

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

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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., $PGA = 0.05-0.3g$) 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 δM_n between the current value M_n obtained after n samples (i.e., soil models)
250 and the final estimate M_N . Due to the lognormal distribution of the AFs (e.g., Li and Assimaki,
251 2010; Aimar et al., 2020), the difference was computed with moments in log-scale:

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

253 According to the criterion, stable estimates of statistical moments are achieved when δM_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 δ_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 δ_X denotes underestimation. Furthermore, being δ_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 δ_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 δ_{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 δ_X with a threshold δ_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 δ_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 δ_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 δ_X for SPSA and LPSA, where data are extracted from GRAs performed on the collection of 91,500
366 soil models for the suite “S-1” of input motions. Results about PGAA and IPSA are plotted in
367 Figure S9 in the Electronic Supplement. The distribution of δ_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 δ_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 , δ_X is always positive (i.e., the NL approach predicts smaller amplification than the
381 EQL scheme) and the difference increases when the deformability is high, with a dramatic
382 variation over a relatively small region in the $V_{S,H}$ - H domain. For instance, $\mu_{\delta, SPSA}$ grows from 0.2
383 up to 0.4 for H increasing from 10 m to 15 m at $V_{S,H} = 160$ m/s, more than doubling itself (Figure
384 7a). Similarly, the variability in the difference undergoes an increase in this area (Figure 6b-d).
385 This is an effect of the large strain level (Figure 4a), for which nonlinear phenomena become
386 relevant. The trend in the increase can still be linked to f_0 , as the peak of the mean δ_X is located on
387 a range of f_0 equal to 1.5-8 Hz (i.e., T_0 equal to 0.12-0.7 s) for PGAA, 2-4 Hz (0.25-0.5 s) for SPSA
388 (Figure 7a) and 2-3.5 Hz (0.3-0.5 s) for IPSA. At long periods, instead, δ_X monotonically increases
389 and is large at f_0 less than 2 Hz (i.e., T_0 longer than 0.5 s; Figure 7b). The reason of this behavior
390 is the mutual effect of larger strain levels and the resonance of soil models, where the differences
391 between the EQL and the NL approach are expected to be large (Rathje and Kottke, 2011). As an
392 effect of the resonance, the location of the boundary depends on the considered AF and it shifts
393 towards deeper and more deformable soil models, as they are associated with lower f_0 values,
394 compatible with the period range investigated in each AF.

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

405 From such considerations, a scheme for the subdivision of soil models is proposed for setting up a
406 simplified assessment of the differences between the EQL and the NL approaches (Figure 8m and
407 Figure 9). The scheme is conceived to cluster together different soil conditions sharing compatible
408 behavior in terms of δ_X . Furthermore, the definition of the clusters accounts for the dependence of
409 δ_X^{max} (i.e., $\sigma_{\ln X}^E$) with respect to $V_{S,30}$ (Table 2). For simplicity, the partition is based on specific
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 δ_X and δ_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 δ_X . This boundary should depend on the
414 investigated period range, as soil models with moderately high f_0 exhibit strong differences at short
415 periods, whereas only thick and deformable models (i.e., low f_0) assume large discrepancies at long
416 periods. In this study, the lowest value of f_0 is considered for simplicity, to be on the safe side.

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

422 Role of input motion characteristics

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 δ_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 δ_X was kept under control. The degree of relationship was quantified through
434 Kendall’s τ_b correlation coefficient (Kendall, 1955), which was estimated together with the p -
435 value, expressing the statistical significance – for $p < 0.05$, τ_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 τ_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, τ_b is larger than 0.5. Note that τ_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 δ_X becomes relevant, by
459 comparing the trend of $\delta_X^{\mu\pm\sigma}$ – estimated through linear fitting – and δ_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 δ_X) for each reference group, as a function of the investigated AF. The color scale
464 defines the upper bound of *PGA* for which EQL and NL analyses provide similar results.
465 Therefore, this result can be used to guide for the selection of the numerical method, considering
466 the parameters of the soil deposit ($V_{S,H}$ and H), the expected level of ground shaking and the
467 specific application for which the GRA is required (i.e., the period range of interest). In deep and
468 soft soil models, motions with *PGA* larger than 0.1g give rise to strong differences. However, for
469 slightly smaller deformability (i.e., $V_{S,H}$ more than 250 m/s), the two schemes provide compatible
470 results at larger *PGA* values, that rise from 0.15g up to 0.3g. Furthermore, the upper bound of *PGA*
471 dramatically increases at longer periods. For instance, LPSA differences are small up to *PGA*
472 values equal to 0.3 for almost all the soil conditions investigated, except the very deformable ones.
473 In stiff and shallow soil models, instead, no threshold is identified since no trend in δ_X is detected,
474 as the inter-method differences are small regardless the entity of the specific input motion.
475 Therefore, in this case the inter-method differences are always small, at least in the range of ground
476 motions of common application. Similar results are obtained for the SAFs with respect to the
477 corresponding spectral intensities (see Figure S16 in the Electronic Supplement).

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, last accessed November 2017). Details
520 about some sites were extracted from the geological databases of Tuscany
521 (www.regione.toscana.it/-/programma-vel, last accessed November 2017), Emilia-Romagna
522 (https://applicazioni.regione.emilia-romagna.it/cartografia_sgss, last accessed November 2017)
523 and Umbria Region
524 (http://storicizzati.territorio.regione.umbria.it/Static/IndaginiGeologicheKmz/Index_kmz.htm,
525 last accessed November 2017). Seismograms used in this study were collected from ITACA, the
526 Engineering Strong Motion Database v1.0 (ESM, <http://esm.mi.ingv.it>, last accessed November
527 2017), Internet-Site for European Strong-Motion Data (ESD, <http://www.isesd.hi.is>, last accessed
528 January 2018) and PEER NGA-West2 Database (<https://ngawest2.berkeley.edu>, last accessed
529 January 2018). EQL analyses were carried out with the SHAKE91 software (Schnabel, 1972; Sun
530 and Idriss, 1992), whereas NL simulations were performed with the DEEPSOIL v7.0 code
531 (Hashash et al., 2017, <http://deepsoil.cee.illinois.edu/>, last accessed December 2017). The ground
532 motion parameters relative to the acceleration time histories were computed with the SeismoSignal
533 software (<https://seismosoft.com/products/seismosignal/>, last accessed January 2018). Data

534 processing and figures were done using MATLAB
535 (<http://www.mathworks.com/products/matlab/>).

536 The Electronic Supplement reports an overview of the results of GRAs and a description of the
537 procedure adopted to estimate the thresholds for the inter-method differences from GMPEs.

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697 List of Figure Captions

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

702 Figure 2. a) Selected ground motions, grouped as “S-1” and “S-2”; b) Definition of the spectral
703 intensity SI_{AB} for the input motion ($SI_{AB,r}$) and the simulated motion ($SI_{AB,s}$) across the period range
704 $[A; B]$.

705 Figure 3. Number of models required to achieve a stable estimate of the EQL-based mean PGAA
706 (a), SPSA (b), IPSA (c) and LPSA (d), as a function of soil model characteristics. Results refer to
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709 and 1% (b), as a function of soil model characteristics. Results refer to the suite “S-1” of input
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711 Figure 5. a) Comparison between the distribution of the inter-method differences for LPSA with
712 the threshold $\delta_{LPSA}^{max,10\%}$. The dark grey area – labeled as “ $\delta > \delta^{max}$ ” in the legend – denotes the region
713 where the inter-method differences for LPSA exceed the threshold $\delta_{LPSA}^{max,10\%}$. Data are extracted
714 from models lying in the dashed area of the $V_{S,H}-H$ domain represented in b) for the Central Italy
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716 Electronic Supplement).

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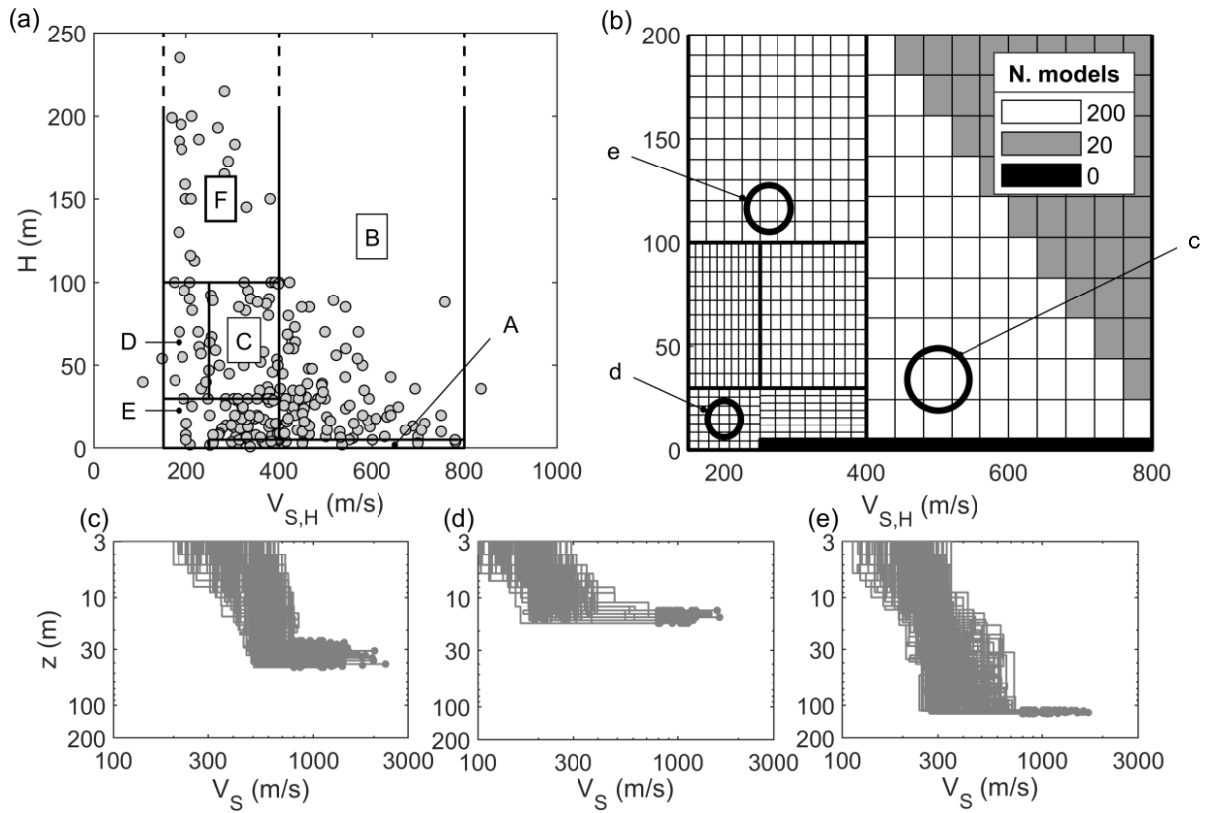
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726 the Kendall’s τ_b coefficient – the p -value is close to 0 in all the considered cases – and the linear
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728 relevant. Data from the suite “S-1” of motions for the whole collection of 91,500 soil models are
729 also displayed in (a)-(l), for comparison purposes.

730 Figure 9. Maximum PGA at which the inter-method differences are negligible for specific
731 applications of GRAs: a) PGAA (i.e., geotechnical applications); b) SPSA (i.e., small buildings);
732 c) IPSA (i.e., intermediate buildings) and d) LPSA (i.e., tall buildings). The dashed area denotes
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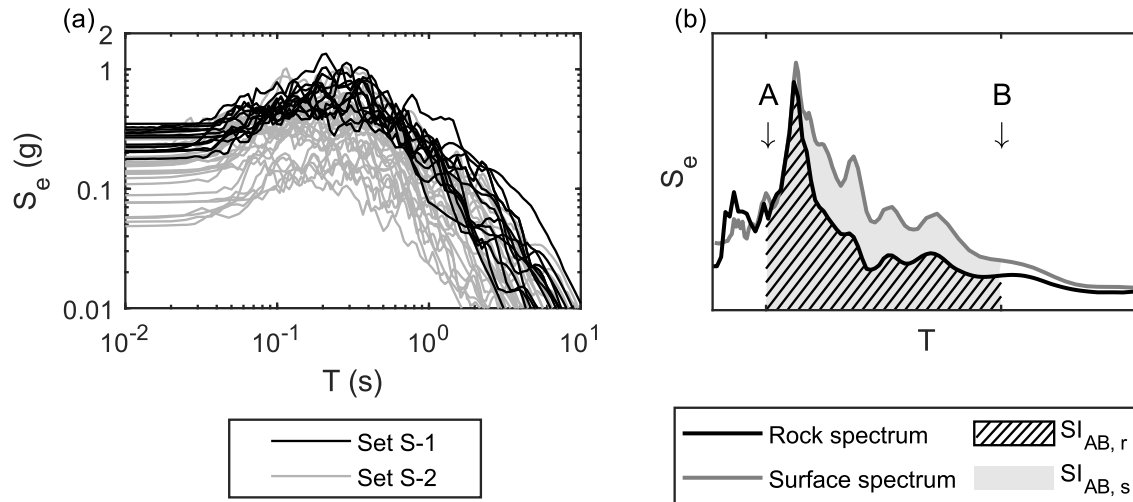
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 739 for the randomly generated V_S profiles; c-e) Examples of randomly generated soil profiles for the
 740 areas identified in b).

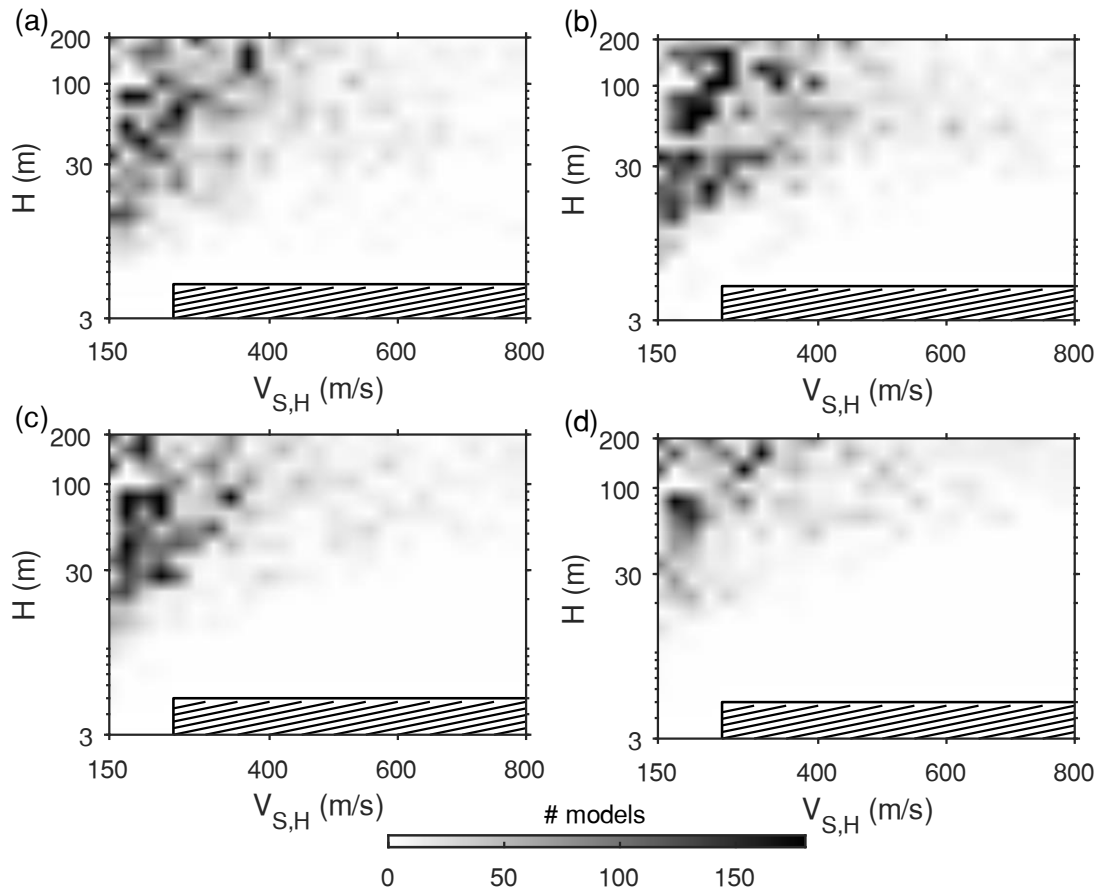
741



742

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 744 intensity SI_{AB} for the input motion ($SI_{AB,r}$) and the simulated motion ($SI_{AB,s}$) across the period range
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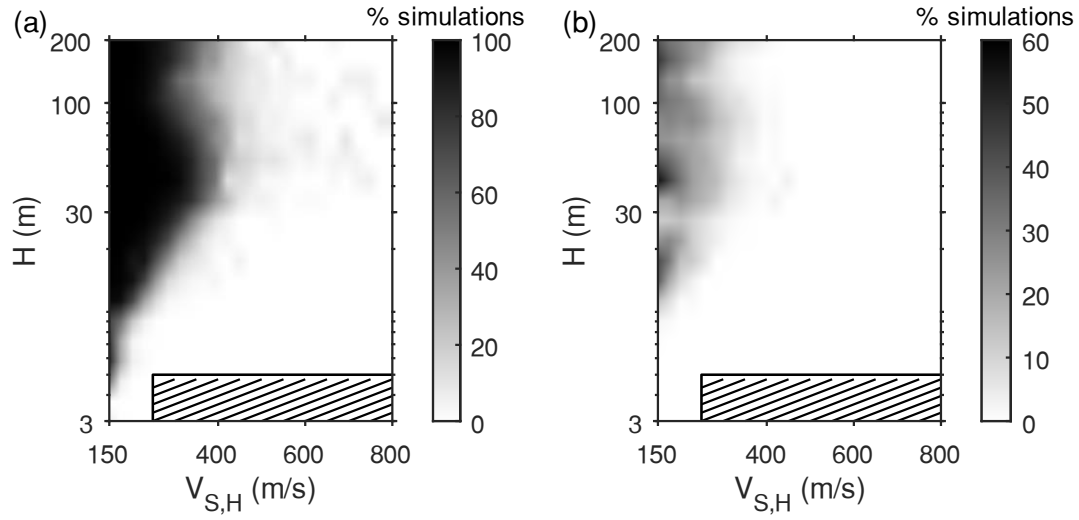


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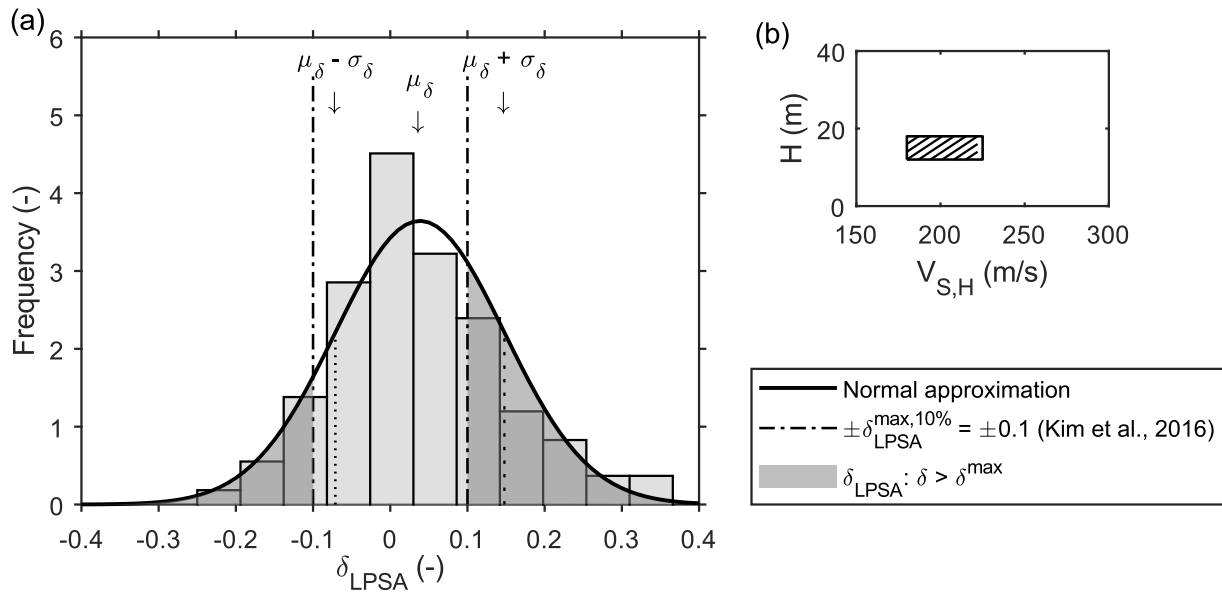
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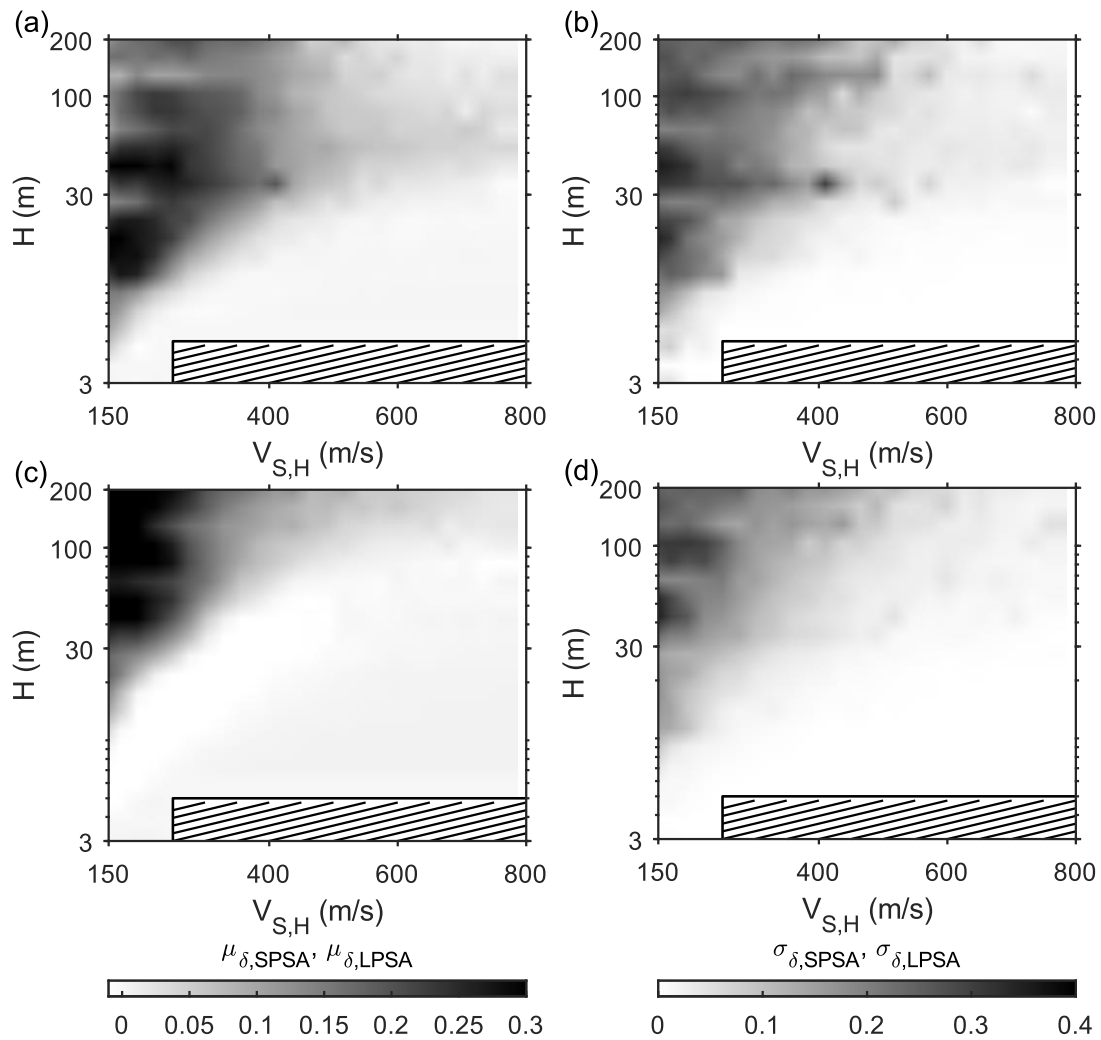
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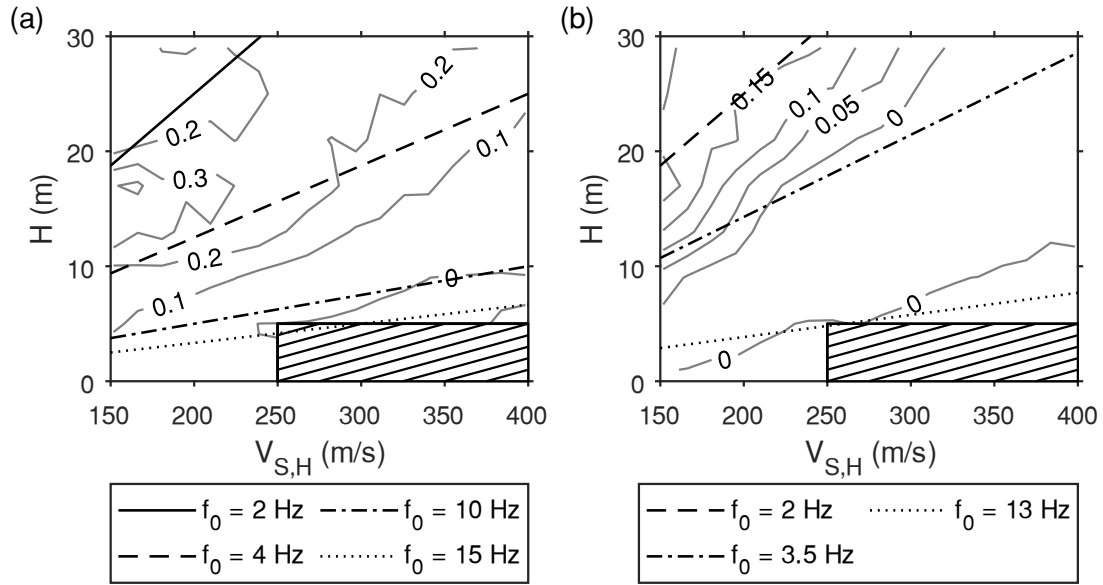


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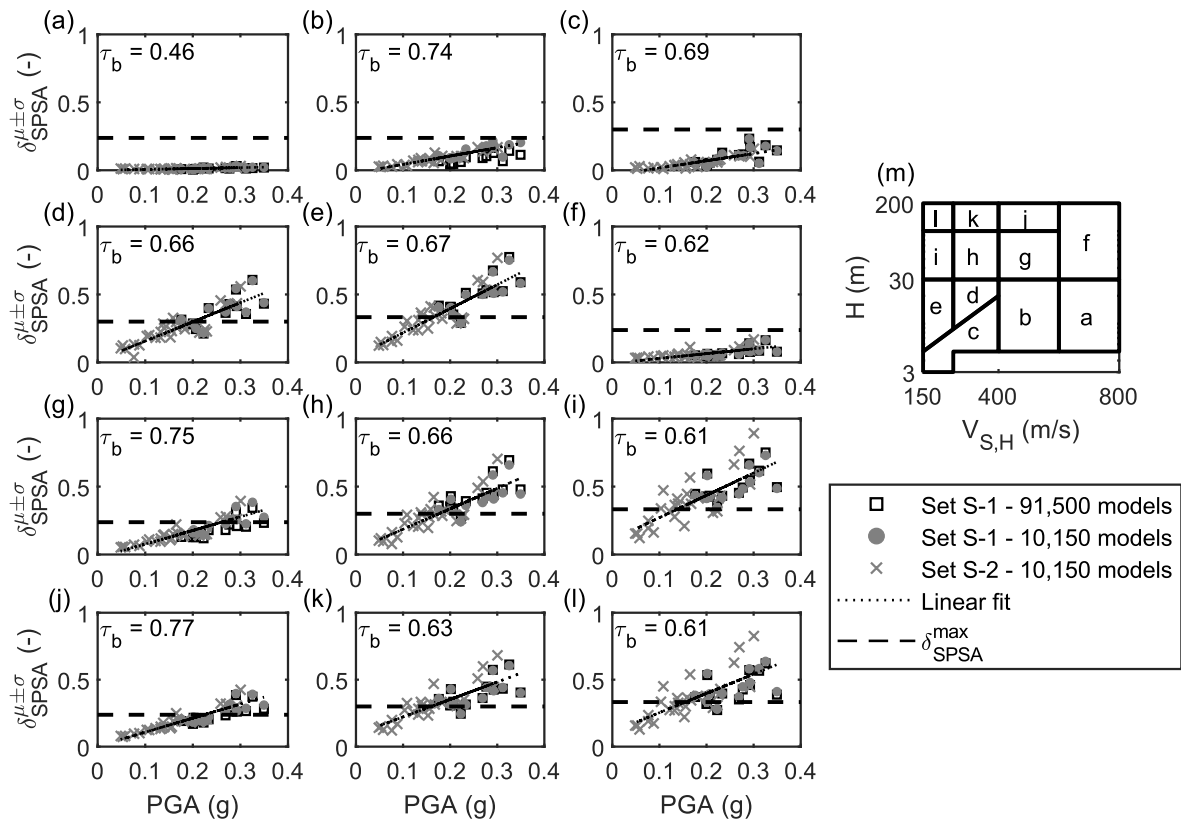
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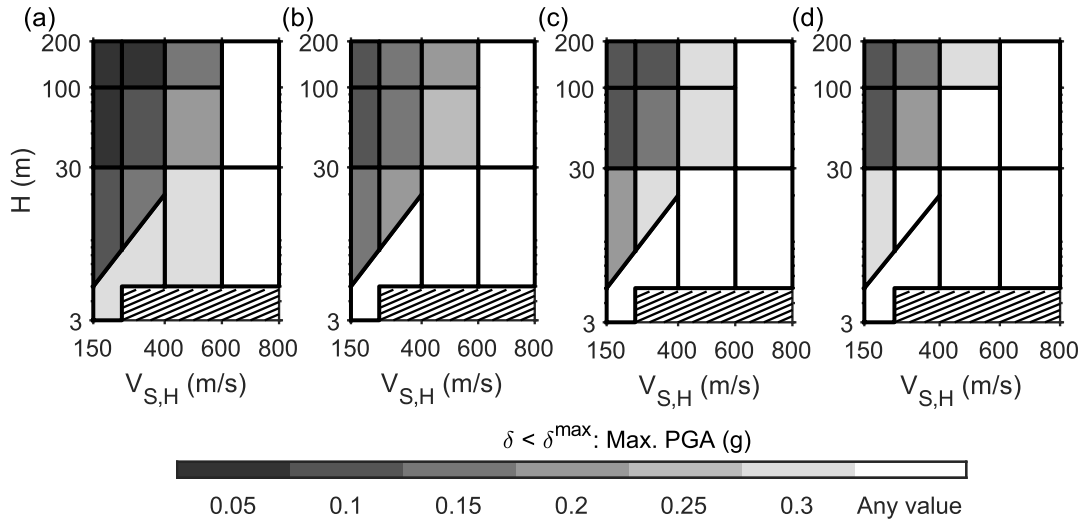
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 782 the region not considered in GRAs.

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

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 ΔT . 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 μ_{SI} and variance σ_{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. μ_{SI} and σ_{SI}^2 , from GMPEs.

925 Empirical data about spectral integrals follow a lognormal distribution, as shown in Figure S4 for
 926 SPSI and LPSI by example. This result was not guaranteed a priori, since spectral integrals derive
 927 from the sum of lognormal variables, for which a closed-form expression for the distribution does
 928 not exist. However, several studies showed that the lognormal distribution fairly approximates the
 929 solution (Fenton, 1960). Thanks to this empirical evidence, spectral integrals can be reasonably

930 described by the mean and the standard deviation in logarithmic scale, i.e. $\mu_{\ln SI}$ and $\sigma_{\ln SI}^2$, which
 931 were derived from the ones computed in normal scale (Ang and Tang, 2007), according to:

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

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

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 τ_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 τ_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 τ_b coefficient and the p -value (in brackets). The considered parameters are the
1005 peak ground acceleration (PGA), peak ground velocity (PGV), peak ground displacement (PGD),
1006 Arias intensity (AI), predominant period (T_p), mean period (T_m), significant duration from 5% to
1007 95% of the Husid plot (D_{5-95}), significant duration from 5% to 75% of the Husid plot (D_{5-75}) and
1008 uniform duration (UD – based on a threshold acceleration equal to 0.025g) and IPSI. The column
1009 labels identify the reference clusters of soil models (see Figure 8m in the Manuscript).

1010 Table S5. Correlation between $\delta_{LPSA}^{\mu\pm\sigma}$ and commonly used ground motion parameters, quantified
1011 through Kendall's τ_b coefficient and the p -value (in brackets). The considered parameters are the
1012 peak ground acceleration (PGA), peak ground velocity (PGV), peak ground displacement (PGD),
1013 Arias intensity (AI), predominant period (T_p), mean period (T_m), significant duration from 5% to
1014 95% of the Husid plot (D_{5-95}), significant duration from 5% to 75% of the Husid plot (D_{5-75}) and
1015 uniform duration (UD – based on a threshold acceleration equal to 0.025g) and LPSI. The column
1016 labels identify the reference clusters of soil models (see Figure 8m in the Manuscript).

1017 List of Supplemental Figure Captions

1018 Figure S1. Mean and standard deviation of EQL-based PGAA (a-b), SPSA (c-d), IPSA (e-f) and
1019 LPSA (g-h), as a function of soil model characteristics. The plots report results for the mean value
1020 (left column) and the standard deviation (right column). Results refer to the suite “S-1” of input
1021 motions. The dashed area denotes the region not considered in GRAs.

1022 Figure S2. Mean and standard deviation of NL-based PGAA (a-b), SPSA (c-d), IPSA (e-f) and
1023 LPSA (g-h), as a function of soil model characteristics. The plots report results for the mean value
1024 (left column) and the standard deviation (right column). Results refer to the suite “S-1” of input
1025 motions. The dashed area denotes the region not considered in GRAs.

1026 Figure S3. Trend of EQL-based SPSA (a) and LPSA (b) for shallow and deformable soil models.
1027 The contour lines denote the mean values of each parameter, whereas the dashed area identifies
1028 the region not considered in GRAs. Results refer to the suite “S-1” of input motions.

1029 Figure S4. Probability plots for SPSI (a-b) and LPSI (c-d) for $V_{S,30}$ 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 τ_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 δ_{PGAA}^{max} to
1053 identify the shaking level at which δ_{PGAA} becomes relevant. For panel (a), we omit the linear fit
1054 because τ_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 τ_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 δ_{IPSA}^{max} to identify the
1062 shaking level at which δ_{IPSA} becomes relevant. For panel (a), we omit the linear fit because τ_b is
1063 smaller than 0.3. Data from the suite “S-1” of motions for the whole collection of 91,500 soil
1064 models are also displayed in (a)-(l), for comparison purposes.

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 τ_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 δ_{LPSA}^{max} to identify the shaking level at which δ_{LPSA} becomes relevant. For panels (a),
1072 (b) and (c), we omit the linear fit because τ_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 τ_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 δ_{SPSA}^{max} to identify the
1081 shaking level at which δ_{SPSA} becomes relevant. For panel (a), we omit the linear fit because τ_b is
1082 smaller than 0.3. Data from the suite “S-1” of motions for the whole collection of 91,500 soil
1083 models are also displayed in (a)-(l), for comparison purposes.

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 τ_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 δ_{IPSA}^{max} to identify the
1090 shaking level at which δ_{IPSA} becomes relevant. For panel (a), we omit the linear fit because τ_b is
1091 smaller than 0.3. Data from the suite “S-1” of motions for the whole collection of 91,500 soil
1092 models are also displayed in (a)-(l), for comparison purposes.

1093 Figure S15. Relationship between $\delta_{LPSA}^{\mu\pm\sigma}$ and $LPSI$ for all the clusters of soil models. Panels (a)-(l)
1094 display the plot of $\delta_{LPSA}^{\mu\pm\sigma}$ versus $LPSI$ derived from GRAs on the set of 10,150 soil models with the

1095 suites “S-1” and “S-2” of input motions. Each panel contains data from each cluster of soil models
1096 and the corresponding location in the V_{SH} - H domain is represented in (m). Panels (a)-(l) also report
1097 the Kendall’s τ_b coefficient – the p -value is close to 0 in all the considered cases, except in (a), (b)
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 δ_{LPSA}^{max} to identify the shaking level at which δ_{LPSA} becomes relevant. For panels (a),
1100 (b) and (c), we omit the linear fit because τ_b is smaller than 0.3. Data from the suite “S-1” of
1101 motions for the whole collection of 91,500 soil models are also displayed in (a)-(l), for comparison
1102 purposes.

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

1106 Supplemental Tables

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- Wonderland Avenue	185°	PEER NGA- West2	6.69	18.99	1.4	0.22	S-1
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 Windward Island	29-Nov-2007	RA-MAMA	NS	ESM	7.4	67.9	1.35	0.24	S-1

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-	270°	PEER NGA- West2	6.00	6.82	1.1	0.27	S-2
		Turkey Flat #1 (0M)							

* Local magnitude.

1117 Table S1. Selected input motions with details about event characteristics and intensity, as well as the suite identification (“S-1” or “S-
 1118 2”). (*continues*)

Event name	Date	Network-Station	Component	Database	Moment 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 [†]	15.4	1.05	0.22	S-2
Armenia Border Region									
Central Italy	06-Oct -1997	IT-ASS	NS	IT	5.4	20.8	0.75	0.14	S-2
Western Turkey	22-Sep-2015	KO-SHAP	NS	ESM	4.3	14.6	1.0	0.18	S-2
Southern Italy	09-Sep-1998	IT-LRS	NS	ITACA	5.6	18	1.0	0.17	S-2
Greece	15-Oct -2016	AC-SRN	EW	ESM	5.5	55.9	1.0	0.29	S-2
Umbria Marche 2 nd	26-Sep-1997	IT-ASS	NS	ITACA	6.0	21.6	1.0	0.16	S-2
shock									
Sicily Italy	26-Dec-2018	IV-EVRN	EW	ESM	4.9	5.3	1.0	0.3	S-2
Duzce	12-Nov-1999	A-C1062	EW	ESM	7.3	32.3	1.0	0.26	S-2

1119

[†] Surface wave magnitude.

1120 Table S2. Correlation between $\delta_{PGAA}^{\mu\pm\sigma}$ and commonly used ground motion parameters, quantified
 1121 through Kendall's τ_b coefficient and the 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
<i>PGA</i>	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)
<i>PGV</i>	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)
<i>PGD</i>	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)
<i>AI</i>	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)
T_p	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)
T_m	-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)
D_{5-95}	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)
D_{5-75}	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)
<i>UD</i>	-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 τ_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 τ_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)
IPSI	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

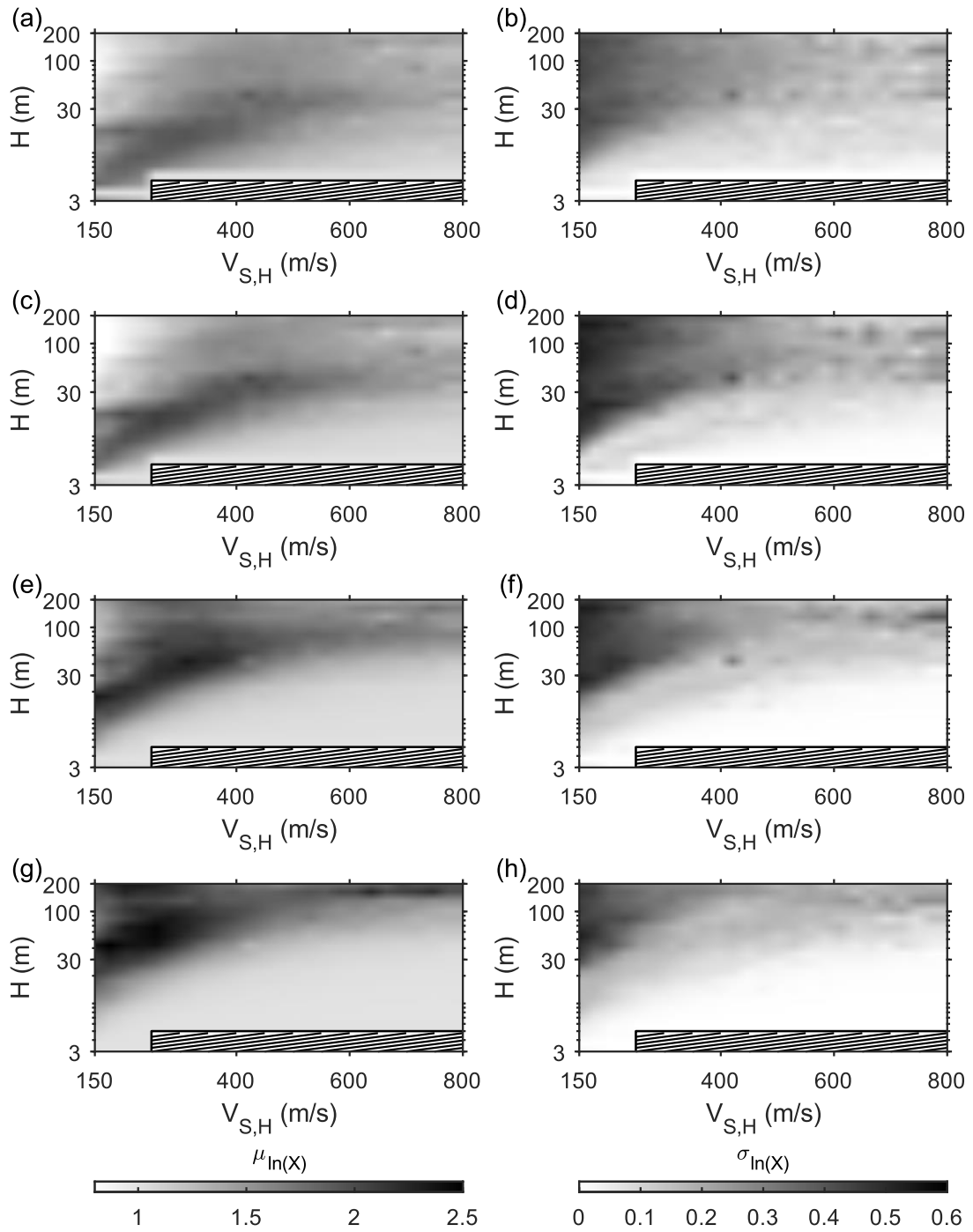
1144 Table S5. Correlation between $\delta_{LPSA}^{\mu\pm\sigma}$ and commonly used ground motion parameters, quantified
 1145 through Kendall's τ_b coefficient and the p -value (in brackets). The considered parameters are the
 1146 peak ground acceleration (*PGA*), peak ground velocity (*PGV*), peak 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
<i>PGA</i>	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)
<i>PGV</i>	-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)
<i>PGD</i>	-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)
<i>AI</i>	-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)
T_p	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)
T_m	-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)
D_{5-95}	-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)
D_{5-75}	-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)
<i>UD</i>	-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)
LPSI	-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)

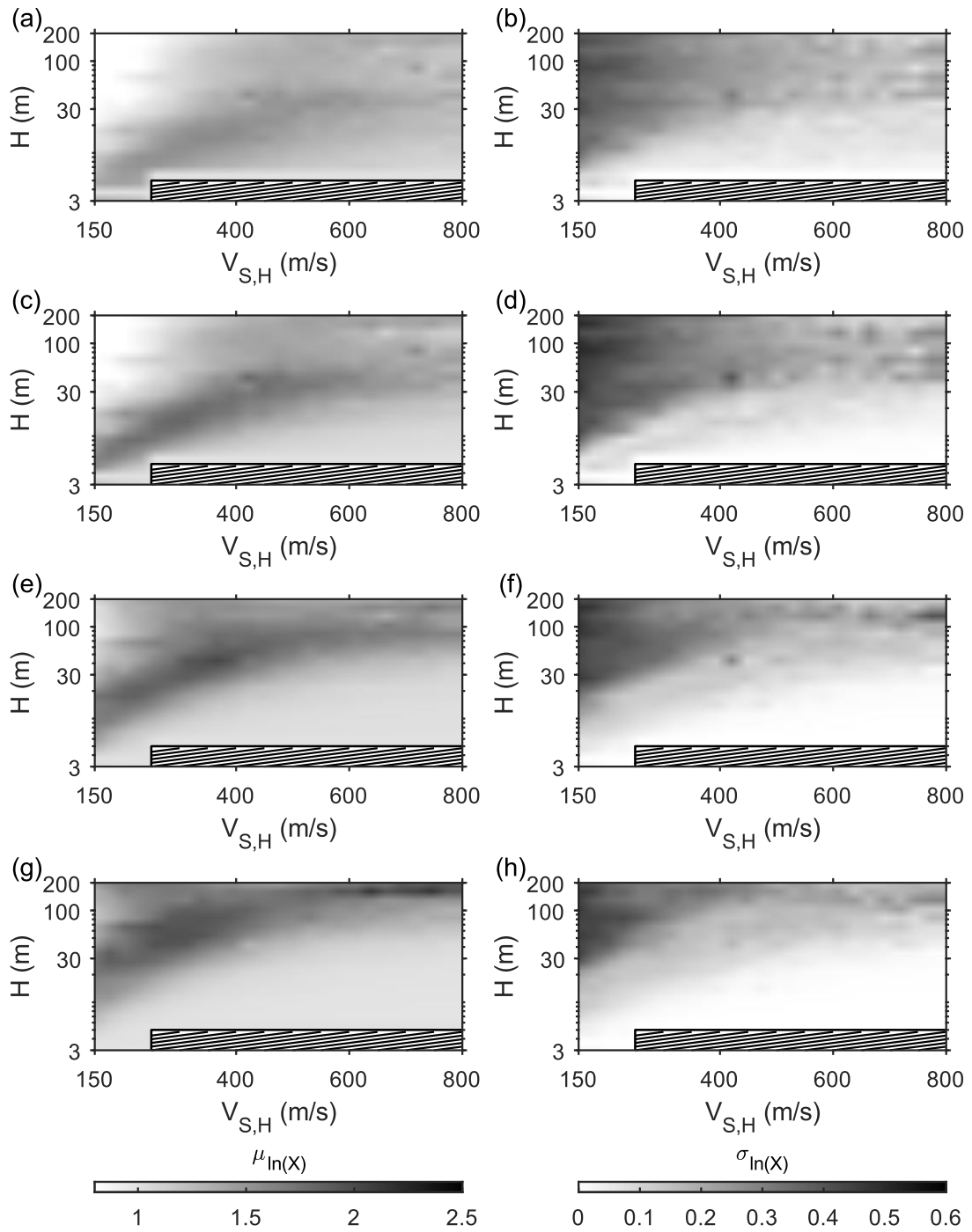
1151

1152 Supplemental Figures

1153

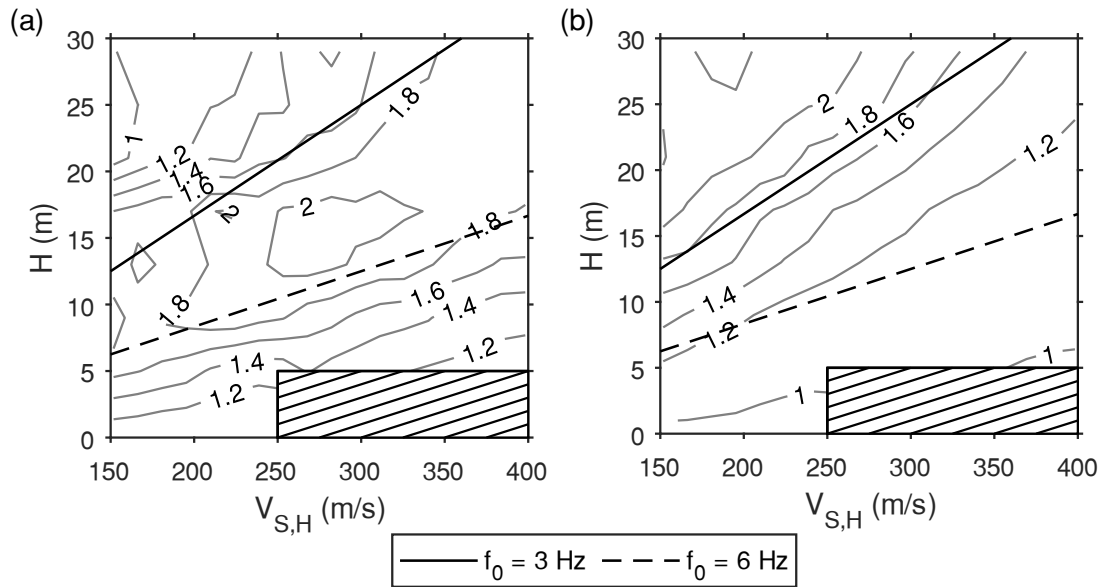


1155 Figure S1. Mean and standard deviation of EQL-based PGAA (a-b), SPSA (c-d), IPSA (e-f) and
1156 LPSA (g-h), as a function of soil model characteristics. The plots report results for the mean value
1157 (left column) and the standard deviation (right column). Results refer to the suite “S-1” of input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

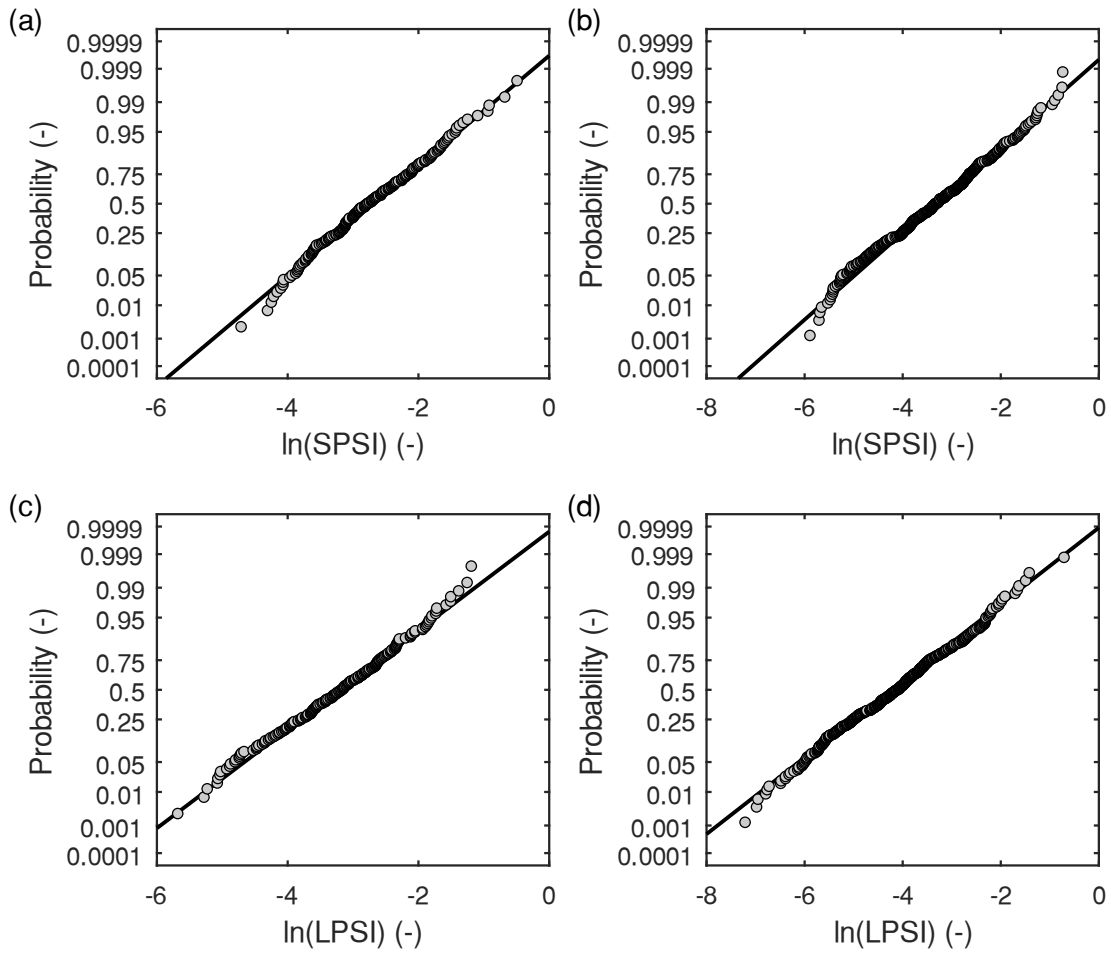


1165

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

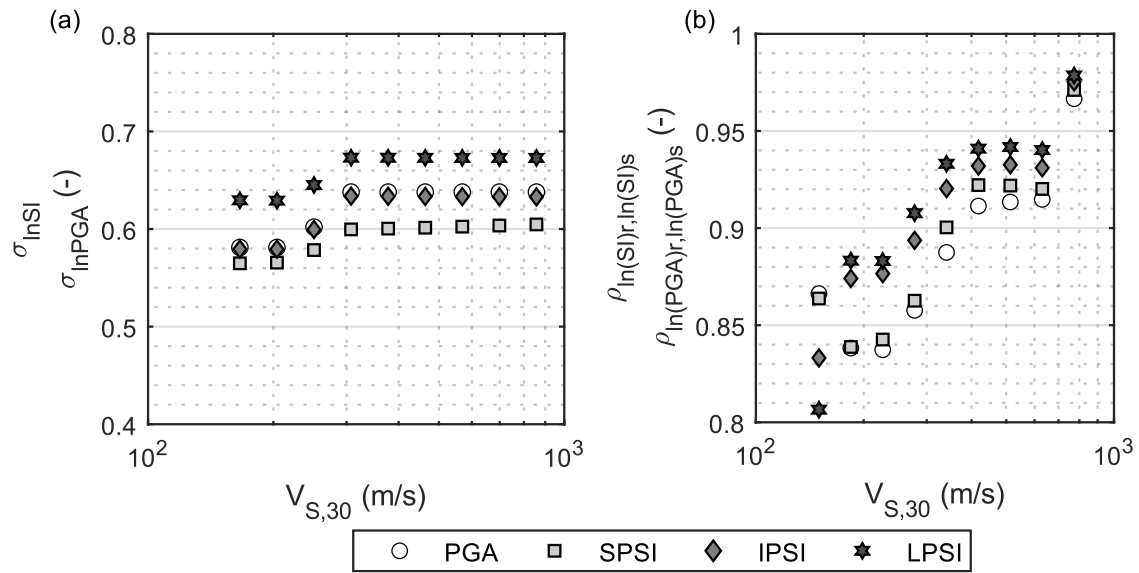
1168 the region not considered in GRAs. Results refer to the suite “S-1” of input motions.



1169

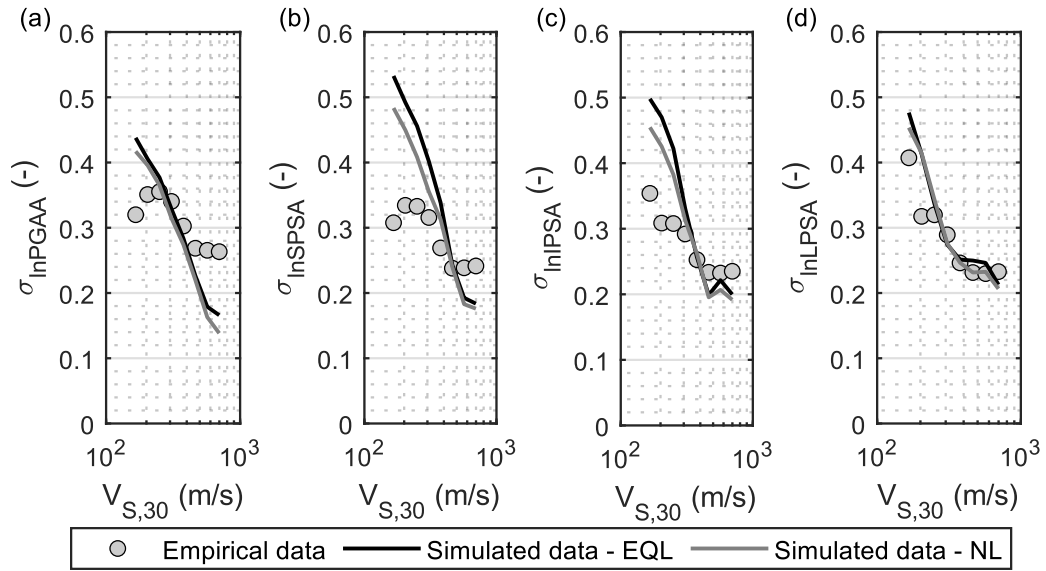
1170 Figure S4. Probability plots for SPSI (a-b) and LPSI (c-d) for $V_{S,30}$ between 225 m/s and 275 m/s

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



1172

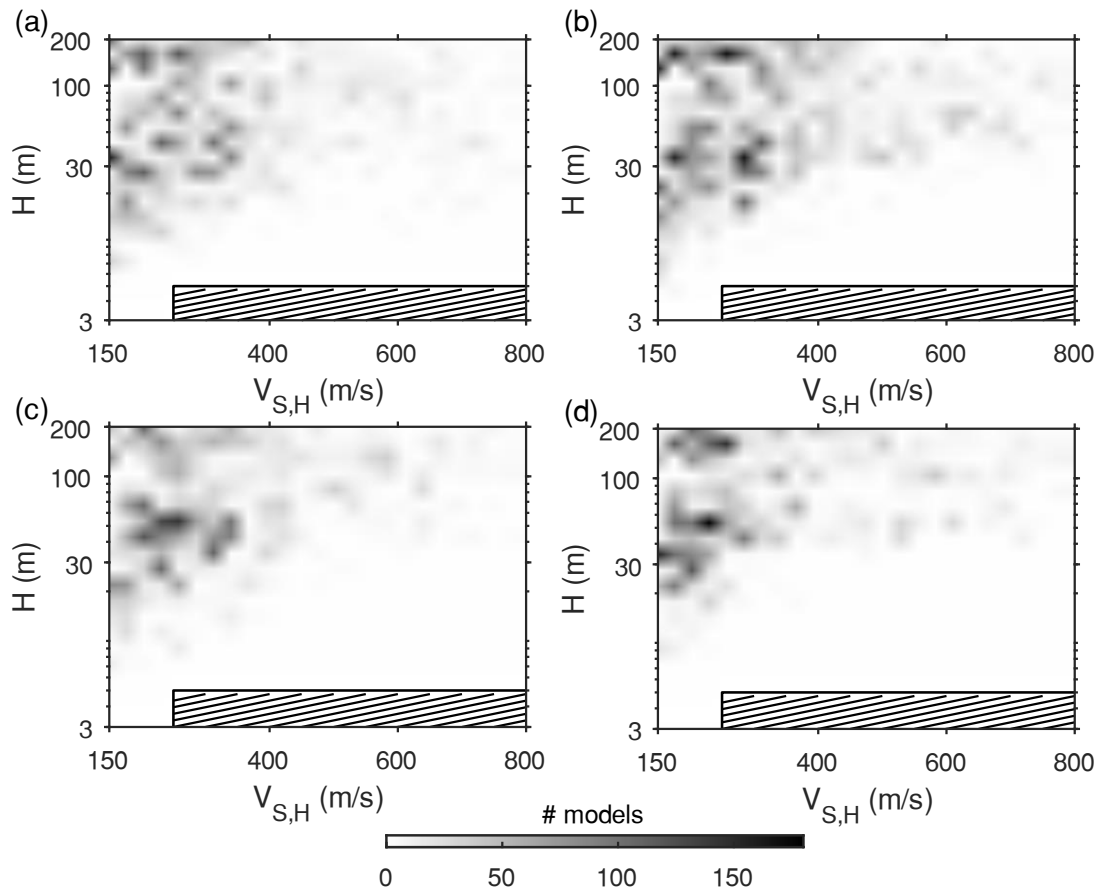
1173 Figure S5. Standard deviation (a) and rock-to-soil correlation (b) of the spectral parameters, as a
 1174 function of soil deposit characteristics (i.e., $V_{S,30}$).



1175

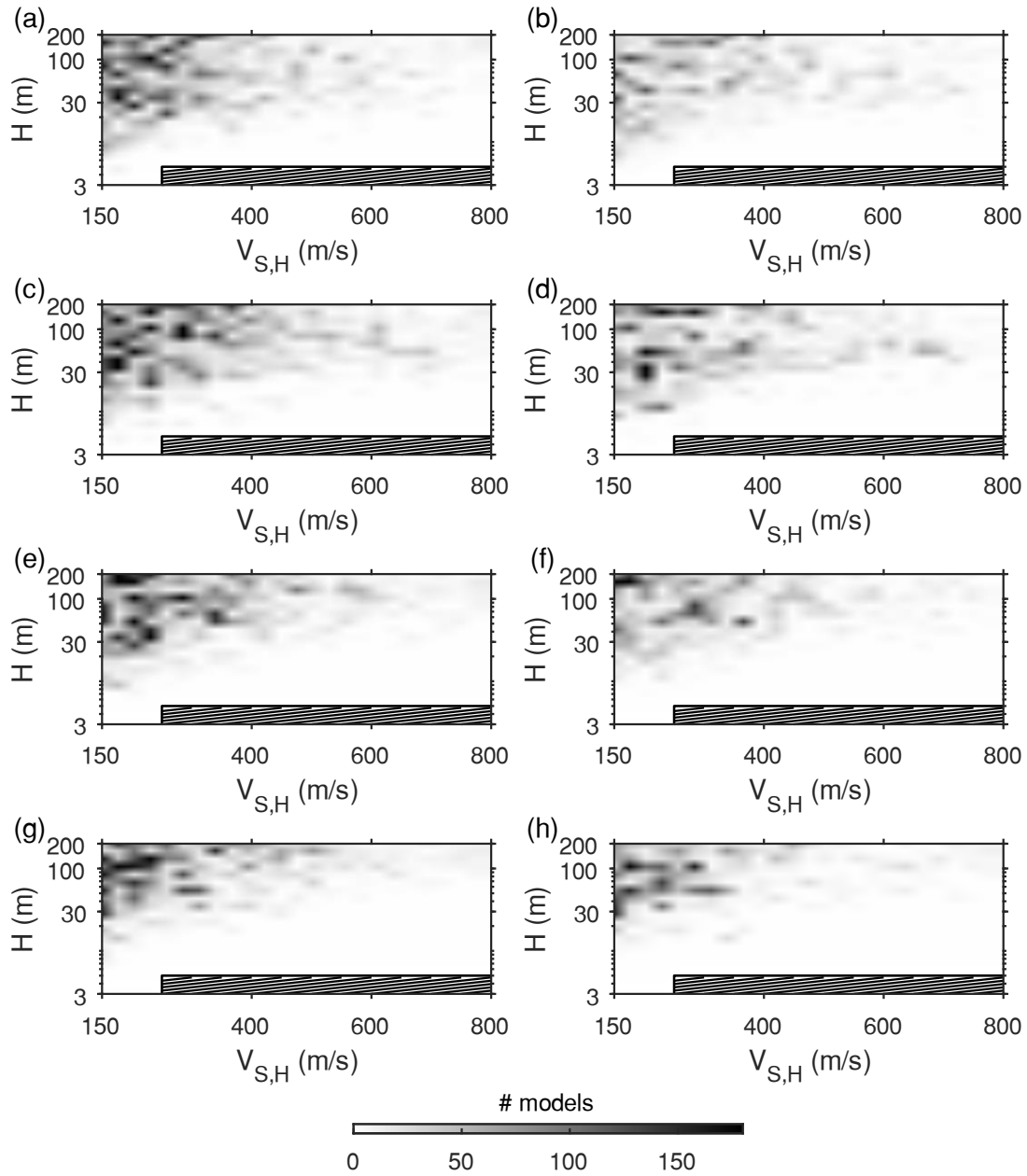
1176 Figure S6. Empirical and simulation-based standard deviation for PGAA (a), SPSA (b), IPSA (c),

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.

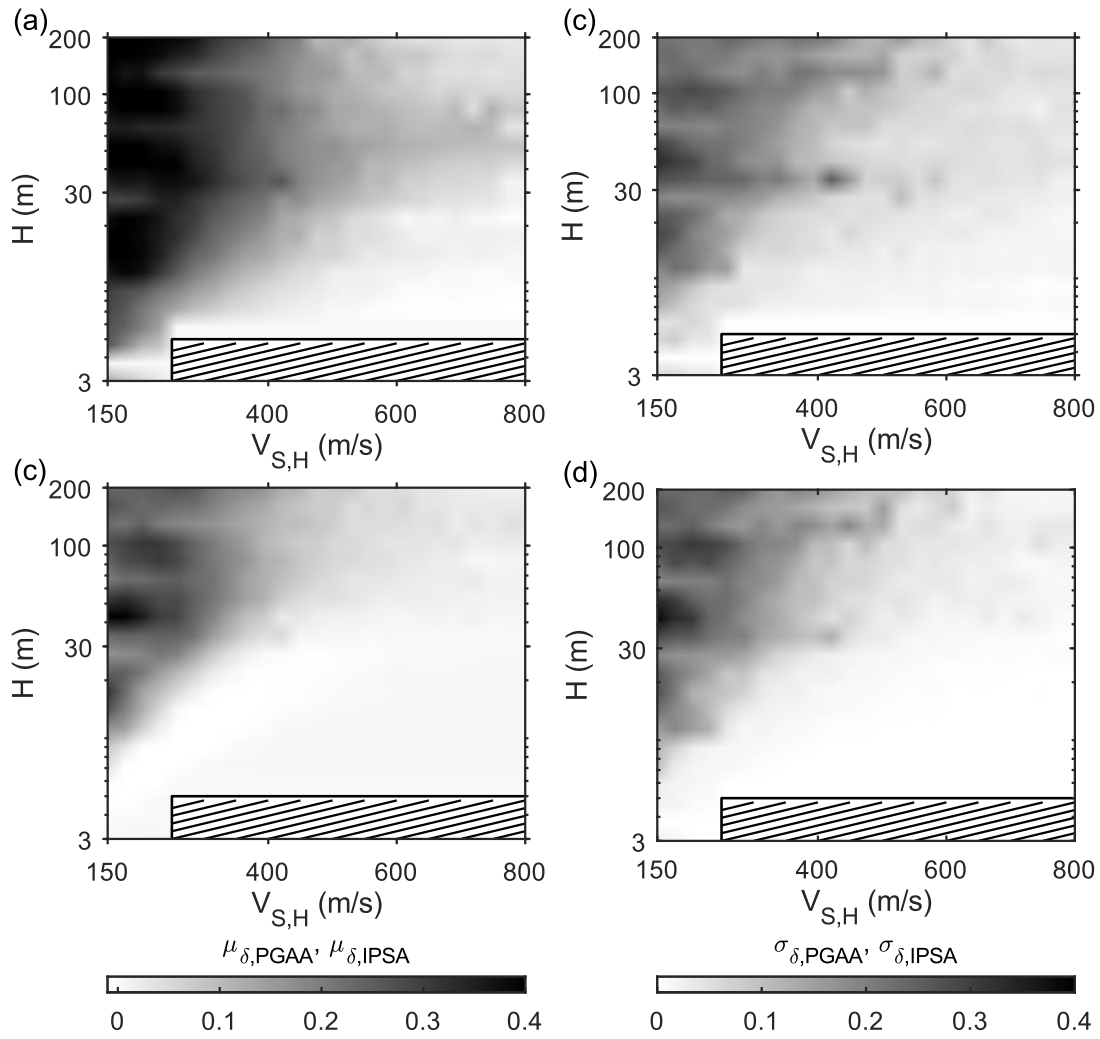


1183

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

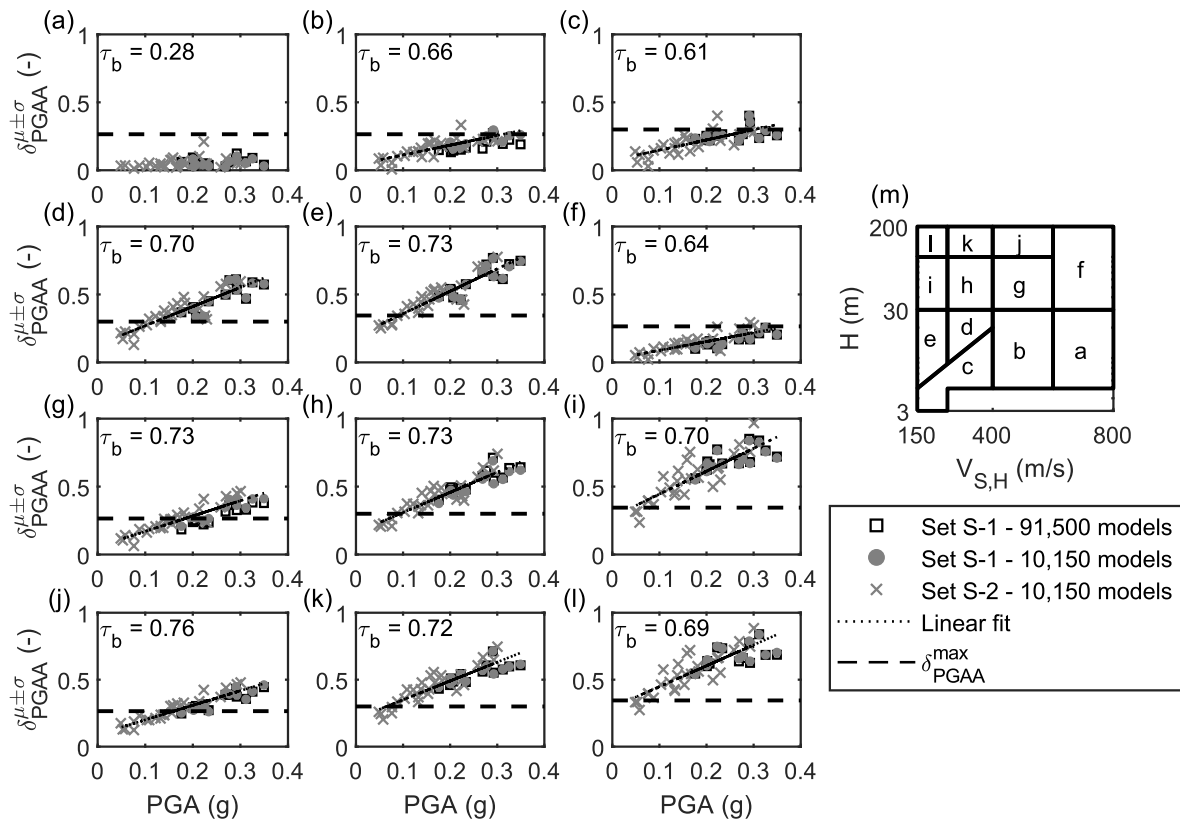
1185 NL-based PGAA (a-b), SPSA (c-d), IPSA (e-f) and LPSA (g-h), as a function of soil model

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

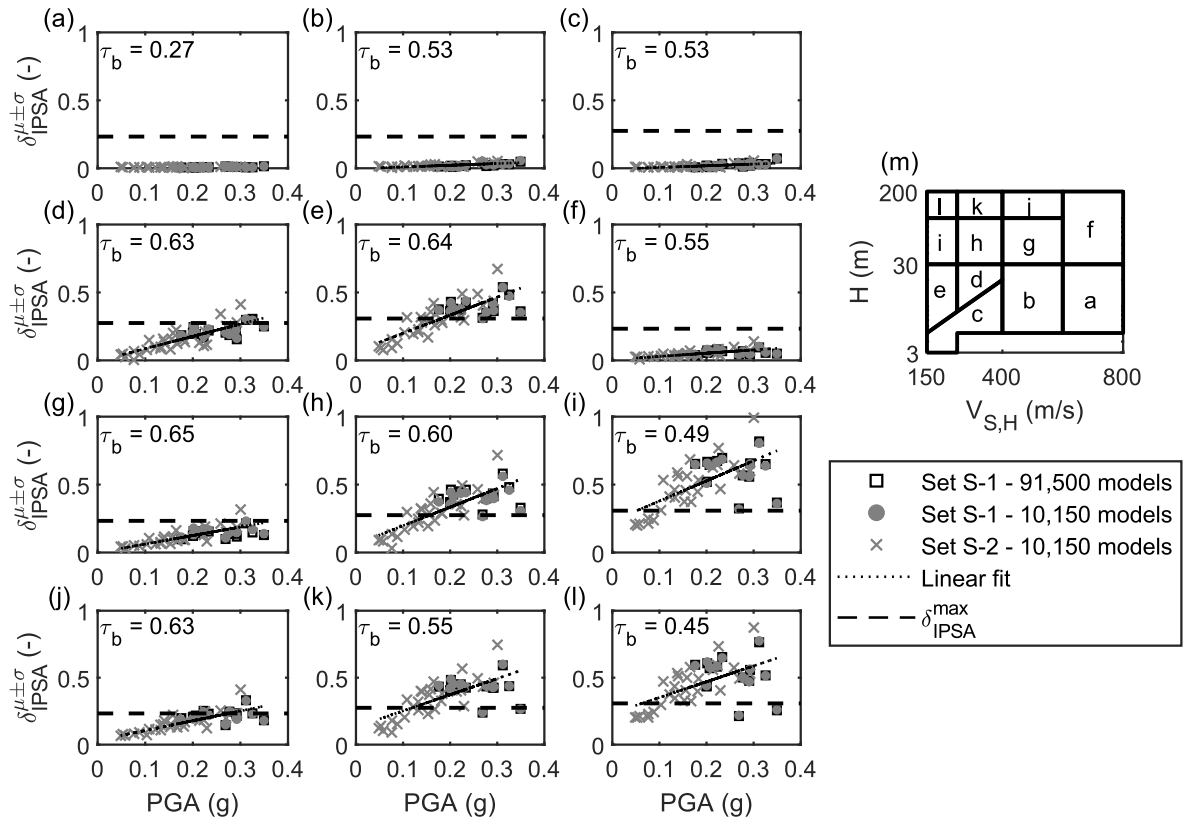
1190 Figure S9. Distribution of $\mu_{\delta,PGAA}$ (a) and $\sigma_{\delta,PGAA}$ (b), as a function of soil model characteristics;
 1191 Distribution of $\mu_{\delta,IPSA}$ (c) and $\sigma_{\delta,IPSA}$ (d), as a function of soil model characteristics. The dashed
 1192 area denotes the region not 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 τ_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 δ_{PGAA}^{max} to
 1200 identify the shaking level at which δ_{PGAA} becomes relevant. For panel (a), we omit the linear fit

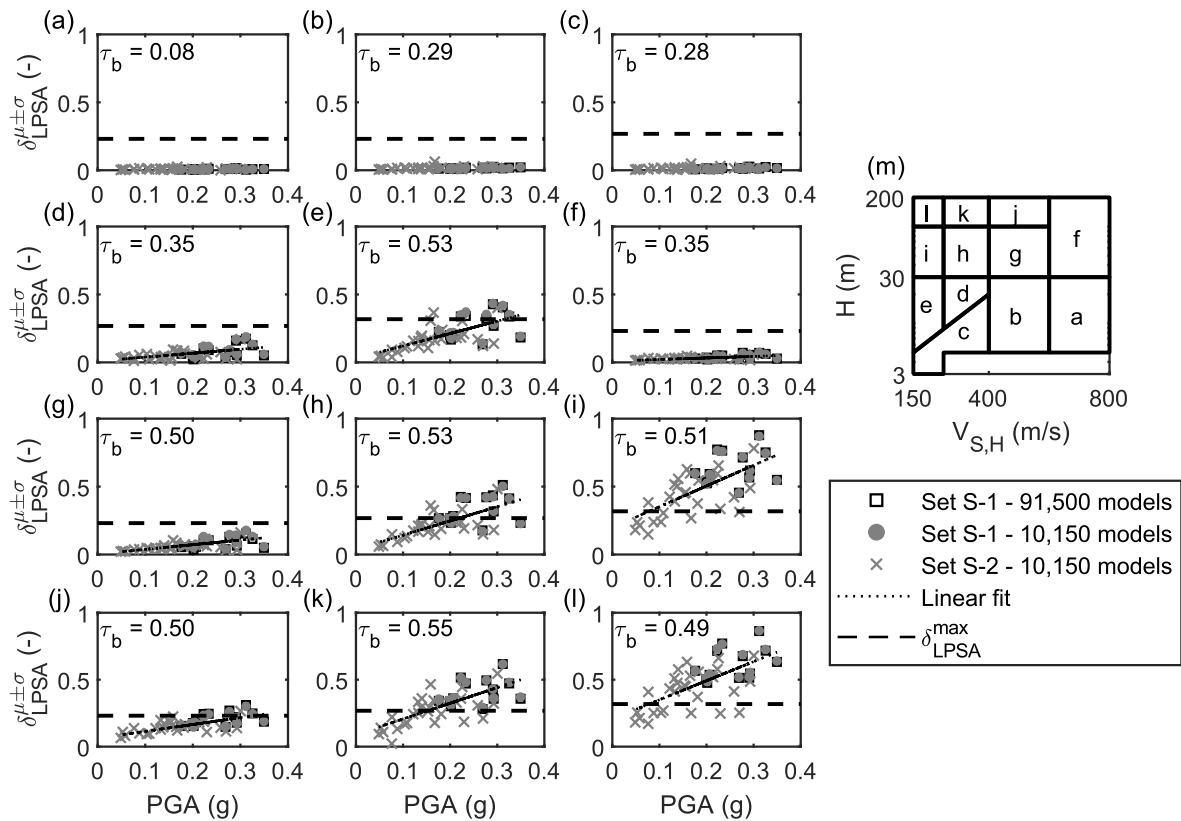
1201 because τ_b is smaller than 0.3. Data from the suite “S-1” of motions for the whole collection of
1202 91,500 soil models are also displayed in (a)-(l), for comparison purposes.



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 τ_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 δ_{IPSA}^{max} to identify the
 1210 shaking level at which δ_{IPSA} becomes relevant. For panel (a), we omit the linear fit because τ_b is

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



1213

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

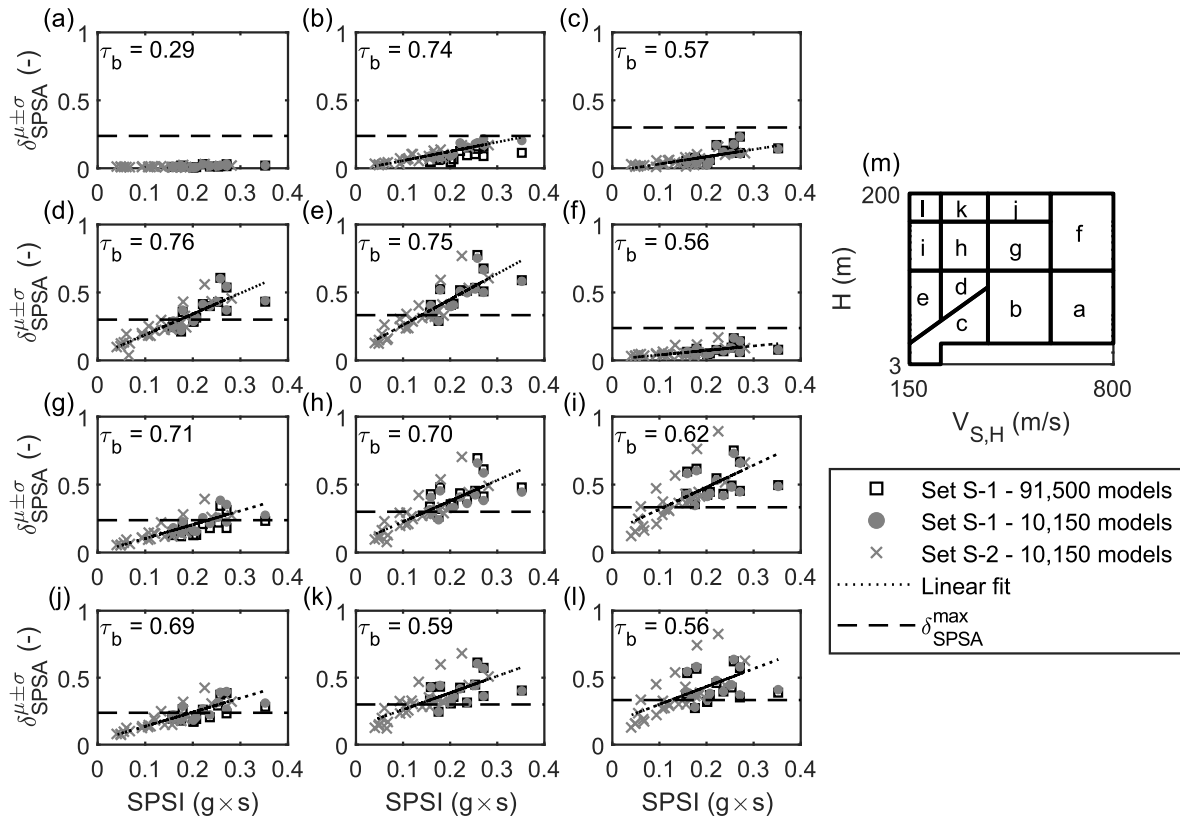
1217 and the corresponding location in the V_{SH} - H domain is represented in (m). Panels (a)-(l) also report

1218 the Kendall’s τ_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 δ_{LPSA}^{max} to identify the shaking level at which δ_{LPSA} becomes relevant. For panels (a),

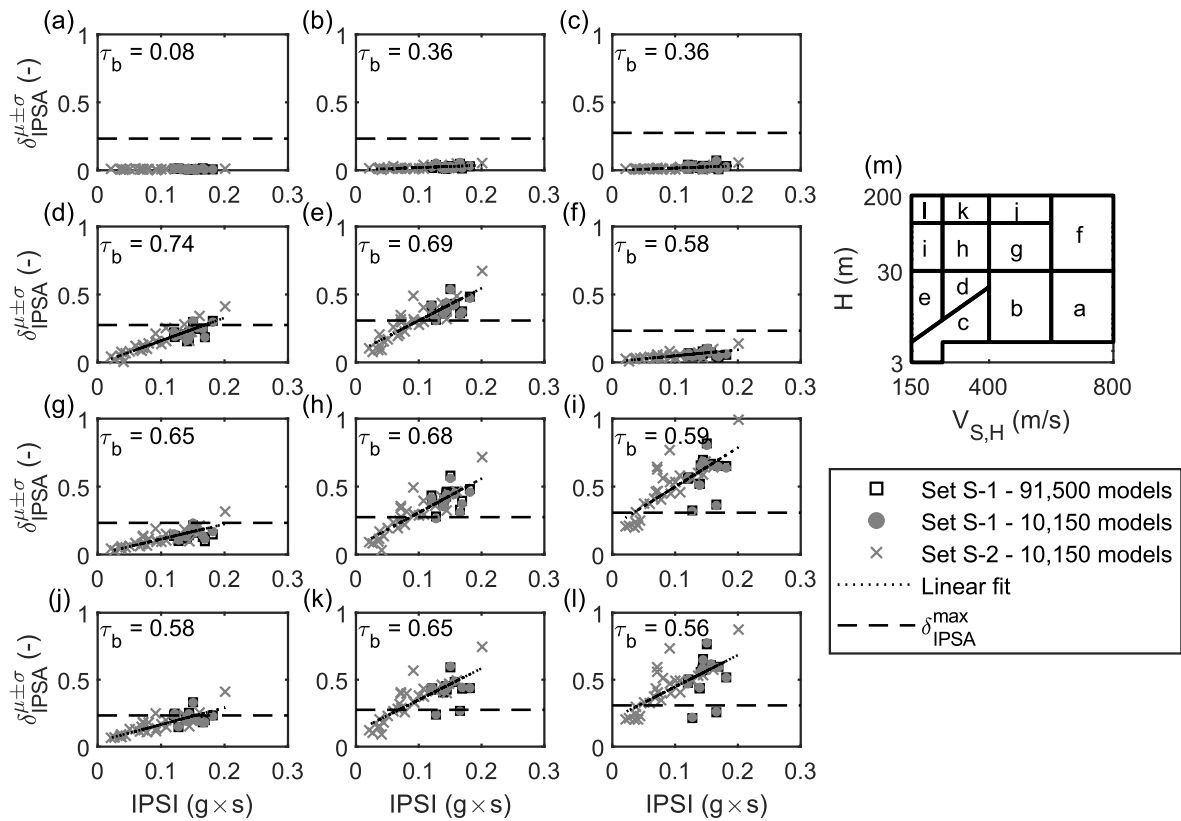
1221 (b) and (c), we omit the linear fit because τ_b is smaller than 0.3. Data from the suite “S-1” of
1222 motions for the whole collection of 91,500 soil models are also displayed in (a)-(l), for comparison
1223 purposes.



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 τ_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 δ_{SPSA}^{max} to identify the
 1231 shaking level at which δ_{SPSA} becomes relevant. For panel (a), we omit the linear fit because τ_b is

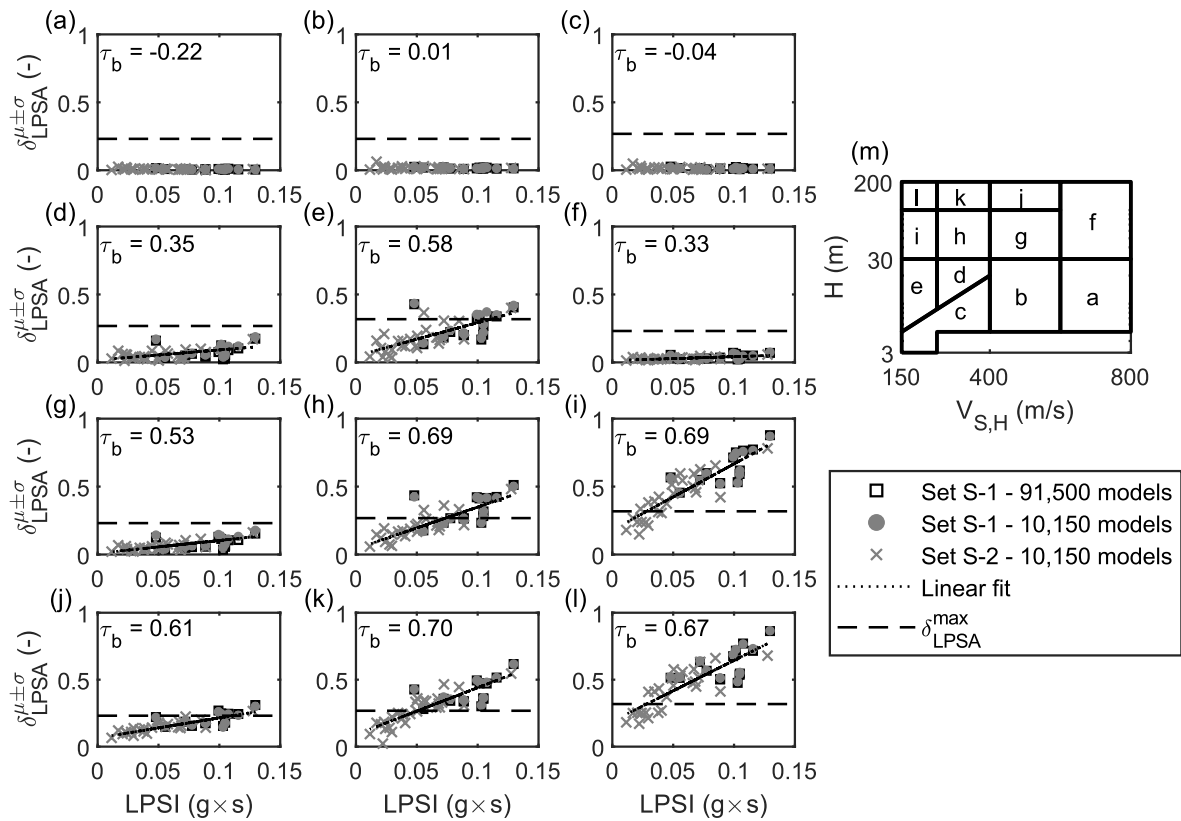
1232 smaller than 0.3. Data from the suite “S-1” of motions for the whole collection of 91,500 soil
1233 models are also displayed in (a)-(l), for comparison purposes.



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 τ_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 δ_{IPSA}^{max} to identify the
 1241 shaking level at which δ_{IPSA} becomes relevant. For panel (a), we omit the linear fit because τ_b is

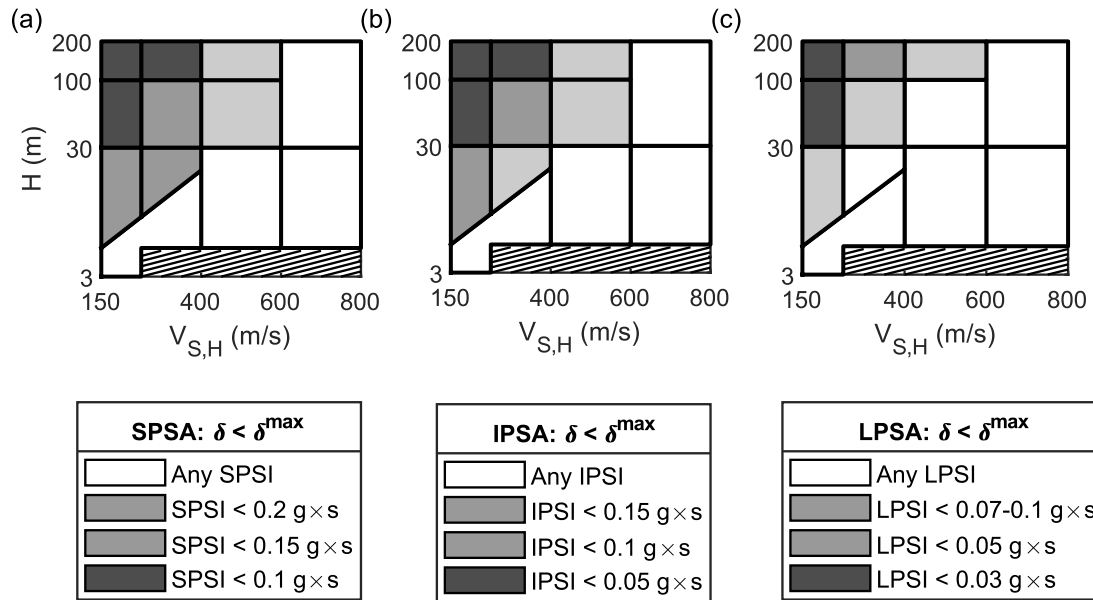
1242 smaller than 0.3. Data from the suite “S-1” of motions for the whole collection of 91,500 soil
1243 models are also displayed in (a)-(l), for comparison purposes.



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 τ_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 δ_{LPSA}^{max} to identify the shaking level at which δ_{LPSA} becomes relevant. For panels (a),

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



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

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