ESTIMATING GROUND-MOTION VARIABILITY: ISSUES, INSIGHTS & CHALLENGES

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ABSTRACT :

The variability (sigma) associated with empirical ground-motion prediction equations has a significant impact on the results of seismic hazard analysis, and in some cases represents the main source of uncertainty. Consequently, numerous attempts have been made at reducing the value of sigma, mostly without success. The root of the problem lies in the fact that the models that are fitted to the data during the regression process are highly idealised with respect to the physical processes actually taking place during the generation and propagation of seismic waves. Assumptions regarding the functional form and measurement errors in both the predicted and the explanatory variables might also contribute to the variability, but their impact generally remains marginal. The present paper reviews the key methodological aspects involved in the estimation of sigma, with the aim of identifying the approaches that are the most promising in terms of reducing the value of sigma.

KEYWORDS: Sigma, Variability, Uncertainty, Ground Motions, Seismic Hazard

1. INTRODUCTION

The prediction of ground-motion levels to be expected at a site is one of the key elements of seismic hazard assessment. This prediction is commonly achieved using empirical ground-motion prediction equations (GMPE) derived through regression analysis on selected sets of instrumentally recorded strong-motion data. These equations relate a predicted variable characterising the level of shaking, most commonly the logarithm of a peak ground-motion parameter (*e.g.*, PGA, PGV) or response spectral ordinate (SA, PSA, PSV, SD), to a set of explanatory variables describing the earthquake source, wave propagation path and site conditions. The explanatory variables usually include the earthquake magnitude, M, a factor describing the style-of-faulting of the causative event, a measure of the source-to-site distance, R, and a parameter characterising the site class. Recent equations sometimes also include additional terms to characterise the location of the site with respect to the rupture plane (hanging-wall factor), to distinguish between ground motions from surface-faulting events and buried ruptures, or to include the effects of sediment depth in the case of deep alluvial basins. Other factors that are known to influence the motion (and many others that are not yet known) are not included in the equation because the information is not readily available, or not predictable in advance.

Even for the factors that are considered in the equation, the representation of the ground motion is very simple compared to the complexity of the physical processes involved in ground-motion generation and propagation. In combination with the limited number of factors considered in the functional form of the equation, these idealisations cause the values in the dataset to depart from the average value predicted by the equation in an apparently random manner. To capture the resulting dispersion, the distribution of the ground-motion residuals (defined as the observed minus predicted values of the variable under consideration, *e.g.* ln(PGA)) is examined. The ground-motion residual distribution is generally assumed to be normal with a mean of zero and a standard deviation σ. Thus, all models can be separated into an explained component which is a function of the explanatory variables, and an unexplained component characterised by σ.

In the context of seismic hazard analysis, it is customary to distinguish between epistemic uncertainty (uncertainty due to incomplete knowledge and data) and aleatory uncertainty (uncertainty due to the random nature of the processes under consideration). Following the nomenclature introduced by Toro *et al.* (1997), each these components of uncertainty is further subdivided into modelling uncertainty (uncertainty regarding the model adopted to represent the ground motion) and parametric uncertainty (uncertainty about the values of the parameters included in the model). The scatter (σ) associated with ground-motion prediction equations is commonly interpreted as the aleatory uncertainty of the ground motion, although it is as yet unclear to what extent it represents genuine randomness (*i.e.*, intrinsic variability of the ground motion), and to which extent it reflects epistemic modelling uncertainty regarding the factors controlling the ground motion (*i.e.*, explainable variations in ground motion that have not yet been included in ground-motion models and may therefore appear as random variations).

As discussed in Restrepo-Vélez and Bommer (2003) and Bommer and Abrahamson (2006), the value of σ has a significant impact on the results of seismic hazard analysis, since it controls the shape of the hazard curves at low annual frequencies of exceedance. Figure 1 summarises the values of σ for equations predicting PGA published to date. This figure shows that the values of σ have remained stable over the past 40 years, despite an increase in the number of available records and the inclusion of additional variables in the equations. The values of σ tend to lie between 0.15 and 0.35 in $\log_{10}$ units (0.35 to 0.80 in ln units), but in some isolated cases may range as high as 0.55 $\log_{10}$ units (1.26 ln units). In view of the lack of evolution of the values of σ and the pronounced influence this parameter has on seismic hazard analysis results at low annual frequencies of exceedance, the possibility of counter-acting the influence of σ by truncating the ground-motion distribution has been investigated (Bommer *et al.*, 2004; Strasser *et al.*, 2008b). Such a truncation could be operated either directly on the amplitude of the ground motion, or on the distribution of ground-motion residuals. However, in view of the difficulty of justifying the choice of the truncation level, the aforementioned studies concluded that for the foreseeable future, research efforts should focus on a better understanding of the nature of σ and the issues related with the estimation of this parameter.

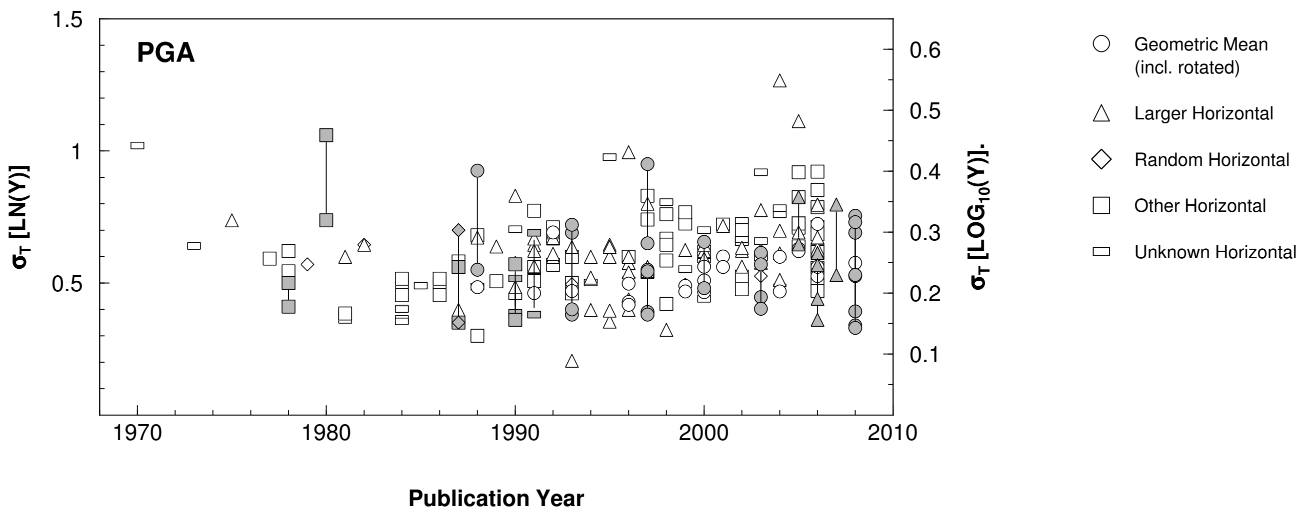

Figure 1 Summary of σ values for PGA equations published to date.

The present paper provides a brief overview of the issues and challenges related to the estimation of σ, with a particular emphasis on the factors influencing the value of σ, as well as approaches that could potentially lead to a reduction of σ. The reader is referred to Strasser *et al.* (2008a) for a more detailed discussion.

2. FACTORS AFFECTING SIGMA

Although the main cause for the scatter is believed to be the fact that the representation of the ground motion is very simple compared to the complexity of the physical processes involved in ground-motion generation and propagation, measurement errors and uncertainties in the values of both predicted and predictor variables might also contribute to the scatter. Additionally, the value of σ may be affected by the selection of given parameter definitions, both for the predicted variable (*e.g.*, horizontal parameter definition) and for the explanatory variables (*e.g.*, choice of distance metric).

The selection and processing of strong-motion data is one of the key stages of the derivation of a new empirical GMPE, to which considerable time and effort is devoted. The quality of the data used will naturally have an impact on the goodness of the fit, once a functional form has been selected. While ensuring that data of insufficient quality does not contaminate the regression, care should be taken not to use overly conservative selection criteria, as this may lead to under-sampling of the tails of the ground-motion distribution, which in turn affects the quality of the variability estimator obtained from the sample, as discussed in Bommer and Scherbaum (2005).

Typically, the strong-motion datasets used in regression include events contributing several accelerograms. As a result, the vectors of explanatory variables of these records are correlated, since the values of the event-specific parameters (*e.g*., magnitude or style-of-faulting) are the same. Furthermore, the uneven number of records contributed by the various events may cause events with a large number of records to exercise an undue influence during the regression process. As a result, it has become customary to separate between the inter-event and intra-event components of variability. The inter-event variability, σ_E (also denoted τ by some authors), can be interpreted as the combined ground-motion variability resulting from event-specific factors (*e.g.*, randomness in the source process) that have not been included in the predictive model. The intra-event variability, σ_A (also denoted σ by some authors), on the other hand, represents the combined ground-motion variability coming from record-specific factors (*e.g.*, randomness in the site amplification for a given site class or a given value of the average shear-wave velocity over the top 30m, $V_{S,30}$). In empirical GMPE, the inter-event variability is generally found to be smaller than the intra-event variability.

Errors in the values of the predictor variables, hereafter referred to as metadata errors, will contribute to the scatter through error propagation. For instance, Rhoades (1997) found that measurement uncertainties on magnitude contributed 57% of the inter-event variability for the dataset he examined. In practice, the influence of metadata errors is curtailed by careful selection of the data used in the derivation of GMPEs. It has now become common practice to exclude records for which the values of the explanatory variables cannot be determined with confidence. The recent GMPE of Abrahamson and Silva (2008) explicitly accounts for the contribution to σ of measurement errors in the explanatory variables, which included magnitude, distance, $V_{S,30}$ and the depth-to-top of rupture. Abrahamson and Silva (2008) found that the uncertainty in $V_{S,30}$ had the largest impact on the value of σ, whereas the contributions from the uncertainties in the other variables were only minor.

Once all data-related issues have been resolved and a functional form has been chosen, the value of σ will essentially depend on the method used for the regression analysis, particularly since only very limited control (in the statistical sense) is possible on the nature of the dataset (*e.g.*, number of recordings contributed by individual events), which is generally determined by data availability and quality. The strong-motion datasets available to researchers for the selection of accelerograms to be included in regression are generally strongly correlated in terms of the magnitude and distance distribution of the data. For earlier datasets predominantly including accelerograms recorded on analogue instruments, the data at larger distances were often almost exclusively contributed by the larger events in the dataset. With the advent of fully digital strong-motion networks, this issue has become less important over the past few decades, as now even small events are commonly recorded out to 100 km. Two-step regression techniques were introduced to prevent these correlations from biasing the regression (*e.g.*, Joyner and Boore, 1993). Biases may also be avoided using a one-stage maximum-likelihood technique based on the random effects approach (*e.g.*, Abrahamson and Youngs, 1992). The great majority of models consider only two components of variability (inter-and intra-event, or inter- and intra-station). Using a three-component variability model including an inter-event, an inter-station and a third component for the remaining record-to-record variability (*e.g.*, Chen and Tsai, 2002) is considerably more complex from a numerical point of view, and furthermore requires datasets including a large number of stations for which recordings from multiple events are available.

3. ISSUES AND CHALLENGES IN THE ESTIMATION OF SIGMA

The ultimate goal of any investigation into the nature of σ is the identification of methods to reduce the value of this parameter. A number of issues associated with the estimation of σ are briefly reviewed below.

3.1. Unbalanced nature of strong-motion datasets

Strong-motion datasets used in the derivation of GMPE are generally of very unbalanced nature (*i.e.*, the numbers of records contributed by individual events are very uneven), and this will affect the correlation structure of the dataset, and thus the estimation of the individual components of variability. As illustrated in Figure 2, a small number of studies have used datasets including multiple recordings from the same stations to derive the inter- and intra-station components of variability. Based on this limited data, the ratio of the inter- to intra-station variability seems to be more variable than the ratio of the inter- to intra-event variability. Comparing the estimates of inter-station variability those of inter-event variability could also provide clues as to the main cause of variability. Alternatively, the relative influence of event-specific and site-specific effects can be investigated using analysis of variance, as proposed by Douglas and Gehl (2008).

It should be noted, however, that the data used in these studies usually comes from seismic sequences including foreshocks and aftershocks, and therefore these findings might not be generally applicable. Aftershock events may differ from similar-sized mainshock events in terms of parameters characterizing the rupture process, such as stress drop. Furthermore, including the aftershock data is likely to increase the relative contribution of small-magnitude events to the dataset, which may also have an impact on the variability, as discussed below.

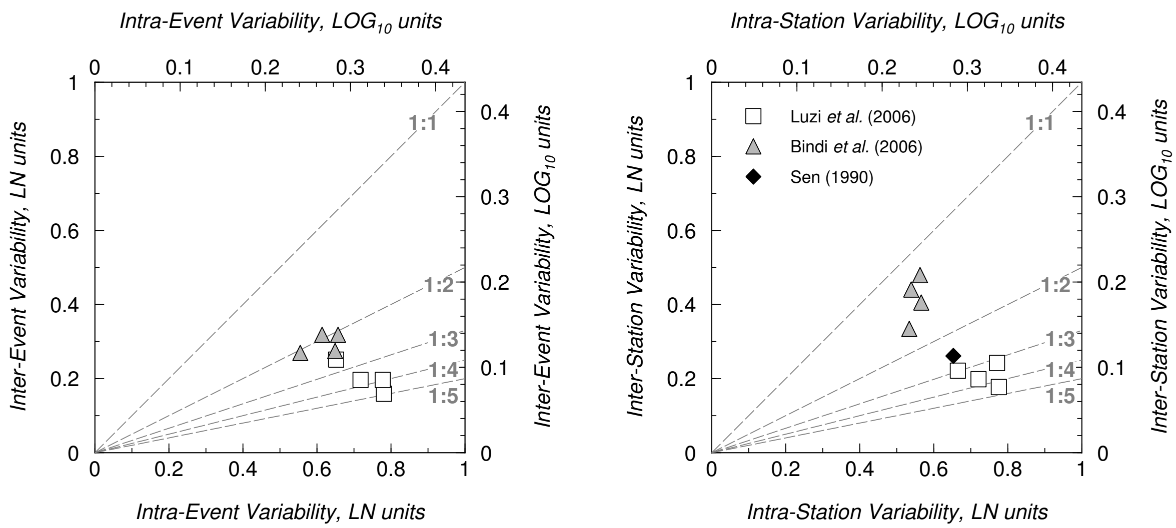

Figure 2 Left plot: Inter-and intra-event variability components for the Luzi *et al.* (2006) and Bindi *et al.* (2006) equations . Right plot: Inter- and intra-station values for the same equations, as well as for Sen (1990).

3.2. Homoscedastic vs. heteroscedastic models

In most equations, the scatter is assumed to be homoscedastic, *i.e.*, independent of the variables included in the equation. However, several authors have found trends relating the scatter to one or more explanatory variables and therefore suggested heteroscedastic models for the scatter, in which σ depends on the predictor variables. Most commonly, heteroscedastic models have found a decrease of the scatter with increasing magnitude (*e.g.*,Sadigh *et al.*, 1997; Ambraseys *et al.*, 2005; Akkar and Bommer, 2007a,b; Bommer et al., 2007). Youngs *et al.* (1995) find that for PGA, the magnitude-dependence of the variability is more pronounced for the inter-event term than for the intra-event term. While explanations suggested by other authors, such as non-linear site effects or a shift of the predominant period of the motion to longer periods with increasing magnitude cannot be discounted entirely, Youngs *et al.* (1995) suggest that the decrease in inter-event variability at larger magnitudes may be related to a decrease of the variability of stress drop at larger magnitudes. Errors in the location and magnitude determination of smaller events, in particular aftershocks, might also contribute to the trend, alongside potential biases introduced by the relative scarcity of data from large-magnitude earthquakes. Furthermore, differences in scaling between ground motions from small-magnitude and large-magnitude events need to be acknowledged both in the estimation of both the median ground-motion and the value of σ.

While most GMPE published to date either ignore a possible dependence of σ on distance, or have found this dependence negligible, Midorikawa and Ohtake (2004) found a significant decrease of the value of σ in the near-source region ($R_{jb} \leq 50$km) for their PGA and PGV equations derived using a large sample of Japanese data. On the other hand, they only found a mild dependence on magnitude. The inconsistencies in the conclusions regarding the relative influence of predictor variables on σ point to the fact that the interaction between the physical processes involved in the generation and propagation of ground motions is complex, and that this complexity is maintained in their impact on the value of σ. In particular, at short source-to-site distances, it is not straightforward to decouple the issue of magnitude-dependence of σ from that of the effects of soil non-linearity. Due to the degradation of the strength and stiffness of the soil under cyclic loading, large-amplitude ground motions are amplified less than small-amplitude motions. This can lead to a dependence of the value of σ on the amplitude of the ground motion, which would indicate that the use of the logarithmic transformation in the functional form of the equations may not be strictly correct (Douglas and Smit, 2001). Since ground motions also scale with magnitude, this dependence of σ on the level of ground motion can also be translated into a dependence on magnitude, as has been done for instance by Campbell and Bozorgnia (2003).

3.3. Modelling of soil non-linearity

Consideration of the non-linear behaviour of surficial geological deposits is one of the aspects of the selection of a functional form for the GMPE that may have an influence on the value of σ. A number of studies have derived separate equations for ground motions on rock and on soil by splitting the underlying dataset in two and carrying out separate regression analyses (*e.g.*, Crouse and McGuire, 1996; Sadigh *et al.*, 1997). Such studies generally find that the σ value for soil sites is lower than that for rock sites. One exception is Sadigh *et al.* (1997), who found larger σ values for deep soil sites than for rock sites. This might be due to the fact that deep soil sites are generally located in basins, and therefore 3D-geometry effects might be increasing the variability more than soil non-linearity decreases it.

Another approach to include the effect of soil non-linearity in ground-motion prediction consists in explicitly including a term modelling the amplification of surface ground motions with respect to their bedrock value. This approach requires the use of a non-linear fitting procedure in order to obtain an unbiased estimate of the coefficients. The non-linear terms can be constrained by considering a site response model (*e.g.*, Abrahamson and Silva, 2008), or from direct regression on the data (*e.g.*, Chiou and Youngs, 2008).When the uncertainties related to soil non-linearity effects are propagated to σ, its value depends both on PGA and on $V_{S,30}$, resulting in distance-dependence when a fixed magnitude value and a given $V_{S,30}$ value are considered. This distance-dependence has been found to be more pronounced for the Abrahamson and Silva (2008) model than for the Chiou and Youngs (2008) equations, due to the use of a 1-D site response model by the former authors.

3.4. Trade-offs in the estimation of σ and μ

The value of σ and the values of the coefficients required to estimate the median ground-motion are determined jointly in the regression, with the value of σ often being used as a gauge for the level of confidence attached to the mean value of the regression parameter, hereafter called μ. In practice, however, trade-offs exist in the estimation of μ and σ. Increasing the number of data points is often considered to increase the accuracy of the estimate of μ, but contamination of the residual distribution may occur if the additional data follow a slightly different distribution from the original dataset. Even in the case where all subsets are characterised by the same variability, broadening of the overall distribution will occur (*i.e.*, σ will increase) if the μ values of the subsets do not coincide. Conversely, approaches that have been developed to "tailor" the value of σ to a specific application by replacing the estimate of variability derived from multiple-source, multiple-site observations by a reduced value obtained based on recordings from a single site and a single source (Atkinson, 2006) carry a penalty of increased epistemic uncertainty on μ. As a result, unless the value of μ at the site of interested can be determined independently (through recordings or numerical simulations), the application of σ-reduction schemes does not necessarily result in a reduction of the overall uncertainty.

3.5. Regional variations in ground motions

As a result of the limited number of local strong-motion recordings available in all but a few regions, indigenous data are often supplemented by tectonically compatible allogenous data (*i.e.*, data from other regions with a similar tectonic environment) in order to obtain better constraints on some of the terms in the regression. This also increases the potential for contamination of the “true” target distribution. As a result, some GMPE developers have favoured the use of smaller datasets from a restricted geographical region. However, σ values for equations derived using data from small geographical areas have generally been found to be higher than those derived using datasets combining several regions (Douglas, 2007). Furthermore, a comparison of predictions from regional equations derived for parts of Europe with those obtained using recently derived pan-European equations (Ambraseys *et al.*, 2005; Akkar and Bommer, 2007a,b) shows that in many cases, the latter exhibit a better fit to the data than the former (Bommer, 2006). This is consistent with the finding that recent equations for ground motions from shallow crustal events perform satisfactorily even outside their intended region of application (*e.g.*, Stafford et al., 2008).

4. DISCUSSION AND CONCLUSIONS

Assessing the variability of ground motions, σ, is an inescapable reality in the ground-motion prediction process, since the appropriate characterisation of ground motions needs to acknowledge the large degree of scatter associated with these motions. The resistance of σ to any efforts made to reduce its value is a matter of great concern to ground-motion prediction in general, and seismic hazard analysis in particular, in view of the significant impact the value of σ has on hazard estimates. This impact has sometimes led to the temptation of ignoring σ altogether, but it is now accepted that the inclusion of σ, rather than being an option that can be switched on and off, is an integral part of any seismic hazard assessment process (Bommer and Abrahamson, 2006) – in other words, σ is here to stay.

So, is there anything that can be done about reducing its value? The scope for a reduction in the value of σ comes mainly from the observation that in practice, σ includes contributions from factors other than the intrinsic variability of ground motions. While σ is generally interpreted as representing aleatory variability, it must be borne in mind that this randomness is referred to the ground-motion model under consideration and therefore, some of the randomness may only be apparent. These contributions can be related to two main sources of uncertainties, which are (i) issues regarding the quality of the data used in regression, and (ii) issues regarding the ground-motion model specification and fitting. In both cases, there is some hope to achieve reductions in σ, although the process may be labour-intensive.

Firstly, contributions to σ that are related to insufficient data quality may be reduced through careful selection and reappraisal of the data. The global strong-motion databank is now sufficiently rich in data to allow the use of more stringent quality criteria in the selection of the recordings to be included in regression analyses, and thus avoid including poor-quality accelerograms and poorly documented records that could lead to artificial inflation of the value of σ. However, data selection criteria based on quality need to be reconciled with the requirement of having a dataset that is well-distributed across the space of the predictor variables, which means that in some cases it may be preferable to include some lower-quality recordings rather than to risk underestimating the true value σ through over-restrictive data selection. In particular, a practice to be avoided is the exclusion of records associated with large residual values, unless the ground motion values can be proven to be clearly erroneous (e.g., resulting from instrument malfunction or a digitization error). The use of robust regression methods (e.g., maximum-likelihood approaches) also allows a reduction of the influence of large residual values on the estimation of σ, compared to the ordinary least-squares case.

Secondly, there is reason to believe that σ can be reduced if the physical processes governing the behaviour of ground motions are better understood and modelled. In this context, better control of sigma can be achieved by considering the components of variability associated with source, path and site characteristics. The consideration of the inter- and intra-event components of variability is becoming increasingly routine in the derivation of ground-motion prediction equations. Other components, such as inter- and intra-site variability, have been investigated, but their applicability remains limited in view of the nature of the strong-motion data available, which includes few stations having recorded multiple events. A better grasp of the physical processes involved in ground-motion generation and propagation may lead to the inclusion of additional terms in the functional form of the equation. While this will generally lead to an improved estimate of the median ground motion, it will not necessarily result in a reduction of σ, as there is a penalty to be paid in terms of parametric uncertainty for the newly added parameters. This means that if the objective is to reduce the value of σ, rather than to have the most accurate estimate of the median, adding new parameters is only worthwhile as long as these parameters can be reliably estimated. The use of numerical simulations might help in estimating these parameters, and more generally filling data gaps, but similarly carries a penalty in terms of modelling and parametric epistemic uncertainty. This points to a trade-off between the accuracy with which the median ground-motion can be estimated, and potential reductions of σ. Ground-motion modellers have hitherto concentrated efforts on the first of these items; in view of the influence σ has on results of seismic hazard analysis, it might be worth concentrating more on the second point, and investigate the derivation of ground-motion models in which the accuracy of the median is partly sacrificed in favour of a lower σ value.

Finally, one observation that can be made is that amongst the large number of physical factors that have been found to influence the value of σ, some at least may not be relevant or applicable to a specific project. There is therefore some scope for reducing the value of σ to be used in a particular application by tailoring it to that specific situation. This can be achieved through the use of heteroscedastic models, which allow σ to vary with selected predictor variables of the ground-motion model (magnitude, distance, $V_{S,30}$) and thus enable the consideration of physical processes such as soil non-linearity effects, or the decrease of stress drop variability with increasing magnitude. Similarly, procedures have been recently developed (Atkinson, 2006; Lin *et al.*, 2008) to tailor σ to a specific source-site configuration. This is potentially the most promising approach to reduce σ, with observed reductions of 10% to 40% in some cases, but again carries a penalty of increased epistemic uncertainty on the median ground motion, which means that the mean hazard is not necessarily reduced. Also, for a general application of the findings of these studies, the sensitivity of the reduction in σ to the source-site configuration considered needs to be assessed, which could be achieved through the use of numerical simulations.

In conclusion, the prospects of reducing σ are not as hopeless as they might seem at first glance. Previous attempts at reducing σ through the use of larger datasets and the inclusion of additional terms in the functional form of predictive equations may have met with little success because the additional uncertainties introduced had not been considered. Approaches to reduce σ that bear these additional uncertainties in mind are admittedly quite labour-intensive, but the effort involved is likely to be worthwhile in the context of seismic hazard analysis.

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