IMPLICATIONS OF CALIFORNIA VERTICAL ARRAY DATA FOR MODELING OF NON-ERGODIC SITE RESPONSE

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Abstract

One-dimensional (1D) ground response analyses are often used with an expectation that they provide an unbiased estimation of site effects, and therefore improve upon site response estimates from ergodic models (i.e. site terms in ground motion models, GMMs). We use California vertical array data to (1) investigate the degree to which 1D analysis provides results compatible with observation, thus checking the typical assumption, and (2) quantify epistemic uncertainty in site response estimates from ground response analysis. Objective (1) was discussed in a previous CSMIP conference paper and a brief update is provided here. We present our methodology and preliminary results for quantifying epistemic uncertainty in site response as estimated from 1D analysis. We decompose prediction residuals into between- and within-site components, and take the between-site standard deviation as a quantification of epistemic uncertainty. Preliminary results suggest values ranging from 0.35-0.5 in natural log units.

Introduction

One-dimensional (1D) ground response analysis (GRA) uses the simulation of shear waves traveling vertically through shallow geological structures to predict the effects of site response on ground motion. The simulations are based on the layering and parameters specific to the site of interest (e.g. shear-wave velocity, modulus reduction, and damping parameters), and this method is being frequently used for predicting the effects of site response for critical projects. For simulating the behavior of the soil in 1D GRA, several approaches are available including linear, equivalent-linear (EL), and nonlinear (NL) methods, the relative benefits of which are discussed elsewhere (Kaklamanos et al, 2013, 2015; Kim et al., 2016; Zalachoris and Rathje, 2015).

When GRA are performed for engineering projects, it is usually with the expectation that they provide an unbiased, site-specific estimate of site response. The site response computed in this manner can be interpreted in the form of a site-specific amplification function, which in turn can be implemented in probabilistic seismic hazard analyses (PSHA) (e.g., McGuire et al., 2001; Stewart et al. 2014). If the ground response computed in this manner accurately reflects the primary physical mechanisms controlling site response, it provides the basis for a non-ergodic hazard analysis, which has appreciable benefits with regard to standard deviation and hazard reduction (e.g., Stewart, 2016).

The essential question in this process is whether GRA are indeed effective at predicting site response. While numerous studies of data from vertical arrays at individual sites have found reasonably good fits to GRA results (e.g., Borja et al., 1999; Elgamal et al., 2001; Lee et al., 2006; Tsai and Hashash, 2009; Yee et al., 2013; Kaklamanos et al. 2015), another study that systematically examined a broad set of such arrays in Japan (KiK-net array; Aoi et al., 2000) found misfits for about 80% of the investigated sites (Thompson et al. 2012). California vertical array data provides an opportunity to further examine this issue for local geological conditions, which differ from those at KiK-net sites (Boore et al. 2011).

Preliminary results from the California vertical array sites were presented by Afshari and Stewart (2015). Those results indicated that the observed site response was reasonably well matched by GRA at some sites (less than 50%). Some additional sites have been investigated since that time as discussed in the next section below, although the basic conclusion has not appreciably changed.

In this paper, we seek to quantify uncertainty in the prediction of site response as estimated from GRA. This is of interest for PSHA in which site terms are taken from the results of GRA, in which case epistemic uncertainties in the site response should be considered using a logic tree (or similar) framework (Bommer et al. 2005). We present a methodology for quantifying these uncertainties, present results as derived from the California data, and compare to comparable results obtained previously for KiK-net sites (Kaklamanos et al., 2013).

Validation of 1D GRA Using California Vertical Array Sites

This paper is an extension of a previous study (Afshari and Stewart, 2015) on the effectiveness of 1D GRA at predicting site response in vertical arrays in California. In the previous study, we described how we used 228 surface/downhole recordings from 10 vertical array sites to compute empirical transfer functions (ETFs), and used linear 1D GRA using the program Deepsoil (Hashash et al., 2016) to compute theoretical transfer functions (TTFs). Thompson et al. (2012) used the Pearson's sample correlation coefficient (r) between ETF and TTF to represent the goodness of fit between the predictions and the observed site response; a value of r=0.6 was taken by Thompson et al. (2012) as the threshold for good fit. We used the same approach to quantify the goodness of fit of transfer functions, which facilitates comparisons between the two regions.

We have also studied alternative damping models for estimating material damping in linear GRA: (1) laboratory-based models (Darendeli, 2001 for clayey soils and Menq, 2003 for granular soils); (2) adjustments to the damping from (1) so that diminutive parameter κ_0 for the soil profile matches target values (Van Houtte et al. 2011); and (3) estimating damping from quality factor (Q_{ef}) as provided by Campbell (2009). Details of each approach are given by Afshari and Stewart (2015). Application in GRA showed under-prediction of damping from (1), over-prediction from (2), and a relatively unbiased prediction from (3).

Figure 1 shows example results for two sites. The Eureka site shows a case in which site response, expressed in the form of smoothed transfer functions, is reasonably well predicted by GRA. The San Bernardino site is an example of poor fit. Of the 12 sites examined to date, qualitatively 4 (33%) can be considered as having a reasonably good fit, as established from fitting criteria described in Thompson et al. (2012) and Afshari and Stewart (2015).

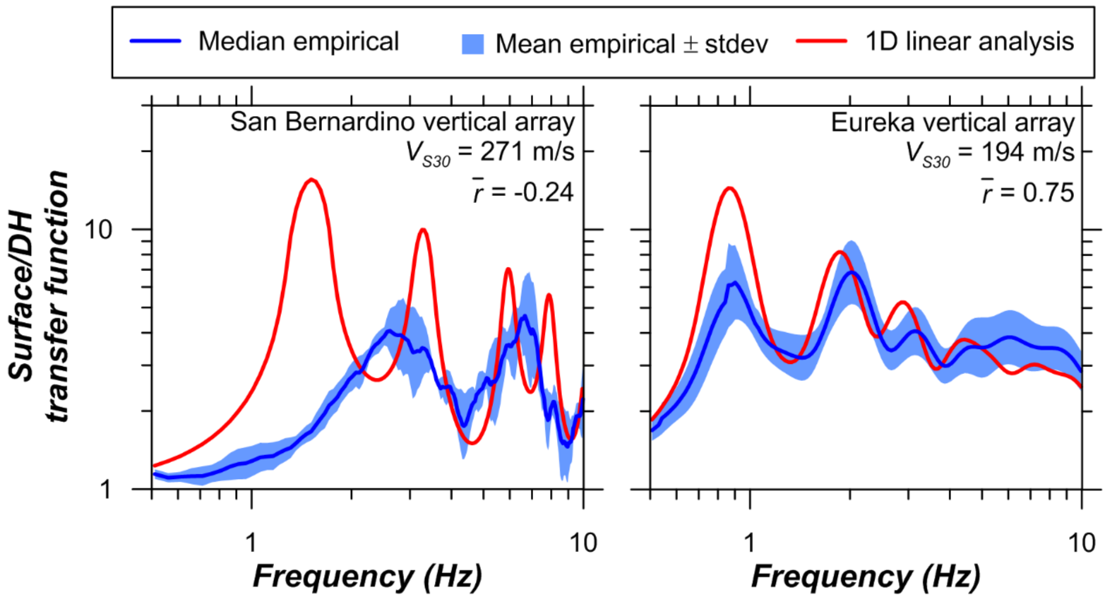

Figure 1. Surface to downhole transfer functions as observed from vertical array data and inferred from 1D analysis for the San Bernardino (poor fit) and Eureka (good fit) sites.

Quantifying Epistemic Uncertainty of GRA Predictions

Our analysis of epistemic uncertainty is based on comparing observations (in this case, the surface recordings at California vertical array sites) to predictions. The sites considered in this study are summarized in Table 1, which is expanded from the data inventory considered in Afshari and Stewart (2015) by two sites. The location of the 12 sites are shown in Figure 2.

Table 1. Summary of site characteristics for California vertical arrays considered in present study.

Station NO	Station Name	Owner	# Rec	Latitude	Longitude	V_{S30} (m/s)	V_S profile Depth (m)[2]	Depth of deepest instrument (m)	Site Period (sec)
68323	Benicia – Martinez Br S Geotech Array	CGS - CSMIP	10	38.033	-122.117	546	31	35	0.22
68206	Crockett – Carquinez Br Geotech Array #1	CGS - CSMIP	8	38.054	-122.225	345	43	45.7	0.34
1794	El Centro – Meloland Geotechnical Array	CGS - CSMIP	19	32.774	-115.449	182	240	195	1.41
89734	Eureka – Geotechnical Array	CGS - CSMIP	14	40.819	-124.166	194	225	136	1.15
24703	Los Angeles – La Cienega Geotech Array	CGS - CSMIP	20	34.036	-118.378	241	280	100	0.87

Station NO	Station Name	Owner	# Rec	Latitude	Longitude	V_{S30} (m/s)	V_S profile Depth (m) [2]	Depth of deepest instrument (m)	Site Period (sec)
24400	Los Angeles – Obregon Park	CGS - CSMIP	23	34.037	-118.178	449	64	69.5	0.54
23792	San Bernardino - I10/215 W Geotech Array	CGS - CSMIP	5	34.064	-117.298	271	92	35	0.64
68310	Vallejo – Hwy 37/Napa River E Geo. Array	CGS - CSMIP	17	38.122	-122.275	509	42	44.5	0.24
UCSB Arrays	Garner Valley Downhole Array	UCSB	10	33.401	-116.403	240	210	150	0.64
UCSB Arrays	Wildlife Liquefaction Array	UCSB	45	33.058	-115.318	203	98	100	1.41
UCSB Arrays	Borrego Valley Field Site	UCSB	21	33.259	-116.321	350	230	238	1.30
UCSB Arrays	Hollister Digital Array	UCSB	23	36.453	-121.365	359	185	192	0.85

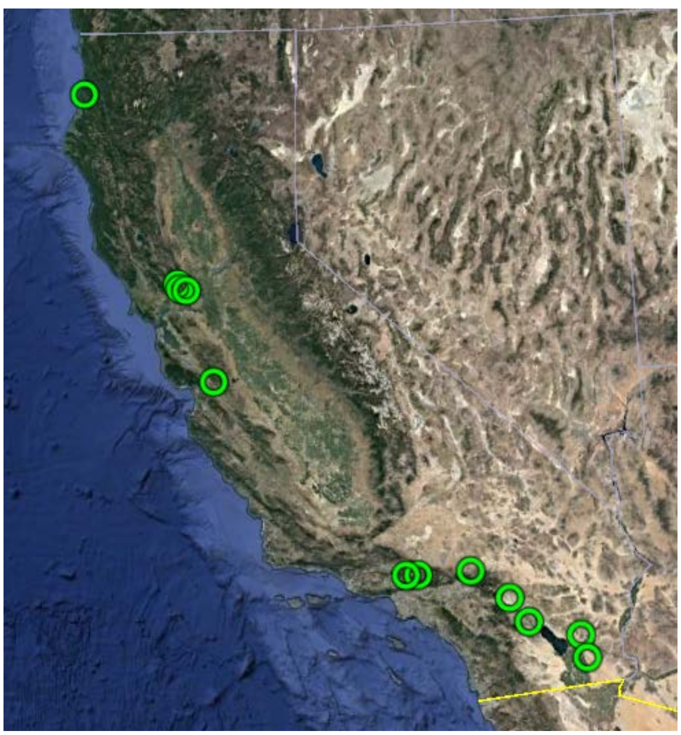

Figure 2. The location of vertical array sites in California used in this study on Google Earth.

As used here, *observations* are 5%-damped pseudo spectral accelerations (PSAs) of the horizontal recorded surface ground motions, rotated to the median single-component value across all non-redundant azimuths (Boore 2010). The observed value for event i, recording j, and site k is denoted Y_{jk} (we do not retain the event subscript).

Predictions are based on single-component 1D GRA for each horizontal component. The procedures followed for these analyses are as described in Afshari and Stewart (2015); for the present calculations we use the Campbell (2009) damping model (Model 1). The GRA are performed independently for the two components, and the resulting ground surface time series are analyzed to develop RotD50 spectra. The resulting PSAs are denoted P_{jk}.

We compute total residuals between the observed and predicted PSAs as follows:

$$R_{jk} = \ln\left(Y_{jk}\right) - \ln\left(P_{jk}\right) \tag{1}$$

Figure 3 shows an example of observed and predicted spectra and residuals for the Eureka Geotechnical Array site (2010 event with **M** 6.5, R_{epi}=48 km). The elastic period of the soil column from the base instrument to the surface is T_0=1.15 sec. For reasons that will be explained further below, it is important to note the lack of site effect for $T > \sim 2T_0$. In this period range, surface and downhole spectra are nearly identical as a result of quarter wavelengths that significantly exceed the profile dimension. The analysis provides a good estimate of observed ground motions for this site.

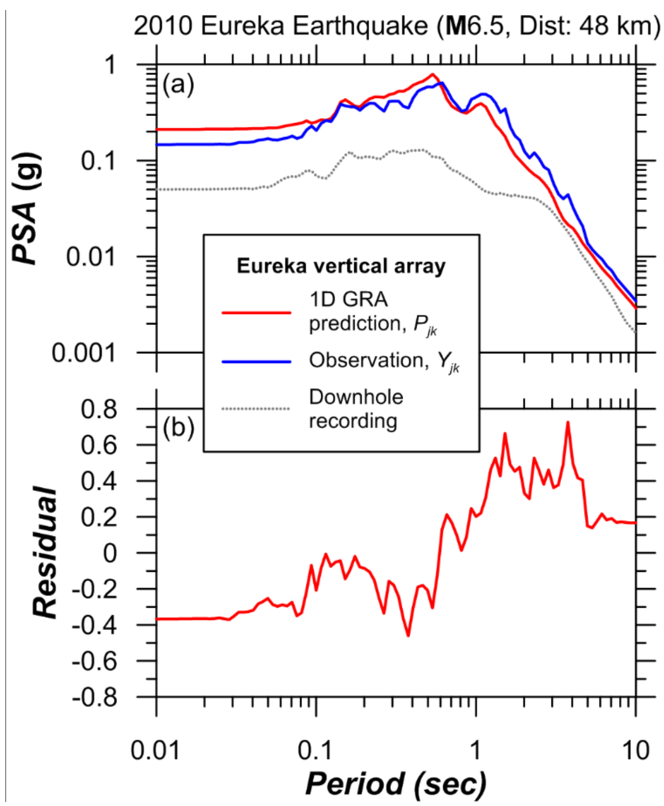

Figure 3. An example of (a) response spectrum plots of the downhole motion, surface recorded motion, and surface predicted motion at Eureka (**M**6.5 epicentral distance: 48 km); (b) The plot of residuals between observed and predicted ground motions.

We perform mixed-effects regression with the LME routine in program R (Pinheiro et al., 2013) to partition the residuals into multiple components:

$$R_{jk} = c_l + \eta_{S,k} + \varepsilon_{jk} \tag{2}$$

where c_l is the overall model bias; $\eta_{S,k}$ is the between-site residual (site term) for site k, which represents the average bias-adjusted deviation of data from the prediction for an individual site; and ε_{jk} is the within-site residual. The residual partitioning does not include an event term, as is typical in most ground motion studies. This is the case because input motions are known from the downhole recording, and those motions would implicitly include the event term.

The overall bias (c_l) is plotted in Figure 4. The relative flat trend and small values of c_l are an indicator that the linear 1D GRA models with damping estimated from Campbell (2009) (Model 1) are providing a relatively unbiased estimate of site response. This is consistent with our previous findings using 10 of the 12 sites from Table 1 (Afshari and Stewart 2015).

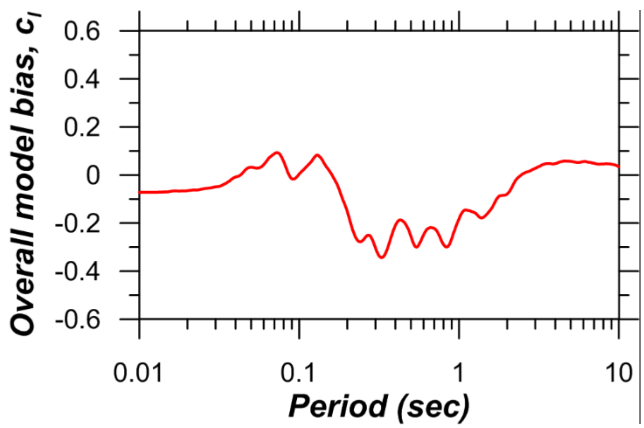

Figure 4. The overall bias (c_l) of GRA model for California vertical array sites in Table 1.

The term $\eta_{S,k}$ indicates misfit of GRA predictions for site k, with large absolute values of η_S indicating poor predictions of site response. Figure 5 shows two examples of η_S-T trends for good- and poor-fit sites (Eureka and San Bernardino, respectively).

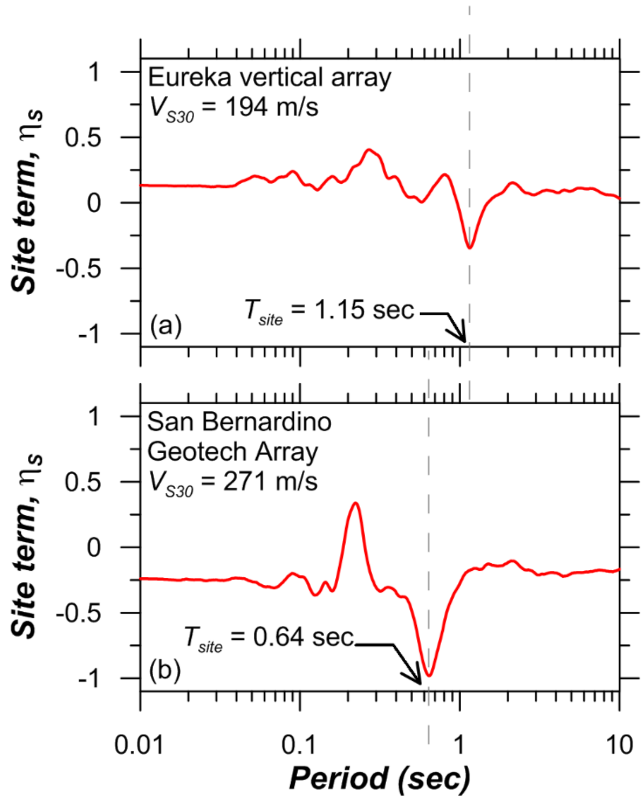

Figure 5. Plots of between-site residuals (η_S) for good-fit and poor-fit sites (Eureka and San Bernardino, respectively). Smaller values of η_S indicate better fit of model to observation.

Standard deviations of the partitioned residuals terms can be combined as follows:

$$\sigma_Y^2 = \tau_S^2 + \phi_{\ln Y}^2 \tag{3}$$

where σ_Y, τ_S, and ϕ_{lnY} are the standard deviations of R_{jk}, $\eta_{S,k}$, and ε_{jk}, respectively. We consider the epistemic uncertainty in GRA predictions to be quantified by τ_S, which represents site-to-site variability. In other words, the epistemic uncertainty regarding how well GRA is able to predict the effects of site response is quantified by τ_S. Term ϕ_{lnY} represents within-site variability in site amplification, which has been shown in prior work to be stable from ground motion array studies from active crustal regions world-wide (Kaklamanos et al. 2013, Rodriguez-Marek et al. 2011, and Lin et al. 2011).

Figure 6 shows our results for τ_S and ϕ_{lnY} along with a prior result based on KiK-net data by Kaklamanos et al. (2013). Also shown in the τ_S plot is the range of site periods among the considered California vertical array sites (0.22-1.41 sec, mean of 0.8 sec). Within the limits of the relatively small data set considered here, we postulate that the values of τ_S for $T < \sim 1.0$ sec comprise a reasonable, first-order estimate of epistemic uncertainty in site response as computed by GRA. Note that these numbers reflect site-response uncertainties only, because they are based on a condition in which input motions are known. Total epistemic uncertainties would be larger, as a result of uncertainties in input motions. We do not consider the τ_S results for $T > \sim 1.0$ sec to provide a valid representation of epistemic uncertainties, because most of the sites are beyond their site period in this range. At these long periods, the site response is controlled by features beyond the domain of the vertical arrays, which are reflected in both the downhole and surface recordings and accounts for the low values of τ_S in this range. As described by Stewart (2016), site response for these long periods should generally be taken from ergodic models, and the corresponding epistemic uncertainties are discussed elsewhere (e.g., Atkinson et al. 2014).

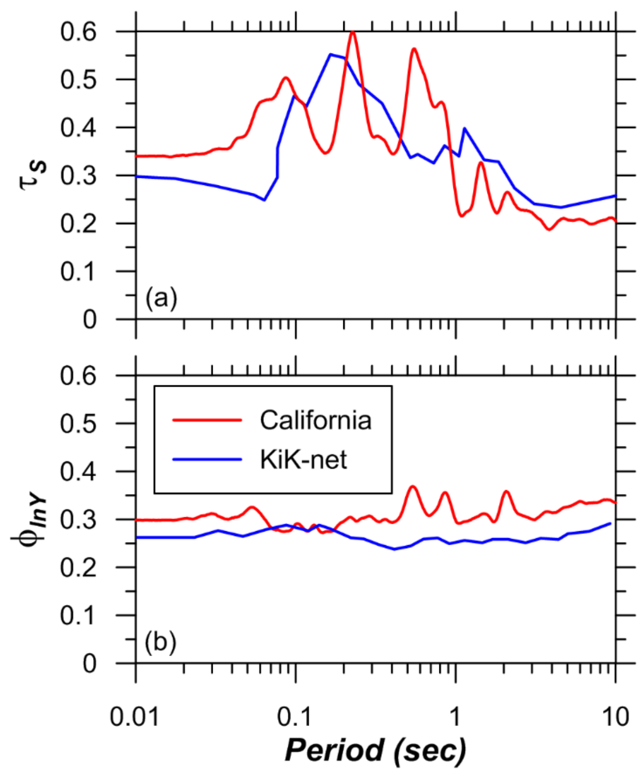

Figure 6. Plots of between-site standard deviation (τ_S) and within-site standard deviation (ϕ_{lnY}) for the sites considered in this study in California and KiK-net sites studied by Kaklamanos et al. (2013).

The results from the present study are similar to the prior results of Kaklamanos et al. (2013) for KiK-net sites. This result is expected for ϕ_{lnY}, but is somewhat surprising for τ_S. We expected larger values of τ_S for KiK-net sites because of the generally lower resolution of shear-wave velocity profiles and other geotechnical data.

Conclusions

California vertical array data indicate a mixed ability for 1D ground response analysis to match observed levels of site amplification. To some extent, this mirrors findings elsewhere from Japan (Thompson et al, 2012), although the percentage of sites for which site response is reasonably well matched is higher (33% in California, vs. 18% in Japan).

We describe a procedure based on partitioning of prediction residuals to quantify epistemic uncertainties in site response as estimated from 1D GRA. This is an important consideration when PSHA is to be performed using site-specific (non-ergodic) site terms as derived from GRA – for such cases epistemic uncertainties in site response should be considered as part of the logic tree. We find site-to-site variability that ranges from 0.35-0.5 for the period range for which GRA results are valid (up to approximately 1.0 sec for the California sites considered here). At longer period, these uncertainties revert to typical uncertainties for alternate GMMs, which are also appreciable.

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