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9 **Abstract**

10 We explore non-linear site effects in the new Japanese ground-motion dataset
11 compiled by Bahrapouri et al. (2020). Following the approach of Seyhan and
12 Stewart (2014), we evaluate the decrease of soil amplification according to the
13 increasing and corresponding ground motion on surface rock ($V_{S30} = 760$ m/s).
14 To better predict the rock ground motion associated to each record we take
15 into account the between-event variability of the ground motion and to better
16 evaluate the impact of non-linearity we correct observed ground motion on soil
17 by the site-specific linear amplification. Instead of grouping the stations by
18 site-response proxy, we focus on individual stations with several strong-motion
19 records. We develop a framework to test recently published non-linear site-
20 amplification models against a linear site-amplification model and also compare
21 the results to recent building codes where non-linearity is included. The results
22 show that the site response varies greatly from site to site, indicating that
23 conventional site proxies, like V_{S30} , are not sufficient to characterise non-linear
24 site response. Out of all the KiK-net stations, twenty stations are selected as
25 having recorded sufficient data to be used in the test. Out of these twenty
26 stations, five stations show signs of non-linearity, that is, the non-linear models
27 performed better than the linear-amplification model for all periods T . For
28 most sites, however, the linear site-amplification models get the best score.
29 This suggest that, for the range of predicted rock motion considered in this
30 study ($PGA < 0.2$ g), non-linearity may not have a sufficiently large impact on
31 soil ground motion to justify the use of non-linear site terms in ground-motion
32 functional forms and seismic building codes for such moderate-level shaking.

33 **Introduction**

34 Near-surface variations in the soil column have a strong effect on the input
35 ground motions generated by earthquakes. The modulations of seismic ground
36 motions by soil properties at a site are generally referred to as site effects. A

37 weak ground motion stimulates only the linear response of the stiff soil column,
38 i. e. the site-specific amplification is constant for any ground-motion intensity.
39 However, for large ground motions and mostly for sites with soft soils, 1-D nu-
40 merical simulations and several observations suggest that the site-specific ampli-
41 fication should decrease with increasing intensity of predicted ground motions
42 for rock conditions (non-reference site method, Bonilla et al., 2005; Stewart
43 et al., 2003; Field et al., 1997). Non-linear site effects have been shown to
44 produce a shift of shear-wave energy towards frequencies lower than the fun-
45 damental resonance frequency of the soil column, accompanied by a relative
46 decrease in amplification at high frequencies (Bonilla et al., 2005; Régnier et al.,
47 2013; Guéguen et al., 2019).

48 Including non-linear site effects in ground-motion prediction models (GMMs)
49 is a challenge. Observations related to non-linearity usually concern particular
50 stations and earthquakes for which strong accelerations have been observed
51 and most physics-based simulations of non-linearity have been developed to
52 reproduce in a deterministic way these observations.

53 GMMs are designed to predict the probability of reaching a level (intensity)
54 of ground motion given the earthquake-source properties (e. g. magnitude), the
55 wave-propagation path (e. g. epicentral distance) and a simplified description of
56 the geotechnical properties at the receiving site (site-response proxy).

57 GMMs need to predict the soil amplification associated to a reference “rock”
58 ground motion at the surface. Such reference rock condition (usually defined
59 by the time-averaged shear-wave velocity in the top 30 m of a 1-D soil column,
60 $V_{S30} = 760$ m/s) is different from the borehole “hard”-rock conditions. A key
61 challenge is to associate each observed soil record to its corresponding reference
62 “rock” motion at the surface.

63 Calibration of such models therefore requires a large number of observations
64 over the entire range of distances, magnitudes and acceleration levels. Such large
65 datasets have not been available until now and recent ground-motion models
66 which have provisioned a non-linear site-amplification component (e.g. Boore
67 et al., 2014; Abrahamson et al., 2014; Chiou and Youngs, 2014) are derived re-

68 lying partly or fully on simulated data. One example is from Seyhan and Stewart
69 art (2014), who developed a semi-empirical non-linear site-amplification model
70 (SS14 from here on) relying both on empirical observations in the ground-motion
71 database NGA-West2 (Next Generation Attenuation Relationships for Western
72 US, Ancheta et al., 2014) created by the Pacific Earthquake Engineering Re-
73 search Center (PEER) and numerically simulated data by Kamai et al. (2014).
74 Seyhan and Stewart (2014) analyzed non-linear site effects and calibrated the
75 SS14 model by quantifying non-linearity as the gradient of decreasing site am-
76 plification with increasing predicted peak acceleration on rock.

77 Non-linear simulations, following the equivalent-linear approach, compen-
78 sate for the lack of data, but may however create some unintentional biases.
79 For example, the response of sedimentary basins to strong seismic motions are
80 often based on linear, elastic solutions incorporating frequency-independent ma-
81 terial properties. It has been shown (e.g. Kausel and Assimaki, 2002) that this
82 procedure may attenuate excessively the high-frequency components of motion
83 in the waves propagating through the medium.

84 Fully non-linear (time-domain) site-response approaches have become in-
85 creasingly popular in the recent years. However, several studies (e.g. Zalachoris
86 and Rathje, 2015; Shi and Assimaki, 2017; Kaklamanos and Bradley, 2018) have
87 shown that even fully non-linear 1D site response calculations do not fully cap-
88 ture the response at sites in the Kiban-Kyoshin network in Japan (KiK-net,
89 Okada et al., 2004).

90 These considerations motivate the testing of the non-linear amplification
91 models developed in the last years. We use the recent ground-motion dataset
92 compiled by Bahrapouri et al. (2020)(BEA20 from here on), which consists of
93 ground-motion data from earthquakes recorded by the KiK-net network between
94 1997 and 2017.

95 Although site amplifications in Japan have been widely studied (e.g. Zhao
96 et al., 2015; Stafford et al., 2017; Derras et al., 2017; Sandikkaya, 2019), the
97 large BEA20 dataset offers new opportunities to explore site effects using well-
98 recorded events and stations.

99 Using this new dataset, we build upon the approach of Seyhan and Stewart
100 (2014) to explore the empirical evidence of non-linearity and test non-linear
101 amplification models. Taking advantage of new techniques to quantify the event
102 and site specifics in ground-motion models (e.g. Stafford, 2014; Kotha et al.,
103 2018), we propose a few relevant changes to the approach to better estimate the
104 non-linearity:

- 105 1. We modify the predicted rock-motion level (peak ground acceleration on
106 rock) by taking into account the variability specific to each event, that is,
107 the systematic deviation of ground-motion recordings from a single event
108 with respect to the predicted GMM median. Considering that earthquakes
109 of the same magnitude can trigger very different levels of ground motions
110 (Bindi et al., 2018, 2019), this modification better approximates the pre-
111 dicted ground motion on rock by including the effects specific to each
112 earthquake (the event specific variability). This has also been done by
113 Chiou and Youngs (2014) and Sandikkaya and Dinsever (2018).
- 114 2. To better investigate the non-linear site effects, we develop a ground-
115 motion model taking into account the linear site amplification. For each
116 observation, we then compute the difference between the observed and
117 predicted linear ground motion. Sites with linear behavior will show resid-
118 uals equal to zero for the full range of predicted rock PGA (peak ground
119 acceleration).
- 120 3. While the gradient of SS14 is calibrated by mixing data from several sites
121 with similar V_{S30} , we are able to investigate individual KiK-net sites that
122 have recorded a high number of ground-motion records of earthquakes that
123 likely have triggered non-linear soil responses. This follows the general
124 understanding that linear and non-linear soil responses are rather site-
125 specific, and poorly captured by V_{S30} alone (Derras et al., 2016; Thompson
126 and Wald, 2016).

127 An additional goal of this paper is to develop a new GMM testing frame-

128 work. We follow the vision of the Collaboratory for the Study of Earthquake
129 Predictability (CSEP) which has developed transparent and reproducible tests
130 of seismicity models with community-agreed testing methods, procedures and
131 protocols, and has improved investigation on the quality of the model input data
132 (Schorlemmer et al., 2018). For ground-motion models, although a large uncer-
133 tainty in seismic-hazard assessment, testing procedures are still under develop-
134 ment (Mak et al., 2017). Nevertheless, with upcoming new and large ground-
135 motion observation datasets (e.g. BEA20, ESM dataset by Lanzano et al., 2019),
136 the testing of ground-motion models can be addressed with new approaches.
137 We build a testing procedure which allows a regular and reproducible update
138 of the test to evaluate if the non-linear site effects predicted by existing site-
139 amplification models are supported by high-quality empirical data. In addition
140 to the SS14 site-amplification model, we test the non-linear site-amplification
141 models of Abrahamson et al. (2014), Hashash et al. (2020) and Sandikkaya et al.
142 (2013). These models are tested against a linear site amplification model.

143 Non-linear site response is also relevant to seismic building codes; examples
144 are the NEHRP 2015 provisions for the US (Building Seismic Safety Council
145 (BSSC), 2015), where site-response adjustment factors are based on SS14, and
146 the German building code (German National Annex to Eurocode 8, Grünthal
147 et al., 2018; Schwarz et al., 2017). The predicted rock ground motions in this
148 study are in the same range as predictions for moderate seismic-hazard coun-
149 tries, hence we finally compare our results with the non-linear site amplifications
150 proposed by the building codes of NEHRP and the German National Annex to
151 Eurocode8.

152 **Dataset and data selection criteria**

153 We use ground-motion records from the Japanese Kiban-Kyoshin network (KiK-
154 net, Okada et al., 2004) compiled into the BEA20 dataset by Bahrapouri et al.
155 (2020). This dataset, which is the updated version of the Dawood et al. (2016)
156 dataset, contains all KiK-net ground-motion record of earthquakes of magni-

157 tude $M_W \geq 3$ between 1997 and 2017, which includes large events triggering
158 non-linear soil response like the Kumamoto sequence in 2016. Compared to Da-
159 wood et al. (2016), who used earthquakes of magnitudes $M_W \geq 4$ recorded until
160 2011, the number of records consequently increases from 147,282 to 351,658.
161 Each ground-motion record in BEA20 is the outcome of an automatic process-
162 ing protocol including filtering, baseline correction, and calculation of intensity
163 measures (Bahrapouri et al., 2020). BEA20 provides a comprehensive event-
164 and site-catalogue and several intensity measures, including spectral acceler-
165 ations and Fourier amplitudes for both surface and borehole recordings. In
166 this study, we focus on the spectral accelerations recorded at the surface. We
167 selected a subset of the data using the following data selection criteria:

- 168 – For each record, there is an associated usable frequency bandwidth which
169 limits the data we can use at period T . Because the usable frequency
170 bandwidth is derived in the automatic processing, Bahrapouri et al.
171 (2020) recommend only using records that qualify the $T \leq 1/(1.25f_{\text{low}})$
172 criteria in regression and residual analyzes at period T , where f_{low} is the
173 low-pass cut-off corner frequency.
- 174 – Following the recommendation of Bahrapouri et al. (2020), we only use
175 ground-motion records for which the usable frequency bandwidth is more
176 than 60% of the range from zero to the Nyquist frequency. In addition, we
177 omit ground-motion records that are flagged as having multiple wave-train
178 arrivals.
- 179 – We only use events with depth ≤ 35 km, recorded at $R_{\text{JB}} < 600$ km. We
180 also omit all offshore events and events whose closest recording is farther
181 than $R_{\text{JB}} = 80$ km. This is to avoid biasing the GMM median with wave
182 propagation in oceanic crust and from possible interface events.
- 183 – We remove all events and stations with three or fewer recordings after
184 all selection criteria are applied to ensure that the event- and site-term is
185 derived on more than one record.

186 An overview of the selected stations is shown in Figure 1 and a map of Japan
187 with the selected stations and events is given in Figure S1 in the Supplementary
188 Material. The BEA20 dataset in comparison with the dataset of Dawood et al.
189 (2016) and the NGA-West2 database are shown in Figure S2 in the Supple-
190 mentary Material. BEA20 contains several well-recorded events and stations
191 with many records (Figure 1b), including records in the range of non-linear soil
192 behavior (Figure 1e); we therefore consider this dataset as an opportunity to
193 investigate empirical site properties.

194 To evaluate the effects of the data selection criteria and to ensure that the
195 final result does not depend on the assumptions made, we conduct a sensitivity
196 test, described in the Result section.

197 **Non-linear models**

198 In this study, we test the non-linear component of four different site-amplification
199 models. In addition to the aforementioned SS14, we test the amplification mod-
200 els by Sandikkaya et al. (2013) and Hashash et al. (2020), named SAB13 and
201 H20 respectively, and the site-amplification model in the GMM of Abrahamson
202 et al. (2014) (ASK14).

203 SS14 was developed based on empirical observations from the NGA-West2
204 database, appended with data from the 1-D numerical simulations of Kamai
205 et al. (2014). SS14 consists of two additive components; a linear and a non-linear
206 site term, and was developed for the GMM of Boore et al. (2014) (BSSA14).
207 The site-amplification model of the ASK14 GMM was derived as a specific
208 component of their GMM and also based on simulations of Kamai et al. (2014).
209 SAB13 is based entirely on empirical data from the SHARE (Seismic Hazard
210 HARmonization in Europe, Yenier et al., 2010) database and developed for pan-
211 European GMMs. H20 was developed for central and eastern North America
212 using 1-D site-response simulations from Harmon et al. (2019). These site-
213 amplification models are all functions of V_{S30} and peak ground acceleration on
214 rock (PGA_{rock}). An overview of the models is provided in Table 1.

215 Method

216 Evaluation of the Seyhan and Stewart (2014) approach using 217 the new dataset

218 Seyhan and Stewart (2014) analyzed non-linearity in the NGA-West2 dataset
219 and calibrated their amplification model by parameterizing non-linear site am-
220 plification as the declining trend of ground-motion record-specific (within-event)
221 residuals with increasing level of predicted ground motion for rock conditions.
222 As a first step of our analysis, we repeat the same procedure as Seyhan and
223 Stewart (2014) on the BEA20 dataset to evaluate how the site amplification
224 depends on the predicted rock ground motion.

225 In a typical engineering ground-motion dataset, each ground-motion obser-
226 vation of an event e at a recording site s is associated with the event’s moment
227 magnitude, M_W , the Joyner-Boore distance of the event from the recording
228 site, R_{JB} , and the time-averaged shear-wave velocity of the top 30 m of the
229 soil column at the recording site, V_{S30} . The ground motions are represented as
230 period-depended spectral accelerations for periods T , $SA(T)$, where the peak
231 ground acceleration (PGA) is at $T = 0$ s.

232 First, for each selected record in BEA20, we use BSSA14 to predict ground
233 motions for the record’s specific M_W , R_{JB} and V_{S30} . We obtain the predicted
234 ground motion on rock by setting $V_{S30} = 760$ m/s, representing the V_{S30} at rock
235 sites.

236 In a second step, and following Seyhan and Stewart (2014), we analyze
237 the residuals between the observation $Y_{e,s}$ and the prediction on rock $\mu_{e,s}$ for
238 an event e at a site s to quantify the amplification due to site effects. We
239 subtract the rock prediction from the corresponding observation to obtain the
240 total residual $\epsilon_{e,s}$:

$$\epsilon_{e,s} = \ln Y_{e,s} - \ln \mu_{e,s} \quad (1)$$

241 The total residual $\epsilon_{e,s}$ is split using the mixed-effects regression algorithm of

242 Bates et al. (2015), as done by e.g. Stafford (2014); Kotha et al. (2016, 2018).
 243 A mixed-effects regression model deals with hierarchical data by including both
 244 fixed-effect and random-effect terms in the regression, where fixed-effects are the
 245 explanatory variables (for example magnitude and distance) and the random
 246 effects are the grouping factors (for example event and site) (Bates et al., 2015).
 247 Here, the random effects of the events and sites are quantified by the mixed
 248 effects regression into the event and site variability:

$$\epsilon_{e,s} = \delta B_e + \delta S2S_s + \delta WS_{e,s} \quad (2)$$

249 The event-term δB_e and site-term $\delta S2S_s$ quantify the systematic deviation
 250 of observed ground motions related to event e and site s , respectively, from the
 251 median predictions of the GMM. The “left-over” residual $\delta WS_{e,s}$ thus captures
 252 the record-to-record variability (e.g. Villani and Abrahamson, 2015; Kotha et al.,
 253 2018; Sahakian et al., 2018).

254 The within-event $\delta W_{e,s}$ residuals are then obtained by subtracting the event-
 255 term from the total residuals, following Equation 5 in Seyhan and Stewart (2014)
 256 using the notation of Al Atik et al. (2010):

$$\delta W_{e,s} = \ln Y_{e,s} - [\mu_{\text{rock},e,s} + \delta B_e] = \epsilon_{e,s} - \delta B_e \quad (3)$$

257 In the final step, we group the within-event $\delta W_{e,s}$ residuals into V_{S30} -bins
 258 and investigate non-linearity as the trend of $\delta W_{e,s}$ with respect to PGA_{rock} ,
 259 see Figure 2. In this figure, the full SS14 site-response model including both
 260 linear and non-linear site-amplification components, is compared to the trend
 261 of the within-event residuals $\delta W_{e,s}$ against PGA_{rock} . The non-parametric trend
 262 is given by the locally-weighted linear-regression fit (LOWESS), an algorithm
 263 developed by Cleveland (1979) for smoothing scatter plots using polynomial fit
 264 and weighted least squares. The residuals are calculated using BSSA14 on the
 265 BEA20 dataset. Figure 2 also shows that for BEA20, representing a dataset
 266 independent of the calibration dataset, SS14 does not quite follow the trend
 267 of the residuals. This misfit between the SS14 model and the KiK-net data,

268 especially at short periods, was also reported by Seyhan and Stewart (2014).

269 This misfit may indicate that the linear site amplification as a function
270 of V_{S30} is region dependent, as has also been discussed by e.g. Kotha et al.
271 (2016). However, Sandikkaya (2019) have shown that regional variations in site
272 amplification for Japan are likely to be insignificant. Other factors may explain
273 those differences. Indeed, it has been shown that KiK-net stations have been
274 installed at mostly stiff sites compared to K-net stations (Aoi et al., 2004; Zhu
275 et al., 2020). Network installation strategies may therefore also have an impact
276 on the dependency of amplification factors on V_{S30} .

277 These considerations motivate the computation of site-specific amplifications
278 (site term) in the next paragraph and the use of site-corrected residuals to
279 analyze the effects of non-linearity.

280 **Proposed modifications to the Seyhan and Stewart (2014)** 281 **approach**

282 To better quantify the reference ($V_{S30} = 760$ m/s) ground motion associated to
283 each observed soil record we propose modifications to the approach of Seyhan
284 and Stewart (2014). Restating the importance of between-event variability, it
285 is now well known that moment magnitudes by itself cannot fully describe the
286 complexity of earthquake rupture characteristics (e.g. Bindi et al., 2018, 2019),
287 meaning that earthquakes of the same magnitude can produce very different
288 levels of ground shaking.

289 We therefore propose to modify the Seyhan and Stewart (2014) approach by
290 taking into account this between-event variability, by including the event-term
291 δB_e in the prediction on rock. The non-linearity is then investigated in the
292 residuals with respect to $PGA_{\text{rock}} \exp(\delta B_e)$.

293 Seyhan and Stewart (2014) calibrated the linear and non-linear components
294 of their site-amplification model as a function of V_{S30} from the within-event
295 residuals. The within-event residuals, $\delta W_{e,s}$, in any V_{S30} -bin contain features
296 of both linear and non-linear site responses from several different sites. The

297 site responses of different sites can be radically different from each other, even
 298 within the same V_{S30} -bin. We therefore suspect that the assumption that all
 299 sites in a V_{S30} -bin have similar linear and non-linear site responses, may bias
 300 the calibration of non-linear amplification models.

301 We propose to remove the site-specific linear site response in terms of $\delta S2S_s$
 302 from the within-event residuals. $\delta S2S_s$ is arguably the most reliable representa-
 303 tion of empirical site response, provided it is estimated from a sufficient number
 304 of site-specific ground-motion observations (Bard et al., 2020).

305 When $\delta S2S_s$ is estimated from numerous small-magnitude events, it is safe
 306 to assume that it captures the site-specific linear soil response. Indeed, several
 307 studies (e.g. Pilz and Cotton, 2019; Thompson and Wald, 2016) have provided
 308 evidence that these terms may have also captured some of the more complex 2-
 309 D/3-D site effects at several KiK-net sites, which often evade the more prevalent
 310 numerical simulations based on simplified 1-D soil V_S - Q profile.

311 Therefore, to better investigate the non-linear site effects, we subtract the
 312 site-specific terms from the within-event residuals, leaving;

$$\delta W_{e,s} - \delta S2S_s = \epsilon_{e,s} - \delta B_e - \delta S2S_s = \delta WS_{e,s} \quad (4)$$

313 This means that, for sites experiencing only linear soil response, the $\delta WS_{e,s}$
 314 should be symmetrically distributed around zero for the full range of $PGA_{\text{rock}} \exp(\delta B_e)$.

315 Figure 3 shows the "left-over" $\delta WS_{e,s}$ residuals with respect to $PGA_{\text{rock}} \exp(\delta B_e)$
 316 grouped into V_{S30} -bins for different periods T . The residuals are calculated us-
 317 ing the BSSA14 GMM and the trend is fitted as before using the LOWESS
 318 algorithm of Cleveland (1979).

319 Instead of analysing non-linearity against within-event $\delta W_{e,s}$ residuals with
 320 respect to PGA_{rock} (as in Figure 2), we now analyze the non-linearity against
 321 the "left-over" $\delta WS_{e,s}$ residuals with respect to $PGA_{\text{rock}} \exp(\delta B_e)$ (Figure 3).
 322 Note that in Figure 3, only the non-linear site-amplification term of SS14 is
 323 plotted against the $\delta WS_{e,s}$ residuals, while the full SS14 model is shown in
 324 Figure 2.

325 Comparing the corresponding residual trends between Figure 2 and 3, we see

326 a significantly better agreement in the latter between the empirical residuals and
 327 the predictions of non-linear amplification by the SS14 model at all periods. This
 328 reasserts that both linear and non-linear site response are highly site-dependent
 329 and that V_{S30} is a poor site proxy for characterizing site amplification. With
 330 this understanding we propose that the site-specific linear site-amplification
 331 should be removed first (using $\delta S2S_s$ as done here or other techniques) before
 332 investigating the residuals for non-linear site-amplification.

333 The modifications to the Seyhan and Stewart (2014) approach described
 334 above, should be generally applied when investigating non-linearity in new
 335 datasets. Furthermore, site amplification should be analysed using individ-
 336 ual stations when possible, and stations grouped by V_{S30} should only be used
 337 when the database in study is not large enough to allow station-specific analy-
 338 sis. When grouping stations by site proxy the derived site amplification will be
 339 depended on the dataset.

340 **Development of a linear ground-motion model**

341 Due to the aforementioned challenges with V_{S30} , we develop a linear GMM
 342 using the same method and functional form as the GMM by Kotha et al. (2018)
 343 (K18 from here on). K18 was derived for the geometric mean of horizontal 5%
 344 damped pseudo-spectral acceleration (PSA):

$$\ln(\text{PSA}) = f_R(M_W, R_{JB}) + f_M(M_W) + \delta B_e + \delta S2S_s + \delta WS_{e,s} \quad (5)$$

345 Here, $f_R(M_W, R_{JB})$ is the magnitude-dependent distance scaling function,
 346 and $f_M(M_W)$ is the magnitude scaling function, which are the fixed effects
 347 capturing the scaling of PSAs with distance and magnitude. As defined above,
 348 the event-term δB_e is the between-event random effect, the site term $\delta S2S_s$
 349 is the site-to-site or site-specific random effect, and $\delta WS_{e,s}$ is the “left-over”
 350 residual capturing the record-to-record variability.

351 δB_e , $\delta S2S_s$ and $\delta WS_{e,s}$ follow period-dependent normal distributions with

352 standard deviation; τ , ϕ_{s2s} and ϕ_0 , respectively:

$$\delta B_e \sim \mathcal{N}(0, \tau), \quad (6)$$

353

$$\delta S2S_s \sim \mathcal{N}(0, \phi_{s2s}) \quad (7)$$

354 and

$$\delta WS_{e,s} \sim \mathcal{N}(0, \phi_0), \quad (8)$$

355 while the total aleatory variability is

$$\sigma = \sqrt{\tau^2 + \phi_{s2s}^2 + \phi_0^2}. \quad (9)$$

356 The distance and magnitude scaling of ground-motion observations is cap-
 357 tured using mixed-effects regression (Bates et al., 2015) in multiple steps (see
 358 Kotha et al. (2018) for a step-by-step description). Unlike other contemporary
 359 models, K18 does not feature a fixed-effect site response based on V_{S30} . Instead,
 360 the $\delta S2S_s$ captures all site-specific response and can be used as an empirical site-
 361 amplification function (Kotha et al., 2018).

362 Because the GMM is derived without any V_{S30} term, the predicted ground
 363 motion, PGA, is not specific to any site conditions. The predicted ground mo-
 364 tion for rock conditions, PGA_{rock} , is therefore derived using a rock-adjustment
 365 term, α_{rock} , which is the mean $\delta S2S_s$ for all sites with $V_{S30} > 760$ m/s (Kotha
 366 et al., 2018). The rock-adjustment term, α_{rock} , is added to the predicted
 367 ground motion, PGA, to obtain the predicted ground motion for rock condi-
 368 tions, PGA_{rock} :

$$PGA_{\text{rock}} = PGA + \alpha_{\text{rock}} \quad (10)$$

369 Whereas K18 is derived for the dataset by Dawood et al. (2016), we derive
 370 the new GMM from the updated BEA20 dataset while using the same method
 371 and functional form as K18. We mainly follow the same data selection criteria
 372 as used for K18 (see Dataset and data selection criteria section), but we adopt
 373 an additional criterion to omit records that might have triggered non-linear soil
 374 response at certain sites. This means that we omit all records with $PGA_{\text{rock}} >$
 375 0.05 g from stations with $V_{S30} < 760$ m/s (Guéguen et al., 2019; Régnier et al.,

2013), and use the records that contain only linear soil response to derive the
GMM. This is to avoid biasing the GMM median predictions and the estimates
of the $\delta S2S_s$ with non-linear soil response, making it a linear GMM.

The earlier omitted data, which was not used in GMM regression (from
stations with $V_{S30} < 760$ m/s with $PGA_{\text{rock}} > 0.05$ g), will then be included
in the dataset used to investigate non-linearity and to test the non-linear site-
amplification models.

The residuals used to analyse non-linearity is derived in two steps; first the
linear GMM is developed on the linear dataset, then the linear GMM is used
to derive the residuals for the testing. The latter step is done on the entire
selected dataset, including the previously omitted data with potential to trigger
non-linear soil response at stations with low V_{S30} . The residuals derived during
the two processes are given in Figure S2 and S3 in the Supplementary Material.

To evaluate how well the linear GMM is developed, we analyse the distribu-
tions of δB_e with respect to magnitude, $\delta S2S_s$ with respect to V_{S30} , and $\delta WS_{e,s}$
with respect to distance (Figure S2). Both δB_e and $\delta WS_{e,s}$ have a mean consis-
tently close to zero and no clear trend with magnitude and distance, respectively.
This confirms that the fixed effects components of the GMM regression has cap-
tured the scaling of magnitude and distance (Equation 5). $\delta S2S_s$, however, have
a downwards trend with V_{S30} . This is to be expected as we did not include a
 V_{S30} site-term in the fixed effects (Kotha et al., 2018).

To ensure that δB_e and $\delta S2S_s$ appropriately quantify the event and site
variability, they are only derived from events and stations with more than three
records. This is applied both when deriving the linear GMM and when deriving
the residuals for the non-linear site-amplification analysis and testing.

When the GMM only predicts the linear ground motion, we can use the cor-
responding site-term $\delta S2S_s$ to correct for linear site response. The final $\delta WS_{e,s}$
derived on the entire selected dataset will, by assumption, then contain any
non-linear site effect. Figure 4 shows the differences between the response spec-
tra and total aleatory variability σ of the original K18 GMM and the updated
GMM derived here. The main differences between the GMMs, particularly in σ ,

407 are likely caused by the different magnitude ranges available in the two different
408 datasets used to derive the models. The BEA20 database contains earthquakes
409 of magnitude $M_W \geq 3$, while Dawood et al. (2016) only included earthquakes
410 of magnitudes $M_W \geq 4$.

411 **Testing of non-linear models**

412 We built a procedure to test the predictions of non-linear site-amplification
413 models given in Table 1 against residuals derived using the dataset and the
414 linear GMM described in the previous sections.

415 Testing is largely a missing part of ground-motion modelling. The Collabora-
416 tory for the Study of Earthquake Predictability (CSEP) has developed advanced
417 testing of seismicity models with community-agreed testing methods (Schorlem-
418 mer et al., 2018). The strategy of CSEP is to set an international standard for
419 testing of earthquake forecasts and seismic hazard models. Tests within CSEP
420 need to be transparent, reproducible and prospective, that is, tested against
421 future observations. For earthquake forecast models, CSEP has long been de-
422 veloping and performed robust testing experiments (e.g. Schorlemmer et al.,
423 2010; Zechar et al., 2013; Tsuruoka et al., 2012; Taroni et al., 2018). A future
424 goal of CSEP is to develop testing procedures for GMMs and seismic hazard
425 models. Although testing of ground-motion models exists (e.g. Delavaud et al.,
426 2009; Mak et al., 2017; Lanzano et al., 2020), testing procedures and testable
427 models are still in development. Ground-motion models with non-linear site
428 terms have previously been tested by Guéguen et al. (2019) using strain as a
429 proxy of non-linear soil response. Here we test the non-linear components of
430 site-amplification models against the "left-over" residuals $\delta WS_{e,s}$.

431 As described in the previous sections and by Seyhan and Stewart (2014), the
432 residual, here $\delta WS_{e,s}$, is assumed to contain the non-linear site response. The
433 trend of $\delta WS_{e,s}$ with respect to $PGA_{\text{rock}} \exp(\delta B_e)$ (prediction on rock including
434 event variability) can then be directly compared to non-linear site-amplification
435 models. This is demonstrated in Figures 5, 6 and 7, where the non-linear site-

436 amplification models are plotted with $\delta WS_{e,s}$ against $PGA_{\text{rock}} \exp(\delta B_e)$. We
 437 test the non-linear site-amplification models against a linear site-amplification
 438 model where the mean of $\delta WS_{e,s} = 0$ for every value of $PGA_{\text{rock}} \exp(\delta B_e)$.
 439 The prediction power of the amplification models is evaluated as the deviation
 440 between the residuals and the amplification curves measured in mean absolute
 441 error (MAE).

442 The MAE is a much used non-parametric score and chosen here for its sim-
 443 plicity. The score MAE_s is calculated for each site s :

$$MAE_s = \frac{\sum_e^N |\delta WS_{e,s} - F_{e,s}|}{N}, \quad (11)$$

444 where N is the number of events e recorded at site s , $\delta WS_{e,s}$ is, as defined
 445 above, the "left-over" residuals assumed to contain the site-response and $F_{e,s}$ is
 446 the modelled site-amplification.

447 It is important to note that the MAE score only measures the deviation be-
 448 tween the residuals and the predictions of the amplification models, and there-
 449 fore does not have a direct physical meaning. The model with the best score
 450 is thus only best in a relative sense that the model with the lowest score has
 451 a smaller deviation from the residuals than a model with a higher score (Mak
 452 et al., 2015).

453 Because non-linear site effects are mainly expected, and modelled, for low
 454 V_{S30} and strong ground motions, we perform the test on a subset of stations
 455 with $V_{S30} < 500$ m/s and more than four records at predicted $PGA_{\text{rock}} > 0.05$ g.
 456 For the same reason, we only calculate the MAE score for ground-motions with
 457 $PGA_{\text{rock}} > 0.05$ g. The MAE scores of each amplification model at each of the
 458 selected stations are given in Tables 2 and S2. For each station, the model with
 459 the lowest score is evaluated as fitting the residuals best and is highlighted in
 460 bold.

461 Results

462 Following the derivation of the linear GMM, we apply the modified SS14 ap-
463 proach described in the previous sections to the selected dataset, including
464 records from soft-soil sites with $\text{PGA}_{\text{rock}} > 0.05 \text{ g}$. We then use the resid-
465 uals to test the non-linear component of the site-amplification models SS14,
466 ASK14, SAB13 and H20. The test is performed for a subset of stations with
467 $V_{\text{S30}} < 500 \text{ m/s}$ and more than four records at predicted $\text{PGA}_{\text{rock}} > 0.05 \text{ g}$.

468 Figure 5 shows how the non-linear amplification curves compare with the
469 residuals for stations grouped by V_{S30} . Figures 6 and 7 show how the non-linear
470 amplification curves compare with the residuals for individual stations. The
471 decreasing amplification that is predicted by non-linear models is not emerging
472 visually from the observed variability of amplifications when the stations are
473 grouped according to V_{S30} (Figure 5) or when the stations with the largest
474 number of high-acceleration records are selected (Figure 6).

475 Out of the 338 KiK-net stations with $V_{\text{S30}} < 760 \text{ m/s}$ and strong-motion
476 records at $\text{PGA}_{\text{rock}} > 0.05 \text{ g}$ in the BEA20 dataset, twenty stations have recorded
477 sufficient data to be selected for the testing exercise, that is, with more than four
478 records at predicted $\text{PGA}_{\text{rock}} > 0.05 \text{ g}$. The data distribution of these stations
479 is given in Figures S4 and S5 in the Supplementary Material. The scores of the
480 models for each of the stations at $T = 0.01 \text{ s}$ are given in Table 2, scores for all
481 periods are given in Table S2 in the Supplementary Material. The amplification
482 model that scores best for each station, that is the model with the lowest score,
483 is highlighted in the tables.

484 Out of the 20 stations and the 4 periods used in the test, a non-linear ampli-
485 fication model has the lowest score 27 out of 80 times. Out of these, 5 stations
486 have a non-linear model with the lowest score consistently for all periods T .
487 These five stations, IBRH12, FKSH12, ISKH04, NARH01 and YMNH14, are
488 shown on Figure 7.

489 However, none of the non-linear amplification models stand out with a bet-
490 ter score significantly more times than the others or consistently for all periods.

491 The non-linear amplification models are therefore from here on mainly consid-
 492 ered in comparison with the linear amplification model, and not with each other.
 493 Indeed, for most stations the linear amplification model gets the best score for
 494 the majority of the periods. That is, for 66.25% of the station-period combina-
 495 tions, the linear amplification model has the lowest score and therefore the best
 496 performance.

497 To ensure that the result does not depend on the data selection or assump-
 498 tions made when deriving the linear GMM and residuals, we conduct a sensi-
 499 tivity test. The assumptions we have considered in the sensitivity test are:

- 500 – Only events with depth ≤ 35 km, recorded at $R_{JB} < 600$ km are used.
- 501 – All events and stations with three or less recordings are removed after all
 502 selection criteria are applied.
- 503 – Non-linear soil behavior is only expected at $PGA_{rock} > 0.05$ g
 - 504 – Applied as cutoff for the dataset used to develop the linear GMM.
 - 505 – Used as criteria for the subset of stations the test is performed on.
 - 506 – Used as cutoff for the residuals the amplification models are tested
 507 on.
- 508 – The test is performed on a subset of stations with $V_{S30} < 500$ m/s where
 509 non-linear soil behavior is mainly expected.
- 510 – The subset of stations the test is performed on has at least four records
 511 at $PGA_{rock} > 0.05$ g.

512 We conduct the sensitivity test by varying these variables as described in
 513 Table 3, and evaluate how the ratio R of the number $N_{model,s,T}$ of stations s
 514 and periods T where each amplification model scores best, to the total number
 515 of stations and periods $N_{s,T}$:

$$R = \frac{N_{model,s,T}}{N_{s,T}} \quad (12)$$

516 Figure 8 shows the result of the sensitivity test. The ratio R is stable with
517 depth, distance and minimum number of records used to derive the residuals.
518 The most unstable assumption appears to be the threshold for expected non-
519 linear soil behavior (Figure 8a, e and g). For the linear amplification model,
520 the ratio of station-period pairs with the lowest score, stays between 0.6 and
521 0.8 using most criteria, but pass 0.8 when using $\text{PGA}_{\text{rock}} > 0.01 \text{ g}$ as the non-
522 linear range when deriving the linear GMM (Figure 8a). This is likely because
523 more records with linear behavior are included in the test, giving the linear
524 amplification model an advantage. However, increasing this threshold does not
525 necessarily give the non-linear amplification models a higher ratio (Figure 8e
526 and g), but rather decrease the number of stations used in the test. This is also
527 the case when increasing the minimum number of records at $\text{PGA}_{\text{rock}} > 0.05 \text{ g}$
528 when selecting stations for the test. These results are also supported by Figure
529 S7 in the Supplementary Material.

530 In addition to varying the variables, we evaluate how the result depends
531 on the different events by resampling the events randomly (bootstrapping), al-
532 lowing one event to occur several times. This bootstrapping is performed 1000
533 times. The bootstrapping shows that the result has a larger variability when
534 varying the events used for the test, with the linear amplification model having
535 a larger variability of the ratio than the non-linear amplification models. This
536 dependency of events is expected considering there is only a small number of
537 events and records in the range where non-linear soil behavior is expected. The
538 ratio R for each bootstrapping set is shown in Figure S8 in the Supplementary
539 Material.

540 Although the sensitivity test and bootstrapping show that the result is gen-
541 erally stable, more stations are still needed to provide a ranking of the am-
542 plification models based on this test. However, the analysis shows that the
543 complex models generally do not fit the data better than a simple linear model
544 and that the result is stable with the different assumptions made during the
545 data selection and in the test. Furthermore, the decrease in amplification trend
546 predicted by the non-linear amplification models is not observed in the range

547 of ground motions considered here. All the tests are easily reproducible with
548 larger datasets.

549 Discussion

550 The main limitations of the test and our analysis of non-linear site effects in
551 general, is the limited number of strong-motion records in the non-linear site-
552 amplification range. Even with the new large BEA20 database, only 338 stations
553 with $V_{S30} < 760$ m/s are associated to rock peak ground acceleration larger than
554 0.05 g and only 20 stations have recorded a sufficient number of records (more
555 than 4) in the range used in the test. Lack of data is, however, an universal issue
556 and similar studies therefore mix stations with similar site proxies to obtain
557 sufficient records to investigate non-linearity (e.g. Seyhan and Stewart, 2014;
558 Guéguen et al., 2019). To improve this study, we plan the inclusion of K-net
559 stations from the same network of KiK-net, where a high number of records
560 with non-linearity have been reported (Chandra et al., 2016). Such a work is
561 ongoing, but however beyond the scope of the present study (development of a
562 transparent testing framework) because of the large amount of work needed to
563 collect and homogeneously process K-net data.

564 Five stations show signs of non-linear soil behavior in that a non-linear
565 amplification model had the best score at all periods T . These five stations
566 all have a relatively high V_{S30} (> 300 m/s) considering that non-linearity is
567 mainly predicted for low V_{S30} . Figure 7 shows that the non-linear amplification
568 models do not predict a strong decrease in amplification for this level of V_{S30} .
569 However, non-linear amplification can occur for sites with high V_{S30} when a
570 high-velocity layer is covered by a shallow low-velocity layer, causing a high
571 impedance contrast (Bonilla et al., 2011). This is in particularly relevant for
572 KiK-net stations, which are mainly installed at stiff sites, either on weathered
573 rock or on thin sediment layers (Aoi et al., 2004).

574 Along with the high variability of observed site response between the differ-
575 ent stations, this suggests that the site proxy V_{S30} is not suitable for charac-

576 terising non-linear site response. The site response of the five stations where a
577 non-linear amplification model had the best score, should therefore be investi-
578 gated further in future studies using alternative site proxies.

579 The dataset used in this study, despite its limitations, samples the range
580 of rock ground motions which are considered in the seismic building codes of
581 moderate seismic-hazard countries. Figure 9 shows that the ground motions on
582 rock (PGA with a 475-year return period) taken into account by the French and
583 German seismic hazard maps (Drouet et al., 2020; Grünthal et al., 2018) are
584 fully consistent with the rock motions explored in this study ($\text{PGA} < 0.2 \text{ g}$).

585 Recent building codes take non-linear site-amplification into account. Two
586 examples are the NEHRP 2015 provisions for the US (Building Seismic Safety
587 Council (BSSC), 2015) where the site-amplification factors were derived from
588 the site-amplification model SS14. Another example is the German seismic
589 building code, where a decrease in amplification is predicted for soft soil at
590 $\text{PGA} > 0.1 \text{ g}$ according to 1D non-linear simulations (Schwarz et al., 2017).

591 In Figure 10, we compare the site-amplification observed in our data with
592 the non-linear site-amplifications proposed by the building codes of NEHRP
593 and the EC8 German national annex. The variability of the observed response
594 and the lack of obvious decrease of the observed amplification with increasing
595 rock ground-motion trend, show that the data analysis does not yet confirm
596 the need to take into account non-linear site effects for such moderate levels
597 of ground motions on rock. For moderate seismicity areas and $\text{PGA} < 0.2 \text{ g}$
598 the consideration of soil non-linearity to decrease amplification factors is then
599 motivated by the results of non-linear site-response modelling or expert opinions,
600 but is not confirmed yet by the statistical analysis of ground-motion data as
601 done in this study. Here, the results show a high variability of responses and no
602 evidence of a systematic decrease of soil amplification.

603 We also note that the models and building codes discussed in this testing
604 exercise all represent ground motions in the response spectra domain. However,
605 as discussed by e.g. Bayless and Abrahamson (2019) and Bora et al. (2016),
606 the response spectra represents a response of a simple structure to the input

607 ground motion and not directly the ground motion itself. Hence, there are some
608 limitations to using response spectra when analyzing the physical properties of
609 the ground motions, for example non-linear site response. Fourier spectra may
610 therefore be a better option to analyze the physical factors controlling non-
611 linearity, and the development and testing of amplification factors should in the
612 future preferably be done in the Fourier domain.

613 **Conclusion**

614 In this study, we developed a transparent and reproducible framework to analyze
615 non-linearity and test non-linear amplification models using residuals between
616 ground-motion predictions and observations. We have applied this new frame-
617 work on a new large dataset by Bahrapouri et al. (2020), building on the
618 method of Seyhan and Stewart (2014). We estimate the reference (surface PGA
619 at $V_{S30} = 760$ m/s) rock motions that excites the soil column by taking into
620 account the event-specific rock acceleration. The analysis is performed on indi-
621 vidual stations with high number of strong-motion records, and thus avoiding
622 mixing site responses of different sites. In order to reduce the bias of linear site
623 amplification on calibration of non-linearity, we remove the linear site amplifi-
624 cation using the site-specific terms of each station.

625 Most published site-amplification models predict a decrease of ground mo-
626 tion due to non-linear site effects for soft soils at accelerations above 0.05 g.
627 However, the actual soil data analyzed in this study do not confirm such a de-
628 crease, at least in the non-linear range $0.05 \text{ g} < \text{PGA} < 0.2 \text{ g}$. The variability of
629 observed amplifications remains large for such level of shaking and no systematic
630 decrease of ground motions is observed. The testing procedure we developed
631 shows that out of the twenty stations selected as having a sufficient number of
632 records to be used in the test, only five stations exhibit signs of non-linearity
633 at all periods. For most sites, however, the non-linear site-amplification mod-
634 els do not fit better with the observations than the linear amplification model.
635 This does not mean that rheological non-linearities do not exist at that level of

636 ground motion, but rather that for the level of predicted rock ground motions
637 considered in this dataset, non-linearity is not significant enough to show a large
638 impact on soil ground motions and justify the use of non-linear site terms in
639 ground-motion functional forms and seismic building codes. Our results also
640 show a large site-to-site variability which indicates that V_{S30} might not be the
641 best site proxy to quantify linear and non-linear site-amplification models.

642 **Data and Resources**

643 The main dataset used was compiled by Bahrampouri et al. (2020) and down-
644 loaded from the DesignSafe repository: <https://doi.org/10.17603/ds2-e0ts-c070>
645 (last accessed September 2020). The mixed-effects regressions were performed
646 using the LMER algorithm in the statistical software R:
647 <https://cran.r-project.org/web/packages/lme4/> (last accessed October 2020).
648 An electronic Supplemental Material with tables and figures mainly comple-
649 menting the data selection and tests conducted in the study, is available.

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886 **Tables**

Table 1: Overview of the non-linear site-amplification models which will be tested in this study.

Non-linear model	ID	Dataset	Data type	Simulated data
Seyhan and Stewart (2014)	SS14	NGA - West2*	Semi-empirical	Kamai et al. (2014)
Abrahamson et al. (2014)	ASK14	NGA - West2	Simulations	Kamai et al. (2014)
Sandikkaya et al. (2013)	SAB13	SHARE SM Databank [†]	Empirical	
Hashash et al. (2020)	H20	NGA-East [‡]	Simulations	Harmon et al. (2019)

* Next-Generation Attenuation Relationships for Western US

† Seismic Hazard HARmonization in Europe

‡ Next Generation Attenuation Relationships for Central and Eastern North-America

Table 2: The mean absolute error (MAE) score of the amplification models with the "left-over" residuals $\delta WS_{e,s}$ for each station at the period $T = 0.01$ s. The lowest score for each station-period pair is highlighted in bold.

Stations	Linear	SS14	ASK14	H20	SAB13	Best-scoring model
CHBH14	0.435	0.466	0.452	0.443	0.488	Linear
FKSH12	0.164	0.152	0.151	0.148	0.152	H20
FKSH14	0.486	0.475	0.466	0.467	0.488	ASK14
FKSH21	0.426	0.508	0.497	0.497	0.501	Linear
IBRH12	0.484	0.469	0.468	0.462	0.470	H20
IBRH13	0.359	0.390	0.385	0.380	0.388	Linear
ISKH04	0.434	0.428	0.426	0.426	0.427	ASK14
KMMH14	0.263	0.344	0.330	0.286	0.354	Linear
KMMH16	0.727	0.798	0.804	0.774	0.799	Linear
NARH01	0.745	0.658	0.674	0.679	0.665	SS14
NGNH18	0.624	0.694	0.686	0.688	0.687	Linear
NGNH29	0.884	0.918	0.914	0.928	0.912	Linear
NIGH06	0.370	0.400	0.394	0.392	0.398	Linear
NIGH09	0.384	0.414	0.412	0.424	0.410	Linear
NIGH11	0.699	0.791	0.789	0.785	0.787	Linear
NIGH13	0.702	0.720	0.717	0.725	0.717	Linear
SMNH01	0.389	0.410	0.412	0.418	0.409	Linear
SZOH35	0.469	0.626	0.612	0.501	0.712	Linear
TTRH07	0.202	0.263	0.269	0.265	0.263	Linear
YMNH14	0.536	0.499	0.501	0.506	0.499	SS14

Table 3: Overview of assumptions made during the data selection and the test, with the values used in the test (center column) and the values applied in the sensitivity test (right column).

Assumption	Value	Sensitivity test
Maximum depth	35 km	15, 25, 35 km
Maximum distance	600 km	150, 300, 600 km
Least number of records for each event and station	3	1, 3, 10
Threshold for PGA_{rock} where non-linearity is expected	> 0.05 g	$> 0.01, 0.02, 0.05, 0.05^*, 0.1$ g
Threshold for V_{S30} where non-linearity is expected	< 500 m/s	$< 350, 400, 500, 550, 600, 760$ m/s
The minimum number of records at $PGA_{\text{rock}} > 0.05$ g	4	1, 2, 3, 4, 5, 7, 10

* threshold applied for borehole data

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984 **Figures**

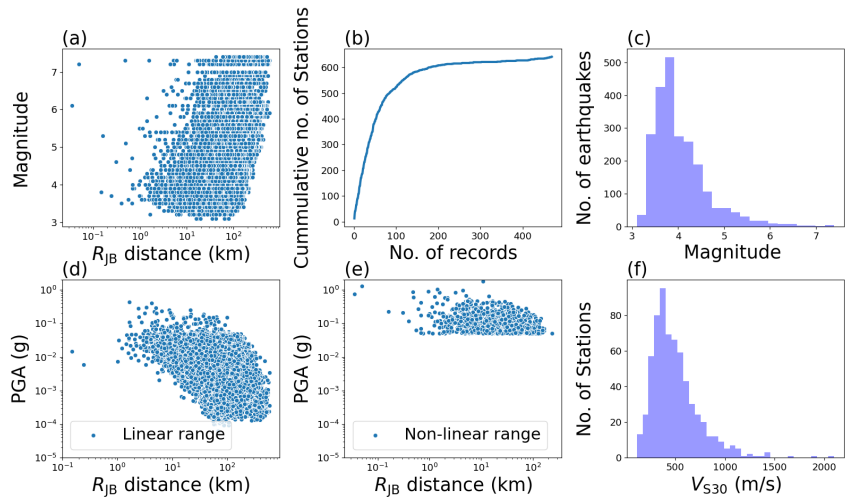


Figure 1: Data and site distribution of the selected records from the database of Bahrampouri et al. (2020) (BEA20). (a) PGA with distance (R_{JB}) and magnitude (M_W), (b) cumulative number of records per stations, (c) number of earthquakes per magnitude. (d) and (e) show the data defined as linear and non-linear, respectively, with PGA and distance. (f) Number of stations per V_{S30} .

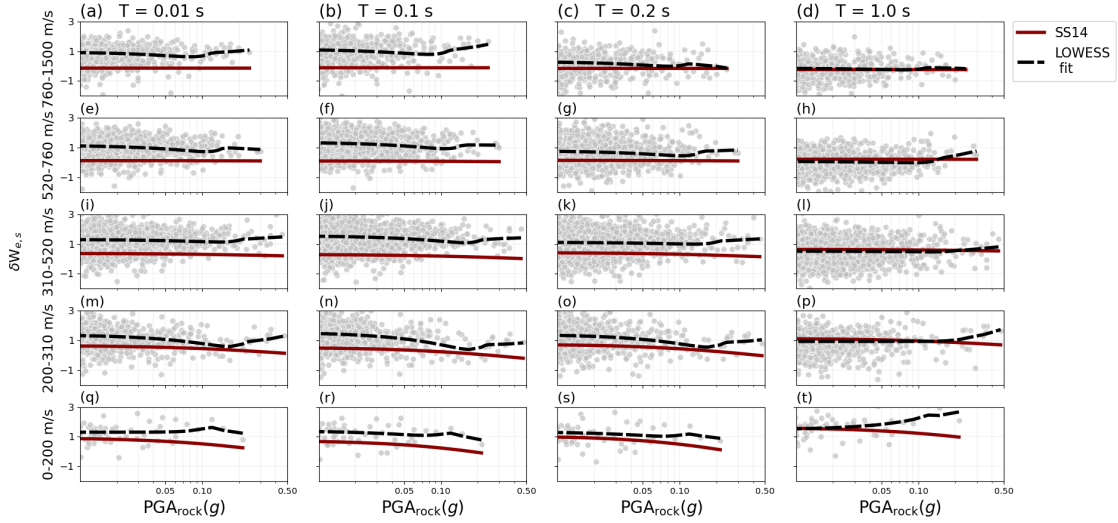


Figure 2: Variations of site-amplification given as within-event residuals ($\delta W_{e,s}$) with respect to peak acceleration for rock conditions (PGA_{rock}), following the approach of Seyhan and Stewart (2014) to investigate non-linearity. The within-event residuals $\delta W_{e,s}$ (y -axis) are grouped by V_{S30} (rows) for spectral periods T (columns), and derived using the Bahrapouri et al. (2020) database (BEA20) and Boore et al. (2014) GMM (BBS14). The range of each V_{S30} -bin is specified in the x-label. The dashed line is the LOWESS (locally weighted linear-regression) fit of the residuals and the bold line is the full SS14 site-amplification model, including both linear and non-linear site component. The large difference between the full Seyhan and Stewart (2014) model (SS14) and the trend of the residuals suggests that the relation between V_{S30} and site-amplification is site dependent.

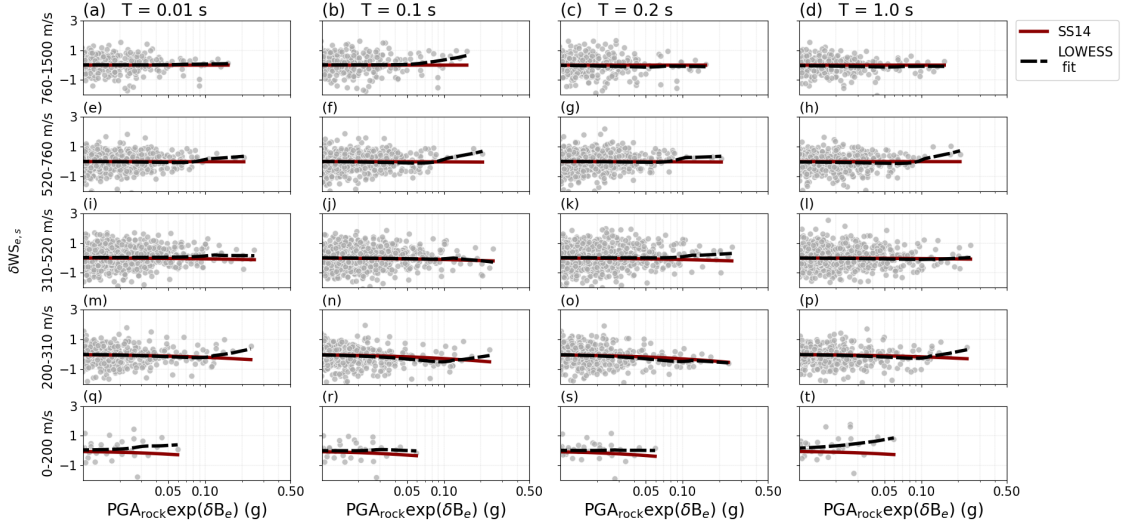


Figure 3: Variations of non-linear site-amplification given as "left-over" residuals ($\delta WS_{e,s}$) with respect to rock peak acceleration with event variability ($PGA_{\text{rock}} \exp(\delta B_e)$), after applying modifications to the approach of Seyhan and Stewart (2014) to investigate non-linearity. The "left-over" residuals $\delta WS_{e,s}$ are grouped by V_{S30} (rows) for spectral periods T (columns), and derived using the Bahrapouri et al. (2020) database (BEA20) and Boore et al. (2014) GMM (BBS14). The range of each V_{S30} -bin is specified in the x-label. The dashed line is the LOWESS (locally weighted linear-regression) fit of the residuals and the bold line is the non-linear component of the Seyhan and Stewart (2014) site-amplification model (SS14). SS14 coincides better with the trend of the residuals after the site-specific linear site amplification (here using $\delta S2S_s$) is removed.

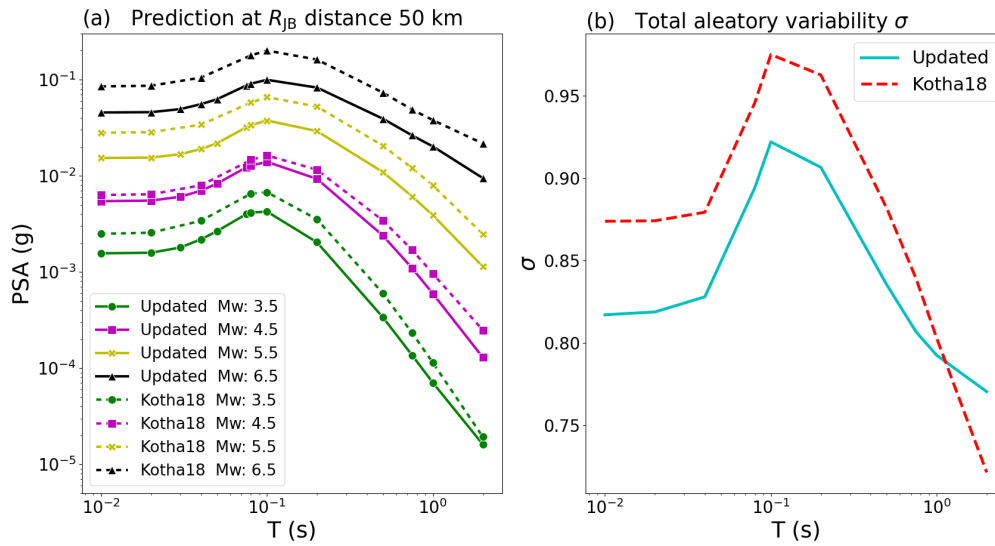


Figure 4: (a) The response spectra of Pseudo Spectral Acceleration (PSA) for the GMM of Kotha et al. (2018) (dashed lines) and the updated GMM derived here (bold lines) at $R_{JB} = 50$ km for different magnitudes. (b) The total aleatory variability σ of Kotha et al. (2018) (dashed line) and the updated GMM (bold line). The main difference between the two models are likely caused by the different magnitude ranges available in the two different datasets used to derive the models.

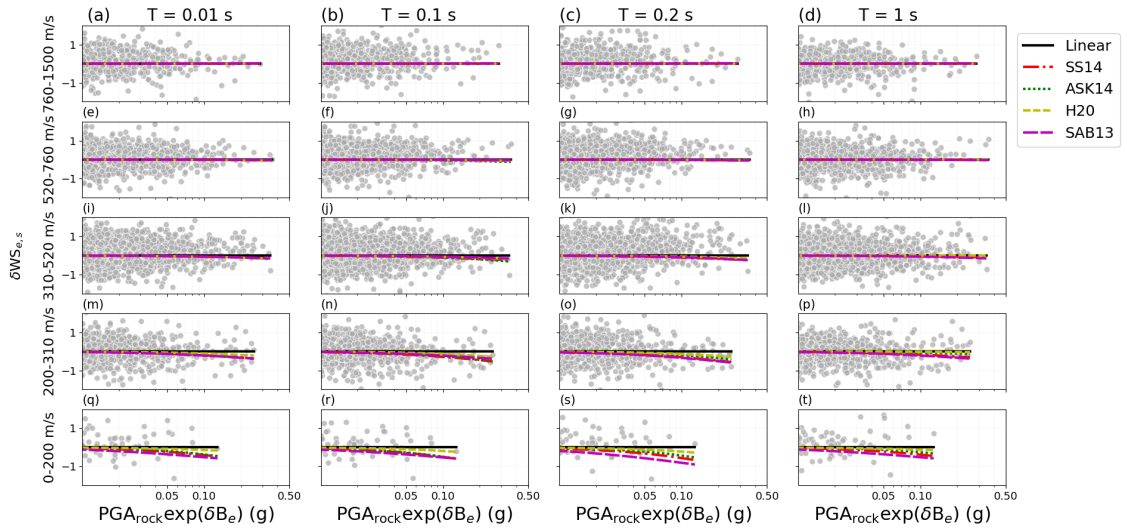


Figure 5: The site-amplification models compared to the "left-over" residuals $\delta WS_{e,s}$ with respect to rock peak acceleration with event variability ($PGA_{\text{rock}} \exp(\delta B_e)$) and stations grouped by V_{S30} (rows) for spectral periods T (columns). The range of each V_{S30} -bin is specified in the x-label. The residual plots show that the decreasing trend for low V_{S30} predicted by the non-linear site-amplification models is not observed in the residuals. The scores for each model and V_{S30} -bin are given in Table S1 in the Supplementary Material.

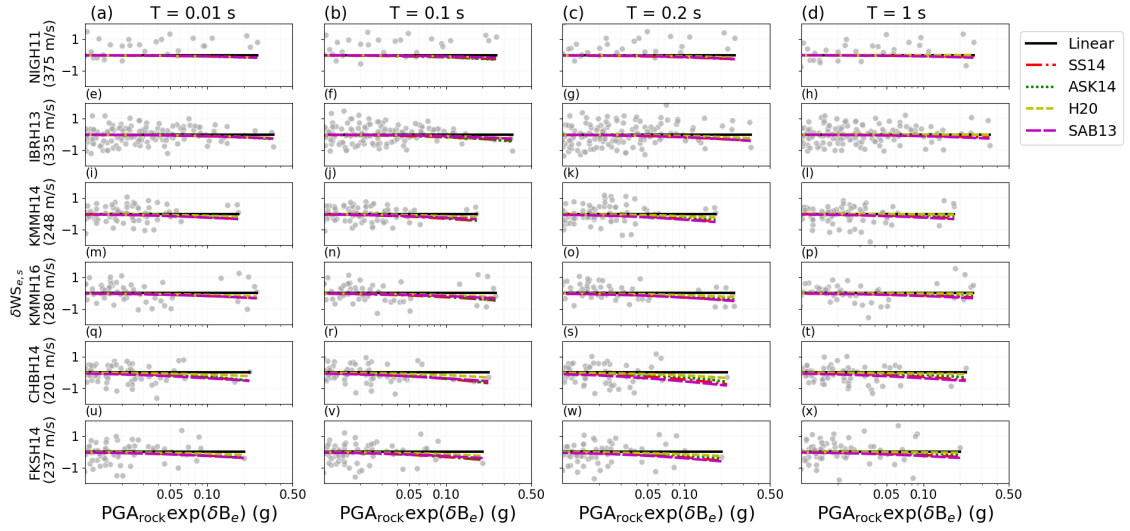


Figure 6: The site-amplification models compared to the "left-over" residuals $\delta WS_{e,s}$ with respect to rock peak acceleration with event variability ($PGA_{\text{rock}} \exp(\delta B_e)$) for spectral periods T (columns) and the selected KiK-net stations (rows) with the highest number of records. The V_{S30} of the stations are given in parenthesis under the station name in the x-label. The site-to-site variability of the residuals is high and the decreasing trend for low V_{S30} predicted by the non-linear site-amplification models is not observed in the residuals. The scores of each model for these stations at $T = 0.01$ s are given in Table 2, and for all periods in Table S2 in the Supplementary Material.

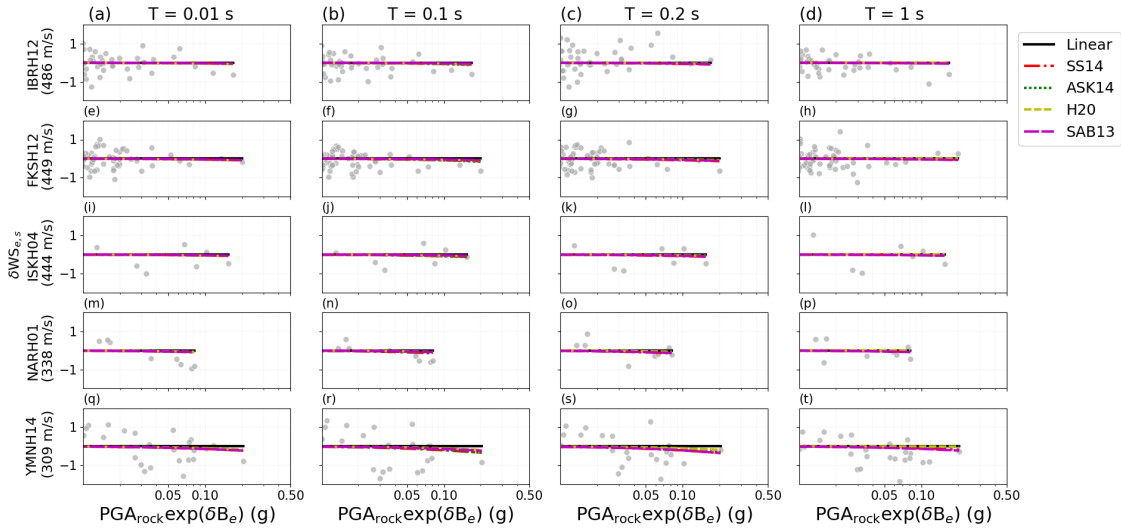


Figure 7: The site-amplification models compared to the "left-over" residuals $\delta WS_{e,s}$ with respect to rock peak acceleration with event variability ($PGA_{\text{rock}} \exp(\delta B_e)$) for spectral periods T (columns) and the selected KiK-net stations (rows) where the non-linear site-amplification models scored better than the linear site-amplification model at all periods. The V_{S30} of the stations are given in parenthesis under the station name in the x-label. The scores of each model for these stations at $T = 0.01\text{ s}$ are given in Table 2, and for all periods in Table S2 in the Supplementary Material.

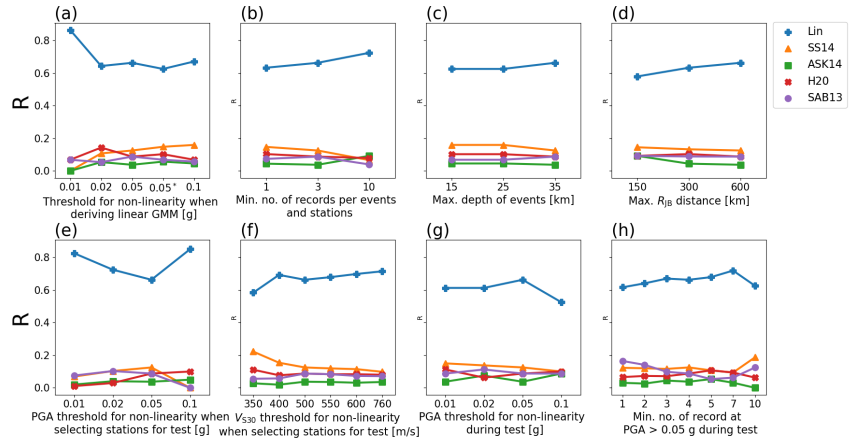


Figure 8: The ratio R of the number of stations and periods where each amplification model scores best, to the total number of stations and periods. Each subplot shows the variation of the ratio when varying the different assumptions made in the process of selecting the data and deriving the linear ground-motion model and residuals for the test. The assumptions and their values are also given in Table 3. The linear amplification model has the highest ratio for all assumptions, and the ratio of each amplification models is stable with depth, distance and minimum number of records used to derive the residuals. The ratio varies the most when applying different thresholds for expected non-linear soil behavior (a, e and g).

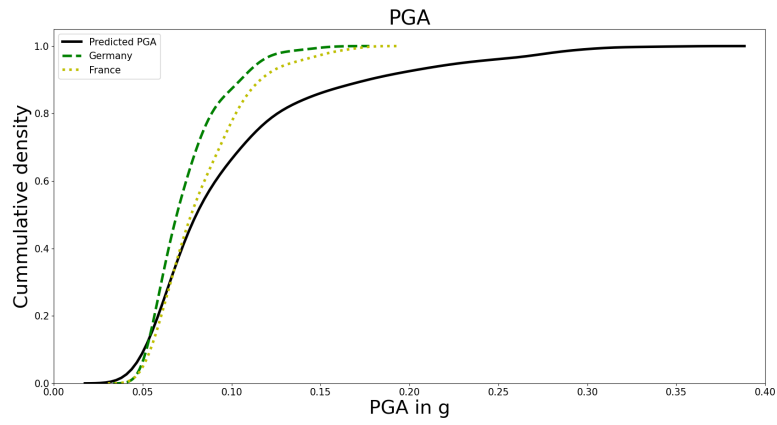


Figure 9: The cumulative density distribution of the predictions for rock conditions with $\text{PGA} > 0.05 \text{ g}$ used in this study (bold line) and that of recent seismic hazard maps of Germany (dashed line) and France (dotted line) for PGA on rock with a 475-year return period. The PGA range used in this study is consistent with the predictions for Germany and France up to $\text{PGA} = 0.2 \text{ g}$.

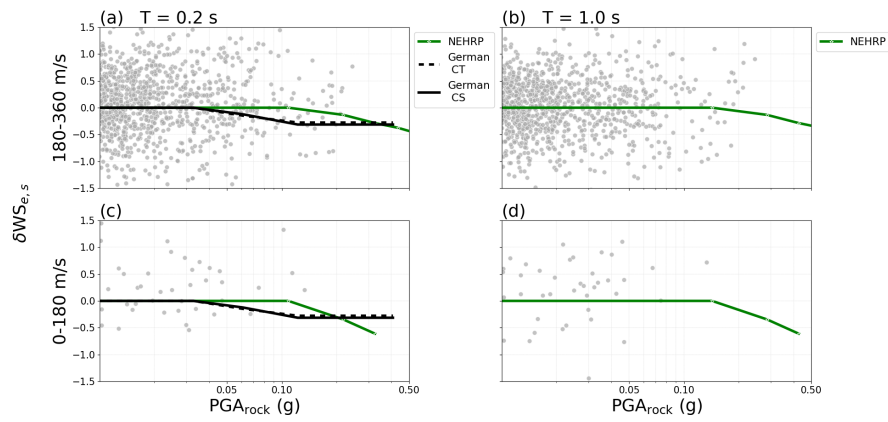


Figure 10: The site-amplification factor of the NEHRP and German seismic building codes compared to the "left-over" residual $\delta WS_{e,s}$ with respect to rock peak acceleration with event variability ($PGA_{rock} \exp(\delta B_e)$) and stations grouped by V_{S30} (rows) for spectral periods T (columns). The range of each V_{S30} -bin is specified in the x-label. The decrease of amplification predicted by the building-code site-amplification factors is not observed in the residuals.