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

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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, κ) 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 (κ) 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 (κ). 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, κ_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_{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_{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 κ_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 κ_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 κ_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 (ϕ_{SS}) (e.g., Al Atik et
263 al., 2010) and the zone-specific between-event standard deviation (τ_{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 ϕ and τ 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 κ_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 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 (τ) of 0.099 and a within-
 346 even standard deviation (ϕ) of 0.627, leading to an overall standard deviation (σ) 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 ϕ and, in
 350 particular, τ , from regression on the Cooper Basin data compared to those obtained by Douglas et al.
 351 (2013). The much lower value of τ can be partly explained by the use of data from a single zone (this
 352 type of τ is called τ_{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 τ 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 τ for none of the
 357 considered GMPEs is lower than 0.2]. This very small τ 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 ϕ 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 κ , 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

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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.

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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%		
		κ [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

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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

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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	κ_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	0.02	1.7971	1.7965±0.0129	1.7982±0.0233	1.7988±0.0335	2
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	0.02	1.7664	1.7648±0.0147	1.7663±0.0257	1.7672±0.0381	6
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	0.02	1.8220	1.8200±0.0172	1.8213±0.0299	1.8224±0.0453	10
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>	<i>200</i>	<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>	<i>200</i>	0.02	2.0125	2.0091±0.0223	2.0091±0.0417	2.0113±0.0631	14
<i>10</i>	<i>200</i>	0.04	1.7867	1.7857±0.0125	1.7865±0.0226	1.7889±0.0289	15
<i>10</i>	<i>200</i>	0.06	2.4931	2.4938±0.0242	2.4953±0.0427	2.4981±0.0603	16
<i>10</i>	<i>600</i>	<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>	<i>600</i>	0.02	2.7308	2.7261±0.0348	2.7252±0.0636	2.7281±0.0997	18
<i>10</i>	<i>600</i>	0.04	1.7389	1.7372±0.0136	1.7378±0.0254	1.7398±0.0357	19
<i>10</i>	<i>600</i>	0.06	2.1503	2.1504±0.0189	2.1520±0.0331	2.1541±0.0462	20
<i>10</i>	<i>1800</i>	<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>	<i>1800</i>	<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>	<i>1800</i>	0.04	1.7710	1.7690±0.0156	1.7695±0.0290	1.7715±0.0424	23
<i>10</i>	<i>1800</i>	0.06	2.0488	2.0487±0.0171	2.0503±0.0300	2.0522±0.0416	24
<i>100</i>	<i>200</i>	<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>	<i>200</i>	0.02	3.0079	3.0031±0.0367	3.0021±0.0695	3.0041±0.1045	26
<i>100</i>	<i>200</i>	0.04	1.7318	1.7298±0.0143	1.7292±0.0283	1.7324±0.0398	27
<i>100</i>	<i>200</i>	0.06	2.0443	2.0440±0.0175	2.0442±0.0306	2.0482±0.0384	28
<i>100</i>	<i>600</i>	<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>	<i>600</i>	<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>	<i>600</i>	0.04	1.9695	1.9666±0.0222	1.9656±0.0430	1.9685±0.0650	31
<i>100</i>	<i>600</i>	0.06	1.8382	1.8374±0.0136	1.8374±0.0246	1.8408±0.0298	32
<i>100</i>	<i>1800</i>	<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>	<i>1800</i>	<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>	<i>1800</i>	0.04	2.1350	2.1317±0.0260	2.1305±0.0499	2.1333±0.0766	35
<i>100</i>	<i>1800</i>	0.06	1.7930	1.7920±0.0130	1.7919±0.0242	1.7952±0.0299	36

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 κ 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).

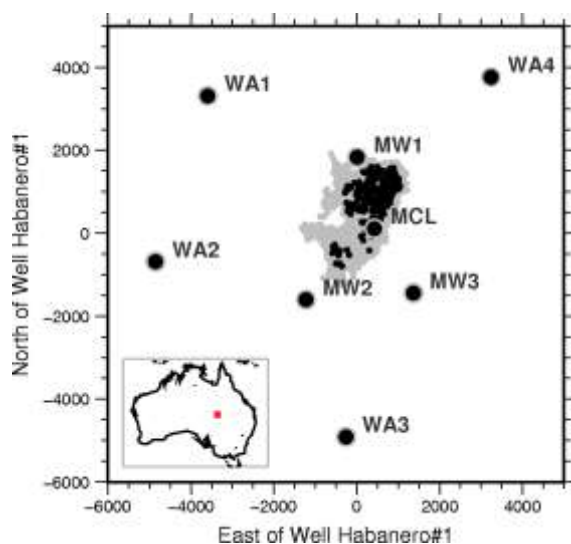
516 Figure 3: Ranking of models against cumulative weights for two different sigmas. See Table 4Table 2
517 for the correspondence between model number and parameters of the stochastic model. Grey numbers
518 indicate models consistent with the spectral analysis and literature (Q equal to 600 to 1800;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

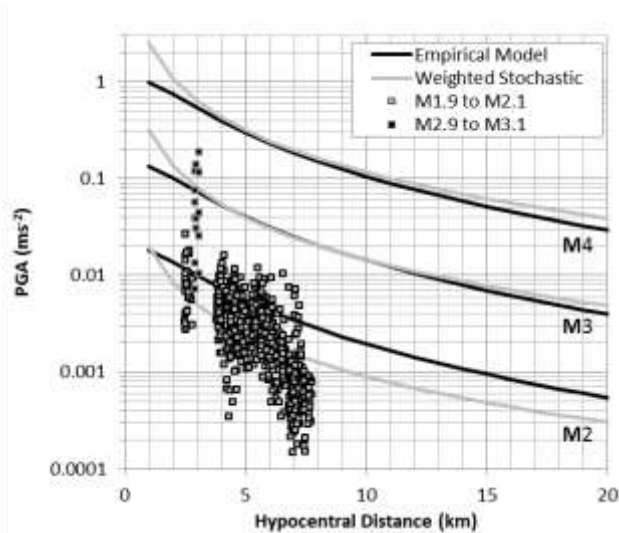
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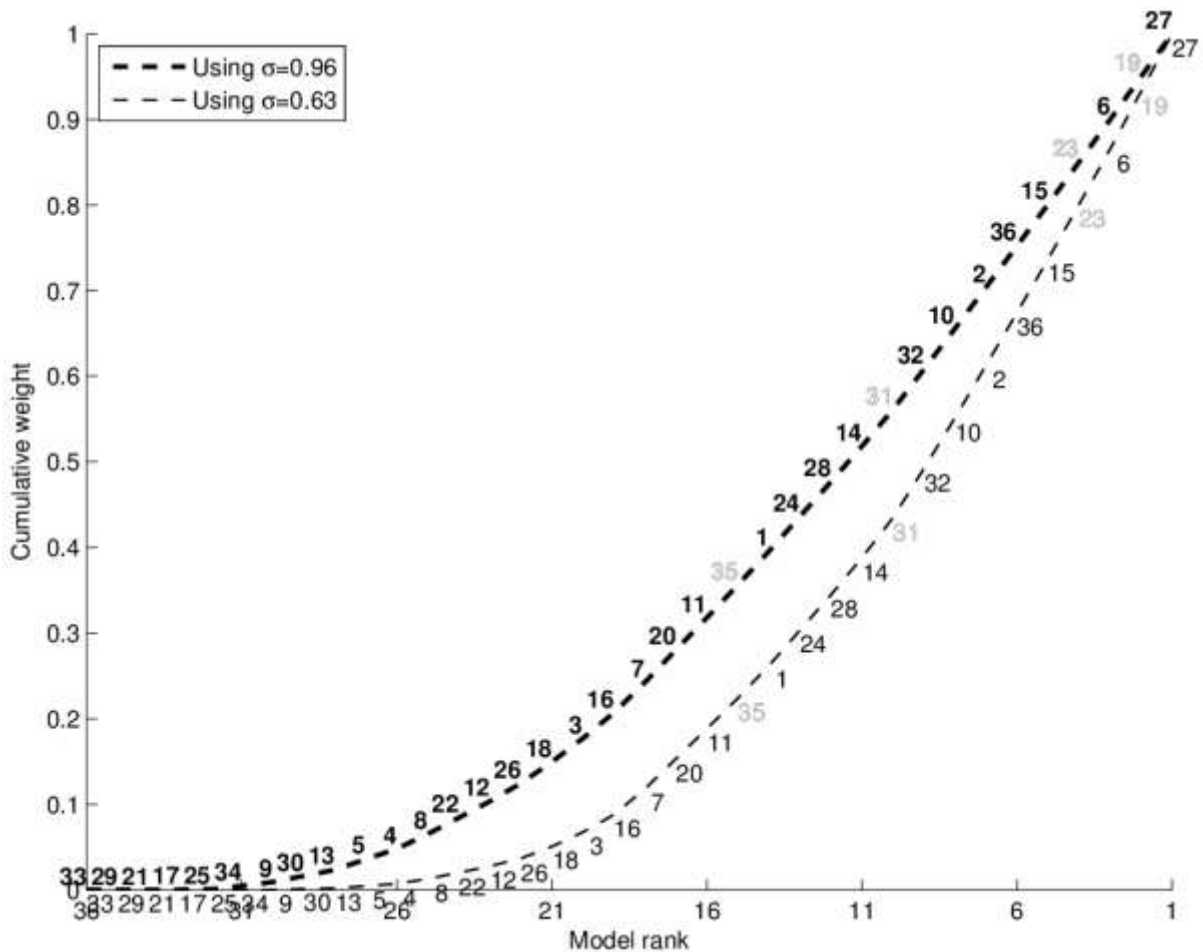
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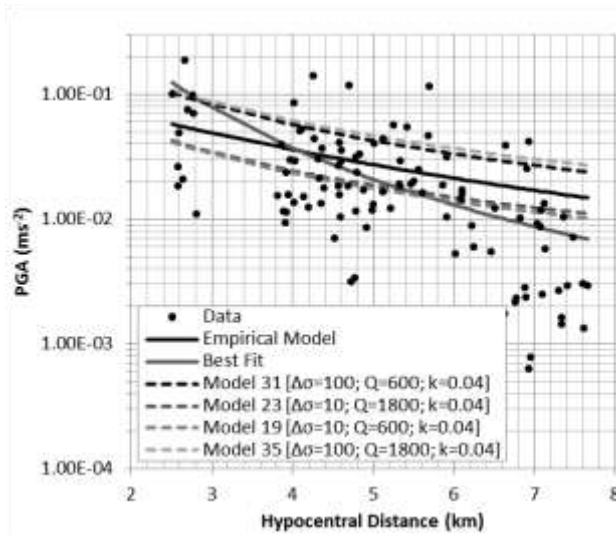
536

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 540 ranks are discrete they are plotted as continuous (dashed) lines for clarity.

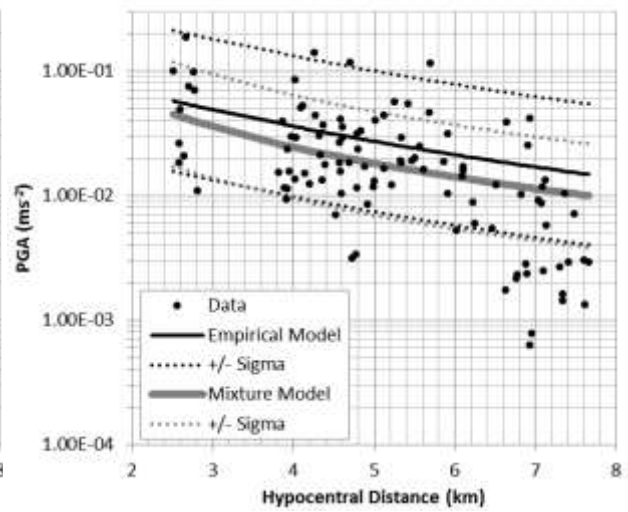
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543 (a)



(b)



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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.
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