SENSITIVITY ANALYSIS OF EARTHQUAKE HAZARD IN HÚSAVÍK, NORTH ICELAND FROM VARIABLE SEISMICITY AND GROUND MOTION MODELS

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ABSTRACT

Individual parameters in probabilistic seismic hazard analysis (PSHA) generally contain large uncertainties that may significantly affect the hazard estimates. The uncertain input parameters, which are based on the interpretations of the limited data available, should preferably be analyzed to evaluate their effects on the variability of PSHA results. In the case for North Iceland, one of the most active seismic zones in northwestern Europe, the historical events in old written records are rather poorly determined, with large uncertainties in their magnitude, location and time of occurrence. The reverse perspective is to apply sensitivity analyses (SA) to study, qualitatively or quantitatively, how changes in the model input assumptions affect the model response and reveal the primary sources of hazard variability. This new information can then be used to prioritize the efforts required to reduce the hazard variability. This study, however, presents a global information-theoretic sensitivity analysis to investigate the influence for uncertainties in the seismicity parameters and ground motion models (GMMs) on the site specific PSHA results in Húsavík, North Iceland. Fast computation time is considered as one of the major advantages of the information-theoretic approach compared to the common global SA methods. The method is utilized for three segments of Húsavík-Flatey Fault to identify the most important input parameters. The results clearly identify the selection of GMMs and the slope of the Gutenberg–Richter relationship as the key controlling parameters affecting the hazard at the selected site in this region. The degree of influence depends on the location of the site, for which the hazard is assessed and the maximum magnitude produced by the selected seismic source.

Keywords: PSHA; Uncertainties; North Iceland; Global information-theoretic

1. INTRODUCTION

Probabilistic seismic hazard analysis (PSHA) was originally established and developed by Cornell (1968) and McGuire (1976, 2004), respectively, as the most acceptable method to evaluate the potentially destructive impacts of earthquakes. Generally, PSHA takes into account the ground motions from the full range of earthquake magnitudes that can occur on each seismic source in order to quantify the annual frequency of exceedance for the parameters of interest. In PSHA, a complex framework is presented combining different models with many inputs that might be contaminated by different sources of uncertainties. The uncertainties can be identified and quantified in all the PSHA steps including the characteristics of the seismic sources, recurrence models described by seismicity parameters and selection of ground motion models (GMMs) (Sabetta, 2014). These uncertainties which are categorized as either epistemic (due to lack of knowledge) or aleatory (reflecting inherent randomness) have

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significant influence on the hazard assessment (Bommer and Abrahamson, 2006; Rodriguez-Marek et al., 2014). Uncertainty analysis can be performed to gain adequate understanding of the relevant variables by considering some distributional form over a sample space of possible values (Limbourg and De Rocquigny, 2010). Moreover, traditional sensitivity analysis (SA) can be applied to quantify how changes in the model parameters affect the model response and thereby the primary sources of variability in the hazard estimates can be revealed. Such analyses allow for better understanding of the behavior of the model, its individual parameters as well as the hazard variability, which can be useful in evaluating how the uncertainties may be reduced through further studies to support the available information (Barani et al., 2007).

Technically, PSHA depends upon several modeling decisions and input parameters. A rigorous assessment of these inputs and their associated uncertainties is necessary to increase the reliability of seismic hazard estimates in the region studied. In traditional PSHA, the spatial and temporal distribution of earthquakes are expressed by the seismicity parameters such as the constant parameter and slope of the Gutenberg–Richter (G-R) relationship (i.e., $\alpha$ and $\beta$), the minimum and maximum magnitudes ($m_{\text{min}}$ and $m_{\text{max}}$). Beauval and Scotti (2004) pointed out that, based the earthquake catalog of France, the choice of $m_{\text{min}}$ can have an important impact on hazard estimates at small return periods (i.e., 1000 years). This was previously confirmed by Bender and Campbell (1989), Bender and Perkins (1993) and Grünthal and Wahlgren (2001). However, $m_{\text{max}}$ is not a key parameter even at large return periods but it becomes increasingly important at lower frequencies (i.e., below 5 Hz). Following the above mentioned studies, Sokolov et al. (2009) illustrated that the impact of $m_{\text{min}}$ and $m_{\text{max}}$ depends on both the ground motion frequency and the return period. However, the degree of influence depends on the location of the site for which the hazard is to be evaluated. Moreover, the G-R parameters have a substantial influence on the hazard results for low frequencies (Molkenthin et al., 2017). On the other hand, the GMMs that estimate the ground-shaking levels at the site, such as peak ground acceleration (PGA) and pseudo spectral acceleration (PSA) from a set of predictive variables, are identified as the most influential element in PSHA studies. The significant impact of GMMs on the assessment of earthquake hazard has been revealed by SA studies for hazard estimation in different parts of the world (Atkinson and Goda, 2011; Cao et al., 2005; Cramer et al., 1996; Cramer, 2001; Giner et al., 2002; Lombardi et al., 2005; Petersen et al., 2004; Sabetta et al., 2005).

The North Iceland Seismic Zone is a broad region of faulting and seismic activity where three parallel WNW trending fault lines represent the Tjörnes Fracture Zone (TFZ), and four NNE trending fault segments represent the main fissure swarms of the Northern Volcanic Zone. Micro earthquake distributions show that the seismic activity in the TFZ mainly takes place on the Húsavík-Flatey Fault (HFF) and the Grimsey lineament, with the third lineament (Dalvík) being much less active. The HFF is the largest transform fault in Iceland but it is mostly located offshore, however, a part of the HFF extends through the town of Húsavík with an estimated potential for a Mw 6.8 earthquake (Metzger et al., 2013). In North Iceland, two site-specific hazard estimates have been carried out so far by Snaebjörnsson and Sigbjörnsson (2007) and Sigbjörnsson and Snaebjörnsson (2007). In these studies, a synthetic catalog was generated by Monte Carlo simulation in order to prevent historical bias. However, a single GMM proposed by Ambraseys et al. (2005) was employed to estimate PGA and PSA for a 475-year return period. In this vein, both the epistemic (due to considering a single GMM) and aleatory (using fully ergodic GMMs) uncertainties were not appropriately taken into account. Therefore, a comprehensive seismic hazard study, which addresses uncertainties in an appropriate way, is vital for such a relatively densely populated region (on the Icelandic scale) with its fast growing modern infrastructures. As a first step in reaching this goal, uncertainty and sensitivity analyses as presented in this study must be conducted. This study investigates the uncertain input parameters to PSHA, which are based on the interpretations of the limited data available, to evaluate their effects on the variability of the site specific PSHA results in Húsavík. Such analyses are of importance in future seismic hazard assessments for Iceland to reveal the primary sources of hazard variability and thereby to gain knowledge about the quality of the evaluated seismic hazard to establish confidence in the results.

2. UNCERTAINTY AND SENSITIVITY ANALYSES

Uncertainty analysis can be used to evaluate the variability in the outcome variable that is due to the uncertainty in the estimation of the input values (Iman and Helton, 1988). The Latin Hypercube
Sampling (LHS) is a type of Monte Carlo sampling which was first proposed by McKay et al. (1979). In LHS, the uncertainty is modelled by treating each input parameter as a random variable and assigning a probability distribution function for each of them. Then, the value of each input parameter is randomly chosen from each of the distributions and after the model is run \(N\) times, distribution functions for each of the outcome variables can be derived. A sensitivity analysis can extend an uncertainty analysis by identifying the contribution of each input to the output. In other words, SA provides knowledge on how the uncertainty in the output can be allocated to different sources of uncertainty in the model input parameters (Saltelli et al., 2000a). By performing SA on a system, the relative importance of different input variables on the model output can be determined as well as which parameters have the most influence on a particular output parameter.

There are two classes of sensitivity analyses: local sensitivity analysis and global sensitivity analysis. Local sensitivity analysis is a one-at-a-time technique that stands for the sensitivity of the model output when only one input factor is changed at a time while all other input factors are held fixed at their nominal (central) value. The main drawback of a local approach is that it is only valid for small variations or a quasi-linear model and does not provide insight about how the interactions between parameters influence the model output. When significant uncertainty exists in the input factors, a reliable estimator of the output uncertainty cannot be obtained by linear sensitivity analysis. Furthermore, the effect of changing a single input factor at a time is determined, and in that case sensitivity information can only be interpreted qualitatively by ranking the input factors in order of significance (Turanyi and Rabitz, 2000). To overcome these limitations another class of methods has been developed in a statistical framework, the so-called, global sensitivity analysis, which does not depend on any initial set of model inputs, but considers the numerical model in the entire domain of possible input parameter variations (Saltelli et al., 2000b).

In this study, a global SA method based on information-theoretic tools is used to quantify the relationship between the input parameters and the output distribution. One of the major advantages of the information-theoretic SA approach is the fast computational time compared to the most often used variance-based global SA method. Assuming an observation \(x\) from the domain \(X\) with probability \(p(x)\) includes an information of \(-\log_2 p(x)\) bits (Shannon, 2001). The entropy, \(H(X)\) of the probability distribution \(p(x)\) that evaluates uncertainty in a random variable due to input perturbation can be shown as:

\[
H(X) = - \int_{x \in X} p(x) \log_2 p(x) \, dx \tag{1}
\]

Assuming a random vector including model parameters \(\Theta\), the conditional entropy of the model parameters given all possible observations can be quantified by:

\[
H(\Theta|X) = \int_{x \in X} p(x) H(\Theta|x) \, dx = - \int_{x \in X} \int_{\theta \in \Theta} p(x)p(\theta|x) \log_2 p(\theta|x) \, d\theta \, dx \tag{2}
\]

The mutual information, \(I\), quantifies the amount of information held in a random variable, through the other random variable. In other words, it is defined as the difference in output uncertainty with and without knowledge of \(X\):

\[
I(\Theta, X) = \int_{\Theta} \int_{X} p(x, \theta) \log_2 \left( \frac{p(x, \theta)}{p(x)p(\theta)} \right) \, dx \, d\theta \tag{3}
\]

where \(p(x, \theta)\) is the joint probability distribution that can be also defined as \(p(x, \theta) = p(\theta|x)p(x)\). Then the mutual information can be simplified as:

\[
I(\Theta, X) = \int_{\Theta} \int_{X} p(\theta|x)p(x) \log_2 \left( \frac{p(\theta|x)p(x)}{p(x)p(\theta)} \right) \, dx \, d\theta
\]
\[
\begin{align*}
    &= \int_{\Theta} \int_{\mathbf{X}} p(\theta|x)p(x) \log_2 p(\theta|x)dx d\theta - \int_{\Theta} \int_{\mathbf{X}} p(\theta|x)p(x) \log_2 p(\theta)dx d\theta \\
    &=-H(\theta|X) - \int_{\Theta} \log_2 p(\theta) \left[ \int_{\mathbf{X}} p(\theta|x)p(x)dx \right] d\theta \\
    &=-H(\theta|X) - \int_{\Theta} p(\theta) \log_2 p(\theta) d\theta = -H(\theta|X) + H(\theta) \tag{4}
\end{align*}
\]

Therefore, the sensitivity index can be obtained by using the mutual information and entropy as:

\[
\eta = \frac{I(\Theta,X)}{H(\Theta)} = \frac{-H(\theta|X) + H(\theta)}{H(\Theta)} = 1 - \frac{H(\theta|X)}{H(\Theta)} \tag{5}
\]

The sensitivity index takes the values between 0 and 1 representing the contribution of each input random variable on the variability of the output.

3. ON THE KEY INPUT PARAMETERS TO PSHA

The key input parameters to PSHA and associated uncertainties are determined from historical and instrumental observations (Sokolov and Wenzel, 2015). These parameters, which are assumed independent, include the spatial and temporal distribution of earthquakes as well as the frequency of occurrence of earthquake magnitudes (i.e., G-R relationship) and the earthquake strong-motion parameters predicted by GMMs. The frequency distribution of earthquakes is presented by Gutenberg and Richter (1944) in a logarithmic relationship. The number of exceedances of each magnitude is divided by the length of the time period to define a mean annual rate of exceedance:

\[
\lambda_m = 10^{a-bm} = \exp(\alpha - \beta m) \tag{6}
\]

where \( \lambda_m \) is the mean annual rate of exceedance of magnitude \( m \), but \( \alpha = a \ln 10 \) and \( \beta = b \ln 10 \) are constants describing the seismicity of a region. In general, \( \alpha \) represents the overall rate of earthquakes in a region, and \( \beta \) indicates the relative ratio of small and large magnitudes. For engineering purposes, however, earthquakes smaller than \( m_{\text{min}} \), which will not cause damage or loss are of limited interest (Kramer, 1996; McGuire, 2004). In other words, \( m_{\text{min}} \) is an engineering parameter which in PSHA framework can be also defined as the lower limit of integration over earthquake magnitudes such that a smaller value would not change the estimated risk to the exposure (Bommer and Crowley, 2017). Thus, if earthquakes smaller than \( m_{\text{min}} \) are ignored, the seismic activity rate can be expressed as \( \lambda_{m_{\text{min}}} = \exp(\alpha - \beta m_{\text{min}}) \). On the other hand, to avoid the inclusion of unrealistically large earthquakes, the density function of earthquake magnitudes is generally truncated by the \( m_{\text{max}} \) (Wheeler, 2009). This limitation on the upper bound of earthquake magnitudes in a specific region, can be due to the nature of the seismic rupture. Therefore, a doubly truncated exponential distribution is used for the density function of earthquake magnitudes:

\[
f_M(m) = \frac{\beta \exp(-\beta(m-m_{\text{min}}))}{1-\exp(-\beta(m_{\text{max}}-m_{\text{min}}))} \tag{7}
\]

Following a classical Cornell–McGuire approach, the annual rate of exceedance of a particular value \( y \), of a ground motion parameter, \( Y \), for \( N \) potential seismic sources can be calculated as:

\[
\lambda(Y > y) = \sum_{i=1}^{N} \lambda_{m_{\text{min}}} \int_{m_{\text{min}}}^{m_{\text{max}}} \int_{0}^{r_{\text{max}}} P(Y > y|m,r) f_M(m) f_R(r) dr dm \tag{8}
\]

where \( P(Y > y|m,r) \) comes from the ground motion model, \( f_M(m) \) and \( f_R(r) \) are the probability distribution functions for magnitude and distance. The G-R parameters are estimated using statistical analysis of historical and instrumental events of an earthquake catalog with different levels of uncertainty. For historical earthquakes, an average standard error applicable to the era of the catalog can usually be deduced, whereas the modern catalogs usually contain an estimate of the standard error of
individual magnitude determinations (Rhoades and Dowrick, 2000). It should be noted that the magnitude uncertainty in the catalog plays a crucial role in the estimation of $\beta$. Since in this study we are not using earthquake catalog to estimate G-R parameters, the effect of magnitude uncertainty in the catalog is indirectly included by the uncertainty assigned for $\beta$. The distance measure is the shortest distance from a site to the surface projection of the rupture surface known as $R_{JB}$ which is the appropriate measurement defined for use with the selected GMs. Moreover, variables reflecting the site conditions in terms of the local geology and topography are not considered herein for the sake of simplicity. Furthermore, all the previously mentioned variables included in the study are assumed as independent stochastic variables, whereas any other variables are simply treated as deterministic constants.

4. APPLICATION TO HÚSAVÍK, NORTH ICELAND

The effect of different input parameters on the results from a site-specific PSHA is studied for the town of Húsavik, North Iceland. Based on the current national seismic hazard map of Iceland, Húsavik is located in the zone of high earthquake hazard with a 10% probability in 50 years (475-year recurrence interval) of peak-ground acceleration (PGA) exceeding 0.5g. The diverse geology and topography under the town is likely to contribute to spatially variable earthquake strong-motions, manifested in part as localized differences in site effects which may lead to increased relative differences in seismic risk (Halldorsson et al., 2012). Moreover, Húsavik is effectively located directly on top of the HFF, but the seismic hazard in the region is primarily due to large earthquakes on this fault (Snaebjornsson and Sigbjornsson, 2007). A “great earthquake in Flatey” as it is called in the medieval annals, occurred in 1260 and was one of the damaging earthquakes known on the HFF. During the past 300 years, four major earthquakes, the last one in 1872, also occurred on the HFF with the magnitudes 6.5-7.0 on the Richter scale. Based on the geological and geophysical findings, Snaebjornsson and Sigbjornsson (2007) for PSHA proposed a simplified view of the seismogenic structures of the TFZ fracture zone, presenting the main significant lineaments. That is the Grímsey fault line (A in Figure 1), the HFF (3 segments: B1, B2 and B3) lineament, and the Dalvík lineament (C).

Figure 1. The seismic line sources applied in probabilistic seismic hazard analysis for TFZ (after Snaebjornsson and Sigbjornsson, 2007). The small map inset at bottom right shows Iceland. The solid red lines indicate seismic source zones.

The key input parameters for PSHA are described in the previous section. They are considered as the uncertain input variables to carry out the SA in this study. It is assumed that these parameters are independent, and for each independent input variable, a density function is assigned. Table 1 shows the assigned distribution and the uncertainty level assumed for each parameter. The annual activity rate is an uncertain parameter assessed tentatively for each segment in such a way that the overall number of earthquakes fit the available data (Sigbjörnsson and Snaebjornsson, 2007). In this study, the uncertainty in the annual activity rate is modeled using a normal distribution with a relatively large standard deviation i.e, 0.5. The $b$-values for these segments are assumed to have a normal distribution, with a mean value of 0.7 and a standard deviation of 0.2 (Halldórsson, 2007). The uncertainty in magnitude estimates tends towards a normal distribution (Sigbjörnsson and Ambraseys, 2003). Here, the $m_{min}$
considered in all cases is equal to 4.0, which is an event that is relatively small and should not have damaging effects on engineered structures. The assumed \( m_{\text{max}} \) was taken as 7.3 for B1, B2 and 6.5 for B3 (Ambraseys and Sigbjörnsson, 2000; Sigbjörnsson and Snaebjornsson, 2007). The standard deviation of 0.3 is assumed for \( m_{\text{min}} \) which is in fair agreement with the estimation of a deterministic and probabilistic \( m_{\text{min}} \) for the TFZ (Kowsari et al., 2017a). Moreover, a continuous uniform distribution of epicenters over the rupture length for each segment of the HFF can be used (Abrahamson, 2000; Shahi and Baker, 2011).

Table 1. Density functions assigned to the input parameters for the three segments of HFF.

<table>
<thead>
<tr>
<th>Input parameters</th>
<th>Density function for each segment of HFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Annual activity level of G-R relationship, ( a )</td>
<td>( N(5.0, 0.5^2) ) ( N(4.2, 0.5^2) ) ( N(4.0, 0.5^2) )</td>
</tr>
<tr>
<td>Slope of G-R relationship, ( b )-value</td>
<td>( N(0.7, 0.2^2) ) ( N(0.7, 0.2^2) ) ( N(0.7, 0.2^2) )</td>
</tr>
<tr>
<td>Minimum magnitude, ( m_{\text{min}} )</td>
<td>( N(4.0, 0.1^2) ) ( N(4.0, 0.1^2) ) ( N(4.0, 0.1^2) )</td>
</tr>
<tr>
<td>Maximum magnitude, ( m_{\text{max}} )</td>
<td>( N(7.3, 0.3^2) ) ( N(7.3, 0.3^2) ) ( N(6.5, 0.3^2) )</td>
</tr>
<tr>
<td>GMMs</td>
<td>( \mathcal{U}(1, ..., 4) ) ( \mathcal{U}(1, ..., 4) ) ( \mathcal{U}(1, ..., 4) )</td>
</tr>
</tbody>
</table>

\( N(\cdot) \), normal distribution; \( \mathcal{U}(\cdot) \), discrete uniform distribution

Two sets of GMMs are used in this study to demonstrate the effect of choice of model on the epistemic uncertainty. The first set includes GMMs proposed by Akkar and Bommer (2010), AB10; Zhao et al. (2006), Zh06; Lin and Lee (2008), LL08 and Ambraseys et al. (2005), Am05. All of which satisfy the minimum requirements proposed by Cotton et al. (2006) and Bommer et al. (2010). The first two GMMs were proposed in the SHARE project as suitable GMMs for PSHA in active regions on oceanic crust. The LL08 was another GMM in the SHARE project but it is chosen here due to its different functional form. The Am05, which was obtained from European and Middle Eastern dataset, is also selected here because it has been applied in several seismic hazard studies in Iceland. The second set contains the recalibrated versions of the GMMs previously mentioned. Bayesian statistics using a Markov Chain Monte Carlo algorithm for inference is applied to recalibrate the selected GMMs to represent available Icelandic PGA data. The recalibration has resulted in new predicted median and standard deviation of residuals (i.e., sigma) of the ground motion models, which now fit the recorded data very well for the distance range where data is available and the standard deviation (sigma) of the PGA estimate is reduced dramatically, as shown in Figure 2.

![Figure 2](image_url)

Figure 2. Left: the original (-O) and recalibrated (-R) GMMs for PGA are shown in gray and black, respectively. The circles show the recorded PGAs of the 2000 and 2008 earthquakes with \( M_w=6.5, 6.4 \) and 6.3 at rock site. The models are evaluated at \( M_w=6.4 \) the weighted average magnitude of the data. Right: standard deviation (in log-10 units) of the GMMs, before (\( \sigma_{\text{org}} \)) and after (\( \sigma_{\text{rec}} \)) recalibration.
4. RESULTS AND DISCUSSIONS

In this study, an uncertainty analysis is performed to evaluate the effect of uncertainty in the input variables on the PSHA results. To illustrate the effect of the selected GMMs, the analyses are carried out in three separate cases: (1) with the first set of GMMs (i.e., only the original models) (2) with the second set of GMMs (i.e., only the recalibrated models) (3) when both sets are applied. A robust sampling method which uses a Monte Carlo (MC) technique and the Latin hypercube sampling (LHS) method (McKay et al., 1979) is applied at two hazard levels with a 2% and 10% probability of exceedance in 50 years. The LHS is used to generate random stochastic inputs from the predefined probability distributions explained in Table 1. Examples of the histograms representing the input parameters for the segment B2 of HFF for the case 1 are shown in Figure 3. Therefore, such uncertain input parameters shown in Figure 3, lead to PSHA outputs (i.e., PGA) with a probability distribution representing the variability of the PSHA results. Figure 4, shows the PGA distributions evaluated for the three cases analyzed, showing the results for 2% (bottom row, in blue) and 10% (top row, in green) probability of exceedance in 50 years. With increasing hazard level, the mean values increase, resulting in larger ground motion levels, as expected. However, different PGA levels are estimated by considering three cases where different sets of GMMs are used. The mean PGA of 0.70g, 0.60g and 0.65g for the 10%-in-50 years and 0.98g, 0.88g and 0.94g for the 2%-in-50 years for case 1, 2 and 3 are obtained, respectively. The results are compatible with a previous PSHA study for Húsavík (Kowsari et al., 2017b) emphasizing the importance of the recalibration in PSHA. The standard deviation of each distribution shows the epistemic uncertainty induced in the PSHA results and the lowest value is seen for case 2, where the recalibrated GMMs are applied.

Figure 3. Histograms of the uncertain input parameters for the segment B2 of HFF for the case 1. A discrete uniform distribution is assigned for the selection of GMMs and the normal distribution is applied for the rest of the input parameters.

Figure 4. Distributions of the model output (i.e., PGA) for three cases with a 2% (bottom row, in blue) and 10% (top row, in green) probability of exceedance in 50 years. The mean and standard deviation of each distribution is also shown.
The model outputs (i.e., logarithm of PGA) shown in Figure 4, should be further statistically analyzed to find the obtained probability distribution and related statistical estimators. For this purpose, the one sample Kolmogorov-Smirnov (K-S) test is carried out. It is a non-parametric test of goodness-of-fit and works by quantifying the distance between the empirical distribution of the sample and the cumulative distribution function of the reference distribution (Cirrone et al., 2004). The one sample K-S test is most often used as a normality test to approve the null hypothesis that samples could realistically have come from a specific reference distribution (here, the Gaussian distribution). Figure 5, shows the K-S test results for the three cases at hazard levels with a 2% (bottom row) and 10% (top row) probability of exceedance in 50 years. As can be seen, the resulting distribution of the logarithm of PGA is normally distributed for case 2 where the recalibrated GMMs are used.

![Figure 5](image-url)

**Figure 5.** Illustration of the one sample Kolmogorov–Smirnov test for three cases at hazard levels with a 2% (bottom row) and 10% (top row) probability of exceedance in 50 years. The red solid line is cumulative distribution function (CDF) and the blue dash-dotted line is the empirical cumulative distribution function.

Finally, the results of a global SA for a PSHA representing each input parameter, the three cases studied and two hazard levels are presented in Figure 6. Selection of appropriate GMMs to reduce the epistemic uncertainty is a major challenge, particularly for regions where an appropriate local GMM does not exist due to low seismicity or limited observational data (Delavaud et al., 2012). Therefore, three cases with different sets of GMMs are taken into account in order to demonstrate the effect of the choice of the model on the final hazard contribution.

In case 1 where the original GMMs are used, the selection of GMMs has highest sensitivity. The slope of the G-R relationship, $b$-value, has a moderate but significant contribution. The contribution of $a$-value and $m_{\text{in}}$ is low but higher than $m_{\text{max}}$. Due to the seismicity parameters of HFF which are shown in Table 1, the seismic activity on the segment from western part of the HFF has been more active than the eastern part of the fault (i.e., $a_1 > a_2 > a_3$). It is also worth mentioning that the seismic activity has been assumed uniform over the whole length of the segments. However, the SA results show the seismicity parameters of segment B2 contribute most to the hazard, which is mainly related to the site location but also to the assumed maximum magnitude on each segment. The site, for which the hazard is assessed has approximately the same distance to segments B2 and B3 (lower distances than segment B1), however, the segment B2 generates earthquakes up to magnitude 7.3 while the $m_{\text{max}}$ for segment B3 is taken as 6.5.

In case 2 where the recalibrated GMMs are applied, the selection of GMMs is not the most influential input parameters because the recalibrated GMMs have a similar behavior at the distance ranges where the data are abundant as shown in Figure 2.
Case 3 can therefore be considered as a general case where both the original and recalibrated GMMs are used. As expected, the most influential input is GMMs which effect on the hazard results has previously been confirmed (Atkinson and Goda, 2011; Cao et al., 2005; Cramer et al., 1996; Cramer, 2001; Giner et al., 2002; Lombardi et al., 2005; Petersen et al., 2004; Sabetta et al., 2005). The G-R parameters, \( b \)- and \( a \)-value have a significant and moderate influence on the hazard results which is also shown by Molkenthin et al. (2017). The impact of \( m_{\text{min}} \) and \( m_{\text{max}} \) depends on ground motion frequency and the level of hazard (Sokolov et al., 2009) as shown in this study through the two probability of exceedance levels studied. In this study, however, they are identified as the less influential inputs. Their impact on different ground motion frequencies will be further explored for this region in a future study. For all cases studied, the SA results showed nearly the same behavior for the two hazard levels but they had a slightly different degree of influence.

Figure 6. Relative contributions of the input parameters to the PSHA outputs for three cases at two hazard levels.

5. CONCLUSIONS

A seismic hazard sensitivity evaluation has been conducted for the three segments of HFF in TFZ, North Iceland. For this purpose, an information theoretic methodology is applied for a global SA. The global SA aims to rank the inputs according to the degree of influence the exhibit on the output values by evaluating a PSHA for multiple sets of randomly and independently selected input values (Lüdtke et al., 2008). The slope of the Gutenberg–Richter relationship, the annual activity level, the earthquake magnitude limits, \( m_{\text{min}} \) and \( m_{\text{max}} \), and GMMs were considered as the input variables to parameterize seismic activity within PSHA. The influence of model inputs uncertainty on the variability of PSHA results was also investigated. The hazard was assessed for PGA on a rock site for 2% and 10% probability of exceedance in 50 years. To show the effect of the selected GMMs, the analyses are performed for three separate cases, where each case represents a different set of GMMs.

The uncertainty analysis is accomplished by randomly varying the input parameters in the PSHA and obtaining the distribution of the ground motion parameter (i.e., PGA). The output distribution is obtained by evaluating the model at thousands sample points randomly sampled from the predefined probability distributions in each run. The standard deviations ranging between 0.22 and 0.30 (in base-10 logarithmic unit) represent the epistemic uncertainty. The sensitivity analysis clearly identifies the selection of GMMs and the slope of the G–R relationship as the key input parameters that control the variability in the PSHA for the region studied. Moreover, the \( a \)-value has a small contribution to the hazard and the earthquake magnitude limits are identified as less influential input variables. It was found, that the degree of influence strongly depends on the earthquake scenarios for the relevant seismic sources. In other words, the location of the site, for which the hazard is assessed and the maximum magnitude
defined are both important factors. The maximum impact is observed close to the most active seismic source with the capability of producing larger earthquakes.

The present study concentrates on the hazard estimation sensitivity due to variability in seismicity parameters and ground motion models. As future tasks, it is necessary to refine this study including more advanced seismic source models, introducing fault parameters as well as near-fault effects in the PSHA. Moreover, a special emphasis will be put on spatial sensitivity analysis by presenting a hazard map for this region showing PSA for the spectral periods of interest, in addition to PGA.

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7. REFERENCES


