# Summary of Modifications to Manuscript GMD-2018-4 

# Bayesian Inference of Earthquake Rupture Models Using Polynomial Chaos Expansion 

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#### Abstract

We would like to thank the editor and referees for their thorough reviews, comments and suggestions. Below is a summary of modifications to the original manuscript, in response to the editor and referees' comments/suggestions.


We hope that with these modifications, the present manuscript will be found suitable for publication in Geoscientific Model Development.

## Editor's comment

Please note GMD's strong preference for the code to be uploaded as a supplement or to be made available at a data repository with an associated DOI (digital object identifier) for the exact model version described in the paper. Could you please add this modification to your manuscript?

## Reply:

The COMPSYN code used in this paper was originally developed by Spudich and Xu (2003) (see below). We are in the process of seeking permission from the authors to make the code publicly available. We hope to make the code available on a dedicated site/repository in the near future (as stated in the revised manuscript).

In addition, we point to the online manual for the code at:
https://www.researchgate.net/publication/260423574 Documentation_of Software_Package_C ompsyn sxv311 Programs for Earthquake_Ground Motion_Calculation_Using_Complete 1D Green's Functions.

Regarding the code for polynomial chaos expansion framework, we have added additional references, as well as a link to an open source toolkit available at http://www.sandia.gov/UQToolkit/

## Referee 1

## General comments

This manuscript investigates an earthquake rupture model subject to 7 random fault plane properties. Polynomial chaos surrogates are built and validated to reproduce the uncertain Peak Ground Velocity (PGV), obtained from a discrete wavenumber/finite element method, at a set of 56 (virtual) stations. A sensitivity analysis is conducted to identify the main influent parameters: a partition of the uncertain input parameters into two groups highlights the strong impact of the hypocenter location. A Bayesian inference is then performed by using a Ground Motion Prediction Equation (GMPE) as observational measures. The results emphasize that additional physical constraints are valuable to increase the sampling efficiency.

The manuscript is clearly constructed and it would be suitable for the readership of the Geoscientific Model Development after the following revisions to clarify some aspects of the paper.

## Specific comments

- page 6: one sentence is missing between line 4 and 5 to provide the number of terms Np in the PC series as a function of the stochastic space dimension nd and the total polynomial order $d, N p=(d+n d)!/(d!n d!)$.

Reply: As suggested by the referee, the revised manuscript specifies the truncation strategy and provides an explicit formula for the size of the truncated basis.

- page 6, line 19: the cross-validation process needs more details (leave-one-out or k-fold version, initial range of variation of the parameter $\gamma$ with the discretization strategy to find the optimal value) with a citation (e.g. the book of Seber and Lee,Linear regression analysis, 2003).

Reply: We used k-fold ( $k=5$ ) cross-validation to determine the optimal $\gamma$. As suggested by the referee, the manuscript has been revised to provide details concerning the determination of the optimal $y$ value. In addition, reference to the suggested citation has been incorporated.

- page 7, section 3.1: the computation of the empirical error (8) with the training set PLHS (blue dots) has only a minor interest because it simply shows that regression is a non-interpolating technique. A comparison between the empirical error estimated with the validation set (red dots) and a cross-validation error obtained with the training set is more relevant.

Reply: In our analysis of representation errors, we have examined both the cross-validation error, as well as the empirical error estimated using the training set, and have observed that the
two error estimates are close to each other. A statement highlighting this observation has been added in the revised manuscript (specifically the caption of Fig. 3).

- page 8, line 12 (middle): the sentence "The overall tendency of PC prediction uncertainty (...) seems to decrease with increasing RIJ distance as well" relies on Fig. 6. This figure is hard to read and a new figure plotting only the (PC) standard deviations should be valuable (with a reminder in the text about the log-scale) to support the statement.

Reply: As suggested by the referee, we have attempted to plot the PC standard deviations independently, but this did not lead to dramatic improvement in the presentation, namely because the distant stations are clustered (in Rjb distance measure). On the other hand, the referee's suggestion concerning the log-scale has been incorporated (caption of Fig. 6).

- page 8, line 16 (top): two stations are selected for plotting the PGV. Their locations must be indicated (for instance with labels on Fig. 2).

Reply: The referee's comment has been implemented. (See Fig. 2) Note, in the revised manuscript, we decided to show PC statistics on Station \#3 and \#22 (instead of \#3 and \#21 in the original manuscript). The reason for this switch is the following: Station \#21 turns out to be very close to station \#3. To better illustrate the validity of our PC surrogates over a distance, we decided to select a station (\#22) that is a bit far from station \#3. (Fig. 4 and Fig. 5 are updated accordingly.)

- page 8, line 12 (middle): The first sentence of the paragraph is incomplete since the complex dependency of PGVs to random inputs is not only due the mappings between the physical parameters and the standardized $R V$ s $f \xi i g 1 \leq i \leq 7$. We can speculate that the complexity of the propagation model (discrete wavenumber/finite element method) plays a major role.

Reply: We agree with the referee that the sentence in question is confusing. Our intention was to highlight that the conditional mapping between canonical rv's and physical parameters makes it difficult to isolate the impact of individual parameters, but that this difficulty can be effectively addressed using global sensitivity analysis. The manuscript has been revised to clarify this aspect.

- page 11: in Fig. 6, the GMPE standard deviation exhibits a higher level than the PC ones. A short discussion would be interesting to explain the causes/sources of this difference.

Reply: It turned out that in our original Fig. 6, we have plotted 2 times the GMPE standard deviation bounds. We apologize for the confusion, and have updated the Fig. 6 with one standard deviation GMPE bounds. The new Fig. 6 shows similar standard deviation bounds
between GMPE and PC statistics in general. However, one should not expect exact match between GMPE and PC statistics, due to difference in random sources underlying the two approaches, and the uninformative PC random variable distribution used to calculate the statistics.

- page 13: a prediction error, defined as the discrepancy between the GMPE and PC series is introduced. This is confusing in Bayesian inference framework where observations (or measured data) are used to infer the model parameters. As GMPE predicted PGVs serve as observational data (see page 11), it would be more clear to replace GMPE by observational data (and to replace prediction error by observational error) in section 4.1.

Reply: We agree with the referee's comments. The manuscript has been revised accordingly.

## Technical Corrections

- page 2, line 9: replace is by are in "data is sufficient".
- page 2, line 16: replace Mw 6.5 by magnitude 6.5.
- page 5, Table 2, line 3: replace yh by zh.
- page 6, line 18: "that" is missing, "note that $[\Psi]$ is station invariant".
- page 8, line 6 (top): the word "indeed" is useless.

Reply: The suggested corrections above have been implemented in the revised manuscript.

## Suggestions

- page 5, line 11: "number of stochastic dimensions" sounds weird. "stochastic space dimension" or "number of uncertain input parameters" are more usual

Reply: As suggested by the referee, we replaced "number of stochastic dimensions" with "stochastic space dimension"

- page 5, line 16: "instead of" seems to be inappropriate here and could be replaced by "which parameterize".
- page 6, line 13: the set of LHS realizations could be written, "... NLHS $=8000$ earthquake rupture model realizations through fڭkg1 $k k \leq N L H S "$ ".
- page 8, line 16: replace "with different PC truncation orders" by "with increasing odd $P C$ truncation orders up to a degree nine".
- page 8, line 17: replace "PC library is sufficient ..." by "PC expansions are sufficiently accurate ...".

Reply: The suggestions above have been implemented in the revised manuscript.

- pages 9 and 10: Fig. 4 and 5. represent distributions obtained with kernel density estimation. It should be mention in the captions or in the text.

Reply: The captions of Figs. 4 and 5 have been modified as suggested.

- page 11, line 5: Move the group of words "for the same magnitude and focal mechanism" in section 3.2 (page 8), line 10 after the reference Boore and Atkinson (2008).

Reply: This suggestion has been implemented.

- page 13: explain a little bit more the partitioning of the data into four concentric groups (e.g. uniform discretization of the RJB interval).

Reply: As suggested by the referee, additional details have been added to the revised manuscript to explain the partitioning of the data into four groups. This partition is motivated by the observation of PGV variability decaying with Rjb distance (Figure 6), and is to ensure that the inference appropriately accounts for different PGV variance at different Rjb distances. (The 4-group partition criterion is added to the legend of Fig. 2).

- There is a huge number of ground motion predictions equations (see for example the report http://www.gmpe.org.uk/gmpereport2014.pdf). A short description of the GMPE model (for instance in an appendix) could be worthwhile to have a self-contained paper.

Reply: In addition to the original reference, the GMPE model [BA2008] used has been discussed in a number of accessible references, which have been incorporated in the revised manuscript, more specifically, the following three resources have been added in the revised manuscript (footnote in the discussion of Fig. 6):

1) http://www.opensha.org/glossary-attenuationRelation-BOORE\ATKIN\} 2 0 0 8
2) http://www.gmpe.org.uk/gmpereport2014.pdf
3) Mai (2009)

Consequently, we feel that addition of an Appendix is not necessary, and may dilute the focus of the work.

## Referee \#2

## General comments

The authors develop a polynomial chaos (PC) expansion representation to provide a surrogate model for a probability distribution of Mw 6.5 strike-slip earthquakes with a fixed fault geometry. Seven parameters are used to describe a particular realization, including the hypocenter location and parameters describing an elliptical asperity, a region of relatively high slip, defining a 7-dimensional stochastic space. The surrogate model allows the rapid estimation of the peak ground velocity (PGV) at each of 56 virtual observation points. The PC expansion is computed using synthetic seismogram observations at these points for a set of 8000 realizations. A second set of 8000 realizations is used for validation, to confirm that the surrogate model constructed from the first set agrees well with the direct simulation results for the second set of realizations.The surrogate model is then used to rapidly compute the PGV for millions of additional realizations in order to gather statistics on the decay of PGV with respect to distance from the fault (measured using the Joyner-Boore distance RJB, the minimal distance to the fault plane as projected to the surface), at the 56 observation points. The mean PGV and standard deviation at each observation point are plotted vs. the distance RJB, and this data compared with the ground motion prediction equation (GMPE) of Boore and Atkinson (2008). The GMPE was derived based on observations of past earthquakes and so it is interesting to see that the statistics generated by the PC expansion generally follows this prediction and lie within one standard deviation of the GMPE as determined by Boore and Atkinson. This suggests that a simplified fault model consisting of a single asperity and a small set of parameters can perhaps predict PGV statistics well, and hence may be useful for predicting other GMPE curves, or for probabilistic seismic hazard analysis more generally. The first 3 sections of the paper give a nice development of these ideas.

I had more trouble understanding the goal of Section 4, which concerns the use of Bayesian inference to determine a probability distribution on the space of PC parameters that yield an event to best match the GMPE. It seems to me that the GMPE is only intended to predict the average and standard deviation of the PGV over a large set of potential earthquakes, and so I do not understand the point of this statistical inversion to try to determine the characteristics of one particular earthquake that best matches the average. The authors conclude that the best match is more likely to have the hypocenter located in the lower right quadrant of the fault plane, and the elliptical patch centered in the lower left quadrant. Why is this useful to know? Is this meant to have geophysical significance, e.g. that real strike-slip earthquakes of this magnitude tend to have their hypocenter and asperities located in this way? How does this relate to the actual slip patterns of the real events that went into the Boore and Atkinson GMPE model, to the extent those are known? There is no discussion in the paper of these topics. I also wonder about the way this inversion is used in Section 4.5, as
discussed in one of my specific comments below. I think the paper would be stronger if the motivation for doing this inversion was better explained, since I found it hard to assess the usefulness of this part of the paper.

## Reply:

1. The referee stated: "It seems to me that the GMPE is only intended to predict the average and standard deviation of the PGV over a large set of potential earthquakes, and so I do not understand the point of this statistical inversion to try to determine the characteristics of one particular earthquake that best matches the average." However, this interpretation is incorrect. This paper focus on the class of earthquakes of magnitude $\mathrm{M}=6.5$ with strike slip focal mechanism. It is true that GMPE predictions for the same class of earthquakes are statistical averages over many earthquakes and regions, the amount of available data for GMPE predictions are still sparse. On the other hand, this paper aimed at exploring the capability of our PC approach in reproducing ground-motions of the same class of earthquake; and our rupture model simulations and PC analyses show that we don't need such GMPE in principle.
2. The referee expressed his/her concern in understanding the conclusion of "the best match is more likely to have the hypocenter located in the lower right quadrant of the fault plane, and the elliptical patch centered in the lower left quadrant." We point out that this particular interpretation/conclusion (hypocenter on the right while elliptical patch on the left of the fault plane) results from the station distribution; if we had put an exactly regular/symmetric station distribution, the patch could also be in the right and the hypocenter in the left. The important message here is that hypocenter and slip patch cannot be in near-surface area of the fault, and they need to have some distance from each other in order to produce the proper seismic radiation pattern, including on-fault directivity. Otherwise, the near-source waveforms, and hence PGVs, would not match. This is consistent with the findings of Mai et al (2005).
3. The referee raised more follow up questions in understanding our conclusions on the most likely fault plane configuration, e. g. "Why is this useful to know? Is this meant to have geophysical significance, e.g. that real strike-slip earthquakes of this magnitude tend to have their hypocenter and asperities located in this way? How does this relate to the actual slip patterns of the real events that went into the Boore and Atkinson GMPE model, to the extent those are known?" We would like to point out that the GMPE (BA2008) relations are based on many earthquakes. Unfortunately, there exist no such detailed source information (i.e. fault plane configuration as considered in our paper) for most of those earthquakes. Furthermore, the GMPE (BA2008) relations do not parameterize any of the source complexity considered in our paper. The important message again is that our finding is backed up by independent observations and physical arguments in Mai et al (2005).
4. Revision has been made to clarify our main conclusions in the conclusion section.

## Specific comments

- Page 3, line 2: The fault plane geometry is fixed with width 10 km and length 27 km . It is stated that this is obtained from 100 realizations following the scaling relation in Wells and Coppersmith (1994). How are 100 realizations used to determine these dimensions?

Reply: Following scaling relations, e.g. Wells and Coppersmith (1994), Mai and Beroza (2000) and Thingbaijam et al (2017), we obtained 100 possible values of rupture lengths for a $\mathrm{M}=6.5$ strike-slip event and found that $\mathrm{L}=27 \mathrm{~km}$ had the highest population in our histogram. We did the same for the rupture width and obtained $\mathrm{W}=10 \mathrm{~km}$. Revision has been implemented to clarify our choice of the fault plane width and length.

- Page 3, lines 5-7: Why is the slip set to Smax/e outside the asperity? How is the slip in the asperity set? Since the area of the asperity varies with the input parameters, the slip must also vary to keep the magnitude fixed. It is stated that Smax varies with the ellipse size but it is not clear how.

Reply: We noticed that the referee might misunderstand our description about the way we set the slip in the whole fault plane.

1) For the slip inside the asperity, we state that "the ellipse is the asperity with Gaussian slip distribution inside".
2) We pointed out in the manuscript that "The maximum slip Smax is chosen such that the mean slip remains constant ( 0.71 m ) when varying the ellipse size." It is important to note that the the moment magnitude Mw depends on the mean slip of the whole fault plane, and not only from the slip of the area of the asperity.
3) The slip between the elliptical patch boundary and dashed rectangle is set to Smax/e, the minimum value at the patch boundary from the Gaussian slip distribution;

- Page 3, line 15-17: For completeness it would be good to state the grid resolution used in the COMPSYN simulation of the seismic signals, and the domain size, boundary conditions imposed, etc.

Reply: As suggested by the referee, the following details have been added to our revision:

COMPSYN solves the equation of motion considering initial conditions of zero displacement and velocity at a reference time t0 and specifying traction or displacement on the bounding surface of the medium (boundary conditions) using the unit outward normal vector (details about the scheme can be seen in Olson et al., 1984). The grid resolution used in COMPSYN is variable and uses a spacing of $1 / 6$ of the minimum shear wavelength at depth $z$. The grid extends a total depth that depends on the wavenumber, which means that the maximum depth decreases when the wavenumber increases.

- Page 3, Figure 2: The 56 observation stations surround the fault plane on all sides. Since the fault plane is vertical and the velocity model is vertically layered, shouldn't the observations be symmetric about $Y=0$ ? If so, it would seem clearer to simply use points in the upper half plane, for example, rather than asymmetric points scattered on both sides.

Reply: We thank the referee for this important observation. In principle this observation is correct, and it is possible to use points in the upper half plane only, as pointed out by the referee, however the stations are not exactly symmetrically arranged, for the very reason to somewhat disturb the symmetry of the problem.

- Page 11, Figure 6: The points here are presumably the mean PGV observed at each of the 56 observation points, plotted vs. the distance RJB. These points are calculated by evaluating the PC expansion at 1,000,000 sample points and are presumably quite accurate estimates of the mean at each observation point. But this figure shows that two points that have very similar RJB can have quite different PGV, presumably because the two points have quite different azimuthal orientation relative to the fault, even though they are the same distance away. This is interesting to observe, but since the GMPE curve ignores orientation it seems like it might also be interesting to try to average over different orientations for each distance. This could be facilitated if a number of observation points were placed at each distance, for a discrete set of distances, i.e., place the observation points on concentric rings with fixed RJB. It also seems like a much larger set of observation points could be used than 56, since the PC model is so quick to evaluate. If many points were placed on many different concentric rings, then one could average over all points at a given distance to get points that might be expected to agree better with the GMPE curve in Figure 6. It would then also be possible to explore in more detail how the PGV varies with orientation along each ring.

Reply: This is a very good observation. We thought about this already: variations in PGV at a given distance are likely due to radiation-pattern effects, in particular directivity. As pointed out by the reviewer, one could now do many more detailed tests, including using the PC approach to explore the ground motion dependency on azimuthal orientation. However, it would require the construction and validation of additional PC representations for a large number of observation stations, which are beyond the scope of this study.

Instead we refer to recently published study by Vyas et al (2016) that exactly addresses this question in great detail, with a range of simulations and 3000 randomly distributed sites.

The following sentences have been added to the discussion of Fig. 6 in our revised manuscript. "It is noted that two stations with similar Rjb distance can have very different PGV values. This is likely due to radiation-pattern effects, in particular directivity, which is addressed in great details by Vyas et al (2016)."

- In Figure 2 there are sets of points that have different colors/symbols that are arranged somewhat in rings, but the distance for each color do not seem to be constant. The use of colors/symbols is not explained anywhere I could find, and should be.

Reply: We have updated Figure 2 to provide details concerning the grouping of observation stations into four sets, and to indicate that the color/symbols are used to highlight this grouping. In addition, we also indicate the locations of two selected stations in Figure 4 and 5.

- Page 5, Table 2: The caption says that "(*) denotes dependent parameters". It is not clear what this means. Does this refer to the comment in line 5 of this page, where it is noted that "These restrictions lead to nonlinear dependency between feasible ranges of different physical parameters"?

Reply: In the revised manuscript, we have modified the caption of Table 2 as follows: "Parameters governing fault plane configurations, (*) denotes parameters whose feasible ranges are dependent on others."

- The fact that some of these parameters are constrained based on the choice of other parameters means that the probability distribution of parameters is not really given by (1) on page 5 as is stated. Some choices from this 7-dimensional box have probability zero due to the constraints, while others have greater probability due to several non-allowed choices mapping to the same set of modified parameters when the asperity falls near the edge of the fault plane. Does this affect the validity of the PC expansion and/or results? At any rate, this should be discussed.

Reply: A brief discussion has been added in the revised manuscript (beginning of section 3 ) in order to highlight the distinction between canonical random variables, which are iid uniform over the 7-dimensional hypercube, and physical parameters whose ranges may be interdependent. The PC expansion is constructed in terms of the canonical random variables, and its validity is tested using cross-validation and empirical error estimates.

- Page 17, Section 4.5: In this section it is stated that a uniform distribution of parameters over the 7-dimensional space ignores various geophysical constraints suggested by previous work. This is discussed in the context of choosing a prior for the Bayesian inference, but it seems like it would be even more important to incorporate these constraints into the analysis of Section 3, where the PC expansion is used to generate statistics on the PGV for comparison with the GMPE. Why should the statistics obtained with the uniform distribution be expected to match the GMPE well if it is known that this is the wrong distribution? This is addressed to some extent in Section 4.5 where the inversion that incorporates these constraints is then used to generate statistics that are compared to the GMPE curve in Figure 15. But at this point the inversion process has been used to to further constrain the posterior distribution based on trying to match the GMPE curve, so comparing the result to the GMPE curve does not seem to provide any validation that the PC expansion could predict the GMPE curve for other scenarios, for example. I may be missing the point here, but I think it needs more explanation.

1. "Why should the statistics obtained with the uniform distribution be expected to match the GMPE well if it is known that this is the wrong distribution?"

Reply: The PC statistics and GMPE results were compared to ensure that the model predictions describe a similar range, which consequently enables us to use the GMPE results as "observation data" for the purpose of parameter inference. Without this, it wouldn't be reasonable to use GMPE reference curve as "observation" in the Bayesian framework.
2. "so comparing the result to the GMPE curve does not seem to provide any validation that the PC expansion could predict the GMPE curve for other scenarios"

Reply: As pointed out earlier, the PC expansion was designed to provide an efficient representation of the rupture model behavior. In building the PC representation, we relied on uninformative prior, that spans a wide range of feasible scenarios. In Section 3, we verified the capability of the PC surrogate in reproducing the rupture model predictions over the considered parameter ranges. As discussed in Alexanderian et al. (2012), one of the advantages of having a suitable representation over a wide range of parameters is that the restriction of parameter ranges can be efficiently performed a posteriori, namely without the need of performing new model simulations. This advantage was specifically exploited in section 4.

As suggested by the referee, additional explanation has been incorporated in the revised manuscript concerning the construction and validation of the PC expansion, and later on the restrictions explored in the Bayesian analysis.

## Technical Corrections

- Page 3, line 2: Presumably the rake is fixed at 0 degrees for a strike-slip event, but this should perhaps be stated?

Reply: As pointed out by the referee, the rake value has been added in the revised manuscript.

- Page 7, line 27: What are the index sets Si and Ti ? The sets are used in the summations of (7a) and (7b) respectively, but not really defined.

Reply: As suggested by the referee, Si and Ti have been specified in the revised manuscript.

- Proper latex fonts for trig functions should be used in expressions such as (A1), e.g. a $\cos \beta$ rather than $\operatorname{acos} \beta$.

Reply: This comment has been incorporated.

## References

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# Bayesian inference of earthquake rupture models using polynomial chaos expansion 

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#### Abstract

In this paper we employed polynomial chaos (PC) expansions to understand earthquake rupture model responses to random fault plane properties. A sensitivity analysis based on our PC surrogate model suggests that the hypocenter location plays a dominant role in peak ground velocity (PGV) responses, while elliptical patch properties only show secondary impact. In addition, the PC surrogate model is utilized for Bayesian inference of the most likely underlying fault plane configuration


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## 1 Introduction

One of the most important challenges seismologists and earthquake engineers face to design large civil structures (e.g. buildings, dams, bridges, power plants) and response plans, especially in highly populated cities prone to large damaging earthquakes, is the reliable estimation of ground-motion characteristics at a given location. Ground-motion prediction equations (GMPEs), which are one of the most important elements for Probabilistic Seismic Hazard Analysis (PSHA), are designed for this purpose. These are obtained from regression analysis by fitting a dataset (empirical and simulated) and are mainly expressed in terms of the site conditions, source-site distance (e.g. rupture distance or Joyner-Boore distance, denoted as $R_{J B}$ distance hereafter ${ }^{1}$ ), magnitude and mechanism, although other terms such as directivity and hanging wall effect are also considered (Abrahamson et al., 2014). The equations can be derived for peak ground displacement (PGD), peak ground velocity (PGV), peak ground acceleration (PGA), and spectral acceleration (SA) for a damping of 5\% at different periods. Ideally, an optimal GMPE has to be robust, and include physical terms to avoid over fitting overfitting the data, which can result

[^0]in the inclusion of too many parameters. When other effects are considered (such as amplitude and duration of rupture directivity(Somerville et al., 1997); Somerville et al. 1997) or more data is available (Atkinson and Boore, 2011), GMPEs are modified to better explain attenuation patterns.

Many efforts have been made to characterize the seismic ground-motion considering both real and simulated data. For example, using real data, five research groups under the Pacific Earthquake Engineering Research Center Next Generation Attenuation (PEER NGA) project derived GMPEs for shallow crustal earthquakes considering an extensive database of recorded ground-motions (Chiou et al., 2008). Later, Arroyo and Ordaz (2010a, b) obtained GMPEs using both synthetic data and two subsets of accelerograms of the NGA database (Chiou et al., 2008). Arroyo and Ordaz (2010b) highlighted the necessity to merge finite fault modeling (Atkinson and Silva, 2000) with observations to obtain GMPEs that better predict the amplitudes in zones where data is insufficientdata are insufficient. Verification and validation studies (Maufroy et al., 2015, 2016) were also conducted in a large effort to understand ground motions and showed the importance of both accurate source parameters and the geological description of the medium to reproduce observed ground motions. Singh et al. (2017) improved the agreement between observed ground motions and GMPEs by including site effects of the area. Numerical simulations have also helped to explain ground-motion characteristics. For instance, Furumura and Singh (2002) described attenuation patterns for both deep in-slab and shallow interplate earthquakes, while Cruz-Jiménez et al. (2009) explained ground-motion amplification due to a volcanic layer. Mahani and Atkinson (2012) modeled the decay of spectral amplitudes in several locations in North America.

In this study we investigate the level of complexity needed in kinematic rupture models of Mw-magnitude 6.5 strike-slip events to produce ground-motions similar to a reference GMPE. To this end, we utilize the PC approach (Ghanem and Spanos, 1991; Xiu and Karniadakis, 2002; Le Maître and Knio, 2010) to build functional representations of PGVs responses of an original source model. Thanks to the significant reduction in computational cost of the PC surrogate models (in comparison with both the original source model and a Bayesian analysis based on MCMC sampling, which requires a prohibitive number of model runs-(Minsonet al., 2014); Minson et al., 2014), it is suitable to utilize the PC surrogates in a Bayesian inference framework (Sudret and Mai, 2013; Sraj et al., 2016; Giraldi et al., 2017). This enable enables us to quantitatively rank different kinematic source models given by the PGVs they produce and identify the most likely one that fits a chosen reference GMPE (expectation). The ranking considers uncertainties in both the GMPE and model parameters. This provides useful insight on the level of complexity needed in kinematic source models for ground-motion simulations to satisfy both observational constraints and engineering/design requirements for seismic safety.

This paper is organized as follows. In Section 2 we provide detailed descriptions of the source model configurations, including the calculation of synthetic seismograms. In section 3, we present the PC analysis of PGVs as a function of random variations of the kinematic models, including the validation of PC surrogate models and discussions of various statistical quantities. In section 4, we conduct a PC based Bayesian inference analysis to identify the most likely kinematic rupture model that best fits a chosen GMPE reference curve. Finally, we conclude our key findings and propose potential improvements for future work in section 5 .


Figure 1. Example of fault plane configuration, the red star denotes hypocenter location, and the ellipse is the asperity with Gaussian slip distribution inside. The slip distribution is tapered in the area between the dashed and solid rectangles.

## 2 Source Model

A magnitude $M_{w}=6.5$ strike-slip earthquake (seismic moment $6.31 \times 10^{18} \mathrm{Nm}-6.31 \times 10^{18} \mathrm{Nm} ;$ rake $=0^{\circ}$ ) on a singlesegment vertical fault plane is considered. The fault plane is chosen to be a rectangle with fixed length $L=27 \mathrm{~km}$ and width $W=10 \mathrm{~km}$ fobtained from-, which are the most frequent values among 100 realizations following the sealing relation in Wells and Coppersmith (1994)sample realizations following scaling relations (e.g. Wells and Coppersmith, 1994; Mai and Beroza, 2000 The top of the fault plane is located 2 km below the ground surface. Figure 1 shows an example configuration of the fault plane, in which the red star denotes the hypocenter and the ellipse is the asperity with Gaussian slip distribution inside. The maximum slip $S_{\max }$ is chosen such that the mean slip (over the entire fault plane) remains constant ( 0.71 m ) when varying the ellipse size (which ensures that the moment magnitude remains constant, $M_{w}=6.5$ ). The slip between the elliptical patch boundary and dashed rectangle (Figure 1) is set to be $S_{\max } / e$ (where $e$ is the Euler's number), the minimum value at the patch boundary from the Gaussian slip distribution. The slip between the solid and dashed rectangles (the horizontal and vertical gaps are $5 \%$ of the length and width of the fault plane, respectively) is tapered to avoid non-physical slip patterns. The entire fault plane is discretized in along-strike and down-dip directions with grid size of 0.02 km . We use a regularized Yoffe function (Tinti et al., 2005) with a rise time $\operatorname{Tr}=1.25 \mathrm{~s}$ following source-scaling relations (Somerville et al., 1999) and slip acceleration time $t_{a c c}=0.225 \mathrm{~s}$, as suggested by Tinti et al. (2005). At each node of the discretized fault plane we assign $T r, t_{a c c}$, slip-rate in along-strike and down-dip directions, and rupture time. We consider a rupture speed of $0.75 V_{s} \mathrm{~km} / \mathrm{s}$ in all source models.

PGVs at a virtual network of $N_{o b s}=56$ stations (Figure 2) are calculated from synthetic seismograms of the two horizontal components of ground motion at each site for a large set of source rupture models. We use COMPSYN (Spudich and Xu, 2003),


Figure 2. A virtual network of $N_{o b s}=56$ stations where PGV responses are reported by the source model. The solid black line at the center denotes the length and location of the fault plane. Note, the 56 stations are grouped into four sets (indicated by different colors/symbols) according to their Rjb distances (see details in section 4).

Table 1. Velocity model used in this study, modified from Boore et al. (1997).

| Depth $(\mathrm{km})$ | $V_{p}(\mathrm{~km} / \mathrm{s})$ | $V_{s}(\mathrm{~km} / \mathrm{s})$ |
| :---: | :---: | :---: |
| 0 | 2.4 | 1.5 |
| 0.5 | 4.4 | 2 |
| 1.5 | 5.3 | 2.7 |
| 2.5 | 5.5 | 2.9 |
| 4 | 5.7 | 3.3 |
| 8 | 6.1 | 3.5 |
| 14 | 6.8 | 3.9 |
| 16.6 | 7.1 | 4.1 |
| 27 | 8 | 4.6 |
| 350 | 8.2 | 4.65 |

Table 2. Parameters governing fault plane configurations, (*) denotes dependent parameters whose feasible ranges are dependent on others.

| Index | Parameter | Physical Interpretation |
| :---: | :---: | :---: |
| 1 | $A R$ | Area ratio, $A R=\frac{\pi a b}{L * W} \in[0.05,0.29]$ |
| 2 | $x_{h}(k m)$ | x-coordinate of the hypocenter $x_{h} \in[-13.5,13.5]$ |
| 3 | $z_{h}(k m)$ | z-coordinate of the hypocenter $y_{h} \subset[5,5] z_{h} \in[-5,5]$ |
| 4 | $a\left(^{*}\right)(k m)$ | Semi-major axis $a \in\left[\sqrt{\frac{A R \cdot L \cdot W}{\pi}}, L / 2\right]$ |
| 5 | $\theta\left(^{*}\right)$ | Inclination angle of the elliptical patch |
| 6 | $x_{c}\left(^{*}\right)(\mathrm{km})$ | x-coordinate of the center of elliptical patch |
| 7 | $z_{c}\left(^{*}\right)(\mathrm{km})$ | z-coordinate of the center of elliptical patch |

a code based on the discrete wavenumber/finite element method proposed by Olson et al. (1984) to calculate the synthetic seismograms up to a maximum frequency of 1.5 Hz at each station of the virtual array. COMPSYN solves the equation of motion considering initial conditions of zero displacement and velocity at a reference time $t_{0}$ and specifying traction or displacement on the bounding surface of the medium (boundary conditions) using the unit outward normal vector (details about the scheme can be seen in Olson et al., 1984). The grid resolution used in COMPSYN is variable and uses a spacing of $1 / 6$ of the minimum shear wavelength at depth $z$. The grid extends a total depth that depends on the wavenumber, which means that the maximum depth decreases when the wavenumber increases. This approach considers a layered 1D velocity structure. We apply the velocity model shown in Table 1, which corresponds to a slightly modified version of the generic model by Boore et al. (1997) for California. The resulting PGVs serve as our quantities of interest (QoIs, each denoted as $\mathcal{Q}_{j}$, for $j=1,2, \ldots, N_{o b s}$ ). We aim at understanding stochastic source model PGV responses to random fault plane configurations of the source process (slip distributions and hypocenter location). To this end, we consider variations in seven physical parameters listed in Table 2, which parameterize the fault plane configurations, i.e. locations of both the hypocenter and elliptical asperity patch, as well as its shape and orientation. We restrict the hypocenter and elliptical patch to be inside the fault plane, and limit the area aspect ratio (AR) of the elliptical patch to the entire fault plane ( $L \times W$ ) between $5 \%$ and $29 \%$. These restrictions lead to nonlinear dependency between feasible ranges of different physical parameters (see Appendix A for more details).

## 3 Polynomial Chaos Framework

PC expansions (Ghanem and Spanos, 1991; Xiu and Karniadakis, 2002; Le Maître and Knio, 2010) ${ }^{2}$ are used in this study to understand earthquake rupture model responses (in terms of PGVs) to random configurations of slip distribution and hypocenter location. We associate each of the physical parameters with a canonical PC random variable $\xi_{i}\left(i \in\left\{1,2, \ldots, n_{d}\right\}\right.$, where $n_{d}=7$ is the ntmber of stochastic dimensionsstochastic space dimension) and assume all $\xi_{i}$ 's are independent and uniformly

[^1]$p(\boldsymbol{\xi})= \begin{cases}2^{-7} & \text { if } \boldsymbol{\xi} \in \boldsymbol{\Xi} \equiv[-1,1]^{7}, \\ 0 & \text { otherwise. }\end{cases}$
Each random parameter vector $\boldsymbol{\xi} \in \boldsymbol{\Xi}$ can be linked uniquely to a realization of the physical parameter vector (See mapping details in Appendix A). We thus focus on constructing functional representations of PGV responses at each station with respect to the canonical variable $\boldsymbol{\xi}$, instead of which parameterize the physical parameters in Table 2. It is worth mentioning that

$$
\begin{equation*}
\mathbb{E}\left[\mathcal{Q}_{j}^{2}\right]=\int_{\boldsymbol{\Xi}} \mathcal{Q}_{j}(\boldsymbol{\xi})^{2} p(\boldsymbol{\xi}) d \boldsymbol{\xi}<+\infty, \quad \forall j \in\left\{1,2, \ldots, N_{o b s}\right\} \tag{2}
\end{equation*}
$$

One can approximate $\mathcal{Q}_{j}(\boldsymbol{\xi})$ using a truncated PC expansion as follows:
$\mathcal{Q}_{j}(\boldsymbol{\xi}) \approx \tilde{\mathcal{Q}}_{j}(\boldsymbol{\xi})=\sum_{\alpha=0}^{N_{p}} c_{\alpha} \Psi_{\alpha}(\boldsymbol{\xi}), \forall j \in\left\{1,2, \ldots, N_{o b s}\right\}$.
where $N_{p}$ is a truncation parameter and $\left(N_{p}+1\right)$ is the number of expansion terms retained in the PC surrogate models. In
this study, we truncated the PC expansion at total polynomial order of nine, which leads to 11440 pelynemials $q=9$. Given $n_{d}=7$, one can calculate the total number of polynomials via
$N_{p}+1=\frac{\left(q+n_{d}\right)!}{q!n_{d}!}=11440$.

By adopting the classical convetion of $\Psi_{0}(\boldsymbol{\xi})=1$, the mean and variance of a PC surrogate $\mathcal{Q}_{j}(\boldsymbol{\xi})$ can be expressed as:
$\mathbb{E}[\tilde{\mathcal{Q}}]=\sum_{\alpha=0}^{N_{p}} c_{\alpha}\left\langle\Psi_{\alpha}, 1\right\rangle=c_{0}$,
and
$\mathbb{V}[\tilde{\mathcal{Q}}]=\mathbb{E}\left[(\tilde{\mathcal{Q}}-\mathbb{E}[\tilde{\mathcal{Q}}])^{2}\right]=\sum_{\alpha, \beta=1}^{N_{p}} c_{\alpha} c_{\beta}\left\langle\Psi_{\alpha}, \Psi_{\beta}\right\rangle=\sum_{\alpha=1}^{N_{p}} c_{\alpha}^{2}\left\|\Psi_{\alpha}\right\|_{L_{2}}^{2}$,
where $\langle\cdot\rangle$ denotes the inner product in the Hilbert space $L_{2}(\boldsymbol{\Xi}, p)$ with respect to the joint distribution $p(\boldsymbol{\xi})$ (Le Maître and Knio, 2010).

To determine the expansion coefficients ( $c_{\alpha}$ 's) in Eq. (3), we rely on a Latin Hypercube Sample (LHS) (McKay et al., 1979) set (denoted as $\mathcal{P}_{L H S}$ hereafter) of $N_{L H S}=8000$ earthquake rupture model realizations through $\left\{\boldsymbol{\xi}_{k}\right\}_{1 \leq k \leq N_{L H S}}$ and solve the following Basis Pursuit Denoising (BPDN) problem (Van Den Berg and Friedlander, 2007, 2008) ${ }^{3}$ at each station:
$\boldsymbol{c}^{*}=\arg \min _{\boldsymbol{c} \in \mathbb{R}^{N_{p}+1}}\|\boldsymbol{c}\|_{l_{1}}$ s.t. $\left\|\mathcal{Q}_{j}-[\Psi] \boldsymbol{c}\right\| \leq \gamma\left\|\mathcal{Q}_{j}\right\|_{l_{2}}, \forall j \in\left\{1,2, \ldots, N_{o b s}\right\}$,
where $\mathcal{Q}_{j}=\left(\mathcal{Q}_{j}\left(\boldsymbol{\xi}_{1}\right), \mathcal{Q}_{j}\left(\boldsymbol{\xi}_{2}\right), \ldots, \mathcal{Q}_{j}\left(\boldsymbol{\xi}_{N_{L H S}}\right)\right)^{T}$ is the model PGV realization vector at the $j$-th station, and $\boldsymbol{c} \in \mathbb{R}^{N_{p}+1}$ is the coefficient vector for the corresponding PC surrogate model. $[\Psi] \in \mathbb{R}^{N_{L H S} \times\left(N_{p}+1\right)}$ denotes the polynomial matrix with each element $[\Psi]_{i, \alpha}=\Psi_{\alpha}\left(\boldsymbol{\xi}_{i}\right)$. Note that $[\Psi]$ is station invariant. The scalar parameter $\gamma$ indicates the model noise level and is determined numerically via a $k$-fold $(k=5)$ cross-validation process- (Seber and Lee, 2012) over a discrete grid of $\chi=\left\{10^{-4}, 10^{-3}, 10^{-2}: 0.005: 0.2\right\}$.

Following Sobol (1993), Homma and Saltelli (1996), variance-based first-order and total order sensitivity indices associated with a subset of random variables $\left(i \subset\left\{1,2, \ldots, n_{d}\right\}\right)$ can be calculated respectively as follows:
$\mathbb{S}_{\boldsymbol{i}}=\frac{\sum_{\alpha \in \mathcal{S}_{i}} c_{\alpha}^{2}\left\|\Psi_{\alpha}\right\|_{L_{2}}^{2}}{\sum_{\alpha=1}^{N_{p}} c_{\alpha}^{2}\left\|\Psi_{\alpha}\right\|_{L_{2}}^{2}}$.
$\mathbb{T}_{\boldsymbol{i}}=\frac{\sum_{\alpha \in \mathcal{T}_{i}} c_{\alpha}^{2}\left\|\Psi_{\alpha}\right\|_{L_{2}}^{2}}{\sum_{\alpha=1}^{N_{p}} c_{\alpha}^{2}\left\|\Psi_{\alpha}\right\|_{L_{2}}^{2}}$,
where $\mathbb{S}_{\boldsymbol{i}}$ (first-order sensitivity) is the relative variance contribution of those polynomials (denoted as index set $\mathcal{S}_{i}$ ) exclusively related to random variables in the subset $\boldsymbol{i}$; while $\mathbb{T}_{\boldsymbol{i}}$ (total order sensitivity) is the relative variance contribution of polynomials (denoted as index set $\mathcal{T}_{i}$ ) involving any of the random variables in $\boldsymbol{i}$ (including cross polynomials between variables in $\boldsymbol{i}$ and its complement $\boldsymbol{i}_{\sim}, \boldsymbol{i} \cup \boldsymbol{i}_{\sim}=\left\{1,2, \ldots, n_{d}\right\}$ ). Note that by definition the two polynomial index sets satisfy $\mathcal{S}_{\boldsymbol{i}} \subset \mathcal{T}_{\boldsymbol{i}}$.

### 3.1 Validation of PC Models

We first validate our PC surrogate models for PGVs at all stations. To this end, we introduce a second independent source model simulation ensemble (again an 8000 member LHS set $\mathcal{P}_{L H S}^{\text {valid }} \subset \boldsymbol{\Xi}$ ) for the purpose of validation. (Note that $\mathcal{P}_{L H S}^{\text {valid }}$ is independent of the training set $\left.\mathcal{P}_{L H S}\right)$. The following relative $l_{2}$ error is then examined for PGVs at each station.
$\epsilon_{j}=\sqrt{\frac{\sum_{k=1}^{N_{L H S}}\left(\tilde{\mathcal{Q}}_{j}\left(\boldsymbol{\xi}_{k}\right)-\mathcal{Q}_{j}\left(\boldsymbol{\xi}_{k}\right)\right)^{2}}{\sum_{k=1}^{N_{L H S}} \mathcal{Q}_{j}\left(\boldsymbol{\xi}_{k}\right)^{2}}}, \forall j \in\left\{1,2, \ldots, N_{o b s}\right\}$,
where $\tilde{\mathcal{Q}}_{j}\left(\boldsymbol{\xi}_{k}\right)$ and $\mathcal{Q}_{j}\left(\boldsymbol{\xi}_{k}\right)$ denote PC and source model responses, respectively, to $\boldsymbol{\xi}_{k}$ at the $j$-th station. $\boldsymbol{\xi}_{k} \in \mathcal{P}_{L H S}$ or $\boldsymbol{\xi}_{k} \in \mathcal{P}_{\text {LHS }}^{v a l i d}$ depending on the sample set used to estimate the errors.

Figure 3 shows relative error estimates of PC surrogate models over the training set ( $\mathcal{P}_{L H S}$, blue dots) and the validation set $\left(\mathcal{P}_{L H S}^{v a l i d}\right.$, red dots). It is not surprising to see slightly larger error estimates on the validation set, as the PC reconstruction

[^2]

Figure 3. Relative $l_{2}$ errors of PC surrogate models. The cross-validation errors are close to the error estimated from validation set. For brevity, we omit the cross-validation errors in the plot.
process is unaware of this data set. However, because almost all error estimates fall below $10 \%$ range, and in light of the close agreement (about 4\% difference) between the blue and red dots, our PC surrogate models are deemed to suitably reproduce source model PGV responses throughout the entire station network.

Apart from the above error estimates, the convergence of PC surrogate models with respect to truncation order is also investigated from a statistical point of view. Figure 4 shows PGV distributions from PC re-sampling on a one-million-member LHS set $\left(\mathcal{P}_{L H S}^{1 E 6}\right)$ at two selected stations, with different-with increasing odd PC truncation orders up to degree 9. It is seen that when the truncation order is larger than five, the difference in the PGV prediction distributions becomes relatively small, suggesting that our ninth-order PC library is sufficient PC expansions are sufficiently accurate for the source model under consideration.

We finally compare distributions of PC and source model predictions, see Figure 5. It is observed that our PC surrogate models are indeed capable of reproducing PGV distributions produced from source model realizations of the validation set $\mathcal{P}_{L H S}^{v a l i d}$. Besides, the excellent agreement between the two PC predicted distribution curves in Figure 5 suggests that our existing 8000 model simulation ensemble is statistically representative, which provides additional confidence in our PC representations.


Figure 4. PC predicted PGV distributions at two selected stations.(Top) Station \# 3-(Bottomas indicated in Figure 2)Station \# 21.. Distribution curves are eneratedobtained using kernel density estimation (Sheather and Jones, 1991) from PC realizations on a one-millionmember LHS set $\mathcal{P}_{L H S}^{1 E 6}$.


Figure 5. Comparison of PGV distributions predicted by the source model (blue solid curve) and PC surrogate model (red dashed curve) respectively at selected stations (as indicated in Figure 2) over the validation sample set $\mathcal{P}_{L H S}^{v a l i d}$. The black dash-dotted curves are PC PGV prediction distributions obtained from PC surrogate model realizations on a one-million-member LHS set $\mathcal{P}_{L H S}^{1 E 6}$. Distributions are obtained using kernel density estimations (Sheather and Jones, 1991).

### 3.2 PC Statistics

The PC surrogate models obtained in the previous section provide immediate access to prediction statistics, as given by Equations (5) and (6). Figure 6 shows means and standard deviations of PC PGV predictions at different stations, along with a reference PGV curve provided median PGV curve predicted by the GMPE in Boore and Atkinson (2008). It is seen that our ${ }^{4} \dot{\sim}$ It is noted that two stations with similar $R$ IB distance can have very different PGV values. This is likely due to radiation-pattern effects, in particular directivity, which is addressed in great detail by Vyas et al. (2016). Besides, it is observed that PC predictions generally scatter around the GMPE curve. The-Though one should not expect exact match between PC statistic and GMPE predictions, due to the difference in random sources underlying the two approaches, and the uninformative uniform canonical PC parameter distributions used to generate PC statistics, it is worth noting that the similar range of PC and GMPE predictions enables us to use the GMPE results as "observations" for the purpose of parameter inference discussed in section 4. One also observe that PGVs are generally largest near the fault plane, and decrease with increasing $R_{J B}$ distance. The overall tendency of PC prediction uncertainty (quantified by the standard deviation bars) seems to decrease with increasing $R_{J B}$ distance as well.

The conditional mapping from random PC parameter canonical PC random variables ( $\boldsymbol{\xi}$ ) to physical fault plane eonfiguration leads to complex dependency of PGV responses to random inputs. To identify configurations makes it difficult to isolate the relative impact of each random parameter (each compenent of $\boldsymbol{\xi}$ ) on model responsesindividual parameters. To address this difficulty, we rely on the global sensitivity analysisin (Homma and Saltelli, 1996; Sobol, 1993). (Homma and Saltelli, 1996; Sobol, 1993), and discuss the statistical significance of each canonical random parameters in the rupture model.

Figure 7 shows both the first and total order sensitivity indices associated with each random parameter at different stations. These sensitivity indices reveal that the model PGV response is most sensitive to the location of the hypocenter ( $x_{h}$ is dominant and $z_{h}$ plays a secondary role) throughout all stations, whereas the remaining random parameters (associated with elliptical asperity patch) are relatively insignificant. While it might be reasonable to neglect the elliptical patch parameters' impact on PGV response variability at far stations (with $R_{J B}$ distance roughly more than 10 km away from the center), it is evident that at near-the-center stations, those elliptical patch parameters can still lead to a considerable impact on PGV response.

To better illustrate the above sensitivity observation, we divided the parameters into the following two groups $\boldsymbol{\xi}_{\text {hypo }}=$ $\left\{\xi_{2}^{x_{h}}, \xi_{3}^{z_{h}}\right\}$ and $\boldsymbol{\xi}_{\text {ellip }}=\left\{\xi_{1}^{A R}, \xi_{4}^{a}, \xi_{5}^{\theta}, \xi_{6}^{x_{c}}, \xi_{7}^{z_{c}}\right\}$ (the superscripts denote the corresponding physical parameters), and calculate the first order sensitivity indices associated with $\boldsymbol{\xi}_{\text {hypo }}$ and $\boldsymbol{\xi}_{\text {ellip }}$ using Equation (8a), denoted as $\mathbb{S}_{\text {hypo }}$ and $\mathbb{S}_{\text {ellip }}$, respectively. Note the combined effect (interaction) of hypocenter location and elliptical patch parameters is simply given by $\mathbb{S}_{\text {hypo }} \times$ ellip $=$ $1-\mathbb{S}_{\text {hypo }}-\mathbb{S}_{\text {ellip }}$. The resulting group sensitivity indices are shown in Figure 8. It is now clear that the hypocenter location alone is responsible for $80-90 \%$ of the variability in PGVs at distant stations. Meanwhile near the center, the hypocenter location alone is associated with only $55-75 \%$ of the PGV variability, suggesting that the elliptical patch parameters play important roles with about $25-45 \%$ contribution to the total PGV variability.

[^3]

Figure 6. Comparison of PC statistics (based on uniform distribution assumption of the canonical PC random parameterparameters) with GMPE results. Dashed Solid black curve denotes the median GMPE prediction, while the dashed lines are GMPE standard deviation boundsef GMPE predictions. Note that log-scales are used in the plot.

## 4 Bayesian Inference

In this section, we utilize a Bayesian approach (Bernardo and Smith, 2001; Berger, 2013; Gelman et al., 2014) to find the most likely fault plane configuration, in the sense that the resulting earthquake rupture model produces PGVs best match the reference GMPE curve by Boore and Atkinson (2008) for for the same magnitude and focal mechanism (Boore and Atkinson, 2008). tional data in our Bayesian inference, and compare $\boldsymbol{d}$ with our PC surrogate model predictions $\tilde{\boldsymbol{d}}(\boldsymbol{\xi})=\left(\tilde{\mathcal{Q}}_{1}(\boldsymbol{\xi}), \tilde{\mathcal{Q}}_{2}(\boldsymbol{\xi}), \ldots, \tilde{\mathcal{Q}}_{N_{o b s}}(\boldsymbol{\xi})\right)^{T}$.

### 4.1 Bayesian Formulation

To formulate the Bayesian problem, we start with Bayes' formula
$p(\boldsymbol{\eta} \mid \boldsymbol{d})=\frac{p(\boldsymbol{d} \mid \boldsymbol{\eta}) p(\boldsymbol{\eta})}{p(\boldsymbol{d})} \propto p(\boldsymbol{d} \mid \boldsymbol{\eta}) p(\boldsymbol{\eta})$,
where $\boldsymbol{\eta}$ is the parameter vector to be inferred, $p(\boldsymbol{\eta})$ is the prior probability distribution of $\boldsymbol{\eta}$, and $p(\boldsymbol{d} \mid \boldsymbol{\eta})$ is the likelihood of observing $\boldsymbol{d}$ given $\boldsymbol{\eta}$. The denominator $p(\boldsymbol{d})$ is the marginal distribution known as evidence. (Note this evidence can be


Figure 7. First (top) and total (bottom) order sensitivity indices at each station.


Figure 8. 1st order sensitivity indices with respect to grouped parameters.
neglected, as the Markov Chain Monte Carlo (MCMC) sampling method (Haario et al., 2001; Roberts and Rosenthal, 2009) utilized below solely relies on the proportionality). We adopt the assumption of independent Gaussian predietion errorGaussian error at each station location, i.e. the discrepancy between GMPE observations (GMPE predicted PGVs) and PC predictions at indicated in Figure 2, and associate each group of stations with a hyper-parameter $\sigma_{l(j)}^{2}(l(j) \in\{1,2,3,4\}$, depending on the $R_{J B}$ distance of the $j$-th station). As a result, the likelihood can be expressed as:
$p(\boldsymbol{d} \mid \boldsymbol{\eta})=\prod_{j=1}^{N_{\text {obs }}} \frac{1}{\sqrt{2 \pi \sigma_{l(j)}^{2}}} \exp \left(-\frac{\left(d_{j}-\tilde{d}_{j}(\boldsymbol{\xi})\right)^{2}}{2 \sigma_{l(j)}^{2}}\right)$,
and accordingly the inference parameter vector $\boldsymbol{\eta}$ reads
$\boldsymbol{\eta}=\left(\xi_{1}, \xi_{2}, \ldots, \xi_{7}, \sigma_{1}^{2}, \sigma_{2}^{2}, \ldots, \sigma_{4}^{2}\right)^{T}$.
Our numerical experiments suggest that the $4-\sigma^{2}$ model above outperforms the model with only one hyper-parameter for all stations. It is noted that we limit the number of uncertainty hyper-parameters ( $\sigma_{i}^{2}$ 's) to four in this study, due to the limited
number of observations (PGVs at limited number of stations). If more observations are available, it might be beneficial to increase the number of hyper-parameters.

The prior distribution of $\boldsymbol{\eta}$, without additional information on the model parameters, is usually given by assumptions of uniform distribution for canonical PC parameters $\boldsymbol{\xi}$, and Jeffrey's priors (Sivia and Skilling, 2006) for hyper-parameters $\sigma_{l}^{2}$ (as
$p(\boldsymbol{\eta})= \begin{cases}\left(\frac{1}{2}\right)^{7} \prod_{l=1}^{4} \frac{1}{\sigma_{l}^{2}} & \forall \boldsymbol{\xi} \in \boldsymbol{\Xi} \text { and } \forall \sigma_{l}^{2}>0, \\ 0 & \text { otherwise, }\end{cases}$
and Bayes' rule reduces to

$$
\begin{align*}
& p(\boldsymbol{\eta} \mid \boldsymbol{d}) \propto p(\boldsymbol{d} \mid \boldsymbol{\eta}) p(\boldsymbol{\eta})= \\
& \begin{cases}\prod_{j=1}^{N_{o b s}} \frac{1}{\sqrt{2 \pi \sigma_{l(j)}^{2}}} \exp \left(-\frac{\left(d_{j}-\tilde{d}_{j}(\boldsymbol{\xi})\right)^{2}}{2 \sigma_{l(j)}^{2}}\right)\left[\left(\frac{1}{2}\right)^{7} \prod_{l=1}^{4} \frac{1}{\sigma_{l}^{2}}\right] & \forall \boldsymbol{\xi} \in \boldsymbol{\Xi} \text { and } \forall \sigma_{l}^{2}>0 \\
0 & \text { otherwise. }\end{cases} \tag{15}
\end{align*}
$$

We rely on the adaptive metropolis MCMC approach (Haario et al., 2001; Roberts and Rosenthal, 2009) to sample the above posterior distribution. It is worth noting that MCMC methods, despite the improved efficiency against the traditional MC approaches, generally require a large number of samples (typically tens of thousands, and even larger depending on the dimensionality of the problem). This is one of the main reasons why we utilize PC techniques, as the use of the corresponding PC surrogates in the MCMC simulation leads to significant reduction in computational cost. In this study, the MCMC sample size for inference is set to $10^{6}$.

### 4.2 Inference Results

As mentioned above, we exploit the PC surrogate models in Bayesian inference analysis and update the posterior distribution of random parameters $\left(\boldsymbol{\xi} \in \boldsymbol{\Xi}\right.$ ), as well as PGV prediction uncertainties ( $\sigma_{l}^{2}$ 's), in light of the GMPE predicted PGV sobservations. Figure 9 shows the posterior probability distributions of hyper-parameters $\sigma_{l}^{2}(l \in\{1,2,3,4\})$. It is evident that $\sigma_{l}^{2}$ decreases with $R_{J B}$ distance (from $l=1$ to $l=4$ ), which supports our previous ansatz from Figure 6.

Similarly, we examine the sampling chains of PC random parameters $\xi_{i}(i \in\{1,2, \ldots, 7\})$. While some parameters (e.g. $\xi_{1}, \xi_{2}, \xi_{3}$ and $\xi_{6}$ ) yield very informative posterior distributions (not shown here), others look relatively less informative. It is noted that our goal is to estimate the posterior distributions of the physical parameters in Table 2, instead of the PC parameters. Thus, it is desired to map the $\boldsymbol{\xi}$ chain into the corresponding physical configuration chain, before inferring the most likely fault plane configuration.

Figure 10 shows the posterior distributions of the physical parameters after mapping from the PC parameter chain of $\boldsymbol{\xi}$ (for brevity, the chain plots of physical parameters are not shown here), as well as the corresponding inference of the fault plane configuration (bottom right panel). It is observed that in light of the GMPE PGV predictionsobservations: 1) the hypocenter location ( $x_{h}$ and $z_{h}$ ) is well identified; 2) The size of the elliptical patch seems to be more likely near the lower bound of the


Figure 9. Posterior probability distributions of prediction uncertainty parameters (each PDF curve is scaled to have unit peak height for better comparison).
prior; 3) The inclination angle of the elliptical patch, as well as the location of the patch, is are less conclusive. For example, despite the clear peak in the inclination angle plot, the posterior distribution is relatively flat, suggesting limited information gain comparing with the prior knowledge. Furthermore, the $x_{c}$ distribution only shows the fact that the ellipse tends to be in the left half of the fault plane; the definite location of the elliptical patch (either $x_{c}$ or $y_{c} z_{c}$ ) is ambiguous. These findings are generally consistent with the results of the sensitivity analysis. Since the model is primarily sensitive to the hypocenter location, perturbing the hypocenter location leads to more effective adjustment in PGV responses. On the other hand, elliptical patch parameters have relatively small impact on PGV variance, which calls for more observational data to pin down those parameters.

One needs to be cautious about the Bayesian inference results discussed above. From the physical point of view, the spatial distribution of those stations (see Figure 2) where PGVs are reported is almost 'symmetric' about the center of the fault plane ( $x=0$ and $y=0$ ), ; as a result, one would expect to see a 'symmetric' twin configuration that are roughly equally plausible from the Bayesian inference. However, this 'symmetric' counterpart is clearly missing in the above inference results. This is probably because when MCMC chain converges to the high probability region of hypocenter location in the bottom right quadrant of the fault plane, it becomes more and more difficult to escape from this high probability region and explore the other side of parameter space. In other words, there could be bi-modal structures in the distributions of $x_{h}$ (as well as $x_{c}$ ) which the previous MCMC process fails to identify (e.g. the configuration in which the hypocenter located on the bottom left quadrant of the fault plane, and the ellipse centered at somewhere in the right half of the fault plane). While in theory it is possible to identify the missing multi-modal distributions of random parameters by further increasing the number of


Figure 10. Prior (dashed black, derived from uniform $\boldsymbol{\xi}$ distribution in $\boldsymbol{\Xi}$ ) and posterior (solid blue) distributions of physical fault plane configuration parameters. The bottom right panel shows the inferred fault plane configuration.


Figure 11. Inferred fault plane configuration with MCMC chain starting from the 'symmetric' counterpart configuration.

MCMC samples, the computational cost can be excessive. Alternatively, we verify our expectation of seeing the 'symmetric' counterpart configuration by re-running the MCMC simulation starting with the 'symmetric' counterpart configuration (i.e. with hypocenter being in the bottom left quadrant of the fault plane, and elliptical patch being in the right side of the fault plane). The resulting fault plane configuration inference is shown in Figure 11. As expected, the new MCMC process ended up with a fault plane configuration that is roughly 'symmetric' to the previous inference result, especially for the hypocenter location.
5 The asymmetric behavior of the elliptical patch stems from the fact that: 1) the $N_{o b s}$ stations are not exactly symmetrically distributed, thus one should not expect exact symmetry; 2) as discussed before, the PGV responses are less sensitive to the elliptical patch properties, leading to ambiguity in inferring these properties.

### 4.3 Inference with Restricted Prior

The previous inference results are all based on almost complete ignorance of dependency between hypocenter location and the slip area (asperity). However, previous studies (Mai et al., 2005; Irikura and Miyake, 2011) suggested some constraints on the relative hypocenter location (Mai et al., 2005) with respect to the asperity, and size of the asperity (Irikura and Miyake, 2011).

In this section, we consider the following restrictions in our inference analysis:
$\mathrm{R}-1$. The elliptical patch is inside the dashed rectangle $\left(\left[L^{\prime}, W^{\prime}\right]=0.9 \times[L, W]\right)$ shown in Figure 1 ;

R-2. The area ratio of the elliptical patch $(A R)$ is between $15 \%$ and $29 \%$ of the fault plane area, i.e. $0.15<A R<0.29$;
$\mathrm{R}-3$. The elliptical patch is not too elongated, i.e. the axis ratio $\frac{a}{b} \leq 3$;

R-4. The hypocenter is located outside but near the elliptical patch, i.e. $x h_{h}=\left(a+3 \zeta h_{1}\right) \cos \left(2 \pi \zeta_{h_{2}}\right)$ and $z_{h}=\left(b+b \frac{3}{a} \zeta h_{1}\right) \sin \left(2 \pi \zeta h_{2}\right)$ $x_{h_{2}}=\left(a+3 \zeta_{b_{2}}\right) \cos \left(2 \pi \zeta_{k_{2}}\right)$ and $z_{h_{1}}=\left(b+b \frac{3}{a} \zeta_{h_{1}}\right) \sin \left(2 \pi \zeta_{k_{2}}\right) \forall\left(\zeta_{h_{1}}, \zeta_{h_{2}}\right) \in[0,1]^{2}$.

The above One of the advantages of having previous PC surrogate models (which were built based on uninformative prior that spans a wide range of feasible scenarios i.e. minimal restrictions as in Table 2) is that the above four additional parameter restrictions can be conveniently incorporated efficiently performed a posteriori, namely without the need of performing new model simulations (Alexanderian et al. 2012).

To begin with, we first incorporate the above restrictions into the Bayesian framework, namely by modifying the previous prior distribution (Equation (14)) as follows:
$p^{*}(\boldsymbol{\eta})= \begin{cases}\left(\frac{1}{2}\right)^{7} \prod_{l=1}^{4} \frac{1}{\sigma_{l}^{2}} & \forall \boldsymbol{\xi} \in \boldsymbol{\Xi}, \forall \sigma_{l}^{2}>0 \text { and all restrictions are satisfied, } \\ 0 & \text { otherwise. }\end{cases}$
However, due to the strong restrictions listed above, the support of the above prior probability distribution (Equation (16)) turns out to be extremely limited in the parameter space $\boldsymbol{\Xi}$, leading to computationally inefficient MCMC sampling (since most of the samples drawn from a proposal distribution will end up not satisfying at least one of the restrictions and thus zero prior probability). To mitigate the difficulty of inefficient sampling due to restricted prior distribution, we introduce a new layer of parameterization, mapping from $\boldsymbol{\Xi}$ to restricted physical configurations. (Details on this new mapping mechanism are given in appendix B.)

Figure 12 shows the MCMC process of drawing random samples from proposal distributions and calculate the resulting posterior probability. Without additional restrictions (orange path), the parameter vector $\boldsymbol{\zeta}=\boldsymbol{\xi}$, and the whole process reduces to the standard MCMC process we used in the previous section. By introducing the new parameterization process (see algorithm 2), we are transforming the original problem, which is based on PC parameter vector $\boldsymbol{\xi}$, into a new inference problem based on $\boldsymbol{\zeta}$ (we denote $\boldsymbol{\zeta}$ as auxiliary random parameter vector hereafter, to distinguish it from the PC parameter vector $\boldsymbol{\xi}$ ). This transformation is based on the mapping from $\boldsymbol{\zeta}$ to $\boldsymbol{\xi}$ (i.e. $\boldsymbol{\xi}=\boldsymbol{\xi}(\boldsymbol{\zeta})$ ) via their commonly associated physical configuration. For clarity, we formulate the new $\boldsymbol{\zeta}$ based Bayesian problem as follows:
$p\left(\boldsymbol{\eta}^{*} \mid \boldsymbol{d}\right) \propto \begin{cases}{\left[\left(\frac{1}{2}\right)^{7} \prod_{l=1}^{4} \frac{1}{\sigma_{l}^{2}}\right] \prod_{j=1}^{N_{o b s}} \frac{1}{\sqrt{2 \pi \sigma_{l(j)}^{2}}} \exp \left(-\frac{\left(d_{j}-\tilde{d}_{j}(\boldsymbol{\xi}(\zeta))\right)^{2}}{2 \sigma_{l(j)}^{2}}\right)} & \forall \boldsymbol{\zeta} \in \boldsymbol{\Xi}, \forall \sigma_{l}^{2}>0, \\ 0 & \text { otherwise. }\end{cases}$
where $\boldsymbol{\eta}^{*}=\left(\zeta_{1}, \zeta_{2}, \ldots, \zeta_{7}, \sigma_{1}^{2}, \sigma_{2}^{2}, \ldots, \sigma_{4}^{2}\right)^{T}$.
Following the same analysis as discussed before, we show the inference results under restrictions in Figure 13. Note that the prior distributions of those physical parameters are different from those in Figure 10, as the new ones are derived from uniformly distributed auxiliary random vector $\boldsymbol{\zeta} \in \boldsymbol{\Xi}$, instead of PC parameters $\boldsymbol{\xi} \in \boldsymbol{\Xi}$. Nevertheless, we see very consistent results of hypocenter location, as well as the location of the elliptical patch, comparing with those in Figure 10. The area aspect ratio $A R$, though larger than the previous inferred value, still favors the lower end of the prescribed parameter range. The elliptical patch ends up with a larger area and longer semi-major axis (compared to the results in Figure 10 and 11). These differences are directly stemming from restrictions R-2 and R-3.


Figure 12. Flow chart demonstrating the random sampling process and the calculation of posterior probability in MCMC. The orange path corresponds to unrestricted sampling process, whereas the blue path incorporates additional restrictions on fault plane configurations. Note $\boldsymbol{Y}$ denotes the fault plane configuration vector in the physical domain, e.g. $\boldsymbol{Y}=\left(A R, x_{h}, z_{h}, a, \theta, x_{c}, z_{c}\right)^{T}$.


Figure 13. Prior (dashed black, derived from uniform $\boldsymbol{\zeta}$ distribution in $\boldsymbol{\Xi}$ ) and posterior (solid blue) distributions of physical fault plane configuration parameters in restricted inference. The bottom right panel shows the inferred fault plane configuration.


Figure 14. Restricted Bayesian MCMC sample chains of the hypocenter (top) and elliptical patch center (middle); the bottom panel shows the correspondence between $x_{h}$ and $x_{c}$ chains


Figure 15. Comparison of PC predicted PGV responses with aforementioned three inferred fault plane configurations with the reference GMPE curve. Dashed lines are standard deviation bounds of GMPE predictions.

Though it is not obvious to see from Figure 13, the restricted Bayesian MCMC process is indeed aware of the existence of the 'symmetric' counterpart configuration. Figure 14 shows the restricted Bayesian MCMC sample chains of both the hypocenter (top panel) and elliptical patch center (middle panel). It is seen that despite the fact the hypocenter samples are mostly clustered around $x_{h}=5 \mathrm{~km}$, there is a sample cloud on the opposite side ( $x_{h}=-5 \mathrm{~km}$ ), corresponding to the 'symmetric' counterpart configuration discussed before. The sample cloud of elliptical center also shows bi-modal distributions, with primary cloud on the left $\left(x_{c}<0\right)$ and secondary 'symmetric' counterpart on the right (around $x_{c}=5 \mathrm{~km}$ ). The correspondence between $x_{h}$ and $x_{c}$ is shown in the bottom panel of Figure 14 , from which it is seen that when $x_{h}$ is positive, $x_{c}$ is more likely to be negative and vice versa, suggesting that hypocenter and ellipse center are in the opposite side of the fault plane, as previous inference results suggested. Note that in this restricted Bayesian MCMC sampling, the total number of samples remains $10^{6}$. The ability to observe the 'symmetric' counterpart clouds is probably due to the fact that by introducing the auxiliary parameter $\boldsymbol{\zeta}$, we dramatically shrunk the sampling space (it is only a small subspace of the original unrestricted parameter space). As mentioned before, introducing the auxiliary parameter $\boldsymbol{\zeta}$ leads to significant efficiency improvement in MCMC sampling process.

Table 3. Comparison of PC predicted PGVs of different inferred configurations with the reference GMPE curve. Unrestricted-1 and 2 correspond to inferences in Figure 10 and Figure 11, respectively.

| Inference | $\epsilon=\sqrt{\frac{\sum_{j=1}^{N_{o b s}\left(\tilde{\mathcal{Q}}_{j}-\mathcal{Q}_{j}^{G M P E}\right)^{2}}}{N_{o b s}}}$ | $r=\sqrt{\frac{1}{N_{o b s}} \sum_{j=1}^{N_{o b s}}\left(\frac{\tilde{\mathcal{Q}}_{j}-\mathcal{Q}_{j}^{G M P E}}{\mathcal{Q}_{j}^{G M P E}}\right)^{2}}$ |
| :--- | ---: | ---: |
| Unrestricted-1 (blue) | 1.1135 | 0.3395 |
| Unrestricted-2 (red) | 1.7413 | 0.3993 |
| Restrict (green) | 1.4564 | 0.3702 |

### 4.4 Comparing PGVs

We summarize the Bayesian analysis by comparing PC predicted PGV responses to the three inferred fault plane configurations discussed above with the reference GMPE curve (see Figure 15 and Table 3). We observe that all three configurations lead to relatively close match between PGV responses-PC predictions and the reference GMPE curve. By comparing either the root- mean-square (rms) error or the relative rms error (see Table 3), we conclude that the red dots (corresponding to the unrestricted inference in Figure 11) clearly show larger discrepancy from the GMPE curve, suggesting smaller likelihood compared to the other two, consistent with our Bayesian analysis. When comparing the blue and green dots (unrestricted inference in Figure 10 versus restricted inference in Figure 13), the former seems to be slightly better, which is expected because of the additional flexibility in fitting the GMPE curve. Nevertheless, it might be better to report the restricted inference results (configuration in Figure 13), as it satisfies all the restrictions learned from previous studies while retaining plausible agreement with the reference GMPE curve.

## 5 Conclusions

An earthquake rupture model was adopted to explore the stochastic dependence of ground motions (in terms of PGVs) on random fault plane configurations. Thanks to the ability to generate two independent source model simulation ensembles with 8000 members each, we were able to build successful PC surrogate models to assess PGV responses over the virtual network of $N_{o b s}=56$ stations from one ensemble, and then to validate the quality of PC models on the other. Our statistical analysis showed that the two 8000-member LHS ensembles of source model simulations are adequate to represent the underlying PGV distributions at all stations, as they closely match with PC predicted distributions over a much larger sample set.

A global sensitivity analysis of PC surrogate models was conducted. The analysis revealed that the source model PGV response is primarily sensitive to the hypocenter location, and much less sensitive to properties of the asperity patch, especially at stations far away from the fault plane (in terms of the $R_{J B}$ distance). While this holds true for all stations, it is noted that asperity patch properties still carry considerable impact ( $20-30 \%$ associated variability) on PGV responses at stations close to the fault plane, and even more influence (additional $10 \%$ variability) if one takes into consideration the interaction between asperity patch and hypocenter location.

Our analysis of PGV variabilities indicated that one needs to be cautious when interpreting PGVs at near fault plane stations, as they are more prone to higher model noise. This is supported by the Bayesian inference analysis, in which four independent model noise parameters ( $\sigma_{l}^{2}$ for $l=1,2,3,4$ ) were introduced and assigned to four eoneentric groups of observational stations, depending on their $R_{J B}$ distances away from the fault plane. The Bayesian inference results clearly showed the decreasing trend of noise parameters ( $\sigma_{l}^{2}$ 's) when moving away from the fault plane (see Figure 9). Further refinement of the noise parameter profile along the $R_{J B}$ distance, though desired, is prohibited by the limited number of available observational stations.

We conducted both unrestricted and restricted Bayesian inference analyses to identify the chosen GMPE reference curve. The key findings are as follows: 1) due Given the station distribution (Figure 2) in this study, it is more likely to have the ere the hypocenter location influence and in return increase the impact of asperity properties. Another potential improvement can be made by refining the station network. As mentioned earlier, the Bayesian inference is primarily limited by the number of available stations at which PGVs are reported. By increasing the number of PGV reporting stations, one may improve the Bayesian inference results (e.g. removing the ambiguity in inferring the elliptical patch location).

Code and data availability. The COMPSYN code (Spudich and Xu, 2003) employed in this study, along with the simulation data are available upon request, and will be made available in the near future on a dedicated site/repository.

## Appendix A: Mapping from PC Random Parameters to Physical Parameters

Let $a$ and $b$ be the lengths of semi-major and minor axes, respectively, of the elliptical patch considered in the fault plane configuration discussed in Section 2, and $A R$ be the area aspect ratio defined by $A R=\frac{\pi a b}{L W}$ (here $L=27 \mathrm{~km}$ and $W=10 \mathrm{~km}$ are the length and width of the fault plane). The elliptical patch centered at the origin ( $x_{c}=0$ and $z_{c}=0$, note the $z$-axis is expressed as.
$\left[\begin{array}{l}x \\ z\end{array}\right]=\left[\begin{array}{c}a \cos \beta \\ b \sin \beta\end{array}\right]$ where $-\pi \leq \beta \leq \pi$
If the elliptical patch is rotated by $\theta \in\left[-30^{\circ},+30^{\circ}\right]$ (a positive angle denotes clockwise rotation), then the ellipse is given by:
$\left[\begin{array}{l}x^{r} \\ z^{r}\end{array}\right]=\left[\begin{array}{cc}\cos \theta & -\sin \theta \\ \sin \theta & \cos \theta\end{array}\right]\left[\begin{array}{l}x \\ z\end{array}\right]=\left[\begin{array}{cc}\cos \theta & -\sin \theta \\ \sin \theta & \cos \theta\end{array}\right]\left[\begin{array}{c}a \cos \beta \\ b \sin \beta\end{array}\right]=\left[\begin{array}{l}a \cos \theta \cos \beta-b \sin \theta \sin \beta \\ a \sin \theta \cos \beta+b \cos \theta \sin \beta\end{array}\right]$
To ensure the resulting elliptical patch is completely confined within the fault plane, we first find the maximum extent of the ellipse in both x - and y -directions. We first calculate the following two $\beta^{*}$ 's,
$\frac{\partial x^{r}}{\partial \beta}=-a \cos \theta \sin \beta-b \sin \theta \cos \beta=0 \Rightarrow \beta_{x}^{*}=\tan ^{-1}\left(-\frac{b}{a} \tan \theta\right)$
$\frac{\partial z^{r}}{\partial \beta}=-a \sin \theta \sin \beta+b \cos \theta \cos \beta=0 \Rightarrow \beta_{z}^{*}=\tan ^{-1}\left(\frac{b}{a} \frac{1}{\tan \theta}\right)$

Next, by substitute the above $\beta_{x}^{*}$ and $\beta_{z}^{*}$ into Equation (A2), we have
$x_{\text {max }}^{r}=\left|a \cos \theta \cos \beta_{x}^{*}-b \sin \theta \sin \beta_{x}^{*}\right|$
$z_{\max }^{r}=\left|a \sin \theta \cos \beta_{z}^{*}+b \cos \theta \sin \beta_{z}^{*}\right|$

These are the maximum extents of the ellipse in $x$ - and $y$-directions, respectively.
When the ellipse is not centered at the origin ( $x_{c} \neq 0$ and/or $z_{c} \neq 0$ ), the following conditions need to be satisfied.

$$
\begin{align*}
\left|x_{c}\right|+x_{\max }^{r} & \leq \frac{L}{2} \\
\left|z_{c}\right|+z_{\max }^{r} & \leq \frac{W}{2} \tag{A5}
\end{align*}
$$

which leads to:
$\left|x_{c}\right| \in\left[0, \frac{L}{2}-x_{\text {max }}^{r}\right]$
$\left|z_{c}\right| \in\left[0, \frac{W}{2}-z_{\text {max }}^{r}\right]$

Note the above constraint on $x_{c}$ is always valid, since $x_{\max }^{r} \leq a \leq \frac{L}{2}$; while the $z_{c}$ constraint requires more treatment as $z_{\text {max }}^{r}$ can be greater than $\frac{W}{2}$ under some rotation angle $\theta$ and semi-major axis $a$. To ensure that $z_{\max }^{r} \leq \frac{W}{2}$, we first check if the prescribed upper bound rotation $\left(30^{\circ}\right)$ is feasible. If not, we solve the following equation for $\theta^{*}$, which corresponding to the maximum feasible rotation angle given $a$ and $A R$.

$$
\begin{equation*}
z_{\text {max }}^{r}=\left|a \operatorname{asin} \sin \theta^{*} \cos \cos \beta_{z}^{*}\left(\theta^{*}, a, A R\right)+b \cos \cos \theta^{*} \sin \sin \beta_{z}^{*}\left(\theta^{*}, a, A R\right)\right|=\frac{W}{2} \tag{A7}
\end{equation*}
$$

and define the upper bound of the rotation angle as
$\hat{\theta}=\min \left(\theta^{*}(P E, a), 30^{\circ}\right)$
5 The resulting rotation angle parameter $\theta$ is then assumed to be uniformly distributed over $[-\hat{\theta}, \hat{\theta}]$.
The mapping from $\boldsymbol{\xi}$ to physical parameters is outlined in the Algorithm 1. With the prior assumption of uniform distribution of $\boldsymbol{\xi}$ in $\boldsymbol{\Xi}$, the corresponding prior distributions of each physical parameter are show in Figure 10 (dashed black curves).

```
Algorithm 1 Unrestricted mapping - PC random parameter \(\boldsymbol{\xi}\) to physical parameters: \(\boldsymbol{Y}=\mathcal{M}_{1}(\boldsymbol{\xi})\)
    Input \(\forall \boldsymbol{\xi}=\left(\xi_{1}, \xi_{2}, \ldots, \xi_{7}\right)^{T} \in \boldsymbol{\Xi}\)
    \(A R=0.05+\frac{1}{2}\left(\xi_{1}+1\right)(0.29-0.05) \quad \quad\left\{\right.\) Map \(\xi_{1}\) to area ratio
    \(x_{h}=-\frac{L}{2}+\frac{1}{2}\left(\xi_{2}+1\right) L \quad\left\{\operatorname{Map}\left(\xi_{2}, \xi_{3}\right)\right.\) to hypocenter location \(\left.\left(x_{h}, z_{h}\right)\right\}\)
    \(z_{h}=-\frac{W}{2}+\frac{1}{2}\left(\xi_{3}+1\right) W\)
    \(a_{\text {min }}=\sqrt{\frac{A R \cdot L \cdot W}{\pi}} \quad\{\) Calculate the lower bound of \(a\) from \(A R\) above
    \(a=a_{\text {min }}+\frac{1}{2}\left(\xi_{4}+1\right)\left(\frac{L}{2}-a_{\text {min }}\right) \quad\left\{\right.\) Map \(\xi_{4}\) to \(a\), and calculate \(\left.b\right\}\)
    \(b=\frac{A R \cdot L \cdot W}{\pi a}\)
    if \(z_{\text {max }}^{r}\left(a, b, 30^{\circ}\right)>\frac{W}{2}\) then
        Solve Equation (A7) for \(\theta^{*}\)
        let \(\hat{\theta}=\theta^{*} \quad\) \{Calculate maximum feasible rotation angle \(\left.\hat{\theta}\right\}\)
    else
        let \(\hat{\theta}=30^{\circ} \quad\) \{Prescribe maximum feasible rotation angle otherwise \}
    end if
    \(\begin{array}{ll}\theta=-\hat{\theta}+\hat{\theta}\left(\xi_{5}+1\right) & \left.\text { \{Map } \xi_{5} \text { to rotation } \theta\right\}\end{array}\)
    Plug \((a, b, \theta)\) into Equation (A4) to calculate \(x_{\text {max }}^{r}\) and \(z_{\text {max }}^{r}\)
    \(x_{c} \in\left[x_{c}^{\min }, x_{c}^{\max }\right]=\left[-\frac{L}{2}+x_{\max }^{r}, \frac{L}{2}-x_{\text {max }}^{r}\right]\)
    \(z_{c} \in\left[z_{c}^{\min }, z_{c}^{\max }\right]=\left[-\frac{W}{2}+z_{\text {max }}^{r}, \frac{W}{2}-z_{\text {max }}^{r}\right]\)
    \(x_{c}=x_{c}^{\min }+\frac{1}{2}\left(\xi_{6}+1\right)\left(x_{c}^{\max }-x_{c}^{\text {min }}\right) \quad\) \{Map \(\left(\xi_{6}, \xi_{7}\right)\) to ellipse center \(\left.\left(x_{c}, z_{c}\right)\right\}\)
    \(z_{c}=z_{c}^{\text {min }}+\frac{1}{2}\left(\xi_{7}+1\right)\left(z_{c}^{\max }-z_{c}^{\text {min }}\right)\)
    return \(\boldsymbol{Y}=\left(A R, x_{h}, z_{h}, a, \theta, x_{c}, y_{c}\right)^{T}\)
        \{Return parameter vector in the physical domain \}
```


## Appendix B: Restricted Mapping

We introduce the auxiliary parameter vector $\boldsymbol{\zeta} \in \boldsymbol{\Xi}$, and design the following mapping process to generate fault plane configu-
ration samples that satisfy our prior configuration restrictions. For clarity, we list again the four restrictions below:

R-1. The elliptical patch is inside the dashed rectangle $\left(\left[L^{\prime}, W^{\prime}\right]=0.9 \times[L, W]\right)$ shown in Fig. 1;
R-2. The area of the elliptical patch $(A R)$ is between $15 \%$ and $29 \%$ of the fault plane area, i.e. $0.15<A R<0.29$;

R-3. The elliptical patch is not too elongated, i.e. $\frac{a}{b}<3$;
R-4. The hypocenter is located outside but near the elliptical patch, i.e. $x_{h}=\left(a+3 \zeta_{h_{1}}\right) \cos \left(2 \pi \zeta_{h_{2}}\right)$ and $z_{h}=\left(b+b \frac{3}{a} \zeta_{h_{1}}\right) \sin \left(2 \pi \zeta_{h_{2}}\right)$ $x_{h_{2}}=\left(a+3 \zeta_{h_{2}}\right) \cos \left(2 \pi \zeta_{h_{2}}\right)$ and $z_{h_{1}}=\left(b+b \frac{3}{a} \zeta_{h_{2}}\right) \sin \left(2 \pi \zeta_{h_{2}}\right) \forall\left(\zeta_{h_{1}}, \zeta_{h_{2}}\right) \in[0,1]^{2} ;$

The mapping process is similar to the one in Algorithm 1, with necessary modifications to satisfy the above conditions. We outline the constrained mapping in Algorithm 2. Note there is one additional condition needs to be verified, i.e. whether or not the hypocenter is inside the fault plane, as it is not guaranteed by the mapping process (this is also indicated in Figure 12).

Author contributions. In this study, Hugo Cruz-Jiménez and Paul Martin Mai created the earthquake rupture model, and generated both the training and validation ensembles of model simulations for building PC surrogates. The PC based statistical analysis and Bayesian inference were conducted by Guotu Li, and Omar M. Knio. Ibrahim Hoteit provided invaluable insights and advice throughout this work.

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```
Algorithm 2 Restricted mapping - auxiliary parameter vector \(\boldsymbol{\zeta}\) to physical parameters: \(\boldsymbol{Y}=\mathcal{M}_{2}(\boldsymbol{\zeta})\)
    Input \(\forall \boldsymbol{\zeta}=\left(\zeta_{1}, \zeta_{2}, \ldots, \zeta_{7}\right)^{T} \in \boldsymbol{\Xi}\)
    \(\left[L^{\prime}, W^{\prime}\right]=0.9 \times[L, W]\)
    \(\left[A R_{l}^{*}, A R_{u}^{*}\right]=\left[\frac{0.15}{0.81}, 0.29\right]\)
    \(A R^{*}=A R_{l}+\frac{1}{2}\left(\zeta_{1}+1\right)\left(A R_{u}^{*}-A R_{l}^{*}\right)\)
    \{Calculate area ratio range w.r.t \(\left[L^{\prime}, W^{\prime}\right]\), the upper bound \((0.29)\) corresponds to the
    maximum circle in \(\left[L^{\prime}, W^{\prime}\right]\)
    \{Map \(\zeta_{1}\) to temporary area ratio \(A R^{*}\) \}
    \(a_{\text {min }}=\sqrt{\frac{A R^{*} \cdot L^{\prime} \cdot W^{\prime}}{\pi}}\)
\{Calculate the lower bound of \(a\) from \(A R^{*}\) \}
    \(a=a_{m i n}+\frac{1}{2}\left(\zeta_{4}+1\right)\left(\frac{L^{\prime}}{2}-a_{m i n}\right)\)
                            \(\left\{\operatorname{Map} \zeta_{4}\right.\) to \(a\), and calculate \(\left.b\right\}\)
    \(b=\frac{A R^{*} \cdot L^{\prime} \cdot W^{\prime}}{\pi a}\)
    \(A R=\frac{\pi a b}{L \cdot W}\)
                                    \{Calculate area ratio w.r.t the original rectangle \([L, W]\) \}
    \(x_{h}=\left(a+3 \frac{\zeta_{2}+1}{2}\right) \cos \left(2 \pi \frac{\zeta_{3}+1}{2}\right) x_{h}=\left(a+3 \frac{\zeta_{2}+1}{2}\right) \cos \left(2 \pi \frac{\zeta_{3}+1}{2 \sim} 2\right.\)
    \(z_{h}=\left(b+b \frac{3}{a} \frac{\zeta_{2}+1}{2}\right) \sin \left(2 \pi \frac{\zeta_{2}+1}{2}\right) z_{h}=\left(b+b \frac{3}{2} \frac{\zeta_{2}+1}{2}\right) \sin \left(2 \pi \frac{\zeta_{2}+1}{2}\right)\left\{\operatorname{Map}\left(\zeta_{2}, \zeta_{3}\right)\right.\) to hypocenter location \(\left(x_{h}, z_{h}\right)\), note the resulting \(\left(x_{h}, z_{h}\right)\) can
                                    be outside the fault plane, in which case the posterior probability is set to zero.
    if \(z_{\text {max }}^{r}\left(a, b, 30^{\circ}\right)>\frac{W^{\prime}}{2}\) then
        Solve Equation (A7) for \(\theta^{*}\) (using \(A R^{*}\) )
        \(\{\) Calculate maximum feasible rotation angle \(\hat{\theta}\) \}
        let \(\hat{\theta}=\theta^{*}\)
    else
        let \(\hat{\theta}=30^{\circ}\)
                            \{Prescribe maximum feasible rotation angle otherwise\}
    end if
    \(\theta=-\hat{\theta}+\hat{\theta}\left(\zeta_{5}+1\right)\)
                                    \(\left\{\operatorname{Map} \zeta_{5}\right.\) to rotation \(\left.\theta\right\}\)
    Plug \((a, b, \theta)\) into Equation (A4) to calculate \(x_{\text {max }}^{r}\) and \(z_{\text {max }}^{r}\)
    \(x_{c} \in\left[x_{c}^{\text {min }}, x_{c}^{\text {max }}\right]=\left[-\frac{L^{\prime}}{2}+x_{\text {max }}^{r}, \frac{L^{\prime}}{2}-x_{\text {max }}^{r}\right]\)
    \(z_{c} \in\left[z_{c}^{\text {min }}, z_{c}^{\max }\right]=\left[-\frac{W^{\prime}}{2}+z_{\text {max }}^{r}, \frac{W^{\prime}}{2}-z_{\text {max }}^{r}\right]\)
    \(x_{c}=x_{c}^{\min }+\frac{1}{2}\left(\zeta_{6}+1\right)\left(x_{c}^{\max }-x_{c}^{\min }\right) \quad\left\{\operatorname{Map}\left(\xi_{6}, \xi_{7}\right)\right.\) to ellipse center \(\left.\left(x_{c}, z_{c}\right)\right\}\)
    \(z_{c}=z_{c}^{\text {min }}+\frac{1}{2}\left(\zeta_{7}+1\right)\left(z_{c}^{\text {max }}-z_{c}^{\text {min }}\right)\)
    return \(\boldsymbol{Y}=\left(A R, x_{h}, z_{h}, a, \theta, x_{c}, y_{c}\right)^{T}\)
        \{Return parameter vector in the physical domain \}
```


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[^0]:    ${ }^{1}$ The Joyner-Boore distance is defined as the shortest distance from a site to the surface projection of the rupture plane.

[^1]:    ${ }^{2}$ An open source toolkit for the PC framework is available at http://www.sandia.gov/UQToolkit/ (Debusschere et al., 2004, 2016)

[^2]:    ${ }^{3}$ The corresponding source code is available at https://github.com/mpf/spgl1

[^3]:    ${ }^{4}$ The interested reader is referred to Mai (2009), http://www.opensha.org/glossary-attenuationRelation-BOOREATKIN_2008 and http://www.gmpe.org.uk/gmpereport2014.pdf for more details on the GMPE employed in this paper.

