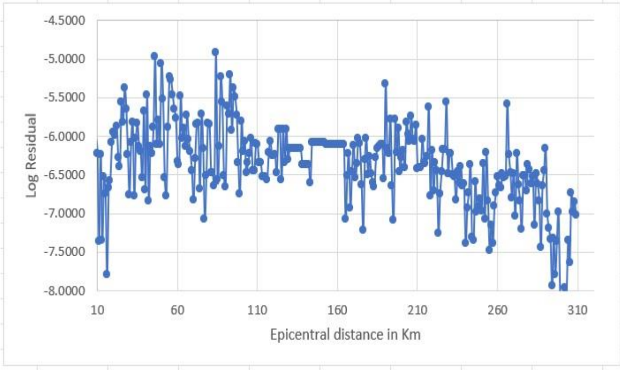

Chart -2(b): : Log Residuals vs Epicentral Distance for NS Component

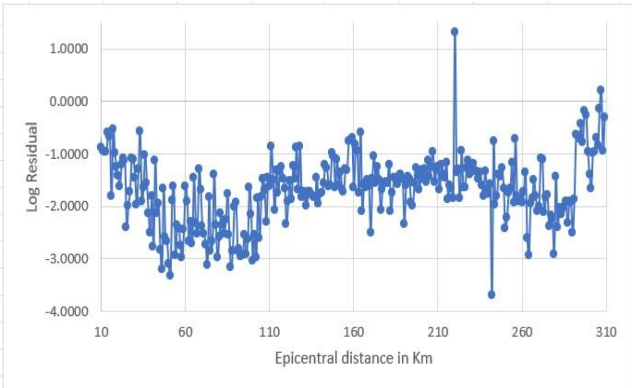

Chart -2(C): : Log Residuals vs Epicentral Distance for UP Component

Charts 2(a–c) display the distribution of log residuals with respect to epicentral distance for the EW, NS, and UP components. The dots correspond to individual residual values obtained by subtracting predicted PGA from observed PGA in logarithmic scale. The residuals are scattered around zero without a clear systematic trend, suggesting the absence of distance-dependent bias. This pattern confirms the stability and reliability of the developed GMPE across different distance ranges.

Scatter plots comparing observed and predicted $\log_{10}$(PGA) values for the East–West (EW), North–South (NS), and Up–Down (UP) components are presented in Charts 3(a)–3(c), respectively

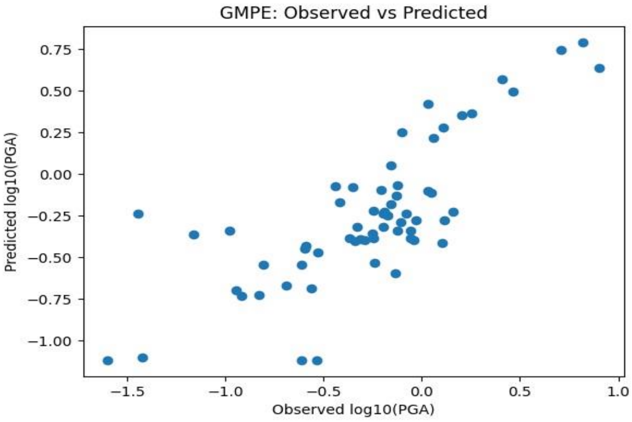

Chart -3(a): Observed vs Predicted log10(PGA) for EW Component GMPE

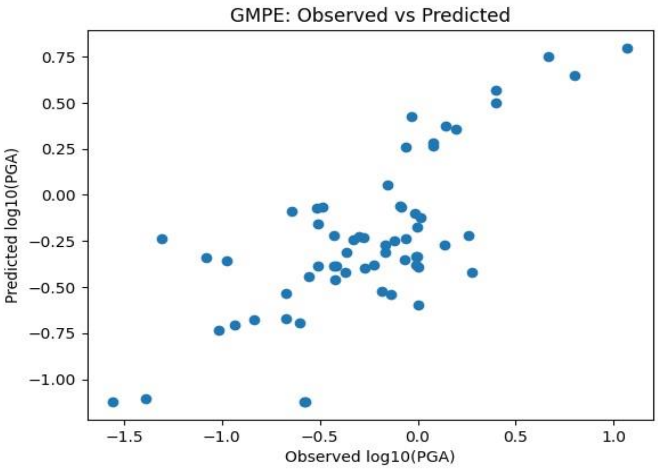

Chart -3(b): Observed vs Predicted log10(PGA) for NS Component GMPE

Charts 3(a–c) illustrate the comparison between observed and predicted $\log_{10}$(PGA) values for the EW, NS, and UP components, respectively. In each plot, the dots represent individual earthquake–station recordings used in the analysis. The clustering of points along a positive linear trend indicates good agreement between measured and estimated values. Overall, the distribution pattern confirms that the developed GMPE performs consistently for all three directional components.

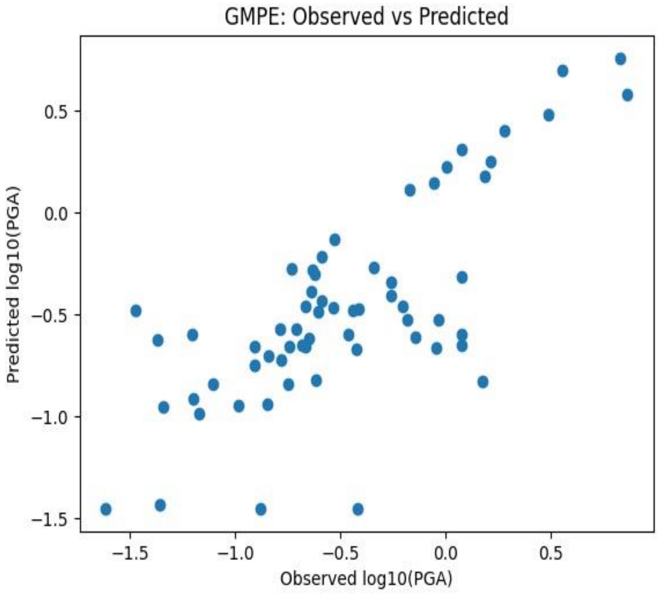

Chart -3(c): Observed vs Predicted log10(PGA) for UP Component GMPE

Residual plots with zero-error reference lines for the EW, NS, and UP components are shown in Charts 4(a)–4(c), respectively, illustrating the dispersion of prediction errors around the zero-bias line.

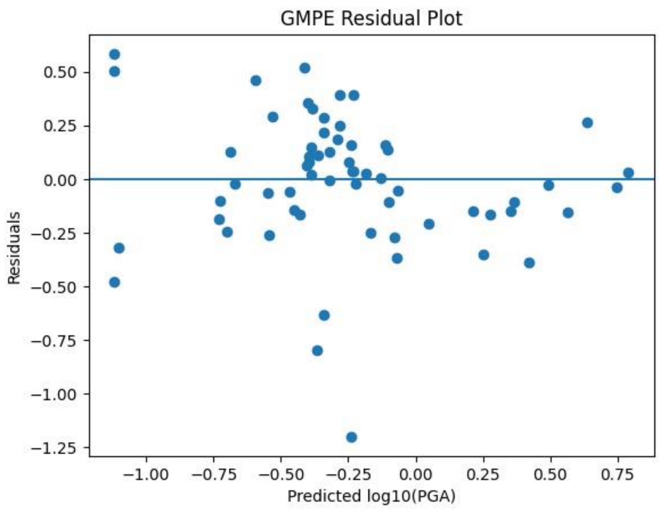

Chart -4(a): Residuals vs Predicted log10(PGA) for EW Component GMPE

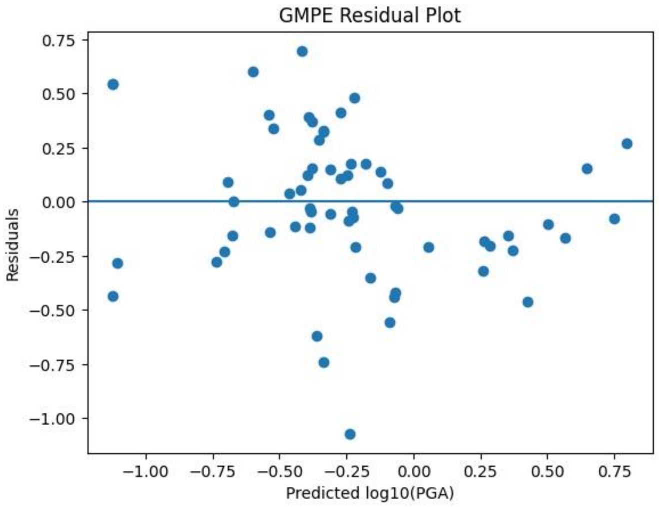

Chart -4(b): Residuals vs Predicted log10(PGA) for NS Component GMPE

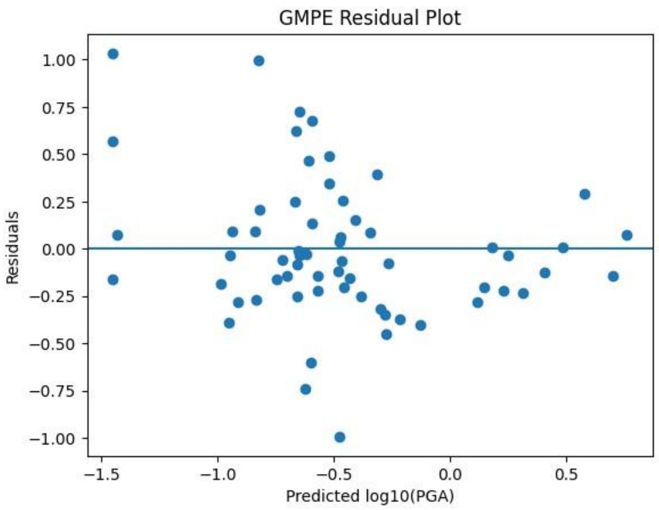

Chart -4(c): Residuals vs Predicted log10(PGA) for UP Component GMPE

Charts 4(a–c) present the residuals plotted against predicted $\log_{10}$(PGA) values for the EW, NS, and UP components. In each plot, the dots represent individual residual values obtained from the difference between observed and model-estimated ground motions. The residuals are generally distributed around the zero-reference line without any clear systematic pattern or funnel-shaped trend. This random dispersion indicates that the developed GMPE does not show magnitude-dependent or prediction-level bias and performs consistently across different ranges of predicted PGA values.

5.3 Machine Learning Model Performance

To enhance prediction capability, five supervised machine learning algorithms Linear Regression (LR), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Random Forest Regression (RFR), and Artificial Neural Network (ANN)—were implemented and compared.

Table -2: Performance metrics for LR model

Performance metrics for LR			
	EW	NS	UP
1.Root mean square (RMSE)	0.6357	0.9113	0.6322
2.R^2 =1-SSR/SST	0.7934	0.7133	0.7767
3.Mean absolute error (MAE)	0.3641	0.4991	0.3380
4.Mean square error (MSE)	0.4042	0.8304	0.3997

Table -3: Performance metrics for SVM model

Performance metrics for SVM			
	EW	NS	UP
1.Root mean square (RMSE)	0.3078	0.2837	0.3410
2.R^2 =1-SSR/SST	0.5985	0.6584	0.6056
3.Mean absolute error (MAE)	0.2226	0.2194	0.2584
4.Mean square error (MSE)	0.0947	0.0805	0.1163

Table -4: Performance metrics for KNN model

Performance metrics for KNN			
	EW	NS	UP
1.Root mean square (RMSE)	0.3574	0.3802	0.4261
2.R^2 =1-SSR/SST	0.4586	0.388	0.3843
3.Mean absolute error (MAE)	0.2561	0.2791	0.3157
4.Mean square error (MSE)	0.1277	0.1445	0.1815

Table -5: Performance metrics for RFR model

Performance metrics for RFR			
	EW	NS	UP
1.Root mean square (RMSE)	0.3229	0.3436	0.3830
2.R^2 =1-SSR/SST	0.5580	0.499	0.5025
3.Mean absolute error (MAE)	0.2167	0.2053	0.2825
4.Mean square error (MSE)	0.1042	0.1180	0.1467

Table -6: Performance metrics for ANN model

Performance metrics for ANN			
	EW	NS	UP
1.Root mean square (RMSE)	0.2849	0.3021	0.3513
2.R^2 =1-SSR/SST	0.6557	0.6128	0.5814
3.Mean absolute error (MAE)	0.2007	0.2317	0.2617
4.Mean square error (MSE)	0.0812	0.0912	0.1234

The performance metrics presented in Tables 2–6 indicate noticeable differences among the evaluated models. The Artificial Neural Network (ANN) model consistently achieves lower MAE, MSE, and RMSE values along with comparatively higher R^2 values across most components. This demonstrates its superior capability in capturing nonlinear relationships between seismic input parameters and ground motion response. In contrast, traditional Linear Regression shows relatively higher error values, reflecting its limitation in representing complex seismic behavior.

5.4 Discussion

The regression results show that peak ground acceleration increases with earthquake magnitude and decreases with hypocentral distance, which follows the expected seismic attenuation behavior. Differences observed among the EW, NS, and UP components indicate directional variations in ground motion due to regional tectonic conditions and local site effects in New Zealand. The comparison of models shows that nonlinear methods perform better than traditional linear regression. In particular, the Artificial Neural Network provides lower prediction errors and higher accuracy, indicating that the relationship between seismic parameters and ground motion is nonlinear. Therefore, combining machine learning techniques with empirical GMPE models improves the reliability of regional seismic hazard assessment.

6. CONCLUSIONS

1. A region-specific Ground Motion Prediction Equation (GMPE) for the New Zealand region was developed using 927 strong-motion records from 23 earthquake events recorded between 2000 and 2021.

2. The regression results show that peak ground acceleration increases with earthquake magnitude and decreases with hypocentral distance, which follows the expected seismic attenuation behavior.

3. The analysis of EW, NS, and UP components indicates directional variations in ground motion characteristics influenced by regional tectonic conditions and local site effects.

4. Among the predictive models, the Artificial Neural Network (ANN) demonstrated better performance with lower prediction errors and higher accuracy compared to Linear Regression (LR), Support Vector Machine (SVM), KNN, and Random Forest models.

Overall, the developed GMPE provides reliable prediction of ground motion for the New Zealand region. The integration of empirical regression analysis with machine learning techniques improves prediction accuracy and contributes to better seismic hazard assessment.

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