of the approach. The goal of the method is to obtain a good representation of the epistemic uncertainty in the main components of the scaling of the response spectrum with the important predictor variables. The basic assumption is that there is a continuous distribution of GMPEs, which can be derived from published models. Then, the selection and weighting of GMPEs is based on the continuous distribution.

The continuous distribution of GMPEs is approximated by the joint distribution of coefficients of a GMPE function. The joint distribution of coefficients is estimated by fitting a common functional form to a set of published GMPEs, and then estimating the variances and correlations between the obtained sets of coefficients. This is done in the following way: We generate response spectral values ($T = 0.2s$) for different magnitude, distance, V_{S30}, Z_{TOR} and focal mechanism values F for the five NGA West 2 GMPEs (Abrahamson et al., 2014; Boore et al., 2014; Campbell and Bozorgnia, 2014; Chiou and Youngs, 2014; Idriss, 2014). For each GMPE i, this gives a data set $D_i = \{(M_1, R_1, V_{S30,1}, Z_{TOR,1}, F_1, y_{i,1}), \ldots, (M_N, R_N, V_{S30,N}, Z_{TOR,N}, F_N, y_{i,N})\}$, where N is the number of artificial data and Y_i is the median prediction of model i. Then, each synthetic data set from the underlying GMPEs is fitted to the following functional form

$$\begin{aligned}
\ln y = \theta_0 + g_M(M) + (\theta_4 + \theta_5(M-5)) \ln \sqrt{R_{RUP}^2 + \theta_6^2} - \theta_7^2 R_{RUP} \\
+ \theta_8^2 Z_{TOR} + \theta_9^2 F_R - \theta_{10}^2 F_{NO} - \theta_{11}^2 \ln \frac{V_{S30}}{760}
\end{aligned} \tag{10}$$

$$g_M(M) = \begin{cases} -\theta_1 + \theta_2(M - 5.5) & M < 5.5 \\ \theta_1(M - 6.5) & 5.5 \leq M \leq 6.5 \\ \theta_3(M - 6.5) & M > 6.5 \end{cases}$$

where $F_R = 1$ for reverse faulting and $F_{NO} = 1$ for normal faulting.

Thus, for each GMPE i there is a vector $\boldsymbol{\theta}_i = \{\theta_0, \ldots, \theta_{11}\}$. We then assume that the coefficient vectors are distributed according to a multivariate normal distribution

$$\begin{pmatrix} \theta_0 \\ \vdots \\ \theta_{11} \end{pmatrix} \sim N\left(\begin{pmatrix} \mu_{\theta 1} \\ \vdots \\ \mu_{\theta 11} \end{pmatrix}, \begin{pmatrix} \Sigma_{1,1} & \ldots & \Sigma_{1,11} \\ \vdots & \ddots & \vdots \\ \Sigma_{11,1} & \ldots & \Sigma_{11,11} \end{pmatrix} \right) \tag{11}$$

where the means and covariances of the coefficients can be estimated from the fitted sets of coefficients. Equation (11) describes a continuous distribution over coefficients for a GMPE

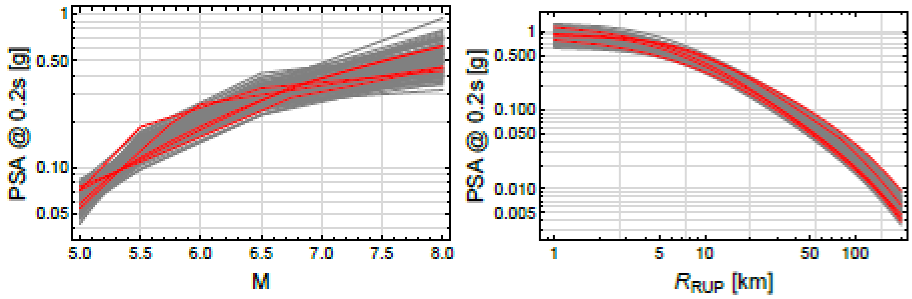

Figure 2: Scaling of base GMPEs, for $R_{RUP} = 20$ and $M = 6$.

parameterized by Equation (10)–hence, it describes a continuous distribution of GMPEs. For the hazard calculation, we sample different sets of coefficients θ from their distribution to cover the space of possible GMPEs. The scaling of the 100 sampled base GMPEs with magnitude and distance, as well as the underlying five NGA West2 models, is shown in Figure 2.

The hanging wall term for the ergodic base GMPE is taken from the SWUS project (Geopentech, 2015). It consists of five different, equally probable models, which were derived similar to the continuous base distribution of the coefficients. Each sampled base set of coefficients is randomly paired with one of the hanging wall models.

The nonlinear site amplification term is taken from the model of Abrahamson et al. (2014).