16th World Conference on Earthquake, 16WCEE 2017

Santiago Chile, January 9th to 13th 2017

Paper N° 2809

Registration Code: S-H1464563140

ON THE SELECTION OF GROUND-MOTION PREDICTION EQUATIONS FOR SEISMIC HAZARD ASSESSMENT IN THE SOUTH ICELAND SEISMIC ZONE

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Abstract

Ground-motion prediction equations (GMPEs) which quantify the attenuation of key earthquake strong-motion parameters with distance, have a major impact on seismic hazard analysis. In GMPEs, the random variability of amplitudes about a median prediction equation is considered as aleatory uncertainty whereas the uncertainty concerning the correct value of the median is epistemic. Epistemic uncertainties which arise from lack of knowledge about models and data should be considered in seismic hazard assessment to reach a reliable result for the region under study. Data-driven model selection would decrease epistemic uncertainties by reducing subjectivity and by guiding the selection process in a quantitative way. In this study, we review the likelihood-based (LH and LLH) and the Euclidean distance-based ranking (EDR) methods, then we introduce a new procedure on the basis of deviance information criterion (DIC), for selecting the proper GMPEs. To showcase the method, eight candidate GMPE models are ranked by LLH, EDR and DIC. The method is not only shown to optimize the selection of GMPEs for the given region in an unbiased way through the Bayesian statistics, but also solves the problem associated with the previous data-driven methods.

Keywords: GMPEs, Aleatory and epistemic uncertainties, deviance information criterion, Bayesian statistics

1. Introduction

Seismic hazard analysis is one of the effective ways to reduce the impact of destructive earthquakes, and requires an appropriate estimate of the expected ground-motion at the site of interest. The estimation of ground-motion can be done by a mathematical expression called ground-motion prediction equation (GMPE) which quantifies the ground motion parameter of interest by given parameters describing source, path and site effects. Seismic hazard practitioners distinguish uncertainties of different natures in a convenient way, adopting the term "aleatory" as the irreducible variability and "epistemic" to characterize all reducible uncertainties [1]. In GMPE, the random variability of amplitudes about a median prediction equation is considered as aleatory uncertainty whereas the uncertainty concerning the correct value of the median is epistemic. The epistemic uncertainty which is related to lack of the knowledge, would be expected to decrease by increasing earthquake data in quality and quantity. However, Douglas [2] by analyzing more than 250 GMPEs over the past four decades in different part of the world, pointed out that epistemic uncertainty in ground-motion prediction has not been reduced and is still large. Therefore, it is important to consider epistemic uncertainty in seismic hazard studies which can be handled by either considering multiple GMPEs in a logic tree format [3] or the representative suite approach that defines a lower, central, and upper GMPE [4,5]. However, the selection of appropriate GMPE is still needed for both the logic tree and representative suite methods, all of which makes the selection of suitable GMPEs challenging particularly for regions where indigenous GMPEs do not exist [6]. Data-driven methods are acceptable approaches which overcome this problem by reducing subjectivity and also guiding the selection process in a quantitative way [7]. The LH (likelihood) method is the exceedance probability-based approach proposed by Scherbaum et al. [8] that calculates the normalized residuals for a set of observed and estimated ground-motion data. In LLH (log-likelihood), Scherbaum et al. [7] suggested an information theoretic approach that overcomes several shortcomings of LH method. LLH is not sample size dependent anymore, and also it does not require any ad hoc assumptions regarding classification boundaries [9]. These likelihood-based approaches inspired Kale and Akkar [10] to propose the Euclidean distance-based ranking (EDR) method which uses the Euclidean distance to account for both aleatory variability in ground motions and the trend between the observed and estimated data. However, these currently used data driven methods, have revealed some shortcoming in their performance for some cases. The LLH method prefers the predictive model with larger sigma, when the observed data are accumulated away from the median estimations of the two GMPEs [10]. On the other hand, the EDR method favors a smaller sigma when two predictions give the same mean, regardless of what the true uncertainty is [11].

Iceland is known as the most seismically active country in Northern Europe where strong earthquakes occur on the average every ten years [12]. The South Iceland Seismic Zone (SISZ) is one of the most active seismic regions of Iceland where the time interval between large earthquake sequences ranges between 45 and 112 years based on the historical catalogue [13]. This zone is located between the Eastern and Western volcanic zones and is 20–30 km wide and 70-80 km long [14], in which the distribution of faults and damage zones of historical earthquakes suggests a width larger than 20 km [15]. A surprising feature of the SISZ is the distribution of the active strike–slip deformation, which involves few left-lateral faults in accordance with the tectonic spreading, which instead is manifested as numerous parallell N–S-trending right-lateral faults, a relatively unique feature known as “bookshelf tectonics” [13,16]. More than 30 destructive earthquakes in SISZ have been documented since AD 1164, either as single events like the earthquakes in 1726, 1829, and 1912 that occurred in the eastern part of the SISZ, or sequences of two or more large events over a period of days to a few years like the five M_S=6.0–6.9 earthquakes sequences in 1896, which struck the area in only 2 weeks [13,17]. The largest historical earthquake, with estimated M_S=7.1, occurred on August 14, 1784, and was followed two days later by a second event of M_S=6.7, approximately 30 km to the west [18] and also the M_S=7 in 1912 was the first instrumentally recorded earthquake which was occurred at the eastern border of the SISZ [19]. All indicates the high seismicity of this region and evitable need to seismic hazard analysis where the selection of appropriate GMPEs is the most important element to reach a consistent hazard estimates. In the present study, we use LLH and EDR methods to rank eight candidate GMPEs in SISZ. Table 1 shows the candidate GMPEs consist of Rupakhety and Sigbjornsson [20], RS09; Akkar and Bommer [21], AB10; Ambraseys et al. [22], Am05; Danciu and Tselentis [23], DT07; Gülkan and Kalkan [24], GK02; Cauzzi and Faccioli [25], CF08; Zhao et al. [26], Zh06 and Lin and Lee [27], LL08 which all of them satisfy the minimum requirements proposed by Cotton et al. [28] and Bommer et al. [29]. Furthermore, the models are selected according to the study of Delavaud et al. [30] which had proposed them as the suitable GMPEs for seismic hazard in Iceland. Moreover, we propose a robust method to rank GMPEs using the theory of deviance information criterion (DIC) which solves the problem associated with the previous data-driven methods.

Table 1. Description of the selected ground-motion prediction equations

GMPE	Mw Range	R Range	Horizontal Component	Site Class	Main Region(s)
RS09 [20]	5.0-7.7	1-97	LARGE	2 classes	Iceland, Greece, Turkey
AB10 [21]	5.0-7.6	0-100	GMEAN	3 classes	Europe and Middle East
Am05 [22]	5.0-7.6	0-100	LARGE	3 classes	Europe and Middle East
DT07 [23]	4.5-6.9	0-136	AAVRG	3 classes	Greece
GK02 [24]	5.0-7.5	0-150	LARGE	3 classes	Turkey
CF08 [25]	5.0-7.2	15-150	GMEAN	4 classes	Worldwide
Zh06 [26]	5.0-8.3	0-300	GMEAN	5 classes	Japan
LL08 [27]	4.1-8.1	15-630	GMEAN	2 classes	Northern Taiwan

Horizontal component: *GMEAN* geometric mean, *LARGE* larger value, *AAVRG* arithmetic average

2. Methods

The Likelihood-based methods

GMPEs relate a predicted variable (Y_{prd}) characterizing the logarithm of an intensity measure to a set of explanatory variables which describe the earthquake source, wave propagation path, and site conditions. The residual or the difference between the observed value (Y_{obs}) and the predicted value is generally assumed to be normal with a mean of zero and a standard deviation σ:

$$Y_{obs} = Y_{prd} + \delta = Y_{prd} + \varepsilon\sigma \tag{1}$$

where ε is the normalized residual which represents a measure of the goodness-of-fit of the equation at the particular data point [31]. Scherbaum et al. [8] showed that some statistical methods such as variance reduction, chi-square test, Pearson correlation and Kolmogorov–Smirnov statistic are not reliable measures to select the most appropriate model for a given ground-motion dataset. Also, the Nash-Sutcliffe model efficiency coefficient [32] which was used by Kaklamanos and Baise [33] just quantifies the accuracy of the median relationships and does not address the standard deviation relationships. Therefore, after trying aforementioned statistical methods, Scherbaum et al. [8] pointed out that a good measure for the goodness-of-fit of a ground-motion model is the probability for the absolute value of a random sample from the normalized distribution to fall into the interval between the modulus of a particular observation $|\varepsilon_0|$ (expressed as normalized variable) and ∞ for a positive ε_0, that is:

$$u(\varepsilon_0) = \frac{1}{\sqrt{2\pi}} \int_{\varepsilon_0}^{\infty} \exp\left(\frac{-\varepsilon^2}{2}\right) d\varepsilon = \frac{1}{2}\left(Erf(\infty) - Erf\left(\frac{\varepsilon_0}{\sqrt{2}}\right)\right) \tag{2}$$

where $Erf(\varepsilon)$ is the error function with the generalized form of:

$$Erf(\varepsilon_0, \varepsilon_1) = \frac{2}{\sqrt{\pi}} \int_{\varepsilon_0}^{\varepsilon_1} e^{-t^2} dt = Erf(\varepsilon_1) - Erf(\varepsilon_0) \tag{3}$$

Therefore, the likelihood of the normalized residual can be expressed as:

$$LH(|\varepsilon_0|) \equiv 2 \cdot u(|\varepsilon_0|) = Erf\left(\frac{|\varepsilon_0|}{\sqrt{2}}, \infty\right) = \frac{2}{\sqrt{\pi}} \int_{\frac{|\varepsilon_0|}{\sqrt{2}}}^{\infty} e^{-t^2} dt \tag{4}$$

Consequently, they categorized different ground-motion into four classes based on the obtained LH value and the median, mean and standard deviation of normalized residuals which is shown in Table 2.

Table 2. The criteria proposed by Scherbaum et al. [8] to classification of different GMPEs

Class	Description
A	As a highest capability class requires a median LH value of at least 0.4, the absolute value of both measures of the central tendency of the normalized residual distribution, and their standard deviations not deviate by more than 0.25 from zero. In addition, their normalized sample standard deviation must be smaller than 1.125.
B	As an intermediate capability class requires a median LH value of at least 0.3, an absolute value of the mean and the median of the normalized residuals, and their standard deviations must be less than 0.5. In addition, their normalized sample standard deviation less than 1.25.
C	As the lowest accepted capability class, requires a median LH value of at least 0.2, an absolute value for the mean and the median of the normalized residuals, and their standard deviations must be less than 0.75. In addition, the normalized sample standard deviation is required to be less than 1.5.
D	Includes models that do not meet the criteria for any of the A, B and C categories.

Although the LH method was proven to be an acceptable approach for ranking the GMPEs, its dependence on data size and subjectivity in choosing the threshold LH value which is shown in Table 2, led Scherbaum et al. [7] to propose the LLH method that overcomes these weaknesses. This approach within an information theory framework, measures a Kullback–Leibler distance between two models f and g:

$$D(f,g) = E_f[\log_2(f)] - E_f[\log_2(g)] \tag{5}$$

where E_f is the expected value taken with respect to f. This distance describes the amount of information loss if model f is replaced by model g and for model comparison, their relative Kullback–Leibler distance is only interested where the expectation of the unknown model f drops out as a constant [9]. Therefore, the second expectation ($-E_f[\log_2(g)]$) can be estimated by the average sample log likelihood (LLH) as a ranking criterion for the N number of observations:

$$LLH = \frac{1}{N}\sum_{i=1}^{N}\log_2(g(x_i)) \tag{6}$$

The Euclidean distance-based method

Based on the Euclidean distance (i.e., the square root of a sum of squares of the differences between N data pairs) between the observed and estimated ground-motion data, Kale and Akkar [10] proposed a ranking criterion called as EDR:

$$EDR^2 = \kappa \frac{1}{N}\sum_{i=1}^{N} MDE_i^2 \tag{7}$$

where MDE is the modified Euclidean distance and κ parameter is the ratio of original and corrected Euclidean distances which can be obtained by:

$$\kappa^2 = \frac{\sum_{i=1}^{N}(a_i - Y_i)^2}{\sum_{i=1}^{N}(a_i - Y_{c,i})^2} \tag{8}$$

where a_i and Y_i are the natural logarithms of the ith observed and estimated data, respectively. The parameter $Y_{c,i}$ stands for the corrected estimation of the ith data after modifying Y_i with the straight line fitted on the logarithms of the estimated and observed data [10]. The MDE considers the discrete occurrence probabilities of absolute differences between the logarithms of observed data (a_i) and a range of ground-motion estimates (y_j, j=1,…,N) computed from a GMPE [34] and can be obtained by:

$$MDE = \int_0^{|d_{\max}|} d \times \frac{1}{\sqrt{2\pi} \times \sigma_D} \times \exp\left(\frac{-(d-\mu_D)^2}{2\sigma_D^2} \right) dd + \int_0^{|d_{\max}|} d \times \frac{1}{\sqrt{2\pi} \times \sigma_D} \times \exp\left(\frac{-(-d-\mu_D)^2}{2\sigma_D^2} \right) dd \tag{9}$$

where μ_D and σ_D are the residual and standard deviation of GMPE. The $|d|_{\max} = \max(|\mu_D \pm 3 \times \sigma_D|)$ which the multiplier of 3 lead to cover approximately 99.7% of the differences between the observation and estimations of a candidate GMPE [10].

3. The Deviance information criterion

The deviance has an important role in statistical model comparison because of its connection to the Kullback-Leibler information measure and is defined as:

$$D(y,\theta) = -2 \log p(y|\theta) \tag{10}$$

where, θ is the unknown parameter and y is the observed data. In the limit of large sample sizes, the model with the lowest expected deviance, will have the highest posterior probability, thus, it seems reasonable to estimate expected deviance as a measure of overall model fit [35]. A summary based on $D(y,\theta)$ that does not depend on θ is given by:

$$D_{\hat{\theta}}(y) = D\{y, \hat{\theta}(y)\} \tag{11}$$

where $\hat{\theta}$ is a point estimate for θ such as the mean of the posterior simulations. Another summary is the posterior mean of $D(y,\theta)$, which can be estimated with:

$$\hat{D}_{avg}(y) = \frac{1}{L} \sum_{l=1}^{L} D(y, \theta^l) \tag{12}$$

where θ^l is the l-th draw from posterior distribution. The estimated average discrepancy (eq. 12) is a better summary of model error than the discrepancy of the point estimate since it averages over the range of possible parameter values [35]. Therefore, the expected deviance can be approximately estimated with a summary statistic called the DIC:

$$DIC = \hat{D}_{avg}^{pred}(y) = 2\hat{D}_{avg} - D_{\hat{\theta}}(y) \tag{13}$$

The DIC which is developed by Spiegelhalter et al. [36] is a Bayesian version or generalization of the well-known Akaike Information Criterion (AIC) [37], related also to the Bayesian (or Schwarz) Information Criterion (BIC) [38] and has been suggested as a criterion of model fit when the goal is to find a model that will be best for prediction when taking into account uncertainty due to sampling.

4. Application to GMPEs

The key element for model comparison is the posterior distribution. In this study, the unknown parameters, θ, are the GMPE's parameters (i.e., regression coefficients, β, and the variance, σ^2). Assuming that the ground motion data follow a normal distribution:

$$p(y|\beta,\sigma^2)=\prod_{i=1}^{N}\frac{1}{\sigma\sqrt{2\pi}}\exp\left(-\frac{(y_i-\mu(\beta)_i)^2}{2\sigma^2}\right) \tag{14}$$

where, N is the number of observations, y is the observed ground motions, $\mu(\beta)$ is the mean value predicted by GMPE and σ is the standard deviation of GMPE. We do believe that the sigma from the region of origin should not be a determinative measure in selection of GMPE for another region. Therefore, we assume that sigma is unknown and follows a scaled inverse chi-squared distribution because for the normal model, the conjugate prior distribution for σ^2 is scaled inverse-χ^2:

$$p(\sigma^2)\propto(\sigma^2)^{-\frac{\nu}{2}-1}\exp\left(-\frac{\nu}{2}\cdot\frac{s^2}{\sigma^2}\right) \tag{15}$$

where, υ is the number of chi-squared degrees of freedom and s^2 is the scaling parameter. Therefore, the joint posterior distribution of β and σ^2 is given by:

$$p(\sigma^2|y)\propto p(\sigma^2)p(y|\beta,\sigma^2)=Scaled\quad inverse-\chi^2(\sigma^2|N+\nu,\frac{1}{N+\nu}\left\{\nu\cdot s^2+\sum_{i=1}^{N}(y_i-\mu(\beta)_i)^2\right\}) \tag{16}$$

Therefore, the posterior distribution of variance (σ^2) is again a scaled inverse chi-squared distribution with the degrees of freedom, $N+\upsilon$ and the scaling parameter, $\frac{\nu\cdot s^2}{N+\nu}+\sum_{i=1}^{N}(y_i-\mu(\beta))^2$. Regarding to equations (10-13), the model comparison can be done by the deviance of the normal model:

$$\begin{aligned} D(y,\theta) &= -2\log p(y|\theta) = -2\log\left\{\prod_{i=1}^{N}N(y_i|\beta,\sigma^2)\right\} \\ &= N\log(2\pi)+N\log(\sigma^2)+\sigma^{-2}\sum_{i=1}^{N}(y_i-\mu(\beta)_i)^2 \end{aligned} \tag{17}$$

Therefore,

$$\begin{aligned} DIC &= 2\hat{D}_{avg}-D_{\hat{\theta}}(y) \\ &= 2\cdot\frac{1}{L}\sum_{l=1}^{L}\left[N\log(2\pi)+N\log(\hat{\sigma}^2)+\hat{\sigma}^{-2}\sum_{i=1}^{N}(y_i-\mu(\beta)_i)^2\right] \\ &-\left[N\log(2\pi)+N\log(\overline{\sigma}^2)+\overline{\sigma}^{-2}\sum_{i=1}^{N}(y_i-\mu(\beta)_i)^2\right] \end{aligned} \tag{18}$$

where, $\hat{\sigma}^2$ are drawn samples from the posterior distribution and $\overline{\sigma}^2$ is the posterior mean value. To exhibit the performance of the proposed method, eight candidate GMPEs are chosen to be ranked regarding to ground motion data in SISZ. The data used in this study include 105 records with the magnitude range of 5.1-6.5 covering time period 1987-2016. The PGA and spectral acceleration (PSA) at periods 0.2s, 1s, 1.5s and 2s have been chosen as the intensity measures which are shown in Figure 1. To account for the uncertainties due to different orientations of the sensors, a rotation-invariant measure is used [39,40].

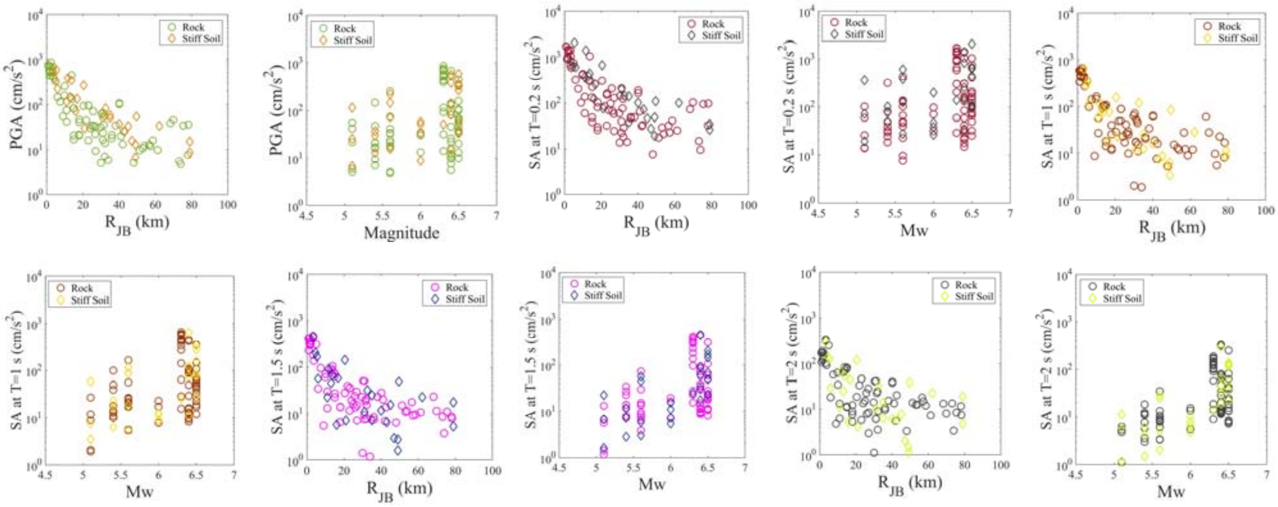

Fig. 1. Distribution of the data used in terms of distance and magnitude versus rotation-invariant PGA and PSA at different periods for rock (circles) and stiff soil (diamonds) sites.

5. Results and Discussions

In this study, we proposed a new method to rank the GMPEs using deviance information criterion in order to apply in seismic hazard studies. The method optimizes the selection of GMPEs for a given region in an unbiased way through the Bayesian statistics, and also leads to more consistent hazard estimates with the proper handling of the uncertainty of strong-motion parameters. The latter has important implications for the efforts of improving estimates of earthquake hazard. Moreover, it overcomes the problems associated with the currently used ranking methods, LLH and EDR. In our proposed method, we assumed that the sigma is unknown and should be determined by the data in the region of interest whereas the LLH and EDR use the sigma from the origin region. For this reason, we used the Bayesian statistic to obtain the posterior estimation of sigma by combining the normal distributed ground motions with the prior distribution of sigma. Suppose that the prior distribution of sigma follows a scaled inverse chi-squared distribution which is conjugated to the normal models. To show the perfomance of the proposed method, eight GMPEs were ranked for South Iceland. The scores of EDR, LLH and DIC of the candidate GMPEs in different periods are shown in Figure 2. A smaller EDR, LLH and DIC value indicates better performance of the predictive model. Also, we have shown the prior and posterior sigma in Table 3.

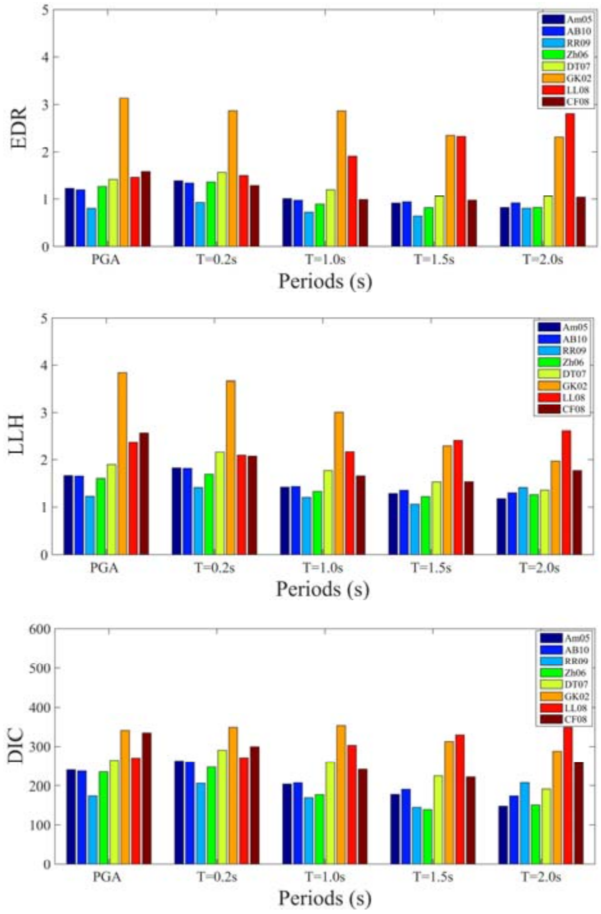

Fig. 2– The scores of the EDR, LLH and DIC in different periods for the candidate GMPEs in SISZ.

The results indicate when the predictions are close to observed ground motions (i.e. small mean residual), LLH in some case selects the model with smaller sigma and when they are accumulated away from observations, LLH favors the models with larger sigma which such a case can be seen in T=1.5s and T=0.2s, respectively. In T=1.5s, RS09 is selected as the best model for its smaller sigma than Zh06 and in T=0.2s, CF08 is preferred than LL08 due to its larger sigma while DIC behaves in opposite because both the updated sigma and residuals are considered. As we mentioned before, when the mean residual of two models are approximately same, EDR favors models with smaller sigma which has been proved in PGA and T=0.2s where it has selected AB10 better than Zh06. Also in T=1.5s, EDR prefers RS09 rather than Zh06 just for its smaller sigma regardless what the residual and true uncertainty are. As can be seen, sigma as a crucial parameter plays an important role in previous studies which should not be based on the prior information. We believe our proposed method works well for all cases because it considers both mean residual and true sigma simultaneously.

Table 3. The prior and posterior standard deviations (in natural logarithm) of the candidate GMPE for SISZ.

Models	Sigma (PGA)		Sigma (T=0.2s)		Sigma (T=1.0s)		Sigma (T=1.5s)		Sigma (T=2.0s)	
	Prior	Posterior	Prior	Posterior	Prior	Posterior	Prior	Posterior	Prior	Posterior
Am05	0.665	0.758	0.726	0.844	0.755	0.638	0.719	0.567	0.719	0.492
AB10	0.642	0.748	0.696	0.831	0.749	0.648	0.736	0.603	0.756	0.557
RS09	0.660	0.558	0.718	0.645	0.659	0.545	0.612	0.486	0.691	0.650
Zh06	0.723	0.740	0.811	0.784	0.775	0.566	0.779	0.472	0.787	0.500
DT07	0.667	0.851	0.700	0.965	0.808	0.830	0.753	0.705	0.732	0.606
GK02	0.561	1.218	0.611	1.266	0.756	1.296	0.788	1.072	0.895	0.952
LL08	0.526	0.875	0.606	0.879	0.798	1.024	0.841	1.154	0.877	1.267
CF08	0.792	1.182	0.866	1.005	0.817	0.763	0.804	0.696	0.758	0.825

Sigma plays an important role in the data-driven methods but it might be contaminated by uncertainties associated with the region of origin. The main advantage of the proposed procedure is to introduce the posterior sigma as a determinative measure to rank the models. Using Bayesian analysis, the posterior distribution of sigma is obtained based on the observed ground motions. In other words, posterior sigma shows the deviance of predicted values from observed ground motions which can solve the problem associated with the LLH and EDR methods. Moreover, in some cases, much dependence of the previous studies on sigma even ignores the residuals as one of the main measures in model selection issues. DIC represents a good interaction between mean residuals and posterior sigma by selecting models with smaller residual and posterior sigma which is quite reasonable. However, the main point that should not be forgotten, is the proposed method like the other data-driven methods works correctly just inside the available data range. We emphasize that the use of scores must be accompanied by the expert judgments in evaluating the performance of a GMPE or in hazard assessment. In this study, a good example is shown for South Iceland where the methods prefer CF08 than some models at some periods despite the fact that this model is linear and does not have a saturation term, leads to the prediction of unrealistically large ground motions in the near-fault region which effectively renders it unsuitable for hazard studies near active faults.

7. Acknowledgements

This study was funded by Grant of Excellence (No. 141261-051) from the Icelandic centre for research which is gratefully acknowledged.

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