

Simplified criteria to select ground response analysis methods for seismic building design: equivalent linear versus nonlinear approaches

*Original*

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1 Simplified criteria to select ground response analysis  
2 methods for seismic building design: equivalent linear vs  
3 nonlinear approaches

4 By Mauro Aimar and Sebastiano Foti

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7 Declaration of Competing Interests

8 The authors acknowledge there are no conflicts of interest recorded.

## 9 Abstract

10 The possible amplification of seismic waves in soil deposits is crucial for the seismic design of  
11 buildings and geotechnical systems. The most common approaches for the numerical simulation  
12 of seismic site response are the Equivalent Linear (EQL) and the NonLinear (NL). Even though  
13 their advantages and limitations have been investigated in several studies, the relative field of  
14 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

29 Seismic waves undergo strong alterations in intensity and frequency content when propagating  
30 through soil deposits. These modifications depend on the soil mechanical properties and the  
31 geometry of the system, in terms of geological layers and surface morphology. Ordinary design  
32 applications typically focus on the effect of soil characteristics and rely on Ground Response  
33 Analyses (GRAs). GRAs assume a one-dimensional (1D) model for the site deposit, thus  
34 simplifying the actual geometry (i.e., lateral variations, local heterogeneities, etc.) to focus on  
35 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 EQL 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 EQL 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 EQL 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  
62 urges for the investigation of the conditions where they start to diverge in a significant way. In this  
63 way, the engineer would have a tool to understand whether EQL simulations are adequate or more  
64 advanced NL analyses are required. Therefore, several criteria to predict the magnitude of the  
65 relative differences were developed. For instance, Assimaki and Li (2012) performed a rigorous  
66 assessment of the inter-method divergence, identifying some controlling parameters linked to the  
67 site conditions and the ground motion. On the other side, many studies proposed an applicability  
68 boundary of the EQL scheme based on the maximum shear strain level (e.g., Kaklamanos et al.,  
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 Eskandarinejad  
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

108 The database was initially generated from 91,500 1D ground models subjected to 13 acceleration  
109 time histories, characterized by high shaking intensity. Then, it was extended considering a  
110 representative subset of 10,150 models under 29 additional ground motions, that span a broad  
111 range of amplitudes and spectral shapes. The simulations were performed according to the EQL  
112 approach, by using the SHAKE91 code (Schnabel, 1972; Sun and Idriss, 1992), and to the NL

113 scheme, with the DEEPSOIL v7.0 software (Hashash et al., 2017; see Data and Resources). For  
114 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  $V_{S,H}$  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  $V_{S,30}$ . 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  $H < 200$   
140 m. Besides, the portion corresponding to very shallow and stiff soil models (i.e.,  $V_{S,H} > 250$  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

148 The cyclic behavior of soils is introduced through the Modulus Reduction and Damping (MRD)  
149 curves, that describe the variation of the secant shear modulus – normalized by its maximum value  
150 – and the shear damping with the shear strain. The MRD curves were estimated from the empirical  
151 relationship by Darendeli (2001) for sandy and clayey materials, by Rollins et al. (1998) for  
152 gravels, and by Sun and Idriss (1992) for rock-like materials (i.e., cemented soils or weathered  
153 rocks). Details about the estimation of the required parameters (e.g., the plasticity index) and the  
154 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.

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

174 NL analyses also require the definition of a viscous damping ratio component, to simulate the  
175 presence of energy dissipation at small strain levels (Vucetic et al., 1998). This component was  
176 assumed equal to the small-strain hysteretic damping estimated from the damping curves (Kwok

177 et al., 2007) and it was incorporated in the NL GRAs with the frequency-independent damping  
178 formulation (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.,  $V_{S,30}$   
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  
186 and 50 km. Figure 2a represents the acceleration response spectra  $S_e$  of the selected ground  
187 motions. Additional information is available in Table S1 in the Electronic Supplement.

188 The selected time histories were clustered into two groups. The first suite (labeled as “S-1”)  
189 consists of 13 high-intensity ground motions, with peak ground acceleration (*PGA*) ranging  
190 between 0.17g and 0.35g. This collection was used for a preliminary assessment of the relative  
191 differences between EQL and NL simulations and to investigate the effect of soil model  
192 characteristics on them. The 29 additional time histories (“S-2”) span a broad range of shaking  
193 amplitudes (i.e.,  $PGA = 0.05\text{-}0.3g$ ) and they were applied to a subset of 10,150 soil models, after  
194 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):

$$202 \quad PGAA = \frac{PGA_s}{PGA_r} \quad (1)$$

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

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

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

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

$$218 \quad SA_{AB} = \frac{SI_{AB,s}}{SI_{AB,r}}. \quad (3)$$

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

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

226 The present study considered three SAFs, i.e. a short-period spectral amplification factor (SPSA),  
227 an intermediate-period spectral amplification factor (IPSA) and a long-period spectral  
228 amplification factor (LPSA). The corresponding period ranges are listed in Table 1. These  
229 parameters were used as proxies for site amplification in the seismic microzonation studies held  
230 in Italy after the Central Italy earthquake in 2016 (Presidenza del Consiglio dei Ministri, 2017).  
231 They are deemed to be relevant for homogeneous groups of buildings – small, intermediate and  
232 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

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

240 First, the quality of EQL simulations was assessed, in terms of convergence of the iterative  
241 procedure. Only 31 simulations encountered this issue, hence they were removed. This feature is  
242 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  $\delta M_n$  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:

$$252 \quad \delta M_n = \frac{|M_N - M_n|}{M_N} \quad (4)$$

253 According to the criterion, stable estimates of statistical moments are achieved when  $\delta M_n$  is smaller  
254 than a threshold equal to 5% and the corresponding  $n$  value represents the number of required  
255 models for this condition. The stability of simulation results was assessed for each reference block  
256 of the discretization of the  $V_{S,H}$ - $H$  domain (Figure 1b), to investigate the effect of soil model  
257 characteristics on the reliability of the estimate. For simplicity, the role of ground motion  
258 characteristics was disregarded, hence moments were estimated from the logarithmic mean of  
259 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

275 simulations allows to achieve a stable estimate of the statistical moments, independently of soil  
276 model characteristics or the considered period range. In this way, the validity of results is ensured,  
277 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

293 This section reports a detailed assessment of the differences between the AFs estimated according  
294 to 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 EQL analyses. On the other side, many studies referred to the ratio  
301 between the EQL-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  $\delta_X$ :

$$307 \quad \delta_X = \ln \frac{X_{EQL}}{X_{NL}}. \quad (5)$$

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

312 The assessment of the divergence between two approaches also requires the definition of a  
313 threshold for the  $\delta_X$  estimator, to identify conditions up to which the magnitude of the relative  
314 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 EQL 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  
332 5a superimposes the distribution of  $\delta_{LPSA}$  with the envelope corresponding to a threshold  $\delta_{LPSA}^{max,10\%}$   
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,  
 338 meaning that a significant number of samples is characterized by a strong divergence between  
 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  
 342 differences by comparing the interval defined by the mean  $\mu_{\delta,X}$  and one standard deviation  $\sigma_{\delta,X}$  of  
 343  $\delta_X$  with a threshold  $\delta_X^{max}$ . Specifically, the comparison involved the maximum between the  
 344 extremes of such interval (in absolute value), labeled as  $\delta_X^{\mu\pm\sigma}$  and defined as follows:

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

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

$$349 \quad \delta_X^{\mu\pm\sigma} < \delta_X^{max} = \sigma_{\ln X}^E \quad (7)$$

350 This criterion assumes deviations to be negligible when they are within the natural dispersion of  
 351 the considered parameter. In this way, this approach can identify either situations when the  
 352 differences are large on average, i.e.  $\mu_{\delta,X}$  significantly deviates from zero, or those when the  
 353 average does not shift but the variability  $\sigma_{\delta,X}$  increases so much that a large number of models  
 354 exceeds the reference envelope.

355 The threshold value  $\delta_X^{max}$ , i.e. the standard deviation  $\sigma_{\ln X}^E$  of each AF, was derived from GMPEs,  
356 according to the procedure illustrated in Derivation of the Threshold Values in the Electronic  
357 Supplement. Table 2 lists the inferred threshold values, that depend on  $V_{S,30}$ , given the sensitivity  
358 of  $\sigma_{\ln X}^E$  to site conditions.

359 In summary, the EQL and NL methods are compared in a statistically consistent way, according  
360 to an objective criterion that specifies when the magnitude of the differences between the predicted  
361 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  
364 approaches starts with a general overview of the distribution of  $\mu_{\delta,X}$  and  $\sigma_{\delta,X}$ . Figure 6 represents  
365  $\delta_X$  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  
367 Figure S9 in the Electronic Supplement. The distribution of  $\delta_X$  across various soil profiles depends  
368 on the range of periods of interest and soil model characteristics, especially in terms of  $V_{S,H}$  and  
369 natural frequency  $f_0$  – computed according to the formula  $f_0 = \frac{V_{S,av}}{4H}$  ( $V_{S,av}$  is the time-weighted  
370 average of the  $V_S$  profile down to the engineering bedrock), whose reciprocal is the fundamental  
371 period  $T_0$ .

372 In shallow soil deposits with high  $f_0$ , the observed  $\delta_X$  values are small. In this case, in fact, the  
373 experienced strain level is small (Figure 4a) and EQL and NL predictions are usually similar to  
374 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  $f_0$ ,  $\delta_X$  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  $\delta_X$  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,  $\delta_X$  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  $V_{S,H}$  appears to be significant for describing the behavior of  $\delta_X$ .  
397 Specifically, the trend of  $\delta_X$  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),  $\delta_X$  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 EQL and NL approaches tend to provide similar output. On the other side, deep and  
401 deformable models exhibit large and positive  $\delta_X$  values. The increase is significant for  $V_{S,H} < 200$   
402 m/s and the mean  $\delta_X$  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  $\delta_X$ . Furthermore, the definition of the clusters accounts for the dependence of  
409  $\delta_X^{max}$  (i.e.,  $\sigma_{\ln X}^E$ ) with respect to  $V_{S,30}$  (Table 2). For simplicity, the partition is based on specific  
410 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  
411 and 100 m). The limits approximately correspond to locations where  $\delta_X$  and  $\delta_X^{max}$  (i.e.,  $\sigma_{\ln X}^E$ )  
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  $\delta_X$ . 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  $f_{\theta}$  does not play a significant role on  
419  $\delta_X$ . In each cluster, the threshold  $\delta_X^{max}$  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

423 Proper modeling of the EQL-NL differences needs to account for the mutual relationship between  
424 discrepancies and specific ground motion parameters. The intensity, the duration and the frequency  
425 content, in fact, may affect the entity of the divergence. In order to cover an adequate range of  
426 motion features and effectively investigate this effect, additional GRAs were run on a subset of  
427 10,150 soil models considering the collection “S-2” of input motions. The ground models are still  
428 representative of different soil conditions in the reference  $V_{S,H}$ - $H$  domain and they are compatible  
429 with the restraints from the stability assessment of statistical moments (Figure 3).

430 The effect of input motion characteristics was first investigated by relating some commonly used  
431 ground motion parameters to  $\delta_X$  (specifically,  $\delta_X^{\mu \pm \sigma}$ ), which was computed separately for each  
432 cluster of soil models (Figure 8m). In this way, the effect of variations in soil model characteristics  
433 on the trend of  $\delta_X$  was kept under control. The degree of relationship was quantified through  
434 Kendall’s  $\tau_b$  correlation coefficient (Kendall, 1955), which was estimated together with the  $p$ -  
435 value, expressing the statistical significance – for  $p < 0.05$ ,  $\tau_b$  is statistically significant. The  
436 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 and  
438 significant duration, as well as spectral intensities.

439 A moderate-to-strong relationship between  $\delta_x^{\mu\pm\sigma}$  and  $PGA$  is observed for PGAA and the SAFs,  
440 although the correlation for IPSA and LPSA is slightly weaker.  $PGA$ , in fact, is directly related to  
441 the rise of nonlinear phenomena and to the amount of divergence between GRA approaches  
442 (Assimaki and Li, 2012). For instance, Figure 8 shows the scatter plot of  $\delta_{SPSA}^{\mu\pm\sigma}$  and  $PGA$  together  
443 with the estimated  $\tau_b$  values, highlighting a strong relationship in several clusters of soil models.  
444 Actually, the trend exhibits strong scattering in deformable soil deposits. Furthermore, in stiff and  
445 shallow models, the effect of the input motion is weak as  $\delta_x^{\mu\pm\sigma}$  is small regardless its entity.  
446 However, in several cases,  $\tau_b$  is larger than 0.5. Note that  $\tau_b$  was computed from the data of the  
447 collection of 10,150 models subjected to the suite of 42 motions (i.e., “S-1” and “S-2”). However,  
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  
450 obtained from the subset. Therefore, the suite of 10,150 models provides results consistent with  
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.

453 Furthermore, the  $\delta_x^{\mu\pm\sigma}$  values for the SAFs exhibit a good level of correlation with the  
454 corresponding  $SI_{AB}$  (e.g.,  $\delta_{SPSA}^{\mu\pm\sigma}$  vs. SPSI), indicating that inter-method differences for these  
455 parameters depend on the frequency content, both in terms of intensity and spectral shape. As for  
456 the other ground motion parameters, rather weak or no significant relationships are noticed.  
457 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  $\delta_X$  becomes relevant, by  
459 comparing the trend of  $\delta_X^{\mu\pm\sigma}$  – estimated through linear fitting – and  $\delta_X^{max}$ , in agreement with (7).  
460 The trend was estimated from the results of the suite “S-1”+”S-2” applied to the subset of 10,150  
461 models, for those cases where a significant correlation was detected (i.e.,  $\tau_b > 0.3$  and  $p < 0.05$ , as  
462 shown in Figure 8). Figure 9 maps the *PGA* levels up to which the condition “ $\delta < \delta^{max}$ ” is met  
463 (i.e., negligible  $\delta_X$ ) 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  $\delta_X$  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).

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

480 deep soil deposits, i.e. for  $H$  less than 30 m, except when very soft layers are involved. This area  
481 includes a broad variety of soil conditions usually found in common applications. Furthermore, at  
482 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.

493 The assessment highlights that the EQL and the NL approach provide similar estimates for stiff  
494 soil models and for the ones with large natural frequency. Conversely, NL simulations widely  
495 underestimate the amplification with respect to the EQL approach in deep and deformable soil  
496 deposits. In intermediate conditions, the entity of the difference strongly depends on the range of  
497 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](http://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](http://www.regione.toscana.it/-/programma-vel), last accessed November 2017), Emilia-Romagna  
522 ([https://applicazioni.regione.emilia-romagna.it/cartografia\\_sgss](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](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.
- 547 Aimar M, Ciancimino A, Foti S (2020). An assessment of the NTC18 stratigraphic seismic  
548 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  
550 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  
555 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  
559 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<sub>30</sub> 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.

572 Groholski DR, Hashash YMA, Kim B, Musgrove M, Harmon J, Stewart JP (2016). Simplified  
573 model for small-strain nonlinearity and strength in 1D seismic site response analysis, *J Geotech*  
574 *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.

584 Idriss IM, Seed HB (1968). Seismic response of horizontal soil layers, *J Soil Mech and Found Div*  
585 **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.

589 Kaklamanos J, Bradley BA (2018). Challenges in Predicting Seismic Site Response with 1D  
590 Analyses: Conclusions from 114 KiK-net Vertical Seismometer Arrays, *Bull Seismol Soc Am* **108**  
591 2816-2838.

592 Kaklamanos J, Bradley BA, Thompson EM, Baise LG (2013). Critical parameters affecting bias  
593 and variability in site-response analyses using KiK-net downhole array data, *Bull Seismol Soc Am*  
594 **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*.

604 Kwok AOL, Stewart JP, Hashash YMA (2008). Nonlinear ground-response analysis of Turkey  
605 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.

609 Li W, Assimaki D (2010). Site-and motion-dependent parametric uncertainty of site-response  
610 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.

613 Minarelli L, Amoroso S, Tarabusi G, Stefani M, Pulelli G (2016). Down-hole geophysical  
614 characterization of middle-upper Quaternary sequences in the Apennine Foredeep, Mirabello,  
615 Italy, *Ann Geophys* **59** 1-8 doi:10.4401/ag-7114.

616 Mononobe N (1929). On determination of earth pressure during earthquake, in: *Proc. World*  
617 *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.

621 Papaspiliou M, Kontoe S, Bommer JJ (2012). An exploration of incorporating site response into  
622 PSHA—Part I: Issues related to site response analysis methods, *Soil Dynam Earthquake Eng* **42**  
623 302-315.

624 Passeri F (2019). Development of advanced geostatistical models of shear wave velocity profiles  
625 to manage uncertainties and variabilities in Ground Response Analyses. Doctoral dissertation,  
626 Politecnico di Torino

627 Passeri F, Foti S, Rodriguez-Marek A (2020). A new geostatistical model for shear wave velocity  
628 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.

632 Rathje EM, Abrahamson NA, Bray JD (1998). Simplified frequency content estimates of  
633 earthquake ground motions, *J Geotech Geoenv Eng* **124** 150-159.

634 Rathje EM, Kottke AR (2011). Relative differences between equivalent linear and nonlinear site  
635 response methods, in: *5th International Conference on Earthquake Geotechnical Engineering*, pp  
636 10-13.

637 Rathje EM, Kottke AR, Trent WL (2010). Influence of input motion and site property variabilities  
638 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-  
644 Noguera S, Musgrove M, Nieto-Ferro A, Pagliaroli A, Pisanò F, Richterova A, Sajana S, Santisi  
645 D'avila MP, Shi J, Silvestri F, Taiebat M, Tropeano G, Verrucci L, Watanabe K (2016).  
646 International benchmark on numerical simulations for 1D, nonlinear site response (PRENOLIN):  
647 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  
656 Benchmark on 1D Nonlinear Site-Response Analysis—Validation Phase Exercise, *Bull Seismol*  
657 *Soc Am* **108** 876-900.

658 Rey J, Faccioli E, Bommer JJ (2002). Derivation of design soil coefficients (S) and response  
659 spectral shapes for Eurocode 8 using the European Strong-Motion Database, *J of Seismol* **6** 547-  
660 555 doi:10.1023/A:1021169715992.

661 Rollins KM, Evans MD, Diehl NB, Daily III WD (1998). Shear modulus and damping  
662 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-  
666 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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681 **Full authors' mailing list**

682 **Mauro Aimar**

683 Department of Structural, Building and Geotechnical Engineering (DISEG), Politecnico di Torino,

684 Corso Duca degli Abruzzi 24, 10129 Torino, Italy

685 mauro.aimar@polito.it

686

687 **Sebastiano Foti**

688 Department of Structural, Building and Geotechnical Engineering (DISEG), Politecnico di Torino,

689 Corso Duca degli Abruzzi 24, 10129 Torino, Italy

690 sebastiano.foti@polito.it

691

692 **Corresponding author**

693 Mauro Aimar, PhD Student, Department of Structural, Building and Geotechnical Engineering

694 (DISEG), Politecnico di Torino, Corso Duca degli Abruzzi 24, 10129 Torino, Italy,

695 mauro.aimar@polito.it

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700 for the randomly generated  $V_S$  profiles; c-e) Examples of randomly generated soil profiles for the  
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702 Figure 2. a) Selected ground motions, grouped as “S-1” and “S-2”; b) Definition of the spectral  
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716 Electronic Supplement).

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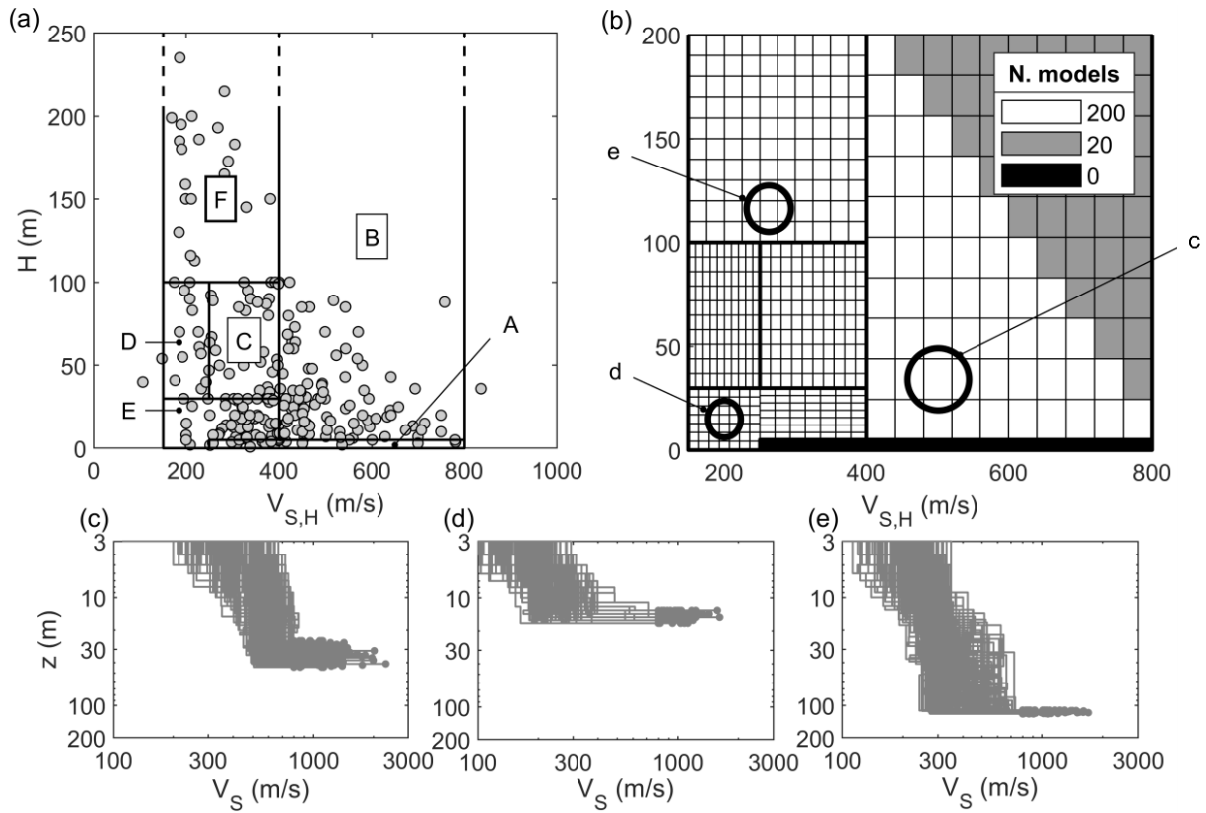
720 Figure 7. Contour plot of  $\mu_{\delta,SPSA}$  (a) and  $\mu_{\delta,LPSA}$  (b) in shallow and deformable soil models. The  
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730 Figure 9. Maximum  $PGA$  at which the inter-method differences are negligible for specific  
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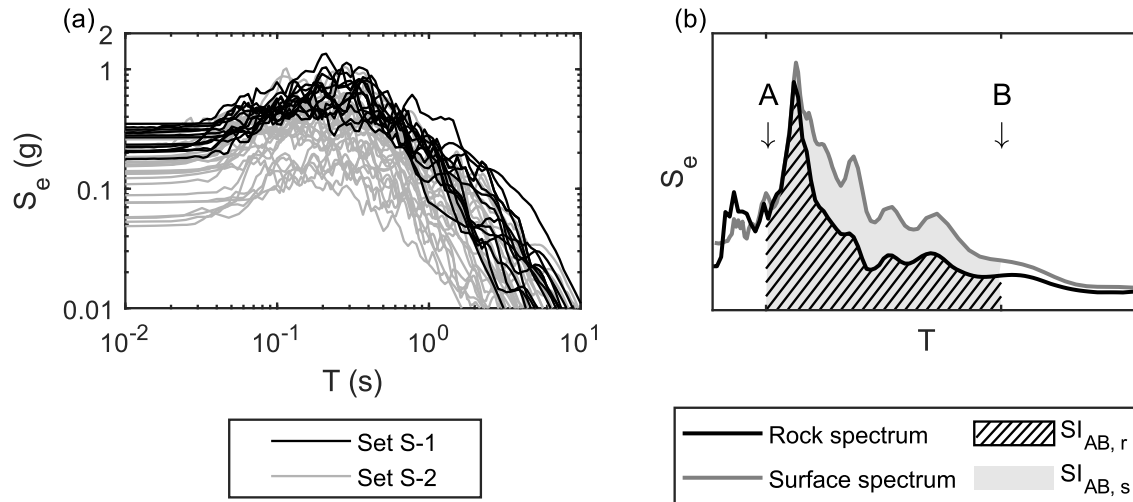
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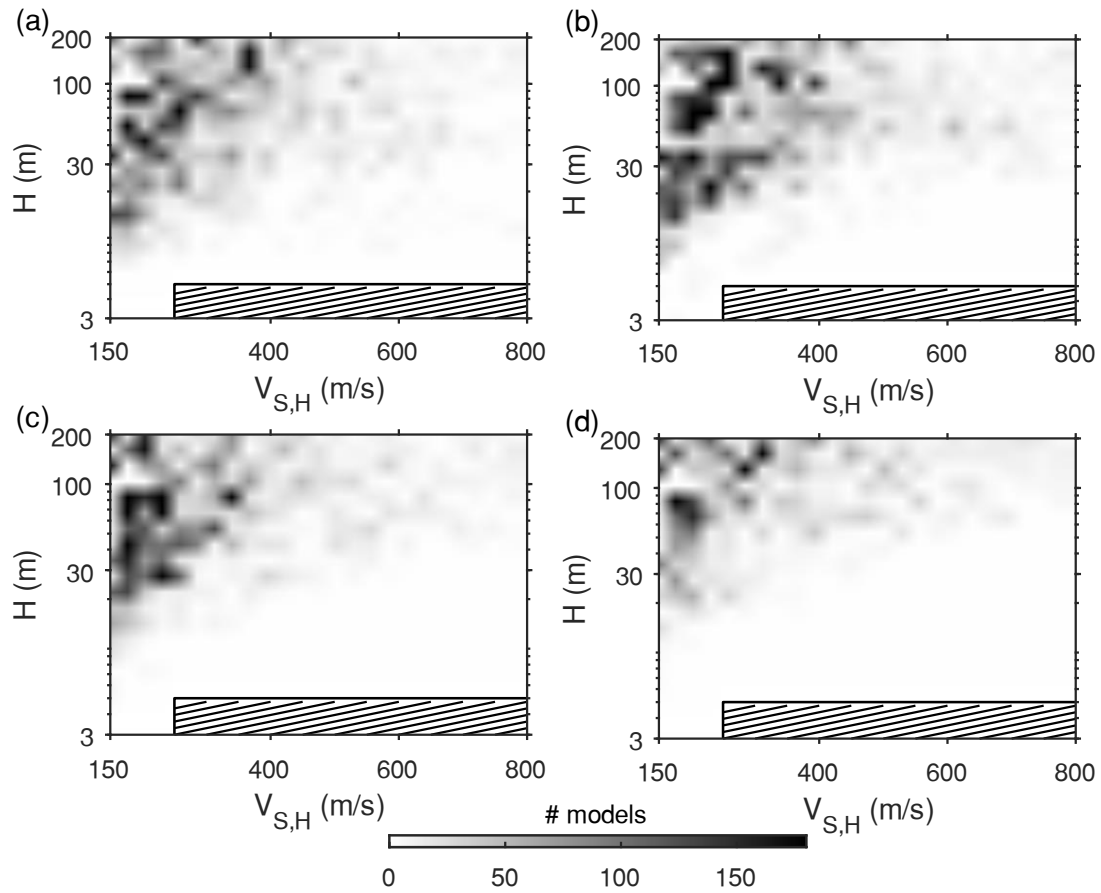
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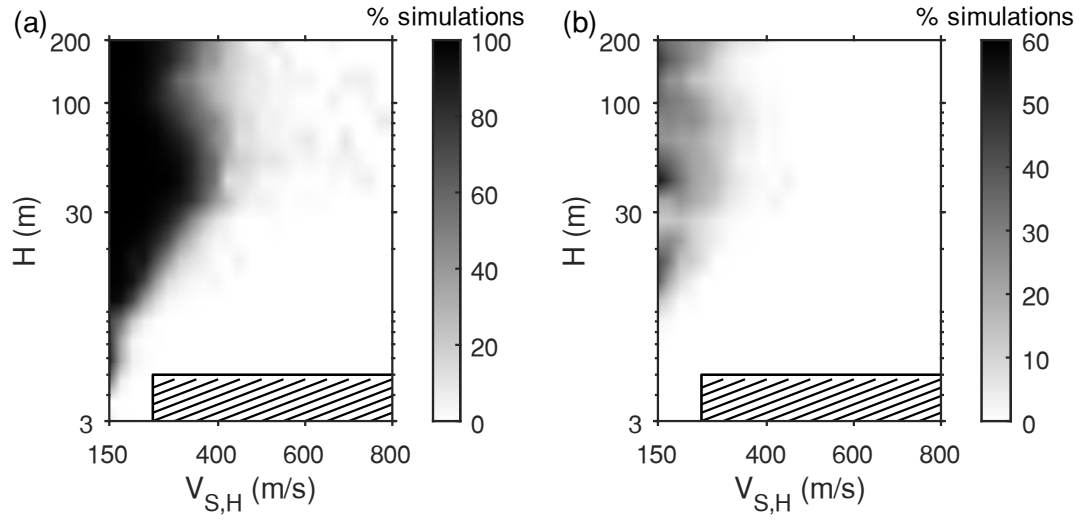


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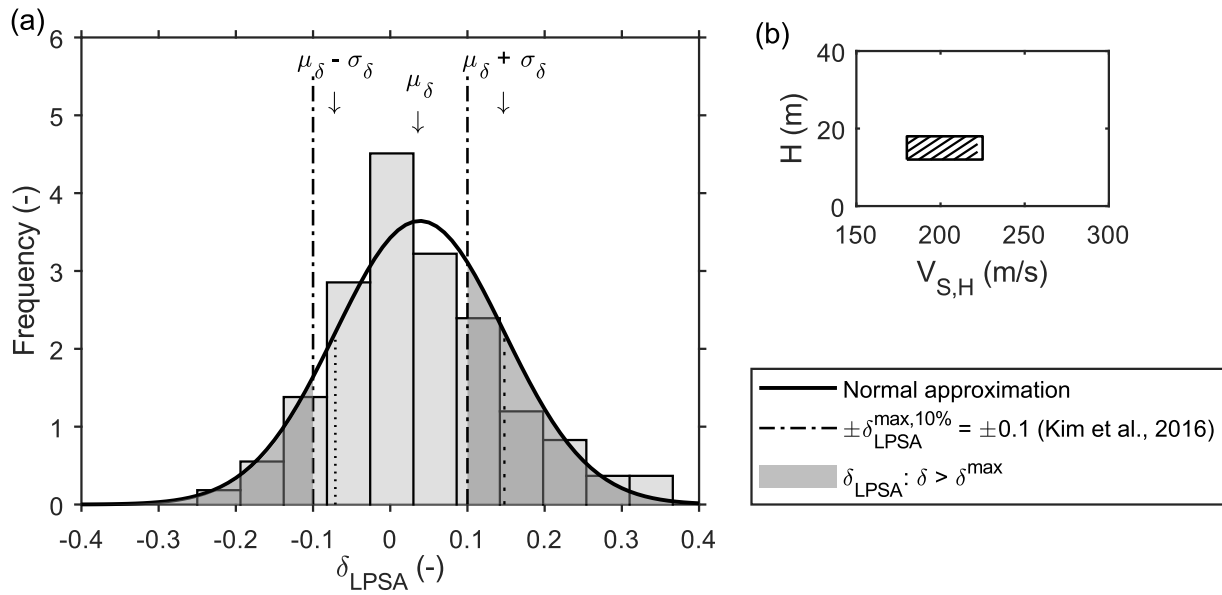
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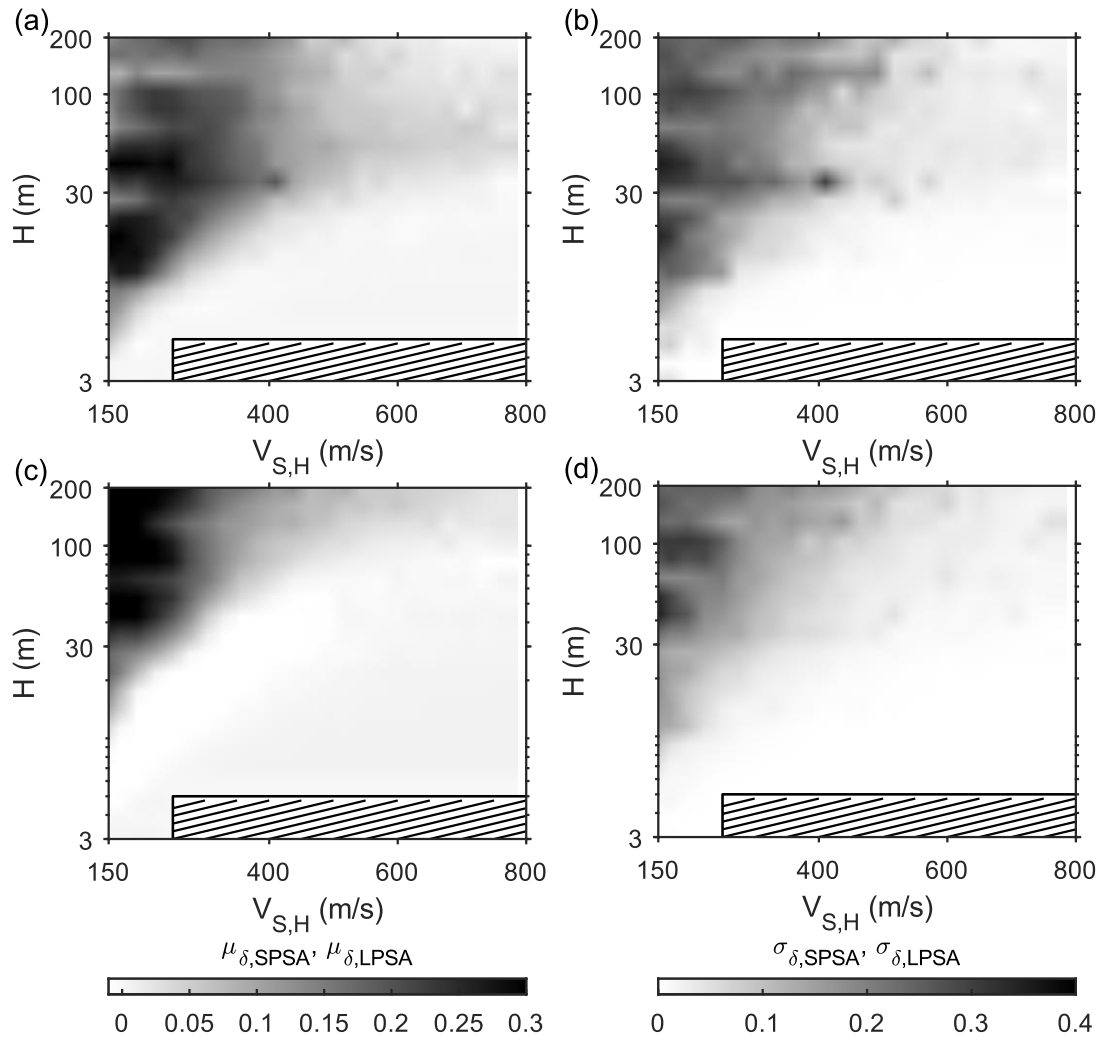
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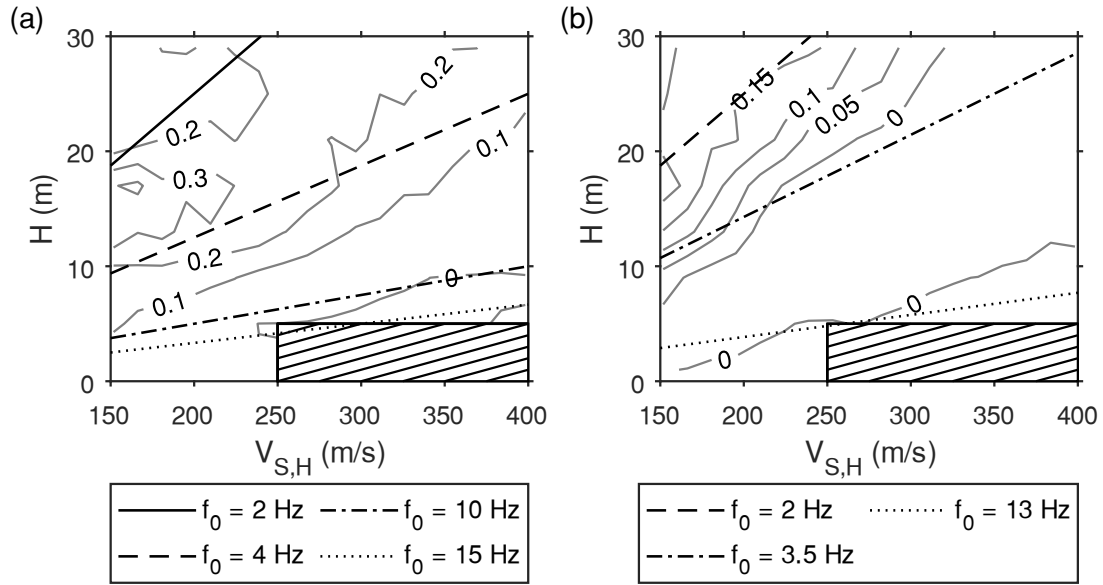


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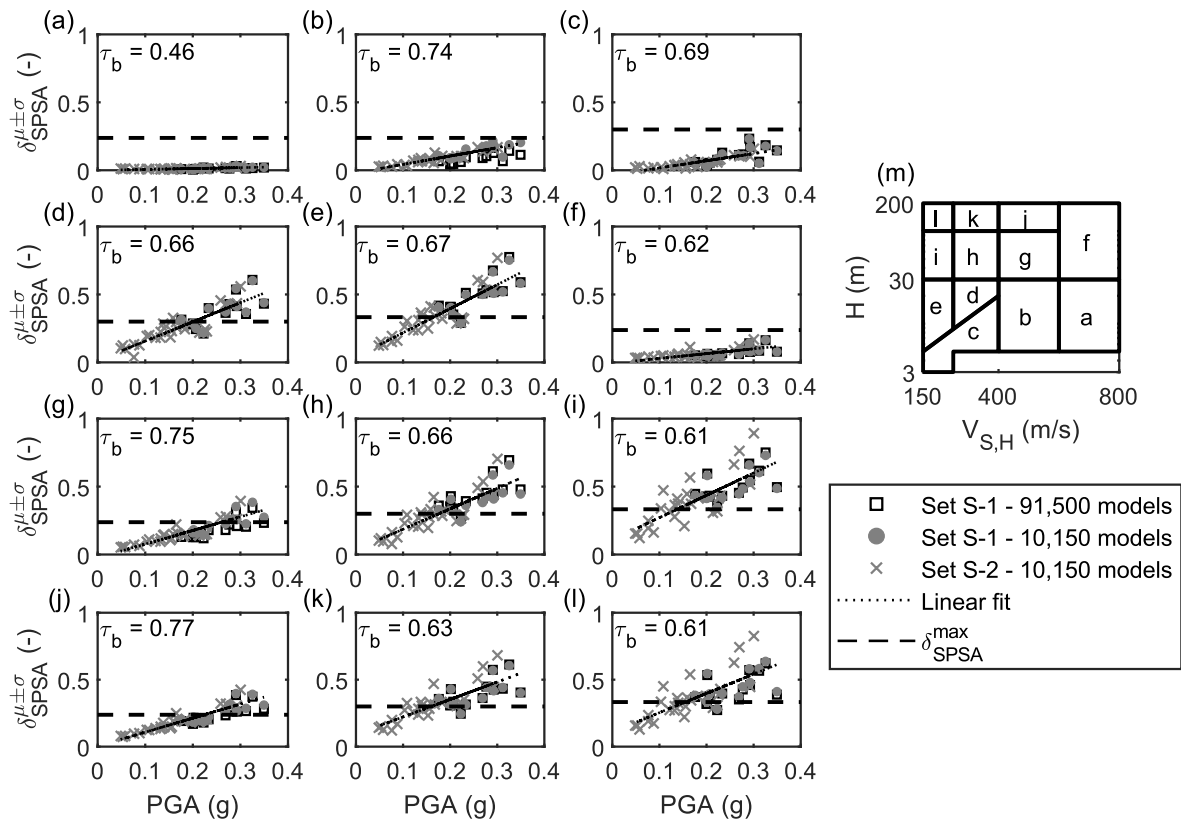
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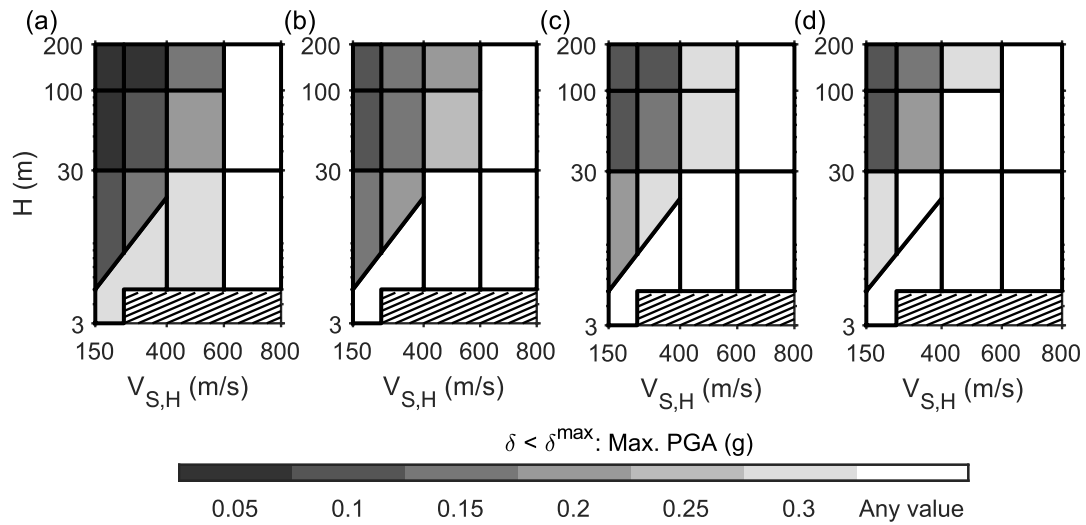
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 782 the region not considered in GRAs.

783

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**

788

789 This electronic supplement starts with an overview of results of GRAs, focusing on the distribution  
790 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  
792 used to quantify the relevance of the inter-method differences) from GMPEs.

## 793 Supplemental Text

### 794 Overview of Results

795 This section reports the results obtained from a basic assessment of the database of GRAs, with a  
796 focus on statistical properties of the AFs. Data are extracted from GRAs performed on the  
797 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.

809 Figure S1 and Figure S2 report the distribution of the mean and the standard deviation of the AFs  
810 across different soil models, computed according to the EQL and the NL approach, respectively.  
811 The EQL or the NL scheme provide similar results, in terms of the dependence of the mean and  
812 the variability with respect to the soil model, even though the NL scheme tends to underpredict the  
813 amplification with respect to the EQL approach (see EQL vs NL in the manuscript). In general,

814 AFs are larger for increasing deformability and thickness of the ground models. Furthermore,  
815 significant differences are observed between shallow models (i.e.,  $H$  less than 30 m) and deeper  
816 ones. This behavior is observed for all the AFs under examination, although some differences for  
817 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

836 depths, in fact, the behavior is quasi linear and the response is mainly controlled by resonance  
837 phenomena, therefore the amplification grows for soil models whose  $T_0$  is closer to the investigated  
838 period range. Conversely, in deeper profiles, the relatively large strain level induces the  
839 lengthening of  $T_0$ . Therefore, SPSA and IPSA tend to decrease as the inelastic  $T_0$  goes beyond the  
840 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

858 the surrounding regions. In this case, in fact, GRAs involve the large-strain branch of the Modulus  
 859 Reduction and Damping (MRD) curves, which is typically characterized by large variability, hence  
 860 its more relevant contribution results in higher data dispersion. However, the standard deviation  
 861 tends to decrease at longer vibration periods (e.g., Figure S1h), as the corresponding wave  
 862 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  $\delta_x^{max}$ , 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.

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

$$872 \quad SI_{AB} = \int_A^B S_e(T) dT \quad (S8)$$

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  $\Delta T$ . Furthermore, for better readability, the subscript  $AB$  is removed from the notation.

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

877 The spectral ordinates  $S_e(T_i)$  are modeled as random variables, hence the sum is a random quantity,  
 878 which can be synthetically described in terms of its mean  $\mu_{SI}$  and variance  $\sigma_{SI}^2$ . These quantities  
 879 can be related to the statistical features of the single spectral ordinates, as follows (Ang and Tang,  
 880 2007):

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

$$882 \quad \begin{aligned} \sigma_{SI}^2 &\approx \Delta T^2 \sum_{i \in [A;B]} \sigma_{Se(T_i)}^2 + 2\Delta T^2 \sum_{i \in [A;B]} \sum_{\substack{j \in [A;B] \\ i < j}} \rho_{Se(T_i), Se(T_j)} \sigma_{Se(T_i)} \sigma_{Se(T_j)} = \\ &= \Delta T^2 \sum_{i \in [A;B]} \sigma_{Se(T_i)}^2 + 2\Delta T^2 \sum_{i \in [A;B]} \sum_{\substack{j \in [A;B] \\ i < j}} \sigma_{Se(T_i), Se(T_j)}, \end{aligned} \quad (S11)$$

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.

888 Statistical information about single spectral ordinates, i.e.  $\mu_{Se(T_i)}$  and  $\sigma_{Se(T_i)}^2$ , was extracted from  
 889 the GMPE proposed by Boore et al. (2014), henceforth denoted as BSSA (2014). This GMPE, in  
 890 fact, provides a reliable estimate of ground motion parameters for a wide variety of source, path  
 891 and site conditions. Besides, the model is characterized by relatively simple functional forms, that  
 892 require a limited number of parameters of immediate estimate. The procedure of computation of  
 893 spectral ordinates assumed a broad set of magnitude and distance bins, where magnitudes ranged

894 between 5.5 and 8 and distances varied between 10 km and 100 km. As for the source mechanism,  
 895 an unspecified fault style was considered. Furthermore, the estimate considered a set of discrete  
 896  $V_{S,30}$  values uniformly distributed in logarithmic scale between 150 m/s and 950 m/s, to  
 897 approximately cover the range of  $V_{S,H}$  of the synthetic ground models. In this way, a reference  
 898 distribution of the spectral ordinates was obtained, which is able to represent various seismic and  
 899 stratigraphic conditions.

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

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

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

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  
 909 logarithmic correlation coefficients  $\rho_{\ln Se(T_i), \ln Se(T_j)}$  is provided by the GMPE proposed by Baker and  
 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:

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

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

$$921 \quad \sigma_{Se(T_i), Se(T_j)} = \begin{cases} \exp\left(2\mu_{\ln Se(T_i)} + \sigma_{\ln Se(T_i)}^2\right) \left(\exp\left(\sigma_{\ln Se(T_i)}^2\right) - 1\right), & T_i = T_j \\ \exp\left(\mu_{\ln Se(T_i)} + \mu_{\ln Se(T_j)} + \frac{1}{2}\left(\sigma_{\ln Se(T_i)}^2 + \sigma_{\ln Se(T_j)}^2\right)\right) \left(\exp\left(\sigma_{\ln Se(T_i), \ln Se(T_j)}^2\right) - 1\right), & T_i \neq T_j \end{cases}$$

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.  $\mu_{SI}$  and  $\sigma_{SI}^2$ , 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:

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

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

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

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

$$946 \quad \ln SA = \ln SI_s - \ln SI_r \quad (S18)$$

947 
$$\ln PGAA = \ln PGA_s - \ln PGA_r \quad (S19)$$

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

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

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

956 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

957 can be estimated according to the procedure above, by selecting a  $V_{S,30}$  bin close to 800 m/s. The

958 variance  $\sigma_{\ln SI_s}^2$  ( $\sigma_{\ln PGA_s}^2$ ), instead, describes the *SI (PGA)* variability on the top of a soil deposit and

959 it was estimated for varying  $V_{S,30}$  (Figure S5a). The correlation coefficient  $\rho_{\ln SI_s, \ln SI_r}$  ( $\rho_{\ln PGA_s, \ln PGA_r}$ )

960 ) represents the degree of linear relationship between *SI (PGA)* values observed on soil deposits

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

963 shown in Figure S5b, the resulting  $\rho_{\ln SI_s, \ln SI_r}$  ( $\rho_{\ln PGA_s, \ln PGA_r}$ ) ranges between 0.8 and 1 and it

964 increases when  $V_{S,30}$  is larger, up to a relatively constant value for  $V_{S,30}$  greater than 400 m/s. The

965 strong correlation between spectral intensities in stiff soils could be an effect of the linear response,

966 where the response spectrum undergoes little variations in the shape. Conversely, at small  $V_{S,30}$   
 967 values, the poor correlation is mainly an effect of the strong nonlinearity, which dramatically  
 968 weakens the degree of relationship at high frequencies. Furthermore, the limited number of data at  
 969  $V_{S,30}$  less than 200 m/s in the NGA-West2 dataset contributes to reducing the degree of correlation.  
 970 Therefore, the estimate of  $\sigma_{\ln SA}^E$  ( $\sigma_{\ln PGAA}^E$ ) accounted for the  $V_{S,30}$ -dependence of  $\rho_{\ln SI_s, \ln SI_r}$  and  
 971  $\sigma_{\ln SI_s}^2$  ( $\rho_{\ln PGA_s, \ln PGA_r}$  and  $\sigma_{\ln PGA_s}^2$ ) The trend is represented in Figure S6. At small  $V_{S,30}$  values, the  
 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,  
 976 the empirical variability is small and quite stable in stiff soils. In this case, the estimated  $\sigma_{\ln SA}^E$  is  
 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

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

989 Table S2. Correlation between  $\delta_{PGA}^{\mu\pm\sigma}$  and commonly used ground motion parameters, quantified  
990 through Kendall’s  $\tau_b$  coefficient and the *p*-value (in brackets). The considered parameters are the  
991 peak ground acceleration (*PGA*), peak ground velocity (*PGV*), peak ground displacement (*PGD*),  
992 Arias intensity (*AI*), predominant period ( $T_p$ ), mean period ( $T_m$ ), significant duration from 5% to  
993 95% of the Husid plot ( $D_{5-95}$ ), significant duration from 5% to 75% of the Husid plot ( $D_{5-75}$ ) and  
994 uniform duration (*UD* – based on a threshold acceleration equal to 0.025g). The column labels  
995 identify the reference clusters of soil models (see Figure 8f in the Manuscript).

996 Table S3. Correlation between  $\delta_{SPSA}^{\mu\pm\sigma}$  and commonly used ground motion parameters, quantified  
997 through Kendall’s  $\tau_b$  coefficient and the *p*-value (in brackets). The considered parameters are the  
998 peak ground acceleration (*PGA*), peak ground velocity (*PGV*), peak ground displacement (*PGD*),  
999 Arias intensity (*AI*), predominant period ( $T_p$ ), mean period ( $T_m$ ), significant duration from 5% to  
1000 95% of the Husid plot ( $D_{5-95}$ ), significant duration from 5% to 75% of the Husid plot ( $D_{5-75}$ ) and  
1001 uniform duration (*UD* – based on a threshold acceleration equal to 0.025g) and *SPSI*. The column  
1002 labels identify the reference clusters of soil models (see Figure 8m in the Manuscript).

1003 Table S4. Correlation between  $\delta_{IPSA}^{\mu\pm\sigma}$  and commonly used ground motion parameters, quantified  
1004 through Kendall's  $\tau_b$  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).

1010 Table S5. Correlation between  $\delta_{LPSA}^{\mu\pm\sigma}$  and commonly used ground motion parameters, quantified  
1011 through Kendall's  $\tau_b$  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  $V_{S,30}$  between 225 m/s and 275 m/s  
1030 (a-c) and  $V_{S,30}$  between 780 m/s and 950 m/s (b-d).

1031 Figure S5. Standard deviation (a) and rock-to-soil correlation (b) of the spectral parameters, as a  
1032 function of soil deposit characteristics (i.e.,  $V_{S,30}$ ).

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 region  
1038 not considered in GRAs.

1039 Figure S8. Number of models required to achieve a stable estimate of statistical moments of the  
1040 NL-based PGAA (a-b), SPSA (c-d), IPSA (e-f) and LPSA (g-h), as a function of soil model  
1041 characteristics. The plots report the results for the mean value (left column) and the standard  
1042 deviation (right column). Results refer to the suite “S-1” of input motions. The dashed area denotes  
1043 the region not considered in GRAs.

1044 Figure S9. Distribution of  $\mu_{\delta,PGAA}$  (a) and  $\sigma_{\delta,PGAA}$  (b), as a function of soil model characteristics;  
1045 Distribution of  $\mu_{\delta,IPSA}$  (c) and  $\sigma_{\delta,IPSA}$  (d), as a function of soil model characteristics. The dashed  
1046 area denotes the region not considered in GRAs.

1047 Figure S10. Relationship between  $\delta_{PGAA}^{\mu\pm\sigma}$  and  $PGA$  for all the clusters of soil models. Panels (a)-(l)  
1048 display the plot of  $\delta_{PGAA}^{\mu\pm\sigma}$  versus  $PGA$  derived from GRAs on the set of 10,150 soil models with  
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  $\tau_b$  coefficient – the  $p$ -value is close to 0 in all the considered cases, except  
1052 in (a), where it equals 0.01 – and the linear trend of  $\delta_{PGAA}^{\mu\pm\sigma}$ , which is compared with  $\delta_{PGAA}^{max}$  to  
1053 identify the shaking level at which  $\delta_{PGAA}$  becomes relevant. For panel (a), we omit the linear fit  
1054 because  $\tau_b$  is smaller than 0.3. Data from the suite “S-1” of motions for the whole collection of  
1055 91,500 soil models are also displayed in (a)-(l), for comparison purposes.

1056 Figure S11. Relationship between  $\delta_{IPSA}^{\mu\pm\sigma}$  and  $PGA$  for all the clusters of soil models. Panels (a)-(l)  
1057 display the plot of  $\delta_{IPSA}^{\mu\pm\sigma}$  versus  $PGA$  derived from GRAs on the set of 10,150 soil models with the  
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)-(l) also report  
1060 the Kendall’s  $\tau_b$  coefficient – the  $p$ -value is close to 0 in all the considered cases, except in (a),  
1061 where it equals 0.01 – and the linear trend of  $\delta_{IPSA}^{\mu\pm\sigma}$ , which is compared with  $\delta_{IPSA}^{max}$  to identify the  
1062 shaking level at which  $\delta_{IPSA}$  becomes relevant. For panel (a), we omit the linear fit because  $\tau_b$  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.

1065 Figure S12. Relationship between  $\delta_{LPSA}^{\mu\pm\sigma}$  and  $PGA$  for all the clusters of soil models. Panels (a)-(l)  
1066 display the plot of  $\delta_{LPSA}^{\mu\pm\sigma}$  versus  $PGA$  derived from GRAs on the set of 10,150 soil models with the  
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)-(l) also report  
1069 the Kendall’s  $\tau_b$  coefficient – the  $p$ -value is close to 0 in all the considered cases, except in (a), (b)  
1070 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  
1071 compared with  $\delta_{LPSA}^{max}$  to identify the shaking level at which  $\delta_{LPSA}$  becomes relevant. For panels (a),  
1072 (b) and (c), we omit the linear fit because  $\tau_b$  is smaller than 0.3. Data from the suite “S-1” of  
1073 motions for the whole collection of 91,500 soil models are also displayed in (a)-(l), for comparison  
1074 purposes.

1075 Figure S13. Relationship between  $\delta_{SPSA}^{\mu\pm\sigma}$  and  $SPSI$  for all the clusters of soil models. Panels (a)-(l)  
1076 display the plot of  $\delta_{SPSA}^{\mu\pm\sigma}$  versus  $SPSI$  derived from GRAs on the set of 10,150 soil models with the  
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)-(l) also report  
1079 the Kendall’s  $\tau_b$  coefficient – the  $p$ -value is close to 0 in all the considered cases, except in (a),  
1080 where it equals 0.01 – and the linear trend of  $\delta_{SPSA}^{\mu\pm\sigma}$ , which is compared with  $\delta_{SPSA}^{max}$  to identify the  
1081 shaking level at which  $\delta_{SPSA}$  becomes relevant. For panel (a), we omit the linear fit because  $\tau_b$  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.

1084 Figure S14. Relationship between  $\delta_{IPSA}^{\mu\pm\sigma}$  and  $IPSI$  for all the clusters of soil models. Panels (a)-(l)  
1085 display the plot of  $\delta_{IPSA}^{\mu\pm\sigma}$  versus  $IPSI$  derived from GRAs on the set of 10,150 soil models with the  
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)-(l) also report  
1088 the Kendall’s  $\tau_b$  coefficient – the  $p$ -value is close to 0 in all the considered cases, except in (a),  
1089 where it equals 0.45 – and the linear trend of  $\delta_{IPSA}^{\mu\pm\sigma}$ , which is compared with  $\delta_{IPSA}^{max}$  to identify the  
1090 shaking level at which  $\delta_{IPSA}$  becomes relevant. For panel (a), we omit the linear fit because  $\tau_b$  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  $\tau_b$  coefficient – the  $p$ -value is close to 0 in all the considered cases, except in (a), (b)  
1098 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  
1099 compared with  $\delta_{LPSA}^{max}$  to identify the shaking level at which  $\delta_{LPSA}$  becomes relevant. For panels (a),  
1100 (b) and (c), we omit the linear fit because  $\tau_b$  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

1107

1108 Table S1. Selected input motions with details about event characteristics and intensity, as well as the suite identification (“S-1” or “S-  
1109 2”). Event characteristics include the epicentral distance and the earthquake magnitude, measured in terms of moment magnitude –  
1110 unless otherwise stated – whereas intensity is represented in terms of *PGA*. For some input motions, intensity parameters are scaled  
1111 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 magnitude (-)	Epicentral distance (km)	Scaling factor (-)	<i>PGA</i> (g)	Suite
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 magnitude (-)	Epicentral distance (km)	Scaling factor (-)	PGA (g)	Suite
North Western Balkan Peninsula	15-Apr-1979	EU-HRZ	EW	ESM	6.9	62.9	1.15	0.29	S-1
Northridge-01	17-Jan-1994	CGS-Pacoima Dam (Downstream)	265°	PEER NGA- West2	6.69	20.36	0.75	0.33	S-1
San Fernando	09-Feb-1971	C&GS-Pasadena- Old Seismo Lab	270°	PEER NGA- West2	6.61	39.17	1.35	0.28	S-1
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 Peninsula	15-Apr-1979	CR-DUB	NS	ESM	6.9	104.4	1.35	0.09	S-2
Whittier Narrows	01-Oct -1987	CGS-Pasadena-CIT Kresge Lab	360°	PEER NGA- West2	5.99	13.85	1.1	0.10	S-2
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

1114

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 magnitude (-)	Epicentral distance (km)	Scaling factor (-)	PGA (g)	Suite
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	X	ESD	6.5	13	0.85	0.12	S-2
South Iceland- aftershock	21-Jun-2000	SM-Selfoss-City Hall	Y	ESD	6.4	15	1.15	0.13	S-2
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	E	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- Turkey Flat #1 (0M)	270°	PEER NGA- West2	6.00	6.82	1.1	0.27	S-2

\* 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 magnitude (-)	Epicentral distance (km)	Scaling factor (-)	PGA (g)	Suite
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 <sup>†</sup>	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 <sup>nd</sup>	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

<sup>†</sup> Surface wave magnitude.

1120 Table S2. Correlation between  $\delta_{PGAA}^{\mu\pm\sigma}$  and commonly used ground motion parameters, quantified  
1121 through Kendall's  $\tau_b$  coefficient and the  $p$ -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).

	Cluster of soil models											
	a	b	c	d	e	f	g	h	i	j	k	l
<b><i>PGA</i></b>	0.28 (0.01)	0.66 (0.00)	0.61 (0.00)	0.70 (0.00)	0.73 (0.00)	0.64 (0.00)	0.73 (0.00)	0.73 (0.00)	0.70 (0.00)	0.76 (0.00)	0.72 (0.00)	0.69 (0.00)
<b><i>PGV</i></b>	0.17 (0.11)	0.43 (0.00)	0.40 (0.00)	0.53 (0.00)	0.57 (0.00)	0.41 (0.00)	0.49 (0.00)	0.53 (0.00)	0.58 (0.00)	0.46 (0.00)	0.54 (0.00)	0.58 (0.00)
<b><i>PGD</i></b>	0.02 (0.87)	0.23 (0.03)	0.16 (0.14)	0.30 (0.00)	0.32 (0.00)	0.22 (0.04)	0.26 (0.02)	0.26 (0.02)	0.29 (0.01)	0.22 (0.04)	0.28 (0.01)	0.30 (0.01)
<b><i>AI</i></b>	0.25 (0.02)	0.48 (0.00)	0.40 (0.00)	0.48 (0.00)	0.52 (0.00)	0.42 (0.00)	0.45 (0.00)	0.46 (0.00)	0.46 (0.00)	0.43 (0.00)	0.46 (0.00)	0.46 (0.00)
<b><i>T<sub>p</sub></i></b>	0.05 (0.63)	0.01 (0.93)	0.01 (0.95)	0.11 (0.31)	0.14 (0.21)	0.08 (0.46)	0.04 (0.74)	0.13 (0.24)	0.20 (0.07)	0.02 (0.90)	0.13 (0.24)	0.18 (0.10)
<b><i>T<sub>m</sub></i></b>	-0.09 (0.41)	-0.12 (0.25)	-0.13 (0.22)	-0.01 (0.97)	0.03 (0.76)	-0.06 (0.56)	-0.07 (0.54)	-0.01 (0.91)	0.05 (0.62)	-0.17 (0.12)	-0.03 (0.76)	0.05 (0.63)
<b><i>D<sub>5-95</sub></i></b>	0.22 (0.04)	0.44 (0.00)	0.41 (0.00)	0.42 (0.00)	0.47 (0.00)	0.32 (0.00)	0.38 (0.00)	0.39 (0.00)	0.43 (0.00)	0.34 (0.00)	0.39 (0.00)	0.40 (0.00)
<b><i>D<sub>5-75</sub></i></b>	0.02 (0.84)	-0.09 (0.43)	0.02 (0.90)	-0.08 (0.50)	-0.07 (0.51)	-0.03 (0.79)	-0.04 (0.69)	-0.11 (0.32)	-0.06 (0.62)	-0.10 (0.40)	-0.10 (0.40)	-0.04 (0.69)
<b><i>UD</i></b>	-0.03 (0.82)	-0.05 (0.64)	-0.06 (0.58)	-0.08 (0.45)	-0.08 (0.47)	-0.14 (0.18)	-0.13 (0.24)	-0.12 (0.26)	-0.09 (0.43)	-0.15 (0.16)	-0.12 (0.26)	-0.09 (0.39)

1127

1128 Table S3. Correlation between  $\delta_{SPSA}^{\mu\pm\sigma}$  and commonly used ground motion parameters, quantified  
1129 through Kendall's  $\tau_b$  coefficient and the  $p$ -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	c	d	e	f	g	h	i	j	k	l
<i>PGA</i>	0.46 (0.00)	0.74 (0.00)	0.69 (0.00)	0.66 (0.00)	0.67 (0.00)	0.62 (0.00)	0.75 (0.00)	0.66 (0.00)	0.61 (0.00)	0.77 (0.00)	0.63 (0.00)	0.61 (0.00)
<i>PGV</i>	0.24 (0.03)	0.56 (0.00)	0.43 (0.00)	0.58 (0.00)	0.58 (0.00)	0.50 (0.00)	0.59 (0.00)	0.56 (0.00)	0.50 (0.00)	0.53 (0.00)	0.46 (0.00)	0.45 (0.00)
<i>PGD</i>	0.11 (0.29)	0.37 (0.00)	0.26 (0.02)	0.35 (0.00)	0.33 (0.00)	0.27 (0.01)	0.34 (0.00)	0.31 (0.00)	0.26 (0.01)	0.30 (0.01)	0.23 (0.03)	0.23 (0.04)
<i>AI</i>	0.11 (0.31)	0.51 (0.00)	0.36 (0.00)	0.57 (0.00)	0.58 (0.00)	0.36 (0.00)	0.52 (0.00)	0.53 (0.00)	0.44 (0.00)	0.49 (0.00)	0.42 (0.00)	0.39 (0.00)
$T_p$	-0.01 (0.93)	0.05 (0.65)	-0.03 (0.83)	0.26 (0.02)	0.28 (0.01)	0.25 (0.02)	0.19 (0.09)	0.27 (0.01)	0.27 (0.01)	0.12 (0.30)	0.23 (0.04)	0.24 (0.03)
$T_m$	-0.01 (0.91)	-0.07 (0.54)	-0.14 (0.20)	0.05 (0.66)	0.06 (0.56)	0.07 (0.52)	0.05 (0.63)	0.06 (0.56)	0.04 (0.70)	-0.05 (0.66)	-0.02 (0.86)	0.00 (1.00)
$D_{5-95}$	0.10 (0.35)	0.49 (0.00)	0.35 (0.00)	0.50 (0.00)	0.50 (0.00)	0.33 (0.00)	0.48 (0.00)	0.45 (0.00)	0.40 (0.00)	0.44 (0.00)	0.37 (0.00)	0.35 (0.00)
$D_{5-75}$	-0.08 (0.49)	-0.03 (0.76)	-0.06 (0.62)	-0.06 (0.62)	-0.06 (0.57)	-0.11 (0.32)	-0.03 (0.78)	-0.07 (0.53)	-0.10 (0.37)	-0.05 (0.66)	-0.09 (0.42)	-0.09 (0.41)
<i>UD</i>	-0.18 (0.09)	-0.06 (0.57)	-0.16 (0.14)	-0.05 (0.64)	-0.05 (0.66)	-0.20 (0.06)	-0.10 (0.37)	-0.08 (0.45)	-0.12 (0.28)	-0.14 (0.20)	-0.17 (0.11)	-0.17 (0.11)
<i>SPSI</i>	0.29 (0.01)	0.74 (0.00)	0.57 (0.00)	0.76 (0.00)	0.75 (0.00)	0.56 (0.00)	0.71 (0.00)	0.70 (0.00)	0.62 (0.00)	0.69 (0.00)	0.59 (0.00)	0.56 (0.00)

1135

1136 Table S4. Correlation between  $\delta_{IPSA}^{\mu\pm\sigma}$  and commonly used ground motion parameters, quantified  
1137 through Kendall's  $\tau_b$  coefficient and the  $p$ -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											
	a	b	c	d	e	f	g	h	i	j	k	l
<i>PGA</i>	0.27 (0.01)	0.53 (0.00)	0.53 (0.00)	0.63 (0.00)	0.64 (0.00)	0.55 (0.00)	0.65 (0.00)	0.60 (0.00)	0.49 (0.00)	0.63 (0.00)	0.55 (0.00)	0.45 (0.00)
<i>PGV</i>	0.16 (0.14)	0.38 (0.00)	0.44 (0.00)	0.64 (0.00)	0.57 (0.00)	0.51 (0.00)	0.56 (0.00)	0.55 (0.00)	0.43 (0.00)	0.59 (0.00)	0.52 (0.00)	0.42 (0.00)
<i>PGD</i>	0.09 (0.39)	0.19 (0.07)	0.30 (0.00)	0.41 (0.00)	0.34 (0.00)	0.28 (0.01)	0.32 (0.00)	0.31 (0.00)	0.24 (0.02)	0.36 (0.00)	0.30 (0.01)	0.25 (0.02)
<i>AI</i>	0.16 (0.14)	0.30 (0.01)	0.34 (0.00)	0.54 (0.00)	0.48 (0.00)	0.45 (0.00)	0.45 (0.00)	0.44 (0.00)	0.32 (0.00)	0.50 (0.00)	0.42 (0.00)	0.30 (0.00)
$T_p$	0.03 (0.78)	0.12 (0.29)	0.09 (0.42)	0.27 (0.01)	0.25 (0.02)	0.18 (0.10)	0.18 (0.10)	0.23 (0.03)	0.21 (0.05)	0.21 (0.06)	0.25 (0.02)	0.21 (0.06)
$T_m$	-0.08 (0.46)	-0.06 (0.56)	0.08 (0.45)	0.15 (0.15)	0.10 (0.35)	0.12 (0.25)	0.09 (0.39)	0.12 (0.29)	0.14 (0.19)	0.09 (0.39)	0.13 (0.24)	0.14 (0.21)
$D_{5-95}$	0.08 (0.48)	0.23 (0.03)	0.27 (0.01)	0.50 (0.00)	0.50 (0.00)	0.44 (0.00)	0.47 (0.00)	0.45 (0.00)	0.39 (0.00)	0.47 (0.00)	0.43 (0.00)	0.37 (0.00)
$D_{5-75}$	-0.13 (0.24)	-0.14 (0.22)	-0.03 (0.76)	0.06 (0.62)	0.11 (0.34)	0.15 (0.18)	0.12 (0.28)	0.12 (0.27)	0.18 (0.11)	0.14 (0.22)	0.18 (0.10)	0.16 (0.14)
<i>UD</i>	-0.13 (0.22)	-0.17 (0.11)	-0.11 (0.31)	-0.02 (0.87)	-0.07 (0.54)	-0.06 (0.60)	-0.07 (0.49)	-0.07 (0.54)	-0.11 (0.32)	-0.03 (0.80)	-0.07 (0.55)	-0.12 (0.28)
<b>IPSI</b>	0.08 (0.45)	0.36 (0.00)	0.36 (0.00)	0.74 (0.00)	0.69 (0.00)	0.58 (0.00)	0.65 (0.00)	0.68 (0.00)	0.59 (0.00)	0.58 (0.00)	0.65 (0.00)	0.56 (0.00)

1143

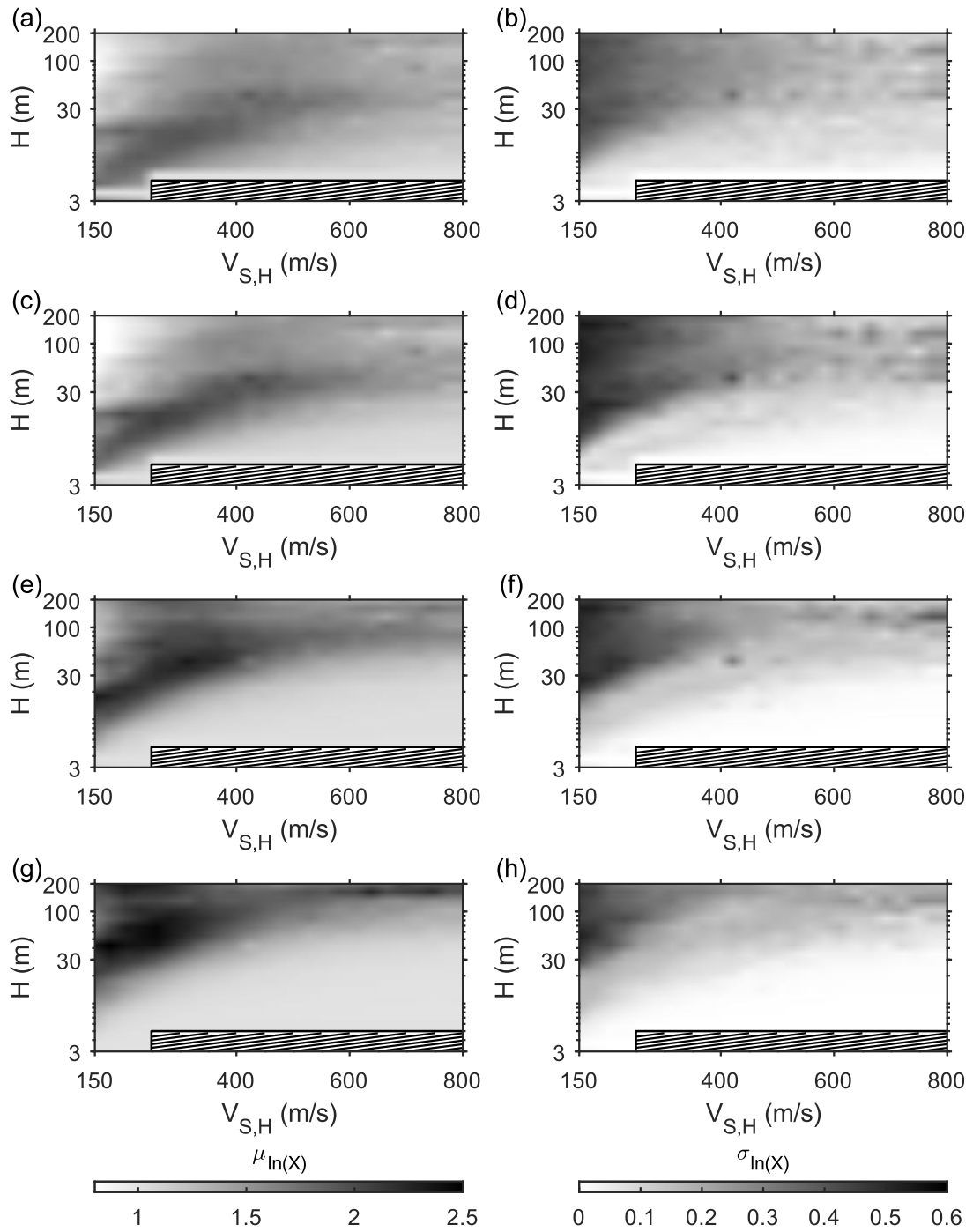
1144 Table S5. Correlation between  $\delta_{LPSA}^{\mu\pm\sigma}$  and commonly used ground motion parameters, quantified  
1145 through Kendall's  $\tau_b$  coefficient and the  $p$ -value (in brackets). The considered parameters are the  
1146 peak ground acceleration ( $PGA$ ), peak ground velocity ( $PGV$ ), 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	l
<b><i>PGA</i></b>	0.08 (0.48)	0.29 (0.01)	0.28 (0.01)	0.35 (0.00)	0.53 (0.00)	0.35 (0.00)	0.50 (0.00)	0.53 (0.00)	0.51 (0.00)	0.50 (0.00)	0.55 (0.00)	0.49 (0.00)
<b><i>PGV</i></b>	-0.02 (0.89)	0.20 (0.07)	0.15 (0.17)	0.42 (0.00)	0.60 (0.00)	0.35 (0.00)	0.50 (0.00)	0.62 (0.00)	0.58 (0.00)	0.57 (0.00)	0.62 (0.00)	0.60 (0.00)
<b><i>PGD</i></b>	-0.16 (0.15)	0.04 (0.70)	0.04 (0.70)	0.25 (0.02)	0.35 (0.00)	0.16 (0.14)	0.28 (0.01)	0.39 (0.00)	0.35 (0.00)	0.36 (0.00)	0.39 (0.00)	0.40 (0.00)
<b><i>AI</i></b>	-0.02 (0.85)	0.14 (0.20)	0.12 (0.28)	0.31 (0.00)	0.44 (0.00)	0.27 (0.01)	0.36 (0.00)	0.44 (0.00)	0.37 (0.00)	0.39 (0.00)	0.43 (0.00)	0.37 (0.00)
<b><i>T<sub>p</sub></i></b>	0.02 (0.88)	0.07 (0.54)	0.09 (0.42)	0.19 (0.09)	0.22 (0.05)	0.14 (0.21)	0.15 (0.18)	0.20 (0.07)	0.21 (0.06)	0.12 (0.30)	0.19 (0.09)	0.21 (0.06)
<b><i>T<sub>m</sub></i></b>	-0.18 (0.10)	-0.14 (0.21)	-0.16 (0.13)	0.08 (0.44)	0.16 (0.13)	0.12 (0.27)	0.10 (0.34)	0.18 (0.10)	0.21 (0.05)	0.18 (0.10)	0.21 (0.05)	0.24 (0.03)
<b><i>D<sub>5-95</sub></i></b>	-0.05 (0.66)	0.16 (0.15)	0.06 (0.60)	0.33 (0.00)	0.50 (0.00)	0.30 (0.01)	0.42 (0.00)	0.53 (0.00)	0.46 (0.00)	0.45 (0.00)	0.49 (0.00)	0.43 (0.00)
<b><i>D<sub>5-75</sub></i></b>	-0.21 (0.06)	-0.21 (0.06)	-0.23 (0.04)	-0.09 (0.45)	0.04 (0.74)	-0.02 (0.86)	0.03 (0.78)	0.12 (0.27)	0.12 (0.27)	0.12 (0.27)	0.12 (0.27)	0.10 (0.40)
<b><i>UD</i></b>	-0.27 (0.01)	-0.28 (0.01)	-0.29 (0.01)	0.00 (1.00)	-0.07 (0.54)	-0.14 (0.19)	-0.11 (0.30)	-0.01 (0.92)	-0.05 (0.67)	0.02 (0.89)	-0.00 (0.99)	-0.01 (0.92)
<b>LPSI</b>	-0.22 (0.04)	0.01 (0.91)	-0.04 (0.74)	0.35 (0.00)	0.58 (0.00)	0.33 (0.00)	0.53 (0.00)	0.69 (0.00)	0.69 (0.00)	0.61 (0.00)	0.70 (0.00)	0.67 (0.00)

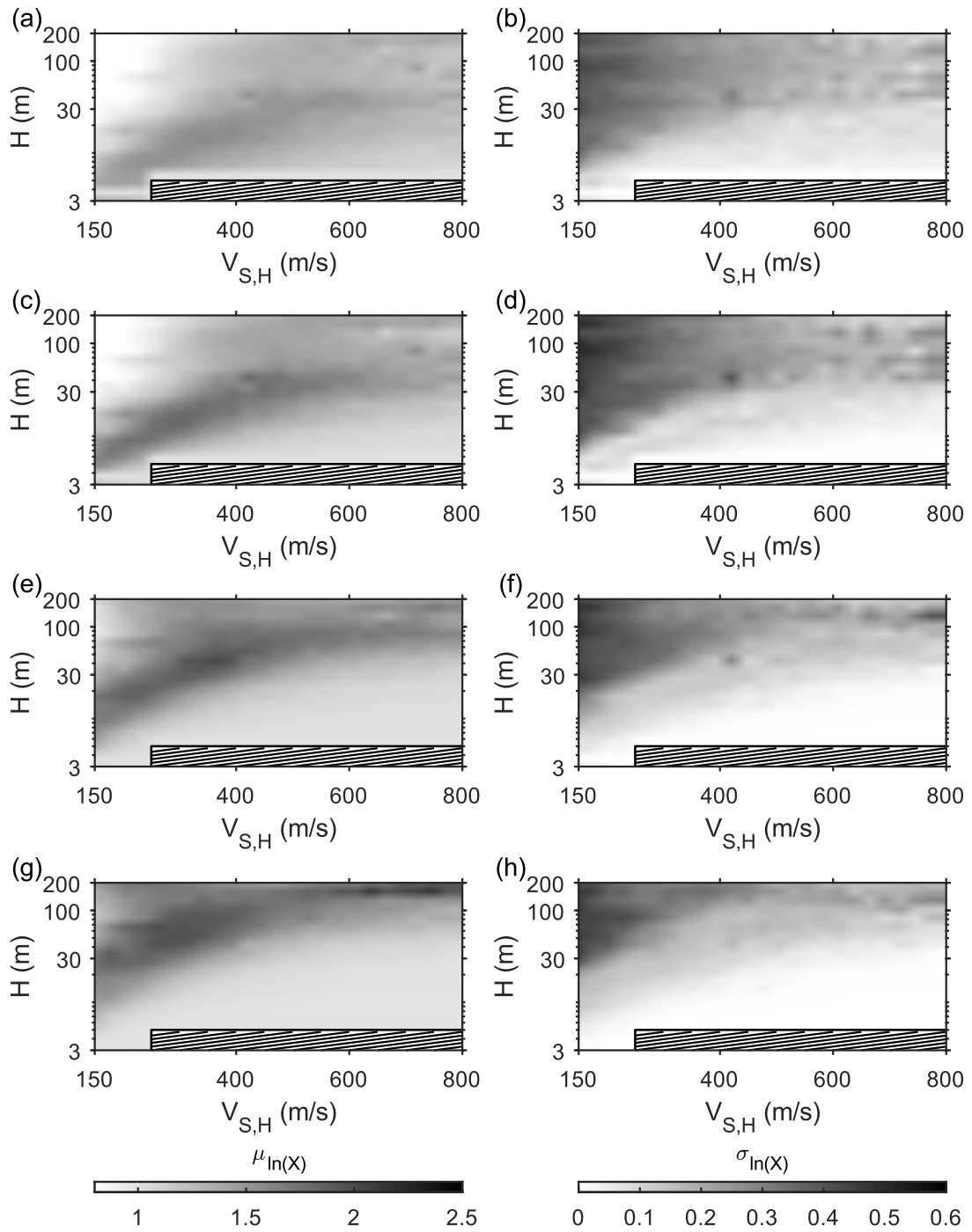
1151

1152 Supplemental Figures

1153

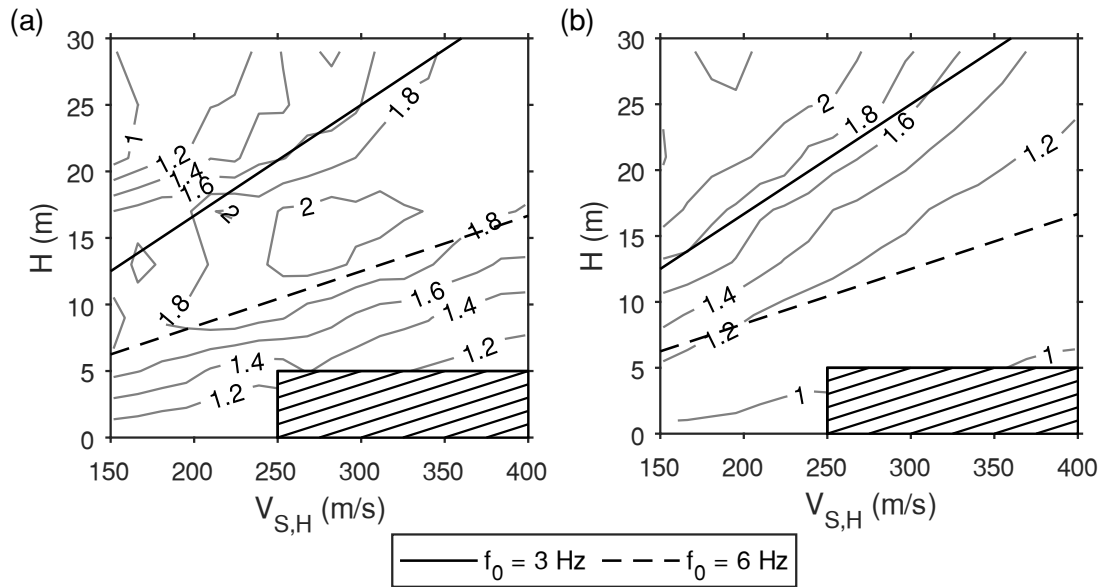


1155 Figure S1. Mean and standard deviation of EQL-based PGAA (a-b), SPSA (c-d), IPSA (e-f) and  
1156 LPSA (g-h), as a function of soil model characteristics. The plots report results for the mean value  
1157 (left column) and the standard deviation (right column). Results refer to the suite “S-1” 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.

1164

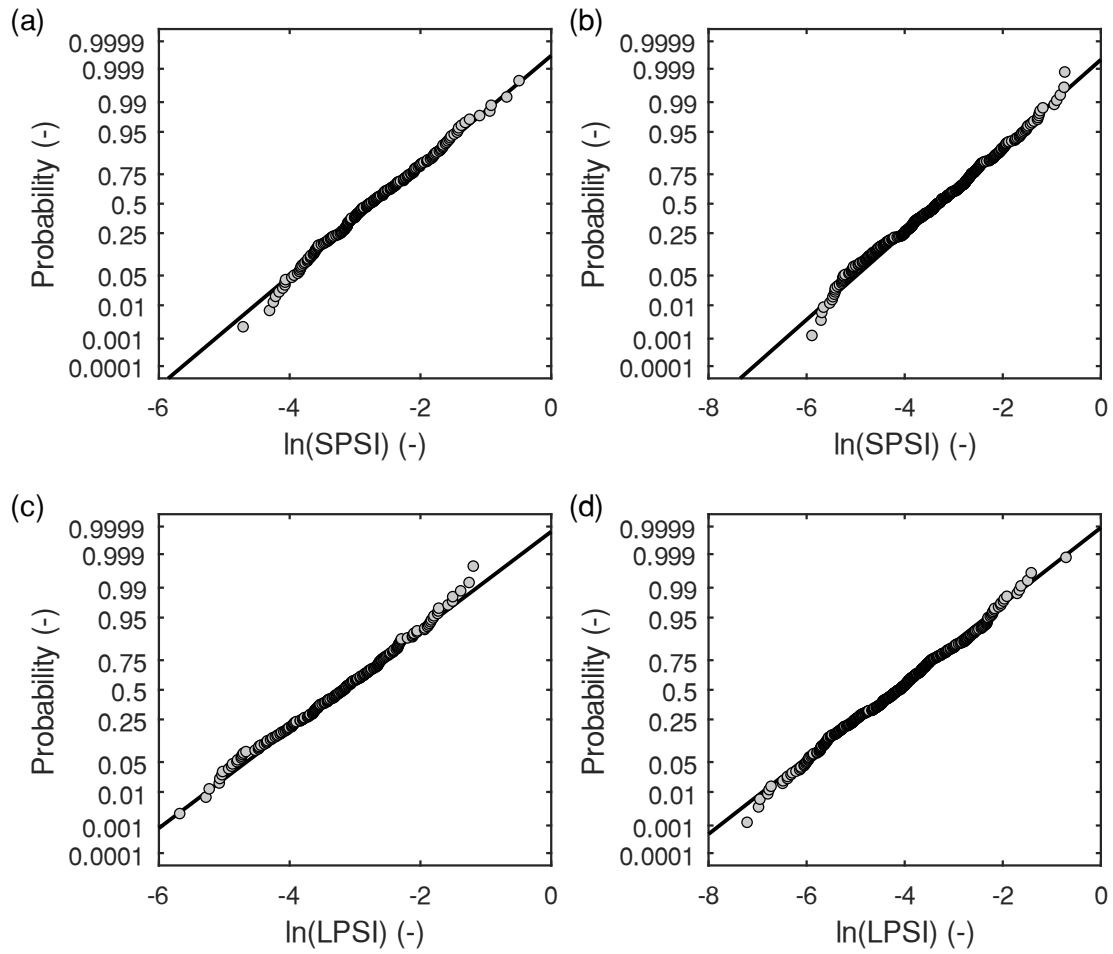


1165

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

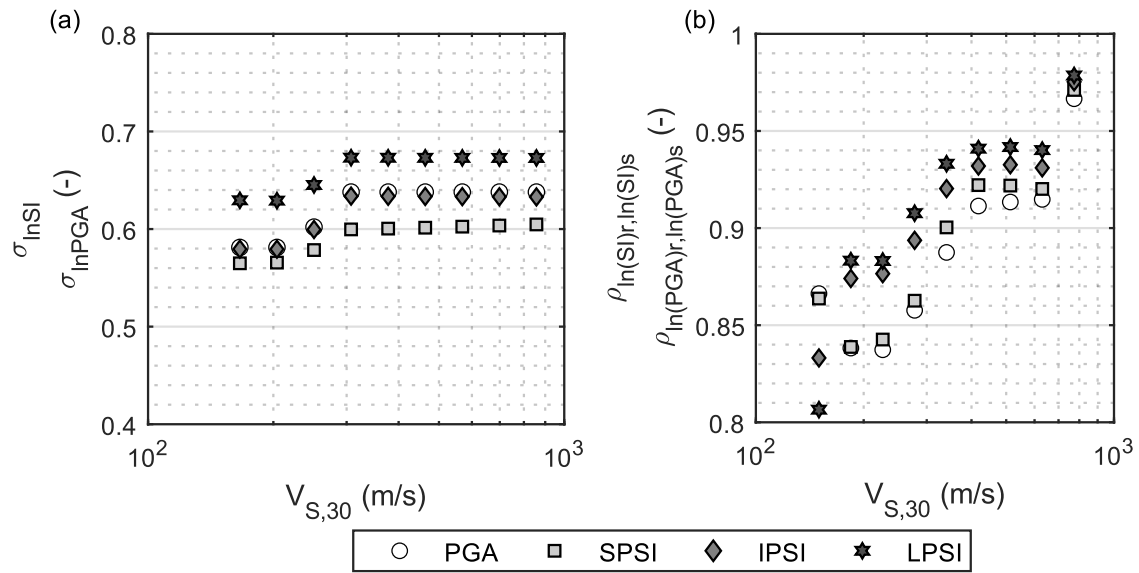
1168 the region not considered in GRAs. Results refer to the suite “S-1” of input motions.



1169

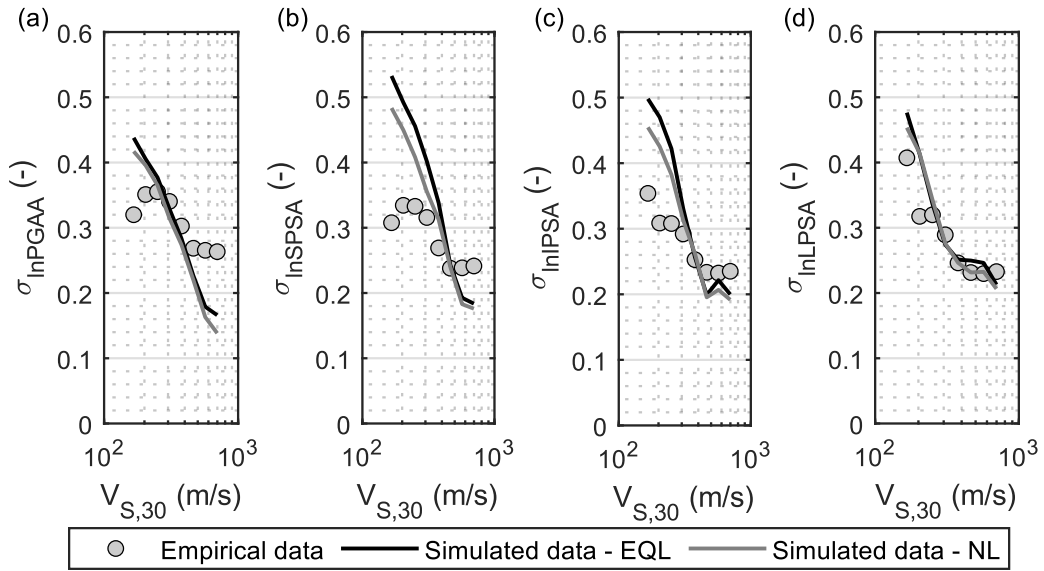
1170 Figure S4. Probability plots for SPSI (a-b) and LPSI (c-d) for  $V_{S,30}$  between 225 m/s and 275 m/s

1171 (a-c) and  $V_{S,30}$  between 780 m/s and 950 m/s (b-d).



1172

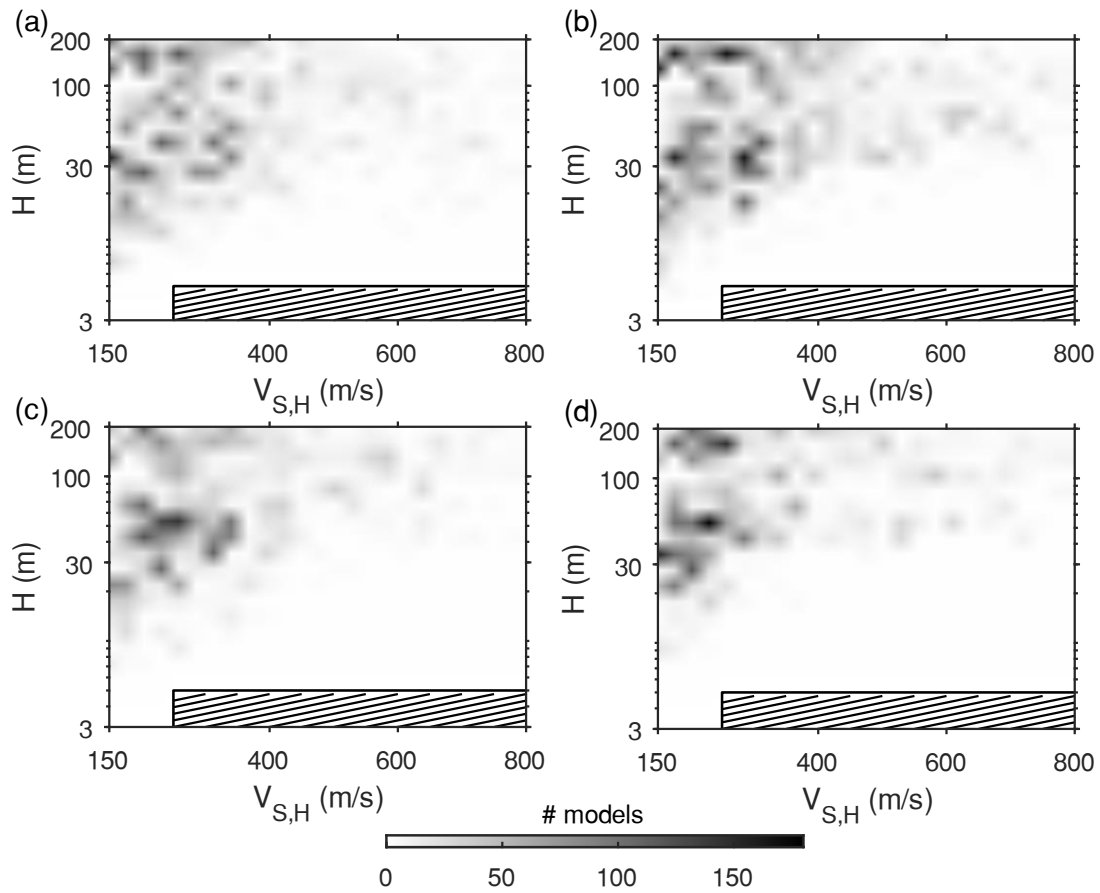
1173 Figure S5. Standard deviation (a) and rock-to-soil correlation (b) of the spectral parameters, as a  
 1174 function of soil deposit characteristics (i.e.,  $V_{S,30}$ ).



1175

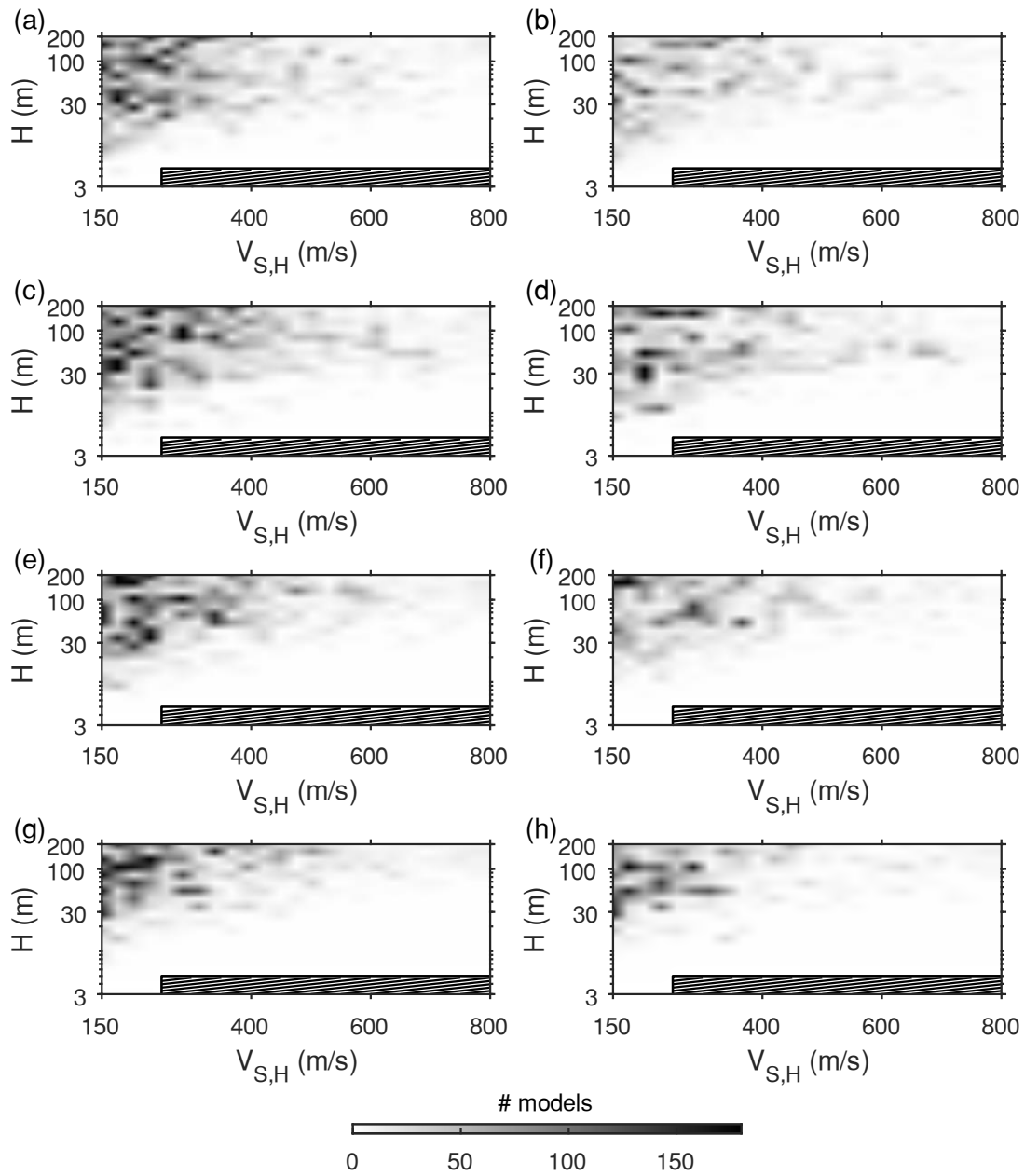
1176 Figure S6. Empirical and simulation-based standard deviation for PGAA (a), SPSA (b), IPSA (c),

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



1178

1179 Figure S7. Number of models required to achieve a stable estimate of the standard deviation of the  
 1180 EQL-based PGAA (a), SPSA (b), IPSA (c) and LPSA (d), as a function of soil model  
 1181 characteristics. Results refer to the suite “S-1” of input motions. The dashed area denotes the region  
 1182 not considered in GRAs.

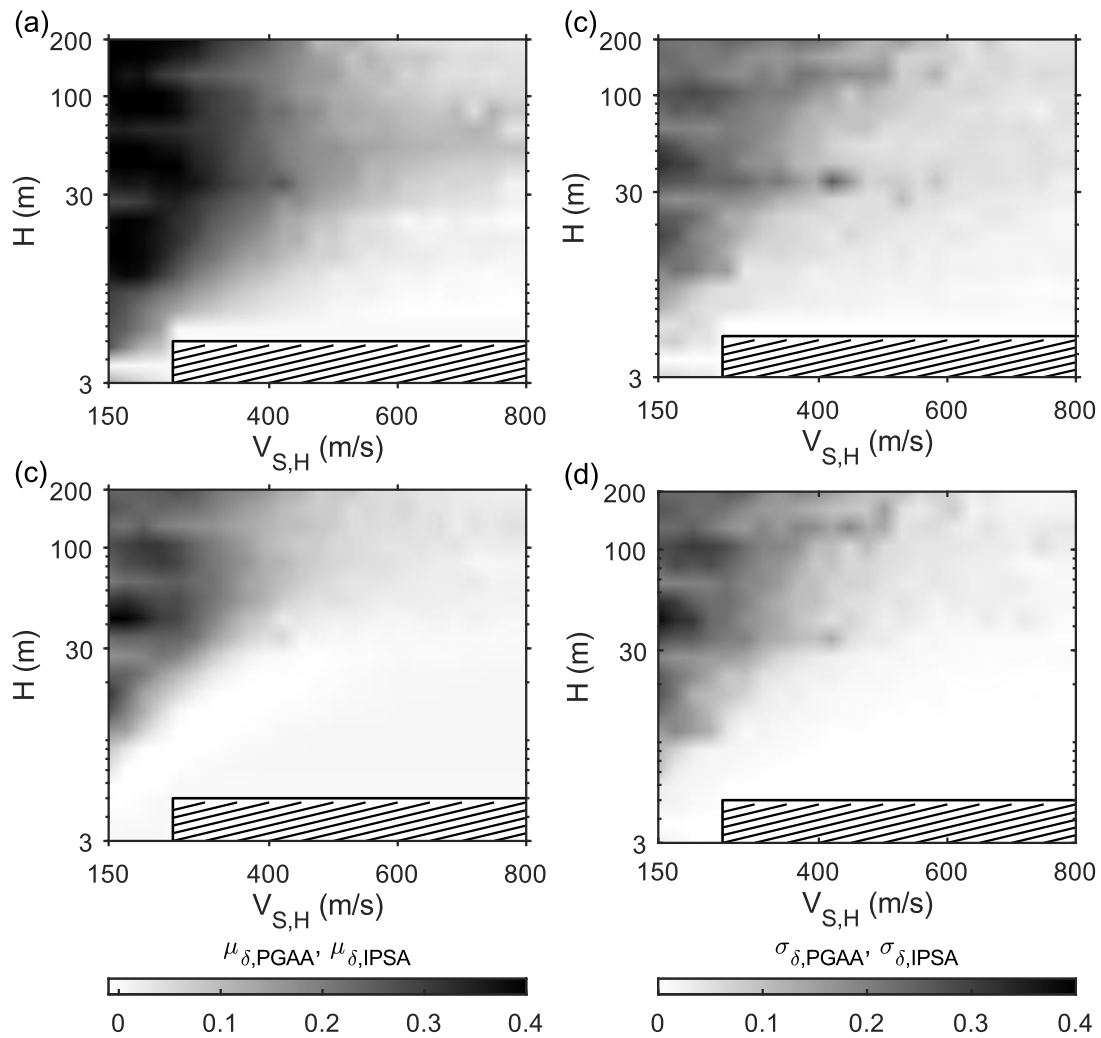


1183

1184 Figure S8. Number of models required to achieve a stable estimate of statistical moments of the

1185 NL-based PGAA (a-b), SPSA (c-d), IPSA (e-f) and LPSA (g-h), as a function of soil model

1186 characteristics. The plots report the results for the mean value (left column) and the standard  
1187 deviation (right column). Results refer to the suite “S-1” of input motions. The dashed area denotes  
1188 the region not considered in GRAs.

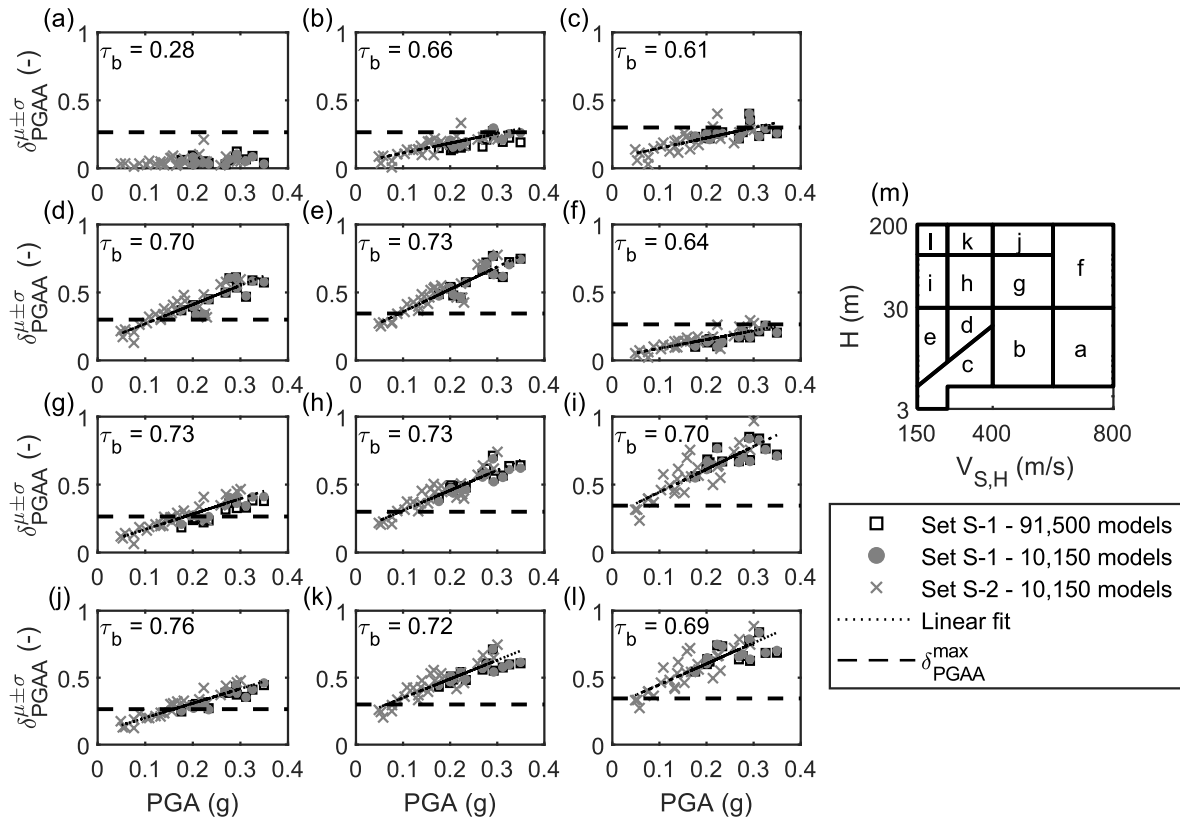


1189

1190 Figure S9. Distribution of  $\mu_{\delta,PGAA}$  (a) and  $\sigma_{\delta,PGAA}$  (b), as a function of soil model characteristics;

1191 Distribution of  $\mu_{\delta,IPSA}$  (c) and  $\sigma_{\delta,IPSA}$  (d), as a function of soil model characteristics. The dashed

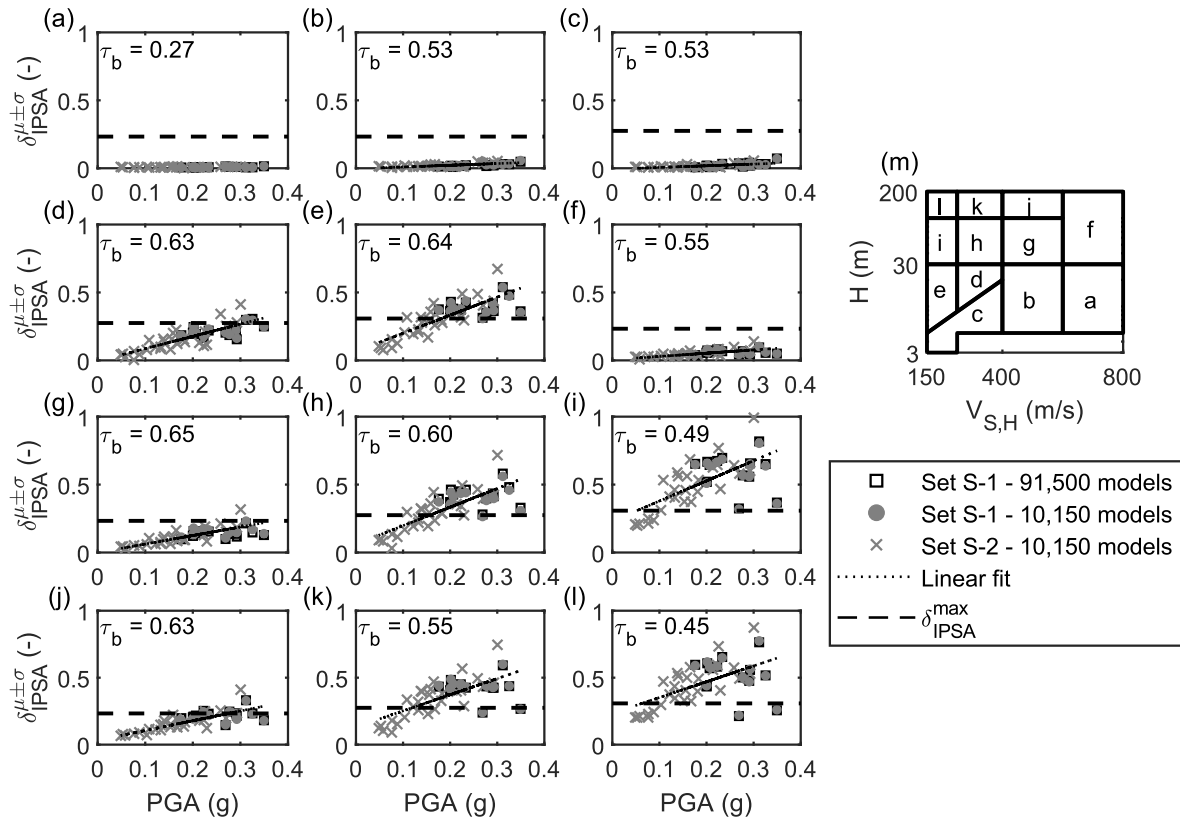
1192 area denotes the region not considered in GRAs.



1193

1194 Figure S10. Relationship between  $\delta_{PGAA}^{\mu\pm\sigma}$  and  $PGA$  for all the clusters of soil models. Panels (a)-(l)  
 1195 display the plot of  $\delta_{PGAA}^{\mu\pm\sigma}$  versus  $PGA$  derived from GRAs on the set of 10,150 soil models with  
 1196 the suites “S-1” and “S-2” of input motions. Each panel contains data from each cluster of soil  
 1197 models and the corresponding location in the  $V_{SH}$ - $H$  domain is represented in (m). Panels (a)-(l)  
 1198 also report the Kendall’s  $\tau_b$  coefficient – the  $p$ -value is close to 0 in all the considered cases, except  
 1199 in (a), where it equals 0.01 – and the linear trend of  $\delta_{PGAA}^{\mu\pm\sigma}$ , which is compared with  $\delta_{PGAA}^{max}$  to  
 1200 identify the shaking level at which  $\delta_{PGAA}$  becomes relevant. For panel (a), we omit the linear fit

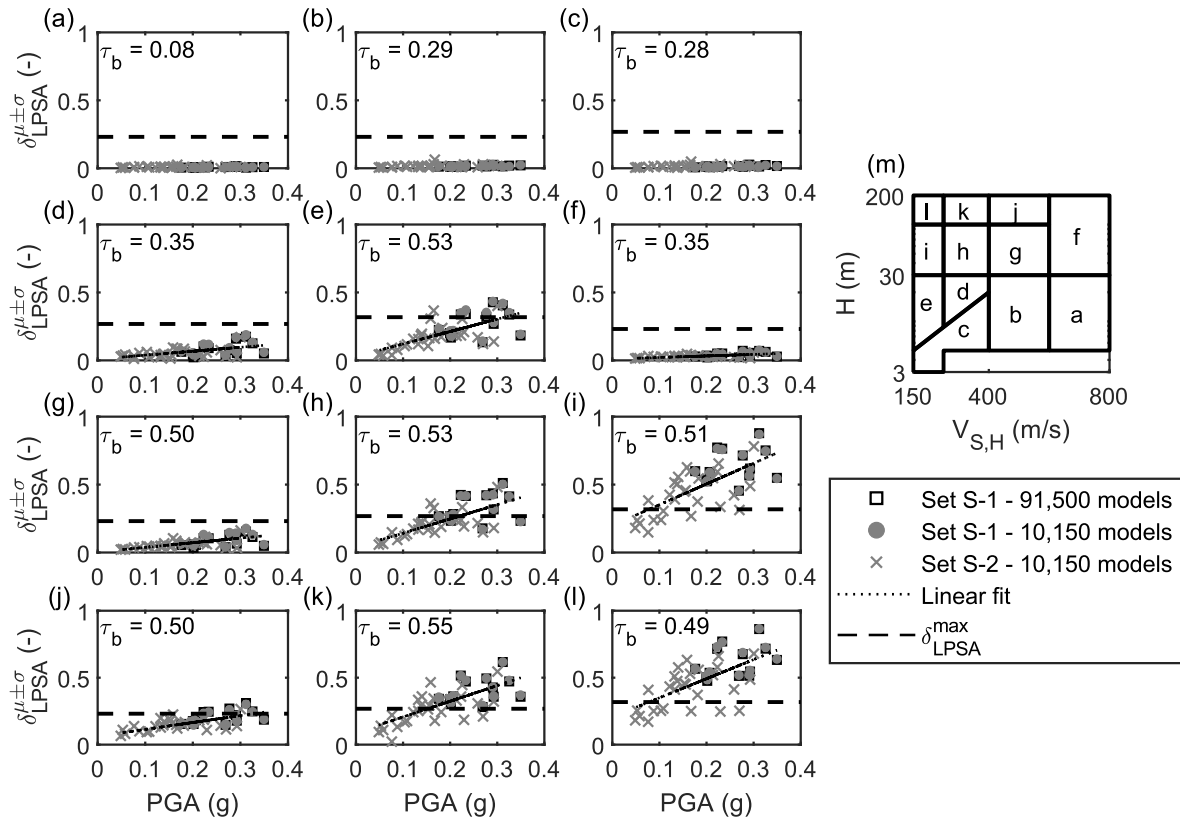
1201 because  $\tau_b$  is smaller than 0.3. Data from the suite “S-1” of motions for the whole collection of  
1202 91,500 soil models are also displayed in (a)-(l), for comparison purposes.



1203

1204 Figure S11. Relationship between  $\delta_{IPSA}^{\mu\pm\sigma}$  and  $PGA$  for all the clusters of soil models. Panels (a)-(l)  
 1205 display the plot of  $\delta_{IPSA}^{\mu\pm\sigma}$  versus  $PGA$  derived from GRAs on the set of 10,150 soil models with the  
 1206 suites “S-1” and “S-2” of input motions. Each panel contains data from each cluster of soil models  
 1207 and the corresponding location in the  $V_{SH}$ - $H$  domain is represented in (m). Panels (a)-(l) also report  
 1208 the Kendall’s  $\tau_b$  coefficient – the  $p$ -value is close to 0 in all the considered cases, except in (a),  
 1209 where it equals 0.01 – and the linear trend of  $\delta_{IPSA}^{\mu\pm\sigma}$ , which is compared with  $\delta_{IPSA}^{max}$  to identify the  
 1210 shaking level at which  $\delta_{IPSA}$  becomes relevant. For panel (a), we omit the linear fit because  $\tau_b$  is

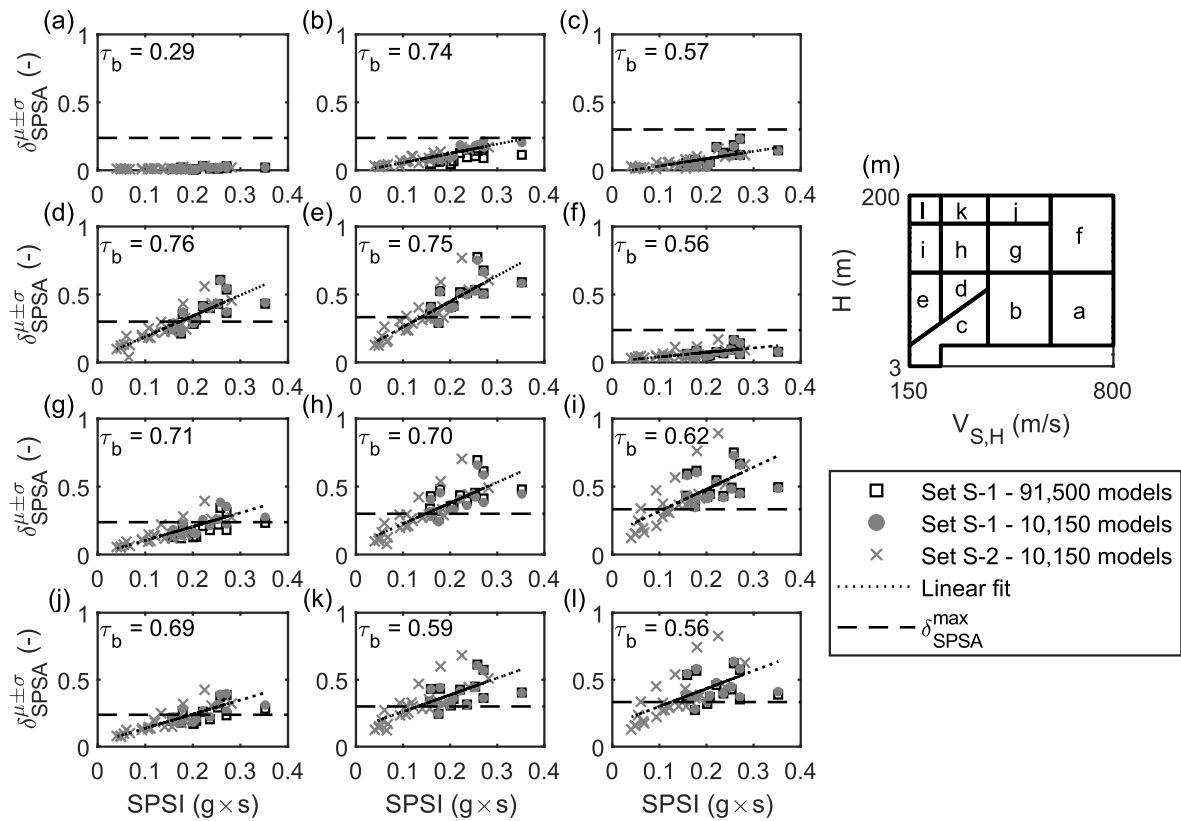
1211 smaller than 0.3. Data from the suite “S-1” of motions for the whole collection of 91,500 soil  
1212 models are also displayed in (a)-(l), for comparison purposes.



1213

1214 Figure S12. Relationship between  $\delta_{LPSA}^{\mu\pm\sigma}$  and  $PGA$  for all the clusters of soil models. Panels (a)-(l)  
 1215 display the plot of  $\delta_{LPSA}^{\mu\pm\sigma}$  versus  $PGA$  derived from GRAs on the set of 10,150 soil models with the  
 1216 suites “S-1” and “S-2” of input motions. Each panel contains data from each cluster of soil models  
 1217 and the corresponding location in the  $V_{SH}$ - $H$  domain is represented in (m). Panels (a)-(l) also report  
 1218 the Kendall’s  $\tau_b$  coefficient – the  $p$ -value is close to 0 in all the considered cases, except in (a), (b)  
 1219 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  
 1220 compared with  $\delta_{LPSA}^{max}$  to identify the shaking level at which  $\delta_{LPSA}$  becomes relevant. For panels (a),

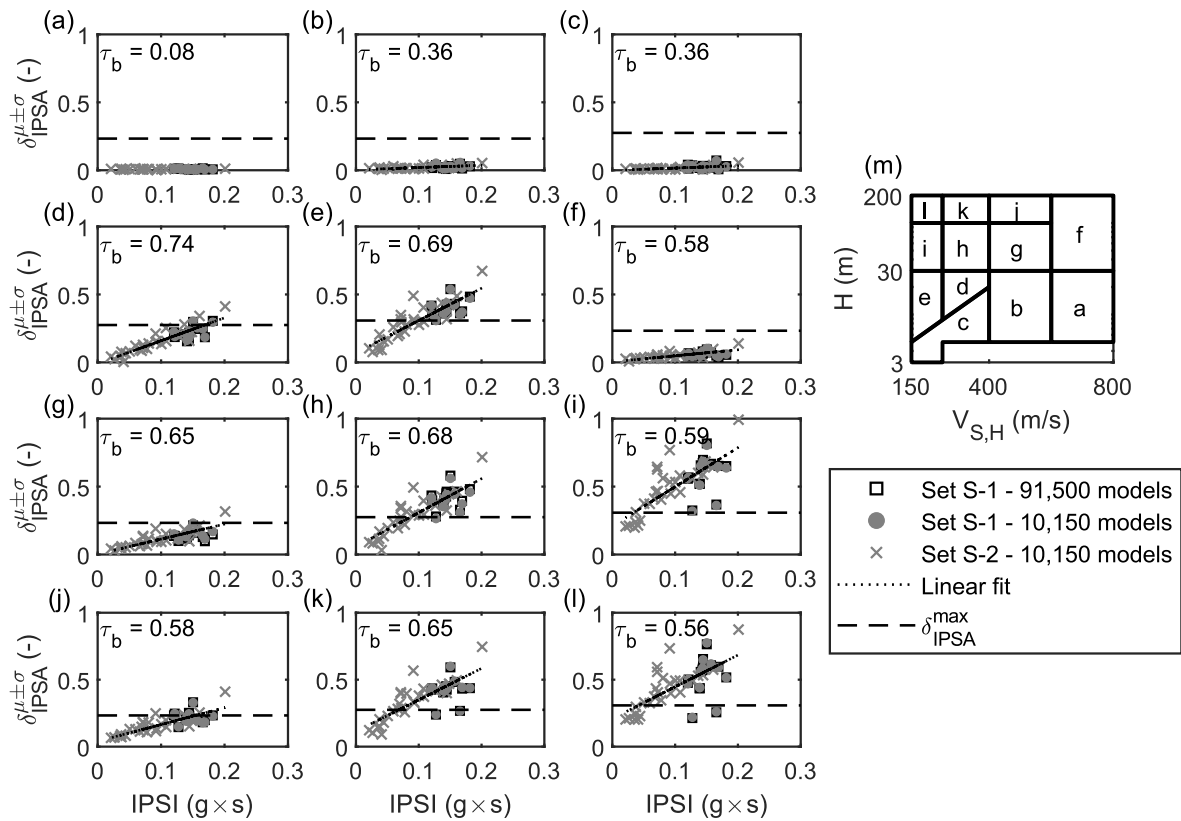
1221 (b) and (c), we omit the linear fit because  $\tau_b$  is smaller than 0.3. Data from the suite “S-1” of  
1222 motions for the whole collection of 91,500 soil models are also displayed in (a)-(l), for comparison  
1223 purposes.



1224

1225 Figure S13. Relationship between  $\delta_{SPSA}^{\mu\pm\sigma}$  and  $SPSI$  for all the clusters of soil models. Panels (a)-(l)  
 1226 display the plot of  $\delta_{SPSA}^{\mu\pm\sigma}$  versus  $SPSI$  derived from GRAs on the set of 10,150 soil models with the  
 1227 suites “S-1” and “S-2” of input motions. Each panel contains data from each cluster of soil models  
 1228 and the corresponding location in the  $V_{SH}$ - $H$  domain is represented in (m). Panels (a)-(l) also report  
 1229 the Kendall’s  $\tau_b$  coefficient – the  $p$ -value is close to 0 in all the considered cases, except in (a),  
 1230 where it equals 0.01 – and the linear trend of  $\delta_{SPSA}^{\mu\pm\sigma}$ , which is compared with  $\delta_{SPSA}^{max}$  to identify the  
 1231 shaking level at which  $\delta_{SPSA}$  becomes relevant. For panel (a), we omit the linear fit because  $\tau_b$  is

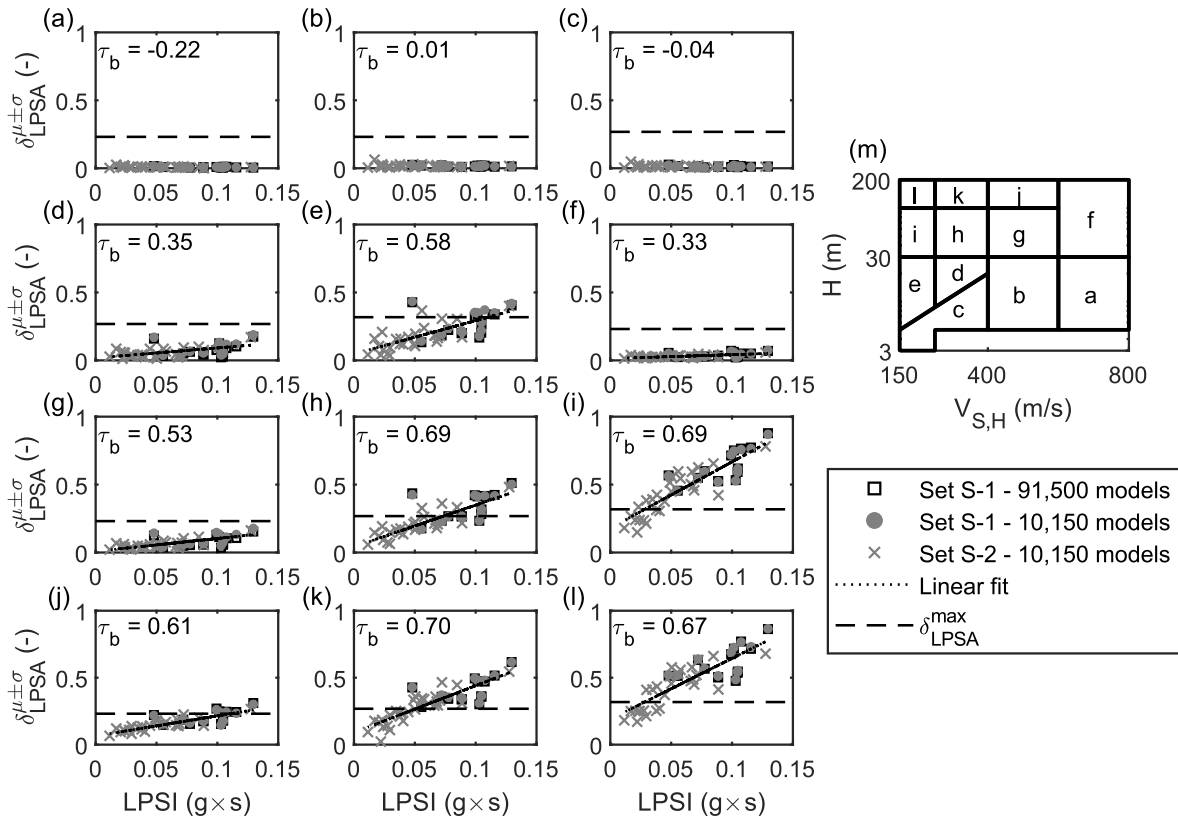
1232 smaller than 0.3. Data from the suite “S-1” of motions for the whole collection of 91,500 soil  
1233 models are also displayed in (a)-(l), for comparison purposes.



1234

1235 Figure S14. Relationship between  $\delta_{IPSA}^{\mu\pm\sigma}$  and  $IPSI$  for all the clusters of soil models. Panels (a)-(l)  
 1236 display the plot of  $\delta_{IPSA}^{\mu\pm\sigma}$  versus  $IPSI$  derived from GRAs on the set of 10,150 soil models with the  
 1237 suites “S-1” and “S-2” of input motions. Each panel contains data from each cluster of soil models  
 1238 and the corresponding location in the  $V_{SH}$ - $H$  domain is represented in (m). Panels (a)-(l) also report  
 1239 the Kendall’s  $\tau_b$  coefficient – the  $p$ -value is close to 0 in all the considered cases, except in (a),  
 1240 where it equals 0.45 – and the linear trend of  $\delta_{IPSA}^{\mu\pm\sigma}$ , which is compared with  $\delta_{IPSA}^{max}$  to identify the  
 1241 shaking level at which  $\delta_{IPSA}$  becomes relevant. For panel (a), we omit the linear fit because  $\tau_b$  is

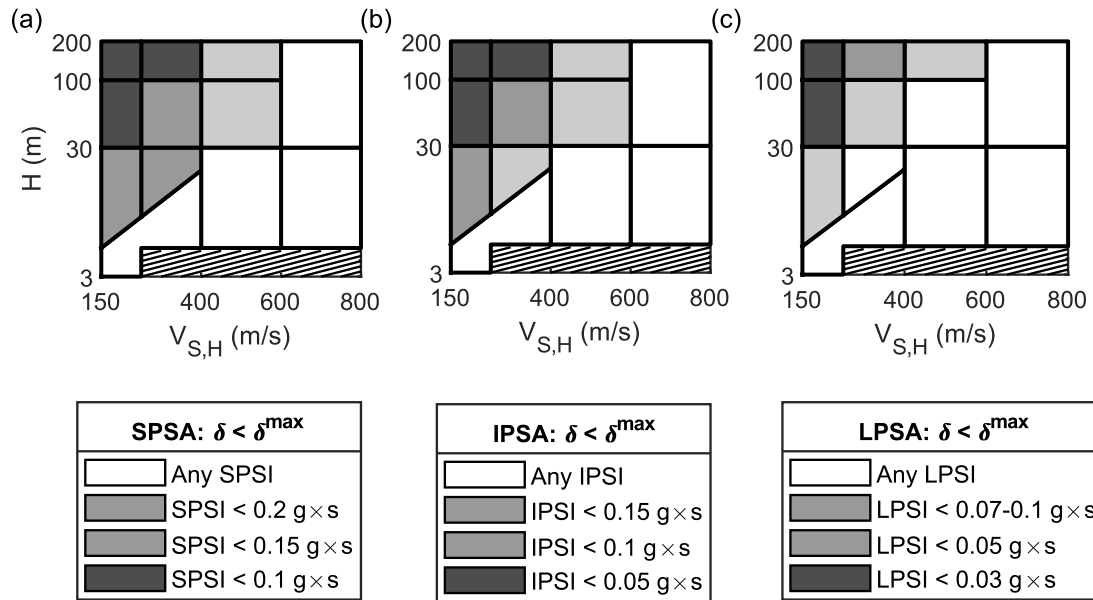
1242 smaller than 0.3. Data from the suite “S-1” of motions for the whole collection of 91,500 soil  
1243 models are also displayed in (a)-(l), for comparison purposes.



1244

1245 Figure S15. Relationship between  $\delta_{LPSA}^{\mu\pm\sigma}$  and  $LPSI$  for all the clusters of soil models. Panels (a)-(l)  
 1246 display the plot of  $\delta_{LPSA}^{\mu\pm\sigma}$  versus  $LPSI$  derived from GRAs on the set of 10,150 soil models with the  
 1247 suites “S-1” and “S-2” of input motions. Each panel contains data from each cluster of soil models  
 1248 and the corresponding location in the  $V_{SH}$ - $H$  domain is represented in (m). Panels (a)-(l) also report  
 1249 the Kendall’s  $\tau_b$  coefficient – the  $p$ -value is close to 0 in all the considered cases, except in (a), (b)  
 1250 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  
 1251 compared with  $\delta_{LPSA}^{max}$  to identify the shaking level at which  $\delta_{LPSA}$  becomes relevant. For panels (a),

1252 (b) and (c), we omit the linear fit because  $\tau_b$  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.



1255

1256 Figure S16. Maximum  $SI$  at which the inter-method differences are negligible for specific  
 1257 applications of GRAs: a) SPSA (i.e., small buildings); b) IPSA (i.e., intermediate buildings) and  
 1258 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** 145-  
1272 156.
- 1273 Baker JW, Cornell CA (2006). Which spectral acceleration are you using?, *Earthq Spectra* **22** 293-  
1274 312.
- 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  
1280 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.

