Predicting Ground Motion from Induced Earthquakes in Geothermal Areas

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Abstract  Induced seismicity from anthropogenic sources can be a significant nuisance to a local population and in extreme cases lead to damage to vulnerable structures. One type of induced seismicity of particular recent concern, which, in some cases, can limit development of a potentially important clean energy source, is that associated with geothermal power production. A key requirement for the accurate assessment of seismic hazard (and risk) is a ground-motion prediction equation (GMPE) that predicts the level of earthquake shaking (in terms of, for example, peak ground acceleration) of an earthquake of a certain magnitude at a particular distance. Few such models currently exist in regard to geothermal-related seismicity, and consequently the evaluation of seismic hazard in the vicinity of geothermal power plants is associated with high uncertainty.

Various ground-motion datasets of induced and natural seismicity (from Basel, Geysers, Hengill, Roswinkel, Soultz, and Vörendaal) were compiled and processed, and moment magnitudes for all events were recomputed homogeneously. These data are used to show that ground motions from induced and natural earthquakes cannot be statistically distinguished. Empirical GMPEs are derived from these data; and, although they have similar characteristics to recent GMPEs for natural and mining-related seismicity, the standard deviations are higher. To account for epistemic uncertainties, stochastic models subsequently are developed based on a single corner frequency and with parameters constrained by the available data. Predicted ground motions from these models are fitted with functional forms to obtain easy-to-use GMPEs. These are associated with standard deviations derived from the empirical data to characterize aleatory variability. As an example, we demonstrate the potential use of these models using data from Campi Flegrei.

Online Material: Sets of coefficients and standard deviations for various ground-motion models.

Introduction

There is growing interest worldwide in using geothermal energy for electrical power production. In Europe, for example, there are at least 40 geothermal projects for electricity generation (most of them very small scale) in various stages of development, according to the International Geothermal Association (see Data and Resources). In areas with sufficient heat but inadequate fluid conductivity, enhanced geothermal systems (EGSs) are being initiated. In an EGS, the permeability of a geothermal reservoir is enhanced using hydraulic stimulation. This procedure induces microearthquakes by design but may also trigger larger events due to existing (tectonic) stresses. These larger events may be felt and provoke alarm in the local population or, in extreme cases, cause damage. In the case of the Deep Heat Mining project (Basel, Switzerland), a main event of relatively moderate magnitude ($M_L$ 3.4, $M_w$ 3.2) was triggered along with thousands of smaller shocks. The increase in seismicity was a cause for concern to the local population and led to a project shutdown and insurance claims amounting to more than $9 million (Giardini, 2009). The review article by Majer et al. (2007) discusses various cases of seismicity triggered and induced by geothermal power production.

The evaluation of seismic hazard requires ground-motion models linking event parameters (e.g., magnitude and location) to site parameters such as peak ground acceleration (PGA; Convertito et al., 2012). These models are generally in
the form of ground-motion prediction equations (GMPEs) although simulations (e.g., Douglas and Aochi, 2008) could be envisioned. GMPEs for induced earthquakes should provide robust predictions for small, shallow earthquakes at close source-to-site distances ($1 \lesssim M_w \lesssim 5$; focal depth $h \lesssim 5$ km; and hypocentral distances $r_{hyp} \lesssim 20$ km), a distance–magnitude–depth range that is poorly covered by existing ground-motion models. Douglas (2011) summarizes almost 300 empirical GMPEs for the prediction of PGA and nearly 200 empirical GMPEs for elastic-response spectral ordinates. In addition, Douglas (2011) lists dozens of GMPEs developed via approaches other than regression analysis on recorded ground-motion data. However, in that study, no GMPEs derived for earthquakes induced by geothermal activity were identified. There are a handful of models available that have used data from nonnatural earthquakes, such as mining-induced tremors (McGarr et al., 1981; McGarr and Fletcher, 2005) and nuclear explosions (Hays, 1980), but their relevance to geothermally induced tremors is not clear despite the fact that mining-related GMPEs often cover the magnitude–distance–depth range of relevance to geothermal projects.

Bommer et al. (2006) developed a GMPE for peak ground velocity (PGV) for use in the area surrounding the Berlin (El Salvador) geothermal power project. The authors did this by adjusting a previously published GMPE, derived from accelerograms of natural seismicity in Europe and the Middle East, so that it better fit ground-motion data from seismic swarms with shallow focal depths in this area; records associated with geothermal power production were not available at the time. This relied on the assumption that shaking from these swarm events and those associated with geothermal power production are similar. After the installation of a monitoring network during and following the period of hydraulic stimulation, ground-motion data from local earthquakes (some of which were induced by the stimulation) were used to update the derived GMPE because the original model was found to overestimate ground motions in the geothermal field. Such an approach could be followed in seismically active areas for which local ground-motion data exist (such as El Salvador), but this adjustment procedure would not be possible for EGS projects in regions with little or no history of earthquakes or ground-motion monitoring. Various previous studies have demonstrated that earthquake shaking from small earthquakes ($M_w \lesssim 6$) shows greater interregion variability than ground motions from larger events (Douglas, 2007; Chiou et al., 2010). Therefore, it is probable that GMPEs for induced seismicity in one (host) region would need adjustment for application in another (target) region.

As part of its Seventh Framework Programme (FP7), the European Commission funded a collaborative international research project, the Geothermal Engineering Integrating Mitigation of Induced Seismicity in Reservoirs (GEISER), to study various aspects of induced seismicity and how they modify the local seismic hazard. The current article is the result of an effort within the GEISER project to develop consensus ground-motion models for the prediction of PGA, PGV, and elastic-response spectral ordinates associated with induced earthquakes in geothermal areas. EGS project operators need to be able to estimate future seismic hazard before reservoir stimulations start; before stimulation, it is likely that ground-motion data would be limited and with a poor magnitude–distance distribution from which to derive site-specific GMPEs. Consequently, we sought generic GMPEs for use in future EGS projects that can be made more site specific once observations become available from local networks.

In this study, available ground-motion data associated with various locations and seismicity types are presented and analyzed to investigate the potential dependence of earthquake shaking on the type of seismicity (natural, geothermal-related events, or induced by gas extraction) and to derive empirical GMPEs based on these data. Stochastic models are then developed that account for epistemic uncertainty in the prediction of median ground motions. These models are used to simulate PGA, PGV, and response spectral accelerations that are then regressed to produce easy-to-use GMPEs. To assign estimates of the aleatory variability to be used with these GMPEs, the empirical data are analyzed to present models of the between-event (interevent) and within-event (intraevent) components of this variability for application within seismic hazard assessments for EGS sites. A possible approach to assign weights to these models is then presented for an example site.

Data Selection and Processing

For this article, we assembled data from surface instruments in Basel (Switzerland), Campi Flegrei (Italy), Geysers (United States), Hengill (Iceland), Roswinkel and Voerendaal (the Netherlands), and Soulz-sous-Forêts (France). Data from Campi Flegrei are only used in the independent validation of the GMPEs developed here. Some of these sets contain records from natural earthquakes (some of which are in areas of natural geothermal activity; i.e., Campi Flegrei and Hengill), geothermal-related events, and shocks induced by gas extraction. Charlety et al. (2007) noted that the smallest geothermal event felt by the local population near Soulz-sous-Forêts was $M_L 1.4$ (a similar threshold holds for tremors felt in the Netherlands). We therefore aim to provide robust predictions down to such magnitudes. In the following sections, more details of these datasets are given; and, following that, methods for the computation of moment magnitudes and the correction for local site responses are presented.

All instrument-corrected data were assessed for their quality through a combination of visual inspection and analysis of the signal-to-noise ratio (SNR). For each record, the frequency range for which the SNR was greater than three was assessed. This criterion led to a rapid drop-off in the number of records available for analysis, from 5 Hz (0.2 s) downward. By 2 Hz (0.5 s), less than half the data can be used, and by 1 Hz (1 s) almost all are unusable. Based on this observation, we do not seek to use spectral accelerations beyond 0.5 s in our analysis, nor do we use data from
earthquakes below $M_w$ 1. An analysis of the influence of high-cut filtering on the observations shows that, contrary to some expectations, response spectral accelerations from accelerograms are not very sensitive to high-frequency noise, confirming the conclusions of Douglas and Boore (2011). However, some records required a high cut-off frequency of less than 10 Hz, which means that the PGA (and other high-frequency parameters) are likely to be significantly reduced. Therefore, we excluded all records requiring a high cut-off frequency of less than 10 Hz. As an initial test, the residuals between the observed PGAs and those predicted by the GMPE of Bommer et al. (2007) were computed. This equation was chosen because it used data down to $M_w$ 3 and hence covered part of the magnitude range of interest. The residual plot showed that a small number of records, predominantly from Geysers, had very low PGAs (more than 100 times smaller) relative to the predicted value. The inclusion of these data could hamper any analysis performed and were therefore removed. Because Geysers contributes thousands of records to the analysis, this removal is not a significant loss. The reason for these very small amplitudes is not known but is likely due to instrument malfunction or misassociation of the record to a particular earthquake.

The distribution of the final selected data in terms of magnitude, hypocentral distance, focal depth, and location is shown in Figure 1. Although records from overlapping magnitude and distance ranges from various sites are included, some data come from distance ranges that are not well covered by data from other sites (e.g., Roswinkel). Because induced seismicity and local monitoring networks are closely localized in space, available records often come from similar distances, and magnitude–distance plots show banding. This lack of overlap in the available data impedes statistical analyses. In total, 3968 records (963 from Basel, 2328 from Geysers, 231 from Hengill, 61 from Roswinkel, 223 from Soultz, and 162 from Voerendaal) from 535 earthquakes and 119 stations are used to develop the GMPEs. Fifty-five records from 22 earthquakes and 13 stations from Campi Flegrei are used in an example application of these GMPEs. The focal mechanisms of the majority of these events are not known but are assumed to be strike-slip faulting when comparing the observations to previously published GMPEs.
Basel

The Basel EGS project was proposed to provide up to 3 MW in electrical production and 20 MW in thermal production. A 200°C reservoir was to be created at a depth of 5 km beneath the city. A dense network of surface sensors (Swiss Seismological Service, SED; Baden Wüttensberg Seismological Service, LED) and borehole sensors (Geo Explorers Ltd.) was deployed to monitor seismicity. The SED surface instruments are either STS-2 broadband seismometers or EpiSensor accelerometers, geographically oriented. Site conditions are well known through the microzonation studies of Havenith et al. (2007) and site investigations undertaken as part of a probabilistic seismic-hazard study for nuclear power facilities in Switzerland (Fäh et al., 2009). Basel lies on a sedimentary basin some several-hundred meters thick. Time-averaged shear-wave velocity down to 30 m ($V_{S30}$) of the sites around Basel tends to be around 400 m/s (National Earthquake Reductions Program [NEHRP] site class C), although rock-site stations at greater distances were also used for determination of magnitudes. The borehole sensors from Geo Explorers Ltd. are short-period geophones with a natural frequency of around 5 Hz and a damping coefficient of 0.2. Although they are located at various depths, we only use those on the surface for the ground-motion analysis (the borehole data were included in the magnitude determination). Some instruments were of unknown orientation, so all data were rotated to the direction of maximum amplitude. All events in the Basel dataset are geothermally induced events located by the SED. Data were corrected for the amplitude and phase response of the instrument and differentiated to provide acceleration-time series.

Campi Flegrei

Campi Flegrei caldera is a volcanic area that includes part of the metropolitan area of Naples (southern Italy), one of most densely populated areas in Europe. It is a large depression (with a radius of about 6 km) formed by huge ignimbritic eruptions, the last one having occurred 15,000 years ago (Deino et al., 2004). For at least the past 2000 years, the area has also been affected by episodes of large uplift and subsidence, as shown by marine ingression levels in Roman and Middle Age monuments and ruins (Dvork and Mastrolorenzo, 1990). The latest episodes of unrest, causing maximum uplift of about 3.5 m in 15 years (peak rate of about 1 m/yr), were from 1969 to 1972 and 1982 to 1984, with about 10 years of stable ground level in the interim. During this final period, maximum uplift rates were recorded by leveling networks and tide gauges (De Natale et al., 2006), and more than 15,000 microearthquakes occurred with magnitudes from 0 to 4.2 (De Natale and Zollo, 1986). As these earthquakes were generally shallow with maximum depths of 3–4 km, they were strongly felt by the local population but did not produce significant damage (De Natale et al., 1988). In January 1984, a digital network owned by the University of Wisconsin was installed at Campi Flegrei, consisting of 13 digital, three-component stations with a 125–250 Hz sampling rate (e.g., Aster et al., 1989). The catalog analyzed here contains the data presented in the aforementioned papers, with the addition of other records that were not analyzed at that time.

Geyser

Geyser is a vapor-dominated geothermal field located in northern California. The main steam reservoir has a temperature of about 235°C and underlies an impermeable caprock with its base 1.1–3.3 km below the surface. Commercial exploitation of the field began in 1960. Since then, seismicity has become more frequent in the area and has increased with further field development (e.g., Majer et al., 2007). The induced seismicity is concentrated within the upper 4 km of the crust, in the reservoir below production wells, and near injection wells.

Different temporary and long-term seismic networks have been deployed in the area during the last five decades. At present, local seismicity is monitored by the dense Berkeley–Geyser (BG) surface seismic network and some nearby stations of the Northern California Seismic Network (NCSN). The BG network consists of 29, three-component stations distributed over an area of about $20 \times 10$ km$^2$, covering the entire geothermal field. Initially, each BG station was equipped with I/O Sensor SM-6 geophones with natural frequencies of 14 Hz. Toward the end of 2009, these instruments were replaced by OYO Geospace GS-11D 4.5 Hz sensors. The BG stations operate in trigger mode, and the waveform segments recorded since the end of July 2007 are made available by the Northern California Earthquake Data Center (NCEDC). No information about $V_{S30}$ of the recording sites is currently available.

We analyzed induced seismicity at Geyser between August 2007 and February 2011. For the study region, there are waveforms of more than 11,000 located events with magnitudes larger than 1.0 available from the NCEDC. The largest earthquake recorded was the 4 January 2009 $M_w$ 4.3 event. We associated all data with events from the NCEDC earthquake catalog, updated the metadata for all traces, and automatically picked the $P$-wave first-arrival times for quality control. Because different magnitude types ($M_D$, $M_L$, and $M_w$) are used in the original catalog, moment magnitude has been recomputed here for all the events with $M \geq 1.5$ (any scale). To compile a representative subset for this study, we divided the available range of catalog magnitude into bins 0.25 units wide. Within each bin, we selected those 10 events with the most validated $P$-wave picks at BG stations to ensure accurate locations and high-quality waveforms.

Hengill

Ground-motion data recorded close to the Hengill (southwestern Iceland) geothermal system by a temporary broadband network installed within the framework of the Integrated Geophysical Exploration Technologies for Deep
Fractured Geothermal Systems (I-GET FP6) project (Jousset and François, 2006) were used here. The temporary network operated from late June 2006 until mid-October 2006 and was composed of seven Güralp Systems broadband instruments (CMG-3ESP and CMG-40TD) distributed to monitor and explore the Hengill hydrothermal system. In addition, data from the three stations (Lennartz LE3D-5s instruments) of the South Icelandic Lowland (SIL) permanent seismic network, operated by the Icelandic Meteorological Office (IMO), nearest Hengill (KRO, HEI, and SAN) were also collected for this study. Some basic site descriptions are available for the temporary stations, which show variations; however, it is assumed that the stations are all located on rock because of the general geology of the Hengill area (shallow volcanic soils overlying lava of various ages). Jousset and François (2006) report previous studies suggesting that cooling, mostly due to natural heat loss, and consequent thermal contraction and cracking in the heat source are responsible for the continuous small-magnitude seismicity in the Hengill area. This was deduced by the non-double-couple focal mechanisms with large explosive components, which may be attributable to fluid flow into newly formed cracks. The IMO earthquake catalog was queried to find those earthquakes with moment magnitudes larger than $M_w$ 1.0 that were recorded by one or more of the ten instruments installed in the Hengill region. The acceleration time histories (derived by time-domain differentiation from the velocity measurements recorded by the broadband sensors) corresponding to these earthquakes were selected.

Roswinkel

The Roswinkel (northeastern Netherlands) natural gas field is situated in a heavily faulted anticline structure in Triassic sandstones at a depth of around 2.1 km. The field was in production from 1980 to 2005, while seismicity was observed from 1992 to 2006, with 39 earthquakes in total and a strongest event of magnitude $M_L$ 3.4 and epicentral intensity of $I_0 = II$. The seismicity that occurred so far has been associated with existing faults on top of the reservoir (van Eck et al., 2006; Dost and Haak, 2007). The dataset used in this study contains 27 events with strong-motion recordings from the Roswinkel village obtained using GeoSIG AC-23 sensors.

Soultz

The Soultz geothermal exploitation began in the late 1980s as a collaborative French–German project. The first subterranean circulation of water using the drilled boreholes was achieved in the late 1990s. The boreholes were then deepened to about 5 km and various reservoir stimulations were undertaken in the first decade of this century. Electricity has been produced since June 2008. The data used here come from three permanent three-component surface stations (FOR, OPS, and SRB) installed by École et Observatoire des Sciences de la Terre (EOST) of the University of Strasbourg in 2003 close to the injection wells of the EGS (Charlety et al., 2007). These stations record amplitudes that are proportional to ground velocity, which is then converted to acceleration by differentiation and application of the calibration factor. The records are of injection experiments conducted in 2003. A high-quality earthquake catalog was provided by EOST. Because the recorded events are all induced in the geothermal reservoir, the records are associated with similar hypocentral distances.

Voerendaal

The Roer Valley Rift System is an active rift system in the Lower Rhine embayment in the border area of the Netherlands, Belgium, and Germany (Dost and Haak, 2007). Most of the seismicity in the area is situated within the Roer Valley graben, and this is associated to the main bounding faults: the Peel boundary fault to the northeast and the Feldbiss fault to the southwest. The village of Voerendaal is located on the South Limburg block, southwest of the Feldbiss fault. The region around Voerendaal has shown anomalous swarmlike seismicity at relatively shallow depths (around 3–8 km). A first swarm was detected in 1985 and lasted for more than a month. Nine events were located in 1985, the largest of which had a magnitude of $M_L$ 3.0 and a maximum epicentral intensity of $I_0 = IV$. After 15 years, a new swarm of events started in the same area on 20 December 2000. This time the swarm lasted for more than a year, with 139 detected events and a strongest event with magnitude $M_L$ 3.9 and intensity of $I_0 = VI$. The dataset used in this study is composed of 136 events from the Voerendaal area between April 1999 and August 2009. The waveforms consist of both short-period recordings from the regional seismic network (Willmore MkIII sensors) and accelerometric recordings from within the Voerendaal village, where three GeoSIG AC-23 strong-motion sensors have been deployed since the start of the second swarm.

Computation of Moment Magnitudes

One of the main difficulties in analyzing data from small earthquakes in different areas is the lack of a mutually consistent magnitude scale. The magnitudes of such small shocks are generally not computed by international agencies, such as the International Seismological Centre (ISC), using teleseismic scales such as surface-wave, body, or moment magnitude. Consequently, local or duration magnitudes are the only measures of the size of small events usually available. These magnitude scales are notorious for being network dependent, and therefore it is difficult to know if, for example, an $M_L$ 2 earthquake in one area is truly the same size as an $M_L$ 2 earthquake in another. In light of this, we have used an automatic procedure to apply the technique presented by Edwards et al. (2010) to calculate moment magnitudes ($M_w$) for the vast majority of earthquakes considered here.
The method is based on the far-field spectral model of Brune (1970, 1971), and it was shown previously to provide magnitudes consistent within ±0.1 units of moment tensor solutions of $M > 3$ events in Switzerland. The method is extended to lower magnitudes, relying only on a sufficient bandwidth (at least one log$_{10}$ unit) of the spectrum being visible above the noise. In their comparison of spectral $M_w$ with Swiss moment tensor solutions, Edwards et al. (2010) showed that the site effect on $M_w$ in Switzerland was negligible because the majority of recordings were from hard-rock sites. However, in the case of limited distance coverage of records analyzed herein, the instruments may be located entirely on sediments. We therefore allowed for site effects in the case of the Basel data, using the rock reference of Poggi et al. (2011).

The Geysers data are also located on sediments, which considerably amplify ground motions. In the case of unknown reference-velocity profile and amplification, there is a coupled trade-off between magnitude and site effects. However, for several events, moment magnitudes have been independently determined by Berkeley Seismological Laboratory (BSL). The moment tensor analysis used for their determination is insensitive to site effects due to the long-period signals that were analyzed. To constrain our joint inversion for site amplification and unknown $M_w$, we fixed the magnitudes of events with known $M_w > 3.5$. Given sufficient recordings across all stations from these events, the resulting inversion for unknown $M_w$ and site effects is decoupled, extending the determination of $M_w$ to low magnitudes. For the Hengill and Soultz data, no reference ($M_w$ or site amplification) exists, so we assume negligible site effects due to the rock-site classifications.

As a check of the calculated $M_w$ values and to determine magnitude-scaling relations between published and recalculated magnitudes, we compared all moment magnitudes to agency magnitudes when possible. Detailed analysis and interpretation of the $M_w$ determination is presented by B. Edwards and J. Douglas (2012, unpublished manuscript). As few independent $M_w$ estimates exist, it is difficult to objectively assess our calculated magnitudes. Nevertheless, comparison with magnitudes from BSL, where values were not fixed ($M_w < 3.5$), showed agreement to within 0.15 units down to $M_w$ 3.2. Furthermore, the scaling of $M_w$ determined for this study was found to be consistent with the $M_L : M_w$ scaling relations of Grünthal et al. (2009) and Goertz-Allmann et al. (2011), down to $M_w$ 1.

For some of the poorly recorded (generally the smallest) earthquakes, moment magnitudes could not be calculated with this approach. In the case of Basel, existing formulas from Goertz-Allmann et al. (2011) were available to estimate $M_w$ from $M_L$ for such events. For the events from other locations, region-specific magnitude-conversion formulas were used (Table 1). These formulas were derived using linear least-squares regression, assuming that the catalog magnitudes are definitive and all errors in $M_w$ are equal. Although the catalog magnitudes are not, in fact, definitive, the majority were provided without error estimates, limiting the scope for analysis. These conversions introduce uncertainties into the analysis, especially when the standard deviations of the formulas are large (i.e., for Hengill and Voerendaal), but they have the benefit of increasing the number of records available for analysis.

### Correction for Site Response

GMPEs are usually corrected for local site response and attenuation conditions relative to a given reference before application in local or regional hazard studies (e.g., Delavaud et al., 2012). Knowing the precise reference site condition of a GMPE is therefore important because not having this information can lead to the introduction of large epistemic uncertainties in probabilistic seismic-hazard analysis. In the case of most GMPEs, the reference condition is rather loosely defined (often in terms of a $V_{30}$ value or an NEHRP site class).

To address the problem of the starkly different site conditions across the different datasets in our study, all waveforms were corrected for a site-specific amplification response in addition to site attenuation, $\kappa$ (Anderson and Hough, 1984). The velocity profile used for the reference condition was the generic rock profile determined by Poggi et al. (2011) for Switzerland, while the corresponding reference attenuation was $\kappa = 0.016$ s (Edwards et al., 2011).

### Table 1
Magnitude-Conversion Formulas Used to Estimate $M_w$ for Those Earthquakes for which $M_w$ Could Not Be Calculated

<table>
<thead>
<tr>
<th>Site</th>
<th>Equation</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Basel</td>
<td>$M_w = 0.594M_L + 0.985$ for $M_L &lt; 2$</td>
<td>0.159 for $M_L &lt; 2$</td>
</tr>
<tr>
<td></td>
<td>$M_w = 1.327 + 0.253M_L + 0.085M_L^2$ for $2 \leq M_L \leq 4$</td>
<td>0.134 for $2 \leq M_L \leq 4$</td>
</tr>
<tr>
<td></td>
<td>$M_w = M_L - 0.3$ for $M_L &gt; 4$</td>
<td>0.175 for $M_L &gt; 4$</td>
</tr>
<tr>
<td>(Goertz-Allmann et al., 2011)</td>
<td>$M_L = 0.134$</td>
<td></td>
</tr>
<tr>
<td>Geysers</td>
<td>$M_w = 0.90M_L + 0.47$</td>
<td>0.08</td>
</tr>
<tr>
<td>Hengill</td>
<td>$M_w = 0.546M_L + 1.072$</td>
<td>0.28</td>
</tr>
<tr>
<td>Roswinkel</td>
<td>$M_w = 0.578M_L + 1.168$</td>
<td>0.10</td>
</tr>
<tr>
<td>Soultz</td>
<td>$M_w = 0.614M_L + 0.433$</td>
<td>0.19</td>
</tr>
<tr>
<td>Voerendaal</td>
<td>$M_w = 0.641M_L + 1.018$</td>
<td>0.33</td>
</tr>
</tbody>
</table>
Empirical Analysis

In this section we analyze the ground-motion data to investigate possible differences in shaking from the locations considered here. In agreement with current practice, the geometrical mean of the two horizontal components of pseudospectral acceleration (PSA) for 5% damping is considered. Of particular interest in relation to ground-motion variability is the similarity of time histories observed at a particular geothermal site. Because the recordings are of events in a relatively small source region and the waves follow similar paths to closely spaced receivers, this should provide an insight into single-station, single-source sigma (Atkinson, 2006; Rodriguez-Marek et al., 2011). This issue is discussed in the Aleatory Variability section. The two types of data analysis considered here (analysis of variance [ANOVA] and regression) are complementary because ANOVA does not impose a functional form and relies on many records from overlapping magnitude–distance ranges from different locations, whereas regression analysis requires a functional form (or forms) to be assumed but data from different regions do not need to overlap.

Analysis of Variance

Douglas (2004a,b, 2007) uses one-way ANOVA to test the differences in observed ground motions for a given magnitude and distance in two or more regions. In this technique, ln(PSA)s computed from ground-motion records in different regions are binned into small magnitude and distance intervals, and the mean ln(PSA)s for each magnitude–distance range are computed for each region along with their standard deviations. For bins with sufficient records, ANOVA allows the computation of the significance level of the difference between average ground motions in the different areas. The advantage of this approach over techniques involving the derivation and comparison of GMPEs for the different regions is that no assumptions need to be made on the functional form of the GMPEs. Furthermore, assessing the significance of differences between predictions from GMPEs is not straightforward (Douglas, 2007). The disadvantage of this technique is that it requires dense overlapping datasets for the magnitude–distance ranges of interest because there must be at least two (and preferably many more) records per region per bin, which often limits its application to small earthquakes at moderate distances.

Because of the short (and accurately determined) hypocentral distances, it was decided to use a fine grid for $r_{hyp}$ and a coarser grid for magnitude. Therefore, the data space was gridded into $0.5 \ M_w \times 2 \ km$ bins, within which it was assumed that the ground motions were similar. Bins with more than five records from a single location were identified to highlight those magnitude–distance ranges in which sufficient records for robust ANOVA existed. The average site-corrected spectra for each location and the magnitude–distance bins with data from more than one location are displayed in Figure 2.

This figure indicates that very-near-source ground motions (within 7 km) vary significantly in the different locations across the whole period range of interest. At greater distances, the differences between most of the spectra become insignificant. This apparent difference in ground motions between locations could be attributed to differences in stress drop because the differences are more apparent at short periods and the spectra converge at longer periods. Reasons for these regional differences in stress drop could be related to variations in average focal depths and elastic/mechanical properties of the media. There does not seem to be any correlation between the type of seismicity and ground-motion amplitudes because, for instance, the Soultz spectra are generally much higher than average for a certain magnitude–distance range whereas the Basel spectra are generally lower than average, and both are examples of induced seismicity. Similarly Voerendaal and Hengill present significantly different average spectra, and these datasets are both examples of natural seismicity.

Regression Analysis

As a complementary technique to ANOVA, in this section we develop GMPEs by regression analyses of the available ground-motion data. These GMPEs allow the scaling of ground motions with respect to magnitude and distance to be studied and compared to those predicted by the stochastic model developed in the Development of Generic Stochastic Models section. In addition, differences between ground motions from different areas are investigated. Finally, the predictions are compared to those made by existing GMPEs derived from data from moderate and large earthquakes, specifically those by Ambraseys et al. (2005; herein referred to as AB05), Bommer et al. (2007; referred to as BM07), and Massa et al. (2008; referred to as MS08), to see if such models can be extrapolated to the prediction of shaking from small events.

We derive a specific GMPE using nonlinear mixed-effect regression (Lindstrom and Bates, 1990; Abrahamson and Youngs, 1992), which accounts for between-event and within-event variabilities (Al Atik et al., 2010). Only records with $r_{hyp} < 50 \ km$ are used. The model selected for regression (model 1) has a standard functional form (equation 1) accounting for first-order effects of magnitude scaling, near-source saturation, geometrical spreading, and anelastic attenuation:

$$
\ln Y = a + bM + c \ln \sqrt{r_{hyp}^2 + h^2} + d r_{hyp},
$$

where $Y$ is the response variable corresponding to PGA, PGV, or PSA at various structural periods (in SI units) and $a$, $b$, $c$, $d$, and $h$ are regression coefficients. Coefficients obtained from the regression analysis, along with their uncertainties and the two principal components of the standard deviation, are reported in Table 2 for PGA, PGV, and PSA for three selected periods. (See Table S1 of the electronic supplement to this article for coefficients for periods up to 0.5 s.)
Figure 2. Average site-corrected response spectra observed in each location in $M_{w}$-$r_{hyp}$ bins of $0.5 \times 2$ km (y axes show log(PSA) where PSA is in m/s$^2$ and x axes show structural period in s). A triangle means a significant difference was found at the 5% level between PSAs at the different locations, and a circle implies no significant difference was found. Filled symbols indicate more than five records from a location are in the $M_{w}$-$r_{hyp}$ bin, and unfilled indicates five records or less.

Table 2

Coefficients for Model 1 for Selected Periods in which $\tau$ is the Between Event, $\phi$ the Within Event, and $\sigma$ the Total Standard Deviations

<table>
<thead>
<tr>
<th>Period</th>
<th>$a \pm \sigma_a$</th>
<th>$b \pm \sigma_b$</th>
<th>$c \pm \sigma_c$</th>
<th>$d \pm \sigma_d$</th>
<th>$\phi$</th>
<th>$\tau$</th>
<th>$\sigma$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Uncorrected for site effects (PGA) 0.01</td>
<td>$-5.984 \pm 0.427$</td>
<td>$2.146 \pm 0.069$</td>
<td>$-1.772 \pm 0.208$</td>
<td>$2.511 \pm 0.595$</td>
<td>$-0.023 \pm 0.011$</td>
<td>0.792</td>
<td>0.829</td>
</tr>
<tr>
<td></td>
<td>$-6.444 \pm 0.329$</td>
<td>$2.376 \pm 0.056$</td>
<td>$-1.410 \pm 0.167$</td>
<td>$1.751 \pm 0.704$</td>
<td>$-0.039 \pm 0.009$</td>
<td>0.815</td>
<td>0.623</td>
</tr>
<tr>
<td></td>
<td>$-9.513 \pm 0.243$</td>
<td>$2.805 \pm 0.058$</td>
<td>$-0.776 \pm 0.121$</td>
<td>$1.948 \pm 0.688$</td>
<td>$-0.057 \pm 0.008$</td>
<td>0.800</td>
<td>0.612</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.800</td>
<td>0.612</td>
<td>1.007</td>
</tr>
<tr>
<td>PGV</td>
<td>$-10.367 \pm 0.449$</td>
<td>$2.018 \pm 0.136$</td>
<td>$-1.124 \pm 0.183$</td>
<td>$2.129 \pm 0.895$</td>
<td>$-0.046 \pm 0.010$</td>
<td>1.811</td>
<td>0.745</td>
</tr>
<tr>
<td>Corrected for site effects (PGA) 0.01</td>
<td>$-6.514 \pm 0.423$</td>
<td>$1.995 \pm 0.085$</td>
<td>$-1.468 \pm 0.200$</td>
<td>$2.490 \pm 0.688$</td>
<td>$-0.029 \pm 0.010$</td>
<td>0.730</td>
<td>1.079</td>
</tr>
<tr>
<td></td>
<td>$-7.991 \pm 0.229$</td>
<td>$2.376 \pm 0.063$</td>
<td>$-0.827 \pm 0.106$</td>
<td>$1.058 \pm 1.049$</td>
<td>$-0.056 \pm 0.006$</td>
<td>0.589</td>
<td>0.787</td>
</tr>
<tr>
<td></td>
<td>$-10.024 \pm 0.219$</td>
<td>$2.784 \pm 0.057$</td>
<td>$-0.850 \pm 0.103$</td>
<td>$1.080 \pm 0.979$</td>
<td>$-0.041 \pm 0.006$</td>
<td>0.554</td>
<td>0.658</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.572</td>
<td>0.698</td>
<td>0.903</td>
</tr>
<tr>
<td>PGV</td>
<td>$-9.999 \pm 0.681$</td>
<td>$1.964 \pm 0.122$</td>
<td>$-1.405 \pm 0.321$</td>
<td>$2.933 \pm 1.088$</td>
<td>$-0.035 \pm 0.016$</td>
<td>1.029</td>
<td>1.553</td>
</tr>
</tbody>
</table>
The magnitude scaling of the derived GMPEs (coefficient \( b \)) closely matches the magnitude dependencies reported by Douglas and Jousset (2011) from previous empirical GMPEs derived using data from small (\( M_w \leq 3 \)) natural and mining-related earthquakes (their fig. 1), thereby suggesting that the magnitude scaling of induced, mining, and natural seismicity are comparable. Comparing the coefficient \( b \) of the GMPEs for PGV with the coefficients for PGA and PSA shows that the PGV for small events is associated with very high frequencies, and hence the method of Bommer and Alarcón (2006) to estimate PGV from PSA (0.5 s) is not recommended for such earthquakes. The regression coefficients \( c \) and \( d \) indicate fast decay with distance, which could be attributable to strong anelastic attenuation (i.e., low \( Q \) values). Except at high frequencies, the total standard deviation obtained from the regression on site-corrected data is lower than that corresponding to uncorrected data, which shows that the site effect contributes significantly to ground-motion variability. It should be noted that the high-frequency site correction may actually reintroduce some source variability that was effectively hidden by the site attenuation (\( \kappa \)). Consequently, we observe an increase in total \( \sigma \) at high frequencies, including PGA and PGV, driven by an increase in the between-event variability (\( \tau \)).

Figure 3 shows residual plots for data corrected for site response. As is usual, the within-event residual distributions show larger dispersion compared with the between-event distributions. The comparison with other models shows that the residual distributions of BM07 and MS08 are similar to that of our model. On the other hand, the AB05 GMPEs lead to a wide distribution of residuals, which can be attributed to the applicability of this GMPE to larger magnitudes. Indeed, BM07 is based on a dataset in which the minimum \( M_w \) was 3.0, MS08 analyzed data with minimum \( M_w \) of 4.0, and AB05 considered strong-motion data relative to earthquakes with \( M_w \geq 5.0 \).

To investigate what constitutes the largest contribution to the total residuals’ distribution, we analyze them as a function of both magnitude and distance. The obtained results, which for brevity are not reported here, show that the largest contribution to the residual dispersion comes from the distance; and, in particular, data recorded at shorter distances feature higher residual values at all structural periods. This indicates that, for data collected from earthquakes occurring in these areas, it is likely that anelastic attenuation plays an important role. On the other hand, aside from the results obtained from the AB05 model, the residuals as a function of magnitude are characterized by a quite uniform dispersion, mostly centered on zero.

To analyze the effect of focal depth on the regression models, and thus on the predictions of the ground motion, we implemented two additional models to be compared with the model reported in equation (1). From now on we refer only to data corrected for site response. First, we selected a model in which the regression coefficient \( h \) is no longer used in conjunction with \( r_{hyp} \) so as to discuss the relative importance of this coefficient. Second, we implemented a model in which epicentral distance, \( r_{epi} \), is used instead of \( r_{hyp} \). Models 2 and 3 have the following formulations:

\[
\ln Y = a + bM + c \ln r_{hyp} + d r_{hyp},
\]

and

\[
\ln Y = a + bM + c \ln \sqrt{r_{epi}^2 + h^2} + d r_{epi}.
\]

The coefficients and the associated uncertainties for the two models are listed in Table 3. Concerning the PGA, the between- and within-event standard deviations of models 1 and 2 are equal, while the between-event component for \( T \leq 0.1 \) s for model 3 is slightly reduced. This could be a consequence of greater scatter in focal depths, which are more poorly defined than the epicenters.

Unlike moderate and large earthquakes, which rupture a large proportion of the seismogenic layer, small earthquakes, such as those induced and triggered by EGSs, are associated with ruptures of less than a kilometer. Consequently, whether this rupture occurs at a depth of, say, 20 km or at 2 km will have a large impact on the shaking at the surface. To test the effect of the focal depth on the predicted values from the three models, we considered a set of epicentral distances, and for each distance the actual range of focal depths contained in the data is taken into account. For each term composed of depth, \( r_{epi} \) and \( r_{hyp} \), we considered the differences \( \ln Y_{model,i} - \ln Y_{model,j} \) where \( i \) and \( j \) correspond to 1, 2, and 3. We note that the differences depend only weakly on structural period and magnitude. Therefore, we show (in Fig. 4) results only for the PGA and for a representative magnitude, \( M_w \leq 2.5 \). As expected, models 1 and 2 show the same behavior for depths larger than 3 km. The models differ for \( r_{epi} < 1 \) km and focal depths less than 3 km, for which model 2 provides predictions larger than those of model 1. This is due to coefficient \( h \) in model 1, which avoids unrealistic \( Y \) values at small distances. The comparison between models 1 and 2 with respect to model 3 is more important for evaluating the effect of the focal depth. Aside from the absolute values, the differences between models 1 and 3 and those between models 2 and 3 share the same characteristics. In particular, all the models are similar starting from epicentral distances of 10–15 km. On the other hand, a net difference is observed for \( r_{epi} < 5 \) km, with a different trend depending on the depth and an inflection point at about 3 km. For depths less than 3 km, the predictions made by models 1 and 2 are larger than those obtained from model 3, while the opposite is observed for depths greater than 3 km. Thus, depth plays a fundamental role, and \( r_{hyp} \) should be more effective than \( r_{epi} \), particularly at short distances.

As for natural earthquakes (e.g., Douglas, 2007), it is of interest to investigate the effect of the tectonic environment on ground motions from induced events. With this aim, we analyze the residual distributions for each of the six zones. For natural earthquakes, ground motions in different...
Figure 3. Residual distributions and comparisons between data and predictions (corrected data) include (a) PGA, (b) PSA (0.10 s), (c) PSA (0.20 s), and (d) PSA (0.50 s). The lower panels show the data from earthquakes with $2 \leq M_w \leq 3$ and curves corresponding to $M_w 2.5$, while the upper panels show the residual distributions using the GMPEs derived here and those of Ambraseys et al. (2005), Bommer et al. (2007), and Massa et al. (2008). Moreover, for the GMPEs from the present study, the residuals are separated into between-event and within-event components. (Continued)
Predicting Ground Motion from Induced Earthquakes in Geothermal Areas

Figure 3. Continued.
regional stress fields can be significantly different for the same magnitude and source-to-site distance (e.g., McGarr, 1984; Bommer et al., 2003; Convertito and Herrero, 2004).

For induced seismicity, local stress conditions are mostly driven by field operations, which can reactivate existing faults or generate new ones with mechanisms different to those expected from the regional stress field (Oppenheimer, 1986; Li et al., 2011). In Figure 5 we show the PGA residuals as a function of $r_{hyp}$, $M_w$, and depth. It can be noted that dominant contributions come from Geyser and Hengill. As a general comment, for all the models and all the considered structural periods, we do not observe particular correlations among the residuals and the three variables, $M_w$, $r_{hyp}$, and focal depth.

![Figure 4](image_url)

A comparison of predicted PGA of the three models as a function of focal depth.
Development of Generic Stochastic Models

Because the GMPEs developed in the previous section may lead to erroneous predictions for $M_w > 3$ due to limited data, the purpose of this section is to develop stochastic models that are applicable close ($r_{hyp} < 50$ km) to shallow earthquakes of $1 \leq M_w \leq 5$. As discussed earlier in this article, this is outside the magnitude–distance range of the vast majority of published GMPEs. The empirical ground-motion models derived herein combine data from different sites and hence include within their aleatory variability ($\sigma$) large site-to-site variation (this is discussed in detail in the Aleatory Variability section). In keeping with state-of-the-art seismic-hazard assessments, it is preferable to explicitly separate epistemic uncertainty, which can be reduced through the collection of additional data, from true aleatory variability, which is randomness intrinsic to the model. The development of many (site-specific) stochastic models for geographical zones where geothermal exploitation is ongoing or likely in the future allows this separation to be made. The way in which these models could be used in EGS projects and with what values of $\sigma$ is discussed in the Aleatory Variability section.

$Q$ and $\kappa$ values were first obtained for each region and station, respectively, following the spectral fitting method detailed in Edwards et al. (2011). In the case of Geysers, Hengill, and Basel, sufficient data were available to define regional $Q$ values: 199, 657, and 1575 (based on a velocity of $\beta = 3500$ m/s), respectively. However, in the case of Basel, we used $Q = 1200$, based on a study of a much larger Swiss dataset by Edwards et al. (2011). For cases in which $Q$ was not determined (due to records from a narrow distance range), we assumed low attenuation ($Q = 1200$), such that the majority of attenuation was assigned to the station $\kappa$ value. Station $\kappa$ values were estimated based on these $Q$ models such that the average path attenuation, $t^*$, is given by $t^* = \kappa + r_{hyp}/(Q\beta)$.

For selected datasets, we compared $\kappa$ values computed using the methods of Anderson and Hough (1984) and Edwards et al. (2011) and found negligible differences. Stress (drop) parameters (Fig. 6) for the datasets were computed based on the definition assumed by the Stochastic-Method SIMulation (SMSIM) software as $\Delta \sigma = M_0[f_c/(0.4906\beta)^3]$ (Boore, 2003), with the seismic moment $M_0$, and the event–common source corner frequency $f_c$, obtained through a

![Figure 5. Residual analysis with respect to each area for PGA and model 1.](image)

![Figure 6. Observed stress-parameter values from the different datasets. Error bars indicate the uncertainty based on the range of possible $f_c$ values within ±5% of the minimum misfit.](image)
second spectral inversion of log-log spectra with fixed $Q$. There appears to be regional variation of the stress parameter, but this may also be due to the influence of trade-offs in the inversion and data limitations (such as available spectral bandwidth). To address such trade-offs, we include an uncertainty based on the range of possible $f_c$ values within ±5% of the minimum misfit, although this is based on the assumption of known attenuation.

To capture the range of possible median ground motions for different stress-drop and attenuation scenarios, we simulated $3 \times 3 \times 4 = 36$ different stochastic models. The models were made using a combination of $Q$ (200, 600, and 1800), Brune (1970, 1971) $\omega^2$ stress parameter ($\Delta \sigma$, 1, 10, and 100 bar), and $\kappa$ (0.005, 0.02, 0.04, and 0.06 s). The choice of these values was designed to cover the range of observed average values. In fact, the 36 models could be reduced to 12 if we consider that, for the magnitude range of interest and moderate $\kappa$ and $Q$, the stress parameter is relatively insignificant (Douglas and Jousset, 2011). A known rock reference is imposed through the specification of the amplification and corresponding site-attenuation model of Poggi et al. (2011) and Edwards et al. (2011). The duration model is the theoretical model presented by Herrmann (1985), while geometrical spreading is assumed to follow $1/r$ decay. The stochastic model parameters are listed in Table 4.

While these models do not explicitly represent the region-specific data, in Derivation of Weights for Stochastic Models we describe a method for the production of a mixture model to best describe a particular dataset and region. In the same way, it will be possible to produce a best-estimate model for a new region (given an expected stress parameter $\Delta \sigma$, $\kappa$, and $Q$ value), which can then be dynamically updated when data become available. In these simulations we do not aim to address the issue of ground-motion variability, rather we are looking to cover epistemic uncertainty of potential median ground-motion models. Indeed, because of the complex interaction of stochastic-model parameters, it is difficult to justify the use of simulated ground motions for analyzing such variability (Rietbrock et al., 2013). Instead, we provide measures of variability based on empirical analysis of data, as described in the Aleatory Variability section.

A comparison of the generic model with $Q = 600$, $\kappa = 0.02$ s, and stress parameter 10 bar with a model for Switzerland (Edwards and Fäh, 2013) based on weak-motion data is shown in Figure 7. The comparison with the Swiss model shows they are quite similar, although the Swiss model has a magnitude-dependent stress parameter, which leads to a higher PSA for $M_w 4.5$ events. Furthermore, the Swiss model shows stronger geometrical decay in the first 20 km, then less decay at greater distances.

To make the developed stochastic model easier to use for hazard assessments, median ground motions (PGA, PSA, and PGV) for various magnitudes and distances are predicted using the stochastic model and random-vibration theory implemented in SMSIM (Boore, 2005) to which functions are fitted.

### Table 4

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Source type</td>
<td>(Brune 1970, 1971)</td>
</tr>
<tr>
<td>Stress parameter</td>
<td>1, 10, 100 bar</td>
</tr>
<tr>
<td>$Q$</td>
<td>200, 600, 1800</td>
</tr>
<tr>
<td>Geometrical decay</td>
<td>$1/R$</td>
</tr>
<tr>
<td>$\kappa$</td>
<td>0.005, 0.02, 0.04, 0.06 s</td>
</tr>
<tr>
<td>Amplification function</td>
<td>Frequency Amplification</td>
</tr>
<tr>
<td></td>
<td>0.10, 0.20, 0.40, 0.80, 1.60, 3.20, 6.42, 12.0, 100</td>
</tr>
<tr>
<td>$V_{50}$</td>
<td>1100 m/s</td>
</tr>
<tr>
<td>Duration</td>
<td>$1/f_c + 0.05R_{hyp}$</td>
</tr>
<tr>
<td>Density ($\rho$), velocity ($\beta$)</td>
<td>2800 kg/m$^3$, 3500 m/s</td>
</tr>
<tr>
<td>Partition factor, radiation, free surface</td>
<td>0.71, 0.55, 2</td>
</tr>
</tbody>
</table>

**Figure 7.** A comparison of simulated PGA and PSA (gray lines) at 0.1 and 0.4 s to the model of Edwards and Fäh (2013) for the Swiss foreland for $M_w$ 1.5, 3, and 4.5. For the comparison, the generic model with $Q = 600$ is used along with $\kappa = 0.02$ s and a $\Delta \sigma$ of 10 bar.
by regression analysis. This is the same approach adopted by, for example, Atkinson and Boore (2006). To focus on induced events, simulations were performed at distances of \( r_{hyp} \) to 50 km in 1 km intervals and magnitudes 1–5 in intervals of 0.25 for PGA, PGV, and PSA at 18 periods (0.01, 0.02, 0.03, 0.04, 0.05, 0.075, 0.1, 0.15, 0.2, 0.3, 0.4, 0.5, 0.75, 1, 1.5, 2, 4, and 10 s). To capture the behavior of the predicted ground motions, various functional forms were tested, and it was found that the following simple functional form was sufficient:

\[
\ln Y = b_1 + b_2(M_w - 3) + b_3(M_w - 3)^2 + b_4(M_w - 3)^3 + b_5 \ln(r_{hyp} + b_6) + b_6(r_{hyp} + b_7).
\]

(4)

The standard deviations from using a standard least-squares regression to fit this functional form to the simulated PSAs are all smaller (much smaller for \( T > 0.1 \) s) than 0.3 (natural log), thus showing that the functional form is adequate. The coefficients of the 36 fitted models are listed in Table S2 of the electronic supplement.

Rather than present individual models for different \( \Delta \sigma \), \( Q \), and \( \kappa \), an attempt was made to derive a single model using a functional form based on the theoretical dependency of the Fourier amplitude spectrum on these three parameters. However, the regression equations obtained by this approach were associated with large standard deviations, and predictions from the metamodel did not closely match the simulations. Therefore, we do not recommend these equations, and the coefficients are not given here. Atkinson and Boore (2006, 2007) propose an approximate procedure to adjust \( \Delta \sigma \) in their GMPEs, derived using the stochastic model without listing coefficients for many different values of the stress parameter. These equations were tested to adjust the models for 10 bar up and down, but it was found that the predictions from the adjusted models for larger events (\( M_w \geq 4 \)) and \( T > 0.1 \) s did not match those from the individual GMPEs for \( \Delta \sigma = 1 \) bar and 100 bar. Therefore, the adjustments of Atkinson and Boore (2006, 2007) are not recommended for the models presented here.

Comparisons of the different generic models are shown in Figure 8. Even close to the source (\( r_{hyp} < 10 \) km), the predictions from the stochastic models with different \( Q \) diverge as the distance increases. However, the effect of \( \Delta \sigma \) is limited below \( M_w \) 3 and for higher \( \kappa \) This effect is initially surprising; however, as shown by Douglas and Jousset (2011), for example, high-frequency attenuation (\( Q \) and \( \kappa \)) means that changing \( \Delta \sigma \) has a limited impact because it changes the plateau of the source spectrum for frequencies higher than the corner frequency, but these frequencies are then highly attenuated by the path and site. As the corner frequency decreases (magnitude increases), the impact of the high-frequency attenuation becomes less important and the models

\[ M_{w2} \]

\[ M_{w3} \]

\[ M_{w4} \]

\[ M_{w5} \]

\[ r_{hyp} \]

\[ T > 0.1 \] s
with different $\Delta \sigma$ diverge. For small events, $\kappa$ is indeed controlling the different values of PSA, particularly at high frequencies. However, for larger events (e.g., $M_\text{w} = 5$), the stress parameter has a strong influence. Therefore, although it is not critical for fitting small events, the choice of stress parameter may have a strong impact on hazard if magnitudes approach 5.

Empirical model 1 (black curve) is roughly in the middle of the generic stochastic models for $M_\text{w} \leq 4$, for which there are sufficient records to constrain the regression. It is, however, at the higher end of predictions for $M_\text{w} = 5$, for which the regression is unconstrained by data and the assumption of the same (linear) magnitude scaling used for smaller events breaks down (Douglas and Jousset, 2011).

Because of the large epistemic uncertainty in the prediction of median ground motions from geothermal areas, the approach followed here is to propose a set of possible stochastic models that we suggest should be used as a basis of logic trees for seismic-hazard assessments associated with geothermal projects. At the beginning of a project when no ground-motion data are available from a site, the various models derived here could be assigned equal weight within the logic tree or weighted dependent on previous estimates of $Q$, $\Delta \sigma$, and $\kappa$ in the region. Once seismograms become available from the local network installed as part of the project, the weights can be revised by comparing these data to the different models and assessing the likelihood of each model to be the correct one for the site. A simple example of this type of approach is presented in the next section.

Derivation of Weights for Stochastic Models

As an example of the possible application of the GMPEs derived above, we use the independent dataset from Campi Flegrei. These data are measurements of natural seismicity within a geothermally active zone rather than of induced events, but they are selected because they have many of the characteristics that EGS site records would have, such as small magnitudes, shallow focal depths, and short hypocentral distances. Only 55 records were analyzed from this site so the situation corresponds to either prestimulation monitoring of background seismicity or early on in the stimulation process. We analyzed 14 seismic events recorded by various networks during the bradiseismic crises of 1982–1984 and 8 events recorded during the smaller crisis of 2006. We selected earthquakes having a clear $S$ wave with respect to the background noise recorded by at least three stations. The analyzed earthquakes have depths between 1 and 4 km below sea level, and almost all are located close to the center of the Campi Flegrei caldera. Spectra of ground displacement of a 2.56 s time window containing the $S$-wave first arrival (starting 0.3 s before the $S$-wave arrival time) were fitted by using a theoretical $\omega^2$ model corrected for both $Q = 125$ and $\kappa = 0.015$ s (De Natale et al., 1987) to estimate low-frequency levels, $\Omega_0$, and corner frequencies, $f_c$. The observed spectra were also corrected for the site functions found by Tramelli et al. (2010).

Seismic moments were obtained from the spectra using this relationship (Aki and Richards, 2002):

$$M_0 = \frac{4\pi \rho V_S^3 r_{\text{hyp}} \Omega_0}{FR_0},$$

with $\rho = 2000$ kg/m³, $V_S = 1700$ m/s, $F$ is the free-surface correction, and the average $S$-wave radiation-pattern coefficient, $R_0$, is 0.3 (De Natale et al., 1987). The stress drop, $\Delta \sigma$, was calculated using the Brune (1970, 1971) model, $\Delta \sigma = 0.44M_0/r^3$, where the source radius $r$ is given by 0.37$V_S/f_c$. The stress drops calculated for the earthquakes of the 1982–1984 crises are close to 5 bar, as previously found by De Natale et al. (1987), while the values found for the 2006 earthquakes are a little higher, as shown in Table 5.

Based on the values of $Q$ (125) and $\kappa$ (0.015 s) estimated by De Natale et al. (1987) and the value of $\Delta \sigma$ (5 bar) found here, it could be argued to give highest weight within a seismic-hazard assessment for this area to the GMPEs for $Q = 200$, $\kappa = 0.02$ s, and $\Delta \sigma = 1$ bar and 10 bar, which are the nearest available stochastic models of the 36 derived here. However, given the large epistemic uncertainties on these estimates of $Q$, $\kappa$, and $\Delta \sigma$ for Campi Flegrei, a more observational-based approach may be preferred due to the limited data.

The magnitudes of the available data only covers the range of $0.4 \leq M_\text{w} \leq 2.1$, and over this range the effect of $\Delta \sigma$ is limited. Consequently, we only consider a single stress parameter (1 bar). We also exclude the models using $\kappa = 0.005$ s, which is unrealistic for Campi Flegrei sites. This means that the 36 potential GMPEs are reduced to $3 \times 3 = 9$ models, which include $Q = 200, 600,$ and 1800 and $\kappa = 0.02, 0.04,$ and 0.06 s. Figure 9 compares the predicted and observed PSA (0.1 s) and PSA (0.5 s) for data within 0.5 $M_\text{w}$ units of the mean magnitude of the analyzed data ($M_\text{w} = 1.4$), which shows the large inherent variability in observed ground-motion data from small earthquakes and the difficulty in preferring certain models over others. Nevertheless, the lower group of stochastic models (corresponding to $\kappa = 0.06$ s) provides a better fit than the other GMPEs. Consequently, slightly higher weights for these GMPEs could be appropriate, but the other models cannot be excluded from the logic tree because of the high-epistemic uncertainty when conducting seismic-hazard assessments using limited observations (such as this case). Figure 9 also illustrates that empirical model 1 and the stochastic models predict similar ground motions for this magnitude and range of distances. In practice, ground-motion data from a local monitoring network installed as part of an EGS project would allow continual updating of the weights assigned to each of the considered GMPEs as the epistemic uncertainty in the median ground motions decreases as more data are recorded.

Aleatory Variability

One of the most active areas of engineering seismology research in the past decade is in the understanding and characterization of aleatory variability of earthquake
In addition, magnitudes were all carefully recomputed for this study using a consistent method.

A comparison between the aleatory variabilities of various recent GMPEs and those for the empirical model 1 is shown in Figure 10. One clear difference between the variabilities of recent GMPEs for moderate and large earthquakes and model 1 and the mining-related GMPE of McGarr and Fletcher (2005) is the strong period dependency of these two models with a peak in $\sigma$ for very short periods and a rapid decrease as period increases. As shown in Figure 8, shaking, commonly summarized by the standard deviation ($\sigma$) of the logarithm of a ground-motion parameter such as PGA (e.g., Strasser et al., 2009, and the references therein). It is important that the $\sigma$ used within a probabilistic seismic-hazard assessment correctly captures the true variability in the ground motion and that it is not unrealistically small or large.

One cause of overestimated $\sigma$ is that the independent parameters (metadata), such as magnitude and distance, are inaccurate. This would lead to a mapping of these uncertainties into the computed $\sigma$. This has been proposed as a possible reason for the common observation that ground motions from small earthquakes seem to be more variable than those from large earthquakes. This is because metadata of small earthquakes are likely to be poorer than those of large earthquakes because national and international seismic networks have difficulty locating and quantifying the size of small shocks (e.g., Youngs et al., 1995). The analyses conducted here should provide estimates of $\sigma$ largely free of contributions from inaccurate metadata because the records used all come from locations well covered by high-quality local seismic networks. As an example, Jousset et al. (2011) relocalized local earthquakes as part of a tomographic study for the Hengill area. The locations reported by IMO (used here) and Jousset et al. (2011) are generally within 0.5 km horizontally and within 1 km vertically of one another. Tremors within geothermal reservoirs are probably even more accurately located because of dense local arrays.

The first 14 rows indicate analyzed earthquakes from 1982 to 1984; the last 8 rows show those from 2006.

Table 5

<table>
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<tr>
<th>Event</th>
<th>$f_c$ (Hz)</th>
<th>$\Delta\sigma$ (bar)</th>
<th>$M_d$ (N m)</th>
<th>$M_{st}$</th>
<th>Northing (m)</th>
<th>Easting (m)</th>
<th>Depth (m)</th>
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</table>

The first 14 rows indicate analyzed earthquakes from 1982 to 1984; the last 8 rows show those from 2006.
there is much variation in predictions from the derived stochastic models at very short periods, which is being mapped in empirical models into the aleatory variability rather than being considered as epistemic uncertainty in the values of \( \Delta \sigma, \kappa, \) and \( Q \). In addition, the sigmas of these two GMPEs are much higher than those of the other considered GMPEs. These observations can be related to much higher (more than twice for PGA) between-event variabilities \( \tau \). The within-event variabilities \( \phi \) from all models are comparable. This is despite the finding of Douglas and Jousset (2011) that variations in near-surface attenuation (characterized by \( \kappa \)) lead to larger variations in high-frequency ground motions from small earthquakes than they do in large earthquakes due to the interaction between source-corner frequency and attenuation. Such an effect would affect \( \phi \), which could be an explanation for slightly higher values at short periods for model 1. Although the reduction in \( \phi \) from using the site-corrected data is evident, this site correction leads to higher \( \tau \) (due to the reduction of the local attenuation, \( \kappa \), to that consistent with a hard-rock site). Because \( \kappa \) acts as a low-pass filter, this reduction recovers a previously unseen source variability.

Are the much higher \( \tau \) values from the data analyzed here realistic? Or should a different model for \( \tau \) be developed or adopted, such as one of the Next Generation Attenuation (NGA) models (Abrahamson et al., 2008)? One reason for much larger short-period \( \tau \) is greater variability in \( \Delta \sigma \); another is variations in focal depth, which would have a stronger effect for small shocks than for large events. Any variation among records from a single station of induced earthquakes of similar magnitudes in a well-constrained zone is almost entirely due to differences in the source (e.g., mechanism and stress drop). Many records from Soultz and Basel fall into this category. These data allow estimates of this component of \( \tau \) to be made. The \( \tau \) computed here is based on regression analysis of data from six different zones, and future EGS sites will likely only be affected by a single source, which should be less variable than multiple sources. Therefore, zone-specific \( \tau \) have been computed for Soultz and Basel, which are well-defined induced seismicity sources with sufficient data for robust statistics. These are computed from the between-event residuals with respect to model 1 for these two zones. These zone-specific \( \tau_{\text{ZS}} \) values are compared to the overall \( \tau \) in Figure 11. \( \tau_{\text{Soultz}} \) and \( \tau_{\text{Basel}} \) are much lower than the original \( \tau \) and are also similar to \( \tau \) of previously published GMPEs (Fig. 10). This implies that the high \( \tau \) values obtained by regressing on data from six zones is due in large part to the aleatory variability in the earthquake sources between zones that should not be accounted for in site-specific hazard assessments for EGS. However, if this component of aleatory variability is removed from the hazard assessment, then it requires that the epistemic uncertainty in the assessment of median ground motion for the considered EGS be correctly accounted for (see Derivation of Weights for Stochastic Models).

By studying many records from California, Atkinson (2006) concludes that in the situation of a single station recording earthquakes on a single fault, the associated

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**Figure 10.** A comparison of aleatory variabilities of various recent GMPEs for an \( M_w 3 \) earthquake and a rock site (\( V_{S30} = 1000 \) m/s) using natural logarithms: (a) total \( \sigma \); (b) within-event \( \phi \); and (c) between-event \( \tau \). A comparison of aleatory variabilities (left, total \( \sigma \); middle, within-event \( \phi \); and right, between-event \( \tau \)) of various recent GMPEs for an \( M_w 3 \) earthquake and a rock site (\( V_{S30} = 1000 \) m/s) using natural logarithms. Six commonly used GMPEs for active crustal regions (Zhao et al., 2006; Abrahamson and Silva, 2008; Boore and Atkinson, 2008; Campbell and Bozorgnia, 2008; Chiou and Youngs, 2008; Akkar and Bommer, 2010) are considered, along with one model for natural seismicity covering a similar magnitude-distance range to the data used here (Bindi et al., 2007), one model for mining-induced seismicity (McGarr and Fletcher, 2005; the authors of this model only report the total \( \sigma \) of their model), and the sigmas for model 1 (uncorrected and corrected for site response).
variability of the ground motions (characterized in terms of standard deviation) is about 60% of its value for many sites recording earthquakes on various faults. Geothermal power projects offer an ideal situation in which single-station, single-source adjustments of $\sigma$ could and should be made. In areas of low and moderate seismicity (the case for most current EGS projects; e.g., Soultz) the ground motions of induced seismicity close to an EGS are likely to dominate those from natural seismicity for high probabilities of exceedance (short return periods) and hence the geothermal reservoir could be considered as a single source. For regulatory and production purposes, it is likely that a dense monitoring network will be installed close to the EGS. Consequently, it would be possible to characterize the local site conditions and estimate the site-correction factors for locations affected by the induced seismicity. Therefore, the aleatory variability will be lower without a consequential increase in the epistemic uncertainty.

Single-station $\phi$, (also called $\phi_{SS}$ by Rodriguez-Marek et al., 2011) was computed using the approach of Atkinson (2006) and model 1 (both data uncorrected and corrected for site response) for all 62 stations recording 10 or more earthquakes in all considered zones. As previously found by Atkinson (2006) and Rodriguez-Marek et al. (2011), $\phi_{SS}$ varies considerably from one station to the next. The mean single-station $\phi$ ($\phi_{SS}$) is plotted on Figure 11 alongside the estimate of this variability by Rodriguez-Marek et al. (2011) for Japanese surface stations and the $\phi$ found for model 1. As expected, the removal of variability coming from mixing sites leads to a significant drop in $\phi$ and values of $\phi_{SS}$ similar to those reported by Rodriguez-Marek et al. (2011). Stations recording the induced seismicity at Soultz and Basel (that are close to the ideal single-station, single-fault situation) do not show lower values of $\phi_{SS}$. Using these values of $\phi_{SS}$ for site-specific hazard assessments requires that the epistemic uncertainty in the estimation of the median-site correction for considered locations be accounted for (see Derivation of Weights for Stochastic Models). Table S3 of the electronic supplement provides the estimates of $\phi_{SS}$, $\tau_{Soultz}$, and $\tau_{Basel}$ derived here.

Conclusions

This article has investigated ground motions generated by induced earthquakes and those associated with EGSs in particular. We sought to answer the question of whether ground motions from induced earthquakes are significantly different than those from natural earthquakes using various statistical techniques. We developed stochastic models and subsequently GMPEs to estimate earthquake shaking in terms of PGA, PSA, and PGV that are valid from $M_w$ 1 to 5. We also developed a homogenized database of PSA and corresponding metadata from several sites (Basel, Geysers, Hengill, Roswinkel, Soultz, and Voerendaal). To account for varying site conditions, a correction for site-specific amplification and attenuation was applied to the data. We showed that this resulted in a reduction in $\sigma$ over the mid- to long-period range but an increase in $\sigma$ in the short-period range (i.e.,

![Figure 11](image-url)
< 0.1 s). This is because site attenuation effectively hides a significant proportion of source variability for microearthquakes. As we brought the sites to a relatively hard-rock condition (κ = 0.016 s), this source variability was reintroduced, as seen in the increase in τ values. Clearly, subsequent correction to a suitable surface condition will tend to reduce this uncertainty in high-frequency spectral ordinates as high damping is typically applied in the upper layers. Nevertheless, hard-rock predictions are usually sought in order to predict bedrock-referenced ground motions for hazard assessments. This high τ is, therefore, an important feature to consider. A further observation was that source effects varied considerably from region to region. Combining the regions to produce a common τ leads to unrealistically high values. We infer that the high, combined τ is due to the mapping of epistemic uncertainty into the aleatory component. Strong variation in mean stress drop was observed across the study regions, which is a likely source of regional variability. However, in hazard assessments, this should be treated as epistemic uncertainty, which may be reduced in the case of sufficient observations. Restricting the computation of τ to the region-specific case, we instead observe uncertainty in ground-motion prediction due to variations in stress drop, which may not be predicted. Our uncertainty model is thus constructed using a combination of sources. Epistemic uncertainty is covered by implementing various prediction models, which may be weighted or eliminated according to expert judgment or observations. Aleatory variability is covered in terms of single-site, single-region σ, which is comprised of φ_{SS} and single-region τ.

Given the significant site-to-site variability in geothermal events highlighted in this study, the application of a unique empirical GMPE, as developed as part of this study, would lead to bias, in addition to overestimation of ground-motion variability at a specific site. Effectively, the site-to-site variability (φ) includes a significant component of epistemic uncertainty. Neglecting this component in any hazard analysis would lead not only to bias, but also to the possibility of the residual mismatch lying outside the predicted uncertainty. Nevertheless, to a first approximation, in light of no other seismological information, the use of the empirical GMPEs with total σ ensures that the possible range of ground motions is covered.

On the other hand, given a database of site-specific earthquake recordings, or the potential to update our knowledge (reduce epistemic uncertainty) with time, we are presented with the opportunity to better represent the observed ground motions, possibly based on extrapolation of physical parameters. To this end, a logic-tree approach is commonly taken in order to account for epistemic uncertainty in probabilistic seismic-hazard assessment, with weights assigned related to the belief of the analyst that, for example, a given ground-motion model is the correct one. Given the range of the 36 stochastic ground-motion models presented in this study, we can foresee that the weighting of such models is (at least partially) determined through either residual or likelihood analyses (Scherbaum et al., 2009; Kale and Akkar, 2013). Alternatively, spectral parameters (such as Δσ, Q, and κ) could be determined from available data to better select relevant models. In this case, the site-to-site component of variability should be appropriately reduced (Rodriguez-Marek et al., 2011) because this is accounted for through different stochastic models to cover the epistemic uncertainty.

For applications of the stochastic GMPEs, we recommend at first to consider the 36 different models to account for epistemic uncertainty in the median with between-event variability τ equal to the average of the values of τ_{SS} derived for Soultz and Basel and within-event variability ϕ equal to the values of φ_{SS} computed here. Also we recommend that data recorded by local seismic networks (which will often be installed as part of an EGS project) be used to subsequently winnow and weight the stochastic GMPEs and potentially adjust the associated models for τ and ϕ, which are likely to be site specific. However, the adjustment of these variabilities requires a considerable number of records for stable estimates to be made, as does the assessment of weights for the GMPEs.

The GMPEs developed here could be used within probabilistic seismic-hazard assessment accounting for induced seismicity as performed, for example, by van Eck et al. (2006) for induced seismicity related to gas extraction in the Netherlands and by Convertito et al. (2012) for geothermally induced seismicity at Geyers. In addition to being applicable to ground motions associated with induced seismicity from geothermal power production, the GMPEs presented here may also be applicable for hazard assessments of geological carbon dioxide storage projects, which involve the injection of high-pressure fluids into geological structures, but their value for this situation has not yet been evaluated.

**Data and Resources**

The data from Basel were provided by Geo Explorers Ltd, the Swiss Seismological Service, and the Landeserdienst Baden-Württemberg. Campi Flegrei data were preprocessed in the framework of the coordination project, “Integrated Seismic Methods Applied to the Investigations of the Active Volcano Structure: An Application to the Campi Flegrei Caldera,” launched by the Dipartimento della Protezione Civile of the Istituto Nazionale di Geofisica e Vulcanologia (INGV) during the 2000–2004 National Framework Program, coordinated by the National Group of Vulcanology (GNV) of INGV (see Capuano et al., 2006). Waveforms from the Lawrence Berkeley National Laboratory Geysers/Calpine seismic network (BG) and the related earthquake catalog have been retrieved from the publicly accessible website of the Northern California Earthquake Data Center (NCEDC, www.ncedc.org, last accessed May 2012). The data from Hengill were recorded by a temporary network installed within the framework of the I-GET FP6 project (Jousset and François, 2006), which were provided by Philippe Jousset. Data from Voerendaal and Roswinkel...
were recorded by the Seismology Division of the Koninklijk Nederlands Meteorologisch Instituut. The data from Soultz were recorded by a permanent network installed by École et Observatoire des Sciences de la Terre (EOST) of the University of Strasbourg and were provided by Michel Frogneux (EOST). Information on current geothermal projects was obtained from the website of the International Geothermal Association (www.geothermal-energy.org, last accessed December 2012).

Acknowledgments

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