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Comparative performance of regional and global GMPEs for moderate and large earthquakes: A case study of Gölyaka (2022) and Pazarcık (2023)

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Abstract

This study evaluates the predictive performance of Turkey-adjusted NGA-West1 and global NGA-West2 Ground Motion Prediction Equations (GMPEs) using strong-motion data from the 2022 Gölyaka (Mw 5.9) and 2023 Pazarcık (Mw 7.7) earthquakes. Three analysis scenarios were developed based on Vs30 site classifications defined by TBEC 2018: Vs30 = 180–360 m/s records from both earthquakes and Vs30 = 360–760 m/s records from the Pazarcık event. Median spectral values predicted by GMPEs were compared with observed medians within the period range T = 0–10 s. Multiple statistical techniques including Likelihood (LH), Log-Likelihood (LLH), Euclidean Distance Ranking (EDR), Mean Distance Error (MDE), and the √κ indice were applied to assess model performance. Results show that GMPE performance varies significantly by earthquake magnitude, source characteristics, and soil class. The results indicate that GMPE performance varies significantly depending on earthquake magnitude, source characteristics, and site conditions, and no single model provides superior performance across all scenarios. Turkey-adjusted models generally showed strong performance, particularly under medium-to-soft soil conditions, while some models demonstrated improved predictive capability for the Pazarcık earthquake under rock and stiff-soil conditions. In contrast, several models showed comparatively lower agreement with the observed data. Overall, the findings highlight the significant influence of site classification on GMPE selection and support the use of multi-model logic-tree approaches to reduce epistemic uncertainty in probabilistic seismic hazard analysis (PSHA).

1. Introduction

Throughout history, earthquakes have posed serious threats to humanity and have been prominent among natural disasters affecting communities. The prediction of future hazards and the mitigation of the destructive effects of earthquakes have been the main focus of scientific research. Ground motion prediction equations play a crucial role in this context. However, the prediction of earthquakes is subject to uncertainties due to issues such as regional variations of these equations and their compatibility with future earthquakes. Therefore, the selection of Ground Motion Prediction Equations (GMPEs) is a crucial step in modern seismic hazard studies. These equations provide measurements of ground motion intensity, such as Peak Ground Acceleration (PGA) or Spectral Acceleration (SA), associated with parameters such as magnitude, distance, fault type, and soil class.

The regional suitability of ground motion prediction equations has become a research topic due to the incorporation of data from various regions [1-7]. To select the most appropriate ground motion prediction equations for earthquake calculations in a given region, various pre-selection methods, and statistical approaches are employed with confidence and expertise. The selection of ground motion equations has been made based on objective criteria suggested by Cotton et al. [8] and Bommer et al. [9] related to tectonic regionalization. It is essential to use prediction equations that are consistent with the tectonic structure of the region, are peer-reviewed, have an adequate database, and are up-to-date with the research's scope and the regression method. By following these criteria can be ensured that the selected equations are reliable and appropriate for the research's objectives.

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Table 1. NGA-West1 and NGA-West2 GMPE models

GMPE model	Abbreviation
Abrahamson et al. [13]	ASK14
Boore at al. [14]	BSSA14
Chiou & Youngs [15]	CY14
Campbell & Bozorgnia [16]	CB14
Abrahamson & Silva [10] (TR-adjusted)	TR-AS08
Boore & Atkinson [10] (TR-adjusted)	TR-BA08
Campbell & Bozorgnia [10] (TR-adjusted)	TR-CB08
Chiou & Youngs [10] (TR-adjusted)	TR-CY08

While several local GMPEs have been developed specifically for Türkiye, the primary objective of this study is not to test purely local equations. Instead, this research focuses strictly on evaluating the predictive performance of Turkey-adjusted NGA-West1 equations which were regionalized to incorporate Türkiye's specific tectonic characteristics and directly comparing them against the updated, statistically robust global NGA-West2 models. Although purely local GMPEs may reflect regional tectonic features, they typically introduce higher statistical uncertainties because they rely on more limited and less stable datasets. In contrast, the prediction equations developed within the global NGA-West1 and NGA-West2 frameworks offer comprehensive data coverage, statistical robustness, and verified reliability, making them highly preferred in modern seismic hazard calculations [10]. Therefore, restricting the scope to these specific adjusted and global models enables a focused and consistent comparative analysis without introducing the high uncertainties associated with purely local models. Table 1 presents the evaluated Turkey-adjusted NGA-West1 and global NGA-West2 GMPEs [11,12].

Probabilistic assessments of differences between observed and predicted ground motions based on existing strong-motion data have enabled the statistical evaluation of GMPEs. This approach provides valuable information on the ability of empirical models to predict ground motion in various regions [17]. Scherbaum et al. [8,18] proposed Maximum Likelihood (LH) and Logarithmic Likelihood (LLH) methods to statistically compute the similarity between observed and predicted spectral values obtained from ground motion data. While LH has been widely used for the selection and ranking of GMPEs in many global studies, LLH is considered a more advanced method as it incorporates the standard deviation of GMPEs based on the Kullback-Leibler distance. In addition, LLH has been used as a selection and ranking technique to identify appropriate GMPEs for specific active seismic regions. It is important to note that both methods have their strengths and limitations. The LH and LLH approaches has been utilized to evaluate the suitability of GMPEs in specific geographical regions in several research [4,19,20-22]. Kale and Akkar [23] proposed an alternative ranking and selection methodology called Euclidean Distance Ranking (EDR). EDR method, similar to LH and LLH, exploits the relationship between observed and predicted data using Euclidean distance. EDR has been used to assess the applicability of GMPEs with comparison by other methods such as LH and LLH investigations [12,21,24,25]. Kale [24,26] proposed integrating LH, LLH, and EDR tests instead of using a specific tool to select appropriate GMPEs. In the EDR ranking procedure, the MDE indice represents the aleatory uncertainty of GMPEs. The second indice used for ranking GMPEs in the EDR approach indicates the trend between observed data and the corresponding median of GMPEs, serving as an indicator of bias. This bias is quantified by the parameter k, which compares the Euclidean distance of the original observed data set with that of the corrected values. For an ideally unbiased model, the k parameter would be exactly one [27]. Villani et al. [28] and Nizamani and Park [29] employed LLH and EDR approaches, respectively, to assess the suitability of various GMPEs for the United Kingdom and the Korean Peninsula. Probabilistic assessments of Ground Motion Prediction Equations (GMPEs) have advanced significantly in recent years, driven by the adoption of sophisticated statistical methodologies. Sotiriadis and Margaris [30] emphasize the efficacy of Maximum Likelihood (LH) and Logarithmic Likelihood (LLH) techniques in evaluating GMPE performance. These methods, including measures such as Kullback-Leibler distance, enable a comprehensive assessment of both bias and aleatory variability in predicted ground motions, crucial for understanding seismic behavior across diverse regions [8,18]. In parallel, the Euclidean Distance Ranking (EDR) method, proposed by Kale and Akkar [24], enhances GMPE selection by quantifying discrepancies between observed and predicted data tailored to specific seismic settings. These modern approaches stand in contrast to older methods like the Chi-square and Kolmogorov-Smirnov tests, which are now considered limited in their ability to account for the complex variability and biases inherent in ground motion data [31,32]. Therefore, the preference for modern statistical methods over older approaches is underscored by their capability to offer advanced modeling techniques, nuanced performance evaluations across diverse geographic regions, and tailored selection criteria specific to seismic conditions. By integrating advanced metrics like LH, LLH, and EDR, researchers can more precisely assess the suitability and reliability of GMPEs. This approach not only enhances the understanding of ground motion dynamics in earthquake engineering and seismology but also improves predictive accuracy in seismic hazard assessments, ensuring more informed decision-making processes.

This study aims to evaluate the performance of GMPEs for the southeastern and northern regions of Türkiye, which were affected by the devastating Mw: 7.7 earthquake on February 6, 2023, and the moderate Mw: 5.9 earthquake on

November 23, 2022. Since low acceleration levels often correspond to weak motions typically associated with distant-fault events, they offer limited value for assessing the predictive performance of GMPEs. Therefore, in this study, earthquake records located within a 300 km radius, exhibiting spectral acceleration (SA or PGA) values greater than 0.1 g and possessing well-defined Vs30 site conditions, were selected. Additionally, only stations with measured Vs30 values within the selected Vs30 ranges were included in the analysis. The primary reason for station exclusion was the lack of directly measured Vs30 values required for accurate site classification according to TBEC 2018. This approach enabled a more reliable examination of the correlations between the TR-Adjusted NGA-West1 and NGA-West2 ground motion prediction models. The prediction performance of the GMPEs was evaluated using statistical methods such as Likelihood Analyses (LH), Logarithmic Likelihood (LLH), and Euclidean Distance Ranking (EDR). The study proposes a ranking of the most suitable GMPEs for earthquakes in various regions of Türkiye, taking into account regional differences. The findings provide fundamental data that will contribute to more accurate assessments in future seismic hazard estimation studies.

2. Data-driven methodology

In the calculations of Probabilistic Seismic Hazard Analysis (PSHA), LH [8], LLH [18], and EDR [25] methods are widely utilized for constructing logic trees, and these methods have been employed in numerous global projects [12,33-36]. These methods are used in selecting GMPEs and evaluating their prediction performance. The LH method computes the standard residuals of observed and predicted ground motion data, with a value of 0.5 considered as the median in the LH method. The LLH method relies on a logarithmic likelihood approach to determine the distance between the continuous probability distribution of the observation-based data set f(x) and the continuous probability models of the prediction-based data set g(x). The EDR method, developed by Kale and Akkar [23], assumes a normal distribution with mean and standard deviation parameters for the differences (D) between observational data and predicted values, as well as the logarithm of the prediction model data. The trend between observational data and predicted values is quantified as the root of the sum of squares of differences (D) in the EDR method, referred to as Euclidean distance (DE).

The Modified Euclidean distance (MDE) for the cumulative distribution of differences (D) between seismic data and predicted values within a specified standard deviation range is calculated using Eq. (5). The parameter κ, representing the trend between observational ground motion data and corresponding median prediction values, is determined by the ratio of original (DEoriginal) and corrected (DEcorrected) Euclidean distances, as calculated in Eq. (6). The DEcorrected value is derived from the coefficient obtained through linear regression analysis of observational data and median prediction values. Small values of the EDR indice indicate that the considered data set is well-represented by the candidate prediction equation. The EDR indice integrates the impact of standard deviation and the level of trend between observational data and median ground motion equation predictions (Table 2).

The ground motion records from the earthquakes that occurred on November 23, 2022, in Gölyaka (Düzce) and February 6, 2023, in Pazarcık (Kahramanmaraş) were comparatively analyzed using ground motion prediction equations. The location information and soil properties of the selected earthquake recording stations are provided in Tables 3 and 4. These stations were chosen based on their measured Vs30 values and records of significant peak ground acceleration exceeding 0.1 g from the Gölyaka and Pazarcık earthquakes, all located within 300 km from the epicenter. Vs30 values were directly measured and sourced from AFAD. In the evaluation of the Ground Motion Prediction Equations (GMPEs) used in this study, the closest distance to the rupture plane (Rrup) parameter, which accounts for fault geometry as required by the NGA-West1 and NGA-West2 models, was utilized instead of simple epicentral distances. This specific distance metric is of critical importance, especially for seismic events with extensive rupture lengths, such as the Mw 7.7 Pazarcık earthquake. Accordingly, an independent finite fault model was not developed in this study; rather, the Rrup values for the stations were obtained directly from the Disaster and Emergency Management Authority (AFAD) Strong Motion Database (TADAS). AFAD calculates the Rrup distances of the stations for such major earthquakes using its own official finite fault models and provides them through its database [38].

Table 2. Equations used [37]

$LH(\lvert z_0\rvert) = Erf(\lvert z_0\rvert/\sqrt{2};\infty) = 2/\sqrt{(2\pi)}\int_{(\lvert z_0\rvert)}^{\infty} exp(-z^2/2)dz$	(1)
$LLH(g,x) = -1/N\sum_{(i=1)}^{N} log_2 g(x_i)$	(2)
$EDR = \sqrt{(\kappa \cdot 1/N\sum_{(i=1)}^{N} MDE_i^2)}$	(3)
$DE = \sqrt{(\sum_{(i=1)}^{N}(p_i - q_i)^2)}$	(4)
$MDE = \sum_{(j=1)}^{n}\lvert d_j\rvert \cdot Pr(\lvert D\rvert < \lvert d_j\rvert)$	(5)
$\kappa = DE_{original}/DE_{corrected}$	(5)
z_0: Normalized residual, $Erf(z)$: Error function	

Table 3. Earthquake record stations for Gölyaka earthquake

Station	Latitude	Longitude	Province	Vs30
8109	31.0144	40.781	Düzce	183
8106	31.1124	40.7671	Düzce	312
8101	31.1489	40.8436	Düzce	282
8102	31.1644	40.8342	Düzce	242
1407	31.0112	40.5776	Bolu	273
1411	31.6175	40.6846	Bolu	229
5406	30.6225	40.6703	Sakarya	271
5414	31.025	40.823	Sakarya	318

Table 4. Earthquake record stations for Pazarcık Earthquake

Station	Latitude	Longitude	Province	Vs30
4615	37.138	37.3868	Kahramanmaraş	484
4616	36.8384	37.3755	Kahramanmaraş	390
4632	36.7737	37.256	Kahramanmaraş	428
2704	37.8022	37.0088	Gaziantep	721
3137	36.4885	36.6929	Hatay	688
3145	36.4064	36.6454	Hatay	533
3142	36.3661	36.498	Hatay	539
201	38.2674	37.7612	Adıyaman	391
6304	38.5132	37.3651	Şanlıurfa	376
3125	36.1326	36.2381	Hatay	448
3135	35.8831	36.4089	Hatay	460
3139	36.4144	36.5838	Hatay	272
3141	36.2197	36.3726	Hatay	338
3124	36.1722	36.2387	Hatay	283
3126	36.1375	36.2202	Hatay	350
3136	36.2472	36.1159	Hatay	344

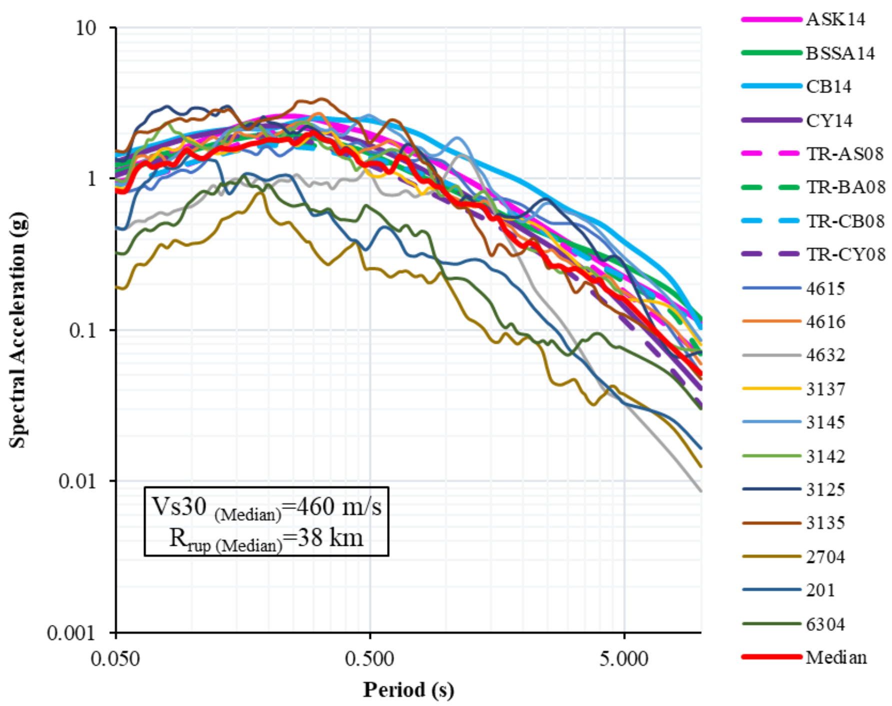
3. Results

To be used in data-driven testing methods, the median values obtained from the GMPEs were compared with the median spectral values of the observed data. The period range considered for data-driven testing methods is T = 0–10 s. In this study, three different scenarios were evaluated. The Vs30 values of the stations in the dataset were classified according to the Turkish Seismic Building Code 2018 (TBEC 2018) [39]. Accordingly, the records from the Kahramanmaraş and Gölyaka earthquakes with Vs30 = 180–360 m/s, and the records from the Kahramanmaraş earthquake with Vs30 = 360–760 m/s, were analyzed as separate scenarios (Fig. 1).

LH, LLH, EDR, MDE, and √κ analyses were conducted across the the period range T=0-10 s range to evaluate the compatibility of predicted and observed data spectra for the November 23, 2022 Gölyaka (Düzce) and February 6, 2023 Pazarcık (Kahramanmaraş) earthquakes (Figs. 2-4). Smaller values of EDR, MDE, and LLH indicate better performance, while LH values close to 0.5 indicate the best performance. Additionally, models with √κ values closest to 1 exhibit superior performance. Fig. 4a demonstrates that for the November 23, 2022, Gölyaka (Düzce) earthquake, the TR-CY08, BSSA14, and CY14 models exhibit superior performance across LH, LLH, EDR, MDE, and √κ analyses. Fig. 4b illustrates that for the Pazarcık (Kahramanmaraş) earthquake on February 6, 2023, with Vs30 = 360-760 m/s, the TR-CB08, CB14, TR-CY08, and ASK14 models demonstrate the best performance in LH, LLH, EDR, MDE, and √κ analyses. Fig. 4c highlights that for the Pazarcık (Kahramanmaraş) earthquake on February 6, 2023, with Vs30 = 180-360 m/s, the TR-AS08, ASK14, TR-CB08, and TR-CY08 models exhibit the best performance in LH, LLH, EDR, MDE, and √κ analyses. Table 5 presents the average indice values for LH, LLH, EDR, MDE, and √κ analyses. The models are ranked in Table 5 from best to worst performance.

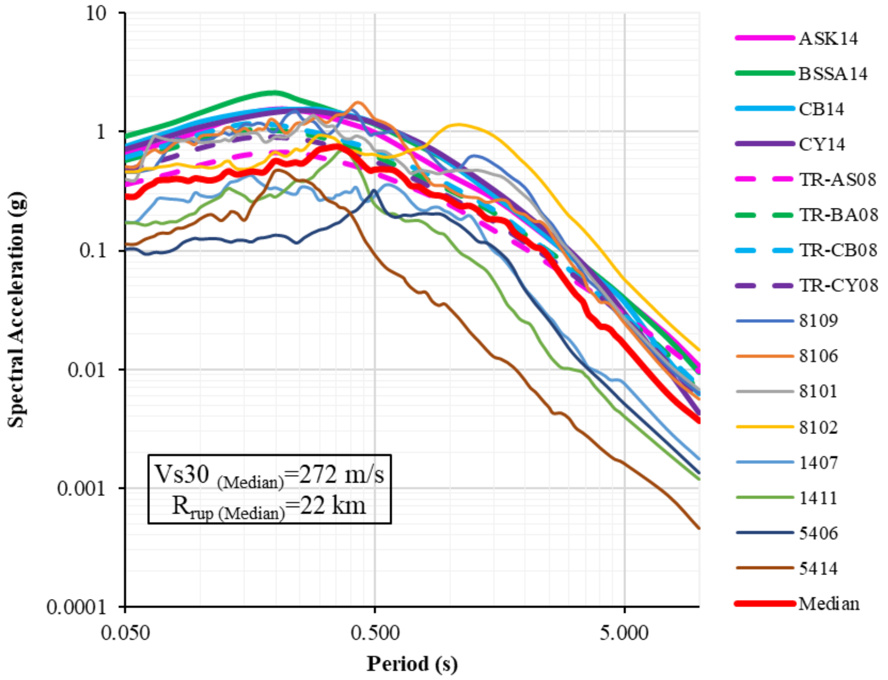
Following the ranking of GMPEs, weight assignments are carried out for their application in logic tree implementations [2,3,5,7-9,12,23,26,40-44]. Subsequently, the equations are assigned different weights to create subgroups. Hazard curves for each site in the research area and for each considered period value are obtained for logic tree applications, determining the median trend for the selected return periods. Finally, the results from all periods are evaluated to reach the ultimate logic tree application. The primary objective of this method is to prevent any influence on the results of probabilistic seismic hazard analysis by a selected logic tree application's ground motion prediction equation in a reducing or enhancing manner [26]. Therefore, this research established a ranking among ground motion prediction models to be used in logic tree applications for Probabilistic Seismic Hazard Analysis (PSHA) studies. While a weighting scheme that relies on ranking enhances the distinctions between the GMPEs, it serves as a valuable tool for generating a global score and aiding in the final selection process. Fig. 5 displays the un-normalized weight (UNW) [45] for each GMPE across the three applied ranking methods. The models were evaluated using this scoring system from 8 to 1, with high scores assigned to well-performing models and low scores given to less effective ones. The November 23, 2022, Gölyaka (Düzce) and February 6, 2023, Pazarcık (Kahramanmaraş) earthquakes were compared based on these scores (Figs. 5 and 6).

In Fig. 5a, when comparing the BSSA14 and TR-BA08 models, it is observed that the BSSA14 model exhibits better performance trends for the Gölyaka and Pazarcık earthquakes (Vs30=360-760 m/s). However, for the Pazarcık earthquake (Vs30=180-360 m/s), the TR-BA08 model shows higher scores in terms of EDR, MDE, and √κ analyses. Similarly, in Fig. 5b, the ASK14 model demonstrates superior trends for the Gölyaka and Pazarcık earthquakes (Vs30=30-760 m/s) compared to the TR-AS08 model. For the Pazarcık earthquake (Vs30=180-360 m/s), however, the TR-AS08 model receives higher scores in EDR, MDE, and √κ analyses. Fig. 5c reveals that the CY14 model exhibits better trends for both Gölyaka and Pazarcık earthquakes (Vs30=30-760 m/s) compared to the TR-CY08 model. Conversely, for the Pazarcık earthquake (Vs30=180-360 m/s), the TR-CY08 model scores higher in EDR, MDE, and √κ analyses. In Fig. 5d, when comparing the CB14 and TR-CB08 models, the CB14 model shows better trends for the Gölyaka and Pazarcık earthquakes (Vs30=30-760 m/s). For the Pazarcık earthquake (Vs30=180-360 m/s), however, the TR-CB08 model performs better in terms of EDR, MDE, and √κ analyses. In summary, the CY14 and CB14 models performs well for the Gölyaka earthquake, the ASK14 model performs well for the Pazarcık earthquake (Vs30=360-760 m/s), and the TR-AS08 model excels for the Pazarcık earthquake (Vs30=180-360 m/s) (Fig. 6).

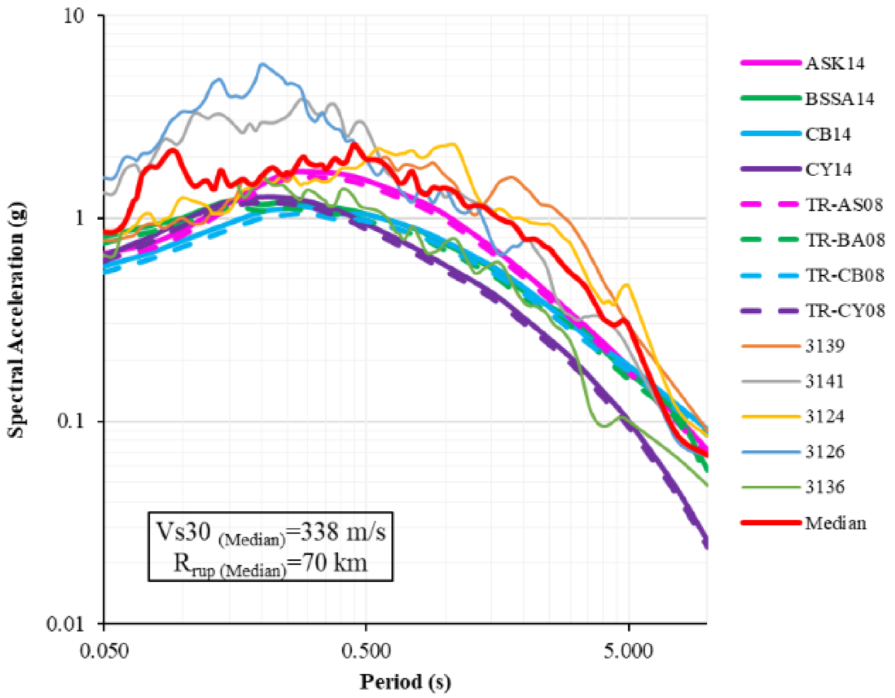


(a)

Fig.1. Comparison of spectra with NGA-West2 equations (a) 23 November 2022 Gölyaka earthquake (b) 6 February 2023 Pazarcık (Kahramanmaraş) earthquake for Vs30 = 460 m/s (c) 6 February 2023 Pazarcık (Kahramanmaraş) earthquake for Vs30 = 338 m/s



(b)



(c)

Fig.1. Continued

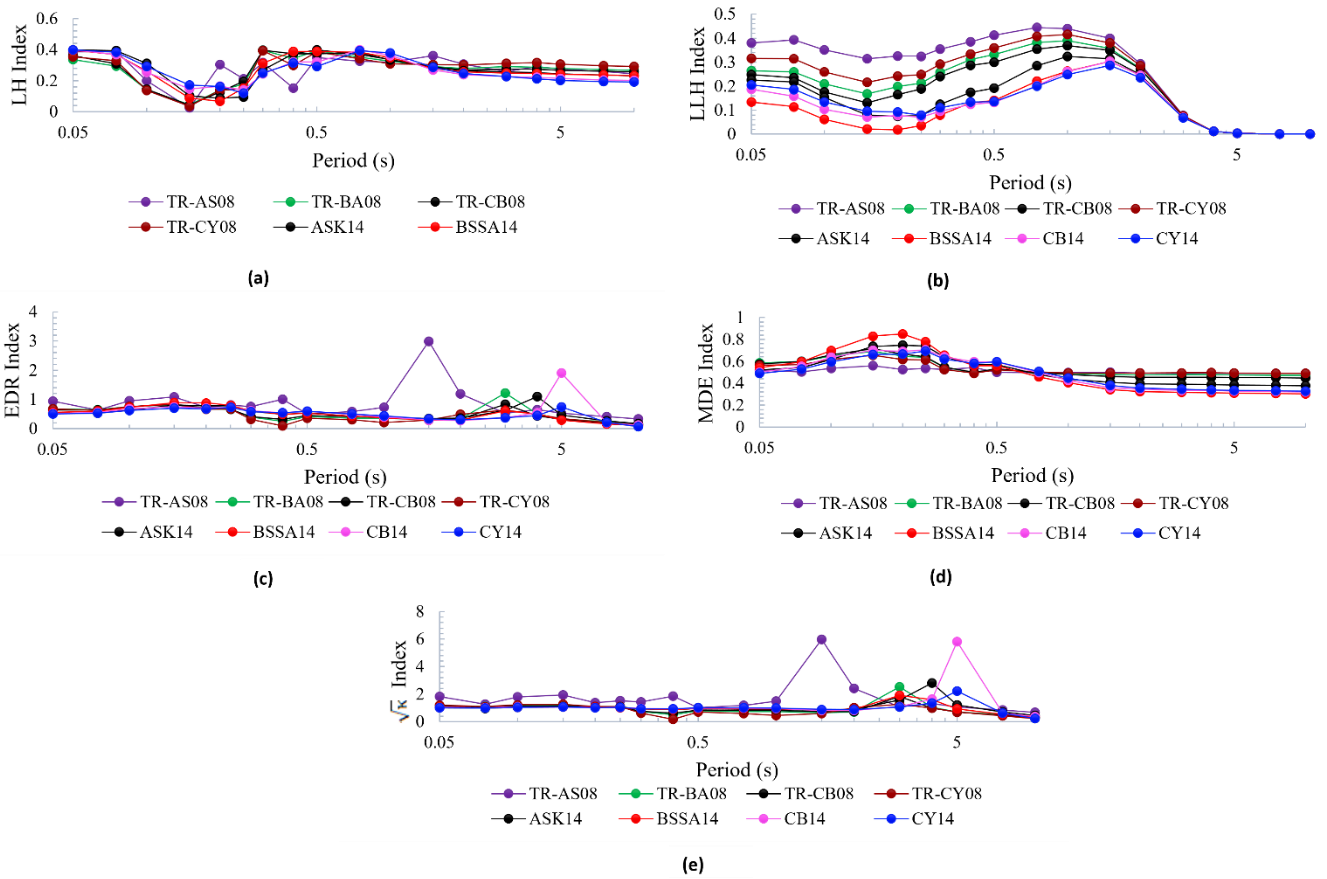


Fig.2. 23 November 2022 Gölyaka (Düzce) earthquake (a) LH; (b) LLH (c) EDR (d) MDE and (e)√κ analyzes Vs30 = 360-760 m/s

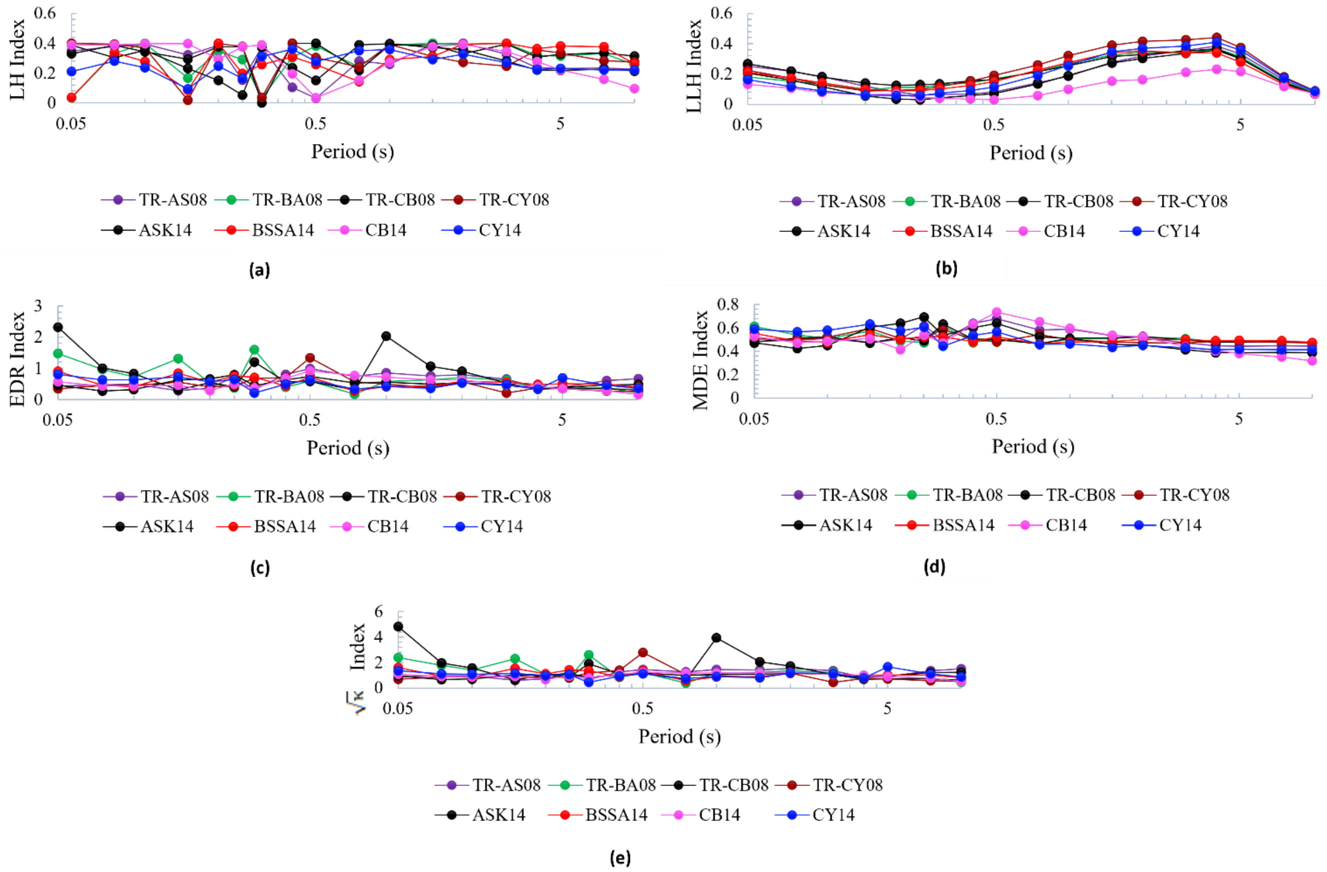


Fig. 3. 6 February 2023 Pazarcık (Kahramanmaraş) earthquake (a) LH; (b)LLH (c) EDR (d) MDE and (e)√κ analyzes Vs30 = 360-760 m/s

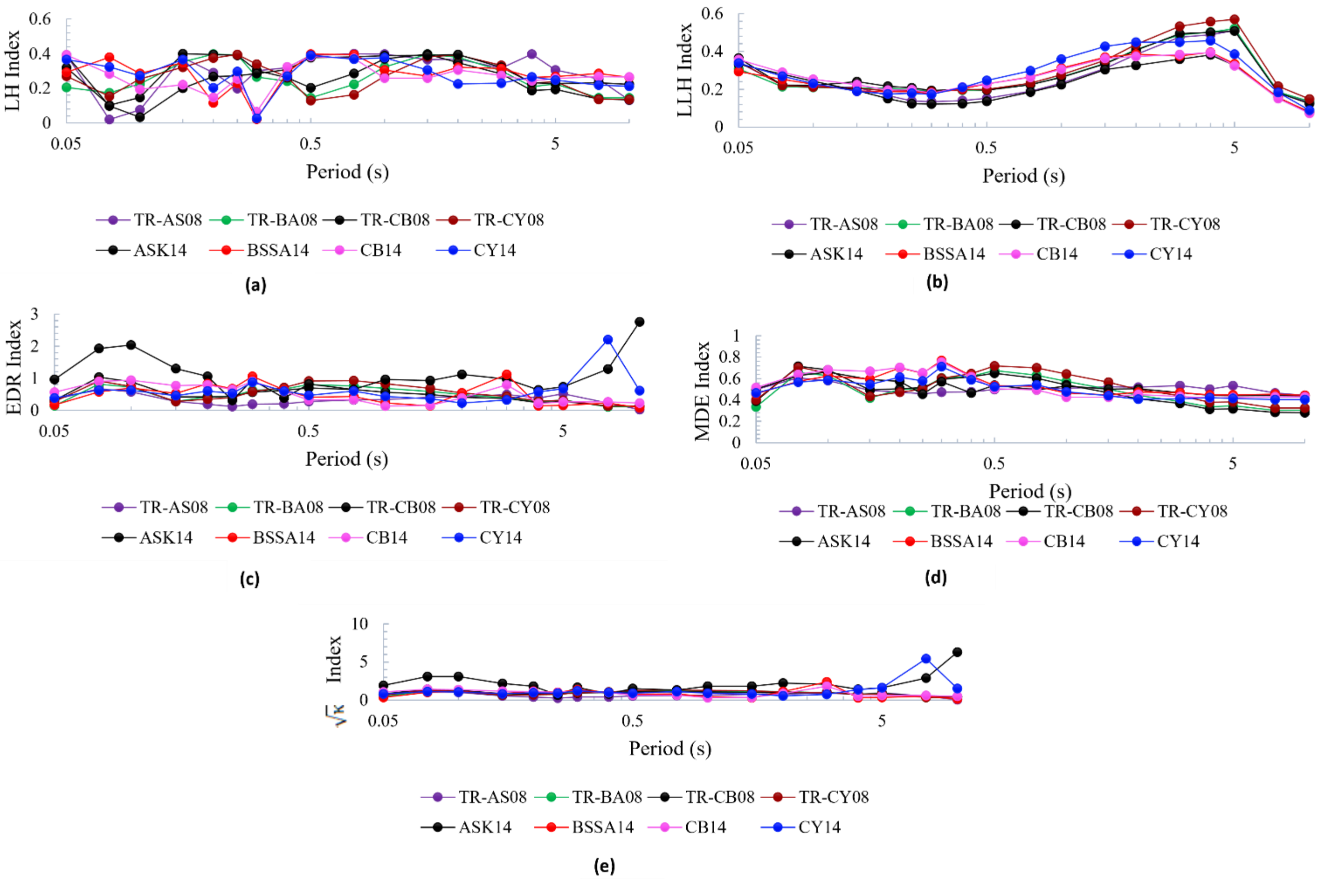


Fig. 4. 6 February 2023 Pazarcık (Kahramanmaraş) earthquake (a) LH; (b) LLH (c) EDR (d) MDE and (e)√κ analyzes Vs30 = 180-360 m/s

Table 5. Average indices

GMPE	Gölvaka Earthquake Vs30 = 360–760 m/s	Pazarcık Earthquake Vs30 = 360–760 m/s	Pazarcık Earthquake Vs30 = 180–360 m/s
	LH		
ASK14	0.272093	0.272644	0.279561
BSSA14	0.272613	0.281923	0.280418
CB14	0.261131	0.286208	0.264902
CY14	0.26233	0.259577	0.275789
TR-AS08	0.276749	0.281838	0.294619
TR-BA08	0.273081	0.295745	0.263687
TR-CB08	0.275093	0.327788	0.269913
TR-CY08	0.277833	0.300151	0.265865
	LLH		
ASK14	0.143259	0.159223	0.224478
BSSA14	0.103201	0.195725	0.25683
CB14	0.117829	0.106109	0.264905
CY14	0.123934	0.188061	0.283908
TR-AS08	0.272969	0.186578	0.257274
TR-BA08	0.20598	0.200496	0.277435
TR-CB08	0.189349	0.213699	0.28307
TR-CY08	0.231246	0.230797	0.292987

Table 5. Continued

GMPE	Gölvaka Earthquake Vs30 = 360–760 m/s	Pazarcık Earthquake Vs30 = 360–760 m/s	Pazarcık Earthquake Vs30 = 180–360 m/s
	EDR		
ASK14	0.5438	0.508453	1.100608
BSSA14	0.504424	0.545936	0.478762
CB14	0.569809	0.499785	0.511096
CY14	0.493262	0.514228	0.620586
TR-AS08	0.852312	0.593175	0.33135
TR-BA08	0.50316	0.664476	0.477549
TR-CB08	0.486747	0.770601	0.479969
TR-CY08	0.447574	0.488543	0.523143
	MDE		
ASK14	0.518628	0.499443	0.513424
BSSA14	0.508397	0.499988	0.539549
CB14	0.494468	0.499524	0.536899
CY14	0.489747	0.499855	0.505342
TR-AS08	0.510594	0.520897	0.504976
TR-BA08	0.538974	0.512194	0.487124
TR-CB08	0.532952	0.503999	0.486403
TR-CY08	0.534884	0.506049	0.522117
	$\sqrt{\kappa}$		
ASK14	1.064428	1.013098	2.134501
BSSA14	0.988101	1.078817	0.844974
CB14	1.227175	0.968532	0.903532
CY14	1.008931	1.019747	1.277015
TR-AS08	1.664348	1.123293	0.636378
TR-BA08	0.917152	1.244137	0.919331
TR-CB08	0.892927	1.511716	0.933183
TR-CY08	0.812921	0.963813	0.934956

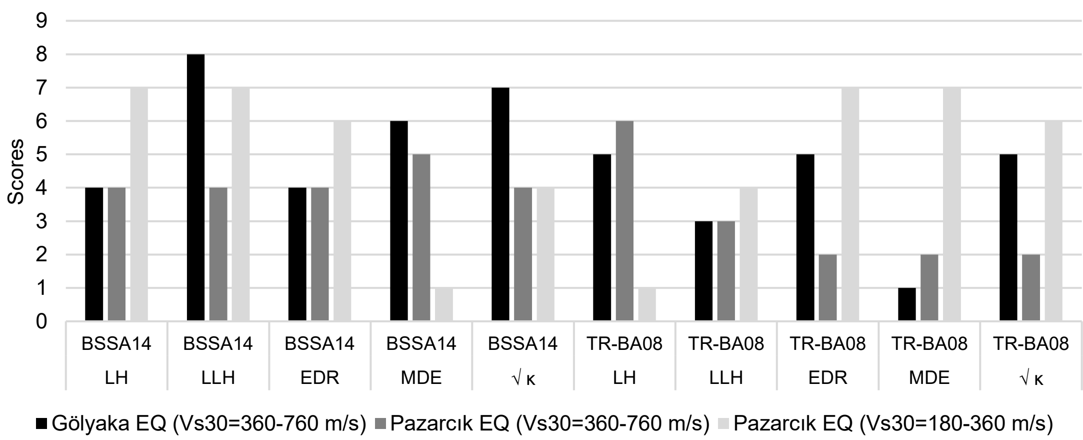


Fig. 5. Comparison of scores (a) BSSA14 and TR-BA08 (b) ASK14 and TR-AS08 (c) CY14 and TR-CY08 (d) CB14 and TR-CB08

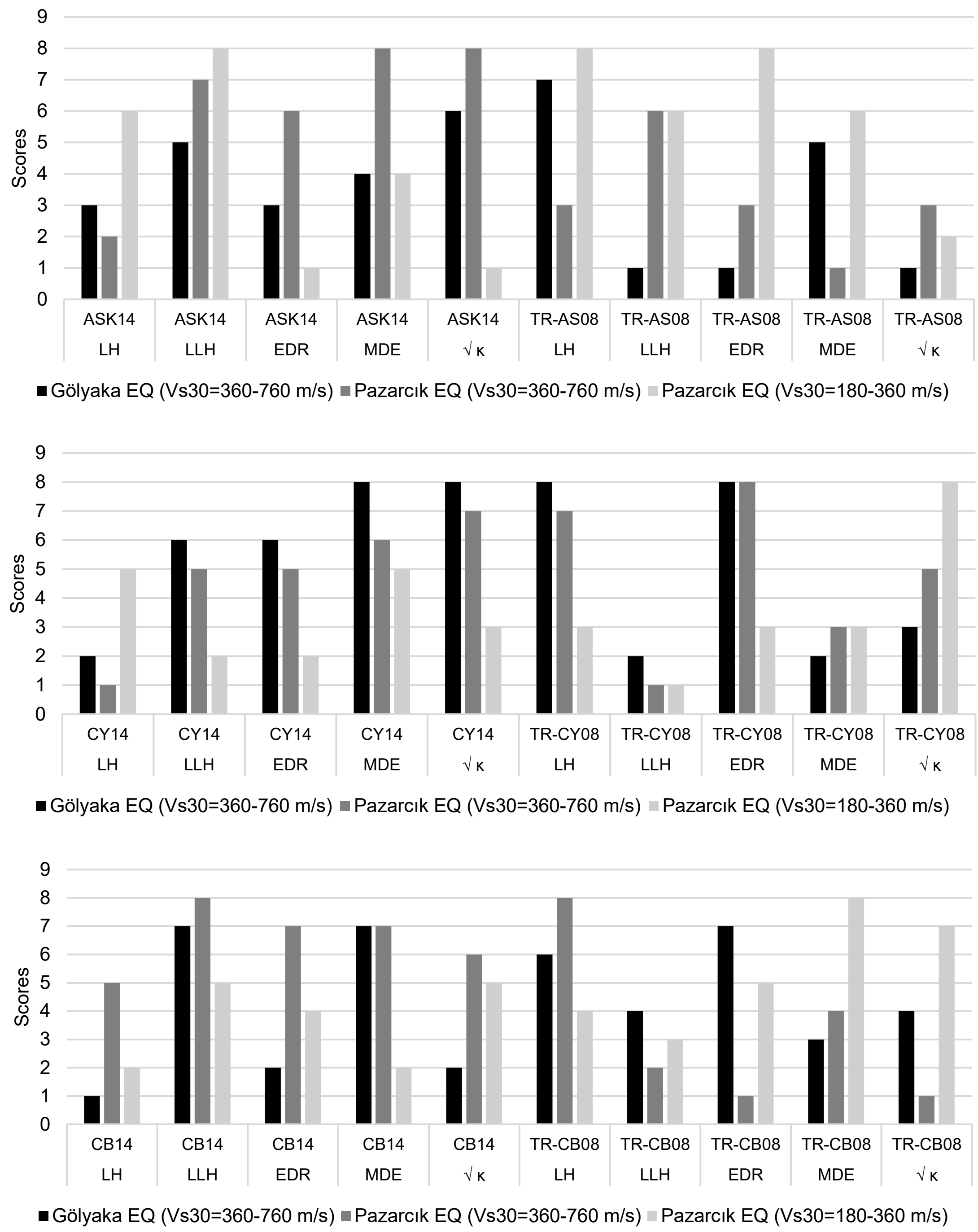


Fig. 5. Continued

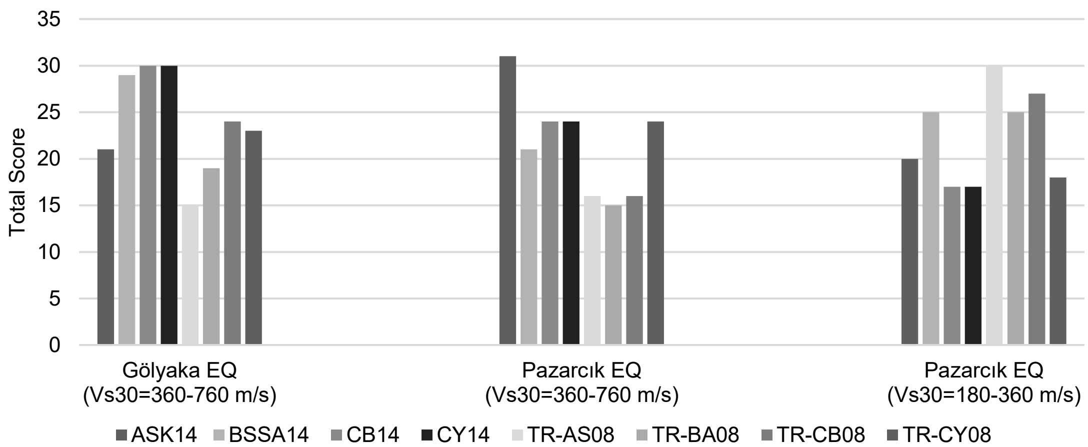


Fig. 6. Total scores for GMPEs

4. Discussion

The observed differences in GMPE performance across site classes can be explained by the underlying physical assumptions of the models. Under rock and stiff-soil conditions (Vs30 = 360–760 m/s), TR-CB08 showed better performance, likely due to its stronger sensitivity to source scaling and attenuation effects, which dominate when local site amplification is limited. In contrast, CY14 and TR-CY08 generally showed competitive performance under medium-to-soft soil conditions (Vs30 = 180–360 m/s), possibly because their formulations more effectively capture Vs30-dependent nonlinear site amplification. These findings suggest that GMPE performance depends not only on statistical fit but also on how well each model represents source, path, and site effects. Therefore, using multiple GMPEs within a logic-tree framework remains important for reducing epistemic uncertainty in PSHA.

5. Conclusions

Based on the comprehensive statistical analyses conducted in this study, the key findings regarding the performance of Ground Motion Prediction Equations (GMPEs) for the Gölyaka (Mw 5.9) and Pazarcık (Mw 7.7) earthquakes are summarized as follows:

1. The performance of GMPEs varies significantly depending on earthquake magnitude, source characteristics, and site conditions. The results obtained for the Gölyaka (Mw 5.9) and Pazarcık (Mw 7.7) earthquakes clearly demonstrate that no single model exhibits superior performance across all scenarios.
2. The TR-CY08 model shows strong overall performance among the Turkey-adjusted models. The low residuals and low EDR scores observed particularly on medium–soft soil conditions indicate the model's enhanced applicability for regional studies.
3. The TR-CB08 model exhibits the highest performance for the Pazarcık earthquake under rock and stiff soil conditions. This finding highlights the effectiveness of the Turkey-adjusted calibration in improving predictive capability for large-magnitude earthquakes and for short-to-intermediate spectral periods.
4. TR-AS08 and TR-BA08 generally demonstrate lower performance, while ASK14 shows moderate but scenario-dependent agreement with observations.
5. When the EDR, LH, LLH, MDE, and $\sqrt{\kappa}$ analyses are evaluated collectively, it becomes evident that site class has a significant effect on GMPE performance.
6. A balanced distribution of performance was observed between the Turkey-adjusted models and NGA-West2 models across different metrics in both earthquake scenarios. Therefore, rather than relying on a single model, the use of multiple GMPEs within a logic-tree framework is necessary.
7. The scores computed using the UNW method provide a practical basis for weighting GMPEs in logic-tree applications.
8. This study provides one of the few comprehensive multi-criteria evaluations of GMPE performance using strong-motion data from the 2022 Gölyaka and 2023 Pazarcık earthquakes.

Declarations

Conflict of interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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Author contributions

All authors contributed equally to this study. All authors have read and approved of the final manuscript and accept equal responsibility for its content.

Data availability statement

The data presented in this study are available on request from the corresponding author.

Use of generative AI and AI-assisted technologies

During the preparation of this work, the author(s) used ChatGPT to improve the manuscript's clarity, grammar, and academic style. The author(s) reviewed and edited the content and took full responsibility for the published article.

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