



**HAL**  
open science

## Selecting ground-motion models developed for induced seismicity in geothermal areas

Benjamin Edwards, John Douglas

► **To cite this version:**

Benjamin Edwards, John Douglas. Selecting ground-motion models developed for induced seismicity in geothermal areas. *Geophysical Journal International*, 2013, 195 (2), pp.1314-1322. 10.1093/gji/ggt310 . hal-00849230

**HAL Id: hal-00849230**

**<https://brgm.hal.science/hal-00849230>**

Submitted on 30 Jul 2013

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

1 **Selecting ground-motion models developed for induced seismicity in geothermal areas**

2 Benjamin Edwards<sup>1</sup> and John Douglas<sup>2</sup>

3 <sup>1</sup>Swiss Seismological Service, ETH, Zürich, Switzerland

4 <sup>2</sup> Seismic and Volcanic Risks Unit, Risks and Prevention Division, BRGM, Orléans, France

5 *Accepted --/----. Received --/----; in original form 05/2013.*

6 *Abbreviated title:* Selecting ground-motion models

7

8 *Corresponding author:*

9 Benjamin Edwards

10 Swiss Seismological Service

11 Eidgenössische Technische Hochschule (ETH) Zürich

12 Sonneggstrasse 5

13 8092 Zurich, Switzerland

14 Email: [edwards@sed.ethz.ch](mailto:edwards@sed.ethz.ch)

15 Tel: +41 44 632 89 63

16

17

18

19

20 *Summary*

21 We present a case study of the ranking and weighting of ground-motion prediction equations (GMPE)  
22 for seismic hazard assessment of Enhanced Geothermal Systems (EGSs). The study region is Cooper  
23 Basin (Australia), where a hot-fractured-rock project was established in 2002. We test the applicability  
24 of 36 GMPEs based on stochastic simulations previously proposed for use at EGSs. Each GMPE has a  
25 set of corresponding model parameters describing stress drop, regional and local (near-surface)  
26 attenuation. To select suitable GMPEs for Cooper Basin from the full set we applied two methods. In  
27 the first, seismograms recorded on the local monitoring network were spectrally analysed to determine  
28 characteristic stress and attenuation parameters. In a second approach, residual analysis using the log-  
29 likelihood (LLH) method was used to directly compare recorded and predicted short-period response  
30 spectral accelerations. The resulting ranking was consistent with the models selected based on spectral  
31 analysis, with the advantage that a transparent weighting approach was available using the LLH  
32 method. Region-specific estimates of variability were computed, with significantly lower values  
33 observed compared to previous studies of small earthquakes. This was consistent with the limited  
34 range of stress-drops and attenuation observed from the spectral analysis.

35 *Keywords:* geothermal power, induced seismicity, ground-motion prediction, seismic hazard, spectral  
36 analysis

37 *Introduction*

38 Ground shaking from seismicity associated with stimulation and exploitation of a geothermal reservoir  
39 for heat and power production can be a significant nuisance to the local population and can, in some  
40 cases, lead to building damage. The Deep Heat Mining project (Basel, Switzerland) in 2006 triggered  
41 an  $M_L$  3.4 ( $M_w$  3.2) mainshock and thousands of smaller shocks and led to insurance claims of more  
42 than \$9 million (Giardini, 2009). Two earthquakes ( $M_L$  2.4 and 2.7) occurred in the vicinity of the  
43 Landau (Germany) geothermal power plant in 2009, which caused macroseismic intensities up to V+,  
44 while at another German geothermal project (Insheim) two felt tremors ( $M_L$  2.2 and 2.4) occurred  
45 during reservoir stimulation in 2010 (Groos et al., 2013). Most recently, in July 2013, a geothermal  
46 project in St. Gallen, Switzerland triggered a widely felt  $M_L$  3.5 ( $M_w$  3.4) event, which was followed by  
47 numerous smaller aftershocks. In Majer et al. (2012) seven steps are proposed to help assess and  
48 mitigate the seismic risk posed by geothermal systems. Step 5 of the proposal is to “quantify the  
49 hazard from natural and induced seismic events” through either probabilistic or deterministic  
50 approaches. They suggest a two-stage approach to quantify the hazard: a baseline estimate initially  
51 established through regional seismicity, with further refinement to a site-specific hazard assessment  
52 through the analysis of induced seismicity recorded on the local monitoring network. This article  
53 addresses the second stage.

54 A necessary component of any study that seeks to assess the seismic hazard (and/or risk) associated  
55 with geothermal projects is a ground-motion model that estimates measures of shaking [e.g. peak  
56 ground acceleration, (PGA)] given an earthquake scenario (e.g. in terms of magnitude and source-to-  
57 site distance). Motivated by a lack of suitable models in the public literature, Douglas et al. (2013)  
58 derived a set of stochastic and empirical ground-motion models for application in geothermal areas.  
59 These models were based on analyses of thousands of near-source seismograms of small earthquakes,  
60 most of which were induced by geothermal activity or gas extraction, while some were natural shallow  
61 events.

62 Because of the considerable epistemic uncertainty in the estimation of ground motions in geothermal  
63 areas, Douglas et al. (2013) presented ground-motion prediction equations (GMPEs) for 36 stochastic  
64 simulation models (Boore, 2003) that sought to capture this uncertainty. The ranges of the key  
65 parameters of these stochastic models (stress parameter,  $\Delta\sigma$ ; path attenuation,  $Q$ ; near-surface  
66 attenuation,  $\kappa$ ) were defined based on the analysis of seismograms collected from numerous regions.  
67 The analysis highlighted considerable variation in these parameters among regions and sites. When  
68 conducting a seismic hazard assessment for a given geothermal project it is not known *a priori* which  
69 of the 36 models are most applicable. Consequently Douglas et al. (2013) recommended, in the  
70 absence of other information by which to constrain the stochastic parameters for a given site, that a  
71 logic tree is used for seismic hazard analysis with all 36 models as branches. Subsequently, as  
72 seismograms are recorded at the geothermal project site, the applicability of some models should  
73 become evident and hence their associated branches could be assigned higher weights, while others  
74 may be down-weighted or even dropped completely. There are two complementary ways in which the  
75 branch weights can be updated: direct assessment of the stochastic parameters, and comparison of  
76 ground-motion predictions and observations.

77 As a demonstration of the use of the stochastic simulation GMPEs and the proposed procedure for the  
78 assessment of the logic-tree weights, Douglas et al. (2013) present a simple analysis for Campi Flegrei  
79 (Italy), for which some seismograms from small, shallow (but natural) earthquakes were available.  
80 However, the small number of seismograms available (only 55), their limited bandwidths and low  
81 quality of the metadata meant that the logic-tree weights could not be significantly updated. The aim  
82 of this article is to use a much larger and higher-quality dataset from an Enhanced Geothermal System  
83 (EGS), to better demonstrate the proposed selection procedure and to investigate how many records  
84 are required to significantly reduce the epistemic uncertainty in ground-motion prediction for EGSs.  
85 The dataset comes from Cooper Basin (Australia), which was not considered by Douglas et al. (2013)  
86 when developing their ground-motion models.

87 The next section summarizes the 36 stochastic models developed by Douglas et al. (2013). Douglas et  
88 al. (2013) did not recommend their empirical models for application because they were derived using

89 data from a narrow magnitude-distance range (roughly  $M_w$  1 to 3 and  $R_{hyp} < 10\text{km}$ ) and a simple  
90 functional form was adopted. Because the stochastic models were based on simulated ground motions  
91 from a wider range of magnitudes and distances and a more complex functional form was fit to these  
92 simulations, they are considered more robust than the empirical equations for  $M_w$  1 to 5 and  $R_{hyp}$  1 to  
93 50km. As with empirical models, however, extrapolation of stochastic models outside their range of  
94 applicability is not recommended. Following the introduction of the models, the dataset from Cooper  
95 Basin EGS is presented. The subsequent section derives estimates of the stochastic parameters from  
96 these data and investigates the impact of the number of seismograms used to estimate the parameters.  
97 Based on this analysis a set of weights for the 36 models is proposed. A second set of weights is  
98 proposed in the following section based on comparisons between the observed response spectral  
99 accelerations and those predicted by the 36 GMPEs.

#### 100 *Ground-motion models for induced seismicity*

101 Ground motions from small earthquakes, particularly those recorded in the near-source region, often  
102 exhibit large variability for a given magnitude and distance, the principal independent parameters for  
103 GMPEs. There are two explanations for this common observation: the first is related to the fact that  
104 meta-data for small earthquakes are often poorer quality (e.g., routine automatic locations as opposed  
105 to manually-reviewed locations). The second reason (exacerbated by the first) is that ground motions  
106 from small events are more sensitive to changes in hypocentral depth, while site-attenuation ( $\kappa$ ) tends  
107 to filter out, to varying degrees, the dominant high-frequencies associated with smaller earthquakes  
108 (Douglas and Jousset, 2011). Furthermore, it is often observed that the variability of the stress-drop (or  
109 conversely, slip velocity) is significantly higher for small events than for larger events (e.g., Cotton et  
110 al., 2013). Whether an artefact of inversion procedures (e.g., not properly accounting for attenuation),  
111 or reality, this nevertheless reflects the greatly differing proportion of high-frequency energy observed  
112 in small earthquakes of similar size.

113 Analysing data from six independent regions (Basel, Soultz, Geysers, Hengill, Roswinkel and  
114 Vorendaal), Douglas et al. (2013) found that a significant reduction in the overall prediction  
115 uncertainty was obtained by accounting for region-specific biases. As discussed, this can be  
116 interpreted as either systematic bias in the meta-data, or alternatively, region-specific ‘characteristic  
117 seismicity’ and recording conditions. Since magnitudes were recomputed homogeneously and  
118 hypocentral depths are generally well-constrained for sources directly below the recording network  
119 (typical in geothermal installations), Douglas et al. (2013) suggested that differences in source, path  
120 and site conditions were the likely cause of region-specific differences. They proposed a suite of 36  
121 stochastic models with different source, path and site properties to cover the range observed in their  
122 datasets.

123 In terms of seismic hazard assessment, these 36 models can be considered to cover the epistemic  
124 uncertainty: in the case of a completely unknown site, we cannot distinguish between any of the  
125 models, and must weight them equally. In reality, of course, some information about the site of interest  
126 will always be available: for instance, if the EGS is not located on outcropping hard-rock, then we can  
127 already rule out the models with the lowest levels of site attenuation ( $\kappa$ ). Each of the 36 models has its  
128 own associated aleatory variability, which corresponds to a region-specific model. An initial ‘naïve’  
129 application of these GMPEs would be similar in terms of the resulting mean hazard to using the single  
130 empirical GMPE developed by Douglas et al. (2013) using data from all regions (along with the  
131 associated high aleatory variability). In terms of the hazard distribution, the obvious difference is that  
132 the empirical model leads to only one curve, whilst the stochastic models generate 36 individual  
133 hazard curves, representing the epistemic uncertainty. However, in the case of improved knowledge of  
134 the site’s seismicity, or recording conditions, we can begin to reassess the weighting of the 36 models,  
135 reducing the epistemic uncertainty. The advantage in this case is clear, since region-specific GMPEs  
136 cannot typically be assessed due to limited recorded distance and magnitude ranges, the stochastic-  
137 model approach allows us to refine the logic tree in the case of improved knowledge, which will be  
138 quickly available after the installation of a monitoring network, or even beforehand when local data  
139 already exist.

#### 140 *Ground-motion data used for model selection*

141 The data used in this article comes from a sensitive seismic network set up to monitor the geothermal  
142 exploitation of the reservoir at Cooper Basin (South Australia). A hot-fractured-rock project was  
143 launched at Cooper Basin in 2002 to exploit the Habanero granite reservoir at depths between 4 and  
144 4.5km. Various boreholes and stimulation experiments have been conducted since and triggered  
145 earthquakes have been located and characterized (Baisch et al., 2006). The data used here come from  
146 2005 (data from 2003 are available but there is uncertainty over the calibration factors of the  
147 seismometers). Data from eight stations (Stang, 2011) installed by Q-Con [McLeod #1 (MCL), WA1-  
148 4 and MW1-3] are used (Figure 1), all of which are located below the surface (all at depths of less than  
149 357m, except for McLeod #1 at 1.8km). High-quality earthquake catalogues were provided by Q-Con  
150 for these data. The available records come from earthquakes with moment magnitudes between 1.7  
151 and 3.1 (roughly following a standard Gutenberg-Richter distribution), hypocentral distances between  
152 2.4 and 7.8km (roughly uniformly-distributed) and depths between 3.9km and 4.5km (roughly  
153 normally-distributed with a peak around 4.2km). All records have been converted from velocity to  
154 acceleration through time-domain differentiation and application of calibration factors. Following the  
155 approach detailed in Douglas et al. (2013) and Edwards and Douglas (2013), all earthquakes used here  
156 have had their moment magnitudes consistently recalculated.

#### 157 *Estimation of stochastic parameters*

158 As noted, the estimation of suitable stochastic model parameters allows the reduction of epistemic  
 159 uncertainty related to ground-motion prediction in the study region for the magnitude and distance  
 160 range of the data. For earthquakes outside the range of observations (particularly larger magnitudes),  
 161 however, there still remains considerable epistemic uncertainty because it is not certain that the most  
 162 appropriate stochastic parameters (or the best-fitting models) for the available data necessarily apply  
 163 for such scenarios. In a first step we look for existing parameters published in the literature. At Cooper  
 164 Basin, Baisch et al. (2009) found an average whole-path  $Q_p=112\pm 21$  and  $\Delta\sigma=4.7$ bars (0.47MPa) from  
 165 the analysis of over 6000 events. Assuming  $Q_p\approx Q_s$  and taking the measured  $V_p=3.7\text{kms}^{-1}$  and  
 166  $V_p:V_s=1.9$  from Baisch et al. (2009) we obtain path attenuation ( $t^*$ ) of approximately 0.02s between  
 167 the event cloud and the surface. Due to the almost vertical propagation through the basin, this  $t^*$  can  
 168 be completely assigned to the site-specific term,  $\kappa_0$ . Regional values of Q have been computed for  
 169 Australian earthquakes by Allen et al. (2006, 2007). For southeastern Australia Allen et al. (2007)  
 170 found:

$$\log Q(f) = 3.66 - 1.44 \log f + 0.768 (\log f)^2 + 0.058 (\log f)^3 \quad 1$$

171 for frequencies (f) 0.78 to 19.9 Hz, leading to consistently high Q (1063 to 6671), whilst for  
 172 southwestern Australia Allen et al. (2006) found:

$$Q(f) = 457f^{0.37} \quad 2$$

173 for frequencies 1.07 to 25.0 Hz. The study of Allen et al. (2007) computed a corresponding  
 174 geometrical attenuation of  $r_{\text{hyp}}^{-1.3}$  in the first 90km (where  $r_{\text{hyp}}$  is hypocentral distance) based on the  
 175 decay of long-period displacement spectra. The central-east location (Figure 1) of Cooper Basin may  
 176 be slightly better described by 'southeastern Australia'. However, in light of the known trade-off  
 177 between Q and geometrical decay, we may prefer to use the latter Q estimate for southwestern  
 178 Australia, which corresponds to the  $r_{\text{hyp}}^{-1}$  geometrical spreading model adopted by Douglas et al.  
 179 (2013). This frequency dependent Q model (Equation 2) corresponds to 457 at 1Hz and 1503 at 25Hz,  
 180 which could foreseeably be accommodated through frequency-dependent weighting of the Douglas et  
 181 al. (2013) models developed with frequency independent Q. Stress drop terms derived by Allen et al.  
 182 (2006) lie between 1 and 100 bars (0.1 and 10MPa) but show a trend that increases with magnitude,  
 183 albeit weakly.

184 To provide further estimates of the parameters, without the numerous assumptions that may be  
 185 required by using values from the literature, we here also present the average Q,  $\Delta\sigma$  and  $\kappa_0$  values as  
 186 determined from subsets of the data used for this study. We test the impact of using 10, 25 and 50% of  
 187 all data in order to simulate the effect of a developing database for a new network installation.

188 *Kappa estimation*

189 We estimated site  $\kappa_0$  consistent with the models of Douglas et al. (2013) through least-squares  
190 minimization of spectra computed over the duration of shaking. The window duration was based on 5-  
191 95% of the velocity-squared integral, with spectral models fit between 10 and 100Hz in the lin-log  
192 domain. The models were based on the Brune (1970) source with single event-common corner-  
193 frequency and attenuation modelled using an exponential function (Anderson and Hough, 1984); refer  
194 to Douglas et al. (2013) and Edwards et al. (2011) for an exhaustive description of the fitting  
195 procedure. At least two instruments were required to have recorded each event to include it in the  
196 processing. To estimate the impact of limited data on the choice of model weights, we simulated  
197 different stages of data collection through random sampling of the events for which we had good  
198 recordings at two or more instruments.

199 Since the hypocentral distance was very limited, choice of Q has a minimal impact on kappa: we chose  
200  $Q=1200$  to be broadly consistent with the results of Allen et al. (2006), who found values of between  
201 457 at 1Hz and 1503 at 25Hz. However, choosing the  $Q=600$  model from Douglas et al. (2013) would  
202 only have an impact of approximately  $\Delta\kappa_0=0.001s$  (2-4%). We observe that the kappa values  
203 determined for the Cooper Basin stations were dependent on the location of the borehole. Instrument  
204 McLeod #1, located at the centre of the network (1.8km depth) has the lowest value (0.028s),  
205 consistent with the significant depth at which it is located. Stations MW01, MW02 and MW03 (the  
206 inner ring) lie within approximately 2.5km of the central station (depths 109 to 357m) and show the  
207 highest kappa values (0.041 to 0.047s). Stations WA01, WA02 and WA03 (outer ring) lie within 5km  
208 of the central station and show moderate values of kappa (0.03 to 0.037s), despite being located  
209 shallower than stations MW01, MW02 and MW03 (at depths of 96 to 110m). The similarity of the  
210 kappa values for each ring of the network is remarkable, and may be due to similar geology for these  
211 stations or, since the earthquakes are all located near to the well-head, due to the similarity of the  
212 propagation paths to each of the stations of a given ring.

213 We estimated the impact of reduced datasets by bootstrapping 100 times over random subsamples of  
214 the complete dataset; measuring the changes in absolute value and scatter. The impact of a reduced  
215 dataset (even down to 10% of the original events: corresponding to an average of 14 events) was  
216 minimal in terms of the average kappa, with changes of only a few per cent (Table 1). In the case of  
217 the standard deviation, the reduced datasets led to significant underestimation of the true uncertainty.  
218 This should not be an issue in our application, however, since we are interested in the median values;  
219 aleatory variability is independently assigned based on the work of Douglas et al. (2013).

## 220 *Stress parameter estimation*

221 Source corner frequencies of the spectra were re-estimated, fixing  $Q=1200$  and  $\kappa_0$  as in Table 1. An  
222 inversion was performed in the log-log domain, again minimizing the least-squares misfit of the



223 spectral model. Given the moment magnitude determined by Edwards and Douglas (2013), we can  
224 then estimate the stress-parameter as:

$$\Delta\sigma = M_0 \left( \frac{f_c}{0.4906\beta} \right)^3 \quad 3$$

225 where  $\beta=3500\text{m/s}$  and  $M_0$  is estimated following the original formulation of the moment magnitude  
226 by Hanks and Kanomori (1979).

227 After selecting events with available  $M_w$  and  $f_c$  estimates a total of 95 earthquakes from Cooper Basin  
228 were assigned stress parameters. The log-average was 19 bars with a standard deviation of 0.5 (ln  
229 units; a factor of 1.65). Repeating the analysis with sub-selections of the events from Cooper Basin we  
230 obtain standard deviations on both the mean and standard-deviation of the target value (Table 2). We  
231 see that even with only 25% of the events, the mean stress-parameter  $\langle \ln[\Delta\sigma] \rangle$  (and the variability of  
232 individual event stress-parameters  $\sigma_{\ln[\Delta\sigma]}$ ) is robust, with a variability (represented by the standard  
233 deviation) of a factor of 1.12. Reducing the dataset to 10% (around 9-10 events) we begin to observe  
234 larger (albeit not significant) deviations from the mean.

235 Based on the spectral analysis we can choose to assign weights to the models based on expert  
236 judgement. We select models from Douglas et al (2013) with  $Q=600$  and  $Q=1800$  (covering the range  
237 observed in the literature for this region), and based on the limited range of measured surface  
238 attenuation values,  $\kappa=0.04\text{s}$  (Table 1). In order to cover the 19 bar average seen in the spectral  
239 analyses, we then make a further selection of models with 10 and 100 bar stress-parameter. This leaves  
240 four candidate models (Table 3). No preference in terms of weighting is given to GMPEs based on the  
241 two different  $Q$  models due to the uncertainty of this parameter (Table 3). The final weighting of the  
242 four selected models is then given by 0.365 for the two 10 bar and 0.135 for the two 100 bar models.  
243 These weights were chosen such that the log-average equivalent stress-parameter of the weighted  
244 model was 19 bars: i.e.,  $2 \times 0.365 \times \log(10\text{bar}) + 2 \times 0.135 \times \log(100\text{bar}) \approx \log(19\text{bar})$ . The resulting  
245 weighted stochastic GMPE is shown in Figure 2 for PGA along with predictions from the purely  
246 empirical model of Douglas et al. (2013) and recorded data. The weighted stochastic model shows  
247 better fit to the recorded data from small events, while for the few events with  $M \approx 3$ , both models  
248 predict similar motions.

#### 249 *Residual analyses*

250 In this section we analyse residuals computed from the 36 ground-motion models and data from  
251 Cooper Basin. 2089 pairs of horizontal time-histories were available for this analysis from the eight  
252 local stations and 427 earthquakes. From these time-histories the geometric-means of the pseudo-  
253 spectral accelerations (PSAs) for 5% damping from each pair are computed for 0.01s (100Hz, assumed  
254 equal to PGA) and 0.05s (20Hz) natural periods. The limited bandwidth of the seismometers installed

255 at Cooper Basin does not allow accurate PSAs to be computed for frequencies lower than about 15Hz.  
256 Consequently the engineering use of these data is limited to examining the response to shaking of stiff  
257 structures (e.g., low-rise masonry buildings) and non-structural elements. The observed and predicted  
258 response spectra shown by Douglas et al. (2013) show that PSA(0.05s) is likely to be close to the peak  
259 PSA for the magnitude range covered by the Cooper Basin data. In this section, these two sets of PSAs  
260 are statistically compared to the 36 ground-motion models proposed by Douglas et al. (2013). These  
261 models consist of: the equations for the median PSAs derived using the stochastic method and the  
262 aleatory-variability models for the single-station within-event standard deviation ( $\phi_{SS}$ ) (e.g., Al Atik et  
263 al., 2010) and the zone-specific between-event standard deviation ( $\tau_{ZS}$ ) equal to the average of the  
264 models for this variability for the Soultz and Basel EGSs. The impact of changing the model for the  
265 aleatory variability is investigated below.

266 Scherbaum et al. (2009) and Kale and Akkar (2013) propose methods to judge the applicability of  
267 GMPEs to a given set of ground-motion data. These methods consist of the calculation of variables:  
268 log-likelihood (LLH, Scherbaum et al., 2009) and Euclidian Distance Ranking (EDR, Kale and Akkar,  
269 2013), which are both based on the differences between the natural logarithms of the observed and  
270 predicted PSAs, although the influence of the aleatory variability is different in the two cases. Because  
271 we are assuming the same aleatory variability for all tested models we could simply use the  
272 differences in mean residuals to rank the models but the use of the LLH values allows us to weight the  
273 different models in a mathematically rigorous way (see below). The lower the value of LLH and EDR,  
274 the closer the match between the observations and predictions. The large number of records available  
275 from Cooper Basin enables us to investigate the impact of the number of records available on the  
276 results of the GMPE testing. Generally geothermal projects will have fewer records available with  
277 which to judge the applicability of the available GMPEs (especially before stimulation or early on in  
278 the stimulation phase) and hence it is useful to study whether the GMPE testing is sensitive to the  
279 number of records used.

280 Based on comparisons between the LLHs and EDRs (and the implied ranking of models) computed  
281 for PSA(0.01s) and PSA(0.05s) it was found that LLH and EDR are strongly linearly correlated for  
282 both periods, as are these values for the two structural periods. Therefore, for brevity, in the rest of this  
283 section only LLHs (and GMPE ranking and logic-tree weights derived from these values) for  
284 PSA(0.01s) are presented. LLH is preferred to EDR as a measure of the applicability of GMPEs  
285 because of the direct link between a set of LLHs and logic-tree weights in the case of well-distributed  
286 data and similar model extrapolation behaviour (as is the case for physically-based stochastic models).  
287 About a third of the seismograms from Cooper Basin required high-cut filters that removed ground  
288 motions with periods below 0.05s (frequencies above 20Hz), which could be affecting PSA(0.01s).  
289 However, repeating the analyses described below with and without these seismograms showed that the  
290 influence of these band-limited records on the results is minimal. Therefore, all 2089 geometric-mean

291 observations of PSA(0.01s) were used, from which normalized residuals were computed. For the total  
292 variability, we use a value of 0.96 (ln units), the value computed from the estimates of  $\phi$  and  $\tau$  given  
293 by Douglas et al. (2013).

294 To test the stability of the LLH values with respect to the number of records being used a bootstrap  
295 procedure was followed whereby 100 random sets of 1044 (half the total), 522 (quarter of the total)  
296 and 261 (eighth of the total) samples are selected from the 2089 available and the analysis repeated.  
297 From these results the mean and standard deviation (from the 100 results) of the LLH of each ground-  
298 motion model were computed (Table 4). As expected, the standard deviation increases as the number  
299 of available records decreases. Surprisingly, however, the standard deviations remain low and  
300 consequently the LLHs are stable, even when only an eighth of the records are used. This suggests that  
301 even a few hundred seismograms would enable robust logic-tree weights to be computed for hazard  
302 assessments of EGS projects if it were assumed that the highest-weighted models apply for  
303 magnitudes and distances outside the range covered by observations.

304 It is interesting to note that the best-performing models are for values of  $\Delta\sigma$ ,  $Q$  and  $\kappa_0$  similar to those  
305 previously reported for the Cooper Basin area or calculated above. This suggests that logic-tree  
306 weights can be preliminarily assessed based on values of these key parameters taken from the  
307 literature (if they are mutually consistent) or from seismological analyses of data, without statistically  
308 comparing the observations and predictions.

309 The definition of LLH allows a direct computation of logic-tree weights (Scherbaum et al., 2009).  
310 Such an approach is not necessarily appropriate in terms of a probabilistic seismic hazard assessment,  
311 however, because the weights do not represent the probability of a given model being correct  
312 (Delavaud et al., (2012). Instead, LLH-based weights represent a given model's ability to fit the  
313 observed data, favouring 'better models'. Typically, the goal of a complete logic-tree based hazard  
314 analysis is to capture not only the centre and body, but also the range of possibilities. In this sense the  
315 LLH weights, by design, will not cover the entire range (i.e., extreme scenarios not yet recorded). To  
316 bypass this limitation, Delavaud et al. (2012), suggest weighting based on expert judgement, with help  
317 from LLH information. However, a fully transparent approach for logic-tree weighting still does not  
318 exist. Considering this limitation, we adopt the LLH-based logic-treeweights for this analysis.  
319 Nevertheless, for the purpose of hazard assessment in geothermal zones, we would recommend further  
320 expert elicitation to ensure that the complete range of possible models are appropriately considered in  
321 the logic tree.

322 Applying the equation of Scherbaum et al. (2009) to the values of LLH listed in Table 4 for the  
323 complete dataset gives the weights summarized in Figure 3, from which it can be seen that roughly  
324 half of the models contribute about 75% of the total weight. Modifying the standard deviation  
325 associated with each model from 0.96 [the sigma proposed by Douglas et al. (2013), for use with the

326 stochastic models] to 0.64 (the sigma obtained by regression analyses on the Cooper Basin data, see  
 327 below) does not alter the model ranking but it slightly increases the distinction between models.  
 328 Therefore, the model weights are concentrated in the best ranked models (75% of the weight is  
 329 contributed by roughly a third of the models). In terms of computational efficiency the use of 36  
 330 models in a logic tree may be problematic. In this case it may be useful to trim the number of models  
 331 from the total 36 before weighting. As discussed previously, LLH weighting tends to favour models  
 332 which better predict the data. By using the LLH weighting of the full set of models it should,  
 333 therefore, be possible to find and remove models that do not add any information about possible  
 334 epistemic uncertainty. For instance, if the highest and second-highest weighted models predict very  
 335 similar ground-motions, then the second model can be removed without affecting the hazard results.  
 336 Such analysis is, however, beyond the scope of this article.

### 337 *Aleatory Variability*

338 To assess the aleatory variability of the Cooper Basin ground-motion data, random-effects regression  
 339 was performed using the functional form of Model 1 of Douglas et al. (2013):

$$340 \quad \ln \text{PSA}(0.01s) = a + bM_W + c \ln \sqrt{r_{hyp}^2 + h^2} + dr_{hyp} \quad 4$$

341 where  $\text{PSA}(0.01s)$  is in  $\text{m/s}^2$ ,  $M_W$  is moment magnitude and a, b, c, d and h are regression coefficients.  
 342 The limited distance range of the Cooper Basin data does not allow robust estimates of h (describing  
 343 near-source saturation) and d (describing anelastic attenuation) to be found and, therefore, these  
 344 coefficients are constrained to zero. The coefficients obtained from using the entire 2089 records are:  
 345  $a=-6.899$ ,  $b=2.569$  and  $c=-2.589$  with a between-event standard deviation ( $\tau$ ) of 0.099 and a within-  
 346 even standard deviation ( $\phi$ ) of 0.627, leading to an overall standard deviation ( $\sigma$ ) of 0.635. Comparing  
 347 these coefficients to those obtained by Douglas et al. (2013) from regression on data from six areas  
 348 indicates slightly higher magnitude dependence (coefficient  $b$ ) and faster attenuation (coefficient  $c$ ) for  
 349 Cooper Basin data. The most noticeable difference, however, is the much smaller values of  $\phi$  and, in  
 350 particular,  $\tau$ , from regression on the Cooper Basin data compared to those obtained by Douglas et al.  
 351 (2013). The much lower value of  $\tau$  can be partly explained by the use of data from a single zone (this  
 352 type of  $\tau$  is called  $\tau_{ZS}$  by Douglas et al., 2013) but it appears that ground motions at Cooper Basin are  
 353 much less variable than those at other EGS sites; Douglas et al. (2013) found for Basel  $\tau_{ZS}=0.637$  and  
 354 for Soultz  $\tau_{ZS}=0.902$ .

355 The value of  $\tau$  for Cooper Basin is even lower than those associated with GMPEs derived from  
 356 moderate and large earthquakes [see Figure 10c of Douglas et al. (2013), where  $\tau$  for none of the  
 357 considered GMPEs is lower than 0.2]. This very small  $\tau$  can be related to the small variability in the  
 358 stress drops of Cooper Basin: found to be 0.5 ln-units, corresponding to a factor of 1.65. This is

359 significantly lower than most other studies: for instance, Allmann and Shearer (2009) find a value of  
360 1.46 ln-units for global intra-plate events; Edwards and Fäh (2013) find 1.83 ln-units and 1.43 ln-units  
361 for the Swiss foreland and Alpine regions respectively; Oth et al. (2010) find 1.38 ln-units for  
362 Japanese earthquakes and Rietbrock et al. (2013) find 1.38 ln-units for UK events. Cotton et al. (2013)  
363 showed that spectral analysis methods applied to small earthquakes often led to significantly larger  
364 stress variability than seen in larger events. They presented the required variability in stress parameter  
365 corresponding to the aleatory variability of several GMPEs and concluded that the variability should  
366 lie between 0.26 and 0.59 ln-units for large events. The difference may relate to the strong regional  
367 variability in source, path and site effects for small earthquakes, either real or due to parameter trade-  
368 off. Treated independently, the data from Cooper Basin (a limited source zone) and the consistency of  
369 wave propagation may mean that the observed variability usually inherent with such small events is  
370 not apparent. One issue to consider, in this case, is whether the observed variability truly reflects the  
371 possible future variability: e.g., do we account for a near-surface event outside of the seismic cloud as  
372 was the case for the largest event related to the Berlín (El Salvador) geothermal project (Bommer et  
373 al., 2006), or of significantly different stress-drop?

374 Single-station  $\phi$  was calculated for the eight Cooper Basin stations as  $\phi_{SS}=0.493$ , which is again  
375 smaller than that obtained by Douglas et al. (2013),  $\phi_{SS}=0.576$ . The relatively low value is consistent  
376 with the limited range of station kappa values (with three distinct groups corresponding to the middle,  
377 inner and outer stations). The total sigma (combining the between- and within-event variability) is,  
378 therefore, much lower than that for the empirical models of Douglas et al. (2013) and it is more in line  
379 with those associated with GMPEs for moderate and large earthquakes. This demonstrates that at least  
380 some of the large variability in the empirical models of Douglas et al. (2013) is due to mixing data  
381 from various sites when deriving these models.

### 382 *Reduction of epistemic uncertainty*

383 As highlighted by Douglas et al. (2013) the disadvantages of applying their empirical GMPE are  
384 twofold. Firstly, the limited magnitude-distance range means that application to rarer, but potentially  
385 damaging events, is tenuous and, secondly, the aleatory variability assigned to their equation was  
386 strongly contaminated by epistemic uncertainty from combining several regional datasets (e.g., due to  
387 differences in seismicity and attenuation). Effectively the empirical model can be thought of as a  
388 mixture model: comprising several different sets of source and propagation behaviour, but without  
389 consideration of the increased sigma relative to a predictive relation. Nevertheless, it is not trivial to  
390 isolate such effects given limited recordings. Douglas et al. (2013) suggest that to reduce the  
391 uncertainty, stochastic simulation models can be used. Of course, such models are not without  
392 uncertainty outside their ‘calibrated’ model-space: the magnitude and distance range over which the  
393 simulation model can be tested against recorded seismograms. However, unlike empirical models, due

394 to their physical basis, alternative models can be easily developed to cover the epistemic uncertainty  
395 outside the magnitude range available in instrumental databases. For this purpose, Douglas et al.  
396 (2013) provided 36 GMPEs to cover a range of simulation parameters: with various  $\kappa$ ,  $Q$  and  $\Delta\sigma$ . A  
397 further benefit of testing and weighting simulation models, as performed here for Cooper Basin, is that  
398 it can help to limit the influence of epistemic uncertainty contamination related to mixing different  
399 sites.

400 The analysis undertaken here showed that the stochastic models can be selected based on spectral  
401 analysis, or on LLH testing. Four stochastic models performed well in LLH testing, whilst also having  
402 stochastic model parameters consistent with the results of spectral analysis: Models 31, 23, 19 and 35.  
403 These models, along with the empirical model of Douglas et al. (2013) and the best fitting empirical  
404 model just using the Cooper Basin data are shown in Figure 4a. We see that the preferred stochastic  
405 models are similar to the empirical model based on Cooper Basin data (Equation 4), while the best-  
406 fitting model for the dataset shows a slightly faster decay. By producing weights following Scherbaum  
407 et al. (2009) the resulting weighted median stochastic model (from all 36 weighted component  
408 models) is shown in Figure 4b. The weighted median model leads to lower PGA at  $M < 3$  (up to a  
409 factor of 1.5) than the empirical model of Douglas et al. (2013), while the aleatory variability is  
410 reduced by over 25%.

#### 411 *Conclusions*

412 In this study we have taken an existing EGS site as a case study of the proposals by Majer et al. (2012)  
413 and Douglas et al. (2013) to characterize the expected ground motions. To simulate the realistic  
414 temporal development of a seismic database and corresponding earthquake catalogue, we randomly  
415 resampled the full databases to one half, one quarter and one eighth of the full dataset. Following the  
416 approach of Douglas et al. (2013), we then developed weighted median models to describe the sub-  
417 datasets. It was found that both spectral analysis for the stochastic model parameters and residual  
418 analysis provided complementary results, with the highest weighted models from Douglas et al. (2013)  
419 consistent with both existing literature and values determined here. Using the LLH method we were  
420 able to automatically assign weights using a consistent and transparent approach. The resulting models  
421 were shown to significantly reduce the epistemic uncertainty related to ground-motion prediction for  
422 EGS projects.

423

#### 424 *Acknowledgments*

425 This study was partially funded by GEISER (Geothermal Engineering Integrating Mitigation of  
426 Induced Seismicity in Reservoirs) project funded under contract 241321 of the EC-Research Seventh  
427 Framework Programme (FP7). We thank Geodynamics Ltd. (Australia) and QCon (Germany) for the

428 data from Cooper Basin. We thank Julian Bommer and an anonymous reviewer for their detailed  
429 comments on an earlier version of this article.

430 *References*

431 Allen, T. I., Dhu, T., Cummins, P. R., Schneider, J. F. (2006), Empirical attenuation of ground-motion  
432 spectral amplitudes in southwestern Western Australia, *Bulletin of the Seismological Society of*  
433 *America*, **96**, 572-585.

434 Allen, T. I., Cummins, P. R., Dhu, T., Schneider, J. F. (2007), Attenuation of ground-motion spectral  
435 amplitudes in southeastern Australia, *Bulletin of the Seismological Society of America*, **97**, 1279-1292.

436 Allmann, B. P., Shearer, P. M. (2009). Global variations of stress drop for moderate to large  
437 earthquakes, *Journal of Geophysical Research*, **114**, B01310.

438 Al Atik, L., Abrahamson, N., Bommer, J. J., Scherbaum, F., Cotton, F., Kuehn, N. (2010). The  
439 variability of ground-motion prediction models and its components, *Seismological Research Letters*,  
440 **81**(5), 794–801, doi: 10.1785/gssrl.81.5.794.

441 Anderson, J. G., Hough, S. E. (1984), A model for the shape of the Fourier amplitude spectrum of  
442 acceleration at high frequencies, *Bulletin of the Seismological Society of America*, **74**(5), 1969-1993.

443 Baisch, S., Weidler, R., Vörös, R., Wyborn, D., de Graaf, L. (2006), Induced seismicity during the  
444 stimulation of a geothermal HFR reservoir in the Cooper Basin, Australia, *Bulletin of the*  
445 *Seismological Society of America*, **96**(6), 2242–2256, doi: 10.1785/0120050255

446 Baisch, S., Vörös, R., Weidler, R., Wyborn, D. (2009), Investigation of fault mechanisms during  
447 geothermal reservoir stimulation experiments in the Cooper Basin, Australia, *Bulletin of the*  
448 *Seismological Society of America*, **99**, 148-158.

449 Boore, D. M. (2003), Simulation of ground motion using the stochastic method, *Pure and Applied*  
450 *Geophysics*, **160**(3-4), 635–676, doi: 10.1007/PL00012553.

451 Bommer, J. J., Oates, S., Cepeda, J. M., Lindholm, C., Bird, J., Torres, R., Marroqun, G., Rivas, J.  
452 (2006), Control of hazard due to seismicity induced by a hot fractured rock geothermal project,  
453 *Engineering Geology*, **83**, 287–306, doi: 10.1016/j.enggeo.2005.11.002.

454 Brune, J. N. (1970), Tectonic stress and the spectra of seismic shear waves from earthquakes, *Journal*  
455 *of Geophysical Research*, **75**(26), 4997-5009.

456 Cotton, F., R. Archuleta and M. Causse (2013). What is sigma of the stress drop?, *Seismological*  
457 *Research Letters* **84**, 42-48.

458 Delavaud, E., Cotton, F., Akkar, S., Scherbaum, F., Danciu, L., Beauval, C., Drouet, S., Douglas, J.,  
459 Basili, R., Sandikkaya, M. A., Segou, M., Faccioli, E., Theodoulidis, N. (2012). Toward a ground-  
460 motion logic tree for probabilistic seismic hazard assessment in Europe, *Journal of Seismology*, **16**,  
461 451-473, doi: DOI 10.1007/s10950-012-9281-z.

462 Douglas, J., Edwards, B., Convertito, V., Sharma, N., Tramelli, A., Kraaijpoel, D., Cabrera, B.M.,  
463 Maercklin, N., Troise, C. (2013), Predicting ground motion from induced earthquakes in geothermal  
464 areas, *Bulletin of the Seismological Society of America*, **103**(3), 1875-1897, doi: 10.1785/0120120197.

465 Douglas, J., Jousset, P. (2011), Modeling the difference in ground-motion magnitude-scaling in small  
466 and large earthquakes, *Seismological Research Letters*, **82**, 504-508.

467 Edwards, B., Douglas, J. (2013), Magnitude scaling of induced earthquakes, *Geothermics*, submitted.

468 Edwards, B. and D. Fäh (2013), A stochastic ground-motion model for Switzerland, *Bulletin of the*  
469 *Seismological Society of America*, **103**(1), 78-98.

470 Edwards, B., Fäh, D., Giardini, D. (2011), Attenuation of seismic shear wave energy in Switzerland,  
471 *Geophysical Journal International*, **185**, 967-984.

472 Giardini, D. (2009), Geothermal quake risks must be faced, *Nature*, **462**, 848-849, doi:  
473 10.1038/462848a.

474 Groos, J., Zeiß, J., Grund, M., Ritter, J. (2013), Microseismicity at two geothermal power plants in  
475 Landau and Insheim in the Upper Rhine Graben, Germany, *Geophysical Research Abstracts*, **15**,  
476 EGU2013-2742.

477 Hanks, T. C., Kanamori, H. (1979), A moment magnitude scale, *Journal of Geophysical Research*,  
478 **84**(B5), 2348-2350.

479 Kale, Ö, Akkar, S. (2013), A new procedure for selecting and ranking ground-motion prediction  
480 equations (GMPEs): The Euclidean-distance based ranking (EDR) method, *Bulletin of the*  
481 *Seismological Society of America*, **103**(2A), 1069-1084.

482 Majer, E., Nelson, J., Robertson-Tait, A., Savy, J., Wong, I. (2012), Protocol for addressing induced  
483 seismicity associated with Enhanced Geothermal Systems. U.S. Department of Energy, Technical  
484 Report: DOE/EE-0662.

485 Oth, A., Bindi, D., Parolai, S., DiGiacomo, D. (2010), Earthquake scaling characteristics and the scale-  
486 (in)dependence of seismic energy-to-moment ratio: insights from KiK-net data in Japan, *Geophysical*  
487 *Research Letters*, **37**, L19304.



- 488 Rietbrock, A., Strasser, F., and Edwards, B. (2013), A stochastic earthquake ground-motion prediction  
489 model for the United Kingdom, *Bulletin of the Seismological Society of America*, **103**(1), 57-77.
- 490 Scherbaum, F., Delavaud, E., Riggelsen, C. (2009), Model selection in seismic hazard analysis: An  
491 information-theoretic perspective, *Bulletin of the Seismological Society of America*, **99**(6), 3234-3247,  
492 doi: 10.1785/0120080347.
- 493 Stang., H. (2011). Documentation of the Habanero Seismic Monitoring Network. Geodynamics Ltd.,  
494 Australia, Technical report #SMR-GDY054.

495 *Tables*

496

497 Table 1 : kappa (and the standard deviation  $\pm\sigma$ ; and standard error  $\pm\sigma_e$ ) determined for the sites of Cooper Basin, along with the impact of reduced datasets.

Station	Depth [m]	100%				50%			25%			10%		
		$\kappa$ [s]	$\pm\sigma$ [s]	#	$\pm\sigma_e$ [s]	$\Delta\{\kappa_0\}$ [%]	$\Delta\{\pm\sigma\}$ [%]	$\Delta\{\#\}$ [%]	$\Delta\{\kappa_0\}$ [%]	$\Delta\{\pm\sigma\}$ [%]	$\Delta\{\#\}$ [%]	$\Delta\{\kappa_0\}$ [%]	$\Delta\{\pm\sigma\}$ [%]	$\Delta\{\#\}$ [%]
MCL	1783	0.0277	0.0133	113	0.0013	0.31	-2.23	-49	1.16	0.22	-76	-1.09	-13.89	-91
WA01	97.5	0.0335	0.0159	48	0.0023	-0.27	-1.47	-51	2.51	-3.36	-76	-4.20	-22.33	-90
WA02	96	0.0371	0.0136	49	0.0019	0.81	-3.17	-51	0.28	-10.13	-77	0.30	-30.00	-91
WA03	110	0.0307	0.0158	81	0.0018	0.28	-0.58	-49	1.28	-2.46	-75	1.04	-9.48	-90
WA04	97.5	0.0380	0.0149	109	0.0014	-0.05	-0.10	-50	0.26	-1.10	-76	3.34	-7.47	-90
MW01	357	0.0470	0.0128	161	0.0010	0.16	-1.80	-50	0.47	-2.81	-76	0.14	-7.29	-90
MW02	109	0.0405	0.0217	223	0.0015	0.05	-0.80	-50	-0.65	-1.09	-76	-1.55	-3.41	-90
MW03	239	0.0469	0.0134	194	0.0010	0.03	-1.09	-49	0.60	-0.90	-76	0.45	-4.16	-90

498

499 Table 2 : Statistical analysis of stress parameter. All values in natural log-scale.  $\langle \ln[\Delta\sigma] \rangle$  is the ln-average stress-parameter  
 500 and  $\sigma_{\ln[\Delta\sigma]}$  is the standard deviation of the individual event stress-parameters;  $\sigma_{\langle \ln[\Delta\sigma] \rangle}$  is the standard deviation of the mean  
 501 and  $\sigma_{\sigma_{\ln[\Delta\sigma]}}$  is the standard deviation of the standard deviation over 1000 randomizations.

Percent of Data	$\langle \ln[\Delta\sigma] \rangle$ [bars]	$\langle \Delta\sigma \rangle$ [bars]	$\sigma_{\langle \ln[\Delta\sigma] \rangle}$	$\sigma_{\ln[\Delta\sigma]}$	$\sigma_{\sigma_{\ln[\Delta\sigma]}}$
100	2.93	18.67	0.000	0.502	0.000
75	2.91	18.40	0.024	0.497	0.015
50	2.92	18.56	0.041	0.528	0.055
25	2.93	18.78	0.111	0.502	0.110
10	2.78	16.20	0.163	0.390	0.076

502

503

504 Table 3: Weighting scheme for the selected models based on Q and  $\Delta\sigma$ .

Model	Model Description	Q Weight	$\Delta\sigma$ Weight	Total Weight
19	$\Delta\sigma=10\text{bar}$ ; $Q=600$ ; $\kappa =0.04\text{s}$	0.25	0.365	0.365
23	$\Delta\sigma=10\text{bar}$ ; $Q=1800$ ; $\kappa =0.04\text{s}$	0.25	0.365	0.365
31	$\Delta\sigma=100\text{bar}$ ; $Q=600$ ; $\kappa =0.04\text{s}$	0.25	0.135	0.135
35	$\Delta\sigma=100\text{bar}$ ; $Q=1800$ ; $\kappa =0.04\text{s}$	0.25	0.135	0.135

505

506  
507  
508

Table 4: Mean LLHs and their standard deviations (computed using a bootstrapping procedure) for the 36 ground-motion models and various proportions of the Cooper Basin dataset. Models indicated in bold are the twelve best performing models whilst those in italics are the twelve worst performing.

$\Delta\sigma$	Q	$\kappa_0$	All data	Half	Quarter	Eighth	No.
1	200	0.005	2.1007	2.0969±0.0228	2.0978±0.0407	2.0992±0.0622	1
1	200	<b>0.02</b>	<b>1.7971</b>	<b>1.7965±0.0129</b>	<b>1.7982±0.0233</b>	<b>1.7988±0.0335</b>	<b>2</b>
1	200	0.04	2.6115	2.6129±0.0255	2.6157±0.0464	2.6159±0.0705	3
1	200	<i>0.06</i>	<i>3.7752</i>	<i>3.7780±0.0384</i>	<i>3.7816±0.0694</i>	<i>3.7818±0.1068</i>	4
1	600	<i>0.005</i>	<i>3.7820</i>	<i>3.7755±0.0438</i>	<i>3.7750±0.0787</i>	<i>3.7788±0.1238</i>	5
1	600	<b>0.02</b>	<b>1.7664</b>	<b>1.7648±0.0147</b>	<b>1.7663±0.0257</b>	<b>1.7672±0.0381</b>	<b>6</b>
1	600	0.04	2.2444	2.2453±0.0205	2.2482±0.0372	2.2479±0.0574	7
1	600	0.06	3.2774	3.2798±0.0337	3.2836±0.0609	3.2831±0.0955	8
1	1800	<i>0.005</i>	<i>5.2068</i>	<i>5.1987±0.0584</i>	<i>5.1963±0.1035</i>	<i>5.2031±0.1685</i>	9
1	1800	<b>0.02</b>	<b>1.8220</b>	<b>1.8200±0.0172</b>	<b>1.8213±0.0299</b>	<b>1.8224±0.0453</b>	<b>10</b>
1	1800	0.04	2.1426	2.1432±0.0190	2.1461±0.0344	2.1457±0.0533	11
1	1800	0.06	3.1200	3.1222±0.0321	3.1261±0.0580	3.1253±0.0916	12
<i>10</i>	200	<i>0.005</i>	<i>4.5300</i>	<i>4.5227±0.0477</i>	<i>4.5232±0.0891</i>	<i>4.5248±0.1319</i>	13
<i>10</i>	200	<b>0.02</b>	<b>2.0125</b>	<b>2.0091±0.0223</b>	<b>2.0091±0.0417</b>	<b>2.0113±0.0631</b>	<b>14</b>
<i>10</i>	200	<b>0.04</b>	<b>1.7867</b>	<b>1.7857±0.0125</b>	<b>1.7865±0.0226</b>	<b>1.7889±0.0289</b>	<b>15</b>
<i>10</i>	200	0.06	2.4931	2.4938±0.0242	2.4953±0.0427	2.4981±0.0603	16
<i>10</i>	600	<i>0.005</i>	<i>8.9585</i>	<i>8.9475±0.0758</i>	<i>8.9457±0.1397</i>	<i>8.9512±0.2162</i>	17
<i>10</i>	600	0.02	2.7308	2.7261±0.0348	2.7252±0.0636	2.7281±0.0997	18
<i>10</i>	600	<b>0.04</b>	<b>1.7389</b>	<b>1.7372±0.0136</b>	<b>1.7378±0.0254</b>	<b>1.7398±0.0357</b>	<b>19</b>
<i>10</i>	600	0.06	2.1503	2.1504±0.0189	2.1520±0.0331	2.1541±0.0462	20
<i>10</i>	1800	<i>0.005</i>	<i>11.9403</i>	<i>11.9273±0.0952</i>	<i>11.9222±0.1716</i>	<i>11.9328±0.2782</i>	21
<i>10</i>	1800	<i>0.02</i>	<i>3.1481</i>	<i>3.1427±0.0406</i>	<i>3.1414±0.0734</i>	<i>3.1450±0.1168</i>	22
<i>10</i>	1800	<b>0.04</b>	<b>1.7710</b>	<b>1.7690±0.0156</b>	<b>1.7695±0.0290</b>	<b>1.7715±0.0424</b>	<b>23</b>
<i>10</i>	1800	0.06	2.0488	2.0487±0.0171	2.0503±0.0300	2.0522±0.0416	24
<i>100</i>	200	<i>0.005</i>	<i>8.3257</i>	<i>8.3160±0.0695</i>	<i>8.3176±0.1313</i>	<i>8.3168±0.1878</i>	25
<i>100</i>	200	0.02	3.0079	3.0031±0.0367	3.0021±0.0695	3.0041±0.1045	26
<i>100</i>	200	<b>0.04</b>	<b>1.7318</b>	<b>1.7298±0.0143</b>	<b>1.7292±0.0283</b>	<b>1.7324±0.0398</b>	<b>27</b>
<i>100</i>	200	<b>0.06</b>	<b>2.0443</b>	<b>2.0440±0.0175</b>	<b>2.0442±0.0306</b>	<b>2.0482±0.0384</b>	<b>28</b>
<i>100</i>	600	<i>0.005</i>	<i>16.2242</i>	<i>16.2098±0.1033</i>	<i>16.2079±0.1929</i>	<i>16.2123±0.2911</i>	29
<i>100</i>	600	<i>0.02</i>	<i>4.5644</i>	<i>4.5579±0.0529</i>	<i>4.5557±0.0985</i>	<i>4.5585±0.1523</i>	30
<i>100</i>	600	<b>0.04</b>	<b>1.9695</b>	<b>1.9666±0.0222</b>	<b>1.9656±0.0430</b>	<b>1.9685±0.0650</b>	<b>31</b>
<i>100</i>	600	<b>0.06</b>	<b>1.8382</b>	<b>1.8374±0.0136</b>	<b>1.8374±0.0246</b>	<b>1.8408±0.0298</b>	<b>32</b>
<i>100</i>	1800	<i>0.005</i>	<i>21.2923</i>	<i>21.2752±0.1278</i>	<i>21.2684±0.2330</i>	<i>21.2802±0.3724</i>	33
<i>100</i>	1800	<i>0.02</i>	<i>5.4541</i>	<i>5.4468±0.0607</i>	<i>5.4438±0.1120</i>	<i>5.4475±0.1760</i>	34
<i>100</i>	1800	0.04	2.1350	2.1317±0.0260	2.1305±0.0499	2.1333±0.0766	35
<i>100</i>	1800	<b>0.06</b>	<b>1.7930</b>	<b>1.7920±0.0130</b>	<b>1.7919±0.0242</b>	<b>1.7952±0.0299</b>	<b>36</b>

509

510 *List of Figure Captions*

511 Figure 1: Map of microseismic monitoring network (McLeod #1: MCL, MW01-3 and WA01-3).  
512 Catalogued events from 2005 are indicated by grey symbols, those used in the spectral analysis for  
513 determination of  $\kappa$  and  $\Delta\sigma$  are shown by black symbols.

514 Figure 2: Comparison of median PGA predictions from the weighted stochastic GMPE (with weights  
515 based on spectral analysis) and the empirical model of Douglas et al. (2013).

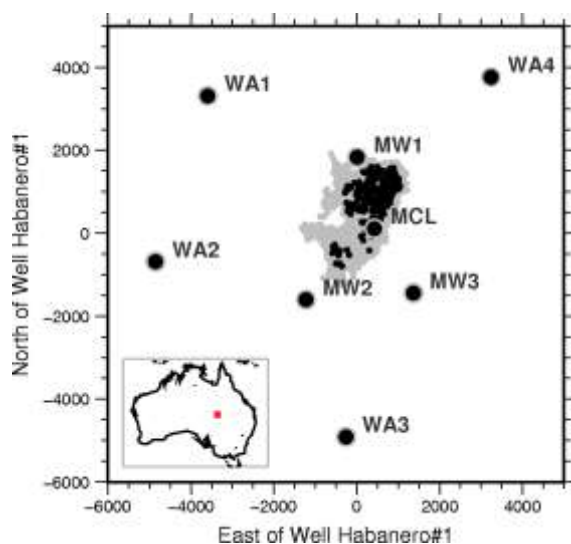
516 Figure 3: Ranking of models against cumulative weights for two different sigmas. See Table 4Table 2  
517 for the correspondence between model number and parameters of the stochastic model. Grey numbers  
518 indicate models consistent with the spectral analysis and literature (Q equal to 600 to 1800;  $\Delta\sigma$  equal  
519 to 10 to 100 bars; and  $\kappa_0 = 0.04$  s).

520 Figure 4: (a) PGA data for Cooper basin for events with  $2.5 < M < 3.1$  and the selected predictions  
521 (stochastic and empirical) from Douglas et al. (2013) for M2.8 along with the best fit of the data to  
522 equation 3. (b) The empirical model of Douglas et al. (2013) along with the weighted median  
523 stochastic model (from LLH testing) including their variabilities.

524

525 *Figures*

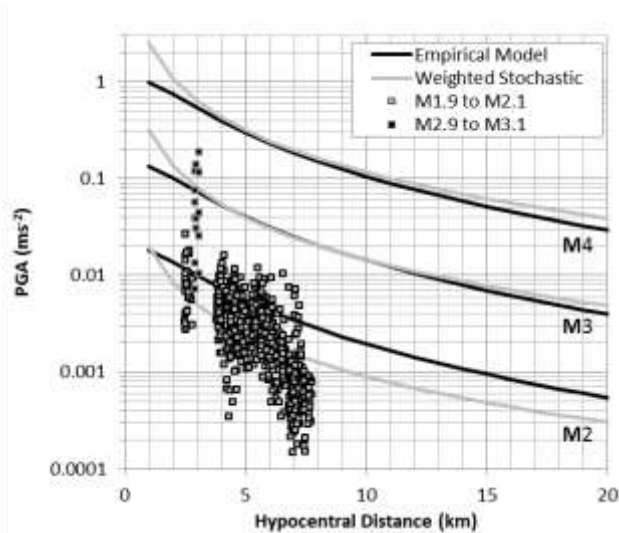
526



527

528 Figure 1: Map of microseismic monitoring network (McLeod #1: MCL, MW01-3 and WA01-3). Catalogued events from  
529 2005 are indicated by grey symbols, those used in the spectral analysis for determination of  $\kappa$  and  $\Delta\sigma$   
530 are shown by black symbols.

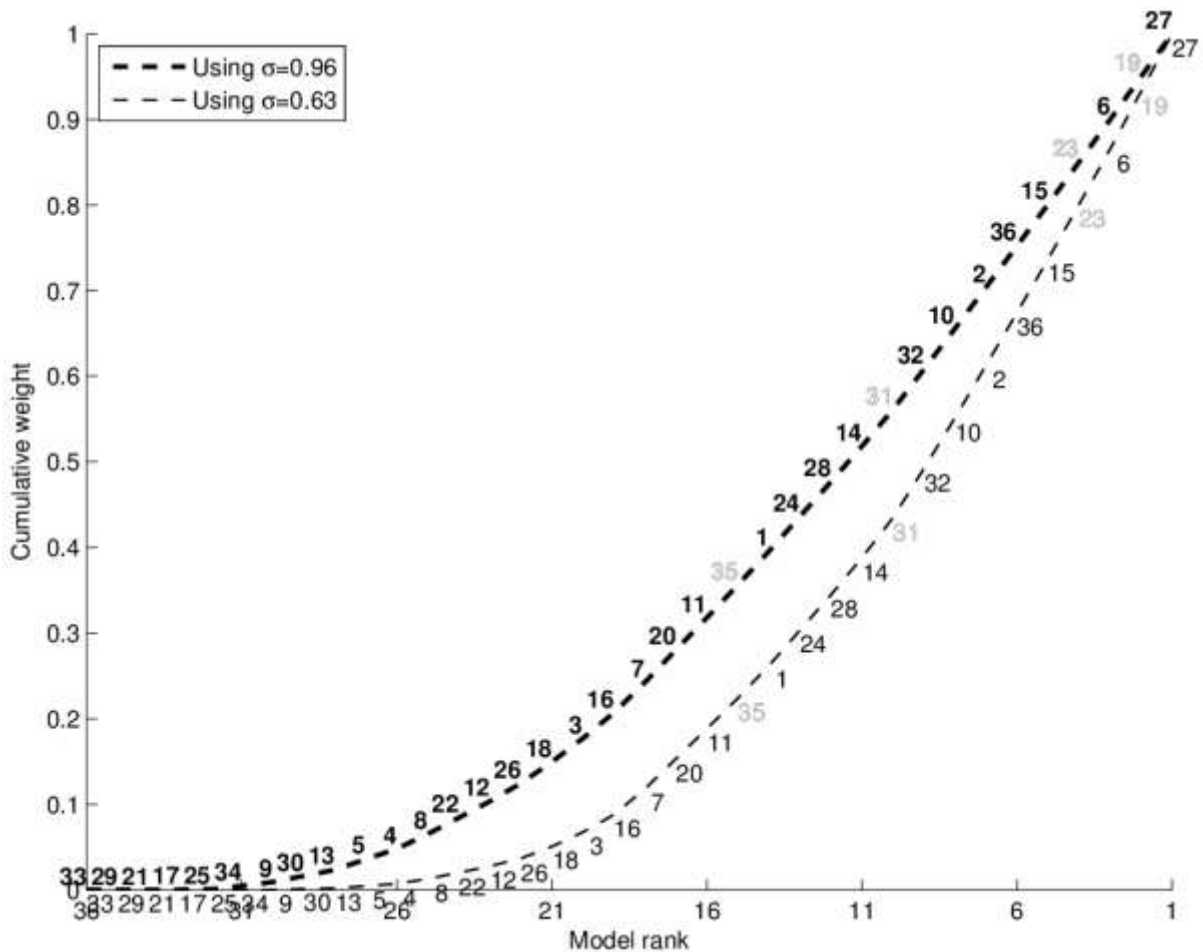
531



532

533 Figure 2: Comparison of median PGA predictions from the weighted stochastic GMPE (with weights based on spectral  
 534 analysis) and the empirical model of Douglas et al. (2013).

535



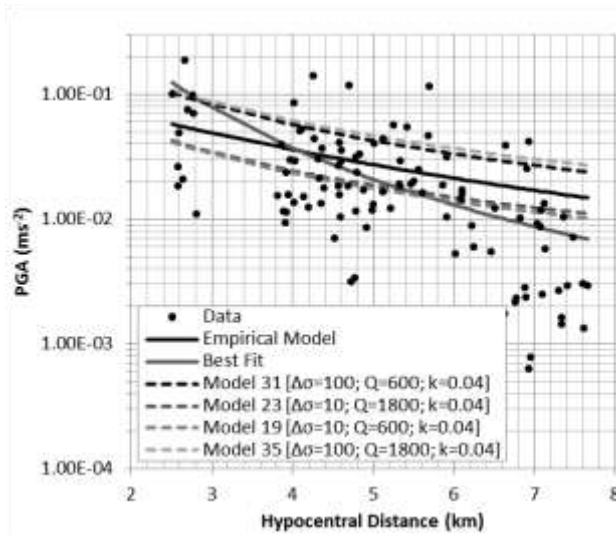
536

537 Figure 3: Ranking of models against cumulative weights for two different sigmas. See Table 4Table 2 for the correspondence  
 538 between model number and parameters of the stochastic model. Grey numbers indicate models consistent with the  
 539 spectral analysis and literature ( $Q$  equal to 600 to 1800;  $\Delta\sigma$  equal to 10 to 100 bars; and  $\kappa_0 = 0.04$  s). Note that although the  
 540 ranks are discrete they are plotted as continuous (dashed) lines for clarity.

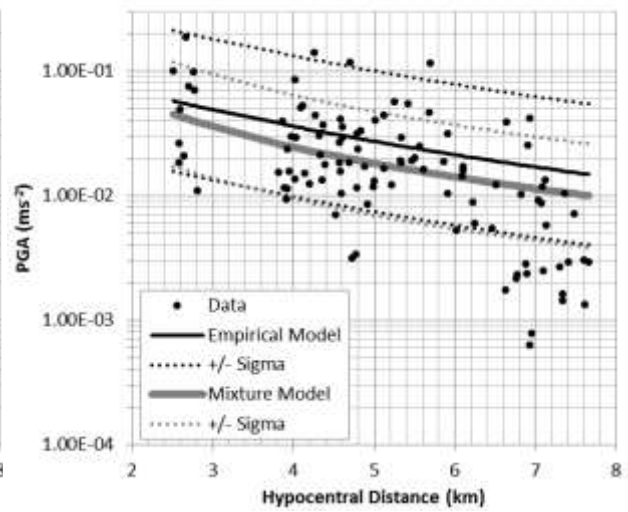
541

542

543 (a)



(b)



544

545 Figure 4: (a) PGA data for Cooper basin for events with  $2.5 < M < 3.1$  and the selected predictions (stochastic and empirical)  
546 from Douglas et al. (2013) for  $M2.8$  along with the best fit of the data to equation 3. (b) The empirical model of Douglas et  
547 al. (2013) along with the weighted median stochastic model (from LLH testing) including their variabilities.  
548