MODELLING PAN-EUROPEAN GROUND MOTIONS FOR SEISMIC HAZARD APPLICATIONS

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Abstract

Ground motion models (GMMs) are a key component in seismic hazard assessment and in seismic risk analysis. The consideration of both aleatory and epistemic sources of variability may have significant influence on the results and are vital because of their influence on the over- or under-estimation of the final assessment of losses. Recent research has shown that the commonly used framework of weighted logic trees for the choice of GMMs is not necessarily the best suited to account for epistemic uncertainty. Recently, a simple and alternative procedure has been proposed in which a GMM suite is defined with only three representative models (lower, central and upper) derived from available median models. This alternative model is equivalent to the use of multiple models, provided the same range of epistemic uncertainty is sampled. The representative suite approach was applied to the European context for developing a Pan-European GMM for EC8 ground type B and normal or strike slip faulting style for its implementation in risk analysis of critical infrastructures Europe wide, within the framework of the European funded project INFRARISK. The proposed new Pan-European representative GMM is based on the most recent GMMs developed using the common RESORCE strong-motion database of European and Near and Middle East acceleration records. It is shown to perform well when tested against new ground-motion observations from the ESM-Engineering Strong-Motion database and even slightly better than other available GMMs. The procedure is efficient and transparent limiting the sample space to three GMMs and reducing both complexity of the modelling and computational efforts.

Keywords: Ground-Motion Model, Epistemic Uncertainty, Seismic Hazard, Seismic Risk, Pan-European

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1. Introduction

Attenuation relationships, ground motion prediction equations (GMPEs) or, in general (e.g., Mak et al., 2017) ground motion models (GMMs), represent a key component of seismic hazard analysis (SHA), whether it is performed as a single scenario, or by deterministic or probabilistic approaches (Douglas and Edwards, 2016). Hence the importance of selecting appropriate GMMs, as well as the evaluation of their associated uncertainties to be modelled in any SHA. These uncertainties represent a key source of variability in modelled ground motions, and may have significant influence on the overestimation or underestimation of expected losses in seismic risk analysis.

The standard practice considers two uncertainty components (Atkinson et al. 2014; Douglas and Edwards 2016), i.e., one representing the random variability about the median predicted value (aleatory variability); and one related to lack of knowledge for giving the correct value of the median (epistemic uncertainty). There is no general agreement on the definition of either component, a clear distinction between the two being very critical to avoid mixing and/or any double-counting (Bommer et al. 2005; Bommer and Scherbaum 2008; Atkinson 2011; Atkinson et al. 2014; Stafford 2015; Douglas and Edwards 2016; Douglas 2018a).

The development of new databases and GMMs over the past few years has not, apparently, contributed to decreasing uncertainty, especially regarding aleatory variability (Strasser et al 2009), although site-specific hazard has benefitted from moving from the ergodic to partial non-ergodic assumption (Douglas and Edwards 2016). The epistemic component shows relative reduction, but mostly because still most available ground-motion data used to build GMMs come from a limited range of magnitudes and distances (Douglas and Edwards 2016). The usual approach to handle epistemic uncertainty is by designing a logic tree that considers alternative GMMs and associated weights, trying to represent the distribution of possible ground motions (Bommer et al. 2005; Bommer and Scherbaum 2008; Bommer 2012; Atkinson et al. 2014; Douglas and Edwards 2016). This approach is not necessarily the best suited for modelling epistemic uncertainty in GMMs (Bommer and Scherbaum 2008; Atkinson 2011), and in most cases it could fail to capture the center, body and range of technically defensible interpretations of the available data and models (Atkinson et al. 2014), as it is required for the practical implementation of levels 3 and 4 (Kammerer and Ake 2012) of the SSHAC recommendations (SSHAC 1997) for probabilistic seismic hazard analysis (PSHA), mostly used in design and assessment of critical infrastructure (e.g., nuclear power plants among many others).

An alternative approach to model epistemic uncertainty in GMMs consists in the definition of a representative suite of models, which capture the uncertainty by using one or more central models along with high and low alternatives. This so-called backbone approach (Atkinson et al 2014; Douglas 2018a, 2018b) has been applied, e.g., for the 2015 national seismic hazard maps of Canada (Atkinson and Adams 2013), and it is implemented in some PSHA codes (e.g., Assatourians and Atkinson 2013). The common practice includes three representative GMMs (lower, central and upper) derived from existing median models. Atkinson and Adams (2013), after several sensitivity tests, show that the three-GMM suite produce similar PSHA results to those using multiple GMPEs, provided that the same range of epistemic uncertainty is sampled. Some advantages of this approach are highlighted in Atkinson and Adams (2013) as: (a) The selection of median GMPEs to build the representative model can be carried out without applying weighting coefficients, eliminating the subjective expert-based judgement that is usually associated with the logic tree approach. Nevertheless, there is still a significant degree of judgment when considering implicitly that median ground motions should not be outside the range predicted by the selected GMPEs; (b) Values are computed for discrete combinations of magnitudes and distances, without requiring a given functional form, thus allowing for a flexible expression of the median and the epistemic uncertainties; even though the fundamental physical properties of the earthquake process are not explicit; (c) The three-GMM representative suite can be readily used as an input to probabilistic risk analysis, because the central model and the upper/lower bounds can be sampled with specified weights. Because only three possible inputs are sampled, the associated computational effort is reduced when compared to a complex logic tree with multiple choices of GMPEs.

The approach has been recently discussed by Douglas (2018a, 2018b), who advocates its use showing the advantages over the classic logic trees with multiple GMPE; although he considers that the representative suite or backbone approach may provide a good model of the epistemic uncertainty just for regional SHA, and would not be completely feasible for site-specific studies in regions with very limited data. Douglas (2018a) proposes a three-set logic tree, based on the backbone approach, with three branches in each set. Scaling factors are applied to account for regional differences, and weights are updated when local data is available. The estimation of these scaling factors remains, however, a challenging task, requiring a careful balance between expert judgement and empirical analyses.

In the present study, the representative suite approach was applied to the European context for risk analysis of critical infrastructure in the framework of the European-funded project INFRARISK (www.infrarisk-fp7.eu). To this end, a selection of available GMPEs based specifically on European ground-motion databases has been performed, as detailed in Section 2. Section 3 develops the steps required to derive the three representative sub-models that account for epistemic uncertainty for EC8 ground type B (CEN 2004). The issue of the quantification of aleatory variability for the developed model is addressed in Section 4, because such knowledge is essential when using the GMM in a probabilistic framework. Finally, the resulting three-GMM representative suite is compared to actual ground motion records extracted from the ESM-Engineering Strong-Motion database (Luzi et al. 2016, Lanzano et al. 2019) for evaluating its performance as a Pan-European representative model.

2. Selection of GMPEs

The most recently developed GMPEs that seek to capture epistemic uncertainty using the common database of Pan-European strong-motion records RESORCE (Akkar et al 2014a) were compiled in a special issue of the Bulletin of Earthquake Engineering in 2014 (Douglas 2014). The RESORCE database results from the integration and uniform processing of European and Near and Middle East acceleration records, including some earthquake-specific studies. It consists of 5,882 multi-component accelerograms from 1,540 strong-motion stations and 1,814 earthquakes recorded between 1967 and 2012 (Akkar et al. 2014a). For the derivation of our representative GMM suite we selected four of those GMPEs (Table 1), namely AK14 (Akkar et al. 2014b), BI14 (Bindi et al. 2014), BO14 (Bora et al. 2014) and DE14 (Derras et al. 2014). The selection is based on the common characteristics of their data selection criteria which allow for the development of a single model.

Table 1

Based on the magnitude and distance validity domains of the underlying GMPEs (Table 1), the representative GMM suite is developed for M_w between 4.0 and 7.0, and for Joyner-Boore distance, R_{jb} , between 1 and 200 km. Because the selected models directly use average shear-wave velocity to 30 m depth, $V_{s,30}$, as a proxy to soil amplification, the GMM suite is developed for EC8 ground type B, i.e., $V_{s,30}$ between 360 and 800 m/s. Regarding focal depth, the only one of the four GMPEs that accounts for this parameter (i.e., DE14) uses an average depth of 10 km, justified by the vast majority of superficial earthquakes that compose the RESORCE database. Normal and strike-slip earthquakes are also by far the most common types of events that are present in the database (Akkar et al. 2014a), therefore the GMPEs that contain both of these styles of faulting (i.e., BI14 and DE14) are considered twice(first with normal faulting, and second with strike-slip), arriving to six GMPEs for developing the new GMM suite. For illustration purposes a subset of GM parameters, within the period range common to all models, is considered, i.e., average horizontal component of PGA and spectral acceleration, SA, at periods, T, 0.1s, 0.2s, 0.3 s, 0.5s, 1.0s and 2.0s.

Fig. 1

The six median GMPEs are plotted in Fig. 1, for two selected M_w magnitudes (5.0. 6.0), three ground-motion parameters (PGA, SA[0.2s], SA[2.0s]), and $V_{s,30}$ = 580 m/s (average value for EC8 ground type B). They are compared to actual ground-motion records (average horizontal component) extracted from the RESORCE database with the following criteria: normal or strike-slip faulting style, M_w within +/- 0.2 magnitude bins (Gasperini et al. 2012), focal depth between 0 and 20 km, $V_{s,30}$ in the interval [500;660[m/s, and Joyner-Boore distance, R_{jb}, from 1 to 200 km. This determines a data subset of 74 values. For the RESORCE records for which R_{jb} is not available, the epicentral distance is converted to Joyner-Boore distance metrics using the approach given by Atkinson and Adams (2013), and the M_w-rupture length relationships from Leonard (2010). RESORCE data in Fig. 1 are represented by the geometric mean and associated standard deviation of the GM parameter computed in R_{jb} distance bins of width 0.4 $\log_{10}$ units with a 50% overlap, apart for the first bin, which is 1.0 $\log_{10}$ units in width (these distance bins, in km, are: [1.0;10.0], [6.3;15.8], [10.0;25.1], [15.8;39.8], [25.1;63.1], [39.8;100.0], [63.1;158.5], [100;251.2])

3. Development of a Pan-European representative GMM

In the present study, the proposed approach is demonstrated through the derivation of a representative GMM suite with three models (lower, central and upper) for normal or strike-slip faulting and EC8 ground type B ($V_{s,30}$ between 360 and 800 m/s), using the six selected GMPEs (Table 1 and Fig. 1). To account for the additional epistemic uncertainty introduced by the ground type definition a slight variant from the original approach by Atkinson and Adams (2013) has been adopted. Rather than fixing a reference site condition ($V_{s,30}$=760 m/s) to obtain the three representative models, a GMM accounting for the whole ground type B representative velocity range (360-800 m/s) is provided in the present study.

The three representative models (lower, central and upper) of the GMM suite are obtained applying the following procedure:

1. Computation of GM parameters from the six median GMPEs at three $V_{s,30}$ values – i.e., 360 m/s for the upper model, 580 m/s for the central model, and 800 m/s for the lower model – and for a set of discrete combinations of magnitude and distance values (M_w 4.0 to M_w 7.0 at 0.1 units intervals, and R_{jb} distance from 1 to 200 km at 0.1 $\log_{10}$ units intervals).
2. The central model, $\langle y_{580} \rangle$, is computed by processing the geometric mean of the selected GMPEs evaluated for $V_{s,30}$ = 580 m/s, i.e., $\langle y_{580} \rangle = (y_{580,1} \times \ldots \times y_{580,6})^{1/6}$. The upper and lower models are obtained in a similar way by their corresponding geometric mean plus one standard deviation, $\langle y_{360} \rangle + \sigma$, and minus one standard deviation, $\langle y_{800} \rangle - \sigma$, respectively. That provides an initial estimate of epistemic uncertainty.
3. Standard deviation is smoothed by a triangular three-point weighted smoothing to avoid pinching effects at some distances where values could be close to each other. For example, the smoothed standard deviation at distance k is computed as follows:

$$\sigma^{s}_{\log_{10} y,k} = 0.25\,\sigma_{\log_{10} y,k-1} + 0.5\,\sigma_{\log_{10} y,k} + 0.25\,\sigma_{\log_{10} y,k+1} \quad (1)$$

By this approach no specific distribution of $V_{s,30}$ is assumed within EC8 ground type B. It is just a propagation of the lack of knowledge in the interval where only upper and lower bounds are known.

The resulting GMM suite, with upper and lower branches accounting for epistemic uncertainties (due to both the choice of GMPE model and the variability within the $V_{s,30}$ interval) is plotted in Fig. 2, for selected magnitudes and GM parameters.

Fig. 2

4. Aleatory variability

4.1. Total variability σ_{tot}

Once the epistemic uncertainty has been quantified for the proposed GMM suite, aleatory variability, σ_{ale}, needs to be assessed as well, in order to ensure that the model is fully characterized and usable in the context of a probabilistic seismic risk analysis. Each of the underlying GMPEs considered here has a different model of aleatory variability, which makes it difficult to compute and analytically determine the aleatory variability of the developed representative GMM suite.

However, because the selected GMPEs are based on the RESORCE database, it is reasonable to use RESORCE values in order to extract the level of aleatory variability that should be attributed to the representative GMM suite. Therefore, the following procedure is implemented:

1. For each of the selected RESORCE values (i.e., 1,037 values within soil type B corresponding to the criteria defined in Section 2), $y_{obs,i}$, the residual, ε_i, with respect to the central model of the representative GMM suite, $\langle y_{580} \rangle_i$, is computed, as follows:

$$\varepsilon_i = \log_{10} y_{obs,i} - \log_{10} \langle y_{580} \rangle_i \quad (2)$$

2. Using the selected RESORCE values, an approximation of the total standard deviation, σ_{tot}, can be computed from the vector $\boldsymbol{\varepsilon}$ of the residuals ε_i by:

$$\sigma^2_{tot} = Var(\boldsymbol{\varepsilon}) \quad (3)$$

3. This total standard deviation, σ_{tot}, is estimated with respect to the central model of the representative GMM suite, so that it represents the global variability that cannot be explained if the aforementioned epistemic uncertainties are not taken into account. Therefore, it is possible to extract the aleatory variability, σ_{ale}, by using the quadratic combination of the uncertainty sources (i.e., assuming that they are independent):

$$\sigma_{ale}^2 = \sigma_{tot}^2 - \sigma_{epi}^2 \quad (4)$$

where σ_{epi} corresponds to the epistemic variability estimated in Section 3 (i.e., the $\sigma_{\log_{10} y}^{s}$ variable in Equation 1).

From Section 3, it can be seen that the values of σ_{epi} are specific to a given magnitude, distance and ground-motion parameter of interest. Conversely, the σ_{tot} variability is computed from residuals over various bins of magnitudes and distance ranges, in order to guarantee enough data values to generate stable estimates of the residuals' standard deviations. In total, nine bins are selected, resulting from the combination of three magnitude intervals (i.e., [4.0;5.0[, [5.0;6.0[and [6.0;7.5]) and three distance intervals (i.e., [1;20[; [20;60[and [60;200]). The results are detailed in Table 2. Following Equation 4, the aleatory variability, σ_{ale}, should depend on magnitude and distance, following the evolution of the epistemic uncertainty. For this reason, σ_{ale} values in Table 2 are averaged over each bin's magnitude and distance ranges. The physical meaning of this behaviour maybe that, for some combinations of magnitude and distance, the underlying GMPEs provide very different values, which has the effect of explaining a large part of the observed dispersion in the residuals.

Table 2

From Table 2 it follows that the aleatory part is dominating in the total variability, especially for higher magnitude ranges, thus limiting the importance of the epistemic uncertainty due to the choice of GMPEs. It should also be noted that the variability of $V_{s,30}$ within the whole soil class B is implicitly incorporated into the σ_{epi} part, due to the way the representative GMM has been built (see Section 3). However, the distinction between epistemic uncertainty and aleatory variability may be adjusted depending on whether the developed model accounts for inter-event variability (Atkinson and Adams, 2013), as discussed in the following sub-section.

4.2. Intra- and inter-event aleatory variability components

In order to obtain a fully characterised probabilistic model, the aleatory variability, σ_{ale}, has to be further decomposed into its intra- and inter-event components, which are usually represented by the standard deviations σ_{intra} and σ_{inter}. Extracting these two terms is not practical for the proposed formulation of the representative GMM suite. However, Atkinson (2011) suggests to empirically quantify the aleatory variability (intra-event term only) by simply evaluating the average data scatter around a trend line, using the following procedure:

- Definition of some discrete distance bins (e.g. five logarithmically spaced bins across the 1-200km range).

- Selection of earthquake events containing a large number of relevant ground-motion records (e.g., Atkinson (2011) recommends at least 30 observations per event), for which a sufficient number of observations in a given distance bin is available (e.g., at least 10).
- For each event and distance bin, define a simple linear regression of the ground-motion parameter versus distance. The actual equation of this regression is not important, since the objective is not to come up with a GMM but to set up a baseline for the computation of data scatter.
- Evaluation of the standard deviation of the residuals from the regression. This standard deviation can then be seen as the aleatory variability of the random scatter of the ground-motion parameters.

This empirically-based method only quantifies the intra-event component, σ_{intra}, of the aleatory variability, σ_{ale}, because it is obtained from ground-motion distributions within single events (Atkinson 2011). The approach has been applied to the RESORCE database, although the density of the accelerometric data in Europe is far from that of North America used in Atkinson (2011). Therefore, it was not possible to find earthquake events from RESORCE fitting all the criteria recommended above. It should be also noted that Atkinson (2011) selected ground motions recorded on any soil class, thanks to the use of a correction factor that accounts for the site amplification. In our application, only 12 RESORCE events having more than 10 observations on EC8 soil class B have been selected, as shown in Table 3.

Table 3

The limited number of observations per event prevents the use of distance bins, as advocated by Atkinson (2011), in order to obtain a more accurate regression line, and to limit the effect of the non-linear decrease of the ground-motion values with respect to distance. Despite this data limitation, the examples in Fig. 3 show an adequate linear trend for applying the proposed approach without distance bins.

Fig. 3

The standard deviations of the residuals from the linear fit of each of the 12 RESORCE selected events are outlined in Table 3. It has been checked that they are not dependent on magnitude or distance range, and therefore they may be averaged for each ground-motion parameter considered. This is summarized in Table 4, where averaged sigma values obtained by applying Atkinson (2011) approach are compared with those following the procedure described by equations 2 to 4. Aleatory variability, σ_{ale}, in Table 4 has been averaged for all combination of magnitude and distance only for illustration purposes. Magnitude- and distance-specific values should be used when applying the representative GMM suite.

Table 4

The empirical approach introduced by Atkinson (2011) assumes the inter-event component of the aleatory variability is epistemic in nature, because of uncertainty in stress drop (source) and attenuation (path) for each single event. That means aleatory variability includes only the intra-event component. This argument is especially significant when Monte Carlo approaches are applied for PSHA (e.g., Musson 1999; Hong and Goda 2006; Assatourians and Atkinson 2013; Atkinson and Goda 2013; García-Fernández et al. 2018); where ground motion is calculated for each even in a long time-span synthetic catalogue. The median GMM to be used for each earthquake is selected by random draw from available models, and then it is perturbed to represent epistemic uncertainty for that particular event by adding an increment to the median GM as a function of the distance, with random coefficients depending on the source size (or stress parameter) and the path effects (attenuation). That way, epistemic uncertainty includes inter-event variability. Douglas (2018a), although not considering this approach, includes statistical and regional uncertainty (anelastic attenuation, and stress parameter) as branches of his three-set logic tree for handling epistemic uncertainty.

In this application to European GMPEs, the epistemic uncertainty is obtained by the differences between the individual median GMPEs selected, as explained in Section 3 above. Atkinson and Adams (2013) include, in addition, a delta factor function of distance that increases epistemic uncertainty to account for the binned observations. The limitation on data availability in the European-Mediterranean region, as compared to North America, prevents calculating a similar delta factor; therefore, the inter-event component would not be fully captured into the estimated epistemic uncertainty. However, values in Table 4 seem to be consistent, in the sense that the estimated averaged aleatory variability, σ_{ale}, remains larger than the intra-event component σ_{intra} that has been calculated with limited data using Aktinson (2011) method. This result shows that, provided more well-recorded earthquakes become available, a more robust model of aleatory uncertainties (i.e., including a decomposition of the intra- and inter-event terms) might be derived for the representative GMM suite.

Finally, the slight difference between σ_{tot} and σ_{ale} in Table 4 confirms the limited impact of epistemic uncertainties in the present case, while a large part of the variability remains unexplained by the representative GMM suite. Therefore, we propose to include the inter-event component, σ_{inter}, of the aleatory variability as part of the epistemic bounds in our model, following the framework initially introduced by Atkinson (2011) and Atkinson and Adams (2013). The σ_{inter} component may be estimated by considering the quadratic combination of all identified sources of uncertainty:

$$\sigma_{tot}^2 = \sigma_{intra}^2 + \sigma_{inter}^2 + \sigma_{epi}^2 \quad (5)$$

Because we focus here on a purely data-driven approach in order to get a first estimate of the uncertainty terms of the proposed GMM suite, the following assumptions are used to compute σ_{inter}:

- Both terms σ_{intra} and σ_{tot} are assumed to be constant over all combinations of magnitude and distance, and are estimated from the averaged values in Table 4.
- The term σ_{epi} varies with magnitude and distance (see Equation 1).

Fig. 4

However, once the σ_{inter} component has been estimated, the fully characterised probabilistic GMM suite is built by considering the dependency over magnitude and distance, i.e., the nine magnitude-distance bins in Table 2. This limitation is mostly due to the lack of data points to support a robust statistical estimation over a wide range of magnitude-distance combinations. The resulting GMM suite, along with a fully characterised probabilistic model, is then represented in Fig. 4, for selected magnitudes and GM parameters.

5. Validation

The potential bias of the proposed Pan-European representative GMM suite is evaluated by comparing the PGA and SA(T) predictions of the GMM suite to ground-motion values extracted from the latest version (Lanzano et al. 2019) of the ESM-Engineering Strong-Motion database (Luzi et al. 2016), which contains the most up-to-date accelerometric data from earthquakes mainly recorded in the European-Mediterranean and the Middle-East regions. This database has updated RESORCE with additional records up to 2016 and a new manual processing following Paolucci et al. (2011). Using the ESM strong-motion flat-file 2018 (Lanzano et al. 2019), 2,904 new ground-motion records have been extracted, for the time period 2012-2016, following the criteria presented in Section 2 (i.e., magnitude between 4.0 and 7.0, normal or strike-slip faulting mechanisms, focal depth less than 20 km, Joyner-Boore distance between 1 and 200 km, and EC8 ground type B). The short time interval of this selection (around 4 years), makes this ESM sub-set heavily biased towards small magnitude events (mostly M_w between 4.0 and 5.0, with the largest one corresponding to M_w 6.8). However, using this ESM new data for validation, even if limited, should provide a more objective way for assessing the performance of GMMs developed using data from the RESORCE database.

The ranking approach proposed by Scherbaum et al. (2004), and applied by Drouet et al (2007) for the selection of GMPEs in the Pyrenean area is used here. It relies on the computation of the residuals *Y* and normalised residuals *Z*, with respect to the selected GMMs:

$$Y = \log_{10} y_{obs} - \log_{10} y_{gmm} \tag{6}$$

$$Z = \frac{\log_{10} y_{obs} - \log_{10} y_{gmm}}{\sigma_{gmm}} \tag{7}$$

As suggested by Scherbaum et al. (2004) and Drouet et al. (2007), three statistical measures are estimated for both *Y* and *Z*, namely the median, the mean and the standard deviation. Additionally, the likelihood parameter LH_Z of the normalized residual *Z* provides a reliable measure of the goodness-of-fit of a model, as it gives the likelihood of actually observing the given value, as a function of the underlying model (Scherbaum et al. 2004). The proposed likelihood parameter is expressed as follows:

$$LH_Z = 1 - erf\left(\frac{|Z|}{\sqrt{2}}\right) \tag{8}$$

where *erf* is the error function. Using this formulation, LH_Z tends towards 1 as the residual *Z* tends towards 0, and decreases with increasing *Z*.

Here we will follow the original scheme by Scherbaum et al. (2004) applying those metrics to the normalised residuals *Z*. In order to assess qualitatively the ability of the GMMs to match the observations dataset, the ranking system of Table 5 (Scherbaum et al. 2004) is applied. It includes three categories (A, B, C), each one requiring fulfilling the specified criteria for the four defined metrics. A model not meeting any of the criteria is classified unacceptable (class D).

Table 5

Values of the four performance metrics and corresponding ranking, as applied to the ESM sub-set for the different GMMs (only normal faulting version of BI14 and DE14 are included because strike-slip versions provide very similar values) and selected ground-motion parameters, are shown in Table 6, and plotted in Figure 5.

Table 6

Fig. 5

The developed GMM suite performs significantly well in appropriately representing observed ground motions from the ESM sub-set, when compared to the overall prediction capability of the selected GMMs (Figure 5). It also appears that the considered GMMs tend to provide a poor fit when predicting short-period parameters (e.g., PGA, SA at 0.1s and 0.2s). This effect may be due to the inadequacy of the RESORCE models to deal with low magnitude scaling at short periods. However, another comparison has been carried out with only a subset of ESM database (i.e., only events with M_w 4.5 and greater): the outcomes are very similar with the ones in Table 5 and Fig. 6, thus preventing us from concluding on this issue.

Three of the GMMs (AK14, BI14 and the developed GMM suite) stand out in the ranking of Table 6 to model the ESM-subset for the seven ground-motion parameters considered. Comparing the respective values of the four performance metrics (Figure 6), the new GMM suite shows, in general, a better and more stable performance predicting the ground motion observations.

Fig. 6

6. Conclusions

This paper has demonstrated the application to a Europe wide context of the representative GMM suite approach (Atkinson 2011; Atkinson and Adams 2013; Atkinson et al 2014), which is considered a much better approach in ground-motion characterization analysis because of its flexibility and transparency (Atkinson et al 2014). Six models among the recently developed GMPEs derived from the RESORCE strong-motion database (Akkar et al 2014a; Douglas 2014) have been selected in order to develop a Pan-European GMM suite for EC8 soil class B and normal or strike-slip faulting style, built upon three representative models (lower, central and upper) that cover the V_{S30} interval defining EC8 soil class B.

While epistemic uncertainty due to the availability of multiple GMMs is able to be properly addressed by this approach, some issues remain when quantifying the associated aleatory variability. An appealing alternative is the fully data-driven procedure suggested by Atkinson (2011) to empirically assess the aleatory variability, without double-counting uncertainty sources that may already be contained in the epistemic component. However, the relative scarcity of recorded ground-motion data in Europe prevents such empirical models to be accurately constrained. Therefore, a modified data-driven approach has been proposed, based on the residuals of the RESORCE ground-motion observations with respect to the central model of the developed Pan-European GMM suite. Results show that aleatory variability dominates the total variability; therefore, to obtain a fully characterized probabilistic model the aleatory variability is further decomposed into intra- and inter-event components, following Atkinson (2011) empirical approach that considers the epistemic nature of the inter-event component. Based on this assumption, the computed inter-event component is included as part of the epistemic bounds of the developed GMM suite.

The new GMM suite is validated using a sub-set of the recent ESM-Engineering Strong-Motion database (Luzi et al. 2016, Lanzano et al. 2019), and compared to the selected GMPEs used in its development by applying the categorization scheme proposed by Scherbaum et al. (2004). The developed GMM suite shows its appropriateness with a better and more stable performance when it is compared to the different models and their capability for predicting ESM sub-set observed ground motions.

Because the Pan-European representative GMM suite is generated for discrete magnitude-distance combinations, without any functional form, it has the ability to smooth out the local discrepancies (e.g. overestimation or underestimation) that may appear when only a single GMM is considered. The novel way of obtaining the three representative models (lower, central and upper) of the GMM suite allows for considering the additional epistemic uncertainty arising for the V_{s30} of the ground type. This GMM suite can be directly applied in PSHA codes handling GMMs without a given functional form, like e.g., EqHaz (Assatourians and Atkinson 2013); being especially suited for Monte Carlo-based software. Additionally, a weighting scheme can be introduced in PSHA applications to favour average (central model), low (upper model) or high (lower model) V_{s30} values. By limiting the sampling space to three GMMs (upper, central, lower), the developed GMM suite allows for an easier and efficient handling of epistemic uncertainty, as compared to the widely applied logic tree approach. This results in greatly reducing both complexity of the modelling and computation efforts. Finally, the full performance of the Pan-European representative GMM suite will be further tested within a probabilistic loss assessment framework, comparing the results with a standard implementation through a GMM logic tree.

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TABLE CAPTIONS

Table 1 Main characteristics of the selected GMPEs: AK14 (Akkar et al. 2014b), BI14 (Bindi et al. 2014), BO14 (Bora et al. 2014) and (DE14 (Derras et al. 2014).

Table 2 Total variability, σ_{tot}, with respect to the central model of the GMM suite, and aleatory variability, σ_{ale}, for different ground motion parameters, averaged over selected magnitude and distance bins. **Nb** refers to the number of data values in each magnitude-distance bin.

Table 3 Selected earthquakes for the computation of intra-event variability using the approach by Atkinson (2011). '**No. Obs.**' is the number of relevant records that have been retrieved from the RESORCE database, for each event. '**Sigma value**' is the standard deviation of the residuals with respect to the linear regression in Fig. 4.

Table 4 Comparison of the estimated variability models for the representative GMM suite (averaged values).

Table 5 Ranking criteria with respect to the four performance metrics, according to Scherbaum et al. (2004).

Table 6 Values of the four performance metrics and ranking applied to the 2012-2016 subset of the ESM strong-motion flat-file 2018 (Lanzano et al. 2019), for the different GMMs and the ground-motion parameters considered.

FIGURE CAPTIONS

Fig. 1 Selected GMPEs with $V_{s,30}$ = 580 m/s, Mw values of 5.0 and 6.0, and ground-motion parameters PGA, SA[0.2s] and SA[2.0s] (solid line = normal faulting, dashed line = strike-slip faulting). The AK14, BI14, BO14 and DE14 models (see Table 1) are represented respectively by the blue, green, red and cyan curves (dotted green and cyan curves correspond to strike-slip version of BI14 and DE14, respectively). The green dots represent records from the RESORCE database for a central $V_{s,30}$ interval of EC8 ground type B of [500;660[m/s. The black dots and the vertical black lines correspond to the geometric mean and associated standard deviation of the RESORCE data over eight selected distance bins with a 50% overlap (see text for details).

Fig. 2 Pan-European representative GMM suite. Central model (black crosses), and Upper and Lower models (red crosses). Colour dots represent records from the RESORCE database for four $V_{s,30}$ intervals of EC8 ground type B (i.e., red dots for [360;500[m/s, green dots for [500;660[m/s, blue dots for [660;800] m/s, and open circles for unspecified $V_{s,30}$). Black dots and the vertical black lines correspond to the geometric mean and associated standard deviation of the RESORCE data over eight selected distance bins with a 50% overlap (see text for details)

Fig. 3 Linear fit (solid lines) of PGA versus distance from some of the earthquakes selected from the RESORCE database. Diamonds represent records on soil class B with $V_{s,30}$ in interval for [360;500[m/s, full dots for [500;660[m/s, crosses for [660;800] m/s, and open circles for unspecified $V_{s,30}$.

Fig. 4 Pan-European representative GMM suite. Central model (black crosses). Upper and Lower models (red crosses). Total variability, σ_{tot}, (blue dots). 'Extended' epistemic uncertainty (green dots), combining σ_{inter} and $\sigma_{epi}$$\cdot\left(i.e., \sqrt{\sigma_{inter}^2 + \sigma_{epi}^2}\right)$

Fig. 5 Values (colour open circles) of the four performance metrics, mean(Z), median(Z), std(Z) and median(LH_Z) for seven ground-motion parameters and five GMMs (see text for details). The bold blue open circles correspond to the proposed GMM suite. Solid and dashed lines are included just to joint values for each GMM.

Fig. 6 Comparison of the four performance metrics values for the three GMMs best classified to predict observed ground motions from the ESM sub-set, following the ranking scheme by Scherbaum et al. (2004).

colour figure 1

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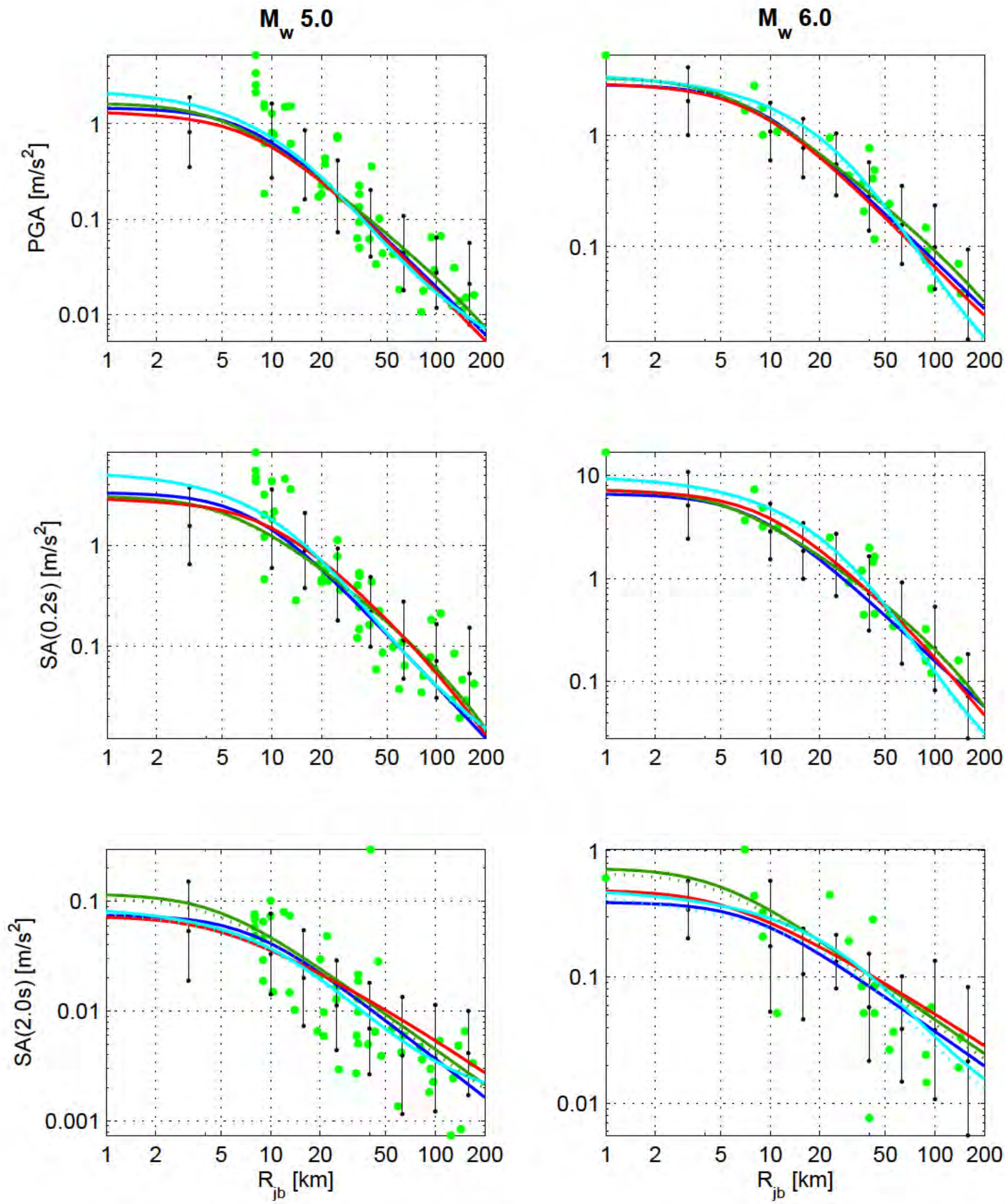
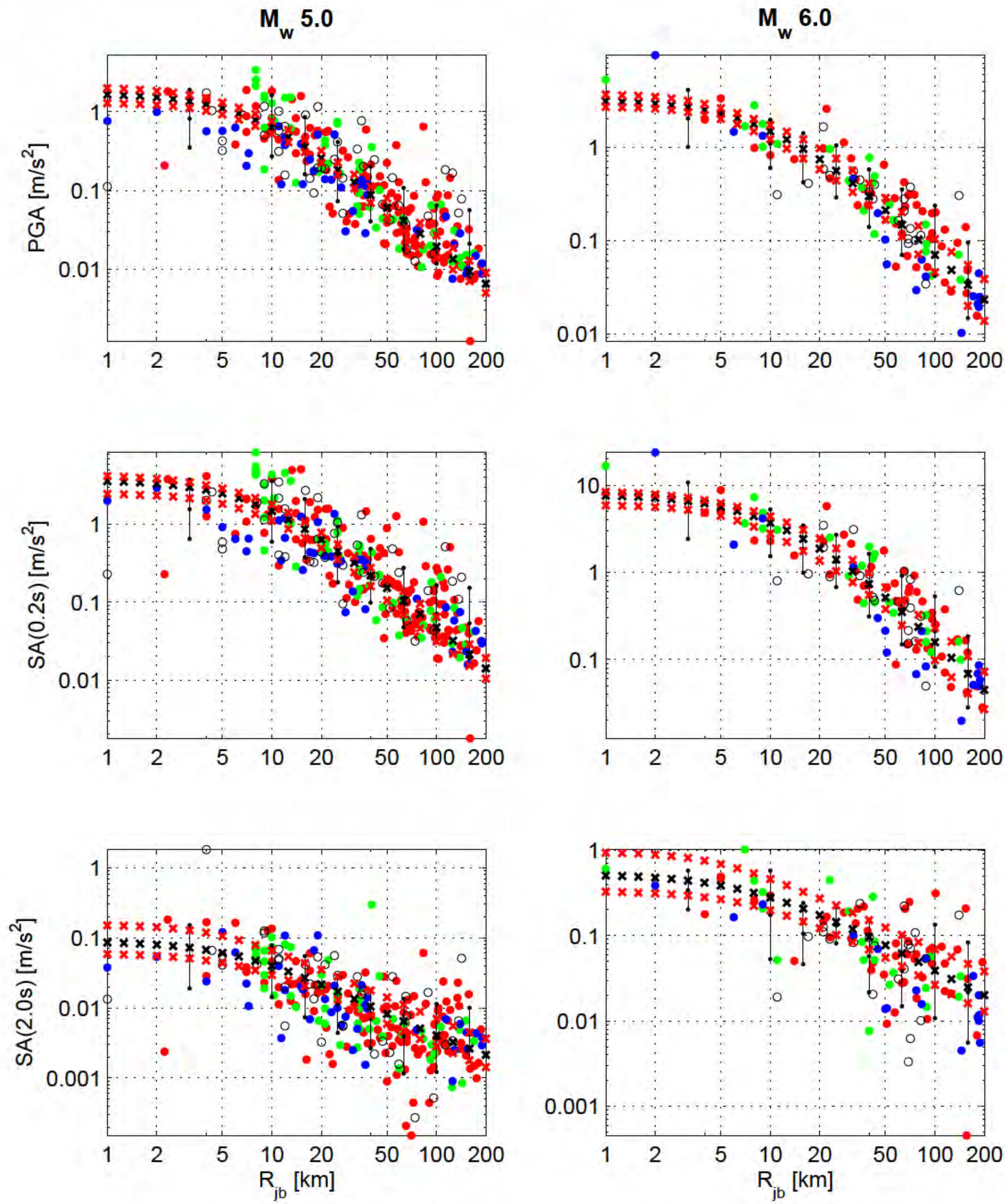
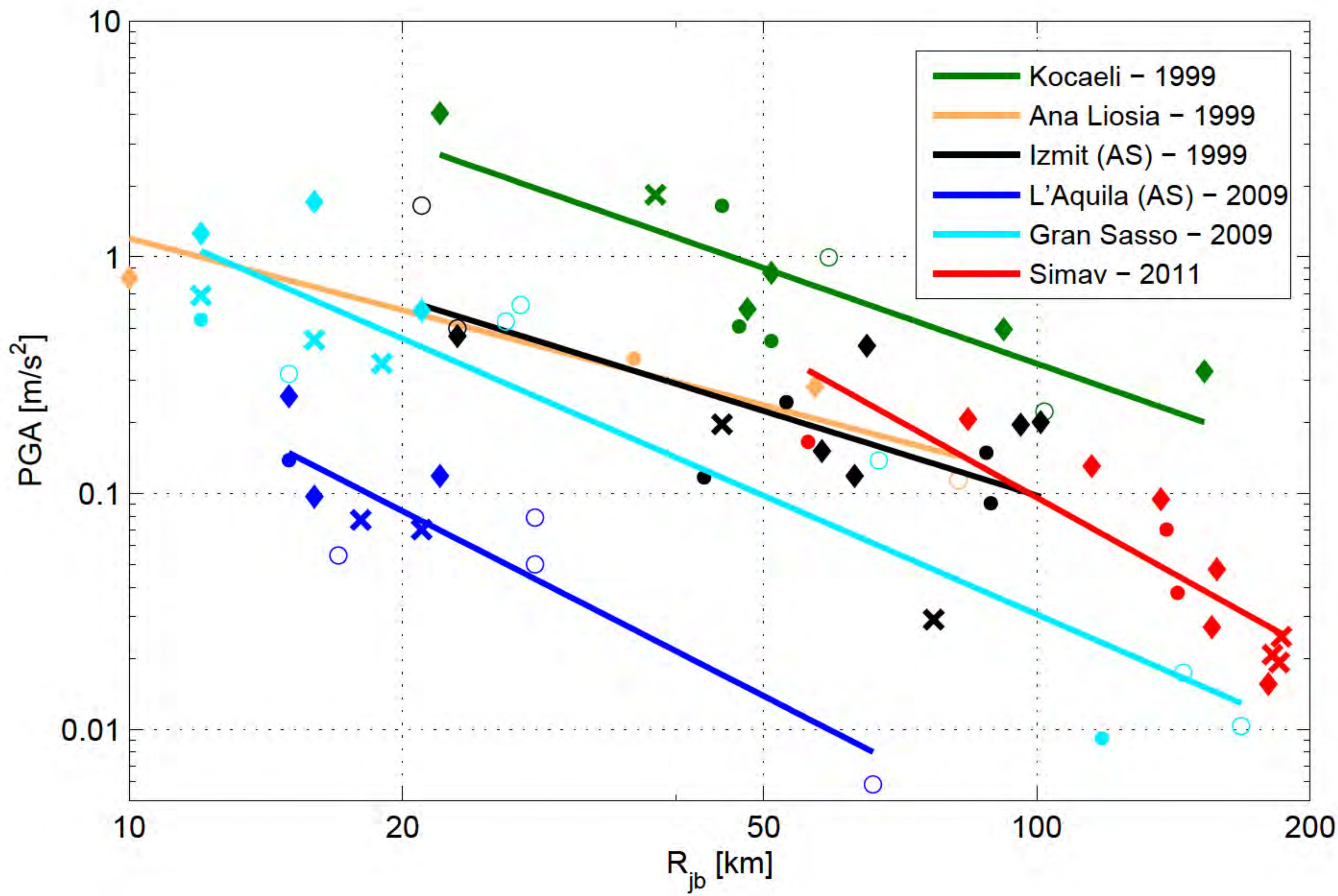
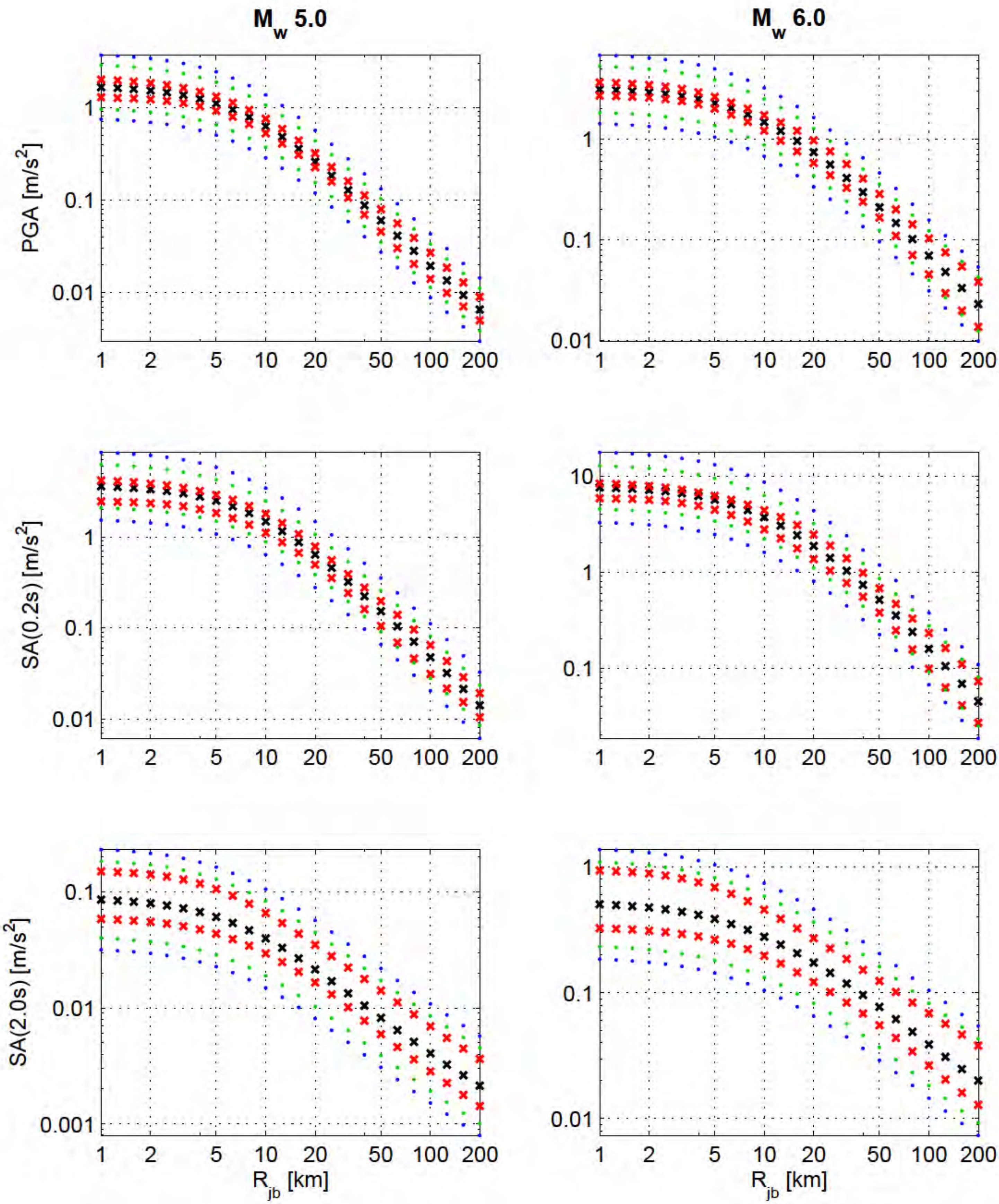




M_w 5.0
M_w 6.0
PGA [m/s²]
SA(0.2s) [m/s²]
SA(2.0s) [m/s²]
R_jb [km]
R_jb [km]
1
0.1
0.01
0.001
10
1 2 5 10 20 50 100 200



Kocaeli − 1999
Ana Liosia − 1999
Izmit (AS) − 1999
L'Aquila (AS) − 2009
Gran Sasso − 2009
Simav − 2011
PGA [m/s^2]
R_{jb} [km]
10
1
0.1
0.01
10
20
50
100
200



M_w 5.0
M_w 6.0
PGA [m/s^2]
SA(0.2s) [m/s^2]
SA(2.0s) [m/s^2]
R_{jb} [km]
R_{jb} [km]
1
0.1
0.01
10
0.001
1 2 5 10 20 50 100 200

colour figure 5

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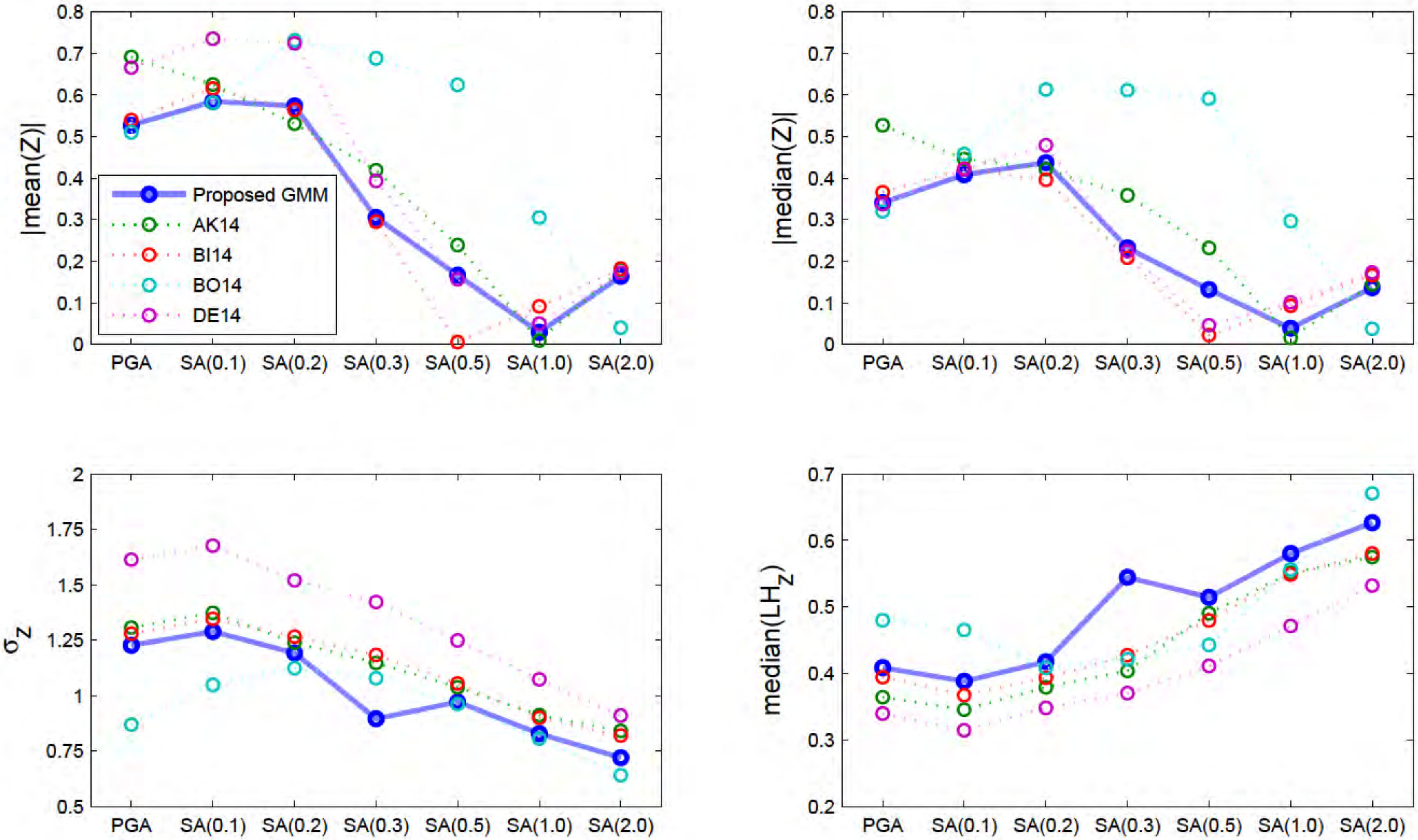

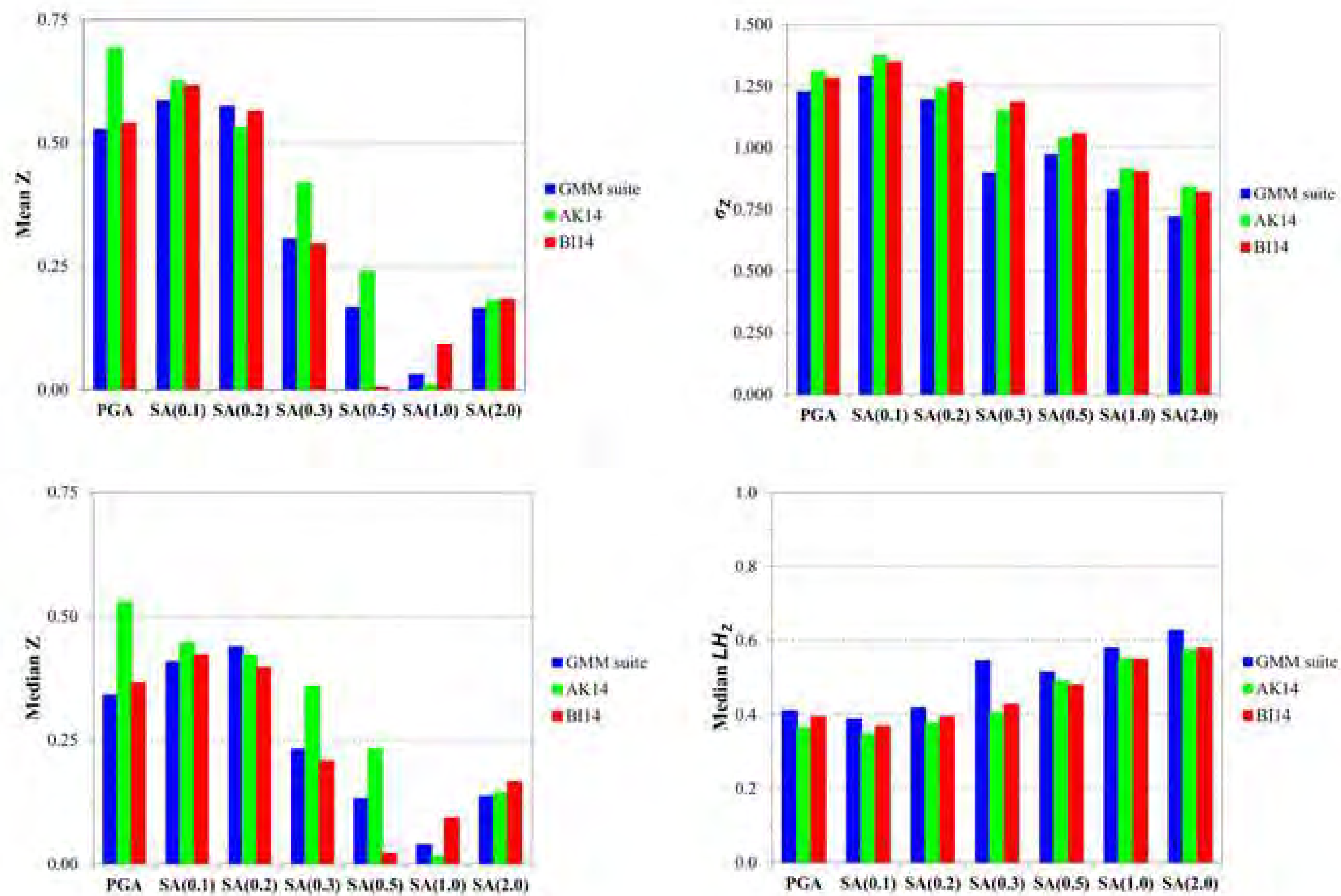
Mean Z
0.75
0.50
0.25
0.00
PGA SA(0.1) SA(0.2) SA(0.3) SA(0.5) SA(1.0) SA(2.0)
GMM suite
AK14
BI14
σ_Z
1.500
1.250
1.000
0.750
0.500
0.250
0.000
PGA SA(0.1) SA(0.2) SA(0.3) SA(0.5) SA(1.0) SA(2.0)
GMM suite
AK14
BI14
Median Z
0.75
0.50
0.25
0.00
PGA SA(0.1) SA(0.2) SA(0.3) SA(0.5) SA(1.0) SA(2.0)
GMM suite
AK14
BI14
Median LH_Z
1.0
0.8
0.6
0.4
0.2
0.0
PGA SA(0.1) SA(0.2) SA(0.3) SA(0.5) SA(1.0) SA(2.0)
GMM suite
AK14
BI14

	AK14	BI14	BO14	DE14
M_w range	4.0 – 7.6	4.0 – 7.6	4.0 – 7.6	3.6 – 7.6
Distance range	0 – 200 km	0 – 300 km	0 – 200 km	1 – 547 km
Distance metric	R_{epi}, R_{hypo}, R_{jb}	R_{hypo}, R_{jb}	R_{jb}	R_{jb}
Site amplification model	$V_{s,30}$	$V_{s,30}$ or soil class	$V_{s,30}$	$V_{s,30}$
Style of faulting	Normal Reverse	Normal Reverse Strike-slip Unknown	No distinction made	Normal Reverse Strike-slip
Model accounting for focal depth	No	No	No	Yes
GM parameters	PGA, SA [0.05,0.1,0.2,0.3, 0.5,1.0,2.0]s, PGV	PGA, SA [0.1,0.2,0.3,0.5, 1.0,2.0]s, PGV	PGA, SA [0.05,0.1,0.2,0.3, 0.5,1.0,2.0]s	PGA, SA [0.05,0.1,0.2,0.3,0.5, 1.0,2.0]s, PGV

	M_w bin	R_{jb} bin	Nb	PGA	SA(0.1s)	SA(0.2s)	SA(0.3s)	SA(0.5s)	SA(1.0s)	SA(2.0s)
σ_{tot}	[4.0-5.0[	[1;20[	217	0.370	0.385	0.380	0.365	0.392	0.422	0.473
	[4.0-5.0[	[20;60[	233	0.361	0.391	0.380	0.375	0.362	0.380	0.420
	[4.0-5.0[	[60;200]	89	0.413	0.430	0.420	0.440	0.478	0.502	0.516
	[5.0-6.0[	[1;20[	110	0.324	0.341	0.359	0.323	0.329	0.362	0.375
	[5.0-6.0[	[20;60[	122	0.285	0.328	0.312	0.298	0.324	0.349	0.363
	[5.0-6.0[	[60;200]	152	0.326	0.356	0.350	0.324	0.336	0.367	0.417
	[6.0-7.5]	[1;20[	23	0.223	0.301	0.223	0.267	0.253	0.240	0.281
	[6.0-7.5]	[20;60[	41	0.242	0.288	0.288	0.246	0.300	0.320	0.391
	[6.0-7.5]	[60;200]	50	0.270	0.30	0.328	0.294	0.317	0.315	0.390
σ_{ale}	[4.0-5.0[	[1;20[	217	0.360	0.366	0.359	0.349	0.376	0.415	0.467
	[4.0-5.0[	[20;60[	233	0.355	0.384	0.374	0.362	0.341	0.369	0.416
	[4.0-5.0[	[60;200]	89	0.398	0.414	0.406	0.427	0.460	0.486	0.504
	[5.0-6.0[	[1;20[	110	0.319	0.330	0.351	0.320	0.322	0.352	0.367
	[5.0-6.0[	[20;60[	122	0.281	0.322	0.307	0.294	0.318	0.345	0.361
	[5.0-6.0[	[60;200]	152	0.313	0.343	0.338	0.307	0.319	0.357	0.411
	[6.0-7.5]	[1;20[	23	0.218	0.296	0.215	0.254	0.226	0.206	0.257
	[6.0-7.5]	[20;60[	41	0.237	0.282	0.283	0.240	0.292	0.316	0.387
	[6.0-7.5]	[60;200]	50	0.245	0.279	0.305	0.256	0.280	0.291	0.375

Earthquake	**Date**	**M_w**	**No. Obs.**	**Sigma value**		
				PGA	**SA(0.2s)**	**SA(2.0s)**
Irpinia	23/11/1980	6.9	11	0.220	0.275	0.258
- (Italy)	16/01/1981	5.2	10	0.305	0.330	0.206
Kocaeli	17/08/1999	7.6	12	0.145	0.190	0.328
Ano Liosia	07/09/1999	6.0	10	0.142	0.147	0.136
Izmit (AS)	13/09/1999	5.8	14	0.302	0.272	0.338
Izmit (AS)	11/11/1999	5.6	12	0.309	0.376	0.335
Duzce	12/11/1999	7.1	12	0.335	0.362	0.229
L'Aquila	06/04/2009	6.3	16	0.266	0.359	0.278
L'Aquila (AS)	07/04/2009	5.6	13	0.328	0.364	0.268
L'Aquila (AS)	08/04/2009	4.1	10	0.195	0.206	0.222
Gran Sasso	09/04/2009	5.4	14	0.281	0.360	0.223
Simav	19/05/2011	5.9	12	0.192	0.203	0.520

Method	Sigma	PGA	SA(0.2s)	SA(2.0s)	Source
Atkinson (2011)	σ_{intra}	0.252	0.287	0.278	Table 3
This paper	σ_{tot}	0.337	0.359	0.422	Table 2
	σ_{ale}	0.328	0.348	0.415	

Rank	**Mean *Z***	**Median *Z***	σ_Z	**Median** LH_z
A	< 0.25	< 0.25	< 1.125	> 0.4
B	< 0.50	< 0.50	< 1.250	> 0.3
C	< 0.75	< 0.75	< 1.500	> 0.2
D		UNACCEPTABLE		

GMM	Metric	PGA	SA(0.1)	SA(0.2)	SA(0.3)	SA(0.5)	SA(1.0)	SA(2.0)
GMM suite	Mean Z	0.527	0.585	0.574	0.305	0.166	0.030	0.164
	Median Z	0.341	0.408	0.438	0.232	0.132	0.039	0.137
	σ_Z	1.227	1.289	1.193	0.896	0.972	0.829	0.720
	Median LH_z	0.409	0.388	0.418	0.545	0.514	0.580	0.627
	Rank	C	C	C	B	A	A	A
AK14	Mean Z	0.692	0.625	0.531	0.419	0.239	0.010	0.180
	Median Z	0.527	0.446	0.421	0.359	0.232	0.016	0.144
	σ_Z	1.307	1.374	1.239	1.148	1.038	0.913	0.841
	Median LH_z	0.364	0.346	0.379	0.404	0.491	0.551	0.575
	Rank	C	C	C	B	A	A	A
BI14	Mean Z	0.540	0.616	0.564	0.295	0.005	0.091	0.182
	Median Z	0.366	0.422	0.396	0.208	0.022	0.093	0.166
	σ_Z	1.280	1.346	1.266	1.184	1.055	0.901	0.820
	Median LH_z	0.394	0.368	0.394	0.428	0.480	0.549	0.580
	Rank	C	C	C	B	A	A	A
BO14	Mean Z	0.512	0.581	0.731	0.688	0.624	0.305	0.040
	Median Z	0.319	0.458	0.613	0.612	0.591	0.297	0.037
	σ_Z	0.873	1.049	1.124	1.079	0.962	0.807	0.641
	Median LH_z	0.480	0.465	0.408	0.421	0.443	0.556	0.671
	Rank	B	C	C	C	C	B	A
DE14	Mean Z	0.666	0.735	0.724	0.393	0.157	0.050	0.172
	Median Z	0.338	0.421	0.479	0.224	0.046	0.101	0.173
	σ_Z	1.614	1.676	1.520	1.423	1.249	1.073	0.911
	Median LH_z	0.340	0.315	0.349	0.371	0.411	0.471	0.532
	Rank	D	D	D	C	B	A	A