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Spatial correlation analysis of CyberShake simulations, considering multiple ruptures

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ABSTRACT

This paper studies the correlation of mixed-source data from CyberShake simulations. A subset of the rupture catalog is selected, and ground motion residuals are combined to investigate the correlations from mixed sources. The average correlation for all stations and sources is consistent with a reference empirical model. However, the variation of correlations from different sources for a pair of stations depends on their distances and geological conditions. A network analysis algorithm is applied to detect patterns for correlations from mixed sources. The detected communities show similar geological conditions and commonality of selected rupture geometry, but the difference between community correlations is less significant than the single-source result. It suggests that the mixed-source data tend to average out the non-stationary influence of source and path effects from a single rupture, which leads to a nearly stationary correlation.

Introduction

Earthquake shaking intensity varies spatially. Ground motion residuals (the difference between an observed intensity measure and the prediction) are correlated at nearby sites, and influence the risk of infrastructure systems (Baker et al., 2021). Current correlation models use observed ground motions and assume that these correlations depend mainly on separation distance (e.g., Boore et al., 2003; Wang and Takada, 2005; Goda and Hong, 2008; Jayaram and Baker, 2009; Goda and Atkinson, 2010; Esposito and Iervolino, 2011; Foulser-Piggott and Stafford, 2012; Loth and Baker, 2013; Markhvida et al., 2018; Heresi and Miranda, 2019). Recent research has investigated the variations of correlations with rupture geometry and site conditions using simulations (Chen and Baker, 2019) or densely recorded ground motion data (Chen et al., 2021). However, different characteristics of correlations are observed from simulated and instrumental data. It is anticipated that this is caused by the difference in data aggregation: simulation data are from a fixed rupture source, while the instrumental data comes from multiple sources.

This paper collects a mixed-source data set from the CyberShake platform, and studies correlations to bridge between the correlation characteristics of simulated and instrumental ground motions. We first select a rupture catalog and estimate site-specific correlations from mixed sources. A correlation deviation graph is constructed, and community detection is conducted to detect patterns in correlations.

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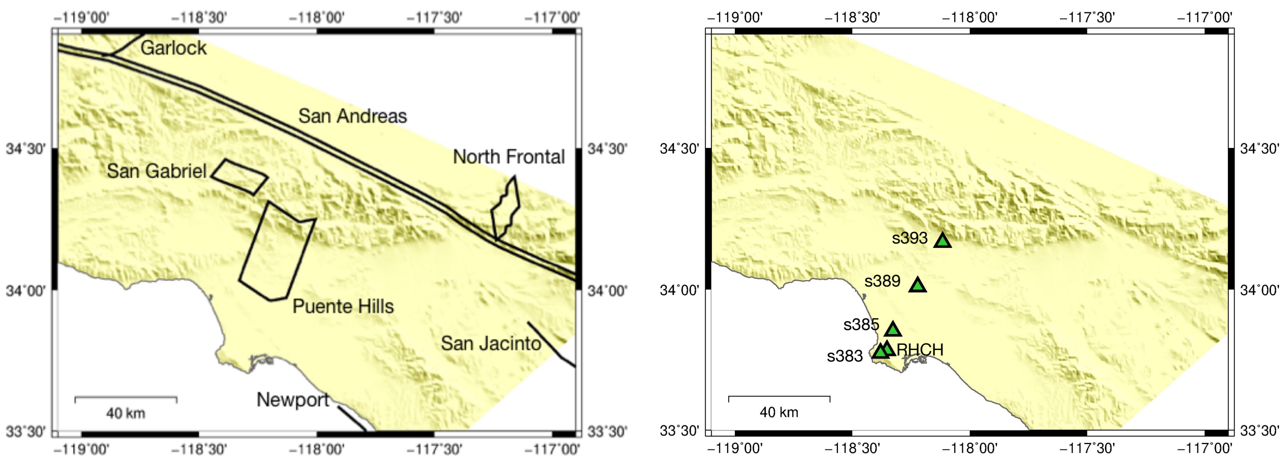
Detecting highly correlated regions

Our analysis approach first estimates site-specific correlations for all pairs of stations. We compute a site-specific correlation for a pair of stations (j,k) using the within-event residuals from all earthquake simulations. We use a correlation deviation graph to detect highly correlated regions, where nodes are stations, and edges describe their correlation deviation. For a pair of stations (j,k), we use the correlation deviation as their edge weight A_{jk} in a graph:

$$A_{jk} = \left[Z\left(\hat{\rho}(j,k)\right) - Z\left(\rho(j,k)\right)\right] \times \sqrt{(n-3)} \tag{2}$$

where $\rho(j,k)$ is the correlation coefficient predicted from a reference correlation model, and $Z(x)$ is the Fisher transformation. A_{jk} quantifies the correlation deviation of a pair of stations relative to an empirical model. A positive A_{jk} indicates that stations (j,k) are higher correlated than the empirical model prediction and vice versa. Highly correlated regions groups of stations with positive edge weights are maximized within the group. We use the signed spectral clustering community detection algorithm on the graph (Chen and Baker, 2021) to find such groups.



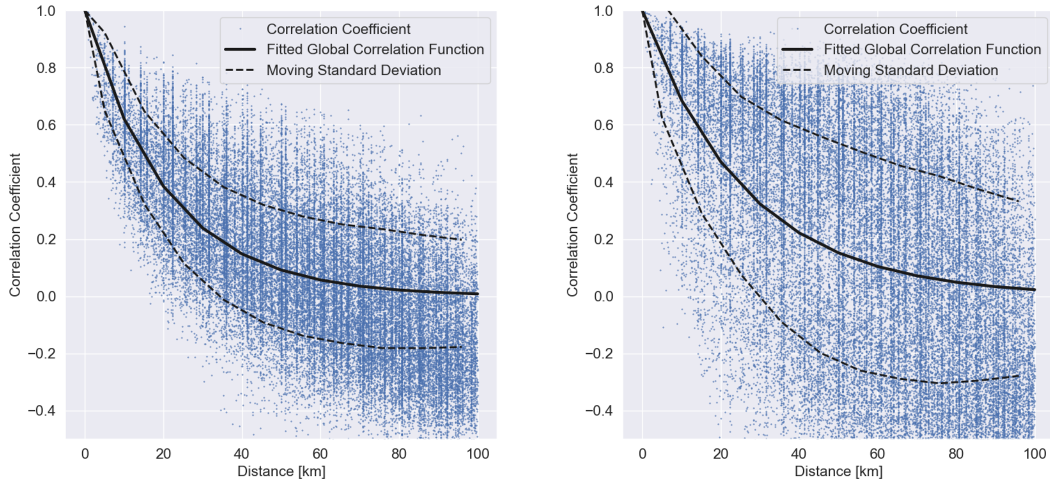
(a) (b)

Figure 1: a) Locations of the ruptures and their surface projections (shown with black lines) for this study. b) Locations of five example stations for this study.

Results

We selected seven ruptures from the CyberShake platform, ranging in magnitude from 6.5 to 8.1 (Figure 1a), and collected a total of 611 realizations from these ruptures. These ruptures were selected because they are relatively close to the region, and thus have sufficient recordings at each station. We calculate the residuals of spectral acceleration (SA) at a period of $T = 3s$ using the method described in Chen and Baker (2019), and select the stations with the ground motions from all seven ruptures (333 total stations).

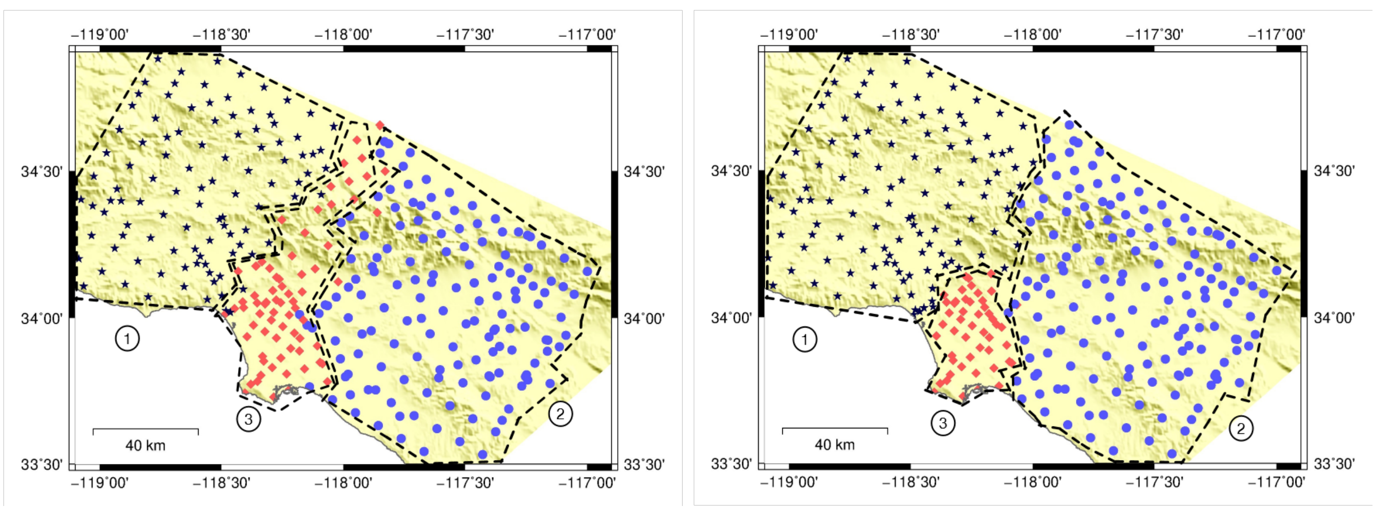
We use the community detection method to detect patterns from all pairwise correlations. To assure that all ruptures have equal influence on the estimated correlations, we select ten simulations from each rupture and combine them as the mixed-source data set. Then we estimate the site-specific correlations and construct the corresponding correlation deviation graph using this data set. Figure 2a shows the calculated correlation coefficients for all pairs of stations plotted versus separation distance. Compared with comparable results from only the Puente Hills rupture (Figure 2b), the variation for mixed sources is much lower. This is expected, as the mixed sources average out the non-stationary influence of source and path effects from a single rupture.



(a) (b)

Figure 2: Correlation coefficients of all pairs of stations from (a) the mixed-source data set (b) single-source Puente Hills data set.

Figure 3a shows the community detection results for the correlation deviation graph obtained from spectral clustering. The detected communities are approximately consistent with the communities detected for the Puente Hills case (Figure 3b). However, in Figure 3a, the basin community (Community 3) extends towards the northwest. This could be caused by average wave propagation path effects from different ruptures. Figure 4a shows the refitted correlation models for stations within and across communities from the mixed-source data. Compared with Figure 4b, the difference between community correlations is less significant. This again suggests that the mix of individual sources leads to more stationary correlation.



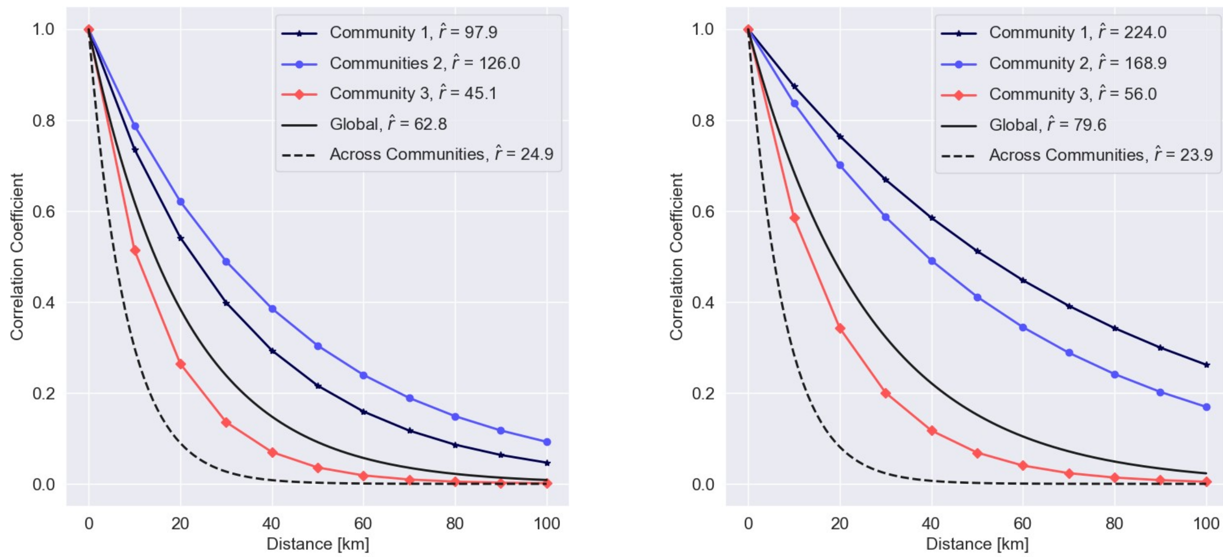
(a) (b)

Figure 3: Detected communities using the correlation deviation graph and spectral clustering from (a) the mixed-source data set (b) single-source Puente Hills data set. Nodes of different communities are shown in different symbols. Dashed lines and numbers show the major communities.

Discussion and conclusions

We studied the correlations from mixed-source CyberShake simulation data and qualitatively compared the correlations with the single-source examples. The correlations estimated from the mixed sources show a lower level of non-stationarity, as the influence of source and path effects tends to average out among ruptures.

However, higher correlations persist in some regions, showing effects from similar geological conditions and commonality of selected rupture geometry.



(a) (b)

Figure 4: Correlation models for different communities from (a) the mixed-source data set (b) single-source Puente Hills data set. Community numbers refer to the communities in Figure 3. The global model is from Figure 2 and the Across Communities model is fit to all pairs of stations that belong to different communities. $r\hat{}$ is the fitted range parameter for an exponential model (Baker and Chen, 2020).

The results here provide insights regarding the limitations of current correlation models. The data sets used to calibrate a correlation model are aggregated from multiple earthquake sources (e.g., Goda and Hong, 2008; Jayaram and Baker, 2009). This aggregation might fundamentally limit the ability to detect any systematic non-stationary effects. Alternatively, some correlation models are calibrated from data of a single source (e.g., Boore et al., 2003). However, single-source data only has one recording per location, and therefore uses an over-simplified model (e.g., semivariogram) to accommodate the lack of repetitive recordings. This also limits the ability to infer any source-specific non-stationary correlation effects. Although source-specific effects might be represented by varying model parameters of different sources (e.g., Wang and Takada, 2005; Heresi and Miranda, 2019), the uncertainty in model parameter estimation could make this hard to examine (Baker and Chen, 2020).

Since the size of empirical ground motion data is unlikely to grow rapidly in the near future, it is challenging to calibrate empirically derived correlation models with refined stationarity assumptions. The results here point towards a path for how to improve future correlation models: Numerical simulations of ground motions have advantages for developing region-specific and source-specific correlation models. Additionally, dense seismic network instruments also help to detect region-specific correlation effects and can be used to validate the correlations from simulations.

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