



**Douglas, John and Edwards, Benjamin (2016) Recent and future developments in earthquake ground motion estimation. *Earth-Science Reviews*, 160. 203–219. ISSN 1872-6828 , <http://dx.doi.org/10.1016/j.earscirev.2016.07.005>**

This version is available at <https://strathprints.strath.ac.uk/56975/>

**Strathprints** is designed to allow users to access the research output of the University of Strathclyde. Unless otherwise explicitly stated on the manuscript, Copyright © and Moral Rights for the papers on this site are retained by the individual authors and/or other copyright owners. Please check the manuscript for details of any other licences that may have been applied. You may not engage in further distribution of the material for any profitmaking activities or any commercial gain. You may freely distribute both the url (<https://strathprints.strath.ac.uk/>) and the content of this paper for research or private study, educational, or not-for-profit purposes without prior permission or charge.

Any correspondence concerning this service should be sent to the Strathprints administrator: [strathprints@strath.ac.uk](mailto:strathprints@strath.ac.uk)

# Recent and future developments in earthquake ground motion estimation

John Douglas<sup>a,\*</sup>, Benjamin Edwards<sup>b</sup>

<sup>a</sup>*Department of Civil and Environmental Engineering; University of Strathclyde; James Weir Building; 75 Montrose Street; Glasgow; G1 1XJ; United Kingdom*

<sup>b</sup>*Department of Earth, Ocean and Ecological Sciences; School of Environmental Sciences; University of Liverpool; Jane Herdman Building; Liverpool; L69 3GP; United Kingdom*

---

## Abstract

Seismic hazard analyses (SHA) are routinely carried out around the world to understand the hazard, and consequently the risk, posed by earthquake activity. Whether single scenario, deterministic analyses, or state-of-the-art probabilistic approaches, considering all possible events, a founding pillar of SHA is the estimation of the ground-shaking field from potential future earthquakes. Early models accounted for simple observations, such that ground shaking from larger earthquakes is stronger and that ground motion tends to attenuate rapidly away from the earthquake source. The first ground motion prediction equations (GMPEs) were, therefore, developed with as few as two principal predictor variables: magnitude and distance.

Despite the significant growth of computer power over the last few decades, and with it the possibility to compute kinematic or dynamic rupture models coupled with simulations of 3D wave propagation, the simple parametric GMPE has remained the tool of choice for hazard analysts. There are numerous reasons for this. First and foremost GMPEs are robust and reliable

---

\*Corresponding author

*Email addresses:* [john.douglas@strath.ac.uk](mailto:john.douglas@strath.ac.uk) (John Douglas),  
[ben.edwards@liverpool.ac.uk](mailto:ben.edwards@liverpool.ac.uk) (Benjamin Edwards)

within the model space considered during their derivation, and many can be extrapolated to a degree beyond this space with some confidence. With ever expanding datasets and improved metadata the models are becoming more and more useful: a range of predictor variables are now used, describing the source, path and site effects in detail. GMPEs are also relatively easy to implement and computationally inexpensive. Despite this, probabilistic hazard calculations using GMPEs and accounting for uncertainties can still take several days to run. Full simulation-based approaches, therefore, clearly lie outside the computation budget afforded to most projects.

As well as the ever expanding list of predictor variables, other recent developments have also significantly improved the predictive power of GMPEs. This has allowed them to maintain their advantage over more ‘physical’ simulation techniques. Possibly the biggest aspect of this is not related to the median ground-shaking field, but rather its variability (and correlation in space and with oscillator period). This is a major advantage of empirical as opposed to simulation approaches, which typically struggle to replicate the covariance of input variables and, consequently, the variance of the ground motion. In this article we summarize some of the recent advances in ground motion prediction equations, including their application in SHA. We begin with a summary of the current state-of-the-art, then introduce the main additional predictor variables now used. Region- and event-type (tectonic or induced) specific predictions and adjustments are then discussed. Additional topics include advances in estimating ground-motion variability (epistemic and aleatory) and expanding GMPEs to predict other intensity measures or waveform features. The article concludes with a discussion on the path forward in earthquake ground motion prediction.

*Keywords:* seismology, earthquake engineering, earthquake, induced

1 **1. Introduction**

2 Seismic hazard assessment for a given site is founded on two pillars:  
3 firstly, a seismic-source model quantitatively describing all possible earth-  
4 quakes in the vicinity (generally within about 300 km) and, secondly, a  
5 ground-motion model expressing the shaking that would happen at the site  
6 given the occurrence of each of these earthquakes. This article focuses on the  
7 second of these components; nevertheless, when considering ground-motion  
8 models it is vital to bear in mind the descriptions of earthquakes contained  
9 within the seismic-source model. These descriptions invariably consist of  
10 the earthquake's geographical location (and depth), its magnitude and, in-  
11 creasingly, its faulting mechanism and other characteristics (e.g. rupture  
12 geometry).

13 The results of seismic hazard assessments are vital inputs to earthquake  
14 engineering as they provide the motions that need to be resisted by struc-  
15 tures and infrastructure constructed at the site. In the past most earthquake  
16 engineering analyses were based on the response spectral representation of  
17 shaking (e.g. Newmark and Hall, 1982; Chopra, 1995) or other pseudo-  
18 static methods. Consequently only estimates of scalar intensity measures  
19 (IMs), the principal ones being peak ground acceleration (PGA) and velocity  
20 (PGV) and elastic response spectral accelerations (SA) at various structural  
21 periods between 0 and commonly 2 s, were required for engineering analy-  
22 sis. In the past decade or so, Incremental Dynamic Analysis (Vamvatsikos  
23 and Cornell, 2002) and other time-history-based approaches have become  
24 increasingly used. There is a growing need, therefore, for seismic hazard

25 analysts to provide a time-history representation of earthquake shaking in  
26 addition to estimates of various IMs.

27 As stated by Douglas et al. (2015), although the characterization of  
28 earthquake shaking by a single number (an IM) is a great simplification,  
29 it makes seismic hazard assessment much more straightforward since the  
30 link between the seismic-source and ground-motion models can be expressed  
31 as a closed-form equation [ground motion prediction equations (GMPEs),  
32 also known as attenuation relation(ship)s] to estimate the probability of  
33 exceeding a given level of earthquake shaking. These probabilities are cal-  
34 culated through probabilistic seismic hazard assessment (PSHA) (Cornell,  
35 1968; McGuire, 1976), which is the basis of most current seismic design maps,  
36 e.g. the National Annexes of Eurocode 8 (Comité Européen de Normalisa-  
37 tion, 2005) and ASCE-7 (ASCE, 2013). Consequently it is still common to  
38 assess seismic hazard using PSHA through ground-motion models that re-  
39 turn IMs. Then, based on this analysis and if needed, to obtain earthquake  
40 time-histories for the most important scenarios, generally defined using dis-  
41 aggregation (Bazzurro and Cornell, 1999), either through selection from a  
42 databank of natural accelerograms (NIST, 2011) or simulations of artificial  
43 records (Douglas and Aochi, 2008).

44 Because of the key role they still play in seismic hazard assessment, this  
45 review focuses on GMPEs derived empirically (i.e. from seismograms of real  
46 earthquakes). The purpose of this article is not to repeat the historical re-  
47 view of empirical ground motion estimation presented by Douglas (2003a)  
48 nor the overall scope of the review of all methods for ground-motion pre-  
49 diction by Douglas and Aochi (2008). Rather, this article seeks to review  
50 the great advances in ground-motion prediction over the past decade and to  
51 provide the reader with an overview of the principal topics of research. The

52 article concludes with some recommendations for future developments.

53 Although much of the following discussion concerns topics that are rel-  
54 evant for all tectonic regimes (e.g. shallow active crustal, subduction and  
55 stable continental) the examples are mainly taken from studies related to  
56 ground motions in shallow active crustal environments. A review focused  
57 on other tectonic regimes may emphasize other issues (e.g. the importance  
58 of focal depth for subduction events and simulation-based ground-motion  
59 models for stable continental regions). The wealth of data from shallow  
60 active crustal areas means that epistemic uncertainties are probably lower  
61 than in other tectonic regimes (e.g. Douglas, 2010b, Compare Figures 2, 8  
62 and 10). For instance, in some tectonic regimes (e.g. oceanic crust, deep  
63 Vrancea-type and the Himalaya) there are few strong-motion observations to  
64 constrain ground-motion models and consequently the epistemic uncertainty  
65 for these regions is much higher than for shallow active crustal areas.

## 66 **2. Summary of current state of practice**

67 It has now been more than fifty years since the first ground-motion model  
68 accounting for both magnitude and distance dependence was derived (Es-  
69 teva and Rosenblueth, 1964). Models are currently published at the rate of  
70 more than one per month and, at the last count, the total number of empir-  
71 ical equations for the prediction of PGA was 400 with many more based on  
72 simulations (Douglas, 2016). The close match between the rate of increase  
73 in strong-motion recordings and the number of GMPEs is shown in Figure 1.  
74 The rapidly increasing number of GMPEs led Bommer et al. (2010) to rec-  
75 ommend criteria for the selection of GMPEs to retain only those models for  
76 consideration that could be thought of as representing the state of the art.

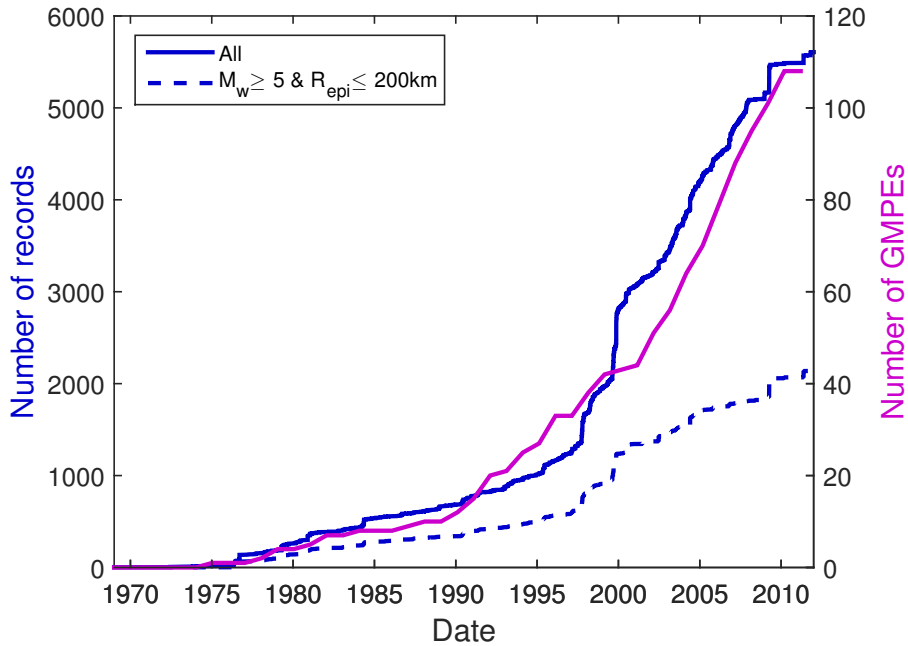


Figure 1: Available strong-motion records from RESORCE (Akkar et al., 2014b) (left-hand axis) and number of published GMPEs from Douglas (2016) (right-hand axis) against date for Europe and the Middle East (up to 2012).

77 They also suggest that these criteria could be used as a quality assurance  
 78 step to guide publication of new GMPEs.

79 A brief comparison between the first ground-motion model (Esteva and  
 80 Rosenblueth, 1964) and the recently-published GMPE of Abrahamson et al.  
 81 (2014) helps demonstrate the developments in this field. The GMPE of  
 82 Esteva and Rosenblueth (1964) was based on only 46 records and its three  
 83 coefficients were estimated via standard least-squares regression. In contrast  
 84 the model of Abrahamson et al. (2014) is based on over 15 000 records from  
 85 more than 300 earthquakes and its roughly 40 coefficients were determined  
 86 based on random-effects regression (Abrahamson and Youngs, 1992) or con-

87 strained based on ground-motion simulations or physical reasoning. Little  
88 information is provided on the data behind the model of Esteva and Rosen-  
89 blueth (1964) and it is thought that these data were obtained from various  
90 sources with seemingly little regard to their consistency or validity. In con-  
91 trast, the model of Abrahamson et al. (2014) is the outcome of careful data  
92 collection via the NGA projects (Power et al., 2008; Bozorgnia et al., 2014).  
93 The GMPE of Esteva and Rosenblueth (1964) is only for PGA and PGV  
94 because before the Caltech Blue Books (Brady et al., 1973) response spec-  
95 tra were difficult to obtain; whereas the model of Abrahamson et al. (2014)  
96 provides predictions for PGA, PGV and pseudo-SA at 22 periods between  
97 0.01 and 10 s. Finally, as is common for early GMPEs, Esteva and Rosen-  
98 blueth (1964) do not report the standard deviation ( $\sigma$ ) of their equation;  
99 whereas Abrahamson et al. (2014) concentrate much of their effort on de-  
100 riving a complex  $\sigma$  that models the different components of ground-motion  
101 variability.

102 In the decade or so since the review by Douglas (2003a) GMPE devel-  
103 opers have concentrated on: improvements in the estimation of the ground-  
104 motion variability associated with their models and its components (see  
105 Section 5); a move away from simple regression-based curve fitting; at-  
106 tempts at using non-parametric techniques; the use of much more and higher  
107 quality data; attempts at including additional independent parameters (see  
108 Section 3); a better appreciation of epistemic uncertainty (see Section 6);  
109 extensions of spectral models to shorter ( $< 0.1$  s) and longer ( $> 2$  s) peri-  
110 ods using individually-processed<sup>1</sup> records, often from digital instruments; a

---

<sup>1</sup>The extension to shorter periods is aided by the observation (Douglas and Boore, 2011; Bommer et al., 2012) that SA is relatively unaffected by high-cut filtering.



111 more careful consideration of how the models perform beyond their ‘comfort  
112 zones’, e.g.: for  $\mathbf{M} < 5$ ,  $\mathbf{M} > 7$  and  $R < 10$  km; and making the models  
113 easier to use and test within PSHA (see Section 4). In addition, there has  
114 been a growing interest in developing models for other IMs, e.g. peak ground  
115 displacement, Arias intensity and various duration measures (see Section 7).

### 116 2.1. Current de facto standards

117 As demonstrated by the review of Douglas (2003a) many different choices,  
118 in terms of dependent and independent variables, derivation technique and  
119 functional form, were made by GMPE developers until the 1990s. In the  
120 past couple of decades, however, there has been a general convergence to a  
121 set of *de facto* standards.

122 Most developers now present models for PGA, increasingly PGV, and  
123 pseudo-SA for 5% of critical damping based on the geometric mean of the  
124 values from two horizontal components, or the orientation-independent hor-  
125 izontal component (Boore et al., 2006). They often use records from public  
126 online databases (e.g. Akkar et al., 2014b; Chiou et al., 2008) that have  
127 been low-cut filtered with record-specific cut-offs that are then respected  
128 when considering the reliable frequency ranges of their models.

129 The size of an earthquake is invariably characterized in terms of mo-  
130 ment magnitude ( $\mathbf{M}$ ), although this is sometimes estimated from other mag-  
131 nitudes, commonly local magnitude ( $M_L$ ) (e.g. Bindi et al., 2005; Goertz-  
132 Allmann et al., 2011), duration magnitude ( $M_d$ ) (e.g. Bakun, 1984; Edwards  
133 and Douglas, 2014) or surface wave magnitude ( $M_s$ ) (e.g. Ambraseys and  
134 Free, 1997), through region-specific equations. Generally the earthquake is  
135 characterized into three faulting mechanisms (styles of faulting): normal,  
136 strike-slip and reverse. It is now common to consider nonlinear magnitude

137 scaling (see Section 4.2).

138       The length of the travel path from source to site is generally measured  
139 either in terms of the distance to the surface projection of the rupture (the so-  
140 called Joyner-Boore distance,  $r_{jb}$ ) (Joyner and Boore, 1981) or, accounting  
141 for the depth, the distance to the causative fault (the so called rupture dis-  
142 tance,  $r_{rup}$ ). For smaller earthquakes, where point sources can be assumed,  
143 these distance metrics become equal to epicentral ( $r_{epi}$ ) and hypocentral  
144 ( $r_{hyp}$ ) distances, respectively. Some recent studies present models for both  
145 finite-fault ( $r_{rup}$  or  $r_{jb}$ ) and point-source ( $r_{epi}$  or  $r_{hyp}$ ) distance metrics so  
146 that the correct GMPE is available when used within PSHA for point sources  
147 (e.g. within area sources) (Bommer and Akkar, 2012) without having to per-  
148 form conversions. It is also common to account for magnitude-dependent  
149 decay of IMs with distance (see Section 4.2).

150       Because boreholes were typically drilled to 30 m and because of its subse-  
151 quent use within many projects and design codes, e.g. Eurocode 8, the time-  
152 average shear-wave velocity in the top 30 m ( $V_{s,30}$ ) is the common way that  
153 near-surface site conditions are characterized within recent GMPEs, either  
154 directly or, when insufficient information is available, through site classes.  
155 It is still relatively uncommon for GMPEs to account directly for potential  
156 nonlinear site amplification because this behavior is rare within observed  
157 strong ground motions. Within PSHA non-linear effects generally require  
158 a simulation-based site term to be adopted, often from a stand-alone study  
159 (Kamai et al., 2014; Seyhan and Stewart, 2014; Sandikkaya et al., 2013).

160       Finally it has become standard to use either random-effects (Abraham-  
161 son and Youngs, 1992) or one- or two-stage maximum-likelihood regression  
162 (Joyner and Boore, 1993) to estimate the free coefficients of the model.  
163 These techniques, applied to the same data, would lead to very similar

164 results, although the latter may be more susceptible to trade-offs. Both  
165 techniques provide estimates of the between- and within-event components  
166 of ground-motion variability (see Section 5).

### 167 **3. Additional independent variables**

168 To obtain GMPEs that estimate more appropriate ground motions for a  
169 given earthquake, path and site, independent variables in addition to mag-  
170 nitude, faulting mechanism, source-to-site distance and a near-surface site  
171 class (or  $V_{s,30}$ ) have been tested and/or included within some recent models.  
172 These attempts are briefly discussed in this section.

#### 173 *3.1. Source parameters*

174 All GMPEs include magnitude as the main source parameter. This is  
175 now routinely moment magnitude due to its robustness, the fact that it  
176 does not saturate, and because it is possible to estimate from historical and  
177 palaeological information. The latter consideration is important in linking  
178 GMPEs to earthquake catalogs, where the longer the available time-period  
179 the more reliable are recurrence relations, particularly at higher magnitudes.  
180 While magnitude is certainly an important factor for ground-motion ampli-  
181 tudes, there are other source parameters that can control the amplitude and  
182 frequency content of radiated seismic energy. The most influential of these  
183 is the earthquake stress drop. While the stress drop has a physical mean-  
184 ing, there are different definitions (e.g. static, dynamic or ‘Brune’). When  
185 referred to in engineering seismology applications ‘stress drop’ or ‘stress  
186 parameter’ is effectively used to refer to the proportion of high-frequency  
187 energy (for a given magnitude) that is radiated from the source (Atkinson  
188 and Beresnev, 1997).

189       Following on from observations of Somerville (2003), model developers of  
190 the NGA West 1 and 2 projects (Power et al., 2008; Bozorgnia et al., 2014)  
191 investigated the impact of depth to the top of the rupture plane ( $Z_{TOR}$ ) on  
192 ground motions. Some of them (e.g. Campbell and Bozorgnia, 2014) find  
193 that using  $Z_{TOR}$  within the model leads to statistically better predictions  
194 with deep earthquakes generating higher ground motions than shallow events  
195 (all other things being equal), which could be explained by higher stress  
196 drops. Possible lower stress drops for aftershocks is behind the decision of  
197 some NGA West developers to exclude data from this type of event (e.g.  
198 Boore and Atkinson, 2008) whereas others (e.g. Chiou and Youngs, 2008)  
199 include terms to account for this difference. This effect appears to be small  
200 and could be related to the way that earthquakes are classified (Douglas and  
201 Halldórsson, 2010). Radiguet et al. (2009) present evidence that SAs from  
202 immature faults are statistically-significantly higher than those from mature  
203 faults, which again could be related to higher stress drops for earthquakes  
204 occurring on immature faults. The maturity of faults has yet to be included  
205 in a GMPE because the age of faults is not a readily-available parameter.  
206 The recent ground-motion model by Bora et al. (2015) includes an explicit  
207 term for the stress (drop) parameter ( $\Delta\sigma$ ) commonly used within stochastic  
208 models (e.g. Atkinson and Silva, 2000; Rietbrock et al., 2013), while Douglas  
209 et al. (2013) and Bommer et al. (2016) present unique GMPEs for a range of  
210  $\Delta\sigma$ . This allows models to be readily employed in areas where the average  
211 stress drop is known but it puts the onus on the user to select an appropriate  
212 median  $\Delta\sigma$  (and uncertainty about this value).

213       Directivity of earthquake ground motion fields is an emerging topic that  
214 has been addressed, for example, in the recent NGA West 2 project (Spudich  
215 et al., 2014). While often clear in large-magnitude earthquake simulations,

216 this issue has seen relatively little focus in recent years. This is primarily due  
217 to the nature of PSHA, which combines all possible earthquake scenarios:  
218 rupture directivity effects, therefore, tend to be smoothed out. However, in  
219 understanding deterministic hazard, or for future analyses, where rupture  
220 directivity preference can be assigned, accounting for this effect may help to  
221 reduce epistemic uncertainty.

### 222 *3.2. Path parameters*

223 Path terms within GMPEs have grown more complex in terms of their  
224 functional form over the past decade with the realization that ground mo-  
225 tions from small and large earthquakes do not decay at the same rate (see  
226 Section 4.2). In addition, because of the availability of ground-motion data  
227 (often from broadband instruments or high-sensitivity strong-motion sen-  
228 sors) at distances greater than 100 km (roughly the limit of analogue strong-  
229 motion recording) a number of GMPEs include terms to model anelastic  
230 attenuation, the rate of which is sometimes considered regionally-dependent  
231 (see Section 4). Cousins et al. (1999), for example, developed a GMPE  
232 for New Zealand that accounts for additional attenuation for travel paths  
233 through volcanic regions by including a term that is a function of the hori-  
234 zontal distance through such zones.

235 Nevertheless, commonly travel path is simply parameterized using source-  
236 to-site distance. This means that the decay rate is the same for all locations  
237 irrespective of the crustal structure. Douglas et al. (2004, 2007) develop a  
238 technique based on simulations to calculate an equivalent hypocentral dis-  
239 tance that captures the impact of crustal structure on ground-motion decay  
240 and, consequently, allows a ground-motion model to be branched into region-  
241 specific models. This approach has yet to be applied for the derivation of a

242 GMPE for use in practice.

243 A handful of GMPEs (generally for use in California) include terms to  
244 model the location of a site with respect to the hanging and foot walls of  
245 the causative fault (e.g. Campbell and Bozorgnia, 2014; Abrahamson et al.,  
246 2014), sometimes by using  $R_x$  (the horizontal, strike-normal distance to the  
247 shallowest part of the surface projection of the fault). The terms to model  
248 this effect are often complex and hence rely on simulations to constrain their  
249 free parameters. For applications in areas without clearly-defined dipping  
250 faults such terms are often turned off when the model is used within PSHA.

### 251 3.3. Site parameters

252 As discussed in Section 2.1, most current GMPEs use  $V_{s,30}$  or site classes  
253 based on  $V_{s,30}$  to characterize the near-surface conditions at a site. In an  
254 attempt to account for the effect of deeper structure on ground motions,  
255 some recent GMPEs for California often use, in addition to  $V_{s,30}$ , either the  
256 depth to the 1 km/s velocity horizon ( $Z_{1.0}$ ) (e.g. Chiou and Youngs, 2014)  
257 or the depth to the 2.5 km/s horizon ( $Z_{2.5}$ ) (e.g. Campbell and Bozorgnia,  
258 2014).  $Z_{1.0}$  and  $Z_{2.5}$  are often strongly correlated but weakly correlated  
259 with  $V_{s,30}$  and hence their use alongside  $V_{s,30}$  adds discriminatory power to a  
260 GMPE. For many parts of the world estimates of  $Z_{1.0}$  and, particularly,  $Z_{2.5}$   
261 are, however, difficult to obtain because they require knowing the shear-wave  
262 velocity down to hundreds or thousands of meters. Consequently, empirical  
263 relationships to estimate these parameters from  $V_{s,30}$  have been proposed  
264 (Boore et al., 2011) to center the predictions at an average  $Z_{1.0}$  or  $Z_{2.5}$ .

265 PSHA is often conducted for a rock site with  $V_{s,30}$  equal or larger than  
266 760 m/s [the NEHRP B/C boundary (National Earthquake Hazard Reduc-  
267 tion Program, 1994)] (see Section 4.4). At high  $V_{s,30}$  the site amplification

268 modeled in the GMPE will be low and any nonlinearity in modeled response  
269 weak. One of the largest changes in PSHA for such sites in the past decade  
270 has been the appreciation that site amplification related to shear-wave ve-  
271 locity is not the whole story but that high-frequency attenuation, generally  
272 modeled by  $\kappa$  (Anderson and Hough, 1984), also needs to be considered.  
273 The effect of an average  $\kappa$  is implicitly captured within empirical GMPEs  
274 through the data that are used. The average  $\kappa$  implied by the shape of the  
275 short-period spectra of GMPEs evaluated for high  $V_{s,30}$  is, however, often  
276 much higher than the  $\kappa$  measured at rock sites. Consequently, as discussed  
277 in Section 4.5, a host-to-target adjustment for  $\kappa$  is required when these  
278 GMPEs are used in a site-specific study. In an attempt to overcome this  
279 requirement, Laurendeau et al. (2013) introduce a term for  $\kappa$  directly into  
280 a GMPE developed from Japanese data. Use of such a model means that  
281  $\kappa$  needs to be known for a site of interest. This is the apparent drawback  
282 of introducing new variables into GMPEs: the requirement for the user to  
283 know their value and their uncertainty for their study. In the past, however,  
284 the user generally assumed that the implicit average value within the data  
285 used to derive the GMPE was appropriate for their site.

#### 286 **4. Regional models**

287 With the rapidly-growing quantity of data from digital strong-motion  
288 networks, which accurately record earthquakes down to **M3** and below, there  
289 has been a move towards the development of GMPEs for small geographical  
290 regions (e.g. national or sub-national) and partially away from models cov-  
291 ering large tectonic regimes, e.g. shallow crustal earthquakes globally. An  
292 idea of the utility of this approach for the development of empirical GMPEs

Table 1: The number of years required to record fifty  $M_w \geq 5$  shallow earthquakes assuming dense strong-motion network covering whole territory (country or state) based on the International Seismological Centre’s earthquake catalog from 1992 to 2012.

Country	Number of years
Japan	7
Turkey	9
Greece	12
California	20
Italy	31
Iceland	140
Spain	250
France	1000
United Kingdom	$\gg 1000$

293 given only data from a country or state can be gained from Table 1. For  
 294 some highly seismically active areas this goal of purely-national GMPEs is  
 295 feasible but for less active (e.g. Spain) or smaller countries (e.g. Iceland) lo-  
 296 cal records would have to be used in conjunction with simulations or foreign  
 297 data to derive robust models.

298 As discussed in Section 4.2, there are difficulties in developing regional  
 299 models for use within standard seismic hazard assessments unless the models  
 300 are derived using data from large events. Therefore, to account for potential  
 301 regional dependency some GMPE developers derive a robust model using  
 302 data from a variety of regions within a single tectonic regime (e.g. shallow  
 303 crustal) and then add terms when required to account for observed regional  
 304 differences. For example, Boore et al. (2014) include terms to model differ-  
 305 ences in anelastic attenuation in China/Turkey and Japan/Italy to other ar-



306 eas (predominantly California). In addition to regional variations in median  
307 predictions, the variability of ground motion may be regionally-dependent.  
308 For example, Abrahamson et al. (2014) differentiate between variability in  
309 Japan and elsewhere.

310 Regional dependence of ground-motion models is, therefore, still a topic  
311 of ongoing research. The issue is somewhat complicated by the sweeping  
312 terms typically used to classify tectonic regions: stable continental, shallow  
313 active crustal and so forth. Within each of these groups significant variability  
314 in both structure and geology exists – meaning that systematic variability  
315 in ground motion may be obscured if only looking at differences within or  
316 between these classes. Nevertheless, it is generally acknowledged that at dis-  
317 tances larger than around 50 km, regional variations in geology and tectonic  
318 structure lead to significant differences in ground motion attenuation (e.g.  
319 Boore et al., 2013; Kotha et al., 2016b,a). On the other hand, differences  
320 at shorter distances are less well understood due to limited data and the  
321 complexity of earthquake sources. Regional differences in stress fields due  
322 to factors such as tectonic loading and structure (Gölke and Coblenz, 1996),  
323 or, at smaller scales, due to fault structure and maturity (Manighetti et al.,  
324 2007) may lead to differences in earthquake stress drop that can be observed  
325 at national (e.g. Goertz-Allmann and Edwards, 2014) or local scales (e.g.  
326 Allmann and Shearer, 2007). The resolution of such analyses is, however,  
327 debated due to the trade-off with attenuation, which is typically assumed to  
328 be homogeneous. Addressing the issue of regionalization of ground-motion  
329 models requires more data, particularly at short distances. In the meantime,  
330 hazard analysts can use hazard disaggregation to understand, to a first or-  
331 der, the sensitivity of possible regional ground motions on seismic hazard.  
332 For instance, hazard is often primarily driven by relatively close earthquakes

333 (< 50 km) and, hence, regional differences in geology will be less important  
334 to understand than differences in fault-rupture kinematics, for example.

#### 335 *4.1. Testing of GMPEs*

336 When conducting a seismic hazard assessment for a region that is not  
337 covered by a selected GMPE it has been increasing common to undertake  
338 a quantitative comparison between predictions and the ground motions ob-  
339 served in the region (Stewart et al., 2015). This has only become possible  
340 for many parts of the world since the advent of digital ground-motion net-  
341 works in the past couple of decades. Various methods have been developed  
342 to undertake this testing but they are invariably based on ‘residuals’<sup>2</sup>, either  
343 total or, more correctly, separated into between- and within-event compo-  
344 nents (Stafford et al., 2008), between predictions and observations. The  
345 most employed techniques are those by Scherbaum et al. (2004), Scherbaum  
346 et al. (2009) and Kale and Akkar (2013). A more informative approach is to  
347 consider plots of the residuals with respect to magnitude, distance and other  
348 variables to understand what parts of the model are causing any misfits (e.g.  
349 Scasserra et al., 2009).

350 A difficulty with such testing is that it is difficult to judge how much  
351 weight should be given to a good or poor match as the available data are  
352 often sparse and/or only available for magnitude and distance ranges of  
353 limited engineering interest (Beauval et al., 2012). If a poor match is found  
354 between observations and predictions and this is judged to be robust then  
355 adjustment factors can potentially be derived to modify the GMPE so that

---

<sup>2</sup>They are not strictly residuals because generally the data compared were not used for the derivation of the tested GMPE.

356 it provides better predictions (Bommer et al., 2006). This approach has  
357 been formalized in the so called referenced-empirical technique by Atkinson  
358 (2010) and variants of it have been applied in various projects, particularly  
359 to adjust models for small and moderate events (e.g. Bourne et al., 2015).

#### 360 *4.2. Scaling of ground motions for small and large earthquakes*

361 In the past decade there has been a push to derive GMPEs to predict  
362 accurately ground motions from earthquakes with  $M < 5$ . Until the estab-  
363 lishment of digital strong-motion networks, which started in many regions  
364 in the late 1990s, ground-motion databases generally became sparse below  
365 about  $M5$ . In addition, for high seismicity areas, where most of the available  
366 data are from, the dominant earthquake scenarios for engineering purposes  
367 are generally at  $M > 5.5$ . Consequently there was little call for GMPEs  
368 that could be used confidently for small earthquakes.

369 The development of such models in the past decade has been driven  
370 by the availability of large sets of records from digital networks with good  
371 coverage down to often  $M3$  for many parts of Europe and elsewhere. Often  
372 these data are used to derive regional GMPEs (see Section 4) generally  
373 without the inclusion of data from larger earthquakes. When applying a  
374 GMPE in a different geographical region than for which it was originally  
375 derived it is important to check it against local data. As shown by, for  
376 example, Douglas (2003b), unless the GMPE was derived using data from  
377 small events and an appropriate functional form was used there will likely  
378 be a large discrepancy between predictions and observations. This has been  
379 used as an argument for a strong regional dependency in ground motions  
380 but, as shown by Cotton et al. (2008) amongst others, it is likely due to the  
381 differing magnitude ranges of the observations and model. Another recent

382 driver in the development of GMPEs that cover the range below **M5**, even  
383 for high seismicity zones, is the need for such models to estimate components  
384 of the ground-motion variability that require many records from the same  
385 site (see Section 5.3).

386 As shown by Douglas (2003b, Figure 4), Douglas and Jousset (2011)  
387 and Baltay and Hanks (2014), empirical GMPEs derived from data from  
388 small earthquakes generally show higher dependency on magnitude, partic-  
389 ularly for short-period IMs, than those models derived for moderate and  
390 large events. This means that extrapolation of these models beyond the  
391 magnitude range for which they were derived often leads to over-prediction.  
392 Fukushima (1996), Douglas and Jousset (2011) and Baltay and Hanks (2014)  
393 demonstrate that a simple stochastic model (Boore, 2003) with a single-  
394 corner source spectrum (Brune, 1970) and high-frequency attenuation (An-  
395 derson and Hough, 1984) reproduces the observed magnitude-scaling of em-  
396 pirical GMPEs and demonstrates why extrapolation of such models is so  
397 problematic. Algorithmic differentiation (Molkenthin et al., 2014) can be  
398 used to study the scaling of GMPEs with respect to its input parameters,  
399 which aids understanding of how the models behave and extrapolate.

400 As well as magnitude-scaling being different for ground motions from  
401 small and large earthquakes, the decay with distance also differs. Earth-  
402 quake magnitude has two effects on the distance dependence of ground-  
403 motion attenuation. The first is due to near-field saturation: as one ap-  
404 proaches a finite source, the contribution from the far ends of the source  
405 become increasingly small due to the distance that the energy must propa-  
406 gate to reach you (attenuation effects) and the time which this takes (scat-  
407 tering and dispersion effects). At short and moderate structural periods,  
408 therefore, the peak amplitudes of a **M7** event are similar to an **M8**. The

409 primary difference is the duration and spatial extent over which the mo-  
410 tions occur, being significantly longer and more widespread in the latter  
411 case. The second effect is the distance dependence of the ground motion  
412 decay. For increasingly large events the finite nature of the source means  
413 that ground motion does not decay as quickly as for small (roughly point)  
414 sources, since the motion at distance is increased by constructive interfer-  
415 ence from later arrivals along the finite fault (e.g. Boore, 2009). In fact,  
416 even for point-source models, Cotton et al. (2008) showed that the decay  
417 of response spectral ordinates is magnitude-dependent due to the influence  
418 of spectral shape. To capture this, functional forms of GMPEs in the past  
419 decade have often used magnitude-dependent decay terms.

#### 420 *4.3. Non-tectonic earthquakes*

421 Although the vast majority of GMPEs are still derived for tectonic earth-  
422 quakes, a growing number of models are available for earthquakes of other  
423 types, e.g. those induced by mining (e.g. McGarr and Fletcher, 2005) or  
424 fluid injection (e.g. Douglas et al., 2013). Seismic hazard assessments for  
425 human-activity-related, induced or triggered earthquakes require ground-  
426 motion models that are adapted to this type of event and it is not *a priori*  
427 clear that shaking from such shocks is similar to that from natural earth-  
428 quakes. In addition, the magnitude, source-to-site distance and focal depth  
429 range of importance for induced seismicity is generally smaller than the fo-  
430 cus of hazard assessments for natural earthquakes. Hence, as discussed in  
431 Section 4.2, this leads to the need to develop models to account for this dif-  
432 ference. The finding of Douglas et al. (2013) that motions from induced and  
433 natural shallow seismicity are statistically similar means that the more abun-  
434 dant data banks of records from small natural shallow earthquakes could be

435 used to derive GMPEs for use within hazard assessments for induced seismic-  
436 ity (e.g. Atkinson, 2015). It could also be argued that with an appropriate  
437 correction for depth [i.e. for distance and stress-drop (Hough, 2014)], data  
438 from deeper natural seismicity could be used to determine ground-motion  
439 fields of larger induced events.

#### 440 *4.4. Prediction for a reference velocity horizon*

441 Ground motion within PSHA is typically estimated for a reference site,  
442 circumventing the geological heterogeneity of the uppermost layers. This  
443 is often at or around the NEHRP class B/C boundary of 760 m/s or the  
444 Eurocode 8 class A/B boundary of 800 m/s (e.g. Delavaud et al., 2012).  
445 Subsequently, the results of microzonation or site-specific response analyses  
446 can be applied in conjunction with these estimates. The reason for this is the  
447 significant variability of resolution, reliability and availability of site-specific  
448 data. Practitioners are, in this way, free to apply their own site specific  
449 corrections to a regionally-consistent hazard map for reference rock.

450 Site response terms within GMPEs are included for two reasons. Firstly,  
451 to enable ground-motion records from all site conditions (including non-  
452 rock stations, which comprise the majority of most strong-motion networks)  
453 to be used to derive GMPE that would be statistically more robust than  
454 using only rock records. A few developers (e.g. Idriss, 2014) exclude records  
455 from sites with low  $V_{s,30}$  because they believe that it is not possible to  
456 capture site response by means of a simple site term. Consequently such  
457 models are generally based on far fewer records but the risk of bias from  
458 site amplification is reduced. The second reason for including site terms in  
459 GMPEs is that such models allow seismic hazard assessments for a variety  
460 of sites (including non-rock sites) to be easily conducted, which could be

461 useful when high accuracy is not a requirement.

462 In a similar way, recent PSHAs (e.g Bommer et al., 2015) predict the  
463 ground motion initially at a subsurface reference rock horizon, choosing a  
464 depth below which lateral variability is considered insignificant (usually at a  
465 wave velocity consistent with ‘engineering’ or hard rock). Site-specific non-  
466 linear amplification is then applied during the hazard calculation based on  
467 site-response analyses. This approach has the benefit of potentially reducing  
468 the site-to-site variability in predicted ground motion. If one assumes the  
469 full range of site variability is captured through this process then the GMPE  
470 component of site-to-site variability  $\phi_{S2S}$  (see Section 5.3) can be set to zero,  
471 leading to non-ergodic single-station sigma (Atkinson, 2006). Practitioners  
472 must be careful in this case that the modeled variability of the site response  
473 is sufficient, but at the same time not so high that ergodic  $\sigma$ s are exceeded  
474 due to uncertainty in site response analyses.

475 The move towards reference-site hazard and reference horizons to make  
476 best use of site-response analyses means that GMPEs are being increasingly  
477 evaluated for relatively high  $V_{s,30}$  (e.g.  $\geq 760$  m/s). This is one of the factors  
478 driving the derivation of new GMPEs. Sites with high  $V_{s,30}$ , however, are  
479 poorly represented in strong-motion databases because many stations are  
480 installed in urban environments on soft and stiff soils (e.g. Akkar et al.,  
481 2010).

#### 482 4.5. Host-to-target adjustments

483 Ground motion is dependent on the shear-wave velocity and attenuation  
484 characteristics of the upper layers of soil and rock. When modifying site  
485 conditions, e.g. changing predictions relevant for California to a site-specific  
486 target in the United Kingdom, hazard analysts must consider the effect of

487 this change on the predicted ground motion. This is done through host-to-  
488 target adjustments.

489 As stated above, GMPEs are typically developed using site descriptors  
490 such as class (e.g. rock, stiff soil and soft soil) or  $V_{s,30}$ . It is important  
491 to note, however, that when using a GMPE estimates are implicitly tied  
492 to a range of possible site types that fall within the site descriptor and  
493 this may be biased by a particular geology. Even GMPEs using  $V_{s,30}$  will  
494 cover a range of site types because many velocity profiles are possible for a  
495 given  $V_{s,30}$ . While different velocity profiles can lead to the same  $V_{s,30}$ , they  
496 may lead to significantly different amplifications (e.g. Castellaro et al., 2008;  
497 Papaspiliou et al., 2012). If a particular velocity structure (e.g. low velocity  
498 soils over a high velocity basement) is characteristic of a region, then ground  
499 motion at a  $V_{s,30}$  in one region may be systematically different to that in  
500 another with a different average structure. As discussed previously, some of  
501 this site variability can be captured by using additional site parameters, such  
502 as  $Z_{1.0}$  or  $Z_{2.5}$ . Recent PSHA studies have, however, moved towards fully  
503 accounting for the effect of site-specific characteristics, by taking advantage  
504 of the wealth of information often available for site-specific hazard analyses.  
505 Such differences are accounted for by using host-to-target adjustments. The  
506 same approach can be used to modify ground-motion predictions made at a  
507 particular  $V_{s,30}$  and provide them at another. This approach is particularly  
508 useful in the case that GMPE predictions are considered unreliable at the  
509 target  $V_{s,30}$ .

510 Since earthquake engineering generally uses SA, direct adjustments of the  
511 Fourier amplitude spectra (FAS) cannot be used to perform host-to-target  
512 adjustments. This is because ground motion at a given oscillator period is  
513 dependent not only on the FAS at that period but also other values around



514 it (e.g. Bora et al., 2015). The host-to-target ratio is, therefore, dependent  
515 on the input ground motion in addition to the different site properties. The  
516 hybrid-empirical method (HEM) based on Campbell (2003) is commonly  
517 used to make host-to-target adjustments. HEM uses stochastic simulations  
518 [typically using random-vibration theory (RVT) (Cartwright and Longuet-  
519 Higgins, 1956)] to generate FAS-compatible response spectra for the host  
520 and target sites, which can then be used to calculate the ratio in terms of  
521 SA.

522 Using RVT through the HEM allows transformations from the Fourier  
523 domain into the response spectral domain. HEM, however, requires a full  
524 seismological model (for source, path and site) of the host and target re-  
525 gions. Because of this Al Atik et al. (2013) developed a method based on  
526 inverse RVT (IRVT) (Vanmarcke and Gasparini, 1976) that can be used to  
527 modify response spectra for host-to-target adjustments in the Fourier do-  
528 main. The method has the advantage that no assumptions on the form  
529 of the host model (GMPE) are required. Working in the Fourier domain  
530 has the advantage that adjustments are independent of the input motion  
531 unlike when working in the response spectral domain. For a given signal  
532 duration (often defined based on simple regional models), IRVT transforms  
533 the response spectrum into a compatible FAS. FAS based host-to-target  
534 conversion can then be applied to the response-spectrum-compatible FAS  
535 before being returned to the response domain through the standard RVT  
536 approach. A limitation of the IRVT approach is that the response spectrum  
537 becomes less sensitive to the FAS as oscillator period decreases. This results  
538 in significant non-uniqueness of the response-spectrum-compatible FAS at  
539 short periods (roughly  $T < 0.05$  s). Nevertheless, an advantage of this ap-  
540 proach is that one can directly estimate seismological parameters from the

541 GMPE-compatible FAS, such as  $\kappa$ .

542 Figure 2 shows an application of the  $V_s$ - $\kappa_0$  corrections to GMPEs used  
543 in the Swiss National Seismic Hazard Maps (Edwards et al., 2016). The  
544 selected target  $V_s$  profile (Poggi et al., 2011,  $V_{s,30} = 1105$  m/s) and  $\kappa_0$  value  
545 (Edwards et al., 2011,  $\kappa_0 = 0.016$  s) define the reference rock for the seismic  
546 hazard map. For each GMPE two possible host  $V_s$  profiles were selected  
547 (with defined  $V_{s,30}$  where the GMPE’s developers considered the best data  
548 coverage for rock). Four  $\kappa_0$  values were also selected for each GMPE using  
549 either  $V_{s,30}$ - $\kappa_0$  correlations or direct measurement using IRVT. The resulting  
550 eight  $V_s$ - $\kappa_0$  corrections for each GMPE were considered to represent the  
551 epistemic uncertainty involved in adjusting GMPEs to the regional reference.  
552 Small but significant differences arise at long periods due to differences in  
553 amplification of the host- $V_s$  profiles. Far more significant, however, is the  
554 epistemic uncertainty evident in the correction at short periods ( $T < 0.1$  s),  
555 which is due to the uncertainty in defining  $\kappa_0$  (e.g. Edwards et al., 2015).  
556 Similar observations are made by Rodriguez-Marek et al. (2014) for a site-  
557 specific hazard assessment.

## 558 5. Aleatory variability

559 Over the past decades there has been a growing realization that predict-  
560 ing shaking in future earthquakes is associated with large uncertainties and  
561 that this uncertainty must be captured within seismic hazard assessments.  
562 It has become standard to split these uncertainties into two components:  
563 those of inherent randomness, referred to as aleatory variability (this sec-  
564 tion) and those relating to a lack of knowledge or understanding, referred  
565 to as epistemic uncertainty (Section 6).

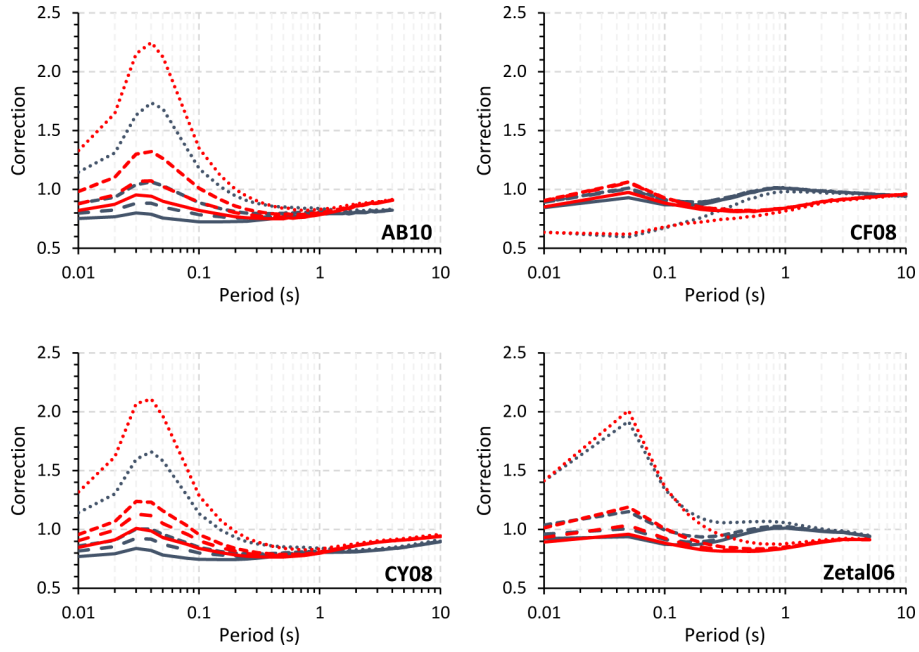


Figure 2:  $V_s$ - $\kappa_0$  corrections proposed for the Swiss National Seismic Hazard Maps by Edwards et al. (2016). Blue/Red indicate different host  $V_s$  profiles (two for each GMPE), line types indicate different  $\kappa_0$  (four for each GMPE) resulting in eight possible corrections per GMPE. AB10: Akkar and Bommer (2010); CF08: Cauzzi and Faccioli (2008); CY08: Chiou and Youngs (2008); and Zetal06: Zhao et al. (2006). The target properties are  $V_{s,30} = 1105$  m/s and  $\kappa_0 = 0.016$  s.

566 The definition of aleatory (and consequently epistemic) variability in-  
567 evitably leads to disagreement and confusion. It could be argued, for in-  
568 stance, that given a perfect model, aleatory variability is, by definition,  
569 zero. However, in current understanding we can at least separate the vari-  
570 ability into parts that can be quantified in terms of scientific uncertainty (e.g.  
571 using different models to predict the same phenomena, such as site ampli-  
572 fication), and those for which there is (at least currently) no scientifically-  
573 based predictive capability (e.g. the stress-drop of the next earthquake). A  
574 more appropriate terminology may therefore be *apparent* aleatory variabil-  
575 ity with respect to a chosen model (written communication, J. J. Bommer,  
576 2016). The advantage of splitting uncertainty into constituent components  
577 is that the logic-tree approach (Kulkarni et al., 1984) can then be used  
578 to branch through the epistemic uncertainty space (e.g. by selecting and  
579 weighting different models) and allowing site or region-specific selections to  
580 be made along with sensitivity studies and analyses (e.g. disaggregation) at  
581 a branch-by-branch level. The distinction between aleatory and epistemic  
582 is particularly important, for example, in the case of a fully probabilistic  
583 seismic risk (or safety) assessment for a safety critical structure such as a  
584 nuclear power plant. Such assessment requires the fractiles of the hazard  
585 to be defined, which can only be correctly calculated with an appropriate  
586 separation of aleatory and epistemic uncertainty.

587 Following Douglas (2003a), Strasser et al. (2009) observe that  $\sigma$  associ-  
588 ated with GMPEs has shown little or no decrease since the 1970s despite  
589 the increasing complexity of models. This fact and the importance of  $\sigma$  on  
590 the results of PSHAs at long return periods, has encouraged attempts to  
591 increase the complexity of models to account for other effects than simply  
592 magnitude, distance and site class (see Section 3). To date these attempts

593 have not led to significant reductions in  $\sigma$  because GMPEs remain simple  
594 representations of complex physical phenomena. Improvements to metadata  
595 do, however, lead to slight reductions in assessed  $\sigma$ . For example, the model  
596 of Chiou and Youngs (2014) is associated with a smaller  $\sigma$  when measured  
597  $V_{s,30}$  is used for a site than when an estimate of this site parameter is em-  
598 ployed.

599 One of the major areas of engineering seismology research in the past  
600 decade has been in separating  $\sigma$  into its different components (Al Atik et al.,  
601 2010; Lin et al., 2011; Rodriguez-Marek et al., 2013) and using the appro-  
602 priate components when conducting a hazard assessment (e.g. Walling and  
603 Abrahamson, 2012). There has also been a move from using whatever data  
604 were available towards selecting to: limit bias, exclude unreliable data, make  
605 analysis easier, and obtain more reliable  $\sigma$  estimates. As noted above, it has  
606 become standard to use random-effects/maximum-likelihood methods to es-  
607 timate between-event ( $\tau$ ) and within-event ( $\phi$ ) components.

608 Records from nearby sites are correlated, which has been recognized by  
609 Jayaram and Baker (2010) when developing a regression technique to ac-  
610 count for spatial correlations and by Boore et al. (1993), who choose only  
611 a single record per site class within a radius of 1 km. These spatial corre-  
612 lations are also important when conducting PSHA for infrastructure with  
613 considerable spatial extent or when computing group earthquake risk over  
614 an extended area.

### 615 *5.1. Between-event variability*

616 Aleatory variability within a given GMPE is usually separated into  
617 between- and within-event components ( $\tau$  and  $\phi$ , respectively). Between-  
618 event terms (random-effects in the context of random-effects regressions),

619 which are source-specific, are thought to be mainly related to stress drop  
620 (Cotton et al., 2013). Using stochastic simulations, Drouet and Cotton  
621 (2015) showed that the between-event variability was strongly controlled  
622 by the stress parameter (as noted previously, ‘stress parameter’ is used to  
623 avoid physical interpretation in terms of pure ‘stress drop’ and rather in-  
624 dicate the proportion of high-frequency energy radiated by an earthquake).  
625 The between-event term can, therefore, be thought of as describing how  
626 energetic the rupture was compared to the average for a given magnitude  
627 (all other things being equal). Such features are not possible (currently)  
628 to predict and, therefore, fall into the category of aleatory variability. The  
629 standard deviation of these event terms is described by  $\tau$ .

630 One of the main ways GMPEs are improving is related to the record-  
631 ing of each earthquake by an increasing number of stations (in particular,  
632 fewer singly-recorded events) so that the source terms (and  $\tau$ ) are better  
633 constrained. This is particularly true for models based on predominantly  
634 Californian or Japanese data but much less so for models derived from data  
635 from Europe and the Middle East (Table 2 and Figure 3). This shows  
636 that despite recent improvements in strong-motion networks in Europe and  
637 Middle East, strong motion databases there remain dominated by poorly-  
638 recorded events. For models based on data with low record-to-event ratios  
639 the source terms (e.g. style-of-faulting factors) and  $\tau$  are poorly constrained.  
640 Additionally, the small number of well-recorded events have a strong influ-  
641 ence on the model.

642  $\tau$  is often found to be heteroscedastic, with decreasing variability as mag-  
643 nitude increases (e.g. Youngs et al., 1995) (Figure 4). Estimated ground-  
644 motion variability from small events ( $M < 5$ ) is often significantly larger  
645 than at moderate and large magnitudes, with many GMPE developers avoid-

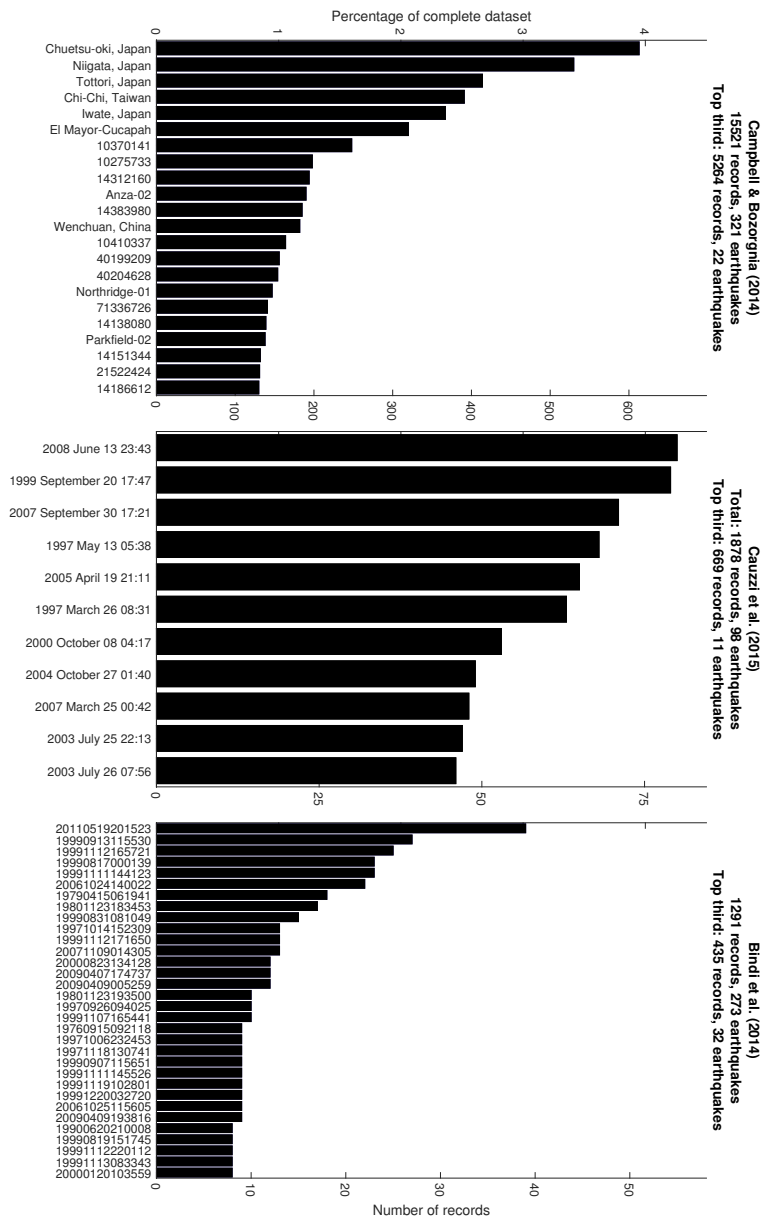


Figure 3: Number of records (bottom axes, different scales for all three subplots) and percentage of total (top axes, same scales for all three subplots) from earthquakes contributing to the top third of total number of records to three recent GMPEs: Campbell and Bozorgnia (2014) (predominantly Californian data), Cauzzi et al. (2015) (predominantly Japanese data) and Bindi et al. (2014) (European and the Middle Eastern data).

Table 2: Ratio (R/E) of number of records (R) per event (E) for four generations of ‘Californian’ and ‘European’ models.

‘Californian’ model	R	E	R/E	‘European’ model	R	E	R/E
Joyner and Boore (1981)	182	23	8	Ambraseys and Bommer (1991)	529	219	2
Boore et al. (1997)	271	20	14	Ambraseys et al. (1996)	422	157	3
Boore and Atkinson (2008)	1574	58	27	Ambraseys et al. (2005)	595	135	4
Boore et al. (2013)	~15000	~350	43	Akkar et al. (2014a)	1041	221	5

646 ing using data from small earthquakes. This is despite the need for models  
647 at lower magnitudes, e.g. for seismic hazard assessment from induced seis-  
648 micity, to examine the applicability of a GMPE in a new region and to  
649 study the various components of ground-motion variability. While models  
650 of ground-motion variability have improved significantly in recent years, we  
651 must be careful not to over-interpret features of these models due to the  
652 limitations of separating the different contributions. In Figure 4 there is  
653 a peak at 0.1s for several models which is difficult to understand in terms  
654 of source variability. During the Hanford PSHA (Hanford.gov, 2014) this  
655 was demonstrated to be an effect of sampling different ranges of site re-  
656 sponse from event to event. The site variability is, therefore, mapped into  
657 between-event terms leading to the peak at 0.1 s.

658 Arguments for observing lower variability at large magnitudes include  
659 the fact that meta-data for large events (e.g. magnitude, depth and mech-  
660 anism) are more reliable. While this is, in general, true, there has been  
661 significant work in recent years to develop reliable earthquake catalogs for  
662 smaller events. Another argument is that, due to large earthquakes having  
663 large rupture sizes, the sensitivity of ground motion to, for example depth or  
664 magnitude, is less. For example,  $M < 5$  events can generally be assumed to  
665 be point sources, with amplitudes decaying in proportion to the reciprocal of  
666 hypocentral distance. On the other hand,  $M > 6$  events emit waves from a



667 range of sources along several kilometers of rupture. Increasing the depth or  
668 size of this fault, whilst changing the distance over which some of the seismic  
669 energy must propagate, will, therefore, have a reduced effect. This is evident  
670 in the saturation of ground-motion amplitudes for increasing magnitude in  
671 GMPEs. Having reliable meta-data for larger events is, therefore, arguably  
672 less important than for small earthquakes for sites not close to major active  
673 faults. For other locations, reliable information on fault geometry and other  
674 properties (e.g. rupture mode) is vital when estimating near-source ground  
675 motions.

676 The limited number of events at large magnitudes leaves  $\tau$  open to under-  
677 sampling (with each event only contributing a single data-point to the esti-  
678 mate of  $\tau$ ). Given that strong-motion databases often include only a handful  
679 of well-recorded events with  $\mathbf{M} > 7$ , the reliability of heteroscedastic  $\tau$  can  
680 be called into question. Comparing values from different GMPEs we can see  
681 that the variability in  $\tau$  estimates is rather high (Figure 4). In reality,  $\tau$  is  
682 likely to be heteroscedastic, but caution should clearly be applied in using  
683 low values at  $\mathbf{M} > 7.5$  coming from extrapolation of trends from smaller  
684 magnitudes (Musson, 2009). Models developed with constant  $\tau$  estimates  
685 for  $\mathbf{M} < 5$  and  $\mathbf{M} > 7$  connected by a linear trend (e.g. Abrahamson et al.,  
686 2014) are an appropriate compromise in this sense.

### 687 *5.2. Within-event variability*

688 Ground-motion variability with respect to a given GMPE for single event  
689 is described by within-event variability ( $\phi$ ). It can be interpreted as describ-  
690 ing the standard deviation of the misfit between GMPE and data after ac-  
691 counting for the between-event terms. In terms of the random-effects frame-  
692 work,  $\phi$  describes the standard deviation of within-event random-effects.

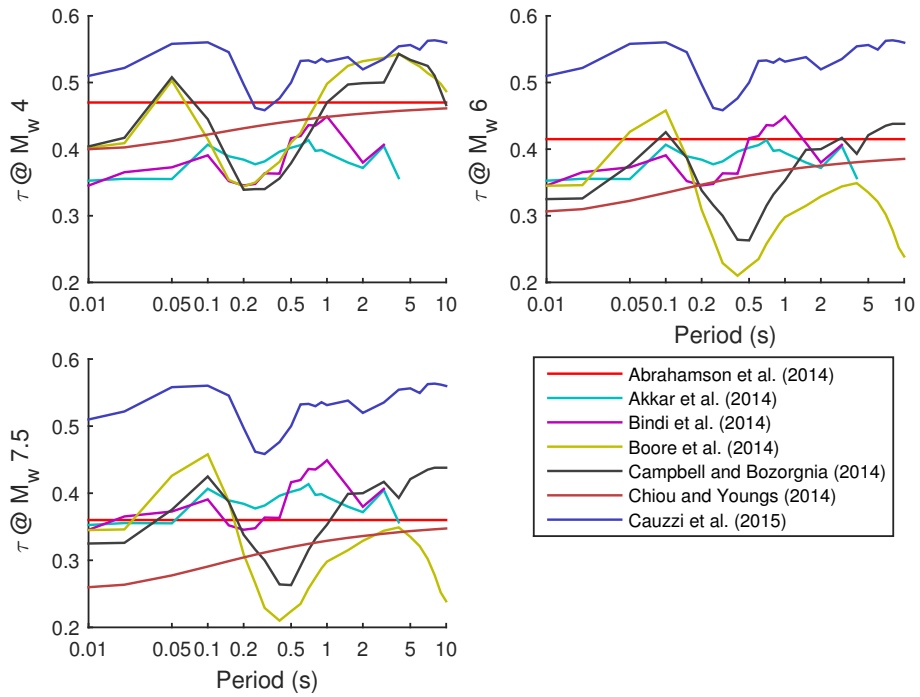


Figure 4: Comparison of the  $\tau$  models of six recent GMPEs: Abrahamson et al. (2014), Boore et al. (2014), Campbell and Bozorgnia (2014) and Chiou and Youngs (2014) (predominantly Californian data); Bindi et al. (2014) and Akkar et al. (2014a) (European and the Middle Eastern data); and Cauzzi et al. (2015) (Japanese data), for  $M_4$ , 6 and 7.5 with respect to response period.

693 The logarithm of ground-motion variability is assumed to be normally dis-  
694 tributed. The total variability of a dataset with respect to a GMPE is then  
695 given by (assuming independence between the two components):  $\sqrt{\tau^2 + \phi^2}$ .  
696 Within-event variability is related to path and site phenomena in addition to  
697 any spatially-dependent source characteristics, such as radiation pattern or  
698 directivity effects. Because of the dominant effect of site amplification and  
699 the significant variability of site effects these are considered to be a signif-  
700 icant source of within-event variability (e.g. Rodriguez-Marek et al., 2011).  
701 In the most recent studies,  $\phi$  is therefore split into components describing  
702 site-to-site variability ( $\phi_{S2S}$ ) and within-site variability ( $\phi_0$ ). Drouet and  
703 Cotton (2015) showed that the within-event variability is controlled by a  
704 number of factors: the most significant being site amplification/attenuation  
705 effects (including  $\kappa$ ) followed by path effects, such as geometrical and anelas-  
706 tic attenuation. Bindi et al. (2014) observe that certain stations contribute  
707 a large proportion of the soft soil (Eurocode 8 class D) sites for European  
708 GMPEs. Some often-triggered stations, therefore, have strong influence on  
709 the model and may reduce the apparent within-event variability.

710 While  $\phi$  is often considered a ‘site term’ it is also observed to be mag-  
711 nitude, distance and  $V_{s,30}$  dependent (Figure 5). For instance, Boore et al.  
712 (2014) and Campbell and Bozorgnia (2014) show that  $\phi$  decreases with mag-  
713 nitude at short periods and increases with magnitude at long periods. Due  
714 to the interaction of ergodic and non-ergodic components of variability it is  
715 difficult to know if this is truly a site-specific effect or due to site-to-site vari-  
716 ability (different sites having recorded different ranges of earthquake magni-  
717 tudes and distances). An effective magnitude-distance dependence of  $\phi$  due  
718 to nonlinearity of soil response has been incorporated into GMPE develop-  
719 ment. For example, Abrahamson et al. (2014) account for soil non-linearity

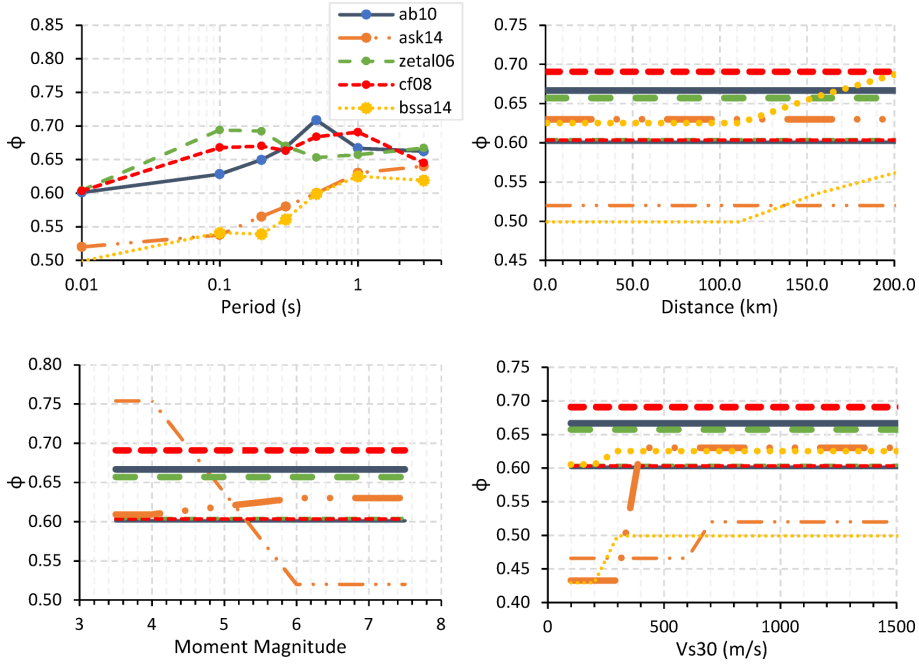


Figure 5: Comparison of estimates of the within-event variability  $\phi$  from some recent GMPEs, where ab10 corresponds to Akkar and Bommer (2010), ask14 corresponds to Abrahamson et al. (2014), zetal06 corresponds to Zhao et al. (2006), cf08 corresponds to Cauzzi and Faccioli (2008) and bssa14 corresponds to Boore et al. (2014).

720 reducing the variability of short-period motions. Focusing on non-ergodic  
 721 sigma, Rodriguez-Marek et al. (2013) present models for single-station  $\phi$   
 722 using data from various tectonic regions. They show a decrease of single-  
 723 station  $\phi$  over all periods, which differs from the observations of ergodic vari-  
 724 ability, where long-period motions show increased  $\phi$  for large earthquakes.

725 An explanation for the different observations of  $\phi$ 's dependency on dis-  
 726 tance and magnitude may be found in the dependence of response spectral  
 727 amplification on the input motion (e.g. Bora et al., 2016). Given that res-  
 728 onance effects in site response depend greatly on the site type (e.g. long-  
 729 period resonance for deep sedimentary basins and high-frequency resonance

730 for thin deposits of alluvium), whether or not input motions (broadly de-  
731 fined by magnitude and distance) excite a particular resonant frequency will  
732 make a difference to ground-motion variability. As a result, depending on  
733 the characteristic site type(s) in a strong-motion database, the sensitivity  
734 of  $\phi$  to magnitude and distance will vary. Rock, or hard-rock sites, will be  
735 mostly independent of input motion, while soil and stiff-soil sites will be  
736 strongly dependent on the input motions, with nearby smaller-magnitude  
737 (higher-frequency) events strongly amplified by high-frequency resonance  
738 peaks.

### 739 *5.3. Single-station variability*

740 The ergodic assumption has been used to derive most GMPEs to date  
741 (Figure 6). This assumption is made to overcome the fact that limited data  
742 are available at individual stations and to provide average (e.g. azimuth-  
743 independent) predictions. The ergodic assumption assumes that spatial  
744 variability can be mapped into variability in time (Anderson and Brune,  
745 1999). Given that station-to-station variability is a significant component of  
746 aleatory variability captured in GMPEs, this assumption cannot be valid for  
747 a single site. To overcome this limitation, the concept of single-station vari-  
748 ability was introduced by Anderson and Brune (1999) and first estimated  
749 using a large set of data by Atkinson (2006).  $\sigma_{SS}$  describes the total vari-  
750 ability (within- and between-event) in SA expected at a single site. Provided  
751 ground-motion variability is separated into  $\phi_0$  and  $\phi_{S2S}$  then simply setting  
752  $\phi_{S2S}$  to zero will result in  $\sigma_{SS}$ . Rodriguez-Marek et al. (2013) showed that  
753  $\sigma_{SS}$  shows remarkably little variability between regions thereby suggesting  
754 that it is the site-to-site variability that drives differences in ground-motion  
755 variability between regions. Although recent work by Al Atik (2015) evi-

756 denced slightly higher values of  $\sigma_{SS}$  based on data from the stable continen-  
757 tal region of central and eastern North America.

758 While  $\sigma_{SS}$  reduces the variability to that consistent with what would  
759 be observed given sufficient recordings at a single site, we must be careful  
760 that the GMPE used for the single site is not biased. When GMPEs are  
761 derived using data from a variety of sites they invariably produce output  
762 that is consistent with the average site within a given site class or for a  
763 given  $V_{s,30}$  in the dataset.  $\phi_{S2S}$  then accounts for the variability between  
764 sites. However, if we are just looking at one site and using  $\sigma_{SS}$  we must  
765 ensure that the GMPE produces a median consistent with our study site.  
766 For this reason host-to-target adjustments (Section 4.5) may be used.

767 Building on current practice of using mixed-effects regression to deter-  
768 mine GMPE coefficients (Abrahamson and Youngs, 1992), Stafford (2014)  
769 presents the use of crossed and nested mixed effects to determine robust  
770 models that are not subject to the short comings of multi-stage approaches  
771 often adopted to separate model components. Using this approach he shows  
772 how site- and region-specific effects can be accounted for within a single  
773 inversion.

## 774 **6. Epistemic uncertainty**

775 Despite rapidly increasing strong-motion databases and the consider-  
776 able improvements in our understanding and modeling of strong ground  
777 motions (see above) each new GMPE published invariably predicts different  
778 levels of average shaking and its variability for every scenario than previ-  
779 ous models. These differences arise from epistemic uncertainty, although  
780 generally this uncertainty is larger than these differences imply. If we had

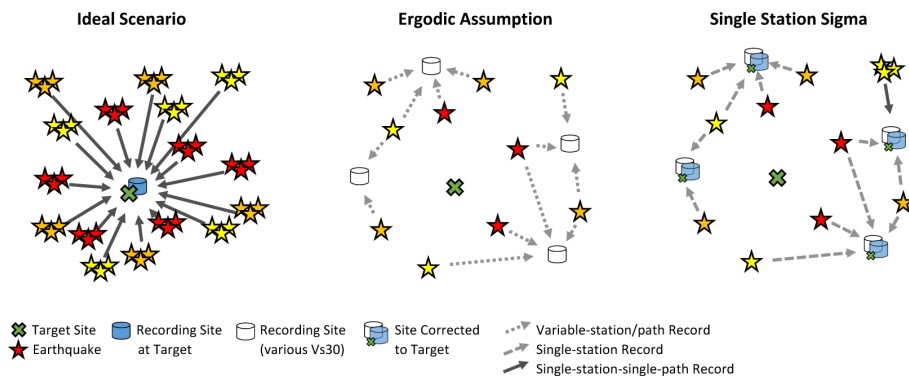


Figure 6: Sketch of transition from ergodic to (partial) non-ergodic assumption. Earthquakes of the same magnitude but with different characteristics (e.g. stress parameter) are indicated by different colored stars. Left: ideal scenario, with numerous events being recorded at a single station. Full separation of uncertainties related to event characteristics ( $\tau$ ), and path and site characteristics ( $\phi$ ) is possible down to single-event-single-path  $\sigma$ . Center: typical scenario, with events sparsely recorded on regional network with various site types (e.g.  $V_{s,30}$ ). An ergodic assumption is used: time equivalent to space to define  $\tau$  and  $\phi$ . Right: advanced approaches correct sites to account for differing response (single-site  $\sigma$ ), while multiple events on the same source (e.g. fault) allow single site-single-path  $\sigma$  to be defined.

781 an infinite amount of data available from every earthquake scenario, travel  
782 path and site then the epistemic uncertainty would reduce to zero as there  
783 would be no need for models, simply selection of the strong-motion records  
784 from the database appropriate for the required scenario. There may still  
785 be aleatory variability in this case because of intrinsic randomness in earth-  
786 quake rupture, wave scattering and so forth but for a given scenario the  
787 true average ground motions and its variability should be defined exactly.  
788 Non-parametric methods (e.g. neural networks) are useful in investigating  
789 ground-motion scaling for well-sampled scenarios (e.g. Derras et al., 2014;  
790 Hermkes et al., 2014). Such data-mining approaches are likely to play an  
791 increasing role as strong-motion databases grow.

792 The day of sufficient observations to no longer require models is many  
793 decades, or even centuries, away for most scenarios of engineering interest.  
794 As shown by Douglas (2010b, 2012) average predicted ground motions for  
795 scenarios close to the barycenter of available data ( $M_w \sim 6$ ,  $R \sim 20$  km) have  
796 remained roughly constant over the past few decades despite improvements  
797 to GMPEs. For well-observed regions such as western North America there  
798 has been some convergence in predictions (Douglas, 2010b). This is because  
799 the same data are used to tune the models. Predictions for scenarios closer  
800 to the edges of available observations (e.g.  $M_w > 7$  and  $R < 10$  km), how-  
801 ever, display larger differences. One question that is rarely raised is: how  
802 representative are the available data of ground motions in that region? For  
803 example, are the few well-recorded  $M > 7$  crustal earthquakes in strong-  
804 motion databases representative of all future large events? Re-sampling and  
805 bootstrap techniques to assess the stability of the models to the removal of  
806 data could be useful in this context (e.g. Berge-Thierry et al., 2003; Bindi  
807 et al., 2014). These approaches, however, only provide guidance on the im-



808 pact of data that are already available and not on the stability of the models  
809 to *future* observations.

810 Another way of understanding epistemic uncertainties is to examine the  
811 statistical confidence limits (e.g. Draper and Smith, 1998) in the median  
812 predictions from a given GMPE (Campbell, 1985). This has been done  
813 by Douglas (2010a), who examined the width of the confidence limits from  
814 three generations of GMPEs for western North America (Joyner and Boore,  
815 1981; Boore et al., 1997; Boore and Atkinson, 2008) and Europe and the  
816 Middle East (Ambraseys and Bommer, 1991; Ambraseys et al., 1996, 2005).  
817 Douglas (2010a) finds that the confidence limits for the western North Amer-  
818 ican models are narrowing (and hence epistemic uncertainty is reducing) but  
819 that this is not seen for the models from Europe and the Middle East, which  
820 he relates to making the models too complex given the number of records  
821 available. Recently, Al Atik and Youngs (2014) compute confidence limits  
822 for the NGA West 2 GMPEs and propose a method to include this uncer-  
823 tainty within a seismic hazard assessment. A third way of examining simi-  
824 larities between models is to use high-dimensional information-visualization  
825 techniques, such as Sammon’s maps (Scherbaum et al., 2010), that display  
826 models on a 2D graph thereby allowing identification of models that predict  
827 similar motions.

828 As strong-motion networks become denser the average number of sta-  
829 tions that record a given earthquake increases, which means that model  
830 source terms (e.g. style-of-faulting factors) and the between-event variabil-  
831 ity ( $\tau$ ) are better constrained in recent GMPEs. Similarly a modern station  
832 generally records more earthquakes leading to better estimates of site terms  
833 and single-station  $\sigma$ . Site terms are now less biased since fewer stations con-  
834 tribute a large proportion of records to strong-motion databases, although

835 the number of records per station remains highly variable.

836 The reduction of epistemic uncertainty (differences in predictions among  
837 models) remains a considerable challenge. It is vital that this uncertainty  
838 is not artificially reduced but that seismic hazard assessments correctly ac-  
839 count for the true uncertainty in ground-motion prediction. There is a  
840 trade-off to be made between including more and more independent vari-  
841 ables to seek to reduce  $\sigma$  but thereby increasing epistemic uncertainty in  
842 the model because these variables are difficult to predict before an earth-  
843 quake and because more variables require more data to constrain the free  
844 coefficients in the GMPE.

845 Only a few GMPE developers (e.g. Douglas et al., 2013) estimate the  
846 epistemic uncertainty in their models. Estimates of the lower bound of the  
847 epistemic uncertainty can be made by comparing multiple models by the  
848 same developer team or by various teams using the same master database  
849 (Douglas et al., 2014a; Abrahamson et al., 2008; Gregor et al., 2014). These  
850 comparisons do not capture the part of uncertainty related to the question:  
851 for which parts of the models are changes likely in the future because of lack  
852 of understanding or knowledge? The motto of US General Colin Powell:  
853 ‘Tell me what you know. Tell me what you don’t know. Then tell me  
854 what you think. Always distinguish which is which’ may be useful in this  
855 context. The first and third parts of this saying are remembered by all  
856 GMPE developers but the second and last parts are often forgotten in the  
857 development of ground-motion models.

858 Logic trees (Kulkarni et al., 1984) are used within seismic hazard assess-  
859 ment to model epistemic uncertainty by assigning weights to each ground-  
860 motion model, for example, depending on the degree of belief that the haz-  
861 ard analyst has in that model being the appropriate one for the study (e.g.

862 Bommer et al., 2005). Consequently there should be a correlation between  
863 the level of understanding about earthquake shaking at the study site (or  
864 regions) and the spread in predicted median ground motions from the logic  
865 tree: wider spread in predictions where knowledge is limited and reinforcing  
866 predictions where knowledge is greater. There is, however, evidence  
867 for ‘group think’ in models. For example, many of the predictions from  
868 the NGA models changed in the same way from 2008 (NGA West 1) to  
869 2014 (NGA West 2), e.g. the predictions for earthquakes with  $M < 5.5$   
870 change considerably [and in agreement with what would be expected (Bom-  
871 mer et al., 2007)] but those for  $M7.5$  change very little (Figure 7). Will such  
872 large changes to predictions also occur when more large earthquakes have  
873 been well recorded? When there are few observations it is uncomfortable  
874 to be out on a limb and for your model to predict greatly different motions  
875 than the majority of models. Consequently, things have changed where new  
876 data (e.g. small magnitudes) are added to strong-motion databases but not  
877 where uncertainty remains high, e.g. close to large events. This leads to  
878 the apparently inconsistent observation made by Douglas (2010b) that the  
879 divergence in predictions of median ground motions from GMPEs for stable  
880 continental regions is lower for large magnitudes (for which there are very  
881 few observations) than for small magnitudes (where data exist).

882 Since about 2010 there has been increasing use of the backbone approach  
883 (Atkinson et al., 2014) to model epistemic uncertainty in ground-motion  
884 prediction. In this approach, rather than use a suite of GMPEs to model  
885 epistemic uncertainty within a logic tree, a single GMPE (or sometimes two  
886 or three GMPEs) is scaled up and down by factors to generate a set of  
887 mutually-exclusive and collectively-exhaustive models. The backbone ap-  
888 proach has the advantage of always having an overall ground-motion model

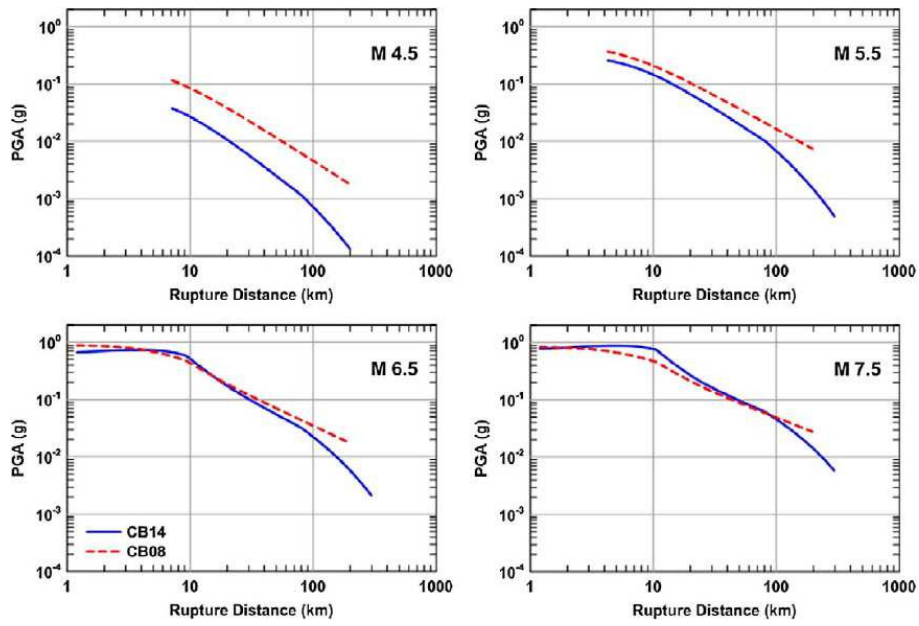


Figure 7: Comparison of predicted median PGA from Campbell and Bozorgnia (2008) (CB08) and Campbell and Bozorgnia (2014) (CB14) on a site with  $V_{s,30} = 760$  m/s for M4.5 to 7.5 from  $45^\circ$ -dipping reverse fault. Figure taken from Campbell and Bozorgnia (2014).

889 that allows the epistemic uncertainty to be defined directly by expert judg-  
890 ment, and which is explicitly definable. The multiple GMPEs approach,  
891 however, leads to varying modeled uncertainties, which may lead to pinch  
892 points for certain scenarios that may not be logical (e.g. where there are  
893 few data but the GMPEs coincide). The backbone approach, however, may  
894 lead to overestimation of epistemic uncertainties when data are abundant  
895 and it can be tricky to calibrate. On the other hand, the availability of  
896 abundant data is unfortunately not presently the case for all relevant sce-  
897 narios (e.g. large magnitude near-source) and using only published GMPEs  
898 without any scaling factors will likely lead to underestimation of the true  
899 epistemic uncertainty.

## 900 **7. Extensions to ground-motion models**

901 As noted above, the vast majority of GMPEs have been derived for PGA  
902 and linear elastic response spectral ordinates (particularly for 5% of critical  
903 damping). Because of its proposed use in liquefaction analysis, its better  
904 correlation with felt and damage reports and its use in some regulations (e.g.  
905 Bommer and Alarcón, 2006) PGV has also become a popular IM for ground-  
906 motion models. In the past decade or so, there has been a growing interest  
907 in deriving models for other IMs (Douglas, 2012), in particular Arias inten-  
908 sity (Arias, 1970) [commonly used in the analysis of earthquake-triggered  
909 landslides (e.g. Harp and Wilson, 1995)], relative significant duration (Tri-  
910 funac and Brady, 1975) and peak ground displacement. A handful of mod-  
911 els for other IMs (e.g. Fourier spectral amplitudes, Japanese Meteorological  
912 Agency seismic intensity, cumulative absolute velocity, mean spectral period  
913 and inelastic response spectral ordinates) have also been published (Douglas,

914 2016). Finally, there is a growing set of macroseismic intensity prediction  
915 equations (Cua et al., 2010). These allow PSHA to be conducted directly  
916 for IMs that have various engineering uses rather than having to conduct  
917 a seismic hazard assessment for PGA, for example, and then convert this  
918 to the required IM. This should lead to smaller overall uncertainties within  
919 risk assessments.

920 Standard GMPEs predict independent scalar IMs. This is what is re-  
921 quired by PSHA to compute uniform hazard spectra, for example. Re-  
922 cent developments in earthquake engineering, e.g. conditional mean spectra  
923 (Baker, 2011), mean that it is important to know the correlation between  
924 spectral ordinates at different structural periods (e.g. Baker and Jayaram,  
925 2008) and between various IMs (e.g. Bradley, 2011). Consequently models  
926 for the estimation of these correlations have been derived. These provide a  
927 more complete assessment of earthquake ground motions.

928 Another way in which the picture of earthquake shaking is becoming  
929 richer is through the derivation of models to estimate the spatial correlation  
930 of motions between neighboring geographical locations (e.g. Goda and Hong,  
931 2008). Such models improve the accuracy of earthquake loss predictions of  
932 spatially-distributed portfolios (e.g. Weatherill et al., 2015).

## 933 **8. Conclusions and ways forward for ground-motion prediction**

934 A number of multinational projects have, over the last decade, brought  
935 significant advances in ground motion characterization for seismic hazard  
936 analyses. These include the NGA West 1 and 2 (Power et al., 2008; Bo-  
937 zorgnia et al., 2014), NGA East (Pacific Earthquake Engineering Research  
938 Center, 2015) and RESORCE (Akkar et al., 2014b) projects. In addition to

939 these initiatives, numerous peer-reviewed articles have improved our knowl-  
940 edge and understanding of ground-motion prediction in a variety of regions,  
941 from active regions with high seismicity (mainly empirical GMPEs) to sta-  
942 ble continental regions with low seismicity (with focus on robust simula-  
943 tion approaches, such as stochastic methods). Despite the significant in-  
944 vestment over the last decades, the aleatory variability in ground-motion  
945 prediction for scenario events appears not to have decreased (e.g. Strasser  
946 et al., 2009). Nevertheless, our understanding of the source and behavior  
947 of ground-motion variability has improved dramatically, with articles barely  
948 mentioning it 20 years ago, to the current state where sometimes roughly  
949 half of a manuscript presenting a new GMPE is dedicated to its charac-  
950 terization. While the total variability is therefore not reduced, the way in  
951 which it is implemented in hazard models is now more realistic. The biggest  
952 improvement is arguably the shift from ergodic towards non-ergodic variabil-  
953 ity. This has reduced the  $\sigma$  used within site-specific (or reference-specific)  
954 hazard analyses by as much as 30%.

955 Despite the great advances of recent years, ground-motion characteriza-  
956 tion is still very much a topic in development. Some authors (e.g. Atkinson,  
957 2012) have predicted that the goal is for numerical simulations to be per-  
958 formed to estimate ground motion and its variability. Despite the increase  
959 in computing power allowing the calculation of shorter-period ground mo-  
960 tions (with current limits around 0.3 to 1 s), the limitation of simulations is  
961 twofold. Firstly, they rely on geophysical characterization of the crust and  
962 shallow subsurface, but at short-periods ( $< 1$  s) the resolution scale of most  
963 available geophysical models is simply insufficient. To overcome this lim-  
964 itation, so-called hybrid approaches are used, where stochastic simulation  
965 models are implemented to some cross-over period (e.g. Graves and Pitarka,

966 2010). Such methods clearly have the same limitations of existing empirical  
967 and stochastic models at short periods. Purely deterministic numerical sim-  
968 ulations are still, therefore, at least several years away. The second limita-  
969 tion of numerical simulations is the understanding of constituent parameters  
970 and their covariances. Engineering practice requires stable and repeatable  
971 models, which GMPEs provide. While numerical simulations can be cali-  
972 brated to provide predictions consistent with observed earthquake shaking,  
973 in practice the input parameters are poorly understood meaning that naive  
974 simulations may be incorrect.

975 Before purely deterministic numerical scenario-simulations become pos-  
976 sible the most promising developments in PSHA lie with the understanding  
977 of ground-motion variability, which drives hazard at long return-periods.  
978 The conceptual approach of single-station (non-ergodic) sigma provides the  
979 framework for this. However, most datasets are still significantly lacking in  
980 data where they are of most relevance for long return-period hazard (records  
981 in the upper tails of the ground-motion distribution from moderate earth-  
982 quakes and large events recorded at near distances). The robustness of mod-  
983 els describing this variability is, therefore, called into question. Improved  
984 approaches for modeling data with mixed sampling in the model space, ob-  
985 taining additional empirical data, and the reliable simulation of such data  
986 is, therefore, of great importance.

987 In some senses, seismology is analogous to economics in that we cannot  
988 do full-scale controlled experiments, e.g. we cannot replay an earthquake  
989 (seismology) or a recession (economics) with slightly altered input param-  
990 eters. Unlike economics, however, in seismology we generally do not have  
991 masses of data. Perhaps there are some statistical tools and approaches that  
992 are used in economics that could be applied to seismological data or models,



993 e.g. in the assessment of epistemic uncertainty. Although as noted by, for  
994 example, Kahneman (2012) experts in economics and in other fields find  
995 it challenging to correctly assess what they know and, equally important,  
996 what they do not know. There is clearly a need in ground-motion prediction  
997 to improve the calibration of the level of epistemic uncertainty modeled by  
998 GMPEs within seismic hazard assessments.

999 Douglas et al. (2014b) find that often the more expensive, carefully-  
1000 undertaken assessments for single sites model *higher* uncertainty than cheaper  
1001 regional assessments, which is a demonstration of an inconsistency in cap-  
1002 turing epistemic uncertainty. However, it should be noted that the primary  
1003 objective of more elaborate assessments, such as those following the SSHAC  
1004 guidelines (Budnitz et al., 1997), is to ensure the capture of epistemic uncer-  
1005 tainty. The higher study levels in SSHAC increase the likelihood of this ob-  
1006 jective being met. Therefore, it should not surprise us that the uncertainty  
1007 ranges from SSHAC Level 3 or 4 studies are greater than those in small  
1008 studies performed more informally by an individual or a small team. On  
1009 the other hand, epistemic uncertainty is reduced by data collection. In the  
1010 Thyspunt PSHA (Bommer et al., 2015), for example, without the historical  
1011 seismicity studies, geological investigations and extensive velocity measure-  
1012 ments at the site, the total uncertainty in the final hazard assessments would  
1013 have been considerably larger. More expensive studies are, therefore, forced  
1014 to undertake more analyses to assure that epistemic uncertainty is reduced,  
1015 as opposed to smaller studies that may simply make an assumption that the  
1016 overall epistemic uncertainty is at a given level.

1017 The growth of unconventional gas and oil extraction and associated fluid  
1018 injection and, to a lesser extent, geothermal energy has led to a significant  
1019 increase in induced seismicity (Rubinstein and Mahani, 2015). This fo-

1020 cus has seen several GMPEs being published for the purpose of predicting  
1021 ground motion from small earthquakes at very short distances. While com-  
1022 mon wisdom would suggest that damage due to induced seismicity, which is  
1023 generally limited to events with  $M < 5$ , is negligible, there have been cases  
1024 of significant insured losses (Giardini, 2009), although what proportion of  
1025 damage is earthquake-related is debatable.

1026 As noted above, some authors (Field et al., 2003; Atkinson, 2012) have  
1027 argued that GMPEs will soon be replaced by numerical simulations of earth-  
1028 quake shaking. Such simulations do provide a much richer representation of  
1029 the earthquake hazard to engineers (full time-histories rather than simply  
1030 intensity measures) and they allow source- and site-specific calculations, al-  
1031 though for a limited structural period range. For poorly-sampled magnitude-  
1032 distance ranges and unusual source (e.g. deep crustal sources), path (e.g.  
1033 strong velocity contrasts) and site conditions (e.g. nonlinear soils) simula-  
1034 tions are invaluable in guiding the development of GMPEs. The general  
1035 consensus is that full-waveform simulation approaches are currently not suf-  
1036 ficiently constrained, however, to form the basis of hazard analyses due to  
1037 their reliance on a full understanding of the physical system (including effects  
1038 such as plastic deformation, fault shape and roughness). They are at a stage,  
1039 however, where simulations provide valuable insight into the expected be-  
1040 havior of source effects and wave propagation in heterogeneous media, which  
1041 can be combined with empirical data and analyses. Although ground-motion  
1042 simulations show significant advances with the advent of high-performance  
1043 computing and the development of better procedures, GMPEs are likely to  
1044 remain a key component of hazard assessments for the foreseeable future.

1045 One attractive approach to ground-motion simulation is ‘virtual earth-  
1046 quakes’ (Denolle et al., 2014), in which the Green’s functions measuring the

1047 Earth's response to point impulses are derived from the ambient seismic field  
1048 (i.e. microtremors) and then these are used to predict ground motion from  
1049 a series of point sources to model fault rupture. This approach captures the  
1050 effect of travel path in the region, e.g. sedimentary basin effects, but it is  
1051 currently restricted to structural periods longer than 3 s. For long periods  
1052 it may be possible to simulate ground motions using this technique for the  
1053 derivation of ground-motion models but an outstanding issue is assessing  
1054 the variability and uncertainty associated with these simulations.

1055 Treverton (2007) discusses the difference between a puzzle and a mys-  
1056 tery. To solve a puzzle you need more information while to solve a mystery  
1057 requires clever analysis of the information that is already available. Ground-  
1058 motion prediction currently is more of a puzzle, because data are limited,  
1059 whilst it is often seen as a mystery, where complex analysis is applied to  
1060 very little data. As noted by Atkinson (2004) for 'every dollar that is spent  
1061 trying to quantify uncertainty, we should spend 10 dollars collecting and an-  
1062 alyzing data that would reduce uncertainty'. While we have seen significant  
1063 changes in many, if not most, recent PSHAs compared to earlier studies,  
1064 due to the advancement of state-of-practice, a significant contribution to  
1065 this can be put down to the availability of new data and better treatment of  
1066 it in PSHA. Collection of more strong-motion data and, equally important,  
1067 the associated metadata (e.g. local site conditions) is the only reliable way  
1068 of reducing uncertainty in ground-motion prediction and hence it should be  
1069 prioritized. With the rapid decrease in the cost of strong-motion instrumen-  
1070 tation and the ease-of-use of new sensors, there is hope that the era of only  
1071 recording a single near-source accelerogram from a **M7.8** earthquake [as was  
1072 the case for the Gorkha (Nepal) earthquake of 25th April 2015] is coming  
1073 to an end. Strong-motion monitoring in seismic areas could be encouraged

1074 by, for example: providing instruments to schools for use as an educational  
1075 tool, installing sensors in public buildings, and requiring instrumentation  
1076 as part of the building code for infrastructure (e.g. power plants). Large  
1077 earthquakes occur infrequently and they present an opportunity to signifi-  
1078 cantly improve our knowledge of earthquake shaking, which is vital in the  
1079 reduction of seismic risk.

1080 Our understanding of earthquake hazard has improved dramatically in  
1081 the past decades. Therefore, is it necessary to continue refining seismic  
1082 hazard assessments when the results are unlikely to change dramatically?  
1083 We argue that such refinement is required if not from a purely scientific  
1084 point of view but because it is important from the regulator's viewpoint  
1085 that all avenues are explored and the best analysis is performed. Many drug  
1086 trials are conducted that demonstrate that a drug is not useful but it is  
1087 not then argued that the trial was a waste of money – why should seismic  
1088 hazard assessment be any different? The seismological community cannot  
1089 be seen to be resting on our laurels and not striving for improved knowledge  
1090 and understanding. In addition, while significant recent advances have been  
1091 made in education, it is necessary to continue to train the next generation  
1092 of engineering seismologists so that they can produce high-quality hazard  
1093 assessments and, equally important, to understand what such assessments  
1094 mean. Examples of this should focus on two important elements: a) hands-  
1095 on experience in real projects (most training is typically theoretical and in  
1096 the authors' experience is not completely aligned with real projects), and b)  
1097 funding science and data collection underlying earthquake engineering and  
1098 engineering seismology.

1099 Finally, while significant advances have been made in ground-motion  
1100 prediction over the past decade, we are continually surprised by unexpected

1101 events. Recent examples include the high PGAs recorded during the **M9**  
1102 Tohoku earthquake (2.7 g); the long-period (3-5 s) motions (over 4 m/s)  
1103 recorded during the **M7.8** Gorkha, Nepal event with recorded peak displace-  
1104 ments of up to 1.87 m; and in lower seismicity areas the Market Rasen (**M4.5**,  
1105 UK) and St Die (**M4.8**, France) earthquakes (Ottemöller and Sargeant, 2010;  
1106 Scherbaum et al., 2004), which exhibited much higher than expected motions  
1107 than expected using local ground-motion models. It is clear, therefore, that  
1108 while advances are welcome in aspects such as median predictions and the  
1109 capture of uncertainty, we still lack full understanding of the fundamentals  
1110 of source-, path- and site-specific earthquake ground motion.

## 1111 **9. Acknowledgments**

1112 Some of the ideas presented here were discussed during the Theme Lec-  
1113 ture of Douglas (2014). We thank Julian Bommer and Fabrice Cotton for  
1114 their careful reviews of an early version of this article, which led to significant  
1115 improvements to the article.

## 1116 **References**

- 1117 Abrahamson, N., Atkinson, G., Boore, D., Bozorgnia, Y., Campbell, K.,  
1118 Chiou, B., Idriss, I. M., Silva, W., Youngs, R., Feb 2008. Comparisons of  
1119 the NGA ground-motion relations. *Earthquake Spectra* 24 (1), 45–66.
- 1120 Abrahamson, N. A., Silva, W. J., Kamai, R., Aug 2014. Summary of the  
1121 ASK14 ground motion relation for active crustal regions. *Earthquake*  
1122 *Spectra* 30 (3), 1025–1055.

- 1123 Abrahamson, N. A., Youngs, R. R., Feb 1992. A stable algorithm for regres-  
1124 sion analyses using the random effects model. *Bulletin of the Seismological*  
1125 *Society of America* 82 (1), 505–510.
- 1126 Akkar, S., Bommer, J. J., Mar/Apr 2010. Empirical equations for the pre-  
1127 diction of PGA, PGV and spectral accelerations in Europe, the Mediter-  
1128 ranean region and the Middle East. *Seismological Research Letters* 81 (2),  
1129 195–206.
- 1130 Akkar, S., Çağnan, Z., Yenier, E., Erdoğan, O., Sandıkkaya, A., Gülkan, P.,  
1131 2010. The recently compiled Turkish strong-motion database: Preliminary  
1132 investigation for seismological parameters. *Journal of Seismology* 14 (3),  
1133 457–479.
- 1134 Akkar, S., Sandıkkaya, M. A., Bommer, J. J., 2014a. Empirical ground-  
1135 motion models for point- and extended-source crustal earthquake scenar-  
1136 ios in Europe and the Middle East. *Bulletin of Earthquake Engineering*  
1137 12 (1), 359–387.
- 1138 Akkar, S., Sandıkkaya, M. A., Şenyurt, M., Azari, A. S., Ay, B. O., Traversa,  
1139 P., Douglas, J., Cotton, F., Luzi, L., Hernandez, B., Godey, S., 2014b.  
1140 Reference database for seismic ground-motion in Europe (RESORCE).  
1141 *Bulletin of Earthquake Engineering* 12 (1), 311–339.
- 1142 Al Atik, L., 2015. NGA-East: Ground-motion standard deviation models for  
1143 central and eastern North America. PEER Report 2015/07, Pacific Earth-  
1144 quake Engineering Research Center, University of California at Berkeley,  
1145 USA.
- 1146 Al Atik, L., Abrahamson, N., Bommer, J. J., Scherbaum, F., Cotton, F.,

- 1147 Kuehn, N., Sep/Oct 2010. The variability of ground-motion prediction  
1148 models and its components. *Seismological Research Letters* 81 (5), 794–  
1149 801.
- 1150 Al Atik, L., Kottke, A., Abrahamson, N., Hollenback, J., 2013. Kappa ( $\kappa$ )  
1151 scaling of ground-motion prediction equations using an inverse random vi-  
1152 bration theory approach. *Bulletin of the Seismological Society of America*  
1153 104 (1), 336–346.
- 1154 Al Atik, L., Youngs, R. R., Aug 2014. Epistemic uncertainty for NGA-West2  
1155 models. *Earthquake Spectra* 30 (3), 1301–1318.
- 1156 Allmann, B. P., Shearer, P. M., 2007. Spatial and temporal stress drop vari-  
1157 ations in small earthquakes near Parkfield, California. *Journal of Geo-  
1158 physical Research* 112 (B04305).
- 1159 Ambraseys, N. N., Bommer, J. J., 1991. The attenuation of ground ac-  
1160 celerations in Europe. *Earthquake Engineering and Structural Dynamics*  
1161 20 (12), 1179–1202.
- 1162 Ambraseys, N. N., Douglas, J., Sarma, S. K., Smit, P. M., 2005. Equations  
1163 for the estimation of strong ground motions from shallow crustal earth-  
1164 quakes using data from Europe and the Middle East: Horizontal peak  
1165 ground acceleration and spectral acceleration. *Bulletin of Earthquake En-  
1166 gineering* 3 (1), 1–53.
- 1167 Ambraseys, N. N., Free, M. W., 1997. Surface-wave magnitude calibra-  
1168 tion for European region earthquakes. *Journal of Earthquake Engineering*  
1169 1 (1), 1–22.

- 1170 Ambraseys, N. N., Simpson, K. A., Bommer, J. J., 1996. Prediction of hori-  
1171 zontal response spectra in Europe. *Earthquake Engineering and Structural*  
1172 *Dynamics* 25 (4), 371–400.
- 1173 Anderson, J. G., Brune, J. N., 1999. Probabilistic seismic hazard assessment  
1174 without the ergodic assumption. *Seismological Research Letters* 70 (1),  
1175 19–28.
- 1176 Anderson, J. G., Hough, S. E., Oct 1984. A model for the shape of the  
1177 Fourier amplitude spectrum of acceleration at high frequencies. *Bulletin*  
1178 *of the Seismological Society of America* 74 (5), 1969–1993.
- 1179 Arias, A., 1970. A measure of earthquake intensity. In: Hansen, R. (Ed.),  
1180 *Seismic Design for Nuclear Power Plants*. The M.I.T. Press, pp. 438–483.
- 1181 ASCE, 2013. Minimum design loads for buildings and other structures. Tech.  
1182 Rep. ASCE/SEI 7-10, Committee on Minimum Design Loads for Buildings  
1183 and Other Structures of the Codes and Standards Activities Division of  
1184 Structural Engineering Institute.
- 1185 Atkinson, G. M., 2004. An overview of developments in seismic hazard anal-  
1186 ysis. In: *Proceedings of Thirteenth World Conference on Earthquake En-*  
1187 *gineering*. Paper no. 5001.
- 1188 Atkinson, G. M., Apr 2006. Single-station sigma. *Bulletin of the Seismolog-*  
1189 *ical Society of America* 96 (2), 446–455.
- 1190 Atkinson, G. M., Apr 2010. Ground motion prediction equations for Hawaii  
1191 from a referenced empirical approach. *Bulletin of the Seismological Society*  
1192 *of America* 100 (2), 751–761.



- 1193 Atkinson, G. M., 2012. Integrating advances in ground-motion and seismic-  
1194 hazard analysis. In: Proceedings of Fifteenth World Conference on Earth-  
1195 quake Engineering.
- 1196 Atkinson, G. M., Apr 2015. Ground-motion prediction equation for small-  
1197 to-moderate events at short hypocentral distances, with application to  
1198 induced-seismicity hazards. *Bulletin of the Seismological Society of Amer-*  
1199 *ica* 105 (2A), 981–992.
- 1200 Atkinson, G. M., Beresnev, I., Jan/Feb 1997. Don't call it stress drop. *Seis-*  
1201 *mological Research Letters* 68 (1), 3–4.
- 1202 Atkinson, G. M., Bommer, J. J., Abrahamson, N. A., Oct 2014. Alternative  
1203 approaches to modeling epistemic uncertainty in ground motions in prob-  
1204 abilistic seismic-hazard analysis. *Seismological Research Letters* 85 (6),  
1205 1141–1144.
- 1206 Atkinson, G. M., Silva, W., Apr 2000. Stochastic modeling of California  
1207 ground motion. *Bulletin of the Seismological Society of America* 90 (2),  
1208 255–274.
- 1209 Baker, J. W., 2011. Conditional mean spectrum: Tool for ground motion  
1210 selection. *Journal of Structural Engineering, ASCE* 137 (3), 322–331.
- 1211 Baker, J. W., Jayaram, N., 2008. Correlation of spectral acceleration values  
1212 from NGA ground motion models. *Earthquake Spectra* 24 (1), 299–317.
- 1213 Bakun, W. H., 1984. Seismic moments, local magnitudes, and coda-duration  
1214 magnitudes for earthquakes in central California. *Bulletin of the Seismo-*  
1215 *logical Society of America* 74 (2), 439–458.

- 1216 Baltay, A. S., Hanks, T. C., Dec 2014. Understanding the magnitude depen-  
1217 dence of PGA and PGV in NGA-West 2 data. *Bulletin of the Seismolog-  
1218 ical Society of America* 104 (6), 2851–2865.
- 1219 Bazzurro, P., Cornell, C. A., Apr 1999. Disaggregation of seismic hazard.  
1220 *Bulletin of the Seismological Society of America* 89 (2), 501–520.
- 1221 Beauval, C., Tasan, H., Laurandea, A., Delavaud, E., Cotton, F., Guéguen,  
1222 P., Kuehn, N., 2012. On the testing of ground-motion prediction equations  
1223 against small-magnitude data. *Bulletin of the Seismological Society of  
1224 America* 102 (5), 1994–2007.
- 1225 Berge-Thierry, C., Cotton, F., Scotti, O., Griot-Pommer, D.-A.,  
1226 Fukushima, Y., 2003. New empirical response spectral attenuation laws  
1227 for moderate European earthquakes. *Journal of Earthquake Engineering  
1228* 7 (2), 193–222.
- 1229 Bindi, D., Massa, M., Luzi, L., Ameri, G., Pacor, F., Puglia, R., Augliera, P.,  
1230 2014. Pan-European ground-motion prediction equations for the average  
1231 horizontal component of PGA, PGV, and 5%-damped PSA at spectral  
1232 periods up to 3.0s using the RESORCE dataset. *Bulletin of Earthquake  
1233 Engineering* 12 (1), 391–430.
- 1234 Bindi, D., Spallarossa, D., Eva, C., Cattaneo, M., 2005. Local and duration  
1235 magnitudes in northwestern Italy, and seismic moment versus magnitude  
1236 relationships. *Bulletin of the Seismological Society of America* 95 (2), 592–  
1237 604.
- 1238 Bommer, J. J., Akkar, S., Feb 2012. Consistent source-to-site distance met-

- 1239 rics in ground-motion prediction equations and seismic source models for  
1240 PSHA. *Earthquake Spectra* 28 (1), 1–15.
- 1241 Bommer, J. J., Akkar, S., Drouet, S., 2012. Extending ground-motion pre-  
1242 diction equations for spectral accelerations to higher response frequencies.  
1243 *Bulletin of Earthquake Engineering* 10 (2), 379–399.
- 1244 Bommer, J. J., Alarcón, J. E., 2006. The prediction and use of peak ground  
1245 velocity. *Journal of Earthquake Engineering* 10 (1), 1–31.
- 1246 Bommer, J. J., Coppersmith, K. J., Coppersmith, R. T., Hanson, K. L.,  
1247 Mangongolo, A., Neveling, J., Rathje, E. M., Rodriguez-Marek, A.,  
1248 Scherbaum, F., Shelembe, R., Stafford, P. J., Strasser, F. O., May 2015.  
1249 A SSHAC level 3 probabilistic seismic hazard analysis for a new-build  
1250 nuclear site in South Africa. *Earthquake Spectra* 31 (2), 661–698.
- 1251 Bommer, J. J., Dost, B., Edwards, B., Stafford, P. J., van Elk, J., Doorn-  
1252 hof, D., Ntinalexis, M., 2016. Developing an application-specific ground-  
1253 motion model for induced seismicity. *Bulletin of the Seismological Society*  
1254 *of America* 106 (1), 158–173.
- 1255 Bommer, J. J., Douglas, J., Scherbaum, F., Cotton, F., Bungum, H., Fäh,  
1256 D., 2010. On the selection of ground-motion prediction equations for seis-  
1257 mic hazard analysis. *Seismological Research Letters* 81 (5), 783–793.
- 1258 Bommer, J. J., Oates, S., Cepeda, J. M., Lindholm, C., Bird, J., Torres,  
1259 R., Marroqun, G., Rivas, J., 2006. Control of hazard due to seismicity  
1260 induced by a hot fractured rock geothermal project. *Engineering Geology*  
1261 83, 287–306.

- 1262 Bommer, J. J., Scherbaum, F., Bungum, H., Cotton, F., Sabetta, F., Abra-  
1263 hamson, N. A., Apr 2005. On the use of logic trees for ground-motion  
1264 prediction equations in seismic-hazard analysis. *Bulletin of the Seismo-*  
1265 *logical Society of America* 95 (2), 377–389.
- 1266 Bommer, J. J., Stafford, P. J., Alarcón, J. E., Akkar, S., 2007. The influence  
1267 of magnitude range on empirical ground-motion prediction. *Bulletin of*  
1268 *the Seismological Society of America* 97 (6), 2152–2170.
- 1269 Boore, D. M., Mar 2003. Simulation of ground motion using the stochastic  
1270 method. *Pure and Applied Geophysics* 160 (3–4), 635–676.
- 1271 Boore, D. M., Dec 2009. Comparing stochastic point-source and finite-source  
1272 ground-motion simulations: SMSIM and EXSIM. *Bulletin of the Seismo-*  
1273 *logical Society of America* 99 (6), 3202–3216.
- 1274 Boore, D. M., Atkinson, G. M., 2008. Ground-motion prediction equations  
1275 for the average horizontal component of PGA, PGV, and 5%-damped  
1276 PSA at spectral periods between 0.01 s and 10.0 s. *Earthquake Spectra*  
1277 24 (1), 99–138.
- 1278 Boore, D. M., Joyner, W. B., Fumal, T. E., 1993. Estimation of response  
1279 spectra and peak accelerations from western North American earthquakes:  
1280 An interim report. *Open-File Report 93-509*, U.S. Geological Survey, 70  
1281 pages.
- 1282 Boore, D. M., Joyner, W. B., Fumal, T. E., Jan/Feb 1997. Equations for  
1283 estimating horizontal response spectra and peak acceleration from western  
1284 North American earthquakes: A summary of recent work. *Seismological*  
1285 *Research Letters* 68 (1), 128–153.

- 1286 Boore, D. M., Stewart, J. P., Seyhan, E., Atkinson, G. M., 2013. NGA-  
1287 West2 equations for predicting response spectral accelerations for shallow  
1288 crustal earthquakes. Tech. Rep. 2013/05, Pacific Earthquake Engineering  
1289 Research Center, College of Engineering, University of California, Berke-  
1290 ley.
- 1291 Boore, D. M., Stewart, J. P., Seyhan, E., Atkinson, G. M., Aug 2014. NGA-  
1292 West 2 equations for predicting PGA, PGV, and 5%-damped PSA for  
1293 shallow crustal earthquakes. *Earthquake Spectra* 30 (3), 1057–1085.
- 1294 Boore, D. M., Thompson, E. M., Cadet, H., 2011. Regional correlations of  
1295  $V_{S30}$  and velocities averaged over depths less than and greater than 30  
1296 meters. *Bulletin of the Seismological Society of America* 101 (6), 3046–  
1297 3059.
- 1298 Boore, D. M., Watson-Lamprey, J., Abrahamson, N. A., Aug 2006.  
1299 Orientation-independent measures of ground motion. *Bulletin of the Seis-  
1300 mological Society of America* 96 (4A), 1502–1511.
- 1301 Bora, S. S., Scherbaum, F., Kuehn, N., Stafford, P., Jun 2016. On the  
1302 relationship between Fourier and response spectra: Implications for the  
1303 adjustment of empirical ground-motion prediction equations (GMPEs).  
1304 *Bulletin of the Seismological Society of America* 106 (3), 1235–1253.
- 1305 Bora, S. S., Scherbaum, F., Kuehn, N., Stafford, P., Edwards, B., Aug 2015.  
1306 Development of a response spectral ground-motion prediction equation  
1307 (GMPE) for seismic-hazard analysis from empirical Fourier spectral and  
1308 duration models. *Bulletin of the Seismological Society of America* 105 (4),  
1309 2192–2218.

- 1310 Bourne, S. J., Oates, S. J., Bommer, J. J., Dost, B., van Elk, J., Doornhof,  
1311 D., Jun 2015. Monte Carlo method for probabilistic hazard assessment of  
1312 induced seismicity due to conventional natural gas production. *Bulletin*  
1313 *of the Seismological Society of America* 105 (3), 1721–1738.
- 1314 Bozorgnia, Y., Abrahamson, N. A., Al Atik, L., Ancheta, T. D., Atkinson,  
1315 G. M., Baker, J. W., Baltay, A., Boore, D. M., Campbell, K. W., Chiou,  
1316 B. S.-J., Darragh, R., Day, S., Donahue, J., Graves, R. W., Gregor, N.,  
1317 Hanks, T., Idriss, I. M., Kamai, R., Kishida, T., Kottke, A., Mahin, S. A.,  
1318 Rezaeian, S., Rowshandel, B., Seyhan, E., Shahi, S., Shantz, T., Silva, W.,  
1319 Spudich, P., Stewart, J. P., Watson-Lamprey, J., Wooddell, K., Youngs,  
1320 R., Aug 2014. NGA-West2 research project. *Earthquake Spectra* 30 (3),  
1321 973–987.
- 1322 Bradley, B. A., 2011. Correlation of significant duration with amplitude and  
1323 cumulative intensity measures and its use in ground motion selection.  
1324 *Journal of Earthquake Engineering* 15 (6), 809–832.
- 1325 Brady, A. G., Trifunac, M. D., Hudson, D. E., Feb 1973. Analyses of strong  
1326 motion earthquake accelerograms — response spectra. Tech. rep., Earth-  
1327 quake Engineering Research Laboratory — California Institute of Tech-  
1328 nology.
- 1329 Brune, J. N., Sep 1970. Tectonic stress and the spectra of seismic shear waves  
1330 from earthquakes. *Journal of Geophysical Research* 75 (26), 4997–5009.
- 1331 Budnitz, R. J., Apostolakis, G., Boore, D. M., Cluff, L. S., Coppersmith,  
1332 K. J., Cornell, C. A., Morris, P. A., 1997. Recommendations for proba-  
1333 bilistic seismic hazard analysis: Guidance on uncertainty and use of ex-

- 1334     perts. Tech. Rep. NUREG/CR-6372, US Nuclear Regulatory Commission,  
1335     Washington D.C., two volumes.
- 1336     Campbell, K. W., Aug 1985. Strong motion attenuation relations: A ten-  
1337     year perspective. *Earthquake Spectra* 1 (4), 759–804.
- 1338     Campbell, K. W., 2003. Prediction of strong ground motion using the hybrid  
1339     empirical method and its use in the development of ground-motion (atten-  
1340     uation) relations in eastern North America. *Bulletin of the Seismological*  
1341     *Society of America* 93 (3), 1012–1033.
- 1342     Campbell, K. W., Bozorgnia, Y., 2008. NGA ground motion model for  
1343     the geometric mean horizontal component of PGA, PGV, PGD and 5%  
1344     damped linear elastic response spectra for periods ranging from 0.01 to  
1345     10s. *Earthquake Spectra* 24 (1), 139–171.
- 1346     Campbell, K. W., Bozorgnia, Y., Aug 2014. NGA-West2 ground motion  
1347     model for the average horizontal components of PGA, PGV, and 5%-  
1348     damped linear acceleration response spectra. *Earthquake Spectra* 30 (3),  
1349     1087–1115.
- 1350     Cartwright, D. E., Longuet-Higgins, M. S., 1956. The statistical distribution  
1351     of the maxima of a random function. *Proceedings of the Royal Society of*  
1352     *London Series A — Mathematical and Physical Sciences* 237 (1209), 212–  
1353     232.
- 1354     Castellaro, S., Mulargia, F., Rossi, P. L., 2008. Vs30: Proxy for seismic  
1355     amplification? *Seismological Research Letters* 79 (4), 540–543.
- 1356     Cauzzi, C., Faccioli, E., Oct 2008. Broadband (0.05 to 20s) prediction of

- 1357 displacement response spectra based on worldwide digital records. *Journal*  
1358 *of Seismology* 12 (4), 453–475.
- 1359 Cauzzi, C., Faccioli, E., Vanini, M., Bianchini, A., Jun 2015. Updated pre-  
1360 dictive equations for broadband (0.01–10s) horizontal response spectra  
1361 and peak ground motions, based on a global dataset of digital accelera-  
1362 tion records. *Bulletin of Earthquake Engineering* 13 (6), 1587–1612.
- 1363 Chiou, B., Darragh, R., Gregor, N., Silva, W., Feb 2008. NGA project  
1364 strong-motion database. *Earthquake Spectra* 24 (1), 23–44.
- 1365 Chiou, B. S.-J., Youngs, R. R., 2008. An NGA model for the average horizon-  
1366 tal component of peak ground motion and response spectra. *Earthquake*  
1367 *Spectra* 24 (1), 173–215.
- 1368 Chiou, B. S.-J., Youngs, R. R., Aug 2014. Update of the Chiou and Youngs  
1369 NGA model for the average horizontal component of peak ground motion  
1370 and response spectra. *Earthquake Spectra* 30 (3), 1117–1153.
- 1371 Chopra, A. K., 1995. *Dynamics of Structures — Theory and Application to*  
1372 *Earthquake Engineering*. Prentice Hall International, Inc.
- 1373 Comité Européen de Normalisation, Sep 2005. Eurocode 8, Design of struc-  
1374 tures for earthquake resistance — Part 1: General rules, seismic actions  
1375 and rules for buildings. European Standard NF EN 1998-1.
- 1376 Cornell, C. A., Oct 1968. Engineering seismic risk analysis. *Bulletin of the*  
1377 *Seismological Society of America* 58 (5), 1583–1606.
- 1378 Cotton, F., Archuleta, R., Causse, M., 2013. What is sigma of the stress  
1379 drop? *Seismological Research Letters* 84 (1), 42–48.



- 1380 Cotton, F., Pousse, G., Bonilla, F., Scherbaum, F., Oct 2008. On the discrep-  
1381      ancy of recent European ground-motion observations and predictions from  
1382      empirical models: Analysis of KiK-net accelerometric data and point-  
1383      sources stochastic simulations. *Bulletin of the Seismological Society of*  
1384      *America* 98 (5), 2244–2261.
- 1385 Cousins, W. J., Zhao, J. X., Perrin, N. D., Dec 1999. A model for the atten-  
1386      uation of peak ground acceleration in New Zealand earthquakes based on  
1387      seismograph and accelerograph data. *Bulletin of the New Zealand Society*  
1388      *for Earthquake Engineering* 32 (4), 193–220.
- 1389 Cua, G., Wald, D. J., Allen, T. I., Garcia, D., Worden, C. B., Gerstenberger,  
1390      M., Lin, K., Marano, K., Oct 2010. “Best practices” for using macroseis-  
1391      mic intensity and ground motion intensity conversion equations for hazard  
1392      and loss models in GEM1. Tech. Rep. 2010-4, GEM Foundation, Pavia,  
1393      Italy.
- 1394 Delavaud, E., Cotton, F., Akkar, S., Scherbaum, F., Danciu, L., Beauval,  
1395      C., Drouet, S., Douglas, J., Basili, R., Sandikkaya, M. A., Segou, M.,  
1396      Faccioli, E., Theodoulidis, N., 2012. Toward a ground-motion logic tree for  
1397      probabilistic seismic hazard assessments in Europe. *Journal of Seismology*  
1398      16 (3), 451–473.
- 1399 Denolle, M. A., Dunham, E. M., Prieto, G. A., Beroza, G. C., Jan  
1400      2014. Strong ground motion prediction using virtual earthquakes. *Science*  
1401      343 (6169), 399–403.
- 1402 Derras, B., Cotton, F., Bard, P.-Y., 2014. Towards fully data driven ground-  
1403      motion prediction models for Europe. *Bulletin of Earthquake Engineering*  
1404      12 (1), 495–516.

- 1405 Douglas, J., 2003a. Earthquake ground motion estimation using strong-  
1406 motion records: A review of equations for the estimation of peak  
1407 ground acceleration and response spectral ordinates. *Earth-Science Re-*  
1408 *views* 61 (1–2), 43–104.
- 1409 Douglas, J., Aug 2003b. A note on the use of strong-motion data from  
1410 small magnitude earthquakes for empirical ground motion estimation. In:  
1411 Skopje Earthquake 40 Years of European Earthquake Engineering (SE-  
1412 40EEE).
- 1413 Douglas, J., 2010a. Assessing the epistemic uncertainty of ground-motion  
1414 predictions. In: *Proceedings of the Ninth U.S. National and 10th Cana-*  
1415 *dian Conference on Earthquake Engineering: Reaching Beyond Borders.*  
1416 Paper no. 219.
- 1417 Douglas, J., 2010b. Consistency of ground-motion predictions from the past  
1418 four decades. *Bulletin of Earthquake Engineering* 8 (6), 1515–1526.
- 1419 Douglas, J., 2012. Consistency of ground-motion predictions from the past  
1420 four decades: Peak ground velocity and displacement, Arias intensity and  
1421 relative significant duration. *Bulletin of Earthquake Engineering* 10 (5),  
1422 1339–1356.
- 1423 Douglas, J., Aug 2014. Fifty years of ground-motion models. In: *Proceedings*  
1424 *of Second European Conference on Earthquake Engineering and Seismol-*  
1425 *ogy (a joint event of the 14th ECEE & 31st General Assembly of the*  
1426 *ESC).*
- 1427 Douglas, J., 2016. Ground motion prediction equations 1964-2016. Website:  
1428 <http://www.gmpe.org.uk>. Last accessed June 20 2016.

- 1429 Douglas, J., Akkar, S., Ameri, G., Bard, P.-Y., Bindi, D., Bommer, J. J.,  
1430 Bora, S. S., Cotton, F., Derras, B., Hermkes, M., Kuehn, N. M., Luzi, L.,  
1431 Massa, M., Pacor, F., Riggelsen, C., Sandikkaya, M. A., Scherbaum, F.,  
1432 Stafford, P. J., Traversa, P., 2014a. Comparisons among the five ground-  
1433 motion models developed using RESORCE for the prediction of response  
1434 spectral accelerations due to earthquakes in Europe and the Middle East.  
1435 *Bulletin of Earthquake Engineering* 12 (1), 341–358.
- 1436 Douglas, J., Aochi, H., 2008. A survey of techniques for predicting earth-  
1437 quake ground motions for engineering purposes. *Surveys in Geophysics*  
1438 29 (3), 187–220.
- 1439 Douglas, J., Aochi, H., Suhadolc, P., Costa, G., 2007. The importance of  
1440 crustal structure in explaining the observed uncertainties in ground mo-  
1441 tion estimation. *Bulletin of Earthquake Engineering* 5 (1), 17–26.
- 1442 Douglas, J., Boore, D. M., 2011. High-frequency filtering of strong-motion  
1443 records. *Bulletin of Earthquake Engineering* 9 (2), 395–409.
- 1444 Douglas, J., Edwards, B., Convertito, V., Sharma, N., Tramelli, A., Kraai-  
1445 jpoel, D., Cabrera, B. M., Maercklin, N., Troise, C., Jun 2013. Predicting  
1446 ground motion from induced earthquakes in geothermal areas. *Bulletin of*  
1447 *the Seismological Society of America* 103 (3), 1875–1897.
- 1448 Douglas, J., Halldórsson, H., 2010. On the use of aftershocks when deriv-  
1449 ing ground-motion prediction equations. In: *Proceedings of the Ninth*  
1450 *U.S. National and 10th Canadian Conference on Earthquake Engineer-*  
1451 *ing: Reaching Beyond Borders*. Paper no. 220.
- 1452 Douglas, J., Jousset, P., Jul/Aug 2011. Modeling the difference in ground-

- 1453 motion magnitude-scaling in small and large earthquakes. *Seismological*  
1454 *Research Letters* 82 (4), 504–508.
- 1455 Douglas, J., Seyedi, D. M., Ulrich, T., Modaresi, H., Foerster, E., Pitilakis,  
1456 K., Pitilakis, D., Karatzetzou, A., Gazetas, G., Garini, E., Loli, M., Jan  
1457 2015. Evaluation of seismic hazard for the assessment of historical ele-  
1458 ments at risk: Description of input and selection of intensity measures.  
1459 *Bulletin of Earthquake Engineering* 13 (1), 49–65.
- 1460 Douglas, J., Suhadolc, P., Costa, G., 2004. On the incorporation of the  
1461 effect of crustal structure into empirical strong ground motion estimation.  
1462 *Bulletin of Earthquake Engineering* 2 (1), 75–99.
- 1463 Douglas, J., Ulrich, T., Bertil, D., Rey, J., Sep/Oct 2014b. Comparison  
1464 of the ranges of uncertainty captured in different seismic-hazard studies.  
1465 *Seismological Research Letters* 85 (5), 977–985.
- 1466 Draper, N. R., Smith, H., 1998. *Applied Regression Analysis*, 3rd Edition.  
1467 John Wiley & Sons.
- 1468 Drouet, S., Cotton, F., Aug 2015. Regional stochastic GMPEs in low-  
1469 seismicity areas: Scaling and aleatory variability analysis — Applica-  
1470 tion to the French Alps. *Bulletin of the Seismological Society of America*  
1471 105 (4), 1883–1902.
- 1472 Edwards, B., Cauzzi, C., Danciu, L., Faeh, D., 2016. Assessment, adjustment  
1473 and weighting of ground motion prediction models for the 2015 Swiss  
1474 Seismic Hazard Maps. *Bulletin of the Seismological Society of America*  
1475 106 (4), in press.

- 1476 Edwards, B., Douglas, J., 2014. Magnitude scaling of induced earthquakes.  
1477 Geothermics 52, 132–139.
- 1478 Edwards, B., Fäh, D., Giardini, D., May 2011. Attenuation of seismic shear  
1479 wave energy in Switzerland. Geophysical Journal International 185 (2),  
1480 967–984.
- 1481 Edwards, B., Ktenidou, O.-J., Cotton, F., Abrahamson, N., Van Houtte,  
1482 C., Fäh, D., Sep 2015. Epistemic uncertainty and limitations of the  $\kappa_0$   
1483 model for near-surface attenuation at hard rock sites. Geophysical Journal  
1484 International 202 (3), 1627–1645.
- 1485 Esteva, L., Rosenblueth, E., 1964. Espectros de temblores a distancias mod-  
1486 eradas y grandes. Boletín Sociedad Mexicana de Ingeniería Sísmica 2,  
1487 1–18, in Spanish.
- 1488 Field, E. H., Jordan, T. H., Cornell, C. A., 2003. OpenSHA: A developing  
1489 community-modeling environment for seismic hazard analysis. Seismolog-  
1490 ical Research Letters 74 (4), 406–419.
- 1491 Fukushima, Y., 1996. Scaling relations for strong ground motion prediction  
1492 models with  $M^2$  terms. Bulletin of the Seismological Society of America  
1493 86 (2), 329–336.
- 1494 Giardini, D., Dec 2009. Geothermal quake risks must be faced. Nature 462,  
1495 848–849.
- 1496 Goda, K., Hong, H. P., Feb 2008. Spatial correlation of peak ground motions  
1497 and response spectra. Bulletin of the Seismological Society of America  
1498 98 (1), 354–365.

- 1499 Goertz-Allmann, B. P., Edwards, B., 2014. Constraints on crustal attenua-  
1500 tion and three-dimensional spatial distribution of stress drop in Switzer-  
1501 land. *Geophysical Journal International* 196 (1), 493–509.
- 1502 Goertz-Allmann, B. P., Edwards, B., Bethmann, F., Deichmann, N., Clin-  
1503 ton, J., Fäh, D., Giardini, D., 2011. A new empirical magnitude scaling  
1504 relation for Switzerland. *Bulletin of the Seismological Society of America*  
1505 101 (6), 3088–3095.
- 1506 Gölke, M., Coblenz, D., 1996. Origins of the European regional stress field.  
1507 *Tectonophysics* 266 (1–4), 11–24.
- 1508 Graves, R. W., Pitarka, A., Oct 2010. Broadband ground-motion simulation  
1509 using a hybrid approach. *Bulletin of the Seismological Society of America*  
1510 100 (5A), 2095–2123.
- 1511 Gregor, N., Abrahamson, N. A., Atkinson, G. M., Boore, D. M., Bozorgnia,  
1512 Y., Campbell, K. W., Chiou, B. S.-J., Idriss, I. M. ad Kamai, R., Sey-  
1513 han, E., Silva, W., Stewart, J. P., Youngs, R., Aug 2014. Comparison of  
1514 NGA-West2 GMPEs. *Earthquake Spectra* 30 (3), 1179–1197.
- 1515 Hanford.gov, November 2014. Hanford sitewide prob-  
1516 abilistic seismic hazard analysis. Available at:  
1517 <http://www.hanford.gov/page.cfm/OfficialDocuments/HSPSHA>. Last  
1518 accessed June 2016.
- 1519 Harp, E. L., Wilson, R. C., 1995. Shaking intensity thresholds for rock falls  
1520 and slides: Evidence from 1987 Whittier Narrows and Superstition Hills  
1521 earthquake strong-motion records. *Bulletin of the Seismological Society*  
1522 of America 85 (6), 1739–1757.

- 1523 Hermkes, M., Kuehn, N. M., Riggelsen, C., 2014. Simultaneous quantifi-  
1524 cation of epistemic and aleatory uncertainty in GMPEs using Gaussian  
1525 process regression. *Bulletin of Earthquake Engineering* 12 (1), 449–466.
- 1526 Hough, S. E., 2014. Shaking from injection-induced earthquakes in the cen-  
1527 tral and eastern United States. *Bulletin of the Seismological Society of*  
1528 *America* 104 (5), 2619–2626.
- 1529 Idriss, I. M., Aug 2014. An NGA-West2 empirical model for estimating  
1530 the horizontal spectral values generated by shallow crustal earthquakes.  
1531 *Earthquake Spectra* 30 (3), 1155–1177.
- 1532 Jayaram, N., Baker, J. W., Dec 2010. Considering spatial correlation in  
1533 mixed-effects regression and the impact on ground-motion models. *Bul-*  
1534 *letin of the Seismological Society of America* 100 (6), 3295–3303.
- 1535 Joyner, W. B., Boore, D. M., Dec 1981. Peak horizontal acceleration and  
1536 velocity from strong-motion records including records from the 1979 Im-  
1537 perial Valley, California, earthquake. *Bulletin of the Seismological Society*  
1538 *of America* 71 (6), 2011–2038.
- 1539 Joyner, W. B., Boore, D. M., Apr 1993. Methods for regression analysis  
1540 of strong-motion data. *Bulletin of the Seismological Society of America*  
1541 83 (2), 469–487.
- 1542 Kahneman, D., 2012. *Thinking, Fast and Slow*. Penguin, London, UK.
- 1543 Kale, O., Akkar, S., Apr 2013. A new procedure for selecting and ranking  
1544 ground-motion prediction equations (GMPEs): The Euclidean-distance  
1545 based ranking (EDR) method. *Bulletin of the Seismological Society of*  
1546 *America* 103 (2A), 1069–1084.

- 1547 Kamai, R., Abrahamson, N. A., Silva, W. J., Aug 2014. Nonlinear horizontal  
1548 site amplification for constraining the NGA-West2 GMPEs. *Earthquake*  
1549 *Spectra* 30 (3), 1223–1240.
- 1550 Kotha, S. R., Bindi, D., Cotton, F., 2016a. Erratum to: Partially non-  
1551 ergodic region specific GMPE for Europe and Middle-East. *Bulletin of*  
1552 *Earthquake Engineering*In press.
- 1553 Kotha, S. R., Bindi, D., Cotton, F., Apr 2016b. Partially non-ergodic re-  
1554 gion specific GMPE for Europe and Middle-East. *Bulletin of Earthquake*  
1555 *Engineering* 14 (4), 1245–1263.
- 1556 Kulkarni, R. B., Youngs, R. R., Coppersmith, K. J., 1984. Assessment of  
1557 confidence intervals for results of seismic hazard analysis. In: *Proceedings*  
1558 *of Eighth World Conference on Earthquake Engineering*. Vol. 1. pp. 263–  
1559 270.
- 1560 Laurendeau, A., Cotton, F., Ktenidou, O.-J., Bonilla, L.-F., Hollender, F.,  
1561 Dec 2013. Rock and stiff-soil site amplification: Dependency on  $V_{S30}$  and  
1562 kappa ( $\kappa_0$ ). *Bulletin of the Seismological Society of America* 103 (6), 3131–  
1563 3148.
- 1564 Lin, P.-S., Chiou, B., Abrahamson, N., Walling, M., Lee, C.-T., Cheng, C.-  
1565 T., Oct 2011. Repeatable source, site, and path effects on the standard  
1566 deviation for empirical ground-motion prediction models. *Bulletin of the*  
1567 *Seismological Society of America* 101 (5), 2281–2295.
- 1568 Manighetti, I., Campillo, M., Bouley, S., Cotton, F., 2007. Earthquake scal-  
1569 ing, fault segmentation, and structural maturity. *Earth and Planetary*  
1570 *Science Letters* 253 (3), 429–438.



- 1571 McGarr, A., Fletcher, J. B., Feb 2005. Development of ground-motion pre-  
1572 diction equations relevant to shallow mining-induced seismicity in the  
1573 Trail Mountain area, Emery County, Utah. *Bulletin of the Seismologi-  
1574 cal Society of America* 95 (1), 31–47.
- 1575 McGuire, R. K., 1976. FORTRAN computer program for seismic risk anal-  
1576 ysis. Open-File Report 76-67, United States Department of the Interior  
1577 Geological Survey.
- 1578 Molkenhain, C., Scherbaum, F., Griewank, A., Kuehn, N., Stafford, P., Oct  
1579 2014. A study of the sensitivity of response spectral amplitudes on seismo-  
1580 logical parameters using algorithmic differentiation. *Bulletin of the Seis-  
1581 mological Society of America* 104 (5), 2240–2252.
- 1582 Musson, R. M. W., Mar 2009. Ground motion and probabilistic hazard.  
1583 *Bulletin of Earthquake Engineering* 7 (3), 575–589.
- 1584 National Earthquake Hazard Reduction Program, 1994. Recommended Pro-  
1585 visions for Seismic Regulations for New Buildings. FEMA 222A.
- 1586 Newmark, N. M., Hall, W. J., 1982. *Earthquake Spectra and Design*. Earth-  
1587 quake Engineering Research Institute, Berkeley, USA.
- 1588 NIST, Nov 2011. Selecting and scaling earthquake ground motions for per-  
1589 forming response-history analyses. Tech. Rep. NIST GCR 11-917-15, Na-  
1590 tional Institute of Standards and Technology.
- 1591 Ottemöller, L., Sargeant, S., 2010. Ground-motion difference between two  
1592 moderate-size intraplate earthquakes in the United Kingdom. *Bulletin of  
1593 the Seismological Society of America* 100 (4), 1823–1829.

- 1594 Pacific Earthquake Engineering Research Center, Apr 2015. NGA-East: Me-  
1595 dian ground-motion models for the central and eastern North America  
1596 region. Tech. Rep. 2015/04, PEER, University of California, Berkeley,  
1597 USA.
- 1598 Papaspiliou, M., Kontoe, S., Bommer, J. J., Nov 2012. An exploration of  
1599 incorporating site response into PSHA — Part I: Issues related to site  
1600 response analysis methods. *Soil Dynamics and Earthquake Engineering*  
1601 42, 302–315.
- 1602 Poggi, V., Edwards, B., Fäh, D., Feb 2011. Derivation of a reference shear-  
1603 wave velocity model from empirical site amplification. *Bulletin of the Seis-  
1604 mological Society of America* 101 (1), 258–274.
- 1605 Power, M., Chiou, B., Abrahamson, N., Bozorgnia, Y., Shantz, T., Roblee,  
1606 C., Feb 2008. An overview of the NGA project. *Earthquake Spectra* 24 (1),  
1607 3–21.
- 1608 Radiguet, M., Cotton, F., Manighetti, I., Campillo, M., Douglas, J., 2009.  
1609 Dependency of near-field ground motions on the structural maturity of the  
1610 ruptured faults. *Bulletin of the Seismological Society of America* 99 (4),  
1611 2572–2581.
- 1612 Rietbrock, A., Strasser, F., Edwards, B., Feb 2013. A stochastic earthquake  
1613 ground-motion prediction model for the United Kingdom. *Bulletin of the  
1614 Seismological Society of America* 103 (1), 57–77.
- 1615 Rodriguez-Marek, A., Cotton, F., Abrahamson, N. A., Akkar, S., Al Atik,  
1616 L., Edwards, B., Montalva, G. A., Dawood, H. M., Nov 2013. A model for

1617 single-station standard deviation using data from various tectonic regions.  
1618 Bulletin of the Seismological Society of America 103 (6), 3149–3163.

1619 Rodriguez-Marek, A., Montalva, G. A., Cotton, F., Bonilla, F., Jun 2011.  
1620 Analysis of single-station standard deviation using the KiK-net data. Bul-  
1621 letin of the Seismological Society of America 101 (3), 1242–1258.

1622 Rodriguez-Marek, A., Rathje, E. M., Bommer, J. J., Scherbaum, F.,  
1623 Stafford, P. J., 2014. Application of single-station sigma and site response  
1624 characterization in a probabilistic seismic hazard analysis for a new nu-  
1625 clear site. Bulletin of the Seismological Society of America 104 (4), 1601–  
1626 1619.

1627 Rubinstein, J. L., Mahani, A. B., Jul/Aug 2015. Myths and facts on wastew-  
1628 ater injection, hydraulic fracturing, enhanced oil recovery, and induced  
1629 seismicity. Seismological Research Letters 86 (4), 1060–1067.

1630 Sandikkaya, M. A., Akkar, S., Bard, P.-Y., 2013. A nonlinear site amplifica-  
1631 tion model for the new pan-European ground-motion prediction equations.  
1632 Bulletin of the Seismological Society of America 103 (1), 19–32.

1633 Scasserra, G., Stewart, J. P., Bazzurro, P., Lanzo, G., Mollaioli, F., 2009. A  
1634 comparison of NGA ground-motion prediction equations to Italian data.  
1635 Bulletin of the Seismological Society of America 99 (5), 2961–2978.

1636 Scherbaum, F., Cotton, F., Smit, P., Dec 2004. On the use of response  
1637 spectral-reference data for the selection and ranking of ground-motion  
1638 models for seismic-hazard analysis in regions of moderate seismicity: The  
1639 case of rock motion. Bulletin of the Seismological Society of America  
1640 94 (6), 2164–2185.

- 1641 Scherbaum, F., Delavaud, E., Riggelsen, C., 2009. Model selection in seis-  
1642 mic hazard analysis: An information-theoretic perspective. *Bulletin of the*  
1643 *Seismological Society of America* 99 (6), 3234–3247.
- 1644 Scherbaum, F., Kuehn, N. M., Ohrnberger, M., Koehler, A., Nov 2010.  
1645 Exploring the proximity of ground-motion models using high-dimensional  
1646 visualization techniques. *Earthquake Spectra* 26 (4), 1117–1138.
- 1647 Seyhan, E., Stewart, J. P., Aug 2014. Semi-empirical nonlinear site am-  
1648 plification from NGA-West 2 data and simulations. *Earthquake Spectra*  
1649 30 (3), 1241–1256.
- 1650 Somerville, P. G., 2003. Magnitude scaling of the near fault rupture direc-  
1651 tivity pulse. *Physics of the Earth and Planetary Interiors* 137, 201–212.
- 1652 Spudich, P., Rowshandel, B., Shahi, S. K., Baker, J. W., Chiou, B. S. J.,  
1653 2014. Comparison of NGA-West2 directivity models. *Earthquake Spectra*  
1654 30 (3), 1199–1221.
- 1655 Stafford, P. J., 2014. Crossed and nested mixed-effects approaches for en-  
1656 hanced model development and removal of the ergodic assumption in em-  
1657 pirical ground-motion models. *Bulletin of the Seismological Society of*  
1658 *America* 104 (2), 702–719.
- 1659 Stafford, P. J., Strasser, F. O., Bommer, J. J., 2008. An evaluation of the  
1660 applicability of the NGA models to ground-motion prediction in the Euro-  
1661 Mediterranean region. *Bulletin of Earthquake Engineering* 6 (2), 149–177.
- 1662 Stewart, J. P., Douglas, J., Javanbarg, M., Abrahamson, N. A., Bozorgnia,  
1663 Y., Boore, D. M., Campbell, K. W., Delavaud, E., Erdik, M., Stafford,

- 1664 P. J., 2015. Selection of ground motion prediction equations for the Global  
1665 Earthquake Model. *Earthquake Spectra* 31 (1), 19–45.
- 1666 Strasser, F. O., Abrahamson, N. A., Bommer, J. J., Jan/Feb 2009. Sigma:  
1667 Issues, insights, and challenges. *Seismological Research Letters* 80 (1),  
1668 40–56.
- 1669 Treverton, G. F., Jun 2007. Risks and riddles. *Smithsonian Magazine* 38 (3),  
1670 98–102.
- 1671 Trifunac, M. D., Brady, A. G., Jun 1975. A study on the duration of strong  
1672 earthquake ground motion. *Bulletin of the Seismological Society of Amer-*  
1673 *ica* 65 (3), 581–626.
- 1674 Vamvatsikos, D., Cornell, C. A., 2002. Incremental dynamic analysis. *Earth-*  
1675 *quake Engineering and Structural Dynamics* 31, 491–514.
- 1676 Vanmarcke, E. H., Gasparini, D. A., 1976. Simulated earthquake motions  
1677 compatible with prescribed response spectra. Tech. Rep. R76-4, Dept. of  
1678 Civil Engineering, Massachusetts Inst. of Technology, Cambridge, USA.
- 1679 Walling, M. A., Abrahamson, N. A., 2012. Non-ergodic probabilistic seis-  
1680 mic hazard analyses. In: *Proceedings of Fifteenth World Conference on*  
1681 *Earthquake Engineering*. Lisbon, Portugal, paper no. 1627.
- 1682 Weatherill, G. A., Silva, V., Crowley, H., Bazzurro, P., 2015. Exploring the  
1683 impact of spatial correlations and uncertainties for portfolio analysis in  
1684 probabilistic seismic loss estimation. *Bulletin of Earthquake Engineering*  
1685 13 (3), 957–981.
- 1686 Youngs, R. R., Abrahamson, N., Makdisi, F. I., Sadigh, K., Aug 1995.

- 1687 Magnitude-dependent variance of peak ground acceleration. Bulletin of  
1688 the Seismological Society of America 85 (4), 1161–1176.
- 1689 Zhao, J. X., Zhang, J., Asano, A., Ohno, Y., Oouchi, T., Takahashi, T.,  
1690 Ogawa, H., Irikura, K., Thio, H. K., Somerville, P. G., Fukushima, Y.,  
1691 Fukushima, Y., 2006. Attenuation relations of strong ground motion in  
1692 Japan using site classification based on predominant period. Bulletin of  
1693 the Seismological Society of America 96 (3), 898–913.