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Simplified criteria to select ground response analysis
 methods for seismic building design: equivalent linear vs
 nonlinear approaches
 By Mauro Aimar and Sebastiano Foti
 Declaration of Competing Interests
 The authors acknowledge there are no conflicts of interest recorded.

9 Abstract

The possible amplification of seismic waves in soil deposits is crucial for the seismic design of buildings and geotechnical systems. The most common approaches for the numerical simulation of seismic site response are the EQuivalent Linear (EQL) and the NonLinear (NL). Even though their advantages and limitations have been investigated in several studies, the relative field of applicability is still under debate.

15 This study tested both methods over a wide population of soil models, which were subjected to a 16 set of acceleration time histories recorded from strong earthquakes. A thorough comparison of the 17 results of the EQL and the NL approaches was carried out, to identify the conditions where the 18 relative differences are significant. This assessment allowed for the definition of simplified criteria 19 to predict when the two schemes are compatible or not for large expected shaking levels. The 20 proposed criteria are based on simple and intuitive parameters describing the soil deposit and the 21 ground motion parameters, which can be predicted straightforwardly. Therefore, this study 22 provides a scheme for the choice between the EQL and the NL approach, that can be used even at 23 the preliminary design stages. It appears that the EQL approach provides reliable amplification 24 estimates in soil deposits with thickness up to 30 m, except for very deformable soils, but this 25 depth range may be extended at long vibration periods. This result reveals a good level of reliability 26 of the EQL approach for various soil conditions encountered in common applications, even for 27 high-intensity shaking.

28 Introduction

Seismic waves undergo strong alterations in intensity and frequency content when propagating through soil deposits. These modifications depend on the soil mechanical properties and the geometry of the system, in terms of geological layers and surface morphology. Ordinary design applications typically focus on the effect of soil characteristics and rely on Ground Response Analyses (GRAs). GRAs assume a one-dimensional (1D) model for the site deposit, thus simplifying the actual geometry (i.e., lateral variations, local heterogeneities, etc.) to focus on stratigraphic amplification.

36 Notwithstanding their simplicity, GRAs are affected by uncertainties due to several factors. 37 Following the scheme devised by Idriss (2004) and Rathje et al. (2010) and extended by Passeri 38 (2019), the main sources of uncertainties are the shear-wave velocity (V_S) profile, the Modulus 39 Reduction and Damping (MRD) curves, the shear strength, the small-strain damping, the input 40 motions selection and the type of nonlinear approach. The latter is related to the nonlinear, 41 hysteretic behavior of the soil under dynamic loading. Several methods have been proposed for 42 modeling, but the most popular ones are the EQuivalent Linear (EQL) scheme and the NonLinear 43 (NL) technique. The EQL approach models the soil response in the frequency domain as a viscous-44 elastic medium, whose mechanical properties are time-invariant and compatible with the estimated 45 strain level (Idriss and Seed, 1968). The NL scheme, instead, solves the dynamic equilibrium 46 equation for the soil column – typically modeled as a multiple-degree-of-freedom lumped-mass 47 system – through a numerical time-stepping scheme.

48 The EOL approach is relatively simple and intuitive, but several studies questioned the reliability 49 at high strain levels (e.g., Baturay and Stewart, 2003; Kaklamanos and Bradley, 2018). Conversely, 50 NL analyses seem to be more suitable with strong motions and in the presence of soft soil deposits 51 (e.g., Hartzell et al., 2004). On the other side, their implementation involves advanced constitutive 52 models whose construction requires a large number of parameters, some of which not associated 53 with measurable soil properties (Stewart et al., 2008). Besides, the time-stepping algorithms for 54 NL computations suffer from limited numerical stability, whereas the EOL method works with a 55 closed-form solution of the wave equation. The consequence of these issues is a strong code-to-56 code variability of NL simulations (Régnier et al., 2016; Régnier et al., 2018). Furthermore, some 57 studies even questioned the reliability of NL analyses, since the matching between simulated and 58 observed amplification data was sometimes poor (Zalachoris and Rathje, 2015; Kaklamanos and 59 Bradley, 2018). For these reasons, the EOL approach is still widely used, also to identify pitfalls 60 in NL results (Stewart et al., 2014).

61 The acknowledgment of the limitations in the NL scheme and the efficiency of the EQL approach urges for the investigation of the conditions where they start to diverge in a significant way. In this 62 63 way, the engineer would have a tool to understand whether EOL simulations are adequate or more 64 advanced NL analyses are required. Therefore, several criteria to predict the magnitude of the relative differences were developed. For instance, Assimaki and Li (2012) performed a rigorous 65 66 assessment of the inter-method divergence, identifying some controlling parameters linked to the site conditions and the ground motion. On the other side, many studies proposed an applicability 67 boundary of the EQL scheme based on the maximum shear strain level (e.g., Kaklamanos et al., 68 69 2013; Kaklamanos et al., 2015). This quantity, in fact, has an excellent degree of correlation with 70 the trend of the differences. Kim et al. (2016), Carlton and Tokimatsu (2016) and Eskandarineiad 71 et al. (2017) referred to an indicator of the maximum strain level, defined as the ratio between the 72 peak ground velocity and $V_{s,30}$, i.e. the average V_s over the top 30 m of the soil deposit (Idriss, 73 2011). This solution offers an a priori criterion for the selection of the most appropriate technique 74 to model the soil nonlinear response. These studies, however, were mainly based on empirical 75 observations over downhole arrays, thus investigating a limited number of soil conditions which 76 actually may not represent the whole range of engineering interest. Alternatively, some studies 77 also integrated hypothetical ground models representative of typical soil conditions, but this just 78 filled the gap in a partial way as they dealt with idealized soil profiles, rather than real ones (e.g., 79 Carlton and Tokimatsu, 2016). In addition, they often proposed a single value as boundary for the 80 applicability for the EQL and the NL method, whereas the reliability of each approach may depend 81 on the model characteristics (Aristizábal et al., 2018).

82 The present study assesses the differences between the results of EQL and NL simulations 83 considering a large database of ground response analyses. The database collects the results of 84 GRAs on a set of 91,500 ground models, that are representative of various geological conditions 85 of engineering interest and span a wide range of deformability and depth. The analyses are 86 performed with reference to a suite of 42 ground motions, characterized by various amplitude 87 levels and spectral shapes. A total of 1,483,850 GRAs are performed in this study, for each method. 88 The differences between EQL and NL results are analyzed with respect to amplification parameters 89 based either on the peak ground acceleration or on integrals of the spectral ordinates across some 90 period ranges of engineering interest. The assessment considers the effect of the soil deposit 91 conditions and the ground motion characteristics in an explicit way, to identify the conditions for

92 which the two approaches start to diverge significantly. For this purpose, a novel criterion is 93 proposed, based on the comparison between the distribution of the inter-method differences and 94 the one of the corresponding amplification parameter, derived from Ground Motion Prediction 95 Equations (GMPEs). Specifically, this study assumes a condition where the differences between 96 the two approaches are large compared to the intrinsic variability of the parameter, thus resulting 97 in a physically consistent assessment. The result is a simplified criterion to predict where the two 98 schemes diverge, which can be used in a predictive way during the preliminary stages of the design. 99 Furthermore, the study provides an insight into the performances of EQL and NL analyses in 100 different soil conditions.

101 The present paper starts with a section presenting the procedure of construction of the database of 102 GRAs, with a particular focus on the generation of the 1D ground models. After a quick overview 103 of the results of the database, the paper reports the assessment of the differences between EQL and 104 NL methods. First, the criteria to estimate and assess the inter-method differences are defined. 105 Then, the effect of the soil model and the ground motion characteristics are presented, with a focus 106 on the simplified predictive scheme.

107 Database of ground response analyses

The database was initially generated from 91,500 1D ground models subjected to 13 acceleration time histories, characterized by high shaking intensity. Then, it was extended considering a representative subset of 10,150 models under 29 additional ground motions, that span a broad range of amplitudes and spectral shapes. The simulations were performed according to the EQL approach, by using the SHAKE91 code (Schnabel, 1972; Sun and Idriss, 1992), and to the NL scheme, with the DEEPSOIL v7.0 software (Hashash et al., 2017; see Data and Resources). For
each approach, 1,483,850 analyses were carried out.

115 Generation of V_S profiles

116 The 1D ground models were generated with a Monte-Carlo randomization based on a collection 117 of 252 real-world stratigraphic profiles. Data were obtained from Italian and international 118 databases (i.e., the Italian Accelerometric Archive v2.3, the Site Characterization Database for 119 Seismic Stations in Switzerland and the dataset of the Seismic Hazard and Alpine Valley Response 120 Analysis project) and regional databases of Italy (see Data and Resources). Furthermore, the set 121 includes some sites investigated in specific studies, i.e. Comina et al. (2011), Minarelli et al. (2016) 122 and Capilleri et al. (2009). The randomization procedure followed the geostatistical model 123 proposed in Passeri (2019) and Passeri et al. (2020), where each real ground model was taken as 124 the base-case soil profile, from which layers' thicknesses and S-wave velocities were generated 125 with a suitable number of realizations.

126 In order to optimize the generation of the ground models, this study refers to the site classification 127 scheme proposed in the Final Draft of revision of Part 1 of Eurocode 8 (EC8-1; European 128 Committee for Standardization, 2020; Figure 1a). This scheme, in fact, proposes effective proxies 129 for a synthetic description of 1D ground models, i.e. the bedrock depth and the equivalent shear-130 wave velocity. The bedrock depth H corresponds to the depth of the interface between the soil 131 deposit and the engineering bedrock, where V_s becomes larger than 800 m/s. The equivalent shear-132 wave velocity V_{SH} is equal to the time-weighted average of the V_S profile down to the engineering 133 bedrock, when H is smaller than 30 m. Otherwise, it equals $V_{5,30}$. Each site category proposed in

134 the scheme clusters various soil conditions sharing a similar response to ground motions. 135 Therefore, the generated ground models were resampled to get uniform and consistent coverage 136 in each site category. Specifically, every site category was discretized into 100 homogeneous 137 blocks and 200 profiles were considered for each one (Figure 1b). This number was lowered to 20 138 for deep deposits with very stiff layers (e.g., deep stratifications of altered rock), due to their 139 limited presence in nature. For simplicity, the investigated $V_{S,H}$ -H domain was limited at H < 200140 m. Besides, the portion corresponding to very shallow and stiff soil models (i.e., $V_{SH} > 250$ m/s 141 and H < 5 m) was disregarded since the stratigraphic amplification was not considered relevant in 142 this case. Figure 1c-e shows some generated profiles taken from different regions of the reference 143 $V_{S,H}$ -H domain.

144 The resulting population of 1D ground models exhibits realistic features and represents various 145 soil deposits of engineering interest in a uniform way. Thus, it is capable to map effectively the 146 stratigraphic amplification in different conditions.

147 Soil nonlinearity

The cyclic behavior of soils is introduced through the Modulus Reduction and Damping (MRD) curves, that describe the variation of the secant shear modulus – normalized by its maximum value – and the shear damping with the shear strain. The MRD curves were estimated from the empirical relationship by Darendeli (2001) for sandy and clayey materials, by Rollins et al. (1998) for gravels, and by Sun and Idriss (1992) for rock-like materials (i.e., cemented soils or weathered rocks). Details about the estimation of the required parameters (e.g., the plasticity index) and the derivation of the material type are available in Aimar et al. (2020).

155 Some studies questioned the capability of empirical formulations of MRD curves in predicting the 156 behavior at large strains, as they do not take into account the shear strength of the material (Yee et 157 al., 2013; Afacan et al., 2014; Stewart et al., 2014; Groholski et al., 2016). However, the 158 incorporation of the shear strength would introduce additional uncertainties about the empirical 159 correlations used for its estimate and the modeling of rate effects (Stewart et al., 2014). 160 Furthermore, Kaklamanos and Bradley (2018) observed that the quality of strength-corrected 161 estimates does not significantly improve with respect to the ones based on empirical MRD curves. 162 Finally, from the interpretation of the results provided by Zalachoris and Rathje (2015), even if the 163 strength correction modifies the EQL and NL-based estimates, the relative differences do not vary 164 with the same order of magnitude, even at moderate-to-high strain levels. Therefore, this study did 165 not account for the effect of shear strength in an explicit way, to limit uncertainties focusing on 166 the analysis of the inter-method differences.

The cyclic shear stress-strain relationship was introduced in NL GRAs through the Modified Kondner-Zelasko model (Kondner and Zelasko, 1963; Matasović and Vucetic, 1993), whose parameters were calibrated according to the pressure-dependent hyperbolic model with damping reduction factor (MRDF procedure; Phillips and Hashash, 2009). The fitting procedure adopted the root mean square error between the estimated and the above-mentioned MRD curves as the objective function, which was minimized through the sequential quadratic programming algorithm (Nocedal and Wright, 2006).

NL analyses also require the definition of a viscous damping ratio component, to simulate the presence of energy dissipation at small strain levels (Vucetic et al., 1998). This component was assumed equal to the small-strain hysteretic damping estimated from the damping curves (Kwok et al., 2007) and it was incorporated in the NL GRAs with the frequency-independent dampingformulation (Phillips and Hashash, 2009).

179 Seismic inputs

180 The seismic inputs are 42 acceleration time histories, selected from international strong-motion 181 databases, as the Italian Accelerometric Archive v2.3, the Engineering Strong Motion Database 182 v1.0, the Internet-Site for European Strong-Motion Data and the PEER NGA-West2 Database (see 183 Data and Resources). The motions are recorded on rock-like outcropping flat formations (i.e., $V_{5,30}$ 184 larger than 800 m/s) and derive from shallow crustal events in active tectonic regions with moment 185 magnitude ranging between 4 and 7.5, whereas epicentral distances mostly vary between 10 km and 50 km. Figure 2a represents the acceleration response spectra S_e of the selected ground 186 187 motions. Additional information is available in Table S1 in the Electronic Supplement.

The selected time histories were clustered into two groups. The first suite (labeled as "S-1") consists of 13 high-intensity ground motions, with peak ground acceleration (*PGA*) ranging between 0.17g and 0.35g. This collection was used for a preliminary assessment of the relative differences between EQL and NL simulations and to investigate the effect of soil model characteristics on them. The 29 additional time histories ("S-2") span a broad range of shaking amplitudes (i.e., *PGA* = 0.05-0.3g) and they were applied to a subset of 10,150 soil models, after a check on their representativeness based on results of the previous stage.

195 Reference parameters

196 This study describes seismic amplification through amplification factors (AFs) related to the 5%-197 damped elastic response spectrum, as it merges various features of the ground shaking (i.e., 198 intensity and frequency content) and it is relevant in structural and geotechnical engineering.

199 The first parameter is the *PGA* amplification factor PGAA, defined as the ratio between the *PGA* 200 value computed on the surface (*PGA_s*) and the one on the rock outcropping formation (*PGA_r* – in 201 this case, the value of the corresponding input motion):

$$PGAA = \frac{PGA_s}{PGA_r}$$
(1)

This parameter is relevant for applications requiring an estimate of the peak acceleration, e.g.
liquefaction assessment (Youd and Idriss, 2001) or pseudo-static approaches for estimating earth
pressure (Okabe, 1924; Mononobe, 1929).

On the other side, due to the frequency-dependence of the stratigraphic amplification, the modifications in the response spectrum should be tracked period by period, across a range of engineering interest. Alternatively, a synthetic representation of the frequency content of the ground motion is the spectral intensity SI_{AB} , that is the integral of the response spectrum S_e over a range of periods [*A*; *B*]. This parameter was introduced by Rey et al. (2002) and it is defined as follows:

212
$$SI_{AB} = \int_{A}^{B} S_e(T) dT.$$
 (2)

11

The spectral intensity summarizes information of spectral ordinates on different periods, thus representing an indicative value for a family of structures with compatible dynamic characteristics. The corresponding amplification factor (i.e., the spectral amplification factor, SAF) SA_{AB} can be defined as the ratio between the SI_{AB} value computed on the surface ($SI_{AB,s}$) and the one on the rock outcropping formation ($SI_{AB,r}$):

$$SA_{AB} = \frac{SI_{AB,s}}{SI_{AB,r}}.$$
(3)

219 Figure 2b provides a graphical representation of the quantities SI_{AB.s} and SI_{AB.r}.

The SAF captures the variations in intensity and frequency content of the ground motion induced by the soil deposit. Given the averaging nature, its use entails the partial loss of detailed information at single vibration periods, hence it is not suitable for the design of specific structures. However, it is useful for preliminary assessments and planning purposes, especially for seismic microzonation studies. In addition, the handling of data is easier, as the spectral behavior over a range of vibration periods can be investigated with a single parameter.

The present study considered three SAFs, i.e. a short-period spectral amplification factor (SPSA), an intermediate-period spectral amplification factor (IPSA) and a long-period spectral amplification factor (LPSA). The corresponding period ranges are listed in Table 1. These parameters were used as proxies for site amplification in the seismic microzonation studies held in Italy after the Central Italy earthquake in 2016 (Presidenza del Consiglio dei Ministri, 2017). They are deemed to be relevant for homogeneous groups of buildings – small, intermediate and tall buildings, respectively. Furthermore, the adopted parameters are capable to provide relevant

| 233 | information about the EQL-NL deviations in the corresponding period ranges, since these intervals |
|-----|---|
| 234 | are narrow enough to minimize internal variations of the inter-method spectral differences. |

235 Overview of Results

This section reports some key results of the database of GRAs, with a focus on the reliability of simulations. Data are extracted from GRAs performed on the collection of 91,500 soil models for the suite "S-1" of input motions. Additional information about the distribution of the AFs is available in the Electronic Supplement.

First, the quality of EQL simulations was assessed, in terms of convergence of the iterative procedure. Only 31 simulations encountered this issue, hence they were removed. This feature is indeed critical for analyses involving medium-to-large strain levels (Papaspiliou et al., 2012).

243 Then, the quality of the database was assessed by verifying the stability of the sample moments 244 inferred from the Monte Carlo simulation. Specifically, the number of models necessary to achieve 245 a stable value of the statistical moments of the AFs distribution was estimated and this was 246 compared to the actual number of profiles, to ensure the reliability of results. For this purpose, the 247 criterion proposed by Bellin et al. (1994) was adopted. The method tracks the variation of a sample 248 moment M (mean or standard deviation) of each AF in the Monte Carlo simulation, in terms of 249 relative difference δM_n between the current value M_n obtained after *n* samples (i.e., soil models) 250 and the final estimate M_N . Due to the lognormal distribution of the AFs (e.g., Li and Assimaki, 251 2010; Aimar et al., 2020), the difference was computed with moments in log-scale:

$$\delta M_n = \frac{|M_N - M_n|}{M_N} \tag{4}$$

13

According to the criterion, stable estimates of statistical moments are achieved when δM_n is smaller than a threshold equal to 5% and the corresponding *n* value represents the number of required models for this condition. The stability of simulation results was assessed for each reference block of the discretization of the *V*_{*S*,*H*}-*H* domain (Figure 1b), to investigate the effect of soil model characteristics on the reliability of the estimate. For simplicity, the role of ground motion characteristics was disregarded, hence moments were estimated from the logarithmic mean of results with respect to the input motions, computed for each soil model.

260 For instance, Figure 3 shows results of the stability assessment for the EQL-based mean value of 261 each AF. The rate at which stability is achieved is strongly influenced by soil deformability. In 262 stiff ground models (i.e., $V_{S,H}$ greater than 400 m/s), only 10-20 models are usually required to 263 obtain stable values of statistical moments, whereas more profiles are required in soft soil deposits. 264 This may be a consequence of strong nonlinear behavior, where the MRD curves dramatically 265 affect the response. In this case, the weak correlation between the modulus reduction curve and 266 the damping curve induces a slower convergence towards a stable value of statistical moments (Li 267 and Assimaki, 2010). Furthermore, more soil models are required for achieving a stable estimate 268 at short vibration periods (Figure 3a-c), with respect to longer periods. A possible reason is that 269 high-frequency components are sensitive to local variations in the soil deposit, i.e. thin layers, 270 rather than the global features of the ground model. Therefore, they strongly depend on the details 271 of the single V_S realizations, entailing stronger variations in the sample moments. Similar findings 272 are observed for the variance (Figure S7 in the Electronic Supplement) and in NL GRAs (Figure 273 S8). However, the number of considered models (shown in Figure 1b) exceeds the amount of 274 required data (Figure 3) in the whole investigated $V_{S,H}$ -H domain. Therefore, the number of simulations allows to achieve a stable estimate of the statistical moments, independently of soil
model characteristics or the considered period range. In this way, the validity of results is ensured,
from the stochastic point of view.

278 The maximum shear strain from EQL simulations was finally analyzed. Figure 4a represents the 279 distribution of soil models whose maximum shear strain exceeds 0.1%, where the linear elastic 280 model is no more reliable due to the rise of nonlinear phenomena (Kaklamanos et al., 2013; 281 Zalachoris and Rathje, 2015; Kaklamanos and Bradley, 2018). This result is useful for an 282 appropriate interpretation of the variations of the EQL-NL differences across different soil models. 283 A large number of soil models characterized by $V_{S,H}$ less than 400 m/s exhibit large strains, without 284 any effect of H, except for the shallow ones. Instead, Figure 4b reports the number of simulations 285 exceeding a strain level equal to 1%. The corresponding results are less reliable since that strain 286 level is the upper bound of the range of validity of the MRD curves – used for the EQL GRAs or 287 to infer the nonlinear parameters used in NL simulations. This critical condition is mainly observed 288 in deformable soil models (i.e., $V_{S,H} < 400$ m/s), but the amount consisted on average in 30% of 289 the cases, with a local peak of 60%. Therefore, the bias partially affects the quality of the results 290 in very soft ground models but some indications about the ground motion amplification may still 291 be obtained.

292 EQL vs NL analyses

This section reports a detailed assessment of the differences between the AFs estimated accordingto the EQL scheme and the NL approach.

295 Several authors focused on the comparison of site response estimates, by assessing the similarity 296 between different simulation approaches and, in some cases, comparing them with observed data. 297 Generally, discrepancies in the estimates were investigated according to different metrics. For 298 instance, Rathje and Kottke (2011) estimated the relative difference between the median 299 amplification functions (i.e., the ratios of spectral ordinates between the output and the input 300 motions) resulting from NL and EOL analyses. On the other side, many studies referred to the ratio 301 between the EOL-based spectral ordinates and the ones obtained from the NL scheme, or to its 302 logarithm (e.g., Kwok et al., 2008; Kaklamanos et al., 2013; Kim and Hashash, 2013; Zalachoris 303 and Rathje, 2015; Carlton and Tokimatsu, 2016; Kaklamanos and Bradley, 2018).

304 In this study, the adopted estimator of the inter-method difference is the logarithm of the ratio 305 between the corresponding estimates of the AF *X*, where *X* is PGAA, SPSA, IPSA, or LPSA. The 306 quantity is denoted as δ_X :

$$\delta_{X} = \ln \frac{X_{EQL}}{X_{NL}}.$$
(5)

A positive value indicates overestimation of the AF from the EQL scheme with respect to the NL approach, whereas a negative δ_X denotes underestimation. Furthermore, being δ_X derived from the ratio of two lognormal quantities (e.g., Li and Assimaki, 2010; Aimar et al. 2020), it is normally distributed.

The assessment of the divergence between two approaches also requires the definition of a threshold for the δ_X estimator, to identify conditions up to which the magnitude of the relative differences is not significant. For clarity, this condition is hereafter labeled as " $\delta < \delta^{max}$ ". The 315 threshold value should correspond to a condition where the inter-method difference is large 316 "enough" with respect to the application of interest, depending on the amount of statistical 317 fluctuation that may affect the estimate. Some studies compared the average difference with an 318 envelope corresponding to the critical threshold. For instance, Kim et al. (2016) assumed the 319 relative difference between EOL and NL estimates to be relevant when, on average, it is larger 320 than 10-30%. Alternatively, Carlton and Tokimatsu (2016) compared the mean difference with a 321 fraction of the standard deviation of the parameter under examination, which was calculated from 322 GMPEs. According to this criterion, the inter-method difference is negligible when it is small with 323 respect to the variability affecting the ground motion amplification. In this way, they accounted 324 for the background of application and, specifically, the uncertainties involved in site response 325 estimates.

326 In this study, we propose a criterion that inherits the main features from the one proposed by 327 Carlton and Tokimatsu (2016) to investigate the relative differences. Actually, some modifications 328 were applied to improve the quality of the comparison. Many studies, in fact, assessed the inter-329 method divergence by comparing the threshold with the mean of the differences. On the other side, 330 a more accurate description of the data distribution should include both the mean and information 331 about statistical dispersion, otherwise the assessment would be misleading. For instance, Figure 5a superimposes the distribution of δ_{LPSA} with the envelope corresponding to a threshold $\delta_{LPSA}^{max,10\%}$ 332 333 approximately equal to 10% (Kim et al., 2016). Results are referred to shallow deformable soil 334 models for a given input motion, as highlighted in Figure 5b. The mean of the distribution lies 335 within the envelope; hence the two approaches appear to be compatible with each other. On the 336 other side, the interval defined by one standard deviation partly lies beyond the acceptable value.

337 Specifically, 40% of the selected soil models exhibit non-negligible discrepancies in the response, meaning that a significant number of samples is characterized by a strong divergence between 338 339 EQL and NL estimates. This issue is a side effect of using only the mean, which is not an 340 exhaustive descriptor of the statistical distribution when the data variability is high, as in the case 341 of the ground motion amplification. For this reason, the present study investigated the relative differences by comparing the interval defined by the mean $\mu_{\delta,X}$ and one standard deviation $\sigma_{\delta,X}$ of 342 δ_X with a threshold δ_X^{max} . Specifically, the comparison involved the maximum between the 343 extremes of such interval (in absolute value), labeled as $\delta_{\chi}^{\mu\pm\sigma}$ and defined as follows: 344

345
$$\delta_X^{\mu\pm\sigma} = \max\left(\left|\mu_{\delta,X} \pm \sigma_{\delta,X}\right|\right) \tag{6}$$

The threshold δ_X^{max} was assumed equal to the empirical-based standard deviation $\sigma_{\ln X}^E$ of the parameter in exam (in agreement with Carlton and Tokimatsu, 2016). Therefore, the condition " $\delta < \delta^{max}$ " (i.e., negligible relative differences) is achieved when the following inequality holds:

$$\delta_X^{\mu\pm\sigma} < \delta_X^{\max} = \sigma_{\ln X}^E \tag{7}$$

This criterion assumes deviations to be negligible when they are within the natural dispersion of the considered parameter. In this way, this approach can identify either situations when the differences are large on average, i.e. $\mu_{\delta,X}$ significantly deviates from zero, or those when the average does not shift but the variability $\sigma_{\delta,X}$ increases so much that a large number of models exceeds the reference envelope. The threshold value δ_X^{max} , i.e. the standard deviation $\sigma_{\ln X}^E$ of each AF, was derived from GMPEs, according to the procedure illustrated in Derivation of the Threshold Values in the Electronic Supplement. Table 2 lists the inferred threshold values, that depend on $V_{S,30}$, given the sensitivity of $\sigma_{\ln X}^E$ to site conditions.

In summary, the EQL and NL methods are compared in a statistically consistent way, according to an objective criterion that specifies when the magnitude of the differences between the predicted results is large with respect to the variability of the phenomenon.

362 Role of soil model characteristics

363 The assessment of the effect of soil conditions on the divergence between the EQL and the NL approaches starts with a general overview of the distribution of $\mu_{\delta,X}$ and $\sigma_{\delta,X}$. Figure 6 represents 364 365 δ_X for SPSA and LPSA, where data are extracted from GRAs performed on the collection of 91,500 366 soil models for the suite "S-1" of input motions. Results about PGAA and IPSA are plotted in Figure S9 in the Electronic Supplement. The distribution of δ_X across various soil profiles depends 367 368 on the range of periods of interest and soil model characteristics, especially in terms of $V_{S,H}$ and natural frequency f_0 – computed according to the formula $f_0 = \frac{V_{S,av}}{AH}$ ($V_{S,av}$ is the time-weighted 369 370 average of the V_S profile down to the engineering bedrock), whose reciprocal is the fundamental 371 period T_0 .

In shallow soil deposits with high f_0 , the observed δ_X values are small. In this case, in fact, the experienced strain level is small (Figure 4a) and EQL and NL predictions are usually similar to each other (e.g., Kwok et al., 2008; Stewart et al., 2008; Assimaki and Li, 2012). Furthermore, the 375 difference is slightly negative over a region whose size is broader for long periods. This region fits 376 a range of f_0 approximately equal to 10-15 Hz (i.e., T_0 equal to 0.07-0.1 s) for SPSA, 5-14 Hz 377 (0.075-0.2 s) for IPSA and 3-13 Hz (0.08-0.3 s) for LPSA. An example of this is reported in Figure 378 7 for SPSA and LPSA. Therefore, the NL scheme slightly overestimates the amplification at 379 periods slightly larger than T_0 . Conversely, this region was not identified for PGAA.

380 For small f_0 , δ_X is always positive (i.e., the NL approach predicts smaller amplification than the 381 EQL scheme) and the difference increases when the deformability is high, with a dramatic 382 variation over a relatively small region in the $V_{S,H}$ -H domain. For instance, $\mu_{\delta,SPSA}$ grows from 0.2 383 up to 0.4 for H increasing from 10 m to 15 m at $V_{S,H} = 160$ m/s, more than doubling itself (Figure 384 7a). Similarly, the variability in the difference undergoes an increase in this area (Figure 6b-d). 385 This is an effect of the large strain level (Figure 4a), for which nonlinear phenomena become 386 relevant. The trend in the increase can still be linked to f_0 , as the peak of the mean δ_X is located on 387 a range of f_0 equal to 1.5-8 Hz (i.e., T_0 equal to 0.12-0.7 s) for PGAA, 2-4 Hz (0.25-0.5 s) for SPSA 388 (Figure 7a) and 2-3.5 Hz (0.3-0.5 s) for IPSA. At long periods, instead, δ_X monotonically increases 389 and is large at f_0 less than 2 Hz (i.e., T_0 longer than 0.5 s; Figure 7b). The reason of this behavior 390 is the mutual effect of larger strain levels and the resonance of soil models, where the differences 391 between the EQL and the NL approach are expected to be large (Rathje and Kottke, 2011). As an 392 effect of the resonance, the location of the boundary depends on the considered AF and it shifts 393 towards deeper and more deformable soil models, as they are associated with lower f_0 values, 394 compatible with the period range investigated in each AF.

395 As for deep ground models (i.e., H > 30 m), the role of the bedrock depth is not as relevant as in 396 shallow soil deposits and only V_{SH} appears to be significant for describing the behavior of δ_X . 397 Specifically, the trend of δ_X is consistent with the one for the shear strain (Figure 4a). For less 398 deformable soil models (i.e., $V_{S,H} > 400$ m/s), δ_X values and their variability are generally small, 399 except for a slight increase in deeper models. Stiff soil models, in fact, undergo small nonlinearity 400 and the EOL and NL approaches tend to provide similar output. On the other side, deep and 401 deformable models exhibit large and positive δ_X values. The increase is significant for $V_{S,H} < 200$ 402 m/s and the mean δ_X reaches the maxima values for intermediate bedrock depths, close to 40 m, 403 where the observed strain level is large (Figure 4a). Furthermore, the magnitude of the maximum 404 difference increases at longer vibration periods (Figure 6c).

405 From such considerations, a scheme for the subdivision of soil models is proposed for setting up a 406 simplified assessment of the differences between the EQL and the NL approaches (Figure 8m and 407 Figure 9). The scheme is conceived to cluster together different soil conditions sharing compatible 408 behavior in terms of δ_X . Furthermore, the definition of the clusters accounts for the dependence of δ_X^{max} (i.e., $\sigma_{\ln X}^E$) with respect to $V_{S,30}$ (Table 2). For simplicity, the partition is based on specific 409 boundaries in terms of V_{S,H} (located at 250 m/s, 400 m/s and 600 m/s) and H (located at 5 m, 30 m 410 and 100 m). The limits approximately correspond to locations where δ_X and δ_X^{max} (i.e., $\sigma_{\ln X}^E$) 411 412 undergo the strongest variations. At small depths, the clustering follows a more complex geometry, 413 since boundaries try to mimic the strong effect of f_0 on δ_X . This boundary should depend on the 414 investigated period range, as soil models with moderately high f_0 exhibit strong differences at short 415 periods, whereas only thick and deformable models (i.e., low f_0) assume large discrepancies at long 416 periods. In this study, the lowest value of f_0 is considered for simplicity, to be on the safe side.

417 Conversely, deep soil deposits (i.e., H > 30 m) are clustered according to a more regular geometry 418 of boundaries, as variations mainly depend on $V_{S,H}$, whereas f_0 does not play a significant role on 419 δ_X . In each cluster, the threshold δ_X^{max} was assigned based on the $V_{S,30}$ distribution inside each 420 cluster, thus accounting for the relative differences between $V_{S,H}$ and $V_{S,30}$ in shallow ground 421 models, i.e. with H < 30 m.

422 Role of input motion characteristics

Proper modeling of the EQL-NL differences needs to account for the mutual relationship between discrepancies and specific ground motion parameters. The intensity, the duration and the frequency content, in fact, may affect the entity of the divergence. In order to cover an adequate range of motion features and effectively investigate this effect, additional GRAs were run on a subset of 10,150 soil models considering the collection "S-2" of input motions. The ground models are still representative of different soil conditions in the reference $V_{S,H}$ -H domain and they are compatible with the restraints from the stability assessment of statistical moments (Figure 3).

The effect of input motion characteristics was first investigated by relating some commonly used ground motion parameters to δ_X (specifically, $\delta_X^{\mu\pm\sigma}$), which was computed separately for each cluster of soil models (Figure 8m). In this way, the effect of variations in soil model characteristics on the trend of δ_X was kept under control. The degree of relationship was quantified through Kendall's τ_b correlation coefficient (Kendall, 1955), which was estimated together with the *p*value, expressing the statistical significance – for p < 0.05, τ_b is statistically significant. The assessment included common ground motion parameters, i.e. the peak values of time histories, the 437 Arias intensity, the predominant and mean period (Rathje et al., 1998) and the uniform and438 significant duration, as well as spectral intensities.

A moderate-to-strong relationship between $\delta_{\chi}^{\mu\pm\sigma}$ and *PGA* is observed for PGAA and the SAFs, 439 440 although the correlation for IPSA and LPSA is slightly weaker. PGA, in fact, is directly related to the rise of nonlinear phenomena and to the amount of divergence between GRA approaches 441 (Assimaki and Li, 2012). For instance, Figure 8 shows the scatter plot of $\delta_{SPSA}^{\mu\pm\sigma}$ and PGA together 442 with the estimated τ_b values, highlighting a strong relationship in several clusters of soil models. 443 444 Actually, the trend exhibits strong scattering in deformable soil deposits. Furthermore, in stiff and shallow models, the effect of the input motion is weak as $\delta_x^{\mu\pm\sigma}$ is small regardless its entity. 445 446 However, in several cases, τ_b is larger than 0.5. Note that τ_b was computed from the data of the collection of 10,150 models subjected to the suite of 42 motions (i.e., "S-1" and "S-2"). However, 447 448 Figure 8 also reports results from "S-1" applied to the whole set of 91,500 models, for comparison 449 purposes. There is no significant difference between these data and the corresponding ones obtained from the subset. Therefore, the suite of 10,150 models provides results consistent with 450 451 the whole database. Similar considerations are valid for the other AFs; the corresponding data are 452 shown in Figure S10-S12 in the Electronic Supplement.

Furthermore, the $\delta_{X}^{\mu\pm\sigma}$ values for the SAFs exhibit a good level of correlation with the corresponding SI_{AB} (e.g., $\delta_{SPSA}^{\mu\pm\sigma}$ vs. SPSI), indicating that inter-method differences for these parameters depend on the frequency content, both in terms of intensity and spectral shape. As for the other ground motion parameters, rather weak or no significant relationships are noticed. Detailed results are available in Table S2-S5 and Figure S13-S15 in the Electronic Supplement.

458 The identified relationships help in estimating the shaking level where δ_X becomes relevant, by comparing the trend of $\delta_X^{\mu\pm\sigma}$ – estimated through linear fitting – and δ_X^{max} , in agreement with (7). 459 The trend was estimated from the results of the suite "S-1"+"S-2" applied to the subset of 10,150 460 models, for those cases where a significant correlation was detected (i.e., $\tau_b > 0.3$ and p < 0.05, as 461 shown in Figure 8). Figure 9 maps the PGA levels up to which the condition " $\delta < \delta^{max}$ " is met 462 463 (i.e., negligible δ_X) for each reference group, as a function of the investigated AF. The color scale 464 defines the upper bound of PGA for which EQL and NL analyses provide similar results. 465 Therefore, this result can be used to guide for the selection of the numerical method, considering 466 the parameters of the soil deposit ($V_{S,H}$ and H), the expected level of ground shaking and the 467 specific application for which the GRA is required (i.e., the period range of interest). In deep and 468 soft soil models, motions with PGA larger than 0.1g give rise to strong differences. However, for 469 slightly smaller deformability (i.e., $V_{S,H}$ more than 250 m/s), the two schemes provide compatible 470 results at larger PGA values, that rise from 0.15g up to 0.3g. Furthermore, the upper bound of PGA 471 dramatically increases at longer periods. For instance, LPSA differences are small up to PGA 472 values equal to 0.3 for almost all the soil conditions investigated, except the very deformable ones. 473 In stiff and shallow soil models, instead, no threshold is identified since no trend in δ_X is detected, 474 as the inter-method differences are small regardless the entity of the specific input motion. 475 Therefore, in this case the inter-method differences are always small, at least in the range of ground 476 motions of common application. Similar results are obtained for the SAFs with respect to the 477 corresponding spectral intensities (see Figure S16 in the Electronic Supplement).

In summary, inter-method differences exhibit a complex behavior, strongly dependent on soil
 model characteristics and the input motions intensity. However, they are negligible in moderately
 24

deep soil deposits, i.e. for *H* less than 30 m, except when very soft layers are involved. This area
includes a broad variety of soil conditions usually found in common applications. Furthermore, at
long periods, this region can be extended to deeper deposits and stronger shaking levels.

483 Conclusions

484 The study interpreted a large database of GRAs to investigate differences between the equivalent 485 linear and the nonlinear approach. The assessment adopted a novel criterion to evaluate the 486 magnitude of the differences. The approach compares the interval defined by the corresponding 487 mean and one standard deviation – which is representative of the statistical distribution of results 488 - with an envelope defined by the standard deviation of the corresponding amplification parameter. 489 This solution allows a rigorous assessment of the significance of the inter-method divergence, as 490 it explicitly accounts for the dispersion of results and also the intrinsic variability of the 491 amplification itself. The proposed criterion has general validity and can be used in any study of 492 seismic site response to assess the congruence of EQL and NL approaches.

The assessment highlights that the EQL and the NL approach provide similar estimates for stiff soil models and for the ones with large natural frequency. Conversely, NL simulations widely underestimate the amplification with respect to the EQL approach in deep and deformable soil deposits. In intermediate conditions, the entity of the difference strongly depends on the range of vibration periods and also on the natural frequency of the soil deposit.

498 The role of input motion characteristics was also investigated. A good level of correlation was 499 observed between the differences and the peak ground acceleration of the corresponding input 500 motions. This result allowed to identify threshold shaking values at which the two schemes 501 significantly diverge, as a function of soil model characteristics.

502 Figure 9 can be considered a valuable tool for guiding geotechnical engineers during the 503 preliminary steps of the design. Indeed, it provides a criterion to predict the critical conditions 504 where the divergence between the EQL and the NL approach becomes significant, thus helping in 505 the selection of the method considering the specific application. The results of this study prove 506 that the EQL scheme is compatible with the NL approach in soil deposits with thickness up to 30 507 m, except in very soft soils. In more deformable soils, instead, the two approaches are consistent 508 with each other up to PGA values close to 0.1-0.2g. Furthermore, the field of applicability can be 509 extended to deeper models and higher seismicity levels when the period of interest is longer, up to 510 0.3g. This range encompasses various site conditions typically found in common applications. 511 Therefore, this result positively contributes to the reliability of the EQL scheme for a broad field 512 of soil conditions of engineering interest, even under intense motions.

513 Data and Resources

514 Geological and geotechnical information about real soil deposits were retrieved from the following 515 databases: the Italian Accelerometric Archive v2.3 (ITACA, http://itaca.mi.ingv.it, last accessed 516 November 2017), the Site Characterization Database for Seismic Stations in Switzerland (SED, 517 http://stations.seismo.ethz.ch, last accessed November 2017) and the dataset of the Seismic Hazard 518 and Alpine Valley Response Analysis project (SISMOVALP, 519 www.risknat.org/projets/sismovalp/CD2/CDROM.html, last accessed November 2017). Details 520 about some sites were extracted from the geological databases of Tuscany 521 (www.regione.toscana.it/-/programma-vel, last accessed November 2017), Emilia-Romagna 522 (https://applicazioni.regione.emilia-romagna.it/cartografia sgss, last accessed November 2017) 523 and Umbria Region 524 (http://storicizzati.territorio.regione.umbria.it/Static/IndaginiGeologicheKmz/Index kmz.htm, 525 last accessed November 2017). Seismograms used in this study were collected from ITACA, the 526 Engineering Strong Motion Database v1.0 (ESM, http://esm.mi.ingv.it, last accessed November 527 2017), Internet-Site for European Strong-Motion Data (ESD, http://www.isesd.hi.is, last accessed 528 January 2018) and PEER NGA-West2 Database (https://ngawest2.berkeley.edu, last accessed 529 January 2018). EQL analyses were carried out with the SHAKE91 software (Schnabel, 1972; Sun 530 and Idriss, 1992), whereas NL simulations were performed with the DEEPSOIL v7.0 code 531 (Hashash et al., 2017, http://deepsoil.cee.illinois.edu/, last accessed December 2017). The ground 532 motion parameters relative to the acceleration time histories were computed with the SeismoSignal 533 software (https://seismosoft.com/products/seismosignal/, last accessed January 2018). Data

534 processing and figures were done using MATLAB

- 535 (http://www.mathworks.com/products/matlab/).
- 536 The Electronic Supplement reports an overview of the results of GRAs and a description of the
- 537 procedure adopted to estimate the thresholds for the inter-method differences from GMPEs.

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544 References

- 545 Afacan KB, Brandenberg SJ, Stewart JP (2014). Centrifuge modeling studies of site response in
- 546 soft clay over wide strain range, *J Geotech Geoenv Eng* **140** 04013003.
- Aimar M, Ciancimino A, Foti S (2020). An assessment of the NTC18 stratigraphic seismic
 amplification factors, *Ital Geotech J* 1 5-21.
- 549 Aristizábal C, Bard P-Y, Beauval C, Gómez JC (2018). Integration of site effects into probabilistic
- seismic hazard assessment (PSHA): A comparison between two fully probabilistic methods on the
- 551 euroseistest site, *Geosciences* **8** 285.
- 552 Assimaki D, Li W (2012). Site-and ground motion-dependent nonlinear effects in seismological
- 553 model predictions, *Soil Dynam Earthquake Eng* **32** 143-151.
- 554 Baturay MB, Stewart JP (2003). Uncertainty and bias in ground-motion estimates from ground
- response analyses, *Bull Seismol Soc Am* **93** 2025-2042.

| 556 | Bellin A, Rubin Y, Rinaldo A (1994). Eulerian-Lagrangian approach for modeling of flow and |
|-----|--|
| 557 | transport in heterogeneous geological formations, Water Resour Res 30 2913-2924. |

558 Capilleri P, Grasso S, Maugeri M, Cavallaro A (2009). Caratterizzazione geotecnica e

- amplificazione sismica nella zona industriale di Catania, in: XIII Convegno Nazionale ANIDIS,
- 560 *l'Ingegneria Sismica in Italia*, Bologna, Associazione Nazionale Italiana di Ingegneria Sismica.
- 561 Carlton B, Tokimatsu K (2016). Comparison of equivalent linear and nonlinear site response 562 analysis results and model to estimate maximum shear strain, *Earthq Spectra* **32** 1867-1887.
- 563 Comina C, Foti S, Boiero D, Socco LV (2011). Reliability of VS,30 Evaluation from Surface-
- 564 Wave Tests, *J Geotech Geoenv Eng* **137** 579-586 doi:10.1061/(ASCE)GT.1943-5606.0000452.
- 565 Darendeli MB (2001). Development of a new family of normalized modulus reduction and 566 material damping curves. Doctoral Dissertation, University of Texas at Austin
- 567 Eskandarinejad A, Jahanandish M, Zafarani H (2017). Divergence between nonlinear and
 568 equivalent-linear 1D site response analyses for different VS realizations of typical clay sites, *Pure*569 *Appl Geophys* **174** 3955-3978.
- 570 European Committee for Standardization (2020). Eurocode 8: Earthquake resistance design of
 571 structures. EN1998-1-1 Working Draft N969.
- Groholski DR, Hashash YMA, Kim B, Musgrove M, Harmon J, Stewart JP (2016). Simplified
 model for small-strain nonlinearity and strength in 1D seismic site response analysis, *J Geotech Geoenv Eng* 142 04016042.

- 575 Hartzell S, Bonilla LF, Williams RA (2004). Prediction of nonlinear soil effects, *Bull Seismol Soc*576 *Am* 94 1609-1629.
- 577 Hashash YMA, Musgrove MI, Harmon JA, Ilhan O, Xing G, Groholski DR, Phillips CA (2017).
- 578 DEEPSOIL 7.0, User Manual. Urbana, IL.
- 579 Idriss I (2004). Evolution of the state of practice, in: Int. Workshop on the Uncertainties in
- 580 Nonlinear Soil Properties and Their Impact on Modeling Dynamic Soil Response, Richmond, CA,
- 581 Pacific Earthquake Engineering Research Center, Richmond, CA.
- 582 Idriss I (2011). Use of Vs30 to represent local site conditions, in: 4th IASPEI/IAEE International
- 583 Symposium. Effects of source geology on seismic motion, pp 23-26.
- Idriss IM, Seed HB (1968). Seismic response of horizontal soil layers, *J Soil Mech and Found Div*94 1003-1031.
- 586 Kaklamanos J, Baise LG, Thompson EM, Dorfmann L (2015). Comparison of 1D linear,
 587 equivalent-linear, and nonlinear site response models at six KiK-net validation sites, *Soil Dynam*588 *Earthquake Eng* 69 207-219.
- Kaklamanos J, Bradley BA (2018). Challenges in Predicting Seismic Site Response with 1D
 Analyses: Conclusions from 114 KiK-net Vertical Seismometer Arrays, *Bull Seismol Soc Am* 108
 2816-2838.
- Kaklamanos J, Bradley BA, Thompson EM, Baise LG (2013). Critical parameters affecting bias
 and variability in site-response analyses using KiK-net downhole array data, *Bull Seismol Soc Am* **103** 1733-1749.

- 595 Kendall MG (1955). *Rank Correlation Methods*. Hafner Publishing Co.
- 596 Kim B, Hashash YMA (2013). Site response analysis using downhole array recordings during the
- 597 March 2011 Tohoku-Oki earthquake and the effect of long-duration ground motions, *Earthq*598 *Spectra* 29 S37-S54.
- 599 Kim B, Hashash YMA, Stewart JP, Rathje EM, Harmon JA, Musgrove MI, Campbell KW, Silva
- 600 W (2016). Relative differences between nonlinear and equivalent-linear 1-D site response
- 601 analyses, *Earthq Spectra* **32** 1845-1865.
- 602 Kondner RL, Zelasko JSA (1963). Hyperbolic stress-strain formulation for sands, in: Proceedings
- 603 of 2nd Pan-American conference on soil mechanics and foundations engineering.
- Kwok AOL, Stewart JP, Hashash YMA (2008). Nonlinear ground-response analysis of Turkey
 Flat shallow stiff-soil site to strong ground motion, *Bull Seismol Soc Am* 98 331-343.
- 606 Kwok AOL, Stewart JP, Hashash YMA, Matasovic N, Pyke R, Wang Z, Yang Z (2007). Use of
- 607 exact solutions of wave propagation problems to guide implementation of nonlinear seismic
- 608 ground response analysis procedures, *J Geotech Geoenv Eng* **133** 1385-1398.
- Li W, Assimaki D (2010). Site-and motion-dependent parametric uncertainty of site-response
 analyses in earthquake simulations, *Bull Seismol Soc Am* 100 954-968.
- 611 Matasović N, Vucetic M (1993). Cyclic characterization of liquefiable sands, J Geotech Eng 119
- 612 1805-1822.

- Minarelli L, Amoroso S, Tarabusi G, Stefani M, Pulelli G (2016). Down-hole geophysical
 characterization of middle-upper Quaternary sequences in the Apennine Foredeep, Mirabello,
 Italy, *Ann Geophys* 59 1-8 doi:10.4401/ag-7114.
- Mononobe N (1929). On determination of earth pressure during earthquake, in: *Proc. World Engineering Congress*, pp 177-185.
- 618 Nocedal J, Wright SJ (2006). Sequential quadratic programming. Numerical optimization.
- 619 Okabe S (1924). General theory on earth pressure and seismic stability of retaining wall and dam,
- 620 in: *Proc. Civil Engineering Society*, vol 6, pp 1277-1323.
- Papaspiliou M, Kontoe S, Bommer JJ (2012). An exploration of incorporating site response into
 PSHA—Part I: Issues related to site response analysis methods, *Soil Dynam Earthquake Eng* 42
- 623 302-315.
- Passeri F (2019). Development of advanced geostatistical models of shear wave velocity profiles
 to manage uncertainties and variabilities in Ground Response Analyses. Doctoral dissertation,
 Politecnico di Torino
- Passeri F, Foti S, Rodriguez-Marek A (2020). A new geostatistical model for shear wave velocity
 profiles, *Soil Dynam Earthquake Eng* 136.
- 629 Phillips C, Hashash YMA (2009). Damping formulation for nonlinear 1D site response analyses,
- 630 Soil Dynam Earthquake Eng **29** 1143-1158.
- 631 Presidenza del Consiglio dei Ministri (2017). Ordinanza n. 24 del 12 Maggio 2017.

- Rathje EM, Abrahamson NA, Bray JD (1998). Simplified frequency content estimates of
 earthquake ground motions, *J Geotech Geoenv Eng* 124 150-159.
- 634 Rathje EM, Kottke AR (2011). Relative differences between equivalent linear and nonlinear site
- response methods, in: *5th International Conference on Earthquake Geotechnical Engineering*, pp
 10-13.
- Rathje EM, Kottke AR, Trent WL (2010). Influence of input motion and site property variabilities
 on seismic site response analysis, *J Geotech Geoenv Eng* 136 607-619.
- 639 Régnier J, Bonilla LF, Bard PY, Bertrand E, Hollender F, Kawase H, Sicilia D, Arduino P,
- 640 Amorosi A, Asimaki D, Boldini D, Chen L, Chiaradonna A, Demartin F, Ebrille M, Elgamal A,
- 641 Falcone G, Foerster E, Foti S, Garini E, Gazetas G, Gélis C, Ghofrani A, Giannakou A, Gingery
- 642 JR, Glinsky N, Harmon J, Hashash Y, Iai S, Jeremić B, Kramer S, Kontoe S, Kristek J, Lanzo G,
- 643 Di Lernia A, Lopez-Caballero F, Marot M, McAllister G, Mercerat ED, Moczo P, Montoya-
- Noguera S, Musgrove M, Nieto-Ferro A, Pagliaroli A, Pisanò F, Richterova A, Sajana S, Santisi
 D'avila MP, Shi J, Silvestri F, Taiebat M, Tropeano G, Verrucci L, Watanabe K (2016).
 International benchmark on numerical simulations for 1D, nonlinear site response (PRENOLIN):
 Verification phase based on canonical cases, *Bull Seismol Soc Am* 106 2112-2135
- 648 doi:10.1785/0120150284.
- 649 Régnier J, Bonilla LF, Bard PY, Bertrand E, Hollender F, Kawase H, Sicilia D, Arduino P,
- 650 Amorosi A, Asimaki D, Boldini D, Chen L, Chiaradonna A, DeMartin F, Elgamal A, Falcone G,
- 651 Foerster E, Foti S, Garini E, Gazetas G, Gélis C, Ghofrani A, Giannakou A, Gingery JR, Glinsky
- 652 N, Harmon J, Hashash Y, Iai S, Kramer S, Kontoe S, Kristek J, Lanzo G, Di Lernia A, Lopez-

- 653 Caballero F, Marot M, McAllister G, Mercerat ED, Moczo P, Montoya-Noguera S, Musgrove M,
- 654 Nieto-Ferro A, Pagliaroli A, Passeri F, Richterova A, Sajana S, Santisi D'Avila MP, Shi J, Silvestri
- 655 F, Taiebat M, Tropeano G, Vandeputte D, Verrucci L (2018). PRENOLIN: International
- Benchmark on 1D Nonlinear Site-Response Analysis—Validation Phase Exercise, *Bull Seismol Soc Am* 108 876-900.
- Rey J, Faccioli E, Bommer JJ (2002). Derivation of design soil coefficients (S) and response
 spectral shapes for Eurocode 8 using the European Strong-Motion Database, *J of Seismol* 6 547555 doi:10.1023/A:1021169715992.
- Rollins KM, Evans MD, Diehl NB, Daily III WD (1998). Shear modulus and damping
 relationships for gravels, *J Geotech Geoenv Eng* 124 396-405.
- 663 Schnabel PB (1972). SHAKE: A computer program for earthquake response analysis of
 664 horizontally layered sites, EERC Report 72-12.
- 665 Stewart JP, Afshari K, Hashash YMA (2014). Guidelines for performing hazard-consistent one-
- dimensional ground response analysis for ground motion prediction, PEER Report 2014. Berkeley.
- 667 Stewart JP, Kwok AOL, Hashash YMA, Matasovic N, Pyke R, Wang Z, Yang Z (2008).
- 668 Benchmarking of nonlinear seismic ground response analysis procedures, PEER Report 2008/04.
- 669 Sun J, Idriss IM (1992). User's manual for SHAKE91: a computer program for conducting
- 670 equivalent linear seismic response analyses of horizontally layered soil deposits. Davis, California.
- 671 Vucetic M, Lanzo G, Doroudian M (1998). Damping at small strains in cyclic simple shear test, J
- 672 *Geotech Geoenv Eng* **124** 585-594.
- 673 Yee E, Stewart JP, Tokimatsu K (2013). Elastic and large-strain nonlinear seismic site response
 674 from analysis of vertical array recordings, *J Geotech Geoenv Eng* 139 1789-1801.
- 675 Youd TL, Idriss IM (2001). Liquefaction resistance of soils: summary report from the 1996
- 676 NCEER and 1998 NCEER/NSF workshops on evaluation of liquefaction resistance of soils, J
- 677 *Geotech Geoenv Eng* **127** 297-313.
- 678 Zalachoris G, Rathje EM (2015). Evaluation of one-dimensional site response techniques using
- 679 borehole arrays, *J Geotech Geoenv Eng* **141** 04015053.
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697 List of Figure Captions

Figure 1. a) Representation of the available real soil profiles in the $V_{S,H}$ -H domain, superimposed by the site categories proposed in the Final Draft of revision of the EC8-1; b) Resampling scheme for the randomly generated V_S profiles; c-e) Examples of randomly generated soil profiles for the areas identified in b).

Figure 2. a) Selected ground motions, grouped as "S-1" and "S-2"; b) Definition of the spectral intensity SI_{AB} for the input motion ($SI_{AB,r}$) and the simulated motion ($SI_{AB,s}$) across the period range [A; B].

Figure 3. Number of models required to achieve a stable estimate of the EQL-based mean PGAA
(a), SPSA (b), IPSA (c) and LPSA (d), as a function of soil model characteristics. Results refer to
the suite "S-1" of input motions. The dashed area denotes the region not considered in GRAs.

Figure 4. Percentage of simulations where the EQL-based maximum shear strain exceeds 0.1% (a)
and 1% (b), as a function of soil model characteristics. Results refer to the suite "S-1" of input
motions. The dashed area denotes the region not considered in GRAs.

Figure 5. a) Comparison between the distribution of the inter-method differences for LPSA with the threshold $\delta_{LPSA}^{max,10\%}$. The dark grey area – labeled as " $\delta > \delta^{max}$ " in the legend – denotes the region where the inter-method differences for LPSA exceed the threshold $\delta_{LPSA}^{max,10\%}$. Data are extracted from models lying in the dashed area of the $V_{S,H}$ -H domain represented in b) for the Central Italy (10-26-2016) MMO input motion (more details about this motion are available in Table S1 in the Electronic Supplement). Figure 6. Distribution of $\mu_{\delta,SPSA}$ (a) and $\sigma_{\delta,SPSA}$ (b), as a function of soil model characteristics; Distribution of $\mu_{\delta,LPSA}$ (c) and $\sigma_{\delta,LPSA}$ (d), as a function of soil model characteristics. The dashed area denotes the region not considered in GRAs.

Figure 7. Contour plot of $\mu_{\delta,SPSA}$ (a) and $\mu_{\delta,LPSA}$ (b) in shallow and deformable soil models. The dashed area denotes the region not considered in GRAs.

Figure 8. Relationship between $\delta_{SPSA}^{\mu\pm\sigma}$ and PGA for all the clusters of soil models. Panels (a)-(l) 722 display the plot of $\delta_{SPSA}^{\mu\pm\sigma}$ versus *PGA* derived from GRAs on the set of 10,150 soil models with the 723 724 suites "S-1" and "S-2" of input motions. Each panel contains data from each cluster of soil models 725 and the corresponding location in the V_{SH} -H domain is represented in (m). Panels (a)-(l) also report 726 the Kendall's τ_b coefficient – the p-value is close to 0 in all the considered cases – and the linear trend of $\delta_{SPSA}^{\mu\pm\sigma}$, which is compared with δ_{SPSA}^{max} to identify the shaking level at which δ_{SPSA} becomes 727 728 relevant. Data from the suite "S-1" of motions for the whole collection of 91,500 soil models are 729 also displayed in (a)-(l), for comparison purposes.

Figure 9. Maximum *PGA* at which the inter-method differences are negligible for specific
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c) IPSA (i.e., intermediate buildings) and d) LPSA (i.e., tall buildings). The dashed area denotes
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784 Electronic Supplement to

- 785 Simplified criteria to select ground response analysis methods for seismic
- ⁷⁸⁶ building design: equivalent linear vs nonlinear approaches
- 787 By Mauro Aimar, and Sebastiano Foti

- 789 This electronic supplement starts with an overview of results of GRAs, focusing on the distribution
- of the amplification factors (AFs) with respect to soil model characteristics. The second section
- 791 describes the procedure adopted to estimate the standard deviation of the AFs (i.e., the thresholds
- used to quantify the relevance of the inter-method differences) from GMPEs.

793 Supplemental Text

794 Overview of Results

This section reports the results obtained from a basic assessment of the database of GRAs, with a focus on statistical properties of the AFs. Data are extracted from GRAs performed on the collection of 91,500 soil models for the suite "S-1" of input motions.

798 For the sake of simplicity, the analysis only accounted for the role of soil model characteristics, 799 whereas the effect of ground motion characteristics of the seismic input was disregarded. 800 Therefore, results were averaged – in logarithmic scale – with respect to the input motions, 801 obtaining a representative response for each ground model, which is compatible with the high 802 seismicity level. To investigate the effect of soil model characteristics, results were clustered 803 according to the original discretization of the $V_{S,H}$ -H domain, i.e. with reference to the blocks 804 adopted for their generation (Figure 1b in the Manuscript). Since the AFs tend to assume a 805 lognormal distribution (Li and Assimaki, 2010; Aimar et al., 2020), valid statistics for their 806 description are the mean value and the standard deviation - in logarithmic scale. In this way, this 807 strategy defined a characteristic value of AFs for a neighborhood of $V_{S,H}$ and H and it was possible 808 to describe the variation of those quantities across different soil conditions in an effective way.

Figure S1 and Figure S2 report the distribution of the mean and the standard deviation of the AFs across different soil models, computed according to the EQL and the NL approach, respectively. The EQL or the NL scheme provide similar results, in terms of the dependence of the mean and the variability with respect to the soil model, even though the NL scheme tends to underpredict the amplification with respect to the EQL approach (see EQL vs NL in the manuscript). In general, AFs are larger for increasing deformability and thickness of the ground models. Furthermore, significant differences are observed between shallow models (i.e., *H* less than 30 m) and deeper ones. This behavior is observed for all the AFs under examination, although some differences for varying vibration periods are remarkable.

818 At small depths, soil models characterized by high f_0 exhibit limited amplification, ranging 819 between 1 and 1.2. The minimum f_0 above which the ground motion amplification is negligible 820 (i.e., smaller than 1.2) depends on the range of spectral periods captured by each amplification 821 parameter. Specifically, it approximately equals 25 Hz (i.e., T_0 equal to 0.04 s) for PGAA, 15 Hz 822 (0.07 s) for SPSA, 8.5 Hz (0.12 s) for IPSA, 6 Hz (0.17 s) for LPSA. An example of this is reported 823 in Figure S3 for the EQL-based SPSA and LPSA. In this region, the AFs involve vibration periods 824 that are longer than the T_0 values of the soil models. Therefore, the corresponding wave 825 components sample a wide portion of the profile, thus inducing little amplification (Stewart et al., 826 2014). As a consequence, the induced strain levels are small (Figure 4a in the manuscript) and 827 there is almost no amplification with little variability. This region, instead, was not identified for 828 PGAA. On the other side, the amplification exhibits a peak over a region located at $V_{S,H}$ smaller 829 than 400 m/s, whose size is broader at long vibration periods. This region (defined by amplification 830 greater than 1.8) fits a range of f_0 approximately equal to 4-8 Hz (i.e., T_0 equal to 0.12-0.25 s) for 831 PGAA, 3-6 Hz (0.15-0.3 s) for SPSA (Figure S3a) and 2-4 Hz (0.25-0.5 s) for IPSA. At long 832 periods, instead, the region encompasses a broad variety of deformable models, with f_0 smaller 833 than 3 Hz (i.e., T_0 larger than 0.3 s), as shown in Figure S3b. The presence of the peak can be 834 associated with the transition from linear behavior to moderately relevant nonlinearity, due to the 835 large strain level observed at moderately deep models (Figure 4a in the Manuscript). At small

depths, in fact, the behavior is quasi linear and the response is mainly controlled by resonance phenomena, therefore the amplification grows for soil models whose T_0 is closer to the investigated period range. Conversely, in deeper profiles, the relatively large strain level induces the lengthening of T_0 . Therefore, SPSA and IPSA tend to decrease as the inelastic T_0 goes beyond the reference period range, differently from LPSA.

841 When the soil thickness is large, the effect of f_0 is less relevant as H increases and the amplification 842 mostly depends on $V_{S,H}$, i.e. on the deformability of shallow layers. In moderately stiff models, the 843 amplification is always larger than the unity and it increases at lower $V_{S,H}$ values. The response, in 844 fact, is still controlled by linear phenomena and the impedance contrast mostly affects the 845 stratigraphic amplification, due to the small strain level (Figure 4a in the Manuscript). Then, the 846 value saturates to a maximum value and it decreases in deformable soil models. The location and 847 the magnitude of the peak amplification depend on the specific amplification parameter. On the 848 one side, the maximum moves towards lower $V_{S,H}$ values and the peak amplitude is larger at 849 intermediate-to-long vibration periods (Figure S1e-g). On the other side, the decrease is stronger 850 and localized on a broader region for PGAA and SPSA, even including de-amplification for $V_{S,H}$ 851 less than 200 m/s (Figure S1c). Deformable soil models, in fact, undergo high strain levels and 852 nonlinear phenomena arise, as shown in Figure 4a in the Manuscript. Therefore, the high damping 853 induces strong attenuation, which damps especially low-period waves as they involve more cycles 854 per unit length. On the other side, the stiffness reduction induces strong amplification of the long-855 period components, with respect to the other ones, due to the lengthening of the fundamental period 856 of the ground model. As an additional effect of the high strain level, deep and deformable soil 857 models are also characterized by strong variability, which is around two times the one observed in the surrounding regions. In this case, in fact, GRAs involve the large-strain branch of the Modulus Reduction and Damping (MRD) curves, which is typically characterized by large variability, hence its more relevant contribution results in higher data dispersion. However, the standard deviation tends to decrease at longer vibration periods (e.g., Figure S1h), as the corresponding wave components sample a large portion of the soil profile and they are less sensitive to local variations.

863 Derivation of the Threshold Values

864 The threshold value δ_X^{max} , i.e. the standard deviation $\sigma_{\ln X}^E$ of the ground motion amplification 865 parameters (i.e., PGAA, SPSA, IPSA, LPSA), was derived from predictive models for the ground 866 motion.

As for the spectral amplification factors (SAFs – i.e., SPSA, IPSA and LPSA), the estimate required to merge two different aspects intervening in the empirical estimate of spectral ordinates, i.e. GMPEs and conditional spectra. Recalling the definition, SAFs describe the amplification of spectral intensities, where the spectral intensity SI_{AB} is defined as the integral of the elastic response spectrum $S_e(T)$ over a range [*A*; *B*] of vibration periods of interest:

$$SI_{AB} = \int_{A}^{B} S_{e}(T) dT$$
 (S8)

873 Since numerical codes used for GRAs estimate the spectral ordinates at discrete vibration periods, 874 the integral is reduced into a sum. For simplicity, the sampling period is assumed to be constant 875 and equal to ΔT . Furthermore, for better readability, the subscript *AB* is removed from the notation.

876
$$SI = SI_{AB} \approx \sum_{i \in [A;B]} S_e(T_i) \Delta T_i = \Delta T \sum_{i \in [A;B]} S_e(T_i)$$
(S9)

The spectral ordinates $S_e(T_i)$ are modeled as random variables, hence the sum is a random quantity, which can be synthetically described in terms of its mean μ_{SI} and variance σ_{SI}^2 . These quantities can be related to the statistical features of the single spectral ordinates, as follows (Ang and Tang, 2007):

881
$$\mu_{SI} \approx \Delta T \sum_{i \in [A;B]} \mu_{Se(T_i)}$$
(S10)

882

$$\sigma_{SI}^{2} \approx \Delta T^{2} \sum_{i \in [A;B]} \sigma_{Se(T_{i})}^{2} + 2\Delta T^{2} \sum_{i \in [A;B]} \sum_{\substack{j \in [A;B] \\ i < j}} \rho_{Se(T_{i}),Se(T_{j})} \sigma_{Se(T_{i})} \sigma_{Se(T_{j})} = \Delta T^{2} \sum_{i \in [A;B]} \sigma_{Se(T_{i})}^{2} + 2\Delta T^{2} \sum_{\substack{i \in [A;B] \\ i < j}} \sigma_{Se(T_{i}),Se(T_{j})}, \qquad (S11)$$

883 where $\mu_{Se(T_i)}$ and $\sigma_{Se(T_i)}^2$ are the mean and variance of the spectral ordinates at the period T_i , and 884 $\rho_{Se(T_i),Se(T_j)}$ is the coefficient of correlation between spectral ordinates at periods T_i and T_j . The 885 variance, in fact, is the combination of the sum of the variances of the single spectral ordinates and 886 an additional term, which accounts for the covariance $\sigma_{Se(T_i),Se(T_j)}$ – hence, the linear correlation – 887 among the spectral ordinates at different vibration periods.

Statistical information about single spectral ordinates, i.e. $\mu_{Se(T_i)}$ and $\sigma_{Se(T_i)}^2$, was extracted from the GMPE proposed by Boore et al. (2014), henceforth denoted as BSSA (2014). This GMPE, in fact, provides a reliable estimate of ground motion parameters for a wide variety of source, path and site conditions. Besides, the model is characterized by relatively simple functional forms, that require a limited number of parameters of immediate estimate. The procedure of computation of spectral ordinates assumed a broad set of magnitude and distance bins, where magnitudes ranged between 5.5 and 8 and distances varied between 10 km and 100 km. As for the source mechanism, an unspecified fault style was considered. Furthermore, the estimate considered a set of discrete $V_{S,30}$ values uniformly distributed in logarithmic scale between 150 m/s and 950 m/s, to approximately cover the range of $V_{S,H}$ of the synthetic ground models. In this way, a reference distribution of the spectral ordinates was obtained, which is able to represent various seismic and stratigraphic conditions.

For each bin, the GMPE estimates the mean and the variance of each spectral ordinate in logarithmic scale, i.e. $\mu_{\ln Se(T_i)}$ and $\sigma_{\ln Se(T_i)}^2$, respectively. These quantities were converted into the natural scale, as necessary for the summation (Ang and Tang, 2007).

903
$$\mu_{Se}(T_i) = \exp(\mu_{\ln Se(T_i)}) + \frac{1}{2}\sigma_{\ln Se(T_i)}^2$$
(S12)

904
$$\sigma_{Se(T_i)}^2 = \exp\left(2\mu_{\ln Se(T_i)} + \sigma_{\ln Se(T_i)}^2\right) \left(\exp\left(\sigma_{\ln Se(T_i)}^2\right) - 1\right)$$
(S13)

905 The BSSA (2014) model provides an estimate of the spectral ordinates at separate vibration 906 periods, without accounting for mutual relationships of the spectral content across the periods, that 907 influence the spectral shape. Information about the correlation structure can be retrieved from 908 studies about the conditional mean spectrum (Baker and Cornell, 2006). An estimate of the logarithmic correlation coefficients $\rho_{\ln Se(T_i),\ln Se(T_i)}$ is provided by the GMPE proposed by Baker and 909 910 Bradley (2017). The model is consistent with the BSSA (2014) GMPE, as they share the same 911 dataset (i.e., NGA-West2 - see Data and Resources). In this case, the estimate of the correlation 912 coefficients among the spectral ordinates does not require specific information about magnitude,

913 distance, $V_{S,30}$ and fault style. By combining this quantity with the standard deviation of the single 914 spectral ordinates, the covariance matrix $\sigma_{\ln Se(T_i),\ln Se(T_j)}$ can be obtained. Note that, differently from 915 the correlation coefficients, $\sigma_{\ln Se(T_i),\ln Se(T_j)}$ depends on magnitude, distance, $V_{S,30}$ and fault style as 916 it involves the standard deviation of the single spectral ordinates, i.e. $\sigma_{\ln Se(T_i)}$, according to the 917 following formula:

918
$$\sigma_{\ln Se(T_i),\ln Se(T_j)} = \rho_{\ln Se(T_i),\ln Se(T_j)} \sigma_{\ln Se(T_i)} \sigma_{\ln Se(T_j)}$$
(S14)

919 Finally, the covariance matrix was converted into the corresponding one in natural scale, i.e. 920 $\sigma_{se(T_i), Se(T_i)}$:

921
$$\sigma_{Se(T_{i}),Se(T_{j})} = \begin{cases} \exp\left(2\mu_{\ln Se(T_{i})} + \sigma_{\ln Se(T_{i})}^{2}\right)\left(\exp\left(\sigma_{\ln Se(T_{i})}^{2}\right) - 1\right), T_{i} = T_{j} \\ \exp\left(\mu_{\ln Se(T_{i})} + \mu_{\ln Se(T_{j})} + \frac{1}{2}\left(\sigma_{\ln Se(T_{i})}^{2} + \sigma_{\ln Se(T_{j})}^{2}\right)\right)\left(\exp\left(\sigma_{\ln Se(T_{i}),\ln Se(T_{j})}^{2}\right) - 1\right), T_{i} \neq T_{j} \end{cases}$$
922 (S15)

923 By merging this information in equations (S3)-(S4), it was possible to infer the statistical 924 parameters of spectral integrals, i.e. μ_{SI} and σ_{SI}^2 , from GMPEs.

925 Empirical data about spectral integrals follow a lognormal distribution, as shown in Figure S4 for 926 SPSI and LPSI by example. This result was not guaranteed a priori, since spectral integrals derive 927 from the sum of lognormal variables, for which a closed-form expression for the distribution does 928 not exist. However, several studies showed that the lognormal distribution fairly approximates the 929 solution (Fenton, 1960). Thanks to this empirical evidence, spectral integrals can be reasonably 930 described by the mean and the standard deviation in logarithmic scale, i.e. $\mu_{\ln SI}$ and $\sigma_{\ln SI}^2$, which 931 were derived from the ones computed in normal scale (Ang and Tang, 2007), according to:

932
$$\mu_{\ln SI} = \ln\left(\frac{\mu_{SI}^2}{\sqrt{\mu_{SI}^2 + \sigma_{SI}^2}}\right)$$
(S16)

933
$$\sigma_{\ln SI}^2 = \ln\left(\frac{\sigma_{SI}^2}{\mu_{SI}^2} + 1\right)$$
(S17)

The $\sigma_{\ln SI}^2$ value strongly depends on site conditions in the range of magnitudes and distances of interest, as highlighted in Figure S5a. In stiff sites, the value is stable and undergoes small variations, whereas it suddenly drops at $V_{S,30}$ smaller than 300 m/s. Furthermore, the variability is stronger at long periods with respect to high frequencies. These observations are consistent with the trend of $\sigma_{\ln Se(T_i)}^2$ predicted according to the BSSA (2014) model.

As for PGAA, the derivation of $\sigma_{\ln PGA}^2$ was immediate, since the BSSA (2014) model provides an estimate of this quantity. Figure S5a shows the resulting trend, obtained with the same set of magnitudes, distances and $V_{5,30}$ bins as the spectral intensities.

942 On the other side, the AFs under examination are defined as the ratio between the simulated motion 943 (i.e., spectral intensity or peak ground acceleration) computed at the surface (i.e., SI_s or PGA_s) and 944 the corresponding one estimated for the input motion (i.e., SI_r or PGA_r). The expression becomes 945 the following one in logarithmic scale:

$$\ln SA = \ln SI_s - \ln SI_r \tag{S18}$$

$$\ln PGAA = \ln PGA_{\rm s} - \ln PGA_{\rm s} \tag{S19}$$

948 In equation (S11), the generic SAF is labeled as SA.

947

949 Thanks to the assumption of lognormal distribution of *SI* (*PGA*), the quantity ln(*SA*) (ln(*PGAA*)) 950 is normally distributed, since it is equal to the difference of two normal random variables. 951 Therefore, the corresponding variability can be described in terms of the logarithmic standard 952 deviation $\sigma_{\ln SA}^{E}$ ($\sigma_{\ln PGAA}^{E}$), which is derived through the theorem of propagation of the variance 953 (Ang and Tang, 2007):

954
$$\sigma_{\ln SA}^{E,2} = \sigma_{\ln SI_s}^2 + \sigma_{\ln SI_r}^2 - 2\rho_{\ln SI_s,\ln SI_r}\sigma_{\ln SI_s}\sigma_{\ln SI_r}$$
(S20)

955
$$\sigma_{\ln PGAA}^{E,2} = \sigma_{\ln PGA_s}^2 + \sigma_{\ln PGA_r}^2 - 2\rho_{\ln PGA_s,\ln PGA_r}\sigma_{\ln PGA_s}\sigma_{\ln PGA_r}$$
(S21)

The variance $\sigma_{\ln SI_r}^2$ ($\sigma_{\ln PGA_r}^2$) refers to a ground motion recorded on a rock-like formation and it 956 957 can be estimated according to the procedure above, by selecting a $V_{S,30}$ bin close to 800 m/s. The variance $\sigma_{\ln PGA_s}^2$ ($\sigma_{\ln PGA_s}^2$), instead, describes the SI (PGA) variability on the top of a soil deposit and 958 it was estimated for varying $V_{S,30}$ (Figure S5a). The correlation coefficient $\rho_{\ln SI_s,\ln SI_r}$ ($\rho_{\ln PGA_s,\ln PGA_r}$ 959) represents the degree of linear relationship between SI (PGA) values observed on soil deposits 960 961 and on rock formations. An indicative value was inferred from the NGA-West2 database (see Data 962 and Resources), by comparing the empirical distributions of SI_r and SI_s (PGA_r and PGA_s). As shown in Figure S5b, the resulting $\rho_{\ln SI_{c},\ln SI_{c}}$ ($\rho_{\ln PGA_{c},\ln PGA_{c}}$) ranges between 0.8 and 1 and it 963 964 increases when $V_{5,30}$ is larger, up to a relatively constant value for $V_{5,30}$ greater than 400 m/s. The 965 strong correlation between spectral intensities in stiff soils could be an effect of the linear response,

where the response spectrum undergoes little variations in the shape. Conversely, at small $V_{5,30}$ values, the poor correlation is mainly an effect of the strong nonlinearity, which dramatically weakens the degree of relationship at high frequencies. Furthermore, the limited number of data at $V_{5,30}$ less than 200 m/s in the NGA-West2 dataset contributes to reducing the degree of correlation.

Therefore, the estimate of $\sigma_{\ln SA}^{E}$ ($\sigma_{\ln PGAA}^{E}$) accounted for the $V_{S,30}$ -dependence of $\rho_{\ln SI_{c},\ln SI_{r}}$ and 970 $\sigma_{\ln SI_s}^2$ ($\rho_{\ln PGA_s, \ln PGA_r}$ and $\sigma_{\ln PGA_s}^2$) The trend is represented in Figure S6. At small $V_{S,30}$ values, the 971 972 standard deviation dramatically increases, due to the weak correlation between the spectral 973 intensities recorded on rock and on soil. However, the variability is small compared to the one 974 predicted by the simulations, especially at short periods. This could be an effect of over-975 randomization of the V_S profiles and of the MRD curves (Stewart et al., 2014). On the contrary, the empirical variability is small and quite stable in stiff soils. In this case, the estimated $\sigma^{E}_{\ln SA}$ is 976 977 consistent with the simulation-based results, except for SPSA, where it is slightly underestimated 978 by simulations. A similar discrepancy is also observed for PGAA. Note that the correlation is also 979 the reason for the opposite trend of SA (and PGAA) with respect to the corresponding SI (PGA). 980 This standard deviation, in fact, is referred to an amplification parameter, rather than a ground 981 motion quantity itself.

982 List of Supplemental Table Captions

Table S1. Selected input motions with details about event characteristics and intensity, as well as the suite identification ("S-1" or "S-2"). Event characteristics include the epicentral distance and the earthquake magnitude, measured in terms of moment magnitude – unless otherwise stated – whereas intensity is represented in terms of *PGA*. For some input motions, intensity parameters are scaled according to a scaling factor. Information about the criteria adopted for its estimate is available in Aimar et al. (2020).

Table S2. Correlation between $\delta_{PGAA}^{\mu\pm\sigma}$ and commonly used ground motion parameters, quantified through Kendall's τ_b coefficient and the *p*-value (in brackets). The considered parameters are the peak ground acceleration (*PGA*), peak ground velocity (*PGV*), peak ground displacement (*PGD*), Arias intensity (*AI*), predominant period (T_p), mean period (T_m), significant duration from 5% to 95% of the Husid plot (D_{5-95}), significant duration from 5% to 75% of the Husid plot (D_{5-75}) and uniform duration (*UD* – based on a threshold acceleration equal to 0.025g). The column labels identify the reference clusters of soil models (see Figure 8f in the Manuscript).

Table S3. Correlation between $\delta_{SPSA}^{\mu\pm\sigma}$ and commonly used ground motion parameters, quantified through Kendall's τ_b coefficient and the *p*-value (in brackets). The considered parameters are the peak ground acceleration (*PGA*), peak ground velocity (*PGV*), peak ground displacement (*PGD*), Arias intensity (*AI*), predominant period (T_p), mean period (T_m), significant duration from 5% to 95% of the Husid plot (D_{5-95}), significant duration from 5% to 75% of the Husid plot (D_{5-75}) and uniform duration (*UD* – based on a threshold acceleration equal to 0.025g) and SPSI. The column labels identify the reference clusters of soil models (see Figure 8m in the Manuscript).

Table S4. Correlation between $\delta_{IPSA}^{\mu\pm\sigma}$ and commonly used ground motion parameters, quantified 1003 1004 through Kendall's τ_b coefficient and the *p*-value (in brackets). The considered parameters are the 1005 peak ground acceleration (PGA), peak ground velocity (PGV), peak ground displacement (PGD), 1006 Arias intensity (AI), predominant period (T_p) , mean period (T_m) , significant duration from 5% to 1007 95% of the Husid plot (D_{5-95}), significant duration from 5% to 75% of the Husid plot (D_{5-75}) and 1008 uniform duration (UD - based on a threshold acceleration equal to 0.025g) and IPSI. The column 1009 labels identify the reference clusters of soil models (see Figure 8m in the Manuscript). Table S5. Correlation between $\delta_{LPSA}^{\mu\pm\sigma}$ and commonly used ground motion parameters, quantified 1010

1011 through Kendall's τ_b coefficient and the *p*-value (in brackets). The considered parameters are the

1012 peak ground acceleration (PGA), peak ground velocity (PGV), peak ground displacement (PGD),

1013 Arias intensity (AI), predominant period (T_p) , mean period (T_m) , significant duration from 5% to

1014 95% of the Husid plot (D_{5-95}), significant duration from 5% to 75% of the Husid plot (D_{5-75}) and

1015 uniform duration (UD – based on a threshold acceleration equal to 0.025g) and LPSI. The column

1016 labels identify the reference clusters of soil models (see Figure 8m in the Manuscript).

1017 List of Supplemental Figure Captions

1018 Figure S1. Mean and standard deviation of EQL-based PGAA (a-b), SPSA (c-d), IPSA (e-f) and

1019 LPSA (g-h), as a function of soil model characteristics. The plots report results for the mean value

1020 (left column) and the standard deviation (right column). Results refer to the suite "S-1" of input

- 1021 motions. The dashed area denotes the region not considered in GRAs.
- 1022 Figure S2. Mean and standard deviation of NL-based PGAA (a-b), SPSA (c-d), IPSA (e-f) and

1023 LPSA (g-h), as a function of soil model characteristics. The plots report results for the mean value

1024 (left column) and the standard deviation (right column). Results refer to the suite "S-1" of input

- 1025 motions. The dashed area denotes the region not considered in GRAs.
- 1026 Figure S3. Trend of EQL-based SPSA (a) and LPSA (b) for shallow and deformable soil models.
- 1027 The contour lines denote the mean values of each parameter, whereas the dashed area identifies

1028 the region not considered in GRAs. Results refer to the suite "S-1" of input motions.

- 1029 Figure S4. Probability plots for SPSI (a-b) and LPSI (c-d) for V_{5,30} between 225 m/s and 275 m/s
- 1030 (a-c) and $V_{5,30}$ between 780 m/s and 950 m/s (b-d).
- Figure S5. Standard deviation (a) and rock-to-soil correlation (b) of the spectral parameters, as a function of soil deposit characteristics (i.e., $V_{5,30}$).
- 1033 Figure S6. Empirical and simulation-based standard deviation for PGAA (a), SPSA (b), IPSA (c),
- 1034 LPSA (d), as a function of soil deposit characteristics (i.e., $V_{S,30}$).
- 1035 Figure S7. Number of models required to achieve a stable estimate of the standard deviation of the
- 1036 EQL-based PGAA (a), SPSA (b), IPSA (c) and LPSA (d), as a function of soil model

1037 characteristics. Results refer to the suite "S-1" of input motions. The dashed area denotes the region1038 not considered in GRAs.

Figure S8. Number of models required to achieve a stable estimate of statistical moments of the NL-based PGAA (a-b), SPSA (c-d), IPSA (e-f) and LPSA (g-h), as a function of soil model characteristics. The plots report the results for the mean value (left column) and the standard deviation (right column). Results refer to the suite "S-1" of input motions. The dashed area denotes the region not considered in GRAs.

Figure S9. Distribution of $\mu_{\delta,PGAA}$ (a) and $\sigma_{\delta,PGAA}$ (b), as a function of soil model characteristics; Distribution of $\mu_{\delta,IPSA}$ (c) and $\sigma_{\delta,IPSA}$ (d), as a function of soil model characteristics. The dashed area denotes the region not considered in GRAs.

Figure S10. Relationship between $\delta_{PGAA}^{\mu\pm\sigma}$ and *PGA* for all the clusters of soil models. Panels (a)-(1) 1047 display the plot of $\delta_{PGAA}^{\mu\pm\sigma}$ versus PGA derived from GRAs on the set of 10,150 soil models with 1048 1049 the suites "S-1" and "S-2" of input motions. Each panel contains data from each cluster of soil 1050 models and the corresponding location in the V_{SH} -H domain is represented in (m). Panels (a)-(l) 1051 also report the Kendall's τ_p coefficient – the *p*-value is close to 0 in all the considered cases, except in (a), where it equals 0.01 – and the linear trend of $\delta_{PGAA}^{\mu\pm\sigma}$, which is compared with δ_{PGAA}^{max} to 1052 1053 identify the shaking level at which δ_{PGAA} becomes relevant. For panel (a), we omit the linear fit because τ_b is smaller than 0.3. Data from the suite "S-1" of motions for the whole collection of 1054 1055 91,500 soil models are also displayed in (a)-(1), for comparison purposes.

Figure S11. Relationship between $\delta_{IPSA}^{\mu\pm\sigma}$ and *PGA* for all the clusters of soil models. Panels (a)-(l) 1056 display the plot of $\delta_{IPSA}^{\mu\pm\sigma}$ versus PGA derived from GRAs on the set of 10,150 soil models with the 1057 1058 suites "S-1" and "S-2" of input motions. Each panel contains data from each cluster of soil models 1059 and the corresponding location in the V_{SH} -H domain is represented in (m). Panels (a)-(1) also report 1060 the Kendall's τ_b coefficient – the *p*-value is close to 0 in all the considered cases, except in (a), where it equals 0.01 – and the linear trend of $\delta_{IPSA}^{\mu\pm\sigma}$, which is compared with δ_{IPSA}^{max} to identify the 1061 1062 shaking level at which δ_{IPSA} becomes relevant. For panel (a), we omit the linear fit because τ_b is 1063 smaller than 0.3. Data from the suite "S-1" of motions for the whole collection of 91,500 soil 1064 models are also displayed in (a)-(l), for comparison purposes.

Figure S12. Relationship between $\delta_{LPSA}^{\mu\pm\sigma}$ and *PGA* for all the clusters of soil models. Panels (a)-(l) 1065 display the plot of $\delta_{LPSA}^{\mu\pm\sigma}$ versus *PGA* derived from GRAs on the set of 10,150 soil models with the 1066 1067 suites "S-1" and "S-2" of input motions. Each panel contains data from each cluster of soil models 1068 and the corresponding location in the V_{SH} -H domain is represented in (m). Panels (a)-(1) also report 1069 the Kendall's τ_b coefficient – the *p*-value is close to 0 in all the considered cases, except in (a), (b) and (c), where it equals 0.48, 0.01 and 0.01, respectively – and the linear trend of $\delta_{LPSA}^{\mu\pm\sigma}$, which is 1070 compared with δ_{LPSA}^{max} to identify the shaking level at which δ_{LPSA} becomes relevant. For panels (a), 1071 (b) and (c), we omit the linear fit because τ_b is smaller than 0.3. Data from the suite "S-1" of 1072 1073 motions for the whole collection of 91,500 soil models are also displayed in (a)-(l), for comparison 1074 purposes.

Figure S13. Relationship between $\delta_{SPSA}^{\mu\pm\sigma}$ and SPSI for all the clusters of soil models. Panels (a)-(l) 1075 display the plot of $\delta_{SPSA}^{\mu\pm\sigma}$ versus SPSI derived from GRAs on the set of 10,150 soil models with the 1076 1077 suites "S-1" and "S-2" of input motions. Each panel contains data from each cluster of soil models 1078 and the corresponding location in the V_{SH} -H domain is represented in (m). Panels (a)-(1) also report 1079 the Kendall's τ_b coefficient – the *p*-value is close to 0 in all the considered cases, except in (a), where it equals 0.01 – and the linear trend of $\delta_{SPSA}^{\mu\pm\sigma}$, which is compared with δ_{SPSA}^{max} to identify the 1080 1081 shaking level at which δ_{SPSA} becomes relevant. For panel (a), we omit the linear fit because τ_b is 1082 smaller than 0.3. Data from the suite "S-1" of motions for the whole collection of 91,500 soil 1083 models are also displayed in (a)-(l), for comparison purposes.

Figure S14. Relationship between $\delta_{IPSA}^{\mu\pm\sigma}$ and *IPSI* for all the clusters of soil models. Panels (a)-(l) 1084 display the plot of $\delta_{IPSA}^{\mu\pm\sigma}$ versus *IPSI* derived from GRAs on the set of 10,150 soil models with the 1085 1086 suites "S-1" and "S-2" of input motions. Each panel contains data from each cluster of soil models 1087 and the corresponding location in the V_{SH} -H domain is represented in (m). Panels (a)-(1) also report 1088 the Kendall's τ_b coefficient – the *p*-value is close to 0 in all the considered cases, except in (a), where it equals 0.45 – and the linear trend of $\delta_{IPSA}^{\mu\pm\sigma}$, which is compared with δ_{IPSA}^{max} to identify the 1089 1090 shaking level at which δ_{IPSA} becomes relevant. For panel (a), we omit the linear fit because τ_b is 1091 smaller than 0.3. Data from the suite "S-1" of motions for the whole collection of 91,500 soil 1092 models are also displayed in (a)-(l), for comparison purposes.

1093 Figure S15. Relationship between $\delta_{LPSA}^{\mu\pm\sigma}$ and *LPSI* for all the clusters of soil models. Panels (a)-(l) 1094 display the plot of $\delta_{LPSA}^{\mu\pm\sigma}$ versus *LPSI* derived from GRAs on the set of 10,150 soil models with the 1095 suites "S-1" and "S-2" of input motions. Each panel contains data from each cluster of soil models 1096 and the corresponding location in the V_{SH} -H domain is represented in (m). Panels (a)-(l) also report 1097 the Kendall's τ_b coefficient – the *p*-value is close to 0 in all the considered cases, except in (a), (b) and (c), where it equals 0.04, 0.91 and 0.74, respectively – and the linear trend of $\delta_{LPSA}^{\mu\pm\sigma}$, which is 1098 compared with δ_{LPSA}^{max} to identify the shaking level at which δ_{LPSA} becomes relevant. For panels (a), 1099 1100 (b) and (c), we omit the linear fit because τ_b is smaller than 0.3. Data from the suite "S-1" of 1101 motions for the whole collection of 91,500 soil models are also displayed in (a)-(l), for comparison 1102 purposes.

- 1103 Figure S16. Maximum SI at which the inter-method differences are negligible for specific
- 1104 applications of GRAs: a) SPSA (i.e., small buildings); b) IPSA (i.e., intermediate buildings) and
- 1105 c) LPSA (i.e., tall buildings). The dashed area denotes the region not considered in GRAs.

1106 Supplemental Tables

Table S1. Selected input motions with details about event characteristics and intensity, as well as the suite identification ("S-1" or "S-2"). Event characteristics include the epicentral distance and the earthquake magnitude, measured in terms of moment magnitude – unless otherwise stated – whereas intensity is represented in terms of *PGA*. For some input motions, intensity parameters are scaled according to a scaling factor. Information about the criteria adopted for its estimate is available in Aimar et al. (2020).

| Event name | Date | Network-Station | Component | Database | Moment | Epicentral | Scaling | PGA | Suite |
|----------------------|--------------|------------------|-----------|-----------------|---------------|---------------|------------|------|-------|
| | | | | | magnitude (-) | distance (km) | factor (-) | (g) | |
| Central Italy | 26-Oct-2016 | IT-MMO | NS | ITACA | 5.9 | 16.2 | 1.2 | 0.20 | S-1 |
| Central Italy | 30-Oct -2016 | IV-T1212 | NS | ITACA | 6.5 | 10.5 | 0.8 | 0.20 | S-1 |
| Iwate, Japan | 13-Jun-2008 | KNET-IWT010 | NS | PEER NGA- West2 | 6.9 | 23.17 | 0.9 | 0.20 | S-1 |
| Loma Prieta | 18-Oct -1989 | CGS-Gilroy Array | 90° | PEER NGA- West2 | 6.93 | 28.64 | 0.7 | 0.29 | S-1 |
| | | #1 | | | | | | | |
| Northridge-01 | 17-Jan-1994 | CGS-LA- | 185° | PEER NGA- West2 | 6.69 | 18.99 | 1.4 | 0.22 | S-1 |
| | | Wonderland | | | | | | | |
| | | Avenue | | | | | | | |
| North Western Balkan | 15-Apr-1979 | EU-ULA | NS | ESM | 6.9 | 19.7 | 1.0 | 0.18 | S-1 |
| Tottori, Japan | 06-Oct -2000 | KIKNET-SMNH10 | EW | PEER NGA- West2 | 6.61 | 31.41 | 1.0 | 0.25 | S-1 |
| Izmit | 17-Aug-1999 | TK-4101 | EW | ESM | 7.6 | 3.4 | 1.0 | 0.23 | S-1 |
| Martinique Region | 29-Nov-2007 | RA-MAMA | NS | ESM | 7.4 | 67.9 | 1.35 | 0.24 | S-1 |
| Windward Island | | | | | | | | | |

1112 Table S1. Selected input motions with details about event characteristics and intensity, as well as the suite identification ("S-1" or "S-

1113 2"). (*continues*)

| Event name | Date | Network-Station | Component | Database | Moment | Epicentral | Scaling | PGA | Suite |
|----------------------|--------------|------------------|-----------|-----------------|---------------|---------------|------------|------|-------|
| | | | | | magnitude (-) | distance (km) | factor (-) | (g) | |
| North Western Balkan | 15-Apr-1979 | EU-HRZ | EW | ESM | 6.9 | 62.9 | 1.15 | 0.29 | S-1 |
| Peninsula | | | | | | | | | |
| Northridge-01 | 17-Jan-1994 | CGS-Pacoima Dam | 265° | PEER NGA- West2 | 6.69 | 20.36 | 0.75 | 0.33 | S-1 |
| | | (Downstream) | | | | | | | |
| San Fernando | 09-Feb-1971 | C&GS-Pasadena- | 270° | PEER NGA- West2 | 6.61 | 39.17 | 1.35 | 0.28 | S-1 |
| | | Old Seismo Lab | | | | | | | |
| Kobe, Japan | 16-Jan-1995 | KIKNET-KBU090 | 90° | PEER NGA- West2 | 6.90 | 25.4 | 1.0 | 0.31 | S-1 |
| Chi Chi Taiwan 05 | 22-Sep-1999 | CWB-TTN042 | NS | PEER NGA- West2 | 6.20 | 92.27 | 0.92 | 0.08 | S-2 |
| Irpinia | 23-Nov-1980 | IT-ALT | EW | ITACA | 6.9 | 23.4 | 0.92 | 0.05 | S-2 |
| Loma Prieta | 18-Oct -1989 | CGS-PJH | 45° | PEER NGA- West2 | 6.93 | 92.21 | 0.9 | 0.08 | S-2 |
| North Western Balkan | 15-Apr-1979 | CR-DUB | NS | ESM | 6.9 | 104.4 | 1.35 | 0.09 | S-2 |
| Peninsula | | | | | | | | | |
| Whittier Narrows | 01-Oct -1987 | CGS-Pasadena-CIT | 360° | PEER NGA- West2 | 5.99 | 13.85 | 1.1 | 0.10 | S-2 |
| | | Kresge Lab | | | | | | | |
| Northern Algeria | 29-Oct -1989 | FC-ALG | NS | ESM | 5.9 | 50 | 1.4 | 0.05 | S-2 |
| Sicilia | 13-Dec-1990 | IT-NOT | NS | ITACA | 5.6 | 48.3 | 0.92 | 0.06 | S-2 |

1115 Table S1. Selected input motions with details about event characteristics and intensity, as well as the suite identification ("S-1" or "S-

1116 2"). (*continues*)

| Event name | Date | Network-Station | Component | Database | Moment | Epicentral | Scaling | PGA | Suite |
|-------------------|--------------|---------------------|-----------|-----------------|---------------|---------------|------------|------|-------|
| | | | | | magnitude (-) | distance (km) | factor (-) | (g) | |
| Martinique Region | 29-Nov-2007 | RA-SFGA | NS | ESM | 7.4 | 144.8 | 1.15 | 0.07 | S-2 |
| Windward Island | | | | | | | | | |
| South Iceland | 17-Jun-2000 | SM-Minni-Nupur | Х | ESD | 6.5 | 13 | 0.85 | 0.12 | S-2 |
| South Iceland- | 21-Jun-2000 | SM-Selfoss-City | Y | ESD | 6.4 | 15 | 1.15 | 0.13 | S-2 |
| aftershock | | Hall | | | | | | | |
| Central Italy | 26-Oct -2016 | IT-CLO | NS | ITACA | 5.9 | 10.8 | 0.7 | 0.13 | S-2 |
| Greece | 07-Sep-1999 | HI-ATH4 | 3 | ESM | 5.9 | 19.7 | 1.27 | 0.14 | S-2 |
| Cosenza | 25-Oct -2012 | IT-MRM | EW | ITACA | 5.2 | 2.4 | 1.2 | 0.21 | S-2 |
| Whittier Narrows | 01-Oct -1987 | CGS-Pasadena-CIT | 90° | PEER NGA- West2 | 5.99 | 13.85 | 1.0 | 0.11 | S-2 |
| | | Kresge Lab | | | | | | | |
| Albania | 08-Apr-2017 | AC-PHP | Е | ESM | 5.0^{*} | 41.1 | 1.0 | 0.15 | S-2 |
| Greece | 11-Jul-2016 | HL-NVR | NS | ESM | 3.8 | 17.5 | 1.0 | 0.18 | S-2 |
| Central Italy | 26-Oct -2016 | IT-CLO | EW | ITACA | 5.9 | 10.8 | 1.23 | 0.22 | S-2 |
| Southern Italy | 30-Sep-1995 | IT-SNN | EW | ITACA | 5.2 | 27.8 | 1.0 | 0.12 | S-2 |
| Parkfield-02, CA | 28-Sep-2004 | CGS-Parkfield- | 270° | PEER NGA- West2 | 6.00 | 6.82 | 1.1 | 0.27 | S-2 |
| | | Turkey Flat #1 (0M) | | | | | | | |

* Local magnitude.

1117 Table S1. Selected input motions with details about event characteristics and intensity, as well as the suite identification ("S-1" or "S-

1118 2"). (*continues*)

| Event name | Date | Network-Station | Component | Database | Moment | Epicentral | Scaling | PGA | Suite |
|-------------------------------|--------------|-----------------|-------------|-----------------|-----------------|---------------|------------|--------------|-------|
| | | | | | magnitude (-) | distance (km) | factor (-) | (g) | |
| Northridge-01 | 17-Jan-1994 | CGS-Vasquez | 0° | PEER NGA- West2 | 6.69 | 38.07 | 1.05 | 0.16 | S-2 |
| | | Rocks Park | | | | | | | |
| Turkey-Georgia- | 30-Mar-1989 | A-STRS | NS | ESM | 4.0^{\dagger} | 15.4 | 1.05 | 0.22 | S-2 |
| Armenia Border Region | | | | | | | | | |
| Central Italy | 06-Oct -1997 | IT-ASS | NS | IT | 5.4 | 20.8 | 0.75 | 0.14 | S-2 |
| Western Turkey | 22-Sep-2015 | KO-SHAP | NS | ESM | 4.3 | 14.6 | 1.0 | 0.18 | S-2 |
| Southern Italy | 09-Sep-1998 | IT-LRS | NS | ITACA | 5.6 | 18 | 1.0 | 0.17 | S-2 |
| Greece | 15-Oct -2016 | AC-SRN | EW | ESM | 5.5 | 55.9 | 1.0 | 0.29 | S-2 |
| Umbria Marche 2 nd | 26-Sep-1997 | IT-ASS | NS | ITACA | 6.0 | 21.6 | 1.0 | 0.16 | S-2 |
| shock | | | | | | | | | |
| Sicily Italy | 26-Dec-2018 | IV-EVRN | EW | ESM | 4.9 | 5.3 | 1.0 | 0.3 | S-2 |
| Duzce | 12-Nov-1999 | A-C1062 | EW | ESM | 7.3 | 32.3 | 1.0 | 0.26 | S-2 |

1119

[†] Surface wave magnitude.
| 1120 | Table S2. Correlation between $\delta_{PGAA}^{\mu\pm\sigma}$ and commonly used ground motion parameters, quantified |
|------|---|
| 1121 | through Kendall's τ_b coefficient and the <i>p</i> -value (in brackets). The considered parameters are the |
| 1122 | peak ground acceleration (PGA), peak ground velocity (PGV), peak ground displacement (PGD), |
| 1123 | Arias intensity (AI), predominant period (T_p) , mean period (T_m) , significant duration from 5% to |
| 1124 | 95% of the Husid plot (D_{5-95}), significant duration from 5% to 75% of the Husid plot (D_{5-75}) and |
| 1125 | uniform duration (UD – based on a threshold acceleration equal to 0.025g). The column labels |
| 1126 | identify the reference clusters of soil models (see Figure 8m in the Manuscript). |

| | а | b | с | d | e | f | g | h | i | j | k | 1 |
|------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| DCA | 0.28 | 0.66 | 0.61 | 0.70 | 0.73 | 0.64 | 0.73 | 0.73 | 0.70 | 0.76 | 0.72 | 0.69 |
| ТОА | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| PCV | 0.17 | 0.43 | 0.40 | 0.53 | 0.57 | 0.41 | 0.49 | 0.53 | 0.58 | 0.46 | 0.54 | 0.58 |
| 107 | (0.11) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| РСЛ | 0.02 | 0.23 | 0.16 | 0.30 | 0.32 | 0.22 | 0.26 | 0.26 | 0.29 | 0.22 | 0.28 | 0.30 |
| 100 | (0.87) | (0.03) | (0.14) | (0.00) | (0.00) | (0.04) | (0.02) | (0.02) | (0.01) | (0.04) | (0.01) | (0.01) |
| AI | 0.25 | 0.48 | 0.40 | 0.48 | 0.52 | 0.42 | 0.45 | 0.46 | 0.46 | 0.43 | 0.46 | 0.46 |
| | (0.02) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| т | 0.05 | 0.01 | 0.01 | 0.11 | 0.14 | 0.08 | 0.04 | 0.13 | 0.20 | 0.02 | 0.13 | 0.18 |
| I p | (0.63) | (0.93) | (0.95) | (0.31) | (0.21) | (0.46) | (0.74) | (0.24) | (0.07) | (0.90) | (0.24) | (0.10) |
| Т | -0.09 | -0.12 | -0.13 | -0.01 | 0.03 | -0.06 | -0.07 | -0.01 | 0.05 | -0.17 | -0.03 | 0.05 |
| 1 m | (0.41) | (0.25) | (0.22) | (0.97) | (0.76) | (0.56) | (0.54) | (0.91) | (0.62) | (0.12) | (0.76) | (0.63) |
| D | 0.22 | 0.44 | 0.41 | 0.42 | 0.47 | 0.32 | 0.38 | 0.39 | 0.43 | 0.34 | 0.39 | 0.40 |
| D5-95 | (0.04) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| D | 0.02 | -0.09 | 0.02 | -0.08 | -0.07 | -0.03 | -0.04 | -0.11 | -0.06 | -0.10 | -0.10 | -0.04 |
| D3-75 | (0.84) | (0.43) | (0.90) | (0.50) | (0.51) | (0.79) | (0.69) | (0.32) | (0.62) | (0.40) | (0.40) | (0.69) |
| | -0.03 | -0.05 | -0.06 | -0.08 | -0.08 | -0.14 | -0.13 | -0.12 | -0.09 | -0.15 | -0.12 | -0.09 |
| UD | (0.82) | (0.64) | (0.58) | (0.45) | (0.47) | (0.18) | (0.24) | (0.26) | (0.43) | (0.16) | (0.26) | (0.39) |

Cluster of soil models

| 1128 | Table S3. Correlation between $\delta_{SPSA}^{\mu\pm\sigma}$ and commonly used ground motion parameters, quantified |
|------|---|
| 1129 | through Kendall's τ_b coefficient and the <i>p</i> -value (in brackets). The considered parameters are the |
| 1130 | peak ground acceleration (PGA), peak ground velocity (PGV), peak ground displacement (PGD), |
| 1131 | Arias intensity (AI), predominant period (T_p) , mean period (T_m) , significant duration from 5% to |
| 1132 | 95% of the Husid plot (D_{5-95}), significant duration from 5% to 75% of the Husid plot (D_{5-75}) and |
| 1133 | uniform duration (UD – based on a threshold acceleration equal to 0.025g) and SPSI. The column |
| 1134 | labels identify the reference clusters of soil models (see Figure 8m in the Manuscript). |

| | Cluster of soil models | | | | | | | | | | | |
|--|------------------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| | a | b | с | d | е | f | g | h | i | j | k | 1 |
| DCA | 0.46 | 0.74 | 0.69 | 0.66 | 0.67 | 0.62 | 0.75 | 0.66 | 0.61 | 0.77 | 0.63 | 0.61 |
| I GA | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| DCV | 0.24 | 0.56 | 0.43 | 0.58 | 0.58 | 0.50 | 0.59 | 0.56 | 0.50 | 0.53 | 0.46 | 0.45 |
| rov | (0.03) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| DCD | 0.11 | 0.37 | 0.26 | 0.35 | 0.33 | 0.27 | 0.34 | 0.31 | 0.26 | 0.30 | 0.23 | 0.23 |
| FGD | (0.29) | (0.00) | (0.02) | (0.00) | (0.00) | (0.01) | (0.00) | (0.00) | (0.01) | (0.01) | (0.03) | (0.04) |
| A T | 0.11 | 0.51 | 0.36 | 0.57 | 0.58 | 0.36 | 0.52 | 0.53 | 0.44 | 0.49 | 0.42 | 0.39 |
| AI | (0.31) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| T_p | -0.01 | 0.05 | -0.03 | 0.26 | 0.28 | 0.25 | 0.19 | 0.27 | 0.27 | 0.12 | 0.23 | 0.24 |
| | (0.93) | (0.65) | (0.83) | (0.02) | (0.01) | (0.02) | (0.09) | (0.01) | (0.01) | (0.30) | (0.04) | (0.03) |
| т | -0.01 | -0.07 | -0.14 | 0.05 | 0.06 | 0.07 | 0.05 | 0.06 | 0.04 | -0.05 | -0.02 | 0.00 |
| 1 m | (0.91) | (0.54) | (0.20) | (0.66) | (0.56) | (0.52) | (0.63) | (0.56) | (0.70) | (0.66) | (0.86) | (1.00) |
| D | 0.10 | 0.49 | 0.35 | 0.50 | 0.50 | 0.33 | 0.48 | 0.45 | 0.40 | 0.44 | 0.37 | 0.35 |
| D 5-95 | (0.35) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| n | -0.08 | -0.03 | -0.06 | -0.06 | -0.06 | -0.11 | -0.03 | -0.07 | -0.10 | -0.05 | -0.09 | -0.09 |
| AI T _p T _m D5-95 D5-75 UD | (0.49) | (0.76) | (0.62) | (0.62) | (0.57) | (0.32) | (0.78) | (0.53) | (0.37) | (0.66) | (0.42) | (0.41) |
| UD | -0.18 | -0.06 | -0.16 | -0.05 | -0.05 | -0.20 | -0.10 | -0.08 | -0.12 | -0.14 | -0.17 | -0.17 |
| UD | (0.09) | (0.57) | (0.14) | (0.64) | (0.66) | (0.06) | (0.37) | (0.45) | (0.28) | (0.20) | (0.11) | (0.11) |
| SPSI | 0.29 | 0.74 | 0.57 | 0.76 | 0.75 | 0.56 | 0.71 | 0.70 | 0.62 | 0.69 | 0.59 | 0.56 |
| | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| | | | | | | | | | | | | |

Cluster of soil models

| 1136 | Table S4. Correlation between $\delta_{IPSA}^{\mu\pm\sigma}$ and commonly used ground motion parameters, quantified |
|------|---|
| 1137 | through Kendall's τ_b coefficient and the <i>p</i> -value (in brackets). The considered parameters are the |
| 1138 | peak ground acceleration (PGA), peak ground velocity (PGV), peak ground displacement (PGD), |
| 1139 | Arias intensity (AI), predominant period (T_p) , mean period (T_m) , significant duration from 5% to |
| 1140 | 95% of the Husid plot (D_{5-95}), significant duration from 5% to 75% of the Husid plot (D_{5-75}) and |
| 1141 | uniform duration (UD – based on a threshold acceleration equal to 0.025g) and IPSI. The column |
| 1142 | labels identify the reference clusters of soil models (see Figure 8m in the Manuscript). |

| | Cluster of soil models | | | | | | | | | | | |
|---------------|------------------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| | а | b | c | d | e | f | g | h | i | j | k | l |
| DCA | 0.27 | 0.53 | 0.53 | 0.63 | 0.64 | 0.55 | 0.65 | 0.60 | 0.49 | 0.63 | 0.55 | 0.45 |
| FGA | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| PGV | 0.16 | 0.38 | 0.44 | 0.64 | 0.57 | 0.51 | 0.56 | 0.55 | 0.43 | 0.59 | 0.52 | 0.42 |
| 10/ | (0.14) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| | 0.09 | 0.19 | 0.30 | 0.41 | 0.34 | 0.28 | 0.32 | 0.31 | 0.24 | 0.36 | 0.30 | 0.25 |
| FGD | (0.39) | (0.07) | (0.00) | (0.00) | (0.00) | (0.01) | (0.00) | (0.00) | (0.02) | (0.00) | (0.01) | (0.02) |
| A T | 0.16 | 0.30 | 0.34 | 0.54 | 0.48 | 0.45 | 0.45 | 0.44 | 0.32 | 0.50 | 0.42 | 0.30 |
| AI | (0.14) | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| т | 0.03 | 0.12 | 0.09 | 0.27 | 0.25 | 0.18 | 0.18 | 0.23 | 0.21 | 0.21 | 0.25 | 0.21 |
| I p | (0.78) | (0.29) | (0.42) | (0.01) | (0.02) | (0.10) | (0.10) | (0.03) | (0.05) | (0.06) | (0.02) | (0.06) |
| т | -0.08 | -0.06 | 0.08 | 0.15 | 0.10 | 0.12 | 0.09 | 0.12 | 0.14 | 0.09 | 0.13 | 0.14 |
| 1 m | (0.46) | (0.56) | (0.45) | (0.15) | (0.35) | (0.25) | (0.39) | (0.29) | (0.19) | (0.39) | (0.24) | (0.21) |
| D | 0.08 | 0.23 | 0.27 | 0.50 | 0.50 | 0.44 | 0.47 | 0.45 | 0.39 | 0.47 | 0.43 | 0.37 |
| D 5-95 | (0.48) | (0.03) | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| D | -0.13 | -0.14 | -0.03 | 0.06 | 0.11 | 0.15 | 0.12 | 0.12 | 0.18 | 0.14 | 0.18 | 0.16 |
| D 5-75 | (0.24) | (0.22) | (0.76) | (0.62) | (0.34) | (0.18) | (0.28) | (0.27) | (0.11) | (0.22) | (0.10) | (0.14) |
| UD | -0.13 | -0.17 | -0.11 | -0.02 | -0.07 | -0.06 | -0.07 | -0.07 | -0.11 | -0.03 | -0.07 | -0.12 |
| UD | (0.22) | (0.11) | (0.31) | (0.87) | (0.54) | (0.60) | (0.49) | (0.54) | (0.32) | (0.80) | (0.55) | (0.28) |
| IPSI | 0.08 | 0.36 | 0.36 | 0.74 | 0.69 | 0.58 | 0.65 | 0.68 | 0.59 | 0.58 | 0.65 | 0.56 |
| | (0.45) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |

| 1144 | Table S5. Correlation between $\delta_{LPSA}^{\mu\pm\sigma}$ and commonly used ground motion parameters, quantified |
|------|---|
| 1145 | through Kendall's τ_b coefficient and the <i>p</i> -value (in brackets). The considered parameters are the |
| 1146 | peak ground acceleration (PGA), peak ground velocity (PGV), peak ground displacement (PGD), |
| 1147 | Arias intensity (AI), predominant period (T_p) , mean period (T_m) , significant duration from 5% to |
| 1148 | 95% of the Husid plot (D_{5-95}), significant duration from 5% to 75% of the Husid plot (D_{5-75}) and |
| 1149 | uniform duration (UD – based on a threshold acceleration equal to 0.025g) and LPSI. The column |
| 1150 | labels identify the reference clusters of soil models (see Figure 8m in the Manuscript). |

| | Cluster of soil models | | | | | | | | | | | |
|---------------|------------------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| | a | b | c | d | e | f | g | h | i | j | k | 1 |
| PCA | 0.08 | 0.29 | 0.28 | 0.35 | 0.53 | 0.35 | 0.50 | 0.53 | 0.51 | 0.50 | 0.55 | 0.49 |
| IUA | (0.48) | (0.01) | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| PGV | -0.02 | 0.20 | 0.15 | 0.42 | 0.60 | 0.35 | 0.50 | 0.62 | 0.58 | 0.57 | 0.62 | 0.60 |
| 107 | (0.89) | (0.07) | (0.17) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| PGD | -0.16 | 0.04 | 0.04 | 0.25 | 0.35 | 0.16 | 0.28 | 0.39 | 0.35 | 0.36 | 0.39 | 0.40 |
| TOD | (0.15) | (0.70) | (0.70) | (0.02) | (0.00) | (0.14) | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| AT | -0.02 | 0.14 | 0.12 | 0.31 | 0.44 | 0.27 | 0.36 | 0.44 | 0.37 | 0.39 | 0.43 | 0.37 |
| AI | (0.85) | (0.20) | (0.28) | (0.00) | (0.00) | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Т | 0.02 | 0.07 | 0.09 | 0.19 | 0.22 | 0.14 | 0.15 | 0.20 | 0.21 | 0.12 | 0.19 | 0.21 |
| 1 p | (0.88) | (0.54) | (0.42) | (0.09) | (0.05) | (0.21) | (0.18) | (0.07) | (0.06) | (0.30) | (0.09) | (0.06) |
| Т | -0.18 | -0.14 | -0.16 | 0.08 | 0.16 | 0.12 | 0.10 | 0.18 | 0.21 | 0.18 | 0.21 | 0.24 |
| 1 m | (0.10) | (0.21) | (0.13) | (0.44) | (0.13) | (0.27) | (0.34) | (0.10) | (0.05) | (0.10) | (0.05) | (0.03) |
| Dr. 65 | -0.05 | 0.16 | 0.06 | 0.33 | 0.50 | 0.30 | 0.42 | 0.53 | 0.46 | 0.45 | 0.49 | 0.43 |
| D3-95 | (0.66) | (0.15) | (0.60) | (0.00) | (0.00) | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| D | -0.21 | -0.21 | -0.23 | -0.09 | 0.04 | -0.02 | 0.03 | 0.12 | 0.12 | 0.12 | 0.12 | 0.10 |
| D 5-75 | (0.06) | (0.06) | (0.04) | (0.45) | (0.74) | (0.86) | (0.78) | (0.27) | (0.27) | (0.27) | (0.27) | (0.40) |
| UD | -0.27 | -0.28 | -0.29 | 0.00 | -0.07 | -0.14 | -0.11 | -0.01 | -0.05 | 0.02 | -0.00 | -0.01 |
| UD | (0.01) | (0.01) | (0.01) | (1.00) | (0.54) | (0.19) | (0.30) | (0.92) | (0.67) | (0.89) | (0.99) | (0.92) |
| LPSI | -0.22 | 0.01 | -0.04 | 0.35 | 0.58 | 0.33 | 0.53 | 0.69 | 0.69 | 0.61 | 0.70 | 0.67 |
| | (0.04) | (0.91) | (0.74) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |

1152 Supplemental Figures



- 1155 Figure S1. Mean and standard deviation of EQL-based PGAA (a-b), SPSA (c-d), IPSA (e-f) and
- 1156 LPSA (g-h), as a function of soil model characteristics. The plots report results for the mean value
- 1157 (left column) and the standard deviation (right column). Results refer to the suite "S-1" of input
- 1158 motions. The dashed area denotes the region not considered in GRAs.



- 1160 Figure S2. Mean and standard deviation of NL-based PGAA (a-b), SPSA (c-d), IPSA (e-f) and
- 1161 LPSA (g-h), as a function of soil model characteristics. The plots report results for the mean value
- 1162 (left column) and the standard deviation (right column). Results refer to the suite "S-1" of input
- 1163 motions. The dashed area denotes the region not considered in GRAs.



1166 Figure S3. Trend of EQL-based SPSA (a) and LPSA (b) for shallow and deformable soil models.

1167 The contour lines denote the mean values of each parameter, whereas the dashed area identifies

1168 the region not considered in GRAs. Results refer to the suite "S-1" of input motions.



Figure S4. Probability plots for SPSI (a-b) and LPSI (c-d) for $V_{S,30}$ between 225 m/s and 275 m/s (a-c) and $V_{S,30}$ between 780 m/s and 950 m/s (b-d).



1173 Figure S5. Standard deviation (a) and rock-to-soil correlation (b) of the spectral parameters, as a





1176 Figure S6. Empirical and simulation-based standard deviation for PGAA (a), SPSA (b), IPSA (c),

1177 LPSA (d), as a function of soil deposit characteristics (i.e., $V_{S,30}$).



Figure S7. Number of models required to achieve a stable estimate of the standard deviation of the
EQL-based PGAA (a), SPSA (b), IPSA (c) and LPSA (d), as a function of soil model
characteristics. Results refer to the suite "S-1" of input motions. The dashed area denotes the region
not considered in GRAs.



Figure S8. Number of models required to achieve a stable estimate of statistical moments of the
NL-based PGAA (a-b), SPSA (c-d), IPSA (e-f) and LPSA (g-h), as a function of soil model

- characteristics. The plots report the results for the mean value (left column) and the standarddeviation (right column). Results refer to the suite "S-1" of input motions. The dashed area denotes
- 1188 the region not considered in GRAs.



Figure S9. Distribution of $\mu_{\delta,PGAA}$ (a) and $\sigma_{\delta,PGAA}$ (b), as a function of soil model characteristics; Distribution of $\mu_{\delta,IPSA}$ (c) and $\sigma_{\delta,IPSA}$ (d), as a function of soil model characteristics. The dashed area denotes the region not considered in GRAs.



Figure S10. Relationship between $\delta_{PGAA}^{\mu\pm\sigma}$ and *PGA* for all the clusters of soil models. Panels (a)-(1) display the plot of $\delta_{PGAA}^{\mu\pm\sigma}$ versus *PGA* derived from GRAs on the set of 10,150 soil models with the suites "S-1" and "S-2" of input motions. Each panel contains data from each cluster of soil models and the corresponding location in the *V*_{SH}-*H* domain is represented in (m). Panels (a)-(1) also report the Kendall's τ_b coefficient – the *p*-value is close to 0 in all the considered cases, except in (a), where it equals 0.01 – and the linear trend of $\delta_{PGAA}^{\mu\pm\sigma}$, which is compared with δ_{PGAA}^{max} to identify the shaking level at which δ_{PGAA} becomes relevant. For panel (a), we omit the linear fit

- 1201 because τ_b is smaller than 0.3. Data from the suite "S-1" of motions for the whole collection of
- 1202 91,500 soil models are also displayed in (a)-(l), for comparison purposes.



Figure S11. Relationship between $\delta_{IPSA}^{\mu\pm\sigma}$ and *PGA* for all the clusters of soil models. Panels (a)-(1) display the plot of $\delta_{IPSA}^{\mu\pm\sigma}$ versus *PGA* derived from GRAs on the set of 10,150 soil models with the suites "S-1" and "S-2" of input motions. Each panel contains data from each cluster of soil models and the corresponding location in the *V_{SH}-H* domain is represented in (m). Panels (a)-(1) also report the Kendall's τ_b coefficient – the *p*-value is close to 0 in all the considered cases, except in (a), where it equals 0.01 – and the linear trend of $\delta_{IPSA}^{\mu\pm\sigma}$, which is compared with δ_{IPSA}^{max} to identify the shaking level at which δ_{IPSA} becomes relevant. For panel (a), we omit the linear fit because τ_b is

- 1211 smaller than 0.3. Data from the suite "S-1" of motions for the whole collection of 91,500 soil
- 1212 models are also displayed in (a)-(l), for comparison purposes.



1213

Figure S12. Relationship between $\delta_{LPSA}^{\mu\pm\sigma}$ and *PGA* for all the clusters of soil models. Panels (a)-(l) display the plot of $\delta_{LPSA}^{\mu\pm\sigma}$ versus *PGA* derived from GRAs on the set of 10,150 soil models with the suites "S-1" and "S-2" of input motions. Each panel contains data from each cluster of soil models and the corresponding location in the *V*_{SH}-*H* domain is represented in (m). Panels (a)-(l) also report the Kendall's τ_b coefficient – the *p*-value is close to 0 in all the considered cases, except in (a), (b) and (c), where it equals 0.48, 0.01 and 0.01, respectively – and the linear trend of $\delta_{LPSA}^{\mu\pm\sigma}$, which is compared with δ_{LPSA}^{max} to identify the shaking level at which δ_{LPSA} becomes relevant. For panels (a),

- 1221 (b) and (c), we omit the linear fit because τ_b is smaller than 0.3. Data from the suite "S-1" of
- 1222 motions for the whole collection of 91,500 soil models are also displayed in (a)-(l), for comparison
- 1223 purposes.



Figure S13. Relationship between $\delta_{SPSA}^{\mu\pm\sigma}$ and *SPSI* for all the clusters of soil models. Panels (a)-(1) display the plot of $\delta_{SPSA}^{\mu\pm\sigma}$ versus *SPSI* derived from GRAs on the set of 10,150 soil models with the suites "S-1" and "S-2" of input motions. Each panel contains data from each cluster of soil models and the corresponding location in the V_{SH} -H domain is represented in (m). Panels (a)-(1) also report the Kendall's τ_b coefficient – the *p*-value is close to 0 in all the considered cases, except in (a), where it equals 0.01 – and the linear trend of $\delta_{SPSA}^{\mu\pm\sigma}$, which is compared with δ_{SPSA}^{max} to identify the shaking level at which δ_{SPSA} becomes relevant. For panel (a), we omit the linear fit because τ_b is

- smaller than 0.3. Data from the suite "S-1" of motions for the whole collection of 91,500 soil
- 1233 models are also displayed in (a)-(l), for comparison purposes.



1234

Figure S14. Relationship between $\delta_{IPSA}^{\mu\pm\sigma}$ and *IPSI* for all the clusters of soil models. Panels (a)-(l) display the plot of $\delta_{IPSA}^{\mu\pm\sigma}$ versus *IPSI* derived from GRAs on the set of 10,150 soil models with the suites "S-1" and "S-2" of input motions. Each panel contains data from each cluster of soil models and the corresponding location in the *V*_{SH}-*H* domain is represented in (m). Panels (a)-(l) also report the Kendall's τ_b coefficient – the *p*-value is close to 0 in all the considered cases, except in (a), where it equals 0.45 – and the linear trend of $\delta_{IPSA}^{\mu\pm\sigma}$, which is compared with δ_{IPSA}^{max} to identify the shaking level at which δ_{IPSA} becomes relevant. For panel (a), we omit the linear fit because τ_b is

- smaller than 0.3. Data from the suite "S-1" of motions for the whole collection of 91,500 soil
- 1243 models are also displayed in (a)-(l), for comparison purposes.



1244

Figure S15. Relationship between $\delta_{LPSA}^{\mu\pm\sigma}$ and *LPSI* for all the clusters of soil models. Panels (a)-(l) display the plot of $\delta_{LPSA}^{\mu\pm\sigma}$ versus *LPSI* derived from GRAs on the set of 10,150 soil models with the suites "S-1" and "S-2" of input motions. Each panel contains data from each cluster of soil models and the corresponding location in the *V_{SH}-H* domain is represented in (m). Panels (a)-(l) also report the Kendall's τ_b coefficient – the *p*-value is close to 0 in all the considered cases, except in (a), (b) and (c), where it equals 0.04, 0.91 and 0.74, respectively – and the linear trend of $\delta_{LPSA}^{\mu\pm\sigma}$, which is compared with δ_{LPSA}^{max} to identify the shaking level at which δ_{LPSA} becomes relevant. For panels (a),

- 1252 (b) and (c), we omit the linear fit because τ_b is smaller than 0.3. Data from the suite "S-1" of
- 1253 motions for the whole collection of 91,500 soil models are also displayed in (a)-(l), for comparison
- 1254 purposes.



Figure S16. Maximum *SI* at which the inter-method differences are negligible for specific
applications of GRAs: a) SPSA (i.e., small buildings); b) IPSA (i.e., intermediate buildings) and
c) LPSA (i.e., tall buildings). The dashed area denotes the region not considered in GRAs.

1259 Data and Resources

1260 Data used for the derivation of the thresholds of the inter-method differences were extracted from

- 1261 the PEER NGA-West2 Database (https://ngawest2.berkeley.edu, last accessed January 2018). Ground
- 1262 motion parameters relative to the acceleration time histories were computed with the SeismoSignal
- 1263 software (https://seismosoft.com/products/seismosignal/, last accessed January 2018). Data processing
- 1264 and figures were done using MATLAB (http://www.mathworks.com/products/matlab/).

1265 References

- 1266 Aimar M, Ciancimino A, Foti S (2020). An assessment of the NTC18 stratigraphic seismic
 1267 amplification factors, *Ital Geotech J* 1 5-21.
- 1268 Ang AH-S, Tang WH (2007). Probability concepts in engineering planning and design: Emphasis
- 1269 on application to civil and environmental engineering. John Wiley & Sons.
- 1270 Baker JW, Bradley BA (2017). Intensity measure correlations observed in the NGA-West2
- 1271 database, and dependence of correlations on rupture and site parameters, *Earthq Spectra* 33 1451272 156.
- Baker JW, Cornell CA (2006). Which spectral acceleration are you using?, *Earthq Spectra* 22 293312.
- 1275 Boore DM, Stewart JP, Seyhan E, Atkinson GM (2014). NGA-West2 equations for predicting
- 1276 PGA, PGV, and 5% damped PSA for shallow crustal earthquakes, *Earthq Spectra* **30** 1057-1085.
- 1277 Fenton L (1960). The sum of log-normal probability distributions in scatter transmission systems,
- 1278 IRE Transactions on communications systems 8 57-67.
- 1279 Li W, Assimaki D (2010). Site-and motion-dependent parametric uncertainty of site-response
- analyses in earthquake simulations, *Bull Seismol Soc Am* **100** 954-968.
- 1281 Stewart JP, Afshari K, Hashash YMA (2014). Guidelines for performing hazard-consistent one-
- 1282 dimensional ground response analysis for ground motion prediction, PEER Report 2014. Berkeley.