# Ranking of GMPEs for Seismic Hazard Analysis in Iran Using LH, LLH and EDR Approaches

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## ABSTRACT

*One of the most critical steps of seismic hazard and risk analysis is selecting the appropriate GMPEs to address strong ground motion based on earthquake parameters. In fact, appropriate modeling of this epistemic source of uncertainty in analysis is a non-trivial approach that is an active area of research. From statistical point of view, this issue can be resolved by measuring the good-of-fit, which describes how well a model fits a set of observations. In this study, the suitability of a set of local, regional and global GMPEs based on the three approaches of LH, LLH and EDR for two distinct seismotectonic regions of Iran have been assessed. Analyses show general compatibility between the order of ranking in both approaches of LH and LLH while the order of ranking in EDR approach shows significant differences. This contradiction come from their conceptual differences, in which the approaches like LH and LLH the overall performance of a model is assessed in an index and the individual effect of other parameters are not examined.*

**Keywords:**
Seismic hazard; Risk analysis; Ranking of GMPEs; Seismotectonic regions; Iran; LH and LLH methods; EDR index

## 1. Introduction

Estimation of probabilistic seismic hazard in a region is one the most important challenges in the field of engineering seismology. The main goal of such analysis is to estimate the probability of the occurrence of a given ground motion parameter in future time window. Such information provides valuable basis for deriving of design ground motion parameters in structural codes and standards. Additionally, it is a key step for the evaluation of seismic risk and loss estimation in a region. The most prevalent approach for quantifying such parameters is the approach proposed by Cornell (1968) [1] and then enhanced by Mc-Guire [2]. This approach is formed based on the total probability theorem in which the probability of the occurrence of a given strong ground motion is estimated by integrating possible earthquake sources and their resulting ground motion values over time. Despite of its straightforward implementation of the conventional approach, the proper way of incorporating of uncertainties in analysis is a great challenge and is one of the most active areas of the research. The terms aleatory and epistemic describe the key elements of total uncertainties. The first one describes the uncertainty due to intrinsic randomness nature of the event, which is modeled and calculated by the basic formulation of the conventional approach, and the latter one represents the uncertainty due to lack of scientific knowledge about the model and its parameters. This source of uncertainty is taken into account by means of the logic tree approach that is described by Bommer et al. [3]. The main focus of this paper is manipulating of the epistemic uncertainty related to the selection, ranking and weighting of ground motion prediction equations (GMPEs), which is necessary for performing PSHA analysis in the conventional approach.

GMPEs describe the decay of ground motion with distance as a function of earthquake magnitude, distance, and site characteristics to compute the probability of exceedance acceleration from a given value. The point that should be considered in this regard is that the GMPEs are derived from incomplete knowledge about the earthquake source and wave propagation throughout a complex media. Therefore, full reality cannot be modeled in GMPEs. This means that all GMPEs are approximate relation for the estimation of unknown true value. In this manner, selection of the most appropriate GMPEs and determining of their corresponding weights to be used in logic tree is a challenging issue. From statistical point of view, this issue can be resolved by measuring the good-of-fit that describes how well a model fits a set of observations. In this regard, two approaches of the likelihood and average log likelihood (LH and LLH) proposed by Scherbaum et al. [4-5] are popular amongst the seismologists. In both approaches, the suitability of a GMPE model is examined by residual of observed data with respect to the predictive models. Hintersberger et al. [6], Ghasemi et al. [7], Delavaud et al. [8], Mousavi et al. [9], Zafarani and Mousavi [10] used these approaches for the selection and ranking of GMPEs in different regions. Kale and Akkar [11] represent an alternative approach based on the Euclidian Distance (EDR) for ranking of GMPEs. In that approach, ranking procedure is done based on the two different indices; the ground motion uncertainty and the biased between the observed ground motion data set and the median value of GMPEs. Pavel et al. [12] evaluated the applicability of various GMPEs in Vrancea sub crustal seismic zones by implementing the EDR approach.

In this paper, the suitability of a set of candidate GMPEs for Iranian plateau based on the approaches of LH, LLH and EDR will be assessed, and the result of different approaches will be compared. These analyses will be performed for two different seismotectonic zones of Zagros, and Alborz and central Iran (Figure 1). This separation is due to the differences in seismotectonic and geological characteristics between those regions which are reflected in the studies of Mirzaie et al. [13], Berberian [14], and Nowrozi [15].

In following, first, a brief review of the principles of the ranking approaches of LH, LLH and EDR will be presented. Then, testing dataset used for ranking of GMPEs in Zagros and Alborz regions will be introduced. Finally, the result of various approaches of the ranking procedures in two regions for a set of candidate GMPEs will be represented and compared comprehensively.

## 2. The LH, LLH and EDR Ranking Procedures of GMPEs

Scherbaum et al. [4] studied various approaches of the hypothesis testing methods for the evaluation of the suitability of GMPEs and proposed a quantitatively likelihood approach (LH). In that approach, the goodness of fit of a model to some observed data is assessed based on a likelihood parameter as LH value that determines the probability of exceedance of the normalized residuals for any observation with the following relation.

$$LH(|Z_0|) = \frac{2}{\sqrt{\pi}} \int_{\frac{|Z_0|}{\sqrt{2}}}^{\infty} e^{-t^2} dt = Erf\left(\frac{|Z_0|}{\sqrt{2}}, \infty\right) \quad (1)$$

where $Z_0$ is a normalized residual and defined as the difference between the observed and predicted value divided by the standard deviation of GMPE and $Erf$ is an error function for normalized residual. By this equation, the normalized residual is assumed to follow the lognormal distribution map into a uniform distribution as LH. In this approach, an ideal model, which is assumed to follow a lognormal distribution with zero mean and unit variance, transforms into an evenly uniform distribution with a median LH value equal to 0.5. Any deviation in the mean and

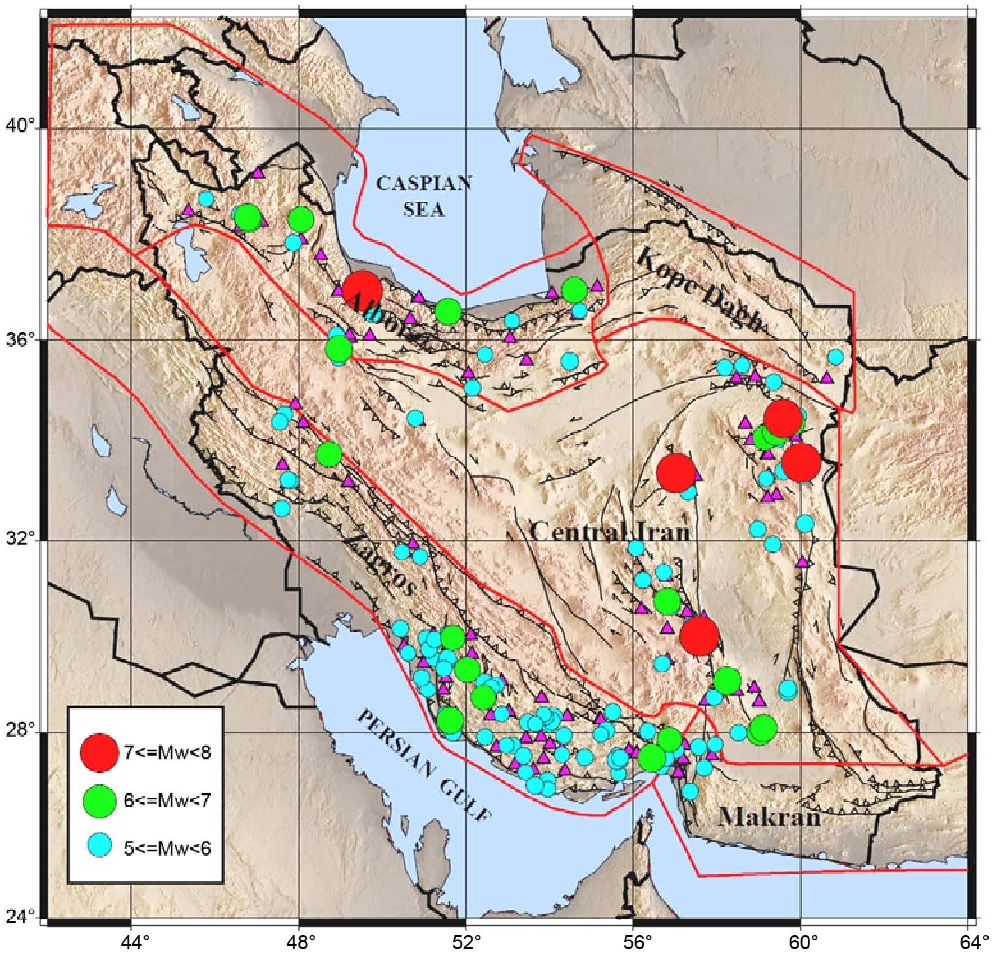



**Figure 1.** Seismotectonic map of Zagros, and Alborz and Central Iran.

standard deviation of the lognormal distribution will be reflected in the median and standard deviation of the LH values. Scherbaum et al. [4] represent a classification scheme for GMPEs based on the median value of LH (MEDLH), absolute value of the mean and median of normalized residual (MEDNR and MEANNR), and their standard deviation (STDNR).

It should be mentioned that the LH procedure represented by Scherbaum et al. [4] is based on the total residual and the variability of inter-event (i.e. event to event) and intra- event (i.e. within event) residuals are not considered. This issue may result in biased; especially in cases where certain events provide large numbers of records to the overall dataset [16]. To this end, Stafford et al. [16] represented a modified equation for the calculation of LH as follows:

$$\ln L = \sum_{i}^{N_E} \sum_{j}^{n_i} \ln\left[\frac{1}{\sigma}\varphi\left(\frac{LnY_{ij} - LN\widehat{Y}_{ij} - \eta_i}{\sigma}\right)\right] \quad (2)$$

where $\eta_i$ is the inter-event residual of the i$^{th}$ earthquake and determined by Equation (3).

$$\eta_i = \frac{\tau^2 \sum_j^{N_E} r_{ij}}{\tau^2 N_E + \sigma^2} \quad (3)$$

In Equations (2) and (3), the $N_E$ is the total number of earthquakes contributing records to the dataset, with the ith event contributing ni records, and $\varphi(x)$ is the probability density function of the standard normal distribution; $r_{ij}$ is the total residual that is defined as the difference between the observed value $(Y_{ij})$ and median estimate $(\widehat{Y}_{ij})$. It should be noted that in this study, the separation of inter-event and intra-event residual is not considered because our testing dataset is not composed of events with a large number of observations that may bias the results. The distribution of inter-event and intra-event residual is assessed visually.

The dependency of LH method to ground motion data size and the need for subjectively decision about the threshold of acceptance are the main shortcoming of LH approach. To overcome these weaknesses, Scherbaum et al. [5] represent an alternative approach for assessing the appropriateness of GMPEs based on the information theory. In term of information theory, the relative information loss or the Kullback-Leibler distance that is defined as the difference between the expected value of the true model and the expected value of approximate model with respect to the true model, is used as an index for suitability of an approximate model.

$$D(f,g) = E_f(\log_2(f)) - E_f(\log_2(g)) \quad (4)$$

By this scheme, in comparison of two approximate models (e.g. $g1$ and $g2$) the expectation of the unknown true term cancelled out from the formulation and just the expectation of the approximate model with respect to the true model is remained, and this term is estimated by the average log likelihood.

$$LLH \approx \frac{1}{N}\sum_{i=1}^{N}\log_2(g(x_i)) \quad (5)$$

In Equation (5), the LLH value that represents the probability of occurrence of observed samples by the consideration of the probability distribution of the GMPEs is used as an index for appropriateness. In this context, the lower value of LLH implies the better model. It should be noted, in theory, that the LLH approach can be applied to whatever amount of data, but a question come to mind "what is the minimum number of required observation to achieve a stable result?" In this regard, Beauval et al. [17] performed a synthetic test on the LLH values and pointed out that at least ~40 observation is required to achieve stable results. Scherbaum et al. [5] represent the following relation for assigning appropriate weights to the GMPEs based on the LLH values:

$$w_j = \frac{2^{-\log_2^{(LLH_j)}}}{\sum_{j=1}^{k} 2^{-\log_2^{(LLH_j)}}} \quad (6)$$

Although the LH and LLH are the powerful approaches for selecting and ranking of GMPEs, they may result in unrealistic ranking of GMPEs due to combining of all characteristics of a model in formulations. In these approaches, the other features of a model like aleatory uncertainty, magnitude scaling, distance scaling and site effect are not tested separately. Kale and Akkar [11] by implementation of an illustrative example, showed that in cases that two models represent similar values of median, the LLH approach favors the model with higher values of standard deviation. In particular, this conservative aspect of LLH in seismic hazard analysis of critical structure such as nuclear power plants, which is designed for a very long return period, may culminated in inappropriate selection and ranking of GMPEs. Based on the above explanation, Kale and Akkar [11] introduced an alternative approach for ranking of GMPEs based on the Euclidean distance concept. In that approach, the aleatory uncertainty of GMPEs and the bias between the observed ground motion data and the predicted values, as the two major features of GMPEs, are considered in assessing the appropriateness of GMPEs with different indices and the ultimate ranking is represented based on the combination of these indices. The consideration of the aleatory uncertainty of GMPEs in ranking procedure is analogous to the implementation of predictive models in PSHA. That is by assumption of the normal distribution for the logarithmic distribution of GMPEs, the estimation of various levels of probability is obtained. Then, by the summation of the differences between the observed data and the possible range of GMPE with consideration a band which is a multiplier of standard deviation, the modified Euclidean distance (MDE) is obtained. In the context of the EDR ranking procedure, the MDE index stands for the aleatory uncertainty of GMPEs. The second index of ranking of GMPEs in EDR approach is the trend between the observed data and corresponding median of GMPEs that is an indicator of the bias. The bias is measured by the κ parameter, which is the ratio of Euclidean distance original observed data set and the Euclidean distance of the corrected values. Clearly, for an ideal unbiased model the κ parameter will be equal to one. The final form of the EDR ranking procedure that is a combination of the above indices is represented as below:

$$EDR = \sqrt{\kappa \frac{1}{N}\sum_{i=1}^{N} MDE^2} \quad (7)$$

where $N$ is the number of observed dataset. In Equation (7), the κ parameters act as penalty in the case that there is bias between the model and observed data. Based on the above formulation, the smaller value of EDR represents the better model.

## 3. Composition and Processing of the Testing Database

In many researches, the differences of seimo-tectonic and geological characteristics between Zagros, and Alborz and Central Iran zones are highlighted. Accordingly, in this study, the suitability of various GMPEs are evaluated separately in these two regions. Based on Mirzaie et al. [13], the Zagros and Makran considered as a single region and Azerbaijan-Alborz, Kopeh-Dagh, and central-east Iran considered as another region (Figure 1).

Providing a reliable database for testing the appropriateness of GMPEs is a fundamental pre-requisite for such analysis. This database should cover earthquake parameters, station characteristics and record information. In this research, the dataset used to test the applicability of GMPEs has been acquired from the Iranian Strong Ground Motion Network operated by Building and Housing Research Center (BHRC). In addition, the high-quality dataset represented by Zafarani and Soghrat [18] is considered in developing the strong ground motion dataset. The final dataset is composed of 348 three-component accelerograms from 93 earthquakes in which 180 records from 42 earthquakes belong to Alborz and Central Iran and 168 records of 51 earthquakes belong to the Zagros region. It should be mentioned that the database is selected somehow to be compatible with the validity range of candidate GMPEs. To this end, the dataset restricted to the events with epicentral distance between 5 to 100 Km and the moment magnitude greater than 5.0. In Figure (1), the distribution of selected earthquakes and stations is depicted. In attached electronic file, a detailed characteristics of the database including the date and time of event, magnitude, location of events and station, epicentral distance, VS30 and the code number is presented.

The earthquake parameters of the dataset are extracted from the Global Centroid Moment Tensor (GCMT) in which for all events, full waveform inversion was performed and moment tensor, moment magnitude and focal depth are available. The style of faulting for each event has been determined based on the obtained moment tensor and adopting the approach proposed by Frohlich and Apperson [19]. Considering the GCMT catalog, all distance metrics including $R_{rup}$, the shortest distance between the station and the rupture surface, $R_{jb}$, the Joyner-Boore distance that is closest horizontal distance to the surface projection of the causative fault, $R_{epi}$, epicentral distance and $R_{hyp}$, hypocentral distance for all events have been determined. Reliable estimation of distance parameters is a critical feature of the database since various GMPEs use different distance metrics for describing the source to site distance. In Figure (2), the magnitude distance distribution of the dataset in Zagros and Alborz and

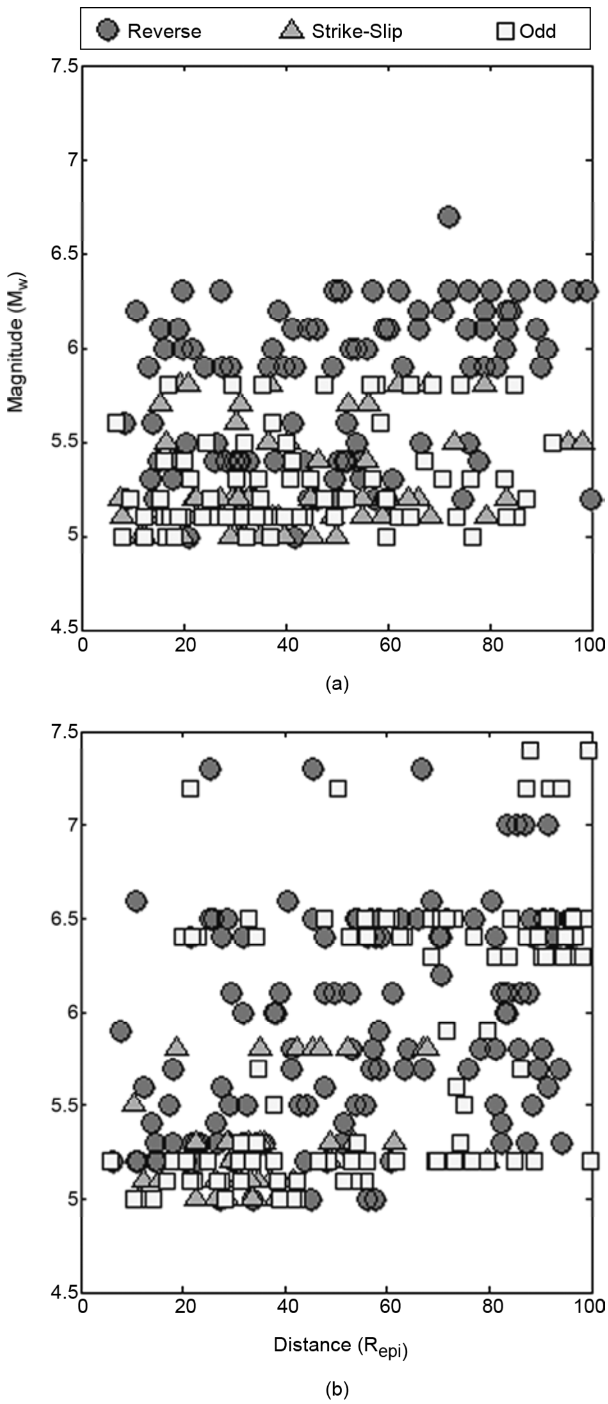



**Figure 2.** Magnitude distance distribution of events based on the style of faulting in a) Zagros b) Alborz and central Iran.

central Iran with respect to various styles of faulting is shown. As it is clear, the dominant rupture mechanism is reverse that is followed by odd and strike-slip. Regarding the events with unknown style of faulting, a sensitivity analysis was performed. The analysis indicates that the order of ranking is not significantly changed by omitting events with unknown style of faulting and averaging ground motion shaking resulting from strike-slip and reverse mechanisms. Nevertheless, in the final analysis, only events with known mechanism is used. This restriction filtered out 85 and 105 records from the Zagros and Makran as well as Alborz and Central Iran, respectively.

For processing the uncorrected time histories, a uniform procedure based on the nonlinear adaptive wavelet de-noising method proposed by Ansari et al. [20] has been used. Ansari et al. [20] pointed out that the displacement response spectra of wavelet de-noising records are more stable than conventional filtered records with respect to different correction functions. By using that approach, it is possible to retrieve a large number of records that were not possible to be corrected using conventional approach of correction.

The soil characteristic of stations is another critical parameter that should be considered in the database. The soil amplification is modeled in the GMPEs either by the definition of a dummy variable stands for different soil types or by the average shear wave velocity over the top 30 meters (VS30) which is applied in the more recent GMPEs. Although the shear wave velocity (VS30) can be estimated by the proxy approaches such as the topography slope [21] or using Horizontal to Vertical Spectral Ration (HVSR) [22]. Here, for reducing the uncertainty, only records are considered in the database which the VS30 is measured. In Figure (3), the magnitude distance distribution of events for different soil types based on the definition of National Earthquake Hazard Reduction (NEHRP) is presented.

The way of combining two horizontals, orthogonal components of ground motion records to a single value is another point that should be considered in database. While the older GMPEs use simple parameters such as the maximum value, average or the geometric mean of two horizontal components, recent GMPEs utilizes the more complicated parameters such as GMROT50 and the average horizontal rotation independent (RotD50) defined by Boore et al. [23] and Boore [24]. The latter is the definition that is used in the NGA-West2 models. Some studies have shown that the ratio of GMRotI50 to geometric mean is near unity. Zafarani et al. [25] used the geometric mean in developing their relation. Here, to avoid any inconsistency, all of the above definitions of the combination of horizontal components for each record have been obtained, and for evaluation of various GMPEs the corresponding

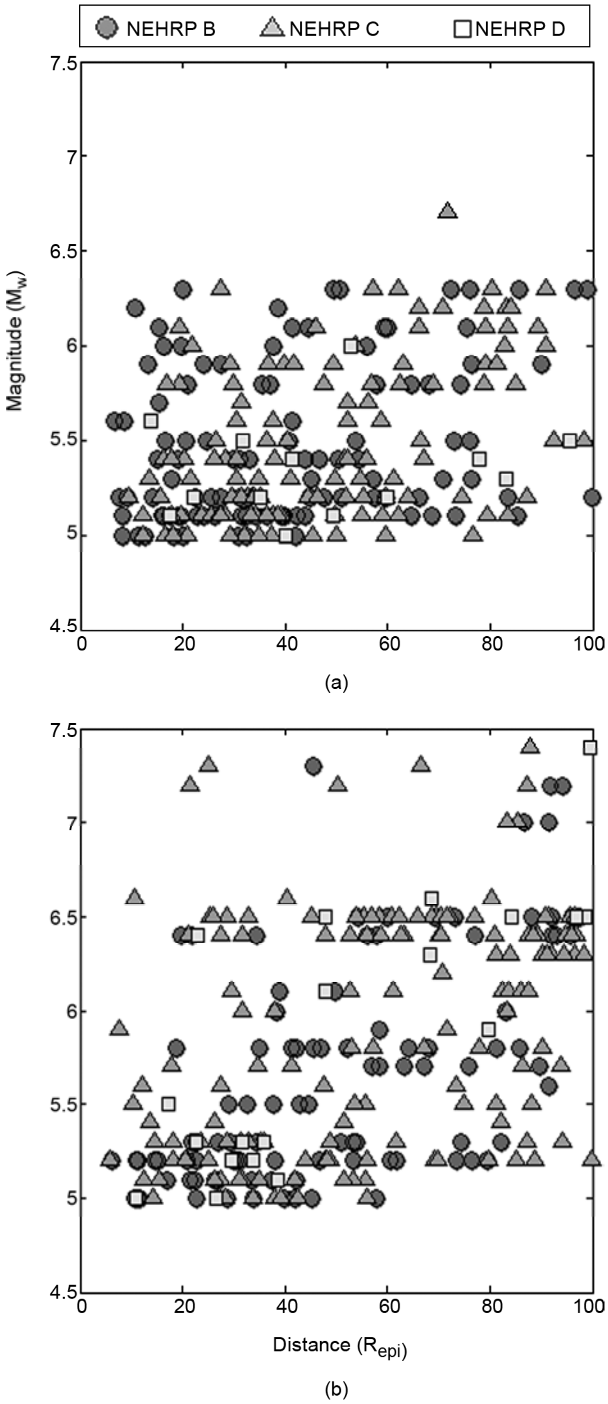



**Figure 3.** Magnitude distance distribution of events based on the soil type in a) Zagros b) Alborz and central Iran.

definitions with respect to the predictive model were used.

## 4. Selection of the Candidate GMPEs

Selecting appropriate predictive models amongst a large amount of available GMPEs needs a series of criteria. This subject is of interest of many researchers including Cotton et al. [26] and Bommer et al. [27]. Cotton et al. [26] proposed seven criteria for the selection and ranking of GMPEs and later Bommer et al. [27] has updated those criteria. Accordingly, 11 candidate GMPEs have been selected. In Table (1), list of candidate GMPEs with their abbreviation and their main characteristics are presented. Amongst them, the relation of Getal09 has been developed specially for the region of Iran, relations of AB10, AC10 and Ketal15 have been developed based on the regional dataset, the relation of NGA-WEST2 has been developed based on the global dataset, and Zetal06 and Ketal06 have been developed mainly based on the Japan's events. It should be noted that the relations of Zafarani and Soghrat [39] and Soghrat et al. [40] are not considered in the candidate GMPEs, because these relations have been presented for a specific zone of Iran not the whole country.

Amongst the candidate GMPEs, the relation of Getal09 is the simplest model which uses a dummy variable for considering different soil types. Style of faulting is not considered in that relation, which do not comply with the criteria of Bommer et al. [27] and therefore, should be disregarded. However, because of the good performance of this relation

**Table 1.** Main characteristics of candidate Ground Motion Prediction Equations.

| GMPE | Acronym | Main Region | Magnitude (Mw) | Distance Metric | Component* | Period Range | Site Effect (Number of Soil Classes) |
|---|---|---|---|---|---|---|---|
| Kale et al. [28] | Ketal15 | Turkey, Iran | 4.0-8.8 | $R_{jb}$, 0-200 | PGA, PGV, SA in G | 0-4 sec | Vs30 |
| Ghasemi et al. [29] | Getal09 | Iran, West Eurasia | 5.0-7.4 | $R_{hyp}$, 0-100 | PSA in GMRotI50 | 005-3.0 sec | Dummy Variable (2) |
| Akkar Bommer [30] | AB10 | Europe, Middle East | 5.0-7.6 | $R_{jb}$ 0-100 | PGA, SA in G | 0-3.0 sec | Dummy Variable (2) |
| Akkar Cagnnon [31] | AC10 | Turkey | 4.0-7.4 | $R_{jb1}$-200 | PGA, PGV, SA in G | 0-2.0 sec | Vs30 |
| Abrahamson et al. [32] | ASK14 | Worldwide shallow Crustal with Concentration from California | 3.0-7.9 | $R_{rup}$, 0-400 | PGA, PGV, SA in RotD50 | 0-10 sec | Vs30 |
| Campbell and Bozorgnia [33] | CB14 | Worldwide Shallow Crustal with Concentration from California | 3.0-7.9 | $R_{rup}$, 1-300 | PGA, PGV, SA in RotD50 | 0-10 sec | Vs30 |
| Boore et al. [34] | BSSA14 | Worldwide Shallow Crustal with Concentration from California | 3.0-7.9 | $R_{rup}$, 0-400 | PGA, PGV, SA in RotD50 | 0-10 sec | Vs30 |
| Chiou and Youngs [35] | CY14 | Worldwide Shallow Crustal with Concentration from California | 3.5-7.9 | $R_{rup}$, 1-300 | PGA, PGV, SA in RotD50 | 0-10 sec | Vs30 |
| Idriss [36] | I14 | Worldwide Shallow Crustal with Concentration from California | 4.5-7.9 | $R_{rup}$, 1-200 | PGA, SA in RotD50 | 0.01-10 sec | Vs30 |
| Zhao et al. [37] | Zetal06 | Japan + some Foreign | 4.9-7.2 | $R_{hyp}$, 0-280 | PGA, PGV, SA in G | 0-5.0 sec | Dummy Variable (4) |
| Kanno et al. [38] | Ketal06 | Japan + some Foreign | 5.0-8.0 | $R_{rup}$, 1-400 | PGA, PGV, SA in G | 0-5.0 sec | Vs30 |

* G: Geometric mean, GMRotI50, rotation-independent average horizontal component, RotD50, average horizontal rotation independent (RotD50)

reflected in the studies of Zafarani and Mousavi [10] and Mousavi et al. [9], it is preferred to retain this relation. Ketal15 is the most recent and the most complicated predictive model among the regional candidate GMPEs. It considers the nonlinear soil behavior as well as the rupture mechanism that is a rare feature in Iranian GMPEs relations. In that relation, the effects of regional differences between Iran and Turkey that originates from differences in Q factors, kappa, and near-surface velocity are considered. AB10 has been developed based on the data of Europe and Middle East; in that relation different soil types have been considered in the relation by a simple dummy variable that imposed a high value of uncertainty. The relation of AC10 has been developed based on the compiled Turkish database for estimation of peak ground acceleration, velocity and spectral acceleration. In that relation, the style of faulting and the linear and nonlinear response of the soil are considered in estimation of the ground motion values.

The NGA-West2 models are another group of GMPEs used in the ranking procedure. The NGA-West2 project is a large multidisciplinary, multiyear research program on the Next Generation Attenuation (NGA) models for shallow crustal earthquakes in active tectonic regions. This is the second phase of the NGA project that is followed by the NGA-West1 in which five developer teams work independently but interactively with each other to develop ground motion models applicable to different geographical regions. Updating NGA models for small, moderate and large events, developments relation for vertical component, considering damping scaling, modeling of directivity, analysis of epistemic uncertainty, and further development of site response are the key issues of NGA-West2 project. The main features of each model are comprehensively published in a series of reports by Pacific Earthquake Engineering Research Center (PEER). Besides, in Gregor et al. [41] a detailed comparison of NGA-West2 is introduced. In this study, the five NGA-West2 models (ASK16, BSSA16, CB16, CY16, and IM16) are considered in the ranking procedure of GMPEs based on the Iranian ground motion database.

The major challenging issue in implementation of the NGA-West2 models in Iran is the lack of sufficient knowledge about some of the input parameters. Parameters such as depth to top of rupture ($Z_{TOR}$), depth parameters of $Z_{1.0}$ and $Z_{2.5}$ that are defined as the depth at which the velocity of shear velocity is equal to 1.0 Km/s and 2.5 Km/s, and $R_X$ used for quantifying the hanging-wall are the most important parameters that should be estimated reasonably. Here, the general strategy for estimating these parameters is to use the recommendation relations or values of the model developer and in cases that no recommendation has been represented by the developers, the default value proposed by the Kaklamanos et al. [42] is used. Kaklamanos et al. [42] proposed some empirical relation in term of source, distance, and site parameters for estimation of the unknown parameters, when implementing the NGA models in engineering practice. It should be noticed that Jahanandish et al. [43] developed a correlation between $Z_{1.0}$ and $V_{S30}$ based on the randomly generated profiles.

The last group of GMPEs model is developed based on the data from Japan. Zhao et al. [37] present a GMPE model for shallow crust earthquakes in Japan. In their model, the site effect is considered by a dummy variable for different soil classes. The relation of Ketal06 is other model developed based on the Japan database. This relation has simple functional form. In that relation, the style of faulting is not used as a model predictor. Zafarani and Farhadi [44] show that these two Japanese relationships have a good performance for small to moderate earthquakes of Iran.

## 5. Ranking of Candidate GMPEs

In this study, the candidate models are ranked based on the three approaches of the LH, LLH and EDR and the order of ranking by each approach will be compared. This analysis is performed for the Peak Ground Acceleration (PGA) and six periods of 0.1, 0.2, 0.5, 1.0, 1.5 and 2.0 second. As the first ranking procedure, the LH is adopted. As it is discussed, this method uses the normalized residual and the LH values for assessing the suitability of a candidate model. The result of this approach can be evaluated by the visual inspection or a quantitative approach based on the classification scheme presented by Scherbaum et al. [4]. In Figure (4), the results of the ranking procedure for two distinct seismotectonic regions based on the classification of Scherbaum et al. [4] is depicted. Detailed statistical measurements including the median of LH, both central tendency parameter and the standard deviation of the normalized residual used in the classification procedure are presented in the attached electronic file. To provide an overall index for evaluating the performance of GMPEs in all periods, a scoring procedure is adopted in which a model with rank A to D in each period given a score equal to 4.0 to 1.0. By summation of the scores in all periods, the performance of GMPEs can be evaluated. It should be mentioned in this scoring procedure that the score of PGA that is not covered by the relation of Getal09 and I14 is excluded. In Table (2), the final order of ranking based on the LH approach is presented. As

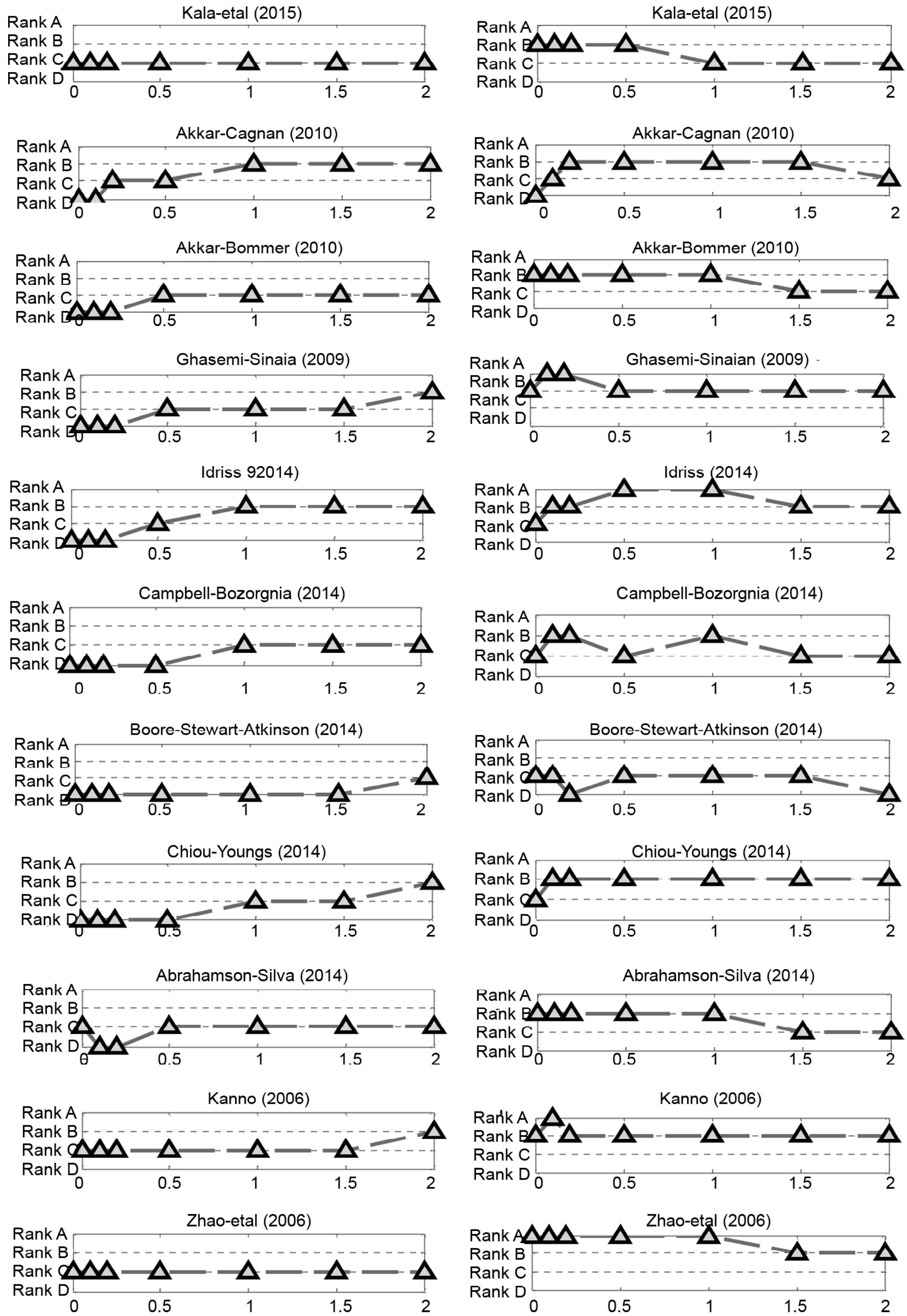



**Figure 4.** Performance of the candidate GMPEs based on the LH ranking procedure in a) Zagros region b) Alborz and central Iran.

shown, the general performance of GMPEs in the Alborz and Central region is much better than Zagros that is originated from the discrepancies of the seismotectonics features in those regions. Interestingly, in both regions, the relation of I14 shows good performance and the relation of CB14 and BSA14 are the worst models. It is worth noting that the relation of I14, which shows a good performance based on the LH ranking procedure is the simplest model among the NGA-West2. Generally, applying the simple functional form of GMPEs will culminate in a higher value of aleatory uncertainty. This means that the developer rather than incorporating the more complicated parameters in their models (due to the lack of information or any other reason) scarify the aleatory uncertainty. In some cases, this higher values of uncertainty in ranking procedure (like the LH which all aspect of a model performance and accuracy evaluated in an overall index) may result in an inappropriate ranking. Typical example of this issue is the relation of Getal09, which is ranked among the top models in both regions while the reliability of top rank of Getal09 should be analyzed separately by consideration of bias, standard deviation, and other parameters. In Figures (5) to (7), the distribution of total, intra-event and inter-event residuals of candidate GMPEs in the Zagros region, and Alborz and central Iran in periods of T=0.0, 0.5 and 1.0 second are illustrated. As depicted, in some candidate GMPEs such as Ketal06 and Zetal06, the residuals have uniform distribution around zero base line; while in some other models, the residuals trend to deviate from zero base line. Interestingly, in AC10 which shows a good performance based on the LH criteria, their corresponding residuals show deviation from zero base line. This issue points out the weakness of the LH criteria in revealing bias. In LH approach, the overall goodness of fit of a model is assessed in lumped manner. As a result, the error of different components can be compensated through the normalizing residuals. In Figures (8) to (10), the distribution of the estimated values of GMPEs and the observed data with $V_{S30}$ greater than 500 (m/s) in periods of $T$ = 0.0, 0.5 and 1.0 seconds are presented.

The LLH is used as another approach for ranking of GMPEs. This method that is proposed by Scherbaum et al. [5] uses the information theory for ranking of models. As it is discussed in that ranking procedure, a lower value of LLH indicates the better model. In Figure (11), the LLH values of all candidate models in discrete periods for Zagros as well as Alborz and Central Iran are depicted. The average of the LLH values in different periods, except the PGA that is not covered by the relation of Getal09 and I14, is used as an index for the overall performance of GMPEs for all periods. In Table (3), the final ranking of GMPE models based on the average of LLH values in all periods for two distinct seismotectonic regions is presented. By comparing the final ranking (Tables 2 and 3), which are obtained based on the LH and LLH, it can be observed that there is a general agreement between the orders of rankings. In both approaches the top five models in two seismotectonic regions are approximately the same. According to Scherbaum et al. [5], this consistency in the ranking order of the LH and LLH is not surprising due to their correlation, which is shown by an illustrative example in Scherbaum et al. [5]. In Table (4), the corresponding weights of the top five GMPE models based on LH and LLH approaches according to Equation (6) are presented.

**Table 2.** The final ranking of candidate GMPEs in the two distinct seismotectonic region.

| Zagros | Score | Alborz and Central Iran | Score |
|---|---|---|---|
| AC10 | 15 | Zetal06 | 26 |
| Ketal06 | 15 | Getal09 | 23 |
| Ketal15 | 14 | I14 | 22 |
| I14 | 14 | Ketal06 | 22 |
| Zetal06 | 14 | CY14 | 20 |
| Getal09 | 12 | AB10 | 19 |
| ASK14 | 12 | ASK14 | 19 |
| AB10 | 11 | Ketal15 | 18 |
| CY14 | 11 | AC10 | 17 |
| CB14 | 10 | CB14 | 17 |
| BSSA14 | 8 | BSSA14 | 12 |

**Table 3.** The final ranking of candidate GMPEs based on the average of LLH in all periods in different seismotectonic region.

| Zagros | LLH | Alborz and Central Iran | LLH |
|---|---|---|---|
| Zetal06 | 2.35 | Zetal06 | 1.88 |
| Ketal15 | 2.35 | Getal09 | 1.88 |
| Getal09 | 2.37 | AB10 | 1.91 |
| Ketal06 | 2.41 | Ketal15 | 1.95 |
| I14 | 2.50 | I14 | 1.97 |
| ASK14 | 2.51 | Ketal06 | 1.97 |
| AC10 | 2.60 | CY14 | 1.97 |
| CY14 | 2.60 | ASK14 | 2.01 |
| CB14 | 2.65 | CB14 | 2.03 |
| AB10 | 2.67 | AC10 | 2.08 |
| BSA14 | 2.81 | BSA14 | 2.41 |

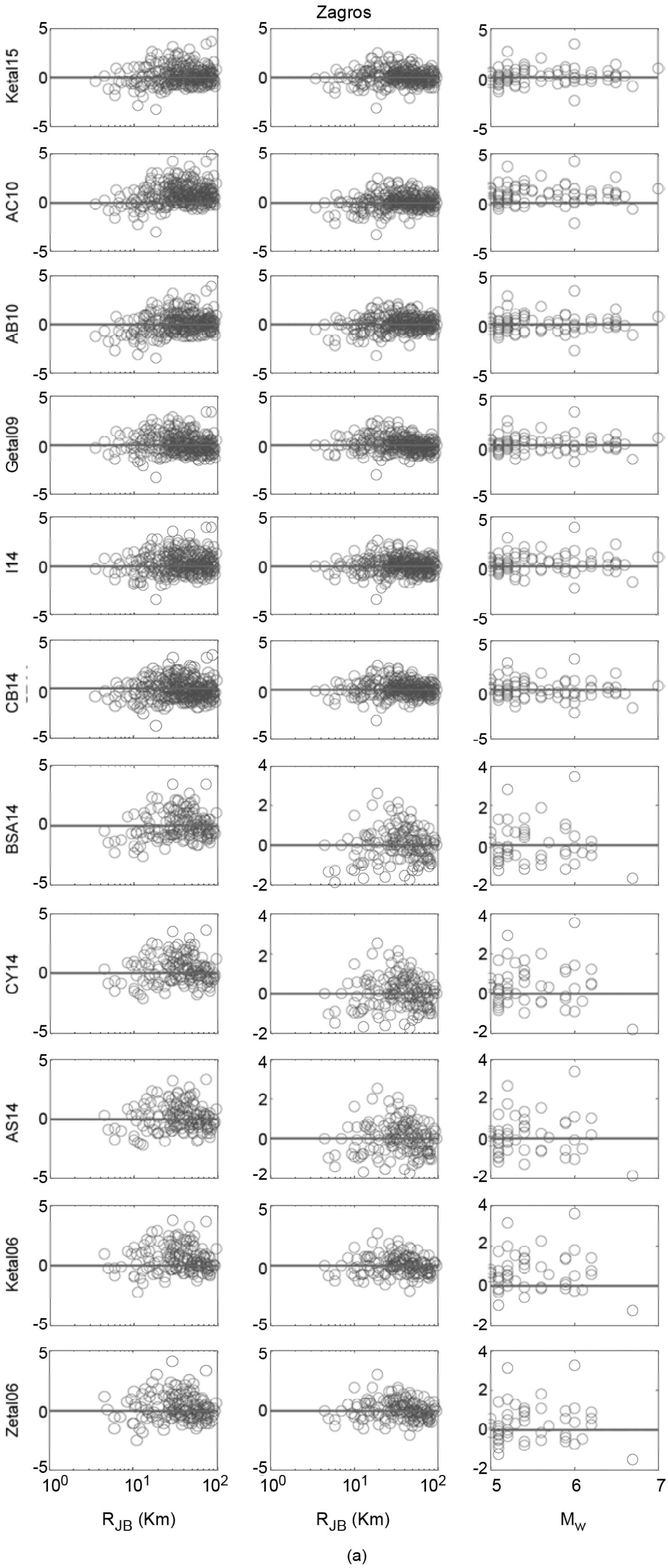
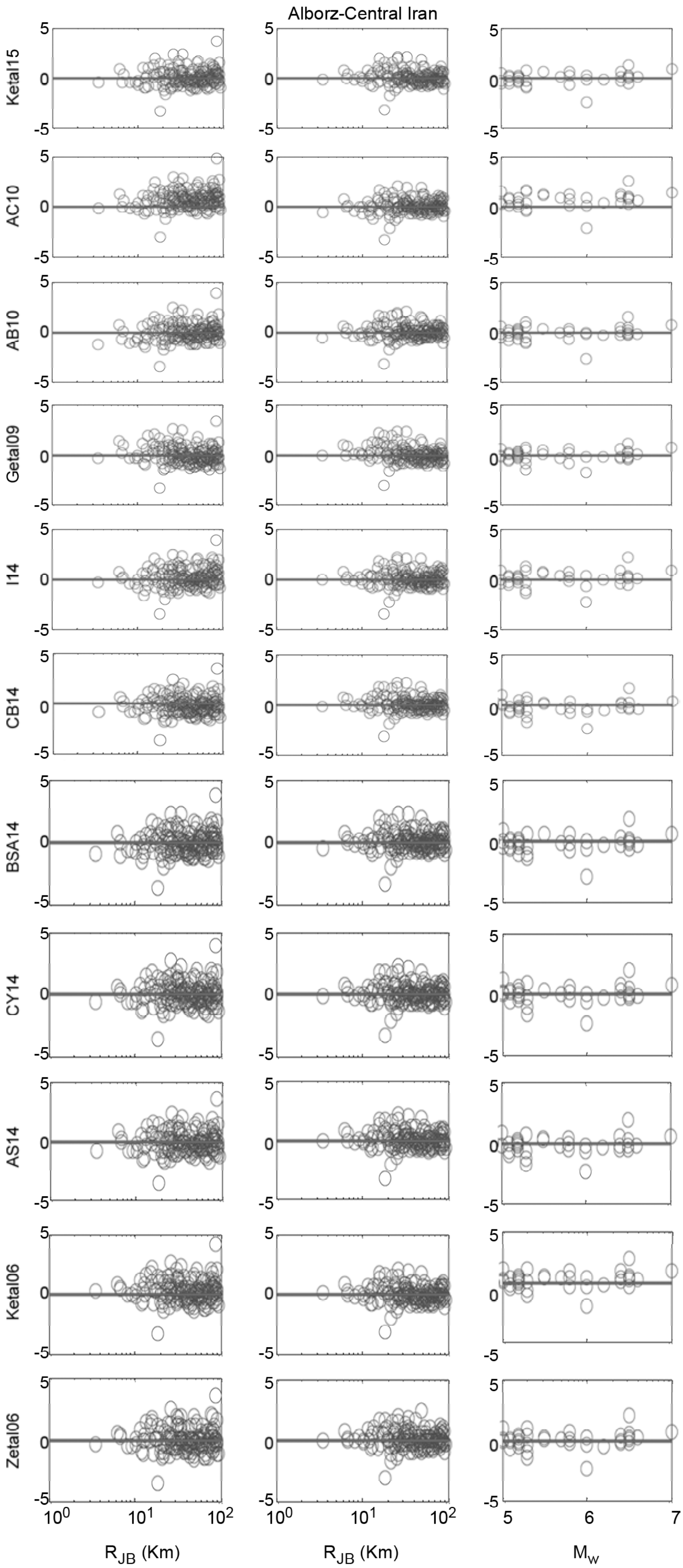



**Figure 5a.** Distribution of total, intra-event and inter-event residuals of candidate GMPEs in Zagros in T=0 (sec).




(b)

**Figure 5b.** Distribution of total, intra-event and inter-event residuals of candidate GMPEs in Alborz and central Iran in T=0 (sec).

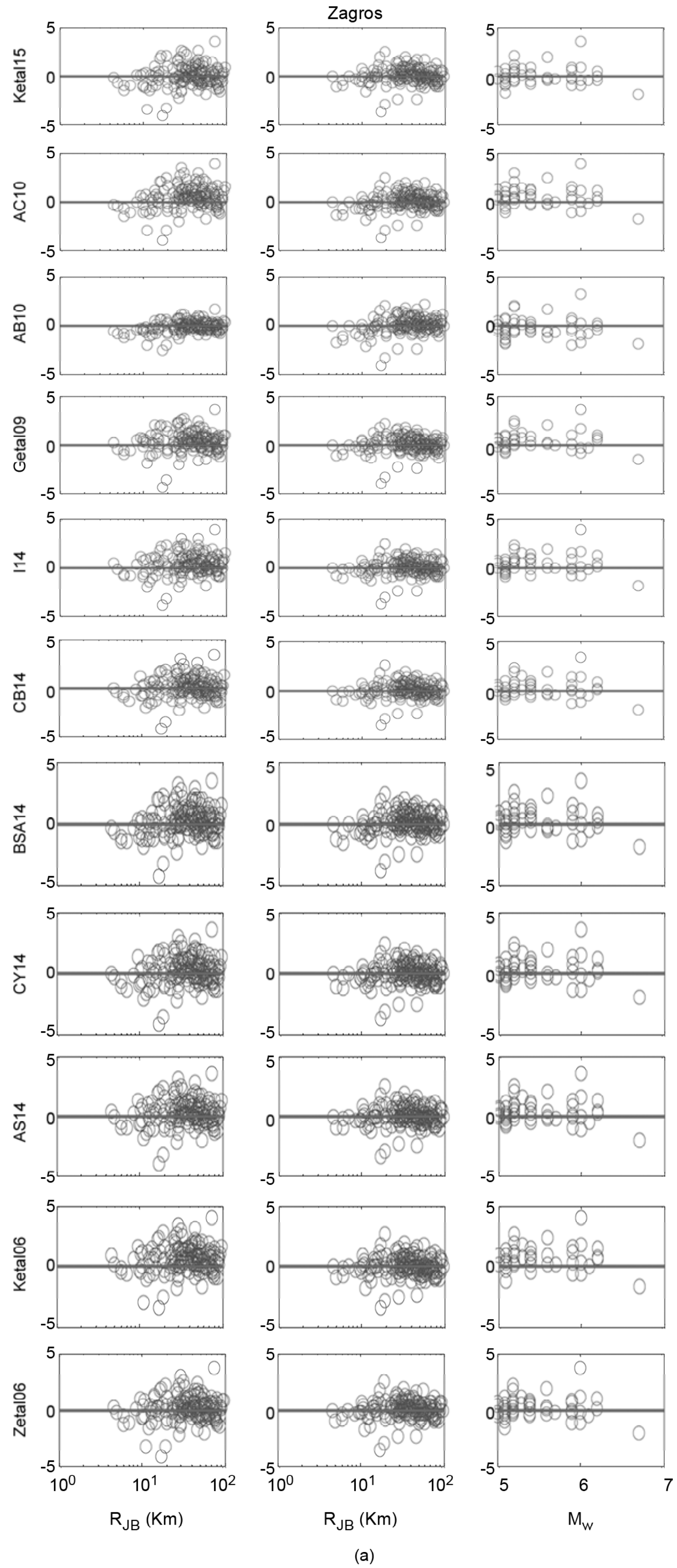
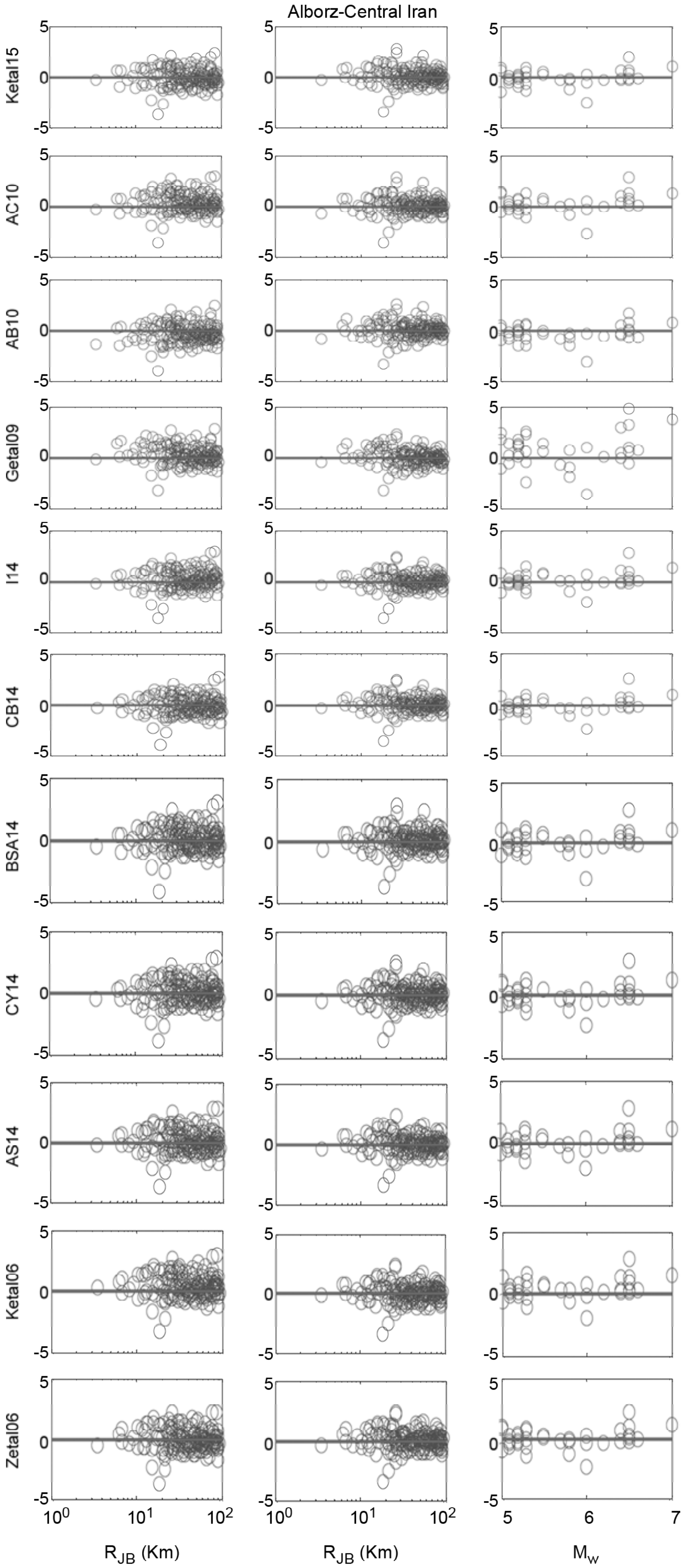



**Figure 6a.** Distribution of total, intra-event and and inter-event residuals of candidate GMPEs in Zagros in T=0.5 (sec).




(b)

**Figure 6b.** Distribution of total, intra-event and inter-event residuals of candidate GMPEs in Alborz and central Iran in T=0.5 (sec).

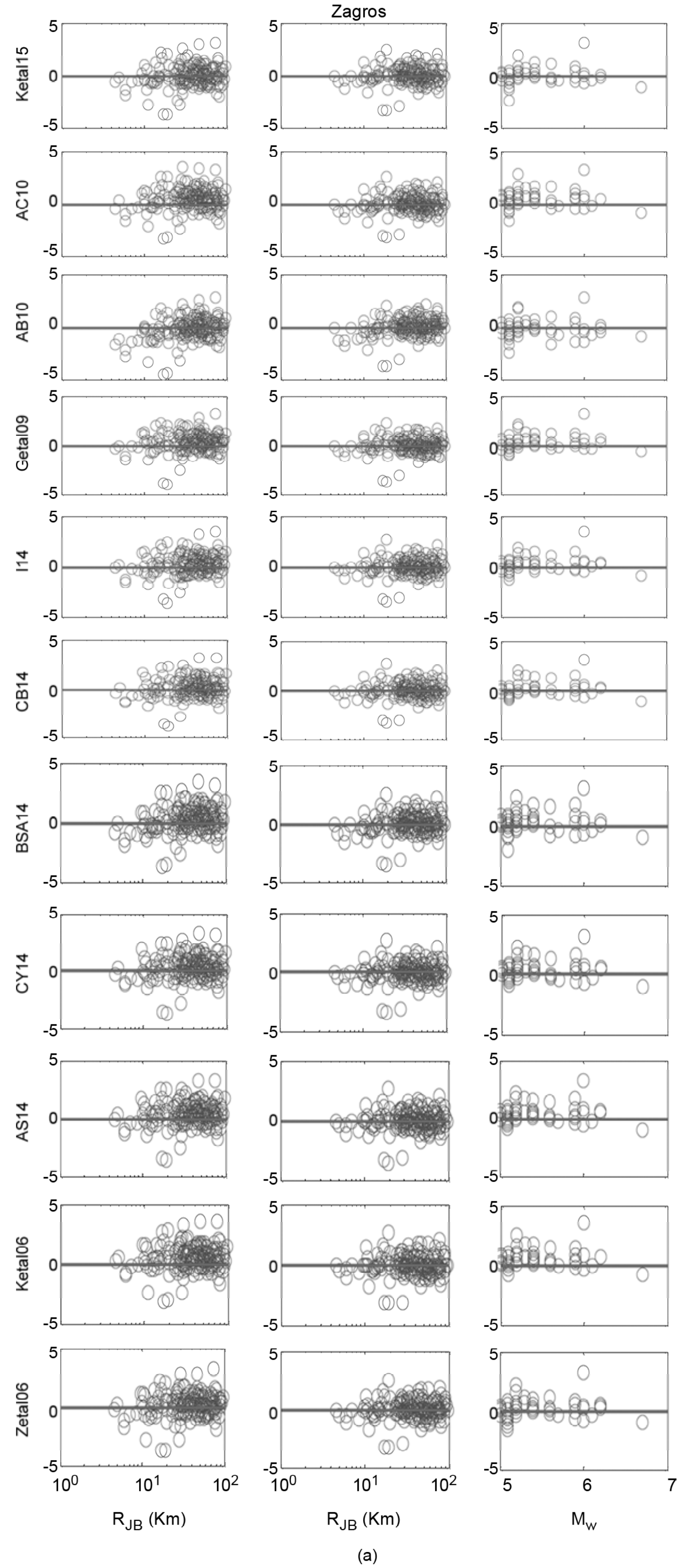



**Figure 7a.** Distribution of total, intra-event and and inter-event residuals of candidate GMPEs in Zagros in T=1 (sec).

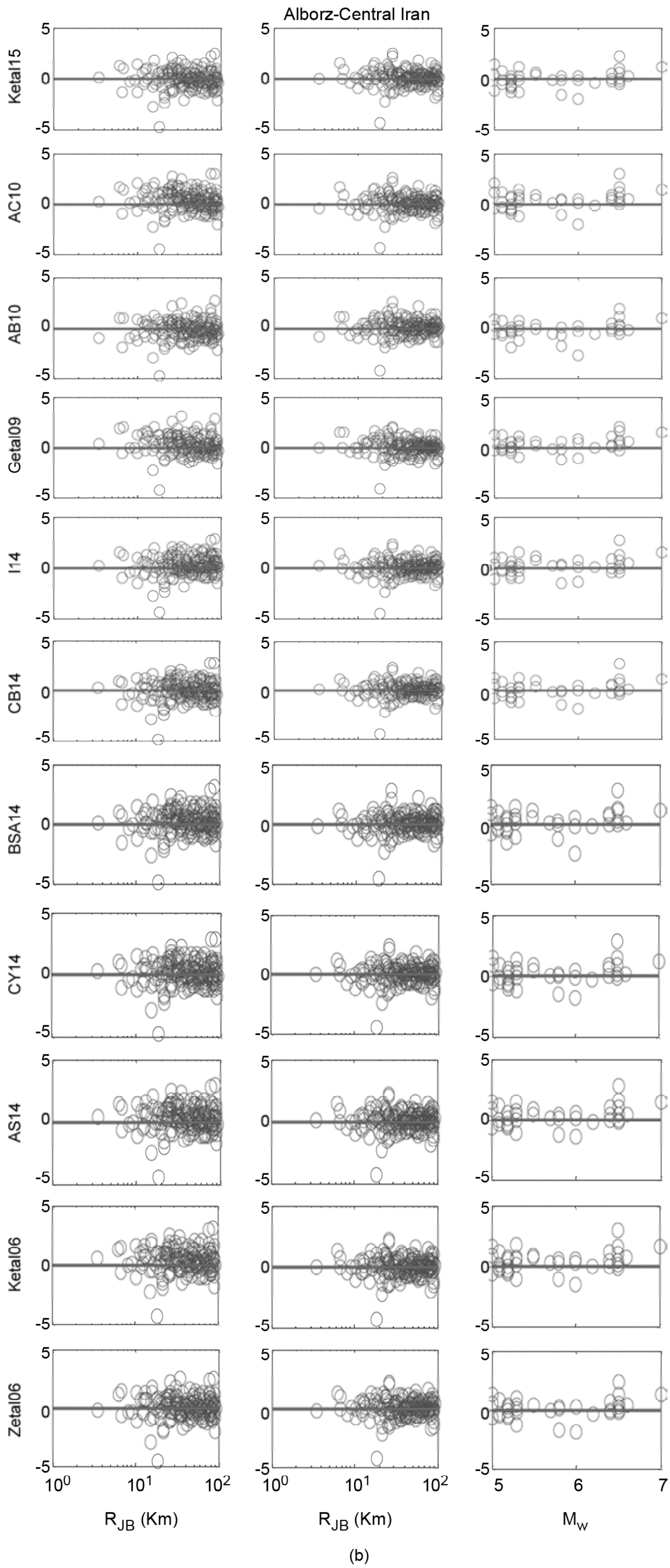



**Figure 7b.** Distribution of total, intra-event and inter-event residuals of candidate GMPEs in Alborz and central Iran in T=1 (sec).

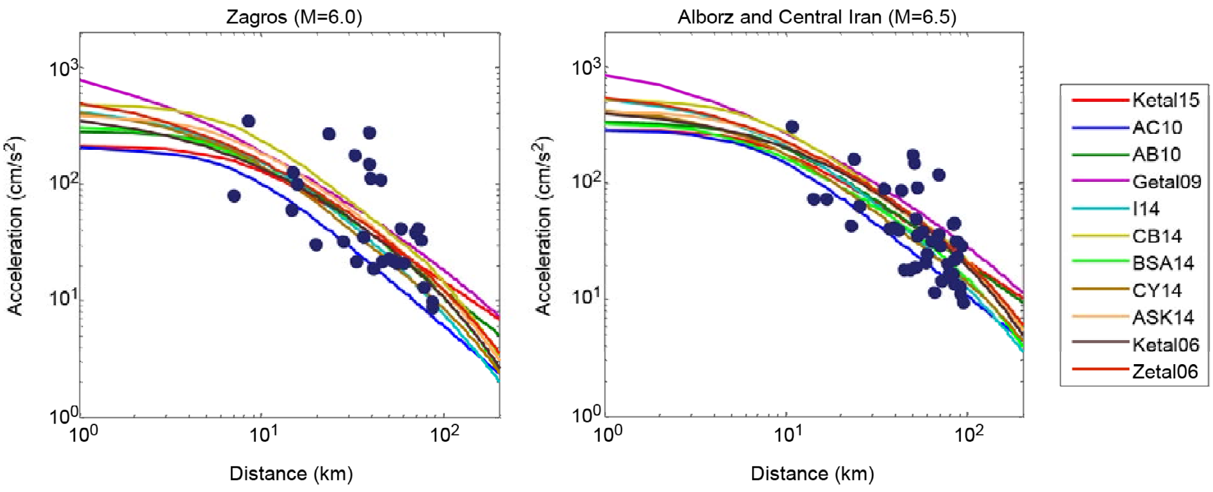



**Figure 8.** Distribution of the estimated value of GMPEs and observed data with $V_{s30}$>500 (m/s) in Zagros and Alborz and Central Iran in T=0.0 (sec).

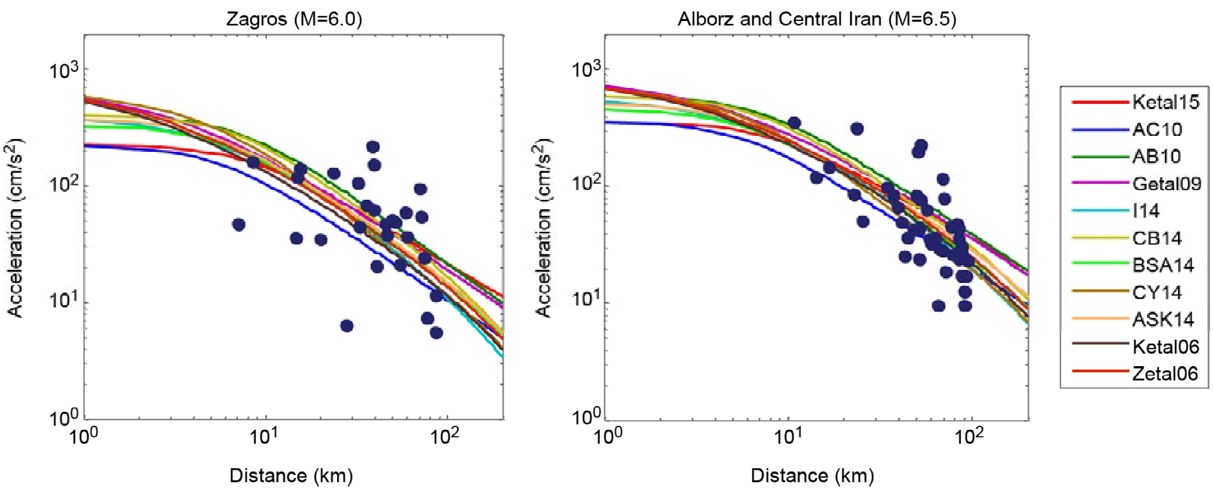



**Figure 9.** Distribution of the estimated value of GMPEs and observed data with $V_{s30}$>500 (m/s) in Zagros and Alborz and Central Iran in T=0.5 (sec).

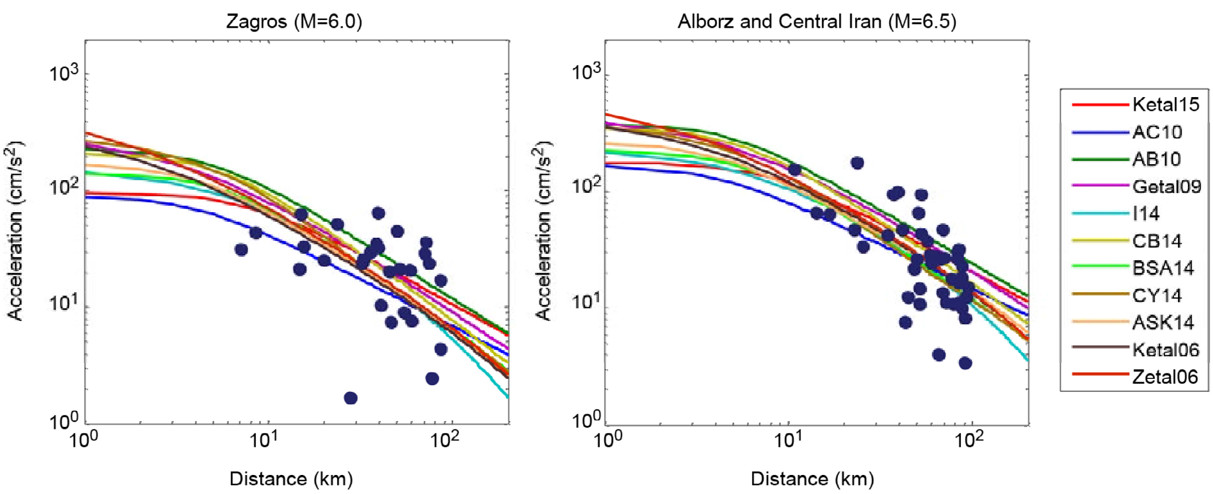



**Figure 10.** Distribution of the estimated value of GMPEs and observed data with $V_{s30}$>500 (m/s) in Zagros and Alborz and Central Iran in T=1.0 (sec).

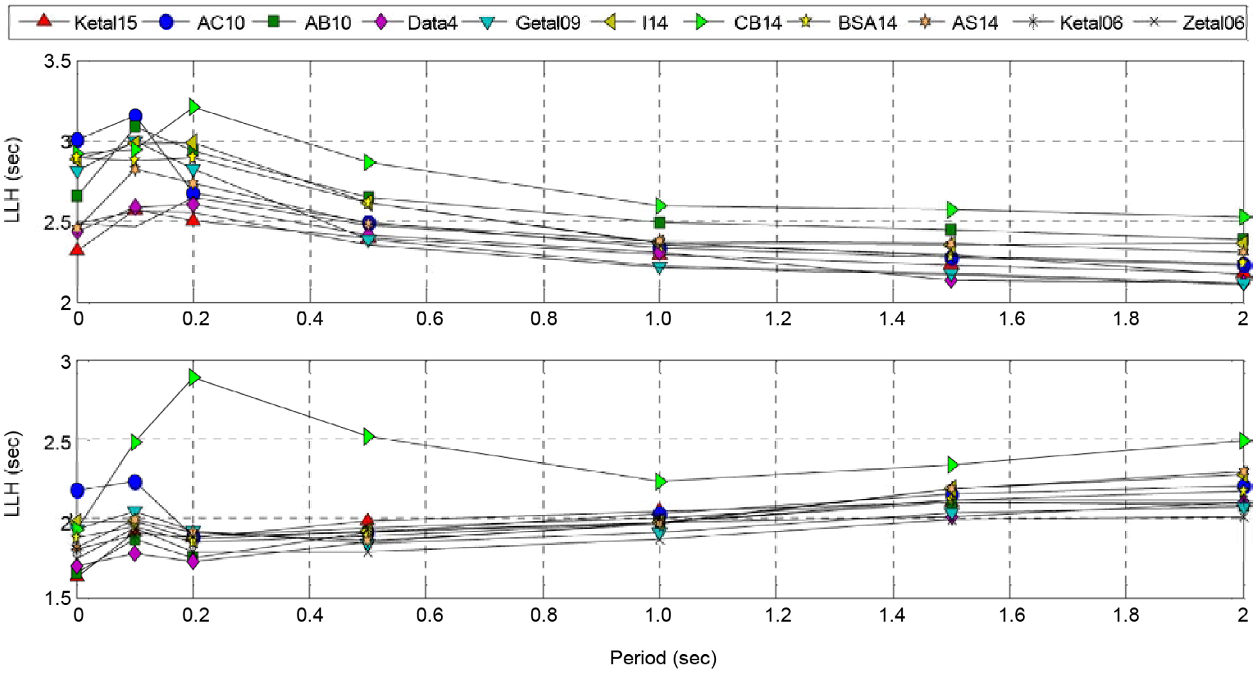



**Figure 11.** The LLH values of candidate GMPEs model in different periods for the Zagros (top) and Alborz and central Iran (bottom).

**Table 4.** The corresponding weight of the top five GMPEs model based on LH and LLH values in two different distinct region.

| Zagros | Weight | Alborz and Central Iran | Weight |
|---|---|---|---|
| Ketal15 | 0.205 | Ketal15 | 0.200 |
| Getal09 | 0.205 | Getal09 | 0.205 |
| I14 | 0.185 | I14 | 0.195 |
| Ketal06 | 0.200 | Ketal06 | 0.195 |
| Zetal06 | 0.205 | Zetal06 | 0.205 |

Although the approach of LLH is a robust approach for ranking of GMPEs, similar to the LH method, this procedure provides an overall sense about the performance of model and in some cases this method may suffer from inconsistent handling of the aleatory uncertainty associated with GMPEs. As it is discussed in the former section, between two models with similar median value, the LLH approach favors the model with higher value of uncertainty (see Kale and Akkar, [11]). Evenly, in this approach, the bias in the median of predicted value of GMPE and the observed is obscured by the normalizing scheme.

The EDR approach is used as the last procedure for ranking of GMPEs. Unlike the LLH value, which an overall performance of the model is presented by an index, in EDR method, the two main features of GMPEs, i.e. the ground motion variability and the bias between the median of the model and observed is considered separately in ranking. Based on the purpose of the seismic hazard study, a specific index can be considered in ranking of GMPEs. For instance, when the purpose of PSHA is providing the seismic load in very long return periods, the MDE index that concerns with aleatory uncertainty should be considered. In Figure (12), the performance of candidate models in different periods based on the indices of MDE, κ and EDR in two distinct regions is depicted. In Table (5), the final ranking of candidate models based on each index obtained by averaging in all period except PGA (i.e. T=0) is presented. As shown, based on each index, the order of ranking shows some differences. As a case in point, in Alborz and Central Iran region based on the index of MDE that stands for the aleatory uncertainty, the top five models are Getal09, CB14, Ketal15, ASK14 and CY14, while based on the κ index that stands for the bias between the model predictive and observed value, the top five models are CY14, BSA14, AC10, AB14 and Ketal06. When the combination of these indices are considered, the top five models are CB14, CY14, BSA14, Ketal15 and ASK14. In Table (6), the corresponding weights of the top five GMPE models based on EDR approach by implementing Equation (6) in which the LLH values are replaced by EDR values is presented.

By comparing the order of ranking based on the

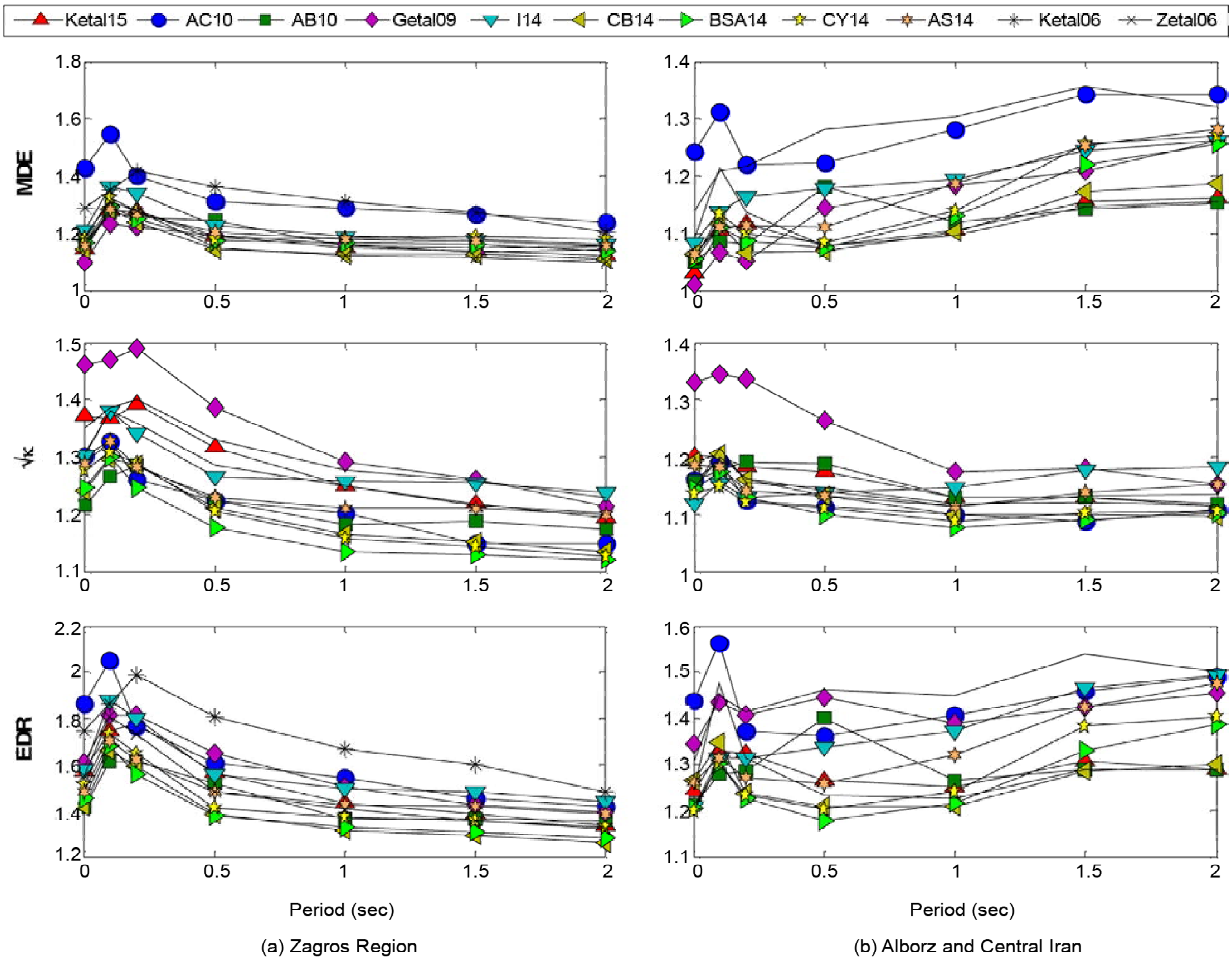



**Figure 12.** Performance of GMPEs based on the indices of MDE, κ and EDR in different periods.

**Table 5.** The final ranking of candidate GMPEs based on the different indices in different seismotectonic regions.

| Zagros Region | | | | Alborz and Central Iran | | | |
|---|---|---|---|---|---|---|---|
| | **MDE** | $\sqrt{\kappa}$ | **EDR** | | **MDE** | $\sqrt{\kappa}$ | **EDR** |
| CB14 | 1.173 | 1.213 | 1.424 | CB14 | 1.154 | 1.141 | 1.314 |
| BSA14 | 1.199 | 1.196 | 1.434 | CY14 | 1.181 | 1.114 | 1.316 |
| CY14 | 1.219 | 1.216 | 1.481 | BSA14 | 1.189 | 1.116 | 1.327 |
| AB10 | 1.214 | 1.219 | 1.483 | Ketal15 | 1.161 | 1.160 | 1.346 |
| ASK14 | 1.201 | 1.250 | 1.504 | ASK14 | 1.176 | 1.149 | 1.351 |
| Zetal06 | 1.187 | 1.287 | 1.531 | Zetal06 | 1.181 | 1.147 | 1.353 |
| Ketal15 | 1.190 | 1.301 | 1.549 | AB10 | 1.183 | 1.157 | 1.367 |
| Getal09 | 1.169 | 1.367 | 1.599 | I14 | 1.189 | 1.151 | 1.370 |
| I14 | 1.240 | 1.293 | 1.604 | Getal09 | 1.140 | 1.256 | 1.423 |
| AC10 | 1.354 | 1.230 | 1.673 | Ketal06 | 1.264 | 1.147 | 1.453 |
| Ketal06 | 1.314 | 1.320 | 1.737 | AC10 | 1.303 | 1.126 | 1.467 |

**Table 6.** The corresponding weight of the top five GMPEs model based EDR values in two different distinct region.

| **Zagros** | **Weight** | **Alborz and Central Iran** | **Weight** |
|---|---|---|---|
| CB14 | 0.210 | CB14 | 0.200 |
| BSA14 | 0.210 | BSA14 | 0.205 |
| CY14 | 0.200 | CY14 | 0.205 |
| ASK14 | 0.200 | ASK14 | 0.195 |
| Zetal06 | 0.190 | Zetal06 | 0.195 |

LH and LLH with EDR approach, obvious differences are tangible. The CB14 that is among the worst models based on the ranking procedure of LH and LLH is the best model based on the EDR ranking. This contradiction in the ranking order is originated from the conceptual differences of each procedure. While in the LH and LLH, only the overall performance of the predictive model is assessed in EDR, the uncertainty and the bias of model contribute individually in the ranking of GMPEs. By this separation in EDR, some strengths and weaknesses of a model, which cannot be captured by the LH and LLH approach can be seen. As a case in point, the EDR analysis shows that the bias in the observed and median estimated value is more pronounced than the variability of GMPEs. Especially, this issue is more tangible in the Zagros region where the κ values are much higher.

It is worth noting that all the above-mentioned explanations do not mean that a ranking procedure is superior to the other methods. In fact, all these ranking approaches are a guidance tool for experts to establish a suitable ground motion logic tree. The agreement of the ranking order of various approaches may only provide a more confidence and defensible logic tree, while the contradiction order of ranking by different approaches only warns the experts for further studies and selecting the most appropriate models based on the object of the seismic hazard analysis.

## 6. Conclusion

In this study, the suitability of a set of local, regional and global GMPEs models based on the three approaches of LH, LLH and EDR for two distinct seismotectonic regions of Iran have been assessed. The likelihood and average log likelihood approaches (LH and LLH) are applied as the first and the second approaches for ranking of GMPEs. Analysis shows general compatibility between the order of ranking in both approaches, which based on the correlation of LH and LLH (Scherbaum et al., [5]) this consistency is not surprising. In both approaches, the local, regional, and global models with simpler functional form are ranked among the top models. However, it should be noted that in LH and LLH methods, the overall performance of a predictive model is examined by normalized residual in term of an index, that is the bias and aleatory uncertainty and other aspects of a model are evaluated in a lumped manner. This fact may result in inappropriate order of ranking. If one characteristic of the predictive model is in error, the effect could be obscured through the compensating errors in the analysis [45]. Similar issue was pointed by Kale and Akkar [11] that in cases where two models yield similar median values, the LLH method favors the model with higher value of standard deviation that is a conservative view and in cases that the purpose of the PSHA has a very long return period may result in unrealistic values.

The Euclidian Distance approach (EDR) proposed by Kale and Akkar [11] used as the last ranking procedure for examining the performance of candidate GMPEs. In that approach, the two main features of a predictive model, i.e. the aleatory uncertainty and the trend of the median and observed data are considered separately by different indices. The order of ranking in that procedure shows significant differences from the LH and LLH.

The main reason to this contradiction is originated from their conceptual differences. In the approaches like LH and LLH, the overall performance of the model is assessed in an index and the individual effects of other parameters are not examined. A Typical example in this regard is the relation of Getal09 that, based on the LH and LLH, shows a good performance while based on the EDR approach are ranked among the worst models. In the EDR approach, the Getal09 shows a high value of bias between the observed seismicity and the predictive value of GMPE which this issue in LH and LLH that assess all aspects of GMPE is faded through the analysis.

In conclusion, it should be emphasized that all testing approaches for evaluation of candidate models are only a guidance tool for experts to build a more defensible logic tree to select the most appropriate model with consideration of the purpose of seismic hazard analysis.

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