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Los Angeles

HVSR Database and Application for Site Response Prediction in California

A dissertation submitted in partial satisfaction of the
requirements for the degree Doctor of Philosophy in Civil Engineering

by

Francisco Javier Gonzalez Ornelas

2026

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2026

ABSTRACT OF THE DISSERTATION

HVSR Database and Application for Site Response Prediction in California

by

Francisco Javier Gonzalez Ornelas

Doctor of Philosophy in Civil Engineering

University of California, Los Angeles, 2026

Professor Jonathan P. Stewart, Chair

Professor Scott J. Brandenberg, Co-Chair

Microtremor-based horizontal-to-vertical spectral ratios (mHVSR) are derived from Fourier Amplitude Spectra of ambient ground motions and can reveal site features such as resonances or lack thereof. Despite this promise, mHVSR curves have not previously found significant engineering application, likely because: (1) mHVSR data have not been available in sufficient quantities to support ground motion model development and (2) difficulties linking mHVSR

parameters to site response. This research addresses both needs by enhancing mHVSr data availability and developing mHVSr-conditioned site response models for California sites.

I extended and improved the available mHVSr data by temporarily deploying seismometers at sites of interest (often locations of permanent accelerometers) and downloading data from permanent broadband seismometers. At California vertical array sites, mHVSr curves were measured in expanding concentric circles and used to characterize spatial heterogeneity. In total, I added 1844 mHVSr curves from 1096 sites to a public database.

Low-frequency microtremor signals are often influenced by oceanic and atmospheric effects unrelated to site stratigraphy. Such ordinates can be large and sensitive to processing details, while also being important for sites in deep basins. I documented issues affecting low-frequency ordinates for certain sensor types, investigated their causes, and provided recommendations to improve data quality.

I propose a framework for developing parametric site response models conditioned on V_{S30} and mHVSr-derived parameters. This framework predicts common site response features, including resonant peaks, ascending or descending ramps (reflecting energetic response at the upper plateau), or flat responses relative to ergodic models. mHVSr parameters help predict which features are most likely and the attributes of those features. Machine learning models are also provided conditional on mHVSr attributes. Both parametric and machine learning models reduce site-to-site standard deviations by 0.1-0.2 natural log units at long periods, which is a substantial benefit.

Overall, results from this work highlight the value of mHVSR as a practical and informative site characterization tool. It also provides models that can be applied to improve the fidelity of site response modeling and reduce its associated uncertainties.

The dissertation of Francisco Javier Gonzalez Ornelas is approved.

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2026

To my wife and parents, thank you for always believing in me

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2. **Ornelas, FJG,** de la Torre, CA, Zhang, Z, Buckreis, TE, Brandenburg, SJ, and Stewart, JP (2026). Preliminary findings on the application of mHVSr for data-driven site response prediction in California. *GeoCongress 2026: Earthquake Engineering and Soil Dynamics*, Salt Lake City, UT, ASCE Geo-Institute, 10 pages
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1. O'Donnell, TM, Hudson, KS, **Ornelas, FJG,** Stewart, JP, Brandenburg, SJ, Nweke, CC, and Zimmaro, P (2024). Site characterization and liquefaction analysis at Searles Lake, CA following 2019 Ridgecrest Earthquake Sequence, *Report No. 2024-03*. UCLA Garrick Institute for the Risk Sciences.

1 Introduction

1.1 Motivation for this research

Current ground motion models (GMMs) developed for active tectonic regions in the NGA-West2 project (Bozorgnia et al. 2014) and the ongoing NGA-West3 project (<https://www.risksciences.ucla.edu/nhr3-nga-west3-home>) include site amplification models derived using global datasets, but with regional customization as warranted by the data. Such models are referred to as *ergodic* (Anderson and Brune, 1999), as they assume that ground motions for different sites and events across the globe or within a particular region can be used to characterize ground motions for a single site, albeit with large uncertainty. The site amplification models are typically conditioned on simplified site-condition proxies, such as the time-averaged shear-wave velocity in the upper 30 m (V_{S30}) and depths to shear-wave velocity isosurfaces (e.g., z_1 or $z_{2.5}$). The use of models conditioned solely on these parameters is likely to be biased for sites with profiles that deviate significantly from the mean profile conditioned on the proxies or that have spatially heterogeneous velocity structures. Such biases can arise from site-specific resonances and frequency-dependent site effects associated with geological features that are not directly accounted for in the site proxies. These missing features in the conditioning variables for ergodic models contribute to their large uncertainties.

One of the difficulties in reducing uncertainty in ergodic site amplification models is finding site proxies that are both practical to obtain and that have predictive power for site effects

such as resonance. In recent decades, the microtremor-based horizontal-to-vertical spectral ratio (mHVSr) method has shown promise as a tool for identifying site resonance, with the lowest spectral peak commonly interpreted as an indicator of the fundamental site frequency (f_0) (Lermo and Chavez-Garcia 1993; Lachet et al. 1996). Moreover, the overall shape of the mHVSr spectrum has been shown to have varying degrees of correlation with site response in response spectral space, highlighting its potential for capturing frequency-dependent amplification (Buckreis et al. 2024; Pinilla-Ramos et al. 2022; Senna et al. 2008). For this reason, mHVSr would appear to have potential for use as the basis for additional site parameters that could be used in tandem with V_{S30} . Broadly speaking, this research aims to increase the availability of mHVSr data for use in site response modeling, to improve understanding of what frequency ranges in mHVSr curves are more or less reliable for forward applications, and to develop means by which mHVSr can be used for different applications related to site response prediction.

The data collection and analysis carried out in this research is built upon prior work within the broader research community (which is summarized in Chapter 3) and within the University of California, Los Angeles (UCLA) geotechnical engineering research group. In particular, prior researchers in the UCLA group developed the shear-wave velocity (V_s) profile database (VSPDB) (Kwak et al., 2021), which was initially developed to archive and disseminate shear-wave velocity profile data and related metadata across California. The database was extended to include HVSr (earthquake and microtremor-based) by Wang et al. (2022), which introduced a schema for organization of HVSr data and metadata. The database has been further expanded as part of the work presented in this dissertation and in total contains 2942 HVSr curves, 31.8 % of which are near strong motion recording stations. That data provides the basis for work investigating applications of mHVSr for site response prediction.

1.2 Research objectives and scope

The objectives of the research presented in this dissertation are broadly related to HVSR data and HVSR-based models. The data objectives were to increase the number of sites with mHVSR data in California to support model development research and to improve data processing procedures with a specific focus on low frequency mHVSR ordinates. The modeling objectives were two-fold. First, I sought to develop an ergodic site response model conditioned on features from mHVSR curves and V_{S30} that would be able to model commonly encountered site response features (i.e., period-variations of site terms that are flat, peaked response, or contain ramps) and thereby reduce modeling uncertainty. Second, I sought to evaluate whether data from multiple mHVSR curves at different locations across a site could be effectively utilized to assess site response complexity, which has implications for the model error associated with one-dimensional ground response analyses.

To achieve these objectives, the scope of my work included the following:

1. Collection of mHVSR data at sites using either field deployments of temporary arrays or permanently installed seismometers. Most of the data that was collected was at sites where a strong motion station is present, while other sites were examined as part of efforts to investigate effects of different field installation methods or because the sites are of engineering interest.
2. All of the data compiled in this research is publicly available in the shear-wave velocity profile database (VSPDB; Kwak et al. 2021). During the time this research was conducted, the schema for the overall database inclusive of HVSR components was improved. By making our data available shortly after it was compiled, we support the work of other researchers.

3. Because many mHVSr curves, for diverse site conditions, transition as frequency decreases below ~ 0.2 Hz to large values (referred to as a “low-frequency ramp”), I sought to understand what causes these low frequency ordinates and their physical meaning. This subject is important because low-frequency components of mHVSr are needed to identify peaks associated with very deep impedance contrasts (e.g., as might be expected in deep sedimentary basins such as in Los Angeles and the Imperial Valley). Low frequency mHVSr was investigated to identify dependencies on processing procedures and installation type. By accounting for these effects, we are better equipped to reliably identify low-frequency site resonances.
4. A specific application that was investigated was the use of multiple mHVSr curves from different locations around a site to identify sites with relatively consistent versus relatively variable geotechnical conditions. The principal motivation for this work was to evaluate the potential use of mHVSr variability metrics as a predictor of the effectiveness of one-dimensional ground response analysis for modeling site response. The investigations were performed at 19 downhole array sites in California.
5. Another application that was investigated was to relate parameters derived from mHVSr to features observed in site-specific site response data. I focused on site response features that remain after removing V_{S30} -based model predictions. Using 686 sites with both mHVSr data and site responses derived from earthquake recordings, I identified four major site response attributes: (1) flat responses with respect to period; (2) peaked responses; (3) ascending ramp features (amplification increases with period); and (4) descending ramp features. mHVSr was used both to help identify when each of the four site response features is likely to be encountered and, for the peak and ramp features, to

constrain models that capture those features. The modeling effort considered peak features from mHVS_R, mHVS_R ordinates, V_{S30} , depth parameters, and site geomorphic categories. These models are designed for applications with ergodic ground motions models such as those derived from NGA projects.

1.3 Organization

The organization of this thesis is as follows:

Chapter 2 presents a literature review of the analysis of microtremors and the eventual development of microtremor-based HVS_R. It also describes the processing procedures used to develop HVS_R and an overview of why mHVS_R has the potential to be used in ground motion modeling. Furthermore, it presents a literature review of prior HVS_R-conditioned site response models, and the outcomes of using HVS_R.

Chapter 3 describes the collection of microtremor data at ground motion stations prior to the start of this research, the collection of data from field deployments at ground motion sites and other sites of engineering interest, and the extraction of microtremor data from sites with permanently installed seismometers. Furthermore, it describes how the data was processed and the additional steps that were incorporated to reduce drift and wobble within the data.

Chapter 4 presents work investigating the low-frequency reliability of mHVS_R ordinates. It describes different investigations that were carried out to better understand the large mHVS_R ordinates that occur at frequencies below 0.1-0.2 Hz. Lastly, it presents the results of Rayleigh wave H/V ratios compared to mHVS_R within the Central Valley region of California.

Chapter 5 presents the use of spatially distributed mHVS_R as a means to assess site heterogeneity and whether this is predictive of the effectiveness of 1D GRA. This chapter presents alternative

correlation metrics to make this assessment and uses these results to evaluate whether sites with spatial similarity and good correlation can reduce model error from 1D GRA.

Chapter 6 describes five essential elements for the present development of an mHVSr-conditioned site response model. First, I identify appropriate sites for consideration in this study based on the availability of earthquake recordings and mHVSr. Second, I will describe how site responses were derived from ground motion data. Third, I will describe how peaks, ramps, and flat sites are identified from observed site responses. Fourth, I will describe how peaks were identified in mHVSr curves. Fifth, describe the development of a decision tree classifier model that provides probabilities of different site response features conditional on mHVSr and other site proxies.

Chapter 7 presents the other five elements of model development, including (1) parametric models for peak-only sites, (2) parametric models for ramp sites, (3) parametric models for flat sites, (4) machine learning models to predict total site response, and (5) residuals analyses used to refine the models and characterize their effects on site-to-site uncertainty.

Finally, Chapter 8 summarizes the research scope and findings. It also provides recommendations on how practitioners can use mHVSr in terms of site characterization or ground motions modelling. It concludes with recommendations for future research.

2 HVSR Background

2.1 Early Literature of Microtremor Attributes

Microtremor-based Horizontal-to-Vertical Spectral Ratios (mHVSr) are computed using frequency-dependent Fourier amplitude spectral ordinates from horizontal and vertical ground motion recordings from a three-component seismometer. The recorded ground motions consist of ambient vibrations or microtremors caused by natural (e.g., wind, ocean waves) and anthropogenic (e.g., traffic, machinery) sources.

In the late 19th century, investigators attempted to understand small amplitude vibrations defined as microtremors or ambient vibrations that were present in the absence of earthquakes. The earliest studies of this are in Italy, by Bertelli (1872), who noticed small vibrations recorded by a horizontal pendulum tromometer and investigated the cause of these continuous microtremors. Subsequent studies in Japan, such as Omori (1909), used similar tools to analyze pulsatory oscillations caused by barometric disturbances such as tropical cyclones, which were found to follow similar characteristics of earthquake vibrations, meaning that the wavefield of a site excited by a strong motion were considered to have similar properties to that of microtremors that naturally propagate through a site.

These early studies highlighted that microtremors were present globally, which prompted further studies that evaluated the source of such microtremors. Gutenberg (1921, 1931, 1936) demonstrated that long period microtremors are generated by ocean wave activity (e.g., surf impacting coastline) and can be observed coherently over continental scales. These studies showed that oceanic disturbances such as storm-generated waves in the deep ocean or surf impacting the

coast can produce seismic-energy that propagates globally as waves with periods greater than 4 sec. Figure 2.1 from the Gutenberg (1931) study compares wave energy propagating across multiple sites across north America from March 24 – 27, 1930 all showing similar amplification on March 26, attributed to high surf along the coast on that day.

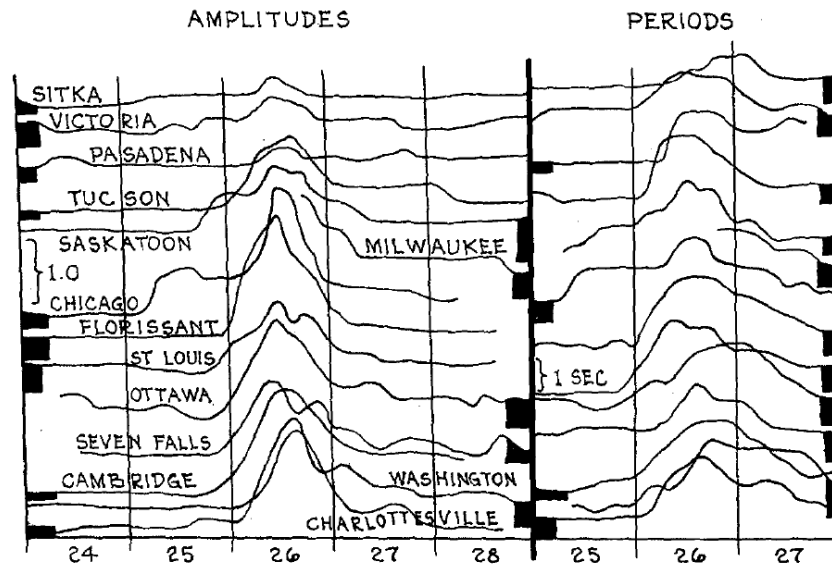


Figure 2.1. Comparison of amplitude and period between multiple stations across North America from March 24 through March 27, 1930. Figure reproduced from Gutenberg (1931).

Gutenberg (1958) later synthesized findings from his prior studies and those of others and related different microseism bands to distinct meteorological and oceanic disturbances. Building on these understandings of microtremors, subsequent studies refined understanding of wave propagation caused by microtremors from natural or anthropogenic sources (Tomoda and Aki, 1952; Wilson, 1953; Akamatu 1956).

Although these early investigations focused primarily on the origin and characteristics of ambient vibrations, they also motivated the development of array-based ambient noise methods for estimating subsurface structure. Two such techniques are the spatial auto-correlation analysis of signal (SPAC) (Aki 1957) and frequency-wave number analyses ($f-k$) (Capon et. al. 1967;

Capon 1969; Lacoss et. al. 1969). SPAC evaluates spatial similarity of seismic wavefields recorded by an array of seismometers by quantifying the correlation between signals at different sensor locations as a function of inter-station distance (i.e., lag). Frequency-wavenumber analysis characterizes seismic wave propagation by transforming array recordings into the frequency-wavenumber domain, where the distribution of energy with respect to frequency is used to estimate dominant frequencies and a wavenumber vector is used to estimate wave propagation direction and phase velocities. Subsequent studies found that the frequency-domain characteristics of microtremors, particularly predominant period and spectral amplitude, are related to local subsurface conditions and earthquake site response, which could be used to estimate parameters used for seismic design such as soil classification and seismic force coefficients (Kanai and Tanaka, 1961).

Although these early studies did not develop the HVSR method, which would first be formulated several decades later, they demonstrated that microtremors contain valuable information about local subsurface conditions and site response. These findings provided the foundation for later developments in which the ratio of the horizontal-to-vertical spectral components was introduced as a means of extracting site-specific resonance information from microtremor recordings. The next section provides a more detailed discussion of the development of HVSR and its application in engineering analyses.

2.2 Background on HVSR

2.2.1 Wave Composition of Microtremors

Following the pioneering studies presented in Section 2.1, additional studies have investigated the wave types in microtremor wavefields. A synthesis of the major findings from the recent studies is as follows:

- Frequencies below 0.1 Hz consist of surface waves such as fundamental mode Rayleigh Waves (Li et al. 1984; Horike, 1985; Yamanaka et al. 1994; Bonnefoy-Claudet et al. 2006).
- At higher frequencies, the wavefield seems to be a mix of body waves and surface waves (Bonnefoy-Claudet et al. 2006). However, Bonnefoy-Claudet et al. (2004) found a relationship indicating that the microtremor noise field seems to be dominated by surface waves when a large impedance contrast is present and may consist of body waves when a smaller impedance contrast is present.

While the microtremor wave field is likely mixed in wave composition, a majority of studies suggest that microtremors consist mainly of surface waves instead of body waves. Body waves are the dominant wave type for earthquake strong shaking conditions, which consist of an initial p-wave followed by shear waves and then surface waves. Such characteristics would be expected to control earthquake HVSr (eHVSr), which is computed similarly to mHVSr, but uses earthquake motions instead of microtremors. There is evidence for sites responding differently to earthquake excitation vs microtremors, as reflected in differences between eHVSr and mHVSr spectra. For example, Satoh et al. (2001) found inconsistencies between HVSrs derived mainly from body waves and surface waves for 20 sites in the Sendai basin of Japan. Trifunac and Todorvska (2000) found a lack of correlation between areas of large, long-period mHVSr ordinates and the strong ground motions and damage patterns in the 1994 Northridge, California earthquake. Wang et al. (2023) examined 297 sites with both eHVSr and mHVSr measurements and found that distinct

HVSR features were identified at approximately half of the sites, indicating that such features are frequently observed rather than exceptional. Similarly, Vantassel et al. (2024) investigated whether eHVSR and mHVSR aligned for a dataset of 161 sites in Southern California, finding that only 68% of sites were similar to each other. As a practical matter, earthquake recordings are seldom available at sites for which forward predictions of ground motions are to be performed, which is why mHVSR is preferred as a means by which to derive parameters to be used in predictive models. Due to these differences, mHVSR is emphasized in this study.

2.2.2 Theoretical Basis for and Applications of HVSR

Nogoshi and Igarashi (1971) presented early research that laid the foundation for the HVSR technique by showing that mHVSR peaks aligned with the theoretical fundamental site frequency for Rayleigh waves. Subsequently, Nakamura (1989) proposed a conceptual understanding of the link between site fundamental frequency and HVSR peaks, which requires assuming that the horizontal shear wave field is amplified as seismic waves propagate through soil deposits, whereas amplification of the vertical component experiences comparatively less amplification. This became known as Nakamura's method (or technique) in common parlance.

Lermo and Chavez-Garcia (1993) investigated the amplification of shear waves at different angles of incidence through a stepped halfspace, finding that both horizontal and vertical components are amplified at site frequencies, but that the amplification of the horizontal exceeded that of the vertical, as shown in Figure 2.2. This finding extends the concept from Nakamura (1989) of HVSR peaks indicating site frequencies for the case of non-vertical incidence. The resonances that are seen in mHVSR curves have been found to be mainly associated with the ellipticity of fundamental mode Rayleigh Waves, or surface waves (Lachet and Bard 1994; Kudo 1995; Bard

1998). Recognizing this, Field and Jacob (1993) showed that the peaks of an HVSR spectrum corresponding to Rayleigh waves propagating through a stepped halfspace align with the fundamental frequency identified from vertically propagating shear waves (Figure 2.3). Lermo and Chavez Garcia (1994) subsequently found similar results for site profiles in Mexico City. These two studies are very important in the evolution of mHVSR-based techniques, because they showed that the shear wave peaks (needed for engineering application) can be identified from the mHVSR attributes of surface waves.

Subsequent studies found from observations that the lowest frequency resonant peak associated with an HVSR spectrum is consistent with that of the fundamental frequency, f_0 (Lachet et al. 1996, Theodulidis et al. 1996, Ghofrani et al. 2013). For example, Lachet et al. (1996) evaluated three techniques for site-effect evaluation using mHVSR, HVSR derived from receiver functions (referred to as eHVSR hereafter), and standard spectral ratios (SSR) derived from motions between a site and a reference station at sites in Thessaloniki Greece. They found that mHVSR peaks correlated with SSR and eHVSR peaks but underpredicted the peak amplitude. They also found that mHVSR, eHVSR, and SSR ordinates were correlated relatively strongly for frequencies $< f_0$. Ghofrani et al. (2013) developed a site amplification model based on surface to borehole ratios conditioned on time-averaged shear wave velocity in the upper 30 m (V_{S30}), f_0 derived from eHVSR, and eHVSR ordinates after the Tohoku earthquake in Japan. They found the peaks in eHVSR aligned very well with the surface to borehole ratios. Figure 2.4 highlights the correlation between eHVSR, the surface to borehole ratios and the amplification model Ghofrani et al. (2013) developed. These studies highlight the ability of HVSR to identify fundamental frequency, whether derived from microtremors or earthquakes.

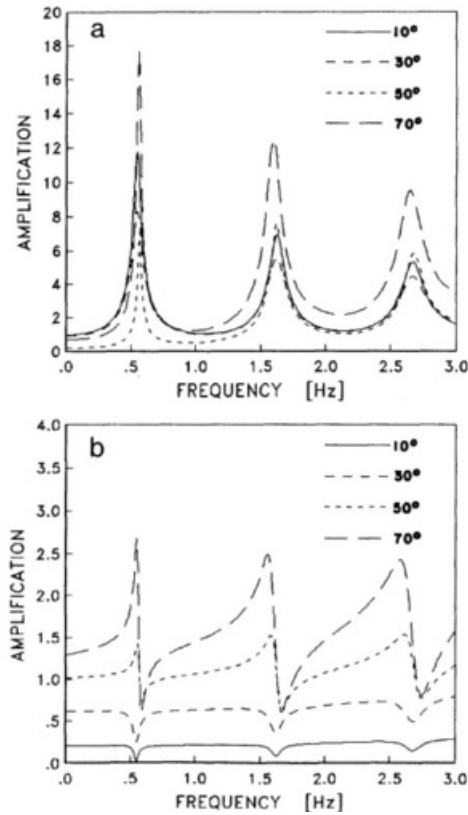


Figure 2.2. Transfer functions of horizontal and vertical motion relative to the horizontal amplitude of incident motion for a plane layer model. Figure reproduced from Lermo and Chavez-Garcia (1993).

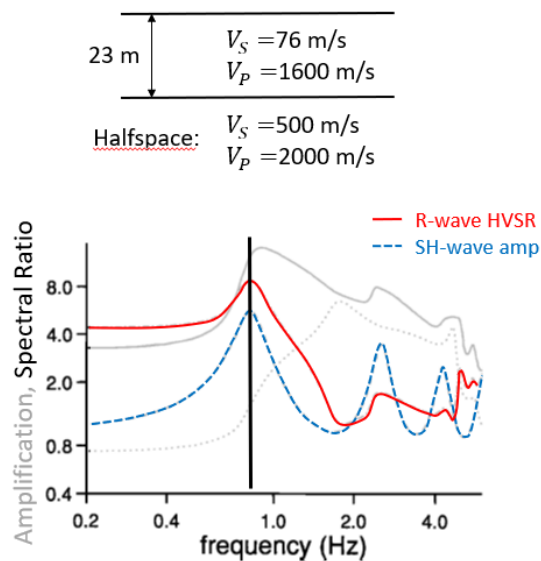


Figure 2.3. Comparison between amplification caused by primarily Rayleigh wave energy and SH-wave energy. Figure reproduced from Field and Jacobs (1993).

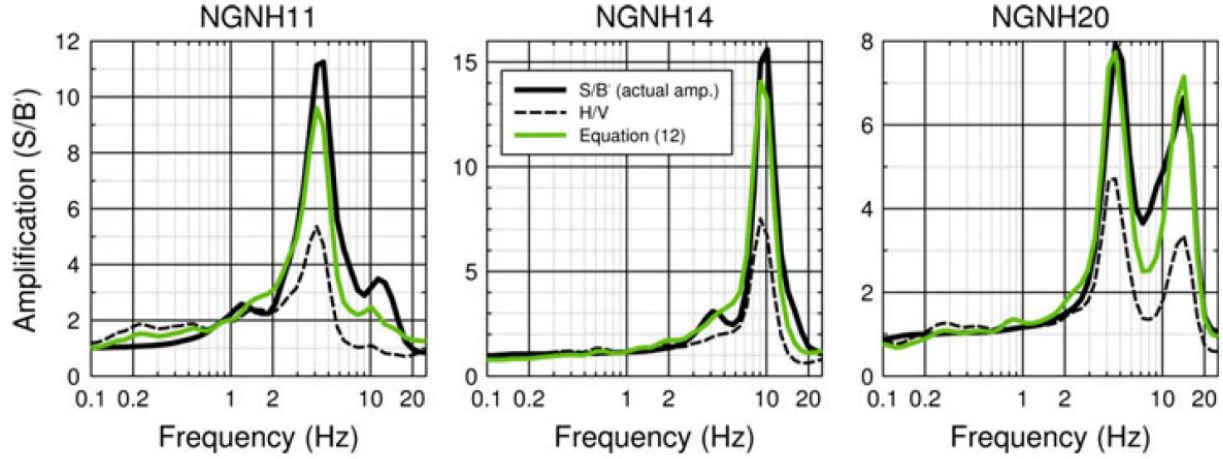


Figure 2.4. Comparison between surface-to-borehole ratios, eHVSr, and a site amplification developed by Ghofrani et al. (2013). Figure reproduced from Ghofrani et al. (2013).

One application of HVSr site frequencies is to infer seismic velocity structure. While not the subject of this dissertation, I summarize the line of reasoning behind these studies. Resonant site frequencies (f_n) are related to shear wave velocity (V_s) as follows (Kramer and Stewart, 2025):

$$f_n = (2n + 1) \frac{V_s}{4H} \quad (n = 0, 1, 2, \dots n) \quad (2.1)$$

where V_s is the shear wave velocity of a soil layer overlying viscoelastic bedrock, H is the uniform elastic or viscoelastic layer thickness, and f_n are resonant frequencies, which can be correlated to peaks in mHVSr curves. Many combinations of V_s and H could be used to obtain the same f_n values, which makes inversion of V_s from f_n a non-unique process. Nonetheless, the relationship in Eq. 2.1 has prompted the development of inversion techniques implemented in software such as *HV-inv* (Garcia-Jerez et al. 2016), which are used to infer shear wave velocity associated with certain layers at a site from characteristics of a HVSr spectrum. As noted by Molnar et al. (2022), different assumptions can be made regarding velocity gradients and wave fields, but in the absence of knowledge of these features, the non-uniqueness problem remains. As a practical matter, such issues can only be overcome with the introduction of additional site data to constrain the inversion,

which has typically taken the form of joint inversion of dispersion curves with mHVSr (Foti et al. 2011; Piña-Flores et al. 2017; Teague et al. 2018).

2.3 HVSr Processing Procedures

mHVSr is calculated as the ratio of the horizontal-to-vertical components of Fourier Amplitude Spectra (FAS). Many details affect this calculation, and studies have developed procedures to standardize the processing of microtremor data for the evaluation of mHVSr ordinates. One of the first major endeavors to do this was the Site EffectS Assessment using AMbient Excitations (SESAME) project by Bard (2004). This document laid out the fundamentals for microtremor processing and is what others have used as the basis for codes that implement processing procedures. A processing package that applies SESAME guidelines as-published is *Geopsy* (Wathalalet 2020). Other packages have allowed for adjustments to certain settings, including R packages such as *hvsrProc* to address common peak identification problems (Wang 2020) (subsequently adapted for Python as *hvsrprocpy*; Ornelas et al. 2024c), python libraries such as *hvsrpy* that select peaks in a manner that seeks to reduce the appearance of uncertainty (Vantassel 2020; Vantassel 2025), and *SpRIT*, which provides an integrated workflow for HVSr processing and interpretation (Rjbalikian et al. 2026). The general processing steps that these packages follow are:

1. Process the raw waveform data recorded by a three-component seismometer.
2. Divide the raw waveform data into individual discrete time windows, 10 windows are typically needed to reliably compute a mean mHVSr curve.
3. Apply a weighted mean detrend to each individual window to remove a linear trend in the raw waveform data, which may be attributed to drift (discussed in Section 3.4.1).

4. Apply a Tukey windowing function to each individual discrete time window, which entails tapering the ends of each window to minimize edge effects.
5. Apply a high-pass Butterworth filter to remove any additional inconsistencies in each individual window.
6. Perform anti-triggering, which removes spikes of ground motion typically triggered by cultural vibration sources using either manual or automatic routines (depending on the package) (discussed in Section 3.3.1).
7. Once the windows with large amplitude spikes are removed, the Fast Fourier Transform (FFT) of each individual window is computed. Then, compute a Fourier Amplitude Spectra (FAS) of each window for each component.
8. Apply a smoothing function to each of the FAS ordinates, typically using the Konno and Ohmachi (1998) smoothing function with a smoothing factor of 40 (as recommended by Cox et al. 2020).
9. Take the geometric mean or RotD50 of the two horizontal component FAS curves.
10. Take the ratio of the combined horizontal and vertical components of the FAS curves for each individual discrete time window to compute the HVSR ordinates.

These are the main steps that have been used to develop a majority of past mHVSR curves; further explanations are provided in Section 3.3. The ten-step procedure produces multiple HVSR curves (one for each non-removed window). A mean or median of the multiple curves is often used for forward applications. Modifications to these existing processing procedures are proposed herein to incorporate pre-processing of the data. This was found to be necessary mainly for temporary deployments where drift and wobble (defined in Section 3.3.3) can affect microtremor recordings.

2.4 HVSR-Derived Proxies for Site Response Assessment

Time-averaged shear wave velocity in the upper 30 m, V_{S30} , in conjunction with depths to shear-wave velocity isosurfaces (i.e., $z_{1.0}$ or $z_{2.5}$), are used as independent variables in site amplification components of ground motion models (GMMs) (e.g., Next Generation Attenuation [NGA] West2 Project: Bozorgnia et al. 2014). Parameters such as V_{S30} were initially used for predictive site amplification models due to their potential to be used to discriminate sites with different seismic site responses (Borcherdt and Glassmoyer 1992; Borcherdt 1994). These parameters are typically found through site-specific measurements (e.g., Yong et al. 2013) or approximated by proxy-based approaches (e.g., Wills et al. 2015; Yong, 2016; Parker et al. 2017). However, GMMs that only use these parameters have been associated with large uncertainty when predicting site amplification, due to the incompleteness of V_{S30} and z_1 as descriptors of site condition. Although these site proxies capture important aspects of near-surface geology, they only partially describe site-specific geological structures and the complexities inherent in seismic site response. Consequently, two sites with identical V_{S30} may have different shear-wave velocity profiles, variability that cannot be distinguished by V_{S30} and z_1 alone. These limitations have prompted numerous studies to question the accuracy of these parameters as predictors of site amplification (Castellaro et al. 2008; Kokusho and Sato, 2008; Cadet et. al. 2010; Lee and Trifunac, 2010; Di Alessandro et al. 2012; Hassani and Atkinson 2016b).

Mispredictions of V_{S30} -based ergodic models can be particularly significant for sites with strong impedance contrasts or other complex velocity structures that are not adequately characterized by V_{S30} alone (Hassani et al. 2019). A large body of literature found that the application of fundamental frequency, f_0 in tandem with V_{S30} or alone has the potential to significantly reduce variability of GMMs. For example, in Italy (Barani et al. 2008, 2010; Luzi et

al. 2011; Di Alessandro et al. 2012) using the Italian database ITACA (Luzi et al. 2008), in Japan (Cadet et al. 2008; Cadet et al. 2012; Zhao and Xu, 2013; Kwak et al. 2017, Wang et al. 2022) using the KiK-net database (Aoi et al. 2001) and NGA-Subduction database (Bozorgnia et al. 2022), and in Eastern North America (Hassani and Atkinson, 2016c; Hassani and Atkinson 2018a, b; Harmon et al. 2019) using the NGA-East database (Goulet et al. 2021). In each of these cases, consideration of f_0 in the formulation of the site response model reduced variability in the predictions of site amplification, even more significantly in tandem with V_{S30} . Compared to traditional methods of capturing shear-wave velocity profiles (e.g., refraction survey, cross-hole survey, down-hole survey), which can be costly, mHVSr ordinates can be used to capture the fundamental frequency of a site and can be accomplished at a relatively low cost (Molnar et al. 2022). For this reason, there is potential benefit to utilizing such parameters as independent variables in next-generation site amplification models.

2.5 HVSR Applications for Site Response Modeling

To address the limitation of conventional site proxies such as V_{S30} and z_1 , numerous studies have investigated the incorporation of parameters derived from HVSR into site amplification models, some using peak frequency or fundamental frequency (Cadet et al. 2012; Hassani et al. 2016; Kwak et al. 2017; Harmon et al. 2019; Wang et al. 2022; Buckreis et al. 2024; Roberts et al. 2026) and others the ordinates directly (Senna et al. 2008; Ghofrani et al. 2013; Pinilla-Ramos et al. 2022; Buckreis et al. 2024). Most of those studies have used eHVSR due to its easy availability from ground motion databases, but some recent work has focused on mHVSR for the reasons provided in Section 2.4.

2.5.1 HVSR-Based Site Classification

There have been studies that proposed to solely use f_0 derived from HVSR for various site classification applications. Cadet et al. (2008) evaluated 500 sites from the KiK-Net database to derive a site classification framework based on f_0 and V_{S30} from non-invasive survey techniques such as mHVSr, Multichannel Analysis of Surface Waves (MASW) and Spectral Analysis of Surface Waves (SASW). They found the largest variance reduction when using f_0 and V_{S30} in tandem. Luzi et al. (2011) analyzed the potential for f_0 to be used as a parameter in soil classification for Italian sites, as f_0 had been found to better encapsulate site-specific attributes. They found that f_0 should be used in the absence of V_{S30} information. However, these studies show that even though f_0 is a better parameter to use than V_{S30} to predict site amplification, the use of them in tandem can reduce the variability to a greater degree.

2.5.2 HVSR-Conditioned Regression Models

Subsequent studies extended beyond using f_0 alone by incorporating additional characteristics from eHVSr (which was used due to its availability from public ground motion databases) into site amplification models. Kwak et al. (2017) used eHVSr parameters from the KiK-net (Aoi et al. 2001) and NGA-West2 (Ancheta et al. 2014) databases to condition site amplification models in Japan. They found that peak characteristics from parameterized eHVSr spectra using a Gaussian pulse fit (Ghofrani and Atkinson 2014) such as the peak frequency, amplitude, and width provides site-specific information that can be added to existing V_{S30} -based site-amplification models to improve predictions and reduce within-event standard deviation by as much 0.07 natural log units. However, they noted that mHVSr would likely be better to model site amplification in future model development, but they consider their approach viable, since they found that peak frequencies in eHVSr and mHVSr reasonably aligned. Ghofrani et al. (2013) developed a site amplification model utilizing eHVSr ordinates in tandem with V_{S30} and f_0 for sites that recorded

the 2011 Tohoku, Japan earthquake and reported, as expected, that their model produced near zero averaged residuals for the data used to train it. Hassani et al. (2018a) took eHVS_R from the NGA-West2 database to derive fundamental peak frequencies to be used for the conditioning of site amplification models in California, in combination with V_{S30} -based models. The incorporation of this term was motivated by significant peak fundamental frequency dependent trends in the observed residual site terms (residuals computed using the Boore et al. (2014) GMM) that are not captured by V_{S30} -based amplification models. These trends are shown in Figure 2.5 along with the multi-linear segment fits that were proposed by Hassani et al. (2018a). They also found that by comparing NGA-West2 and CENA models (from Hassani and Atkinson 2018b), there were similar peak fundamental frequency-dependent trends at low frequencies, whereas significant regional differences occurred at higher frequencies (also shown in Fig 2.5). Roberts et al. (2026) evaluated whether HVS_R-derived parameters could reduce uncertainties for a California-based geospatial model developed by Roberts et al. (2025) (peak frequencies from both mHVS_R and eHVS_R were used). As shown in Figure 2.6, following a similar approach to Hassani et al. (2018b), they fit a multi-linear function to residual site terms plotted against peak frequency.

The use of peak frequency as a model parameter against which to plot site residuals (Hassani and Atkinson 2018ab; Roberts et al. 2026) leaves out of the fitting process a significant amount of information contained in mHVS_R curves. Two other methods for site response modeling that use regression methods with easily understood functional forms and that are conditioned on multiple aspects of mHVS_R are: (1) parametrized peak models, which represent resonant site response using characteristics from an mHVS_R such as fundamental or peak frequency and amplitude (conceptually similar to Kwak et al. 2017, but using mHVS_R), and (2)

broadband descriptor models, which use mHVSr ordinates, either averaged or at individual frequencies, to capture broader period-dependent effects of site response.

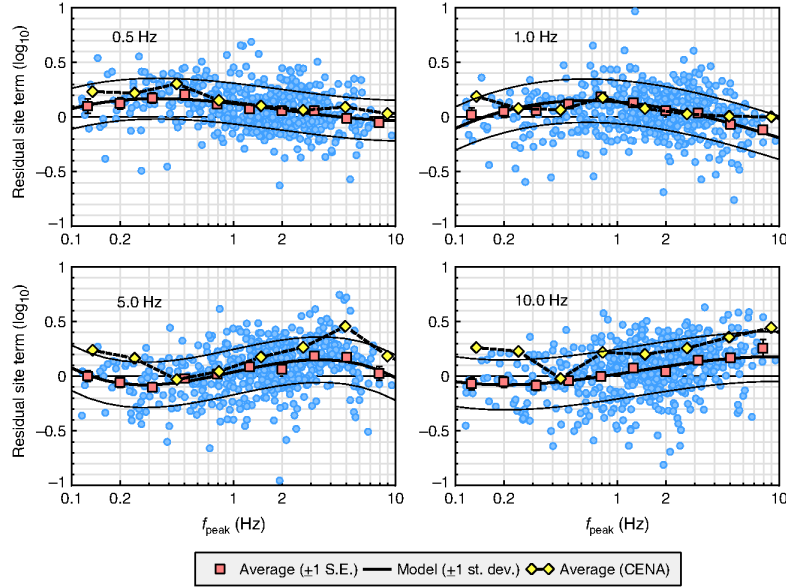


Figure 2.5. Residual site terms for California sites computed using the Boore et al. (2014) GMM plotted vs site frequency inferred from eHVSr. A polynomial fit to the data is also shown along with similar fits for CENA data. Figure from Hassani and Atkinson (2018a).

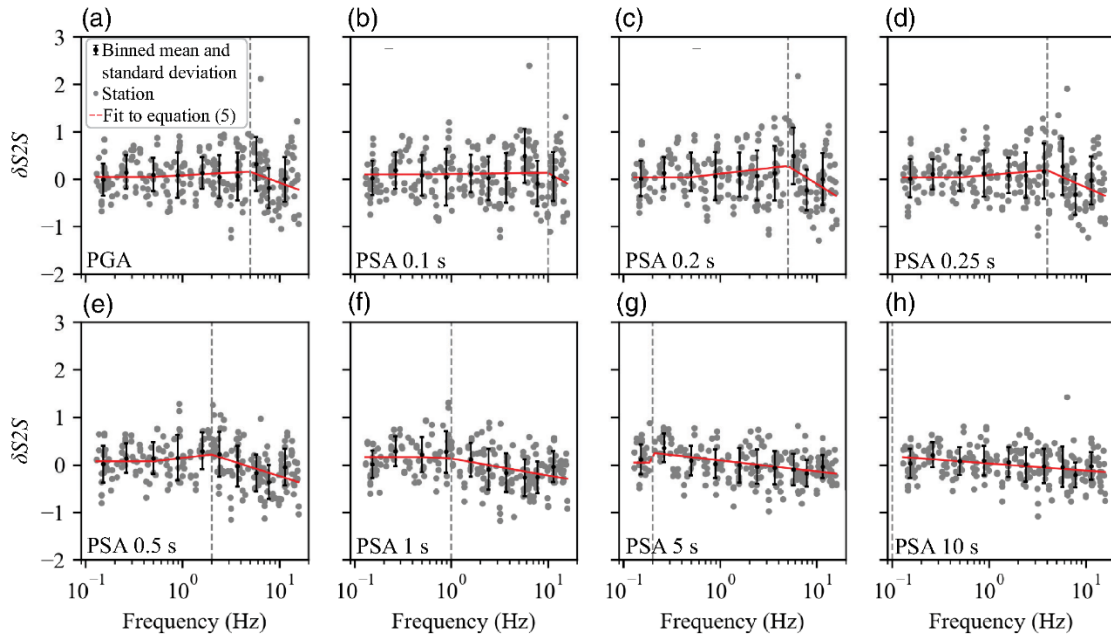


Figure 2.6. Residual site terms for California sites computed using the Boore et al. (2014) GMM coupled with geospatial site amplification model (Roberts et al. 2025) plotted vs site frequency

inferred from a combination of mHVSr and eHVSr. A multi-linear fit to the data is shown that mirrors the approach of Hassani and Atkinson (2018a,b). Figure from Roberts et al. (2026).

The first approach parameterizes the fundamental or dominant mHVSr peak and incorporates the resulting peak characteristics (e.g., amplitude or width) into existing site amplification models. Buckreis et al. (2024) developed a site amplification model for the Sacramento-San Joaquin Delta region of California conditioned on V_{S30} and parameters derived from mHVSr curves such as the fundamental frequency and amplitude extracted from Gaussian pulse fits. Figure 2.7 shows the link between mHVSr curves (with fitted peaks where justified by the data) and site terms derived from a model that includes V_{S30} -scaling. As shown in Figure 2.7, not all sites have mHVSr peaks, but among those sites with mHVSr peaks, most also have site response peaks. By modeling those peaks, they found that site-to-site variability was reduced by as much as 0.1 natural log units within the Delta region. Similarly, Wang et al. (2022) developed a site amplification model for the deltaic region in Hokkaido Japan using features from a Gaussian pulse fit of mHVSr. Their study found a reduction of about 0.2-0.3 natural log units of site-to-site variability, when compared to a global average model for Japan. A novelty of these two studies is that they are some of the first that relate peak parameters extracted from fitted functions of mHVSr and site terms to develop a linear site response model. Moreover, Buckreis et al. (2024) also used mHVSr ordinate averages to capture broadband features in site terms (e.g. ramp-like features).

The broadband descriptor approach relates mHVSr ordinates directly to either linear site amplification or the residual site terms. Senna et al. (2008) developed a model using mHVSr ordinates to predict surface-to-downhole spectral ratios of motions for sites in different categories defined by surface geology or topography. Pinilla-Ramos et al. (2022) investigated the use of fundamental frequency, the period-dependent amplitude of mHVSr, and the normalized amplitude of mHVSr as independent variables to de-trend site terms. They found that the

normalized amplitude of mHVS spectra, taken as the mHVS ordinate at a particular frequency divided by the geometric mean of the mHVS between 0.25 and 15 Hz, reduces the variability much more than the use of fundamental frequency, with the main benefit being at long periods.

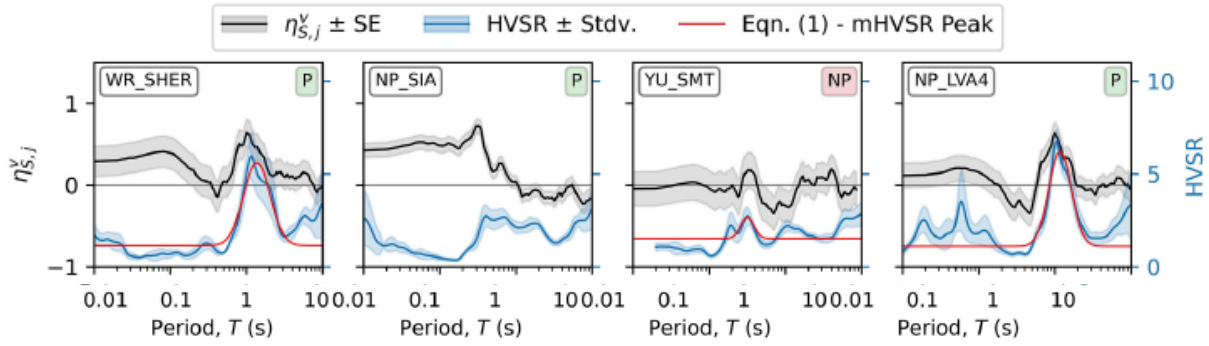


Figure 2.7. Period-dependent residual site terms for four sites in the California Delta region (black) plotted together with mHVS curves (blue). The red lines are fits to the mHVS peaks, where peaks are significant. Figure from Buckreis et al. (2024).

2.5.3 HVS-Based Machine Learning Models

Site response models have been developed using machine learning (ML) approaches utilizing training parameters derived from HVS. Many studies have used ML to develop full GMMs based on existing site proxies and within specific regions (Derras et al. 2014; Khosravikia and Clayton 2021; Kubo et al. 2020). However, Esteghamati et al. (2022) was among the first studies to systematically investigate the use of eHVS in tandem with existing site proxies using three different machine learning models to gain insights into the improvement of predictions of site amplification models. They used eHVS derived from the KiK-net database to improve site amplification derived from a FAS-based model developed by Bahrampouri (2021) using three ensemble-based ML approaches. These models do not produce equations that can be readily plotted or visualized and operate effectively as “black box” models. As such, model performance is assessed by site-to-site uncertainty reduction relative to the Bahrampouri (2021) model that does

not include HVSR parameters. They found that a support vector machine learning model provided the greatest reduction in site-to-site variability at long periods. Zhu et al. (2022) developed site amplification models using a random forest regressor for different combination of site parameters, including eHVSR-based parameters, for sites within Japan using the KiK-Net database. They found a significant reduction of site-to-site uncertainty (0.1-0.2 natural log units) from a random forest model that utilized V_{S30} , z_1 , eHVSR peak parameters, and a surface roughness parameter. Anbazhagan et al. (2023) developed a site amplification model using the 196 mHVSR curves from the Pinilla-Ramos et al. (2022) study. Using a neural network approach, they found a 10% reduction of site-to-site variability at short periods.

2.5.4 Closure

All the studies presented in this section have shown that HVSR has the potential to better describe site-specific attributes of site response and that doing so reduces site-to-site variability. The largest reductions are found for ML models. In this dissertation, I built upon the prior work by developing models with functional forms that have physical meaning along with ML models, in both cases using the largest database considered to date containing information for sites across California. The aim is to use mHVSR in combination with other site parameters to capture commonly encountered features of site response that are missed by V_{S30} -conditioned models. Model development is presented in Chapters 6 and 7.

3 mHVSr Data Collection and Processing

Portions of this chapter were presented at the 2024 World Conference on Earthquake Engineering, Milan Italy (Ornelas et al. 2024b). Other parts of this chapter are also published in a journal paper in Earthquake Spectra (Ornelas et al. 2026a).

As mentioned in Chapter 2, mHVSr can provide parameters such as site fundamental frequency and its ordinates can be correlated with site response at long periods. In order for different attributes of HVSr to be utilized in research to develop such relationships with site response (my work on such topics is presented in Chapters 5-7), a large database of mHVSr curves co-located with strong motion stations is essential. In this chapter I discuss measurements to extract HVSr that were performed at various locations across California at sites with strong motion stations (e.g., downhole vertical array sensors, accelerometers), permanent seismometer stations, and other features of engineering interest (e.g., liquefaction case histories). I also discuss an expansion of the shear-wave velocity (V_s) profile database (VSPDB; Kwak et al. 2021) that incorporates mHVSr data that I collected in field deployments with collaborators as well as data from permanent stations across California and surrounding regions.

While processing the new data, I encountered issues, the resolution of which led to the development of updated processing procedures. In this chapter I will discuss the new data from field deployments (field measurement methods, site metadata, results), the new data from permanent stations, the issues encountered during data processing, and the updated processing procedures that were developed to address the processing issues.

3.1 mHVSr Data in the VSPDB Database

3.1.1 Schema and Data Reviews

The shear-wave velocity (V_S) profile database (VSPDB; Kwak et al. 2021) is a relational database containing geotechnical and geophysical data with an emphasis on V_S profile data. The initial database for seismic velocities and related information was developed by Ahdi et al. (2018). Wang et al. (2022) extended the database to include HVSr data from earthquake and microtremor sources, which involved updating the schema to incorporate HVSr metadata and HVSr curves, processing and uploading of the data, and developing tools for users to interact with the data. Figure 3.1 shows the tables of the schema developed by Wang et al. (2022) to incorporate HVSr into the VSPDB, which lists the metadata fields and processing parameters for HVSr.

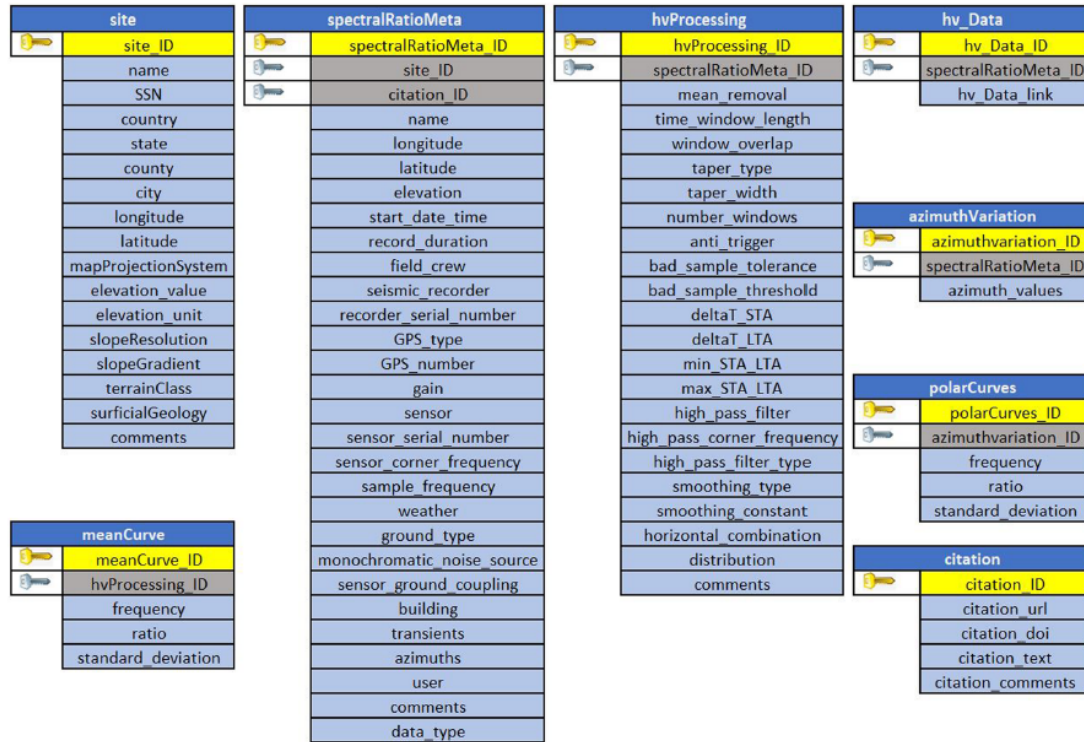


Figure 3.1. Illustration of the breakdown of the schema used for inputting mHVSr data into the previous VSPDB, from Wang et al. (2022).

During routine use of the VSPDB by researchers and practicing engineers, issues were identified with the schema and data tables, which are documented in Choi (2024). This led to updates to the

core schema and velocity-related tables, also documented in Choi (2024), but not to HVSR data or tables. As part of an effort to improve the HVSR components of the VSPDB, I aided in two ways, which were: (1) schema-related and (2) data-related. The schema-related changes were related to the tables and field items within the tables. Figure 3.2 shows the updated schema. The data-related changes were an outcome of visually inspections of each of the curves within the previous VSPDB, which identified some issues with the curves themselves.

The table-related revisions to the schema can be summarized as follows:

- A *tests* table was added. Previously, if more than one mHVSR curve was available at a site, multiple entries of mHVSR curves would be entered for the site. This could create the impression of duplicate entries for distinct tests. This update provided every test with a unique entry within a particular site.
- The tables were all renamed to include the prefix “*hvsr_*” to clarify that they belonged to the HVSR part of the database.
- The original *spectralRatioMeta* and *hvProcessing* metadata tables shown in Figure 3.1 were consolidated into the *hvsr_metadata* table.
- The *azimuthVariation* table was deleted due to having redundant information. For example, the same information from the *azimuthVariation* table was found in the *polarCurves* table.
- The *hv_Data* table, which only included links to repositories in which the data was located, was deleted and brought into the *citations* table.

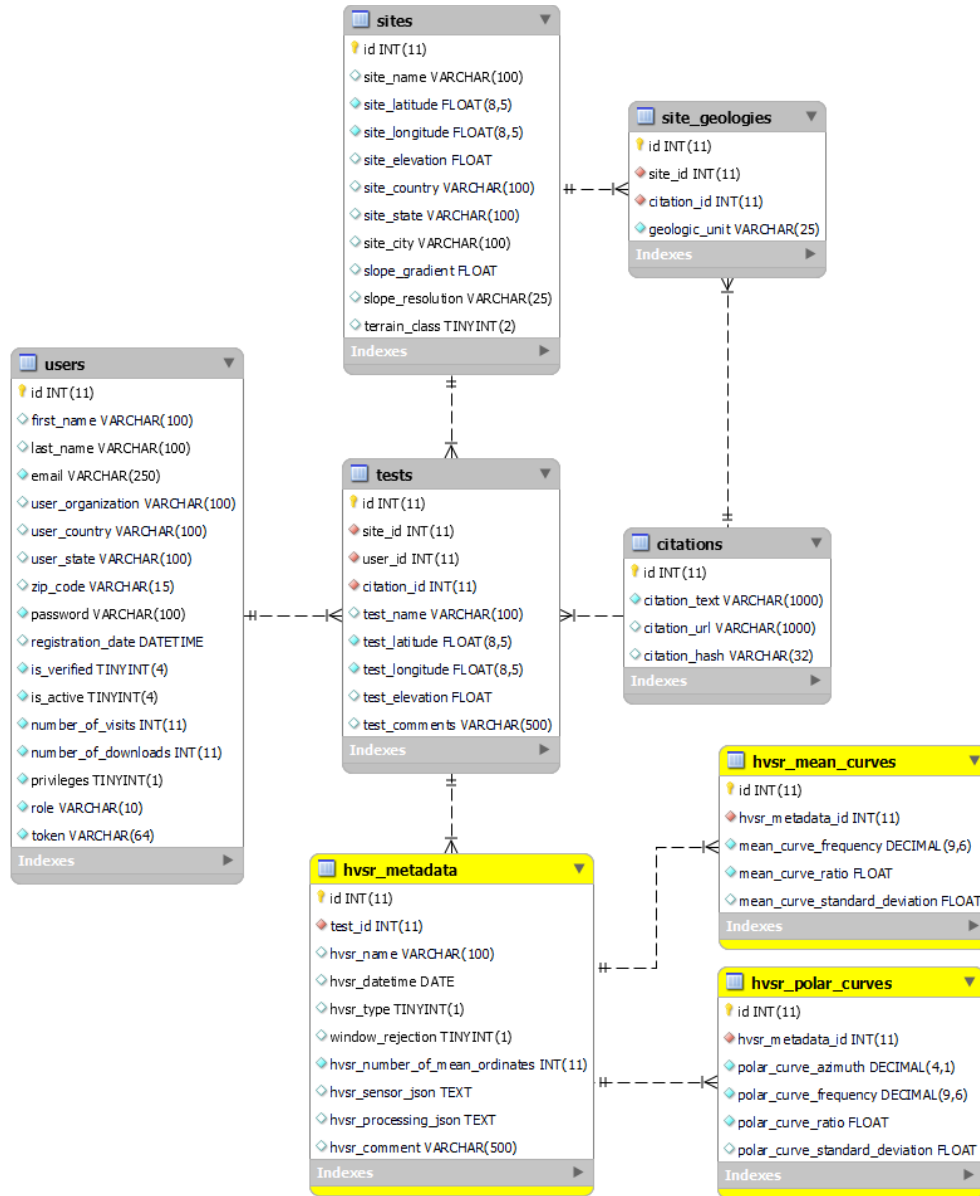


Figure 3.2. Illustration of the schema used for organizing mHVSr data in the updated VSPDB.

The field-related revisions to the schema are summarized as follows:

- Addition of information from pre-processing steps (described in Section 3.4) that required new fields indicating whether these steps were executed on the raw time series (i.e., binary flag *pre_proc_applied*).

- Some fields containing various processing parameters that were in a column format were moved to JavaScript Object Notation (JSON) strings. These fields are rarely queried.
- Introduction of datatypes to help with data integrity. For example, coordinates are a FLOAT(8,5) number (8 values, 5 decimal points). Azimuths in the *hvsr_polar_curves* table are DECIMAL(4,1). These changes allow Structure Query Language (SQL) search operations to check for exact equalities (i.e. Float values cannot return exact equalities).
- Use of a common “DATE” format for all fields containing dates.

Despite these modifications, the core structure of the database remained relatively similar to what was developed by Wang et al. (2022). As indicated previously, I performed visual checks of HVSR data prior to its integration into the updated VSPDB shown in Figure 3.2. This involved evaluation of 2084 HVSR curves that were within the previous VSPDB. Among those curves, 657 were flagged as having issues. The issues that were identified are summarized in Table 3.1.

Table 3.1. Summary of issues and total number of curves that had these issues.

Description of Issue	No. of Curves
1. Repeat/duplicate curves	38
2. Units for sampling rate not in Hz	32
3. Mean HVSR appears to be unsmoothed (i.e., jagged)	650
4. Mean HVSR is sparsely sampled	650
5. Generally suspicious data (e.g., flatling, strange artifacts, other than jagged)	1
6. Missing citation	3
7. Missing significant metadata	650

Most of the curves that were flagged from the visual checks were sparsely sampled with respect to frequency compared to the other curves within the database. Most of the data used a standardized

set of 500 logarithmically spaced frequencies, whereas the sparsely sampled curves had fewer frequencies, which produced a jagged appearance. Figure 3.3 compares the frequencies used in the NGA project with the frequencies used by *hvsrProc* (Wang 2021) and identifies common frequencies between the two. About 70 percent of HVSr curves within the VSPDB were sampled at the frequencies used in *hvsrProc* due to the data being processed using that tool, so about 30% have sparser frequency sampling. Those data are from Geometrics Inc. and Petralogix.

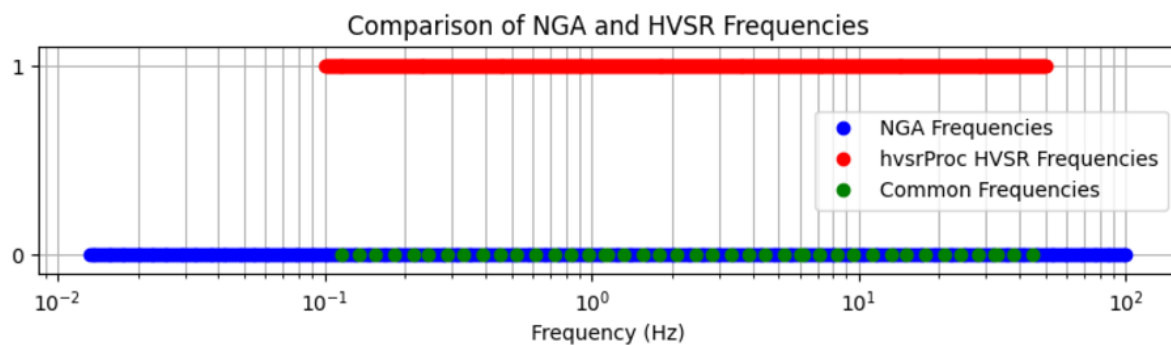


Figure 3.3. Comparison between the number of frequencies within the NGA project and frequencies that are output from *hvsrProc*. The green dots illustrate the common set of frequencies that the two share.

Many HVSr curves lacked important metadata related to data processing such as smoothing type, window length, data type (earthquake vs microtremor), horizontal combination, and how many windows were rejected. The metadata that was deemed crucial to determine was: window length, smoothing type, horizontal combination, tapering, accepted windows, data type (e.g., microtremor vs earthquake), which tools were used (*hvsrProc*, *hvsrpy*, *hvsrprocpy*, *geopsy*), and anti-triggering methods (manual, fully automated).

In total, about a third of the data were rejected due to the HVSr curves being duplicate, suspicious, or lacking processing metadata. As a result of the data checks that were performed, the VSPDB now has more complete metadata than before, and poorly sampled data is more clearly identified.

3.1.2 Data Incorporated

The Wang et al. (2022) study described the development of the original HVSR data schema for the VSPDB and presented the methods used to process the data. They extracted data from temporary deployments to record microtremors, microtremor data from permanent installations, and data from earthquakes (eHVSR). The methods used to process the data were similar to *Geopsy* (Wathelet et al. 2020), which follows SESAME (2004) guidelines, but differ in terms of the combination of the horizontal components, computing HVSR amplitudes and the resampling and decimation of points. Wang et al. (2022) utilized the median component of the two horizontals across azimuths (RotD50; Boore 2010). Moreover, they computed HVSR amplitudes either using arithmetic or lognormal mean and standard deviation, whereas *Geopsy* only performs this computation lognormally. Lastly, they resampled HVSR curves using log-linear interpolation to reduce the size of the arrays before data entry into the database.

In total, Wang et al. (2022) provided 1352 HVSR curves from 941 sites. The data sources were:

- 588 mHVSR curves from 191 sites (Yong et al. 2013)
- mHVSR data from 638 sites from Geometric Inc. (Hayashi and Craig 2017; Hayashi and Burns 2020)
- 33 mHVSR curves from strong motion sites in the Sacramento-San Joaquin Delta region (Buckreis et al. 2021)
- 40 mHVSR curves from strong motion sites maintained by the California Strong Motion Instrument Program (CSMIP) part of the California Geologic Survey (GeoVision, 2016, 2018; Petralogix, 2017)
- 24 mHVSR curves from strong motion sites and sites of engineering interest from ENGEO Inc. (Dave Teague, personal Communication, 2020).

- 402 mHVSr curves from permanent stations from IRIS (Trabant et al. 2012).

As part of this research, I collected additional data by deploying to the field at multiple strong motion stations across California for sites without a broadband seismometer (because data can be extracted remotely). Non-seismic (microtremor) recordings derived from continuously streamed accelerometers have been found to not be reliable (Wang et al. 2023). Section 3.2 describes the data collection from the field deployments. The data collected is summarized as follows:

- 264 mHVSr curves from 16 vertical array sites,
- 7 mHVSr curves from a site in Searles lake
- 18 mHVSr curves at 9 sites within western Los Angeles basin
- 12 mHVSr curves at 6 sites in northern Los Angeles within San Fernando valley
- 2 mHVSr curves at 2 sites within the Santa Clarita valley
- 33 mHVSr curves at 23 sites within the Imperial Valley
- 14 mHVSr curves at 4 sites at the University of California, Los Angeles

I have also incorporated data into the VSPDB from studies by other researchers, which is further described in Section 3.2.9. These studies are follows (all in California):

- 384 mHVSr curves from Garner Valley, Borrego Valley, Delaney Park, and Treasure Island (Hallal et al. 2025).
- 15 mHVSr curves from Tarzana (Nweke et al. 2024a)
- 10 mHVSr curves from Brentwood (Nweke et al. 2024b)
- 7 mHVSr curves from SF Bay Area (Pinilla-Ramos 2024)
- 6 mHVSr curves from Griffith Park (Nweke et al. 2024c)
- 4 mHVSr curves from Baldwin Hills (Nweke et al. 2024d)
- 1 mHVSr curve from Treasure Island downhole array (Hallal and Cox, 2021)

- 1 mHVSr curve from San Clemente Island (Pinilla-Ramos et al. 2022)
- 1 mHVSr curve from Borrego Valley (Hallal and Cox, Person. Comm.)

As described in Section 3.3., I also added data from 1,103 permanent seismometer stations at 1024 sites across California and surrounding regions (Ornelas et al. 2025a). Table 3.2 summarizes the number of mHVSr curves and sites within the VSPDB.

Table 3.2. Number of tests and sites belonging to their specific citation within the VSPDB.

Citation ID	Citation Name	No. of Tests	No. of Sites
742	Ornelas et al. (2025a)	1,103	1,024
1	Yong et al. (2013)	562	182
197	Trabant et al. (2012)	398	366
754	Hallal et al. (2025)	384	4
578	Ornelas et al. (2023a)	248	18
196	Buckreis et al. (2021)	40	40
745	Ornelas et al. (2025b)	33	23
130	ENGEO	24	24
744	Ornelas et al. (2025c)	18	9
735	Ornelas et al. (202X)	18	18
724	Nweke et al. (2024a)	15	1
115	GEOVision (2018)	15	15
728	Ornelas et al. (2026b)	14	4
743	Ornelas et al. (2025d)	12	6
116	GEOVision (2016)	12	12
725	Nweke et al. (2024b)	10	1
585	Ornelas et al. (2023b)	7	1
756	Pinilla-Ramos (2024)	7	7
726	Nweke et al. (2024c)	6	1
36	SCEDC (2013)	6	6
727	Nweke et al. (2024d)	4	1
580	Ornelas et al. (2024b)	2	1
582	Hallal & Cox (2021)	1	1
79	Geometrics	1	1
581	Pinilla-Ramos et al. (2022)	1	1
584	Hallal & Cox (Pers. comm.)	1	1

In total, I added about 1844 mHVSr curves from 1096 sites across California into the database. This brings the total mHVSr recording in the database to 2942 curves from 1476 sites. Figure 3.4 shows locations of all the mHVSr measurements that were added as part of

the work presented in this thesis along with the locations of mHVSr measurements included in the VSPDB that preceded the present work.

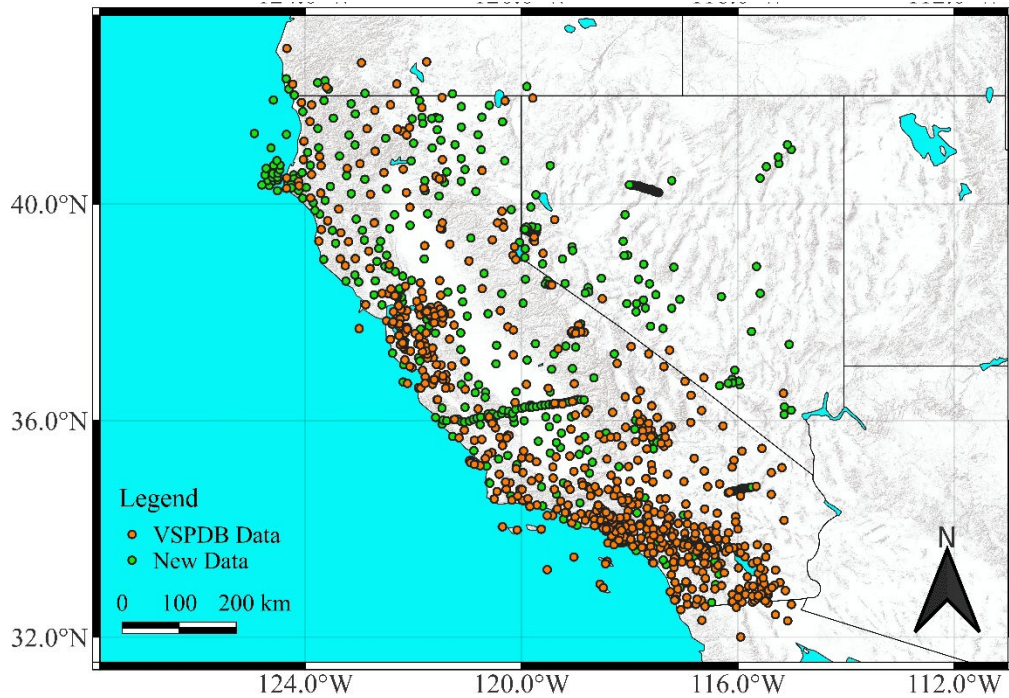


Figure 3.4. Overall map of current mHVSr data that is in the VSPDB, along with the new data added shown in green.

3.2 mHVSr Data Collection from Field Deployments

mHVSr data were collected from field deployments as part of multiple investigations over the course of this research. These deployments included several common features including the equipment that was utilized, how the equipment was anchored to the ground, and the approximate length of time that signals were recorded at a given location.

In this section, I will describe each of the major deployments. Details regarding how the field work was conducted are provided for the first section (3.2.1) and are omitted for later sections.

3.2.1 California Vertical Array Investigation

From late August to early September 2022, mHVSr data was collected with the help of Christopher de la Torre from the University of Canterbury (UC) at 16 sites in California each having a downhole vertical array (Ornelas et al. 2023), which are stations with accelerometers at the surface and at one or more depths. The ground motion and geotechnical data for the downhole array stations can be found in the Afshari et al. (2019) dataset from DesignSafe (Rathje et al. 2017). In addition to the 16 sites investigated in our fieldwork, data were also retrieved from work of prior investigations at four additional vertical array sites. These data were obtained as personal communication (2024) with Prof. Brady Cox for the Wildlife Liquefaction Array and were taken from the Hallal et al. (2025) dataset for the Garner Valley array (34 measurements), Treasure Island, and Borrego Valley Digital Array. The digital data for the Wildlife Liquefaction Array data has not been publicly disseminated and is not included in the VSPDB.

In the field deployments for the present study and from the prior work (Cox 2024; Hallal et al. 2025), data were collected at multiple locations across each site in an approximately two-dimensional grid to support investigations of spatial variability of mHVSr results. Data from the surface station of the vertical array were not used because ambient noise recordings from accelerometers have been found to produce poor mHVSr results (Wang et al. 2023). For this reason, one of the mHVSr surveys was located as close as possible to the surface instrument in the array. Figure 3.5 shows the locations of the 20 sites where testing was performed. Table 3.3 provides site locations, their associated CSMIP ID numbers, VSPDB ID numbers, V_{S30} values, depths to 1 km/s ($z_{1.0}$), depths to bottom of downhole array (z_{DH}), number of recorded earthquake events at the downhole array, and the number of mHVSr tests taken at each site.

The data were collected using 3-component broadband temporarily deployed seismometers. The manufacturer of the seismometers were Nanometrics Inc., and the seismometers used were a 120

s (0.0083 Hz) trillium compact horizon, which were equipped with a Pegasus PGS-140 digitizers. The seismometers have a flat frequency bandwidth from 0.0083 Hz-100 Hz (0.01 sec. – 120 sec.). The tests were performed in concentric circles, each expanding further from the vertical array, with four tests performed along each circle where possible. Tests were performed for about 1-2 hours at different times of the day deploying about 5 sensors at a time, recording the data at a rate of 200 samples per second (Hz). The recording time was selected based on the length of the time windows and the cycles per window needed to resolve frequencies down to 0.1 Hz (described in Section 3.3).

The target radial distance from the vertical array for each circle was 50, 100, 250, and 500 m. Figure 3.6 shows an example of the target test layouts. In some cases, deploying all four sensors at each radial distance was not achievable due to site restrictions such as waterbodies (Figure 3.6a). In other cases, access to certain areas near the vertical array was also restricted, such as private property preventing us from entering. Figure 3.6b shows an example of a proposed layout where testing was possible at all points at a site. The naming convention of the tests used was based on the site number (Table 3.2), the distance from the vertical array, and the index of the test. For example, the first test at site 2 and a radius 50 m was named 2.50.1. A test at the vertical array or close to it would be 2.0.0, meaning that it is 0 m away and the only test taken there.

The sensor deployment protocol was to bury the instrument such that the bottom of the sensor was 2-4 inches (~50-100 mm) below the surface, when possible, to improve coupling with the ground and to avoid excess drift from occurring and distorting the spectra at lower frequencies¹

¹ Subsequent to this field exercise, we were advised by Nanometrics that full sensor burial could improve coupling and reduce the sensors' response to low-frequency noise and local slab-tilt. As of this writing, current protocols are for burial depths of 4 to 6 inches from ground surface to top of sensor.

(our practices have since evolved to fully bury the sensors, such that the top is below ground line). In cases where the sensor could not be buried, such as sites with concrete or landscape (e.g. grass), the sensor was put on pegs to provide coupling during testing. Sensors were levelled and one of the horizontal components was oriented toward the north. Moreover, the landscape was also taken into consideration, and we tried to avoid areas where trees might distort the record and introduce noise. Lastly, we also utilized a plastic 19-liter (5-gal) bucket to cover the sensor and separate it from wind. Figure 3.7a shows an example of the set-up up of the sensors with the bubble level and sensor-oriented north and in this case not buried, Figure 3.7b shows an example of a sensor buried. Based on SESAME (2004) guidelines it is important to remove tall grass or plants that might introduce long period noise into the recording, such as grass or other plants that might wave when there is wind. Figure 3.8 shows an mHVSr mean curve that explains the importance of removing long grasses which can significantly distort long period mHVSr results. This was taken into account when setting up the sensor that is shown in Figure 3.7a.

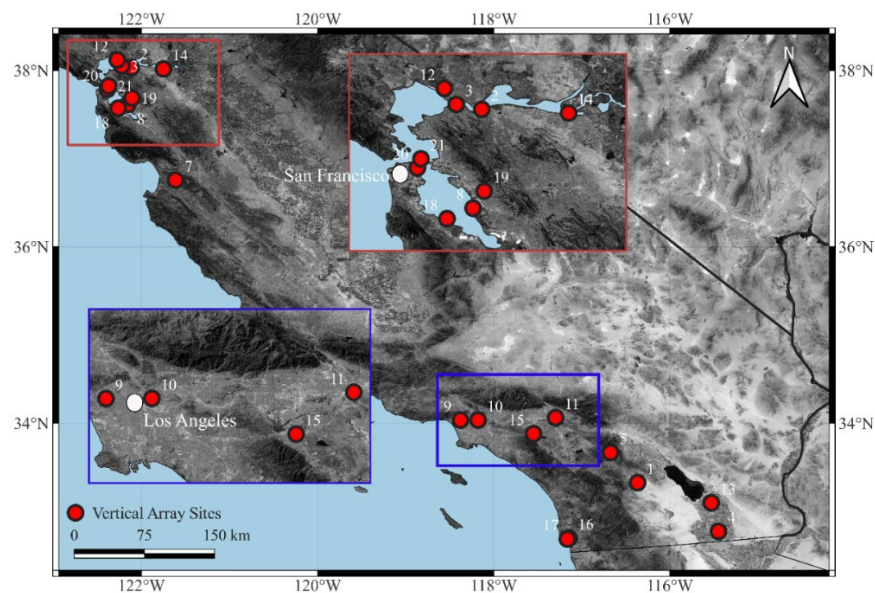


Figure 3.5. Locations of vertical array stations, where mHVSr was performed. Stations based on vertical array sites that were analyzed in Afshari et al. (2019).

Table 3.3. Description of each vertical array site where mHVSr surveys were performed. Stations based on vertical array sites that were analyzed in Afshari et al. (2019).

Site No.	CSMIP Station No.	VSPDB ID	Site name	V_{S30} (m/s)	Latitude	Longitude	No. of events	No. of mHVSr	Z_{DH} (m)	$Z_{1.0}$ (m) ¹
1	UCSB	NA	Borrego Valley	340	33.322	-116.376	16	29	238	230
2	68323	1783	Benicia-Martinez	547	38.0335	-122.117	10	17	35	196
3	68206	1801	Crockett-Martinez Br	335	38.0539	-122.225	8	15	45.7	32
4	1794	1818	El Centro-Meloland	238	32.7739	-115.449	19	17	195	1300
5	UCSB	NA	Garner Valley	265	33.669	-116.674	10	30	150	90
7	UCSB	1835	Hollister Digital Array	385	36.7576	-121.613	23	15	188.8	150
8	58798	1865	Hayward – San Mateo	185	37.6169	-122.154	5	4	91	591.6
9	24703	1869	La Cienega	242	34.0362	-118.378	20	18	100	847
10	24400	1874	Obregon Park	452	34.037	-118.178	23	34	69.5	527
11	23792	1875	San Bernardino	252	34.0637	-117.298	5	16	35	362
12	68310	1891	Vallejo – Hwy 37	528	38.1217	-122.275	17	17	44.7	35
13	UCSB	NA	Wildlife Liquefaction Array	200	33.0974	-115.53	21	31	100	1395
14	67266	1909	Antioch – San Joaquin	253	38.0179	-121.751	4	14	102.4	570
15	13186	1923	Corona I15/Hwy 91	321	33.8817	-117.549	31	16	41.8	23
16	3192	1939	Coronado East	329	32.6983	-117.145	10	15	91	116
17	3193	1954	Coronado West	214	32.6882	-117.164	21	14	109	129
18	58798	1968	Foster City San Mateo	810	37.5728	-122.264	7	18	38.3	20
19	58487	1986	Hayward-580W	489	37.6887	-122.107	5	20	91	43
20	58961	2006	San Francisco	391	37.7866	-122.389	9	14	40	27
21	58642	NA	Treasure Island	157	37.825	-122.374	11	34	122	88

1. $Z_{1.0}$ represents the depth to $V_S = 1000$ m/s and the values are taken directly from V_S profile from de la Torre et al. (2022) or from the GMDB (Buckreis et al., 2025) as derived using the equation in that source.

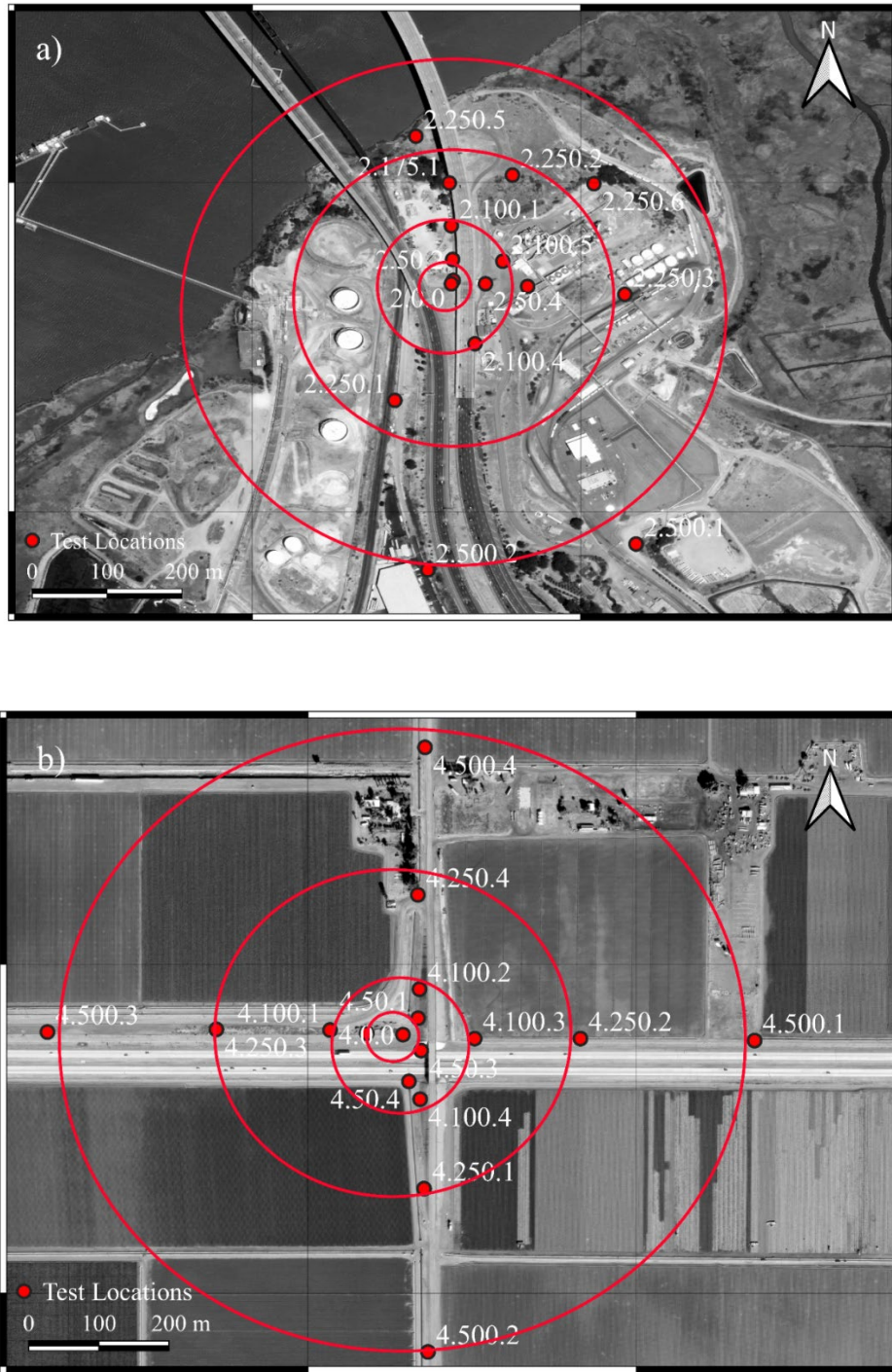


Figure 3.6. Layout of mHVSr measurement locations: (a) plan view of Benicia-Martinez South site (Site 2 in Table 1); (b) plan view of El Centro-Meloland site (Site 4). Numbers indicate test names – the first digit indicates the site number, the second indicates the distance from the vertical array, and the last indicates the index of the test.

For the four sites for which spatial mHVSr curves were retrieved from prior investigations, the arrays were either nominally circular but with different radii (Wildlife Liquefaction Array, Garner Valley, Borrego Valley Digital Array) or irregular (Treasure Island). The available measurement locations were sampled to align as much as possible with the configurations used by Ornelas et al. (2023) as depicted in Figure 3.6. In the case of the Wildlife Liquefaction Array (Site 13), the 13.0.0 test is designated as the one closest to the vertical array. This location is not centered within the test radii due to the instrument layout, which was influenced by the Alamo River, which constrained testing around the vertical array. The layouts for all sites showing the mHVSr locations from the original studies as well as the locations selected for the present study are shown in Appendix A of Ornelas et al. (2026a).

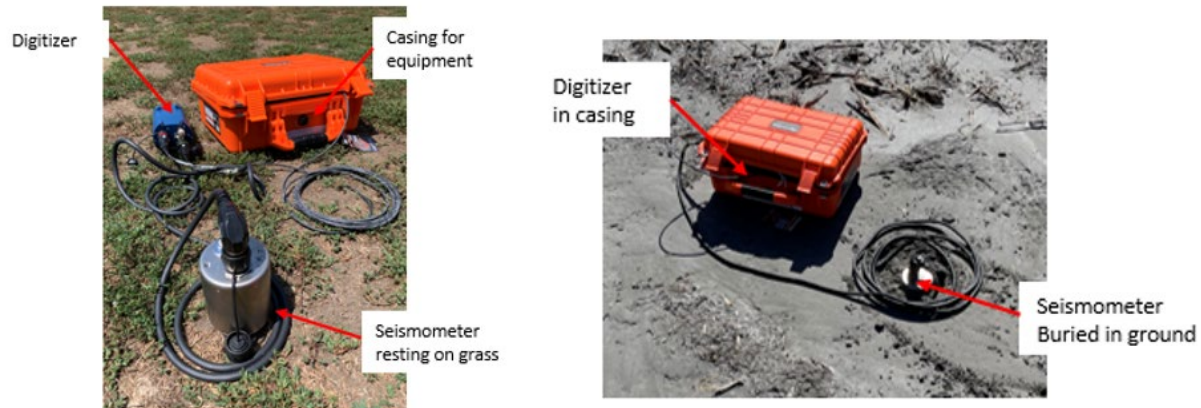


Figure 3.7. (a) left: Layout of the seismometer and the digitizer used during testing at the vertical array site described in Table 2.1 for the case resting on the ground, (b) right: Layout of the seismometer and the digitizer used during testing at the vertical array site described in Table 2.1 for the case buried in the ground.

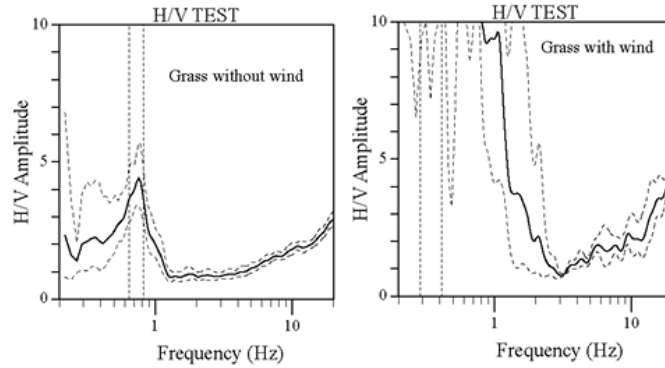


Figure 3.8. Example of what can occur in an mHVSr curve when grass is not removed prior to performing a test, from SESAME (2004).

3.2.2 MAM Arrays

Microtremor Array Measurements (MAM) were performed during one of the investigations described in Section 3.2.1. The MAMs were performed at Obregon Park in the city of Los Angeles (See Table 3.2). Linear MAMs were performed on Whittier Blvd and Eastern Ave at the same time that arrays of instruments in a triangular configuration were deployed in Obregon Park. Figure 3.9 shows the location and layout that the testing was performed, relative to the vertical array.

The surveys were performed for about 3 hours, and each test was performed at distances of 50, 100, 250, 500, and 1000 meters. Typically, MAM arrays are deployed with the aims of developing dispersion curves, which was the research interest of Prof. C. Nweke at USC. I used the data solely for mHVSr to supplement the VSPDB.

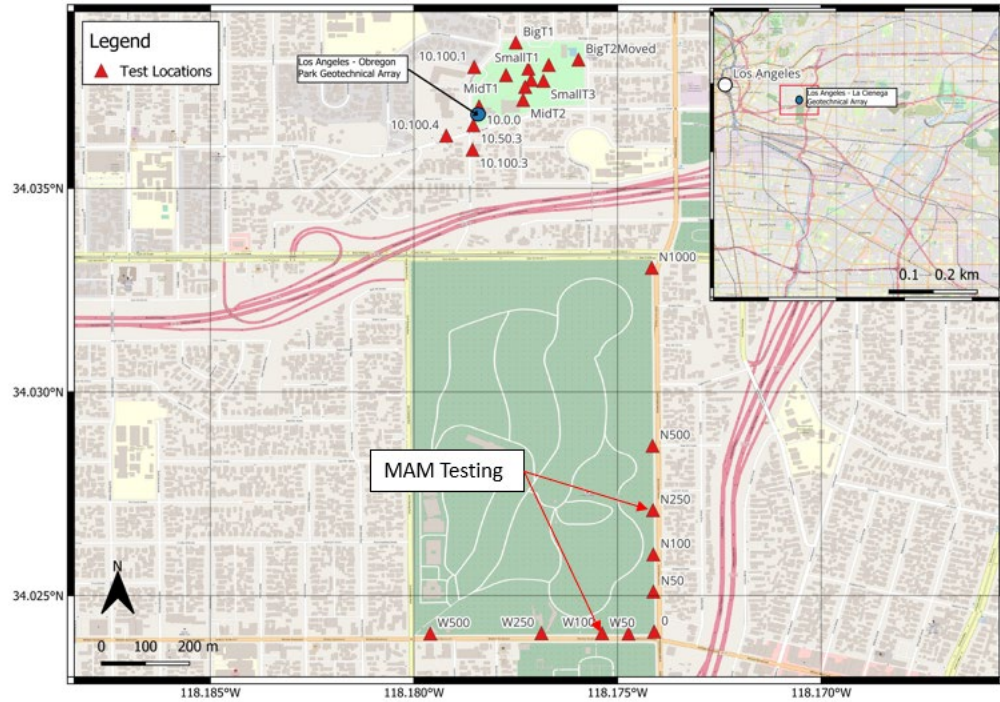


Figure 3.9. Image of approximate layout followed when conducting MAM surveys. This image was for station 10 used for this study (see Table 3.2) which is the Obregon Park vertical array. MAM array was performed south of the vertical array site.

3.2.3 Searles Lake Investigation

From May 21, 2023- May 23, 2023, five mHVSr surveys were performed at different locations around the Searles Valley lakebed (Ornelas et al. 2023) to better characterize site conditions at sites that experienced liquefaction during the 2019 Ridgecrest earthquake (Zimmaro et al. 2020). The mHVSr surveys were published in a previous project report (O'Donnell et al. 2024). The Searles Valley Basin consists of a large endorheic dry lake which contains sediments such as Borax and rock salt, which formed around the late quaternary period. This lakebed exhibited surface manifestation of liquefaction in the form of sand boils in different areas around the lake, following the Ridgecrest Earthquake sequence (RES) on July 4-5, 2019. The information that these surveys provide can give us insight into site resonances which are anticipated to be significant due to large

impedance contrasts. Moreover, we can better understand geologic variability when multiple surveys are evaluated at different areas around the site. Figure 3.10 shows the location of the sites where testing was performed.

The mHVSr surveys were performed using Nanometrics Inc. 120s trillium compact horizon 120 with a flat response of 0.0083 Hz-100 Hz. These broadband seismometers were paired with Pegasus PGS-140 digitizers to record the data. Similar to what was used in the previous investigation, the sensors were also covered by 19-liter bucket and buried when possible 2-4 inches. However, in the case of this study we also placed an electrical insulating blanket (also called EMF blanket) to see the effect of electrical noise on the sensor. Figure 3.11 shows a case where the plastic bucket had an EMF blanket placed over it to reduce the amount of electrical noise experienced. The duration of the tests varied, but they were all around 2–3-hours to have more time windows to average when computing an mHVSr mean curve. The mHVSr data were processed using the processing procedures discussed in Section 3.4.2.

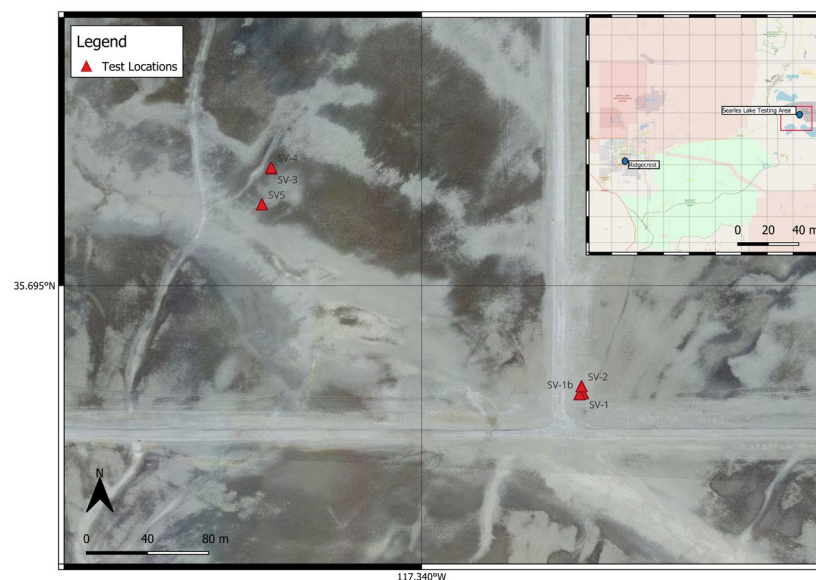


Figure 3.10. Image of approximate layout followed when conducting mHVSr surveys at the Searles Valley lakebed.

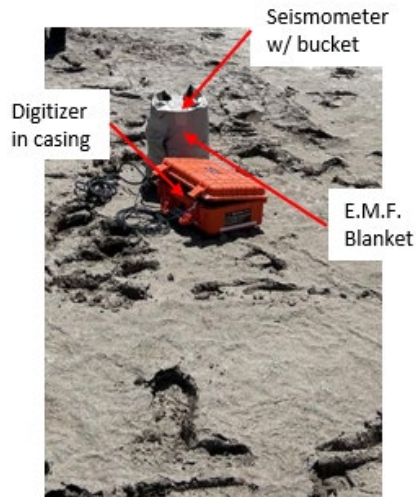


Figure 3.11. Layout of the seismometer and the digitizer used during testing at the Searles Valley Lakebed. In this image an EMF blanket was used to reduce the amount of electrical noise produced.

3.2.4 Investigation in Imperial Valley

From May 6-8, 2024, 33 mHVSr measurements were completed within the Imperial Valley Basin (IVB), which is a prominent sedimentary basin located in southern California, east of San Diego, within the Salton Trough. This tectonically active region, part of the San Andreas Fault system, is characterized by low-lying topography, with much of the Imperial Valley situated below sea level. To support development of site response models (Chapters 6 and 7), I collected mHVSr data at strong motion stations with multiple earthquake recordings from accelerometers but no seismometer. These stations recorded historic events such as the 1979 Imperial Valley Earthquake. Figure 3.12 shows the location of all the HVSr measurements that were performed co-located with accelerometer stations. The tools used to perform these measurements are described in section 3.2.1. The duration of the tests varied, but I aimed to record data for at least one hour to have enough time windows to average, the importance of which is further described in Section 3.4.

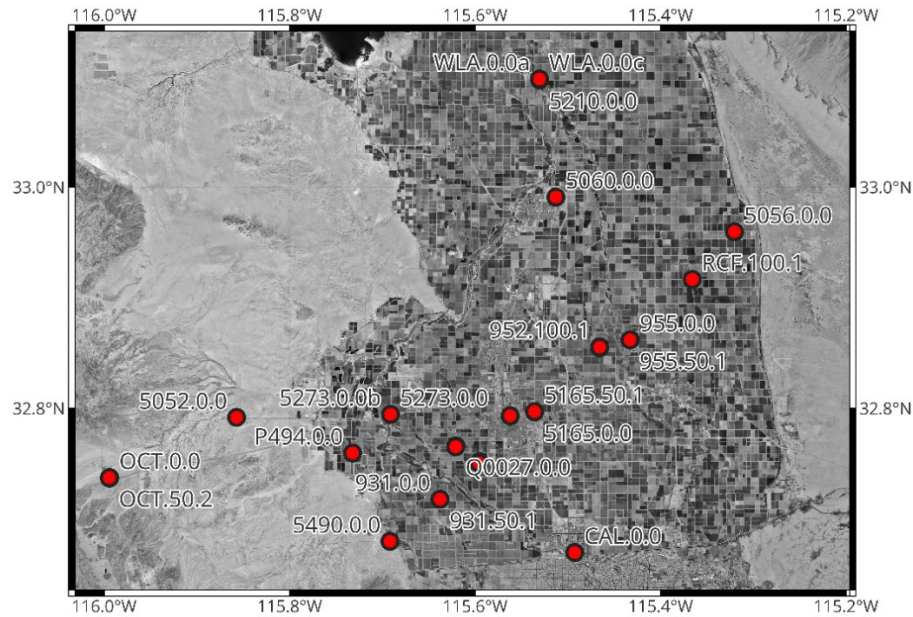


Figure 3.12. Location of the 33 HVSR measurements that were performed within the Imperial Valley basin at strong motion stations.

3.2.5 Investigation in West Los Angeles Basin

On April 18, 2024, 18 mHVSR measurements were completed within the Los Angeles Basin (LAB), which is a major sedimentary basin located in southern California, stretching across a broad area that includes much of the city of Los Angeles. This basin is part of the larger Transverse Ranges geologic province and is characterized by a mix of flat lowlands. The LAB is situated near several active fault systems, including the San Andreas Fault to the north and east and the Newport-Inglewood Fault that originates to the south and passes beneath the western portion of the basin. The basin is composed of a range of sedimentary layers that affect seismic waves and ground motion during earthquakes. To support development of the site response model (Chapters 6 and 7), I collected HVSR data at the locations of strong motion stations with accelerometers that have recorded multiple earthquake events, including the 1994 Northridge earthquake. Figure 3.13 illustrates the locations of the mHVSR sites within the LAB. The tools used to perform this testing

are described in Section 3.2.1. The duration of the tests varied, but I aimed to record data for at least one hour to have enough time windows to average, which the importance of this is further described in Section 3.4.

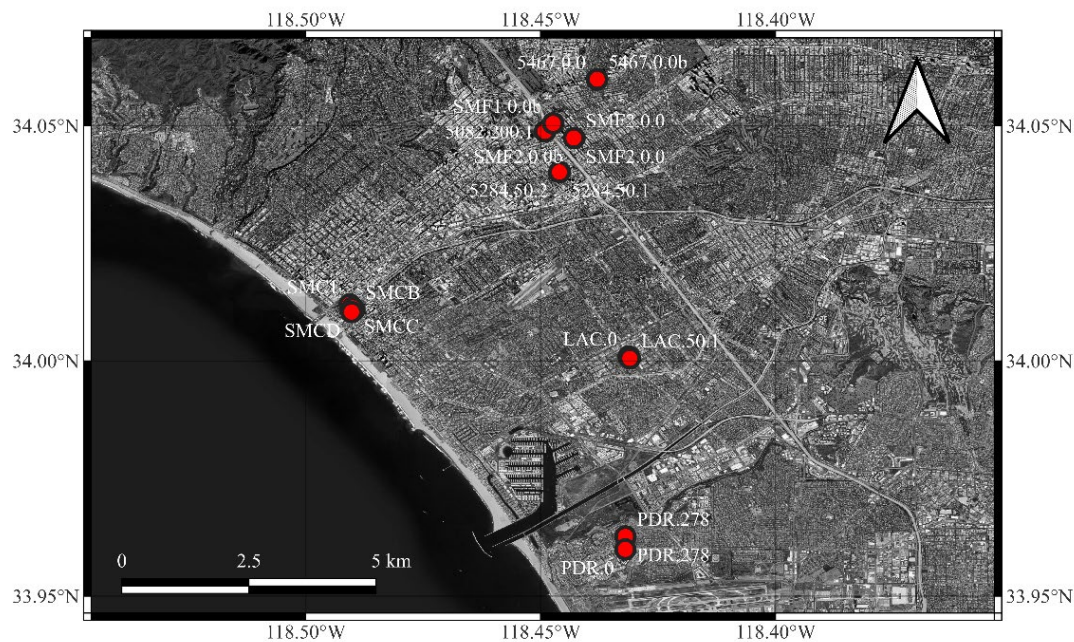


Figure 3.13. Location of the 18 mHVSr curves within the west Los Angeles basin area co-located with strong motion stations.

3.2.6 Investigation in San Fernando Valley

On April 22, 2024, 12 mHVSr measurements were completed within the San Fernando Valley Basin (SFVB), which is a notable sedimentary basin located in southern California, within the greater Los Angeles region. Situated between the Santa Monica Mountains to the south and the San Susana Mountains to the north, the SFVB is part of the Transverse Ranges geologic province. This basin is characterized by relatively flat topography, with an elevation that ranges from 180 to 370 m. To support development of the site response model (Chapters 6 and 7), I collected mHVSr data at strong motion stations with accelerometers that had recorded multiple events including the notable 1994 Northridge earthquake. Figure 3.14 illustrates the locations of the mHVSr

measurements within the SFVB. The tools used to perform this testing are described in Section 3.2.1. The duration of the tests varied, but I aimed to record data for at least one hour to have enough time windows to average, which the importance of this is further described in Section 3.4.

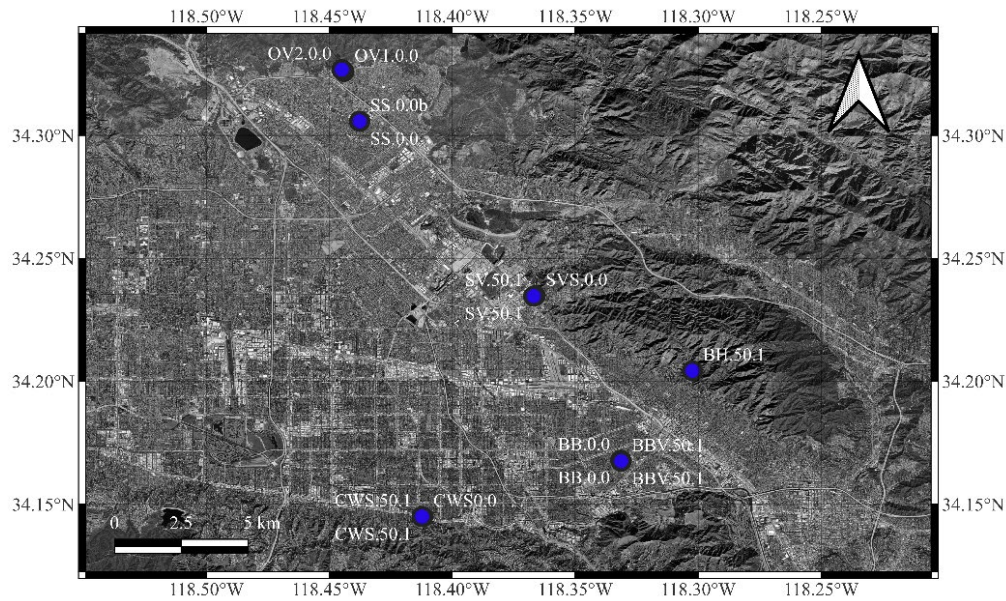


Figure 3.14. Location of the 12 mHVSr curves that were collected within the San Fernando valley area co-located with strong motion stations.

3.2.7 Investigation in Santa Clarita Valley

On December 12, 2023, two HVSR curves were collected in the Santa Clarita Valley area in Southern California. This area is situated north of the San Fernando valley, constrained between the transverse range south of the San Andreas fault. These measurements were performed to collect data near strong motion stations, which recorded ground motions from the 1994 Northridge earthquake. Figure 3.15 shows the locations of the two stations within the Santa Clarita valley.

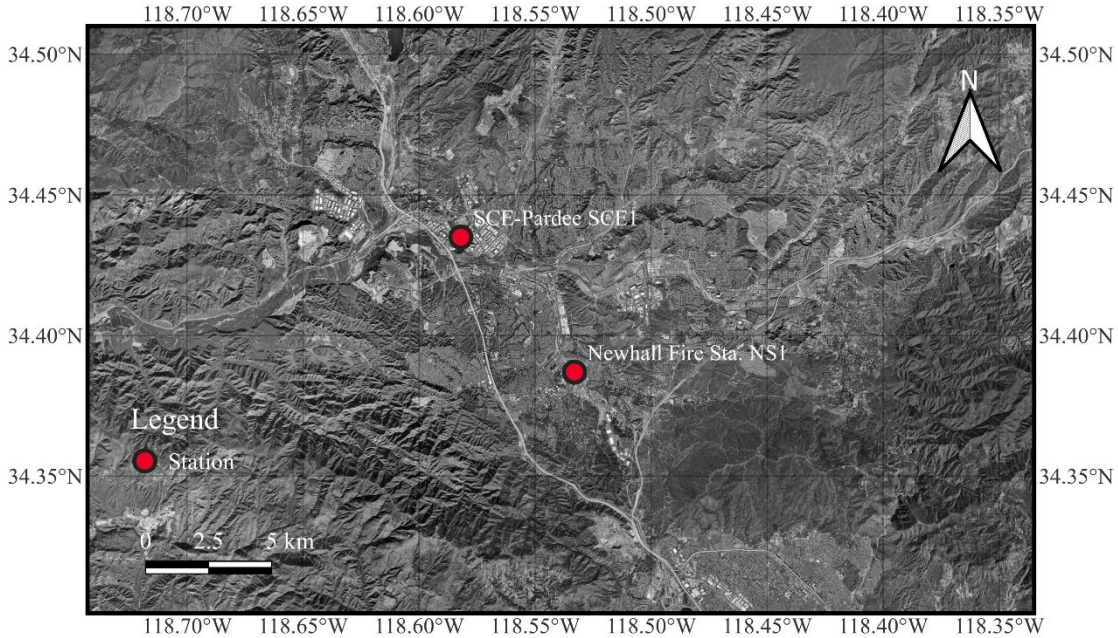


Figure 3.15. Location of the two stations collected within the Santa Clarita valley area co-located with strong motion stations.

3.2.8 Investigation on UCLA Campus

On March 18, 2024, 13 mHVSr measurements were performed at the University of California, Los Angeles (UCLA) campus, which is situated near the Santa Monica Mountains in West Los Angeles (LA), just north of the norther margin of the LA Basin. The geology of the campus consists of primarily younger alluvial deposits overlying relatively shallow bedrock. To support development of the site response model (Chapters 6 and 7), I collected mHVSr data at strong motion stations that had recorded multiple earthquake events. Figure 3.16 illustrates the locations of the mHVSr measurements within the UCLA campus. The test near the UCLA strong motion station was used to investigate the importance of signal drift, as discussed in Section 3.3.3. The tools used to perform this testing are described in Section 3.2.1. The duration of the tests varied, but I aimed to record data for at least one hour to have enough time windows to average, which the importance of this is further described in Section 3.3.

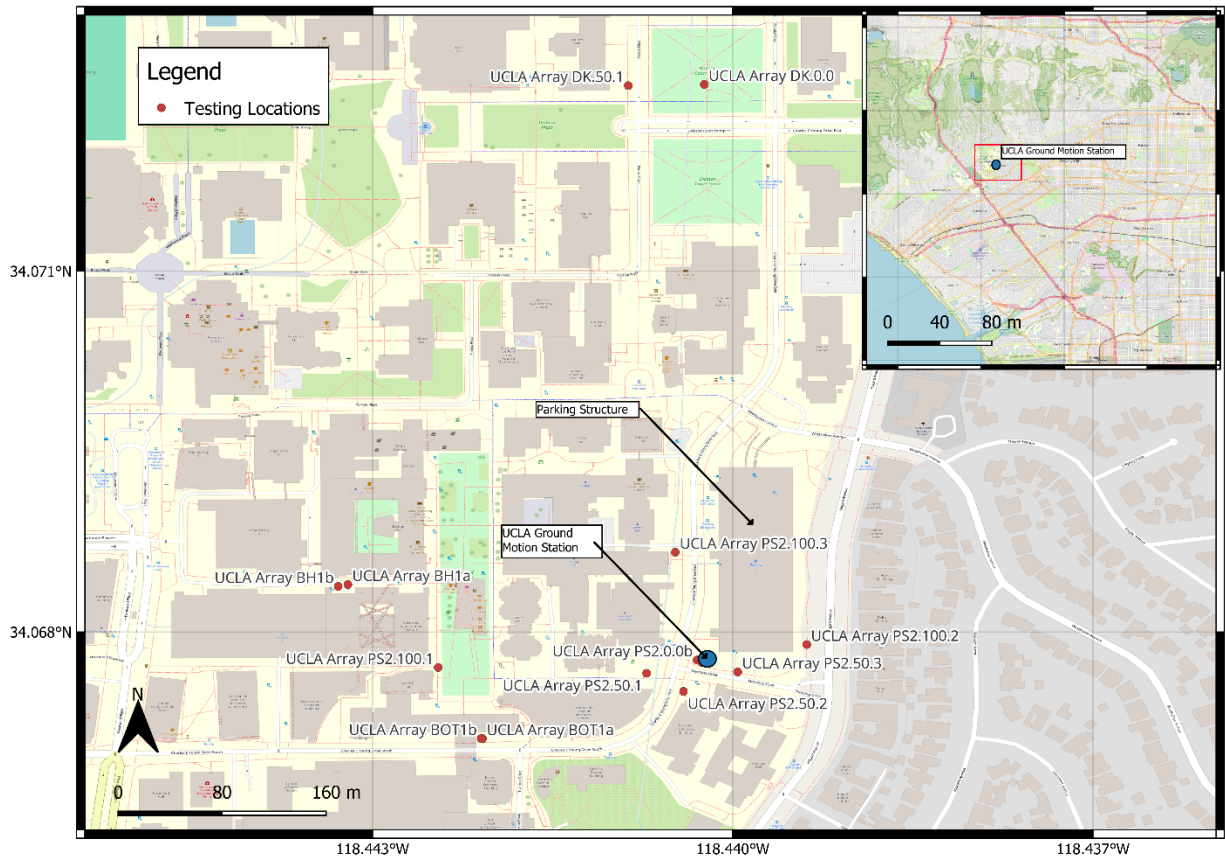


Figure 3.16. Location of the 13 mHVSr curves within the UCLA campus area, one of the curves co-located with a strong motion station as shown in the figure.

3.2.9 mHVSr Data from Other Investigators

I reviewed various literature and DesignSafe datasets to identify publicly accessible mHVSr data that could be added to the VSPDB. The studies investigated were Nweke et al. (2024a-d), Teague et al. (2018), Vantassel et al. (2023), Pinilla-Ramos et al. (2022), Hallal and Cox (2021), Pinilla-Ramos (2024), Hallal et al. (2025), and Anbazhagan et al. (2025).

Pinilla-Ramos et al. (2022) derived mHVSr curves for sites with earthquake ground motion recordings in California. The paper did not provide access to the mHVSr data used in their study, but I investigated whether their sites are in the VSPDB. They used 196 permanent stations for their

study, only 14 of which were not in the VSPDB. Of those 14 stations, 13 were strong motion stations with accelerometers and one had a seismometer. Because mHVSr derived from accelerometers are not reliable (Wang et al. 2023), we did not attempt to retrieve data from those sites using the permanent sensor. We added data from the one seismometer site that had been missing from the VSPDB, which is the SCI2 site in San Clemente Island. Pinilla-Ramos (2024) evaluated the effects of three-dimensional structures on mHVSr spectra and had seven mHVSr curves within the San Francisco Bay area. These microtremor recordings were made available. I processed them using procedures outlined in Section 3.4.1 and input them into the VSPDB.

Vantassel et al. (2023) deployed 196 3-component seismometers in a grid near the Garner Valley downhole array, which were used for mHVSr surveys. The sensors used were Fairfield Nodal Zland 3C equipped with three orthogonal 5 Hz geophones. The dataset is publicly available within DesignSafe but has not been integrated into the VSPDB.

As noted previously (Section 3.2.1), in the early stages of my doctoral research I acquired data from Dr. Cox's group for vertical array sites that they had investigated, including the Treasure Island downhole array (Hallal and Cox, 2020) and Borrego Valley downhole array (Hallal et al. 2025). Hallal et al. (2025) also published passive mHVSr data for multiple temporary arrays that had been installed at Delaney Park, Garner Valley, Borrego Valley, and Treasure Island. The details on the collection of the data for Garner Valley are described in Teague et al. (2018). For Treasure Island and Delaney Park, data collection information is provided in Hallal and Cox (2021). No literature has been published for the data collection in Borrego Valley, but metadata was published within the Hallal et al. (2025) dataset. The sensors used in this study were 120 sec Nanometrics seismometers with Centaur digitizers. Durations varied between 30 min to 2 hr. In total, 384 mHVSr curves were input into the VSPDB from Garner Valley, Delaney Park, Treasure

Island, and Borrego Valley. Two mHVSr curves from personal communication with Prof. Brady Cox for two sites (Borrego and Treasure Island) were input into the VSPDB and have a separate citation ID that can be found in Table 3.1.

Nweke et al. (2024a-d), performed 35 mHVSr measurements at various locations within southern California. These sites were Tarzana (San Fernando valley), Baldwin Hills (LA basin), Brentwood veteran park (West LA), and Griffiths Park (Santa Monica mountains). These data were all collected using the tools described in Section 3.2.1 and vary in duration (some > 1 hr and others ~ 1 hr). These mHVSr curves have been processed and input into the VSPDB.

Anbazhagan et al. (2025) downloaded data from 5,219 permanent stations within North America to derive mHVSr curves. The database was all consistently processed using the python package *hvsrpy* (Vantassel, 2025). The sensor type and where the data is located is within the metadata files in the dataset (Anbazhagan et al. 2025). The dataset is publicly available within DesignSafe but has not been integrated into the VSPDB.

3.3 Permanent Stations

Permanent stations were used to facilitate comparisons between mHVSr curves derived from temporary and permanent deployments and to expand the number mHVSr data within the VSPDB. Our selection criteria focused exclusively on high-gain broadband seismometers, identified as “HH” stations following the Standard for the Exchange of Earthquake Data (SEED) channel codes (IRIS 2012). The majority of the selected stations exhibited a flat frequency bandwidth ranging from 0.0083 to 100 Hz (0.01 to 120 seconds), with sampling rates between 80 and 250 Hz. The number of earthquake recordings at the site was not considered in site selection.

I downloaded and extracted data from 1194 stations across California and surrounding regions (e.g., Nevada, Oregon, Arizona, Mexico) from the Incorporated Research Institution for Seismology (IRIS) (Trabant et al., 2012), which archives data from various data centers, including the Southern California Earthquake Center (SCEDC) and the Northern California Earthquake Data Center (NCEDC) amongst others. Wang et al. (2022) had downloaded data for 142 of these sites and input into the VSPDB. For quality control purposes, checks to catch potential errors in the data were made as described in Section 3.5. This resulted in data retrieval from 1127 stations having useable data. The processing followed the same procedures as for temporary deployments as described in Section 3.4. This dataset was originally presented by Ornelas et al. (2025a). Figure 3.17, show the distribution of stations across California and surrounding regions.

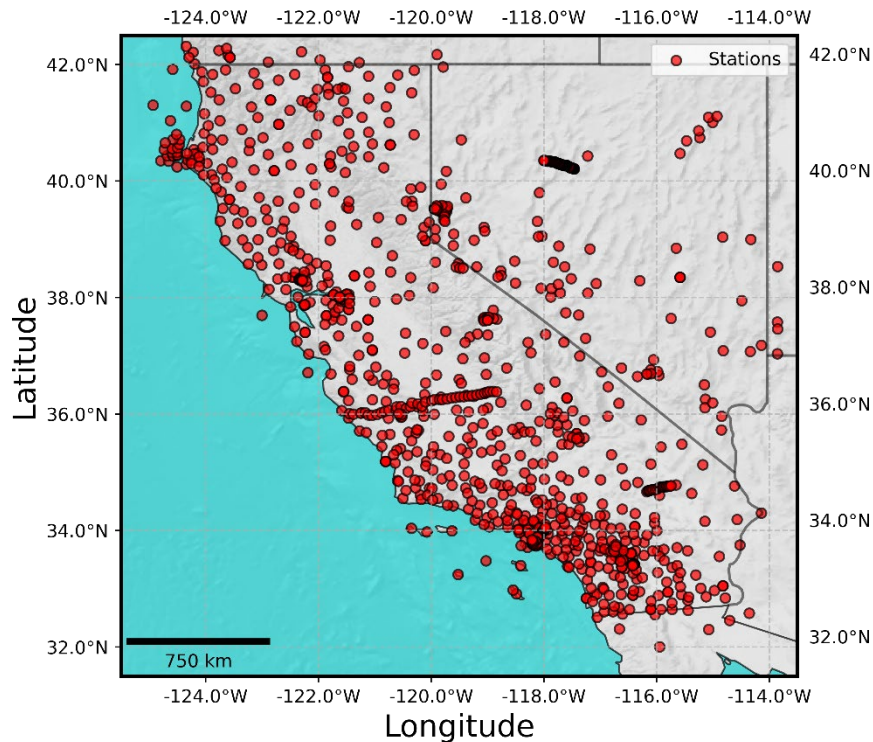


Figure 3.17. Distribution of sites containing high-quality broadband seismometers across California and surrounding regions (e.g., Nevada, Oregon, Mexico).

Table 3.4 presents a subset of permanent stations, which were used to investigate low frequency HVSR. This investigation is presented in Section 4.2. Different processing procedures were applied to permanent seismometers to compare them to processing procedures applied to temporary deployments (described in Sections 3.4.2, 4.2, and 4.3).

Table 3.4. Stations with permanent seismometers considered for analyses in Section 4.2.

Station Code	Station Name	Latitude	Longitude
CZN	Cabazon	33.91375	-116.784
LGB	Laguna Bell	33.9753	-118.149
SMF2	Santa Monica Field 2	34.02201	-118.446
BLA2	Black Rock Canyon Campground 2	34.06931	-116.39
CLO	Camarillo	34.22038	-119.009
DRE	Desert Research Extended Center	32.80532	-115.447
POP	Antelope Valley Poppy Reserve	34.72851	-118.394
RIN	Rinaldi	34.28196	-118.479
RVR	Riverside	33.99351	-117.375
SQC	Sisquoc – FS #23	34.86647	-118.446
STS	State Street	33.79033	-118.199
AFD	Forest Hills Divide #2	38.94596	-120.969
GHGB	Hogback Ridge	39.12745	-122.823
KHMB	Horse Mountain	40.87475	-123.733
LMC	McCloud	41.27416	-122.122
NSM	Sonoma Mountain	38.34879	-122.578
LTC	Tuscan Springs #3	40.20852	-122.126
PHC	Hearst Castle	35.68229	-121.154

3.4 Data Processing Procedures

3.4.1 Initial mHVSR Processing Procedures

After collection of mHVSR data in early stages of my research (for the study described in Section 3.2.1 for which the fieldwork was performed in late August to early September 2022), we sought to process the data to generate mHVSR ordinates following the procedures discussed in Section 2.3. Those processing procedures are based on recommendations in Wang et al. (2022), which is

a modification of SESAME (2004) and Wathelet (2020). The processing was performed using the code *hvsrProc*² by Wang (2021) in Rstudio (R Core Team 2025). When I initially processed the data from the sites in Table 3.3, there were many cases where the raw unprocessed data had appreciable sensor drift across the duration of the records, particularly in the vertical component. In Figure 3.18, an example of this drift is shown in the vertical component as an approximately exponential decay. Moreover, large amplitude, long period oscillations (referred to subsequently as “wobble”) are apparent in the horizontal components (the period of these oscillations is approximately 200 s). This drift at the site in Figure 3.18 (station: 2.250.2), and other sites with similar results, motivated us to investigate methods for processing microtremor data to enhance the reliability of mHVSr ordinates as well as low-frequency ordinates.

As mentioned previously, most of the data recorded during temporary deployments was typically about 1-2 hours in duration. The initial procedure that was used to process the data was to break down a 60-min (3600 sec.) record into individual time windows of 300 seconds. A window length of 300 seconds was used as it would allow us to have 12 discrete windows to average-across when computing the mean mHVSr curve. Allowing for at least 10 cycles per window, the theoretical lowest usable frequency was then $10/300 = 0.03$ Hz. It is important to have at least 10 cycles per window to reliably capture mHVSr ordinates as recommended by SESAME (2004). Each window was detrended to stabilize the signal using a mean removal or constant detrend (also referred to as DC-removal; Oppenheim et al. 1999). Which is defined by:

$$c(t)' = c(t) - \bar{c} \quad (3.1)$$

² More recently, I developed a Python implementation of *hvsrProc*, named *hvsrprocpy* (Ornelas et al., 2026c), which incorporates updates and improvements to HVSr data processing workflows. However, during the early stages of my PhD research, analyses were conducted using the original *hvsrProc* software.

where $c(t)$ ' is the time series in counts after mean removal, and $c(t)$ and $\bar{c}$ are the time series in counts and the mean offset, respectively.

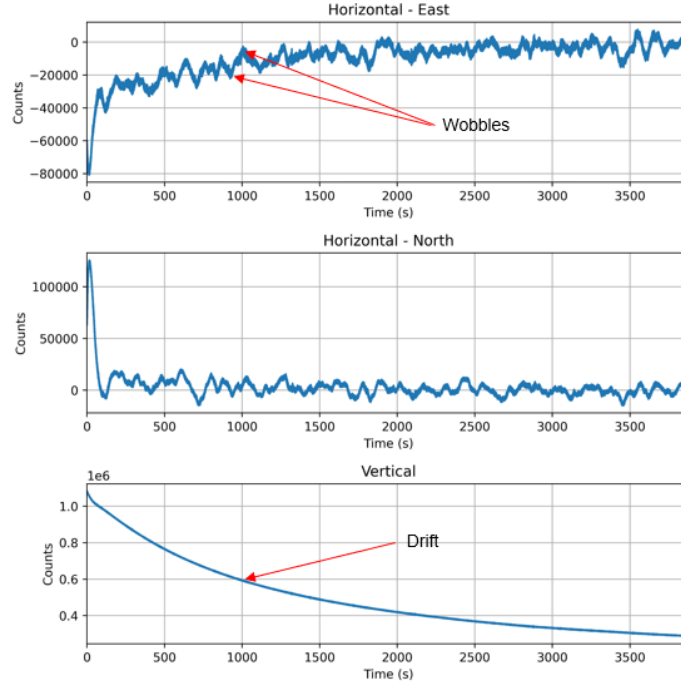


Figure 3.18. Raw time series for all three components of Benicia-Martinez South downhole vertical array, Station: 2.250.2, showing the drift that is occurring in all components, but specifically the vertical.

Moreover, a Tukey (Tukey 1967) windowing function (Tukey window; hereafter) (sometimes referred to as a Cosine-Taper windowing function) and a high-pass Butterworth (Butterworth 1930) filter are also applied to each individual window. The Tukey windowing function is defined as:

$$\text{Window Start: } w_i = \frac{1}{2} \left[1 + \cos \left(\pi \frac{n_b + i - 1}{n_b} \right) \right], i = 1, \dots, n_b \quad (3.2)$$

$$\text{Window End: } w_i = \frac{1}{2} \left[1 + \cos \left(\pi \frac{i - 1}{n_e} \right) \right], i = 1, \dots, n_e \quad (3.3)$$

where n_b is the number of points within the beginning taper, and n_e is the number of points for the end taper. The Tukey window was applied with 5 percent tapering on each side of the individual time window. This way the ends of the window would be more stable when taking the Fast Fourier Transform (FFT) of each window. The Tukey windowing function is similar to a rectangular windowing function (e.g., Dirichlet Window) when the percentage of tapering is zero and similar to a Hann window when tapering is 100 percent, meaning that there is a gradual increase from zero to one at each end of the window depending on the tapering used. The high-pass filtering followed an acausal format, meaning that it was applied in the frequency domain instead of the time domain. The FFT of the mHVSr data were taken and then filtered, then the inverse FFT of the signal was taken to revert to the time domain. The function of the acausal filter is defined by (Gustafsson 1996):

$$Y = \sqrt{\frac{(f/f_c)^{2n_p}}{1+(f/f_c)^{2n_p}}} \quad (3.4)$$

where n_p is the number of poles and f_c is the corner frequency. Each time window was then individually analysed to perform an anti-triggering analysis. This would exclude signals in time windows with amplitudes greater than adjacent windows. Anthropogenic sources can produce these transient, erratic bursts and removal of these windows ensures more constant amplitudes to compute mHVSr mean curves. Figure 3.19 shows the graphical user interface (GUI) from the *hvsrProc* code for a time series at a site in Benicia-Martinez South in which windows can be selected for removal (in the colour gray). The fourth window where we see a large spike in amplitude would likely be removed, as this is likely not a characteristic of the true microtremor wavefield.

Figure 3.20 shows an example of a processed time series that has been separated into discrete 300-second-long-time windows (indicated by alternating colours of blue and pink) where a 5 percent Tukey window and high-pass filter of 0.01 Hz are applied to each window as described by Eq. 3.2, 3.3, and 3.4, respectively. Once the procedures described above are implemented and the time series window selections are completed, the discrete Fourier transform (DFT) using the FFT algorithm of each discrete time window is computed for each component. The equation for the DFT is given as (Cooley and Tukey 1967):

$$C_K = \frac{1}{N} \sum_{j=1}^N a(j) \omega_N^{(j-1)(k-1)} \quad (3.5)$$

$$\omega_N = e^{(-2\pi i)/N} \quad (3.6)$$

where k is the frequency index, N is the number of points, C_K is a Fourier coefficient, and $i = \sqrt{-1}$. The FAS is computed by taking the absolute values of the coefficients multiplied by the sampling rate, dt . The FAS is then smoothed using a Konno and Ohmachi (1998) smoothing factor of $b = 20$, which is applied separately for each frequency (f). When applied to frequency f , the smoothing function is expressed as:

$$W_B(f, f_c) = [\sin(\log_{10}(f/f_c)^b / \log_{10}(f/f_c)^b)]^4 \quad (3.7)$$

where b and f_c are coefficients for bandwidth and corner frequency, respectively. Once the FAS is smoothed the ratio of the geometric mean of the horizontal components over the vertical component FAS are taken to compute the mHVS curve for each discrete window. The mHVS mean curve is then computed as the average of the mHVS curves for individual discrete windows.

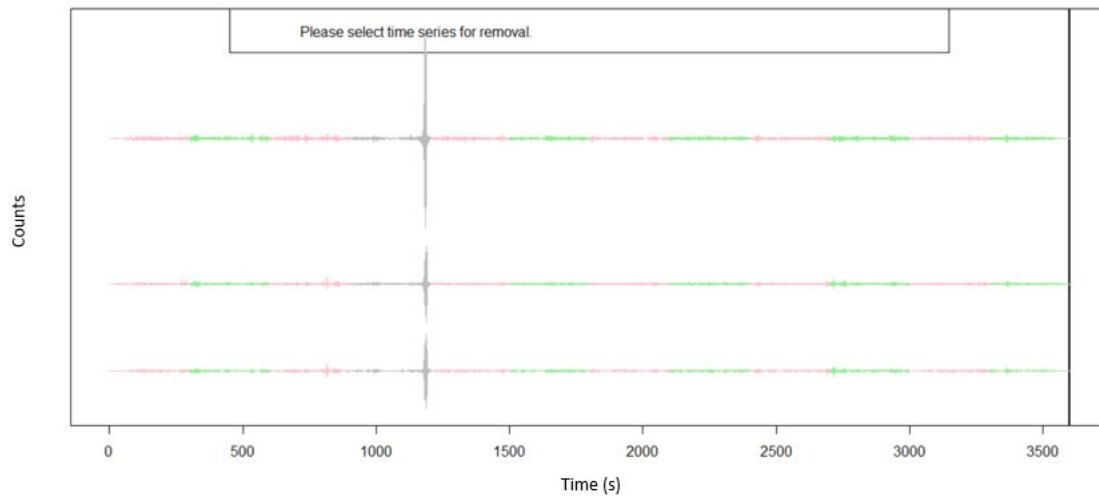


Figure 3.19. Example of antitriggering usage from the GUI in *hvsrProc* on Rstudio, where a window (in gray) is rejected due to the large amplitude relative to other windows.

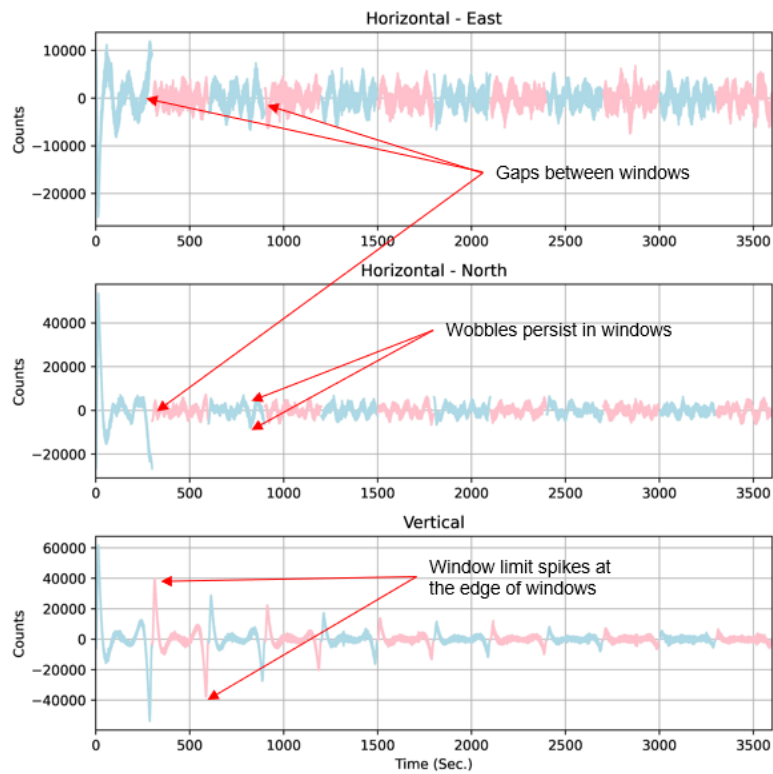


Figure 3.20. Normalized time series data from *hvsrProc* from data shown in figure 2 in Benicia-Martinez Station: 2.250.2 showing discrete 300-second-long-time windows which have been filtered

by 0.01 Hz, Tukey windowed by 5 percent taper, and demeaned, when drift is present in the vertical component. The components are East(top), North(middle), Vertical(bottom).

For the Benicia-Martinez South station 2.250.2 site from Figure 3.20, the as-recorded motions in these plots have not been pre-processed to remove the drift. The large spikes at the edges of windows for the vertical component are a consequence of drift not having been removed prior to windowing. Much of the vertical component data that was processed generated features similar to those seen in Figure 3.20. Moreover, I observed that long period wobble in the horizontal components causes issues within the 300-second-long-time windows, where gaps form within the windows, as seen in Figure 3.20.

These issues affect Fourier amplitudes of this data across a wide frequency range as a result of spectral leakage, potentially distorting mHVS_R ordinates. Spectral leakage can be caused by taking the FFT of a window that is not stationary, which could affect all the components in Figure 3.20 but would be strongest for the vertical component due to the pronounced drift. The distortion of the Fourier amplitudes from spectral leakage can make the vertical components larger than the horizontal components at low frequencies, thus lowering mHVS_R ordinates. Because this is not a true representation of the ground conditions, I updated our procedures to correct for signal drift prior to computing mHVS_R ordinates (Section 3.4.4).

3.4.2 Initial Findings After Processing

The issues described for Benicia-Martinez South Station 2.250.2 in Section 3.4.1 are not unique. When examining trends of results across multiple sites, I noticed there were other issues in mHVS_R curves which prompted me to look further at other processing procedures to better understand their effects. I noticed consistently high dispersion (i.e., between-window variability) at low frequencies. An example of high dispersion at low frequencies is provided in Figure 3.21,

which shows an mHVSr mean curve and standard deviation for a temporary mHVSr survey performed at the El Centro-Meloland vertical array, site 4 from Table 3.2.

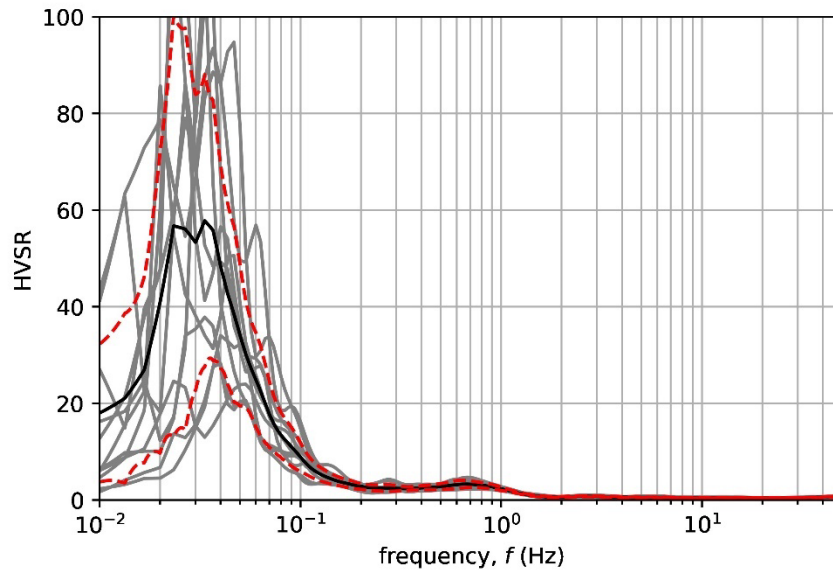


Figure 3.21. mHVSr curves for station 4.0.0 at the El Centro-Meloland vertical array site. The mean curve is in black and the dashed red curves indicate $\pm$ one the standard deviation from the mean. The gray curves indicate mHVSrs for individual windows.

I examined whether record duration or the length of each window would affect the mHVSr spectra. I downloaded 86,400 sec (24 hr) of microtremor data from IRIS station: DRE at 6:00 am PST August 28th, 2022. Figure 3.22 shows the mHVSr mean curves for different window lengths for the 24 hr record at station DRE. I selected this site since it was situated in a relatively quiet environment within the Imperial Valley, which is primarily agricultural. I was interested in determining the reliability of peaks present at frequencies below 0.1 Hz. It was also near the location of a temporary mHVSr survey near the El Centro Meloland downhole array (Figure 3.6; about 3.4 km from the DRE site); this was intentional as I also wanted to compare the two mHVSr curves to see if there were similarities.

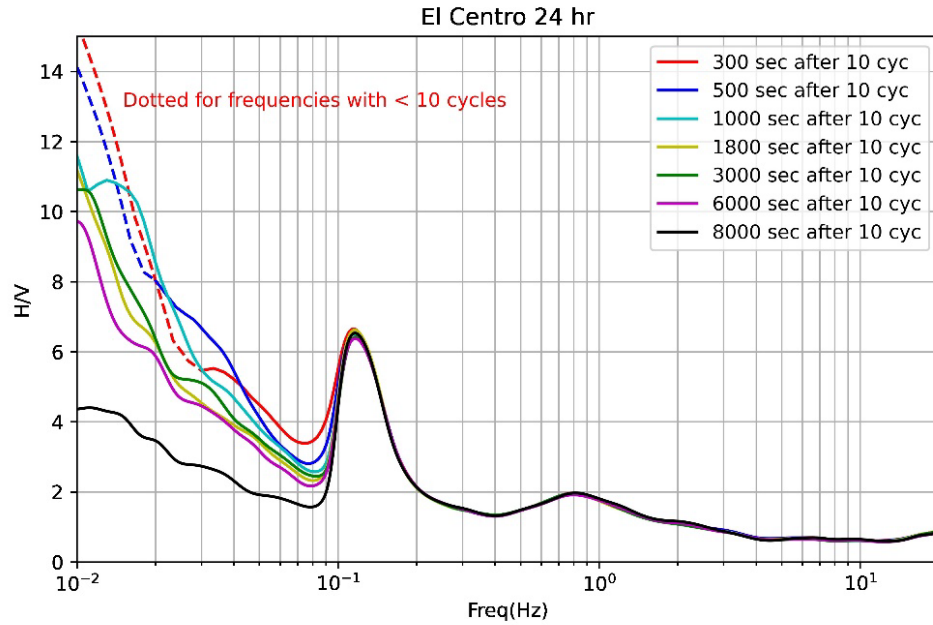


Figure 3.22. mHVSr mean curves for the permanent station DRE for 24 hr of recorded data. The image shows mean curves with varying time window lengths. The dashed line indicates frequencies with less than 10 cycles per window.

I investigated the effects of different window lengths and found that different lengths produced significant differences in the amplitudes of the mHVSr mean curves at frequencies below 0.1 Hz. The HVSr ordinates computed using longer duration windows (e.g., 8000 sec windows length) are significantly lower than the curves derived using shorter duration windows. My interpretation of the reason for this sensitivity to window length is rooted in the number of cycles of motion at a given frequency within a window (more cycles provide more stable mHVSr ordinates). The number of cycles is equivalent to the product of window duration and frequency, so it drops as frequency decreases. Wang et al. (2022) suggested the minimum frequency for which mHVSr ordinates could be reliably estimated is that associated with 200 cycles for the full record duration, which would be reduced to $200/N_{win}$ for an individual window (where N_{win} is the number of windows). For the DRE example, the signal has a duration of 86,400 sec. Consider the cases of 500 sec and 8000 sec window durations, which provide ~ 170 and ~ 10 windows, respectively. The

number of cycles per window would be ~6 and 160, respectively, at a frequency of 0.02 Hz. Figure 3.22 shows with dotted lines the portions of the mHVSr curves where the number of cycles is < 10, which appears to be reasonable threshold with which to judge the efficacy of the results that is conceptually similar to the Wang et al. (2022) criterion of 200 cycles for the signal duration. The temporary deployment near the Meloland array (Figure 3.21) had a 124 min (7440 sec) record duration with 24 windows (310 sec window duration). At 0.02 Hz, the number of cycles per window is again 6, although there are far fewer windows in the signal than for DRE. This may contribute to the much larger low-frequency amplitudes in Figure 3.21 as compared to Figure 3.22. The differences between these results could also be affected by DRE being a permanent station (Figure 3.22), which tends to reduce low frequency ordinates as described in Section 4.2.

I also downloaded microtremor data for a 1-hour record from the DRE station to see if there were differences in mHVSr ordinates caused by using a shorter overall record length (similar to what would be recorded in a typical temporary deployment). This allows for testing of the hypothesis that the smaller number of windows for the Meloland temporary recording may be causing the higher mHVSr ordinates. Figure 3.23 shows the mHVSr mean curves for different window lengths for a 1 hr record at station DRE. The trends of ordinates with respect to window length in this case are less clear than those for the 24 hr record, although the shortest window length (60 sec) produced the highest ordinates at low frequencies. Similar to Figure 3.22, the HVSr curve shown in Figure 3.23 still does not exhibit the large amplitude ordinates that are illustrated in Figure 3.21. This suggests that the differences observed previously between Figures 3.21 and 3.22 may be more related to differences between the two sites (including DRE being a permanent sensor) than to the different numbers of windows.

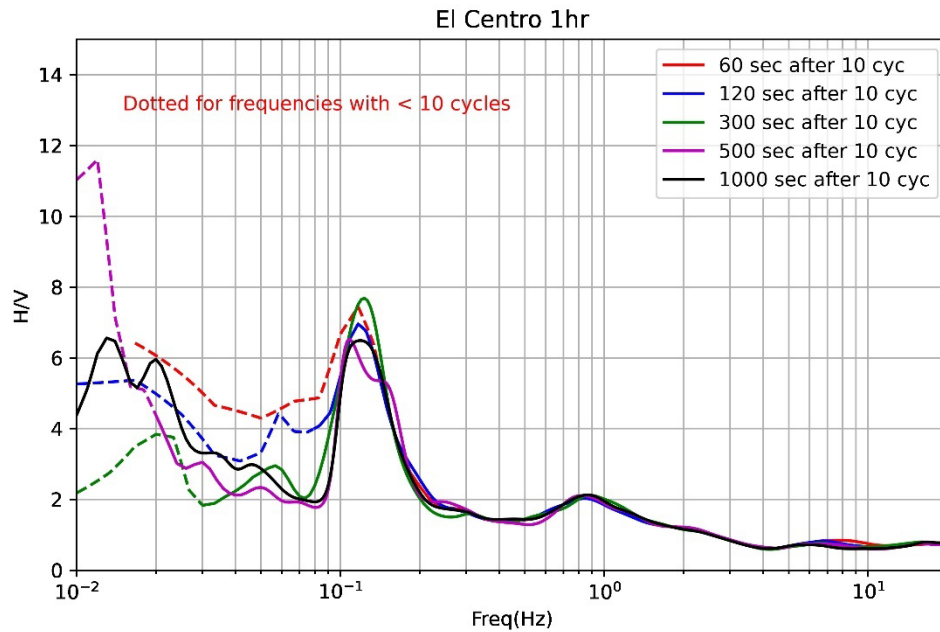


Figure 3.23. mHVSr mean curves for the permanent station DRE for 1 hr of recorded data. The image shows mean curves with varying time windows used, to see the effect of different window lengths. The dashed line indicates frequencies with less than 10 cycles per window.

The window length exercise was repeated for station LGB in the LA Basin, this time using a 6-hr record duration. As shown in Figure 3.24, we again see that shorter windows produce larger amplitudes. However, if the portions of the mHVSr curves with fewer than 10 cycles / window were omitted, the results for different window lengths would be relatively consistent in this case. Based on these observations, it was decided that for an overall signal duration of 3600 sec, a window length of 300 seconds was sufficient to have at least 10 cycles per window and 10 windows to average, which would be expected to provide mHVSr ordinates that are reliable down to frequencies of 0.03 Hz. These findings are consistent with recommendations provided by SESAME (2004). However, additional problems were encountered at these low frequencies that are discussed in Chapter 4.

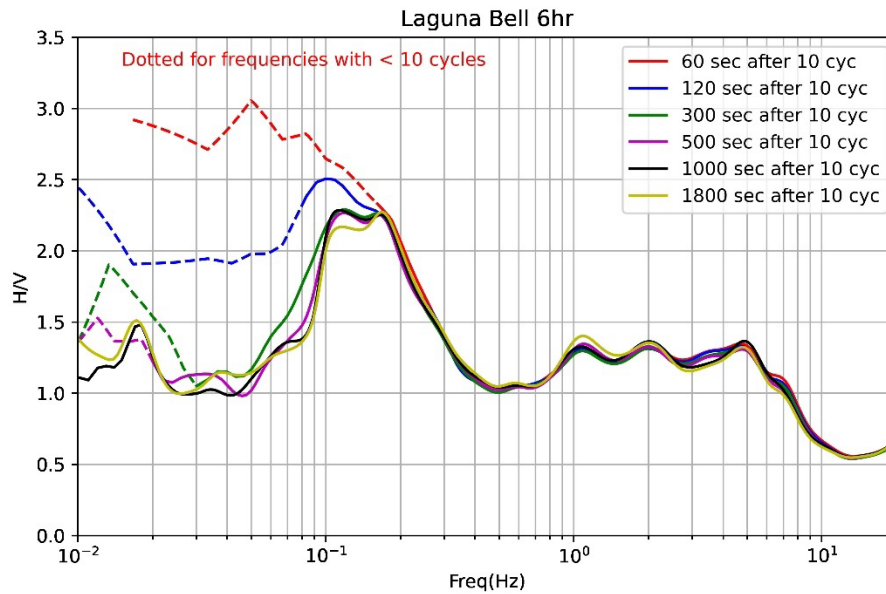


Figure 3.24. mHVSr mean curves for the permanent station LGB for 6 hr of recorded data. Mean curves are shown for varying windows lengths. Dotted lines indicate ordinates with < 10 cycles per window.

We also investigated the effects that certain detrending or tapering had on the development of mHVSr curves. For station DRE in El Centro, I applied different detrend methods as follows:

1. Constant Detrend (detrend 1): Removes the mean (DC offset) from the data.
2. Linear Detrend (detrend 2): Removes the linear trend.
3. Polynomial Detrend (detrend 6): Fits a sixth-order polynomial to remove the trend.

Figure 3.25 shows an example of how the detrending methods compare for a synthetic microtremor signal. Clearly the higher order detrend model is more effective in this case. I also applied different tapering percentages (5 (default) and 10) to see the effect that tapering had in combination with the different detrend methods. Figure 3.26 shows the effects that detrending and tapering had on the DRE site mHVSr mean curves at different frequencies. Figure 3.27 shows similar results for the LGB site.

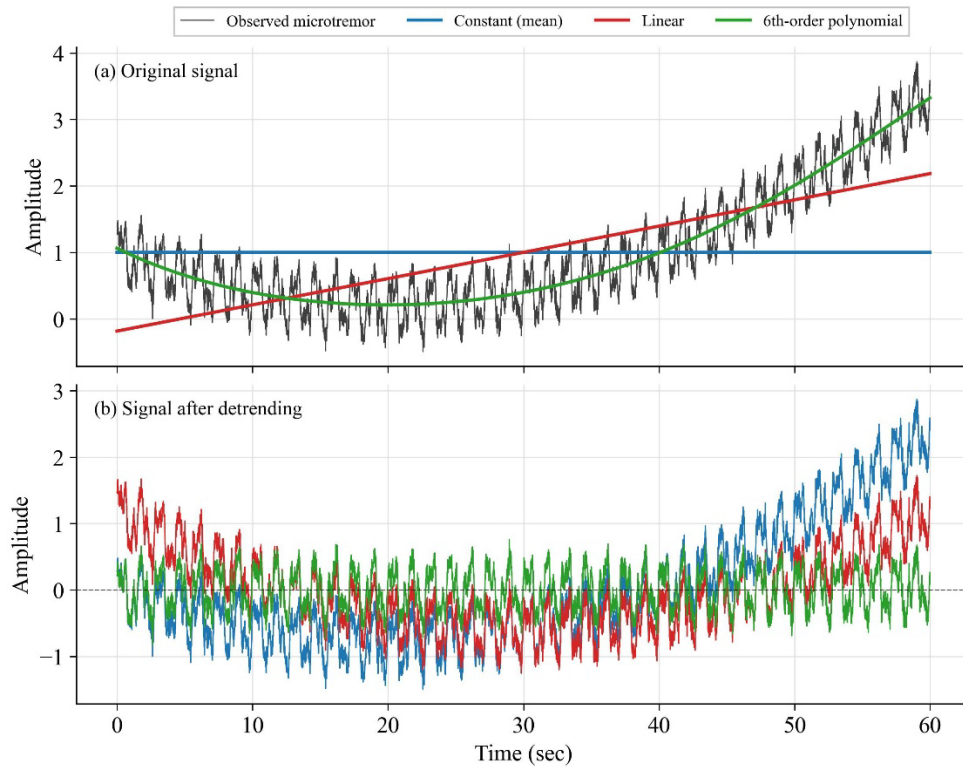


Figure 3.25. Comparison between different detrend methods on a synthetic microtremor recording. (a) Different detrend methods applied to a microtremor recording, (b) results of the different detrend method on the microtremor recording.

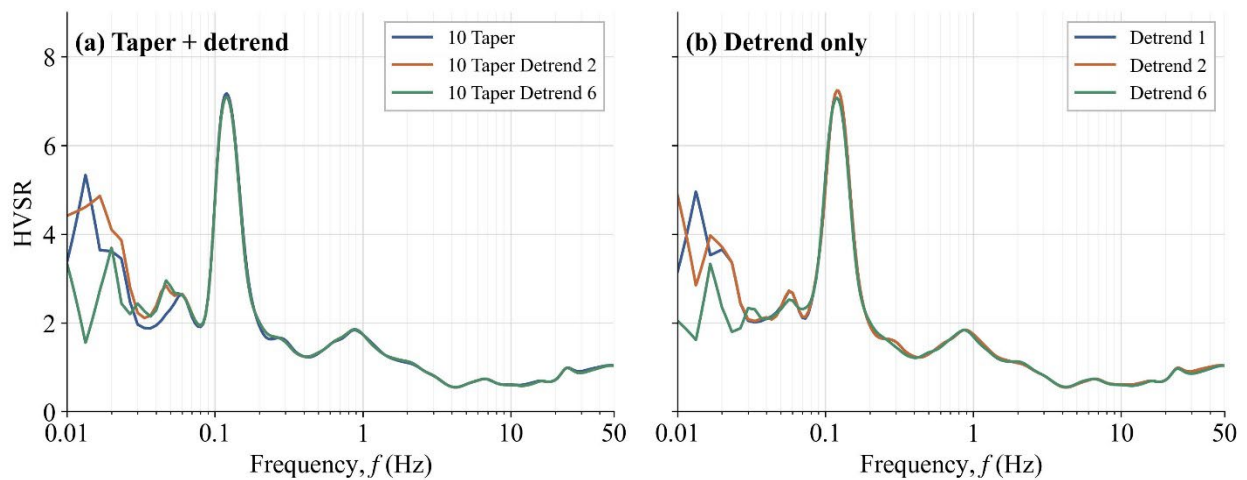


Figure 3.26. mHVSr mean curves for the permanent station DRE for 1 hr of recorded data. The image shows mHVSr mean curves with varying detrend and tapering used, to see their effect on mHVSr ordinates.

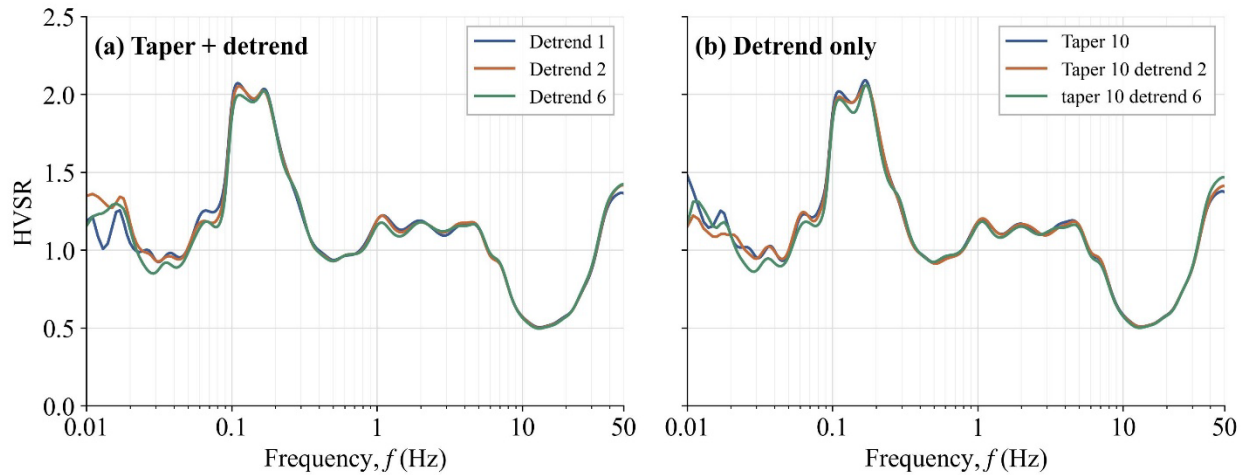


Figure 3.27. mHVSr mean curves for the permanent station LGB for 6 hr of recorded data. The image shows mHVSr mean curves with varying detrend and tapering used, to see their effect on mHVSr ordinates.

The results presented in Figures 3.26 and 3.27 show that the different processing procedures have relatively little impact for frequencies above 0.1 Hz. However, below 0.1 Hz there are slight differences, but they are not as significant as what was seen for alternate window lengths. For the DRE site there is much more impact from applying a 10 percent taper compared to just applying a detrend. However, for the LGB site, there is little to no impact regardless of the detrend or 10 percent taper, except at about 0.018 there seems to be a dip down. Using just a detrend at the LGB site results in a slight ramp-like characteristic. Based on this study we concluded that 5 percent tapering and a constant detrend was sufficient to process the data, which is the recommendation provided in Section 3.4.4.

3.4.3 Short Period and Long Period Configuration Investigation

As noted in Section 3.4.1, sensor drift was experienced in many of the mHVSr surveys that were performed. One of the surveys introduced in Section 3.2 was conducted to investigate this effect; specifically the one at the UCLA strong motion station near a parking structure. The details of how the data were collected are described in Section 3.2.8. Figure 3.28 shows a plan view of the site.

mHVSr data were collected using the tools described in Section 3.2.1. Two mHVSr surveys were performed at a rate of 200 Hz for about 1 hour. One test was done using long period mode and another was done using short period mode, which are configurations that can be set on the sensor to initialize a settling protocol within the sensor. This setting controls the internal settle rate, with short-period mode causing the sensor to internally settle faster and reduce drift. Figure 3.29 shows the time series of a sensor that was configured using long period mode initially. While the horizontal time series are relatively flat, the vertical component has both drift and long-period (~1000 sec) wave-like characteristics.

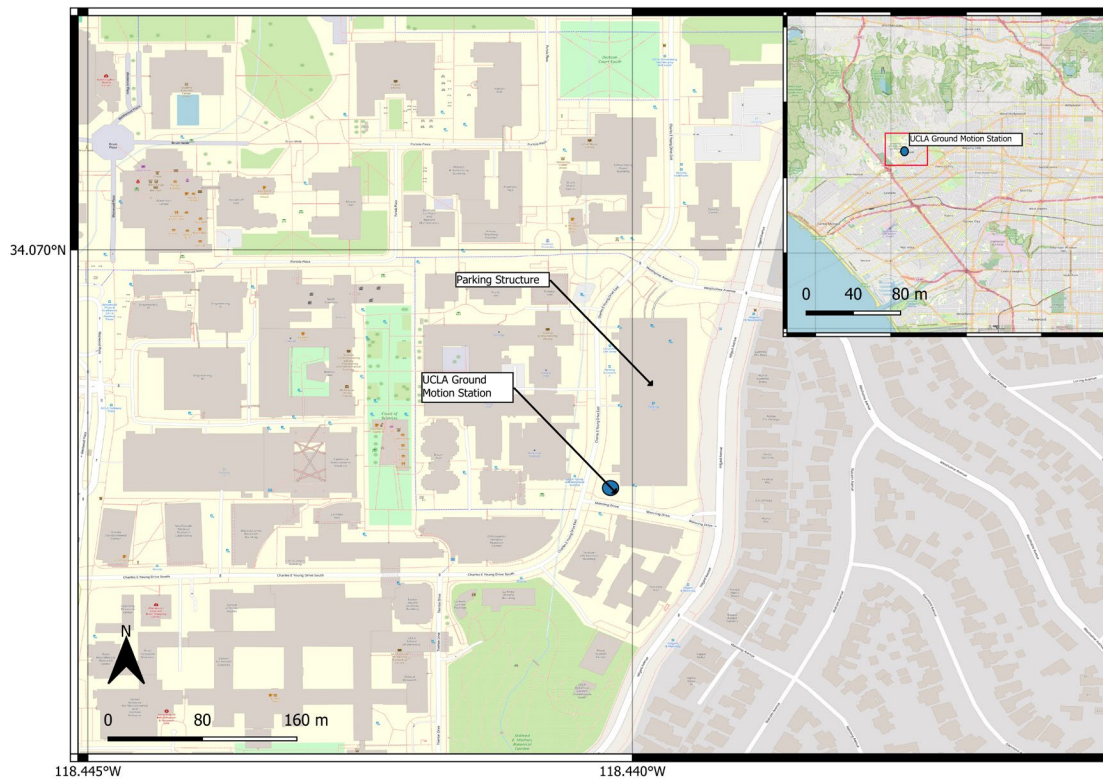


Figure 3.28. Image of approximate layout followed when conducting mHVSr surveys at the UCLA.

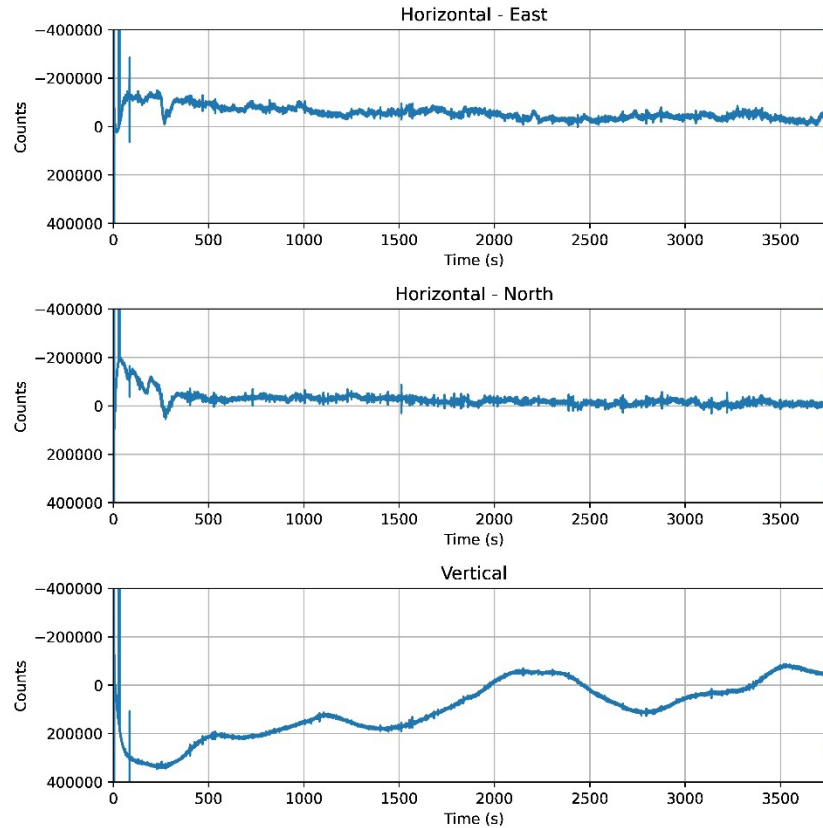


Figure 3.29. Raw time series for the mHVSr temporary deployment done at UCLA parking structure configured using long period mode for a 1 hr recording.

Figure 3.30 shows the time series of a sensor that was configured using short period mode. The horizontal components remain flat. The vertical component lacks drift and has fewer wave-like characteristics than what was observed in short period mode. This demonstrates the importance of configuring the sensor to short period mode, to reduce vertical-component drift and long-period wobble. Drift has a significant effect on mHVSr data and can cause the data to be distorted by external noise, which can give a false representation of true resonance at a site. These effects were seen at other sites where temporary installments of mHVSr were made, for this reason I recommend that short period mode be used in temporary field deployments.

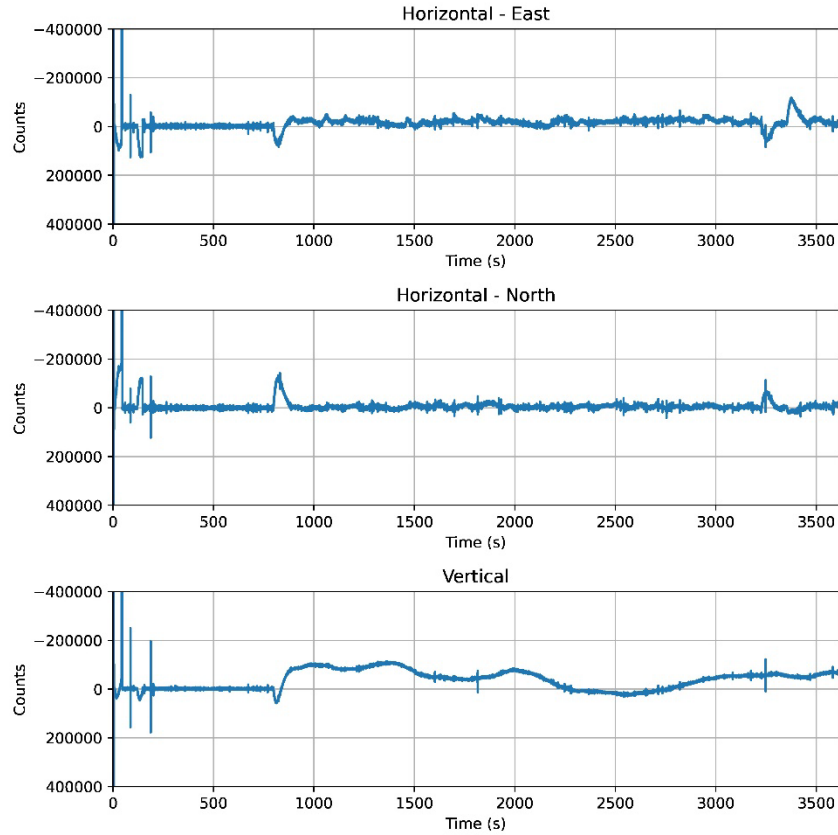


Figure 3.30. Raw time series for the mHVSr temporary deployment done at UCLA parking structure configured using short period mode for a 1 hr recording.

3.4.4 Addition of Pre-processing

After these investigations, I sought to develop new procedures to stabilize the time series data prior to processing to compute mHVSr curves (procedures in Section 3.4.1). Recording data after long “settling” periods (time when the sensor is equilibrating or stabilizing its internal reference due to configuration or deployment setup) reduces but does not eliminate drift. As a practical matter, I aim to develop procedures that would be effective for short-duration (60 min) deployments. Drift removal was applied with the following steps:

1. Demeaning of the entire time series: This entails subtracting a weighted mean, where the weight is taken from a cosine-tapered (or Tukey) window applied to the entire time series.

2. Following de-meaning, apply a Tukey window to the entire time series.
3. Filter the entire time series: This entails applying an acausal high-pass Butterworth filter.

We have found that the mHVSR results are relatively insensitive to the high-pass corner frequency (f_{cHP}) within reasonable bounds, and for the plots herein we have used $f_{cHP} = 0.042$ Hz. The corner frequency for a Butterworth filter is selected at the point where the amplitude is 0.7. Ordinates are not appreciably affected by the filter for frequencies $f > 1.25f_{cHP}$. Accordingly, $1.25f_{cHP} = 0.053$ Hz comprises the lowest usable frequency.

After applying these steps, the signal is stationary, as shown in Figure 3.31 for the Benicia-Martinez station site 2.250.2. I anticipated that the stabilized signal would produce more reliable mHVSR spectral ordinates. Figure 3.32 shows mHVSR curves for sites 2 and 9 from Table 3.2 (Benicia-Martinez and La Cienega) derived from the data with and without drift removal. Without pre-processing (blue line), the mHVSR ordinates appear to be stable at low frequencies, but they only appear this way because the vertical component is contaminated by spectral leakage, which is causing the vertical component to be nearly the same amplitude as the horizontal components. Following pre-processing, the stationary signals produce the mHVSR shown in orange lines in Figure 3.32. As shown by the orange curves in Figure 3.32, at frequencies $< \sim 0.2$ Hz, mHVSR ordinates increase markedly (by about one to two orders of magnitude). The resulting mHVSR curves for both sites have a peak at approximately 0.03 Hz, which is close to the f_{cHP} . Figure 3.33 shows that similar features are observed at additional sites from tests performed at various vertical arrays from Table 3.2. As shown in Figure 3.34, these peaks are caused by a sudden change in Fourier amplitudes in the vertical component due to the application of these processing steps discussed above.

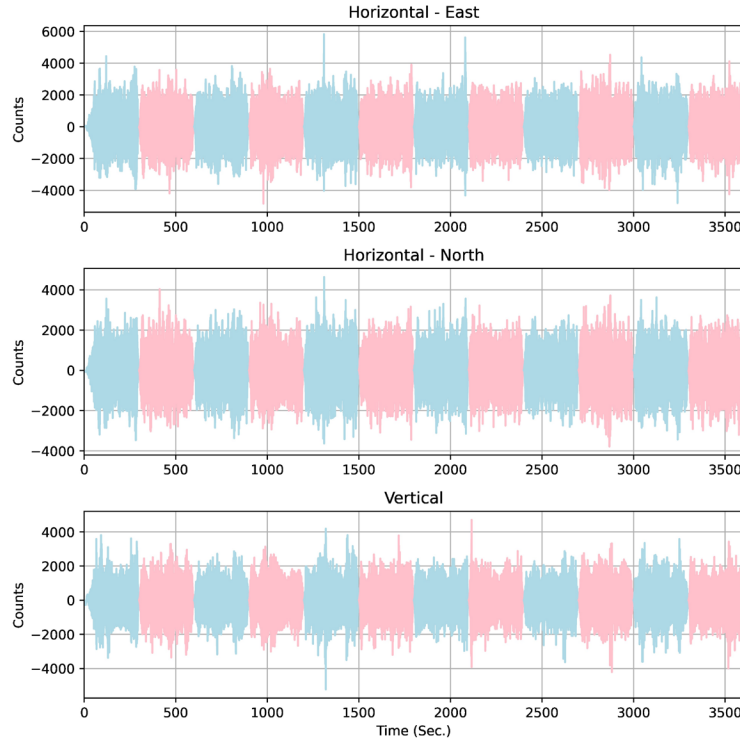


Figure 3.31. Normalized time series from *hvsrProc* from data shown in Figure 2, showing discrete 300-second time windows. The windows have been filtered by 0.01 Hz, Tukey windowed by 5 percent taper, and demeaned, which have corrected the drift and wobble in all components. The components are East(top), North(middle), Vertical(bottom).

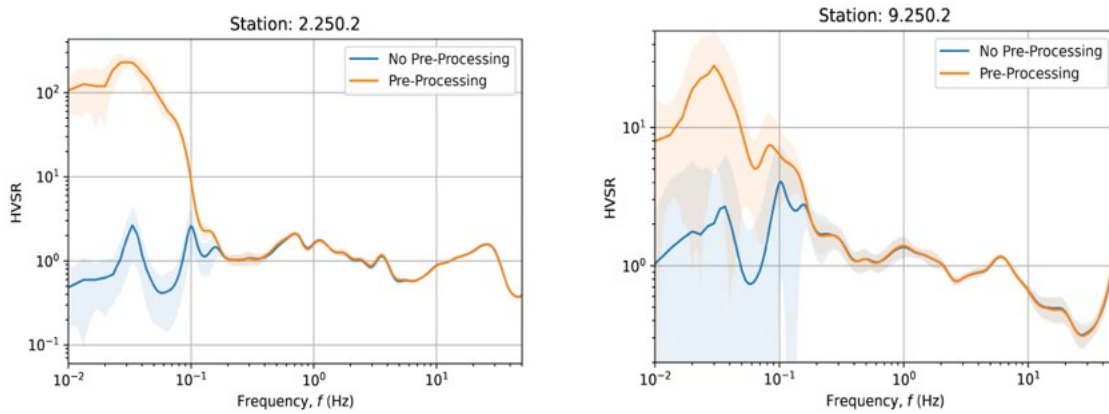


Figure 3.32. (a) left: mHVSr mean curves with standard deviations for site 2.250.2 in Benicia-Martinez South downhole vertical array, (b) right: mHVSr mean curves with standard deviations for site 9.250.2 in La Cienega downhole vertical array. This shows how implementing different processing procedures can have drastic effects on low frequency mHVSr. Also, regardless of location, the same peak characteristics are present at frequencies below 0.1 Hz.

I investigated the causes of the peaks, which may be due to the localized slab-tilt or self-noise of the sensor that is further described in Chapter 4. Either way, the peak in the orange curves in Figure 3.33 and 3.34 near 0.03 Hz has no site-related physical meaning. Moreover, the low-frequency ordinates themselves, even at frequencies above the peak (0.03-0.1 Hz), seem to have no clear relationship to site properties. At higher frequencies (>0.1 Hz) the signal remains unaffected whether the pre-processing steps were applied or not.

I was initially surprised at these findings, given that the sensors used in the deployments are expected to be usable to much lower frequencies (~ 0.0083 Hz) than those where problems emerge. This is concerning, because I was motivated in this research to use mHVSr to evaluate resonances in deep basins (e.g., LA, Ventura, Imperial Valley basins), which would appear to be impossible based on these results. Some additional investigations related to this subject have been undertaken to further investigate the issue, as described in Chapter 4.

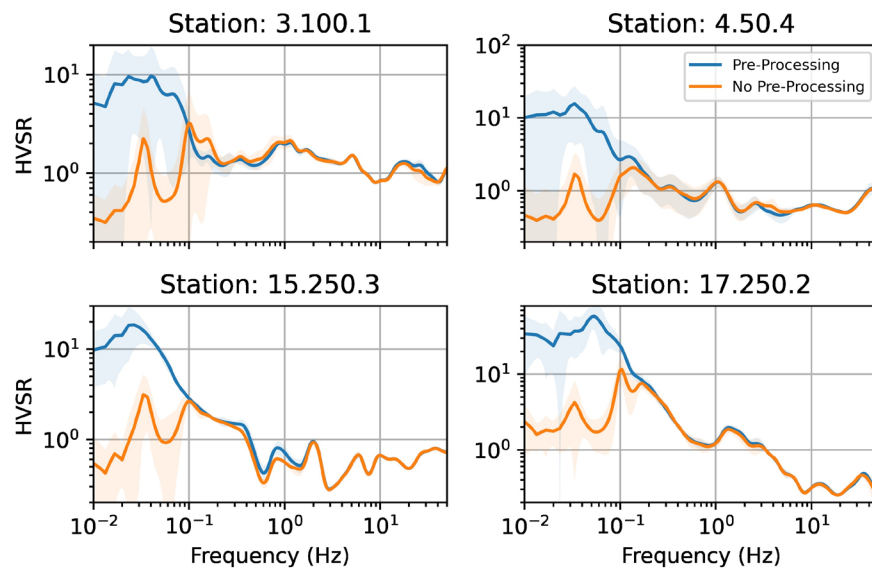


Figure 3.33. mHVSr spectra for 4 different sites, (a) top left: Station 3.100.1 Crockett-Martinez, (b) top right: Station 4.50.4 El Centro-Meloland, (c) bottom left: Station 15.250.3 Corona, (d) bottom

right: Station 17.250.2 Coronado West, each site showing the same peak feature at the same frequency of around 0.02-0.04 Hz, even though these sites are all at different areas of California.

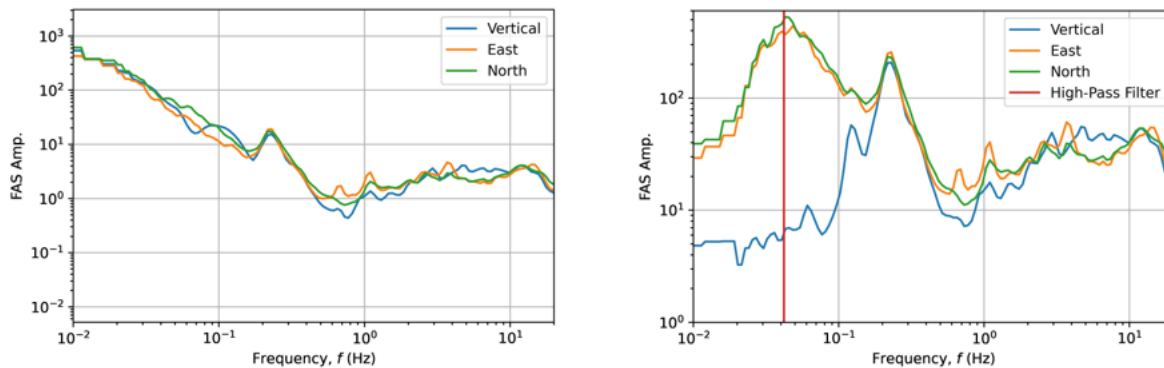


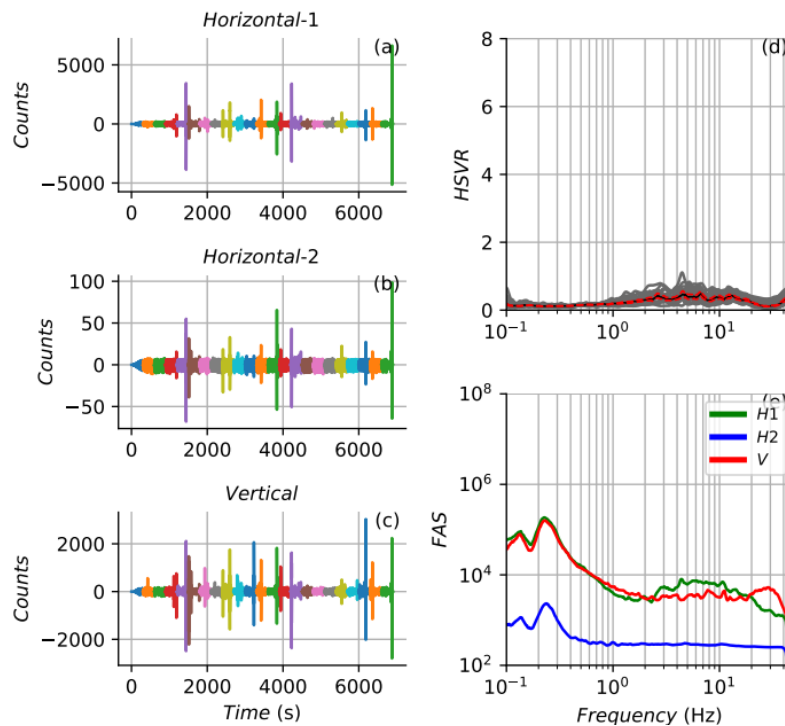
Figure 3.34. (a) left: Fourier Amplitude Spectra (FAS) for site 2.250.2 in Benicia-Martinez South downhole vertical array with no high-pass corner filter applied. (b) right: FAS for site 2.250.2 in Benicia-Martinez South downhole vertical array with high-pass corner filter frequency of 0.042 Hz applied (shown by the blue vertical line). Note the strong drop off at low frequencies for the filtered vertical-component signal.

3.5 Quality Control Checks

Throughout the process of expanding the VSPDB, it was important to visually check the HVSR data (e.g., curves, time series, FAS) prior to inputting them into the database. This was especially important when we extracted microtremors from IRIS for processing and developing of mHVS. The three characteristics that were checked were:

- Was sufficient data available to perform the mHVS processing (i.e., at least 10, 300 sec windows with meaningful data in the time domain)?
- Are there no systematic differences between the three time-series components (i.e., no apparent gain inconsistencies)?
- Are there any individual windows present that could significantly affect the mean mHVS?

Figure 3.35 illustrates examples of cases that would have been excluded from being input into the database. Figure 3.35a shows a station in which the horizontal-2 component appears to have a different gain than the other two components, resulting in an offset in the FAS domain. In Figure 3.35b, the FAS is flatlined or exhibits other irregularities, which result in a corresponding flat mHVSr. Additionally, at higher frequencies, we observed a significant drop in the amplitude of the FAS, which raised further concerns about the quality of the data in these records. Lastly, Figure 3.35c illustrates an example where the horizontal-2 component does not possess usable data, so we are unable to develop mHVSr. These examples were deemed unsuitable for inclusion in the VSPDB.



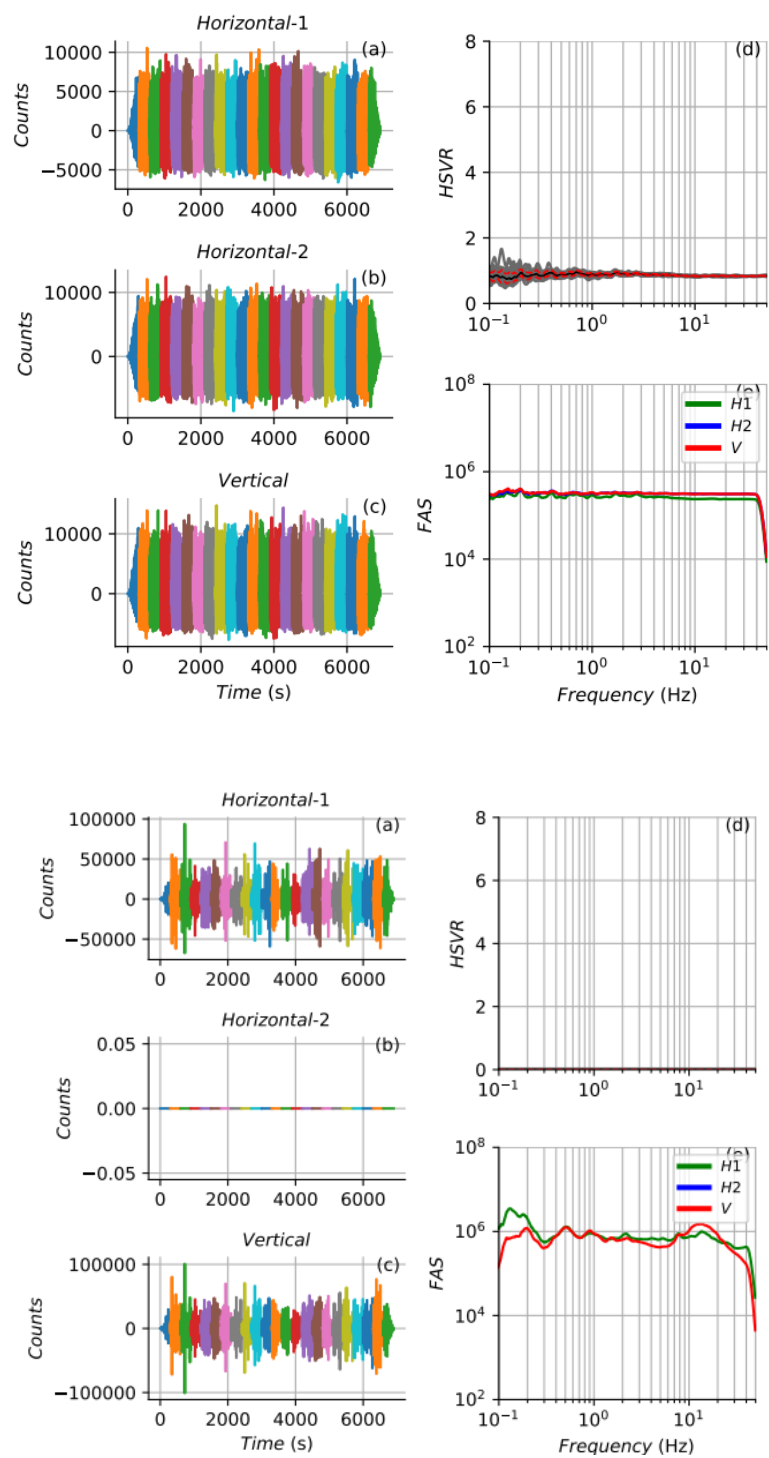


Figure 3.35. Examples of issues encountered while performing quality control: (Top) inconsistent gain; (Middle) flatlining FAS; (Bottom) insufficient data.

3.6 Conclusions

As described in this chapter, I have shown that the current VSPDB contains 1085 sites across California, with 2551 mHVSr curves that are publicly available. I described the schema, how the VSPDB was constructed, how data is stored within the database, and how many sites are currently in the database. I gave an overview of the data collection process and presented the strategy by which the data was collected. I have explained the process by which mHVSr ordinates were computed and how pre-processing of the data mitigates the effects of spectral leakage within windows. Lastly, I showed examples of cases that were deemed unsuitable to be put into the database. Overall, this chapter highlighted the importance of processing procedures when developing mHVSr, and the effects not incorporating the pre-processing step can have on a mHVSr curve. Moreover, this chapter showed the amount of mHVSr data that is publicly available and can be used in other analyses such as site response model development or seismic site characterization.

4 Low Frequency mHVSr Reliability

The content of this chapter comprises a portion of a paper published in the proceedings of the 2024 World Conference on Earthquake Engineering, Milan Italy (Ornelas et al. 2024b).

Low-frequency ambient vibration energy, as characterized by mHVSr, can be useful in identifying characteristics of the subsurface such as resonance caused by large impedance contrasts at a site. However, mHVSr ordinates in this range have been difficult to confidently associate with site geologic structure due to external effects such as atmospheric or oceanic effects causing signal drift or sensor tilt (localized slab-tilt), which can distort low-frequency results. In this chapter, I investigate whether microtremor low frequency issues are different for temporarily deployed instruments and permanently installed seismometers (Section 4.2). In addition, I investigate sensitivities to instrument burial or partial burial depth during temporary deployment (Section 4.3). Lastly, mHVSr is compared to Rayleigh-wave H/V ratios, to evaluate the significance of low frequency HVSr (Section 4.4). The data that are used for analyses in this chapter were introduced in Chapter 3.

4.1 Literature Review of Low Frequency Noise Sources and Measurement

Long-period or low-frequency ambient vibrations (commonly referred to as seismic noise) have been a subject of scientific investigations since the early twentieth century. In this chapter, low frequency ambient vibrations are defined as the components of signals with frequencies below 0.1 Hz (greater than 10 sec period). Understanding the physical origin of these signals is essential to evaluate whether they can be used to infer true earth structure or whether the recorded data are

affected by instrumental and environmental artifacts to an extent that they are not reliable for geotechnical applications.

Some of the earliest pioneering studies of microtremors were done in Italy by Bertelli (1872), who noticed small vibrations recorded by a horizontal pendulum tromometer and investigated the cause of these continuous vibrations. Subsequent studies attempted to understand ambient vibrations, which at the time were defined as “microseisms,” such as Linke (1903), where they used seismograms in the island of Samoa to understand the effects of barometric disturbances caused by storms by evaluating microtremor recordings. They were able to identify the path of the storm based on the change in energy of the microtremors. Omori (1909) performed a similar analysis for sites in Japan, finding that pulsatory oscillations caused by barometric disturbances such as tropical storms recorded by a tromometer affected long period microtremors. They evaluated whether these amplifications could be attributed to the interaction of the pulsatory oscillations with a volcano situated at one of their sites. Gutenberg (1931) performed a systematic study across various seismograph stations in North America to evaluate how low-pressure systems that induced high surf near the coast affected long period microseisms across sites in the North America. He found that high surf along the coast of western north America affected ground vibrations at sites as far away as the Rocky Mountains. However, due to the folded rock structure in the Rocky Mountains, this prevented the propagation of these waves beyond the Rockies due to reflecting and refracting of the seismic energy. Gutenberg (1931), also found that low pressure effects on the northern coast in Canada produced low frequency waves that propagated along the eastern part of north America, indicating even longer wave travel from coastal surf. In his study, he found that the pressure systems could not be the cause of the long period seismic wave, but rather it was attributed to ocean waves and high surf along the coast. Similar effects were also

observed in Europe (Gutenberg 1921). He also showed that the surf-induced waves produced the most energy between 4 and 8 sec (0.12 and 0.25 Hz), and that the wave propagation was sufficiently pervasive as to affect most sites globally. Studies prior to Gutenberg (1931) had noted similar effects (e.g., Linke 1903; Omori 1909).

Many of these prior studies relied on seismographs that relied on conventional spring systems that limited their natural period and sensitivity, which made it difficult to accurately record long period ground motions. Lacoste (1934) developed an early long period seismograph that improved the recording of these long period motions. These long period seismographs were improved by incorporating a spring made of elinvar wire that was arranged so its effective length could approach zero. This produced an unusually large restoring force for a very small displacement. These developments eventually paved the way for a better understanding long period ground motion.

Subsequent investigations sought to understand the physical origins of these low frequency signals. Gutenberg (1936) performed a similar analysis as was done by him five years earlier (Gutenberg 1931) and demonstrated that large-amplitude microseisms or ambient vibrations observed at long periods were primarily generated by oceanic activity along coastlines, with amplitudes decreasing due to attenuation of the wave energy as distance from coast increased. Building upon this work, Longuet-Higgins (1950) found that the wave interference of ocean waves in deep water would probably be a significant source of long period energy compared to wave interference caused by large atmospheric effects associated with large-scale meteorological events, such as a tropical cyclone. Gutenberg (1958) summarized many of the findings from these studies and related dominant source mechanisms to different period ranges of ground excitation. In particular, he attributed periods shorter than 2 sec primarily to anthropogenic activity, 1 to 3 sec

to a combination of cultural and natural sources, 4 to 10 sec to ocean-generated microseisms (e.g., surf along coast), and periods greater than 10 sec to large ocean storms and long-period atmospheric processes.

Although the oceanic origins of long-period microseisms had been investigated, later studies demonstrated that additional processes contribute to long-period ambient vibrations. Haubrich et al. (1963) examined an anomalous long-period peak observed at a site near San Diego and attributed the cause to ocean-generated seismic energy originating from wave interactions occurring up to approximately 322 km offshore. Subsequent studies identified two primary contributions to low-frequency seismic noise: (1) propagating fundamental-mode Rayleigh wave energy caused by oceanic activity and (2) localized energy associated with atmospheric and barometric pressure variations (Capon 1969). Sorrell (1971) demonstrated that atmospheric pressure fluctuations, particularly those generated by wind-induced pressure variations, can significantly influence the horizontal and vertical components of a seismometer recording. However, these pressure-induced effects diminish rapidly with increasing burial depth, becoming substantially reduced at depths on the order of 100 m (Sorrell 1971). Sorrell and Goforth (1973) expanded upon these findings by evaluating transfer functions between observed and modelled long-period ground motions, providing insight into the environmental conditions required for optimal long-period seismograph installations.

Further advancements in broadband instrumentation since 2000 have improved the bandwidth and lowered instrument effects on the recorded signals. Moreover, research on microtremor signal attributes has continued, using the improved data. Studies conducted in the American Southwest (Wilson et. al. 2002; Hutt et. al. 2017) and in the Pacific Northwest (De Angelis and Bodin 2012) confirmed many observations from earlier studies but further identified

localized slab-tilt as a significant contributor to low-frequency seismic signals. These studies demonstrated that atmospheric pressure variations, primarily associated with wind-driven surface loading, can induce localized deformation of the ground surface that produces measurable tilt signals on seismometers. Tilt occurs when changes in the orientation of the instrument alter the projection of the gravitational acceleration vector onto the sensitive horizontal axes of the sensor (De Angelis et al., 2011). Consequently, even small ground-surface deformations can produce apparent seismic signals, particularly at long periods where the sensitivity of broadband instruments is greatest. The conclusions of De Angelis and Bodin (2012) was that burying the sensor within a vault with compliant sides would reduce the effect of the localized slab-tilt but not remove it entirely. Moreover, once a sensor is buried to a certain depth, the self-noise of the sensor would then exert a stronger influence on low-frequency results (Hutt et. al. 2017). The self-noise of the sensor refers to the internal noise generated by the sensor itself, which can be caused by internal electrical noise, thermal motion of the internal components, or mechanical friction in the sensing mechanism. Other studies investigated how sensor installation can affect the sensors' recordings. Castellaro et al. (2022) investigated four effects: foundation effects, pillar effects, surrounding structure effects, and sensor case eigenfrequency. Figure 4.1 shows a schematic of these different installation types. Foundation effects refer to when the sensor is installed on stiff foundation (e.g., concrete slab on soft soils), which perturb the incident wavefield. Pillar effects refer to when a sensor would be installed on a concrete pillar cut away from the foundation to isolate the sensor from the foundation, which can create artificial vibration modes related to pillar response. Surrounding structure effects refers to the effects caused by the structure in which the sensor resides. Lastly, the sensor case eigenfrequency refers how the sensor casing affects the sensor recording, as the casing of the sensor has its own natural resonant period. I met with the

sensor manufacturer Nanometrics Inc. to discuss how these effects could be mitigated. At the request of our research group, they investigated the effects of sensor installation on low frequency results derived from a 120 sec. broadband seismometer by evaluating how different installation types would affect the recording. They utilized a sensor anchored to a platform, and the sensor buried at different depths. They concluded that burial of the sensor would reduce the effects of localized slab-tilt by reducing the amplitude of the horizontal component of the seismometer, but that it could not be removed entirely.

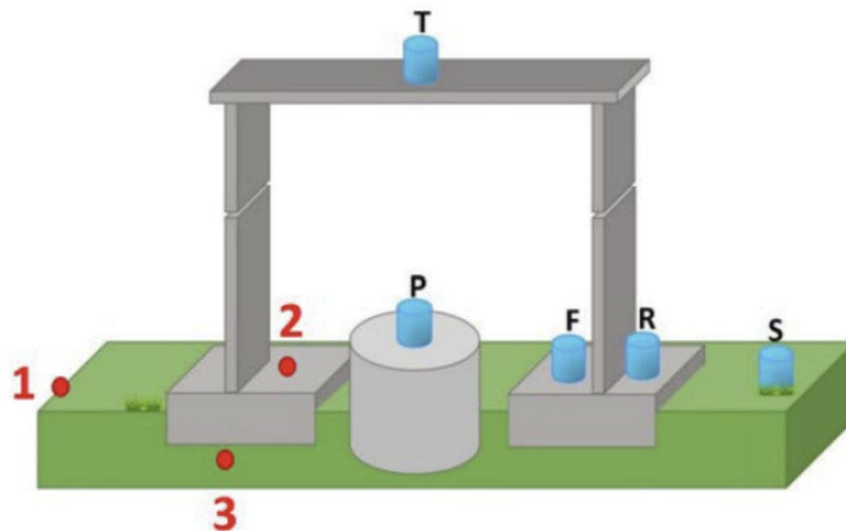


Figure 4.1. Schematic illustration of a typical seismic installation inside a small structure with a direct foundation. T (top) is the measurement point on the top of the structure (to characterize its fundamental mode), P on the pillar, F on the foundation, R on the foundation rim, and S on the natural soil. Figure from Castellaro et al. (2022).

Understanding low-frequency ordinates can be particularly important as it may provide insight on large impedance contrasts at great depths for sites with large sedimentary basins (e.g., Los Angeles Basin, Ventura Basin, Imperial Valley Basin). These previous studies, did not identify a complete solution for eliminating the effects of localized slab-tilt, but they established installation practices and analytical approaches that can reduce the effects of tilt on long periods.

In the remainder of this chapter, I investigate what steps can be taken to understand whether low frequency peaks in HVSR are indicative of true resonances or characteristics of localized slab-tilt, by investigating permanent and temporary installations of broadband seismometers, and also by investigating how HVSRs derived primarily from Rayleigh wave energy compared to mHVSR.

4.2 Comparison of Signal Attributes between Permanent Stations

To better understand the effects sensor installation on long period signals, I investigate the characteristics of non-seismic ambient vibrations from permanently installed seismometers at various locations across California. The aims of this investigation were to (1) understand the features of the recordings in the time and frequency domains, particularly the presence of drift that would not be expected from instrument set up for sensors that have been in place for multiple years; (2) compare Power spectral density (PSD) amplitudes observed from the data to noise models (Peterson 1993); and (3) examine differences between locations and for different sensor types. Each of these aims are important for understanding the mHVSR curves derived from ambient noise recordings. Figure 4.2 shows the locations of 11 permanent stations considered in this investigation, which are located in northern and southern California. Some of the stations in southern California are located in deep sedimentary basins (e.g., Los Angeles basin, Imperial Valley basin), where resonant features are expected at low frequencies that are likely to be affected by signal drift effects (Section 3.3.4).

4.2.1 Evaluation of Low-Frequency Ambient Vibrations Using PSD and mHVSR

Ambient vibration data was extracted on November 4, 2023, around 12:00 am PST for durations of about an hour. The data were extracted from IRIS (Trabant et al. 2012) from the northern and

southern California data centers (NCEDC and SCEDC, respectively); more information about the data is described in Section 3.2.3.

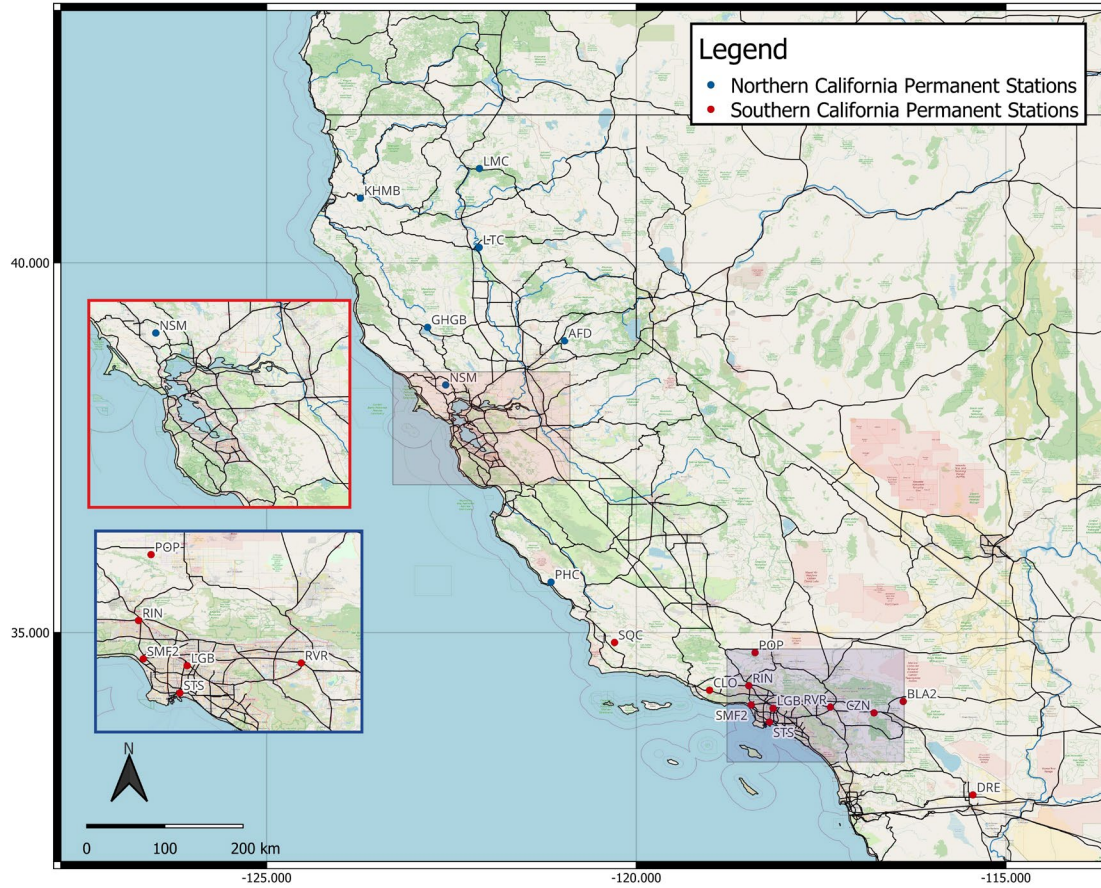


Figure 4.2. Location of the permanent stations in northern (blue) and southern California (red).

The python library *ObsPy* (Beyreuther et al. 2010), which uses a routine by McNamara (2004) was used to generate PSD curves with the results shown in Figure 4.2 (southern California sites). The PSD is defined as (e.g., Kramer and Stewart 2025):

$$PSD(f) = \frac{1}{\pi T_d} |X(f)|^2 \quad (4.1)$$

where $PSD(f)$ is the power spectral density at frequency (f) , $X(f)$ is the Fourier transform of the time-domain signal, and T_d is the duration of the time window used for the Fourier transform. To express in decibels (dB) relative to acceleration the $PSD(f)$ is then taken as:

$$PSD_{dB}(f) = 10 \log_{10} \left(\frac{PSD(f)}{PSD_{ref}} \right) \quad (4.2)$$

where PSD_{ref} is referred to as the reference power level and has a value of unity in the same units as $PSD(f)$. Thus, PSD_{ref} is equal to one, such that $PSD(f)$ equal to the reference level corresponds to 0 dB.

Figure 4.3 shows computed $PSD_{dB}(f)$ spectra for 11 stations in southern California. Also included within Figure 4.3 are the New High Noise Model (NHNM) and the New Low Noise Model (NLNM) curves from Peterson (1993) along with the self-noise of the sensor. Data from most stations have PSD curves that follow the noise models. The largest deviation is in the horizontal component, where some of the stations are slightly above the NHNM, whereas in the vertical direction only one site exceeds the NHNM (CZN in Cabazon). At frequencies above 1 Hz, ordinates for most of the sites are bounded by the noise models except for CZN and STS. Higher noise levels above 1 Hz might be anticipated at these sites due to anthropogenic sources in these areas associated with train and car traffic as well as potentially large machinery. As noted in Section 4.1, Wilson et al. (2002) demonstrated that elevated noise levels within this frequency range are associated with anthropogenic sources. For the differences at lower frequencies (< 0.17 Hz) these are also likely attributed to signal energy caused by atmospheric or oceanic disturbances described in Section 4.1, which can distort the interpretation of low-frequency features attributed to deep subsurface stratigraphy (e.g., Gutenberg 1958; Castellaro and Mulargia, 2012).

Figure 4.3 also differentiates PSDs for five different sensor types at different locations around southern California, all of which are permanently installed seismometers. The types of sensors at each station are indicated in the figure legend. All the sensors were high-quality broadband seismometers and had a flat response down to 0.0083 Hz, meaning that the sensors should have been able to resolve resonant peaks down to at least 0.01 Hz reliably. The stations that contain a Streikensen sensor generally are lower amplitude than the sensors that use a Kinemetrics MBB-2, except for the Laguna Bell station. Moreover, the Palmdale station with the Kinemetrics Omnisensor has one of the lower noise levels compared to other stations, but the station at Joshua tree with the Streikensen sensor has the lowest noise level overall at high frequencies. Interestingly, the Rinaldi station, which is the only station with a Güralp sensor, has a large noise level at high frequencies but has one of the lowest noise levels at low frequencies.

I performed a similar investigation of noise characteristics using data from seven stations in northern California. Data was extracted for the same day and time interval as the data that was used from southern California stations. Figure 4.4 illustrates the PSD curves for these seven stations, with four different sensors used among the stations. For the northern California stations, the PSD curves are all within the bounds of the NHNM and NLNM, meaning that they are all within typical bounds suggesting that anomalous external noise sources are unlikely to be significantly affecting the sensors. The sensors are mostly Nanometrics Inc. sensors, compared to the other sensor types Streikensen, Güralp, and MBB-2, which generally have higher noise than Nanometrics sensors, except the station at Auburn. Moreover, the station Willow Creek, which was instrumented with a Güralp sensor, also experienced a significant drop in the vertical component at low frequencies, as was seen in Figure 4.3 with the Rinaldi station. I computed mHVSr for each of the sensors (11 permanent stations in southern CA, 7 in northern CA) using

the same processing procedures described in Section 3.3. Figures 4.5 and 4.6 show the results for southern and northern California stations, respectively. The results comparing the mHVSr curves to PSD spectra will be presented in the next section.

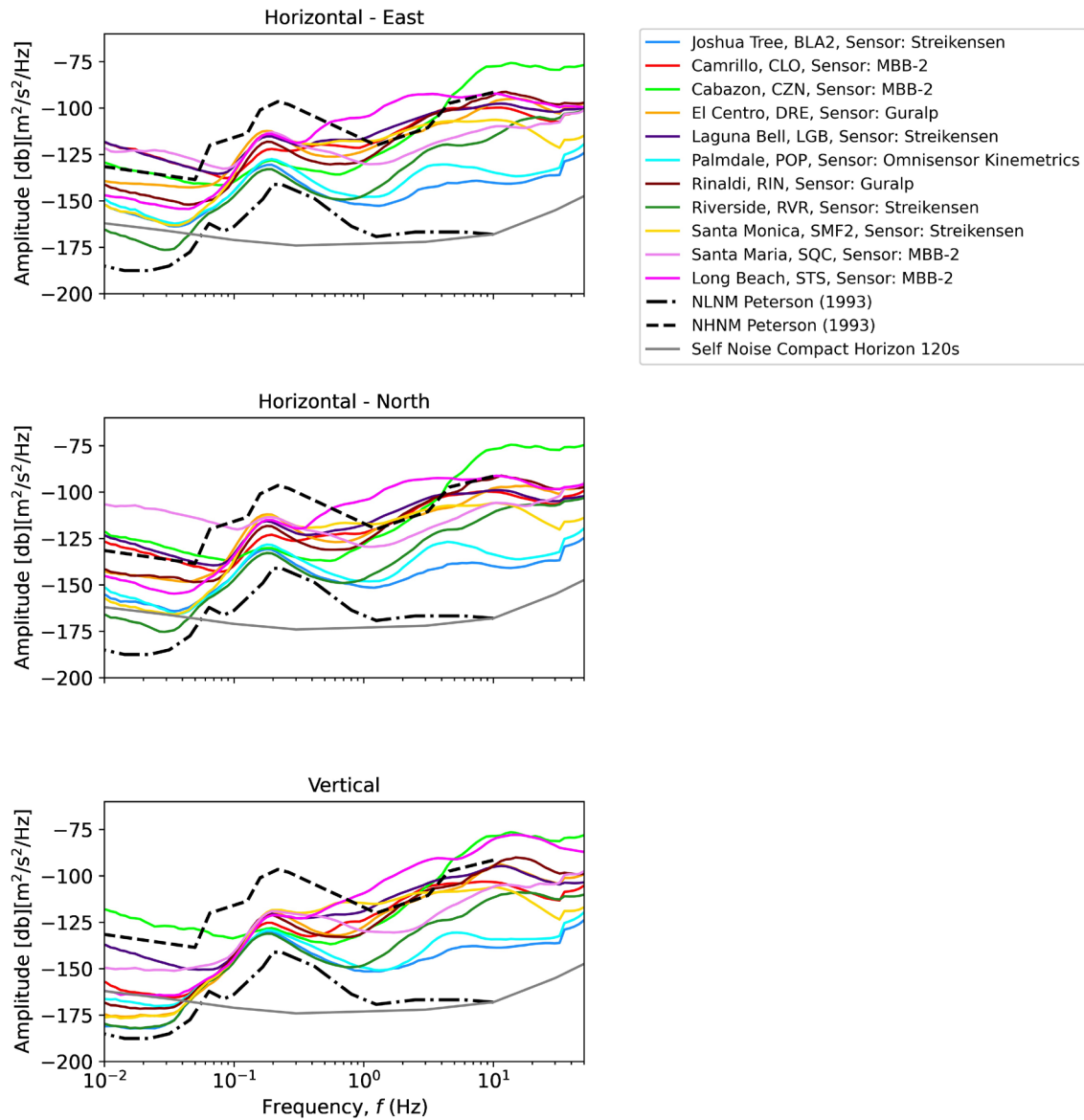


Figure 4.3. Power Spectral Density (PSD) curves for different permanent stations in Southern California, see Figure 4.1 for location of stations. The data are compared with the New Low Noise Model (NLNM) and New High Noise Model (NHNM) by Peterson (1993), to see the differences in noise levels between the temporary and permanent seismometers.

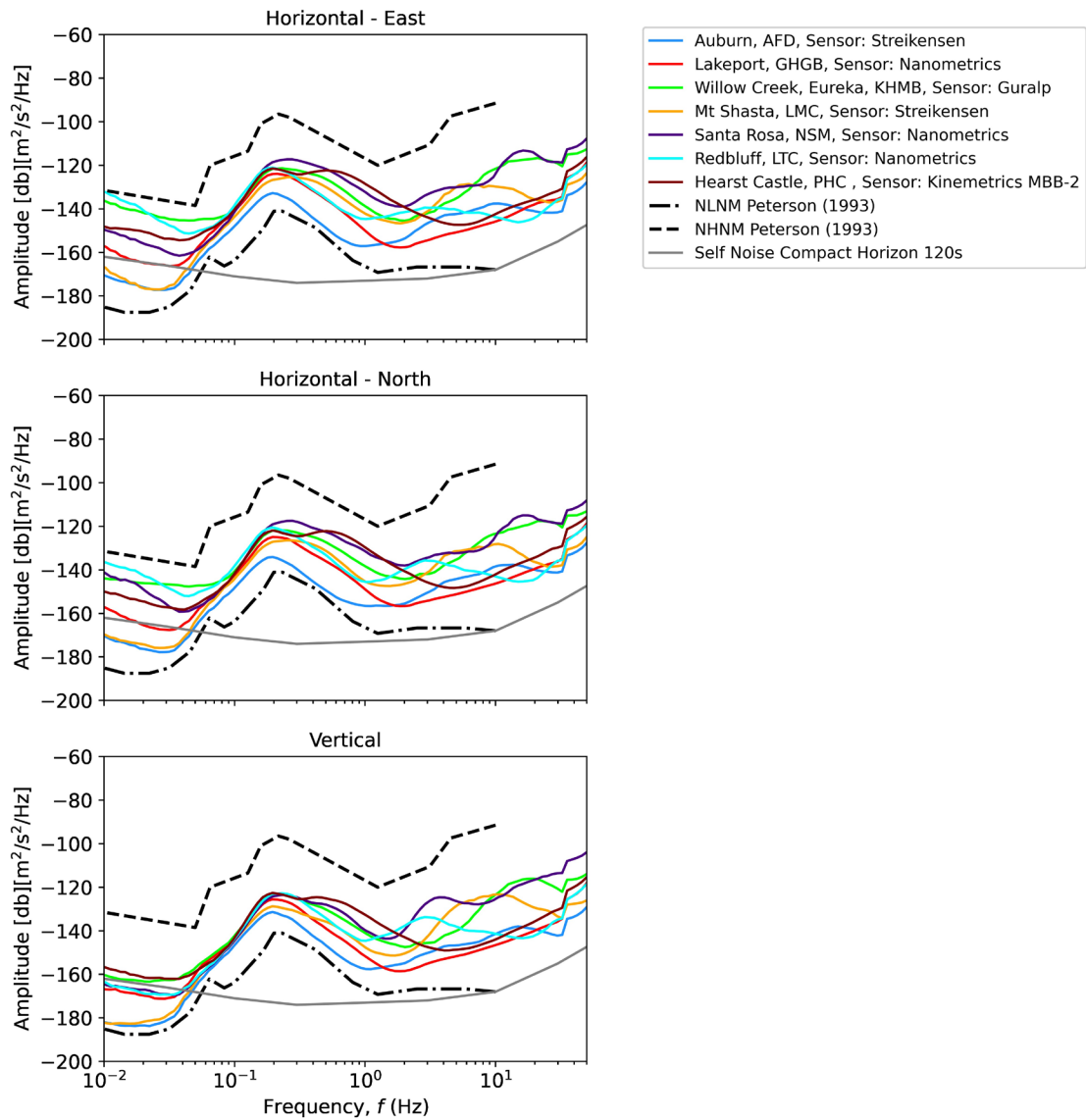


Figure 4.4. Power Spectral Density (PSD) curves for different permanent stations in Northern California, see Figure 4.1 for location of stations. The data are compared with the New Low Noise Model (NLNM) and New High Noise Model (NHNM) by Peterson (1993), to see the differences in noise levels between the temporary and permanent seismometers.

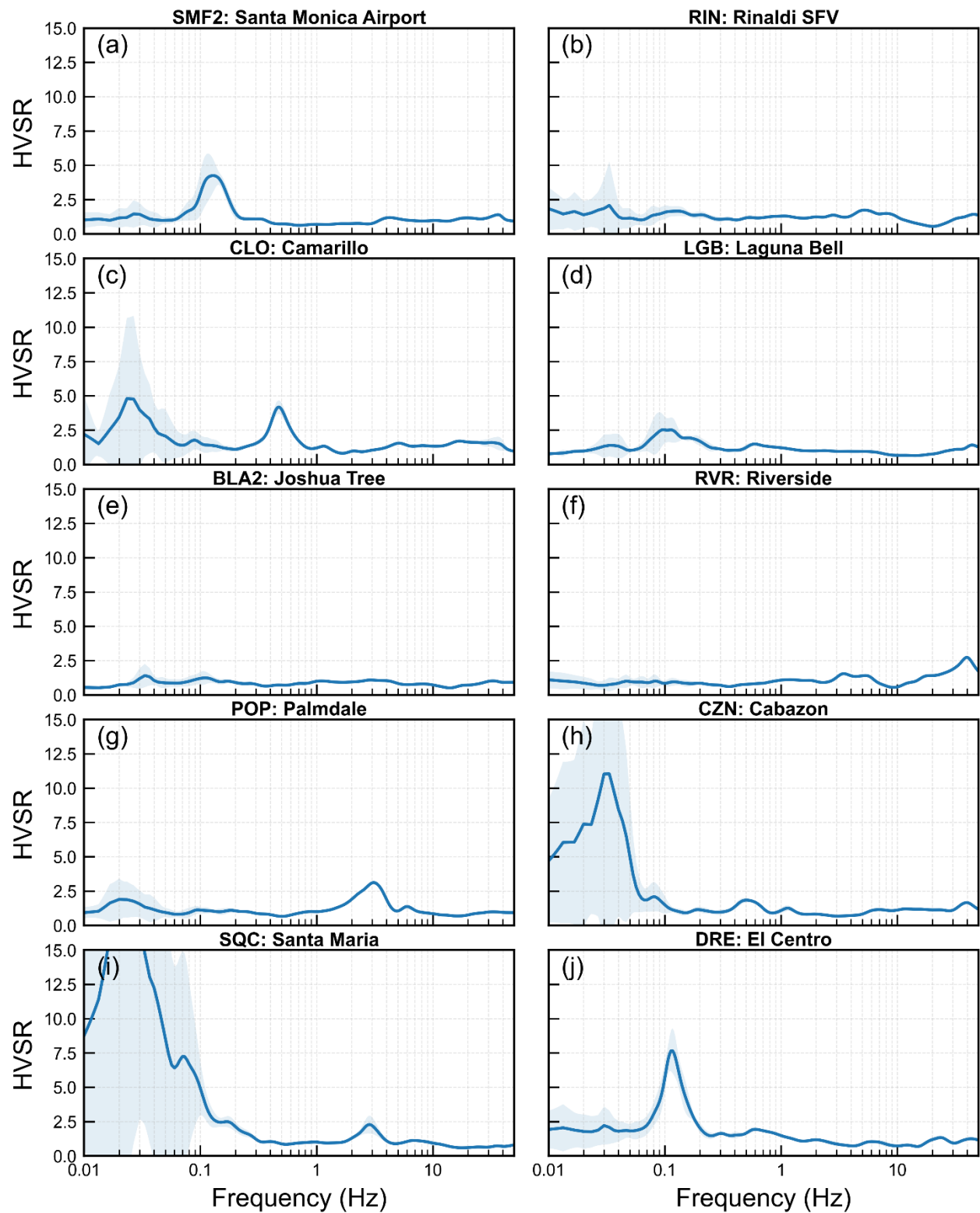


Figure 4.5. mHVSr spectra for 10 permanent stations in Southern California.

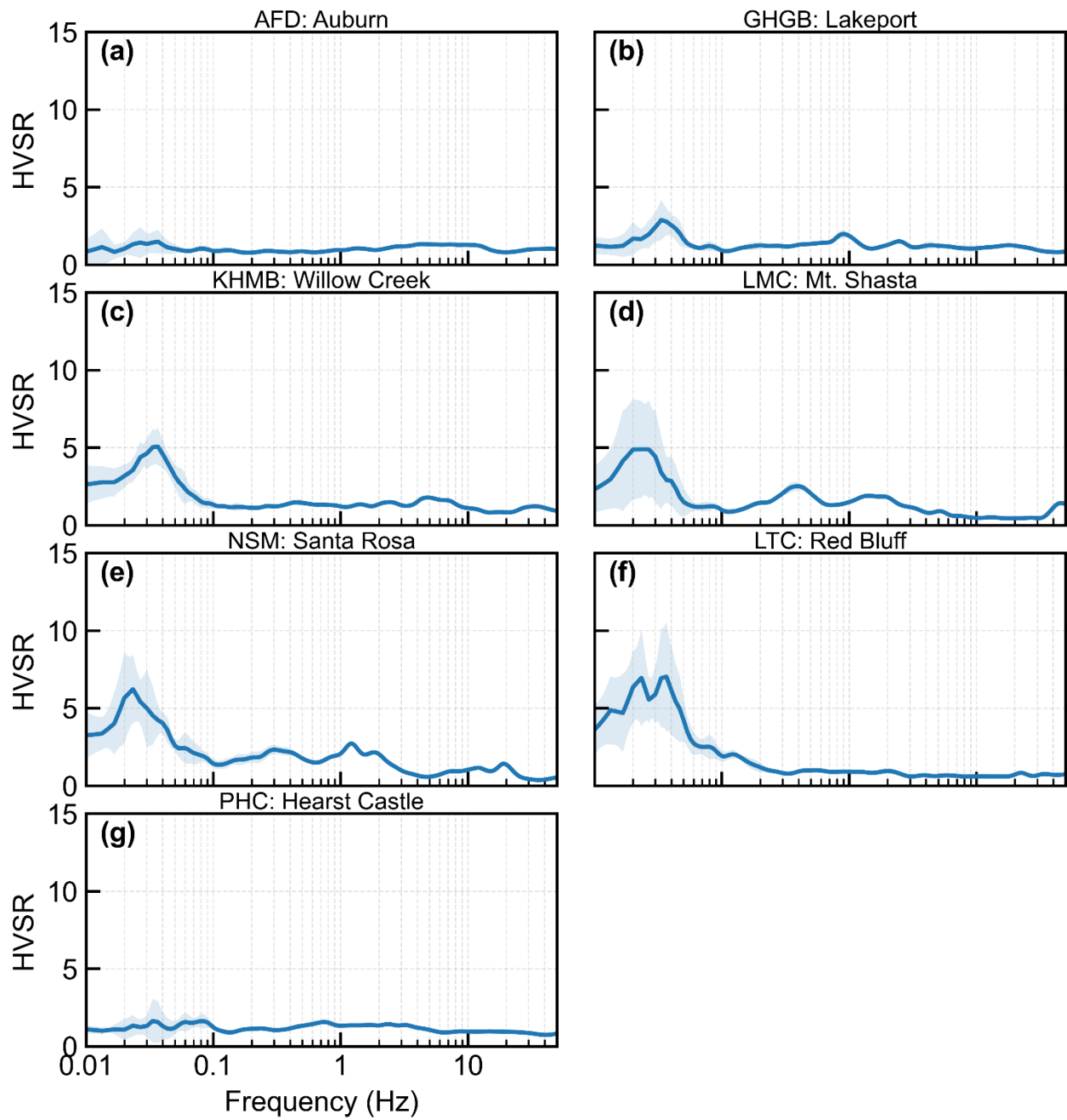


Figure 4.6. mHVSr spectra for the 7 permanent stations in Northern California.

4.2.2 Interpretation of PSD and mHVS

Figure 4.5 shows that most of the southern California mHVS curves are relatively flat with some sites such as CLO, RVR, and POP having peaks at frequencies above 0.1 Hz, which is likely attributed to the horizontal PSD being larger than the vertical components seen in Figure 4.3. These are likely true resonant peak features since the bounds of uncertainty are relatively narrow. Three of the sites (CLO, CZN, and SQC) experience large peaks at frequencies below 0.1 Hz. Inspection of the PSDs in Figure 4.3 for CLO and SQC indicates that these low-frequency peaks are likely attributed to local dips in the vertical PSD relative to horizontal PSDs. On the other hand, station CZN has vertical PSD values that are greater than the horizontal, contrary to the trends from other stations with low-frequency mHVS peaks like CLO and SQZ. For CZN, the FAS of the vertical component is lower than the FAS of the horizontal. Given that mHVS is computed from FAS, the underlying cause of the mHVS peak is the same as CLO, SQZ and many others. It just so happens that the vertical PSD does not reflect this behavior. The reason for this anomaly is under investigation but has not yet been resolved. Three sites have peaks at 0.1 Hz (SMF2, LGB, and DRE); such peaks are commonly encountered worldwide and have been attributed to the interaction of oceanic waves travelling in opposite directions (Gutenberg 1931; Gutenberg 1936; Longuet-Higgins 1950; Castellaro and Mulargia, 2012). Like stations CLO and SQC, the peaks for station SMF2, LGB, and DRE are associated with vertical-component dips, not horizontal component highs. For the sites that experience peaks near 0.1 Hz, there may be a relationship with the sensor type, as all three of the sites that have this large peak feature with high uncertainty (shaded in blue) are instrumented with the Kinometrics MBB-2 velocity sensor, whereas other sensor types (Güralp CMG-3T, Streikenssen STS 2.5, and Kinometrics Omnisensor) have flatter

responses at and below 0.1 Hz. However, these interpretations are tempered by large uncertainties of the low-frequency ordinates.

Figure 4.6 shows that most of the mHVS curves in northern California experience low-frequency peaks, with high uncertainty, which is indicative of a peak formed from the fact that the vertical component noise significantly reduces in amplitude relative to the horizontal, as seen in Figure 4.4. Station PHC, which has a Kinometrics MBB-2 sensor, shows the largest amplitude vertical PSD for frequencies < 0.1 Hz compared the other stations as shown in Figure 4.4; this lack of vertical dip leads to flat (and low) mHVS ordinates (Figure 4.6). Station AFD has a vertical PSD dip below 0.1 Hz, but because horizontal components experience a similar dip, this station too has low mHVS ordinates below 0.1 Hz. All other stations, which have a variety of sensor types, are bounded by the noise models yet still experience large amplitude peaks below 0.1 Hz. None of these mHVS peaks are from peaks in the horizontal component. Rather, the low frequency raise in mHVS are caused by amplitude drops in the vertical components, which has been interpreted to indicate that the peaks do not have a relation to site geologic structure (Castellaro and Mulargia, 2009). For those sites with low frequency peaks, the PSD for both the horizontal and vertical components are bounded between the NHNM and NLNM.

The sensors that were predominantly used in northern California were Nanometrics Inc. sensors, which are what were used for many of the temporary deployments, so it was interesting to see the response of the sensors follows the noise models very well. The reduction in amplitude of the vertical component is indicative of what was described to us by Nanometrics Inc. described in Section 4.1. This difference might explain the large amplitude low frequency mHVS ordinates observed in this study.

This section highlights characteristics of the HVSR and PSD curves for permanent station sites within southern and northern California. The frequency range of interest was below 0.1 Hz, which has been found to have large amplitude ordinates, that are not reflective of stratigraphy. In total, 7 out of the 18 sites (39 %) contained a large amplitude peak below 0.1 Hz. In no case were these peaks associated with local highs (peaks) in the horizontal component. Rather, they mainly controlled by low-frequency dips in vertical amplitudes. Such features may be associated with atmospheric and oceanic effects. While horizontal PSDs do not have peaks at the locations of mHVSR peaks, in some cases they have higher-than-typical ordinates that lie outside of the range of noise models; such sites are often located near large anthropogenic sources.

4.3 Comparison Between Permanent and Temporary Stations

There are several potential causes of low-frequency features in microtremor signals that can create difficulties in the interpretation of mHVSR ordinates. Some of those potential causes are related to the instrument itself or its field installation, while other potential causes are physical processes that produce regional low frequency ground motion features, such as slab tilt. This section explores the differences between low-frequency results from permanent and temporary sensors recording at the same time and same location – the aim is to compare results so that evaluations can be made of the potential effects of different sensor types and installations. This work extends the work presented in Section 4.2, which showed PSD and mHVSR for various permanent stations across California and illustrated how different components from different sensor types are affected at low frequencies. The results are used to assess potential limitations associated with temporary deployments.

mHVSr surveys were performed at a site near a permanent station in Cabazon, California on September 10th, 2023, at 1:33 pm PST by Chukwuebuka Nweke, a professor at the University of Southern California (USC). I processed the data. The permanent station is operated by the Southern California Seismic Network (SCSN) and has the station code CZN. The data from this station is also stored in the VSPDB and is further discussed in Section 3.2.3. The station's location is approximately 220 m south of the Union Pacific Railroad tracks. The permanent sensor used is a Kinemetrics Mini Broadband Seismometer (MBB-2) with a flat response between 0.0083 Hz. and 160 Hz. Figure 4.7 shows the approximate location of where the temporary deployment was performed relative to the permanent station. Moreover, Figure 4.8 shows the set-up of the sensors, and where the sensors are relative to an electric substation nearby.

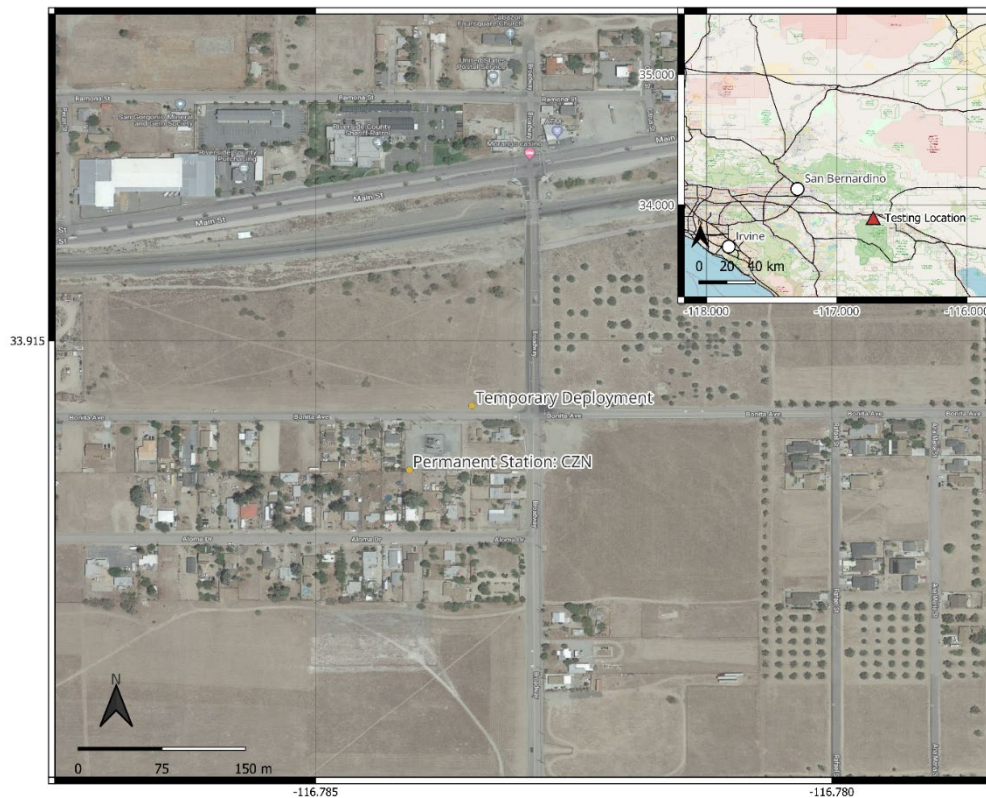


Figure 4.7. Map showing location where mHVSr surveys were conducted at the Cabazon, CA permanent station CZN.

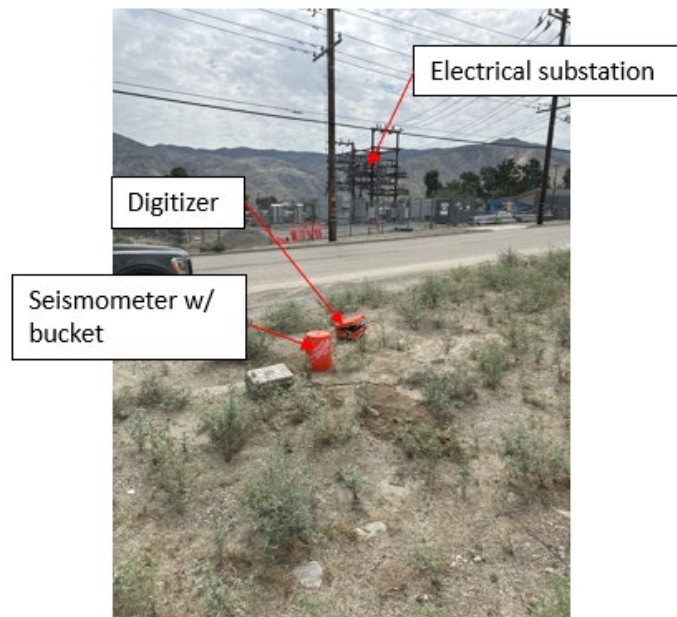


Figure 4.8. Photo showing location of temporary seismometer relative to location of the electrical substation containing the permanent sensor.

Because the permanent sensor has been in place for a long period of time, the “settling” problems commonly encountered with temporary sensors are not expected to be present (discussed in Section 3.3.3). I was interested to see if this would affect low frequency mHVSr ordinates. During the temporary deployment, two sensors were installed with partial burial (top of sensor is approximately at ground line) and burial with 46 cm (18 inches) of soil cover. The type of sensors used for both the temporary deployments were Nanometrics 120s trillium compact horizons with flat responses between 0.0083 – 100 Hz. As noted in Section 3.2.1, current protocols call for sensor burial depth (ground surface to top of sensor) of 6 to 12 inches, which we follow when practical. This practice follows Nanometrics’ recommendations that such burial depths should be applied to improve coupling and reduce the sensors’ response to low-frequency noise and localized slab-tilt. The sensors recorded data for about 3 hours. Data were also captured for the same time interval from the permanent CZN seismometer, which is near the temporary sensor. Data from the CZN

sensor was retrieved from IRIS (Trabant et al., 2012). Figure 4.9 shows time series for the data captured by the permanent seismometer and temporary seismometer during the daytime deployment. In both cases, the horizontal recordings lack drift, whereas the vertical components drift with the largest amount, somewhat surprisingly, from the permanent instrument. In addition, data at midnight were collected from the permanent sensor from IRIS when anthropogenic noise levels are lower.

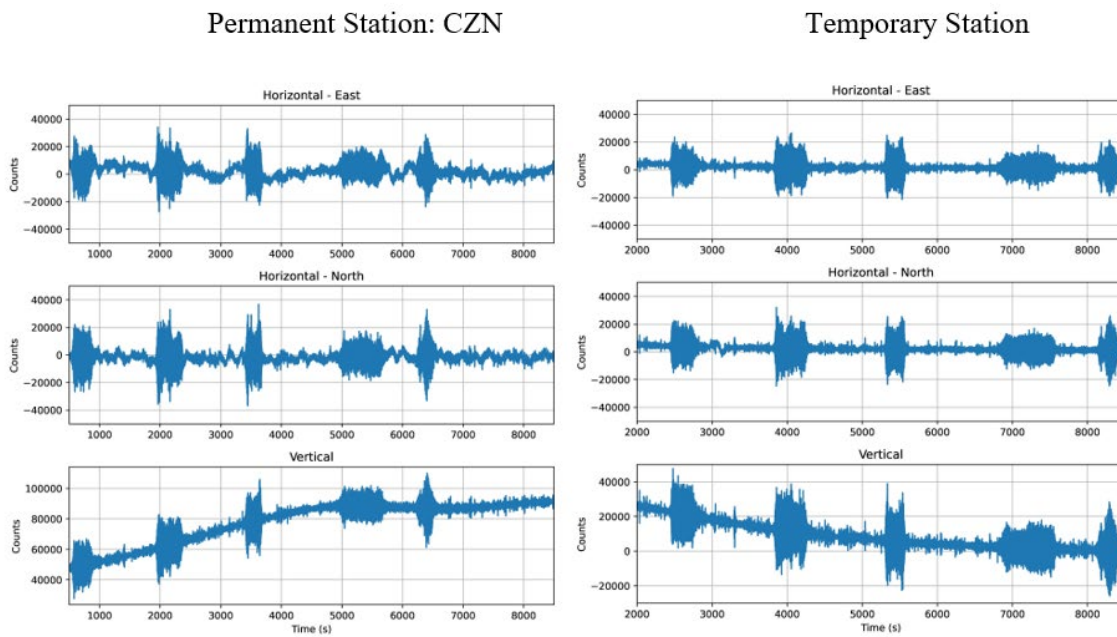


Figure 4.9. (a) left: Raw time series for all three components of permanent station: CZN in Cabazon, showing the drift that is occurring in the vertical component for the recording that was done during the time that the temporary deployment was done. (b) right: Raw time series for all three components of the temporary 46 cm deployment at Cabazon, showing the drift that is occurring in the vertical component for the recording that was done during the time that the temporary deployment was done.

These data were then processed using procedures described in Wang et al. (2022) and in Section 3.3.4, and mHVSr and PSD curves were generated. PSD were computed using *Obspy* (Beyreuther et al. 2010). The reason for computing PSD curves was to facilitate comparisons of the ambient noise recorded at the Cabazon site to published noise models (Peterson 1993), which

are expressed as PSD ordinates, and to provide insight into the ground motion components responsible for peaks. Figure 4.10 compares the permanent and temporary PSD curves, which are seen to be very similar for the horizontal components. All the vertical components but one (permanent sensor 12 am) experience a PSD drop below 0.1 Hz, which would be expected to produce mHVSr increases and peaks at low frequencies. The vertical components have differences in which the data from the permanent seismometer, especially at midnight, have larger amplitudes than the recordings from the temporary deployment. This is likely caused by larger drift experienced in the permanent seismometer. Drift is not always encountered from permanent stations. At other sites (SMF2, DRE, and LGB), we have found permanent stations to produce stationary vertical signals, which in turn produces relatively low-amplitude low frequency mHVSr ordinates, as seen in Figure 4.4.

Also shown in Figure 4.10 are the Peterson (1993) NHHM and NLNM, which can be compared to the site data. The published self-noise of the temporary broadband seismometer is also shown. For all components, the noise levels are much higher than the NHHM for frequencies below 0.06-0.07 Hz, which was also noted in Section 4.2 for this station. Moreover, at frequencies above 2 Hz, the measured microtremor levels in all components are also higher than the NHHM levels. However, at frequencies between 0.07 and 2 Hz the noise levels are bound between the noise models. Based on the study from Wilson et. al (2002), we might expect different noise sources at frequencies below 0.1 Hz relative to those at higher frequencies. The elevated amplitudes below 0.1 Hz may reflect thermal or atmospheric variations at the site. At frequencies above 2 Hz the relatively high noise levels that exceed the models may be due to trains or an electrical substation nearby. In between 0.07 and 2 Hz is where the data is likely most reliable for peak identification and is where resonant peaks in mHVSr are found.

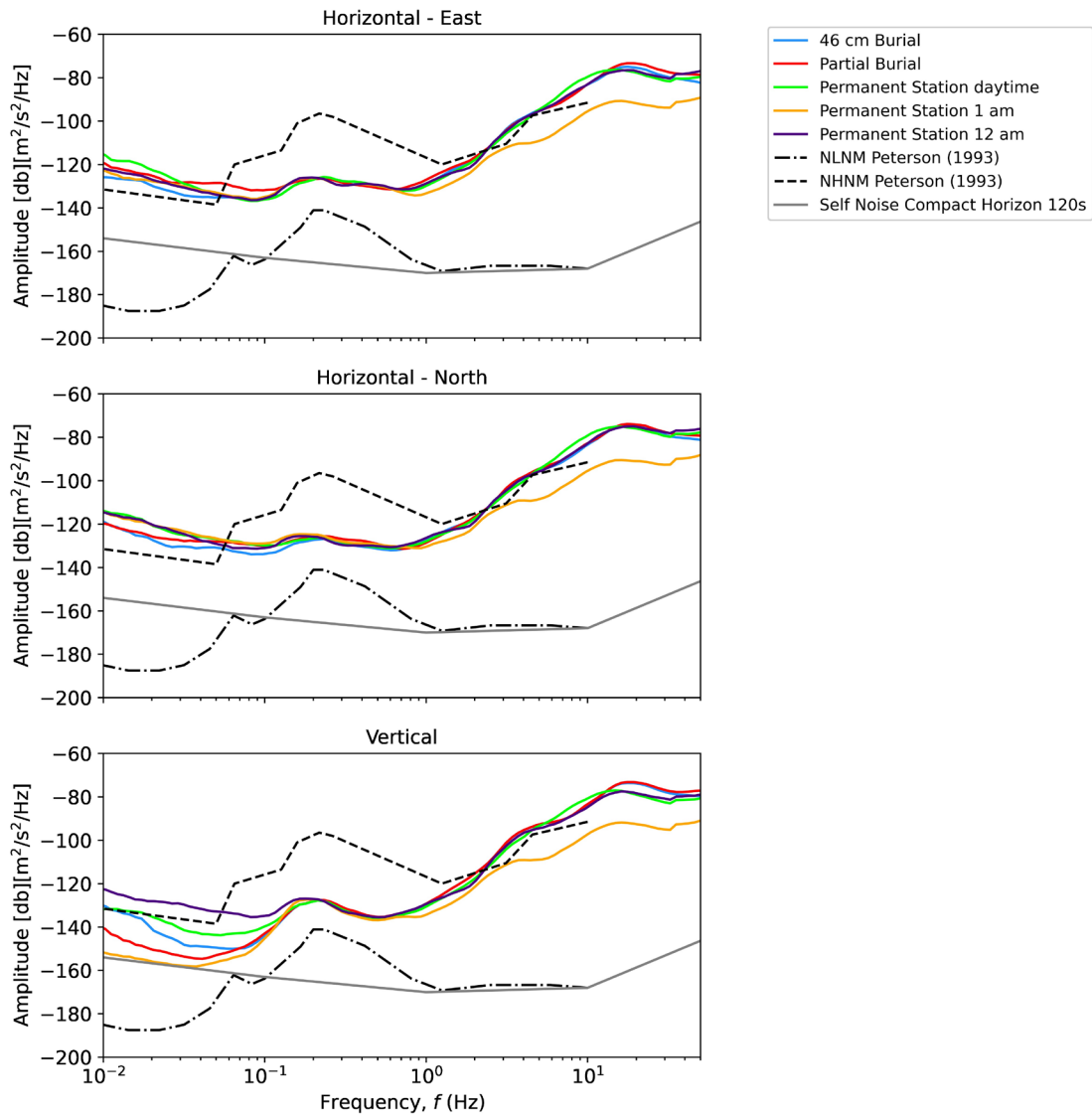


Figure 4.10. Power Spectral Density (PSD) curves for permanent station CZN and temporary stations at various burial depths. Results show the effects of different installations and the effects of signals recorded at different times (permanent seismometer only). The data are compared with the New Low Noise Model (NLNM) and New High Noise Model (NHNM) by Peterson (1993), to see the differences in noise levels between the temporary and permanent seismometers.

Figure 4.11 compares the mHVSR curves produced from the different sensors and different burial depths. All of the mHVSR curves increase below 0.1 Hz and have a peak near 0.04 Hz, which are caused by decreases in the vertical-component PSD in that frequency range (Figure

4.10). When comparing the permanent station with the temporary deployment, the mHVSr curves are similar for the partially buried sensor and the permanent sensor. However, for the 46 cm burial the mHVSr mean curves have reduced amplitude, which had been suggested to be the effect of burial by Nanometrics. This was likely caused by the sensor stabilizing, which dissipated drift, which can be seen in Figure 4.11. Comparisons of results from the permanent sensor for daytime and midnight reveal no significant differences (Figure 4.12). For frequencies greater than 0.1 Hz the curves are very similar, which likely means that the peaks at 0.5-1.0 Hz are likely true resonant peaks.

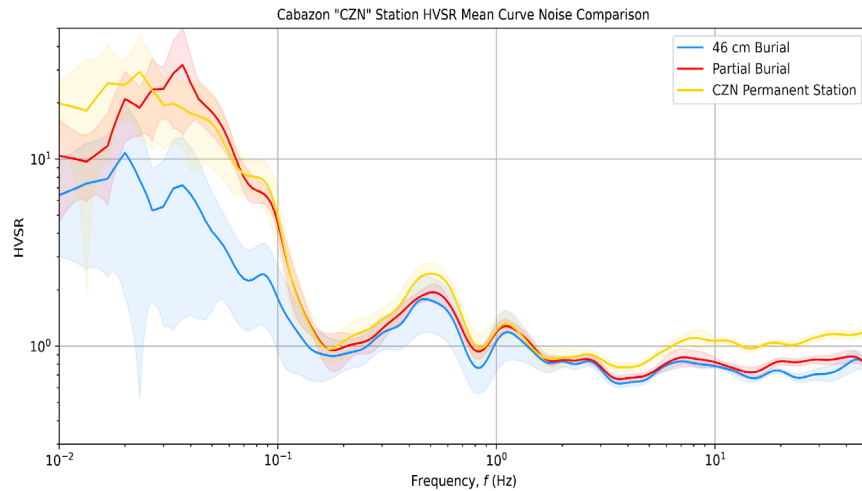


Figure 4.11. mHVSr spectra for permanent station CZN and temporary sensors at different burial depths; results demonstrate differences at low frequencies.

Figure 4.12 compares mHVSr for two types of time-windows: (1) windows with generally low and nearly uniform amplitudes (similar to Figures 3.24 and 3.25 (blue lines) and (2) windows with large amplitudes, most likely caused by trains. Interestingly, mHVSr low frequency ordinates for the large noise cases are significantly reduced from the low-noise cases, whereas at high frequencies there are no appreciable differences. This may be caused by the proximate noise source similarly affecting the vertical and horizontal components. This characteristic also occurs when

using sensors with higher corner frequencies (e.g., 5 Hz Geophones), where the data past the corner frequency drops in amplitude due to all components having effectively the same Fourier amplitudes. The observation demonstrates that mHVSr can be significantly distorted particularly at low frequencies when large transients are active at a site where a sensor is recording, highlighting the importance of recording ambient vibrations during low noise periods.

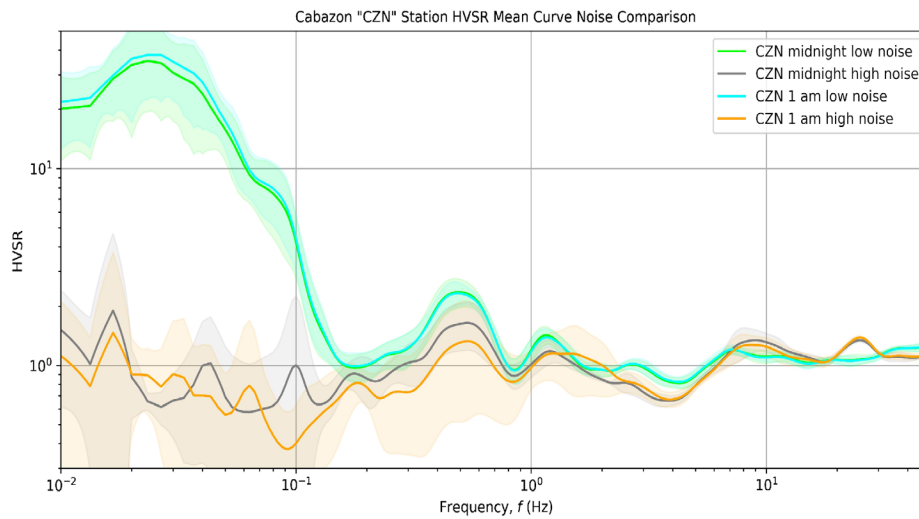


Figure 4.12. mHVSr spectra for permanent station CZN showing the differences between for time intervals with low and high noise.

This section highlights the benefits of recording microtremor data for long periods of time, which allow for more and longer windows than with shorter recordings. By having more windows, the potential influence of a large transient noise source on the overall mHVSr curve is reduced. Furthermore, the train-generated transients within the time series in Figure 4.9 may affect the coupling of the sensor with the ground, and certainly increase vertical component PSDs, which reduces mHVSr amplitudes. These findings reinforce findings from Section 4.2 about low-frequency dips in vertical PSD being the main cause of low frequency peaks. They also

demonstrate the contaminating influence of high-amplitude noise sources that effectively conceal the “real” mHVSr behaviour at low frequency.

4.4 Investigation of Burial Depth Effects

The effects of different levels of sensor burial depth were investigated for a site in Santa Monica north of the Santa Monica fault and hence outside of the Los Angeles basin. The motivation for this work was to evaluate potential variations of mHVSr amplitudes for different burial depths, which extends the work presented in Section 4.3 for a different site and different levels of burial depth. The field work was undertaken by myself and Prof. Chukwuebuka Nweke from the University of Southern California. The test site does not have a permanently installed ground motion instrument.

mHVSr surveys were performed at four depths, resting at the surface, partially buried, buried 15 cm (distance from top of sensor to ground surface = 15 cm), and buried 30 cm. The sensors recorded data for three hours. The sensors used were Nanometrics 120s trillium compact horizons with flat responses between 0.0083 – 100 Hz. They were equipped with Pegasus PGS-140 digitizers to record data continuously at a sampling rate of 200 Hz. The data were obtained on July 31, 2026, between 3:00-7:00 pm (record duration about 200 min. each). The data were then processed using similar procedures to those described in Section 3.2.

Similar to what was done for the permanent station investigation (Section 4.2) and the Cabazon investigation (Section 4.3), I generated PSD curves to better understand the noise levels at the various burial depths. Figure 4.13 shows the distribution of noise levels for each sensor. Most of the sensor noise levels for the horizontal components exceed the noise models at frequencies below 0.06 Hz. Moreover, in the vertical component PSD there is a substantial drop

in amplitude relative to the horizontal components below 0.1 Hz for most of the sensors, except the sensor resting on the surface, which is still slightly exceeding the noise model. Figure 4.13 shows that the area in which the sensors are placed are severely influenced by noise at lower frequencies for the horizontal component compared to the vertical component. This is likely indicative of the localized slab-tilt affecting frequencies below 0.1 Hz described from previous studies discussed in Section 4.1.

Amplitude levels for frequencies between 0.6-6 Hz exceed the noise models for all components. This is likely indicative of large amounts of anthropogenic sources or natural microtremors (e.g. ocean waves) affecting the sensor, as suggested by Wilson et al. (2002). The increase in amplitude shown in Figure 4.13 around 2 Hz is similar to what was seen at the STS station PSD shown in Figure 4.3, which is an area near significant anthropogenic influence. Many of the stations at the Santa Monica site also experienced a dip in the vertical below 0.1 Hz, similar to what was seen at most of the stations in Figure 4.3, 4.4, and 4.10, except for the sensor resting on the surface. The surface sensor may record higher vertical amplitudes due to the lack of coupling of the sensor and surrounding anthropogenic effects. Similar effects were observed for the CZN station, which experiences significantly local noise from train traffic, as shown in Figures 4.3 and 4.10.

Figure 4.14 shows the resulting mHVSr for the different burial depths. In all cases, ordinates increase appreciably at low frequencies. The amount of ordinate increase is reduced as burial depth increases, as observed at the other sites discussed in Section 4.3. The low-frequency ordinates generally decrease as burial depth increases, although curiously the surface sensor is counter to this trend.

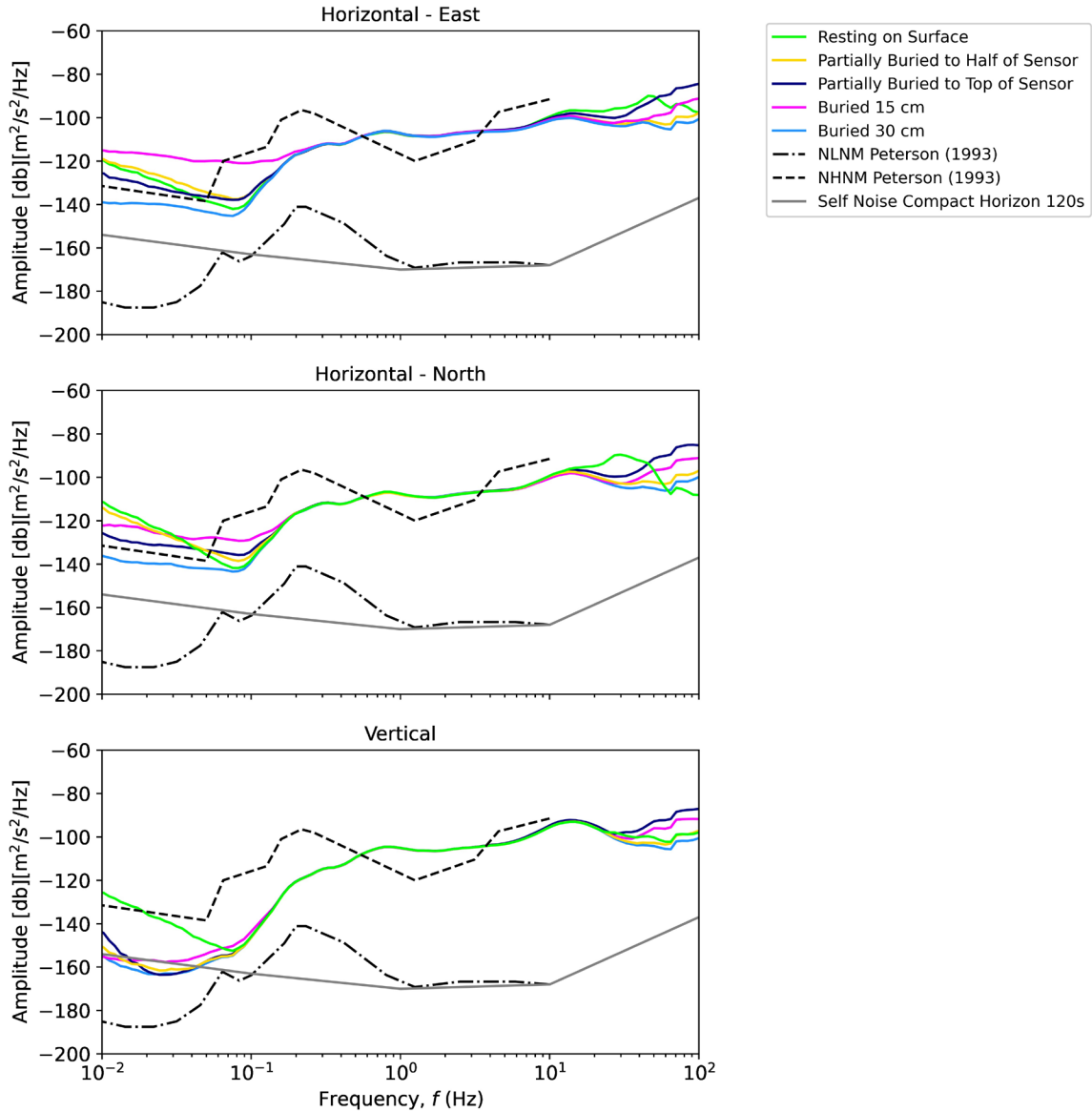


Figure 4.13. Power Spectral Density (PSD) curves for site in Santa Monica showing the effects of sensor depth for a temporary seismometer. The data are compared with the New Low Noise Model (NLNM) and New High Noise Model (NHNM) by Peterson (1993), to see the differences in noise levels between the temporary and permanent seismometers.

This decrease in amplitude from the surface sensor is likely due to the increased amount of noise in the vertical component below 0.1 Hz as shown in Figure 4.13, thus producing smaller amplitude mHVSr ordinates similar to what was seen in Section 4.2.1. The source of the noise may be attributed to coupling issues or localized slab-tilt, which seem to greatly affect surface

mounted mHVSR surveys, causing high amplitude vertical noise. It seems that due to the increased amount of noise, the HVSR ordinates derived around these ranges are likely less reliable due to the influence of additional noise, as shown by the parts of the curve outside of the models in Figure 4.13. These ranges being 0.5 to 5 Hz, and less than 0.07 Hz. Figure 4.14 shows this high amplitude low-frequency peak occurring again at about 0.04 Hz. The peak at 0.04 Hz may be influenced by the high-pass corner frequency used during processing, since the records are typically pre-processed at 0.042 Hz. This high-pass filtering has a significant effect on the vertical component reducing the amplitude compared to the horizontal. This is likely attributed to the vertical component being significantly influenced by drift (Section 3.4.4), causing a significant reduction of the vertical when filtered. Moreover, the horizontal component is likely also affected by long period energy caused by ocean or atmospheric disturbances as discussed in Section 4.1. Due to these differences a peak forms artificially at these frequencies. The peak at about 0.15 Hz occurs just above the ramp up portion at 0.1 Hz also may not represent stratigraphy, but rather these oceanic effects that were described in Section 4.1. As noted by Gutenberg (1931) and other subsequent studies, peaks near 0.1 Hz are commonly observed that have been attributed to high surf colliding along the coast as well as wave interactions in the deeper parts of the ocean, which are observed at many sites globally. Another reason for this peak not being representative of stratigraphy is due to its location geographically, the Los Angeles Basin begins south of the Santa Monica fault. This site lying just north of the fault, there would not be a substantial drop in bedrock around this region, and low frequency resonance would not be expected. The ramp-like characteristic for mHVSR ordinates below 0.1 Hz is likely due to atmospheric, barometric, and oceanic disturbances affecting the sensor.

This section highlights the effects of various burial depths on PSD and HVSR ordinates, specifically at low frequencies. The curves are generally similar until frequencies below 0.12 Hz. The burial depths slightly decrease the mHVSR ordinates with the 30 cm burial depth having the lowest values. However, the sensor placed on the surface experienced even lower ordinates than the buried, due to an increase in amplitude of the vertical component, as seen by the PSD values in Figure 4.13. Moreover, the burial did not seem to have a profound effect on the vertical component PSD, where most of the ordinates were similar. However, in terms of the horizontal component PSD, there was the largest reduction, but only slightly lower than the NHNM. From these findings, it seems that burial depth has the potential to mitigate the effects of these long period effects discussed in Section 4.1, but only slightly. This would insinuate that burial depth, does not seem to have a profound impact on reliability of mHVSR at long periods. These findings also show that placing on the sensor on the surface can have an impact on high frequency ordinates (> 10 Hz), based on the mHVSR ordinates from the sensor resting on the surface in Figure 4.14.

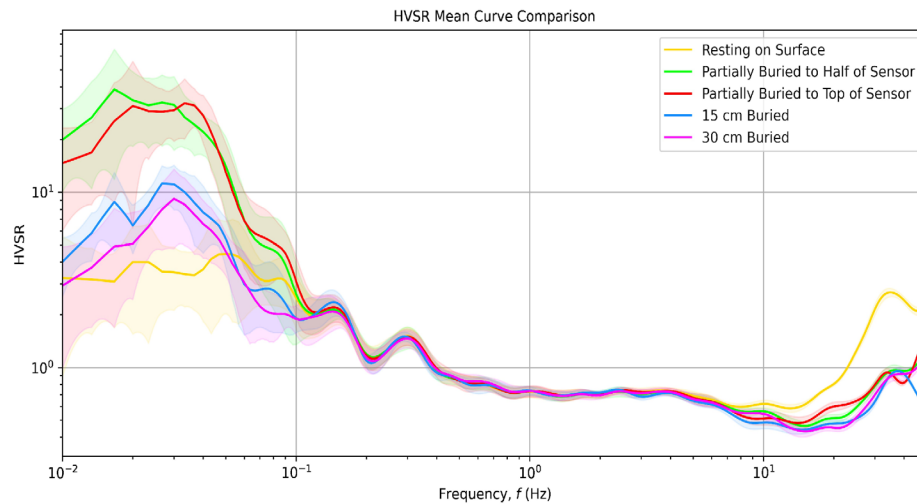


Figure 4.14. mHVSR spectra for a site in Santa Monica, CA, showing the effects of burial depth on ordinates at lower frequencies.

4.5 Comparison of Rayleigh wave H/V and mHVSr for the Central Valley

As described in Section 2.2, the wave composition of ambient noise is complex, involving surface waves (Love and Rayleigh) and body waves that originate from surficial sources and tectonic sources at depth. Part of the uncertainty associated with the interpretation of microtremor HVSr is the non-uniqueness of the wave composition, which cannot generally be known with confidence. If the wave composition were known, it is reasonable to expect that the uncertainty in HVSr interpretation would be significantly reduced.

This concept underlies an approach for microtremor data interpretation advanced by Prof. Fan-Chi Lin at the University of Utah. His work examines full waveform data recorded simultaneously at multiple locations across a sedimentary basin and seeks to isolate the components of ambient vibration associated with Rayleigh waves from all other sources. mHVSr derived from the “cleaned” waveforms have different attributes from those presented elsewhere in this thesis, and in particular, show promise for clearly capturing mHVSr at frequencies below 0.1 Hz.

I worked with Dr. Lin to investigate the differences between mHVSr as measured using ordinary methods with Rayleigh wave H/V ratios evaluated using his methods. As shown in Figure 4.15, the study utilized data from an array that was installed transversely across the San Joaquin Central Valley. The data were extracted from IRIS (described in Section 3.2.3), from the network TO, with station code starting with CC. The array was temporarily active between 2013 and 2015. The installed permanent sensors were high-quality broadband seismometers manufactured by Güralp that had flat responses between 0.0083-50 Hz and sampled at 100 Hz; these sensors are suitable for recording ambient vibrations. I extracted data for a duration of 3 hours on June 1, 2014; the duration was selected with the aim of extracting peaks as low as 0.05 Hz or 20 sec. The data

recovered from the array was processed in two ways – the “typical” manner presented in this thesis and in a customized manner for isolating Rayleigh waves by a student of Dr. Lin (Gabriela Zaldivarandrade). I performed the typical processing using the procedures in Section 3.3, except that I used 600 sec windows when discretizing the waveform into individual windows. As described in Section 3.3.2, the data became more stable as signal duration or the number of windows increased. Figure 4.15 shows the spatial distribution of the peak frequencies, which are lower on the west side of the Central Valley than on the east side, which aligns with the direction of basin thickening (Myer 2005). The peaks in mHVSr were identified using an algorithm developed by Wang et al. (2023), which is discussed in further detail in Section 6.3. Some sites have periods as long as 17.5 sec (frequencies of 0.06 Hz) on the west side of the basin, where sediment thickness is about 9150 m. An open question is whether such peaks represent impedance effects related to the site stratigraphy or are a consequence of tilt or other effects unrelated to geologic structure. I investigate this by evaluating if Rayleigh wave H/V ratios coincide with the peaks in mHVSr.

Ms. Zaldivarandrade processed the Rayleigh wave field from the cross correlation of signals from a large spatial distribution of stations (procedures given in Lin et al., 2014). The Rayleigh wave H/V ratio data were subsequently provided to me by Dr. Hyejeong Kim. Rayleigh wave ellipticity was then evaluated from the vertical and radial components of the records. The H/V ratio is represented by the ratio of these components. Figure 4.16 compares the results between H/V and mHVSr for data from 36 stations that were provided by Dr. Kim. In Figure 4.16, for stations 21 through 28 there is a strong correlation between the mHVSr (shown in orange) and the Rayleigh wave H/V ratio (shown in blue) down to 0.05 Hz, which is different than results presented in Section 4.2.1 where ordinates in this range were not found to be representative

of geologic stratigraphy. This is likely due to the longer duration of the record used to process the mHVSr, which effectively removed the large ramp characteristic seen previously. It could also be attributed to the method in which the sensor was installed at the site and the fact that it was recorded for long periods of time, which would remove the effect of drift commonly found at sensor start-up. If this effect is associated with site geotechnical conditions, it would reflect strong impedance contrasts within the profiles. In a different portion of the array, station 1 and 17 shows an mHVSr ramp characteristic as described for multiple locations in Section 4.2, and the H/V ratio is not correlated to this characteristic, meaning that the wave energy attributed to this ramp is not caused by Rayleigh wave energy. For many stations in Figure 4.16, there is a peak being captured by the Rayleigh wave H/V similar to mHVSr just before the ramp-like characteristic. This suggests that the pre-ramp peak may have physical meaning, whereas the ramp itself can likely be attributed to atmospheric or oceanic effects causing localized slab-tilt affecting the horizontal components of the seismometers at long periods (e.g., De Angelis and Bodin 2012).

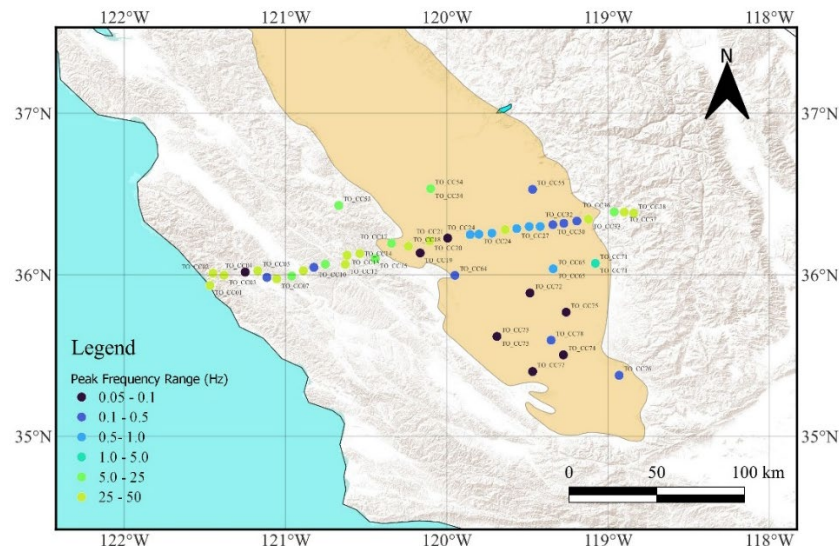


Figure 4.15. Location of sites in TO array, with color-coded markers showing the frequency peak across the San Joaquin Central Valley. The stations are labeled in order from left to right along the array. The orange-colored boundary represents the boundary of the central valley.

It is promising that Rayleigh wave H/V provides stable results at low frequencies that could be indicative of site stratigraphy. The distinction between results from Rayleigh wave ellipticity and mHVSr highlights the effects of the relatively complex microtremor wavefield, which would appear to limit our ability to draw meaning from conventional mHVSr low-frequency ordinates.

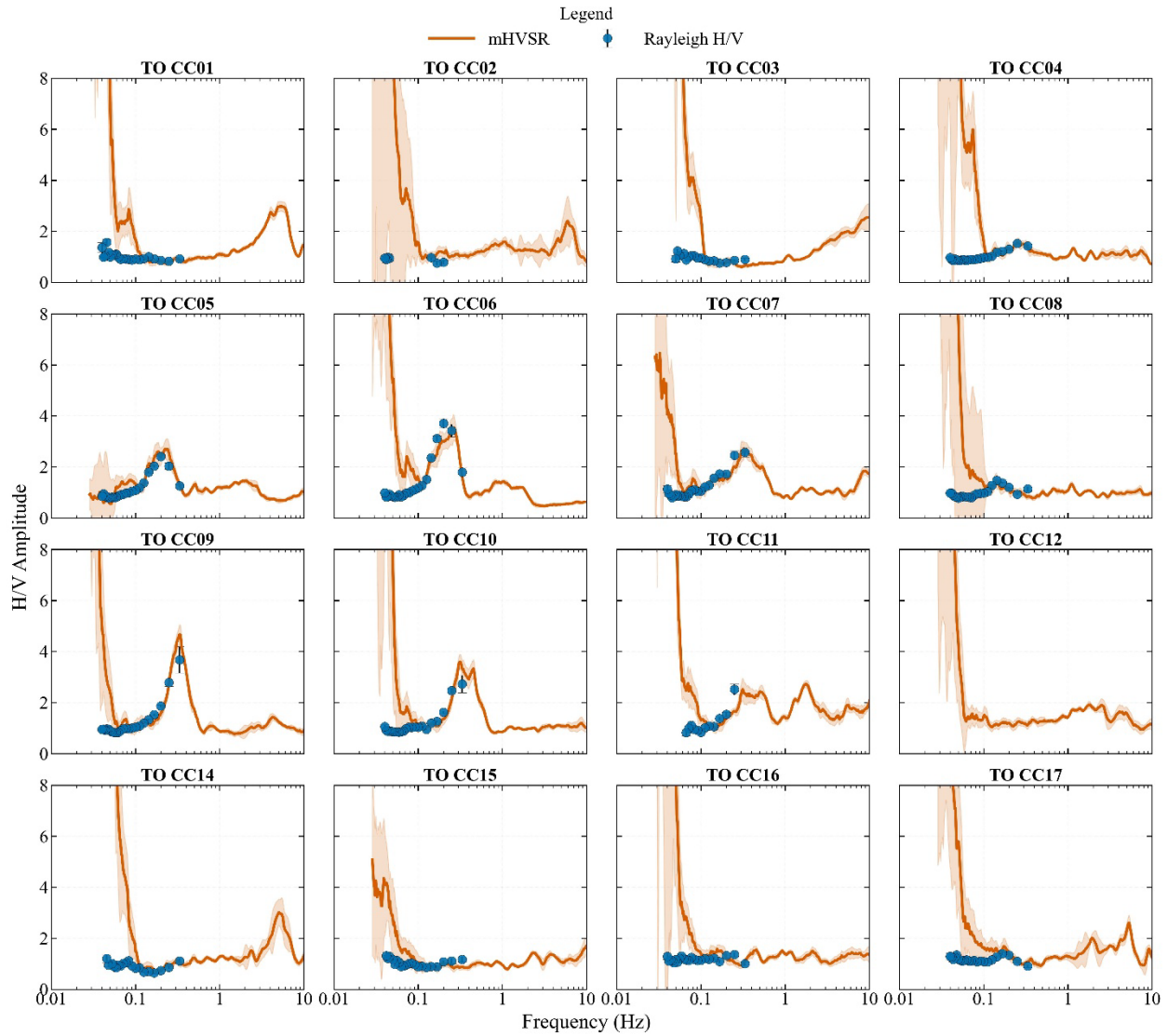


Figure 4.16. Comparison between 36 mean mHVSr curves and Rayleigh wave H/V ratios on the TO array. The blue dots represent the H/V ratio and the orange represents the mHVSr. The error bars represent the uncertainty of the H/V ratio and the shaded regions represent the standard deviation of the mHVSr curve.

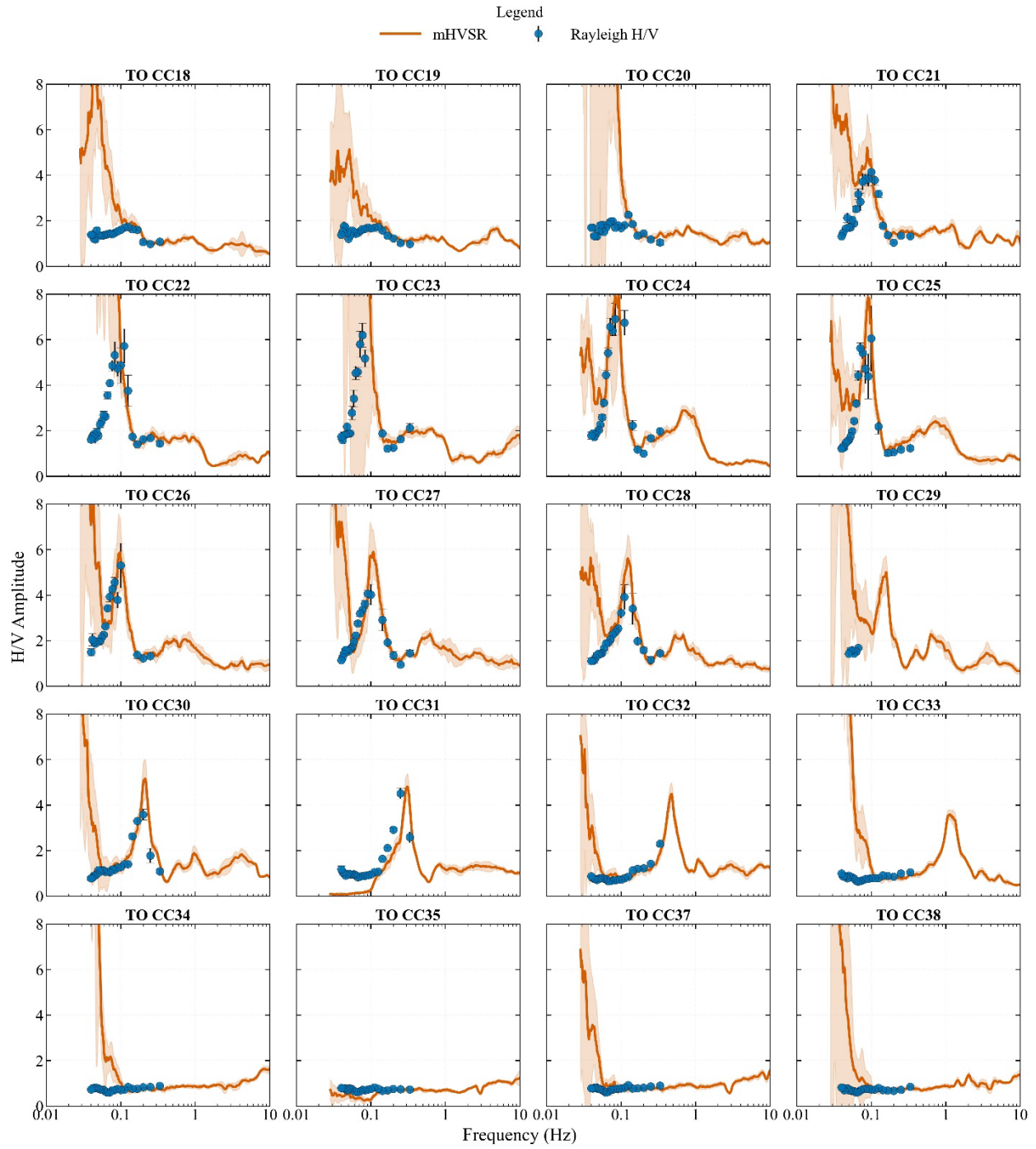


Figure 4.16. Continued

4.6 Conclusions

Results relevant to the reliability of mHVS_R ordinates at low frequencies have been presented in Chapters 2 to 4 of this dissertation. A common indicator that low-frequency results are unreliable is a ramp-up of mHVS_R ordinates for frequencies below 0.1-0.2 Hz. Factors that reduce these ordinates may, in some cases, provide insight into the causes of these features and corrections that can improve reliability. With that in mind, the following summarizes key findings pertinent to this frequency range:

- Low-frequency mHVS_R ordinates are sensitive to drift removal prior to windowing (Section 3.4.4). Drift seemed to be present in many of the temporary deployment records and was generally more pronounced in the vertical component. Failing to remove this drift in the vertical component and improper detrending of the signal results in spectral leakage (i.e., the beginning and end of the windowed time series are different) that manifests as an increase in Fourier spectral ordinates across all frequencies. This has the effect of suppressing mHVS_R ordinates at low frequencies since drift is more prominent in vertical records.
- Low-frequency mHVS_R ordinates are sensitive to the number of low frequency cycles in the signal time windows. Ordinates and uncertainty in the ordinate decrease with increasing numbers of cycles (N) and become unstable (and large) for $N < 10$ (Section 3.4.2). Available data are unclear regarding sensitivity to the number of windows but possibly decrease as the number of windows increases.
- Low-frequency mHVS_R ordinates can decrease appreciably for permanent stations relative to temporary deployments at the same site (Section 3.4.2).

- Prior research identifies noise sources that predominate at low frequencies (Section 4.1). In some cases, such as localized slab-tilt, their occurrence could compromise the reliability of low-frequency mHVSr ordinates as indicators of geologic structure.
- Burying sensors helps to reduce low-frequency mHVSr ordinates (Sections 4.3 and 4.4). Moreover, for high frequency (> 10 Hz) mHVSr surface deployments may provide unreliable measurements (Section 4.4).
- Low-frequency Rayleigh wave H/V ordinates may provide an indication of when a low frequency peak in mHVSr is caused by stratigraphy rather than long period effects (Section 4.5).

The actionable lessons from these investigations are that drift removal should be part of data processing, ordinates should only be considered at a given frequency if $N > 10$, where possible, data from permanent broadband sensors should be used in lieu of co-located data from temporary deployments, and sensors deployed for temporary vibration monitoring should be buried. If all these practices are followed, low-frequency ramps are certainly possible. If ramps are not present and a peak within the low frequency range is observed, that peak is likely to have physical meaning provided the microtremor noise is not unusually energetic (Sections 4.3-4.4). If a ramp is present without undulations (peaks) along the ramp, the ordinates are likely not meaningful for the interpretation of geologic structure. If a ramp is present that includes a local peak, the peak may have physical meaning if it is not near the high pass corner frequency or 0.1 Hz.

5 Utilization of Spatially Distributed mHVSr to Assess the Effectiveness of Ground Response Analysis

The content of this chapter comprises a portion of a journal paper submitted to Earthquake Spectra, Titled Utilization of Spatially Distributed mHVSr to Assess the Effectiveness of Ground Response Analysis (Ornelas et al. 2026a).

One-dimensional ground response analyses (GRA) can introduce model error to site response estimates when wave propagation is not dominated by vertically propagating shear waves. I investigate whether the variability of spatially distributed microtremor horizontal-to-vertical spectral ratios (mHVSr) is related to GRA effectiveness using data from 19 vertical array sites (discussed in Section 3.2) across California. For each site, multiple mHVSr curves were measured at variable distances from the vertical array (average of 20/site). The variability of spatially distributed mHVSr curves is evaluated for various frequency intervals centered on peaks as a function of separation distance using various correlation metrics. I selected the Longest Common Subsequence (LCSS) metric for its ability to align with independent analysts' visual assessments and improve upon previously proposed metrics such as Pearson's r , mean absolute error, and variability of fundamental site frequency derived from HVSr. GRA effectiveness is evaluated using results from prior work in which predicted and observed surface/downhole transfer functions were derived across multiple events for each vertical array, with a wide range of outcomes ranging from excellent alignment to strong misfits. I observe that vertical array sites exhibiting a high degree of spatial similarity in the mHVSr curves, particularly within a low frequency interval corresponding to the fundamental peak of the observed transfer function, tend to show alignment between the predicted and observed transfer functions. Moreover, sites with pronounced low

frequency mHVSr variability were not adequately modeled by GRA. These results show that multi-location mHVSr measurements can provide useful insights regarding site complexity with implications for the reliability of site response modeling.

5.1 Literature on the Effectiveness of 1D GRA

One-dimensional (1D) ground response analyses (GRA) are commonly applied for evaluating the effects of site response on ground shaking. 1D analyses operate under the assumption that the soil profile can be represented by laterally continuous horizontal layers and that the wavefield can be represented by vertically propagating shear waves. Previous studies have evaluated the effectiveness of 1D GRA utilizing data from multiple ($> \sim 5$) vertical array sites in Japan (Thompson et al., 2009, 2012; Kaklamanos et al., 2013; Zalachoris and Rathje, 2015; Kaklamanos and Bradley, 2018; Pilz and Cotton, 2019; Tao and Rathje, 2020) and California (Afshari and Stewart, 2019; de la Torre et al., 2022). Many of these studies have found that the site response predicted by 1D GRA does not accurately capture observed transfer functions for appreciable fractions of vertical array sites where data is available and often overpredicts transfer function amplitudes near fundamental mode frequencies.

Misfits between 1D GRA to observations can arise due to a poorly constrained shear-wave velocity profile and from complexities of the soil profile and wave field associated with site heterogeneities and multidimensional wave propagation phenomena. Such complexities are difficult to anticipate in advance for sites lacking vertical arrays. To address this, a number of recent projects performed according to a Senior Seismic Hazard Analysis Committee (or SSHAC) process (Budnitz et al., 1997) have incorporated model error into their logic trees. This model error characterizes epistemic uncertainty in the use of 1D GRA as the basis for site response modeling.

Using data from California vertical array sites, a model for model error was developed by Stewart and Afshari (2021), which has subsequently been confirmed by Bahrampouri and Rodriguez-Marek (2023) using data from Kiban-Kyoshin network (KiK-net) sites in Japan (Aoi et al., 2000) when typical levels of V_S profile variability are considered in the data interpretation. The approximate level of model error at periods shorter than the soil column period is 0.3 natural log units, which is appreciable. This level of model error represents a network average; individual sites may be relatively accurately or inaccurately modelled by 1D GRA. For cases in which the site response aligns with 1D GRA predictions, lower levels of model error would be technically defensible. However, identifying such sites requires site characterization methods that can be used to evaluate whether a site will behave in a relatively 1D manner. In the absence of abnormally extensive site characterization (i.e., multiple closely-spaced invasive tests to measure V_S profiles or non-invasive tests to measure dispersion curves), we currently lack such methods.

Although limited in number, evidence of site heterogeneity correlation with the ability of 1D GRA to match vertical array transfer functions was presented by Thompson et al. (2012) for two sites in Japan near the town of Honbetsu (stations: TKCH05 and TKCH08). They conducted four spectral analysis of surface waves (SASW) tests at each site and found significantly greater dispersion curve variability at TKCH05 (where 1D GRA results were incompatible with observations) than at TKCH08 (where predictions aligned with observations). Many other studies have investigated variability of velocity structure at various sites (e.g., Toro, 1995; Popescu, 1995; Holzer et al., 2005; Passeri et al., 2019), but without specifically linking that variability to the predictive power of 1D GRA for site response. Additional studies have performed GRA using heterogeneous 2D velocity models based on spatially correlated random fields (e.g., Thompson et al., 2009; de la Torre et al., 2022; Pretell et al., 2022). These studies generally found that

multidimensional heterogeneity reduces amplification at fundamental modes relative to 1D GRA. One important finding from such studies, which partially motivated the present work, is that applying a generic level of soil heterogeneity to all sites may not be appropriate (de la Torre et al., 2022), and that methods to quantify the site-specific level of heterogeneity should be developed.

Microtremor-based horizontal-to-vertical spectral ratios (mHVSR) have been used as a means for evaluating site heterogeneity. Originally introduced by Nogoshi and Igarashi (1971) for characterizing site response to seismic loading, this method was subsequently popularized and further developed by Nakamura (1989) and many others. mHVSR measurements provide a low-cost technique for seismic site characterization, utilizing a three-component seismic instrument to record ambient ground vibrations in both horizontal and vertical directions over a relatively short duration (~1-2 hours) (SESAME, 2004; Molnar et al., 2022). For investigations of site heterogeneity, mHVSR measurements at multiple locations within a site are needed. Such measurements from three sites (Treasure Island, California, Delaney Park, Alaska, and CentrePort, Wellington, New Zealand) have been interpreted to investigate variability of the fundamental resonant frequency (f_0) spatially (Hallal and Cox, 2021a, b; Cheng et al., 2021), which has been proposed as a potential indicator of site complexity. Furthermore, Cheng et al. (2020) examined azimuthal variability in HVSR at various stations in CentrePort, which has been hypothesized to correlate with site subsurface complexity (e.g., Matsushima et al., 2014; Matsushima et al., 2017; Vantassel et al., 2018; Cheng et al., 2020) and is considered in this study because it is a relatively easily measured single-station metric.

In this chapter, I will discuss how I extend the manner by which multi-location mHVSR data are interpreted to characterize variability by using mHVSR curve shapes, whereas prior work had focused solely on f_0 . I then show the relationship between this mHVSR variability and 1D

GRA effectiveness at 19 vertical array sites in California. Although mHVSr measurements were conducted at 20 vertical array sites, one vertical array site (Site 8; discussed in Section 5.2.2) was excluded due to sufficient mHVSr data not being available. The rationale for investigating these potential relationships begins with the results of prior research that has demonstrated that mHVSr curves can identify impedance contrasts associated with the fundamental-mode site resonance (e.g., Lermo and Chavez-Garcia, 1993; Lachet et al. 1996; Ghofrani et al. 2013). When HVSr measurements are obtained from a spatially distributed array of stations, our hypothesis is that the resulting spectral variations can provide insight into lateral changes in stratigraphy, which in turn are expected to influence site response predictability with 1D GRA. For example, if the velocities in different layers at a site were relatively uniform but layer thicknesses changed laterally, peak frequencies would also be expected to be spatially heterogeneous because peak frequency of a soft layer scales inversely with its thickness (Kramer and Stewart, 2025).

I present a framework for evaluating mHVSr spatial variability by analyzing the mean curve (i.e., amplitude ordinates) across various frequency intervals. mHVSr measurements were conducted at 20 vertical array sites in California, both near the array and at a series of stations positioned at distances of approximately 50, 100, 250, and 500 meters from the array in an approximately circular pattern (average of 20/site). I propose a repeatable metric for interpreting spatial variations of mHVSr across these locations. These metrics are compared to indicators of 1D GRA effectiveness, as evaluated by the goodness-of-fit between empirical and theoretical transfer functions from the vertical arrays. Finally, I show the extent to which mHVSr spatial variability metrics can provide insights into model error using the California database.

Following this section, I describe the manner in which spatial variability was evaluated from mHVSr curves, and re-interpretation of matches between 1D GRA and empirical transfer

functions. I then interpret the results in two ways – 1) investigating relationships between mHVSr spatial variability and site response effectiveness metrics based on surface/borehole transfer functions, and 2) implications of the results for the estimation of model error based on residual analysis of ground surface intensity measures.

5.2 Characterization of Site Spatial Variability using mHVSr

5.2.1 Heterogeneity Characterization

Processed mHVSr curves from the database discussed in Section 3.2.1, for each test location within the circular arrays were evaluated for similarity to the mHVSr curves closest to the vertical array. This evaluation began with visual inspections of the data by three different analysts (Prof. Jonathan Stewart, Dr. Christopher de la Torre, and I) to qualitatively assess how correlated the curves are at a given site (i.e., how similar they are in shape and in amplitude). This was followed by computing different correlation metrics, the aim of which was to replicate analysts' judgment. As part of these evaluations, I considered the correlation between curves within frequency intervals defined based on peaks in the suite of mHVSr curves at the site when evaluated in aggregate. The lowest frequency interval that was considered for a given site was selected to include the first-mode peak from the surface/downhole vertical array transfer function, although its actual frequency limits were selected to roughly align with troughs in the suite of mHVSr curves across the site. These frequency intervals were centered on each of the modal peaks regardless of peak amplitude (amplitude thresholds were not enforced due to frequent inconsistencies between mHVSr curves for a given site). The number of frequency domain data points across the full range of the mHVSr curves (N_{freq}) was always 2,479, whereas the number of points in individual frequency intervals (N_{freq}) averaged around 500. Frequencies lower than 0.2 Hz were not

considered due to instabilities in the ordinates that were frequently observed with the instruments used for the work (Trillium Compact; SESAME, 2004; Ornelas et al., 2024b). The mHVSr curves were also organized by radial distance from the vertical array (50, 100, 250, 500 m). These analyses are presented in the following sub-sections.

5.2.2 Analysts' Direct Interpretations

Analysts visually inspected the mHVSr curves from 19 sites from Table 3.3 in Section 3.2.1 for each radial distance and frequency interval. These evaluations were performed for all sites in Table 3.3 except Site 8 (Hayward – San Mateo), for which only four measurements were taken, which is inadequate for the present analyses. These inspections were used to qualitatively evaluate similarity between the mHVSr curve closest to the vertical array (i.e., the reference 0.0 test) and mHVSr curves at different radial distances as well as the similarity among mHVSr curves for a given radial distance. Figure 5.1 shows examples of two sites that the analysts inspected. For Figure 5.1a, the mHVSr curves were judged to be spatially similar, meaning that most of the curves (shown in grey for a given radial distance) have similar shapes and amplitudes when compared to each other and to the reference mHVSr curve (shown in red) for the first two frequency intervals. For the site shown in Figure 5.1b, the mHVSr curves were judged to be spatially variable, due to the vertical spacing of their ordinates and the differences at which resonant features occur. Additional plots showing the mHVSr curves in terms of distance and frequency interval for all sites can be found in Appendix B (Supplemental material) of the journal paper (Ornelas et al. 2026a).

For each site and each of the frequency intervals considered, analysts assigned values of 0 to 3 based on their assessments of the similarity of mHVS curves at a given radial distance with each other and with the center station. The indices indicate the following:

0. No resonant feature was present within the frequency range
1. The curves were poorly correlated
2. Intermediate levels of correlation between curves for the frequency range and radial distance
3. The curves were well correlated for the frequency range and radial distance

In the next sub-section, I consider whether analysts' judgments, as reflected in these indices, can be approximately replicated with computable metrics.

5.2.3 Computed Metrics

Because the indices established from analysts' judgment are qualitative and user-dependent, I sought to identify quantitative correlation metrics, based on mHVS curves, that would align with the analysts' judgment. The following metrics were considered:

- Longest Common Subsequence, LCSS (Vlachos et al., 2002)
- Pearson's sample correlation coefficient, r (e.g., Benesty et al., 2009)
- Mean Absolute Error, MAE (e.g., Willmott and Matsuura, 2005)
- Standard deviations of derived mHVS fundamental frequencies, f_0 (Hallal and Cox, 2021a, b; Cheng et al., 2020; Cheng et al., 2021) and ordinates.

In the following sub-sections, I describe all four metrics that were used in the analysis. However, LCSS and standard deviations were selected as being better able to distinguish correlation and are further described in Section 5.4. All metrics were computed for mHVS curves from various

locations around vertical arrays to assess variability with respect to varying distances and different frequency intervals.

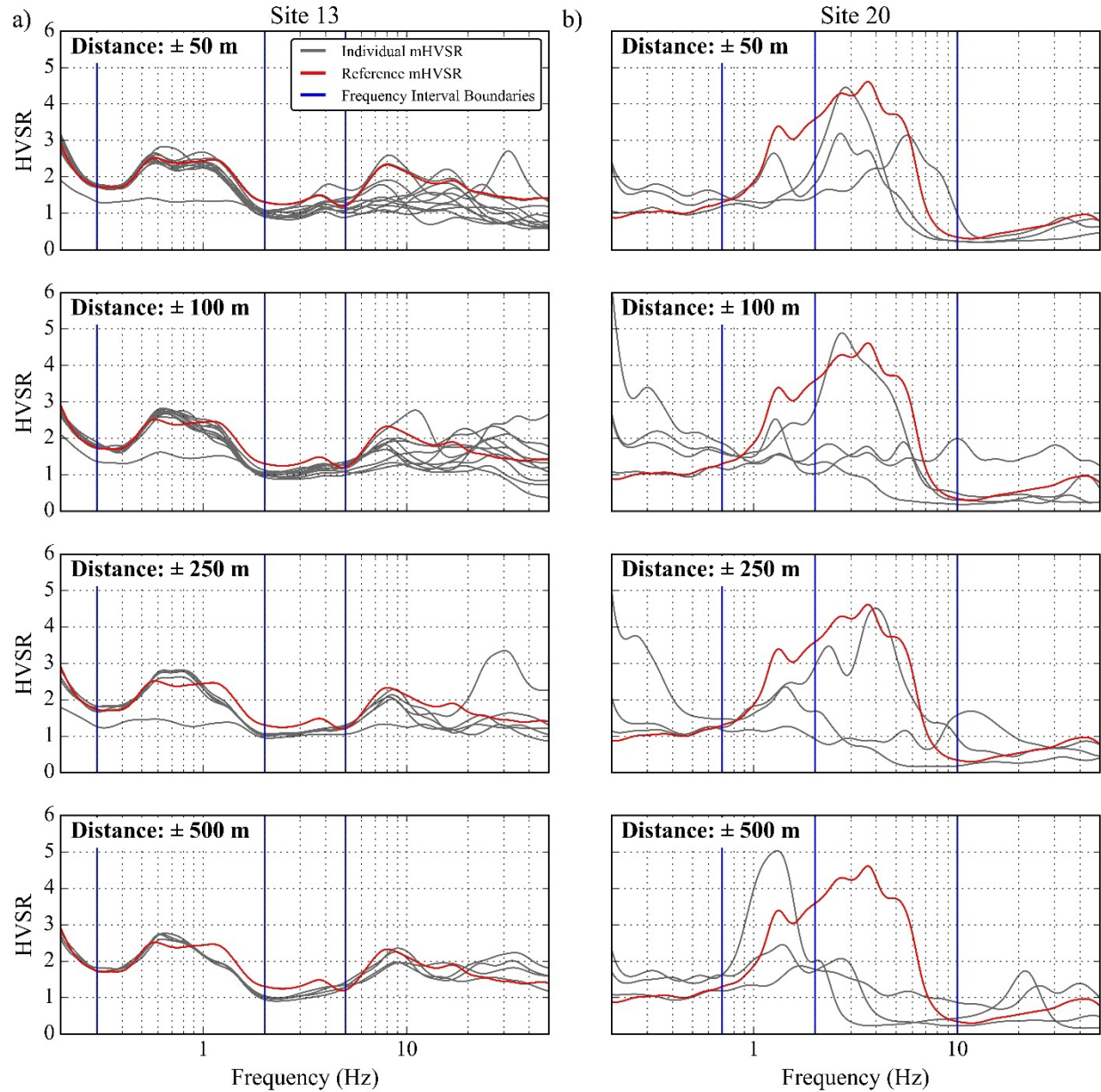


Figure 5.1. Mean mHVSr curves for the reference station (e.g., .0.0 test) and four radial distances (gray lines). The blue vertical lines indicate different frequency intervals associated with distinct resonant peaks. (a) Wildlife Liquefaction Array (Site 13), with similar mHVSr curves and (b) San Francisco Bay Bridge (Site 20) with spatially variable mHVSr curves.

5.2.3.1 PEARSON'S COEFFICIENT

Pearson's r correlation coefficient has been widely utilized in previous research to assess the goodness-of-fit between empirical and theoretical transfer functions (e.g., Thompson et al., 2012; Afshari and Stewart, 2019; Tao and Rathje, 2020; de la Torre et al., 2022). It ranges from -1 to 1 and is defined as follows:

$$r_{ij} = \frac{\sum(HVSR_i(f) - \overline{HVSR_i})(HVSR_j(f) - \overline{HVSR_j})}{\sqrt{\sum(HVSR_i(f) - \overline{HVSR_i})^2} \sqrt{\sum(HVSR_j(f) - \overline{HVSR_j})^2}} \quad (5.1)$$

where the $HVSR_i(f)$ represents the reference mHVSER curve nearest to the vertical array, and $HVSR_j(f)$ represents an mHVSER curve at some radial distance. The summation, shown in Eq. (5.1) is over each frequency, which are equally spaced in logarithmic units, within a given frequency interval. Accordingly, the r coefficients apply to intervals associated with a resonant peak rather than to the entire curve. This calculation measures similarity between the curves, in terms of shape and location, meaning that if the shapes were slightly out of phase (shifted to the right or left), the correlation value would be much lower, even though visually the curves may not appear to be appreciably misaligned. This caused instances where the average Pearson's r for all tests at a site (which I denote as $\bar{r}$) was much lower than what we would have expected. I consider $r \geq 0.6$ to be a good fit, $r = 0-0.6$ to be intermediate fit, and $r < 0$ to be poor fit, which is similar to the ranges used in prior studies (e.g., Afshari and Stewart, 2019).

5.2.3.2 MEAN ABSOLUTE ERROR

Mean Absolute Error (MAE) represents absolute difference between two curves:

$$MAE = \frac{\sum_{i=1}^n |HVSR_m - HVSR_r|}{n} \quad (5.2)$$

where n is the sample size of the two arrays (with lengths equal to each other), and the subscripts r and m represent the reference and measured mHVS curves, respectively. MAE is commonly used to assess the extent to which predicted values deviate from true or observed values, serving as an error metric. It has recently been used to quantify similarity between eHVS and mHVS curves (Vantassel et al., 2024) and to evaluate goodness-of-fit between observed and predicted amplifications at different frequencies (Zhu et al., 2020). Since the differencing calculation in Eq. (5.2) is at given frequencies, curves with similar shapes but shifted in frequency may have large MAE values.

5.2.3.3 LONGEST COMMON SUBSEQUENCE (LCSS)

This correlation metric can be used to estimate the similarity of two curves. It does so in a manner that considers differences between curves in any direction (not just vertically as with r and MAE) and that can accommodate arrays of varying lengths. As such, it has novel features that are advantageous for this application. Our application uses arrays of equal length and evenly spaced frequencies in logarithmic units. The LCSS metric, developed by Vlachos et al. (2002), incorporates two functions to measure similarity between curves. The first, S_1 , is used to evaluate similarity in a 2D plane and is defined as,

$$S_1(A, B, \epsilon, \delta) = \frac{LCSS_{\delta, \epsilon}(A, B)}{\min(n, m)} \quad (5.3)$$

where A and B are taken for the present application as arrays of mHVS ordinates in logarithmic scale of size n and m , respectively (equal for our application), ϵ is a user-selected matching threshold based on the difference between ordinates, δ is a radius parameter referred to as the Sakoe-Chiba radius (Sakoe and Chiba, 1978; also called the warping window size) that controls how far horizontally the operator can allocate matches between points, and the $LCSS_{\delta, \epsilon}$ function

evaluates similarity between paired points in the two arrays. The $LCSS_{\delta,\epsilon}$ function produces symmetric outcomes, meaning that $LCSS_{\delta,\epsilon}(B, A) = LCSS_{\delta,\epsilon}(A, B)$. The second metric, S_2 , from Vlachos et al. (2002) quantifies similarity between translations in space (e.g., 3D planes) and is not used here. I apply this algorithm using the natural log of mHVSr ordinates so that differences between curves are evaluated in a manner that is proportional to their ordinates, which is helpful due to the wide range of ordinates in the data set. This facilitated our efforts to select a consistent set of ϵ and δ values for application to all 19 sites.

The matching threshold parameter ϵ and range parameter δ affect the $LCSS_{\delta,\epsilon}(A, B)$ calculation as follows:

$$LCSS_{\delta,\epsilon}(A, B) = \begin{cases} 0 & A \text{ or } B \text{ empty} \\ 1 + LCSS_{\delta,\epsilon}(A_{n-1}, B_{m-1}) & |a_i - b_j| < \epsilon \ \& \ |j - i| \leq \delta \\ \max(LCSS_{\delta,\epsilon}(A_{n-1}, B), LCSS_{\delta,\epsilon}(A, B_{m-1})) & \text{otherwise} \end{cases} \quad (5.4)$$

where A_{n-1} is array A but with its last element removed (hence its length is $n-1$) and a_i is an individual element of A at position (i). Array A_{n-1} is referred to by Vlachos et al. (2002) as *head(A)*. B_{m-1} and b_j are similarly defined for array B . The second line on the right side of Eq. (5.4) seeks matches by taking the absolute differences (e.g., mHVSr ln ordinates) between points a_i and b_j . If those differences are less than ϵ for length of arrays separated by $\leq \delta$ number of steps on the abscissa, then the $LCSS_{\delta,\epsilon}$ count increases by 1. If the absolute differences exceed ϵ , the maximum $LCSS_{\delta,\epsilon}$ value between the two arrays with one element removed from either array is obtained (as shown in the third line on the right side of Eq. 5.4). Vlachos et al. (2002) indicated that the selection of ϵ is application-dependent. If the curves are close together per the ϵ and δ

metrics, then all the points are perfectly paired; for this condition, $LCSS_{\epsilon,\delta}$ will return an integer representing the number of points that were matched between the two curves, causing S_1 to be unity per Eq. (5.4). As the number of paired points decreases, $LCSS_{\delta,\epsilon}$ decreases, causing S_1 to drop below unity with the minimum possible value being zero.

Figure 5.2 illustrates the effect of δ and ϵ on the pairing of points between mHVS curves (labeled as “reference” and “measured”). The lines between curves represent pairings. In Figure 5.2a, $\delta = 10$, allowing for significant horizontal searching between points. More pairings are made as ϵ increases from 0.3 to 0.65, as expected. In Figure 5.2b, results for narrow horizontal searching ($\delta = 1$) are compared to wider searching ($\delta = 10$). Narrow searching produces essentially vertical matches whereas wider searching allows for horizontal shifts in pairings. I found the ability of $LCSS_{\delta,\epsilon}$ to search in both directions to be advantageous compared to other metrics because it allows users to select ϵ and δ values that align peaks even if they occur at slightly different frequencies, which may better match analysts’ judgements. For the present study I used $\epsilon = 0.25$ and $\delta = 10$.

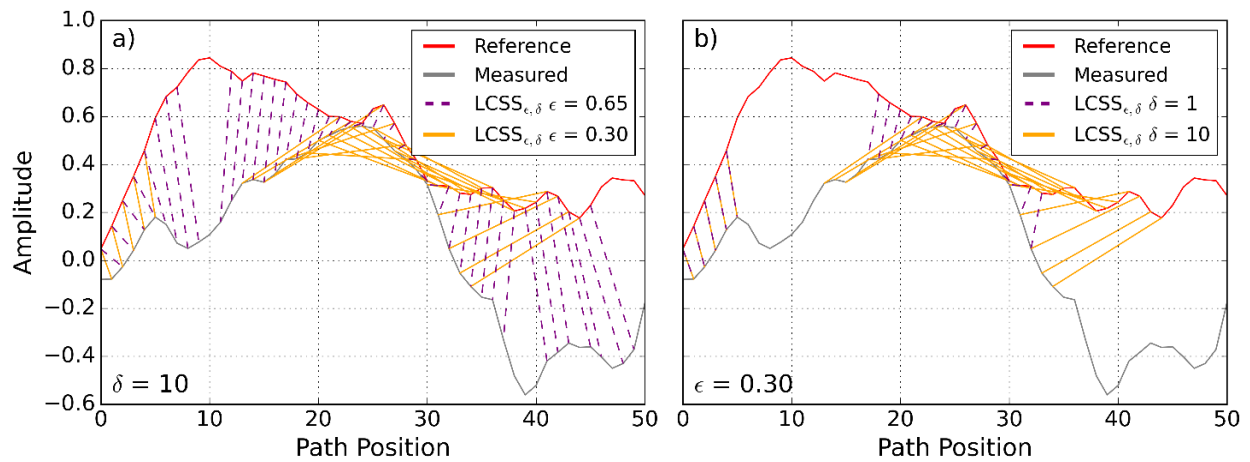


Figure 5.2. Comparison of two mean HVSR curves in natural log units, showing the differences in LCSS paths (used to assess similarity between curves) for two different matching thresholds, for both ϵ and δ . (a) Differences in pairings for two ϵ values for a constant $\delta=10$ and (b) differences in pairings for two δ values for a constant $\epsilon=0.3$. LCSS path position (x-axis) indicates the index value for which HVSR amplitude is sampled.

To conduct our analysis, I utilize the *lcss* function from the *tslearn* library (Tavenard et al., 2020). This script computes similarity measure S_1 between two mHVSR curves across a designated frequency interval. The example results in Figure 5.1 of similar mHVSR curves (Site 13) and dissimilar curves (Site 20) have S_1 metrics in the second and third frequency interval (closest frequency interval associated with the surface/downhole vertical array transfer function) of 0.89 and 0.50, respectively.

5.2.3.4 STANDARD DEVIATION METRICS

I consider standard deviation metrics proposed in prior work and additional metrics introduced here.

As noted previously, Hallal and Cox (2021a, b) and Cheng et al. (2021) proposed that f_0 spatial variability may correlate to subsurface geological complexity and Cheng et al. (2020) examined f_0 azimuthal variability; both are considered here although I note that azimuthal variability had not specifically been proposed as an indicator of site complexity by Cheng et al. (2020). Standard deviations are computed using the natural log of fundamental resonant frequencies, which I denote as $\sigma_{\ln f_{0,H/V}^*}^{spat}$ for spatial variability and $\sigma_{\ln f_{0,H/V}^*}^{azi}$ for azimuthal variability. I denote fundamental frequency as $f_{0,H/V}^*$ because the lowest frequency peak in mHVSR was not always used, instead the peak in mHVSR associated with the lowest frequency peak in the ETF was selected.

In addition to the f_0 variability metrics, I also consider standard deviations that capture spatial variations of mHVSr natural log ordinates within a specific frequency interval, which are denoted ($\bar{\sigma}_{\ln mHVSr}^{spat}$), and across azimuths for the mHVSr test closest to the vertical array for the same frequency range, which are denoted ($\bar{\sigma}_{\ln mHVSr}^{azi}$). Spatial standard deviation ($\bar{\sigma}_{\ln mHVSr}^{spat}$) is computed as follows:

$$\sigma(f)_{\ln mHVSr}^{spat} = \sqrt{\frac{\sum_{test=0}^{N_{test}} (\ln mHVSr(f)_{test,j} - \ln \overline{mHVSr}(f)_j)^2}{N_{test}}} \quad (5.5)$$

$$\bar{\sigma}_{\ln mHVSr}^{spat} = \frac{\sum_{i=0}^{N_{freq}} \sigma(f)_{\ln mHVSr,i}^{spat}}{N_{freq}} \quad (5.6)$$

where $mHVSr(f)_{test}$ represents the array of mHVSr data for an individual test for a specific frequency interval taken at a site j , $\overline{mHVSr}(f)$ represents the average mHVSr data for all individual tests for a specific frequency interval, N_{test} represents the number of tests taken for a specific distance bin or for all distance bins for a site j , and $\sigma(f)_{\ln mHVSr}^{spat}$ represents the standard deviation for each distance bin as a function of frequency. I take the average across all frequencies to compute $\bar{\sigma}_{\ln mHVSr}^{spat}$ (Eq. 5.6), where N_{freq} represents the number of frequencies within the $\sigma(f)_{\ln mHVSr}^{spat}$ (denoted as $\sigma_{\ln mHVSr}^{spat}$ henceforth) used to average. The azimuthal standard deviation ($\bar{\sigma}_{\ln mHVSr}^{azi}$) was computed as:

$$\sigma(f)_{\ln mHVSr}^{azi} = \sqrt{\frac{\sum_{azi=0}^{N_{azi}} (\ln mHVSr(f)_{azi,ref} - \ln \overline{mHVSr}(f)_{ref})^2}{N_{azi}}} \quad (5.7)$$

$$\bar{\sigma}_{\ln mHVSr}^{azi} = \frac{\sum_{i=0}^{N_{freq}} \sigma(f)_{\ln mHVSr,i}^{azi}}{N_{freq}} \quad (5.8)$$

where $mHVS R(f)_{azi,ref}$ are taken from the measurement nearest to the vertical array (*ref*), which are sampled for different azimuths (*azi*), $\overline{mHVS R(f)}$ represents the average mHVS R across azimuths, N_{azi} represents the number of azimuths considered, and $\sigma(f)_{\ln mHVS R}^{azi}$ represents the standard deviation across azimuths for a given frequency. The average across all frequencies is $\bar{\sigma}_{\ln mHVS R}^{azi}$ (Eq. 5.8), where N_{freq} is the number of frequencies, as before. I consider azimuths ranging from 0 to 180 degrees at increments of 10 degrees. Previous studies applied weights to standard deviations to account for variations in tributary areas (Cheng et al., 2021) and the number of selected time windows across different azimuths (Cheng et al., 2020). In the present analysis, standard deviations were calculated without applying spatial or azimuthal weighting.

5.2.4 Comparison of Analysts' Interpretation with Metrics

The associations of the analyst-defined indices with correlation and dispersion metrics are investigated with histograms of computed metrics for results having a given value of analysts' index (1, 2, 3) (the rounded average for the three individual analysts was used). Figure 5.3 shows correlations metrics r , MAE , and S_1 (Eq. 5.3). Figure 5.4 shows dispersion metrics $\sigma_{\ln f_{0,H/V}^*}^{spat}$, $\sigma_{\ln f_{0,H/V}^*}^{azi}$, $\sigma_{\ln mHVS R}^{spat}$ (Eq. 5.5), $\bar{\sigma}_{\ln mHVS R}^{spat}$ (Eq. 5.6), and $\bar{\sigma}_{\ln mHVS R}^{azi}$ (Eq. 5.8). In Figure 5.3, strong agreement between the analysts' indices and the correlation metrics is demonstrated by high values of S_1 and r , and low values of MAE , for index 3 data. For index 1 I see opposite trends, with low r and S_1 values, and high MAE values. Ultimately, I selected the LCSS S_1 metric due to the visually strongest trends with analysts' indices.

As shown in Figure 5.4a, the standard deviation metrics related to spatial correlation produced the expected trends (low dispersion for index 3 and high dispersion for index 1). Regarding standard deviation metrics for azimuthal variability, it is unknown whether they are

related to metrics of spatial variability. To investigate whether such correlations are present, I plot in Figures 5.4b and 5.4c relationships between azimuthal standard deviations and spatial standard deviations and evaluate the significance of the trend utilizing Pearson's r correlation coefficient. Figure 5.4b shows a strong correlation between $\bar{\sigma}_{\ln mHVSR}^{azi}$ and $\bar{\sigma}_{\ln mHVSR}^{spat}$ ($r = 0.84$) indicating that this azimuthal metric has potential as an indicator of spatial variability. On the other hand, Figure 5.4c shows a weak correlation between $\sigma_{\ln f_{0,H/V}^*}^{azi}$ and $\sigma_{\ln f_{0,H/V}^*}^{spat}$ ($r = 0.23$), suggesting limited potential as a site heterogeneity metric. While S_1 is the preferred site complexity metric based on comparisons to analysts' judgement, I also consider spatial standard deviation metrics for their correlations with 1D GRA effectiveness.

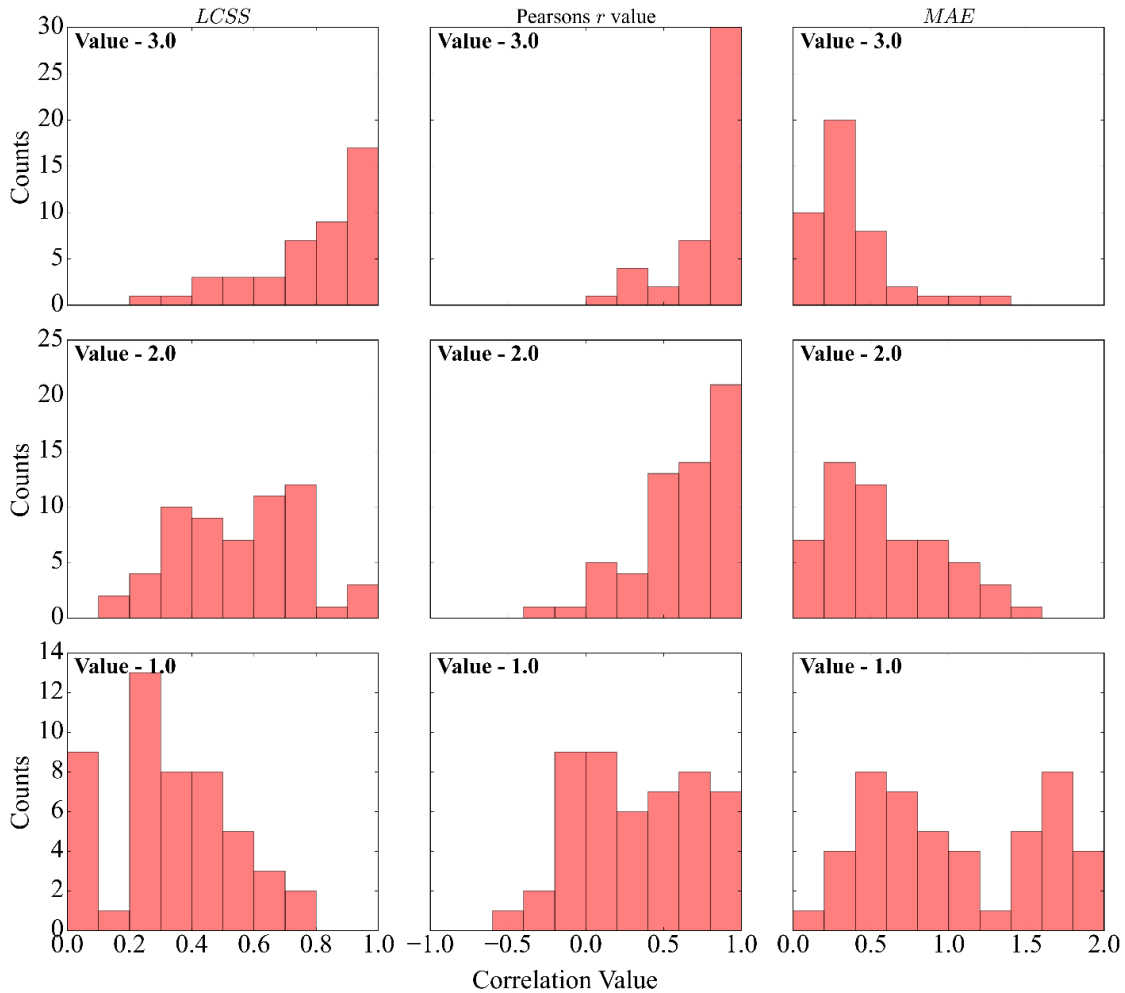


Figure 5.3. Histograms showing distributions of correlation values (r , MAE , S_1) for analyst indices ranging from 3 (strong correlation) to 1 (no appreciable correlation).

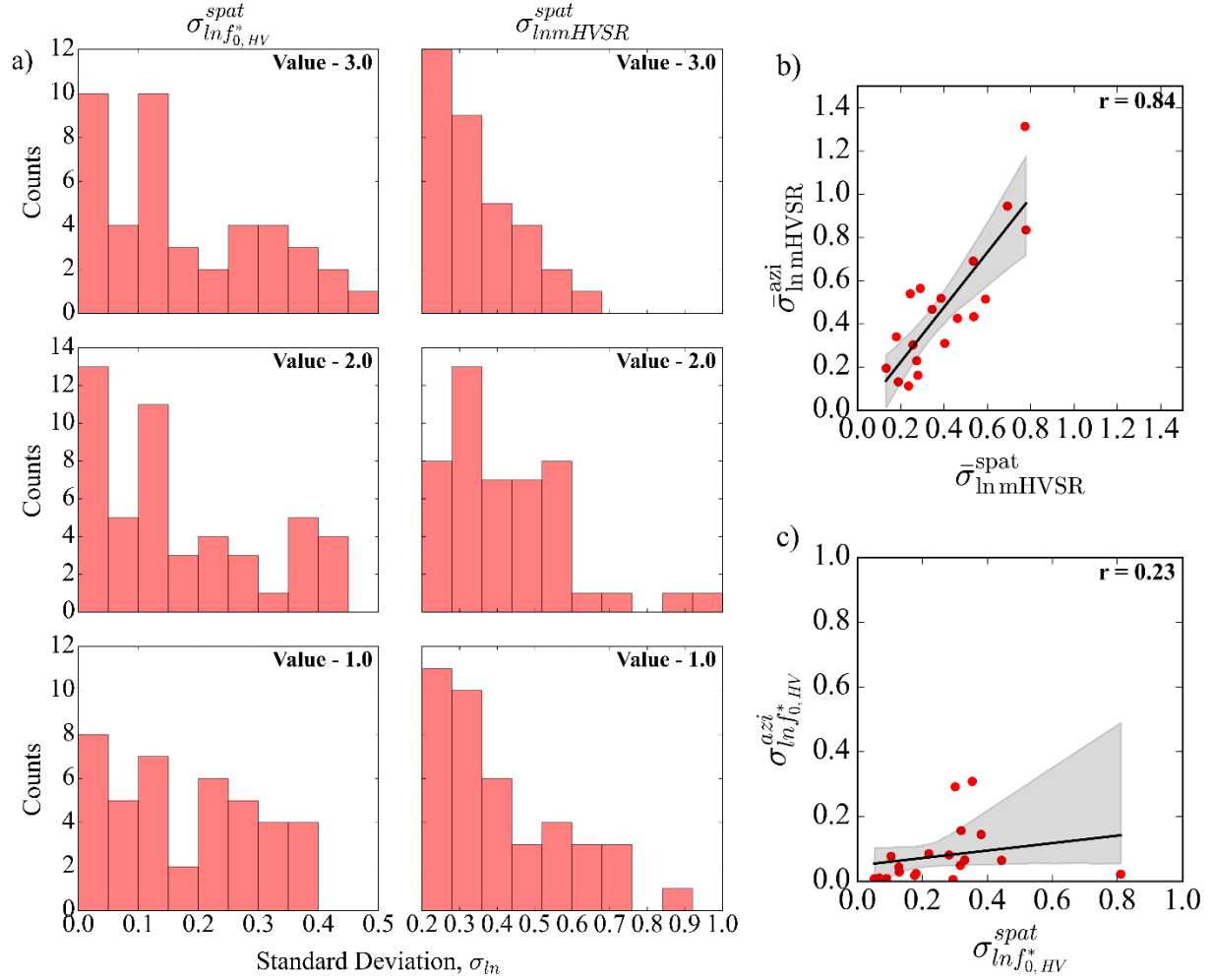


Figure 5.4. (a) Histograms showing distributions of spatial standard deviation values $\sigma_{\ln f_{0,H/V}}^{spat}$ and $\sigma_{\ln mHVSr}^{spat}$ for analyst indices ranging from 3 (strong correlation) to 1 (no appreciable correlation), (b) correlation between $\bar{\sigma}_{\ln mHVSr}^{spat}$ and $\bar{\sigma}_{\ln mHVSr}^{azi}$, and (c) correlation between $\sigma_{\ln f_{0,H/V}}^{spat}$ and $\sigma_{\ln f_{0,H/V}}^{azi}$.

5.2.5 Frequency- and Distance-Dependent of Correlation Metrics

The correlation metrics presented in this section can be computed for different frequency intervals (e.g., as shown in Figure 5.1) and for mHVSr pairs at different separation distances. Figure 5.5 shows how the LCSS S_1 parameter varies across frequency bands and separation distances. Each data point in Figure 5.5 is for an individual frequency interval at a single site. The frequency

intervals are site-specific as described in the *Heterogeneity Characterization* subsection. The black line in Figure 5.5 is from LOWESS regression (Cleveland, 1979) through the data to indicate data trends. The python package used for the analysis was *statsmodels* (Seabold and Perktold, 2010) with the function *lowess*. For each distance bin, the maximum correlation is at low frequencies (about 1-2 Hz), which is generally proximate to the fundamental mode response from the vertical arrays. The average S_1 parameters at these low frequencies are separation distance-dependent, ranging from approximately 0.7 at 50 m to 0.5 at 500 m. As frequency increases beyond this range, the average S_1 parameter decreases, generally reaching values of about 0.35-0.4 at frequencies of 10-30 Hz. Due to the similarity of mean (smoothed curve) S_1 parameters for different distance bins at high frequencies and the different levels of S_1 parameters between distance bins at lower frequencies, I focused on low-frequency S_1 parameters for analyses of their correlation with site response effectiveness, as presented next.

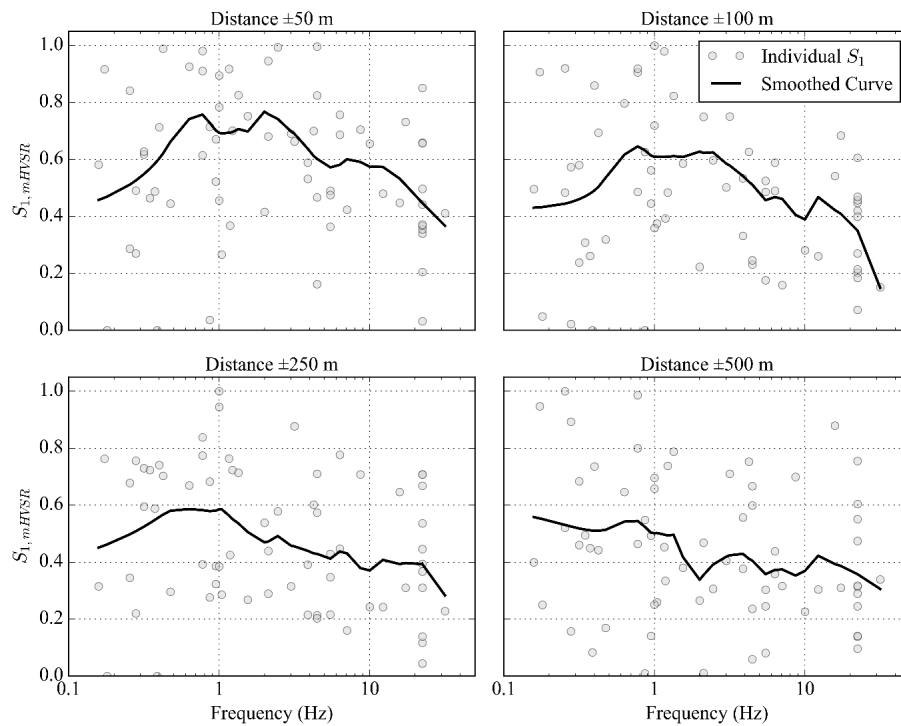


Figure 5.5. Variation of mHVSr similarity metric S_1 with frequency and between-measurement separation distance for data from the 19 vertical array sites considered in this research. The data trend is illustrated using a LOWESS regression.

5.3 Compatibility of Vertical Array Empirical and Theoretical Transfer Functions

As noted in Section 5.1, previous studies have evaluated the effectiveness of 1D GRA using data from vertical array sites in Japan and California. Many of these validation studies have found that the predicted (or theoretical) transfer functions (TTFs) from 1D GRA do not accurately capture empirical transfer functions (ETFs) for appreciable fractions of the vertical array sites. Several of the validation studies investigated whether direct modeling of multidimensional effects such as wave scattering (Thompson et al., 2009; de la Torre et al., 2022), non-vertical incidence (Thompson et al., 2009), and laterally-varying soil/rock layers (Hallal and Cox, 2021a, b) improve ETF-TTF compatibility at vertical array sites, with mixed results. For the purposes of the present study, I retain the use of 1D GRA, because our hypothesis is that ETF-TTF (from 1D GRA) agreement (or divergence) is an indicator of site complexity that can be related to the spatial correlation (or lack thereof) of mHVSr curves.

In this section, I reassess the compatibility between ETFs and TTFs from 1D GRA. Both ETFs and TTFs considered here are taken from de la Torre et al. (2022) for the California vertical array sites considered in Afshari and Stewart (2019). In de la Torre et al. (2022), ETFs were computed as the ratio of the Fourier amplitude spectrum (FAS) for the observed ground surface motion to the FAS for the downhole motion for each event. For each frequency, the median and lognormal standard deviation were calculated across the data for all events recorded at a given site. These ETFs can be considered as ‘within’ transfer functions as they are the ratio of an outcropping surface motion to a within motion at depth. TTFs were computed using 1D GRA in *Opensees*

(McKenna, 2011) with viscoelastic material properties to model the linear site response, consistent with the weak ground motions considered for the ETFs. Both the median ETF and TTF were smoothed using a Konno-Ohmachi smoothing window with $b=100$.

Whereas prior assessments of ETF-TTF relationships for the California data used r (Eq. 5.1), in the present re-interpretation I apply the S_1 metric (Eq. 5.3). Analyses were performed for different frequency intervals corresponding to the lowest modal frequencies in TTF and ETF. For cases where the lowest frequency ETF and TTF peaks do not align, I center the interval on the geometric mean of the two peak frequencies. In cases where ordinates near the lowest frequency peak appear to be unreliable (i.e., ordinates not converging to unity at low frequencies, likely due to different surface-downhole high-pass filter corner frequencies), we use the second mode peak; this only applied to site 10 in the current dataset. The width of the frequency interval is set as twice the log frequency difference between the center and trough to the right of the peak.

I evaluate similarity between logarithmic ordinates of ETF and TTF utilizing an $\epsilon = 0.45$ and $\delta = 20$, which was found to align with visual assessments of goodness-of-fit both in this study and prior work (Afshari and Stewart, 2019; de la Torre et al., 2022). A higher δ value was used for the ETF-TTF assessment than that used for the mHVSr assessment. This was done because the transfer functions have a finer frequency discretization (i.e., typically in the range of 1000 frequency steps for a given frequency interval, whereas mHVSr intervals had about 500 steps). The LCSS operator is agnostic to frequency itself; rather it operates solely based on “steps” between ordinates. As a result, for a finer discretization of the transfer functions an adjustment of δ was needed to align with analyst judgment. The results are summarized in Table 5.1 and shown in Figure 5.6. Mean mHVSr curves at the reference locations (nearest to the vertical array) are also presented in the figures, which will be discussed subsequently. TTFs based on both within-

and outcropping input motions are shown in Figure 5.6, although the fit assessments used only the within TTF results, which are the theoretically correct choice for application of 1D GRA to a vertical array (Kwok et al., 2007).

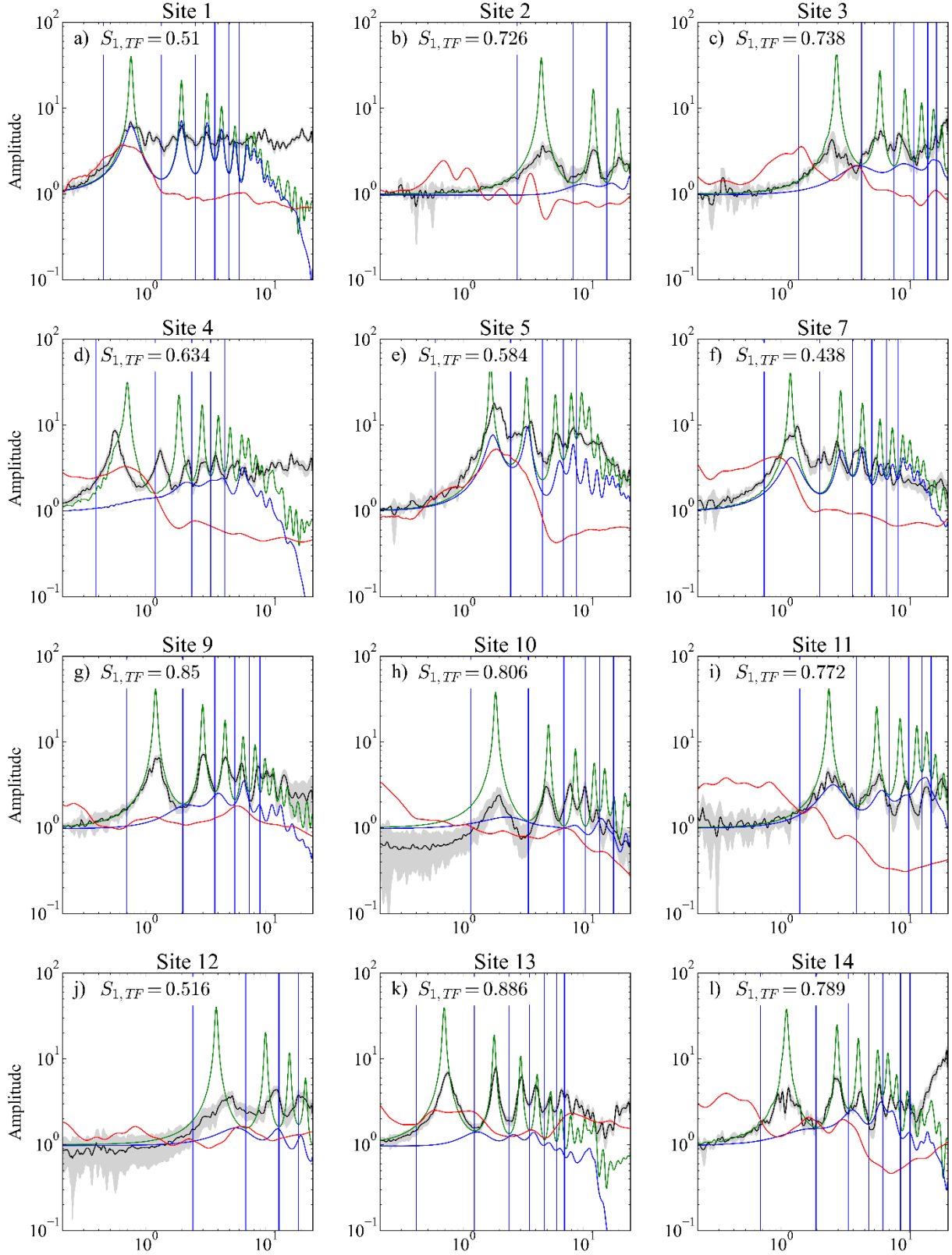
As shown in Figure 5.6b, for site 2 (Benicia-Martinez South), the alignment of the ETF and TTF peaks indicates a strong correlation, as confirmed by the $S_{I,TF}$ value of 0.73 (Table 5.1). In contrast, for site 7 (Hollister Digital Array), shown in Figure 5.6f, the alignment is less favorable, with a corresponding $S_{I,TF}$ value of 0.44. Sites 3, 9, 10, 11, 13, 14, 16, 17, and 21 are additional cases of generally good alignments ($S_{I,TF}$ ranges from 0.74–0.89), while sites 1, 12, 15, 18, 19, and 20 demonstrate poor alignments ($S_{I,TF}$ ranges from 0.27–0.52). In some cases (sites 7 and 20), the poor alignment results from double-peaks in the ETF that are absent from the TTF. I interpret $S_{I,TF} \geq 0.70$ as indicating good alignment, which is observed in 52% of sites, while $S_{I,TF} \leq 0.55$ is classified as a poor alignment, occurring in 37% of sites. Values of $S_{I,TF}$ between 0.55 and 0.70 represent an intermediate ETF-TTF correlation, which is found for sites 4 and 5 (11%). The results for all sites are summarized in Table 5.1.

The variability column in Table 5.1 is based on the geometric mean of the between-event standard deviation of ETFs calculated over the first-mode frequency interval (denoted $\sigma_{\ln ETF}^M$) with the exception of site 10 for which the second mode was used. I note that previous studies (Thompson et al., 2012; Afshari and Stewart, 2019; Tao and Rathje, 2020) have used $\sigma_{\ln ETF}^M = 0.35$ as a threshold value distinguishing between low and high variability sites, although for different levels of smoothing than used here and over a wider frequency interval (generally encompassing the first four modes of the ETF). I utilize a relatively narrow frequency interval centered around f_0 of the ETF, along with a Konno-Ohmachi smoothing parameter of $b = 100$. Using the aforementioned threshold, I find that 42% of sites exhibit high variability, while 58% do not.

The pseudo-resonance column in Table 5.1 identifies whether site’s TTFs show peaks for both the within- and outcropping input motion at the fundamental mode (f_0) of the within TTF. Where both show a peak, the peak is described as a ‘true resonance’, meaning that it is produced by an impedance contrast at or near the bottom of the array, and “0” is entered in Table 5.1. Where only the within TTF has a peak, the peak is described as a ‘pseudo-resonance’ (“1” is entered in Table 5.1), meaning that the peak is caused by the destructive interference of the up-going and down-going waves and not by an impedance contrast (Steidl et al., 1996; Bonilla et al., 2002; Parolai et al., 2009, 2012; Tao and Rathje, 2019). Our findings reveal that 53% of the sites experience pseudo-resonances at f_0 , while 47% do not. Within the context of the present study, these characteristics are relevant because mHVSr peaks aligned with a TTF peak would only be expected for true resonances, as discussed further in Section 5.4.1.

5.4 Relationships Between mHVSr Metrics and GRA Effectiveness

As described in Section 5.2 and 5.3, inferences of site spatial variability from mHVSr utilize the LCSS S_I correlation metric as proposed here and various standard deviation terms. In this section, I assess whether there is a relationship between these mHVSr variability metrics and the effectiveness of 1D GRA. GRA effectiveness is evaluated using ETF-TTF transfer function compatibility, as shown in the prior section, and in terms of model error (e.g., Stewart and Afshari, 2021) using observation-prediction residuals of ground-surface intensity measures (i.e., 5% damped response spectra).



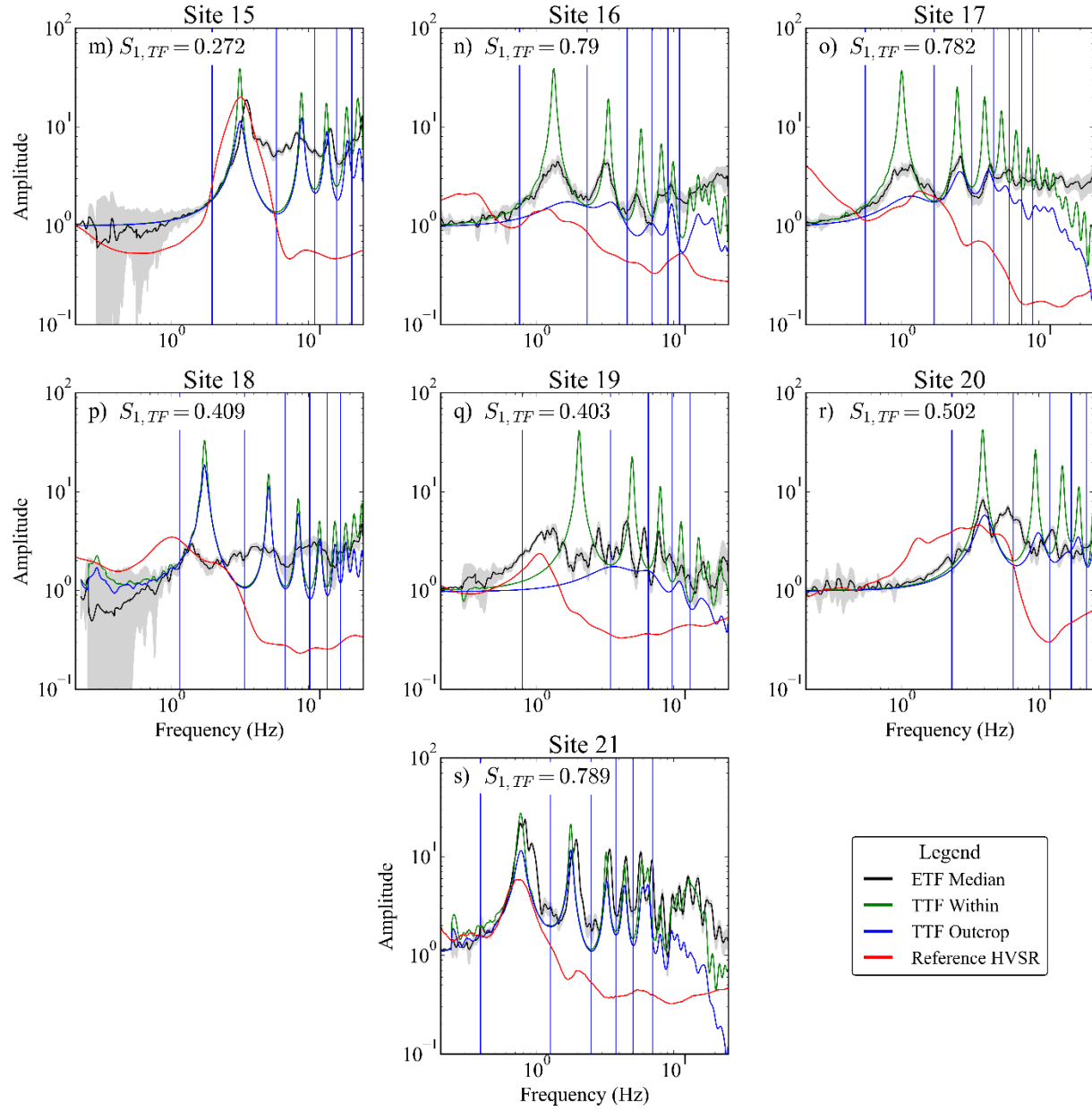


Figure 5.6. Comparison of empirical transfer function (ETF) with theoretical transfer functions derived using within and outcropping representations of input motions: (a-s) site results for each vertical array shown in Table 3.3. The reference HVSR is shown in red, which refers to the HVSR test taken closest to the vertical array (e.g., 0.0 test). The blue vertical lines indicate the frequency intervals used to assess the correlation between curves.

Table 5.1. Results of LCSS correlation analysis for empirical and theoretical transfer functions (ETFs and TTFs) along with other ground response metrics. For mHVSr, the S_1 values are averaged over all considered distance intervals.

Site No.	Site name	$S_{1,TF}$ Value ¹	σ_{lnETF}^M Value ¹	Pseudo-resonance ^{1,2}	Variability ³	Goodness-of-fit	$S_{1,mHVSr}$ Value ¹
1	Borrego Valley Digital Array	0.51	0.33	0	Low	Poor	0.86
2	Benicia-Martinez South	0.73	0.38	1	High	Good	0.75
3	Crockett-Martinez Br #1	0.74	0.43	1	High	Good	0.83
4	El Centro-Meloland	0.63	0.27	1	Low	Intermediate	0.8
5	Garner Valley	0.58	0.47	0	High	Intermediate	0.76
7	Hollister Digital Array	0.44	0.47	0	High	Poor	0.5
9	La Cienega	0.85	0.32	1	Low	Good	0.89
10	Obregon Park	0.81	0.36	1	High	Good	0.83
11	San Bernardino	0.77	0.39	0	High	Good	0.86
12	Vallejo – Hwy 37	0.52	0.5	1	High	Poor	0.79
13	Wildlife Liquefaction Array	0.89	0.21	1	Low	Good	0.99
14	Antioch – San Joaquin S.	0.79	0.28	1	Low	Good	0.68
15	Corona I15/Hwy 91	0.27	0.34	0	Low	Poor	0.57
16	Coronado East	0.79	0.35	1	Low	Good	0.97
17	Coronado West	0.78	0.35	0	Low	Good	0.94
18	Foster City San Mateo	0.41	0.21	0	Low	Poor	0.62
19	Hayward-580W	0.4	0.33	1	Low	Poor	0.55
20	San Francisco Bay Bridge	0.5	0.37	0	High	Poor	0.34
21	Treasure Island	0.79	0.3	0	Low	Good	0.92

1. Derived using first-mode frequency interval in ETF/TTF unless the data in that frequency was considered unreliable, in which case the second-mode frequency was used (Site 10)
2. A value of 1 indicates pseudo-resonance.
3. Represents between-event variability of the recorded ETF.

5.4.1 Transfer Function Representation of Site Response

The compatibility of ETFs and TTFs, as given by the S_1 metric in Table 5.1, are compared in this section to three metrics of mHVSr spatial variability: (1) LCSS S_1 for spatially distributed mHVSr curves, (2) the standard deviation across spatially distributed mHVSr curves for a specific frequency interval averaged across all frequencies within the interval, and (3) fundamental mode site frequency (f_0) variability from spatially distributed mHVSr curves. I also consider the

azimuthal variability metrics related to mHVSr curves and f_0 for a single-station, which have variable levels of correlation with spatial variability (Figures 5.4b-5.4c).

Figure 5.7 compares the S_1 values derived from the first-mode frequency interval of the ETF-TTF (second mode for site 10) with those from the closest associated frequency interval in mHVSr, from Table 5.1. The points are colored to indicate whether the first mode peak reflects pseudo-resonance or true resonance for the site, which facilitates assessment of whether different trends are encountered for the two groups of sites. Across all sites, the positive correlation between the S_1 values supports the hypothesis that mHVSr spatial correlation is predictive of 1D GRA effectiveness. In particular, $S_{1,\text{mHVSr}}$ values ≥ 0.8 corresponds to $S_{1,\text{TF}} \geq 0.7$ (indicating favorable effectiveness of 1D GRA) in 8 out of 9 cases (89%). At the other end of the scale, $S_{1,\text{mHVSr}}$ values ≤ 0.65 correspond to $S_{1,\text{TF}}$ values ≤ 0.55 in 5 of 5 cases (100%). A fit line is shown in Figure 5.7 with its confidence intervals. The regressed slope value is $m = 0.78$, which is much larger than its standard error of 0.17 (21% of the mean estimate), indicating a strong relationship. As a result, I consider the spatial variability of mHVSr measurements to have promise as an indicator for 1D GRA effectiveness.

As shown in Figure 5.7, there are no significant differences between sites exhibiting true resonance and those experiencing pseudo-resonance. This was investigated because it might be anticipated that where the site response (as recorded in the vertical array) aligns with the resonances revealed in mHVSr, the similarity features evaluated from mHVSr may have more predictive power. Since this does not appear to be the case, our interpretation is that site heterogeneity, as parameterized by $S_{1,\text{mHVSr}}$ at the lowest frequency mHVSr peak, is similarly impactful whether or not the vertical array extends deep enough to encompass the impedance contrast that produces that peak. Although not shown for brevity, I evaluated correlation between $S_{1,\text{mHVSr}}$ and $S_{1,\text{TF}}$ for higher frequency

intervals and found no significant correlation. This is somewhat expected given the frequency trends of $S_{1,mHVS}$ as shown in Figure 5.6.

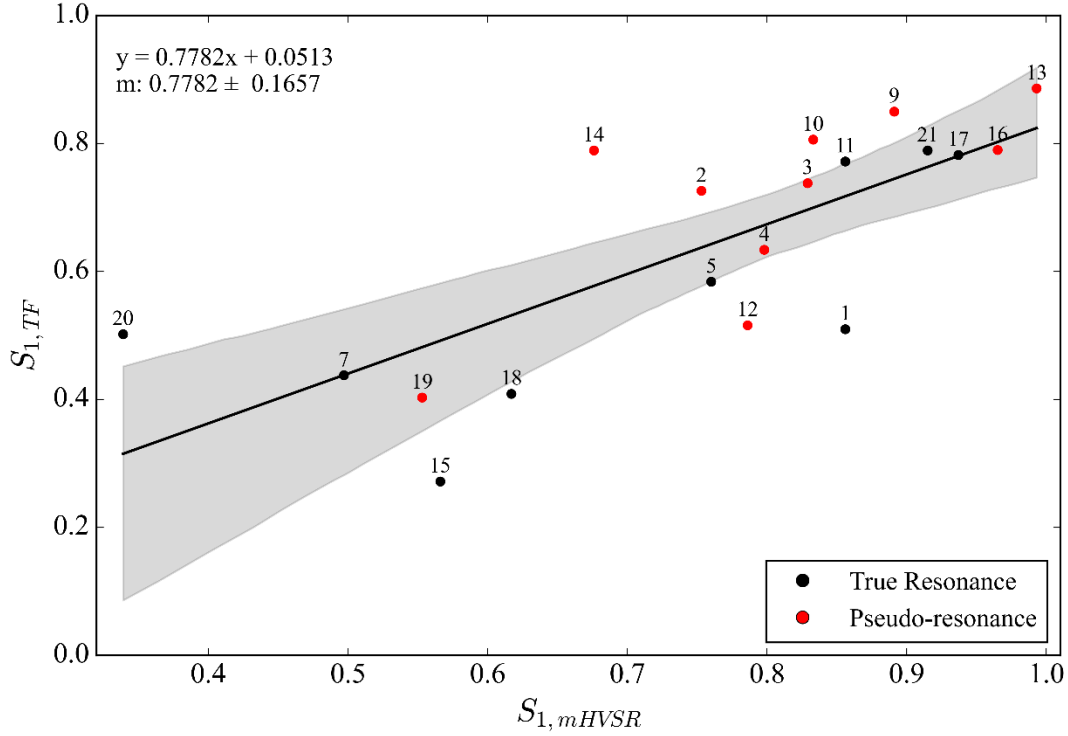


Figure 5.7. Relationship between S_1 values for lowest frequency interval in the ETF-TTF data, denoted $S_{1,TF}$, and the closest frequency interval in mHVS averaged over the radial distances, $S_{1,mHVS}$. The shaded region represents the 95% confidence interval for the observed linear trend.

Figure 5.8 is similar to Figure 5.7 but uses the standard deviation metrics of $\sigma_{\ln f_{0,H/V}}^{spat}$ (similar to that proposed by Hallal and Cox, 2021a,b and Cheng et al., 2021) and $\bar{\sigma}_{\ln mHVS}^{spat}$. Figure 5.8a shows an appreciable decrease of $S_{1,TF}$ with increasing $\bar{\sigma}_{\ln mHVS}^{spat}$, which is a similarly strong trend to that for $S_{1,mHVS}$ in Figure 5.7 (based on similar slope coefficients and ratios of the standard error to the mean slope estimate). Figure 5.8b shows a decrease of $S_{1,TF}$ with increasing $\sigma_{\ln f_{0,H/V}}^{spat}$, but in this case the trend is much weaker and is arguably not statistically significant (ratio of slope standard error to mean estimate of 0.92).

Figure 5.9 shows that the standard deviation metrics based on azimuthal variability have weaker trends than those provided in Figure 5.8. The slope coefficient for $\bar{\sigma}_{\ln mHVS R}^{azi}$ is larger than its standard error (ratio = 0.24), indicating predictive power, whereas the slope for $\sigma_{\ln f_{0,H/V}^{*}}^{azi}$ is much smaller than its error (ratio = 2.5), indicating no statistically significant relationship. The different trends for these parameters mirror the strength of the correlation of $\bar{\sigma}_{\ln mHVS R}^{azi}$ with spatial variability and lack thereof for $\sigma_{\ln f_{0,H/V}^{*}}^{azi}$ (Figures 5.4b-c).

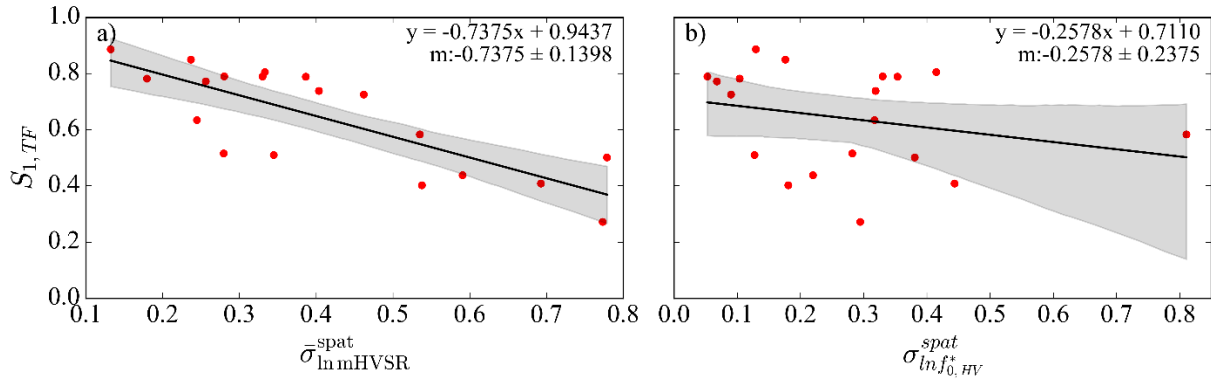


Figure 5.8. Relationship between $S_{1,TF}$ and the spatial variability metrics (a) $\bar{\sigma}_{\ln mHVS R}^{spat}$ and (b) $\sigma_{\ln f_{0,H/V}^{*}}^{spat}$. The shaded region represents the 95% confidence interval for the observed linear trend. The equation of the fit line with slope and standard error values are shown on the top right of each plot.

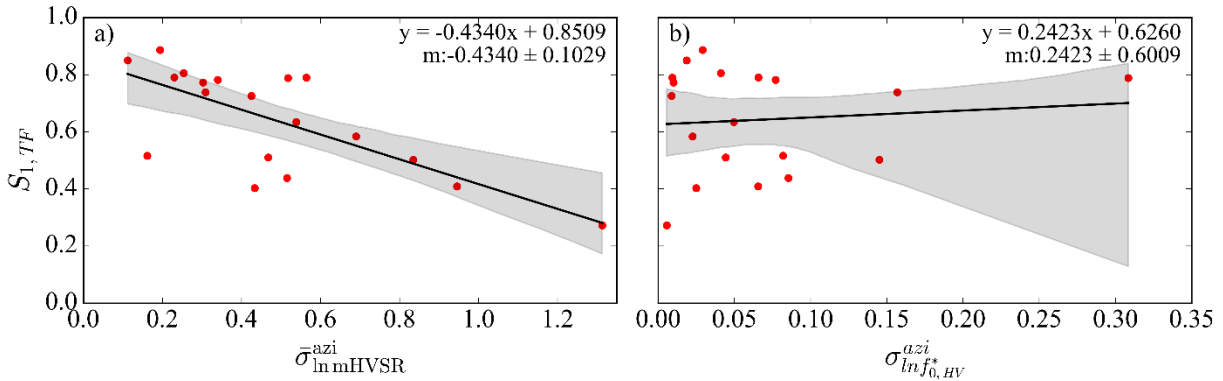


Figure 5.9. Relationship between $S_{1,TF}$ and the azimuthal variability metrics (a) $\bar{\sigma}_{\ln mHVS R}^{azi}$ and (b) $\sigma_{\ln f_{0,H/V}^{*}}^{azi}$. The shaded region represents the 95% confidence interval for the observed linear trend. The equation of the fit line with slope and standard error values are shown on the top right of each plot.

As noted previously, event-to-event variability in ETFs (σ_{lnETF}^M) provides a different performance measure that is investigated for its potential correlation with site variability. Figure 5.10 shows plots σ_{lnETF}^M against $\sigma_{ln mHVS R}^{spat}$, and $S_{1,mHVS R}$. The slopes are not significant, indicating no appreciable correlation, suggesting that the event-to-event variability in transfer functions may not be attributed to site complexity alone.

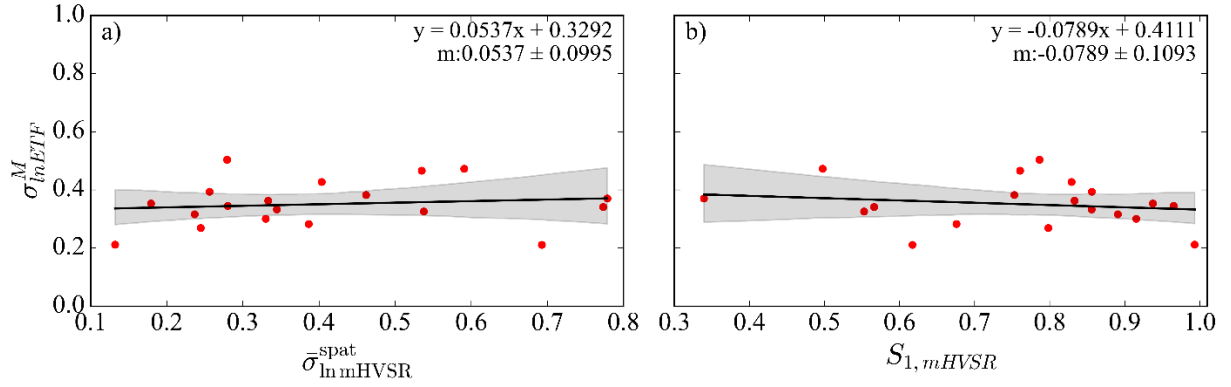


Figure 5.10. Relationship between σ_{lnETF}^M and the variability metrics (a) $\sigma_{ln mHVS R}^{spat}$ and (b) $S_{1,mHVS R}$. The shaded region represents the 95% confidence interval for the observed linear trend. The equation of the fit line with slope and standard error values are shown on the top right of each plot.

5.4.2 Can $S_{1,mHVS R}$ Predict Relative Levels of Model Error?

As described in the *Introduction*, model error represents misfits of 1D GRA relative to actual site response as observed in vertical arrays. The concept of model error was introduced by Stewart and Afshari (2021) using the same California data set considered in the present study. Model error in that study was examined over an ensemble of 21 sites. In this section, I consider whether sites with different levels of mHVS R spatial variability as reflected by the S_1 parameter exhibit different levels of model error.

Model error calculations begin with the calculation of total residuals as follows:

$$\delta_{ij} = \ln(Y_{ij})_{obs} - \ln(\bar{Y}_{ij}) \quad (5.9)$$

where $\ln(Y_{ij})_{obs}$ represents the observed ground motion from event i and site j and $\ln(\bar{Y}_{ij})$ represents the natural log mean predicted motion derived from 1D GRA using the recorded downhole motion as input. The residual in Eq. 5.9 is related to site response only because the surface motion and downhole motion share the same source and have effectively identical source-to-site paths. Between-site residuals were computed using mixed-effects regression (Abrahamson and Youngs, 1992; Gelman and Hill, 2006; Sahakian et al., 2018) with the nonlinear mixed effects (NLME) routine in R (R Core Team, 2019; Pinheiro et al., 2019) to partition the residuals into components:

$$\delta_{ij} = c_k + \eta_{s,j} + \varepsilon_{ij} \quad (5.10)$$

where c_k represents the overall model bias; $\eta_{s,j}$ is the between-site residual (site term; hereafter) for site j , which represents the average bias-adjusted deviation of the prediction for an individual site; and ε_{ij} represents the remaining within-site residual. Model error is the standard deviation of site terms, computed as,

$$\phi_{s2s}^G = \sqrt{\frac{\sum_{j=0}^{N_{sites}} (\eta_{s,j} - \bar{\eta}_s)^2}{N_{sites}}} \quad (5.11)$$

where $\bar{\eta}_s$ represents the average of the site terms for all the sites (value is close to zero) and N_{sites} represents the number of sites. The G superscript in ϕ_{s2s}^G refers to the use of 1D GRA in the prediction model. As in Stewart and Afshari (2021), I considered three sets of site terms from three damping models – laboratory-based damping (D_{min}^L), κ -informed damping (adjustments of D_{min}^L to match change in site diminutive parameter, $\Delta\kappa_0$, over depth of array), and damping derived from

an effective Q (Q_{eff}) model from Campbell (2009). Standard deviations can be computed for each set of site terms, but the number of sites (N) are not equivalent because: (1) four sites lack essential information (soil types) for estimation of D_{min}^L and (2) three sites lack information on $\Delta\kappa_0$ because it could not be inferred from the ground motion data (details in Stewart and Afshari, 2021). Differences among the numbers of sites for different damping models were inconsequential for analyses of the full data (i.e., the ϕ_{S2S}^G values were similar). As in the analysis by Stewart and Afshari (2021), the calculations of standard deviation using Eq. (5.11) omitted ordinates in the period range of $T_{col}/1.5$ to $1.5T_{col}$.

Computed ϕ_{S2S}^G values for two of the three damping models are shown in Figure 5.11 along with the recommended model error from Stewart and Afshari (2021) (approximate average across all sites). Results for the D_{min}^L model are not shown due to data size problems (loss of sites due to lack of soil type information) and because such models neglect scattering effects. The two parts of Figure 5.11 correspond to subsets of sites with different levels of mHVSr spatial variability as represented by S_1 ranges, using the lowest frequency interval corresponding to resonance in the transfer function (with the exception of site 10). A variety of threshold S_1 values were considered, ranging from 0.6 to 0.9, to observe how model error changed between groups. I ultimately selected a threshold $S_{1,mHVSr} = 0.8$.

Although not shown for brevity, the model error computed for the 19 sites in Table 5.1 is consistent with the Stewart and Afshari (2021) model (SA21) (i.e., the loss of two sites was not consequential). However, further reductions of data size through the S_1 -based partitioning process produced numerical inconsistencies, which is shown by the appreciably different results for the Q_{eff} and κ -informed damping models in both Figure 5.11a and 5.11b. These differences arise in large part due to small sample sizes and different sites within the two damping groups. These

inconsistencies lead to inconclusive results. On one hand, results for the κ -informed model show a substantial reduction in model error for $T < 1$ s at spatially similar sites ($S_{1,mHVS\text{R}} > 0.8$) relative to the SA21 model and to the more spatially variable sites ($S_{1,mHVS\text{R}} < 0.8$), which is consistent with expectation. On the other hand, results for the Q_{eff} model are not appreciably different between S_1 groups at short periods and are higher for $T > 0.5$ s for the spatially similar sites ($S_{1,mHVS\text{R}} > 0.8$), which contradicts expectation. As a result, I cannot prove our hypothesis that mHVS\text{R} spatial variability can be used to adjust ergodic model error models like SA21. Nonetheless, I consider this exercise to have value and to be worth revisiting in the future as additional data becomes available.

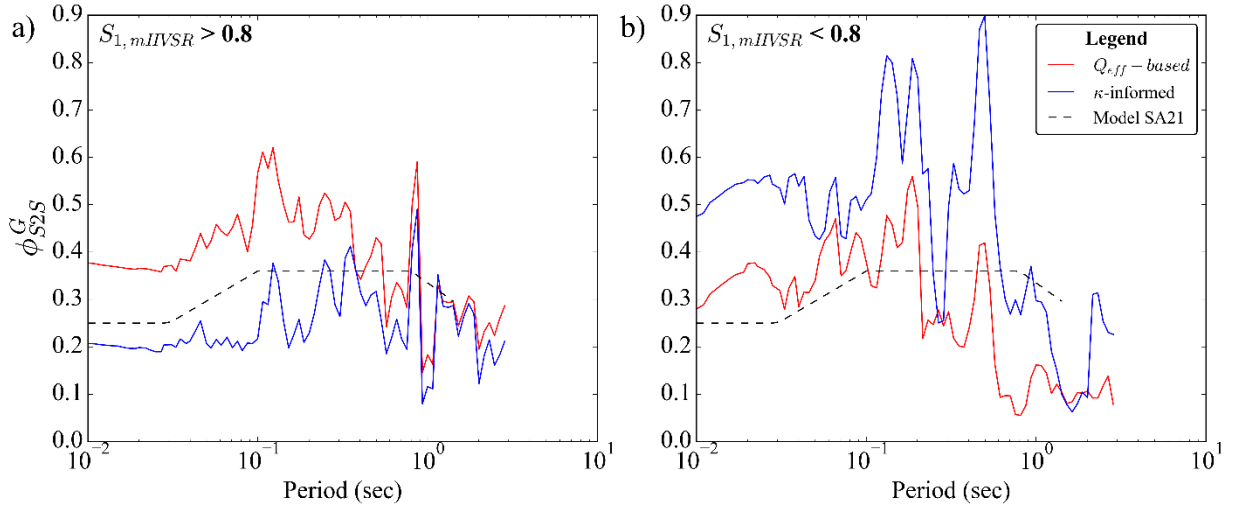


Figure 5.11. Comparison of site response uncertainty (i.e., model error) for two different damping models: κ -informed and Q_{eff} . (a) subset of sites with spatially similar mHVS\text{R} ($S_{1,mHVS\text{R}} > 0.8$); (b) subset of sites with relatively spatially variable mHVS\text{R} ($S_{1,mHVS\text{R}} < 0.8$). Model SA21 is from Stewart and Afshari (2021) and represents the approximate average dispersion for all sites.

5.5 Conclusions

This investigation demonstrated that the spatial correlation of microtremor horizontal-to-vertical spectral ratios (mHVS\text{R}) can serve as an effective indicator for assessing the reliability of 1D

Ground Response Analysis (GRA). By utilizing a dataset of 385 microtremor recordings from 19 vertical downhole array sites across California, I examined the spatial variability of mHVSR through three correlation metrics: Longest Common Subsequence (LCSS) similarity parameter S_1 (Eq. 5.3), Pearson's r coefficient (Eq. 5.1), and Mean Absolute Error, MAE (Eq. 5.2). Among these, S_1 was identified as the most effective metric for characterizing spatial variability, as it more accurately reflects analyst judgment. Our findings revealed that 89% of sites exhibiting a high degree of spatial correlation in mHVSR ($S_{1,mHVSR} > 0.8$) showed observed transfer functions from vertical arrays that were well modeled by 1D GRA. Moreover, all sites with low spatial correlation ($S_{1,mHVSR} < 0.65$) in mHVSR were not adequately modeled by 1D GRA. The analysis focused on frequency intervals encompassing low-frequency peaks in the transfer function and corresponding peaks in mHVSR curves, with higher frequency peaks showing diminished correlation.

I also analyzed various standard deviation metrics derived from mHVSR ordinates and peak frequencies, both considering variability spatially (multiple locations) and azimuthally (single location). While the azimuth-based standard deviation terms were less effective, the spatial variability metrics produced expected trends of lower dispersion being associated with greater 1D GRA effectiveness. I found that the average standard deviation over a given frequency interval of spatially distributed curves (Eq. 5.6) was a more powerful predictor than alternate standard deviation metrics based on f_0 or azimuthal variations.

I tested the hypothesis that sites with different levels of mHVSR variability could have different levels of model error than provided by an ergodic model derived using the data set considered in this study. While there are encouraging signs that spatially similar sites may have reduced model error at short periods, the overall findings are inconclusive due to different trends

for different damping models. This is believed to result from small sample sizes once the database is partitioned based on S_1 and different site populations for different damping models.

One of the important outcomes of this research is that mHVSr offers a promising, low-cost approach for evaluating site spatial variability in the absence of more extensive and costly invasive site characterization data. This variability had demonstrable value regarding the effectiveness of 1D GRA for site response prediction. These results are encouraging given practical challenges implicit to the use of mHVSr data; namely, that they reflect features of the subsurface, but they are also influenced to varying degrees by the nature of the noise field (energy distribution between Love and Rayleigh waves, back-azimuth, proximity to noise sources), which can affect the results. As such, a spatially distributed mHVSr measurement campaign is recommended as a useful tool, in combination with more traditional approaches, for seismic site characterization.

6 Site Response Modelling: Feature Identification and Decision Tree Classifier

A major objective of the research described in this dissertation is the development of site response models applicable to California that are conditioned, at least in part, on mHVSr parameters. Such models have the potential to better account for site-specific effects such as resonances at a particular period. Such effects are not accounted for in the site components of current ground motion models and their incorporation into a modeling framework has the potential to reduce the large site-to-site uncertainty inherent to ergodic models. The workflow for developing such models involved the following major tasks (following the database development presented in Chapter 3):

1. Identify appropriate sites for consideration in this study, which must have both strong motion recordings (for analysis of site effects) and microtremor data for analysis of mHVSr.
2. Derivation of site terms for each site from earthquake ground motion data, visual and more formal identification of common characteristics of those site terms (flat, ramps, peaks) and fitting of those ramp or peak features with suitable functions. This step identifies each site as having no characteristic feature or ≥ 1 feature, with fitted parameters for sites with features.
3. Identification of mHVSr curves from sites as having peaks or not having peaks. For sites with peaks, the peaks are fit and peak parameters are identified.
4. Development of geomorphic categories for the entirety of California, which is used for site categorization during model development.

5. Development of a decision tree classifier, which takes mHVSr parameters and other site parameters and predicts conditional probabilities of a site having different site response characteristics (flat, ramp, peak).
6. Development of a peak-based site response model conditioned on mHVSr parameters for sites with peaks.
7. Development of ramp-based site response models (ascending and descending) for two sets of inputs: (1) inclusive of mHVSr peak parameters and geomorphology for sites with mHVSr peaks and (2) exclusive of mHVSr peak parameters for sites without mHVSr peaks.
8. Development of period-dependent adjustments to an ergodic site response model for sites with a flat site response.
9. Development of a random forest regression ensemble-based machine learning model for general site response (i.e., not in flat, ramp, or peak groups).
10. Residuals analyses to refine mean site response models, including effects of geomorphology and differential depth (δz_1), and to derive effects of the mHVSr models on site-to-site (ϕ_{s2s}) standard deviations. The residuals analyses consider data both within and outside of the California study region.

Tasks 1-5 are presented in this chapter and Tasks 6-10 are presented in Chapter 7.

6.1 Identifying Sites with Co-located mHVSr and Strong Motions

For a site to be included in this modeling effort, it needs to have mHVSr data within a 150 m radius of a strong-motion station. The mHVSr curves were queried using the VSPDB (Kwak et al. 2021; described in Chapter 3). The ground motion data at each of the stations were initially taken from the ground motion database (GMDB) developed by (Buckreis et al. 2025a) and later

updated to the full NGA-West3 ground motion database (Buckreis and Stewart 2025), both of which are significantly expanded relative to the NGA-West2 database (Bozorgnia et al. 2014). The ground motion data were considered from 4,469 stations with 83,644 recordings in California, which were screened as follows:

1. I removed sites with less than four recordings of $M > 4.0$ earthquakes, and I remove events recorded by less than five stations. This was done so that site and event terms derived from earthquake data are reasonably stable.
2. I applied maximum-distance (R_{max}) cutoffs appropriate for sensor type (Mohammed et al., 2024 for CSN stations, Boore et al., 2014 otherwise)
3. I utilized station types of “ground” or “free-field” only.
4. I applied screening for the longest usable period range for each recording based on $T_{max} \leq 1/(1.25 \times f_{c, hp})$, where $f_{c, hp}$ is the maximum of the two-horizontal components.

After screening, I was left with 2,453 California stations with 62,506 usable recordings from 588 events. Figure 6.1 shows some of the key features of this database, including the data distribution in magnitude-distance space (Figure 6.1a), the distribution of median component peak accelerations (Figure 6.1b), and the data counts as a function of oscillator period (Figure 6.1c). The data falloff with oscillator period is a result of screening criteria number 4.

Subsequently, I identified from this group the stations with co-located mHVSr surveys. This led to 686 strong motion sites with mHVSr surveys within a 150-m radius. The locations of these stations are shown in Figure 6.2.

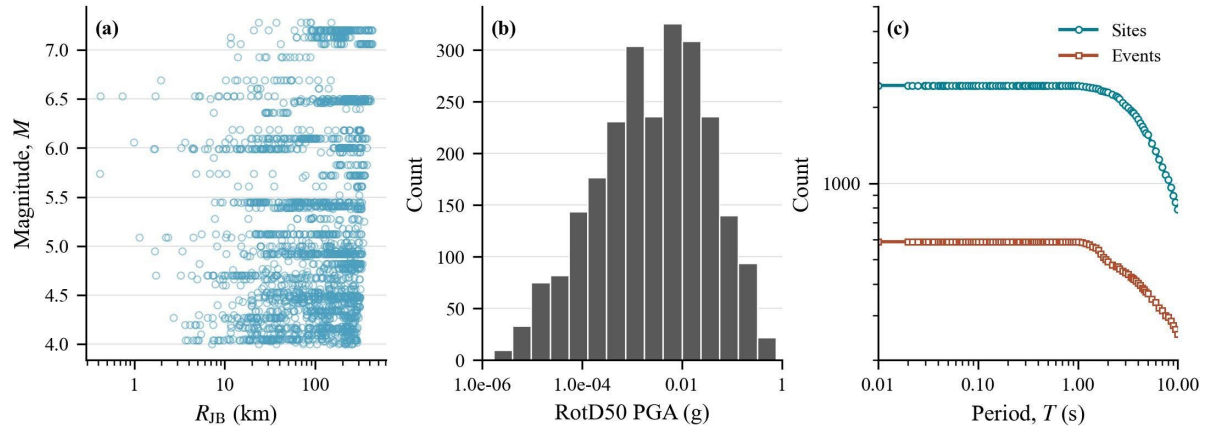


Figure 6.1. Distribution of data post-screening used in ground motion analysis, (a) data points in magnitude-distance space, (b) peak acceleration histogram, (c) amount of sites and events in database as function of oscillator period.

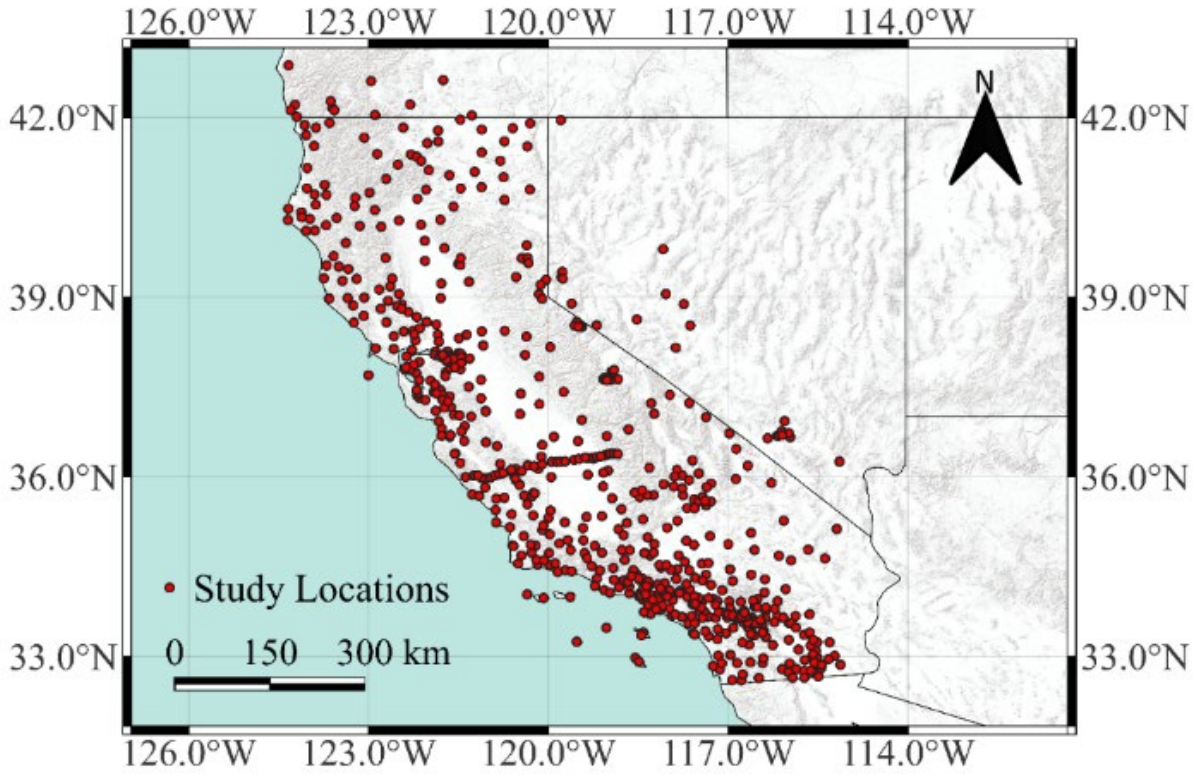


Figure 6.2. Map showing locations of mHVSr curves co-located with strong motion stations across California and surrounding regions.

6.2 Seismic Site Responses Inferred from Earthquake Data

6.2.1 Analysis of Site Terms

Mixed effects analyses were performed to derive site terms for each of the 686 ground motion sites identified in Section 6.1. These analyses required consideration of the larger post-screening database of 2,453 California stations with 62,506 usable recordings from 588 events. The larger database is required because mixed effects calculations entail the use of all stations and events within a network, not just those for the 686 sites that are the subject of this dissertation.

This analysis begins by computing total residuals δ_{ij} for site j in event i , as the difference between the natural log of an observed median-component (Boore 2010) intensity measure (Y_{ij}) and the median predictions of a ground motion model (μ_{ij}),

$$\delta_{ij} = \ln(Y_{ij}) - \mu_{ij}(\mathbf{M}_i, R_{jb,ij}, V_{S30,j}, z_{1.0,j}) \quad (6.1)$$

where $\mathbf{M}_i$ is the event magnitude, $R_{jb,ij}$ is the distance from the site to the ground surface projection of the fault plane (also known as Joyner-Boore distance), and $V_{S30,j}$ and $z_{1.0,j}$ are site parameters. The ground motion model used in this study is BSSA14 (Boore et al. 2014) with induced source and subregional anelastic path adjustments for California by Buckreis et al. (2023). The model is used with default depth parameters, meaning that the depth term $z_{1.0,j}$ is taken as equivalent to the mean depth for the site's V_{S30} . In the Boore et al. (2014) equations, this means that differential depth (δz_1) was taken as zero.

Total residuals were then partitioned into fixed and random effects using mixed-effects regression (Abrahamson and Youngs, 1992; Gelman and Hill, 2006; Sahakian et al., 2018) using the *lme4* package (Bates et al. 2015) in *R* (R core team 2017) as:

$$\delta_{ij} = c_k + \eta_{E,i} + \eta_{S,j} + \varepsilon_{ij} \quad (6.2)$$

where c_k represents the model bias for GMM k , $\eta_{E,i}$ and $\eta_{S,j}$ are random effects that quantify event- and site-specific biases (referred to as event terms and site terms), respectively, and ε_{ij} is the remaining portion of the within-event residual. Figure 6.3 shows the variation of bias term c_k with period. The data show a significant over-prediction bias for $T < 0.1$ sec and under-prediction bias for $T = 0.2-2$ sec that was not evident to the same degree in earlier databases (NGA-West2). Figures 6.4 and 6.5 show variations of $\eta_{E,i}$ with magnitude and ε_{ij} with R_{jb} . The event terms have dependencies with $\mathbf{M}$, which in combination with the bias trends, demonstrate limitations of the Boore et al. (2014) model that are being addressed in the NGA-West3 modeling. The results in Figure 6.5 show no evidence of bias in the path model, which is important because path and site response errors would trade off if path errors were present.

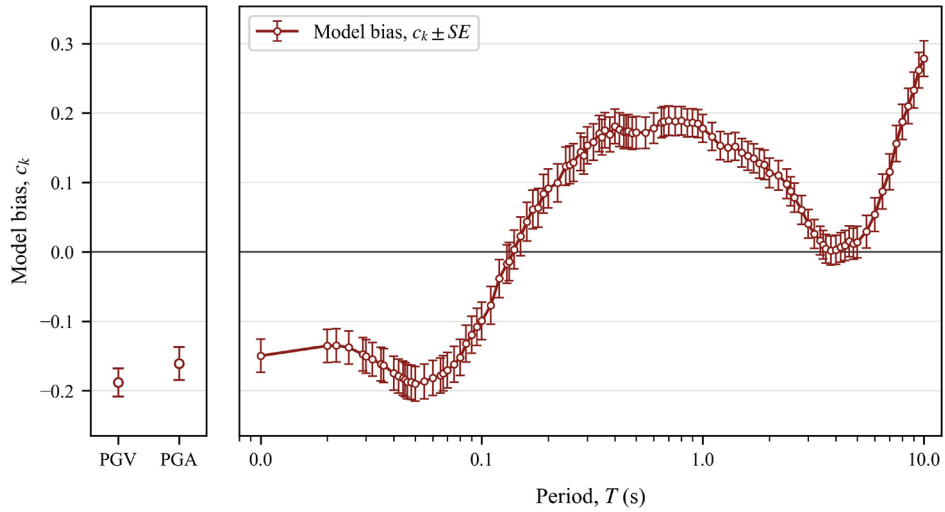


Figure 6.3. Period-dependence of bias term c_k for the considered data set. SE = standard error.

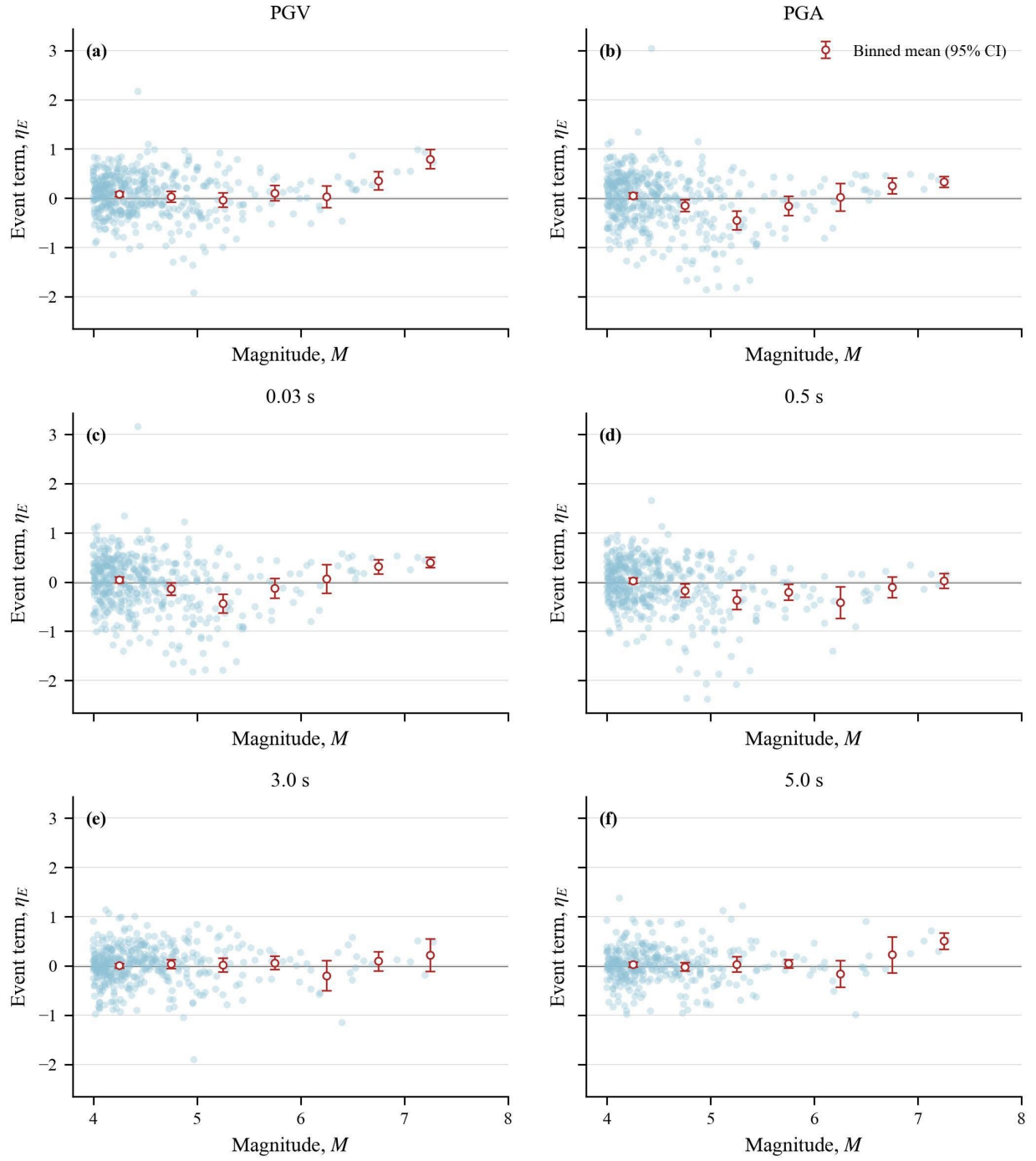


Figure 6.4. Magnitude-dependence of event terms $\eta_{E,i}$ for the considered data set

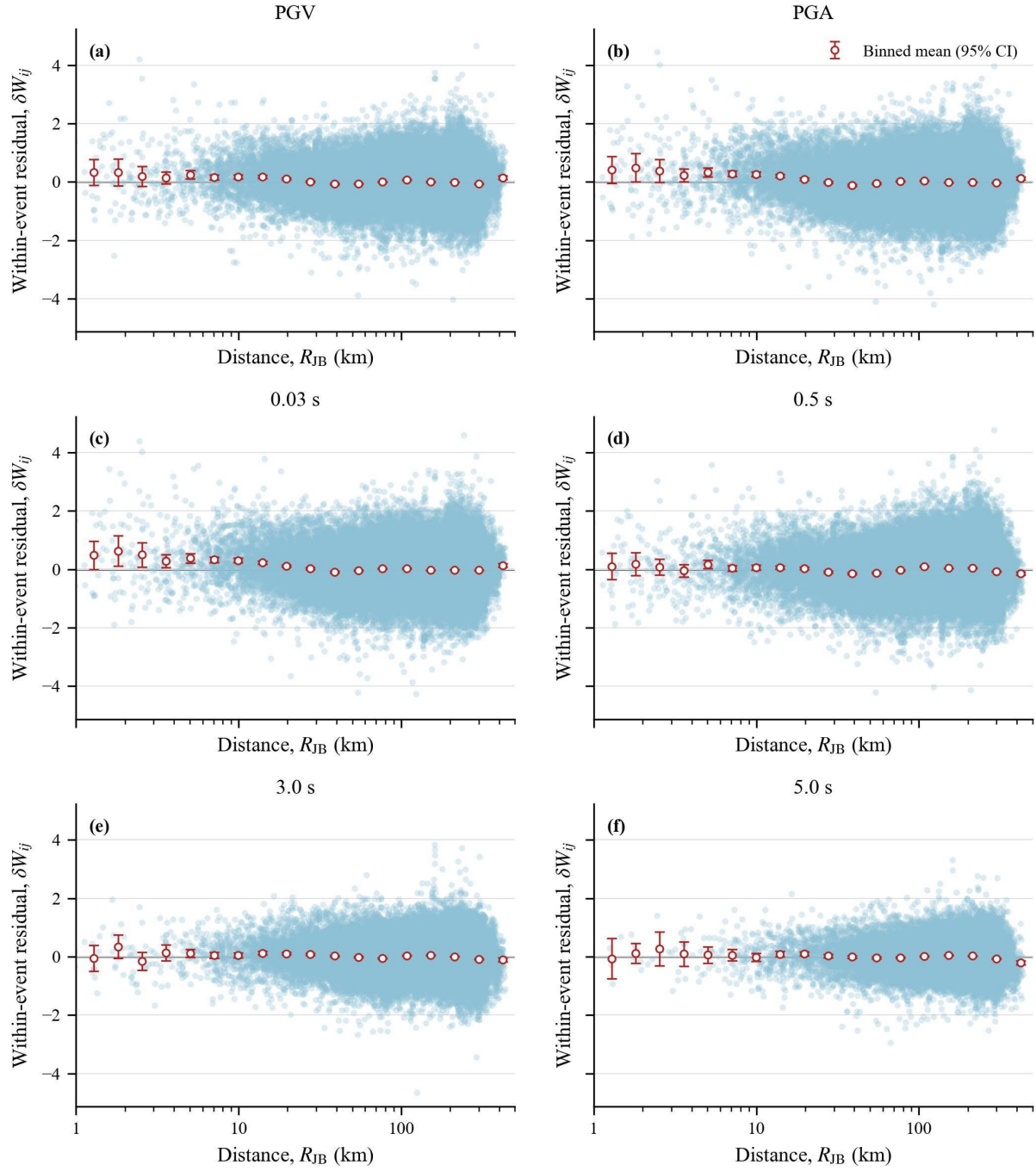


Figure 6.5. Distance-dependence of residual terms ε_{ij} for the considered data set.

Site terms represent site response characteristics beyond those captured by ergodic models. Figure 6.6 shows three example site terms for Sites 1173, 1310, and 422. Site 1173 has a peak at 1.5 sec, which indicates a resonant feature in the site response that is not captured by the Boore et al. (2014) ergodic model. Site 1310 has a ramp characteristic, whereby ordinates start high then transition downward (descending ramp). This indicates that the model under-predicts at short periods and over-predicts at long periods, which can be anticipated for shallow soil sites. While not shown in Figure 6.6, ascending ramp sites are also common, which could be anticipated for especially deep basin sites. Site 422 has a flat, but non-zero, series of site terms. This suggests that the shape of amplification compared to period from the ergodic model aligns with the site-specific response, but is too low by about 0.5 natural log units (factor of ~ 1.6). The site term characteristics shown in Figure 6.6 are typical across the dataset. The work presented here and in Chapter 7 utilizes these site terms as the data in the subsequent model development process.

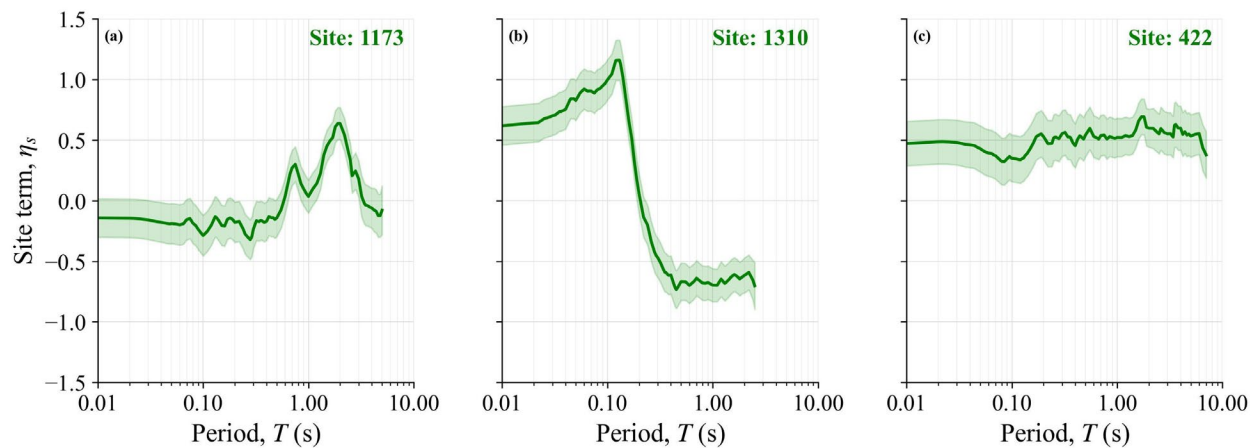


Figure 6.6. Oscillator period-dependence of site terms demonstrating: (a) peak response; (b) descending ramp response; and (c) flat site response.

6.2.2 Identification of Site Term Characteristics

As described in the previous section, there are three types of site response characteristics – peak sites, ramp sites, and flat sites. For sites with ramps, the ramp can be ascending or descending. In this section, I present objective, repeatable procedures to identify whether peaks or ramps are present in the site term – period plots for a given site (similar to Figure 6.6). Moreover, for sites with such features, the features are fitted using applicable functions. The parameters describing these functions are estimated by regression in Chapter 7.

6.2.2.1 PEAK SITES: IDENTIFICATION

Peak identification was performed using a procedure that has two components: (1) tree regression to fit the site term – T data with a stepped function and (2) peak identification based on attributes of the steps near the potential peak. Figure 6.7 shows an example of a decision tree regression (Brieman et al. 1984) (referred to as *tree regression* in prior publications). It uses a smoothing parameter $c_p=0.0003$ that controls step size (adopted from Buckreis et al. 2026).

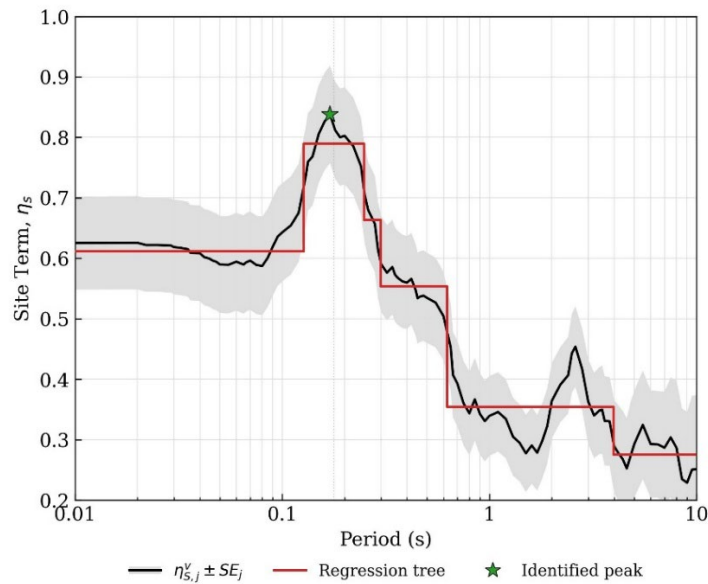


Figure 6.7. Site term curve for Site 62 with tree regression steps plotted over the curve shown in red.

The peak identification follows an algorithm *srPeak* (<https://github.com/tristanbuckreis/srPeak>) that is described in Buckreis (2022) and Buckreis et al. (2026). The criteria considered in that algorithm can be summarized as:

1. Peak should have sufficiently large mean amplitude relative to ordinates at adjacent periods.
2. Peak should be relatively localized (i.e., period range not too wide).
3. The uncertainty in the peak amplitudes or periods should not be too large.

These conditions are implemented in the algorithm presented in Figure 6.8 using parameters that quantify step widths from the tree regression (wid_l , wid_p , and wid_r for left, peak, and right steps, respectively), step amplitudes (amp_l , amp_p , and amp_r), and uncertainty of step amplitudes (k_l and k_r), against configurable threshold parameters: (i) $step_{thres}$ – a step width threshold used to ensure that the steps adjacent to peaks are sufficiently wide; (ii) amp_{thres} – an amplitude threshold used to ensure that the peak step is sufficiently high relative to adjacent steps; (iii) $wid_{max-thres}$ – a maximum width threshold that applies to the peak step, which is applied to ensure the peak is not too wide; (iv) $wid_{min-thres}$ – similar to $wid_{max-thres}$ but a check for minimum step width; and (v) k_{thres} – a threshold that is used to evaluate whether the offset between the peak step amplitude and neighboring step amplitudes are statistically significant relative to the uncertainty in step amplitudes.

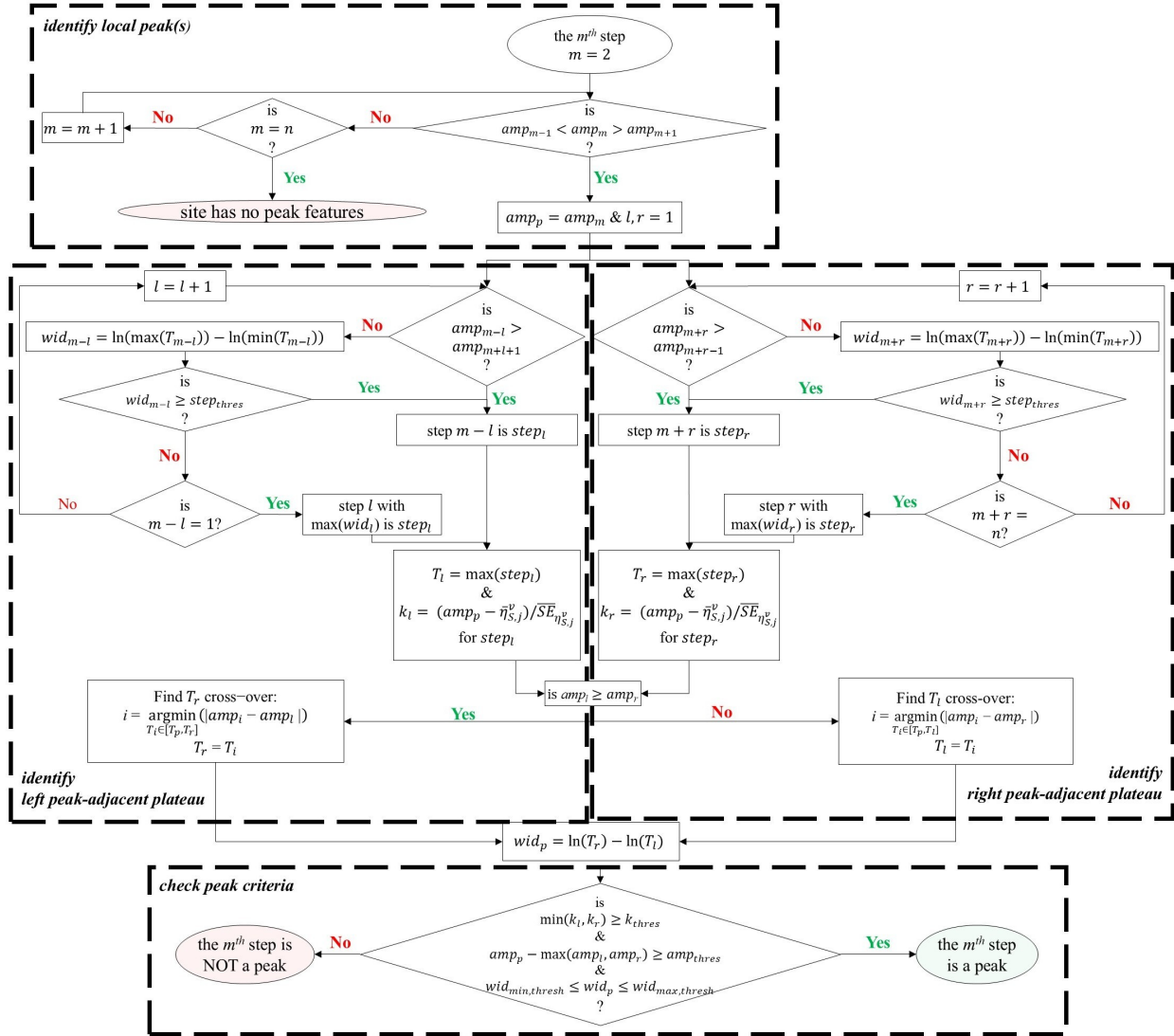


Figure 6.8. Flowchart illustrating site response peak detection algorithm utilizing tree regression stepped results; amp parameters relate to step amplitudes; wid and $step$ parameters relate to step widths; T represents the periods within the step; subscripts l , p , and r indicate the left, peak, and right steps; respectively; n is the total number of steps; $\bar{\eta}_{S,j}^v$ and $\overline{SE}_{\eta_{S,j}^v}$ are the average $\eta_{S,j}^v$ amplitude and standard error within the step, respectively; and $step_{thresh}$, k_{thresh} , amp_{thresh} , $wid_{max-thres}$, and $wid_{min-thres}$ are adjustable algorithm parameters.

The threshold parameters ($step_{thresh}$, amp_{thresh} , $wid_{max-thres}$, and k_{thresh}) can be applied with different levels of conservatism. Smaller values of $step_{thresh}$ and $wid_{max-thres}$, and larger values of amp_{thresh} and k_{thresh} result in a more conservative algorithm (i.e., fewer peaks identified). Conversely, larger values of $step_{thresh}$ and $wid_{max-thres}$, and smaller values of amp_{thresh} and

k_{thres} result in a more liberal algorithm (i.e., more peaks identified). Buckreis (2022) set thresholds to align peak identification with visual assessments of site response peaks in the Delta region. Figure 6.9 shows six examples of cases when a peak was or was not identified from the peak identification algorithm.

For this application, two procedural changes were made that are reflected in Figure 6.8. The first requires peak step width to exceed the minimum value $wid_{min-thres}$. This check was introduced because I found that narrow peaks were not correlated to site resonances. This often occurred for peaks at high frequencies, such as in the example shown in Figure 6.9 for site 2915 for the peak at 0.2 sec. The second change was made to align width parameter wid_p more closely with expectation from visual assessment. In the previous implementation, the width was computed based on the last step within the peak feature (i.e., the horizontal range marked as w_{p-old} in Figure 6.10). In cases where one side of the peak is much lower than the other side, as for site 271 in Figure 6.10, this measure of width was considered too large. The update narrows the width by measuring across the peak from the higher of the two adjacent steps, with the step on the opposite side selected as that with the nearest amplitude.

Table 6.1 shows the threshold values used in the previous version of the algorithm (Buckreis 2022) and the proposed new values. The new values include some threshold adjustments. Relative to Buckreis (2022), amp_{thres} was reduced from 0.27 to 0.13. The motivation for this reduction was visual inspection of sites like site 210 in Figure 6.9. Station 210 was visually judged to have a peak at 2.2 sec. The difference between the amplitude of that peak and the maximum amplitude of adjacent steps (i.e., $amp_p - \max(amp_l, amp_r)$) was 0.135, which fails the prior threshold of $amp_{thres} = 0.27$ but passes at the new threshold of 0.13. Similarly, relative

to Buckreis (2022), $wid_{max-thres}$ was increased from 2.3 to 3.2. Figure 6.9 shows a case (Station 4842) that has a visually clear peak with $wid_p = 3.17$, which would fail to quality as a peak with the prior maximum limit of 2.3 but passes with the adjusted threshold of 3.2. When viewed as a whole, the modifications to threshold parameters were made because the original values were considered too strict in terms of amplitude and width (i.e., they identified peaks that were large in amplitude and narrow). I recognize that the prior thresholds were appropriate for the Sacramento-San Joaquin Delta, which contains soft sediments with clear peaks.

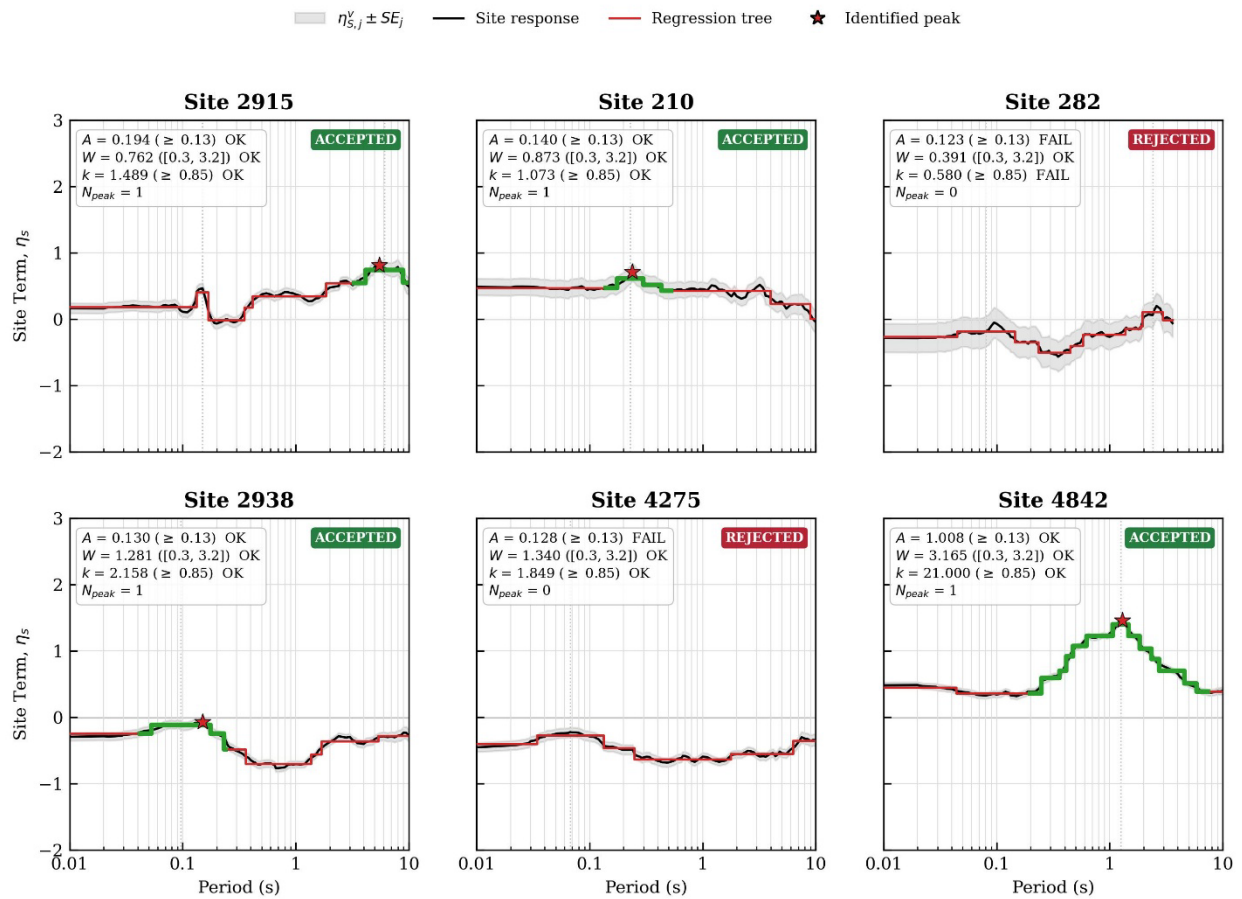


Figure 6.9. Comparison between site terms and peak identification criteria for 6 sites. Red lines indicate the results of tree regression. Green lines over the steps indicate a peak was identified and the series of steps comprising the peak.

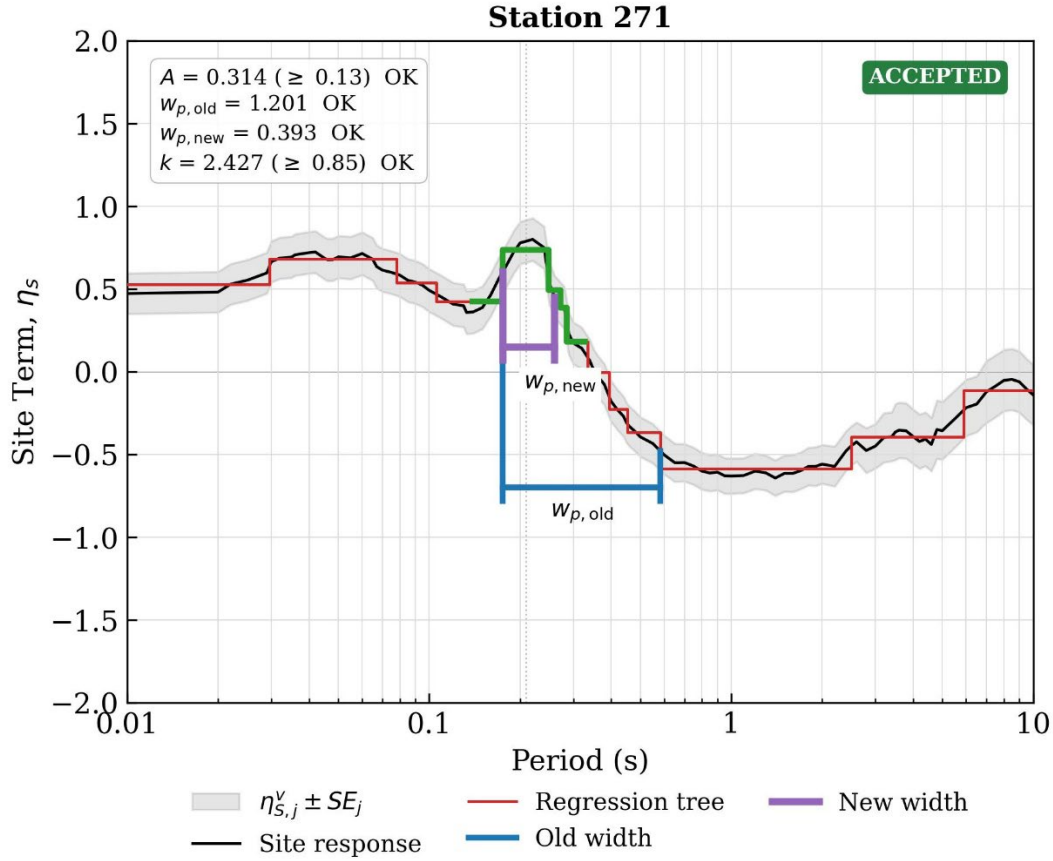


Figure 6.10. Site term curve marking a peak with a large width (horizontal range marked as w_{p-old}) from the prior peak identification algorithm that is narrowed as marked by w_{p-new} with the updated method.

Among the 686 sites in the database, I found that 176 contain only resonance or peak-like characteristics (26%). An additional 281 sites contained peaks as well as ramps, the identification of which is considered in Section 6.2.2.3.

Table 6.1. Threshold values for site response peak identification algorithm.

Version	amp_{thres}	$wid_{min-thres}$	$wid_{max-thres}$	k_{thres}	$step_{thres}$
This study	0.13	0.3	3.2	0.85	0.65
Buckreis et al. (2026)	0.27	NA	2.3	0.9	0.65

6.2.2.2 PEAK SITES: FITTING

When a peak in the site term is identified, the next step is to parameterize the peak. Different functions have been used to represent site response peaks in past work. Kwak et al. (2017) used a Gaussian pulse function that is symmetric in log period space. Buckreis et al. (2024) utilized a Ricker-Wavelet function at short periods and Gaussian pulse at long periods, the aim of which was to capture a commonly observed site response peak shape consisting of a dip in amplitude immediately before the peak feature (lower periods) followed by a transition to a flat section without a dip at longer periods. That function was not suitable for this study, since most of the site terms did not experience a dip at short periods. Accordingly, I returned to the Gaussian pulse function of Kwak et al. (2017) but modified the transitions to flat areas on either side of the peak period. This fitting utilized the function *minimize* from the python package *scipy.optimize* (Virtanen et al. 2020). The initial fitted Gaussian functional form is:

$$F_{\eta_s,i}(T) = c_{0,\eta_s,i} + c_{1,\eta_s,i} \exp \left[- \left(\frac{\ln(T f_{p,\eta_s,i})}{\omega_{p,\eta_s,i}} \right)^2 \right] \quad (6.3)$$

where $f_{p,\eta_s,i}$ is the fitted peak frequency for the i^{th} HVSR peak, $c_{1,\eta_s,i}$ is the peak amplitude relative to neighboring ordinates, $\omega_{p,\eta_s,i}$ is the peak width, $c_{0,\eta_s,i}$ is a period-independent constant, and T denotes oscillator period. Total amplitude, $\alpha_{p,\eta_s,i} = c_{0,\eta_s,i} + c_{1,\eta_s,i}$. Modifications around the peak period are introduced using a smooth Gaussian transition function,

$$\Phi(T) = \exp \left(- \left(\frac{T - T_{p,i}}{\omega_{p,\eta_s,i} * \epsilon} \right)^2 \right) \quad (6.4)$$

where $T_{p,i} = 1/f_{p,\eta_s,i}$ represents the period at which the peak is located, $\omega_{p,i}$ represents the width of the Gaussian pulse, and ϵ represents a tuning parameter to increase the smoothness of the transition. Eqs. (6.3) and (6.4) are combined as follows:

$$\hat{\eta}_s(T) = \begin{cases} F_{\eta_s,i}(T)\Phi(T) + P_L(1 - \Phi(T)), & T < T_p \\ F_{\eta_s,i}(T)\Phi(T) + P_R(1 - \Phi(T)), & T > T_p \end{cases} \quad (6.5)$$

where P_L denotes the plateau value of the site term on the left side of the peak in oscillator-period space, while P_R denotes the corresponding value on the right side. Figure 6.11 provides an example of a site-term curve peak fitted with the function in Eq. (6.5). For this site, the peak is at about 0.2 sec and the flat portion at short periods is higher than the flat portion at long periods. Figure 6.12 shows site term - period plots for 16 stations with identified peaks with a range of peak periods, amplitudes, and widths.

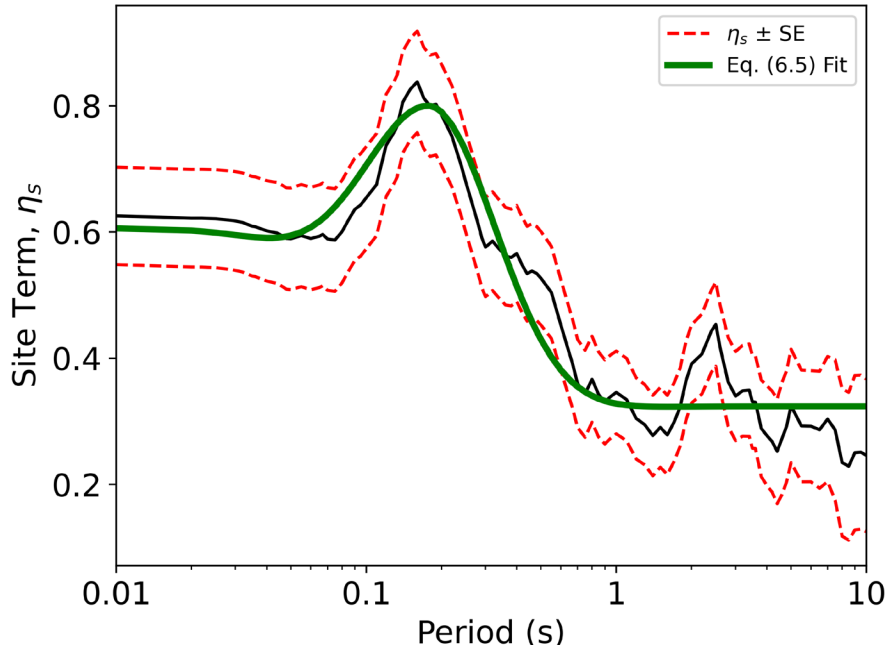


Figure 6.11. Site term curve fitted with adjusted Gaussian pulse fit shown in Eq. 6.5. SE = standard error.

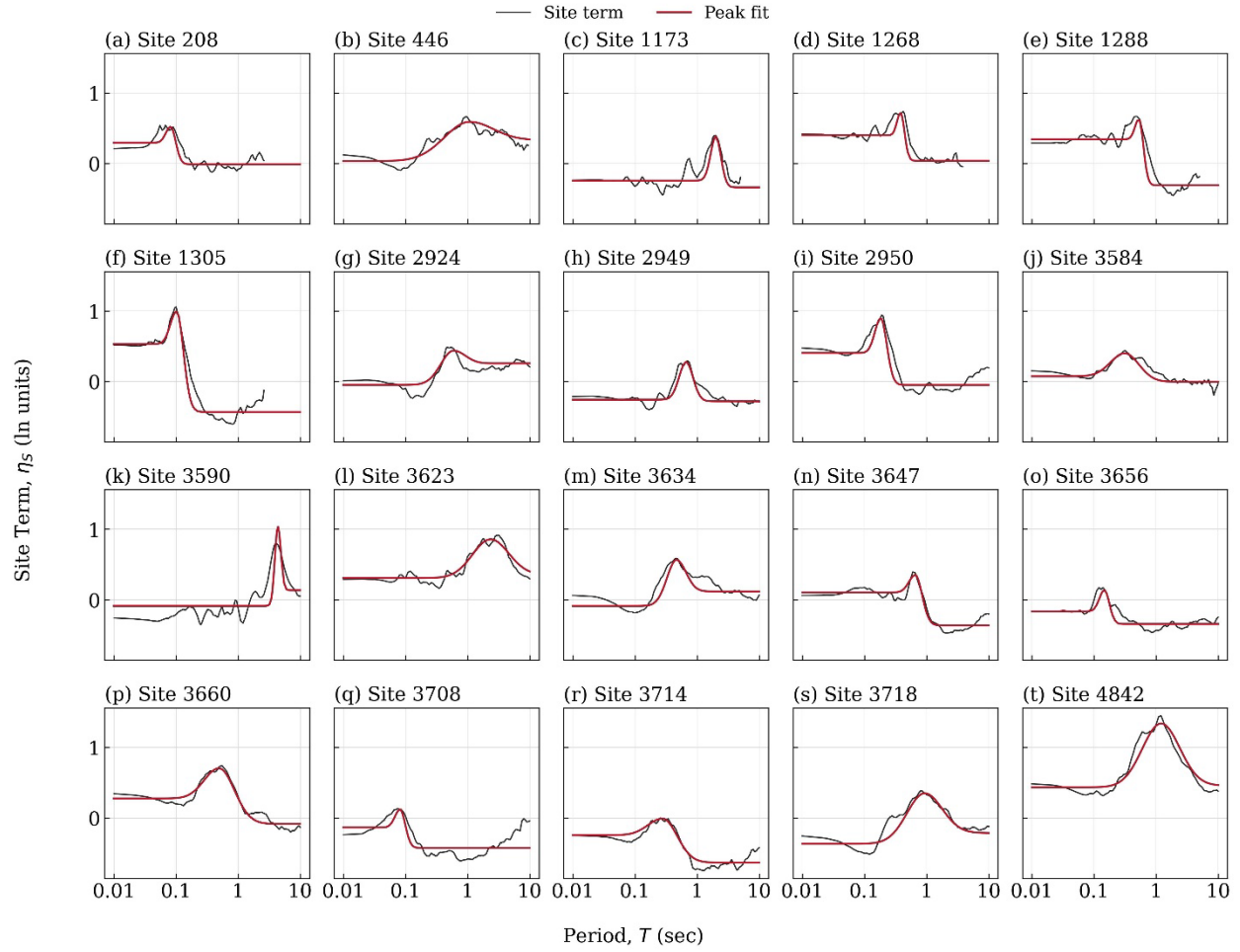


Figure 6.12. Site term curve fitted with adjusted Gaussian pulse fit shown in Eq. 6.5.

6.2.2.3 RAMP SITES: IDENTIFICATION AND FITTING

Site term – period plots for individual stations can exhibit ramps with or without peaks. An example ramp site was presented in Figure 6.6b. In this section, I describe how ramp-like features are identified as being present (analogous to peak identification) and fit. The ramp identification algorithm presented in this section was applied to all sites following the peak identification process presented in Sections 6.2.2a-b. This ramp identification algorithm is updated from an earlier version presented in Ornelas et al. (2025e).

The algorithm fits the site term – period plot using a logistic function illustrated in Figure 6.13,

$$\eta_s^\ell = \frac{L}{1 + \exp\left(k \cdot \ln\left(\frac{T}{T_c}\right)\right)} + a_0 \quad (6.6)$$

where η_s^ℓ represents the logistic function fit (the ℓ superscript is for logistic), L represents the change in amplification from the high to the low portion of the ramp, k represents the slope of the transition in amplification ($k > 0$ indicates descending, $k < 0$ indicates ascending), a_0 is a constant that represents the logistic amplitude on the low end of the ramp in natural log units, T_c is the central period within the ramp, and T represents the variable oscillator period.

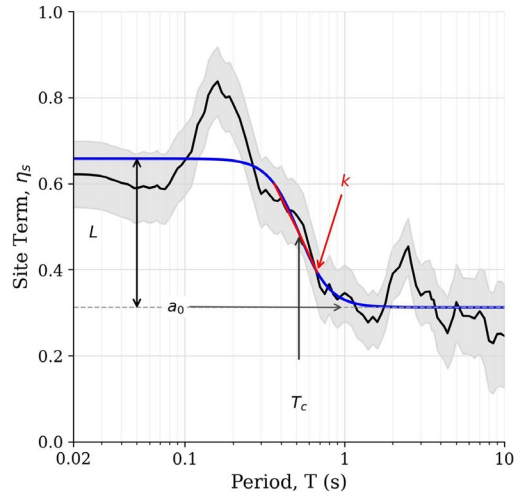


Figure 6.13. Schematic illustration of the physical meaning of ramp fit parameters in Eq. 6.6.

A site term – period curve is classified as ramp-like if the following criteria are met:

1. The coefficient of determination (R^2) value indicating the fit of the logistic function is greater than 0.51. This ensures that the shape of the site term – period data follows a ramp-like shape.
2. The amplification change parameter $L > 0.33$. This ensures that the change in

amplification across the ramp is large enough to be significant.

3. The ramp is sufficiently steep (i.e., $|k| > 0.65$). This check seeks to avoid relatively gradual transitions in site amplification over a broad period range for ramp sites.
4. The uncertainty of the logistic fit (defined as the standard deviation of residuals between site terms and the fit from Eq. 6.6 across all periods) is less than $0.18L$. This ensures that the ramp range is statistically significant relative to the fit uncertainty.

Figure 6.14 shows four example sites, two of which are classified as ramp-like (one ascending, one descending) and two of which were rejected for having ramp-like features. The L parameters for the classified ramp sites (1264 and 1287) are 0.43 and 1.03, respectively. Sites 320 and 228 are examples where Eq. 6.6 was fit to the data, but the site was not classified as a ramp due to low L values of 0.13 and 0.22.

In total, I found that there were 189 sites that were found to be descending ramps and 251 sites found to have ascending ramps (28% and 37%, respectively). Among these sites, 281 also had peaks. Figure 6.15 shows site term - period plots for 16 stations with identified ramps (ascending and descending) with a range of central ramp periods, high-to-low amplitude changes, and widths.

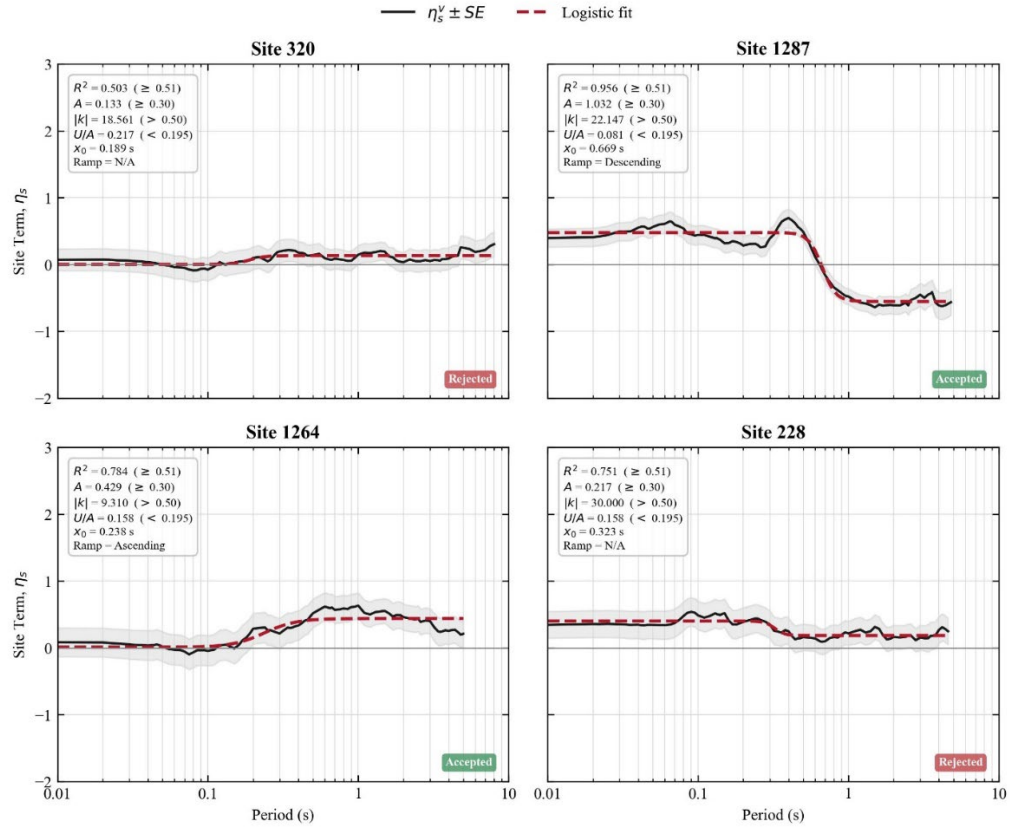


Figure 6.14. Four example site term curves fitted with logistic ramps (Eq. 6.6). Sites 320 and 228 do not meet ramp site criteria whereas Sites 1287 and 1264 do meet the criteria. SE = standard error.

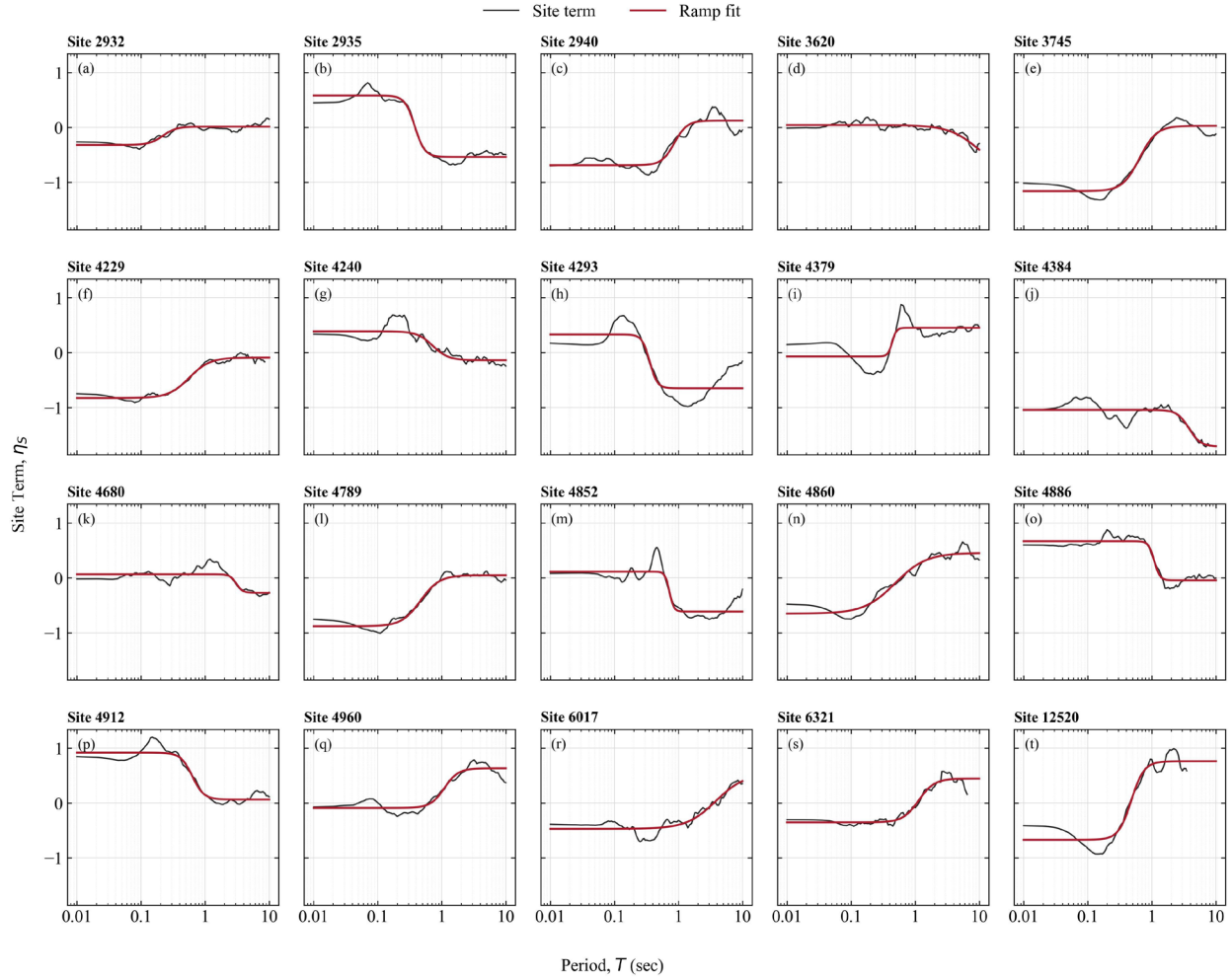


Figure 6.15. Site term curves fitted with ramp function in Eq. 6.6 and classified as ramp sites.

6.2.2.4 FLAT SITES

In this dissertation, flat sites are defined as sites that have neither peaks nor ramps based on the classification criteria presented in Sections 6.2.2.1 and 3. Flat sites may have undulations that could be interpreted as peaks or ramps. Figure 6.16 shows 16 flat sites per the definition in this dissertation. Sites 228, 4147, 542, and 259 have local highs in site terms that could be interpreted as peaks, but do not meet the peak identification criteria. Sites 3635, 2908, and 4074 have amplitude transitions across the period range that could be interpreted as ramps, but do not meet the ramp criteria. Among the 686 sites considered, 70 were found to be flat (10%). We considered

identifying among these 70 sites a subset that was “truly flat” by stricter criteria (similar to those defined by Roberts et al. 2026), but this has not been undertaken as of yet. Site 12436 would be one such candidate.

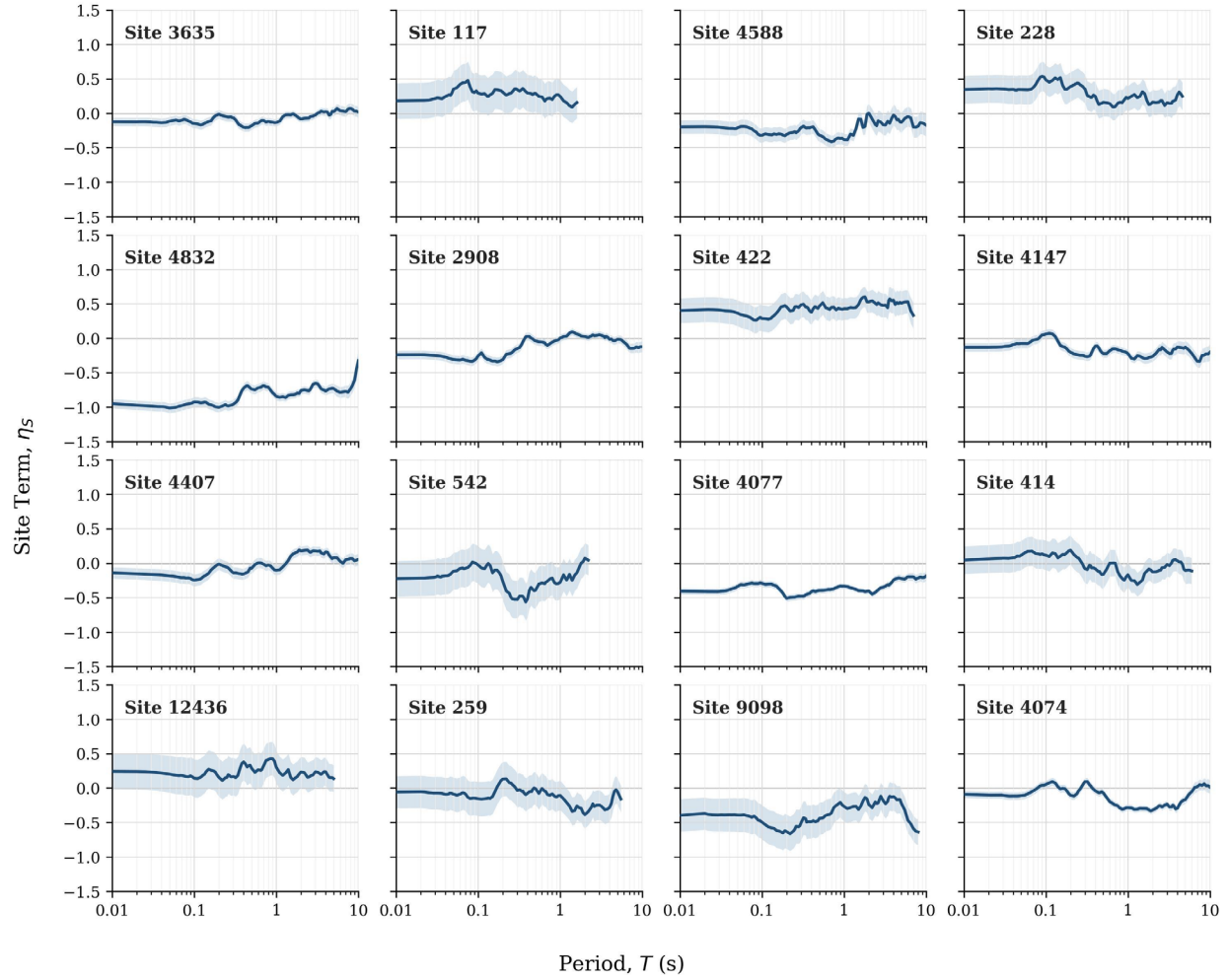


Figure 6.16. Site term curves classified as flat because they lack identified peaks or ramps. The shaded region represents the standard error.

6.3 Attributes of mHVSr Curves

6.3.1 Relationships with Site Terms

Figure 6.17 shows the same three sites with site terms from Figure 6.6, but now with mHVSr curves added by using $1/f$ on the abscissa (i.e., the periods have different meanings, with site

response using oscillator period and mHVSr using inverse frequency). The peak site (Figure 6.17a) has an mHVSr peak in the same general location, which is commonly observed for peaks at long periods. Sites with mHVSr peaks at high frequencies ($> \sim 8$ Hz) are less frequently accompanied by resonance characteristics in site terms, possibly due to the saturation of response spectra at short periods. The ramp site (Figure 6.17b) has an mHVSr peak near the edge of the ramp, which is also a peak location. As will be shown subsequently, high-frequency peaks are often predictive of descending ramps. The flat site (Figure 6.17c) is also flat in site response, although at very different levels. For some flat case sites, mHVSr curves have peaks, often at high frequencies.

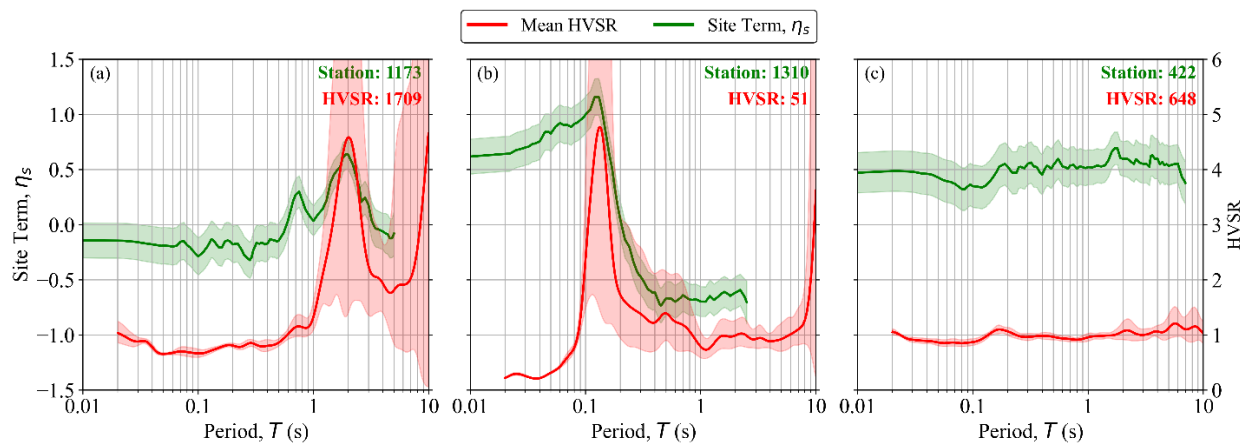


Figure 6.17. Comparison between mHVSr and site response for: (a) peak response site; (b) descending ramp response; and (c) flat site response.

Figure 6.18 shows how mHVSr ordinates (on abscissa) are correlated with site terms at different oscillator periods (on ordinate) using Pearson's r correlation coefficients. The results show that mHVSr is mainly correlated with site terms for frequencies $f < 10$ Hz. The strongest correlations are for $f \approx 0.12$ to 1.2 Hz, for which the correlation occurs over a diffuse range of oscillator periods, but centered on $1/f$.

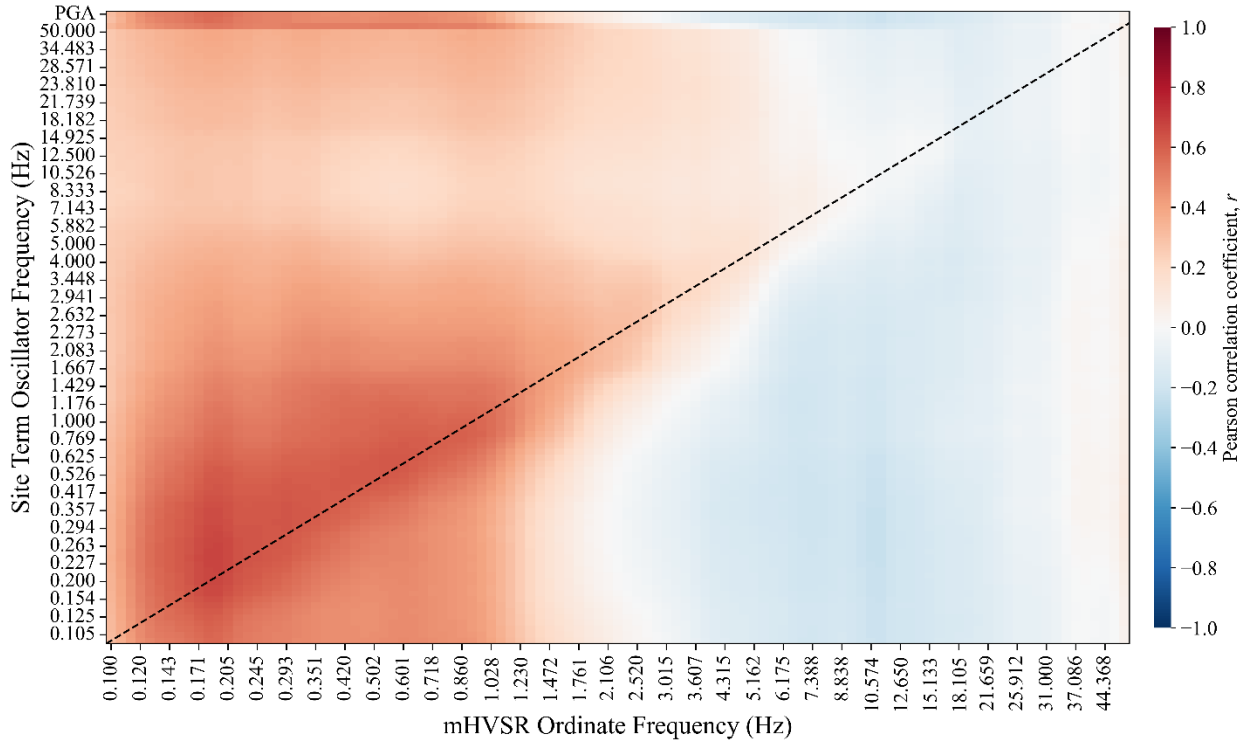


Figure 6.18. Correlation between mHVSr and the observed site response across frequency for the 686 sites used in this study, the red indicates stronger correlation and blue weaker correlation.

6.3.2 mHVSr Curve Characterization

To provide inputs needed for ground motion modeling, mHVSr curves were classified as either containing peaks or not, the latter of which can be considered flat. The peak identification algorithm developed by Wang et al. (2023) was used to identify peaks in mHVSr. Sites that did not pass the peak identification, were deemed as having flat-like characteristics.

As in the interpretation of site response-period plots, peak identification begins with tree regression to produce a stepped representation of the mHVSr curves. An example is shown by the red steps plotted over the data in Figure 6.19. Tree regression requires a smoothing parameter c_p that was set to 0.003, which is the default value in the python implementation code (note that 0.005 was used in the Wang et al. (2023) paper, which used an implementation in R; the different

implementations required different settings).

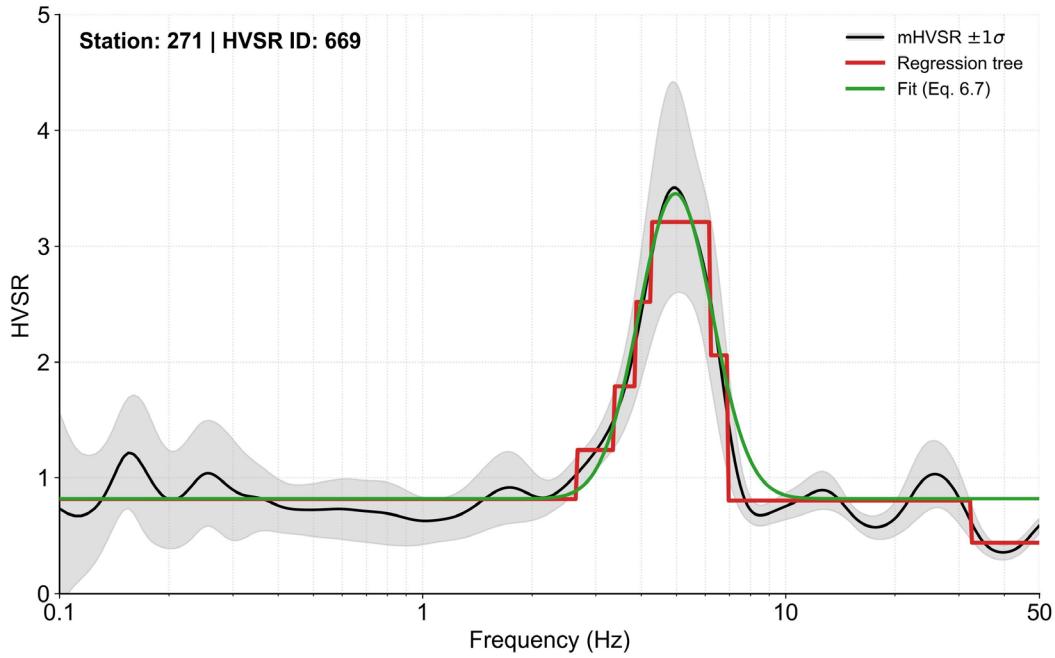


Figure 6.19. mHVS curve fit with tree regression algorithm and fit with a Gaussian pulse (Eq. 6.7).

The peak detection algorithm in Wang et al. (2023) considers each tree regression step in sequence, looking for steps that are higher than neighboring steps. Once those “high steps” are identified, they are evaluated as potential peaks based on the following criteria (where index i indicates the frequency step in the tree regression associated with a high step):

1. The amplitude at step i , $A_i > Amp_{thres}$, where Amp_{thres} is a user-specified absolute amplitude threshold. These amplitudes are in arithmetic units.
2. The amplitude of steps within flat areas to the left and right of step i relative to A_i (referred to as left ratio $R_{\ell,i}$ and right ratio $R_{r,i}$ by Wang et al. 2023) should be less than a ratio threshold $Ratio_{thres}$.
3. The width of the potential peak, measured between the right edge of the left flat step to the left edge of the right flat step (same flat steps as in Step 2) and computed as a natural log

frequency ratio $\Delta \ln f_i$, does not exceed a width threshold $\Delta \ln f_{thres}$.

4. The mHVSr mean amplitude within step i , $\bar{A}_i$, minus $k \times \sigma_{Ai}$ (where k is a threshold parameter and σ_{Ai} is the standard deviation of mHVSr ordinates within step i), should be larger than amplitudes at the left and right flat steps.

Steps 1 and 2 in the procedure are meant to ensure that peaks are sufficiently tall. Step 3 is meant to ensure that peaks are not too wide, and Step 4 is meant to ensure that the high amplitudes at peaks are statistically distinct from neighboring flat areas.

The threshold values used in the algorithm are listed in Table 6.2 along with recommendations from Wang et al. (2023) for “conservative” and “liberal” peak identification. I utilized the liberal threshold values from Wang et al. (2023).

Table 6.2. Threshold values used in mHVSr peak identification.

Method	c_p	Amp_{thres}	$Ratio_{thres}$	k	$\Delta \ln f_{thres}$	$Step_{jump}$
This study	0.003	1.15	0.95	0.8	2.3	0.45
Wang et al. (2023): Conservative	0.005	1.5	0.7	1.0	2.3	0.35
Wang et al. (2023): Liberal	0.005	1.15	0.95	0.8	2.3	0.45

Following these procedures, I assessed whether resonant peaks were present in the mHVSr for each of the 686 sites. This resulted in 425 sites being identified as having peak-like characteristics, which is 62% of the dataset.

If an mHVSr peak was identified, a Gaussian pulse (Ghofrani and Atkinson 2014) was fitted to the mHVSr curve, defined as:

$$F_{H/V,i} = c_{0,i} + c_{1,i} \exp \left[-\frac{1}{2} \left(\frac{\ln(f/f_{p,HV,i})}{2w_{p,i}} \right)^2 \right] \quad (6.7)$$

where $f_{p,i}$ is the fitted peak frequency for the i^{th} HVSR peak, $c_{1,i}$ is the peak amplitude, $w_{p,i}$ is the peak width, $c_{0,i}$ is a frequency-independent constant, and f is frequency in Hz. The absolute amplitude of the peak is computed as, $a_p = c_0 + c_1$. Figure 6.19 shows the fitted peak, for the example mHVSR curves. Features from the Gaussian fit, particularly frequency and amplitude, are considered in site response model development (Chapter 7).

6.4 Geomorphologic Site Classifications

Geomorphological site categories have been demonstrated to be a useful indicator of site response when combined with V_{S30} and depth parameters like $z_{1,0}$ (e.g., Nweke et al. 2022). Such parameters have been compiled in past work for the Los Angeles area (Nweke et al. 2022) and the San Francisco Bay Area (Stewart et al. 2025). To allow these parameters to be considered during site response model development in this project, I assembled these parameters for other regions of California.

In this section, I review literature regarding the meaning and effectiveness of geomorphic categories, I present the framework adopted in this work for delineating geomorphic zones across the state, and I show how the site terms derived in Section 6.2 vary between geomorphic categories.

6.4.1 Geomorphology used in Site Response Literature Review

Nweke et al. (2022) mapped geomorphic zones across southern California as shown in Figure 6.20. While the differentiation between basin and mountain-hill is obvious from terrain, basin edges were defined as sites within 300 m of the basin edge and valleys were defined as small sedimentary

structures with a short direction dimension < 3 km. The classifications were developed visually based on terrain. The boundary between basins and mountain-hill or between valleys and mountain-hill were defined in consideration of surface geology maps and digital elevation models.

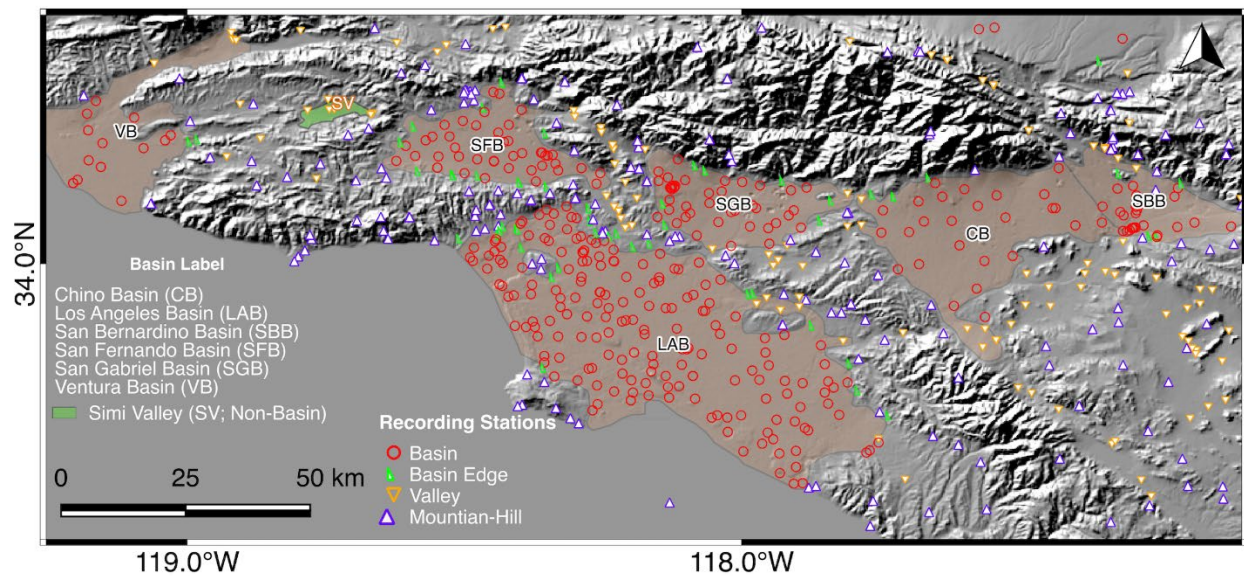


Figure 6.20. Map of southern California showing site classified into geomorphic categories of basin, basin edge, valley, and mountain-hill. Source: Nweke et al. (2022).

Nweke and Shams (2025) identified parameters from digital elevation models (DEMs) that could be used to predict the geomorphology assignments from visual classifications (like those in Nweke et al. 2022). The parameters were ground surface elevation, gradient, curvature, and texture, with texture having the strongest correlation to geomorphology category. They used machine learning methods to then predict geomorphology conditioned on those parameters, using training data from southern California. The model assigns basin probabilities by location, as shown in Figure 6.21. This allows users to evaluate geomorphic categories in southern California without having to make subjective decisions based on their interpretation of geology and terrain shape.

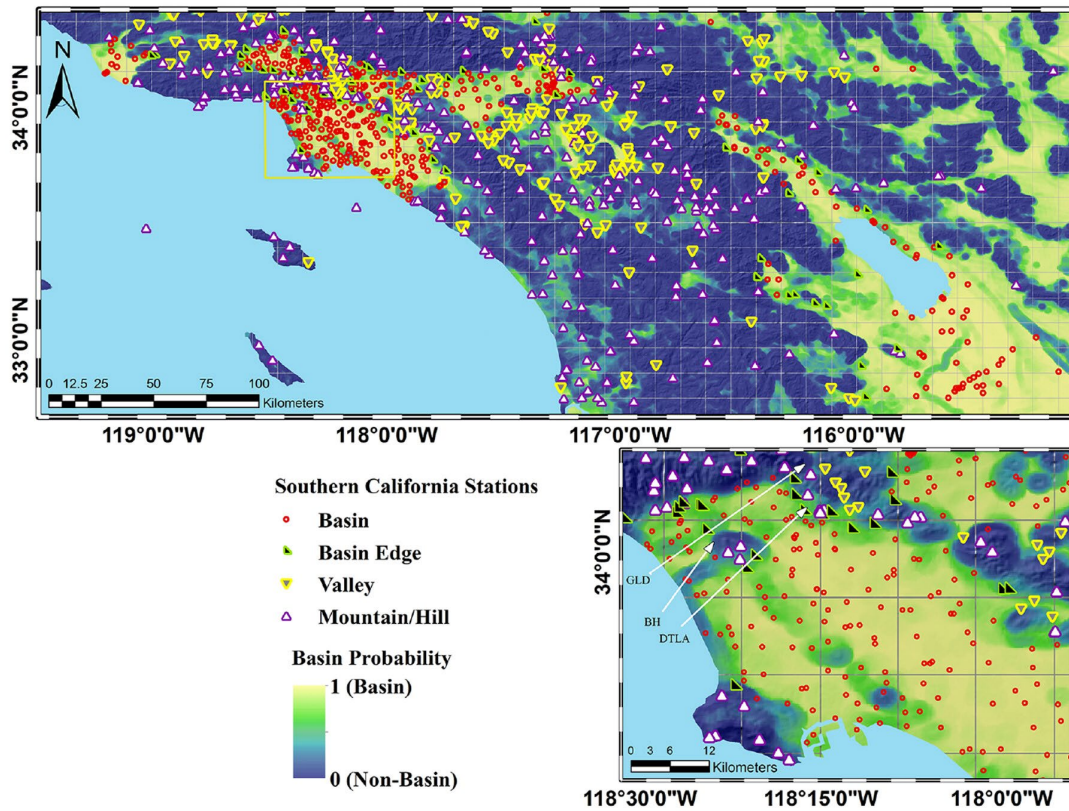


Figure 6.21. Map of southern California showing spatial distribution of basin classification probabilities along with manually assigned categories from Nweke et al. (2022). Source: Nweke and Shams (2025).

In a site response study for the San Francisco Bay Area (SFBA), Stewart et al. (2025) applied similar procedures to those in Nweke et al. (2022), but with two significant changes that were made to reflect geologic conditions in SFBA. First, a shelf geomorphic category was introduced for relatively thin marine or sedimentary soils overlying a firm bedrock basement, which is a common condition west of the Hayward fault around the margins of San Francisco Bay. Second, basins were assigned in particular mountainous areas due to geologic studies that demonstrated these areas have relatively soft Tertiary bedrock overlying stiffer, Cretaceous basement rock. This category was applied to the Livermore area. Figure 6.22 shows the resulting geomorphic map, which was developed in consideration of surface geology, terrain shape, a sub-

regional community velocity model (Aagaard et al. 2021), and maps generated from a series of local geologic studies.

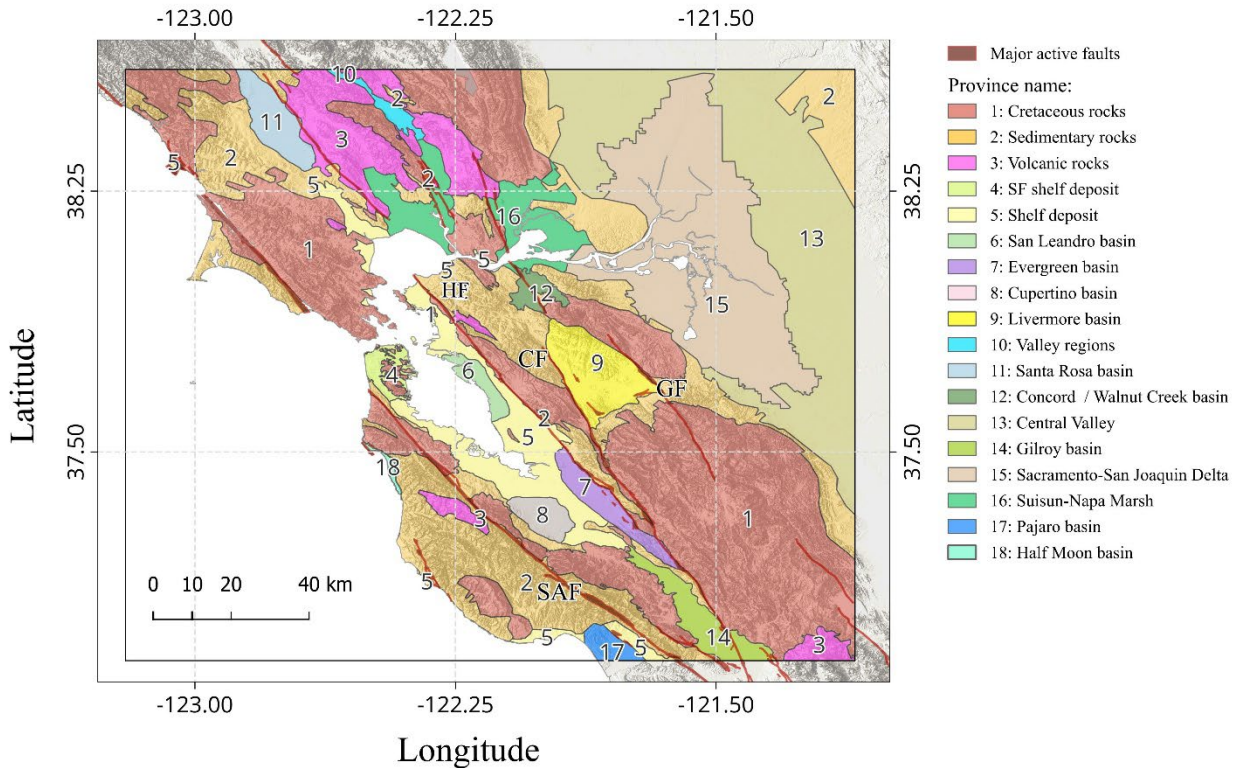


Figure 6.22. Map of SFBA showing selected geomorphic provinces derived in consideration of geology from Wills et al. (2015), isosurface depths from Aagaard et al. (2021), and studies of individual basins. Source: Stewart et al. (2025).

It is important to differentiate the geomorphic categories described above from *geospatial categories*, which are derived solely from topographic information. Geospatial categories are identified from surface topography using a wavelet-based approach that queries DEMs, producing raster layers at the DEM spatial resolution. These raster layers have been interpreted to identify sedimentary basins across western North America based solely on surface characteristics, independent of geologic information and subsurface velocity models (Nie et al. 2026). Only geomorphic categories are considered in the present work.

6.4.2 Framework for Geomorphologic Classification

The objective of geomorphic classifications in this research was to develop a categorization map of the entire state of California. Hence, the geographic domain is much larger than those considered in Nweke et al. (2022) or Stewart et al. (2025). Initially I considered the four categories from Nweke et al. (2022) for the Los Angeles area along with the additional shelf category for SFBA. Instead of placing relatively deep and soft (by bedrock standards) Tertiary units like those near Livermore into the basin group, I created a sixth old basin group for such cases. Table 6.3 shows the geomorphic categories that were assigned to California sites.

Table 6.3. Description of framework used in classification of geomorphology across California and surrounding regions.

Province	Description	Criteria ^{1,2}	Province ID
Old Basin	Softer pre-Quaternary sediments overlying bedrock.	Pre-Quaternary (mainly Tertiary) sedimentary rock, $z_{1,0} \gtrsim 200$ m.	5
Shelf	Shallow sediments overlying bedrock	Quaternary sediments, $z_{1,0} \lesssim 200$ m.	4
Basin	Deep sediments overlying bedrock	Quaternary sediments, short direction width > 3 km. $z_{1,0} \gtrsim 200$ m.	3
Basin-Edge	Along basin margin	Falls within the basin margin and has geologic units of Qal2.	2
Valley	Narrow Sedimentary structure	Quaternary sediments, short direction width < 3 km.	1
Mountain/Hill	Sites without significant sediments, generally having topographic relief.	Pre-Quaternary bedrock units, Tertiary to Mesozoic, generally having irregular morphology.	0

1 All $z_{1,0}$ values are referenced primarily from the National Crustal Model (NCM) (Boyd, 2019), but velocity models from SCEC (Aagaard et al. 2021, Lee et al., 2014; Shaw et al., 2015) were used when available.

2 All geological units are derived from the next generation V_{S30} -based geologic map for California (Wills et al., 2015)

Information sources used to assign geomorphic categories include the following:

- Prior classifications from Nweke et al. (2022) for the Los Angeles region and Stewart et al. (2025) for SFBA. Exceptions are:

- A portion of the Chino Basin in the Los Angeles area that was re-classified as a shelf
 - The Livermore basin which was re-classified as “old basin.”
 - Some portions of the Ventura Basin, Coachella Basin, Imperial Valley Basin, and Los Angeles Basin were refined relative to the Nweke et al. (2022) polygons
 - As indicated in Table 6.3, I introduced a geologic unit requirement for sites to be considered basin edge.
- The National Crustal Model (Boyd, 2019), which was used to predict $z_{1.0}$. This information was used to distinguish between categories differentiated by depth, including basin vs shelf and old basin vs. mountain-hill.
 - The statewide geologic map by Wills et al. (2015), which was used to differentiate Quaternary from older geologic units. For sites outside of California (mainly Nevada), I used the southwestern geology map developed by Utah State University (RS/GIS Laboratory 2004).
 - For regions where a geology map or depth model were not available, I used the ESRI terrain map (Esri 2026) to identify sedimentary sites vs mountain-hill sites in a similar manner to Nweke et al. (2022).

The procedure applied to map the provinces was to utilize QGIS to show overlays of the depth maps, geology maps, and terrain. Using the application, I manually inspected regions across the state from November 2025 to February 2026 (3 months) to assign categories to regions following the criteria from Table 6.3. I drew polygons capturing the area in which a geomorphic province was identified. These polygons were also extensively reviewed by a collaborator in our group Shako Ahmed Mohammed (Lecturer at University of Sulaimani in Iraq). Moreover, they were also

reviewed repeatedly by the broader research team and there were extensive discussions and iterations on the process and specific outlines. The assignment of polygons in shape files facilitates queries to identify geomorphic categories for sites of interest.

Figure 6.23 shows a map of California with the identified categories. Also shown are outlines of five detailed areas. The first of these detailed areas is the Los Angeles metropolitan area, where specific basins are highlighted in Figure 6.24. This map shows the minor adjustments of basin boundaries in this work relative to the prior work of Nweke et al. (2022). Relatively detailed studies of individual basins informed the boundaries shown in Figure 6.24, including Juárez-Zuñiga and Persaud (2025) for the San Fernando Basin and Villa et al. (2023) for the San Gabriel, San Bernardino, and Chino basins.

Figure 6.25 shows a detail map of SFBA, where the old basin province is shown in Livermore and shelf units are shown around the margins of San Francisco Bay. Figure 6.26 shows the San Diego region and inland areas. A basin area is located around San Diego Bay, whereas further north along the coast the units are shelf. Figure 6.27 shows the Mojave Desert area, which is an extension area with horsts and grabens classified as mountain-hill and basins, respectively. The basins have depths > 200 m per the NCM map (Boyd 2019). Figure 6.28 shows both the coastal range mountains east of San Luis Obispo and the Central Valley. The coastal range mountains are predominantly mountain-hill but also include old basin areas with relatively large depths. We considered Faunt et al. (2010) in setting the boundary for the Central Valley.

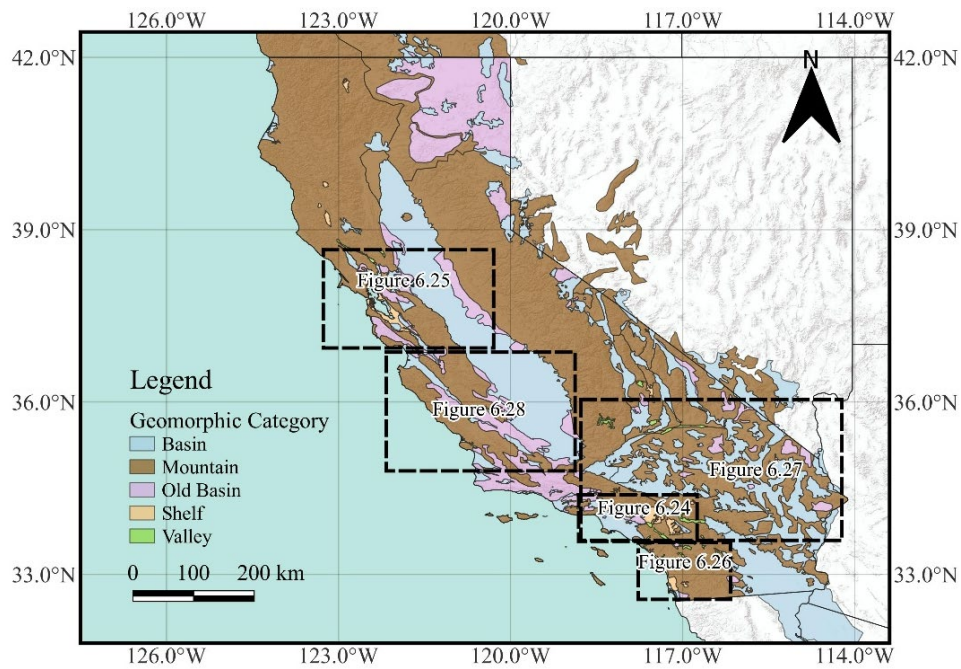


Figure 6.23. Map of California showing geomorphology polygons assigned into categories from Table 6.3.

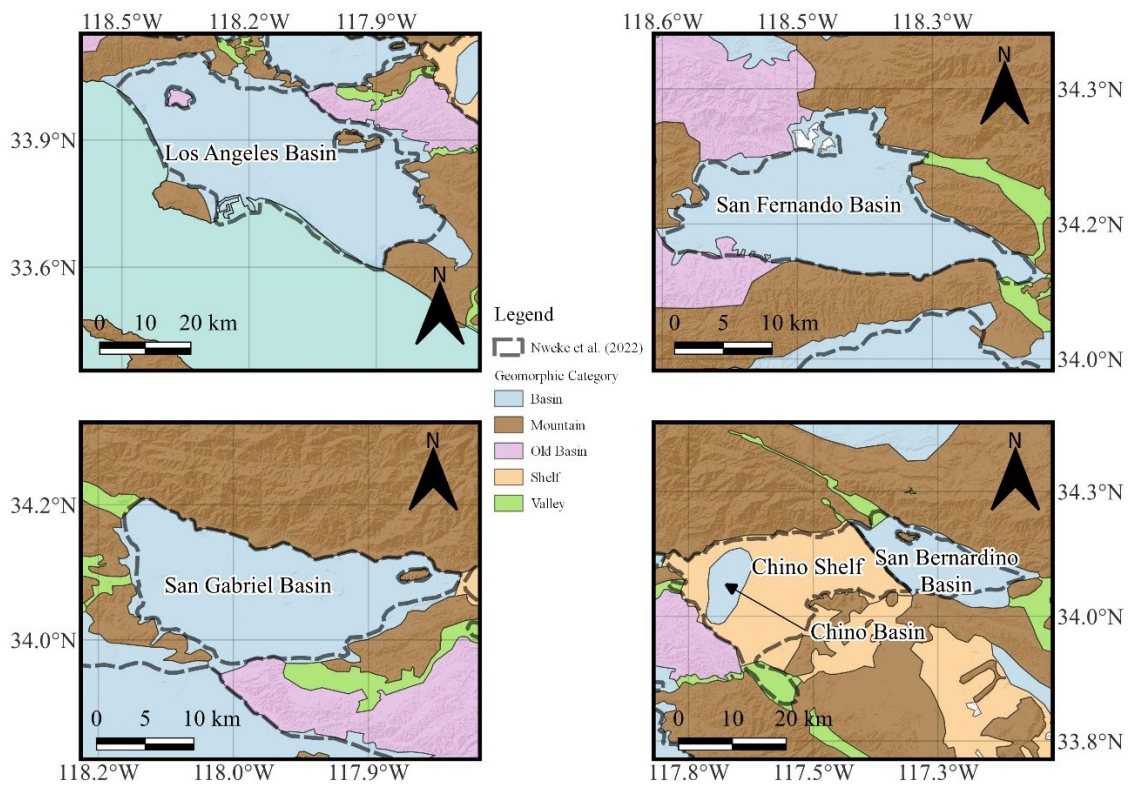


Figure 6.24. Detail map of Los Angeles area basins showing dual shelf and basin categorization of Chino basin and adjustments of basin outlines relative to Nweke et al. (2022).

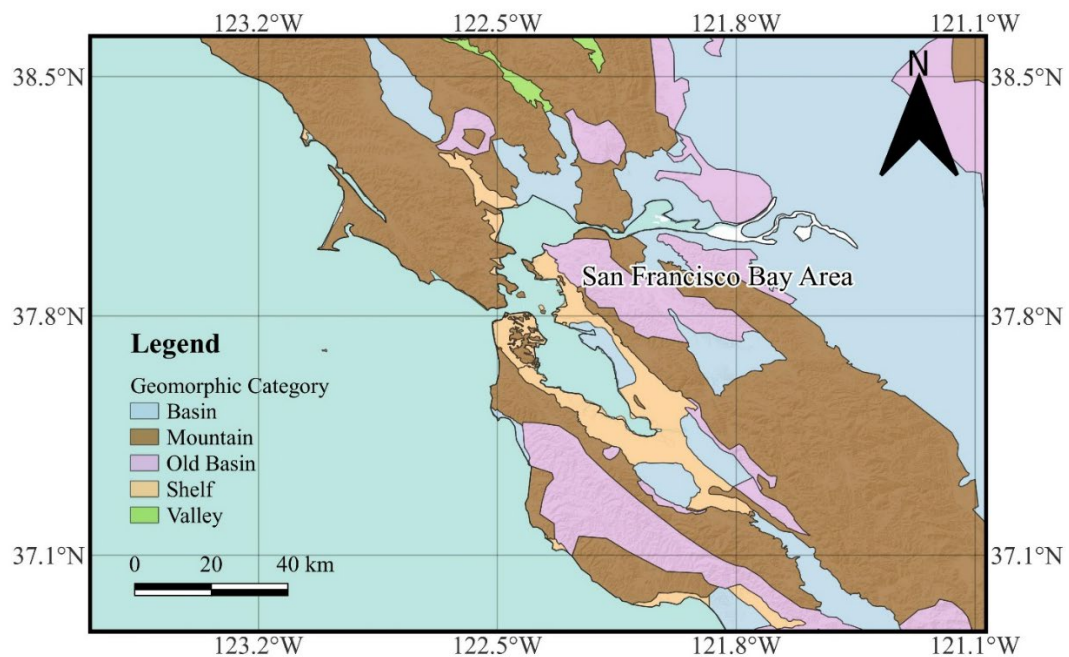


Figure 6.25. Detail map of SFBA geomorphic categories.

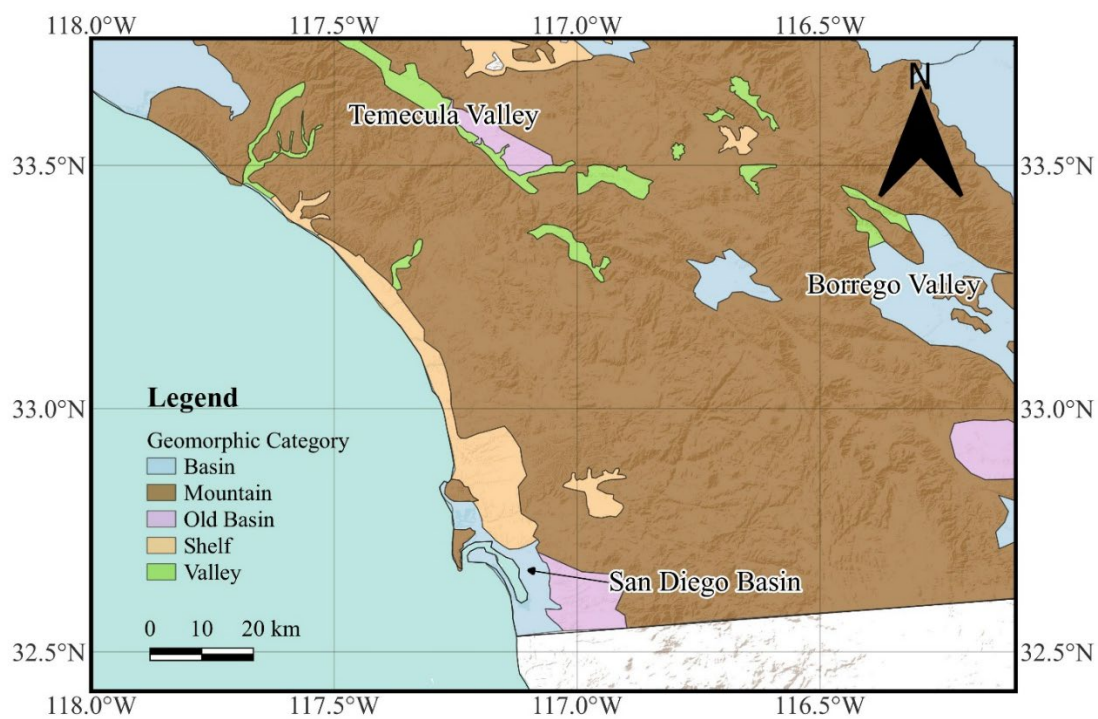


Figure 6.26. Detail map of San Diego and environs geomorphic categories.

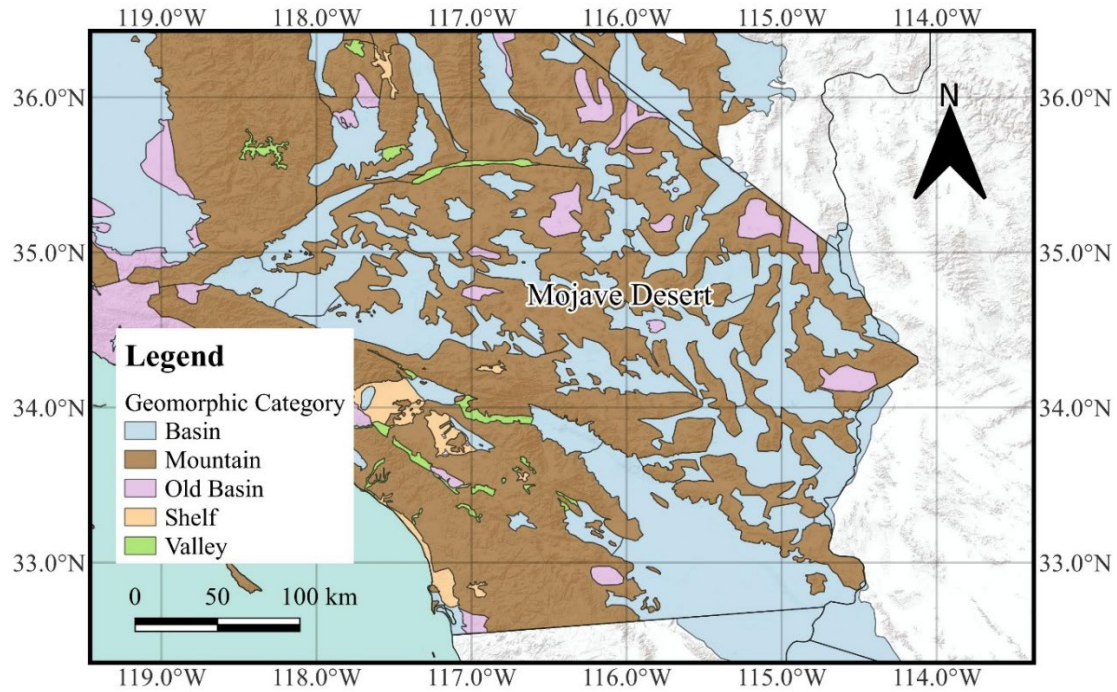


Figure 6.27. Detail map of Mojave Desert and environs geomorphic categories.

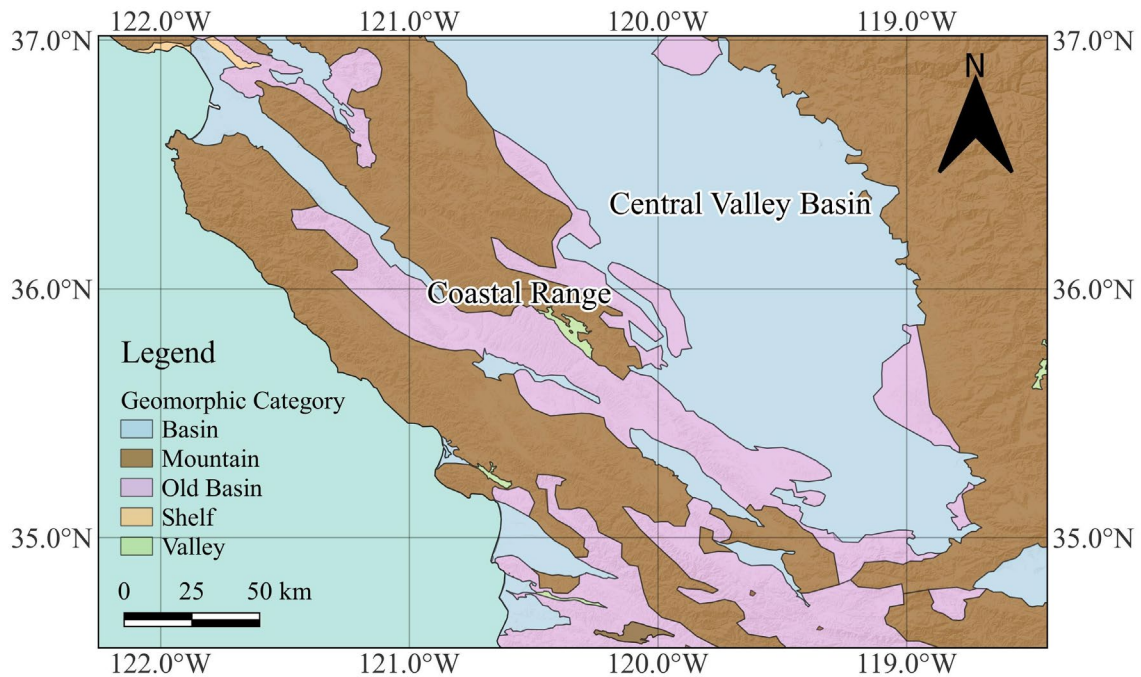


Figure 6.28. Detail map of central coast mountains and Central Valley geomorphic categories.

6.4.3 Overview of Site Terms and mHVSr Curves within Geomorphic Categories

In Figure 6.29, I show how the means of site terms differ between geomorphic categories for sites in each of the major site response feature groups (descending ramp, ascending ramp, flat, peak only). The descending ramp category is dominated by mountain-hill sites and contains most of the valley and shelf sites. The ascending ramp category is most strongly populated with basin sites, as expected, but also has appreciable numbers of mountain-hill sites and old basin sites. The mountain-hill and old basin ascending ramp sites are predominantly within the central coastal range region (Figure 6.28) and north coast. The flat site category has roughly equal numbers of mountain-hill sites and basin sites and few of the other categories. The peak-only category is diverse, with appreciable numbers of mountain-hill, basin, old basin, and valley sites.

The mean site response curves for different geomorphic categories in each of the site feature groups are remarkably consistent, especially among groups with sufficient numbers of sites for results to be statistically meaningful. Whereas ramp features are clearly evident in the category means for both descending and ascending, peaks are not evident in the mean plots because the peaks occur over a wide range of periods and are “smoothed out” in the averaging. Figure 6.30 is similar to Figure 6.29 but shows the individual site term-period plots instead of category means. The main notable feature of these plots that is not evident in Figure 6.29 is the relatively small scatter of results for flat sites and large scatter for peak-only sites. The large scatter for peak only sites is expected given the presence of peaks across a wide range of periods.

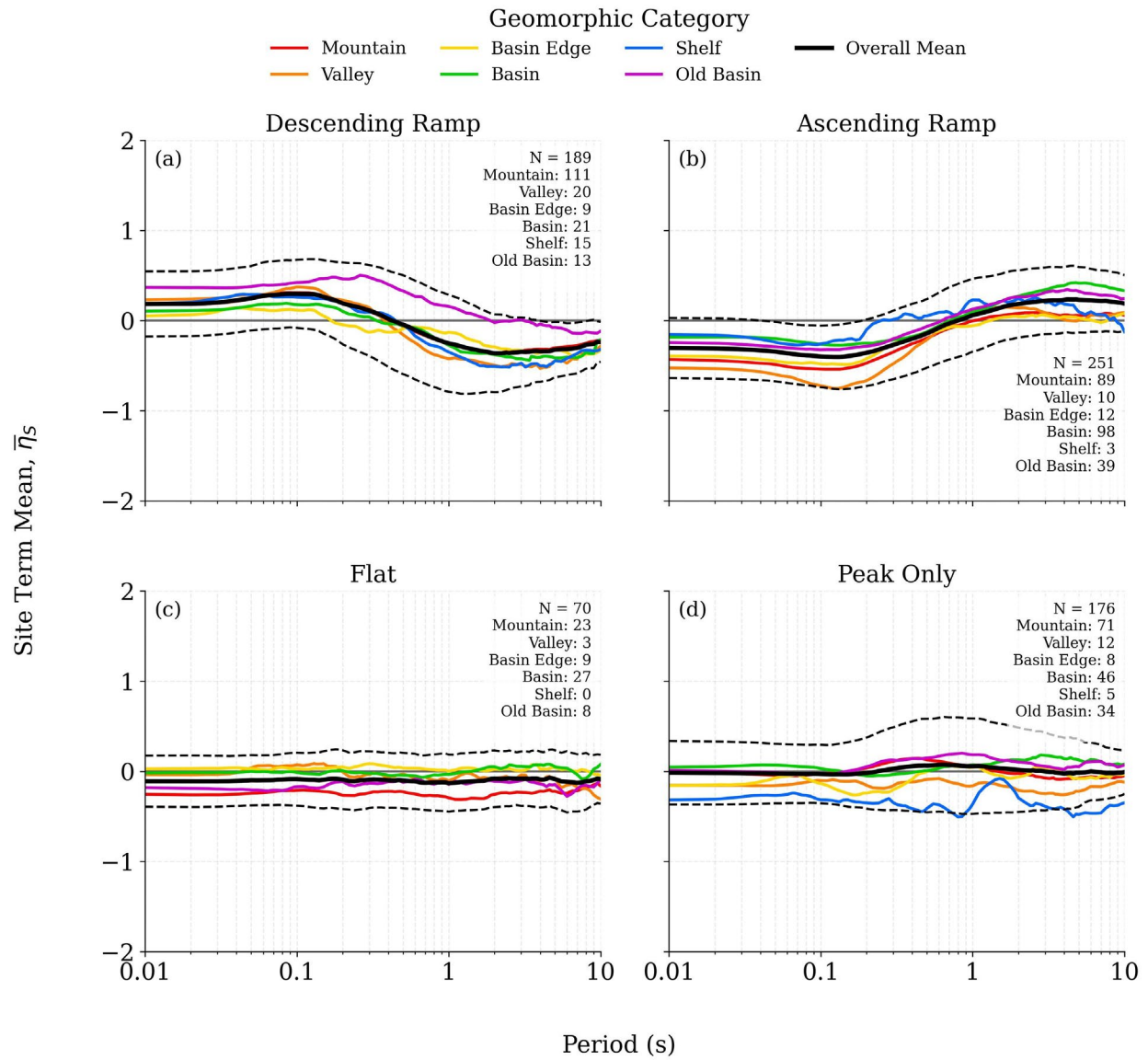


Figure 6.29. Mean site terms within geomorphic categories for the site response feature groups of: (a) descending ramps, (b) ascending ramps, (c) flat sites, and (d) peak-only sites.

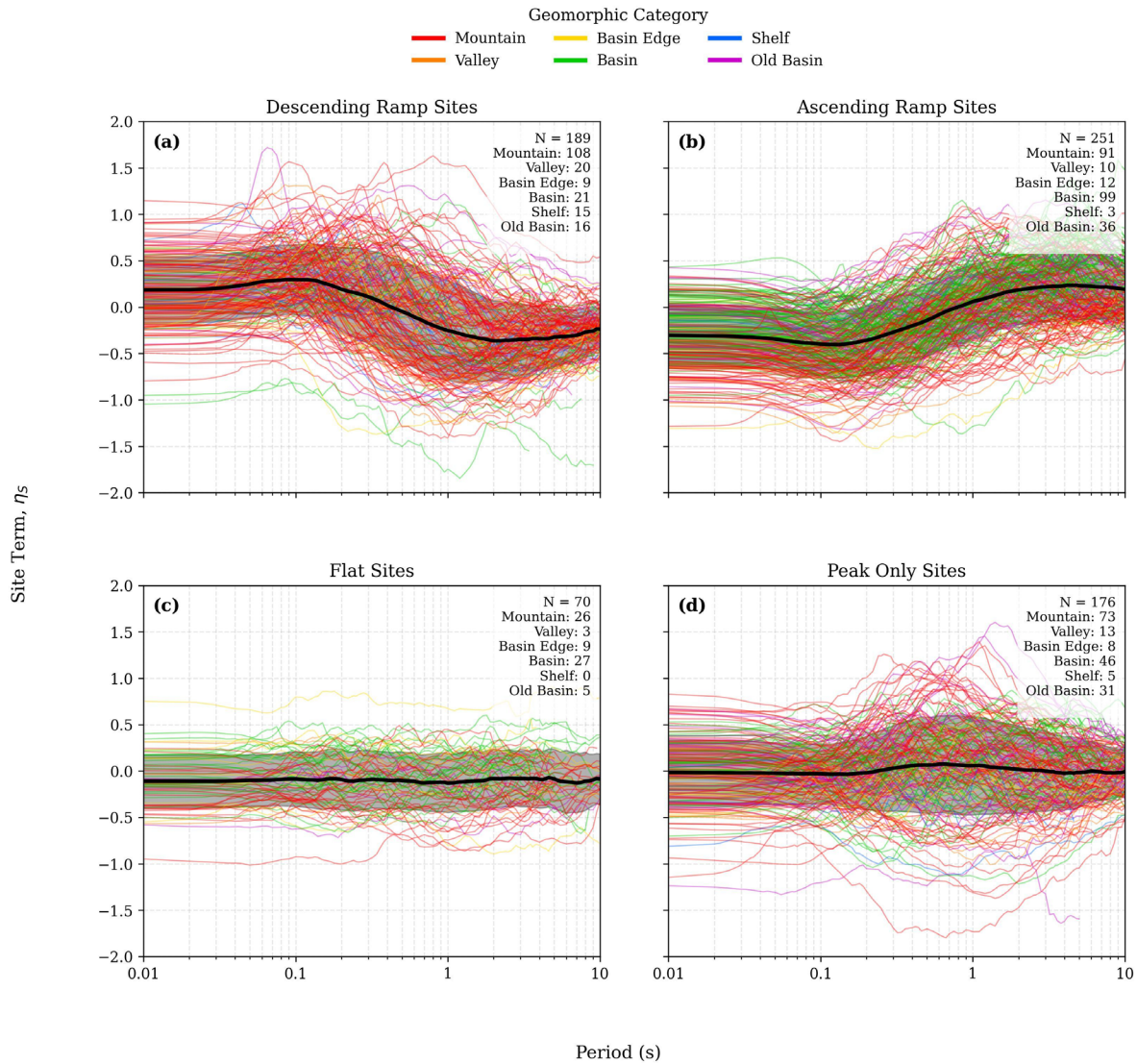


Figure 6.30. Individual site terms response within geomorphic categories for the site response feature groups of: (a) descending ramps, (b) ascending ramps, (c) flat sites, and (d) peak-only sites.

Figure 6.31 shows mHVSr curves for each of the geomorphic categories in common site response groups. The curves are plotted against $1/f$, which is indicated as “Period” in the plots, but it should be noted that the inverse of frequency as used for FAS or mHVSr has a different meaning than oscillator period. For descending ramp sites, most mHVSr curves have peaks near the inflection point of the descending ramps, which is evident for each geomorphic category. The curves for this group also tend to decrease as period increases. For ascending ramp sites, the mHVSr curves tend

to increase as period increases for basin sites but not for mountain-hill sites. Many of the mountain-hill sites, across all geomorphic categories, have high amplitudes in the approximate period range of 0.2-0.6 sec. The flat sites have the lowest mHVSr scatter and a general increase in ordinate as period increases. Peak sites have peaks over a wide range of periods, but across the population, most appear to be 0.2 and 2.0 sec.

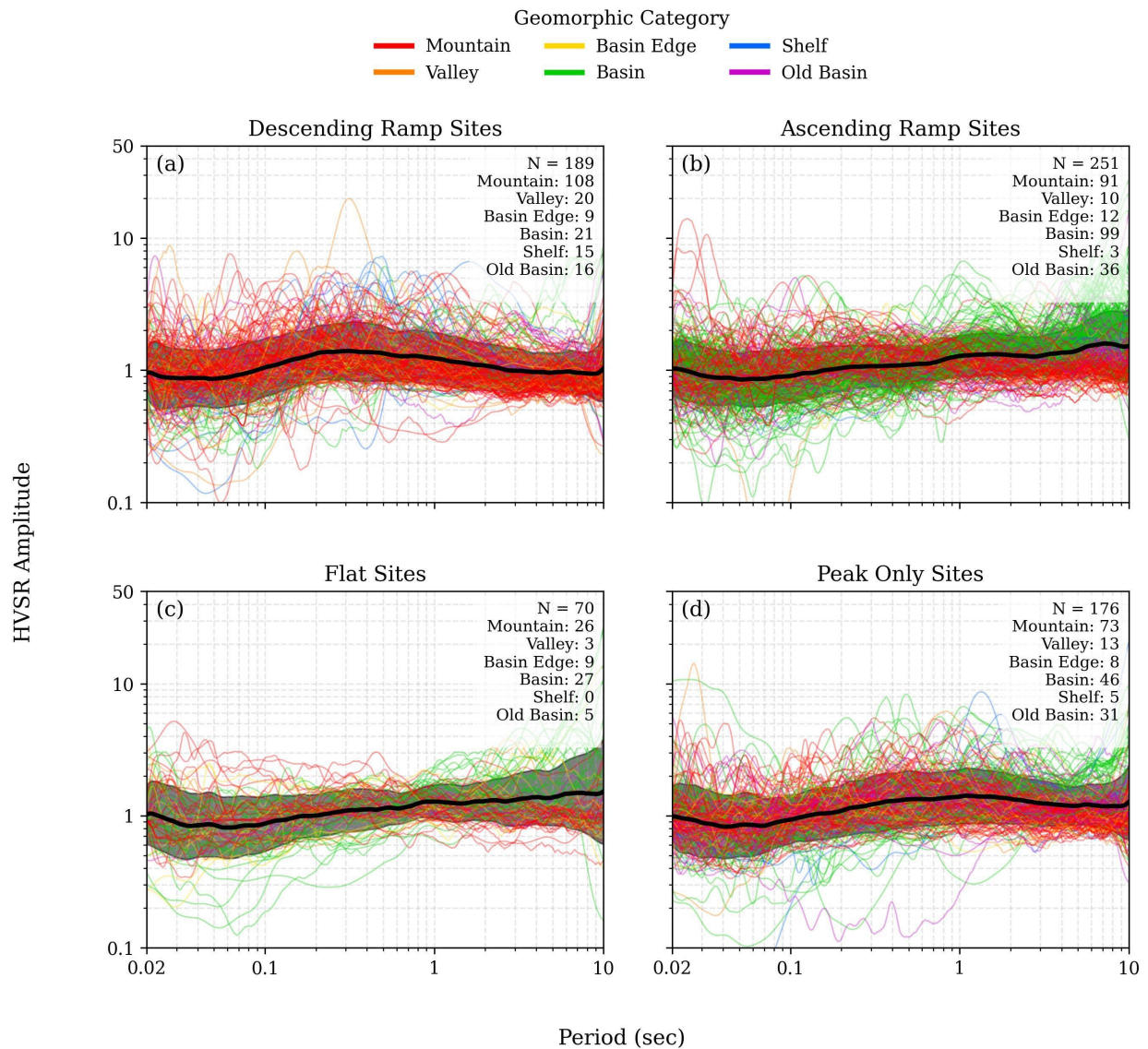


Figure 6.31. Individual mHVSr curves within geomorphic categories for the site response feature groups of: (a) descending ramps, (b) ascending ramps, (c) flat sites, and (d) peak-only sites.

To gain insight into the relationships between joint peak occurrences or non-occurrences in mHVSr curves and site term-period plots, I prepared confusion matrices for each geomorphic category as shown in Figure 6.32. Ideally all sites with mHVSr peaks would also have site response peaks, but this is not the case. The frequency of peak-peak and no peak-no peak (either both have or do not have peaks) is 62%, 72%, 55%, 68%, 70%, and 65% for mountain-hill, valley, basin edge, basin, shelf, and old basin, respectively.

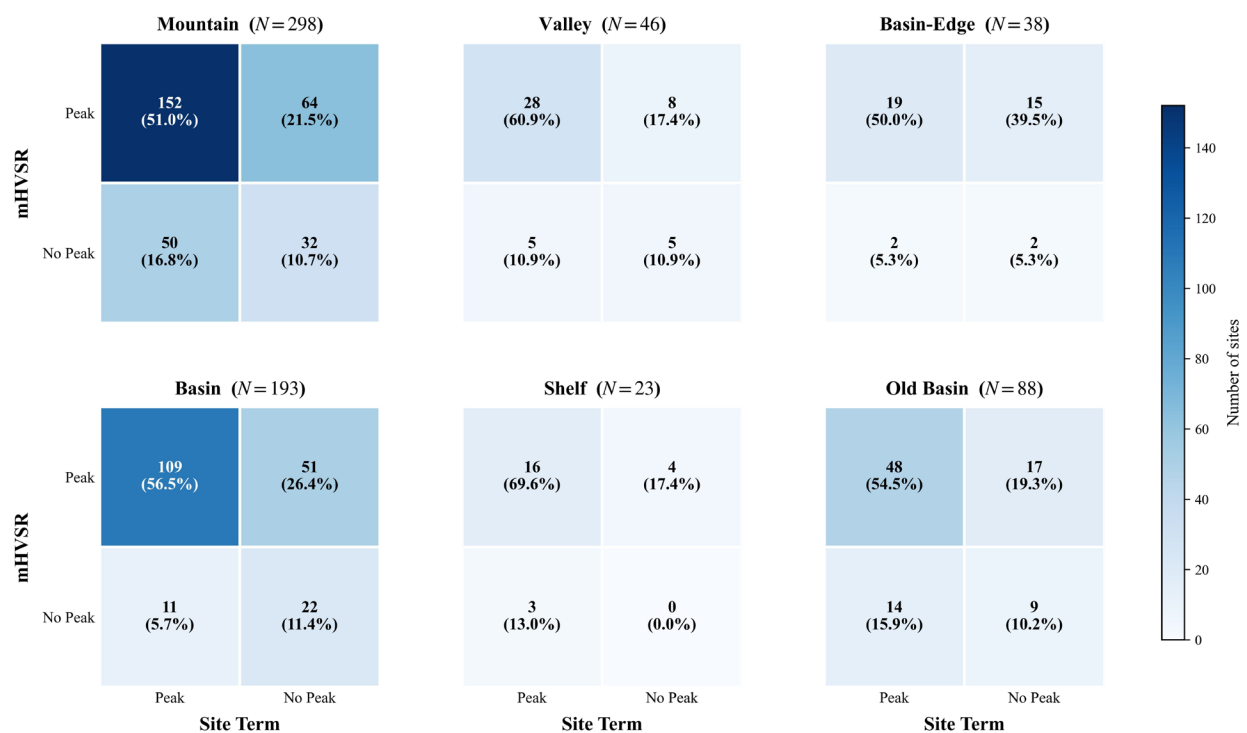


Figure 6.32. Confusion matrices show the relationship between peaks in mHVSr and peaks in the site terms in each of the six geomorphology categories.

The relationships between mHVSr and site response were further investigated by computing, for each geomorphic category, the mHVSr peak or no peak probabilities for each site response feature group, with the results in Figure 6.33. The results show that many mHVSr peak sites correspond to site term ramp sites. For mountain-hill sites, a large portion have descending ramps and mHVSr peaks, which aligns with results from Figure 6.29-6.31. Basin sites have a large number of

ascending ramps and mHVSr peaks, which also align with prior results. These findings are expected because mountain-hill sites likely have thin soil cover or weathered rock near the surface that produces short period resonance, whereas basin sites have thick sediments in my classification scheme (Table 6.3). Basin-edge and valley categories lack dominant site response characteristics but can produce each of the site response features. The shelf category has a large portion of mHVSr peak sites that also have descending ramp characteristics, again indicating short-period resonances. No shelf site was identified as being both flat and having no mHVSr peak. Old basin sites frequently have mHVSr peaks and peaks in site response, whereas among sites without an mHVSr peak, most had ascending ramps.

The data features identified in this sub-section are useful for the identification of relationships between mHVSr peak and no peak occurrence with site response features in different geomorphic categories. The next section discusses the development of a decision tree classifier that identifies probabilities of site response features conditional on mHVSr characteristics, geomorphology category, and other parameters.

6.5 Decision Tree Classifier

In this section I discuss the process by which features from mHVSr curves and other site proxies were selected for development of a classifier model. That model takes the form of a decision tree classifier, which predicts the likelihood of a site response feature. This section also presents the model tuning and development, as well as metrics used to evaluate model performance.

6.5.1 Feature Selection for Model Development

The feature selection process began by evaluating the degree to which various mHVSr parameters are different for sites having the four site response features. For these evaluations, I combined basin, basin edge, shelf, valley and old basin into a combined *sedimentary* group and mountain-hill is referred to as a *non-sedimentary* group. I then evaluated associations between mHVSr and site response features for each group.

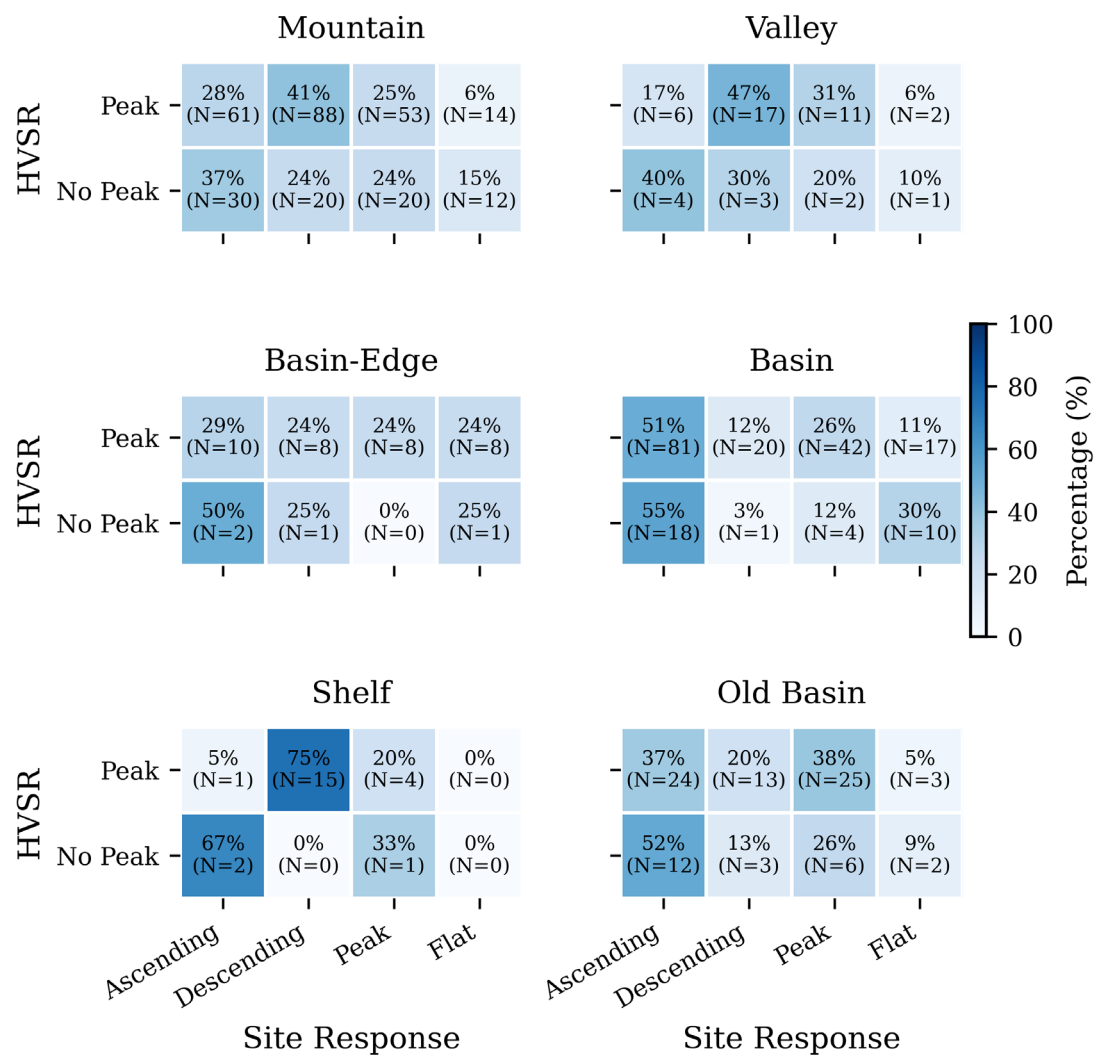


Figure 6.33. Confusion matrices showing relationships between peaks in mHVSr and site response features for each of the six geomorphology categories.

Figure 6.34 shows the distribution of the lowest frequency mHVS_R peak ($f_{0,HV}$; i.e., for sites with multiple peaks and hence multiple values of $f_{p,HV,i}$ in Eq. 6.7, the lowest frequency is selected). The distributions are shown for the four site response features and the sedimentary / non-sedimentary geomorphic groups. Figure 6.35 shows similar distributions for mHVS_R lowest frequency peak amplitude ($a_{0,HV}$; i.e., the value of $a_p = c_0 + c_1$ from Eq. 6.7 corresponding to the lowest frequency peak).

Among sedimentary sites, $f_{0,HV}$ for ascending ramp sites are generally lower than those for descending ramp sites, hence $f_{0,HV}$ is likely to be useful at distinguishing these two features. The distribution of $f_{0,HV}$ for peak sites has significant overlap with that for ramps, but is most similar in shape to ascending ramp. For flat sites, the site counts are too limited to see a strong data trend. The distributions of $a_{0,HV}$ are generally similar between groups, with the exception of flat sites, which have lower amplitudes.

Among non-sedimentary sites, $f_{0,HV}$ values are generally higher for each of the site response feature groups, which is expected. The number of descending ramp sites exceeds those for ascending, as expected, and as noted previously the ascending ramp sites are generally within the coastal ranges (north and central). These sites may have deep sections of moderate-stiffness Tertiary rock, producing relatively long period (for mountain-hill) resonances. From Figure 6.35 it can be seen that the amplitudes for non-sedimentary sites are lower than those for sedimentary sites for each feature type. Figures 6.36 to 6.39 show distributions of mHVS_R ordinates in natural log units at frequencies of 0.12, 0.2, 0.33, and 2 Hz. As before, the distributions are shown for the four site response features and the sedimentary / non-sedimentary geomorphic groups.

Among sedimentary sites, the lowest frequency ordinates (0.12 Hz, Figure 6.35) are

generally larger for ascending ramp sites than for descending ramp sites. This indicates that the ordinates themselves, not just the frequency of the peak, have predictive power for site response feature type. For peak-only sites, the 0.12 Hz ordinates are intermediate between the ascending and descending ramps, with significant overlap. The distribution shapes is similar, but with fewer data, for flat sites. For non-sedimentary sites, the 0.12 Hz ordinates are lower than those for sedimentary sites, but directionally the differences between feature types are similar to those for sedimentary sites. Figures 6.37 and 6.38 show identically formatted results for mHVSr at 0.2 and 0.33 Hz. The distributions are similar to those for 0.12 Hz and the directional differences between sedimentary / non-sedimentary and between site feature groups are largely consistent.

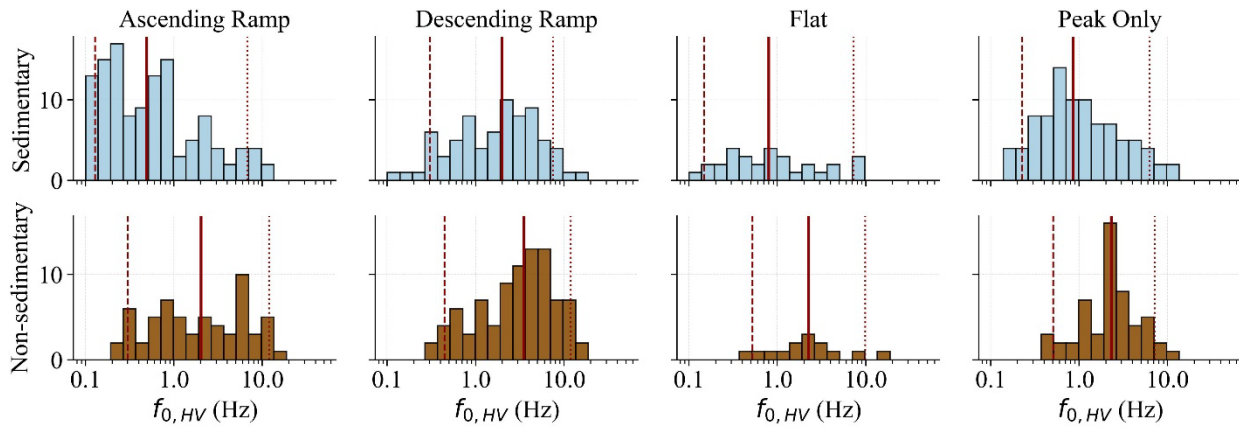


Figure 6.34. Comparison of distributions of mHVSr lowest peak frequency for different site response feature groups and sedimentary / non-sedimentary geomorphic groups. Dashed lines indicate the 5th and 95th percentile, solid line indicates the mean of the distribution.

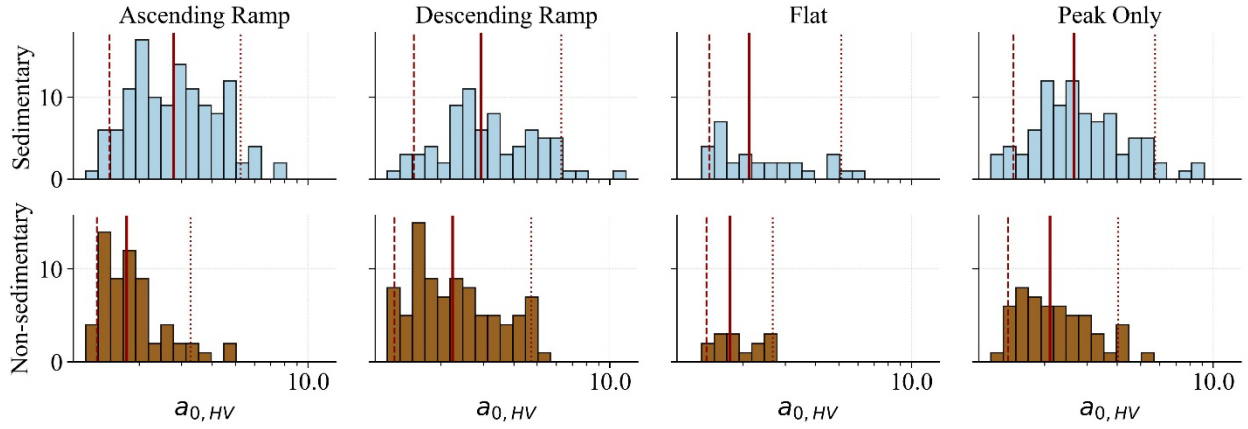


Figure 6.35. Comparison of distributions of mHVSr amplitude for the lowest frequency peak for different site response feature groups and sedimentary / non-sedimentary geomorphic groups. Dashed lines indicate the 5th and 95th percentile, solid line indicates the mean of the distribution.

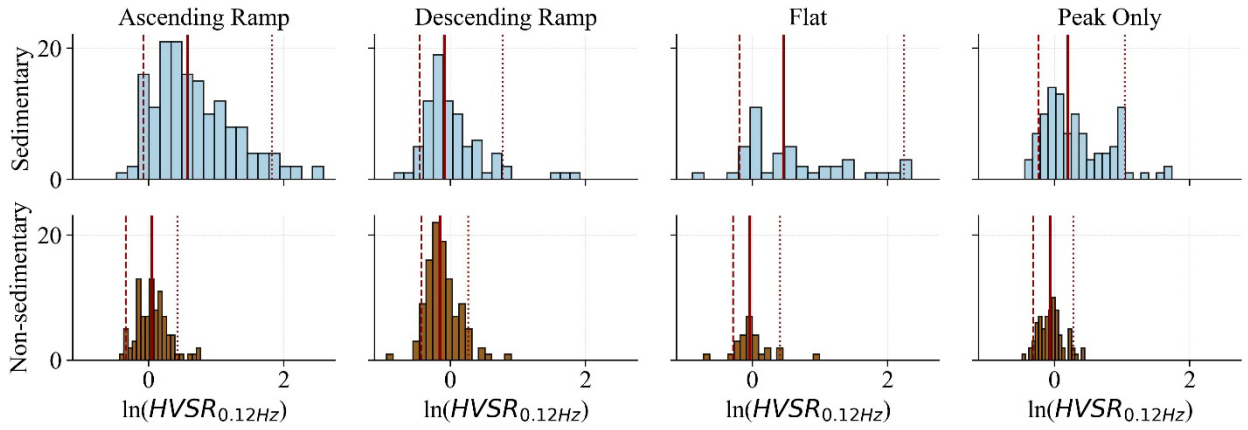


Figure 6.36. Comparison of distributions of natural log amplitude of mHVSr at 0.12 Hz for different site response feature groups and sedimentary / non-sedimentary geomorphic groups. Dashed lines indicate the 5th and 95th percentile, solid line indicates the mean of the distribution.

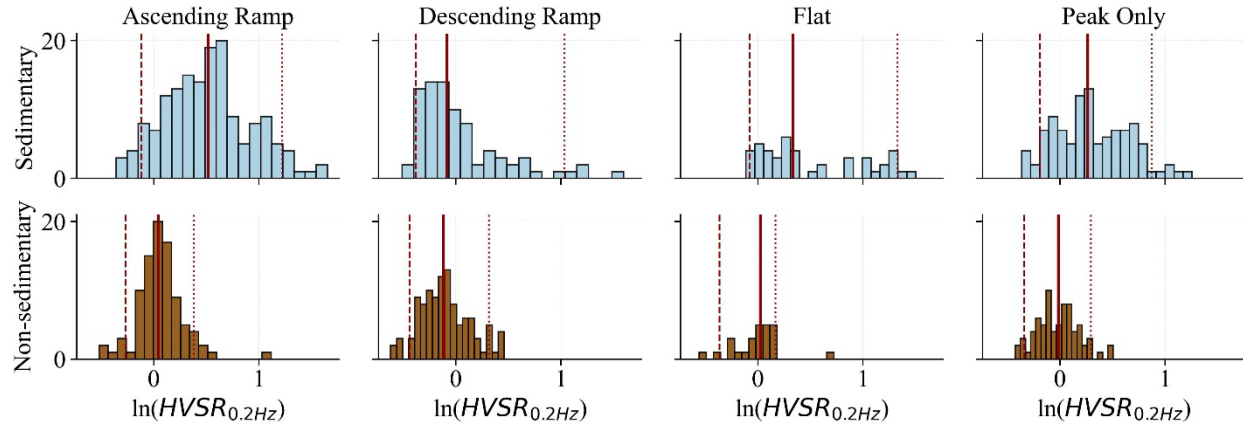


Figure 6.37. Comparison of distributions of natural log amplitude of mHVSr at 0.2 Hz for different site response feature groups and sedimentary / non-sedimentary geomorphic groups. Dashed lines indicate the 5th and 95th percentile, solid line indicates the mean of the distribution.

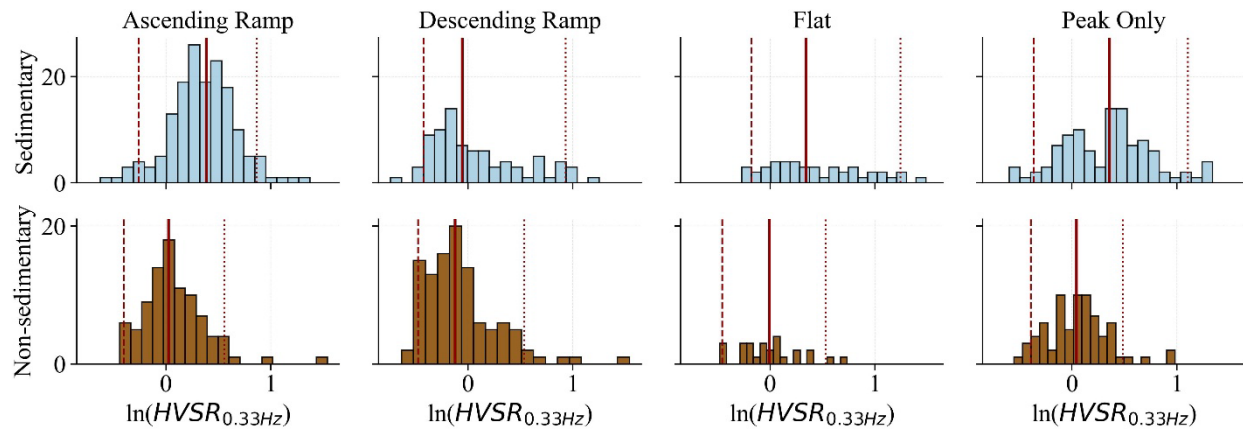


Figure 6.38. Comparison of distributions of natural log amplitude of mHVSr at 0.33 Hz for different site response feature groups and sedimentary / non-sedimentary geomorphic groups. Dashed lines indicate the 5th and 95th percentile, solid line indicates the mean of the distribution.

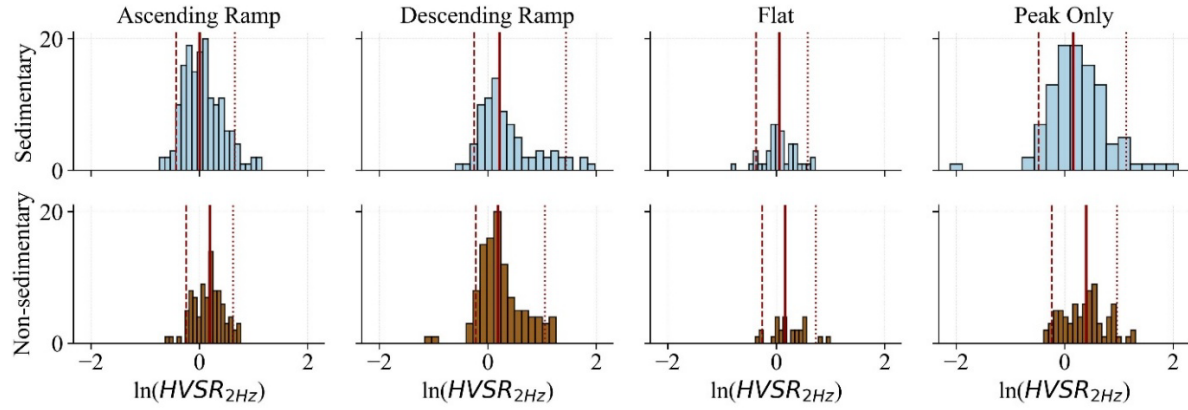


Figure 6.39. Comparison of distributions of natural log amplitude of mHVSr at 2 Hz for different site response feature groups and sedimentary / non-sedimentary geomorphic groups. Dashed lines indicate the 5th and 95th percentile, solid line indicates the mean of the distribution.

Figure 6.39 shows results for mHVSr at 2 Hz. For sedimentary sites, ascending ordinates are lower than descending, which is opposite to the results for low-frequency ordinates in Figure 6.36-6.38. The distributions for peak-only and flat sites have significant overlap with those for the ramp sites. For non-sedimentary sites the ordinates increase in amplitude relative to sedimentary for the ascending and peak sites.

Evaluations of parameter distributions similar to those presented here were evaluated for various additional mHVSr parameters and other site condition proxies to evaluate their ability to predict site response feature type for the sedimentary / non-sedimentary geomorphic category groups. Collectively, these findings demonstrated that mHVSr holds predictive power for site response features. These observations informed the development of a decision tree classifier model, as described below.

6.5.2 Rationale for Selecting a Decision Tree Classifier

As discussed in the previous sub-section, several characteristics of mHVSr were found to be correlated to site response features. Building on these observations, the next objective was to

develop a predictive model capable of classifying a site into one of the identified site response feature types based on appropriate input parameters.

Several supervised machine learning approaches were considered, including ensemble-based methods such as the Random Forest classifier (Breiman, 2001) and simpler statistical models such as multinomial logistic regression (Agresti, 2018). The ensemble-based models are based on multiple individual decision trees and output the class chosen by a majority of the trees. However, this approach obscures how individual trees make predictions (e.g., the reasonableness of sorting in branches within individual trees is difficult to assess). Lacking that understanding, the approach effectively appears to act as a “black box.” I recognize that SHapley Additive exPlanations (SHAP) values (Shapley 1953) can aid in visually interpreting the relative impact of different input parameters on the overall model (e.g., Ornelas et al. 2026c; Durante et al. 2024), which can facilitate interpretation of how the model makes predictions. However, SHAP values do not explicitly reveal the underlying physical decision-making process represented by the ensemble model.

In contrast, simpler classification models provide greater interpretability because the relationships between the predictor variables and the predicted site response features can be directly examined. While these models generally exhibited lower predictive performance than the ensemble approaches, they offer greater insight into the physical characteristics that distinguish the different site response features.

After evaluating several candidate models, I concluded that the relatively simple statistical model of a Decision Tree classifier (Breiman et al. 1984) had an acceptable level of performance

and allowed for multiple input parameters to be used as a classifier to identify the four site response features that were described in Section 6.2.

6.5.3 Decision Tree Model Development

The decision tree model was developed using the python *scikit-learn* library (Pedregosa et al. 2011) using the package *sklearn.tree* and the *DecisionTreeClassifier* function. The classifier was designed to use mHVSr-derived features and other site proxies as input variables to predict one of four site response categories: peak-only, flat, ascending ramp, and descending ramp.

Model development was performed iteratively because the predictive performance and generalization capability of the classifier depend strongly on the selected input features and model hyperparameters (i.e., internal parameters used by the machine learning model). In particular, the potential for overfitting was evaluated by comparing model performance between training and validation datasets. Overfitting occurs when a model achieves substantially higher performance on the training data compared to unseen data, indicating that the model may be learning patterns specific to the training dataset rather than capturing generalizable relationships.

The dataset was divided into a 95% training dataset and a 5% independent testing dataset reserved for final model evaluation. Although an 80/20 training-testing split is commonly used in machine learning applications (e.g., Kuhn and Johnson, 2018), this approach was not adopted because the internal data partitioning required for hyperparameter optimization was performed through a subsequent grid search procedure.

Hyperparameter optimization was conducted using the *GridSearchCV* function within the scikit-learn library. Grid search systematically evaluates combinations of predefined decision tree hyperparameters to identify the model configuration that provides the best balance between

predictive performance and generalization. During this process, a five-fold cross-validation procedure was applied to the training dataset. The training data were randomly divided into five subsets, where four subsets (80%) were used for model training and the remaining subset (20%) was used for validation. This process was repeated five times such that each subset was used once as the validation dataset.

The optimal combination of decision tree hyperparameters was selected based on the cross-validation results, with the objective of maximizing classification performance while minimizing overfitting. Model performance was evaluated using the F_1 -score, which balances precision and recall and is particularly appropriate for multiclass classification problems where class imbalance and misclassification between response categories may occur. The F_1 -score is computed as (van Rijsbergen 1979),

$$F_1 = 2 * \frac{Precision \times Recall}{Precision + Recall} \quad (6.8)$$

where precision is defined as:

$$Precision = \frac{TP}{TP + FP} \quad (6.9)$$

and recall defined as:

$$Recall = \frac{TP}{TP + FN} \quad (6.10)$$

where TP represents true positive, FP represents false positive, and FN represents false negative. During model optimization, several decision tree hyperparameters were systematically varied to evaluate their influence on classification performance and model generalization. The optimized

hyperparameters included the maximum tree depth, minimum number of samples per leaf, and minimum number of samples required for a split.

Other decision tree parameters (i.e., those not optimized) were held constant throughout the optimization process. The splitting criterion was set to “entropy”, which evaluates the impurity or uncertainty of the data distribution within each node, and the class weighting was set to “balanced” to account for potential differences in the number of observations among the four site response classes. The maximum depth parameter controls the maximum number of hierarchical decision levels that the tree can develop. Limiting this parameter prevents the model from becoming excessively complex and reduces the likelihood of overfitting. The minimum samples per leaf parameter defines the minimum number of training observations required within a terminal node. Increasing this value constrains the formation of highly specific decision rules and improves model generalization. The minimum samples split parameter specifies the minimum number of observations required at an internal node before the algorithm permits an additional split. This parameter regulates the complexity of the tree by preventing further partitioning of nodes containing insufficient data. The entropy criterion quantifies the degree of disorder or uncertainty within a node and is used to determine the optimal feature and threshold combination for each split. The entropy formulation is defined as:

$$E = -\sum_{i=1}^n p_i * \log_2(p_i) \quad (6.11)$$

where p_i represents the probability of randomly selecting a site response feature in class i in the node, and n represents the number of classes. Lower entropy values indicate a more homogeneous node, whereas higher entropy values indicate greater uncertainty among class assignments.

Following the grid search optimization, the final decision tree classifier was trained using the optimal combination of hyperparameters identified during cross-validation. The optimized model was retrained using the complete 95% training dataset and subsequently evaluated using the independent 5% validation dataset that was withheld from the model development process.

The final classifier utilized:

- mHVS features expressed in natural logarithmic units at frequencies of 0.125, 0.2, 2, and 4 Hz,
- A binary indicator representing the presence or absence of a discernible mHVS peak at a site (i.e., whether $f_{p,HV}$ was available or not NaN).
- Site parameter, V_{S30} ,
- Site elevation in unit of meters

The overall classification accuracy of the model was 56%. However, evaluation of accuracy for individual site response features revealed substantial variability. The model demonstrated the strongest predictive capability for ascending ramp and descending ramp response classes, achieving F_1 -scores of 0.66 and 0.60, respectively. In contrast, classification performance was substantially lower for the peak-only and flat response classes, with F_1 -scores of 0.38 and 0.33, respectively.

The optimized decision tree configuration consisted of a maximum depth of 5, a minimum of 10 samples per leaf, and a minimum of 5 samples required for node splitting. These parameters provided the best balance between predictive performance and model generalization during the cross-validation procedure.

Figure 6.40 presents the generalization gap of the optimized model, quantified as the difference between the training and validation F_1 -scores for each fold of the five-fold cross-

validation procedure. This comparison provides an assessment of model overfitting by evaluating the degree to which classification performance decreases when the model is applied to unseen validation subsets. Typical indicators of substantial overfitting are often characterized by a performance difference greater than 0.2. However, this threshold should not be regarded as a universal standard, as acceptable levels of overfitting depend on factors such as dataset size and complexity. Larger datasets are generally less susceptible to overfitting and, consequently, may warrant a smaller acceptable difference between training and validation performance. However, in terms of this dataset 0.20 seemed reasonable for the application.

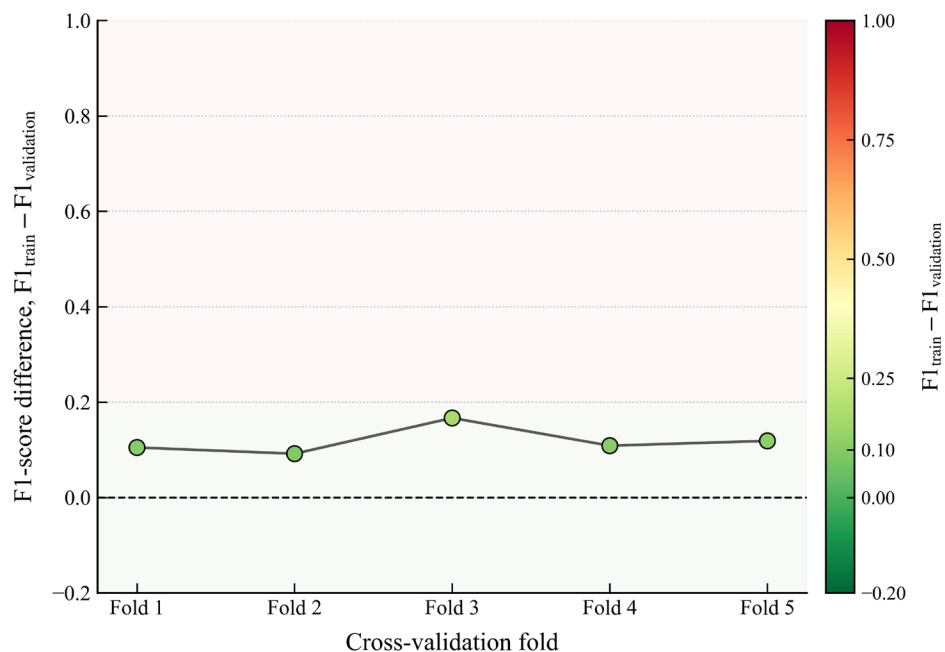


Figure 6.40. Generalization gap for each fold within the five-fold cross-validation used in the grid search.

For the decision tree model described above, none of the five cross-validation folds exhibited a performance difference exceeding 0.2. Although Fold 3 showed the largest discrepancy, this result should not be interpreted in isolation. Within a five-fold cross-validation framework, the objective is not to identify the best-performing model from an individual fold. Rather, cross-validation is

used to evaluate the performance of a given set of hyperparameters across all five folds. The optimal hyperparameter configuration is determined based on its average performance across the folds, after which a final model is trained using the entire training dataset, which in this study comprises 95% of the available data. Consequently, the individual folds primarily serve to assess the stability of model performance and the extent of potential overfitting within each fold, rather than to determine the final model.

6.5.4 Decision Tree Model Results and Performance

The final model developed in sub-section 6.5.3 is illustrated in Figure 6.41, which illustrates how the model reaches decisions based on the input parameters. From Figure 6.41, the model initially separates the site response features based on the natural log mHVS_R ordinate at 0.12 Hz. For values less than -0.06 the site response characteristic is more likely to be descending ramp, whereas greater values indicate ascending ramp is more likely. Within these two distinct domains, the model uses other parameters. For example, within the descending ramp domain, it uses the natural log mHVS_R ordinate at 0.3 Hz to distinguish between peak sites and descending ramp sites.

The performance of the model is evaluated in two ways:

1. Using the conditional probabilities for the different site response features predicted from the decision tree model (e.g., if the feature is predicted as ascending ramp, how frequently are ascending ramp and other features predicted).
2. Using a confusion matrix to relate true classes to predicted classes.

Figure 6.42 illustrates conditional probabilities for each of the site response features. The diagonal in the figure represents true positives whereas off diagonals are mis-predictions. Histograms on

the diagonal, shown in blue, show the distribution of predicted probabilities for the respective outcomes (i.e., prediction of ascending ramp for sites having that feature). Off diagonal grey histograms represent predicted probabilities for incorrect outcomes (e.g., descending ramp probabilities for ascending ramp sites). The objective of this plot is to evaluate how high the probabilities would be for true positives and how low the probabilities would be for incorrect feature identifications. From Figure 6.42, for true ascending ramp sites, predicted ascending ramp probabilities are generally $\lesssim 0.5$ (upper left box of plot). Moving right in the top row, predicted probabilities for other site response features are generally well below 0.5 (means of ~ 0.2). For true descending ramp sites (second row), predicted descending ramp probabilities are bimodal, but the mode is 0.8 (mean is ~ 0.5). Misclassified descending ramp sites have mean probabilities of ~ 0.2 and most are below 0.5. For peak-only sites (third row), predicted peak probabilities are generally low (mean ~ 0.3 , mode 0.2). Distributions of ramp site predicted probabilities (off diagonal) are similar to those for correctly identified peak sites. For flat sites (fourth row), correct predictions of flat sites have relatively high probabilities (mean ~ 0.4) and are lower for misclassified sites. Overall, descending ramp sites appear to be the most accurately predicted feature.

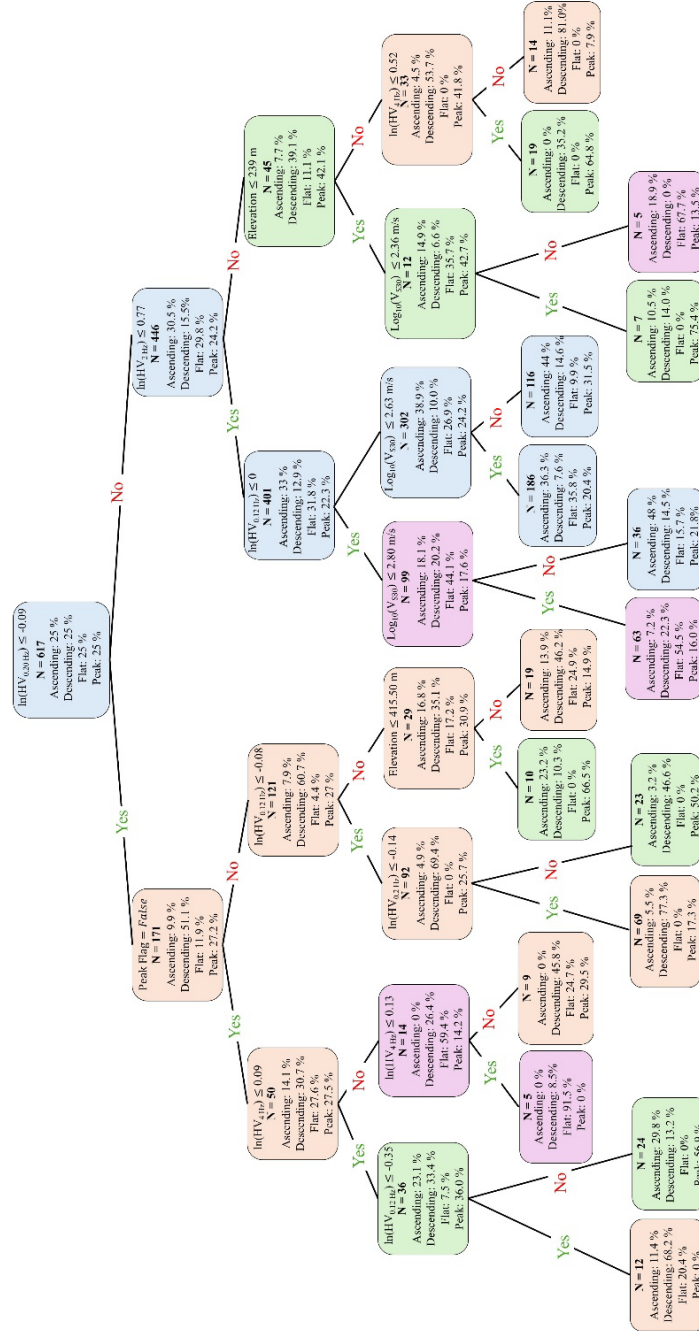


Figure 6.41. Illustration of the final decision tree model. The colors indicate the prediction of the site response characteristic (Orange: descending ramp, blue: ascending ramp, green: peak only, and purple: flat). The color is based on the percentage shown within each box.

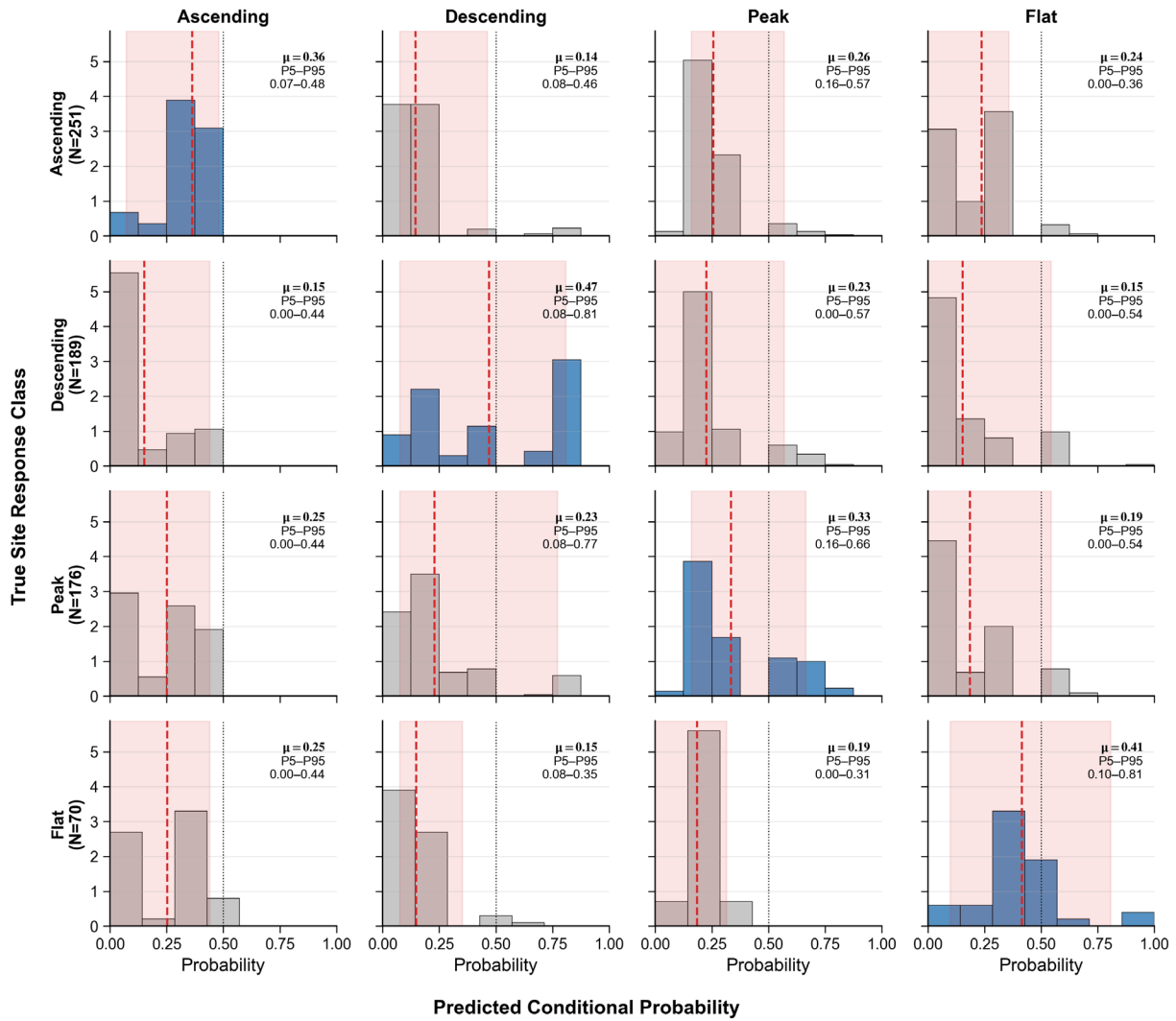


Figure 6.42. Histograms of predicted feature probabilities from the decision tree classifier for different observed feature types. The diagonal shown in blue represents true positives.

Confusion matrices are another method to evaluate performance of the decision tree model. The confusion matrix shows how many site response characteristics were accurately classified and misclassified. Figure 6.43 illustrates the confusion matrix of the decision tree model. In terms of ascending ramp sites, a large majority are accurately classified. However, in Figure 6.42, the probabilities were not high, meaning that many sites were accurately classified but the ascending ramp probabilities were relatively low. On the other hand, while a large number of descending ramp sites were correctly classified, in this case the probabilities of them being correctly identified

are also high. For peak and flat sites, the model struggled to identify them correctly. In both cases, the sites were more likely to be identified as ascending ramps than their actual features. As shown in Figure 6.42, the corresponding predicted probabilities were generally low.

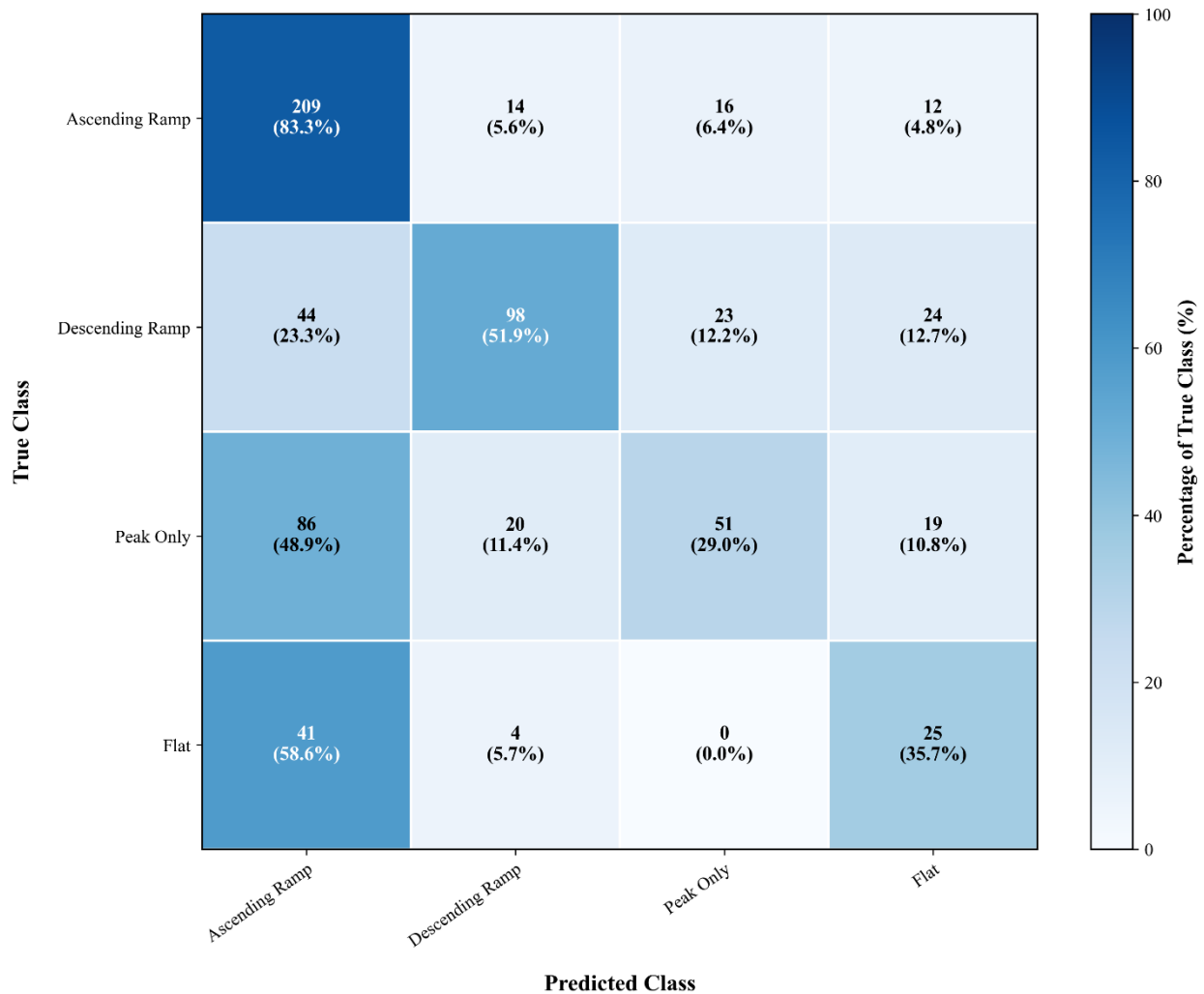


Figure 6.43. Confusion matrix showing the true and predicted classes from the decision tree classifier. The diagonal represents the true positives.

6.6 Conclusions

In this chapter, I have presented five critical steps that are needed to ultimately develop a site response model conditioned on mHVSr parameters for California sites. I demonstrated four site

term characteristics that are commonly encountered, which are peak-only, ascending ramp, descending ramp, and flat. I presented an objective, repeatable algorithm for identifying whether peaks or ramps are present and fitting procedures for peaks and ramps. Using this algorithm, 26% of sites in the dataset contain only peaks, 28% contain descending ramps, 37% contain ascending ramps, and 10% are flat. I also presented methods to objectively and repeatably evaluate whether sites have mHVSr peaks and to fit those peaks use a Gaussian pulse fit where they are present. Using this algorithm, 62% of sites have an mHVSr peak in the dataset (38% do not). Comparison plots showing mHVSr curves with site term – period plots show relationships between mHVSr peak occurrences and site response features.

This chapter also presented a framework for classifying geomorphology. Methods from previous studies were reviewed and applied, with some revision, across the entirety of the state of California. A map was developed containing geomorphic polygons in a shape file that can efficiently be queried and for use in subsequent modeling efforts.

Finally, I describe a probabilistic classification framework based on a decision tree model that was developed to identify site response features such as peak-, flat-, or ramp-like features. The model was conditioned on peak and ordinate parameters from mHVSr and other site proxies. I described the model development process and illustrated model performance. The model performs much better for ramp sites than for peak or flat sites with F_1 -scores as high as 0.66 and 0.60 for ascending and descending ramps, respectively. The distribution of the predicted probabilities were presented and were compared to observed classifications. In many cases, correct site features are identified with probabilities that are modest (~ 0.3 - 0.5), although for descending ramp sites these probabilities are higher (mode of 0.8).

7 Site Response Modelling: Conditional Models for Peak, Ramp, and Flat Response

In this chapter, I develop a series of site response predictive models derived based on results from Chapter 6. I first describe the development of parametric peak-based models, ramp-based models, and flat models. These comprise Tasks 6-8 described in the introduction of Chapter 6. I show how they are linked together by the decision tree classifier from Section 6.5, which provides probabilities that are used as weights to combine the model predictions. I also present the development of a Random Forest model that utilizes mHVS_R ordinates in tandem with V_{S30} (Task 9) and compare this model to predictions of the parametric models. Finally, I compute and interpret data residuals, with an emphasis on how they were used to reduce systematic biases and interpret site-to-site residuals.

The models developed in this chapter are all intended to be added to the V_{S30} -scaling model of Seyhan and Stewart (2014), which is used in Boore et al. (2014), and with the induced source and path term adjustment model developed by Buckreis et al. (2023).

7.1 Site Amplification Model for Sites with Peaks

This section presents site amplification models for sites that are known to have peak-only characteristics as identified in Section 6.2.2.1. This comprises 176 sites, of which 143 have an mHVS_R peak. Since the model is conditioned on mHVS_R peak parameters, it is developed from this subset of 143 sites with both site response and mHVS_R peaks.

Section 6.3.2 describes the methodology used to identify and fit peaks in mHVSr curves. Per the Gaussian function in Eq. 6.7, fitted peak parameters include the fundamental frequency ($f_{p,HV,i}$) and amplitude ($a_{p,HV} = c_{0,HV} + c_{1,HV}$). For mHVSr curves with multiple peaks, the lowest frequency peak is selected, for which the frequency is denoted $f_{0,HV}$ and the amplitude is denoted $a_{0,HV}$. These are *independent variables* that are considered in this section. The *dependent variables* (i.e., those that are estimated through regression models) include the site response peak oscillator frequency f_{p,η_s} , amplitude $\alpha_{p,\eta_s} = c_{0,\eta_s} + c_{1,\eta_s}$, and width ω_{p,η_s} , where f_{p,η_s} , c_{0,η_s} , c_{1,η_s} , and ω_{p,η_s} are defined in Eq. 6.3. The adjustments of flat areas on the left and right sides of the Gaussian peak as provided by Eq. 6.5 are also estimated.

7.1.1 Peak-Based Model using Peak-Only Data

The parameters for the Gaussian peak model in Eq. 6.3 are derived using the 143 available sites by first segregating them into the two geomorphic groups from Section 6.5.1, which are *sedimentary* (basin, basin edge, shelf, old basin, and valley) and *non-sedimentary* (mountain-hill). This separation was motivated by prior work in which distinctions in peak parameter characteristics were observed for sites in different physiographic provinces (Ornelas et al. 2025f), prior to the compilation of geomorphic categories (Section 6.4).

Figure 7.1a shows the relationship between fundamental frequency from mHVSr, $f_{0,HV}$, which reflects peak properties from Fourier Amplitude Spectral ratios, and site response peak frequency, f_{0,η_s} , which represents oscillator frequency because site terms are derived from response spectral ordinates. Individual data points are shown along with binned means and their 95% confidence intervals. The results show that most data points follow a 1:1 line but outliers are present, which are examined subsequently (Section 7.1.2). Similar to prior work (Kwak et al. 2017;

Wang et al. 2022; Buckreis et al. 2024), I allow for the possibility of a shift between the two frequencies through a regressed scaling coefficient p_0 .

$$\ln f_{0,\eta_S} = \ln(p_0 f_{0,HV}) \quad (7.1)$$

Regression was initially performed giving equal weight to each data point, which resulted in $p_0 = 1.029 \pm 0.039$ (the error term indicates the standard error). The small deviation of p_0 from 1.0 relative the error term suggests that it can be taken as unity.

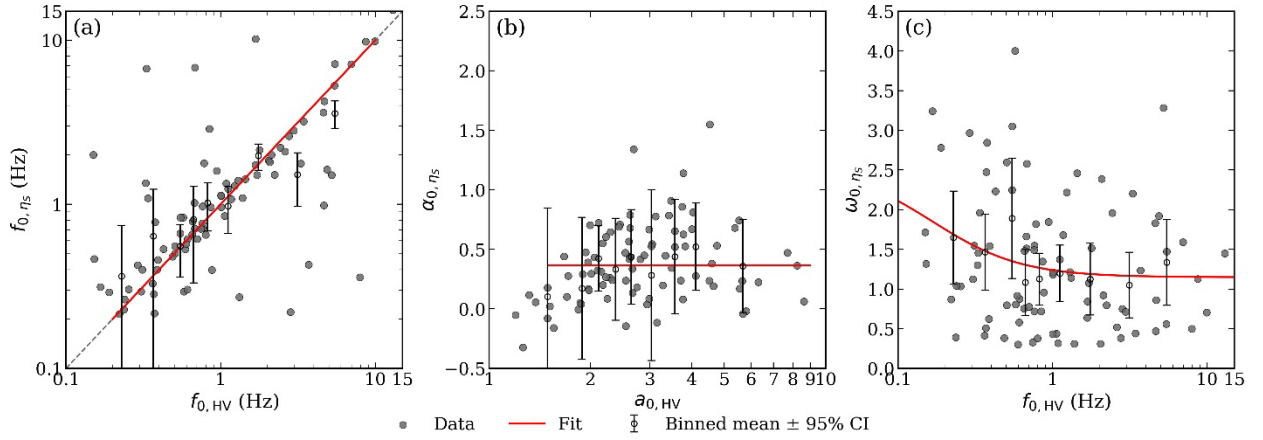


Figure 7.1. Comparison between (a) peak frequency, (b) amplitude, and (c) width of site terms to features from mHVSr such as the peak frequency and peak amplitude for sedimentary sites. The black error bars are binned means and 95 % confidence intervals of the data. The red line is the model fit of the data.

To test the null hypothesis that peak frequency in mHVSr is equal to peak frequency in the site term, I ran a two-sided Wald z -test (Wald 1943). This test involves calculating the z statistic defined as:

$$z = \frac{\hat{p}_0 - 1.0}{SE(\hat{p}_0)} \quad (7.2)$$

where $\hat{p}_0$ is the predicted shift parameter (1.029, the subtracted quantity (1.0) represents the null hypothesis of equal frequencies, and $SE(\hat{p}_0)$ is the standard error of the predicted intercept (0.04).

Under the null hypothesis the statistic is approximately standard normal $z \sim N(0,1)$, then the two-sided p -value is defined as:

$$p = 2[1 - \Phi(|z|)] \quad (7.3)$$

where $\Phi(|z|)$ is the cumulative distribution function (CDF) of the standard normal variable z . The CDF was computed using the python library *stats* (Virtanen et al. 2020). I found a p value of 0.48. If the p -value was less than 0.05 I would reject the null hypothesis, but due to the high p -value the null hypothesis cannot be rejected. Accordingly, I take $p_0 = 1.0$ for sedimentary sites.

Prior to regressing the data in Figure 7.1a using Eq. 7.1, I considered a linear functional form with a slope and intercept. However, this form allowed outliers to exert a strong influence that caused the slope to deviate from the 1:1 trend. Because a large fraction of the data lies near the 1:1 line, I adopted the linear function that does not allow adjustment of slope in Eq. 7.1.

Figure 7.1b shows that the mHVSr absolute peak amplitude $\alpha_{0,HV}$ has no predictive power for the site term absolute peak α_{0,η_s} . I investigated correlations with other parameters such as relative peak amplitude ($c_{1,HV}$) but found a similarly flat trend. As a result, a fixed value of $\alpha_{0,\eta_s} = 0.365$ natural log units is recommended. Past work has found relationships that have predictive power for the site response peak amplitude. Kwak et al. (2017) found amplitude to increase with the relative amplitude of the mHVSr peak, although eHVSr data was used in that study, which could explain the distinction. Buckreis et al. (2024) found amplitude to increase with decreasing peak frequency, although this was for a relatively small geographic domain with unique (and very soft) near-surface soils.

Figure 7.1c shows that the site term peak width (ω_{p,η_s}) decreases as $f_{0,HV}$ increases between about 0.1 and 1.0 Hz, with roughly constant widths for higher frequencies. This relationship was fit using a logistic function,

$$\omega_{0,\eta_s}(f_{0,HV}) = \frac{w_0}{1 + e^{-w_1(\log_{10}(f_{0,HV}) - w_2)}} + w_3 \quad (7.4)$$

where w_0 is the amplitude change across the width of the logistic function, w_1 is the growth rate, w_2 is the midpoint, and w_3 is a constant adjustment. The regression of the coefficients was done using the *curve_fit* function from the *scipy.optimize* package (Virtanen et al., 2020). The regressed coefficients for width and other parameters are in Table 7.1. The present findings of narrower peaks as frequency increases were observed previously by Buckreis et al. (2024). Kwak et al. (2017) did not investigate the relationship between site response peak width and frequency but found no relationship to eHVSR peak width.

Table 7.1. Summary of coefficients used in the models for the peak-based model for different geomorphic groups.

Geomorphic Group	Amplitude Parameters						Width Parameters				
	p_0	α_{0,η_s}	a_0	a_1	a_2	a_3	ω_{0,η_s}	w_0	w_1	w_2	w_3
Sedimentary	1.0	0.365	Na	Na	Na	Na	Na	1.41	-3.45	-0.78	1.15
Non-sedimentary	1.0	Na	0.86	-20.0	0.434	1.00	1.50	Na	Na	Na	Na

Figure 7.2 shows the same plots as in Figure 7.1 but for non-sedimentary sites. In Figure 7.2a, few sites are clustered near the 1:1 line, but the regressed value of $p_0 = 0.979 \pm 0.057$ (p -value of 0.722), so again it was taken as 1.0. Figure 7.2b shows that site term amplitude increases and then saturates as mHVSR amplitude increases for the rock sites in the non-sedimentary group. I fit a logistic function to the data using a similar function to Eq. (7.4),

$$a_{0,\eta_S}(f_{0,HV}) = \frac{a_0}{1 + e^{-a_1(\log_{10}(a_{0,HV}) - a_2)}} + a_3 \quad (7.5)$$

The trend in amplitude is directionally similar to that observed by Kwak et al. (2017). Figure 7.2(c) shows that peak frequency has no predictive power for width for non-sedimentary sites; a constant width of $\omega_{0,\eta_S} = 1.50$ is used for non-sedimentary sites. Table 7.1 summarizes the coefficients.

Three-panel scatter plot compares three different models for lowest frequency peak in mHVSr and site term for sedimentary sites. Gray points indicate peak data, red curves show functional fits, and black markers indicate binned means with 95% confidence intervals.

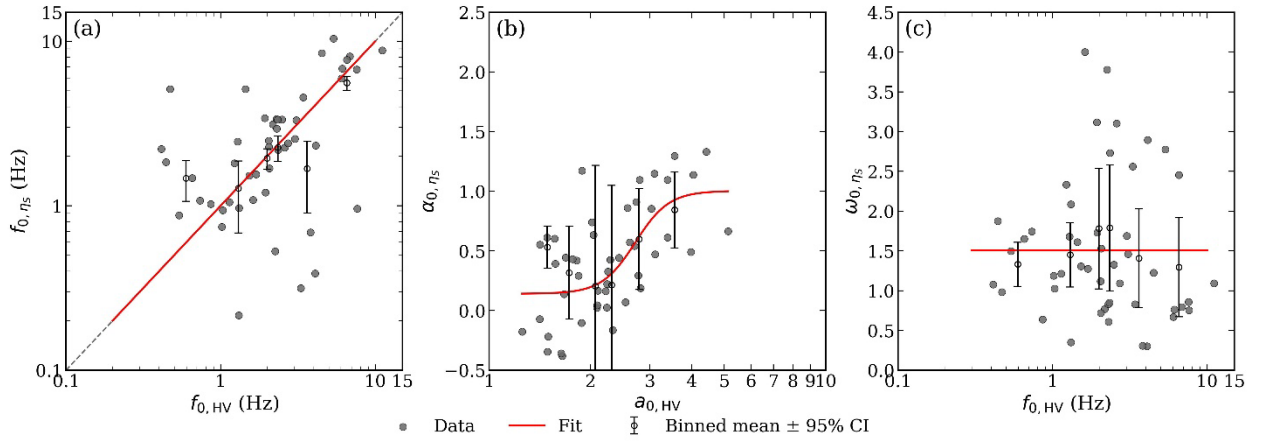


Figure 7.2. Comparison between (a) peak frequency, (b) amplitude, and (c) width of site terms to features from mHVSr such as the peak frequency and peak amplitude for non-sedimentary sites. The black error bars are binned means and 95 % confidence intervals of the data. The red line is the model fit of the data.

The combined model for the Gaussian pulse is the same as Eq. 6.3 but without the constant term,

$$F_{peak}(T, f_{0,HV}, a_{0,HV}) = \alpha_{0,\eta_S} \exp \left[- \left(\frac{\ln(T f_{0,\eta_S})}{\omega_{0,\eta_S}} \right)^2 \right] \quad (7.6)$$

where α_{0,η_S} is taken as a constant for sedimentary sites and from Eq. 7.5 for non-sedimentary; f_{0,η_S} is the peak frequency from Eq. (7.1); and ω_{0,η_S} is the peak width from Eq. 7.4 for sedimentary

sites and a constant for non-sedimentary sites. T represents the 105 oscillator periods from BSSA14 ranging from 0.01 sec to 10 sec.

7.1.2 Model Validation using All Peak Sites

As noted previously, the regressions shown in Figures 7.1-7.2 and Eq. 7.1-7.5 used the 143 sites that have peak-only site response and mHVSr peaks. Some sites with peaks also have ramps. In this section, we validate the regressions from Section 7.1.1 by using a larger data set with all peak sites but again require sites to have mHVSr peaks to be considered. The size of the data set in this case is 372 sites.

Because the final combined model (Section 7.5.1) is weighted based on the conditional probabilities from the decision tree classifier, the present analysis of the combined data weighted the data points using their conditional probability of peak-only as weights, because the models in this section are to be used for the modeling of peaks, not ramps or other features. Figure 7.3 shows the sedimentary site data for the combined data set (i.e., sites that are peak-only, ascending ramp with peak, or descending ramp with peak). Weights of the sites being peak-only are indicated by color-coding of the data points. The same functional forms are used as in Section 7.1.1. Differences in the present case are:

- A larger upward shift of $p_0 = 1.153 \pm 0.035$ was found (p -value = $1.13\text{e-}5$).
- The amplitude model is shifted slightly higher from $a_{0,\eta_s} = 0.365$ to 0.435 .
- The width model is shifted slightly higher (range is from 1.6-2.17)

A similar approach is applied to non-sedimentary sites with the results shown in Figure 7.4. As with sedimentary sites, directionally similar trends were observed for all three parameters. In the case of site frequency, $p_0 = 0.934 \pm 0.037$ was found (p -value = 0.075).

To evaluate the significance of the different fits for the combined dataset (this subsection) and the peak-only sites (Section 7.1.1), I computed residuals between the data shared by both regressions (peak-only sites) and the two sets of predictions (Section 7.1.1 and 7.1.2). These residuals are plotted in Figure 7.5 for the three parameters (frequency, amplitude, width). The differences between the residuals for two modeling frameworks are small. The residuals for peak frequency in Figure 7.5a show a trend with $f_{0,HV}$ that reflects features in the data whereby outliers tend to be above the 1:1 line at low frequencies and below at high frequencies, although most of the residuals are concentrated near zero. The reason for preparing these plots was to evaluate the significance of the differences between the two models (i.e., red vs blue points), which are small relative to the data scatter and not significant for any of the parameters.

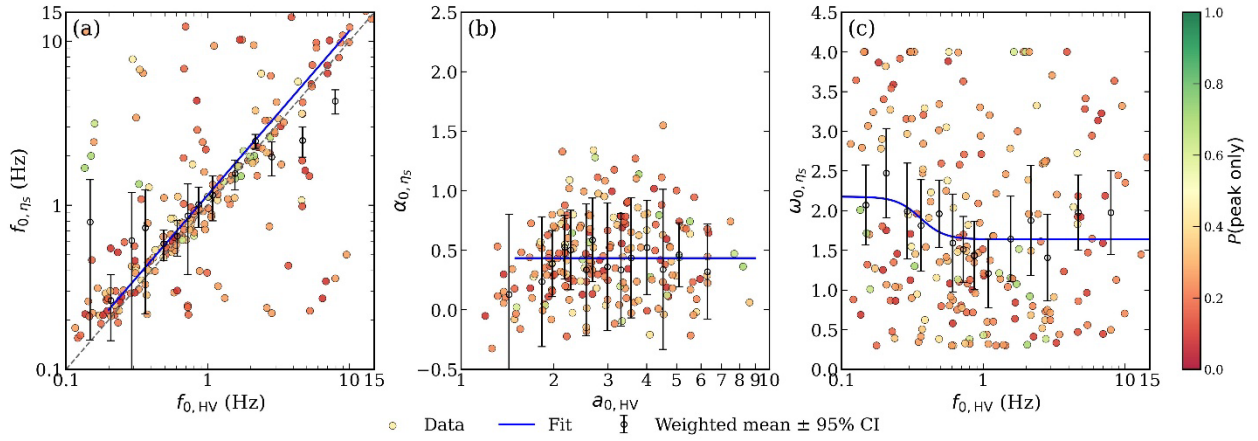


Figure 7.3. Comparison between (a) peak frequency, (b) amplitude, and (c) width of site terms for peak-only and ramp sites to features from mHVSr such as the peak frequency and peak amplitude for sedimentary sites. Data points are colored based on their probability of being peak-only from the decision tree classifier. The black error bars are binned means and 95% confidence intervals of the data. The blue line is the model fit of the data.

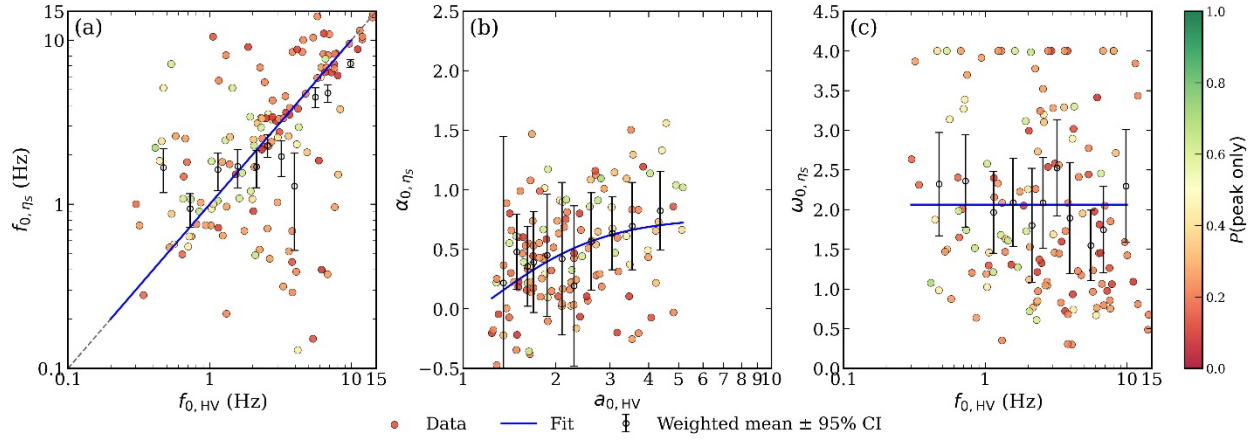


Figure 7.4. Comparison between (a) peak frequency, (b) amplitude, and (c) width of site terms for peak only and ramp sites to features from mHVSr such as the peak frequency and peak amplitude for non-sedimentary sites. Data points are colored based on their probability of being peak-only from the decision tree classifier. The black error bars are binned means and 95 % confidence intervals of the data. The blue line is the model fit of the data.

The practical significance of this finding is that the models developed in Section 7.1.1 can be applied to predict the site response peaks for sites with both peaks and ramps. Moreover, the models are essentially equally effective when applied in forward applications with weights vs when applied with full weight for each data point.

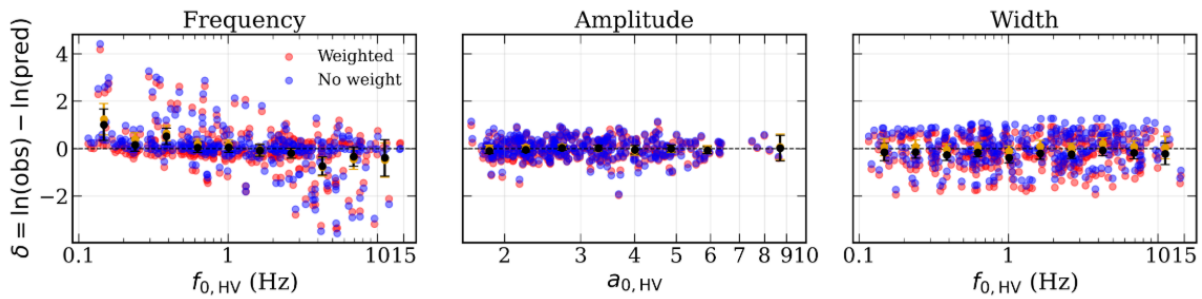


Figure 7.5. Comparison between natural log residuals from using weighted regression (this section) and non-weighted regression (Section 7.1.1) for the 143 sites identified as having peak-only site terms.

7.1.3 Investigation of Outliers

A fundamental expectation of the model development work presented in this thesis is that the frequencies of mHVSr resonant peaks correlate to the frequencies of site response peaks. As shown in Figures 7.1 and 7.2, for a large majority of sites this expectation is realized, but those figures also show that there are sites where the two frequencies do not seem to be correlated with each other. In this section, I evaluate sites that are potential outliers based on the Tukey method (Tukey 1977) (also referred to as the $1.5 \times \text{IQR}$ (Interquartile Range) rule).

The Tukey method utilizes residuals between $f_{0,HV}$ and f_{0,η_S} and then takes the 25th (Q_1) and 75th percentile (Q_3) of the data to compute the interquartile range (difference of Q_1 and Q_3). This interquartile range is then partitioned into a lower boundary ($Q_1 - 1.5 \times (\text{IQR})$) and an upper bound ($Q_3 + 1.5 \times (\text{IQR})$). If an individual residual is less than the lower bound or greater than the upper bound, it is classified as an outlier. Figure 7.6 shows site terms and mHVSr curves for 21 sedimentary sites that were classified as outliers based on this range. Many of the sites (e.g., 1282 and 4006) have a low frequency mHVSr peak and a higher frequency site response peak; the site response peaks at these sites are often close to the low-frequency limit of the site term data. In other cases, they have a secondary, higher frequency, mHVSr peak that aligns with the site term peak. For cases with secondary peaks, the outlier would be reduced by selecting the higher-frequency peak, but model development requires application of consistent protocols, which in this case involved selection of the lowest frequency peak. In forward applications, it is possible to model site response peaks for secondary peaks or even tertiary mHVSr peaks using the models from Section 7.1.1, which is discussed further in Section 7.1.5.

Other outlier sites in Figure 7.6 (e.g., 4364 and 4374) have low frequency site term peaks and relatively high frequency mHVSr peaks. For many of these sites, mHVSr is more correlated with a secondary site term peak rather than the lowest frequency.

Figure 7.7 shows 10 sites that were outliers of the non-sedimentary site model. For many of these sites, the mHVSr fundamental peak is more correlated with a secondary site peak at a higher frequency than the fundamental peak. For some sites, such as site 3736, low-frequency mHVSr peaks occur despite the site having relatively shallow sediments (i.e., $z_{1.0}$ is low, $\delta_{z_1} < 0$); for such sites, long period resonances are not generally expected, but these features may indicate unexpectedly deep impedance contrasts.

7.1.4 Plateau Adjustment Model for Peak-based Model

In Section 6.2.2b, I fit the flat areas (or plateaus) adjacent to peaks, allowing for different natural log amplitudes to the left and right of the peaks (P_L and P_R , respectively). In this section, I investigate whether those plateaus correlate with mHVSr parameters.

Figures 7.8 and 7.9 show the variations of P_L and P_R with the lowest site frequency $f_{0,HV}$ for sedimentary and non-sedimentary sites, respectively. For sedimentary sites, I have not modelled a trend of P_L or P_R with $f_{0,HV}$ but instead used constants of -0.022 and -0.078 natural log units, respectively. For non-sedimentary sites, the trends are fit using logistic functions,

$$P_L(f_{0,HV}) = \frac{P_{L0}}{1 + e^{-P_{L1}(\log_{10}(f_{0,HV}) - P_{L2})}} + P_{L3} \quad (7.7)$$

$$P_R(f_{0,HV}) = \frac{P_{R0}}{1 + e^{-P_{R1}(\log_{10}(f_{0,HV}) - P_{R2})}} + P_{R3} \quad (7.8)$$

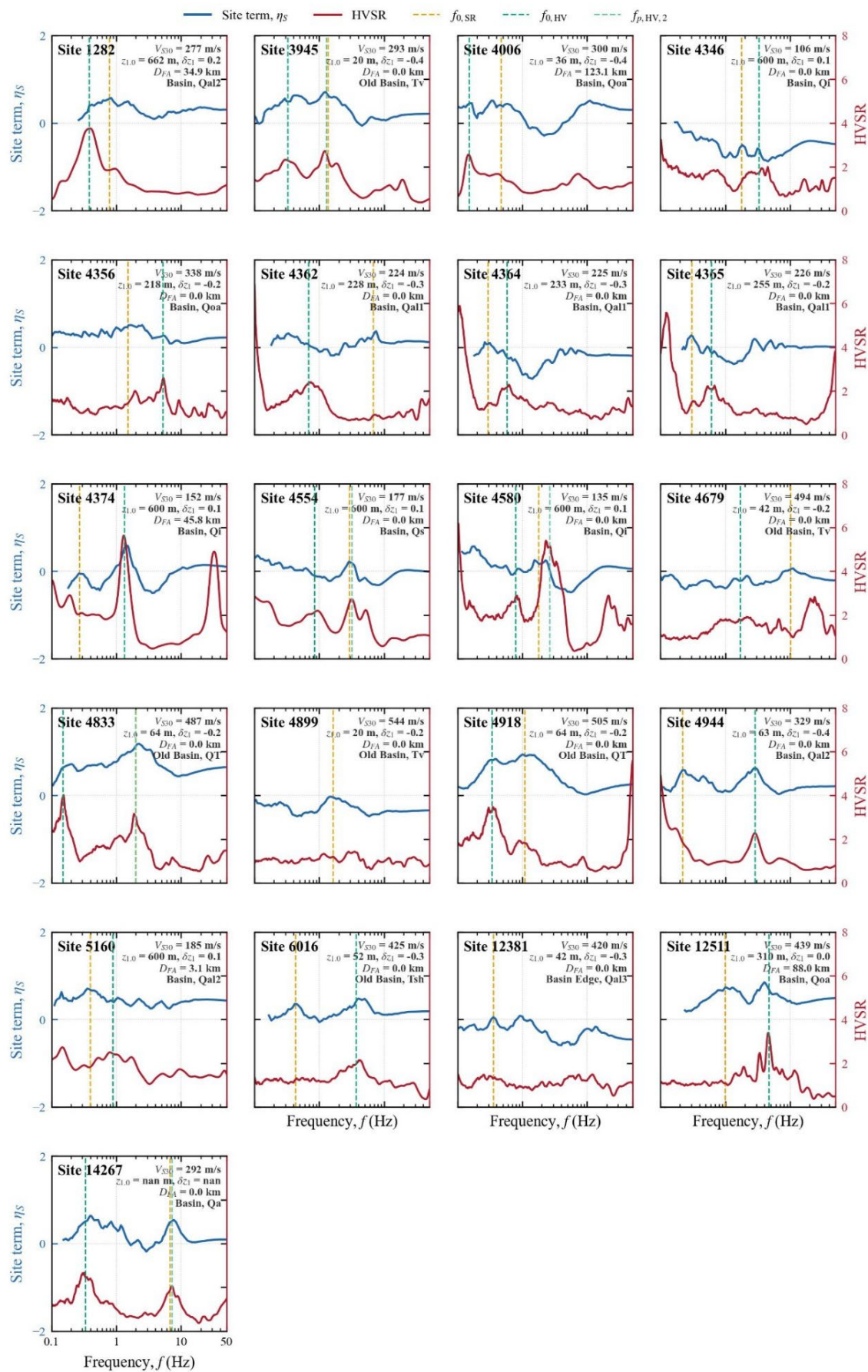


Figure 7.6. Comparison of site terms and mHVSr for 21 sedimentary sites that were deemed frequency outliers. The dashed lines indicate the peaks that were identified.

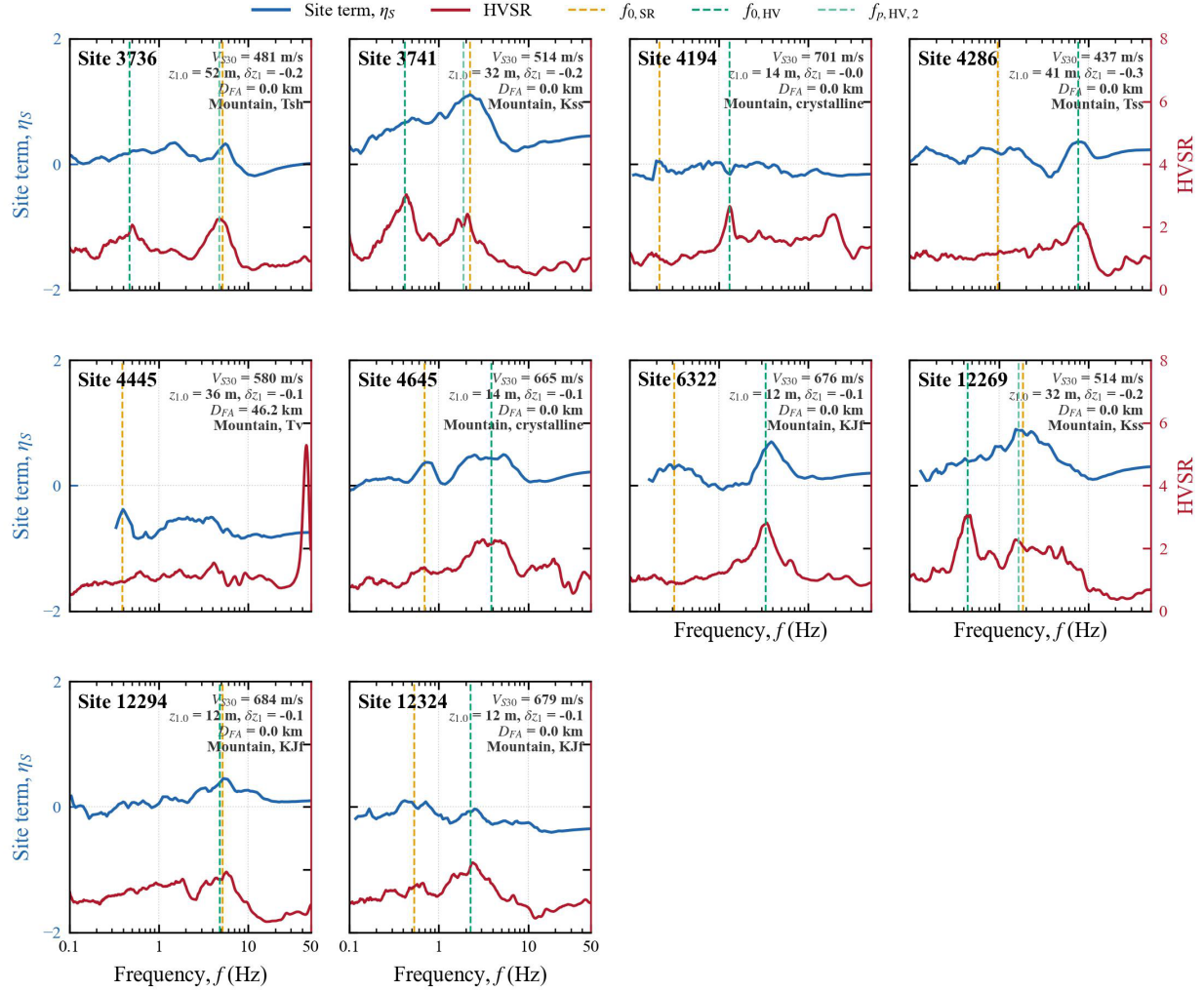


Figure 7.7. Comparison of site terms and mHVSr for 10 non-sedimentary sites that were deemed outliers. The dashed lines indicate the peaks that were identified.

These logistic functions provide small positive ordinates (~ 0.05 - 0.1) for low $f_{0,HV}$ and transition to relatively large negative ordinates (~ -0.45 to -0.55) for high $f_{0,HV}$. Table 7.2 lists the coefficients used for the plateau models.

Table 7.2. Summary of coefficients used in the models for the plateau adjustment to the peak-based model for different geomorphic categories.

Geomorphic Category	P_L	P_R	P_{L0}	P_{L1}	P_{L2}	P_{L3}	P_{R0}	P_{R1}	P_{R2}	P_{R3}
Sedimentary	-0.022	-0.078	Na	Na	Na	Na	Na	Na	Na	Na
Non-sedimentary	Na	Na	0.578	-10	0.51	-0.39	0.70	-10.0	0.62	-0.59

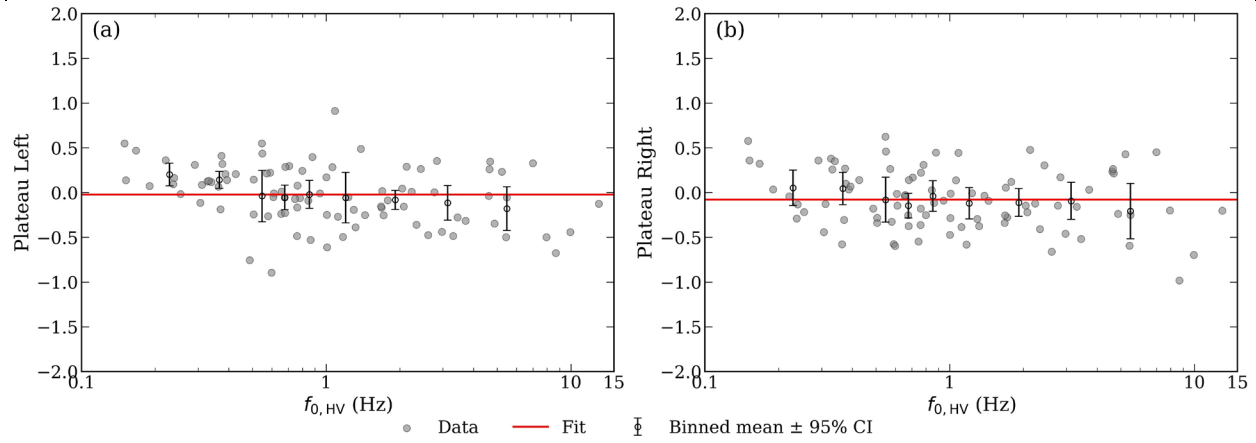


Figure 7.8. Relationships between the (a) left and (b) right plateau amplitudes to mHVSr peak frequency for sedimentary sites. The black error bars are binned means and 95 % confidence intervals of the data. The red line is the model fit of the data.

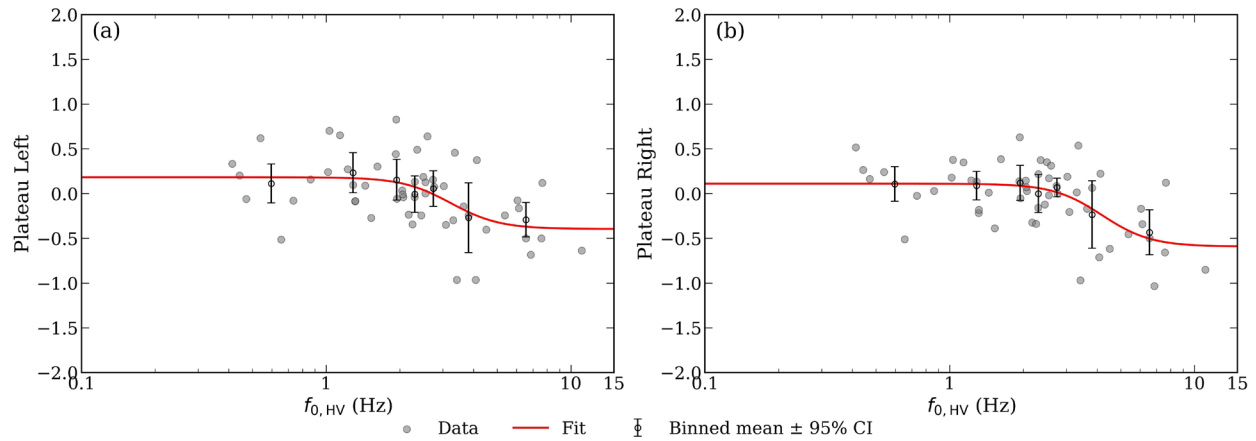


Figure 7.9. Relationships between the (a) left and (b) right plateau amplitudes to mHVSr peak frequency for non-sedimentary sites. The black error bars are binned means and 95 % confidence intervals of the data. The red line is the model fit of the data.

7.1.5 Combined Model for Sites with Peaks

The combined model includes one or more Gaussian functions (for the number of peaks to be considered) from Section 7.1.1 and the plateau model from Section 7.1.4. For the common case in which only one peak is identified, a single peak function is considered based on Eq. 7.6. That peak is combined with a transition function adapted from Eq. 6.5 as follows:

$$F_p(T) = \begin{cases} F_{peak}(T)\Phi(T) + P_L(1 - \Phi(T)), & T < T_p = 1/f_{0,\eta_s} \\ F_{peak}(T)\Phi(T) + P_R(1 - \Phi(T)), & T > T_p \end{cases} \quad (7.9)$$

where $\Phi(T)$ is a Gaussian operator used in the transition function, which is defined as (adapted from Eq. 6.4),

$$\Phi(T) = \exp\left(-\left(\frac{T - 1/f_{0,\eta_s}}{\omega_{0,\eta_s} \times 0.5}\right)^2\right) \quad (7.10)$$

The 0.5 multiplier on ω_{0,η_s} is the selected value of a smoothing parameter. Now suppose there are n peaks within an mHVS curve that are to be considered in the site response model. In this case Eq. 7.6 is applied for each peak i and the resulting Gaussian pulses are summed,

$$F_{peak}^t = \sum_{i=1}^n F_{peak,i} \quad (7.11)$$

where $F_{peak,i}$ represents individual Gaussian pulses from Eq. 7.6. To construct the transition operator, n values of P_L , P_R , and $\Phi(T)$ are evaluated (for each individual period in the case of $\Phi(T)$).

The maximum among the n values is then identified:

$$P_{L,max} = \max_{1 \leq i \leq n} P_{L,i} \quad (7.12a)$$

$$P_{R,max} = \max_{1 \leq i \leq n} P_{R,i} \quad (7.12b)$$

$$\Phi(T)_{max} = \max_{1 \leq i \leq n} \Phi(T)_i \quad (7.12c)$$

where Eq. 7.12c is applied for each period T . The peak model amplification $F_p(T)$ is then computed as follows:

$$F_p(T) = \begin{cases} F_{peak}^t(T)\Phi(T)_{max} + P_{L.max}(1 - \Phi(T)_{max}), & T < T_p = 1/f_{0,\eta_s} \\ F_{peak}^t(T)\Phi(T)_{max} + P_{R.max}(1 - \Phi(T)_{max}), & T \geq T_p \end{cases} \quad (7.13)$$

Among the 372 sites with peaks in the dataset, 114 contain at least two peaks and 10 contain more than 3 peaks.

7.2 Site Amplification Models for Sites with Ramps

This section presents site amplification models for sites that are known to have ramp-like features, which can be ascending or descending as identified in Section 6.2.2.3. This comprises 189 descending ramp sites and 251 ascending ramp sites, among which 161 and 183 have mHVSr peaks, respectively. The modeling in this section is used to estimate dependent variables that describe a logistic function that is adapted from Eq. 6.6:

$$F_{ramp}(T) = \frac{L}{1 + \exp\left(-k \cdot \log_{10}\left(\frac{T}{T_c}\right)\right)} + a_0 \quad (7.14)$$

The dependent variables in Eq. 7.14 are L (amplification change across the logistic function), k (slope parameter; positive for ascending, negative for descending), a_0 (additive constant), and T_c (central period). For the sites with mHVSr peaks, these parameters are estimated using independent variables related to mHVSr peaks. For sites without mHVSr peaks, they are estimated using other mHVSr parameters (i.e. ordinates at particular frequencies or ranges of frequencies). All regressions are performed giving equal weights to all data points, which was

found to be effective for peak sites when compared to results of weighted regressions (details in Section 7.1.2).

7.2.1 Ascending Ramp Models for Sites with mHVSr Peaks

The parameters for the ascending ramp model in Eq. 7.14 are derived using the 183 available sites by first segregating them into the sedimentary and non-sedimentary geomorphic groups. Figure 7.10 shows relationships between various mHVSr parameters and the coefficients in Eq. 7.14 for sedimentary sites. Individual data points are shown along with binned means and their 95% confidence intervals.

Figure 7.10a shows the relationship between amplitude parameter L and the mean natural log geometric mean mHVSr between 0.12-2 Hz ($\ln(\overline{HVSr}_{GM,0.12-2Hz})$). This parameter and others investigated had no predictive power for L , so a constant value of 0.743 is used. Figure 7.10(b) shows that growth rate k decreases as mHVSr peak frequency $f_{0,HV}$ increases from about 0.1-0.35 Hz, after which k saturates. A logistic function was fit to the data to capture this trend as follows:

$$k(f_{0,HV}) = \frac{k_1}{1 + e^{-k_2(\log_{10}(f_{0,HV}) - k_3)}} + k_4 \quad (7.15)$$

where k_1 is the logistic range parameter, k_2 is the growth rate, k_3 is the midpoint, and k_4 is a constant adjustment. The regressed parameters in Eq. 7.15 are provided in Table 7.3. Figure 7.10c shows that the inverse of the midpoint of the logistic function ($1/T_c$) increases as $f_{0,HV}$ increases over the range 0.1-0.3 Hz, after which it saturates at about 2 Hz (0.5 sec).

Ascending Ramp — Sedimentary

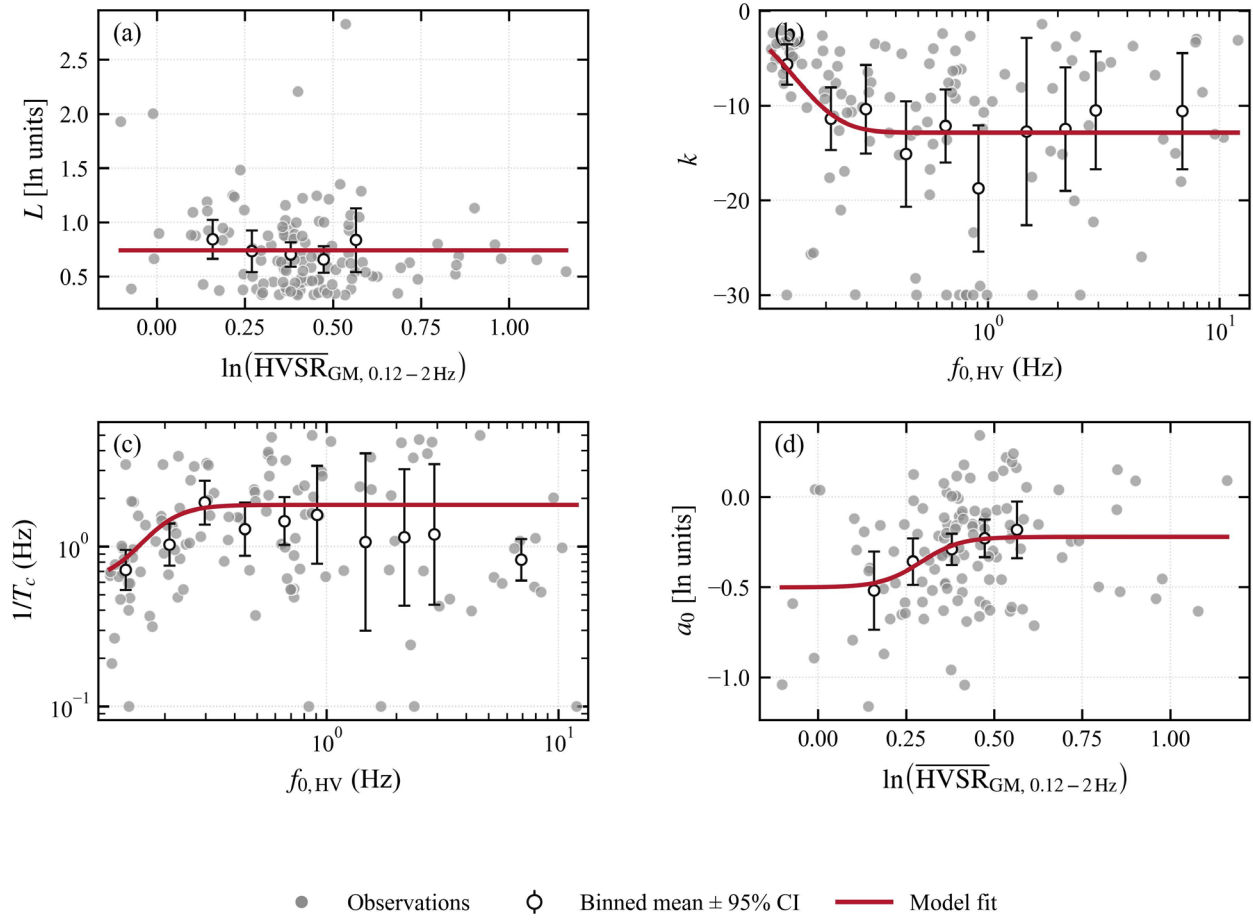


Figure 7.10. Comparison between parameters descriptive of site term ascending ramps and mHVSr parameters for sedimentary sites: (a) range parameter; (b) growth parameter; (c) central frequency; and (d) constant term. Black error bars indicate binned mean and 95% confidence intervals. The red lines indicate the model fits to the data.

The trend is fit with the logistic function,

$$x(f_{0,HV}) = \frac{x_1}{1 + e^{-x_2(\log_{10}(f_{0,HV}) - x_3)}} + x_4 \quad (7.16)$$

where $x = 1/T_c$. The regressed parameters are in Table 7.3. Figure 7.10d shows the trend of the constant adjustment of the logistic function relative to $\ln(\overline{HVSR}_{GM,0.12-2Hz})$. This term is strongly

negative for low $\ln(\overline{HVS\overline{R}}_{GM,0.12-2Hz})$ and approaches zero as $\ln(\overline{HVS\overline{R}}_{GM,0.12-2Hz})$ increases. A logistic function was fit to the data,

$$a_0 \left(\ln(\overline{HVS\overline{R}}_{GM,0.12-2Hz}) \right) = \frac{a_1}{1 + e^{-a_2(\ln(\overline{HVS\overline{R}}_{GM,0.12-2Hz}) - a_3)}} + a_4 \quad (7.17)$$

Table 7.3. Coefficients used in the ascending ramp model conditioned on mHVS $\overline{R}$ parameters for different geomorphic groups.

Category	L	k	x_0	k_1	k_2	k_3	k_4	x_1	x_2	x_3	x_4	a_1	a_2	a_3	a_4
Sedimentary	0.75	Na	Na	17.1	22.6	0.12	-12.8	1.28	-11.2	-0.77	0.51	-0.28	19.0	0.28	-0.22
Non-sedimentary	0.66	-10.7	2.46	Na	Na	Na	Na	Na	Na	Na	Na	-0.38	50	0.12	-0.32

Figure 7.11 shows the same plots as in Figure 7.10 but for the non-sedimentary geomorphic group. There was much less data available for model training for non-sedimentary sites within the ascending ramp category. This was not surprising, as ascending ramps indicate increased long-period site response, which is typical of sedimentary sites. Non-sedimentary (or mountain-hill) sites are expected to have shallow soil or weathered rock profiles, which would generally be expected to have limited long-period site response and strong short-period site response (i.e., descending ramps). The relatively few sites that fall within this category are likely mountainous sites with deep and relatively soft Tertiary units that produce a deep impedance contrast. Figure 7.11(a-c) shows a lack of trends with mHVS $\overline{R}$ parameters for L , k , and $1/T_c$, which are modelled as constants. The constant adjustment was modelled using Eq. 7.17 with the coefficients in Table 7.3.

Ascending Ramp — Non-sedimentary

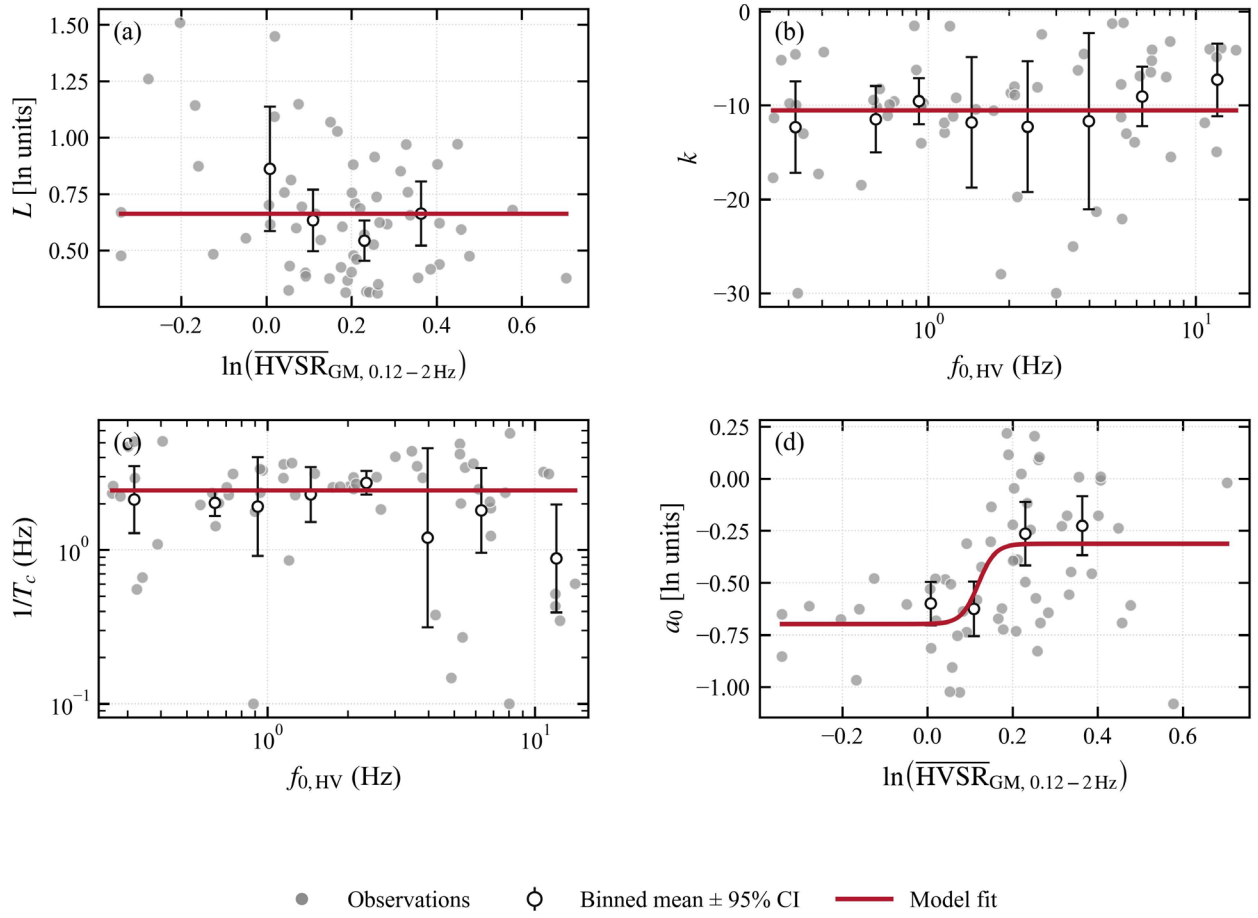


Figure 7.11. Comparison between parameters descriptive of ascending ramps and mHVSr parameters for non-sedimentary sites: (a) range parameter; (b) growth parameter; (c) central frequency; and (d) constant term. Black error bars indicate binned mean and 95% confidence intervals. The red lines indicate the model fits to the data.

7.2.2 Descending Ramp Models for Sites with mHVSr Peaks

The parameters for the descending ramp model in Eq. 7.14 are derived using the 161 available sites by first segregating them into the sedimentary and non-sedimentary geomorphic groups. Figure 7.12 shows the relationships between various mHVSr parameters and the coefficients in Eq. 7.14 for sedimentary sites.

Descending Ramp — Sedimentary

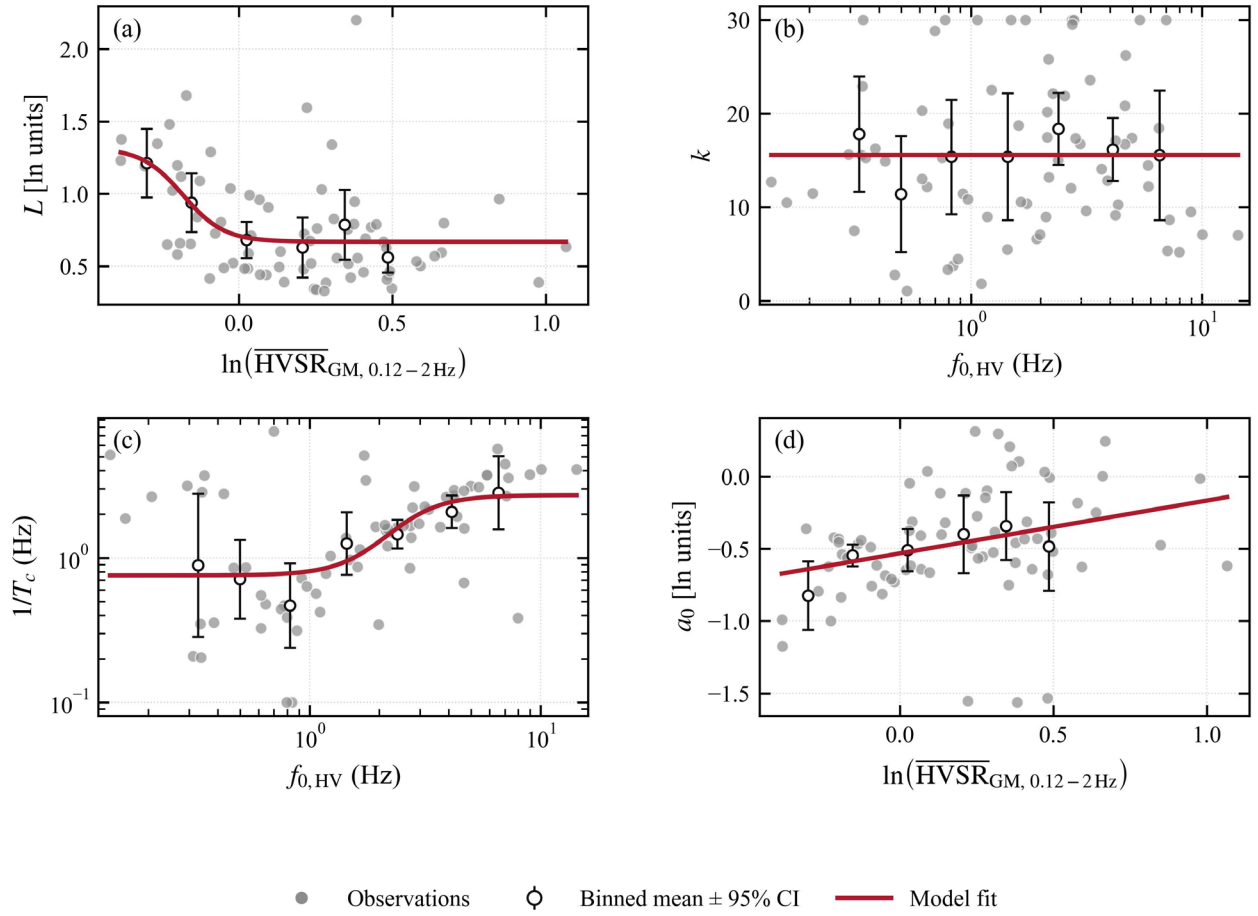


Figure 7.12. Comparison between parameters descriptive of descending ramps and mHVSr parameters for sedimentary sites: (a) range parameter; (b) growth parameter; (c) central frequency; and (d) constant term. Black error bars indicate binned mean and 9% confidence intervals. The red lines indicate the model fits over the data.

Figure 7.12a shows the relationship between amplitude parameter L and the mean natural log geometric mean mHVSr between 0.12-2 Hz ($\ln(\overline{HVSR}_{GM,0.12-2Hz})$). L increases as $\ln(\overline{HVSR}_{GM,0.12-2Hz})$ decreases, meaning that as low frequency mHVSr decreases, site response tends to be more energetic at higher frequencies (or shorter periods). A logistic function was fit to the data,

$$L\left(\ln(\overline{HVSR}_{GM,0.12-2Hz})\right) = \frac{L_1}{1 + e^{-L_2(\ln(\overline{HVSR}_{GM,0.12-2Hz}) - L_3)}} + L_4 \quad (7.17)$$

The regressed parameters in Eq. 7.17 are provided in Table 7.4. Figure 7.12b shows that growth rate is independent of $f_{0,HV}$ (while not shown, it is similarly independent of $\ln(\overline{HVSR}_{GM,0.12-2Hz})$), which is different from the ascending ramp data for sedimentary sites. A constant value of $k = 15.57$ is adopted. Figure 12(c) shows a strong linear trend between $f_{0,HV}$ and the inverse of the mid-period ($1/T_c$) in the logistic function. This is consistent with what was seen visually in the data (e.g., Figures 6.15, 6.16, 6.18), where $f_{0,HV}$ typically occurs at the top of the ramp. The data show no relationship to the 1:1 line shown in gray. A logistic function was fit to the data using Eq. 7.16 with the results shown in Table 7.4. Figure 7.12d shows that the constant adjustment increases with $\ln(\overline{HVSR}_{GM,0.12-2Hz})$, meaning that as low-frequency mHVSr amplitudes increase, site response amplitudes increase across all periods, albeit with tradeoffs with the trends in L at long periods. The linear fit equation follows:

$$a_0(\ln(\overline{HVSR}_{GM,0.12-2Hz})) = a_1 \ln(\overline{HVSR}_{GM,0.12-2Hz}) + a_2 \quad (7.18)$$

where a_1 is slope and a_2 the intercept. These coefficients are provided in Table 7.4.

Table 7.4. Coefficients used in the descending ramp model conditioned on mHVSr parameters for different geomorphic groups.

Geomorphic Category	L_1	L_2	L_3	L_4	k	x_1	x_2	x_3	x_4	a_1	a_2
Sedimentary	0.65	14.8	-0.18	0.66	15.57	0.55	8.61	0.34	-0.12	0.37	-0.53
Non-sedimentary	0.14	34.8	-0.03	0.66	14.7	2.33	1.55	-0.17	-1.50	0.60	-0.44

Figure 7.13 shows the same plots as in Figure 7.12 but for non-sedimentary sites. Compared to the ascending ramp case, descending ramp non-sedimentary sites are relatively numerous because high-frequency resonances for rock sites are common. Identical functional forms were used to those for the sedimentary sites, but with different model coefficients. Figure 7.13a shows that the decrease of L as $\ln(\overline{HVSR}_{GM,0.12-2Hz})$ increases is less pronounced than for

sedimentary descending ramp sites. Figure 7.13b shows an mHVSr parameter-invariant $k = 14.7$. Figure 7.13c shows a larger variation of mid-period ($1/T_c$) with $f_{0,HV}$ than was present for the sedimentary group. Moreover, in the range of $f_{0,HV} = 1-3$ Hz, median $1/T_c$ ranges from 0.6-1.5 Hz, whereas for that same range of $f_{0,HV}$, higher $1/T_c$ values of 0.8 to 2 Hz were encountered for the sedimentary group. Hence, somewhat unexpectedly, descending ramps occur at longer periods for non-sedimentary vs. sedimentary groups. Figure 7.13d shows that the constant adjustment increases more strongly with $\ln(\overline{HVSr}_{GM,0.12-2Hz})$ than for the sedimentary group. Table 7.4 provides the coefficients for the model fits.

7.2.3 Ramp-based models without mHVSr peaks

The ramp models presented in Section 7.2.1-7.2.2 are only useable for sites where a mHVSr peak is present. The numbers of ramp sites without mHVSr peaks are 68 and 28 for ascending and descending sites, respectively. I could have modelled all the sites together, but this would have required not using mHVSr peak frequency, which has very strong correlations with parameters in the logistic site term model. Accordingly, separate models were developed for sites without mHVSr peaks, which are the subject of this section.

Model development in this case follows the same general process from Sections 7.2.1-7.2.2, but without consideration of $f_{0,HV}$; after trial-and-error in which differential depth (δ_{z_1}) and mHVSr ordinates at particular frequencies (e.g., 0.12 Hz, 0.2 Hz) were considered, I selected $\ln(\overline{HVSr}_{GM,0.12-2Hz})$ as the independent variable for these models. Also, due to the limited number of sites without mHVSr peaks, I do not sub-divide into sedimentary and non-sedimentary geomorphic groups. Figures 7.14 and 7.15 show the data points and fits for ascending and descending ramp sites, respectively.

Descending Ramp — Non-sedimentary

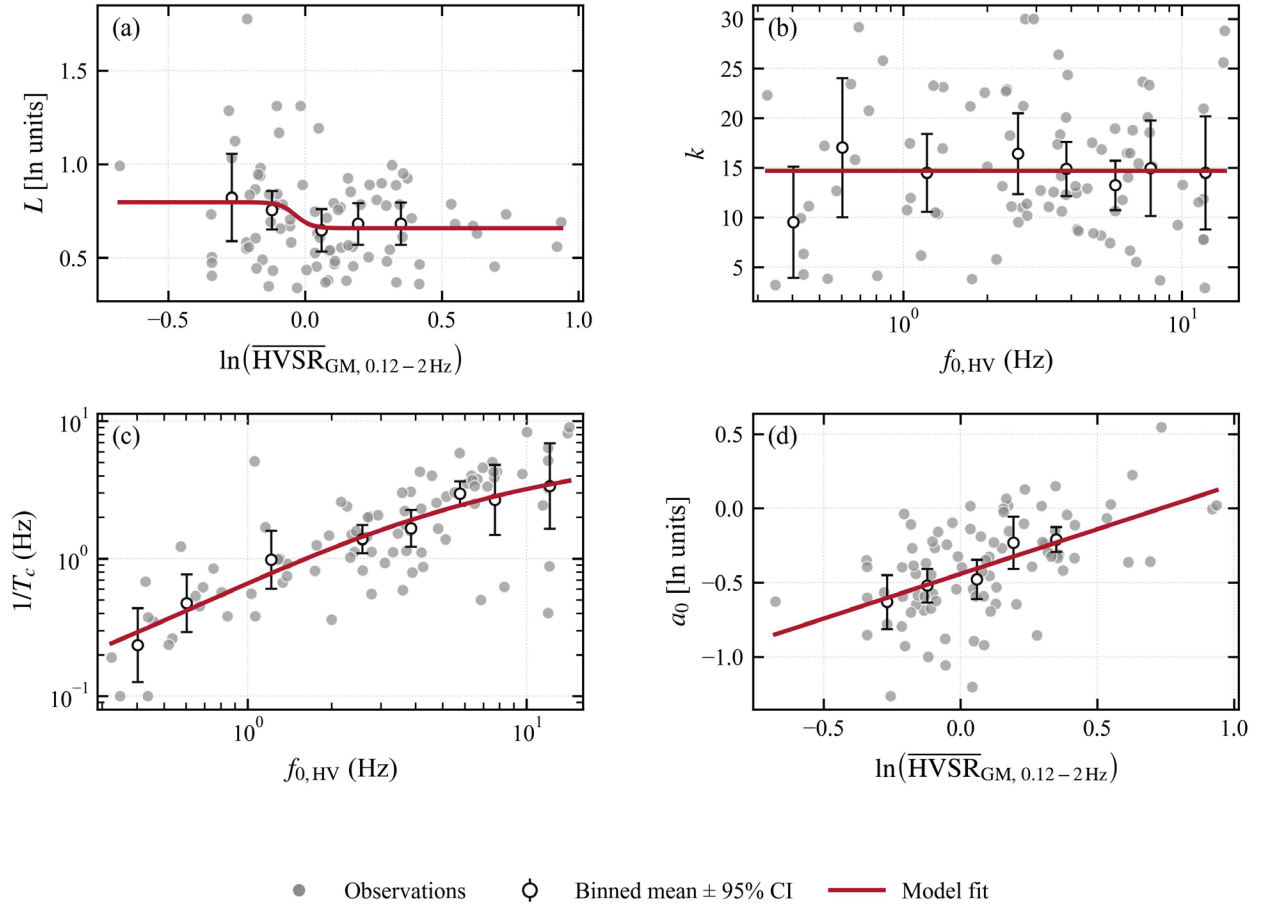


Figure 7.13. Comparison between parameters descriptive of descending ramps and mHVSR parameters for non-sedimentary sites: (a) range parameter; (b) growth parameter; (c) central frequency; and (d) constant term. Black error bars indicate binned mean and 95% confidence intervals. The red lines indicate the model fits to the data.

For the ascending ramp cases, Figures 7.14(a-c) shows a lack of trend for L , k , and $1/T_c$ so fixed values of $L = 0.80$, $k = -8.22$, and $1/T_c = 0.995 \text{ Hz}$ were selected. Figure 7.14d shows that the constant adjustment increases with $\ln(\overline{HVSR}_{GM,0.12-2\text{Hz}})$, which is expected (larger low frequency mHVSR ordinates correlates with higher long-period site response). The logistic fit for the constant term is given by,

$$a_0 \left(\ln(\overline{HVSR}_{GM,0.12-2\text{Hz}}) \right) = \frac{a_1}{1 + e^{-a_2(\ln(\overline{HVSR}_{GM,0.12-2\text{Hz}}) - a_3)}} + a_4 \quad (7.19)$$

Table 7.5 provides the coefficients for the model fits. The trends for L (flat) and a_0 (increasing) can be compared to those in Section 7.2.1 since $\ln(\overline{HVSR}_{GM,0.12-2Hz})$ is the independent variable in both cases; the trends for these two data sets are similar.

Table 7.5. Coefficients used in the ascending and descending ramp models for sites without mHVS peaks.

Ramp-Type	L	L_0	L_1	L_2	L_3	k	x	x_0	x_1	x_2	x_3	a_1	a_2	a_3	a_4
Ascending	0.80	Na	Na	Na	Na	-8.22	0.99	Na	Na	Na	Na	-0.47	29.6	0.13	-0.19
Descending	Na	0.39	50.0	-0.15	0.51	13.5	Na	0.74	-50	0.04	-0.20	-0.39	50.0	-0.18	-0.35

For the descending ramp cases, Figure 7.15b shows a lack of trend for k so a fixed value of $k = 13.5$ was selected. Figure 7.15a shows a descending trend of L with $\ln(\overline{HVSR}_{GM,0.12-2Hz})$ that is modeled with the logistic function in Eq. 7.17. Figure 7.15c shows a decreasing trend of $1/T_c$ with $\ln(\overline{HVSR}_{GM,0.12-2Hz})$ that is modeled as,

$$x \left(\ln(\overline{HVSR}_{GM,0.12-2Hz}) \right) = \frac{x_1}{1 + e^{-x_2(\ln(\overline{HVSR}_{GM,0.12-2Hz}) - x_3)}} + x_4 \quad (7.20)$$

where $x = 1/T_c$. Figure 7.16(d) shows an increasing trend of a_0 with $\ln(\overline{HVSR}_{GM,0.12-2Hz})$ that is modeled with the logistic function in Eq. 7.19. The trends for L (descending) and a_0 (increasing) can be compared to those in Section 7.2.2 since $\ln(\overline{HVSR}_{GM,0.12-2Hz})$ is the independent variable in both cases; the trends for these two data sets are similar. Table 7.5 provides the coefficients for the model fits.

Ascending Ramp

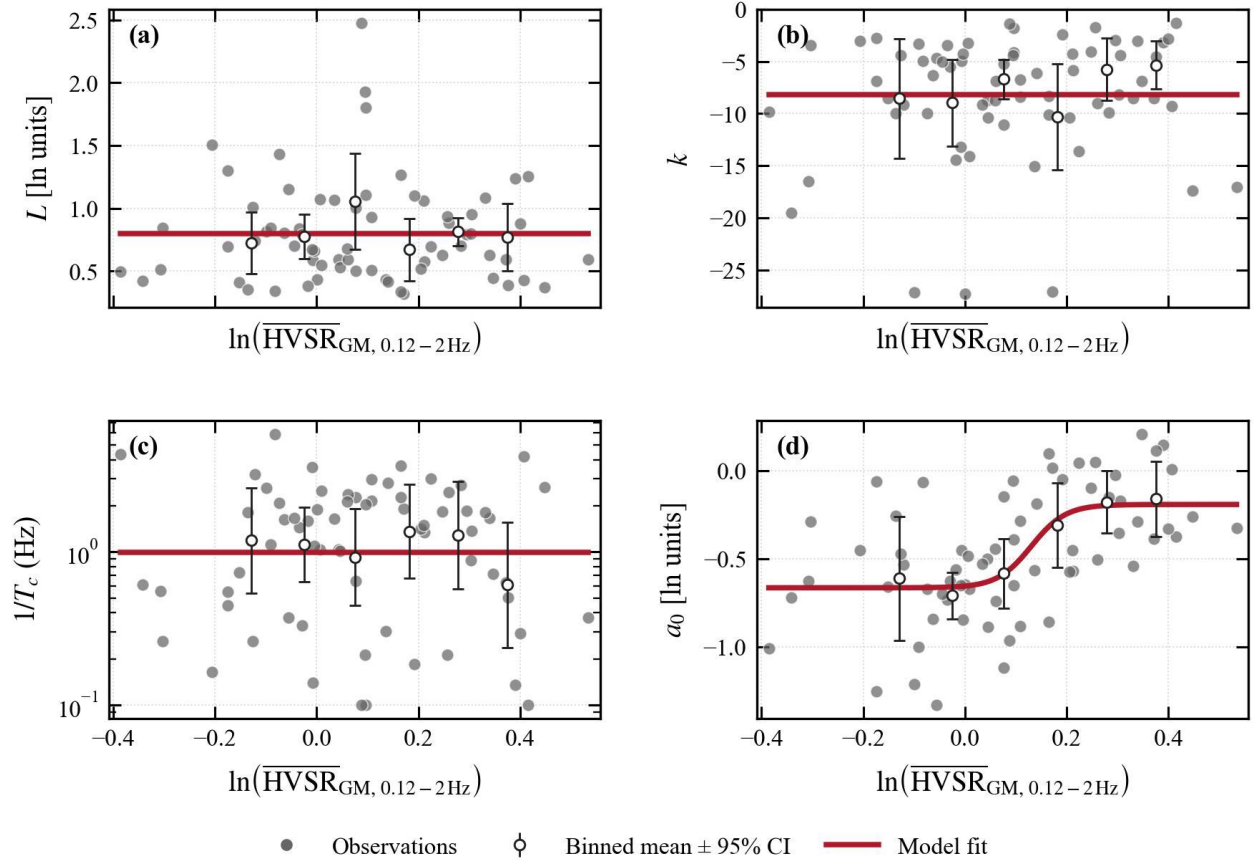


Figure 7.14. Comparison between parameters descriptive of ascending ramps and non-peak mHVSr parameters: (a) range parameter; (b) growth parameter; (c) central frequency; and (d) constant term. Black error bars indicate binned mean and 95% confidence intervals. The red lines indicate the model fits to the data.

Descending Ramp

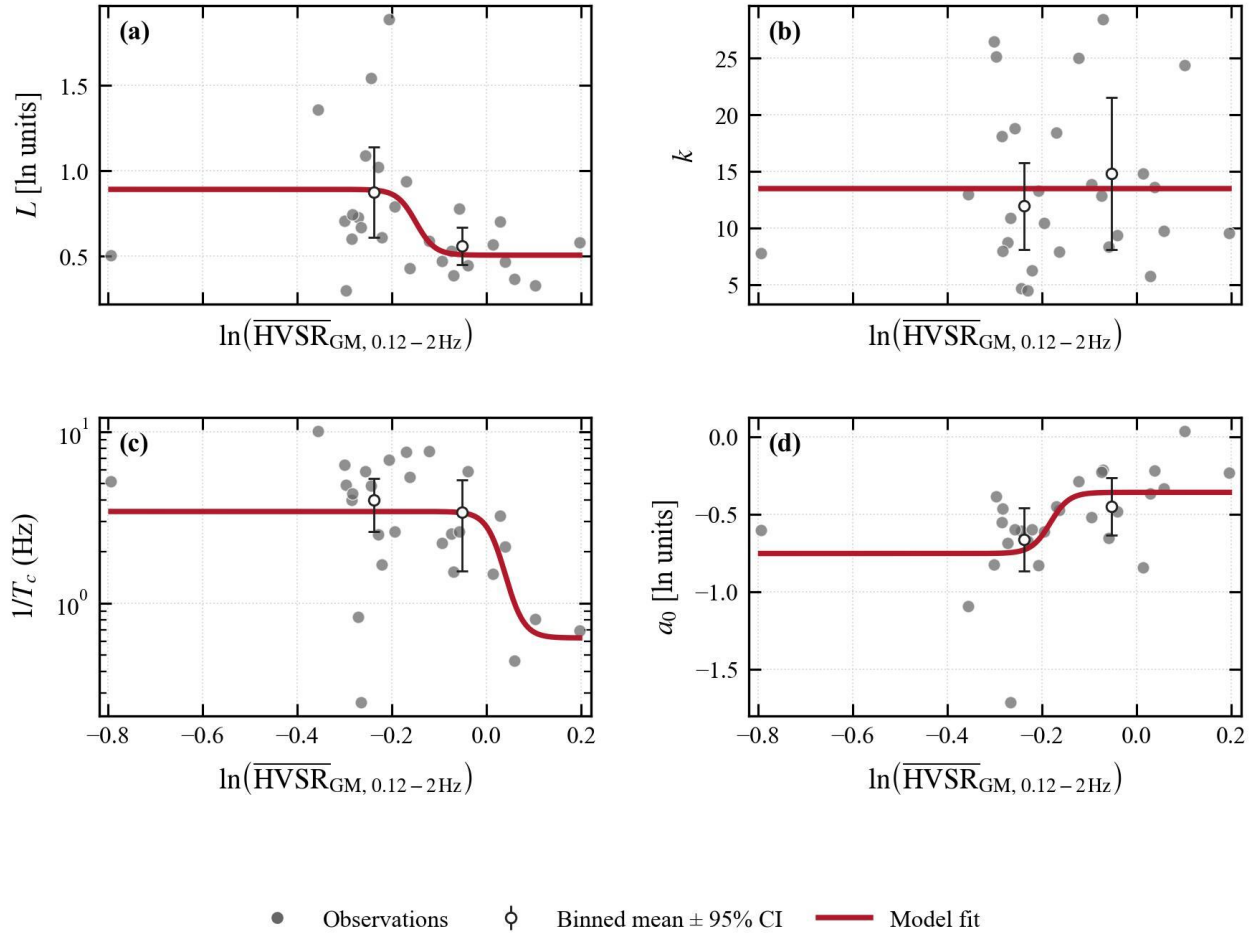


Figure 7.15. Comparison between parameters descriptive of descending ramps and non-peak mHVSr parameters: (a) range parameter; (b) growth parameter; (c) central frequency; and (d) constant term. Black error bars indicate binned mean and 95% confidence intervals. The red lines indicate the model fits to the data.

7.3 Site Amplification Models for Sites without Peak- or Ramp-like Features

This section presents a simple site amplification model for sites that are known to lack peak or ramp features based on the criteria presented in Section 6.2.2.4. This comprises 70 sites, among which 44 have mHVSr peaks. Figure 6.19 shows examples of flat sites.

The models in this section consist of period dependent constants,

$$F_{flat}(T) = c_0 \quad (7.21)$$

I investigated the dependence of c_0 on the sedimentary (but with old basin removed; hence different than previous sedimentary groups in prior section) and non-sedimentary (defined as mountain-hill and old basin in this section). This re-grouping was applied due to similarities that were seen in the data amongst different groups, whereby mountain-hill and old basin sites shared negative site terms. Similarly, valley, basin-edge, and basin sites were combined as they shared mean site terms near zero. No shelf sites were classified as being flat.

Figure 7.16 shows individual site terms for the 31 mountain and old basin sites and the 39 valley, basin-edge, and basin sites. The means for the mountain-hill and old basin group are generally in the range of -0.2 to -0.24 with no trend with period. No weighting was applied in the calculation of the arithmetic average, which are in natural log units. The means for the valley, basin-edge, and basin sites are in the range of -0.05 to 0.05.

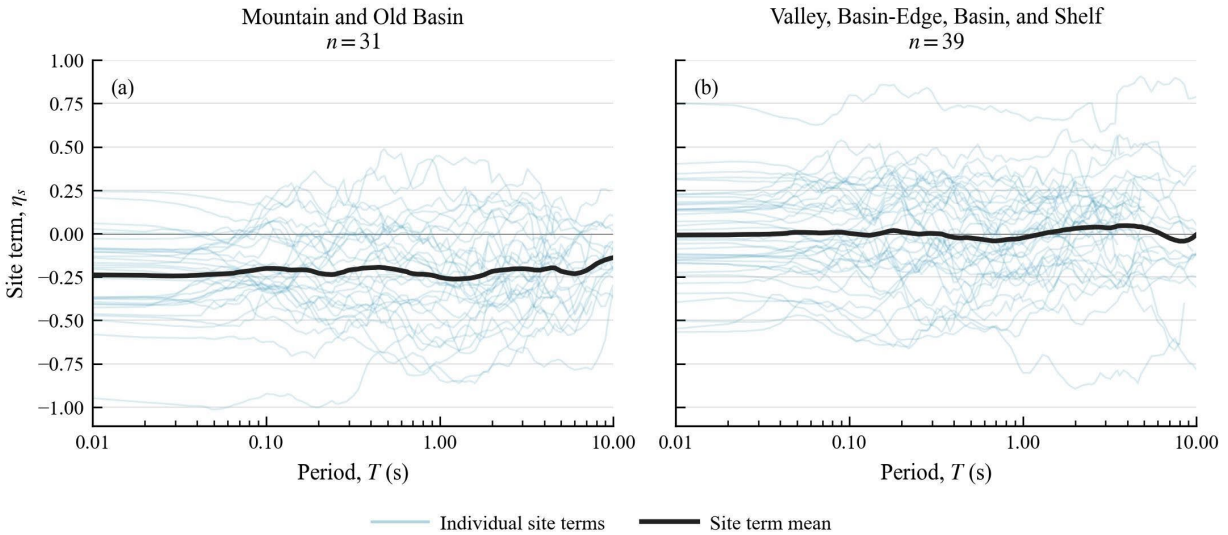


Figure 7.16. Site terms for individual sites and their means for: (a) mountain-hill and old basins, (b) valley, basin-edge, and basin categories.

A Savitsky-Golay smoothing filter (Savitzky and Golay 1964) was applied to smooth the average curves with the results in Figure 7.17. The model in Eq. 7.21 should be applied to any site that has a non-zero probability of being flat based on the decision tree classifier model.

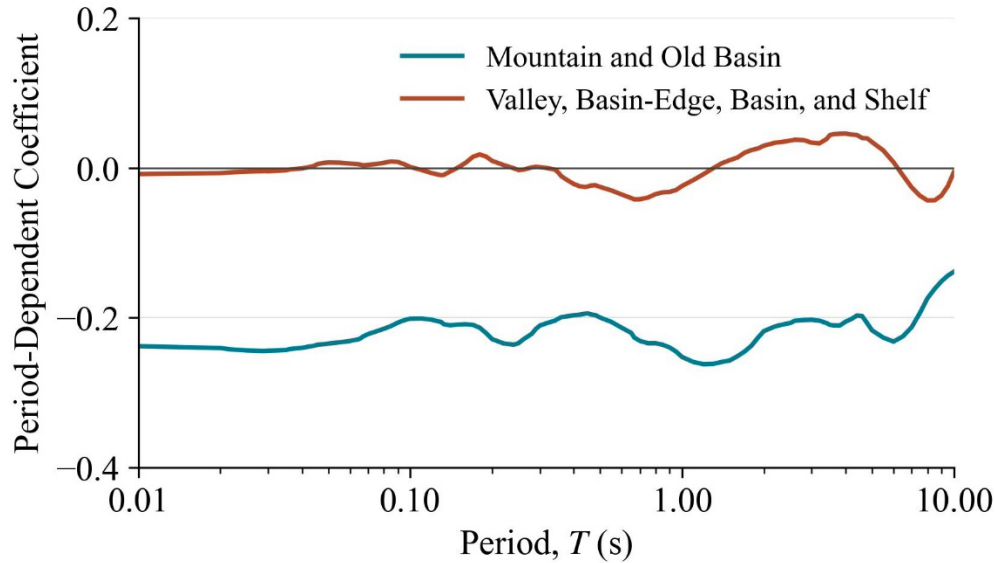


Figure 7.17. Mean coefficients c_0 for flat sites for the indicated geomorphic groups.

7.4 Machine learning-based site amplification models conditioned on mHVSr parameters

The overarching modelling approach presented at the beginning of Chapter 6 emphasized the development of parametric models for commonly observed site effects (peaks, ramps, and flat). Those models were presented in Sections 7.1-7.3. However, Task 9 of 10 was described as “Development of machine learning models for general site amplification (i.e., not in flat, ramp, or peak groups).” This task was included in this research to evaluate potential improvement in site response predictions from ensemble-based machine learning models.

Section 2.5.3 summarized previous studies that have used HVSr-based parameters (eHVSr in some cases, mHVSr in others) to train machine learning models. In this section, I

describe a similar application using 686 available sites with co-located mHVSr curves and site terms (details in Section 6.1). I applied three ensemble-based models, gradient boosting, random forest regressor, and adaptive boosting. Whereas the models described in Sections 7.1-7.3 utilized site terms (residual site response from a V_{S30} -based ergodic model), here I use the full linear site response (denoted f_1), which has been found in past work to produce stronger correlations with HVSr parameters (Pinilla-Ramos et al. 2022; Esteghamati et al. 2022). The full linear site response is computed for site j as (e.g., Stewart et al. 2017):

$$(f_1)_j = F_{lin}^{erg} + \eta_{S,j} \quad (7.22)$$

where F_{lin}^{erg} is the ergodic site response model prediction, and $\eta_{S,j}$ is the site term as described in Section 6.2. Values of f_1 and the mHVSr ordinates were resampled to a common set of 30 frequencies from 0.1 to 25 Hz of: [0.1, 0.121, 0.146, 0.177, 0.214, 0.259, 0.313, 0.379, 0.459, 0.555, 0.671, 0.812, 0.982, 1.188, 1.438, 1.739, 2.104, 2.545, 3.079, 3.724, 4.506, 5.451, 6.594, 7.977, 9.649, 11.673, 14.121, 17.083, 20.666, 25.0]. The site responses described by f_1 are uncertain due to the standard error in η_S . These site response uncertainties are not formally considered in the analyses presented here (i.e., the site response from Eq. 7.22 is taken as deterministic). The site-to-site aleatory variability (denoted ϕ_{S2S}) is closely related to the standard deviation of $\eta_{S,j}$, and hence is sensitive to the predictive power of the site response model (e.g., ergodic model from GMM, parametric models from Sections 7.1-7.3, or machine learning models). As such, the benefits of utilizing mHVSr-trained machine learning models can be quantified by their ability to reduce ϕ_{S2S} .

7.4.1 Feature Selection

I began the analyses by applying *feature selection* to evaluate what features from the portion of the dataset that serves as predictor variables (mHVSR ordinates in this case) contribute the most to the output (site response). Feature selection aims to improve model performance, reduce overfitting, and decrease computational cost, and was previously applied by Esteghamati et al. (2022) in a similar model development process. Feature selection can be applied using filter-based, embedded, and wrapper-based methods.

For the filter-based methods, I utilize:

- Pearson's coefficient correlation, (r)
- Spearman's correlation coefficient, (ρ)
- Mutual Information

Pearson's correlation assesses the degree of linear association between variables. The Spearman correlation evaluates the strength and direction of a monotonic relationship, regardless of its linearity. Mutual Information measures the reduction in entropy of the target variable attributable to a particular predictor, thereby quantifying its contribution to predictive accuracy (e.g., Vinh et al., 2010). Figure 7.18 illustrates correlations between site response and mHVSR ordinates across the frequency range of 0.1 to 30 Hz using the three filter-based methods. The strongest correlations (r and ρ) are observed over the frequency ranges of ~0.1 to 13 Hz in site response and ~0.1 to 20 Hz in mHVSR. The Mutual Information indices are high for a more limited mHVSR frequency interval of 0.1 to 15 Hz. Esteghamati et al. (2022) reached similar conclusions using data from the Kiban-Kyoshin network (KiK-Net; Aoi et al. 2001), finding strong correlations between site response and eHVSR between 0.1 and 22 Hz for Pearson's and Spearman's, and between 0.2 and 10 Hz for mutual information.

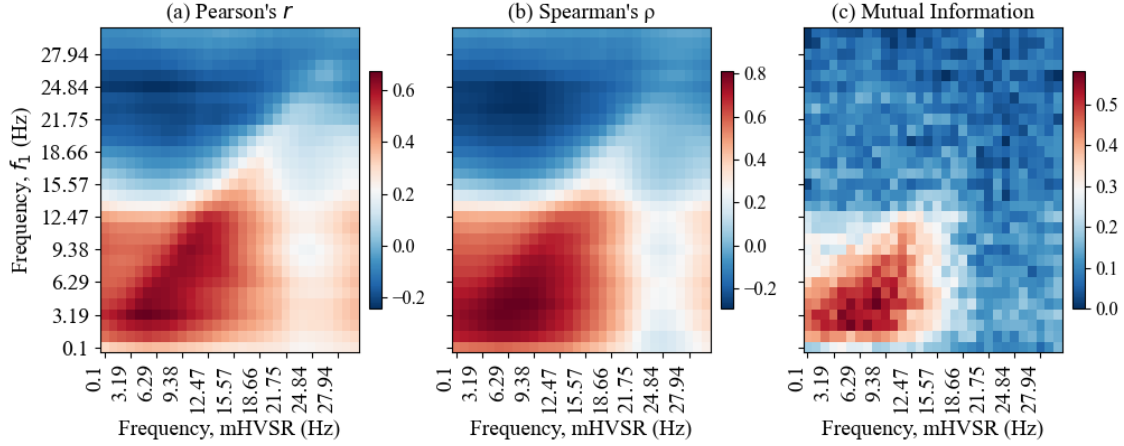


Figure 7.18. Comparison of three filter-based methods for feature selection: (a) Pearson's correlation coefficient (r), (b) Spearman's rank correlation coefficient (ρ), and (c) Mutual Information. The colored gradient represents the performance of the coefficients, with red indicating stronger correlation.

For embedded methods, I used:

- Least Absolute Shrinkage and Selection Operator (LASSO)
- Elastic Net

LASSO (Lasso hereafter) is a regularization technique used in regression models to improve generalization by performing both feature selection and regularization. The objective function that Lasso minimizes is:

$$L(\beta_0, \boldsymbol{\beta}) = \frac{1}{2n} \sum_{i=1}^n (y_i - \beta_0 - \sum_{j=1}^p X_{ij} \beta_j)^2 + \alpha \sum_{j=1}^p |\beta_j| \quad (7.23)$$

where n is the number samples, p is the number of features, y_i is the target value for the i^{th} observation, X_{ij} is the value of the j^{th} feature for the i^{th} observation, β_0 is the intercept, β_j is the j^{th} feature, a vector of β_j for all values of j is $\boldsymbol{\beta}$, and α is the regularization parameter (also referred to in literature as λ). The first term in Eq. 7.23 represents the mean squared error (MSE) and measures model fit to data. The second term represents the L_1 penalty, which discourages large

coefficients by adding a cost proportional to their absolute magnitude. The α parameter controls the L_1 penalty, where higher values promote shrinkage (i.e., fewer features). The L_1 penalty gets applied to every coefficient and the α parameter controls how strongly these coefficients are penalized each time, effectively encouraging the model to keep the coefficients small. Within this study, I utilize a constant value of $\alpha = 0.1$. Minimization of the objective function provides parameter estimates $\hat{\beta}_0$ and $\hat{\boldsymbol{\beta}}$,

$$(\hat{\beta}_0, \hat{\boldsymbol{\beta}}) = \min L(\beta_0, \boldsymbol{\beta}) \quad (7.24)$$

Elastic Net uses a combination of two penalty terms of L_1 and L_2 as defined as:

$$L(\boldsymbol{\beta}) = \sum_{j=1}^p (\alpha \rho |\beta_j| + \alpha(1 - \rho) \beta_j^2) \quad (7.25)$$

where α is defined similarly and controls the ratio of each penalty, and ρ represents the L_1 penalty (also referred to as the mixing parameter). The first and second terms represent Lasso regularization and Ridge regression, respectively. If $\rho = 1.0$ only Lasso is applied, whereas $\rho = 0$ uses only Ridge. For the present study we use $\rho = 0.5$, which represents a mix of both. The minimization operation is represented by Eq. 7.24, but with only $\hat{\boldsymbol{\beta}}$ being estimated in this case.

Figure 7.19 shows the selected features based on Lasso and Elastic Net, where the black boxes indicate non-zero coefficients from the two functions. The patterns in Figure 7.19 have a similar pattern to what was shown in Figure 6.21, where low frequencies have the strongest correlations between mHVSr ordinates and site response. However, Figure 7.19a shows that Lasso indicates fewer correlated ordinates than Elastic Net (Figure 7.19b); specifically, the frequency range with indicated correlations from Lasso is 2-18 Hz. I consider the Lasso results to be more credible due to their similarity with those from filter-based methods.

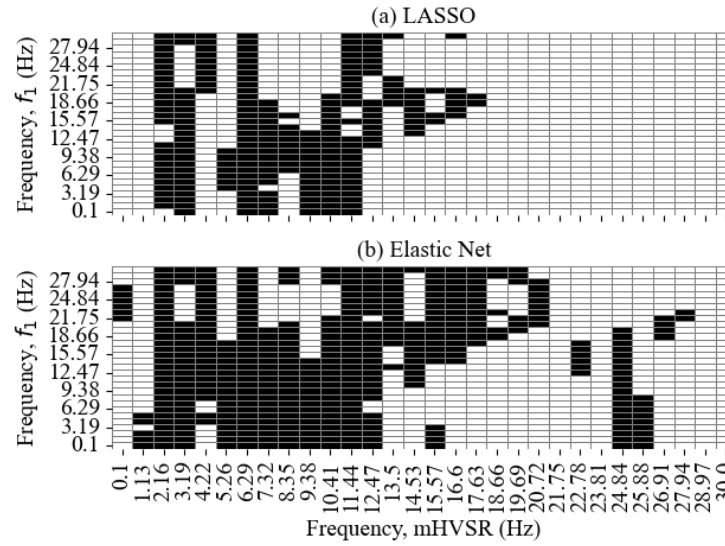


Figure 7.19. Comparison of two embedded methods for feature selection: (a) LASSO and (b) Elastic Net. The figure highlights a binary relationship, where the black regions indicate suggested correlations, corresponding to non-zero correlation coefficients.

Lastly, I explored the use of wrapper-based methods, specifically focusing on Recursive Feature Elimination (RFE). Unlike the previous two feature selection approaches, wrapper methods select features in tandem with model development, meaning the chosen features are influenced by the algorithm used. RFE functions by recursively training a specific machine learning algorithm on all available features, evaluating which features have the greatest impact on model performance. Through this process, less important features are identified and removed, leaving only those deemed most relevant for model development.

Additionally, I investigated the use of feature importance (FI) derived directly from the models, which is not strictly a wrapper-based method. Nonetheless, I employ it as another means to identify key features. This approach evaluates feature importance using metrics such as mean decrease impurity (MDI) and mean decrease accuracy (MDA). Similar to RFE, I first fit the model and then assess which features contribute the most to performance. Features with lower importance scores are filtered out, thereby retaining only the most influential variables.

7.4.2 Evaluation of Three Machine Learning Models

To develop machine learning models to predict site response conditional on mHVS_R, the mHVS_R and site response data are split into 80% training for model development and 20% validation for testing model performance. As described in the introduction of Section 7.4, the machine learning models used are random forest regressor (RF), gradient boosting regressor (GB), and adaptive boosting regressor (ADA), the latter of which is implemented with a decision tree regressor as its base estimator. The three models were all implemented utilizing the python library *sklearn.ensemble* (Pedregosa et al., 2011).

The RF approach builds multiple decision trees using random subsets of the input data (mHVS_R ordinates) and output data (site response ordinates) and seeks to understand how individual data points (referred to in literature as *features*) relate to those data (e.g., Breiman, 2001). The predictions of multiple decision trees are averaged to improve accuracy and reduce overfitting. Complex, non-linear relationships between input features and the target data are developed, making RF suitable for high-dimensional and noisy datasets. A representation of an equation for the RF model is defined as:

$$\hat{y} = \frac{1}{N} \sum_{i=1}^N T_i(\mathbf{X}) \quad (7.26)$$

where $\hat{y}$ is the RF prediction, N is the number of decision trees in the forest, and $T_i(\mathbf{X})$ is the prediction from tree i given a vector of input features $\mathbf{X}$.

GB builds models sequentially, where each new model attempts to correct the errors made by the previous one (e.g., Friedman, 2001). It combines weak learners, typically decision trees, producing a strong predictive model by focusing on the residual errors from earlier iterations. The model is optimized using gradient descent, with the objective of minimizing a loss function (e.g.,

mean square error, MSE, or mean absolute error, MAE). A representation of the gradient boosting models is defined as:

$$\hat{y} = F_0(\mathbf{X}) + \sum_{m=1}^M \eta T_m(\mathbf{X}) \quad (7.27)$$

where $F_0(\mathbf{X})$ is the initial prediction, which is often taken as the mean of y , M is the number of boosting trees, $T_m(\mathbf{X})$ is the prediction from tree m , and η is the learning rate, which controls how much each tree contributes.

ADA combines multiple weak learners, typically decision trees, by focusing on the errors made by previous models (e.g., Drucker, 1997). In each iteration, ADA assigns higher weights to misclassified data points, prompting the model to focus on the harder-to-predict instances in the dataset. Using decision trees as the base estimator, ADA adjusts the contribution of each tree to improve overall prediction accuracy by iteratively reducing bias and variance in the model. A representation of the function for the ADA model is given by,

$$\hat{y} = \sum_{m=1}^M \alpha_m T_m(\mathbf{X}) \quad (7.28)$$

where M is the number of weak learners, which in this case is decision trees, $T_m(\mathbf{X})$ is the prediction from learner m , and α_m is the weight assigned to learner m , based on its performance. The model would then be built sequentially, applying more weight to poor predicted observations, increasing the understanding of the difficult observations.

The independent variables that were considered in the machine learning model training were various ordinates of mHVSr at various frequencies for 30 logarithmically spaced ordinates from 0.1 to 25 Hz. Based on the feature selection findings, specifically using LASSO regression (an embedded method), 16 mHVSr features (i.e. individual ordinates) were utilized in the

development of a preliminary model that was presented in Ornelas et al. (2026c) (later updated as described in Section 7.4.3). The selected ordinates were at frequencies: 0.1, 0.12, 0.15, 0.18, 0.22, 0.27, 0.33, 0.4, 0.48, 0.59, 0.71, 0.87, 1.06, 1.57, 1.91 Hz. During both the training and validation stages, I employed K-fold cross-validation (Pedregosa et al., 2011) with 5 folds to avoid overfitting of the model. In the application of the RF modeling approach, a wrapper-based feature selection approach (Recursive Feature Elimination) is used within each iteration of model development to identify features with the most predictive power and eliminate others, resulting in 15 mHVSr features at frequencies: [0.1, 0.12, 0.15, 0.18, 0.22, 0.27, 0.33, 0.4, 0.48, 0.59, 0.71, 0.87, 1.06, 1.57, 1.91]. The other models (e.g., GB and ADA) utilized feature importance, which follows a similar approach to wrapper-based methods, resulting in mHVSr ordinates at the same frequencies.

A challenge with the use of machine learning models like RF, GB, and ADA is that while mathematical relationships between input and output are derived, they are for practical purposes impossible to understand at that level and lack a physical functional form. To provide insight into how they map mHVSr to site response, we compare in Figure 7.20 predicted and observed site responses for six sites and three types of features in site response (e.g., descending ramp, flat, peak). In Figure 7.20a, an mHVSr peak aligns with a peak in the site response, and a ramp-down feature occurs at higher frequencies that are accurately captured by the machine learning models. Figure 7.20b shows a similar site response peak followed by a ramp-down that is not captured by the models; the poor prediction is likely a consequence of the mHVSr not containing a peak near the site response peak, and its relatively flat shape. These features indicate the strong dependence of model output (site response) on the shape of mHVSr. Similar cases of good and poor matches

are shown in Figures 7.20c-f for flat and peak sites, respectively. In each case, the left side represents good matches and the right-side poor matches.

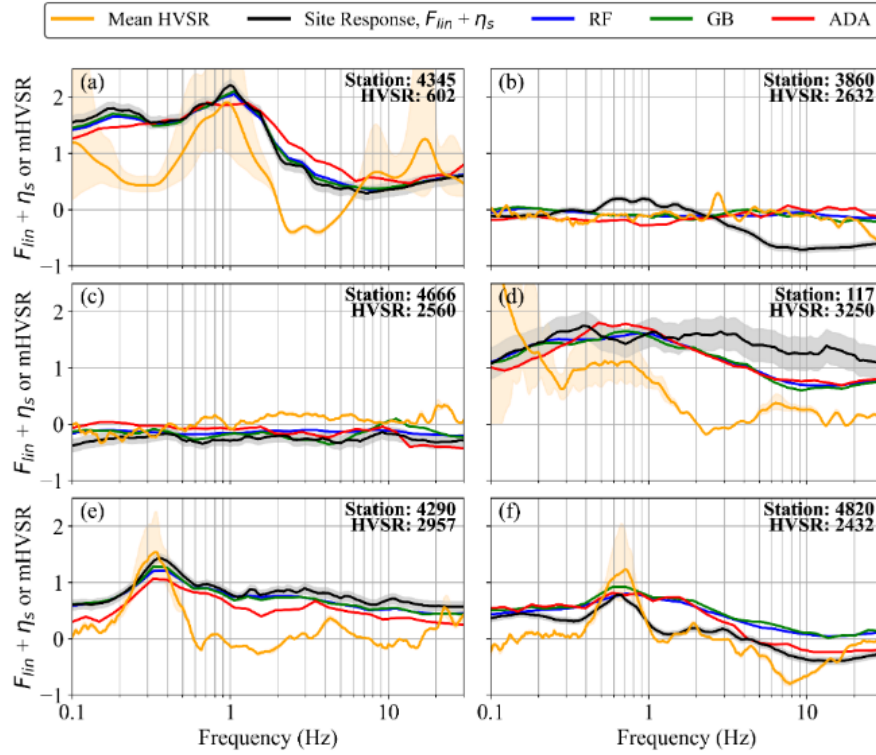


Figure 7.20. Examples of ML model predictions that are compared to observed site responses, demonstrating both good (left) and poor (right) matches, along with the corresponding mHVS in natural log units for (a-b) ramp-down sites, (c-d) flat sites, and (e-f) peak sites.

Aggregated performance of the machine learning models is evaluated using the validation data set and three metrics: site-to-site aleatory variability (ϕ_{S2S}), coefficient of determination (R^2), and MSE. High values of R^2 and low values of MSE and ϕ_{S2S} indicate good mode performance. Figure 7.21 shows these performance metrics for the machine learning models compared to those from Seyhan and Stewart (2014). The machine learning models all perform similarly, with reduced ϕ_{S2S} and MSE and increased R^2 for frequencies $< 2-3$ Hz compared to the ergodic model, but similar behavior to that of the ergodic model at higher frequencies. I am unsure why the machine learning models do not perform better for frequencies $> 2-3$ Hz, but possible explanations are

saturation of spectral ordinates at high oscillator frequencies and high variability of mHVSF features at high frequencies (Ornelas et al., 2026; also discussed in Section 5.2.5). Similar reductions were observed in prior studies at low and high frequencies (Esteghamati et al. 2022 and Anbazhagan et al. 2023, respectively), which reflects the far greater number of input parameters used in machine learning models as compared to models parameterized to capture specific site response features (i.e., peaks, ramps, flat).

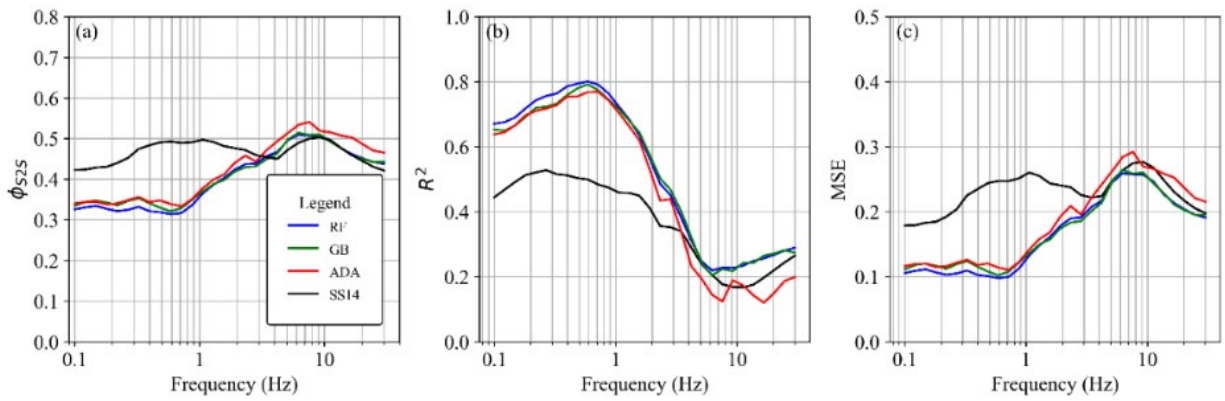


Figure 7.21. Performance metrics of three machine learning models and the SS14 ergodic model: (a) ϕ_{S2S} , (b) R^2 , and (c) MSE.

7.4.3 Development of Random Forest Model

The results presented in Section 7.4.2 showed that a RF regressor provided the lowest site-to-site variability (ϕ_{S2S}) and the greatest accuracy (i.e., highest R^2 and lowest MSE). Accordingly, I selected the RF regressor for model development. However, I did not restrict independent variables to those associated with mHVSF (as identified in Section 7.4.2), but instead supplemented the trial independent variables with other site condition proxies (i.e., V_{S30} , isosurface depths, terrain class, slope gradient, and geomorphic category).

Similar to what was done with the decision tree classifier in Section 6.5, I applied *GridSearchCV* to select the optimum set of hyperparameters while simultaneously avoiding

overfitting of the model. For this model development, I used 95% of the data for training and 5% for validation. Within the *GridSearchCV*, K-fold cross validation is applied, which splits the 95% training dataset into various subsets of 80% training and 20% testing. Details on the operation of K-fold cross validation are provided in Section 6.5.3. Figure 7.22 illustrates each combination of optimized hyperparameters within *GridSearchCV*, where the number of estimators, minimum samples per leaf, and the maximum depth, were varied. The optimization was performed across all considered ground motion parameters. The independent variables considered in the models are generally as marked with the functions along the abscissa of Figure 7.22, but one requires further explanation: the “HVSr” in $F_{lin}(HVSr)$ and $F_{lin}(HVSr, V_{S30})$ uses all 30 mHVSr ordinates to train the model for each of the 30 intensity measures.

Figure 7.22a illustrates the generalization gap, which in the present context of predicting the continuous variable of site response, is defined as the difference in the mean cross validation scores (ΔR^2) between the training and the testing datasets for the five folds for each of the models (Emmert-Streib and Dehmer 2019). Note that this definition of generalization gap is different from the F_1 score difference used in Section 6.5.3, which applied to a decision tree classifier. High values of ΔR^2 (i.e., $> \sim 0.1-0.2$) indicate overfitting. Figure 7.22b illustrates the performance (test set R^2) of the 5% independent validation dataset that was used within each combination of hyper tuning parameters.

In terms of the generalization gap, there is slight overfitting of the following models for three hyperparameter sets [(n=100, leaf=10, depth=6), (n=100, leaf=10, depth=8), (n=200, leaf=10, depth=6), (n=200, leaf=10, depth=8)]: $F_{lin}(HVSr, V_{S30})$, $F_{lin}(HVSr)$, and $F_{lin}(V_{S30})$. However, the other models based on peak-attributes and site condition proxies have $\Delta R^2 < \sim 0.04$ for all hyperparameters, which are below typical overfitting thresholds. In terms of R^2 values for

the training dataset, there is not much difference amongst the different hyperparameter combinations for a given model, but there are large differences between models, with the following having good fits to the testing data: $F_{lin}(HVSR, V_{S30})$, $F_{lin}(HVSR)$, and $F_{lin}(f_{0,HV}, a_{0,HV}, V_{S30}, z_{1.0})$. Based on these results, I selected the hyperparameters of number of estimators = 100, maximum depth = 8, and minimum samples per leaf = 10, which provided the best results and lowest overfitting.

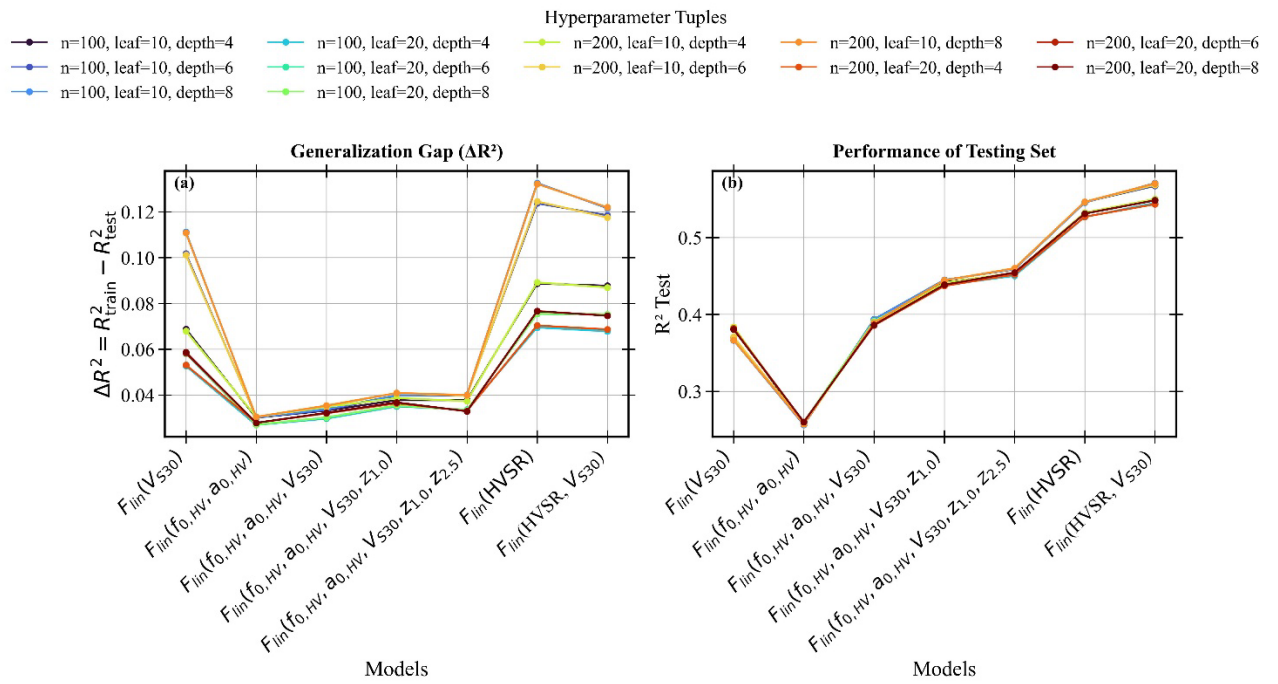


Figure 7.22. Performance comparison of RF models derived using various combinations of hyper tuning parameters using grid search as quantified by the metrics of: (a) generalization gap; and (b) Coefficient of Determination (R^2) of the testing dataset (5%) against the trained models.

As noted previously, the results presented in Figure 7.22 represent an optimization across all periods. In Figure 7.23, I present generalization gap results for the specific spectral periods of 0.05, 0.2, 1, and 3 sec. As shown in Figure 7.23a-b, the gap is relatively small at short periods (0.05 and 0.2 sec). At longer periods, the gap increases to about 0.2 to 0.25 for some models. Due to the limited database size, this overfit is considered tolerable.

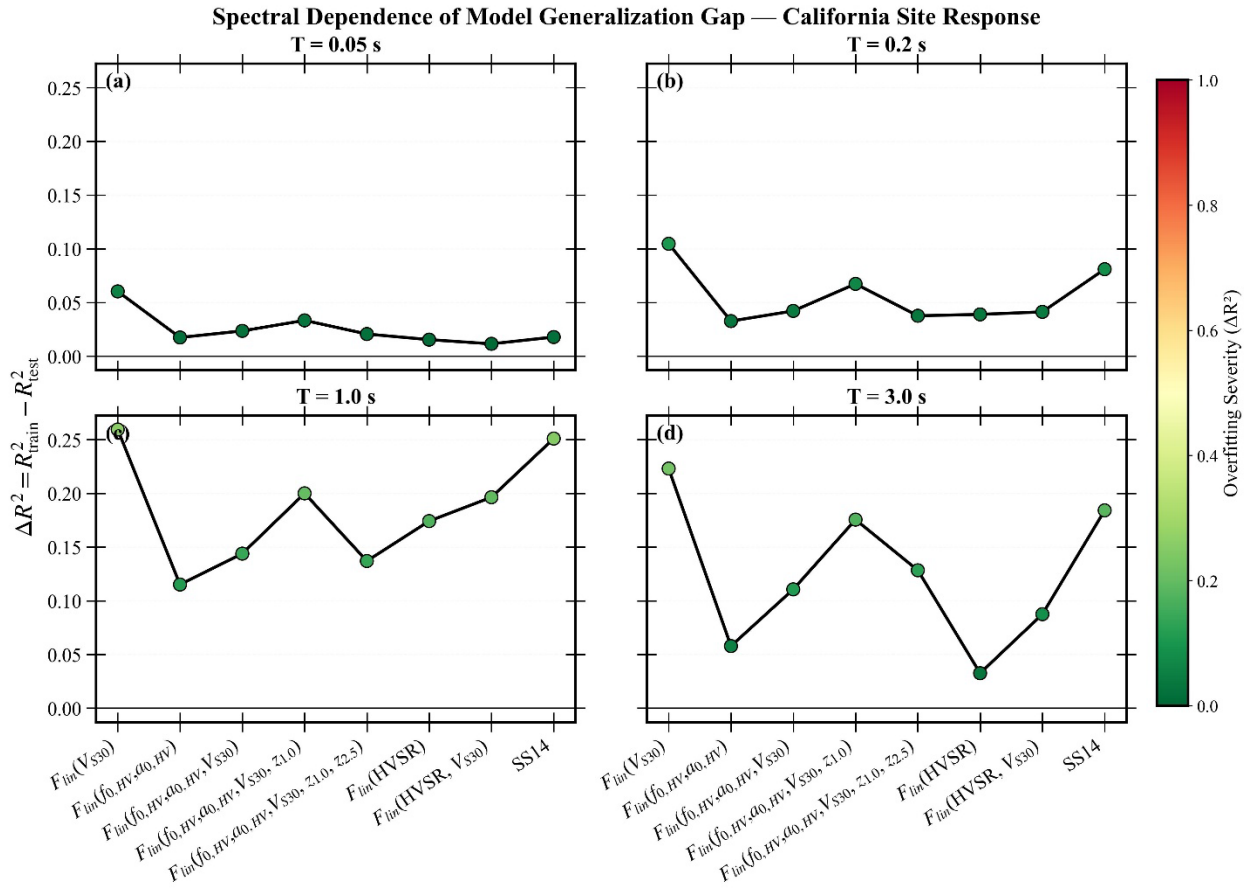


Figure 7.23. Generalization gap for RF models at periods: (a) 0.05 sec, (b) 0.2 sec, (c) 1 sec, and (d) 3 sec.

I evaluate the performance of the models shown previously in Figures 7.22-7.23 based on ϕ_{S2S} reduction compared to the base ergodic model (SS14). Figure 7.24 shows ϕ_{S2S} for the training and testing datasets. Most of the models perform similarly to SS14, with either slight reductions or increases in ϕ_{S2S} . However, models $F_{lin}(HVSR)$ and $F_{lin}(HVSR, V_{S30})$, which use 30 logarithmically spaced mHVSr ordinates without and with V_{S30} , respectively, produce lower ϕ_{S2S} than SS14 across all periods for both the training and the testing datasets. The ~ 0.3 natural log units reduction in uncertainty at long periods is similar to what was shown in Figure 7.21 for the three different ensemble-based machine learning models. However, for this model there are also reductions at short periods. This is likely due to the addition of a grid search to vary the hyper

tuning parameters, improving the understanding of whether models are overfitting. In subsequent sections of this thesis, the $F_{lin}(HVSR, V_{S30})$ model is used for comparison to the parametric models from Sections 7.1-7.3.

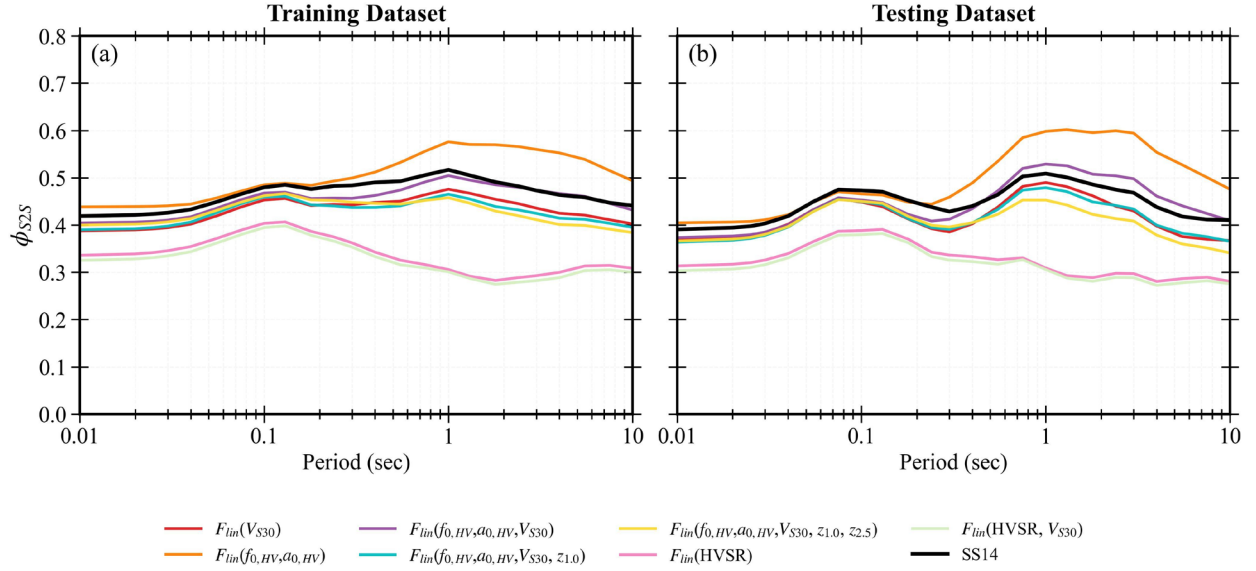


Figure 7.24. Comparisons of ϕ_{S2S} for different machine learning models and the SS14 ergodic model for (a) training data set (95% of the total amount of data) and (b) testing data set (5% of the total).

7.5 Residual Analysis

7.5.1 Synthesized Model Used for Residuals Calculations

As noted in the introduction to this chapter, the peak-only, ramp, and flat models in Sections 7.1-7.3 are intended to be combined using the outcomes of the decision tree classifier from Section 6.5. That combined model, in turn, comprises an additive term to the linear site response component of the Boore et al. (2014) ground motion model as adjusted for induced source and subregional anelastic attenuation effects by Buckreis et al. (2023). The combined mHVSr-based models is given by,

$$F_{HV}(T, \ln(\overline{HVS\overline{R}}_{GM,0.12-2Hz}), f_{0,HV}, a_{0,HV}, G, \mathbf{P}) = P_P F_P + P_{AR} F_{Aramp} + P_{DR} F_{Dramp} + P_F F_{flat} \quad (7.29)$$

where $\mathbf{P} = [P_P \ P_{AR} \ P_{DR} \ P_F]^T$ is a vector of feature probabilities for peaks, ascending ramps, descending ramps, and flat sites, respectively; G indicates the geomorphic group (sedimentary or not sedimentary), and F_P , F_{Aramp} , F_{Dramp} , and F_{flat} are from Eq. 7.9, Eq. 7.14 with ascending ramp parameters, Eq. 7.14 with descending ramp parameters, and Eq. 7.21, respectively. The F_{HV} model is combined with other site components in the ground motion model as:

$$F_{S,ij} = F_{lin,j} + F_{nl,ij} + F_{HV} \quad (7.30)$$

where $F_{lin,j}$ is the linear ergodic site terms that depends on $V_{S30,j}$ and δz_1 , $F_{nl,ij}$ is the nonlinear site amplification term that depends on $V_{S30,j}$ and the intensity of shaking for a reference site, and F_{HV} is as given in Eq. 7.29.

Application of the machine learning model is different. Denoting the model as $F_{ML}(V_{S30,j}, mHVS\overline{R})$, it is integrated with the nonlinear component of the ergodic ground motion model as,

$$F_{S,ij} = F_{ML}(V_{S30,j}, mHVS\overline{R}) + F_{nl,ij} \quad (7.31)$$

Figure 7.25 compares predictions of observed linear site response (Eq. 7.5) with the linear portion of the parametric model (Eq. 7.30), the non-parametric (machine learning) model (Eq. 7.31), and the SS14 global ergodic model. Some notable features of these plots are summarized as follows:

- Sites with peaks are not accurately modeled by SS14, as expected. The mHVSRe-conditioned models capture site peaks in some cases (i.e., 4844, 4240, 12380, 4542, 4786) and miss peaks in others (4726, 4242, 12260, 4543, 6320).
- Sites with ascending ramps are well-captured by the ergodic model when those ramps are relatively gradual over a period range of about 0.2-1.0 sec (3947, 4340, 4960, 12293, 3974, 14262) but are poorly captured by the ergodic model when the ramp is relatively sharp or occurs over a different period range (4811, 3655, 12499, 4067, 12381, 4226). The mHVSRe-conditioned models improve accuracy in almost all cases.
- The ergodic model is unable to capture sites with descending ramps in all cases. Those ramps are well captured by the mHVSRe-conditioned models in most cases (4844, 4652, 12260, 12380, 12504), have the correct shape but miss the short-period plateau in a few cases (4655, 6013), and are poorly modeled in one case (4786).
- Flat sites are generally well captured in shape by the ergodic model due to high V_{S30} , with the general amplitude being accurate in some cases (4145, 4162) and inaccurate in others (4446, 12260). The mHVSRe-conditioned models improve predictions relative to the ergodic model for 4145, 4162, 4446, and 12499 but not for 12260.
- In most cases the machine learning model provides predictions similar to those of the parametric model (4811, 4340, 4844, 4655, 3655, 4145, 4960, 4726, 4447, 4242, 12293, 4226, 3974, 14262, 4652, 12504, 6320). The parametric model is more accurate for five sites (3947, 4162, 4240, 12260, 12380) and the machine learning model is more accurate for five cases (12499, 4067, 12381, 4542, 4786). Overall, the results in Figure 7.25 suggest that the two models provide similar levels of accuracy.

- Site 4447 has a rather gross amplitude misfit that is not captured by any of the considered models.

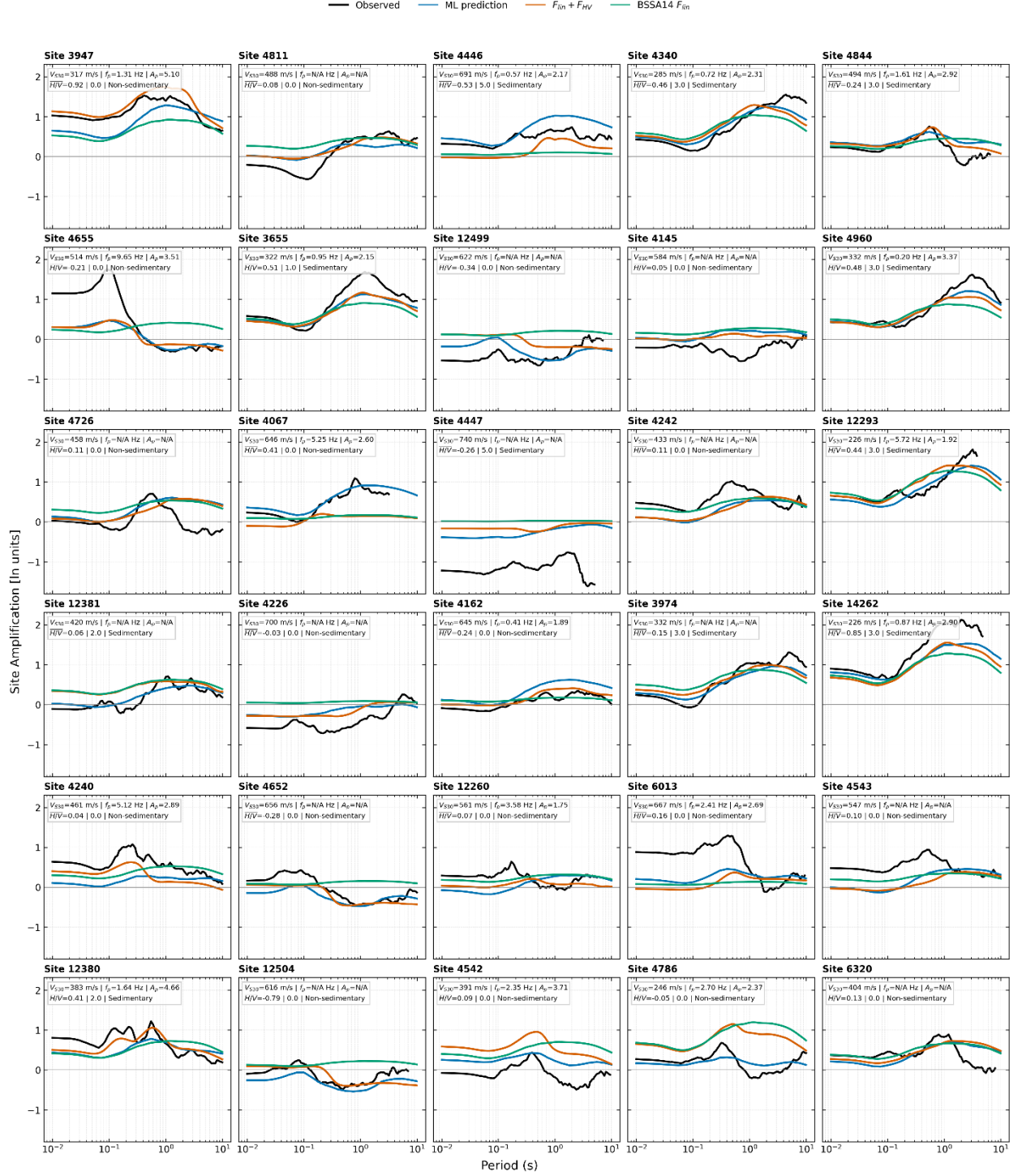


Figure 7.25. Site responses for 30 examples sites illustrating how observations compare to predictions from the mHVSr-based parametric model, the mHVSr-based machine-learning model, and the linear ergodic site amplification predicted from SS14.

7.5.2 Site Term Bias and Site-to-Site Variability

In this section, I compute residuals using the mHVSr-conditioned parametric model (Eq. 7.30) and machine learning model (Eq. 7.31) for site response. The site response models are combined with the Boore et al. (2014) ground motion model with modifications for sub-regional path effects from Buckreis et al. (2023). Total residuals, δ_{ij} , for event i and station j are computed using Eq. 6.1, which are then partitioned into a bias term, random effects for event ($\eta_{E,i}$) and site ($\eta_{S,j}$), and remaining residual (ε_{ij}) using Eq. 6.2. The data used in the residuals calculations are from the NGA-West3 project database (Buckreis and Stewart 2025), which were screened as presented in Section 6.1. This includes global data as well as extensive data across the western US, including California. Most of the California sites considered in the residuals analyses do not have a co-located mHVSr, but by considering the broader global and California data sets, we have better constraint on model bias and event terms. The focus of the residuals calculations for this thesis is the 686 sites identified in Section 6.1 and mapped in Figure 6.2. Because model bias and event terms are computed using a much larger data set than the sites in Figure 6.2, the means of site terms across the 686 sites would not be expected to be zero.

Figure 7.26a shows weighted means of site terms, $\bar{\eta}_S$, across all of the 686 considered sites, whereas Parts b and c of the figure show residuals for subsets of sites with and without mHVSr peaks, respectively. Weighted means are calculated as:

$$\bar{\eta}_S = \sum_{j=1}^{N_S} w_j \bar{\eta}_{S,j} \quad (7.32)$$

where N_S is the number of sites and w_j is the weight given to a particular site, which is computed as,

$$w_j = \frac{n_j}{\sum_j n_j} \quad (7.33)$$

where n_j is the number of events recorded at site j . In each frame of Figure 7.26, $\bar{\eta}_S$ is shown separately for three site amplification models: the mHVSr-conditioned parametric model (Eq. 7.30; denoted “HV Model” in the figure), the mHVSr-conditioned machine learning model (Eq. 7.31; “ML Model”), and the ergodic SS14 model (Base Model). The results in Figure 7.26a indicate negative biases across most spectral periods (i.e., $\bar{\eta}_S < 0$), indicating overprediction, although those biases are reduced with the use of mHVSr conditioned site terms, especially at long periods.

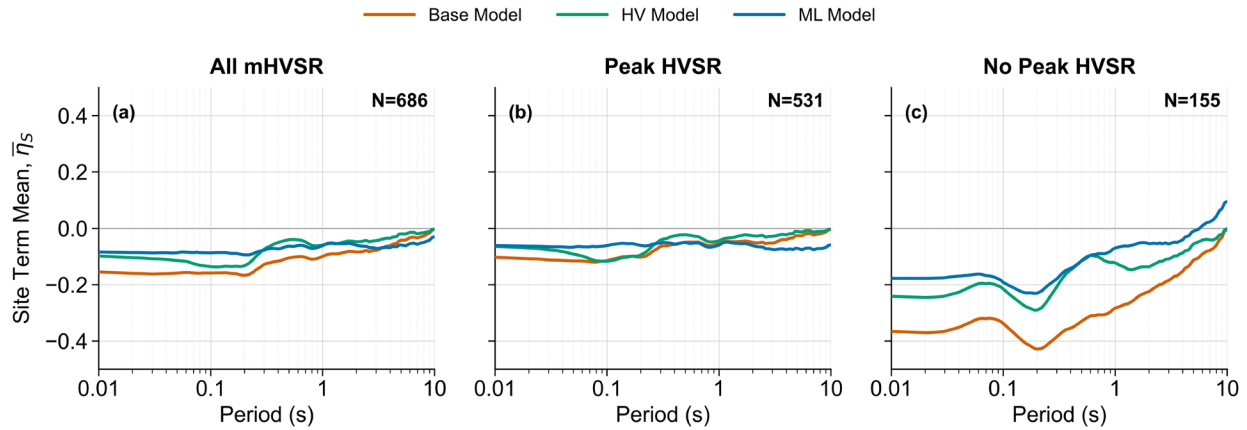


Figure 7.26. Comparison of site term means for both mHVSr-conditioned models and the SS14 base model for: (a) all mHVSr co-located sites, (b) mHVSr peak sites, and (c) mHVSr no peak sites.

The $\bar{\eta}_S$ values for 531 mHVSr peak sites in Figure 7.26b (these are a combination of peak-only sites and ramp sites with peaks) are closer to zero, especially for the machine learning model. For the 155 no peak sites in Figure 7.26c, all the models show large negative $\bar{\eta}_S$ values from 0.01

to ~ 5 sec, although these values are smaller for the mHVSr-conditioned models. In all cases, $\bar{\eta}_S$ approaches zero at long periods.

I computed the site-to-site uncertainty (ϕ_{S2S}) as the square root of the weighted variance,

$$Var_{S2S} = \sum_j w_j (\eta_{S,j} - \bar{\eta}_S)^2 \quad (7.34)$$

Figure 7.27 compares ϕ_{S2S} values for all sites and sites with and without mHVSr peaks. Unlike the mean results, the site-to-site uncertainties are relatively similar in the three groups. In each case, the SS14 ergodic model has the largest ϕ_{S2S} across all periods, and the reductions provided by mHVSr models are larger at long period (i.e., $T > \sim 0.3$ sec) than short periods. The machine learning model achieves the largest ϕ_{S2S} reductions, which is expected because of the vastly larger number of parameters considered and the lack of restraint in the fitting that is provided by smooth equations (as in the parametric models). Moreover, because ϕ_{S2S} for the machine learning model was used with the training data, the uncertainty is likely lower than would be obtained with a testing data set. These results demonstrate the benefits of incorporating mHVSr into site amplification models.

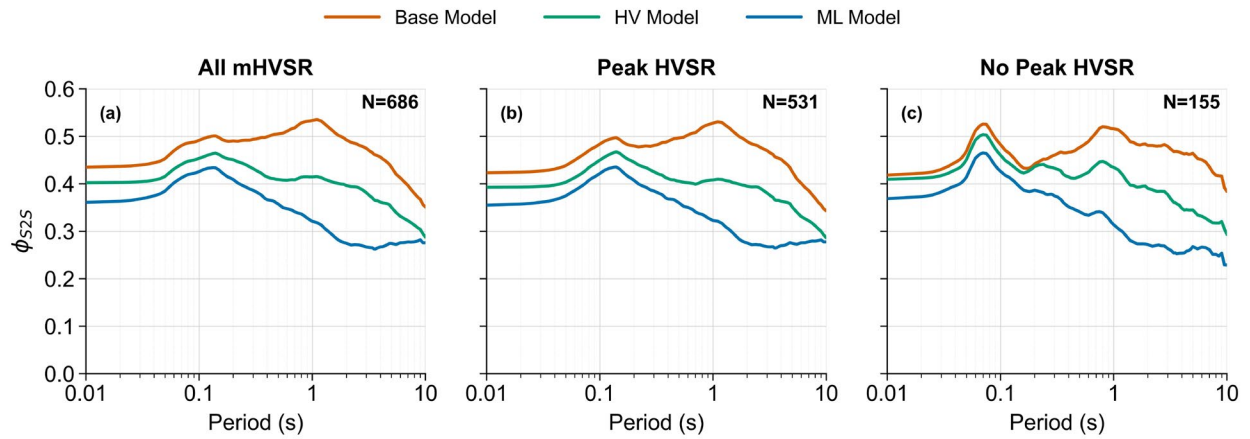


Figure 7.27. Comparison of site-to-site uncertainties (ϕ_{S2S}) for both mHVSr-conditioned models and the SS14 base model for: (a) all co-located sites, (b) mHVSr peak sites, and (c) mHVSr no peak sites.

Figure 7.28 shows $\bar{\eta}_S$ values for the six geomorphic categories presented in Section 6.5. Figure 7.29 presents similar results for ϕ_{S2S} . These plots were prepared to evaluate whether there are significant differences in bias and uncertainty between categories. The negative bias for sites lacking mHVSr peaks in Figure 7.26 largely aligns with results for mountain-hill sites and old basin sites. Basin sites without mHVSr peaks have very little bias at short periods and positive bias (i.e., $\bar{\eta}_S > 0$) for $T > 1.0$ sec. Several categories have appreciable bias in the mHVSr peak group. Valley and shelf sites exhibit similar trends of null to slightly positive $\bar{\eta}_S$ at short periods that transition to $\bar{\eta}_S < 0$ for $T > 0.2$ -0.4 sec. Old basin sites have positive $\bar{\eta}_S$ for $T > \sim 0.2$ sec.

The site-to-site uncertainty plots in Figure 7.29 generally follow the pattern from Figure 7.27 of similar levels of uncertainty for sites with and without mHVSr peaks (the exceptions for basin edge and shelf no-peak sites with high ϕ_{S2S} involve small sample sizes). There are significant differences between geomorphic groups, with basin sites having relatively small $\phi_{S2S} \sim 0.3 - 0.4$ and mountain-hill sites having larger $\phi_{S2S} \sim 0.35 - 0.5$ at short periods with some fall off at longer periods. Lower ϕ_{S2S} in basins relative to mountain-hill sites has been observed previously in the Los Angeles area (Nweke et al. 2022). The reductions of ϕ_{S2S} that are achieved with mHVSr-conditioned models relative to the baseline SS14 model are persistent across all periods for mountain-hill sites and old basin sites, but occur only for $T > \sim 0.3$ -0.5 sec for basin, valley, and shelf sites. In most cases, machine learning models have lower ϕ_{S2S} than do parametric models.

The results presented in Figures 7.26-7.29 support the notion of adjusting the mean parametric model in Eq. 7.30 to remove biases observed from residuals analyses. These adjustments should take into account trends shown in individual figures along with $\bar{\eta}_S$ values for

the population as a whole (i.e., the small bias in Figure 7.26 for the 686 sites considered in this study relative to the overall data population should not impact biases assigned to specific categories, such as mountain-hill no-peak sites). These adjustments have not been developed as of this writing. The uncertainty results also support different ϕ_{S2S} models for different geomorphic categories.

Figure 7.30 shows $\bar{\eta}_S$ computed across all 531 sites with mHVSr peaks for all three models plotted against the product $T \times f_{0,HV}$ (in effect, the ratio of oscillator period to site period). Each model has $\bar{\eta}_S \approx 0$ for $T \times f_{0,HV} \lesssim 0.3$, a peak near unity, and negative values for $T \times f_{0,HV} \gtrsim 1.5$. The underprediction at the site period and the overprediction at longer periods are reduced with the mHVSr-conditioned models relative to SS14. The under-prediction near the site period may be caused by the weighting applied to peak models in the formulation of the model (i.e., Eq. 7.29).

Finally, I consider residuals grouped in a different manner using physiographic provinces in California, which are shown in Figure 7.31. These provinces were developed by Chiou et al. (2010) and were previously considered in the subregional path model of Buckreis et al. (2023) and in an earlier phase of the mHVSr model development (Ornelas et al. 2025). I combined subregions that exhibited similar behavior, specifically:

- Sub-regions in the eastern half of California, including the Sierra Nevada, Eastern California Shear Zone, Basin and Range, and Northeastern California, were combined as “Eastern California”.
- Sub-regions in the northwestern portion of California, including the North Coast, Central Coast, and Bay Area, were combined as “Western California”.

- The South Coast and Colorado Desert subregions were combined as “Southern California”.

Figure 7.32 shows mean site terms ($\bar{\eta}_S$) for sites in different physiographic provinces for all three models (mHVSR conditioned models and SS14 base model).

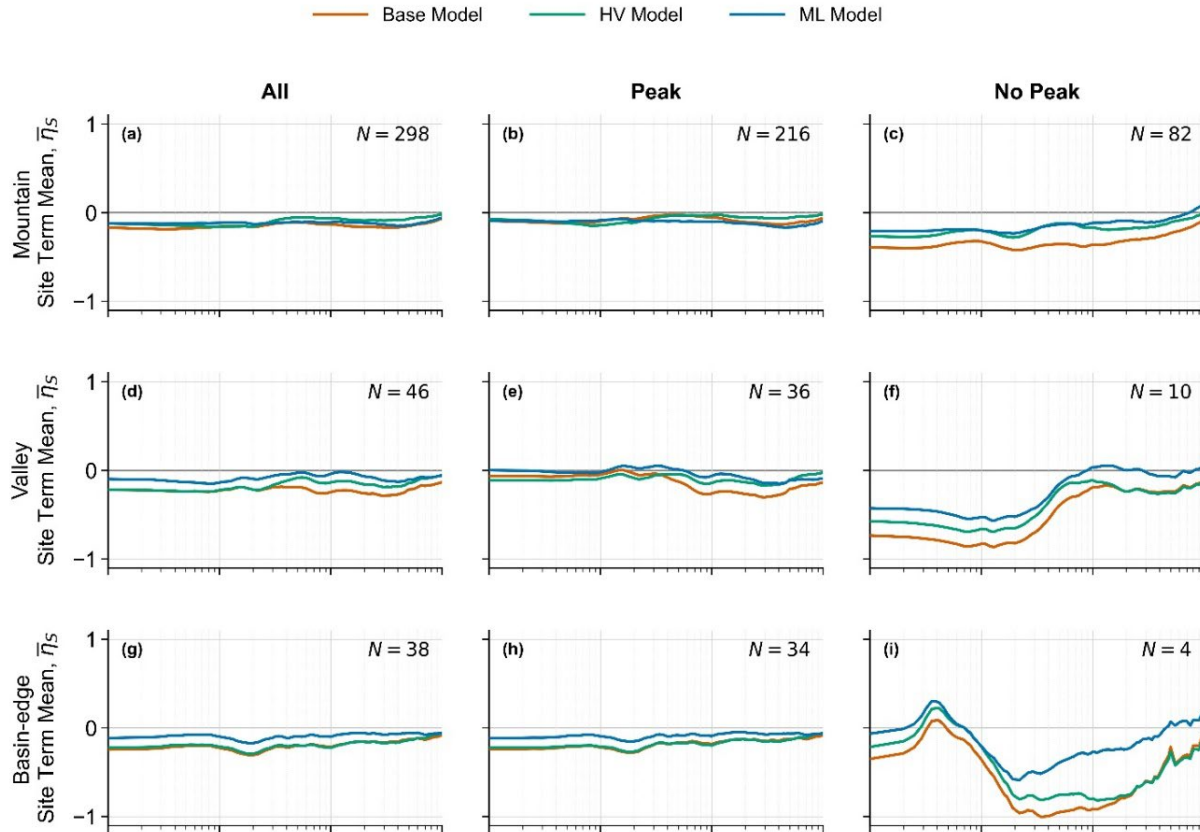


Figure 7.28. Comparison of site term means in geomorphic groups for both mHVSR-conditioned models and the SS14 base model for: (left column) all mHVSR co-located sites, (middle column) mHVSR peak sites, and (right column) mHVSR no peak sites.

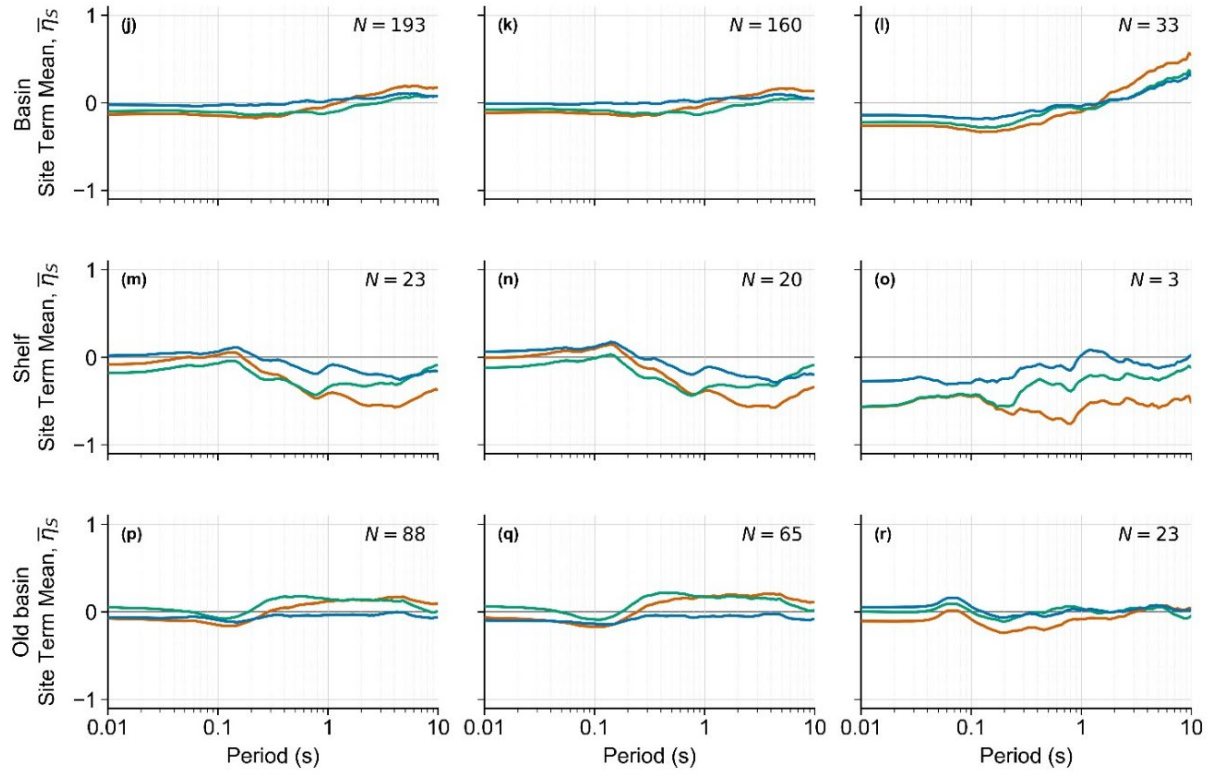


Figure 7.28. *continued.*

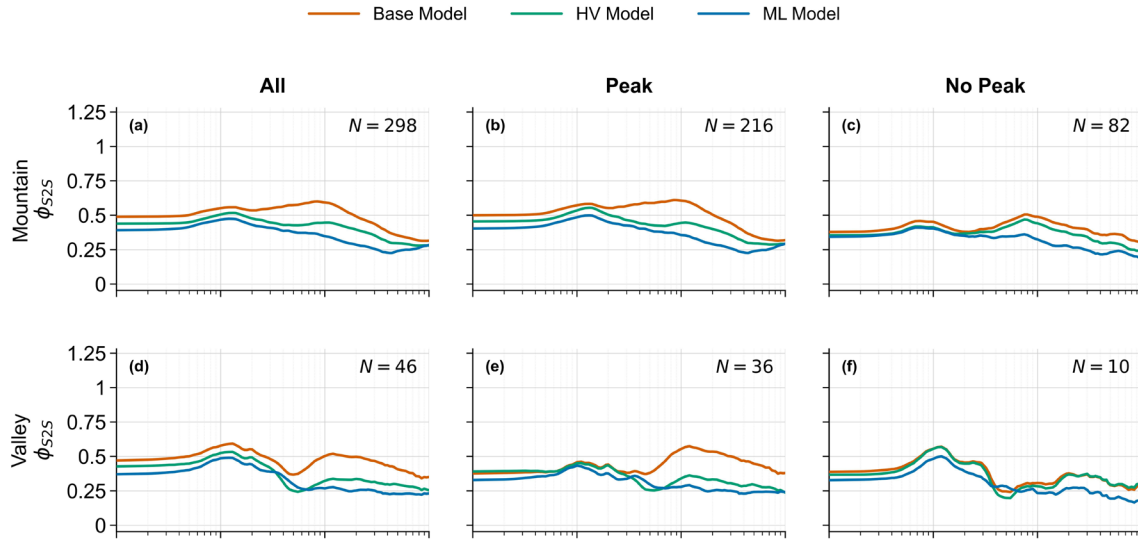


Figure 7.29. Comparison of site-to-site uncertainties (ϕ_{S2S}) in geomorphic groups for both mHVSr-conditioned models and the SS14 base model for: (left column) all mHVSr co-located sites, (middle column) mHVSr peak sites, and (right column) mHVSr no peak sites.

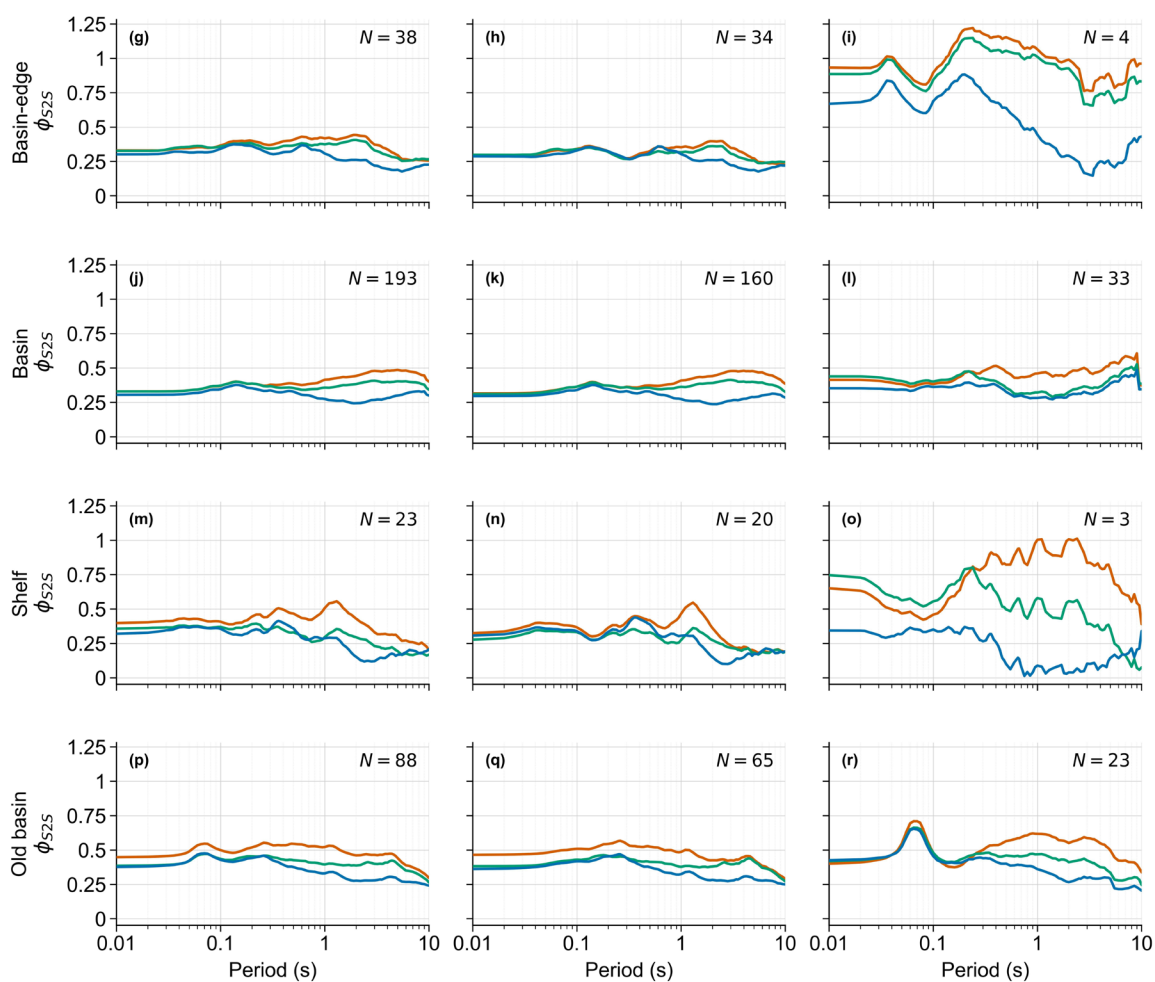


Figure 7.29. *continued.*

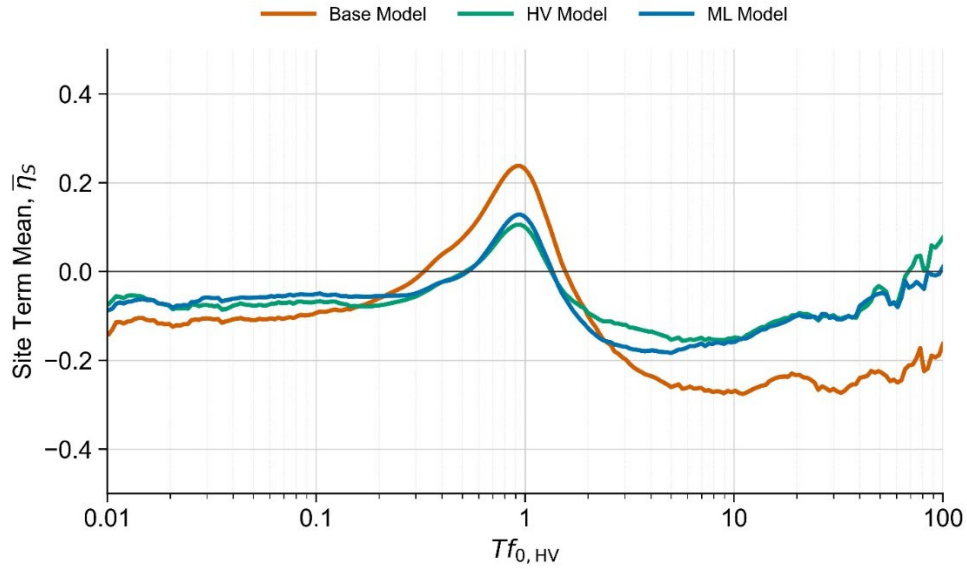


Figure 7.30. Comparison of mean site terms for mHVSr-conditioned models and the SS14 base model with $Tf_{0,HV}$, which shows model performance below, at, and above resonance.

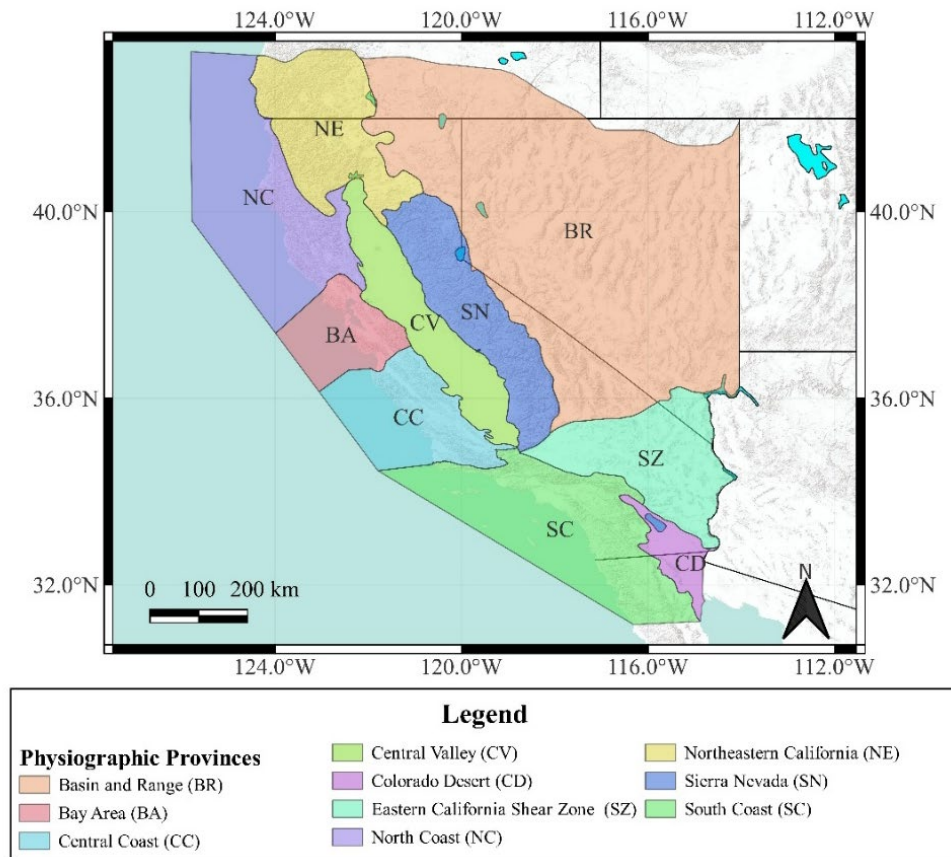


Figure 7.31. California sub-regions defined from physiographic provinces (modified from Buckreis et al. 2023 and Chiou et al. 2010).

Western California and the Central Valley have $\bar{\eta}_S < 0$ at short periods and $\bar{\eta}_S > 0$ at long periods. Southern California has $\bar{\eta}_S \approx 0$ for $T < \sim 0.3$ sec and $\bar{\eta}_S < 0$ at longer periods. Eastern California has $\bar{\eta}_S < 0$ for all periods. The mHVSr-conditioned models have reduced bias from the SS14 base model in all sub-regions and for almost all periods. The machine learning model provides smaller absolute value $\bar{\eta}_S$ than the parametric model in most cases. Many sites in the Western California sub-region have ascending ramp features despite having mountain-hill geomorphic provinces. For this sub-region, these features are captured more accurately by the machine learning model (Eq. 7.31) than the parametric model (Eq. 7.30), which explains different results in Figure 7.32. These strong long-period site responses are associated with mountainous regions with large depths (i.e., old basin geomorphic category) and would be removed by applying a bias adjustment to the old basin category, as noted previously.

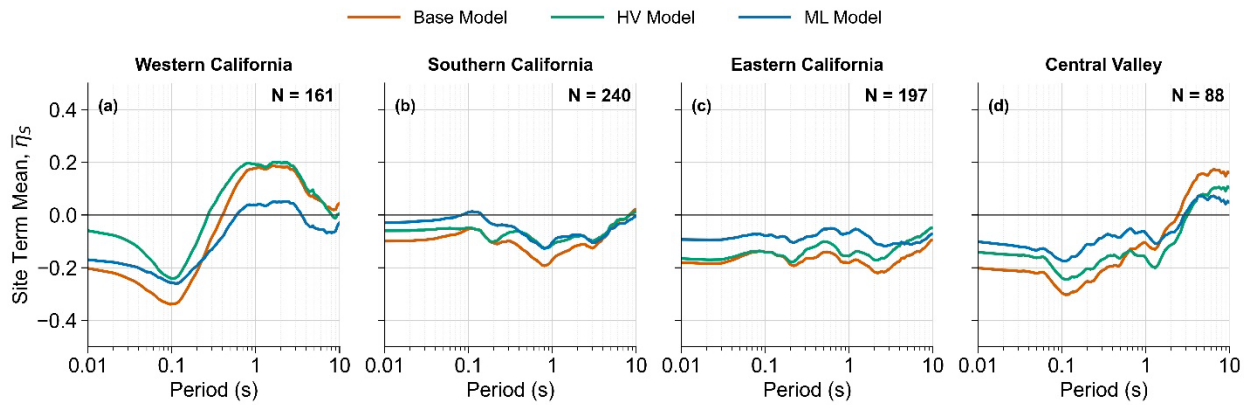


Figure 7.32. Comparison of site term means in physiographic provinces for both mHVSr-conditioned models and the SS14 base model for (a) Western California, (b) Southern California, (c) Eastern California, and (d) Central Valley.

Figure 7.33 shows ϕ_{S2S} for sites in the different physiographic provinces. The two mHVSr-conditioned models provide substantial reductions relative to the SS14 base model in all provinces, except at short periods in the Central Valley. Eastern California has the largest reduction due to

very large ϕ_{S2S} from the ergodic model near 1.0 sec. As before, the machine learning model provides the lowest ϕ_{S2S} values.

The residuals analyses presented in this sub-section highlight the benefits of incorporating mHVSR-conditioned site amplification models into the site components of ground motion models. Whether using a machine learning approach or a parametric approach, uncertainty reduction is significant and model biases are reduced. Additional benefit would be achieved by refining the models in Eq. 7.30 and 7.31 to include adjustments specific to different geomorphic provinces conditional on whether mHVSR peaks are present, as discussed in this sub-section.

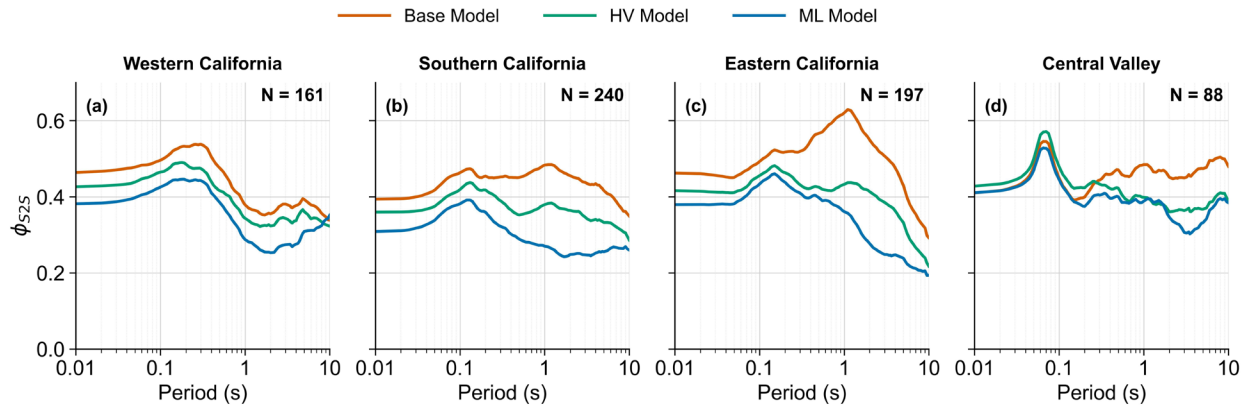


Figure 7.33. Comparison of site-to-site uncertainty (ϕ_{S2S}) in physiographic provinces for both mHVSR-conditioned models and the SS14 base model for (a) Western California, (b) Southern California, (c) Eastern California, and (d) Central Valley.

7.5.3 Evaluation of Nonlinearity of HV Model

The models presented in Sections 7.1-7.3 were developed for a wide range of ground motion amplitudes, but a large majority were relatively weak ground motions. The residuals calculations described in Sections 6.1 and 7.5.1 include F_{nl} term from SS14. For the weak ground motions, this term would have been essentially zero, but for the strong motions it would be negative for short period intensity measures. In this sub-section, I investigate the potential effects of nonlinearity by

evaluating within-event residual δW_{ij}^{HV} relative to peak acceleration for a reference site condition (PGA_r), which is taken as $V_{S30} = 760$ m/s. For this analysis, δW_{ij}^{HV} is computed as:

$$\delta W_{ij}^{HV} = \eta_S^{HV} + \varepsilon^{HV} \quad (7.35)$$

where η_S^{HV} is the site term that is computed using a ground motion model that incorporates the mHVSr-conditioned site amplification model (Eq. 7.30), and ε^{HV} is the remaining residual.

Figure 7.34 shows the variation of δW_{ij}^{HV} for different spectral periods with PGA_r for soft sites with $V_{S30} < 300$ m/s. The black error bars represent the binned means and 95% confidence interval. A flat trend is expected if the site responses from the events in the dataset are either effectively linear or they are nonlinear and accurately modeled by SS14. There is a slight upward trend for $PGA_r > 0.01$ g for PGA and spectral acceleration (Sa) at 0.1 sec oscillator period. This indicates that the nonlinearity in the SS14 model may be slightly too strong for these conditions. The other spectral periods are generally flat. The small upward trend is not anticipated to materially affect the model presented in this chapter. Figures 7.35-7.36 shows similar results for stiffer sites with $V_{S30} = 300 - 500$ m/s and > 500 m/s, respectively. The trends in these plots are flat for all intensity measures.

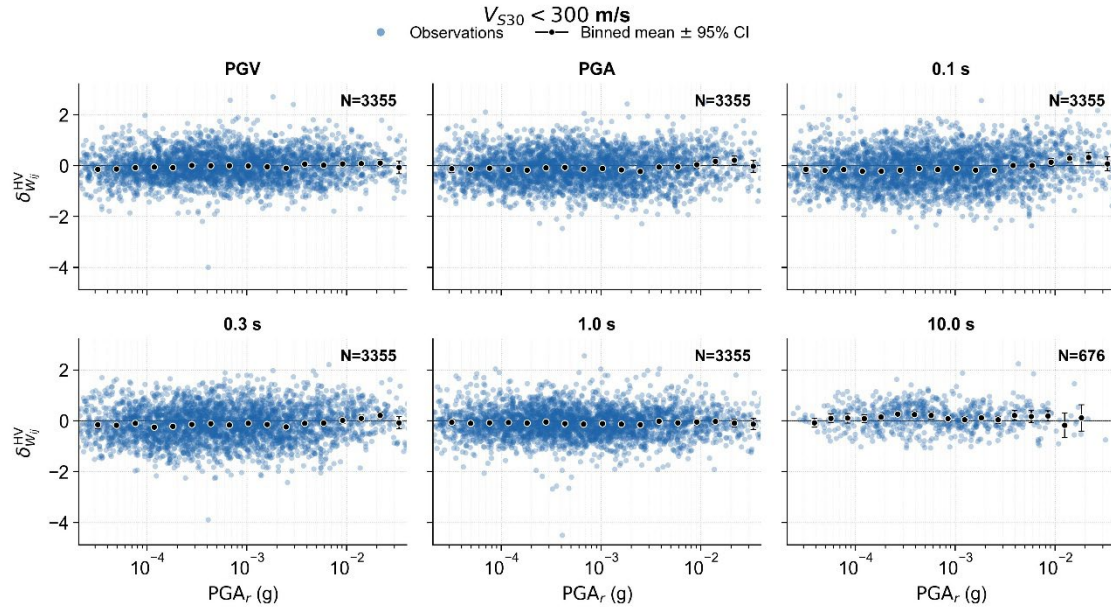


Figure 7.34. Variations of within-event residual (δW_{ij}^{HV}) for different intensity measures with PGA_r for sites with $V_{S30} < 300 \text{ m/s}$.

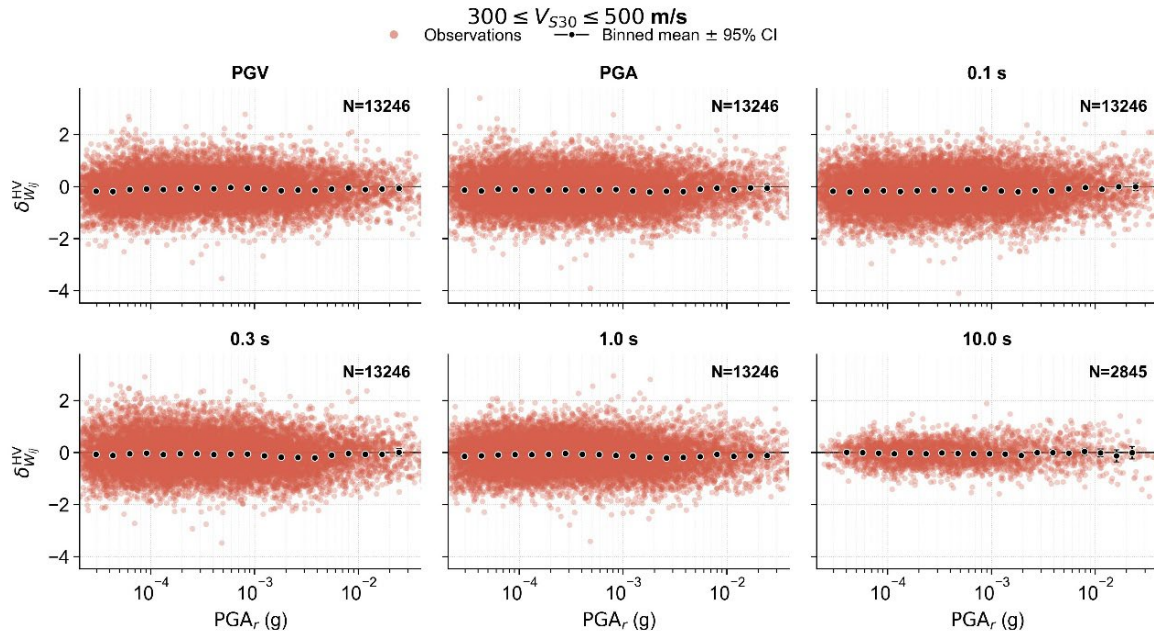


Figure 7.35. Variations of within-event residual (δW_{ij}^{HV}) for different intensity measures with PGA_r for sites with $300 < V_{S30} < 500 \text{ m/s}$.

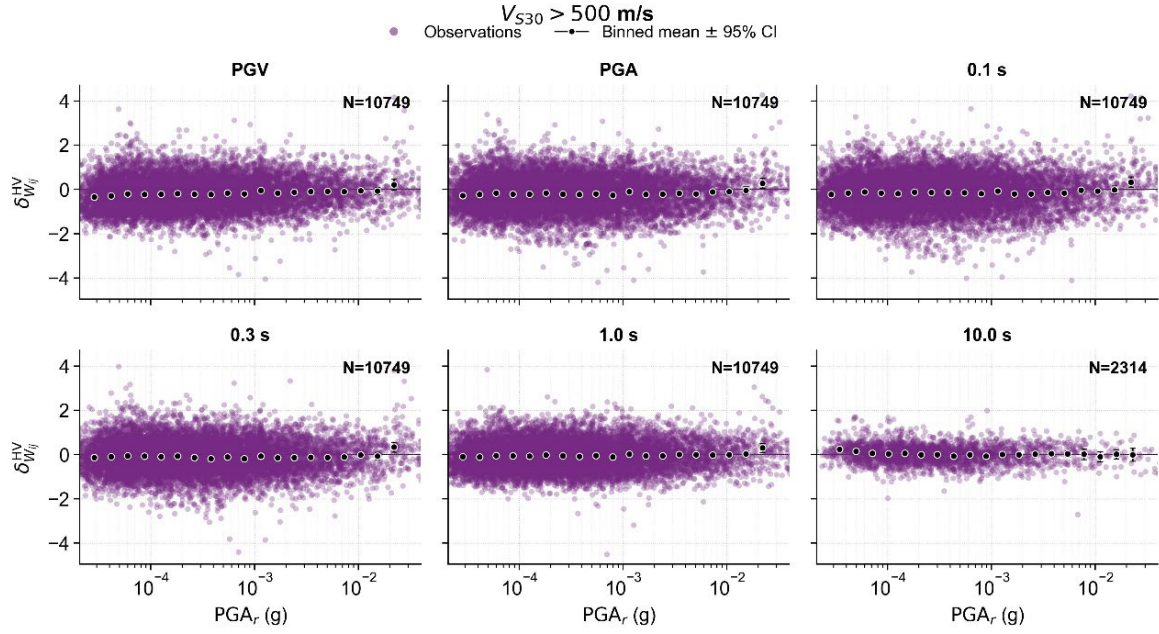


Figure 7.36. Variations of within-event residual (δW_{ij}^{HV}) for different intensity measures with PGA_r for sites with $V_{S30} > 500$ m/s.

7.5.4 Site Term Scaling with Isosurface Depth

7.5.4.1 INTRODUCTION AND DIFFERENTIAL DEPTH

Depths to various shear wave velocity isosurfaces are commonly considered in ground motion modeling as a supplement to V_{S30} . For the 1.0 km/s isosurface, the depth parameter is denoted $z_{1.0}$. In the calculation of residuals (Section 6.2.1), depth-scaling terms in existing models were omitted. This was done because the effects of depth were anticipated to be correlated with other parameters considered in this work, including mHVSr parameters (e.g., $f_{0,HV}$) and geomorphic units. In this section, I examine whether site terms (η_S) derived using the mHVSr-conditioned parametric models (Sections 7.1, 7.2, and 7.3) have correlations with depth parameters.

While $z_{1.0}$ is the directly measured depth parameter for a given site, it is not the parameter used in ground motion models. The issue is that $z_{1.0}$ is correlated with V_{S30} , so using both parameters directly is problematic. To overcome this, the correlation between them has been

developed as shown in Figure 7.37 (provided by Tristan Buckreis from work in the NGA-West3 project), which can be represented by a V_{S30} -conditioned mean, $\bar{z}_{1.0}$

$$\bar{z}_{1.0} = \frac{a_1}{1 + \exp\left(\frac{\ln(V_{S30}) - \ln(v_\mu)}{v_\sigma}\right)} \quad (7.36)$$

where a_1 is a scaling parameter which controls the upper limit of the predicted $z_{1.0}$, v_μ controls the transition of the logistic function (i.e. midpoint), and v_σ is the steepness or spread of the logistic function. For western north America, these parameters are taken as $a_1 = 550$, $v_\mu = 280$, and $v_\sigma = 0.23$. The parameter that is used in ground motion modeling is the difference between $z_{1.0}$ and the $\bar{z}_{1.0}$, i.e., $\delta z_1 = z_{1.0} - \bar{z}_{1.0}$, which removes regression problems associated with multicollinearity (e.g., Curtis and Ghosh, 2011). I consider δz_1 -dependence of η_S in this section.

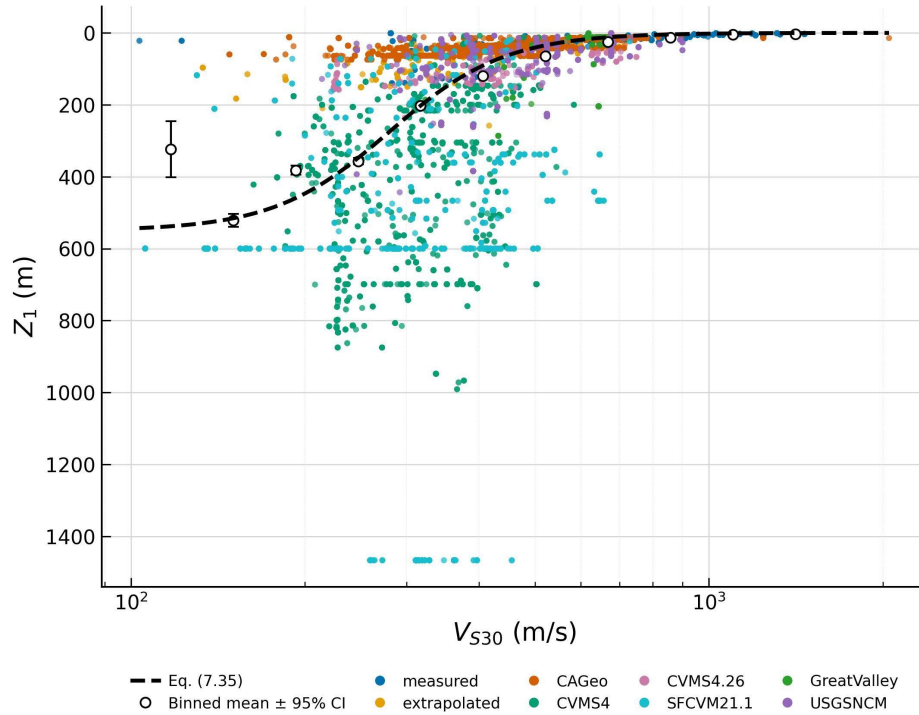


Figure 7.37. Correlation between V_{S30} and 1.0 km/s shear wave isosurface depth $z_{1.0}$ and mean relationship from Eq. 7.35.

7.5.4.2 SCALING AND MEAN MODEL

Figure 7.38 shows the distribution of η_s with δz_1 for all 686 sites using both the mHVSr-conditioned site response model (Eq. 7.30) (orange) and the base ergodic model (SS14) (blue). Interpreting first the base model, no trends with δz_1 are observed at short periods (PGA and Sa at 0.05 s) but upward trends are evident at longer periods for $\delta z_1 > 0$. For example, for Sa at 2.0 s, the mean of site terms for $\delta z_1 > 0.25$ km is 0.24. Directionally similar trends are evident in the site terms for the mHVSr-conditioned model, but the site terms are smaller. For Sa at 2.0 s, the mean for $\delta z_1 > 0.25$ km is reduced to 0.09. This shows that the mHVSr-conditioned model partially accounts for the effects of deep sedimentary structures, but some effects remain. For this reason, I developed an additional basin-depth scaling model to correct for these biases at long periods.

To support this model development, I plot in Figure 7.39 the results from Figure 7.38 for the mHVSr-conditioned model only, but with the data points colored according to geomorphic category. This is motivated by previous studies that have found differences in δz_1 scaling for southern California sites in different geomorphic units (Nweke et al. 2022). Basin and basin edge sites show the largest bias at long periods, which is expected because most large depth sites are in basins. Shelf sites have a negative η_s and $\delta z_1 < 0$, which is expected given their shallow depths. Other categories generally have $\delta z_1 \approx 0$ and inconsistent site term trends (some positive, some negative). I elected to only model depth effects for basin-edge, basin, and shelf categories in a combined manner. The other geomorphic categories, including mountain-hill sites, are assigned zero adjustment based on δz_1 .

To develop the δz_1 -scaling adjustment for the mHVSr-conditioned model, I fit the following equation to the basin, basin edge, and shelf data,

$$F_{\delta z_1}(\delta z_1) = \frac{b}{1 + \exp\left(\frac{-\delta z_1 - x_0}{s}\right)} + a \quad (7.37)$$

where b is the difference in amplitude between low and high δz_1 values, x_0 controls the inflection in the logistic function, s controls the steepness or the width of the logistic function, and a is a constant adjustment for site term values greater than or less than zero. The regression was performed using the python package *scipy.optimize* (Virtanen et al. 2020) with the function *curve_fit*. I did not fit models for periods less than 0.5 s.

Figure 7.40 shows the regressed coefficients along with the smoothed line using LOcally Weighted Estimated Scatterplot Smoothing (LOWESS) smoothing (Cleveland 1979) over the datapoints. The LOWESS smoothing was done using the python package *statsmodels* (Seabold and Perktold 2010). The LOWESS smoothing operator requires two parameters:

- Fraction of data in which the regression is performed, which was set to 70% of the observations (a higher value produces more smoothing).
- The number of iterations of the regression that are performed over the data, which was set to 2 (i.e., 2 robustness iterations were performed to reduce the influence of outliers).

Figure 7.41 shows the predictions from Eq. 7.37 using the smoothed coefficients. Note that the model provides $F_{\delta z_1} = 0$ for $T < 0.5$ sec. The model adequately captures the data trends of $F_{\delta z_1} > 0$ for $\delta z_1 > 0$ and $F_{\delta z_1} < 0$ for $\delta z_1 < 0$ at long periods. For example, for S_a at 2.0 sec, $F_{\delta z_1} = 0.14$ for $\delta z_1 > 0.25$ km and $F_{\delta z_1} = -0.16$ for $\delta z_1 < -0.25$ km.

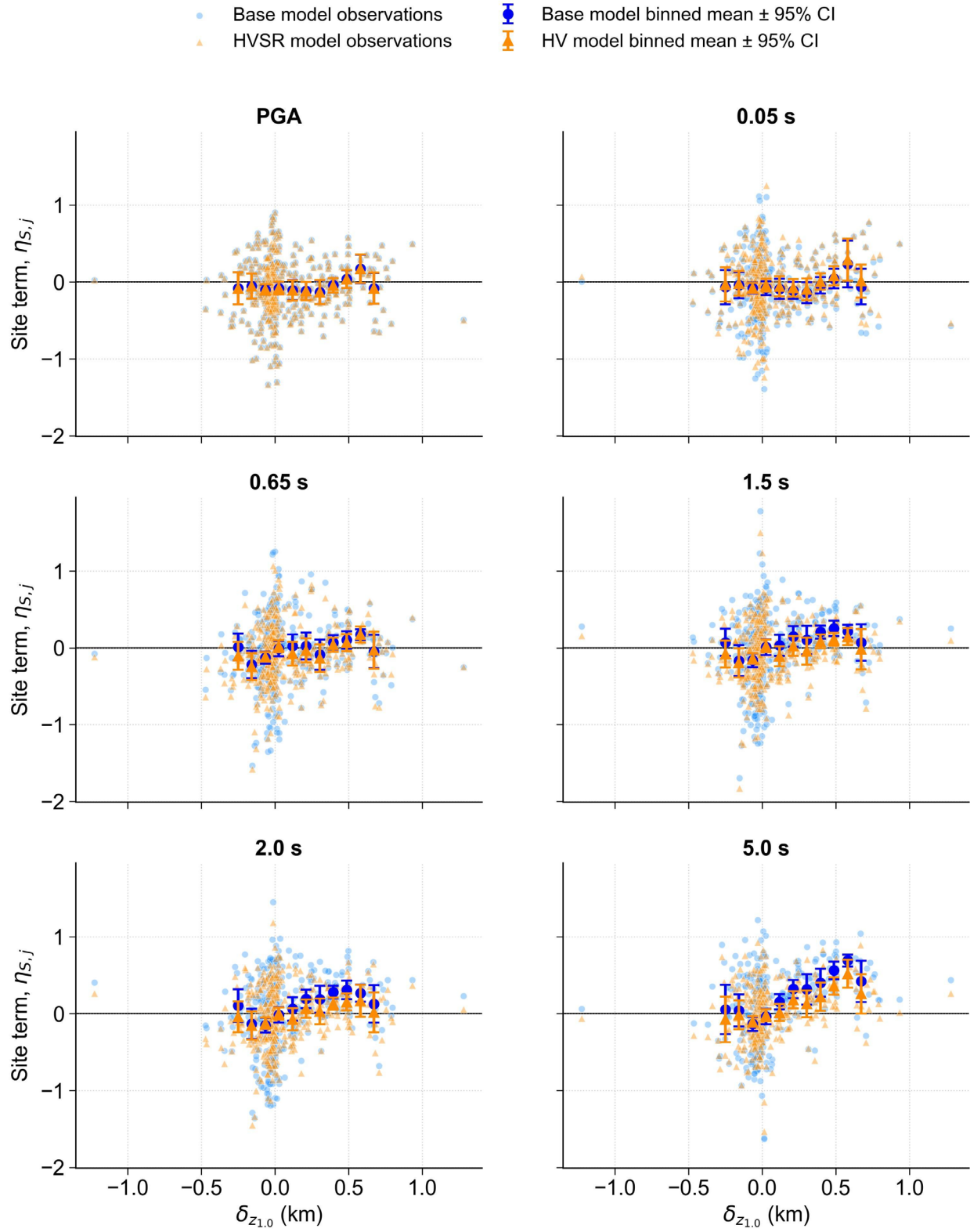


Figure 7.38. Variation of site terms from the mHVSR-conditioned model and SS14 base model with differential depth δ_{Z1} for PGA and five spectral periods (0.05, 0.65, 1.5, 2, and 5 sec).

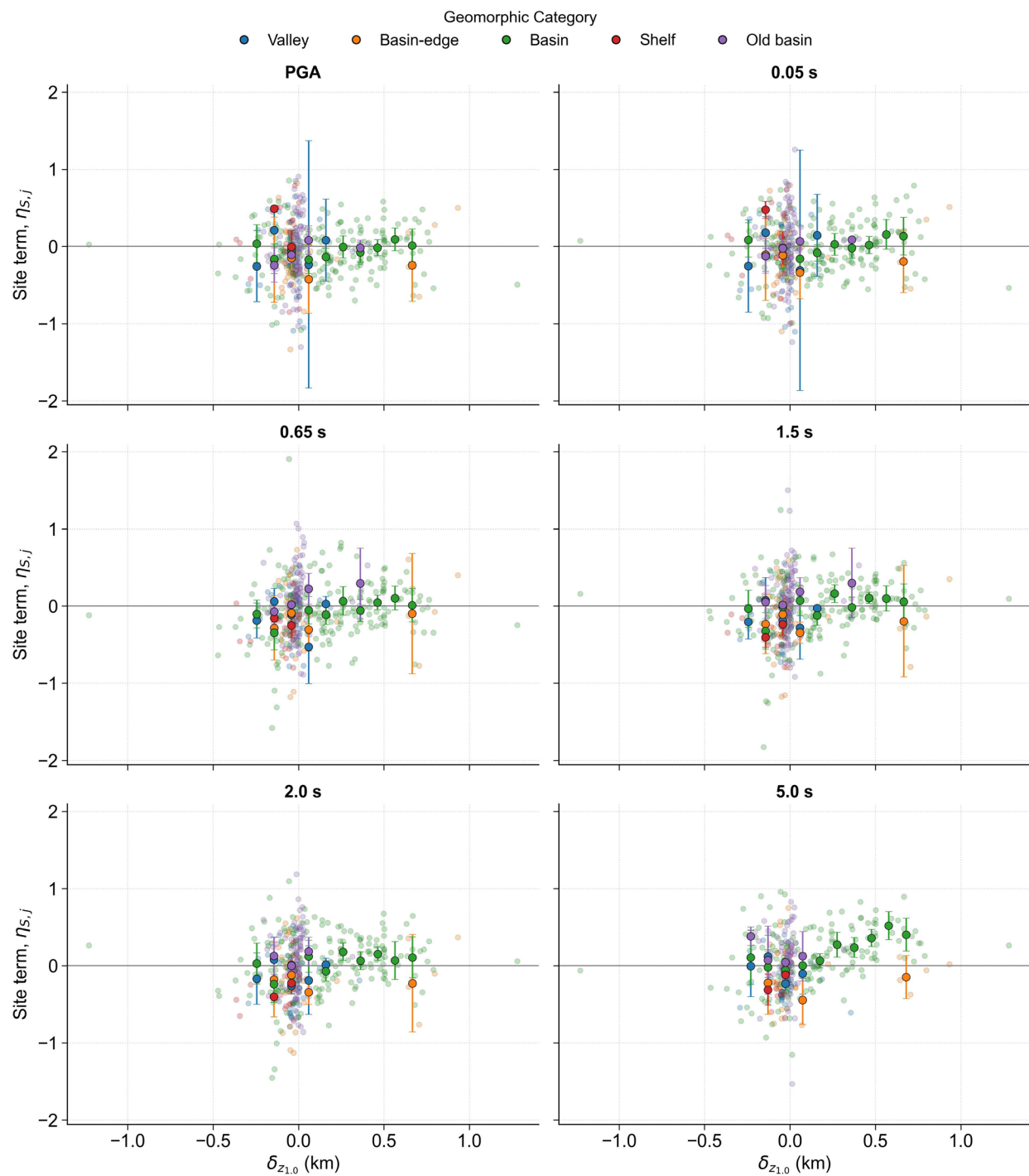


Figure 7.39. Variation of site terms in different geomorphic units from the mHVSR-conditioned model differential depth δ_{z1} for PGA and five spectral periods (0.05, 0.65, 1.5, 2, and 5 sec).

This model is additive to the existing mHVSr-conditioned parametric model given in Eq. 7.29. This updated function is as follows:

$$F_{HV}(T, \ln(\overline{HVSr}_{GM,0.12-2Hz}), f_{0,HV}, a_{0,HV}, G, \mathbf{P}) = P_P F_p + P_{AR} F_{Aramp} + P_{DR} F_{Dramp} + P_F F_{flat} + F_{\delta z_1} \quad (7.38)$$

The depth adjustments provided in Eq. 7.37-7.38 apply only for sites where mHVSr is present. A global or region-specific isosurface-depth scaling should be used when mHVSr is not available.

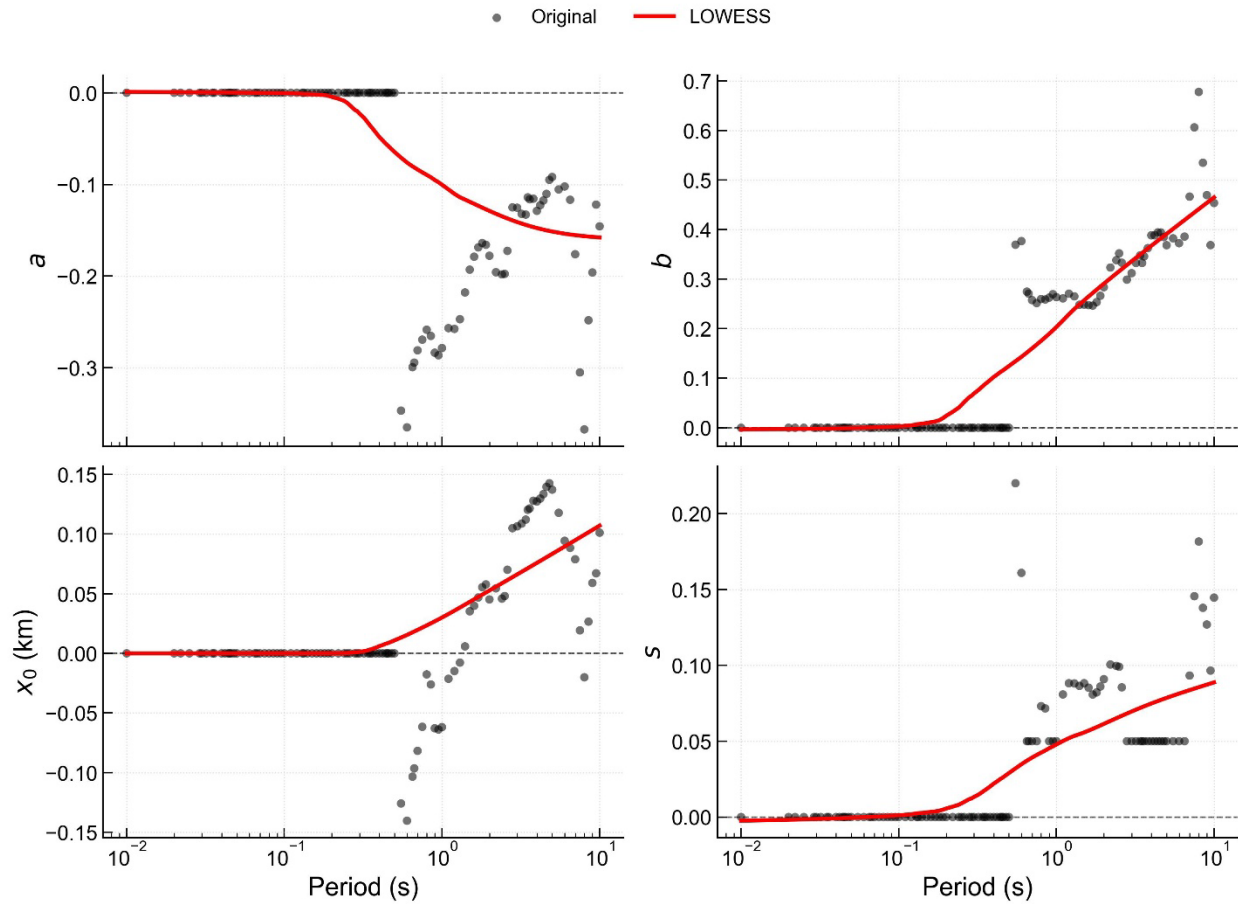


Figure 7.40. Regressed and smooth coefficients for Eq. 7.37. Parameters for $T < 0.5$ sec were manually set to zero.

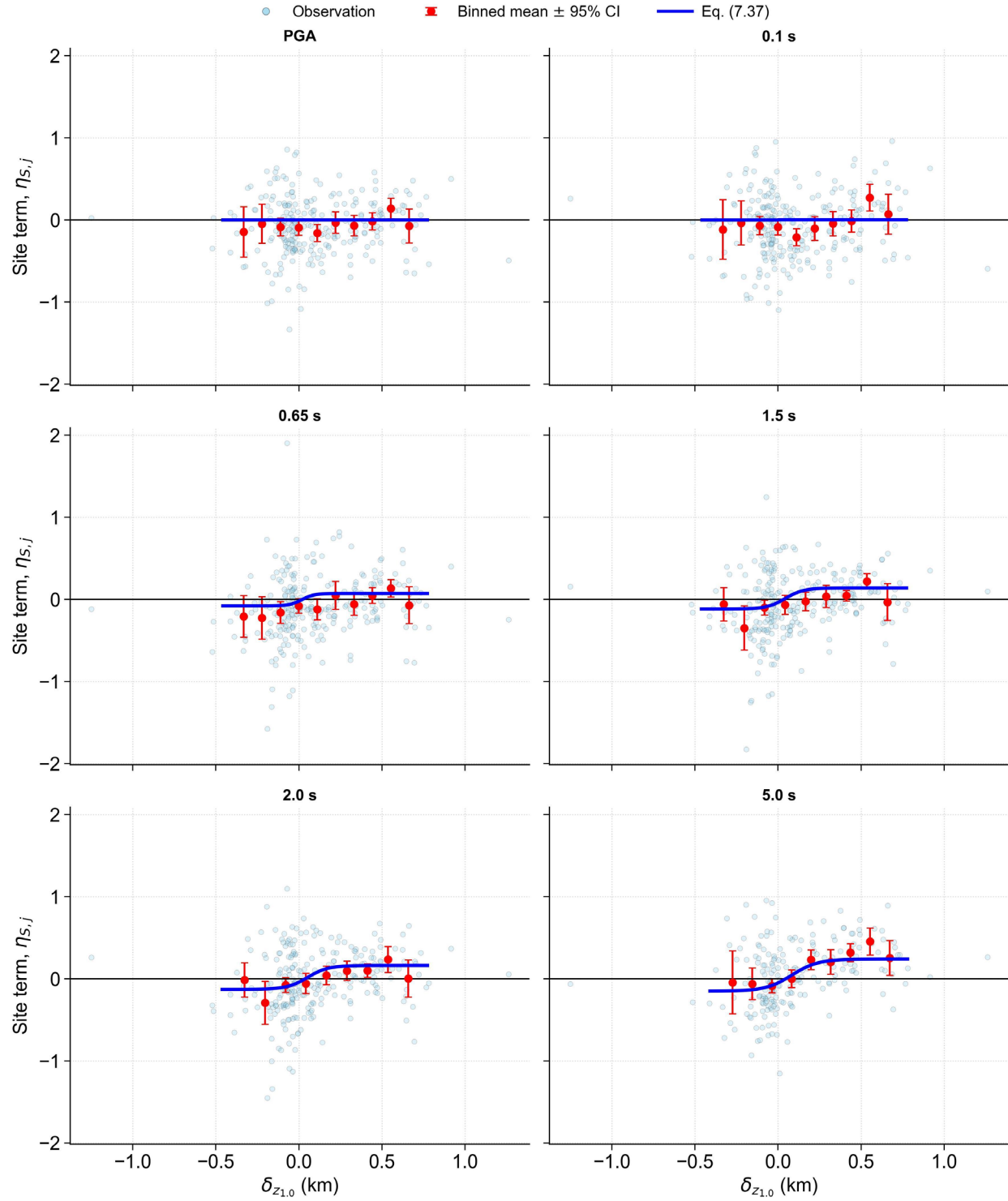


Figure 7.41. Variation of site terms in basin, basin edge, shelf geomorphic units from the mHVSr-conditioned model with differential depth δ_{z1} for PGA and five spectral periods (0.05, 0.65, 1.5, 2, and 5 sec) and model fit from Eq. 7.37.

7.5.4.3 EFFECTS ON RESIDUALS

Total residuals, δ_{ij} , for event i and station j were computed using Eq. 6.1, which are then partitioned into a bias term, random effects for event ($\eta_{E,i}$) and site ($\eta_{S,j}$), and remaining residual (ε_{ij}) using Eq. 6.2. The model used in the residuals calculations is updated from that employed in Section 7.5.2 to include the $F_{\delta_{z1}}$ term as shown in Eq. 7.38.

Figure 7.42 shows site term means, $\bar{\eta}_S$, following the format of Figure 7.26. While there is no appreciable impact of the $F_{\delta_{z1}}$ term for the no peak case, long period $\bar{\eta}_S$ values are brought closer to zero for sites with mHVSr peaks and for the aggregation of all sites. Figure 7.43 shows $\bar{\eta}_S$ within geomorphic categories, following the format of Figure 7.28. Site term means are brought closer to zero for the basin edge, basin, and shelf groups, with negligible impact elsewhere. The reduction of $|\bar{\eta}_S|$ values in those categories occurs for both peak and no-peak sites. Figure 7.44 shows $\bar{\eta}_S$ within physiographic categories, following the format of Figure 7.32. The $F_{\delta_{z1}}$ has negligible impact in western and southern California but reduces $|\bar{\eta}_S|$ in eastern California and the Central Valley.

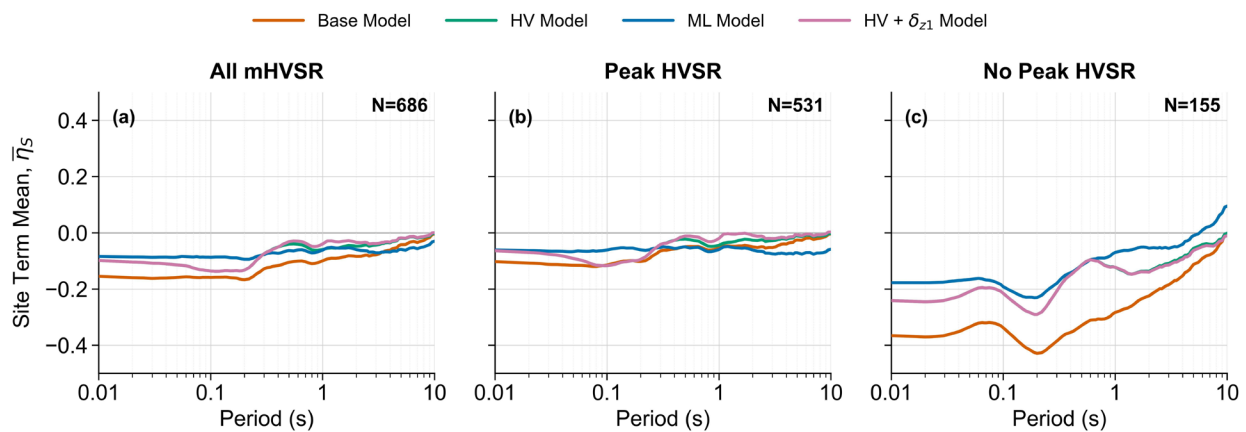


Figure 7.42. Comparison of site term means for mHVSr-conditioned models, with and without δ_{z1} correction, and SS14 for: (a) all mHVSr sites, (b) mHVSr peak sites, and (c) mHVSr no peak sites.

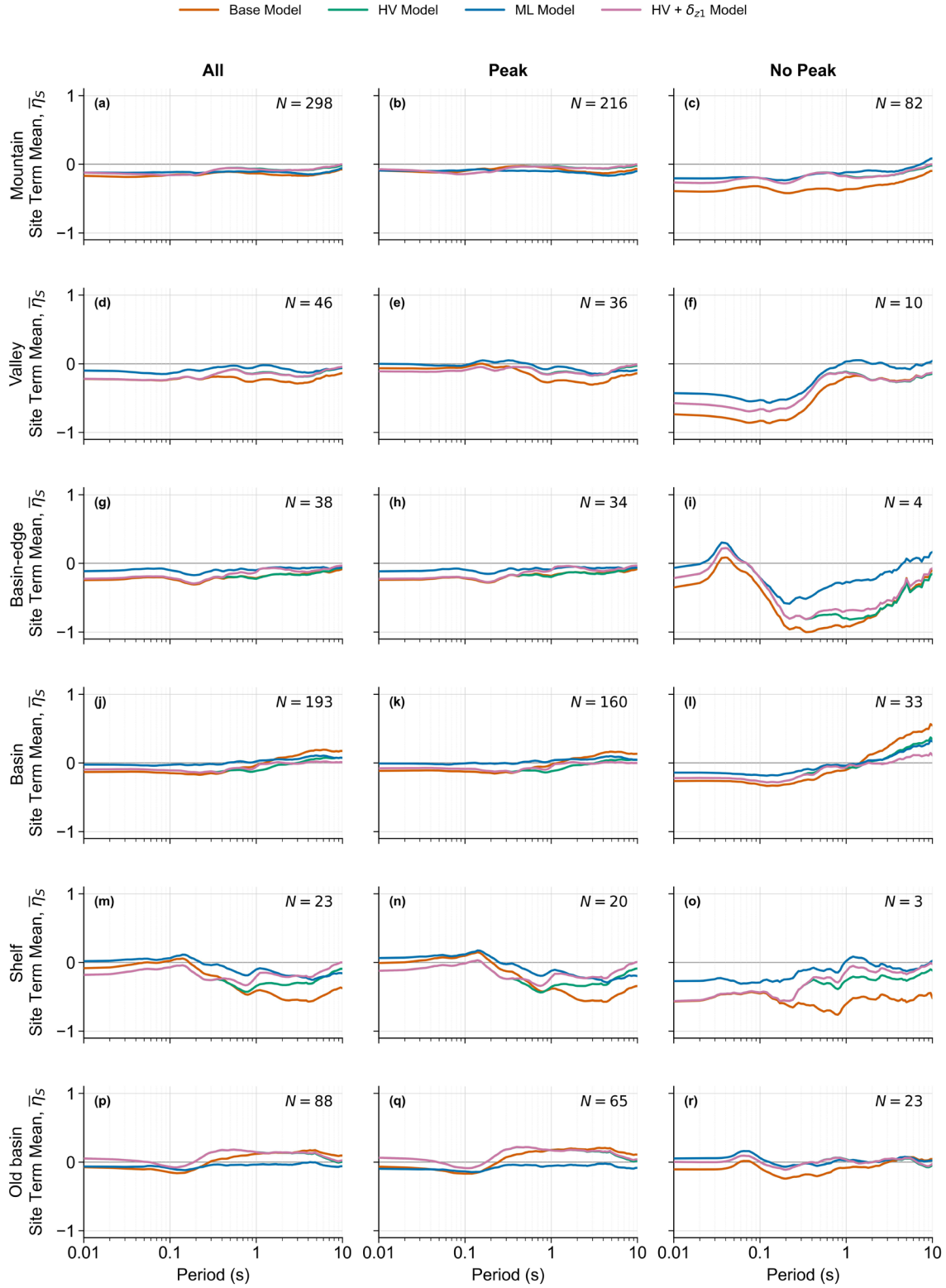


Figure 7.43. Comparison of site term means in geomorphic groups for mHVSr-conditioned models, with and without δ_{z1} correction, and SS14 for: (left column) all mHVSr co-located sites, (middle column) mHVSr peak sites, and (right column) mHVSr no peak sites.

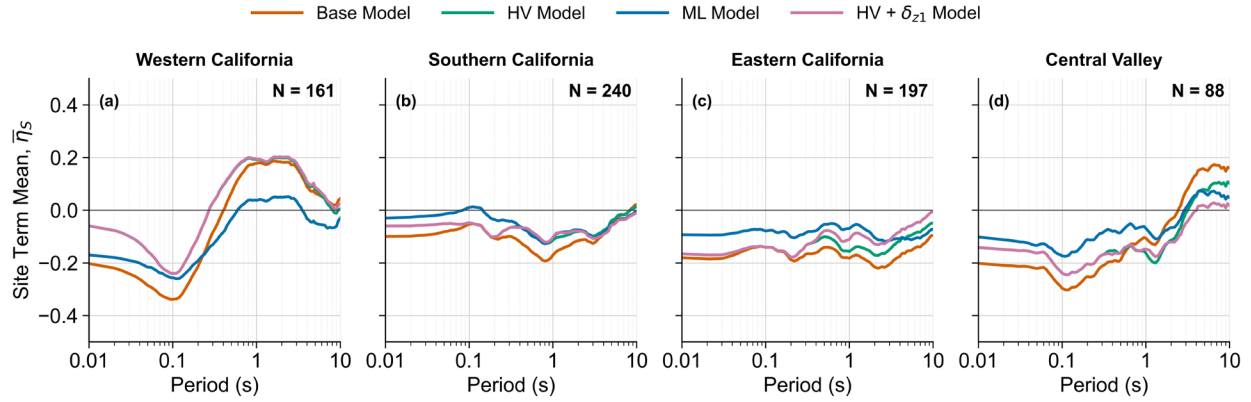


Figure 7.44. Comparison of site term means in physiographic provinces for mHVSr-conditioned models, with and without δ_{z1} correction, and the SS14 base model for (a) Western California, (b) Southern California, (c) Eastern California, and (d) Central Valley.

7.5.4.4 ALEATORY VARIABILITY

Site-to-site standard deviations, ϕ_{s2s} , were computed for comparison to the prior results from Section 7.5.2 (Figure 7.27). Figure 7.45 shows the resulting reductions of ϕ_{s2s} . For all sites (Part a), the reduction begins at 0.5 sec and reaches 0.097 at 5 sec, which is a small effect. The amount of the reduction is smaller for peak sites (about 0.086) and larger for no-peaks sites (0.14). Modest reductions are expected as the model is only applied to basin (192), basin-edge (38), and shelf sites (23), which make up only 37% of the overall dataset.

Figure 7.46 shows an example of the model application for data at station 271, which is a descending ramp site. The mHVSr-conditioned model outperforms the other models but underpredicts the observed site terms at short periods. The isosurface depth scaling model reduces predictions in this case because it is a shelf site with $\delta z_1 < 0$. The machine learning model produces a weaker descending ramp than the parametric model.

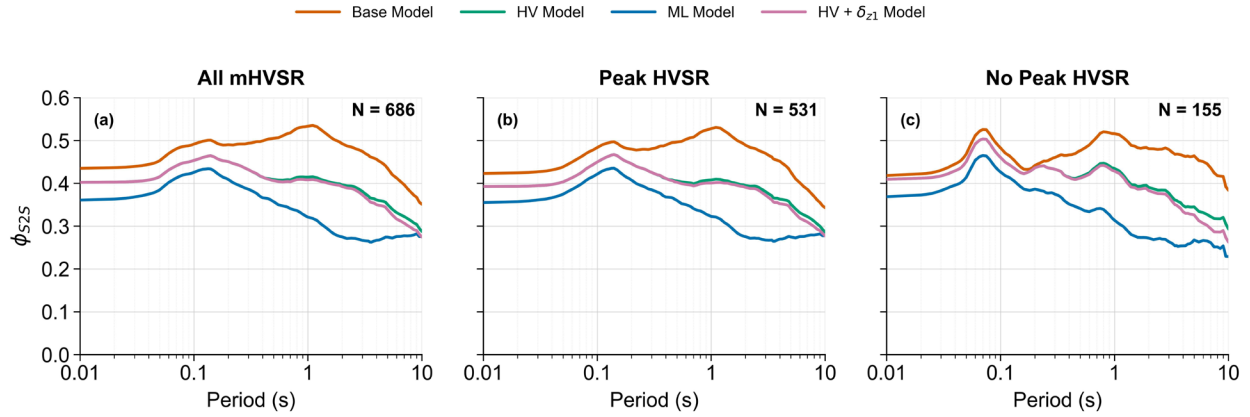


Figure 7.45. Reduction of ϕ_{S2S} for the mHVSr-conditioned model when the isosurface-depth adjustment is applied for: (a) all co-located sites, (b) mHVSr peak sites, and (c) mHVSr no peak sites. Results from base model and machine learning models shown for context.

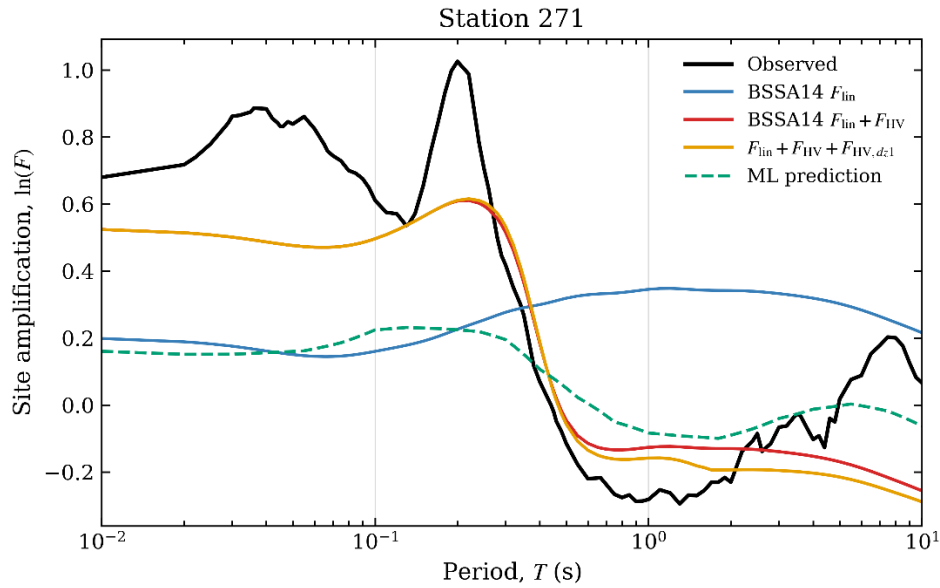


Figure 7.46. Observed site response at station 271 compared to the ergodic base model (SS14), the two mHVSr-conditioned models from Sections 7.1-7.3 and 7.4, and the mHVSr conditioned model supplemented by the isosurface depth correction.

7.6 Conclusions

In this chapter I have presented two models: (1) a parametric mHVSr-conditioned model that captures peak-, ramp-, and flat-like characteristics in site response, and (2) a non-parametric model that is derived using a random forest regressor approach and is conditioned on 30 logarithmically

spaced mHVS_R ordinates for frequencies from 0.1 to 25 Hz in tandem with V_{S30} . The parametric model is additive to the Boore et al. (2014) ground motion model combined with the sub-regional anelastic attenuation model by Buckreis et al. (2023). The non-parametric model replaces the site term in Boore et al. (2014). These models reduce model bias, when averaged across all sites, by almost 0.1 natural log units at short periods and 0.05 natural log units at long periods. Larger reductions on the order of 0.1-0.2 are possible for data subsets (e.g., particular geomorphic categories, physiographic provinces, or sites with mHVS_R peaks). Sites with no peaks had the largest improvement of model bias relative to the base SS14 model of about 0.2 natural log units at all spectral periods. Site-to-site uncertainties are reduced by about 0.1 natural log units for the mHVS_R-based parametric model, with larger reductions of 0.2-0.3 natural log units for the machine learning model at long periods.

The model development presented in this chapter shows the benefits of implementing improved, site-specific site information from mHVS_R into the site terms used in ground motion models. Consideration of geomorphology, or alternatively physiographic provinces, in combination with isosurface depths can further improve the models. Collectively, the proposed models reduce bias and uncertainty.

8 Summary and Conclusions

8.1 Research Objective and Scope

The objectives of this research were broadly related to HVSR data and HVSR-based models. The objectives related to data were to increase the amount of mHVSR data in California, particularly for locations co-located with strong motion sites, to support research on site response modeling. Moreover, that work aimed to improve data processing procedures with a specific focus on low-frequency mHVSR ordinates. There were two principle modeling objectives. The primary objective was to develop an ergodic site response model conditioned on parameters derived from mHVSR curves, in combination with other parameters such as V_{S30} , to improve the modeling of commonly encountered site response features. Those features include site terms (i.e., difference between site response at a particular site and a V_{S30} -conditioned ergodic model) that are flat with respect to period, contain peaks, or contain ascending or descending ramps. The modeling of such effects was expected to reduce uncertainty, which is quantified. A secondary modeling objective was to evaluate whether data from multiple mHVSR curves at different locations across a site could be effectively utilized to assess site response complexity, which has implications for the model error associated with one-dimensional ground response analyses.

In pursuit of these objectives, this research included the following scope items:

1. Collection, processing and entry of mHVSR data into the VSPDB at sites of engineering interest, which were mainly ground motion recording sites.

2. Improvement of the schema for the portions of the VSPDB that contain or describe HVSR data, which was one component of an overall database schema upgrade. Previously uploaded mHVSR data was also reviewed for quality control purposes.
3. Because ordinates of mHVSR curves frequently increase at low frequencies (below ~ 0.1 - 0.2 Hz) to form a ramp-like characteristic, literature review was undertaken to investigate the sources and attributes of low-frequency ambient ground vibrations. Moreover, investigations were performed to evaluate the sensitivity of these portions of mHVSR curves to measurement protocols for the case of temporary deployments and to the procedures used to process the signals.
4. Site investigations were performed involving mHVSR measurements at multiple locations, spatially distributed across sites containing vertical arrays, to interpret site heterogeneity. For each site, heterogeneity metrics were developed from interpretations of the mHVSR curves, which in turn were related to metrics quantifying the effectiveness of one-dimensional (1D) ground response analysis (GRA) derived from the vertical arrays. By linking heterogeneity and GRA effectiveness metrics, it was possible to develop recommendations for evaluating site response effectiveness. Such recommendations could be used to *a priori* identify sites where model error could be reduced from levels predicted by currently available models.
5. Using a large database, 686 sites were identified that have a co-located ground motion instrument and mHVSR measurement. From residuals analyses of earthquake ground motion data from those sites, four characteristic features were observed: variation of site term with period is flat, site terms contain a peak, or site terms contain ramps that either

slope up (ascending) or down (descending) as period increases. Methodologies were developed to objectively identify peaks and ramps from site term – period plots. Procedures were then developed to predict what site term features are likely to be present for a given site based on mHVSr characteristics (i.e., peak parameters and ordinates at individual frequencies or averaged across a frequency range). This was accomplished using a decision tree classifier.

6. Parametric models were developed to predict site amplification for sites with specific features (peak-only, ramps, flat). These models were conditioned on mHVSr parameters and geomorphic categories. The models are applied to a given site using as a weighted sum of each model, with the weights taken as the conditional probabilities from the decision tree classifier. Machine learning models conditioned on mHVSr ordinates and V_{S30} were also derived.

8.2 Research Findings

I summarize major research findings into three main groups within this section: mHVSr data, effectiveness of multi-sensor mHVSr to evaluate site heterogeneity, and applications of mHVSr for site response modeling.

8.2.1 mHVSr Data

I expanded the HVSr database from 1465 sites in California to 2942 sites. This involved both downloading and processing data from seismometers and deploying to the field at sites with accelerometers but no seismometers and other locations of engineering interest. The reason

deployments were needed at accelerometer sites is that microtremor data derived from accelerometers do not provide reliable mHVSr curves (Wang et al. 2023).

From the evaluation of processing procedures, in which different methods of detrending, applying tapering windowing functions, and applying high-pass filtering were investigated, it was determined that signal processing should apply a weighted detrend to data within each time window, taper the time series as a whole and within each window, and apply a high-pass filter. Moreover, I elected to use a window length of 300 sec because it provides an adequate number of cycles (> 10) per window for the frequency range of typical interest, assuming a total signal duration of 1 hr or more. If a shorter signal duration was used in a field deployment, it was determined that the processing should use fewer windows to have at least 10 cycles to average within each window prior to calculating Fourier Amplitude Spectra and mHVSr. The effect of detrending is often to increase low-frequency mHVSr ordinates relative to what would be obtained without these processing steps. Other processing steps have less impact.

A common feature of mHVSr curves is increasing ordinates for frequencies below about 0.2 Hz. Such ordinates often occur for reasons unrelated to the sedimentary structure at a given site, and may in fact obscure potential low frequency resonances. The underlying problem is that microtremor signals can be influenced by complex combinations of wave types, some of which are associated with oceanic or atmospheric disturbances that affect the horizontal component more than the vertical. If Rayleigh wave energy can be isolated from other wave types, there is evidence to suggest that low-frequency mHVSr ordinates are reduced such that they may have the potential to reveal attributes of deep sedimentary structure.

8.2.2 Effectiveness of Multi-Location mHVSr to Evaluate Site Heterogeneity

I found that spatial variability of mHVSr at a given site could be effectively quantified using the Longest Common Subsequence (LCSS) similarity parameter S_1 , which measures correlations between curve shapes in a way that allows modest horizontal shifts. I showed that 89% of sites with a high degree of spatial correlation in mHVSr ($S_{1,mHVSr} > 0.8$) had observed transfer functions from vertical arrays that were well modeled by 1D GRA. Moreover, all sites with low spatial correlation ($S_{1,mHVSr} < 0.65$) in mHVSr were poorly modeled by 1D GRA. The analysis focused on frequency intervals encompassing low-frequency peaks in the transfer function and corresponding peaks in mHVSr curves, with higher frequency peaks showing diminished correlation.

8.2.3 Applications of mHVSr for Site Response Modeling

Analyses of site terms revealed that most sites have characteristics that can be described as peak-only, ramp-like (ascending or descending), or flat. Some sites have both peaks and ramps, with the peaks most often occurring near the edge of the ramp's upper plateau. Algorithms were developed to objectively identify whether peaks or ramps are present and to fit such features. I found that 26% of sites in the dataset are peak-only, 28% contain descending ramps, 37% contain ascending ramps, and 10% are flat. Using previously proposed methods from Wang et al. (2023), I also evaluate whether sites have mHVSr peaks and fit peaks using a Gaussian pulse function. I found that 62% of sites have an mHVSr peak in the dataset (38% do not).

A decision tree classifier was developed to predict probabilities of different site response features conditional on mHVSr curve characteristics and other site proxies, including

geomorphology category. The model performs much better for ramp sites than for peak or flat sites.

I presented two types of site response prediction models: (1) parametric mHVS_R-conditioned models that capture peak-, ramp-, and flat-like site response features, and (2) a non-parametric model that is derived using a random forest regressor approach, conditional on 30 logarithmically spaced mHVS_R ordinates for frequencies from 0.1 to 25 Hz in tandem with V_{S30} . The parametric models are applied as a weighted sum of predicted site responses from the different feature models, with the weights taken from decision tree classifier probabilities. Based on residuals analyses, adjustments conditional on geomorphology category, differential depth δz_1 , and the presence (or lack of presence) of an mHVS_R peak are recommended. Relative to a V_{S30} -conditioned ergodic model, the models developed in this research reduce site-to-site uncertainty by about 0.1-0.2 natural log units, with the greatest reductions at long periods.

8.3 Recommendation for Usage of HVS_R in Analysis

In this dissertation I have discussed a variety of methods to use mHVS_R in terms of collection of the data to its use in various analyses. In this section, I will discuss my recommendations for procedures to ensure mHVS_R curves are collected or used properly for analyses.

In the collection and processing of the mHVS_R data, many of the steps are described in chapter 3, but here I summarize major findings. When collecting mHVS_R, one should utilize a 120 sec broadband seismometer to reliably estimate mHVS_R down to 0.1-0.2 Hz. If sensors with larger corner frequencies are used, it can affect the results. It is important to bury the sensor to improve coupling with the ground. It is also important to cover the sensor with a bucket to reduce external wind from affecting the recording. The duration of the recording should be more than 1 hr to

reliably estimate mHVSr at lower frequencies. I recommend using a window length of 300 sec; this recommendation is driven by how many cycles per window are present in the time series. This window duration was sufficient to reliably acquire results for frequencies as low as 0.1 Hz. In data processing, it is important to apply the preprocessing steps described in Chapter 3, which detrend the time series, apply a Tukey tapering function to the ends of the signal as a whole and the time windows, and to apply a high-pass filter to the entire time series. These steps ensure that drift in the data is removed and that the time series is stable prior to calculation of FAS and mHVSr.

Low frequency portions of mHVSr curves can be difficult to interpret. Previous studies (discussed in Section 4.1) found that the microtremor wavefield is significantly affected by long period energy attributed to oceanic or atmospheric disturbances. These effects cause vertical components to be substantially smaller than horizontal components, causing HVSr to have a ramp-like characteristic below 0.1 Hz. Burying or installing the sensor at depth reduces these effects, but the issue persists. While permanent stations are less affected by these effects, they too have ramp-like characteristics in about 38% of cases. These issues have been observed in urbanized areas and remote areas. Investigations of Rayleigh wave H/V ratios through the cross correlation of recordings from multiple stations revealed that mHVSr ordinates below 0.1 Hz were relatively stable and appeared to be capable of revealing low-frequency peaks that might be obscured in conventional mHVSr.

My investigation of spatially distributed mHVSr as a means for capturing lateral heterogeneity was based on collections of mHVSr in concentric expanding circles at vertical array sites. I perform this analysis by comparing the LCSS correlation metric for the first mode frequency peak to the correlation between observed and theoretical transfer functions. The

comparison of these correlations showed that the mHVSr correlation metric has predictive power for the correlation between theoretical and empirical transfer functions.

Application of the site response model would not involve peak and ramp identification from site terms, assuming no ground motions are available from the site (which is typical). To ensure that mHVSr peak identification is done in a similar manner to that performed in model development, users should utilize the algorithm developed by Wang et al. (2023), which uses a decision tree regressor. The threshold values used in the analysis were the liberal thresholds proposed by Wang et al. (2023). Once the peaks are found in mHVSr, a Gaussian pulse should be fit to the mHVSr curve to extract peak parameters including peak frequency and amplitude (peak width was not found to be informative). Geomorphic categories should also be assigned from among the options in Table 6.3. The natural log ordinates at 0.12, 0.2, 0.3, and 2 Hz from the mHVSr curve along with a flag indicating whether a peak was found in mHVSr are used as inputs to the decision tree classifier, which identifies likelihoods of site response features (e.g., ramp, peak, flat).

The parametric site response models discussed in Chapter 7 capture peak, flat, and ramp site response features. Two of the models, ramp and peak, utilize peak attributes from mHVSr along with the average of ordinates at long periods. The peak-based model specifically only utilizes the peak parameters from mHVSr (peak frequency and amplitude), as these were found to correlate strongly with the peak parameters in site response. Different models are provided for “Sedimentary” and “Non-sedimentary” geomorphic groups. The ramp model was also developed separately for sedimentary and non-sedimentary sites when an mHVSr peak is present at the site. When an mHVSr peak is not present, I utilized the geometric mean of the mHVSr ordinates between 0.5 and 8 sec in natural log units. Flat site response was modelled as period-dependent

adjustments that are different for different geomorphic categories. All three models (peak, ramp, flat) are linked probabilistically using the conditional probabilities from the decision tree classifier. A machine learning model was also developed as part of this study, and is built on a random forest regressor model, and takes as input 30 mHVSr logarithmically spaced ordinates from 0.1 to 15 Hz and V_{S30} . This model provided larger reductions in uncertainty compared to the parametric model, which might be expected because it uses far more model parameters and it is not constrained by smooth functional forms that align with our understanding of interpretable physical mechanisms. For this reason, I recommend the use of the parametric model due to its explainability, and ability to still have large reductions in the site-to-site standard deviation.

8.4 Recommendations for Future Research

The results from this research sets the stage for future work that would facilitate practical implementation of models presented herein and broaden their applicability to regions beyond California.

As discussed in Chapter 4, low frequency mHVSr ordinates have the potential to reveal resonances associated with deep sedimentary structure. However, the mHVSr measurement, processing, and interpretation procedures from this research were often unable to provide results allowing these features to be identified due to unusually large ordinates from ramp-like characteristic below 0.1-0.2 Hz. A promising technique that could be further explored is interpretation of data from arrays of sensors that enable the isolation of Rayleigh waves from other contributors to the microtremor wave field. By taking H/V ratios of the Rayleigh waves for sites in the Central Valley, low frequency peaks were observed that appear to be correlated to a deep

impedance contrast. This technique could be further pursued and standardized to test its applicability and repeatability.

As discussed in Chapter 5, I describe how the spatial variability of mHVSr aids in understating the effectiveness of 1D GRA, finding a strong correlation between the LCSS metric between the transfer functions (empirical and theoretical) and spatial mHVSr. I would like to highlight two main opportunities for further research. The first pertains to the data limitations that did not allow for proving the link between mHVSr LCSS metric and model error. This could be addressed by adding more vertical array sites to the study, which should be possible in California as additional arrays record enough earthquakes to be considered. Data from arrays outside of California could also be considered, provided they have high-quality shear wave velocity data. Second, additional mHVSr variability metrics could be considered. Among these are temporal variations of mHVSr at a single station. The underlying hypothesis is that for simple sites (nearly 1D) temporal variability may be limited whereas at complex sites it may be stronger. Temporal variability for complex sites might occur because waves arriving from various angles might interact with complex stratigraphy differently, thereby producing variable mHVSr. Consideration of azimuthal variations in time should also be investigated.

The work on parametric and machine learning models in Chapter 7 could be extended in the following ways:

- Develop models to address nonlinear effects, which would be expected to lengthen and broaden site response peaks and alter the characteristics of ramps, particularly descending ramps due to their large amplitudes at short periods.

- Evaluate transferability of the parametric and machine learning models by examining site terms for other data rich regions such as Japan, New Zealand, Taiwan, and other western US states. Transferability should be considered separately for the decision tree classifier and the feature-specific fits for peak-only, ramp, and flat models.
- Update the models presented here for compatibility with NGA-West3 ground motion models.

9 References

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