

Evaluation of Existing Methods for Estimation of Shear Wave Velocity for Sites in Alabama

by

Joshua Robert McLeod

A dissertation submitted to the Graduate Faculty of
Auburn University
in partial fulfillment of the
requirements for the Degree of
Doctor of Philosophy

Auburn, Alabama
August 8, 2026

Keywords: Shear wave velocity, site class, V_{s30} , evaluation

Copyright 2026 by Joshua Robert McLeod

Approved by

Dr. Jack Montgomery, P.E., Chair, Alice H. & John M. Ozier Associate Professor of Civil and
Environmental Engineering

Dr. Brian Anderson, P.E., Elton Z. & Lois G. Huff Endowed Professor of Civil and Environmental
Engineering

Dr. Robert Barnes P.E., Arthur H. Feagin Chair Professor of Civil and Environmental Engineering
Dr. Jeffery LaMondia, Elton & Lois Huff Professor of Civil and Environmental Engineering

Abstract

Bridges are critical infrastructure systems and need to be resilient to even the rarest of hazards. Seismic damage to bridges and other infrastructure systems is determined by the seismic loading. Seismic loading is dependent on many factors, namely the magnitude and distance of the earthquake, site effects, and the structure itself. Site effects are of particular importance to this study as they influence the frequency and amplitude content of incoming ground motions. Site effects are included in seismic design with the consideration of shear wave velocity (V_s). V_s is used as a proxy for stiffness of the site as it is directly related to the shear modulus and density of the soil. V_s profiles are included in design codes in the form of site classes based on a time averaged V_s of the upper 30 meters of the subsurface, known as V_{s30} .

The most effective method for determining V_{s30} is by direct measurement. Direct measurement can be expensive and not economically feasible for every project. In more seismically active regions, many researchers have developed indirect methods for determining V_{s30} based on empirical relationships between V_s and results of commonly performed in-situ tests, ambient noise recordings, and even with geospatial features of the site. These methods have proven to be effective in the regions for which they were developed but need validation before use in Alabama.

To evaluate indirect methods for determining V_s , direct measurements were taken at multiple sites across the state. Sites were selected to capture the behavior of soft alluvial sites and due to the availability of high quality boring logs. Direct measurements include multichannel analysis of surface waves (MASW) and seismic refraction. Indirect methods

include SPT and RQD-based correlations, HVSR-based correlations, and geospatial correlations. Direct measurements were taken at 15 sites as a basis for comparison of indirect methods.

Results of comparisons performed on the indirect methods indicate that geospatial correlations provide the best fit to the measured data from this study. Geospatial methods can be applied using GIS based maps and require the least time in application. Geospatial correlations are most effective within the coastal plains province in the state but will tend to be conservative for stiffer sites in other regions. Geospatial methods provide the most accurate estimates of site class with a bias towards conservatism. SPT based correlations are most accurate at shallower depths and tend to underestimate V_s at greater depths. The correlations presented perform best on sands as reflected by calculated statistical measures. SPT based methods can provide reasonable estimates of site class but have a greater risk to provide unconservative estimates compared to geospatial methods. RQD based correlations are more limited in number than SPT based correlations. Results of analysis indicate the presented correlations all provide a poor fit to the database used in this study and are not recommended for use. Poor performance is not unexpected as geology in Alabama differs from the regions these correlations were intended to be used in. The sample size of HVSR curves with a clear peak in this study is limited so conclusions drawn may not be representative of overall trends in the state. High-dimensional models presented in Sharma Wagle et al. (2026) were able to be applied to all curves as they consider the entire HVSR curve as opposed to the peak frequency and its amplitude. The addition of more HVSR curves with clear peaks would allow for better evaluation of correlations that require a clear peak in application.

Artificial Intelligence (AI) Use Disclosure Statement

In the preparation of this dissertation, no Artificial Intelligence (AI) tools were used.

Digital Accessibility Disclosure Statement

In the preparation of this dissertation, the following digital accessibility tools were used to ensure this document complies with federal requirements: Microsoft Word Accessibility Assistant and Adobe Acrobat Accessibility Assistant. The author acknowledges full responsibility for the intellectual content of this work and has made a good faith effort to comply with digital accessibility requirements in publishing, wherein the nature of the content does not significantly change in order to do so. Furthermore, all content has been reviewed and revised to meet these requirements prior to final publication.

Acknowledgements

This has not been an easy journey towards obtaining my doctorate and I would like to thank the many people who made this journey possible. Firstly, I would like to thank my family and friends for their unwavering support of me through this Journey. To my mother for always encouraging me to dream big and for inspiring me with your resilience and strength.

I would like to thank my advisor Dr. Jack Montgomery for allowing me the opportunity to learn and grow here in my time in graduate school at Auburn. The skills I have learned will carry me through the rest of my engineering career.

I would like to thank my committee members: Dr. Anderson, Dr. LaMondia, and Dr. Barnes for being willing to serve on my committee, and for the time taken to review this work and to provide insightful comments to further strengthen this research.

This research would not have been possible without funding provided by the Alabama Department of Transportation. I would also like to thank my good friend and colleague, Dr. Chukwuma Okafor for all his assistance with the project. Field surveys would not have been possible without him.

Table of Contents

Abstract	2
Artificial Intelligence (AI) Use Disclosure Statement	4
Digital Accessibility Disclosure Statement	5
Acknowledgements.....	6
List of Tables.....	11
List of Figures	15
Chapter 1: Introduction.....	33
1.1 Background	33
1.2 Motivation and Objectives.....	36
1.3 Research Tasks	37
1.4 Dissertation Organization.....	37
Chapter 2: Review of Methods to Determine Shear Wave Velocity Profiles	39
2.1 Direct Methods	39
2.1.1 Invasive Methods.....	39
2.1.2 Non-Invasive Methods.....	39
2.1.2.1 Seismic Refraction	39
2.1.2.2 Seismic Reflection	41
2.1.2.3 Multichannel Analysis of Surface Waves.....	42
2.2 Correlation Based Estimates of V_s	42
2.2.1 Correlation with Standard Penetration Testing	43
2.2.1.1 Ohta and Goto 1978.....	44
2.2.1.2 Imai and Tonouchi 1982	46
2.2.1.3 Seed et al. 1983.....	46
2.2.1.4 Jinan 1987	47
2.2.1.5 Lee 1992	47
2.2.1.6 Hasancebi and Ulusay (2007).....	48
2.2.1.7 Wair et al. 2012	50
2.2.1.8 Fatehnia et al. 2015.....	51

2.2.1.9 Anbazhagan et al. 2016.....	52
2.2.2 Correlation to Cone Penetration Testing (CPT).....	53
2.2.2.1 Summary by Wair et al. (2012)	53
2.2.2.2 Mousa and Hussein 2022	54
2.2.3 Correlations for Rock	55
2.2.3.1 El-Naqa 1996	56
2.2.3.2 Biringen and Davie 2013	57
2.2.3.3 Salaamah et al. 2019	60
2.2.4 Correlations with HVSR Measurements	61
2.2.4.1 Ghofrani and Atkinson (2014).....	62
2.2.4.2 McNamara et al. 2015.....	63
2.2.4.3 Hassani and Atkinson 2016	64
2.2.4.4 Stanko and Markušić (2020).....	66
2.2.4.5 Sharma Wagle et al. 2026	67
2.2.5 Geospatial Correlations	68
2.2.5.1 Wald and Allen 2007	68
2.2.5.2 Yong et al. 2012	70
2.2.5.3 Kottke et al. 2012	71
2.2.5.4 Parker et al. 2017	73
2.2.5.5 Geyin and Maurer 2023	74
2.2.5.6 Gann-Phillips et al. 2024	76
2.3 Summary	80
Chapter 3: Methodology.....	81
3.1 Introduction	81
3.2 Direct Methods	81
3.2.1 MASW Data Processing	82
3.2.2 Refraction Data Processing.....	85
3.2.3 SPT Boring Logs.....	87
3.3 Indirect Methods.....	88
3.3.1 Boring Based Correlations to V_s	88
3.3.2 HVSR Based Estimation Methods	89

3.3.2.1 Recording Devices	89
3.3.2.2 Data Collection	91
3.3.2.3 Data Processing	93
3.3.3 Geospatial Methods	93
3.3.4 Statistical Measures for Evaluation of Estimation Methods.....	95
3.3.4.1 Prediction Evaluation Statistics	95
3.3.4.2 Inequality Statistics	96
3.4 Summary of Methodology	96
Chapter 4: Results of Direct Methods.....	98
4.1 Introduction	98
4.2 Cedar Bluff, AL Site	99
4.3 West Alabama Surveys.....	101
4.3.1 Beaver Creek Site	102
4.3.2 Big Prairie Creek Site.....	105
4.3.3 Coldwell Creek Site	107
4.3.4 Moundville, AL Site	109
4.3.5 Greensboro, AL Site	112
4.4 Northwest Alabama Surveys.....	115
4.4.1 Duck River Site	115
4.4.2 Russellville High School Site	117
4.4.3 Bluewater Creek Site	121
4.4.4 Lauderdale County Site.....	123
4.4.5 Blount County Site	125
4.5 Summary	127
Chapter 5: Results of Indirect Methods	129
5.1 Introduction	129
5.2 Results of Boring Based Methods	129
5.2.1 Cedar Bluff Site	130
5.2.2 West Alabama Sites	131
5.2.3 Northwest Alabama Sites	139
5.3 HVSR Results	146

5.4 Geospatial Methods.....	166
5.5 Summary	167
Chapter 6: Evaluation of Approaches for Estimating V_s	169
6.1 Comparison of Boring Based Estimation Methods	170
6.1.1 Comparison of SPT Based Estimation Methods	170
6.1.2 RQD Based Estimation Methods.....	188
6.2 Comparison of HVSR Methods.....	192
6.2.1 Statistical Measures for HVSR Based Estimation Methods	194
6.3 Comparison of Geospatial Methods	196
6.4 Effect on Determining Site Class	199
6.5 Summary	203
Chapter 7: Conclusions and Recommendations	205
7.1 Summary	205
7.2 Conclusions	205
7.3 Recommendations	207
7.4 Future Research	208
References.....	210
Appendix: HVSR Signal Files and Curves	223

List of Tables

Table 1-1: Site class definitions used in AASHTO LRFD bridge design specifications (AASHTO 2023)	36
Table 2-1: Correlation coefficients and probable error for developed equations (Ohta and Goto 1978)	45
Table 2-2: Recommended regression equations (Lee 1992).....	48
Table 2-3: Recommended correlation equations (Wair et al. 2012).....	51
Table 2-4: Correlation equations developed from South India database (Anbazhagan et al. 2016)	53
Table 2-5: CPT based correlation equations presented in Wair et al. 2012. Equations recommended for use are bolded.	54
Table 2-6: Proposed correlation equations presented in Moussa and Hussein (2022)	55
Table 2-7: Geologic classes defined for CENA (Kottke et al. 2012)	72
Table 2-8: Proposed V_{S30} estimation procedures based on large-scale geologic maps, Wisconsin glaciation, location of site in a basin, and topographic gradient (Parker et al. 2017)	74
Table 2-9: Input parameters, sources, and resolutions for Geyin and Maurer V_{S30} model (Geyin and Maurer 2023)	75
Table 2-10: Values of V_{S30} , $Z_{1.0}$, $Z_{0.76}$, and $Z_{3.0}$ from the model database presented in Gann-Phillips et al. 2024 along with median values presented in Ahdi 2018 for comparison	79

Table 3-1. Recommended minimum recording duration according to expected frequency peak (SESAME 2004)	92
Table 4-1: Locations selected for direct measurements	98
Table 4-2: Calculated range of V_S profile for Duck River site	117
Table 4-3: Calculated range of V_S profile for Lauderdale County site	124
Table 4-4: Calculated range of V_S profile for Blount County site	127
Table 5-1: Abbreviations for boring based correlations.....	130
Table 5-2: Results of HVSR surveys	151
Table 5-3: V_{S30} estimates using Ghofrani and Atkinson (2014) model. Cells highlighted in green indicate estimates from HVSR curves with clear peaks while dashed lines indicate locations where the model was not able to be applied.	153
Table 5-4: V_{S30} estimates using McNamara et al. (2015) model. Cells highlighted in green indicate estimates from HVSR curves with clear peaks.	155
Table 5-5: V_{S30} estimates using Hassani and Atkinson (2016) model. Cells highlighted in green indicate estimates from HVSR curves with clear peaks.	157
Table 5-6: V_{S30} estimates using Stanko and <i>Markušić</i> (2020) model. Cells highlighted in green indicate estimates from HVSR curves with clear peaks while dashed lines indicate locations where the model was not able to be applied.	159
Table 5-7: V_{S30} estimates using Sharma Wagle et al. (2026) random forest model. Cells highlighted in green indicate estimates from HVSR curves with clear peaks.	161

Table 5-8: V_{S30} estimates using Sharma Wagle et al. (2026) gradient boosted trees model. Cells highlighted in green indicate estimates from HVSR curves with clear peaks.	162
Table 5-9: V_{S30} estimates using Sharma Wagle et al. (2026) single mode artificial neural network model	164
Table 5-10: V_{S30} estimates using Sharma Wagle et al. (2026) dual mode artificial neural network model. Dashes indicate where the model could not provide an estimate	165
Table 5-11: Results of geospatial correlations	167
Table 6-1: Calculated statistical measures for clays. Bolded values indicate best performing correlations for each statistical measure	184
Table 6-2: Calculated statistical measures for sands. Bolded values indicate best performing correlations for each statistical measure	185
Table 6-3: Calculated statistical measures for clays and silts. Bolded values indicate best performing correlations for each statistical measure	186
Table 6-4: Calculated statistical measures for all soils. Bolded values indicate best performing correlations for each statistical measure	187
Table 6-5: Calculated statistical measures for RQD based estimation methods. Bolded values indicate best performing correlations for each statistical measure	191
Table 6-6: Calculated statistical measures for HVSR based estimation methods. Bolded values indicate best performance for each statistical measure	195

Table 6-7: Calculated statistical measures for geospatial estimation methods. Bolded values indicate best performance for each statistical measure..... 199

Table 6-8: Range of site classes for sites visited in this study along with estimated site classes using the best fit estimation methods from each category. Both boring based estimation methods apply the Biringen and Davie (2013) Ft. Thompson correlation when applicable. Site classes highlighted in yellow indicate underestimation of site class while cells highlighted in red indicate an overestimation of site class. 201

Table 6-9: Range of site classes for sites visited in this study determined by HVSR and Geospatial estimation methods. Cells highlighted in yellow indicate indirect methods underestimate site class while cells highlighted in red indicate indirect methods overestimate site class. Dashes represent where the dual mode artificial neural network model did not provide an estimate. 202

List of Figures

Figure 1-1 Seismic zones near Alabama (Source: Geological Survey of Alabama)	34
Figure 2-1: Diagram of seismic refraction survey (Reynolds 2011)	40
Figure 2-2: Diagram of seismic reflection survey (Reynolds 2011).....	41
Figure 2-3: Diagram of MASW survey (Reynolds 2011).....	42
Figure 2-4: Distribution of soil type and geologic age in Ohta and Goto dataset (Ohta and Goto 1978)	44
Figure 2-5: Complete dataset along with regression (Imai and Tonouchi 1982)	46
Figure 2-6: SPT N value and V_s relationships for (a) all soils, (b) sandy soils, and (c) clayey soils (Hasancebi and Ulusay 2007).....	49
Figure 2-7: SPT N_{60} value and V_s relationships for (a) all soils, (b) sandy soils, and (c) clayey soils (Hasancebi and Ulusay 2007).....	50
Figure 2-8: Proposed correlation for all soil types (Fatehnia et al. 2015).....	52
Figure 2-9: Regression analysis of V_p to RQD (El-Naqua 1996).....	57
Figure 2-10: Correlation to V_s from RQD as developed from South Carolina igneous rock database (Biringen and Davie 2013)	58
Figure 2-11: Correlation to V_s from RQD as developed by Virginia metamorphic rock database (Biringen and Davie 2013).....	59

Figure 2-12: Correlation to V_s from RQD as developed by Florida Fort Thompson and Key Largo databases (Biringen and Davie 2013)	60
Figure 2-13: Combined correlation from all three survey lines for volcanic rock developed from Bener Dam (Salaamah et al. 2019)	61
Figure 2-14: Comparison between HVSR peak frequency and V_{s30} with site class bins overlain. (McNamara et al. 2015)	64
Figure 2-15: Expected relationship between V_{s30} and peak frequency for 3 different sediment layer velocity (V_L) values. (Hassani and Atkinson 2016)	65
Figure 2-16: Expected relationship between V_{s30} and peak frequency for 3 different rock layer velocity (V_R) values. (Hassani and Atkinson 2016)	66
Figure 2-17: Wald and Allen 2007 model for V_{s30} prediction based on topographic slope.....	69
Figure 2-18: Terrain map of the United States (Iwahashi and Pike 2007)	70
Figure 2-19: Mean values of V_{s30} for terrain types with no value provided for type 13 terrain (Yong et al. 2012)	71
Figure 2-20: Map of geologic classes (Kottke et al. 2012)	73
Figure 2-21: V_{s30} predictions from Model1alt with residual kriging for the continental US (Geyin and Maurer 2023)	76
Figure 2-22: Schematic of median V_s profiles developed for Gann-Phillips et al. 2024	78

Figure 2-23: Near surface median V_s profiles for Quaternary Holocene (QH), Quaternary Pleistocene (QP), Quaternary Pleistocene adjusted (QP Adjusted), Memphis (MEM), Tertiary (T), Cretaceous (K), and Cretaceous Adjusted (K Adjusted) groups (Gann-Phillips et al. 2024)	79
Figure 3-1: Example dispersion curve as displayed in Geopsy software package	82
Figure 3-2: Example output ground profiles from inversion analysis in DINVER software package	83
Figure 3-3: Comparison of measured dispersion curve to modeled dispersion curves	84
Figure 3-4: Refraction signal file as displayed in Pickwin with first arrivals of P-wave selected in pink.....	85
Figure 3-5: Travel time curve of a two layered model (Adapted from Reynolds 2011).....	86
Figure 3-6: Example ground profile derived from SPT boring logs	88
Figure 3-7. GEOTinyMK3 low power compact digital seismometer (GEObit Instruments 2023) .	90
Figure 3-8. PASI Gemini-2 HVSR data acquisition unit (PASI 2013).....	91
Figure 3-9. Equipment setup used at various sites for HVSR signal collection (Foti et al. 2018)..	92
Figure 3-10. Field deployment of (a) PASI Gemini (USB connection to PC), (b) Geotiny_21 (https://192.168.1.21:9091), and (c) Geotiny_30 (https://192.168.1.30:9091)	93
Figure 4-1: Map of sites visited as a part of this study (Photo taken from Google Earth).....	99
Figure 4-2: Cedar Bluff MASW survey line	100

Figure 4-3: Results of Cedar Bluff MASW survey showing (A) dispersion curve and (B) 10 best inverted ground profiles along with the range of V_s values taken from the best 1000 profiles	101
Figure 4-4: MASW survey locations for (A) Line 1 and (B) Line 2 for Beaver Creek surveys.....	102
Figure 4-5: Results of first MASW survey conducted at Beaver Creek site showing (A) dispersion and (B) the 10 best fit inverted ground profiles along with the range of V_s values taken from the best 1000 profiles.....	104
Figure 4-6: Results of second MASW survey conducted at Beaver Creek site showing (A) dispersion and (B) the 10 best fit inverted ground profiles along with the range of V_s values taken from the best 1000 profiles.....	104
Figure 4-7: Big Prairie Creek seismic survey line.....	105
Figure 4-8: Results of MASW survey conducted at Big Prairie Creek site showing (A) dispersion and (B) the 10 best fit inverted ground profiles along with the range of V_s values taken from the best 1000 profiles.....	106
Figure 4-9: Coldwell Creek seismic survey line	107
Figure 4-10: Results of MASW survey conducted at Coldwell Creek site showing (A) dispersion and (B) the 10 best fit inverted ground profiles along with the range of V_s values taken from the best 1000 profiles.....	108
Figure 4-11: Moundville seismic survey line (A) 1 and (B) 2.....	109

Figure 4-12: Results of first MASW survey conducted at Moundville site showing (A) dispersion and (B) the 10 best fit inverted ground profiles along with the range of V_s values taken from the best 1000 profiles.....	111
Figure 4-13: Results of second MASW survey conducted at Moundville site showing (A) dispersion and (B) the 10 best fit inverted ground profiles along with the range of V_s values taken from the best 1000 profiles.....	112
Figure 4-14: Greensboro seismic survey line	113
Figure 4-15: Results of MASW survey conducted at Greensboro site showing (A) dispersion and (B) the 10 best fit inverted ground profiles along with the range of V_s values taken from the best 1000 profiles	114
Figure 4-16: Seismic survey line at Duck River site.....	115
Figure 4-17: Appended travelttime curves for Duck River site	117
Figure 4-18: V_p model for Duck River site	117
Figure 4-19: Results of first MASW survey conducted at Russellville High School site showing (A) dispersion and (B) the 10 best fit inverted ground profiles along with the range of V_s values taken from the best 1000 profiles.....	120
Figure 4-20: Results of second MASW survey conducted at Russellville High School site showing (A) dispersion and (B) the 10 best fit inverted ground profiles along with the range of V_s values taken from the best 1000 profiles.....	120

Figure 4-21: Results of MASW survey conducted at Bluewater Creek site showing (A) dispersion and (B) the 10 best fit inverted ground profiles along with the range of V_s values taken from the best 1000 profiles.....	122
Figure 4-22: Seismic refraction survey line at Lauderdale County site	123
Figure 4-26: Results of MASW survey conducted at Lauderdale County site showing (A) dispersion and (B) the 10 best fit inverted ground profiles along with the range of V_s values taken from the best 1000 profiles.....	125
Figure 4-27: Results of MASW survey conducted at Lauderdale County site showing (A) dispersion and (B) the 10 best fit inverted ground profiles along with the range of V_s values taken from the best 1000 profiles.....	125
Figure 4-28: Appended traveltimes curves for Blount County Site	126
Figure 4-29: V_p model for Blount County site	127
Figure 5-1: Boring based estimates plotted alongside the measured profile for Cedar Bluff site. Boundaries of the best 1000 inverted ground profiles are shown by dashed lines. Refer to Table 5-1 for acronym definitions.....	131
Figure 5-2: Boring based estimates plotted alongside the measured profile for Beaver Creek survey line 1. Boundaries of the best 1000 inverted ground profiles are shown by dashed lines. Refer to Table 5-1 for acronym definitions.	133

Figure 5-3: Boring based estimates plotted alongside the measured profile for Beaver Creek survey line 2. Boundaries of the best 1000 inverted ground profiles are shown by dashed lines. Refer to Table 5-1 for acronym definitions.	133
Figure 5-4: Boring based estimates plotted alongside the measured profile for Big Prairie Creek site. Boundaries of the best 1000 inverted ground profiles are shown by dashed lines. Refer to Table 5-1 for acronym definitions.	134
Figure 5-5: Boring based estimates plotted alongside the measured profile for Coldwell Creek site. Boundaries of the best 1000 inverted ground profiles are shown by dashed lines. Refer to Table 5-1 for acronym definitions.	135
Figure 5-6: Boring based estimates plotted alongside the measured profile for Moundville survey line 1. Boundaries of the best 1000 inverted ground profiles are shown by dashed lines. Refer to Table 5-1 for acronym definitions.	137
Figure 5-7: Boring based estimates plotted alongside the measured profile for Moundville survey line 2. Boundaries of the best 1000 inverted ground profiles are shown by dashed lines. Refer to Table 5-1 for acronym definitions.	137
Figure 5-8: Boring based estimates plotted alongside the measured profile for Greensboro site. Boundaries of the best 1000 inverted ground profiles are shown by dashed lines. Refer to Table 5-1 for acronym definitions.....	138
Figure 5-9: Boring based estimates plotted alongside the measured profile for Duck River site. Dashed lines represent the probable range of V_s values from a refraction survey. Refer to Table 5-1 for acronym definitions.....	140

Figure 5-10: Boring based estimates plotted alongside the measured profile for Russellville High School survey line 1. Boundaries of the best 1000 inverted ground profiles are shown by dashed lines. Refer to Table 5-1 for acronym definitions.	142
Figure 5-11: Boring based estimates plotted alongside the measured profile for Russellville High School survey line 2. Boundaries of the best 1000 inverted ground profiles are shown by dashed lines. Refer to Table 5-1 for acronym definitions.	142
Figure 5-12: Boring based estimates plotted alongside the measured profile for Lauderdale County Refraction survey. Dashed lines represent the probable range of V_s values. Refer to Table 5-1 for acronym definitions.	144
Figure 5-13: Boring based estimates plotted alongside the measured profile for Lauderdale County MASW survey. Boundaries of the best 1000 inverted ground profiles are shown by dashed lines. Refer to Table 5-1 for acronym definitions.	144
Figure 5-14: Boring based estimates plotted alongside the measured profile for Bluewater Creek site. Boundaries of the best 1000 inverted ground profiles are shown by dashed lines. Refer to Table 5-1 for acronym definitions.	145
Figure 5-15: Boring based estimates plotted alongside the measured profile for Blount County Refraction survey. Dashed lines represent the probable range of V_s values. Refer to Table 5-1 for acronym definitions.	146
Figure 5-16: Three-component ambient noise recording measured by the PASI Gemini sensor at the Lauderdale County site's second survey location	148

Figure 5-17: HVSR curves for Lauderdale County second survey location as measured by PASI Gemini sensor	148
Figure 5-18: Three-component ambient noise recording measured by the Geotiny 21 sensor at the Cedar Bluff site.....	149
Figure 5-19: HVSR curves for Cedar Bluff site as measured by Geotiny 21 sensor.....	150
Figure 6-1: Plot of (A) residuals against measured V_s for all soil types with a range of $\pm 30\%$ bars overlain and (B) 1:1 plot of measured versus estimated V_s for Ohto and Goto (1978) correlation	171
Figure 6-2: Plot of (A) residuals against measured V_s for all soil types with a range of $\pm 30\%$ bars overlain and (B) 1:1 plot of measured versus estimated V_s for Imai and Tonouchi (1982) correlation	172
Figure 6-3: Plot of (A) residuals against measured V_s for all soil types with a range of $\pm 30\%$ bars overlain and (B) 1:1 plot of measured versus estimated V_s for Seed et al. (1983) correlation equation	173
Figure 6-4: Plot of (A) residuals against measured V_s for all soil types with a range of $\pm 30\%$ bars overlain and (B) 1:1 plot of measured versus estimated V_s for Jinan (1987) correlation equation	174
Figure 6-5: Plots of residuals and direct comparisons of Lee (1992) correlation equations (A) residual and (B) direct comparison plots for the individual soil type equations and (C) residual and (D) direct comparison plots for the combined clay and silt equation	175

Figure 6-6: Plots of residuals and direct comparisons of Hasancebi and Ulusay (2007) correlation equations using an uncorrected SPT blowcount showing (A) residual and (B) direct comparison plots for the all soils equation and (C) residual and (D) direct comparison plots for the individual soil types equations 177

Figure 6-7: Plots of residuals and direct comparisons of Hasancebi and Ulusay (2007) correlation equations using an energy corrected SPT blowcount showing (A) residual and (B) direct comparison plots for the all soils equation and (C) residual and (D) direct comparison plots for the individual soil types equations 178

Figure 6-8: Plots of (A) residuals and (B) direct comparison for the Wair et al. (2012) all soils equation and (C) residuals and (D) direct comparison plot for the individual soils equations .. 180

Figure 6-9: Plot of (A) residuals against measured V_s with a range of $\pm 30\%$ overlain and (B) direct comparison plot for Fatehnia et al. (2015) correlation equation 181

Figure 6-10: Plots of (A) residuals and (B) direct comparison for the Anbazhagan et al. (2016) correlation equation including SPT blowcounts of 100 and (C) residuals and (D) direct comparison plot for the correlation equation excluding SPT blowcounts of 100 182

Figure 6-11: Plot of (A) residuals against measured V_s for all soil types with a range of $\pm 30\%$ bars overlain and (B) 1:1 plot of measured versus estimated V_s overlain by site class bins for El-Naqua (1996) correlation equation 189

Figure 6-12: Plot of (A) residuals against measured V_s for all soil types with a range of $\pm 30\%$ bars overlain and (B) 1:1 plot of measured versus estimated V_s for Biringen and Davie (2013) Ft. Thompson correlation and (C) residuals against measured V_s for all soil types with a range of $\pm$

30% bars overlain and (D) 1:1 plot of measured versus estimated V_s for Biringen and Davie (2013) Key Largo correlation	190
Figure 6-13: 1:1 comparison plots of measured versus estimated V_{s30} for (A) Ghofrani and Atkinson (2014), (B) McNamara et al. (2015), (C) Hassani and Atkinson (2016), and (D) Stanko and Markušić (2020) models. Estimates using clear peak frequencies are represented by black dots while estimates using unclear peak frequencies are represented by a red x.....	193
Figure 6-14: 1:1 comparison plots of measured versus estimated V_{s30} for Sharma Wagle et al. (2026) (A) random forest model (2014), gradient boosted trees model, (C) single mode artificial neural network, and (D) dual mode artificial neural network models. Estimates using clear peak frequencies are represented by black dots while estimates using unclear peak frequencies are represented by a red x.	194
Figure 6-15: 1:1 comparison plots of (A) Wald and Allen (2007) model, (B) Yong et al. (2012) model, (C) Parker et al. (2017) model, (D) Geyin and Maurer (2023) model, and (E) Gann-Phillips et al. (2024) model.....	198
Figure A-1: (A) 3-component signal file and (B) HVSR curve for Beaver Creek survey line 2 measured by PASI Gemini sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.	224
Figure A-2: (A) 3-component signal file and (B) HVSR curve for Big Prairie Creek survey line 1 measured by GTN30 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.....	225

Figure A-3: (A) 3-component signal file and (B) HVSR curve for Big Prairie Creek survey line 2 measured by GTN21 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.....	226
Figure A-4 : (A) 3-component signal file and (B) HVSR curve for Moundville survey line 1 measured by GTN21 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.....	227
Figure A-5: (A) 3-component signal file and (B) HVSR curve for Moundville survey line 2 measured by GTN21 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.....	228
Figure A-6: (A) 3-component signal file and (B) HVSR curve for Moundville survey line 2 measured by GTN30 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.....	229
Figure A-7: (A) 3-component signal file and (B) HVSR curve for Blount County measured by GTN30 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.	230
Figure A-8: (A) 3-component signal file and (B) HVSR curve for Bluewater Creek measured by GTN21 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.	231
Figure A-9: (A) 3-component signal file and (B) HVSR curve for Bluewater Creek measured by GTN30 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.	232

Figure A-10: (A) 3-component signal file and (B) HVSR curve for Duck River measured by GTN21 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.	233
Figure A-11: (A) 3-component signal file and (B) HVSR curve for Duck River measured by GTN30 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.	234
Figure A-12: (A) 3-component signal file and (B) HVSR curve for Lauderdale County survey line 2 measured by GTN21 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.....	235
Figure A-13: (A) 3-component signal file and (B) HVSR curve for Cedar Bluff site measured by GTN30 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.	237
Figure A-14: (A) 3-component signal file and (B) HVSR curve for Beaver Creek survey line 1 measured by PASI Gemini sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.	238
Figure A-15: (A) 3-component signal file and (B) HVSR curve for Beaver Creek survey line 2 measured by GTN21 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.....	239
Figure A-16: (A) 3-component signal file and (B) HVSR curve for Beaver Creek survey line 2 measured by GTN30 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.....	240

Figure A-17: (A) 3-component signal file and (B) HVSR curve for Big Prairie Creek survey line 1 measured by GTN21 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.....	241
Figure A-18: (A) 3-component signal file and (B) HVSR curve for Big Prairie Creek survey line 1 measured by GTN21_B sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.....	242
Figure A-19: (A) 3-component signal file and (B) HVSR curve for Big Prairie Creek survey line 1 measured by GTN30_B sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.....	243
Figure A-20: (A) 3-component signal file and (B) HVSR curve for Big Prairie Creek survey line 1 measured by PASI Gemini sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.	244
Figure A-21: (A) 3-component signal file and (B) HVSR curve for Big Prairie Creek survey line 2 measured by GTN30 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.....	245
Figure A-22: (A) 3-component signal file and (B) HVSR curve for Big Prairie Creek survey line 2 measured by GTN30_B sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.....	246
Figure A-23: (A) 3-component signal file and (B) HVSR curve for Coldwell Creek survey line 1 measured by GTN21 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.....	247

Figure A-24: (A) 3-component signal file and (B) HVSR curve for Coldwell Creek survey line 1 measured by PASI Gemini sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.	248
Figure A-25: (A) 3-component signal file and (B) HVSR curve for Coldwell Creek survey line 2 measured by GTN30 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.....	249
Figure A-26: (A) 3-component signal file and (B) HVSR curve for Greensboro site measured by GTN21 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.	250
Figure A-27: (A) 3-component signal file and (B) HVSR curve for Greensboro site measured by PASI Gemini sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.	251
Figure A-28: (A) 3-component signal file and (B) HVSR curve for Moundville survey line 1 measured by PASI Gemini sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.	252
Figure A-29: (A) 3-component signal file and (B) HVSR curve for Moundville survey line 2 measured by PASI Gemini sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.	253
Figure A-30: (A) 3-component signal file and (B) HVSR curve for Duck River survey line 1 measured by PASI Gemini sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.	254

Figure A-31: (A) 3-component signal file and (B) HVSR curve for Russellville High School survey line 1 measured by GTN21 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

..... 255

Figure A-32: (A) 3-component signal file and (B) HVSR curve for Russellville High School survey line 1 measured by GTN30 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

..... 256

Figure A-33: (A) 3-component signal file and (B) HVSR curve for Russellville High School survey line 1 measured by PASI Gemini sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

..... 257

Figure A-34: (A) 3-component signal file and (B) HVSR curve for Russellville High School survey line 2 measured by GTN21 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

..... 258

Figure A-35: (A) 3-component signal file and (B) HVSR curve for Russellville High School survey line 2 measured by GTN30 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

..... 259

Figure A-36: (A) 3-component signal file and (B) HVSR curve for Russellville High School survey line 2 measured by PASI Gemini sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

..... 260

Figure A-37: (A) 3-component signal file and (B) HVSR curve for Lauderdale County survey line 1 measured by GTN21 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines..... 261

Figure A-38: (A) 3-component signal file and (B) HVSR curve for Lauderdale County survey line 1 measured by GTN30 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines..... 262

Figure A-39: (A) 3-component signal file and (B) HVSR curve for Lauderdale County survey line 1 measured by PASI Gemini sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines. 263

Figure A-40: (A) 3-component signal file and (B) HVSR curve for Blount County site measured by GTN21 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines. 264

Figure A-41: (A) 3-component signal file and (B) HVSR curve for Blount County site measured by PASI Gemini sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines. 265

Figure A-42: (A) 3-component signal file and (B) HVSR curve for Cedar Bluff site measured by GTN30 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.	266
Figure A-43: (A) 3-component signal file and (B) HVSR curve for Cedar Bluff site measured by PASI Gemini sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.	267
Figure A-44: (A) 3-component signal file and (B) HVSR curve for Beaver Creek survey line 1 measured by GTN21 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.....	268
Figure A-45: (A) 3-component signal file and (B) HVSR curve for Lauderdale County survey line 2 measured by GTN30 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.....	269

Chapter 1: Introduction

1.1 Background

Bridges are critical infrastructure systems that need to be designed to be resilient against even rare hazards (AASHTO LRFD). This includes seismic loads, which can cause severe damage to bridges and other structures. Seismic loading is influenced by multiple factors, and all need to be accounted for in design. The magnitude of seismic loading is determined by the distance and magnitude of the earthquake, local site effects, and the structure itself. Distance and magnitude of the controlling earthquake is determined by a disaggregation tool that considers all possible events and their contribution to the hazard (Kramer and Stewart 2025). The controlling earthquake will have the greatest contribution to hazard. As distance from the fault rupture increases, the amount of energy transferred to the structure will decrease. Stiffness of the site, determined by the shear wave velocity of the site, will control what frequencies will be amplified and deamplified. Softer sites with lower shear wave velocities provide the greatest risk as lower frequencies that contribute the most to earthquake damage will tend to be amplified. The structure itself contributes to seismic loading on the structure through multiple ways. The structure can experience resonance and amplification of waves when incoming wavelets contain a significant portion of frequencies near the natural frequency of the structure. Through interactions of the structure and soil, the incoming wavelet will experience period elongation which can cause double resonance when the elongated period matches the structure's natural period.

In less seismically active regions, such as Alabama, it is less common to include seismic design considerations into public infrastructure projects. Recent developments in design philosophy and the adaptation of new building and design codes (AASHTO LRFD Bridge Design Specifications, ASCE 7-22, International Building Code) have led to seismic design considerations becoming more important in these regions. Alabama is influenced by several seismic zones but generally is controlled by the New Madrid and Southern Appalachian seismic zone both shown in Figure 1-1.

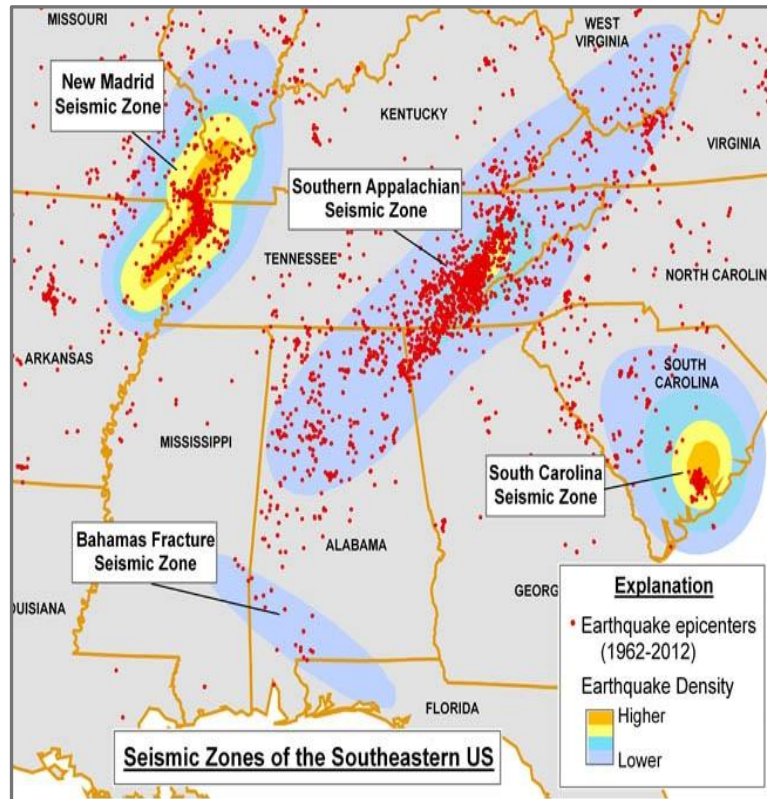


Figure 1-1 Seismic zones near Alabama (Source: Geological Survey of Alabama)

The New Madrid Seismic Zone (NMSZ) is the most active seismic zone within the southeastern United States (Liu and Zoback 1997). The NMSZ is characterized by two parallel strike slip faults bordering the Reelfoot rift along with a cross-over reverse fault (Sexton and Jones 1986, Tuttle et al. 2002). The NMSZ has intraplate activity capable of producing earthquakes of small to moderate intensity. The largest earthquakes produced by this region occurred in 1811 and 1812 with magnitudes greater than 7 (Liu and Zoback 1997). Damage caused by the earthquakes consisted of landslides, liquefaction, settlements, structural damage, failures of riverbanks along the Mississippi River, and subsidence of large tracts of the river. The USGS assigns a probability of occurrence of 25-40% that the NMSZ will produce an earthquake with a magnitude of 6 or greater (USGS 2022). The Southern Appalachian Seismic Zone (ETSZ) is the second most active region in the southeastern US (Powell et al. 1994). Most of the earthquake activity in Alabama comes from the Southern Appalachian Seismic Zone.

Shear wave velocity (V_s) profiles are critical inputs for seismic design because they influence the amplitude and frequencies of estimated ground motions (Abrahamson et al. 2008, Teague and Cox 2016). There are two approaches for measuring V_s , direct and indirect methods. Direct approaches include more invasive procedures, such as downhole or cross hole surveys where geophones are placed into drilled boreholes and are discussed further in section 2.1.1. Non-invasive approaches instead use surface-based surveys that rely on sensors placed on the ground surface. Additional discussion of non-invasive methods of direct measurement can be found in Section 2.1.2.

When direct measurements are not able to be taken, values of V_s are often determined by correlation. Correlations are made to V_s from the results of more commonly performed in-situ tests, such as standard penetration testing (SPT), cone penetration testing (CPT), and rock coring. Correlations are developed using empirical relationships between measured values of V_s and results of in-situ tests, and many correlations have been developed in regions of greater seismic risk. Commonly these correlations will be used to estimate V_s and to determine a seismic site class based on the results of an in-situ testing program. Correlations can provide reasonable estimates of V_s when applied in the regions in which they were developed, however this may not be the case in applications outside of that region. With Alabama historically having had a lower seismic risk, many published correlations have not been evaluated for use in the state.

Shear wave velocity profiles are commonly incorporated into design codes in the form of a site class based on a weighted average of the upper 30 meters (100 feet) of ground, referred to as V_{S30} (AASHTO 2023). V_{S30} is calculated using (1) where d_i is the thickness of each subsequent layer and V_{Si} is the layer's corresponding shear wave velocity.

$$V_{S30} = \frac{\sum_{i=1}^n d_i}{\sum_{i=1}^n \frac{d_i}{V_{Si}}} \quad (1)$$

Site class serves as a proxy for the stiffness of the site and allows for designers to account for more site-specific effects. Site classes range from hard rock (site class A) to very soft soil sites (site class F) (AASHTO 2023, Table 1-1).

Table 1-1: Site class definitions used in AASHTO LRFD bridge design specifications (AASHTO 2023)

Site Class	Soil Type and Profile	$\bar{v}_s$ Calculated or Estimated
A	Hard rock	$\bar{v}_s > 5,000$ ft/s
B	Medium hard rock	$3,000$ ft/s $< \bar{v}_s \leq 5,000$ ft/s
B/C	Soft rock	$2,100$ ft/s $< \bar{v}_s \leq 3,000$ ft/s
C	Very dense sand or hard clay	$1,450$ ft/s $< \bar{v}_s \leq 2,100$ ft/s
C/D	Dense sand or very stiff clay	$1,000$ ft/s $< \bar{v}_s \leq 1,450$ ft/s
D	Medium dense sand or stiff clay	700 ft/s $< \bar{v}_s \leq 1,000$ ft/s
D/E	Loose sand or medium stiff clay	500 ft/s $< \bar{v}_s \leq 700$ ft/s
E	Very loose sand or soft clay	$\bar{v}_s \leq 500$ ft/s
F	Soils requiring site-specific ground response evaluations, such as: • Peats or highly organic clays ($H > 10.0$ ft of peat or highly organic clay where H = thickness of soil) • Very high plasticity clays ($H > 25.0$ ft with $PI > 75$) • Very thick, soft/medium stiff clays ($H > 120$ ft)	

Exceptions: Where the soil properties are not known in sufficient detail to determine the site class, a site investigation shall be undertaken sufficient to determine the site class. Site Classes E or F should not be assumed unless the Owner or those having jurisdiction determines that Site Classes E or F could be present at the site or in the event that Site Classes E or F are established by geotechnical data.

where:

$\bar{v}_s$ = average shear wave velocity for the upper 100 ft of the soil profile

1.2 Motivation and Objectives

When estimation methods are applied in areas outside of their intended use, there is a greater amount of uncertainty present. Without validation the estimation methods will be penalized heavily by reducing values to obtain a conservative estimate. Overly conservative estimates of V_s can place a site into a lower site class and necessitate seismic design. Seismic design considerations increase design costs significantly as they require a much greater deal of effort than designs not requiring them. To reduce uncertainty, these methods need to be evaluated against physical measurements in the state.

This study aims to evaluate existing methods for estimating shear wave velocity at sites in Alabama by comparing their performance against direct measurements, across different categories of estimation procedures, and by providing a comprehensive set of

recommendations for estimating site class for ALDOT and other local agencies. The first objective of this study is to obtain high quality direct measurements of V_s at multiple sites in the state to provide a basis for comparisons to be made. Following collection of direct measurements, the second objective of this study is to collect and apply correlations or predictive models for V_s to results of common in-situ tests, other seismic noise recordings, and to geospatial features of the site. The third objective of this study is to then statistically compare correlations to determine which provides the most accurate and reasonable estimates for V_s in Alabama. Finally, with results of statistical comparisons, comprehensive recommendations for their use are to be provided. It is hoped that results of this work can provide a basis for future work in surrounding states or to develop new correlations.

1.3 Research Tasks

The primary research tasks for this dissertation are provided below:

- Collect a suite of V_{s30} measurements at sites in Alabama for use in future studies
- Evaluate SPT, and RQD based correlation equations for accuracy in estimating V_s for sites in Alabama
- Evaluate HVSr based models for accuracy in estimating V_{s30} for sites in Alabama
- Evaluate geospatial methods for accuracy in estimating V_{s30} for sites in Alabama
- Compare the different methods and provide a comprehensive set of recommendations

1.4 Dissertation Organization

This document will be organized into the following chapters:

- Chapter 1- Introduction: This chapter will provide background information on the importance of V_s in seismic engineering applications as well as discuss its measurement. The chapter will also include motivations for research along with objectives for the research. The organization of this document is also included in this chapter.
- Chapter 2- Literature Review: This chapter describes accepted methods for directly measuring V_s at a site, focusing on multichannel analysis of surface waves (MASW) and seismic refraction, Discussion of accepted correlations to V_s from SPT, CPT, rock quality

designation (RQD), ambient noise recordings, and geospatial based correlations is found in this section.

- Chapter 3- Methodology: This chapter describes the methodology used for collecting and processing field data along with applications of indirect methods considered in this study.
- Chapter 4- Results of Direct Methods: This chapter contains the results of direct methods for measuring V_{S30} . Each site considered will be described by location, geologic conditions, and site-specific data collection parameters.
- Chapter 5- Results of Indirect Methods: This chapter contains results of V_{S30} obtained from indirect measures such as correlations to SPT, RQD, HVSR, and geospatial methods.
- Chapter 6- Comparison of Methods: This chapter contains comparisons of indirect methods to results of direct measurements for each site. Statistical comparisons between methods are provided.
- Chapter 7- Conclusions and Recommendations: This chapter summarizes the results of this dissertation. Along with a summary of results, practical guidance for applications of this work along with guidance for future works is provided.

Chapter 2: Review of Methods to Determine Shear Wave Velocity Profiles

This chapter presents a review of methods to determine shear wave velocity profiles. Multiple types of direct measurements are discussed including invasive and non-invasive methods. Indirect methods presented all rely on correlation to results of common geotechnical in-situ tests, ambient noise recordings, and to multiple geospatial factors.

2.1 Direct Methods

Direct methods involve taking a direct, physical measurement of V_s at a given site. Direct methods can be either classified into invasive or non-invasive methods. Invasive and non-invasive methods will be discussed further in the following sections.

2.1.1 Invasive Methods

Invasive methods for measuring V_s involve placing the seismic source and receiver at different depths below the surface which requires either a borehole to be drilled or for some system of sensors to be placed into the ground using a penetrometer. Some examples of invasive methods for measuring V_s are borehole-based methods such as downhole logging (McDonald et al. 1958, Raikes and White, 1984), cross-hole logging (Ballard 1976, Butler and Curro 1981), and P-S suspension logging (Kaneko et al. 1990, Ohya et al. 1984). Penetrometer based methods include seismic cone penetrometer (Campanella et al. 1986, Robertson et al. 1986) and seismic flat plate dilatometer (Hepton 1988).

2.1.2 Non-Invasive Methods

Non-invasive methods for measuring shear wave velocity are typically surface based and do not require a borehole or penetrometer. Non-invasive methods can include refraction or reflection-based methods along with surface wave-based methods. Discussion of these methods can be found in the following sections.

2.1.2.1 Seismic Refraction

Typical seismic refraction surveys for geotechnical engineering applications are conducted at the surface using a spread of geophones, a source of waves capable of producing adequate energy to survey the desired depth, and a computer to record data (Reynolds 2011).

Energy sources comprise of a number of devices, including blanks fired from a shotgun, a sledgehammer striking a metal plate, or a wave generator (Miller et al. 1986, 1992, 1994). Compressional or P waves generated by the energy source travel in three modes; along the ground surface in the direct wave, by reflection along the top of the refractor, and most importantly the critically refracted wave. Seismic refraction surveys rely on velocity increasing with depth, with deeper layers of soil or rock having a greater velocity than the layer above (Green 1974). Geophones will record first arrivals of waves, and at some distance known as the crossover distance, the critically refracted wave will arrive prior to the direct wave. First arrivals can be picked from geophone records, and a change in slope of the travel time-distance curve will be observed corresponding to the crossover distance.

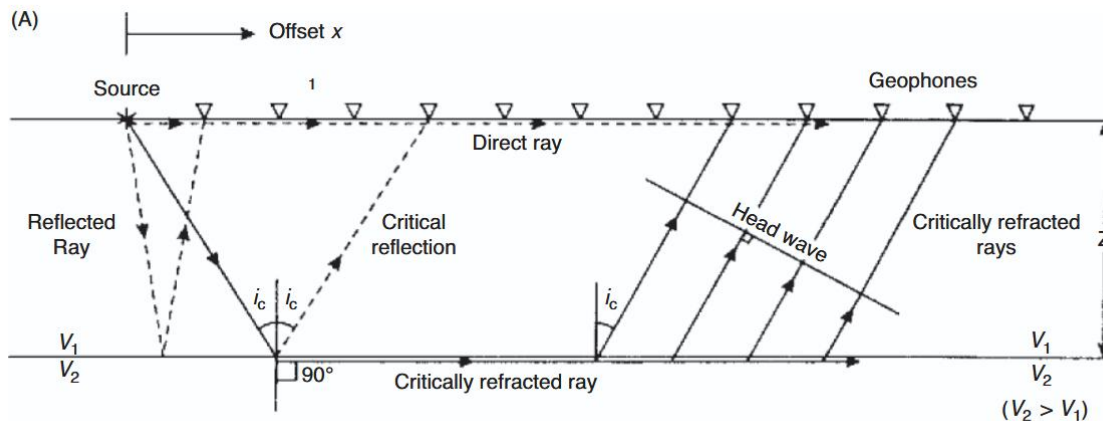


Figure 2-1: Diagram of seismic refraction survey (Reynolds 2011)

For typical surveys either 24 or 48 geophones are used and are spaced evenly along the spread (Reynolds 2011). Geophone spacing and spread length control the depth that is able to be surveyed along with lateral resolution (Musset and Khan 2000). Shots can be taken off either end of the spread in what is called an off-end shot, along the spread in a split-spread shot, or at the start or end of the spread in an on-end shot. Shots will typically be taken from both ends of the spread in what are called forward and reverse shots in relation to their respective locations along the survey line. Multiple shots are taken from each location to stack the files in post processing in order to help eliminate noise. Once shots from a common location are stacked,

first arrivals can be selected. There are a number of software packages available for processing and interpretation of seismic data refraction surveys.

2.1.2.2 Seismic Reflection

Seismic reflection surveys rely on reflection of an incident wave at some impedance contrast at depth (Reynolds 2011). Waves are reflected and the travel times are recorded by sensors at the ground surface. This time is known as two-way travel time (TWTT). At each point of incidence on the reflector in the area corresponding to the first Fresnel zone, incident waves are reflected. The point of reflection is always halfway between the source and receiver and the spacing between reflection points is half of the geophone spacing. Due to this the subsurface coverage is always half of the geophone spread.

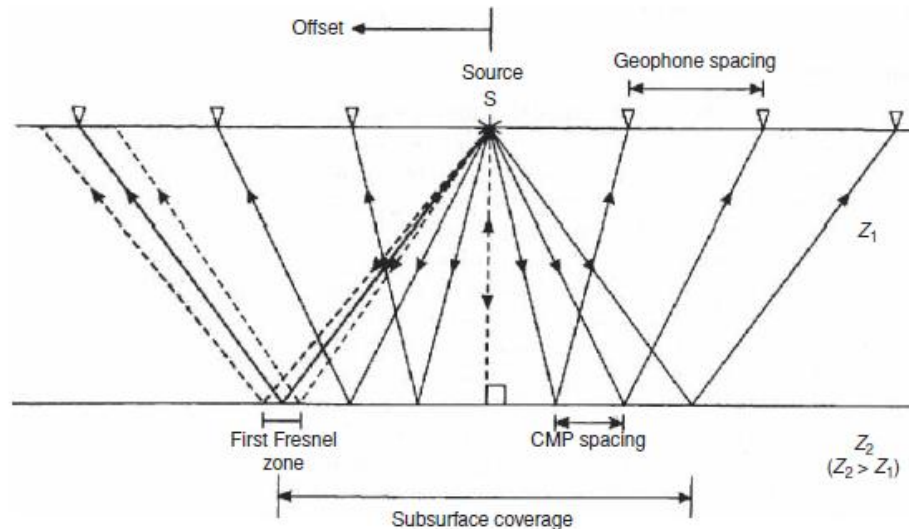


Figure 2-2: Diagram of seismic reflection survey (Reynolds 2011)

Typical reflection surveys for engineering applications use either 12, 24, or sometimes 48 geophones at the ground surface, a seismograph, and an energy source (Reynolds 2011). Different shot locations will be selected to allow for the same point on the reflector to be measured multiple times, referred to as the fold of coverage. 12-fold coverage will typically be the greatest extent required for engineering surveys (Reynolds 2011). Traces from the same point of reflection can be gathered into a common midpoint gather (CMG) for use in interpretation of the subsurface.

2.1.2.3 Multichannel Analysis of Surface Waves

Multichannel Analysis of Surface Waves (MASW) is another popular surface-based technique for measuring the V_s profile of a given site at a relatively shallow depth (Park et al. 1999). The method relies primarily on surface waves that have lower frequencies (approximately 1 to 30 Hz) and has a shallower survey depth that is dependent on site conditions and survey geometry. Either active or passive sources of waves can be used with passive sources having a lower frequency than active sources. The drawbacks to passive surveys are the greater recording length and the lack of control of passive sources.

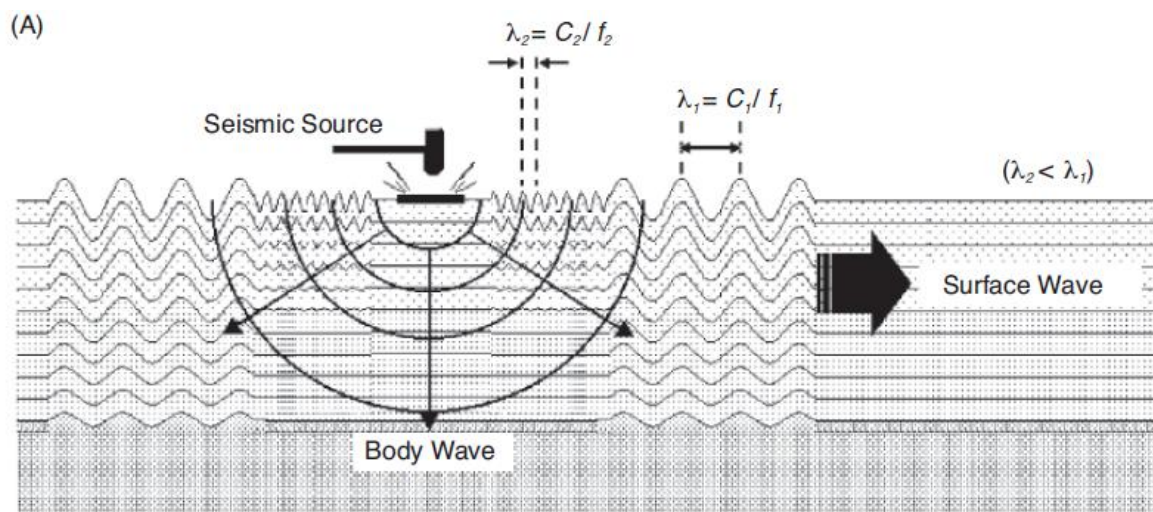


Figure 2-3: Diagram of MASW survey (Reynolds 2011)

MASW surveys assume seismic velocity will increase with depth. With this being true, longer wavelengths will propagate faster than shorter wavelengths as they can propagate through higher velocity layers. Due to this dispersion of travel times, there is a dispersion of frequency. Dispersion curves are created by plotting frequency versus the propagation velocity. The dispersion curve with the lowest velocity is known as the fundamental mode. Multiple modes can exist in the case where there are multiple phase velocities for a given frequency.

2.2 Correlation Based Estimates of V_s

Correlations in this study refer to predictive models and not a statistical correlation between variables. Correlations, or predictive models, for estimating shear wave velocity are

often used when direct measurements cannot be taken. Correlations provide a quick and cost-effective means to estimate V_s but carry a greater degree of uncertainty as compared to direct measurements (Carcamo 2022). Correlations to V_s are commonly made from SPT and CPT results. Correlations can also be made directly to V_{s30} , and those are commonly made to a site's fundamental frequency, topography, and surficial geology.

2.2.1 Correlation with Standard Penetration Testing

One of the most commonly used in-situ tests for geotechnical site explorations is the SPT. SPT is standardized in ASTM D1586 (ASTM International). The test is performed by driving a split spoon sampler a total of 18 inches (0.46 m) in three increments of 6 inches (0.15 m) in a pre-drilled borehole. The number of blows required to drive the split spoon, called a blowcount, is recorded for each interval. The blowcount for the first interval is not considered as it is assumed that the soil at the bottom of the drilled borehole is very highly disturbed and not representative of the in-situ conditions of the soil (Lo Pinto 1966). The second and third blowcounts are summed to give the N value for the SPT boring. Previous work has been done to standardize the SPT by correcting to a common percentage of energy transferred by the hammer to the drill rod (ASTM D6066) and is commonly corrected to 60% hammer efficiency (N_{60}). Corrections for other factors such as rod length, borehole diameter, and effective stress can also be applied to the raw N value (Schmertmann and Palacios 1979, Seed et al. 1985, Riggs 1986, Skempton 1986, Bowles 1996, Rogers 2006). Corrections are necessary for SPT blowcounts to reduce uncertainty due to differences in equipment, site conditions, and other factors.

Correlation from SPT N-value to V_s is commonly performed. In a report by Wair et al. (2012), multiple references for SPT based correlations are presented along with guidance for their applications in California. Some of the references discussed in the report are discussed in the following sections. Additional sources not presented in the report are also included in the discussion.

2.2.1.1 Ohta and Goto 1978

Ohta and Goto (1978) developed V_s correlation equations based on data from 300 sites in Japan, mostly comprised of alluvial plains. The authors identified four index properties that influence V_s : SPT blowcounts, geologic age, soil type, and depth. Corrections to SPT blowcounts and hammer efficiency are not presented by the authors, however hammer efficiency can be assumed to be 67% based off of contemporary studies in Japan (Wair et al. 2012). Geologic age is divided into Holocene and Pleistocene. Soil type is divided into clays/silts, fine sand, medium sand, coarse sand, sand and gravel, and gravel. A histogram describing the distribution of soil types and geologic ages for the sites considered in analysis is provided in Figure 2-4.

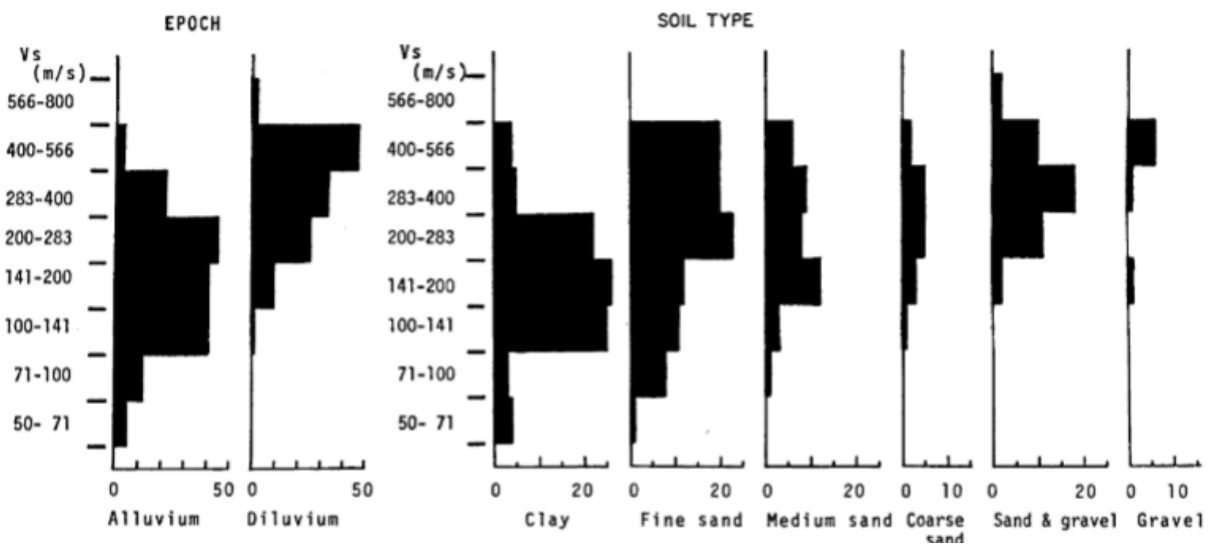


Figure 2-4: Distribution of soil type and geologic age in Ohta and Goto dataset (Ohta and Goto 1978)

Using these indices, a total of 15 equations were developed considering every possible combination and regression analysis was performed. Results of regression analysis for the 15 equations can be found in Table 2-1 and indicated that the best performing correlation equation considers all 4 indices.

Table 2-1: Correlation coefficients and probable error for developed equations (Ohta and Goto 1978)

Concerned Index	Probable Error	Correlation Coefficient
Soil type	36.3%	0.463
Geological epoch	31.5%	0.621
Depth	29.6%	0.670
Geological epoch, Soil type	28.5%	0.696
N-Value	27.4%	0.719
N-Value, Soil type	27.2%	0.726
Depth, Soil type	25.2%	0.765
Depth, Geological epoch	25.1%	0.767
N-Value, Geological epoch	24.2%	0.784
N-Value, Geological epoch, Soil type	24.0%	0.787
N-Value, Depth	22.1%	0.820
Depth, Geological epoch, Soil type	22.0%	0.822
N-Value, Depth, Soil type	21.5%	0.830
N-Value, Depth, Geological epoch	20.3%	0.848
N-Value, Depth, Geological Epoch, Soil type	19.7%	0.856

2.2.1.2 Imai and Tonouchi 1982

Imai and Tonouchi (1982) analyzed a dataset of SPT blowcounts and V_s measurements in Japan totaling 1654 data pairs. Data was collected from 386 boreholes at 250 individual sites. Correlation equations were developed that consider SPT blowcount, geologic age, and depositional environment. Similarly to Ohta and Goto (1978), hammer efficiency is not presented but can also be assumed to be 67% (Wair et al. 2012). Depositional environments considered are alluvial and man-made fill. Figure 2-5. presents the entire dataset along with the regression line.

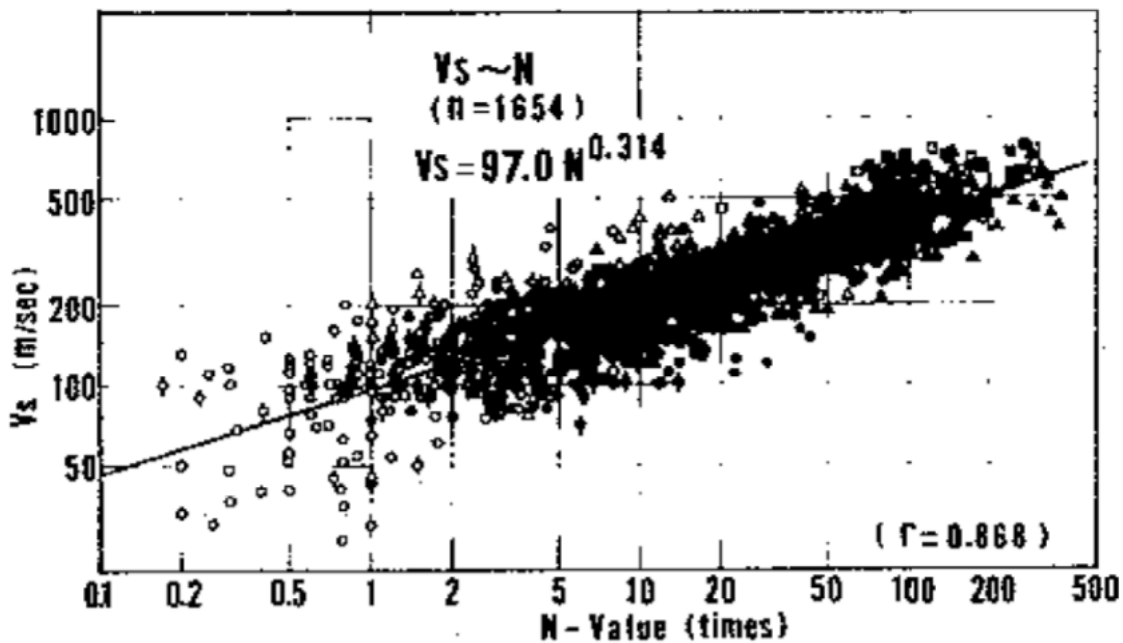


Figure 2-5: Complete dataset along with regression (Imai and Tonouchi 1982)

2.2.1.3 Seed et al. 1983

Seed et al. (1983) sought to correlate liquefaction potential of sands to SPT and CPT data from a database of previous studies. The authors developed an equation for determination of shear modulus based on N_{60} , and additionally presented an equation to determine V_s . The authors presented (2) as a correlation to V_s from N_{60} . The authors presented the limitations of the equation as only being applicable to sands as well as its limitation to a depth of less than 15 meters (50 feet).

$$V_s = 56\sqrt{N_{60}} \quad (2)$$

2.2.1.4 Jinan 1987

The original Jinan 1987 study was not available but was summarized in Wair et al. (2012). The study was conducted at a site in Shanghai China. Soils encountered were a 25 meter (82 ft) thick layer of relatively soft Holocene clays and silts overlying a layer of firmer Pleistocene clays, silts, and sands to the maximum depth tested of 60 meters (197 ft). SPT blowcounts for the top 20 meters (66 ft) were generally less than 5 and blowcounts below that layer ranged from 10 to 40. Hammer efficiency was not reported but can be assumed to be 60% based on contemporary Chinese studies (Seed et al. 1985). The equation derived is presented in (3) and has a coefficient of determination of 0.49.

$$V_s(m/s) = 116.1(N_{60} + 0.31)^{0.20} \quad (3)$$

2.2.1.5 Lee 1992

Lee (1992) used a total of 491 pairs of V_s and SPT data taken from the Taipei basin in Taiwan to develop correlation equation to V_s . Index properties considered in their analysis include SPT blowcount, depth, and soil type. Geologic age was not of consideration as the native soils in the region are of a similar age. Soil types are divided into three groups: sands (SM), clays (CL), silts (ML), along with a group combining clays and silts (CL/ML).

Correlation equations developed follow the simple linear model, the intrinsically linear model, and the multiple regression model. Criteria for detection of multicollinear variables in proposed correlation equations were presented. The two variables of concern in the Lee 1992 study are SPT blowcount and depth as SPT blowcounts tend to increase with depth (Fletcher 1965, Horn 2000). Developed equations with a coefficient of determination greater than 0.7 were not considered as a “rule of thumb” practice to avoid multicollinearity. Stepwise selection as well as the ratio of standard error estimate to mean response of each coefficient were also used to detect multicollinearity. Equations developed for sands were not able to meet these criteria while equations developed for clays and silts were able to. Table 2-2 contains the correlation equations recommended for use from the Lee (1992) study.

Table 2-2: Recommended regression equations (Lee 1992)

Soil Type	Correlation Equation	R ²
SM	$V_S = 71.9(D + 1)^{0.890}$	0.763
CL	$V_S = 86.1N^{0.116}(D + 1)^{0.244}$	0.216
ML	$V_S = 82.8N^{0.134}(D + 1)^{0.233}$	0.423
CL/ML	$V_S = 84.5N^{0.118}(D + 1)^{0.246}$	0.287

2.2.1.6 Hasancebi and Ulusay (2007)

Hasancebi and Ulusay (2007) selected a site located in an alluvial basin in Yenisehir Turkey for analysis. Bedrock of the southern portion of the region consists primarily of schists and marbles of the pre-Neogene era. Typical subsurface conditions consist of a stiff layer of silty clay underlain by a layer of silty sand that is medium dense to loose. In some localities silty clay was observed underlying the layer of sand as well as interbedded gravel at shallow depths. Twelve previously drilled borings along with nine borings drilled for the study were used for analysis. Hammer efficiency was not reported but correlations to energy corrected as well as uncorrected blowcounts were made. V_S was measured using surface based seismic refraction surveys.

In a similar manner to previous studies, soils were categorized based on type. The authors categorized soils as sands or clays/silts. Clays and silts were combined due to the relative lack of silts in the dataset. Regression analysis was performed to develop correlation equations. Figure 2-6 presents the results of regression analysis for uncorrected blowcounts. Figure 2-7 presents the results of regression analysis for energy corrected blowcounts.

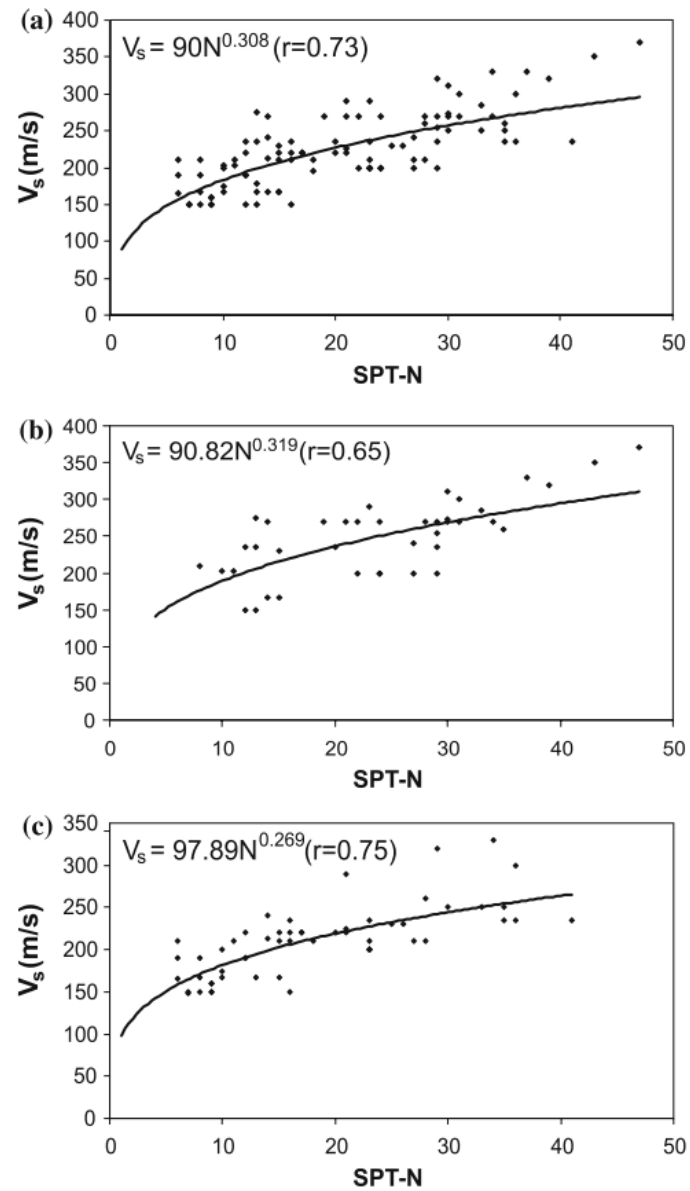


Figure 2-6: SPT N value and V_s relationships for (a) all soils, (b) sandy soils, and (c) clayey soils (Hasancebi and Ulusay 2007)

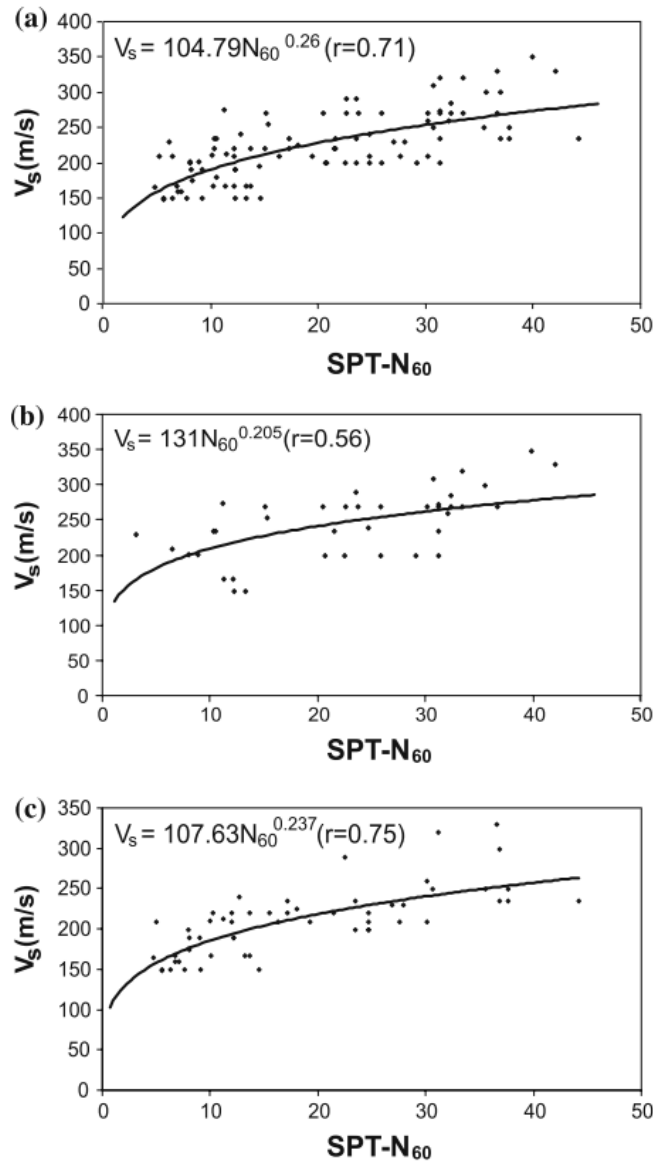


Figure 2-7: SPT N_{60} value and V_s relationships for (a) all soils, (b) sandy soils, and (c) clayey soils (Hasancebi and Ulusay 2007)

2.2.1.7 Wair et al. 2012

Wair et al. (2012) presented guidelines for estimation of V_s in California in a report to the Pacific Earthquake Engineering Research Center (PEER). The report presented the previously discussed references along with additional sources not considered in this study. Along with evaluation of existing correlations, a new set of equations were developed based on data taken from the PEER database.

Equations were developed for sandy soils, clay and silty soils, gravels, and for all soils. Energy corrected blowcounts (N_{60}) should be used for correlation along with corrections for a non-standard practice (i.e., borehole diameter, sampler liner, and rod length). The authors note that correction of SPT blowcounts for effective stress is not necessary as developed equations contain a term for effective stress. Blowcounts are to be capped at a value of 100 to remain consistent with previous building codes. Equations were developed for Quaternary soils, but age scaling factors are provided for Holocene and Pleistocene soils. Table 2-3 presents the developed equations.

Table 2-3: Recommended correlation equations (Wair et al. 2012)

Soil Type	Correlation Equation	Holocene Age Scaling Factor	Pleistocene Age Saling Factor
All Soils	$V_S = 30N_{60}^{0.215}\sigma'_V{}^{0.275}$	0.87	1.13
Clays and Silts	$V_S = 26N_{60}^{0.17}\sigma'_V{}^{0.32}$	0.88	1.12
Sands	$V_S = 30N_{60}^{0.23}\sigma'_V{}^{0.23}$	0.9	1.17
Holocene Gravels	$V_S = 53N_{60}^{0.19}\sigma'_V{}^{0.18}$	---	---
Pleistocene Gravels	$V_S = 115N_{60}^{0.17}\sigma'_V{}^{0.12}$	---	---

Note: V_S in (m/s), σ'_V in kPa

2.2.1.8 Fatehnia et al. 2015

Fatehnia et al. (2015) conducted their study in North Florida. V_S was measured using the MASW technique. The total number of sites was not provided, but the authors do note that 28 boreholes were drilled. For the 28 borings SPT's were conducted continuously from the ground surface to a depth of 15 feet (4.57 meters) and then at an interval of 2.5 feet (0.76 meters) until borings reached termination. The authors do not disclose their criteria for termination or depths where termination was met. A total of 300 SPT blowcounts were obtained for analysis.

The authors used a model tree algorithm to develop their correlation equation. 70% of the data were used for correlation prediction while the remainder 30% were used to measure error. (4) contains the presented correlation equation from uncorrected SPT blowcounts to V_S in units of meters per second. The equation was intended for use on all soil types in the North Florida region. The only presented statistical measure was a correlation coefficient of 0.893 ($R^2=0.797$).

$$V_s = 77.1N^{0.355} \quad (4)$$

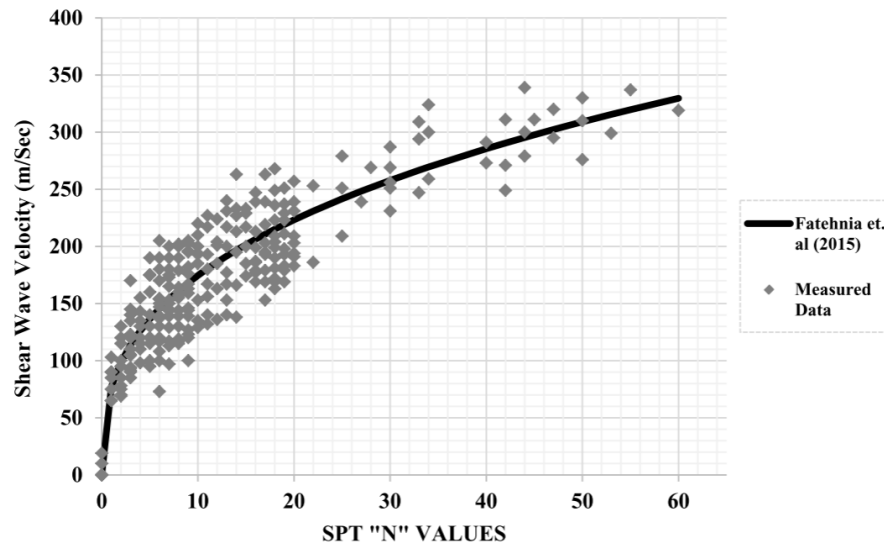


Figure 2-8: Proposed correlation for all soil types (Fatehnia et al. 2015)

2.2.1.9 Anbazhagan et al. 2016

Anbazhagan et al. (2016) developed a set of correlation equations using data taken from multiple sites in India. A total of 51 boreholes were drilled in sites across south India near major cities (Bangalore, Chennai, Coimbatore, and Vizag) with MASW surveys having been conducted near to these boreholes. Soils primarily consisted of clays with blowcounts increasing with depth overlying a fractured layer of quartzite rock to a depth of 40 m (131 ft). SPT blowcounts for the layer of quartzite were taken as 100 which corresponds with the rebound layer the authors described.

Correlations developed include N values of up to 100 to capture some of the behavior of stiffer material above the hard rock input layer used in site response analysis. For comparison to some existing correlations at the time of the study, correlation equations were also computed for the case of neglecting N values of 100. Correlation equations were developed using a power fit. Table 2-4 presents the developed equations for the entire database presented in the authors study.

Table 2-4: Correlation equations developed from South India database (Anbazhagan et al. 2016)

Correlation	Equation	R ²
Excluding SPT N value of 100	$V_s(m/s) = 45.69N^{0.49}$	0.770
Including SPT N value of 100	$V_s(m/s) = 52.29N^{0.45}$	0.823

2.2.2 Correlation to Cone Penetration Testing (CPT)

Another commonly used in-situ test for typical geotechnical site explorations is the cone Penetration Test (CPT). CPT is performed by driving an instrumented cone into the ground at a static rate of 0.2 cm/s (0.08 in/s) and measuring cone tip resistance (q_c) and sleeve friction (f_s) (ASTM D5778). The most common types of CPT testing are the conventional CPT, the piezo-CPT (CPTu), and the seismic CPT (SCPT or SCPTu). The piezo-CPT incorporates a piezometer behind the cone to measure pore water pressure and allows for correction of the tip resistance value due to pore pressures acting on the tip of the cone. The seismic CPT includes a geophone or accelerometer located in the cone tip to allow for downhole measurements of seismic velocities.

In the same report by Wair et al. (2012) the authors provided a list of references for CPT based correlations for V_s , along with recommendations for use of CPT based correlations. Discussion of the recommendations presented in Wair et al. 2012 is provided below along with discussion of additional sources.

2.2.2.1 Summary by Wair et al. (2012)

Wair et al. (2012) compiled a list of CPT based correlations to V_s . Table 2-5 contains the compiled list of correlation equations presented by the authors. Correlation equations were grouped based on soil type with equations for sands, clays, silts, and for all soils presented. Equations for gravels were not presented as CPT is not suitable for gravely soils (Schmertmann 1978). For the sites in California that were considered, the authors recommend the use of the average value obtained from the use of Equations 5.7 (Mayne 2006), 5.9 (Andrus et al. 2005), and 5.10 (Robertson 2009). Since the equations presented were primarily developed for Quaternary and Holocene soils, they can tend to underpredict V_s for Pleistocene soils but are

generally acceptable for all Quaternary soils (Robertson 2009). If the thickness of Holocene and Pleistocene soils is known, age scaling factors can be applied to results. Age scaling factors for Holocene and Pleistocene soils are 0.92 and 1.12 respectively.

Table 2-5: CPT based correlation equations presented in Wair et al. 2012. Equations recommended for use are bolded.

Soil Type	Study	Geologic Age	Number of Data Pairs	R ²	V _s (m/s)
All Soils	Hegazy & Mayne (1995)	Quaternary	323	0.70	$(10.1 \log(q_c) - 11.47)^{1.67} (100 f_s / q_c)^{0.3}$
	Mayne (2006)	Quaternary	161	0.82	$118.8 \log(f_s) + 18.5$
	Piratheepan (2002)	Holocene	60	0.73	$32.3 q_c^{0.089} f_s^{0.121} D^{0.215}$
	Andrus et al. (2007)	Holocene & Pleistocene	185	(H) 0.71 (P) 0.43	$2.62 q_c^{0.395} I_c^{0.912} D^{0.124} SF$
	Robertson (2009)	Quaternary	1035	---	$[(10^{(0.55 I_c + 1.68)}) (q_c - \sigma'_v) / p_a]^{0.5}$
Sand	Sykora & Stokoe (1983)	---	256	0.61	$134.1 + 0.0052 q_c$
	Balidi et al. (1989)	Holocene	---	---	$17.48 q_c^{0.131} \sigma'_v^{0.27}$
	Hegazy & Mayne (1995)	Quaternary	133	0.68	$13.18 q_c^{0.192} \sigma'_v^{0.179}$
	Hegazy & Mayne (1995)	Quaternary	92	0.57	$12.02 q_c^{0.319} f_s^{-0.0466}$
	Piratheepan (2002)	Holocene	25	0.74	$25.3 q_c^{0.163} f_s^{0.029} D^{0.155}$
Clay	Hegazy & Mayne (1995)	Quaternary	406	0.89	$14.13 q_c^{0.359} e_0^{-0.532}$
	Hegazy & Mayne (1995)	Quaternary	229	0.78	$12.02 q_c^{0.319} f_s^{-0.0466}$
	Mayne & Rix (1995)	Quaternary	339	0.83	$9.44 q_c^{0.435} e_0^{-0.532}$
	Mayne & Rix (1995)	Quaternary	481	0.74	$1.75 q_c^{0.627}$
	Piratheepan (2002)	Holocene	20	0.91	$11.9 q_c^{0.269} f_s^{0.108} D^{0.127}$

Units: q_c , q_t , f_s , σ'_v , and σ'_v are in kPa. Depth (D) is in meters (m). $p_a = 100$ kPa. $SF = 0.92$ for Holocene and 1.12 for Pleistocene

2.2.2.2 Mousa and Hussein 2022

Moussa and Hussein (2022) sought to develop a more global approach for estimation of V_s from CPT data specifically targeted towards fine grained soils. The authors use a database of 632 CPT measurements collected from 55 sites in 12 countries for development of their correlation equations. Countries included in the database are the United States, Canada, Norway, the United Kingdom, Ireland, Greece, Sweden, Italy, Egypt, China, Japan, and Australia. Along with the existing database, the authors compiled 165 CPT measurements from Mexico City and New Jersey for validation of their developed equations. Unconsolidated soils were not considered for this study as they tend to behave more erratically as compared to consolidated sediments. A cut-off overconsolidation ratio of 10 was also selected to trim the data.

A total of 7 proposed correlations were developed based on combinations of sleeve friction (f_s), cone tip resistance (q_t), unit weight (γ), depth (d), overconsolidation ratio (OCR), pore pressure (u_2), and characteristic index (I_c). The 7 proposed equations are presented in Table 8. The authors then evaluate these equations with the separate dataset taken from measurements in Mexico City and New Jersey. Following analysis and verification of the proposed equations, the authors recommend that Equations 1 and 2 presented in Table 2-6 to be used for estimation of V_s .

Table 2-6: Proposed correlation equations presented in Moussa and Hussein (2022)

Equation	Variables	V_s (m/s)
1	d, q_t	$35d^{0.032}q_t^{0.284}-121.6$
2	q_t	$45.52q_t^{0.2785}-138.8$
3	q_t, γ	$35q_t^{0.18}\gamma^{0.424}-239.5$
4	q_t, OCR	$147.1q_t^{0.17}\text{OCR}^{0.042}-321.8$
5	q_t, u_2	$65.92q_t^{0.248}u_2^{0.0026}-204.8$
6	q_t, f_s	$1251q_t^{0.04}f_s^{0.0027}-1506$
7	q_t, I_c	$0.337q_t^{0.76}I_c^{0.015}+114$

Note: f_s, q_t , and u_2 in kPa; d in m; γ in kN/m^3

2.2.3 Correlations for Rock

At some sites rock will be encountered within 30 meters (100 feet) of the ground surface. In these cases, correlation to V_s needs to be made from properties of the rock. For typical geotechnical investigations rock is sampled by coring, standardized in ASTM D2113-14. Rock coring is performed using a drill rig, like those used for standard penetration testing, and a specialized drill bit. Once auger or SPT refusal is met the drill bit is attached to drill rods and lowered into the borehole. Water or some other specialized drilling fluid will be circulated to the drill bit to prevent overheating. The rock core will then be removed and analyzed in the field or in the laboratory for rock type and other physical characteristics. For geotechnical investigations rock cores will often be described by a rock quality designation (RQD). RQD is a descriptive quality for rock and is standardized in ASTM D6032-17. RQD is calculated using the number of intact core pieces over 10 cm (4 in) in length for the entire run of rock coring and is

expressed as a percentage. A higher RQD indicates a more intact rock of higher quality as compared to a rock with a lower RQD.

Seismic velocity of rock is not directly tied to RQD however both seismic velocities and RQD tend to decrease as rock becomes more weathered and fractured (Kahraman 2001, Biringen and Davie 2013). There are a limited number of existing correlations to either V_P or V_S from RQD. The following sections will provide discussion on some RQD based correlations.

2.2.3.1 El-Naqa 1996

El-Naqua (1996) conducted a study at the site of a proposed dam in Wadi Mujib, Jordan, to develop correlations between physical properties of rock and seismic velocity. Bedrock at the site consists of mostly yellow limestones interbedded by marls and thin shales. Detailed logging of rock mass from 10 boreholes drilled at the site was performed to determine RQD along with other desired parameters of the rock mass.

Seismic refraction surveys were conducted at the site to measure the compressional wave velocity of the rock mass. Refraction surveys were conducted with two types of seismographs by two different agencies using identical energy sources. The authors perform regression analysis to develop an equation for RQD based on V_P . The dataset along with regression analysis is presented in Figure 2-9 where the dashed lines represent confidence limits of 90 and 95% respectively. The regression equation is presented in (5) and can be rearranged to determine V_P in the form of (6).

V_P can be converted to V_S using known ratios for different soil and rock types. Typical V_P/V_S ratios for sandstone, limestone, and dolomite, similar to rock that is expected to be encountered in Alabama, range from 1.6 to 1.9 (Pickett 1963). Using an average value of 1.75 for V_P/V_S , V_S can be calculated using (7).

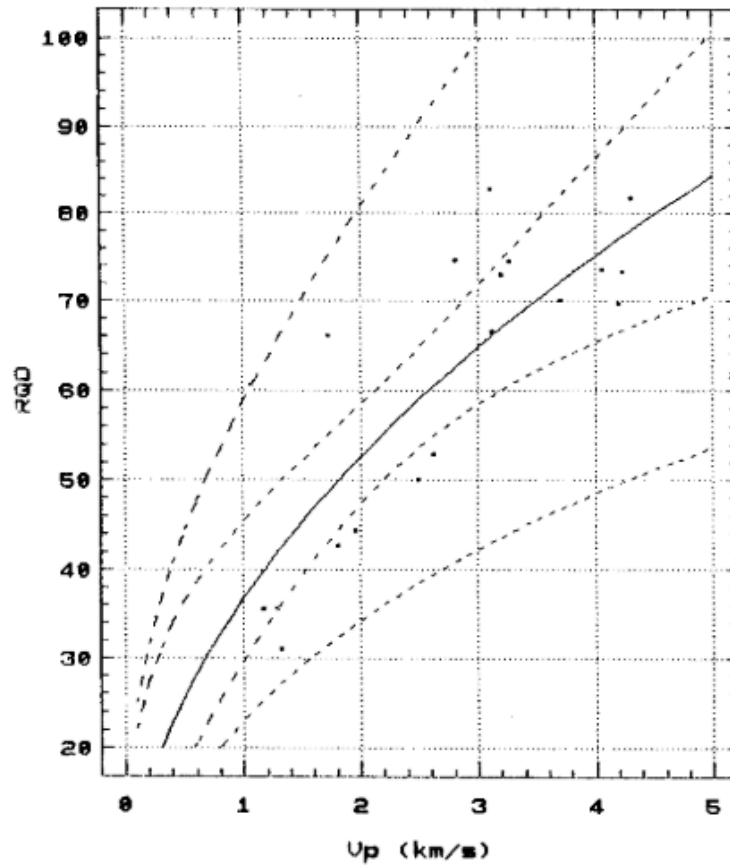


Figure 2-9: Regression analysis of V_p to RQD (El-Naqua 1996)

$$RQD = 36.7 * V_p^{0.52} \quad (5)$$

$$V_p = \sqrt[0.52]{\frac{RQD}{36.7}} \quad (km/s) \quad (6)$$

$$V_s = \frac{\sqrt[0.52]{\frac{RQD}{36.7}}}{1.75} \quad (km/s) \quad (7)$$

2.2.3.2 Biringen and Davie 2013

Biringen and Davie (2013) conducted a study at three separate sites with differing geology. Rock coring was performed in accordance with ASTM D2113, and rock was inspected

in the field for rock type and fracturing by geologists. Suspension logging was performed to measure V_P and V_S .

The first site considered is located in South Carolina. Geology of the site consists primarily of hard igneous rock with some inclusions of metamorphic rock. Rock consists of granodiorite, quartz diorite, gneiss or migmatite. The upper layer of bedrock is moderately weathered with decomposed layers comprising 50% of the volume. A total of thirty boreholes were drilled to depths of 175 to 350 ft (53.4 to 106.7 m). V_S suspension logging was performed in four of the thirty boreholes. RQD and V_S were averaged over an interval of 5 ft (1.5 m). Figure 2-10 presents the combined results of RQD and V_S testing as well as the developed correlation in units of ft/s. The correlation is presented in units of km/s in (8).

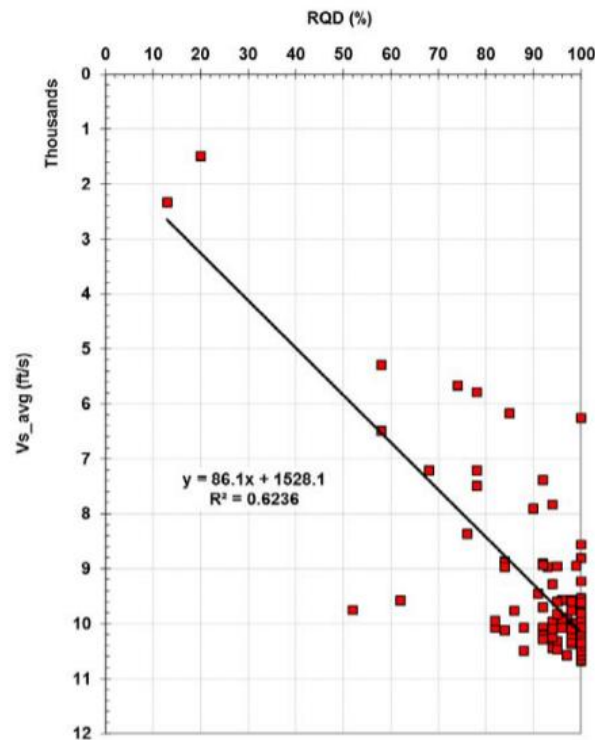


Figure 2-10: Correlation to V_S from RQD as developed from South Carolina igneous rock database (Biringen and Davie 2013)

$$V_S(km/s) = 0.026 * RQD + 0.466 \quad (8)$$

The second of the three sites is located in Virginia. Bedrock of the site is comprised primarily of metamorphic rock, consisting of mainly gneiss, ranging from quartz gneiss with

biotite to biotite granite gneiss, and some biotite hornblende gneiss or quartz gneiss with feldspar or muscovite. Five boreholes were used at this site for suspension logging of V_s with depths ranging from 200 to 300 ft (61 to 91 m). RQD and V_s are averaged in the same manner as for the South Carolina site. Figure 2-11 below presents the data collected as well as the correlation developed for metamorphic rock from the Virginia site in units of ft/s. the correlation is presented in units of km/s in (9).

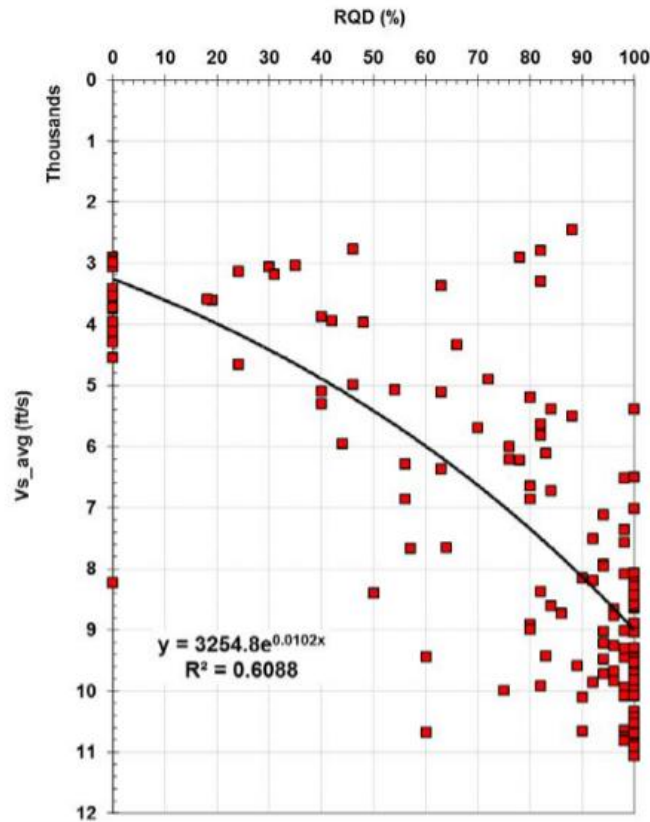


Figure 2-11: Correlation to V_s from RQD as developed by Virginia metamorphic rock database (Biringen and Davie 2013)

$$V_s(km/s) = 0.992e^{0.0102 \cdot RQD} \quad (9)$$

The final site considered in the study is located in Florida. The site is located partially in the Key Largo formation which consists of white coralline limestone, frequently having a very open structure. The Key Largo formation is underlain by the Fort Thompson formation at the

site. The Fort Thompson formation consists of white limestone with varying amounts of shells and some sand. RQD values of both formations range from 0 to 100.

V_s measurements were taken from downhole logging in 10 boreholes. RQD and V_s are averaged over the same intervals as the previous two sites. Regression analysis was performed for both geologic units and developed equations are presented in Figure 2-12 in units of ft/s. Correlations in units of km/s are presented in (10) and (11) for the Ft. Thompson and Key Largo equations respectively.

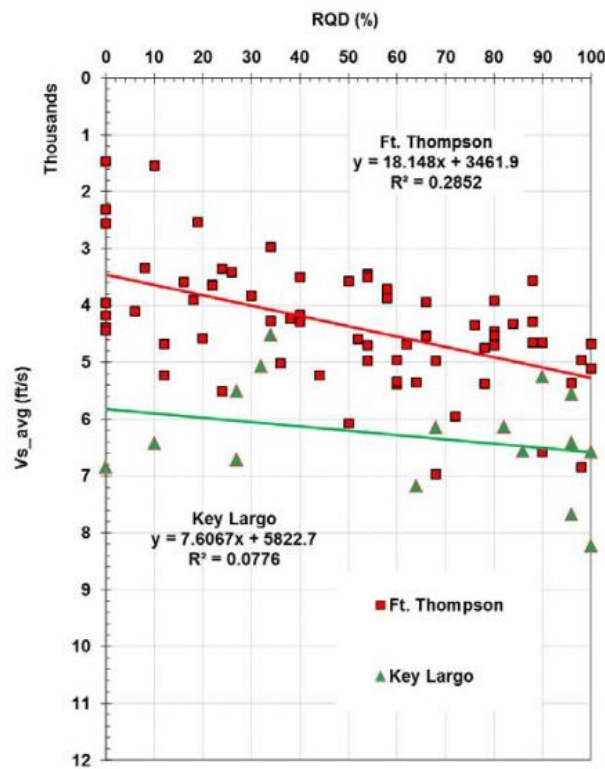


Figure 2-12: Correlation to V_s from RQD as developed by Florida Fort Thompson and Key Largo databases (Biringen and Davie 2013)

$$V_s(km/s) = 0.0553 * RQD + 1.055 \quad (10)$$

$$V_s(km/s) = 0.0232 * RQD + 1.775 \quad (11)$$

2.2.3.3 Salaamah et al. 2019

Salaamah et al. (2019) selected the site of the Bener dam in Indonesia to develop a correlation between RQD and V_p . Data was taken from a report on geologic stabilization of the

dam. The Bener Dam plan is located on the Bogowonto River in Indonesia and is underlain by the Kebobutak Formation. The Kebobutak Formation consists of andesite, tuff, lapilli tuff, agglomerates, and andesite lava.

Seismic surveys consisted of refraction-based surveys conducted at three locations around the dam. A total of 15 boreholes of those drilled for the dam's stabilization were considered in this analysis. Regression analysis was performed on the dataset. Figure 2-13 presents results of V_p and RQD measurements along with the linear regression fit.

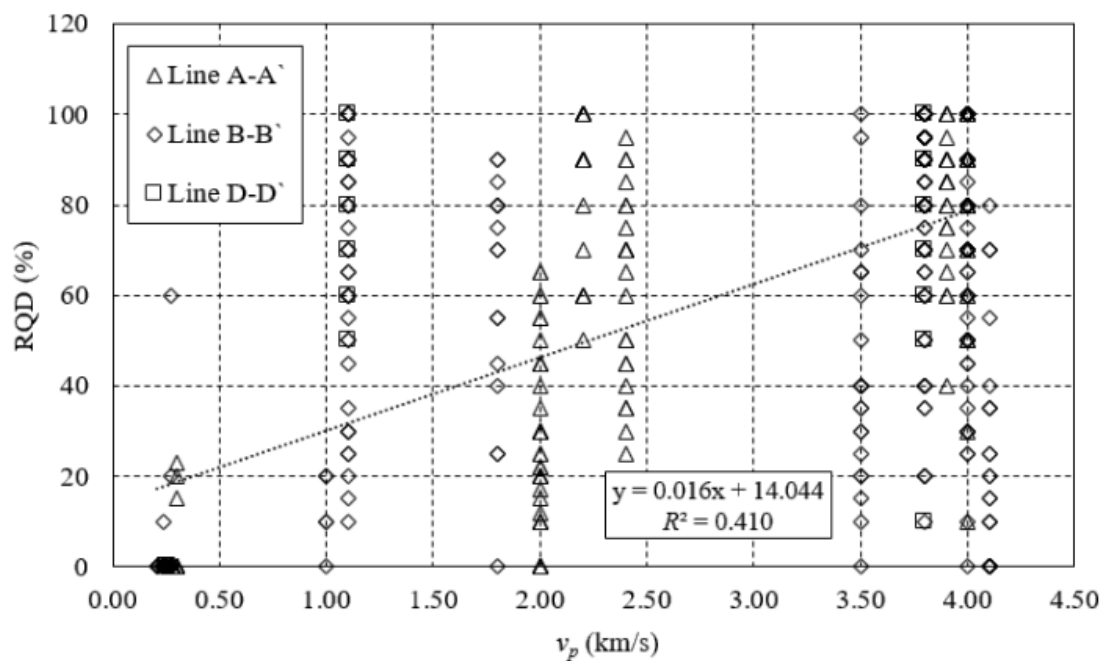


Figure 2-13: Combined correlation from all three survey lines for volcanic rock developed from Bener Dam (Salaamah et al. 2019)

2.2.4 Correlations with HVSr Measurements

The HVSr technique is based on passive measurements of ambient seismic noise and was first introduced in 1989 (Nakamura 1989, 2019). The HVSr method estimates the amplification and resonant frequency of ground motions that are affected by a surface layer (Nakamura 2019). The HVSr method assumes that ground motions amplify the horizontal

components near the fundamental frequency while the vertical component experiences little to no amplification (Nakamura 1989). This was later observed to not always be true based on observations of the Mexico City basin (Lermo and Chávez-García 1993). These findings were later reinforced by the Site Effects Assessment Using Ambient Excitations project (SESAME) funded by the European Union which aimed to standardize HVSR processing. The findings of the project revealed that under certain circumstances namely deep sedimentary basins and soft soils, vertical amplification can occur (SESAME 2004). The SESAME project helped to deepen the understanding of HVSR by issuing guidelines on HVSR data acquisition along with data processing as well as acknowledging some of the limitations of HVSR (Mucciarelli and Gallipoli 2001, Bard 2004).

The peak of the HVSR curve is associated with the fundamental frequency of the site (f_0) as well as the amplification of that frequency (A_0) (Nakamura 2019). The fundamental frequency of the site for a single layered system is also related to the thickness of the layer (H) as well as shear wave velocity for that layer as described in (12) (Kramer and Stewart 2025).

$$f_0 = \frac{V_s}{4H} \quad (12)$$

Empirical correlations to obtain V_{s30} from f_0 have been developed by multiple authors. Discussion of available empirical correlations is found in the following sections.

2.2.4.1 Ghofrani and Atkinson (2014)

Ghofrani and Atkinson (2014) used the Next Generation Attenuation-West2 (NGA-West2) database along with Japanese databases (K-NET and KiK-NET) to develop a correlation equation between f_0 and V_{s30} . The database used by the authors contains all recorded seismic events from 1996 to 2009. Using the HVSR parameters f_0 and A_0 , correlation equations were developed separating the parameters along with an equation combining the two that the authors recommend for use as seen in (13).

$$\begin{aligned} \log_{10}(V_{s30}) &= 2.56(\pm 0.01) + 0.20(\pm 0.02) \log_{10}(f_0) \quad f_0 > 1\text{Hz} \\ \log_{10}(V_{s30}) &= 2.86(\pm 0.01) - 0.46(\pm 0.02) \log_{10}(A_0) \\ \log_{10}(V_{s30}) &= 2.80(\pm 0.02) + 0.16(\pm 0.02) \log_{10}(f_0) - 0.50(\pm 0.03) \log_{10}(A_0) \end{aligned} \quad (13)$$

2.2.4.2 McNamara et al. 2015

McNamara et al. (2015) developed a relationship between HVSR fundamental frequency and V_{S30} for the Central Virginia Seismic Zone (CVSZ). The authors collect data from permanent and portable seismic recording stations located in the CVSZ. A total of 218 permanent seismic stations were considered in this study while 66 total portable seismic stations were considered. Direct measurements of V_{S30} were performed at the locations of the portable seismic stations. Recordings from strong and weak ground motion from permanent recording stations that were used by the authors were processed to isolate the ambient noise spectra from sensor error or spectral transients due to earthquakes. Only recordings with clear peak frequencies were selected for use in development of this correlation, so the authors acknowledge that their correlation is not applicable to sites with complex or weak behavior. Following the selection of HVSR curves, results of HVSR peak frequency are then plotted against measured V_{S30} from the sites of 21 permanent and portable seismic recording stations in Figure 2-14 along with site class bins overlain. A least-squares regression was performed, and it was determined that the two variables have a correlation coefficient of 0.89 ($R^2=0.79$) along with a standard deviation of 78.91 m/s.

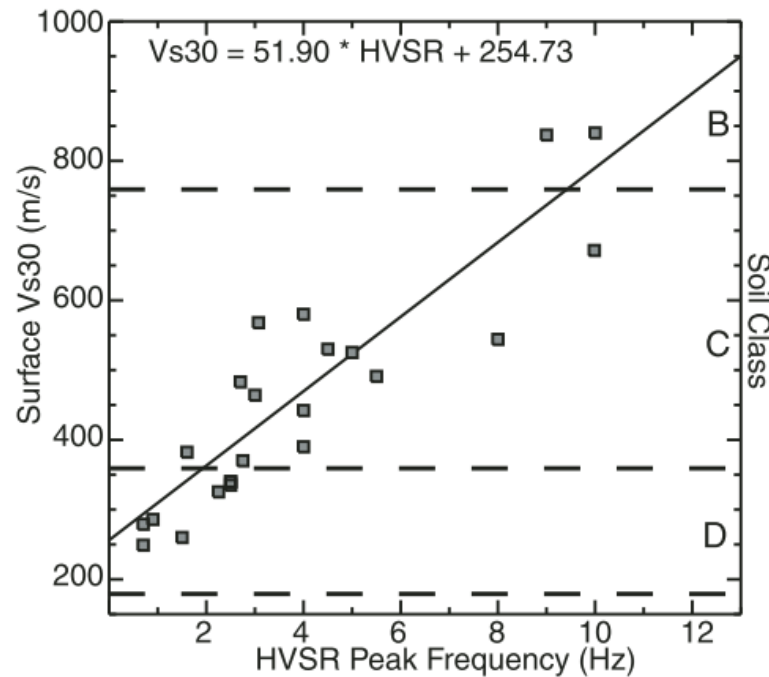


Figure 2-14: Comparison between HVSr peak frequency and V_{s30} with site class bins overlain. (McNamara et al. 2015)

2.2.4.3 Hassani and Atkinson 2016

Hassani and Atkinson (2016) presented a HVSr peak frequency-based method for estimation of V_{s30} derived from data collected at sites throughout Central and Eastern North America. The data selected for this study were taken from the Next Generation Attenuation-East database (NGA East). Recording stations were scattered across CENA, with a large concentration of stations in the region of the Mississippi Embayment and a greater concentration of stations near Ontario from a supplemental database. Site classifications ranged from E to A with site class C being the most common. Data collected from the sites comprised of 3-component peak ground motion amplitudes (peak ground acceleration [PGA], peak ground velocity [PGV], and the 5% damped pseudo-spectral response acceleration spectra [PSA]). The authors only selected data with a signal to noise ratio of two at a minimum.

The authors developed relationships between peak frequency and V_{S30} that are constrained by values of sediment and rock layer velocities. Figure 2-15 details the relationships developed based on changing velocities of the sediment layer, V_L . For these relationships the velocity of the rock layer, V_R , is set at 2000 m/s. The relationship follows a bilinear trend with a “hinge” frequency where the trend changes. The hinge frequency corresponds to a sediment layer thickness of 30m. For deeper sediments or peak frequencies lower than 2 Hz, V_{S30} will remain constant and is equal to the V_L used in the relationship. For Figure 2-16 V_L is fixed to 250 m/s while V_R varies. The same hinge frequency is used as was in which corresponds with the same sediment layer thickness. As peak frequency increases above approximately 2 Hz, V_{S30} will climb more rapidly as compared to changing V_L .

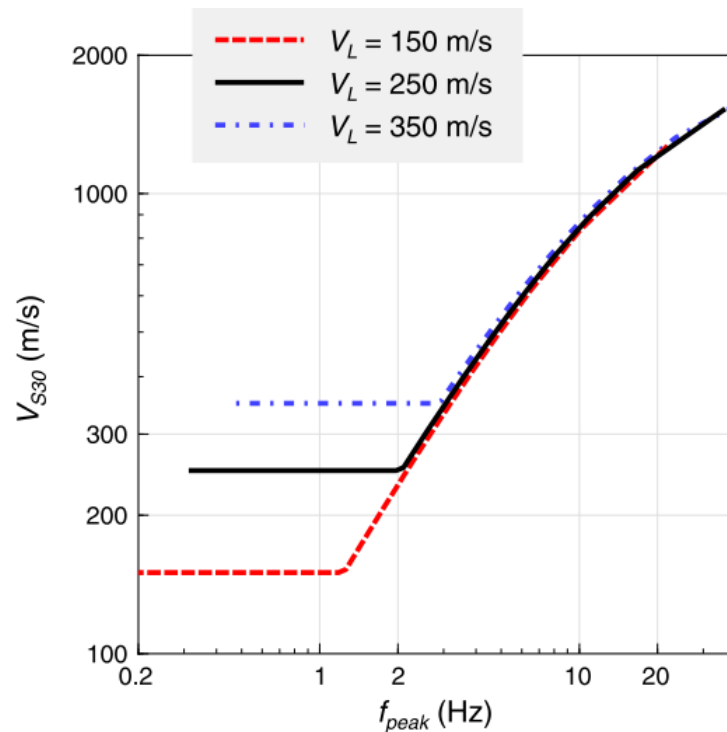


Figure 2-15: Expected relationship between V_{S30} and peak frequency for 3 different sediment layer velocity (V_L) values. (Hassani and Atkinson 2016)

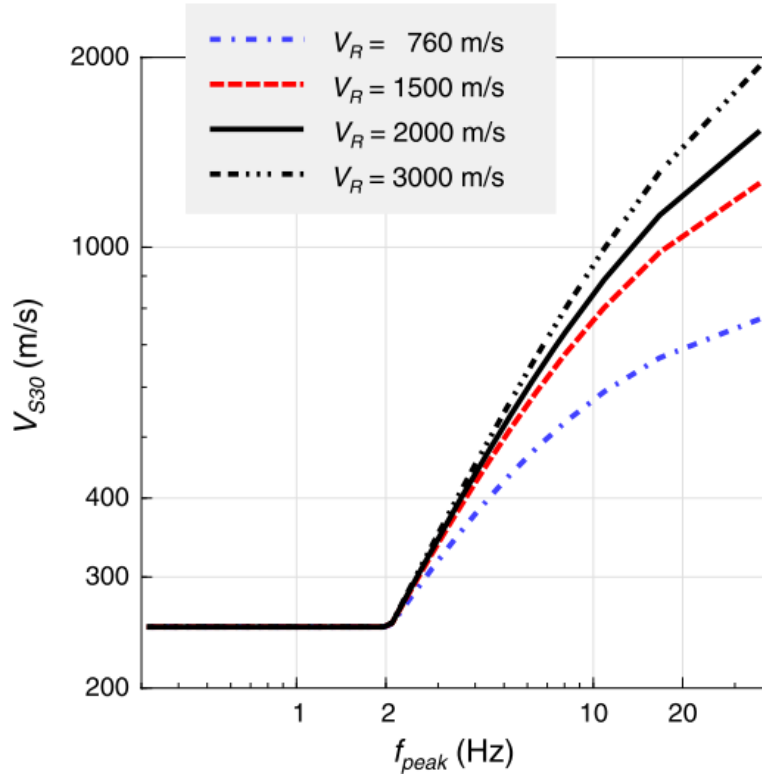


Figure 2-16: Expected relationship between V_{S30} and peak frequency for 3 different rock layer velocity (V_R) values. (Hassani and Atkinson 2016)

The authors then proposed a peak frequency based V_{S30} model following (14). The equation was determined from 41 sites in the NGA East database, and the authors acknowledged the limitations of the relatively low sample size in deriving of the equation. The authors postulated that site geology needs to be considered when applying this model as it may not be suitable for sites with sediments deeper than 30m.

$$\log_{10}(V_{S30}) = \begin{cases} 2.2(\pm 0.04) + 0.63(\pm 0.06) \log_{10}(f_{peak}) & f > 2 \text{ Hz} \\ \log_{10}(250) & f \leq 2 \text{ Hz} \end{cases} \quad (14)$$

2.2.4.4 Stanko and Markušić (2020)

Stanko and Markušić (2020) developed a set of correlation equations based on 244 HVSR curves calculated from 3-component microtremor data in Croatia. V_{S30} was measured using surface based geophysical surveys (MASW and seismic refraction) at the same location or near

where the microtremor data were taken. The study provided equations for different frequency ranges as seen in (15). The authors emphasized that their developed equations can be applied to regions with similar characteristics and cannot be generalized for other areas.

$$\begin{aligned}
 \ln(V_{s30}) &= \ln(208 \pm 20) & f_0 < 1\text{Hz} \\
 \ln(V_{s30}) &= 5.34(\pm 0.9) + 0.46(\pm 0.15) \ln(f_0) & 1\text{Hz} \leq f_0 \leq 10\text{Hz} \\
 \ln(V_{s30}) &= \ln(600 \pm 80) & 10\text{Hz} < f_0 < 30\text{Hz}
 \end{aligned} \tag{15}$$

2.2.4.5 Sharma Wagle et al. 2026

Sharma Wagle et al. (2026) used a database of 2,861 three-component ambient noise recording from 536 unique sites located in New Zealand, Taiwan, Italy, Ecuador, Mexico, and the United States. Of these 2,861 recordings, 252 of these are taken from the Mississippi Embayment at 10 sites. Both a set of low dimensional models that only consider the fundamental frequency of the site along with the peak amplitude, and a set of high dimensional models that consider the entire HVSr curve were developed. Both models integrate topographic information through the use of binned elevation as a proxy for geologic composition as well as topographic position index as a proxy for topographic features.

For development of the models, a machine learning based approach was used, where the data were divided into training and testing sets. Careful consideration was taken to ensure that both datasets were representative of the larger dataset. For the low dimensional model, only HVSr measurements with a clear peak resonance frequency were chosen while the high dimensional model considered HVSr measurements within the frequency range of 0.3 to 50 Hz.

Comparison of the models indicated that high-dimensional models perform better than low-dimensional models. For the high-dimensional models there was little to no difference between single and dual mode artificial neural networks. The authors recommend that for high-dimensional models, the single mode artificial neural network model ($R^2=0.82$) to be used while for low-dimensional models the random forest ($R^2=0.69$) and gradient boosted tree ($R^2=0.68$) models be used.

2.2.5 Geospatial Correlations

In addition to the other indirect methods presented in this section, geospatial methods can also be used to estimate V_{S30} at sites in Alabama. Geospatial methods rely on correlation of some physical property of the site (i.e., slope, geology, terrain classification, etc.) to V_{S30} . Previous work in the application of geospatial methods for estimating V_{S30} in Alabama is presented in Carcamo (2022). Methods applied in Carcamo (2022) are based on terrain (Yong et al. 2012), hybrid slope-geology (Parker et al. 2017), the topographic slope method (Wald and Allen 2007), and the surface geology method (Kottke et al. 2012). Those methods will be applied in this study along with additional studies discussed below.

2.2.5.1 Wald and Allen 2007

Wald and Allen (2007) presented a topographic slope-based model for estimation of V_{S30} . The model is supported by the hypothesis that topography of a site is closely related to geology and therefore can provide a reasonable estimation of V_{S30} of the site. As topographic slope increases, it is likely that surficial geology will be comprised of stiffer materials, thus V_{S30} will increase with topographic slope. Along with topography, sediment fineness is a proxy for lower shear wave velocity (Park and Elrick 1998). Mountain front alluvial fan material typically grades finer as the distance from the mountain front increases and will deposit at decreasing slopes as energy is lost in the fluvial process.

For development of the model, the authors began with correlating 30 arc second topographic data with V_{S30} measurements at seismically active sites. V_{S30} data used for initial correlation were selected from publicly available sources, and include sites in California, Utah, Tennessee, Missouri, Kentucky Washington, and Arkansas. For topography used, the authors employed the Shuttle Radar Topography Mission 30-sec (SRTM30) global topographic data set (Farr and Kobrick 2000). The 30 arc-second dataset was selected rather than some other finer resolution datasets due to it being globally available. The authors presented the limitation that the resolution selected can result in varying slope values for areas of high relief and additional correlations may be required for a more accurate estimate. Along with areas of high relief, in

areas where the resolution of topography data is less than the ridge to valley wavelength, terrain will tend to be artificially flattened.

The authors presented a model for the eastern United States, taken from east of the Rocky Mountains. On a coarse scale the authors indicated that the model is representative of V_{s30} conditions for the region but will tend to underpredict V_{s30} for flatter regions dominated by carbonaceous rock such as South Florida. The authors also noted the limitation of the model in these regions due to a relative lack of V_{s30} measurements. Figure 2-17 presents the model for the Eastern United States.

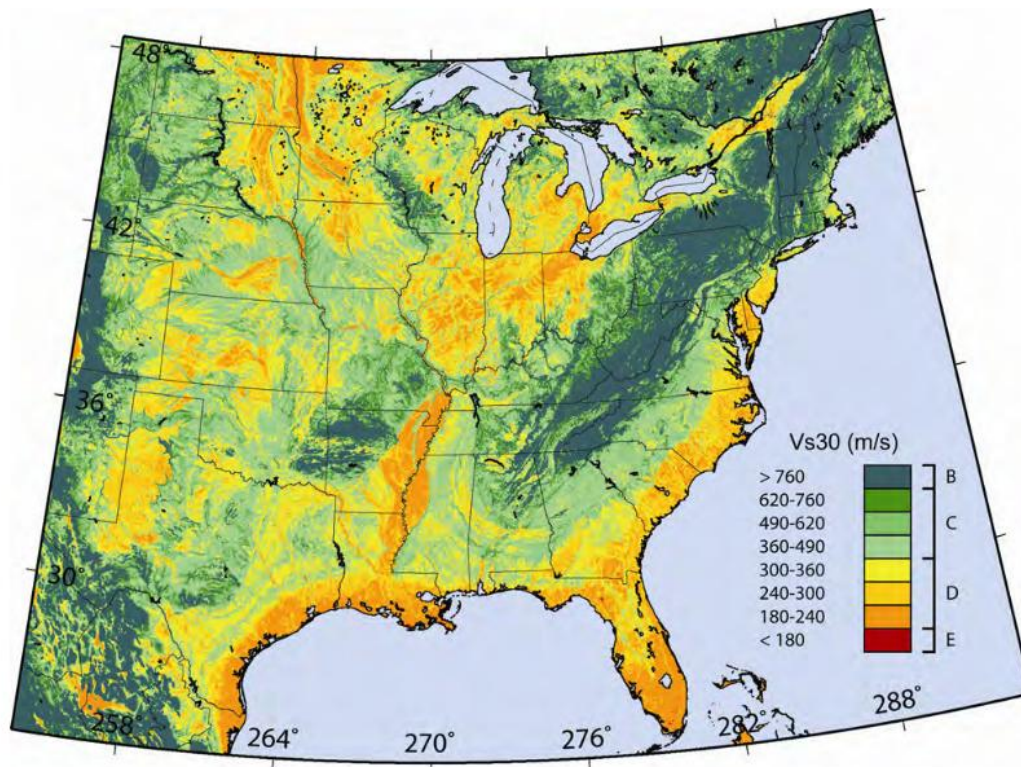


Figure 2-17: Wald and Allen 2007 model for V_{s30} prediction based on topographic slope

2.2.5.2 Yong et al. 2012

Yong et al. (2012). presented a model for estimation of V_{S30} based on geomorphometry. The authors used the terrain classification scheme developed in Iwahashi and Pike (2007) to develop a consistent terrain classification map for global use (Figure 2-18). The algorithm developed divides terrain into 16 possible terrain classes using 3 taxonomic criteria: slope gradient, local convexity, and surface texture. V_{S30} values used to develop the model were taken from a number of sources, primarily from measured results and estimations in the state of California. After establishing the framework for classifying terrain and the selection of a V_{S30} database, a model for the state of California was developed. The model was then validated using statistical methods and through comparison to other existing models. Following comparisons for California, the model was then expanded to the contiguous United States. Figure 2-19 presents mean values of V_{S30} for all terrain types excluding type 13. The authors concluded that the model presented reduces standard deviation in stable continental regions as compared to the Wald and Allen 2007 model.

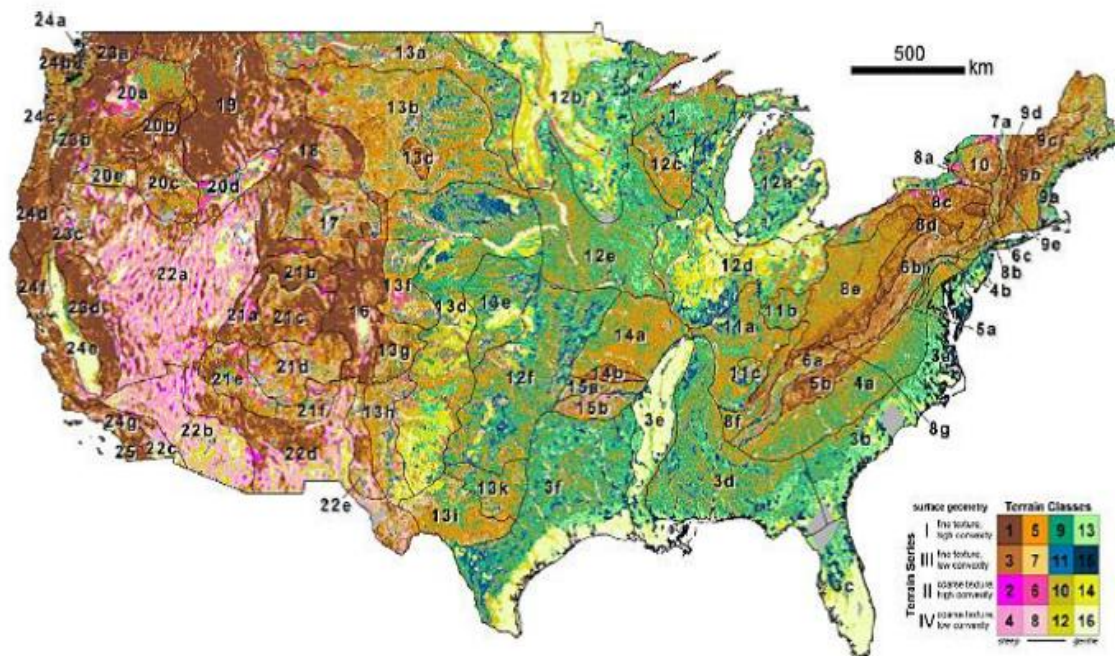


Figure 2-18: Terrain map of the United States (Iwahashi and Pike 2007)

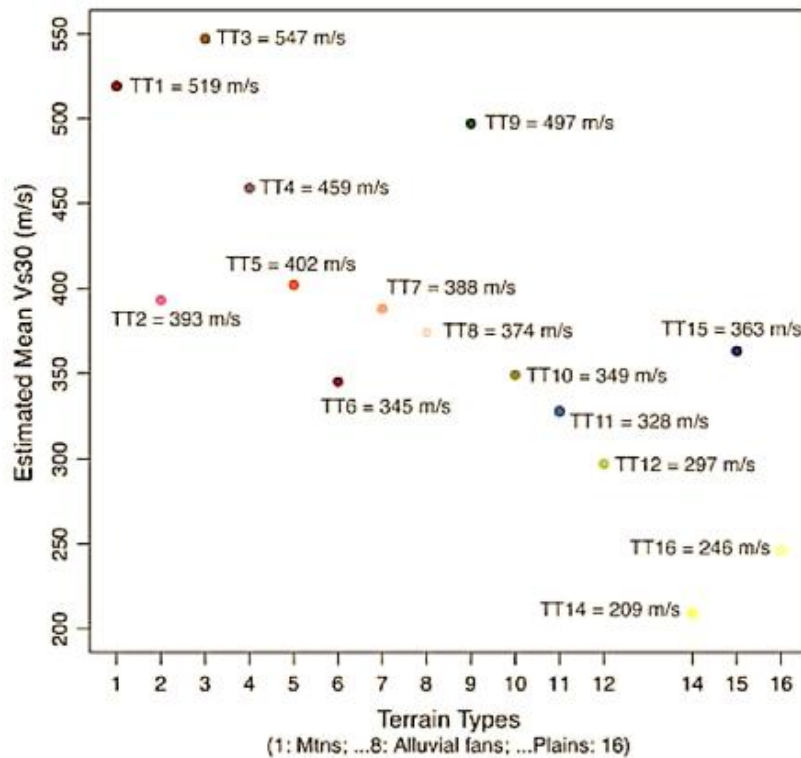


Figure 2-19: Mean values of V_{s30} for terrain types with no value provided for type 13 terrain (Yong et al. 2012)

2.2.5.3 Kottke et al. 2012

Previous models for estimation of V_{s30} tend to be biased towards California or other regions on the West coast that are more seismically active. Wald and Allen's 2007 topographic slope-based model does consider measurements of V_{s30} from Central and Eastern North America (CENA), while the previously discussed Yong et al. 2012 model does not consider any V_{s30} measurements from CENA in development of their model. The authors sought to address the limitations of previous models for estimation of V_{s30} in CENA by developing a model specifically targeted at this region.

The authors used a database of 1930 V_{s30} measurements in CENA from the following list of references: Gombert et al. (2003), Motazedian et al. (2011), Rosenblad et al. (2010), Holzer et al. (2010), Beresnev and Atkinson (1997), Mohanan et al. (2006) and Murphy (2003). This database of measurements was deemed to have a lack of hard rock sites (i.e. $V_{s30} = 2000$ m/s), so a total of 97 values of V_{s30} equal to 2000 m/s inferred from recording stations located on hard

rock sites were added (Siddiqqi and Atkinson 2002). The authors noted that despite the large database there are limitations due to clustered data as well a high concentration of Quaternary Alluvium. Additionally, most of the measurements above 450 m/s were taken from Ottawa Canada.

For development of their model, the authors divided surficial geology into 19 classes documented in Table 2-7. Figure 2-20 presents a map of the geologic classes.

Table 2-7: Geologic classes defined for CENA (Kottke et al. 2012)

Major Geologic Unit (Age)	Sub-Unit	Abbreviation	Thickness (m)	Soil Class	Mean V_{s30} (m/s)	σ_{inv} (m/s)
Old Glacial Sediments (Older than Wisconsin)	Glaciomarine and Lacustrine	OGm	9	ONm	---	---
	Outwash and alluvium	OGO	7	ONa	---	---
	Tills	OGt	16	ONa	---	---
Young Glacial Sediments (Wisconsin and Younger)	Glaciomarine and Lacustrine	YGm	8	YNm	520	0.53
	Outwash and alluvium	Ygo	11	YNa	470	0.67
	Tills	YGt	16	YNa	300	0.45
	Discontinuous Till	YGd	5	YNa	1050	0.39
Old Non-Glacial Sediments (Mid-Pleistocene and older)	Alluvium	ONa	---	---	---	---
	Colluvium	Onc	---	---	---	---
	Loess	ONI	---	---	250	0.11
	Lacustrine, Marine, and Marsh	ONm	---	---	290	0.22
Young Non-Glacial Sediments (Holocene and late Pleistocene)	Alluvium	YNa	---	---	220	0.14
	Colluvium	YNc	---	---	---	---
	Loess	YNI	---	---	---	---
	Lacustrine, Marine, and Marsh	YNm	---	---	230	0.12
	Beach, dune, and sheet sands	YNs	---	---	210	0.18
Residual Sediments	Residual from metamorphic and igneous rock	RRm	---	---	---	---
	Residual from sedimentary rock	RRs	---	---	---	---
	Residual from soils	RSs	---	---	---	---

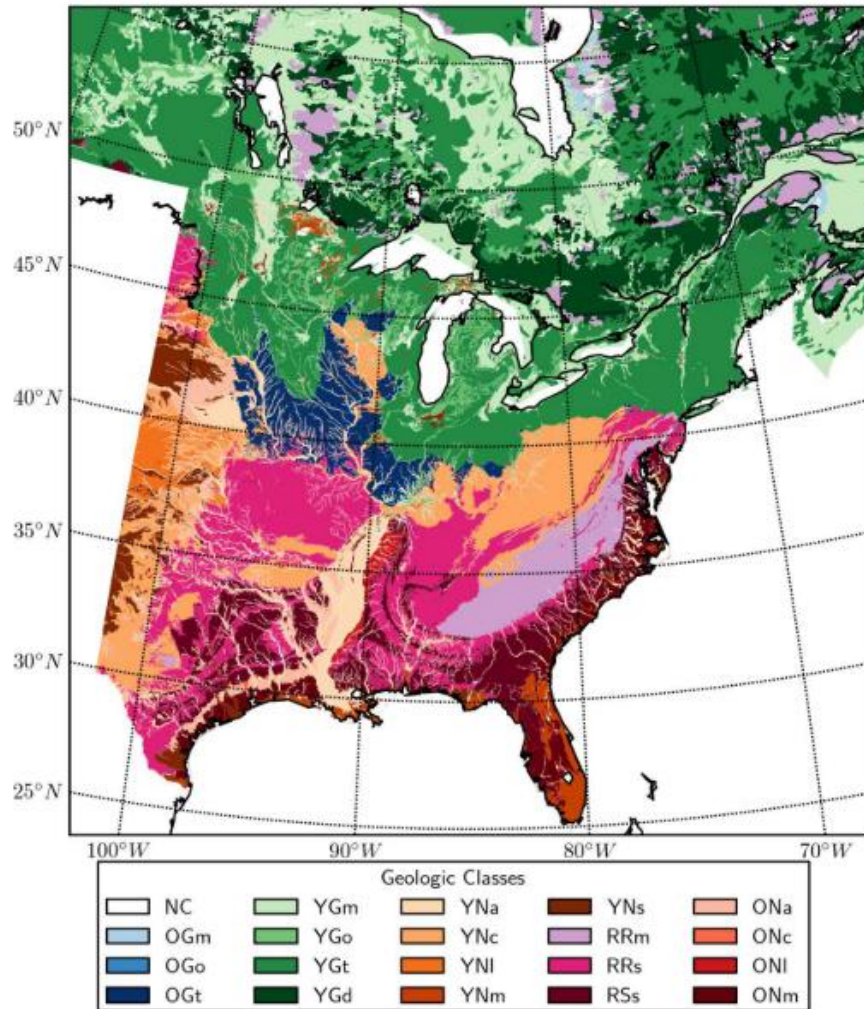


Figure 2-20: Map of geologic classes (Kottke et al. 2012)

2.2.5.4 Parker et al. 2017

Parker et al. (2017) presented a hybrid slope-geology based method for estimation of V_{s30} for CENA. A database of 2775 V_{s30} values were used for development of the model. Unlike the surface geology-based proxy method presented in Kottke et al. (2012), V_{s30} values of greater than 450 m/s were not concentrated in Ottawa with 213 values being located outside of the region. Despite a better effort to limit clustering, the authors still acknowledged the possibility of a regional bias in estimated values.

Groups were developed based on geologic age and are further subdivided based on geologic period and epoch. Table 2-8 presents the age groups. Developed groups were then correlated with the database of V_{S30} and log-log and semilog regressions were then applied.

Table 2-8: Proposed V_{S30} estimation procedures based on large-scale geologic maps, Wisconsin glaciation, location of site in a basin, and topographic gradient (Parker et al. 2017)

Category*							Group Moments			Gradient Relationship				
Group	Era	Period	Epoch	Wisconsin Glaciation?	Other Criteria	N	$\mu_{\ln V}$ (m/s)	$\sigma_{\ln V}$		Semilog		Log-Log		
										c_0	c_1	c_2	c_3	$\sigma_{\ln V}$
1	C	Q	H	No	Alluvium, fluvial, and deltaic	308	210	0.23						
2	C	Q	H	No	All other lithology	183	221	0.29						
3	C	Q	H	Yes	In Ottawa, Canada	981	232	0.67	5.38	9.30				0.67
4	C	Q	H	Yes	Not in Ottawa, Canada	51	308	0.72				7.47	0.295	0.67
5	C	Q	Pli	No		284	271	0.36	5.47	31.4				0.31
6	C	Q	Pli	Yes	Till in Ottawa, Canada	104	777	0.57	6.51	22.4				0.56
7	C	Q	Pli	Yes	Other in Ottawa, Canada	60	377	0.65				7.20	0.22	0.63
8	C	Q	Pli	Yes	Not in Ottawa, Canada	63	448	0.65						
9	C	Q	U	No	Not in sedimentary basin	154	296	0.43				6.21	0.096	0.41
10	C	Q	U	No	In sedimentary basin	151	280	0.29						
11	C	Q	U	Yes	Not in sedimentary basin [†]	66	209	0.31	5.28	24.7				0.29
12	C	T				111	315	0.31				6.07	0.059	0.30
13	M					20	822	0.68						
14	P				In the Illinois basin [‡]	5	513	0.23						
15	P			No	Not in the Illinois basin	96	684	0.61						
16	P			Yes	Not in the Illinois basin	76	972	0.77						
17	pC					37	699	0.85						
18	pC				Site visit; hard-rock confirmation		2000							

*C, Cenozoic; Q, Quaternary; H, Holocene; Pli, Pleistocene; U, undivided; T, Tertiary; M, Mesozoic; P, Paleozoic, pC, Precambrian.

[†]Can be applied for within-basin sites with increased epistemic uncertainty (category unpopulated).

[‡]Because of the small population size, the mean and standard deviation carry a larger degree of epistemic uncertainty than for other groups.

2.2.5.5 Geyin and Maurer 2023

Geyin and Maurer (2023) presented a model for V_{S30} in the United States based on multiple geospatial factors summarized in Table 2-9. The authors sought to create a more accurate and advanced model for national and regional scale by using multiple machine learning techniques. Machine learning was selected for development of this model as the method is not limited on the number of variables that can be modeled.

Table 2-9: Input parameters, sources, and resolutions for Geyin and Maurer V_{S30} model (Geyin and Maurer 2023)

Variable (units)	Source	Range in Data Set	Spatial Resolution
Depth to bedrock (cm)	Shangguan et al. (2017)	0-43,437	250m
Depth to groundwater (m)	Fan et al. (2020)	0-216	~1000m (30 arcsec)
Geologic unit	Horton et al. (2017)	Categorical	25-500m (varies)
Consolidation state	Horton et al. (2017)	0 or 1	25-500m (varies)
Distance to river (m)	Lehner and Grill (2013)	0- 8.4×10^4	~90m (3 arcsec)
Compound topographic index	Verdin (2017)	484-2858	~90m (3 arcsec)
Geomorphologic phenotype	Amatulli et al. (2018)	Categorical	~1000m (30 arcsec)
Topographic slope (%)	---	0-26.7	~1000m (30 arcsec)
Topographic position index	---	-37.38 to 22.94	~1000m (30 arcsec)
Profile curvature	---	-0.0012 to 0.0013	~1000m (30 arcsec)
Tangential curvature	---	-9.0577×10^4 to 9.35069×10^4	~1000m (30 arcsec)
Roughness	---	0-284	~1000m (30 arcsec)
Terrain ruggedness index	---	0-90.88	~1000m (30 arcsec)
Vector ruggedness measure	---	0-0.0457	~1000m (30 arcsec)
Landform entropy	---	0-2.9572	~1000m (30 arcsec)
Landform uniformity	---	0.0536-1	~1000m (30 arcsec)
Landform Shannon index	---	0-2.0467	~1000m (30 arcsec)

A total of 7081 measurements of V_{S30} were used for development of the model.

Measurements of V_{S30} were selected from regions within the continental United States and although the data represents a wide range of geographic and geologic settings, the data are primarily biased towards densely populated areas in regions of higher seismic activity. The authors discuss these limitations in their work as well as bias towards topographic slope. Of the data selected, 80% of the data were selected for model training while the remainder 20% of data were reserved for unbiased testing of the model.

From the training set of data (80% of the full dataset), many provisional models were trained with 3 being selected for further refinement. Of the 3 selected for further refinement, 2 were ensembles of 200 decision trees where relatively weak decision trees are combined to create a stronger model. The third is based on a Gaussian process regression (GPR), where probability distributions are assumed based on the Bayesian approach. The three adopted models were then “stacked” to improve performance and referred to as Model 1. The authors found a reduction in mean squared error (MSE) of 55% as compared to the model presented in Wald and Allen (2009). Predictions of V_{S30} for the continental US were then made based on Model 1 where regression kriging was then applied to update predictions, referred to as Model1alt. Figure 2-21 presents model1alt for the contiguous United States.

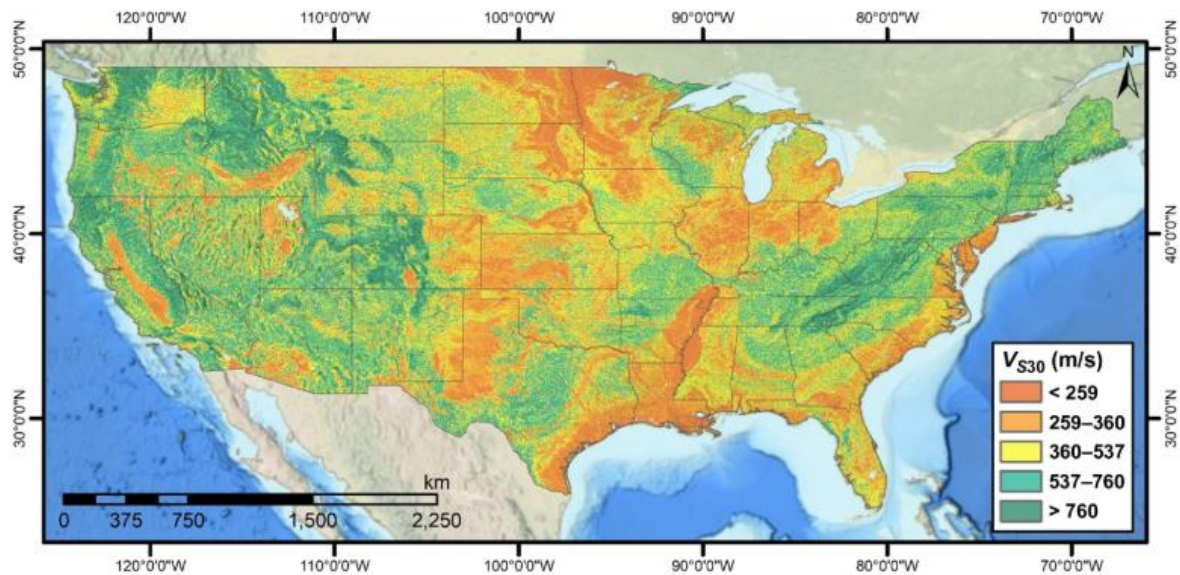


Figure 2-21: V_{S30} predictions from Model1alt with residual kriging for the continental US (Geyin and Maurer 2023)

2.2.5.6 Gann-Phillips et al. 2024

Gann-Phillips et al. (2024) presented a model for estimation of V_{S30} along with shear wave velocity gradients for sites located in the Atlantic and Gulf coastal plains. Coastal plains are characterized by nearly flat thick low-velocity sediments and sedimentary rock overlying high-velocity bedrock at depth. The structure of the coastal plains greatly influences propagation of waves in that lower frequencies will tend to be amplified while higher frequencies will tend to

deamplify. With increasing effort to characterize these coastal plains through projects such as the Next Generation Attenuation Relationships for Central and Eastern North America (NGA East, Goutlet et al. 2021), there has been a demand to develop a more targeted model for these regions specifically as previous models have failed to capture the behavior of these regions appropriately.

Generic V_s profiles for coastal plains were developed using the main components that control site amplification effects. Figure 2-22 shows median V_s profiles developed with 4 main elements. The shallower portion of the profile (to a depth of approximately 200m) was developed based on physical measurements of V_s . The second portion of the profile is developed based on layering ratios that represent multipliers that systematically increase the potential thickness of a layer based on the potential thickness of the overlying layer (Cox and Teague 2016). The next region of the profile is developed based on a power law model fit to the data that was only used to extrapolate data beyond where measurements were taken. The lowest portion of the profile is the impedance contrast at depth where high velocity bedrock is met. The authors estimated this value based on literature review of contemporary studies.

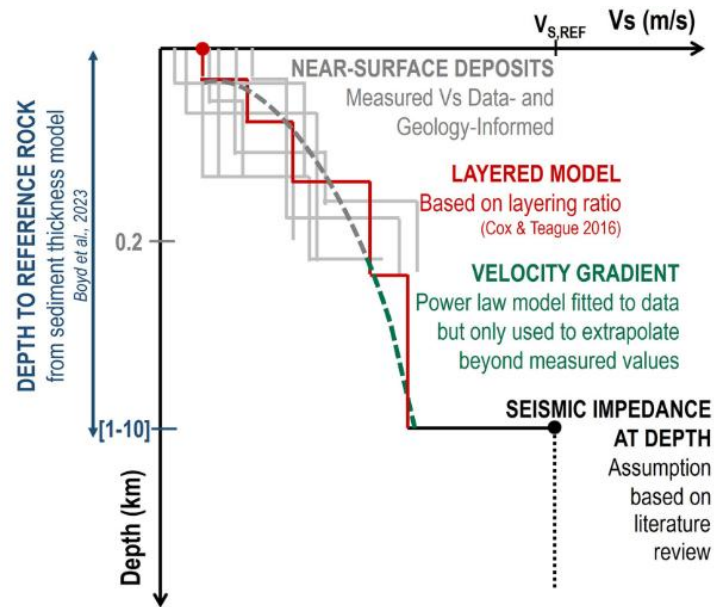


Figure 2-22: Schematic of median V_s profiles developed for Gann-Phillips et al. 2024

Measured V_s profiles are collected from multiple data sources were evaluated using a quality control process outlined by the authors. The author's quality control process is as follows:

- Significant differences compared with nearby profiles are removed
- Located within 5km of a boundary between two geologic units is re-categorized
- Located outside of the geologic grid on the coastline is re-categorized to the nearest geologic unit
- Presence of V_s reversals or values higher than the median V_s for very shallow layers are removed
- Presence of geographically clustered data are re-categorized (i.e. around Memphis, TN and Charleston, SC)

Median profiles of V_s were developed for each of the geologic time periods to depths of 100m and 16km. Figure 2-23 presents V_s profiles to a depth of 100m. From the data it was determined that for the Quaternary Pleistocene (QP) and Cretaceous (K) groups, modifications were required. For the Quaternary Pleistocene, it was observed that values of V_s at depths

ranging from 10 to 50m were lower than those from the Quaternary Holocene group, which was unexpected as younger sediments tend to have lower V_s . The adjusted group was designated as QP adjusted. For the Cretaceous group (K) it was found that velocities at depths greater than those considered for this study were lower than those from the Tertiary group, so a K adjusted group was also presented. For depths of 100m there is no appreciable difference between the standard and adjusted Cretaceous groups. Table 2-10 presents median V_{s30} values along with other design code parameters following the model. Other parameters presented are depth to a V_s value of 1000m/s ($Z_{1.0}$), depth to a V_s value of 760 m/s ($Z_{0.76}$).

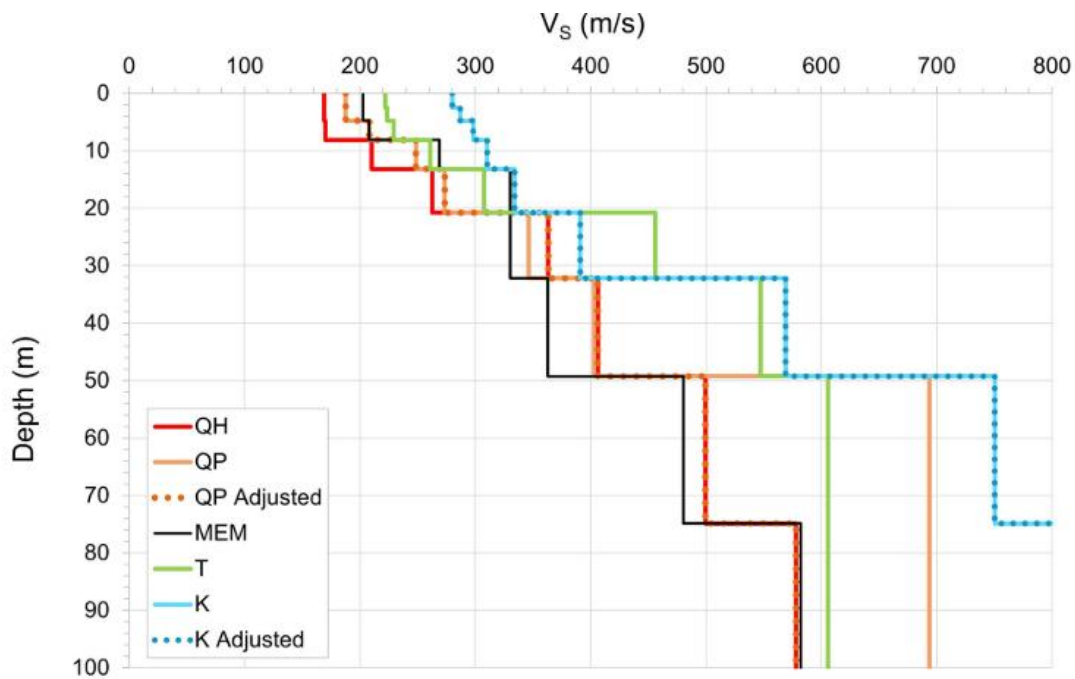


Figure 2-23: Near surface median V_s profiles for Quaternary Holocene (QH), Quaternary Pleistocene (QP), Quaternary Pleistocene adjusted (QP Adjusted), Memphis (MEM), Tertiary (T), Cretaceous (K), and Cretaceous Adjusted (K Adjusted) groups (Gann-Phillips et al. 2024)

Table 2-10: Values of V_{s30} , $Z_{1.0}$, $Z_{0.76}$, and $Z_{3.0}$ from the model database presented in Gann-Phillips et al. 2024 along with median values presented in Ahdi 2018 for comparison

Geologic Group	Median Model V_{s30}	$Z_{1.0}$ (m)	$Z_{0.76}$ (m)	$Z_{3.0}$ (km)	Median V_{s30} (m/s)	Median $V_{s30} \pm 1\sigma$ (m/s)
QH	237	874	582	15.31	202	155-263
QP	261	387	257	14.89	201	147-276
MEM	274	874	387	1.246	266	218-324
T	299	257	171	14.13	297	217-406
K	331	113	74.9	2.646	342	260-451

2.3 Summary

This chapter presented a review of existing methods for determining shear wave velocity profiles. Methods are classified as either direct or indirect. Direct measurements involve taking a direct physical measurement of V_s . These methods are more accurate and subject to less uncertainty but may not be the most cost-effective for every project. Indirect methods provide an estimate based on results of another test. Indirect methods considered in this study rely on correlation to the results of common in-situ tests, ambient noise recordings at sites, or to geospatial features of the site. The presented methods have all demonstrated their accuracy for the regions where they were developed but need to be evaluated for use in Alabama.

Chapter 3: Methodology

3.1 Introduction

The methodology used to measure and estimate V_s for this study is described within this chapter. Methods described in this chapter are non-invasive and either classified as direct or indirect. Sites for this study were selected in collaboration with the Alabama Department of Transportation (ALDOT). Sites of field surveys were the locations of bridges or other infrastructure that also have available SPT borings.

Direct methods used for this study were MASW and seismic refraction. Selection of direct measurements was based on a few factors, namely depth to rock and anthropogenic noise present at each of the sites. Shallower rock sites will tend to have interference due to higher modes increasing the difficulty of selecting the fundamental mode for MASW surveys. Anthropogenic noise, namely traffic noise, will increase the difficulty in selecting first arrivals in refraction surveys.

Indirect methods were applied to all sites visited in this study along with geospatial methods being applied to sites presented in Carcamo (2022). Indirect methods include SPT and RQD based correlations, hereafter referred to as boring based methods, geospatial methods, and HVSr methods.

3.2 Direct Methods

For MASW and refraction surveys, the survey equipment was nearly identical. The source of waves used for both survey techniques was an instrumented sledgehammer striking an aluminum plate on the ground surface. Care was taken that the aluminum plate was coupled with the ground so that the plate would not jump as it was struck by the hammer. Careful effort was taken so that the hammer would strike the plate at roughly the center and was lifted off of the plate after impact to not create any ringing effects. Either large (20 lb) or small (12 lb) sledgehammers were used as a wave source. The smaller hammer was primarily used in MASW surveys while refraction surveys utilized both sledgehammers. 4.5 Hz geophones were used for MASW surveys, and 14 Hz geophones were used for refraction surveys, and a select number of MASW surveys conducted at the same sites as some refraction surveys where the bedrock was

not determined to be too shallow prior to testing. All geophones were recorded using a Geometrics Geode seismograph. The Geometrics Geode controller allows individual preamp gains to be set for each of the geophones. By default, geophones were set to a high gain preamp, but geophones within approximately 6 meters (23 ft) of the shot location were set to a low gain preamp. This was based off field observations of performance of geophones close to the source. Geophones within 2 m (6.6 ft) of the shot location became overloaded regardless of preamp gain, so these were not considered for analysis for either MASW or refraction surveys.

3.2.1 MASW Data Processing

MASW survey data were processed using Geopsy, an open-source software for geophysical applications (Wathelet et al. 2020a). The “Active F-K” tool was used to process the data. The tool utilizes a 2D transform to convert the data to the frequency domain and to obtain the phase velocity dispersion curve for the file (Wathelet 2008). Each file was imported into the software and the transformation was performed. For files that a quality dispersion curve was generated, the generated curve was then saved. The saved curves were then averaged to create a representative dispersion curve for the site. The average curve was resampled to improve the smoothness of the curve.

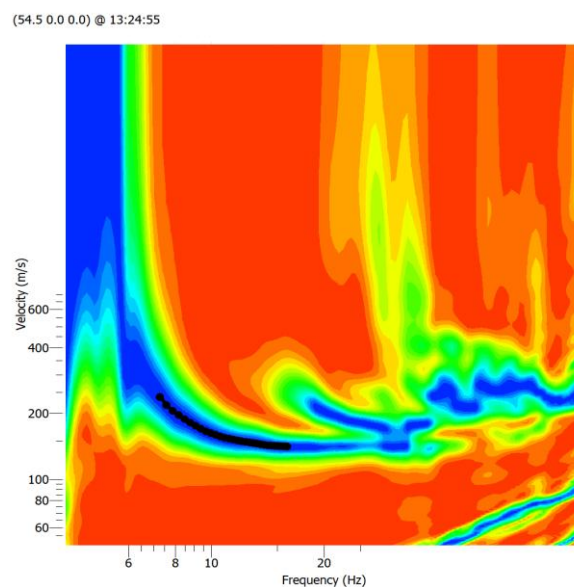


Figure 3-1: Example dispersion curve as displayed in Geopsy software package

The DINVER package within Geopsy was then used to invert the average dispersion curve to provide a one-dimensional profile of V_s at the center of the geophone array. DINVER solves the inversion problem by randomly generating V_s profiles based on inputs provided by the user. Inputs provided are P-wave velocity, S-wave velocity, Poisson's ratio, density, and layering. Parameters can be set as a static value or a range of values for the provided layers and are able to be linked to one another or be considered independent. Following the solution of the inversion by the software, dispersion curves are generated by DINVER and compared to the provided dispersion curve and values of misfit are calculated. The solution generated is not unique, so the software provides output of the different profiles along with their misfit value where misfit is defined as the weighted root mean square standard deviation (Wathelet et al. 2004, Wathelet 2005, Wathelet 2020a)

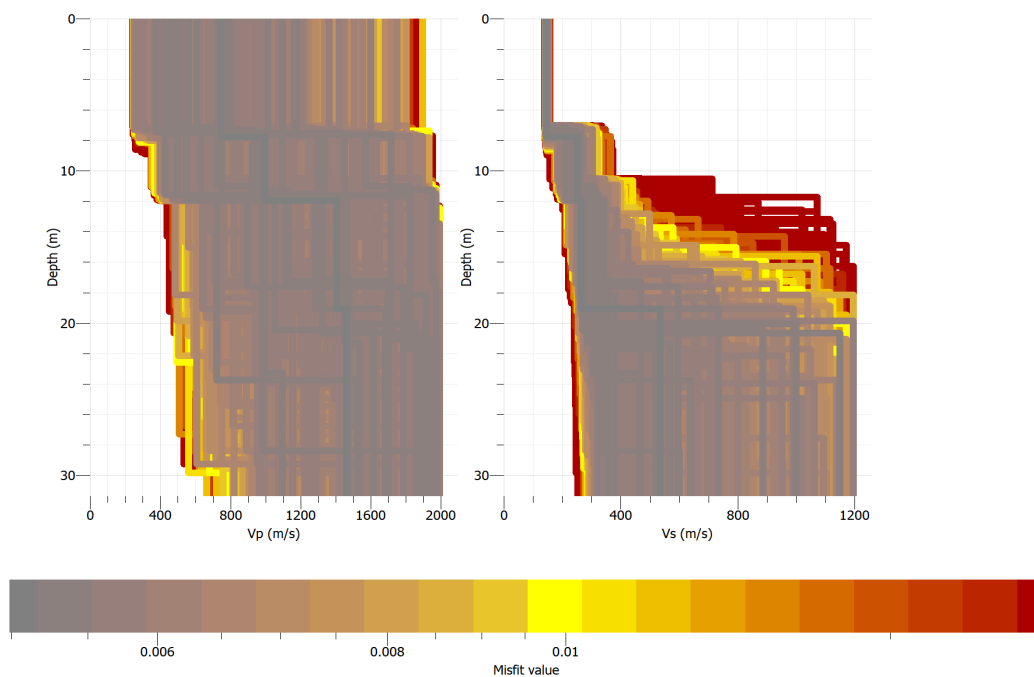


Figure 3-2: Example output ground profiles from inversion analysis in DINVER software package

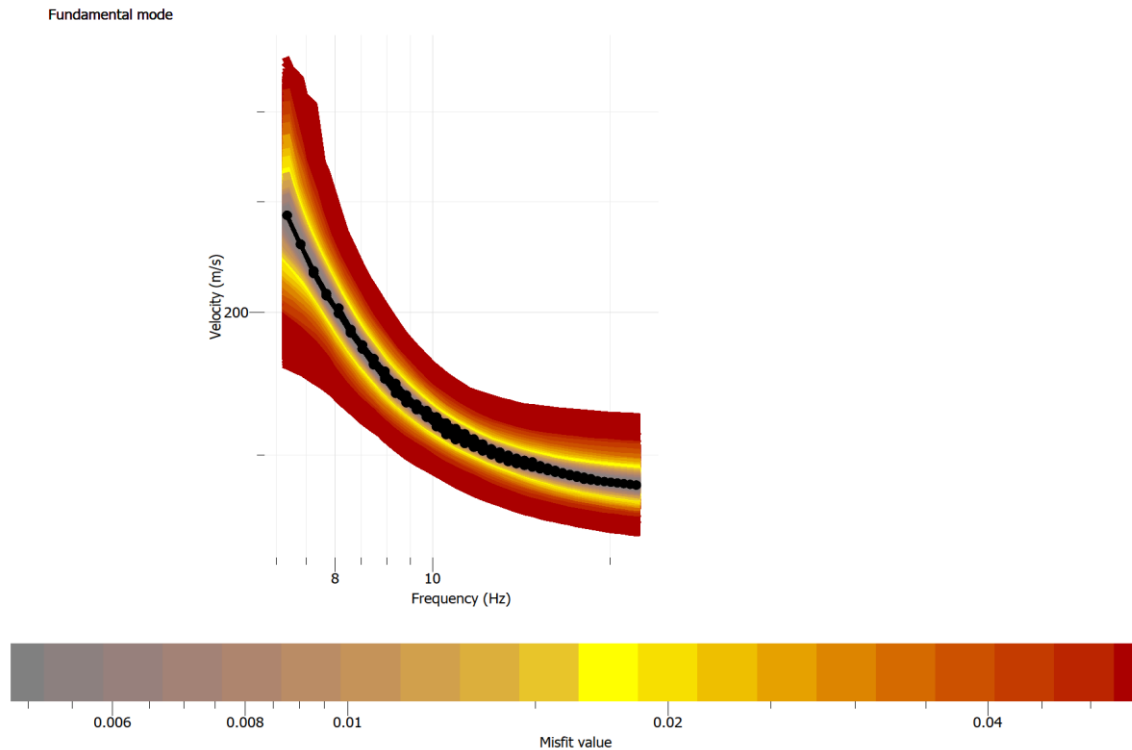


Figure 3-3: Comparison of measured dispersion curve to modeled dispersion curves

In order to provide some measure of uncertainty in MASW inversion, the 1000 best profiles as determined by misfit are plotted alongside the minimum misfit profile. The best 1000 profiles are plotted in the form of a range of the minimum and maximum V_s from the best 1000 profiles at each depth.

Additionally, an exponential distribution was used on the full suite of provisional models to provide a probabilistic distribution for values of V_{s30} . The exponential model ensures that models with a lower value of misfit are exponentially more probable within a Bayesian inversion framework (Wathlet et al. 2004). A user interface tool was developed and is used to provide a probabilistic distribution of V_{s30} values along with site classification. The most likely V_{s30} value determined by the probabilistic distribution was used when evaluating HVSR and geospatial based estimation methods.

3.2.2 Refraction Data Processing

Refraction data were processed using the SeisImager software package provided by Geometrics (Geometrics 2009). Typically, at least 5 shots were taken at each location and stacked to provide enough data to minimize the effect of noise on interpretation of results. The software displays the file as a series of traces from each individual geophone. Each trace is by default normalized to their maximum amplitudes to prevent visual interference from one trace onto the next. First arrivals of the P-wave can then be selected from the software and can then be saved as a pick file, and an example can be seen in Figure 3-4 where the pink line represents the first arrival of the P-wave. Some files and shot locations contain too much noise to confidently determine first arrivals, so those were not considered in analysis.

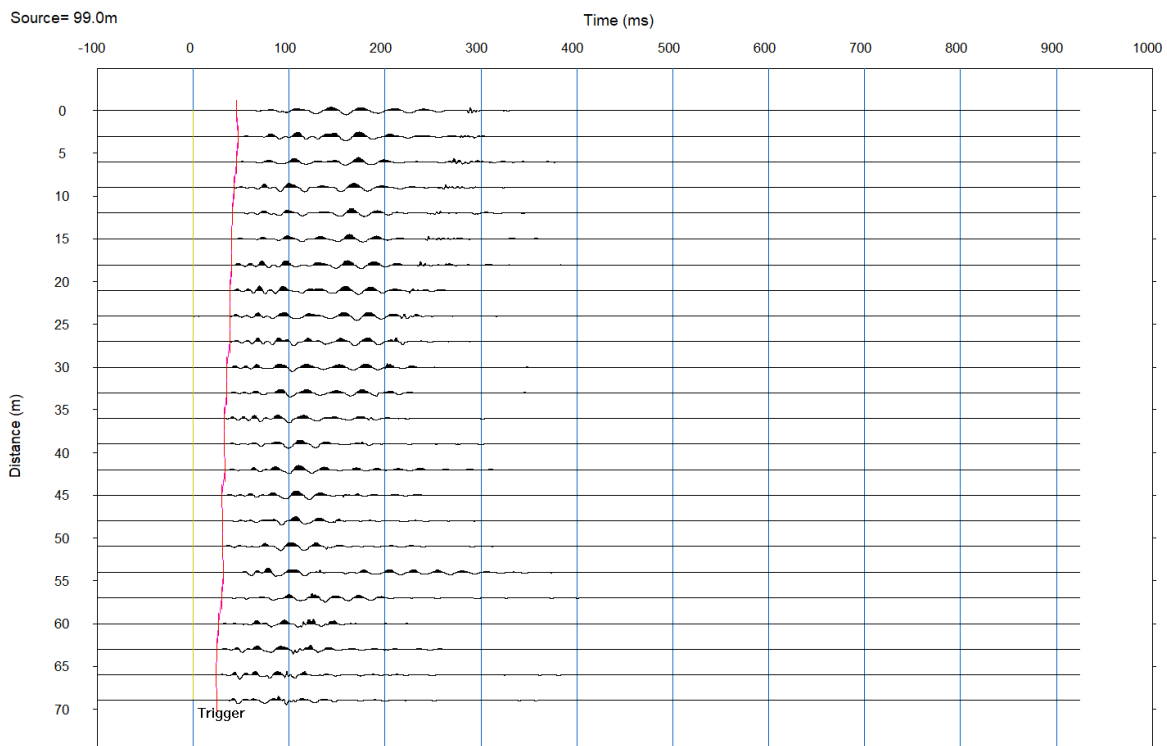


Figure 3-4: Refraction signal file as displayed in Pickwin with first arrivals of P-wave selected in pink

Following the selection of first arrivals, pick files were imported into the Plotrefra software package also provided by Geometrics (Geometrics 2009). Inversions are performed using the time-term method. Layering can be assigned based on observation of the picked first arrivals where changes in slope are indicative of additional layers (Figure 3-5). Once the layering is assigned then the inversion can be performed. An inverted ground profile provides a two-dimensional cross section of V_P below the geophone array. V_P can then be converted to V_S using Poisson's ratio (ν) of the material. Poisson's ratio can vary for different rock and soil types and ranges from 0.05 for very hard rocks to 0.45 for loose unconsolidated sediments but an average value of 0.25 was assumed. The ratio of V_P to V_S can be calculated using Poisson's ratio as shown in (16).

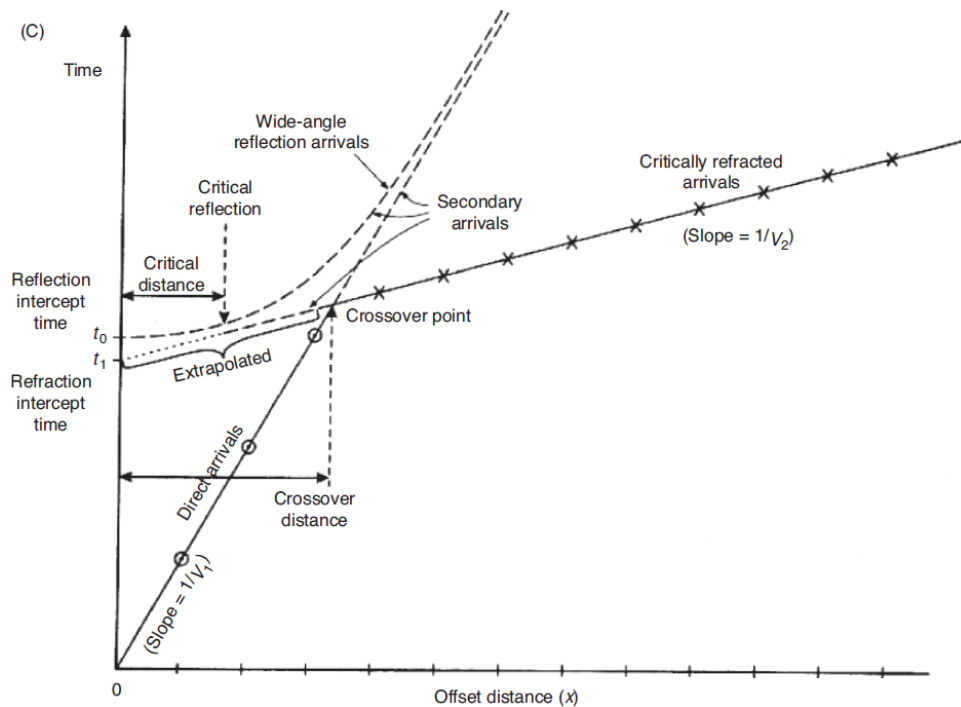


Figure 3-5: Travel time curve of a two layered model (Adapted from Reynolds 2011)

$$\frac{V_P}{V_S} = \frac{(1 - \nu)^{1/2}}{(1/2 - \nu)} \quad (16)$$

V_P can also be converted to V_S using known ratios for different soil and rock types. For unconsolidated sediments, that ratio lies somewhere within the range of 2.0 to 4.0 (Herath et

al. 2020). Careful consideration needs to be given to soil and rock that are beneath the groundwater table. Since the method of seismic refraction survey in this study is a measure of compressional wave velocities, saturated soils will have a V_P that is very close to water (1500 m/s). V_S is not affected in nearly the same capacity as V_P under saturated conditions as shear waves cannot propagate through a fluid (Stümpel et al. 1984). Due to this, V_P/V_S ratios for saturated soils need to be increased to a range of 5.0 to 7.0 to account for saturated effects (Stümpel et al. 1984, Grelle and Guadagno 2009).

3.2.3 SPT Boring Logs

At each of the sites selected for analysis in this study, at least one SPT boring was performed. Boring logs were provided by the Alabama Department of Transportation as well as other agencies. Boring logs are used to create representative ground profiles for the location of each geophysical survey. Ground profiles consist of representative layers of soil based on data provided by boring logs. Representative layers are determined empirically by soil type and SPT blowcounts and rely on experience of the researchers. SPT blowcounts of the layers determined by the researchers are averaged and are assigned a depth of the center of the layer. Plots of the ground profile along with the uncorrected blowcounts (N_{SPT}) and the blowcounts corrected to 60% hammer efficiency (N_{60}) are then created for each of the sites. An example ground profile is provided in Figure 3-6.

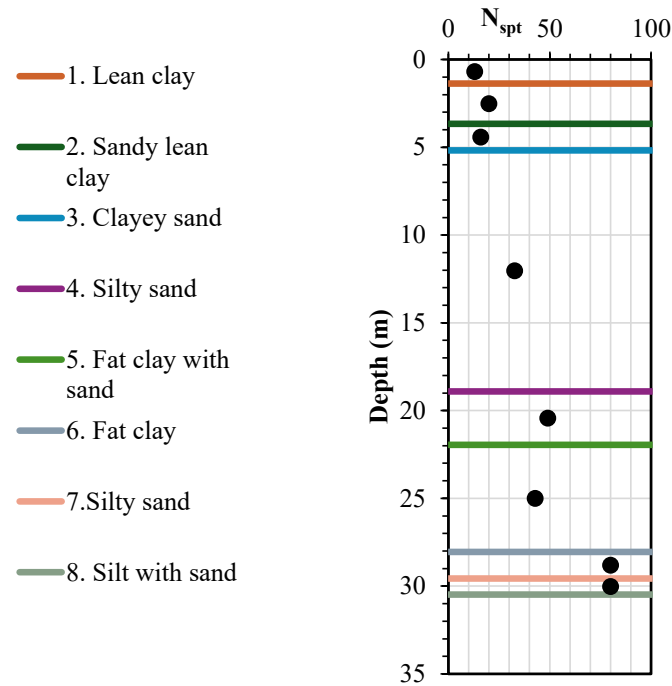


Figure 3-6: Example ground profile derived from SPT boring logs

3.3 Indirect Methods

Indirect methods considered in this study are correlations from soil borings, HVSR, and geospatial based methods. The soil borings section describes the correlations used for estimating V_s along with the methodology required in their application. The HVSR section describes data collection along with processing. Appropriate correlations are also discussed in this section. The geospatial based methods section describes application of the presented methods to sites visited as a part of this study along with sites previously presented in Carcamo (2022).

3.3.1 Boring Based Correlations to V_s

Soil boring based correlations were used at all sites visited as a part of this study. For applying boring based correlations, a spreadsheet tool was developed. For sites located within the West Alabama group of sites, only SPT based correlations were applied due to rock not being encountered in any of the boreholes. At sites in the Northwest Alabama group of sites

both SPT and RQD based correlations were applied as rock was encountered at all sites with the exception of the Russellville High School site.

For SPT based correlations, blowcounts were capped at a value of 100 to remain consistent with guidelines presented in Wair et al. (2012). For blowcounts where sampler refusal was met (i.e., 50/3" or similar) a blowcount of 100 was assigned. The estimated result from these values will be used in calculating V_{s30} but will not be used for evaluation of the correlations since an exact value for the blowcount is not known. It should be noted that the correlations presented in Seed et al. (1983), Jinan (1987), Lee (1992), Hasancebi and Ulusay (2007), and Fatehnia et al. (2015) are extrapolating for SPT blowcounts of greater than approximately 50 as this is near the maximum value of blowcounts used in the development of these correlations. All other presented correlations were developed with SPT blowcounts greater than 50, so correlations will not be extrapolating when applied to higher blowcounts from this study.

3.3.2 HVSR Based Estimation Methods

Alongside direct measurements HVSR surveys were conducted at each of the sites. The following sections will describe the recording devices used, data collection and processing, and application of HVSR based estimation methods.

3.3.2.1 Recording Devices

Single station triaxial geophones were used to record the horizontal (North and East) and vertical (Z) components of the passive signals. Three recorders were acquired for this project from two brands as described hereafter.

GEObit - GEOTinyMK3 Digital Seismometer

Two GEObit GEOTinyMK3 compact digital seismometers (Figure 3-7) were procured to record ambient vibration data during field measurements. The instrument integrates a three-component seismic sensor, digitizer, and recorder within a single enclosure and utilizes a high-resolution 24-bit analog-to-digital converter with configurable sampling rates ranging from 1 to 1000 samples per second. The system includes an internal GPS receiver that synchronizes

measurements to Coordinated Universal Time (UTC), ensuring accurate timing and consistency across sites. The Geobit instrument provides a broadband operational bandwidth of approximately 10 s to 98 Hz, enabling reliable recording of low-frequency ambient vibrations relevant to site response characterization. The instrument is 130 mm (5.1 in) in diameter and 115 mm (4.5 in) in height with a weight of 2.6 kg (5.7 lb). The unit operates on a 9-18 VDC power supply with low power consumption and is designed for continuous operation in harsh field environments (GEObit Instruments 2023). The measurement is configured through the instrument's network interface over an ethernet connection. During measurement, the recorded data are stored locally on a removable SD card within the device but typically retrieved over the ethernet interface. The interface was connected over a manually configured network settings using a static IPv4 address (192.168.1.2) with subnet mask (255.255.255.0) and gateway (192.168.1.1).



Figure 3-7. GEOtinyMK3 low power compact digital seismometer (GEObit Instruments 2023)

PASI - GEMINI-2 HVSr Data Acquisition System

One PASI GEMINI-2 HVSr data acquisition unit was also acquired. The instrument is a portable triaxial geophone system specifically designed for HVSr testing. The instrument consists of three orthogonally oriented geophones housed within a waterproof container and

coupled to a dedicated 24-bit digital acquisition system connected to a field computer via USB interface. The triaxial sensor has a natural frequency of approximately 2 Hz ($\pm 10\%$), which is well suited for detecting the low-frequency ground motions associated with soil resonance and site fundamental frequency estimation. The system allows user-defined acquisition parameters such as sampling interval, recording duration, trigger conditions, and signal stacking, enabling flexible data collection under varying field conditions. The instrument has compact dimensions of approximately 128 mm (5 in) in diameter and 80 mm (3.1 in) in height and a weight of about 2.10 kg (4.6 lb), facilitating rapid deployment and stable placement during field measurements (PASI 2013).



Figure 3-8. PASI Gemini-2 HVSR data acquisition unit (PASI 2013)

3.3.2.2 Data Collection

The reliability of the HVSR depends on consistent measurement procedures, appropriate data processing, and careful interpretation of the results. Established guidelines emphasize the importance of standardized acquisition and quality control procedures to ensure that HVSR measurements produce statistically meaningful estimates of site frequency (SESAME 2004). The duration of the signal recordings is typically controlled by the minimum expected frequency peak of the site, and the recommended values are presented in Table 3-1.

Table 3-1. Recommended minimum recording duration according to expected frequency peak (SESAME 2004)

Minimum Expected f_0 (Hz)	Recommended minimum recording duration (minutes)
0.2	30
0.5	20
1	10
2	5
5	3
10	2

Generally, artifacts with high stiffness are avoided, hence the recordings were located as far from buildings, trees, and utilities as possible. At all the sites in this study, a consistent setup was used to ensure that the devices were isolated and well coupled into the testing site. This was achieved by burying the sensor over half the sensor height with granular material (usually sand) and covering the buried device with a plastic bucket (Figure 3-9) as specified by Foti et al. (2018). Figure 3-10 shows images of field deployment of each instrument used in this study as well as the connection type.

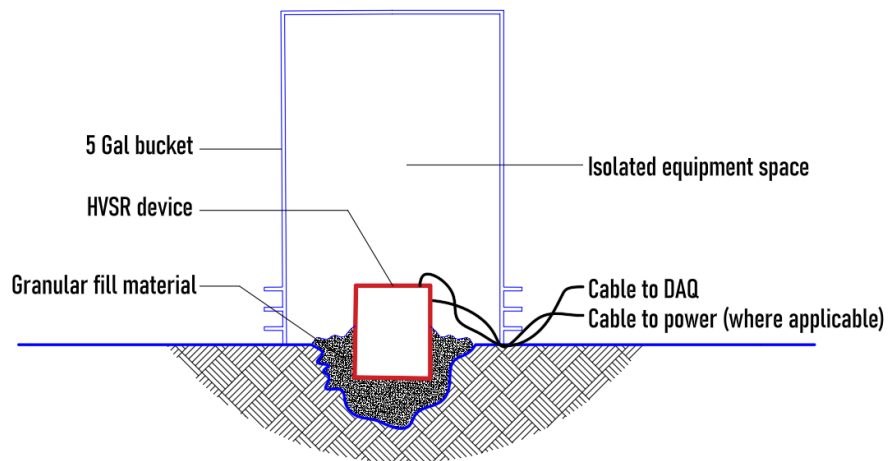


Figure 3-9. Equipment setup used at various sites for HVSR signal collection (Foti et al. 2018)

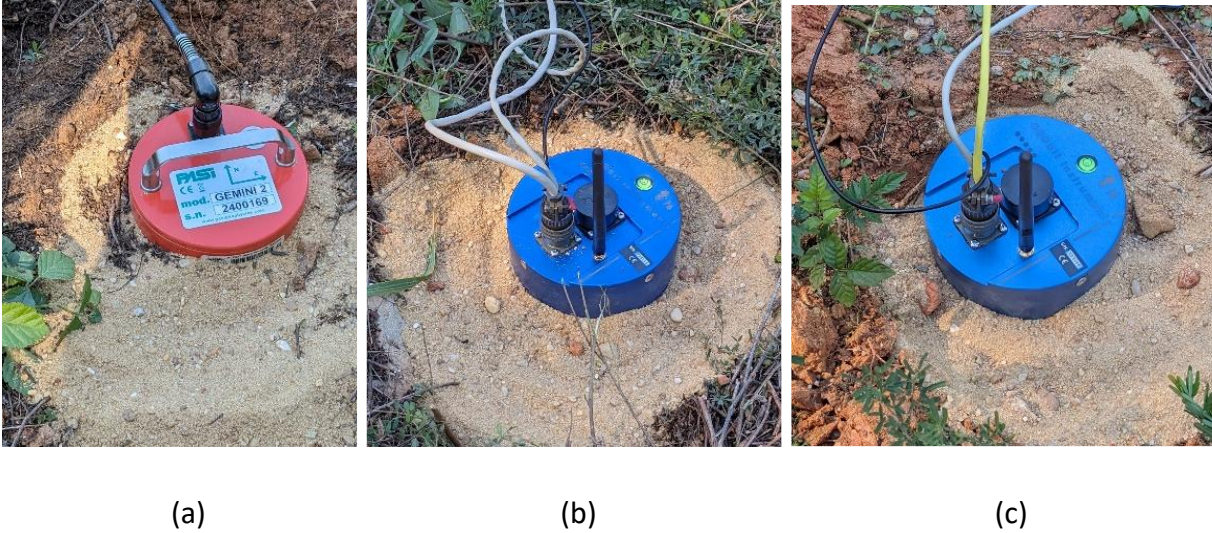


Figure 3-10. Field deployment of (a) PASI Gemini (USB connection to PC), (b) Geotiny_21 (<https://192.168.1.21:9091>), and (c) Geotiny_30 (<https://192.168.1.30:9091>)

3.3.2.3 Data Processing

The open-source tool *HVSRpy* by Vantassel (2025) was used to analyze the collected data. The recorded time histories were first screened to remove transient noise and align the three components. The signals were then divided into stationary time windows of equal duration for frequency-domain processing. For each window, Fourier amplitude spectra of the horizontal and vertical components were computed, smoothed using the linear-rectangular function, and combined to generate individual HVSR curves, from which a representative mean curve and associated statistical parameters were determined. The reliability and clarity of the HVSR peak were evaluated in accordance with the SESAME guidelines (SESAME 2004).

Reliability checks assess the stability and repeatability of the HVSR curve while clarity checks evaluate the definition of the spectral peak and consider factors such as peak amplitude, frequency stability, and the absence of competing peaks within adjacent frequency bands to ensure that the identified resonance frequency represents a distinct and physically meaningful site response. The criteria for the checks are presented in SESAME (2004).

3.3.3 Geospatial Methods

For this study the geospatial methods presented in Wald and Allen (2007), Yong et al. (2012), Parker et al. (2017), Geyin and Maurer (2023), and the Gann-Phillips et al. (2024) were

used. The method presented in Kottke et al. (2012) was not able to be applied as Alabama is classified within the residual sediment units as seen in Figure 2-20.

The method presented in Wald and Allen (2007) was applied using a GIS-based map publicly available from the USGS website (<https://earthquake.usgs.gov/data/vs30/>). The map is imported into ArcGIS then coordinates of sites are input. An estimated value of V_{S30} using the model is then able to be extracted from the map layer.

For application of the method presented in Yong et al. (2012) a GIS based map of the terrain classification presented in Iwashita and Pike (2007) is used. Coordinates of sites are input into ArcGIS and a geologic class is then able to be assigned. Once the terrain classifications are assigned an estimated value of V_{S30} is then able to be provided following the model. (Figure 2-19).

For the method presented in Parker et al. (2017), sites are to be classified based on their geologic age. Geologic age is able to be determined using geologic maps of the state (Osborne et al. 1989). For sites in the Cenozoic era, the geologic period and epoch also need to be determined so that a group can be assigned. The authors propose 18 geologic groups based on the geology age and proximity to the Wisconsin Glaciation. (Table 2-8). Once each site is classified estimates of V_{S30} can be assigned.

For the method presented in Geyin and Maurer (2023), the authors provide their proposed models in the form of geotiff files that are able to be imported into ArcGIS. As with the other geospatial methods, coordinates of sites are to be input into ArcGIS. Using the provided model, an estimated value of V_{S30} is then able to be extracted from the model layer.

For the method presented in Gann-Philips et al. (2024), a geologic map of Alabama is used to determine the proximity of the site to the Coastal Plains Province. For sites located outside of the Coastal Plains Province, the model is not applicable and an estimate of V_{S30} will not be provided. For sites located within the Coastal Plains Province, the geologic map is used to determine the geologic age of formation. Using the geologic age, an estimated value of V_{S30} is then able to be provided from the model. (Table 2-10).

3.3.4 Statistical Measures for Evaluation of Estimation Methods

In order to evaluate the presented estimation methods and to determine the most effective methods for estimating V_s within the state, statistical measures are needed to allow for comparisons between the methods. Statistical measures used for this study aim to determine the fit of estimated to measured data and to determine inequality between the two groups of data. LaMondia et al. (2012) presents a number of statistical measures that are to be used for this study. The following sections will present the two categories of statistical measures used.

3.3.4.1 Prediction Evaluation Statistics

Prediction evaluation statistics provide a measure for fit of estimated data to measured data. Measures selected for this study are mean squared error, percent root mean square error, Theil's Inequality, and mean absolute deviation.

Mean Squared Error

Mean squared error measures the average squared difference between measured and estimated values. Values of mean squared error are always positive and error decreases as values approach zero. Since errors are squared the metric heavily penalizes large variances between measured and estimated data. To allow for more equal weight in error at low and high velocities mean squared error is calculated in natural log units.

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (17)$$

Theil's Inequality

Theil's Inequality uses information entropy to describe the association between pairs of measured and estimated data. Values of Theil's Inequality range between zero and one with lower values reflecting a greater degree of association or low entropy between measured and estimated data.

$$U = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} / \left\{ \sqrt{\frac{1}{n} \sum_{i=1}^n y_i^2} + \sqrt{\frac{1}{n} \sum_{i=1}^n \hat{y}_i^2} \right\} \quad (18)$$

Mean Absolute Deviation

Mean absolute deviation indicates the absolute magnitude of variability between measured and estimated data. Values of mean absolute deviation range between zero and one with lower values indicating a better fit.

$$MAD = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (19)$$

3.3.4.2 Inequality Statistics

For this study the Gini Index is used. The Gini Index is a measure of inequality with values ranging from zero to one with a value of zero indicting total equity or equality between measured and estimated data and a value of one indicating worst inequality.

$$G = \frac{1}{2n^2 \bar{y}} \sum_{i=1}^n \sum_{j=1}^n |y_i - \hat{y}_j| \quad (20)$$

3.4 Summary of Methodology

To allow for evaluation of the presented indirect methods, direct measures needed to be taken. Direct measures used were either MASW or refraction surveys and followed a common methodology. Equipment was nearly identical for both types of surveys with the only variation between the two being the fundamental frequency of geophones used. MASW data were processed using the Geopsy software package, and a range of inverted ground profiles were considered to provide an estimate of uncertainty present in inversion. Additionally, a probabilistic distribution that heavily weights the likelihood of occurrence of profiles with lower misfit values was used to give the most likely value of V_{S30} from each survey. Refraction data were processed using the SeisImager software package. Multiple files were stacked to increase

the signal to noise ratio to better allow for first arrivals of compressional waves to be picked. Inversion yielded two-dimensional models of compressional wave velocity that were able to be converted to shear wave velocity using known ratios.

Boring based correlations were applied using a spreadsheet tool. Blowcounts were capped at a value of 100, and these capped values were only used in calculating V_{s30} . Geospatial correlations were applied through the use of GIS based maps either provided by the authors or from other publicly available sources.

HVSR data were collected using three triaxial geophones. Recording length for HVSR surveys were determined based on the expected fundamental frequency at each site. Sensors were placed as far away from stiff artifacts and buried to half the height of the sensor in a granular material to minimize noise and to ensure proper coupling of the sensor. Recordings were aligned, divided into equal length windows, and processed in the frequency domain to provide mean HVSR curves. Curves were checked for reliability and clarity using standards set forth in SESAME (2004). HVSR correlations were either applied using a spreadsheet tool or using a python based tool for the application of models presented in Sharma Wagle et al. (2026).

Chapter 4: Results of Direct Methods

4.1 Introduction

In order to test the correlations discussed in Chapter 2:, field surveys for direct measurement of V_s were conducted. Sites of field surveys are the locations of bridges or other infrastructure that had corresponding SPT borings. For sites at the location of a bridge, SPT borings are typically drilled to a depth of approximately 100 ft (33 m), which provides enough data to correlate SPT blowcounts to a full depth of 30 m to allow for calculation of V_{s30} without the need to extrapolate data. Borings conducted at the sites of other infrastructure projects do not typically extend to the same depths as bridge borings so extrapolation of deeper layers may be required for comparison of measured V_s to correlated V_s . All sites were in the western and northwestern corridors of the state, which have a higher degree of seismic activity than the rest of the state. V_s was measured using either MASW or seismic refraction. Table 4-1 summarizes the sites selected for direct measurements while Figure 4-1 displays the sites on a map of Alabama.

Table 4-1: Locations selected for direct measurements

Survey Location	Approximate Coordinates	Boring Number	Survey Performed
Cedar Bluff	34.27731, -85.67470	BR-0273 B-04	MASW
Beaver Creek survey line 1	32.13762, -87.78266	4-BR1762L	MASW
Beaver Creek survey line 1	32.13794, -87.78266	4-BR1767L	MASW
Big Prairie Creek	32.54165, -87.68057	8-BR3385R-2	MASW
Coldwell Creek	32.72850, -87.60641	10-BR4135	MASW
Moundville survey line 1	32.84110, -87.61017	11-4588L	MASW
Moundville survey line 2	32.841935, -87.61040	11-4590L	MASW
Greensboro	32.76450, -87.58517	11-BR4292L	MASW
Duck River	34.09289, -86.72132	BR-0091 B-06	Refraction
RHS survey line 1	34.52492, -87.73752	B-03	MASW
RHS survey line 2	34.52517, -87.73774	BRF-0002(545) B-08	MASW
Lauderdale County survey line 1	34.95055, -87.69541	BR-3914 B2	Refraction
Lauderdale County survey line 2	34.95057, -87.69579	BR-3914 B6	MASW
Bluewater Creek	34.85717, -87.41544	B8	MASW
Blount County	33.93987, -86.39477	BR-0053(559)	Refraction

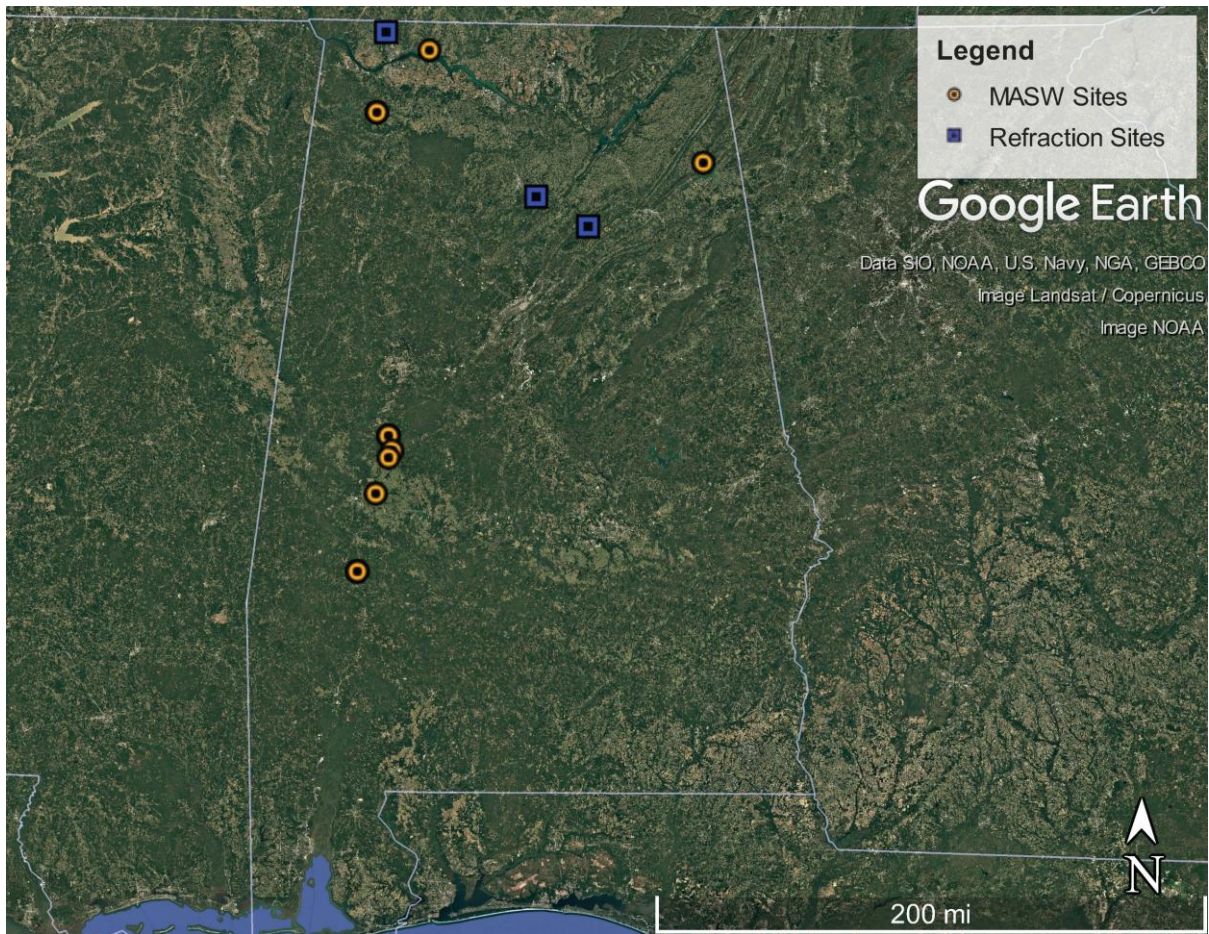


Figure 4-1: Map of sites visited as a part of this study (Photo taken from Google Earth)

4.2 Cedar Bluff, AL Site

Location and Geology

The site is located along Alabama state highway 273 outside of Cedar Bluff, AL (34.27731, -85.67470). The geophysical survey was conducted on January 25, 2025 using an active MASW survey. Terrain was relatively flat and free of vegetation along the survey line. The MASW survey line can be seen in Figure 4-2.

The site is underlain by the Red Mountain formation which is characterized by interbedded yellowish-gray to moderate-red sandstone, siltstone and shale; greenish gray to moderate red fossiliferous partly silty and sandy limestone with few thin hematitic beds (Osborne et al. 1989). From boring logs, soils expected to be encountered at the site are silts and clays underlying a layer of fill material at the ground surface. Rock is expected to be encountered at a depth of approximately 15 m (49 ft).



Figure 4-2: Cedar Bluff MASW survey line

Data Collection

An active MASW survey was conducted at the site. The survey used 24 4.5 Hz natural frequency geophones spaced at 3 meters for a total spread length of 69 meters. Active data were recorded at a sampling frequency of 2000 Hz with a recording length of 1.5 seconds, an offset of 0 seconds, and a delay of -0.1 seconds. No acquisition filters were used. Energy sources for the active survey were placed at multiple locations along the spread, with off-end, end on, and split-spread shots being used.

MASW Results

An example dispersion curve as measured from the site along with the 10 best inverted ground profiles are shown in Figure 4-3. Results indicate that a softer layer extends to a depth of 7.17 meters with a V_s of approximately 277 m/s (909 ft/s) that is underlain by a stiffer layer that extends to a depth of approximately 7.61m (25 ft) with a V_s of 923 m/s (3027 ft/s). This is all underlain by the rock layer, where a greater degree of uncertainty is present as compared to the layers above with a V_s of 4054 m/s (13297 ft/s). This minimum misfit V_s profile provides the site with a V_{s30} of 940 m/s (3083 ft/s) which places the site into the lower end of class B. When considering the exponential distribution from the full ensemble of inverted profiles, the median V_{s30} value is 854 m/s (2801 ft/s) which places the site into class B/C.

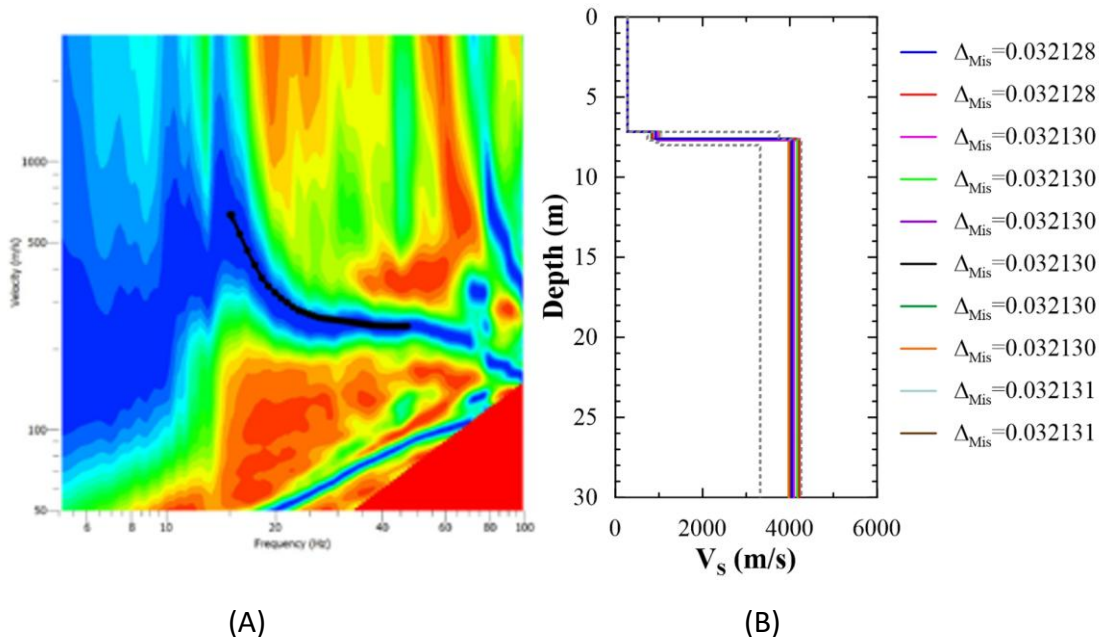


Figure 4-3: Results of Cedar Bluff MASW survey showing (A) dispersion curve and (B) 10 best inverted ground profiles along with the range of V_s values taken from the best 1000 profiles

4.3 West Alabama Surveys

The first aggregated group of sites is referred to as the West Alabama group. All sites are in the western corridor of the state and are tied to projects within the greater west Alabama highway improvement project undertaken by the Alabama Department of Transportation (ALDOT). Each site in the West Alabama group is the site of a bridge or overpass where recent

SPT borings have been performed as a part of bridge replacement project. Each SPT boring is drilled to a minimum of 98 ft (30 m) per ALDOT's requirements for SPT borings for bridge projects. All surveys performed in this group of sites were MASW surveys. Along with active MASW surveys, each survey line also has at least one corresponding passive HVSr survey. Results of HVSr surveys will be presented in Chapter 5 of this work.

4.3.1 Beaver Creek Site

Location and Geology

The Beaver Creek site is located along Highway 43 in Marengo County Alabama (32.13762, -87.78266). Geophysical surveys were performed on February 20, 2025. Terrain is mostly flat at the site with minimal vegetation at the locations of seismic surveys. Two geophysical surveys were conducted at this site as documented in Figure 4-4.

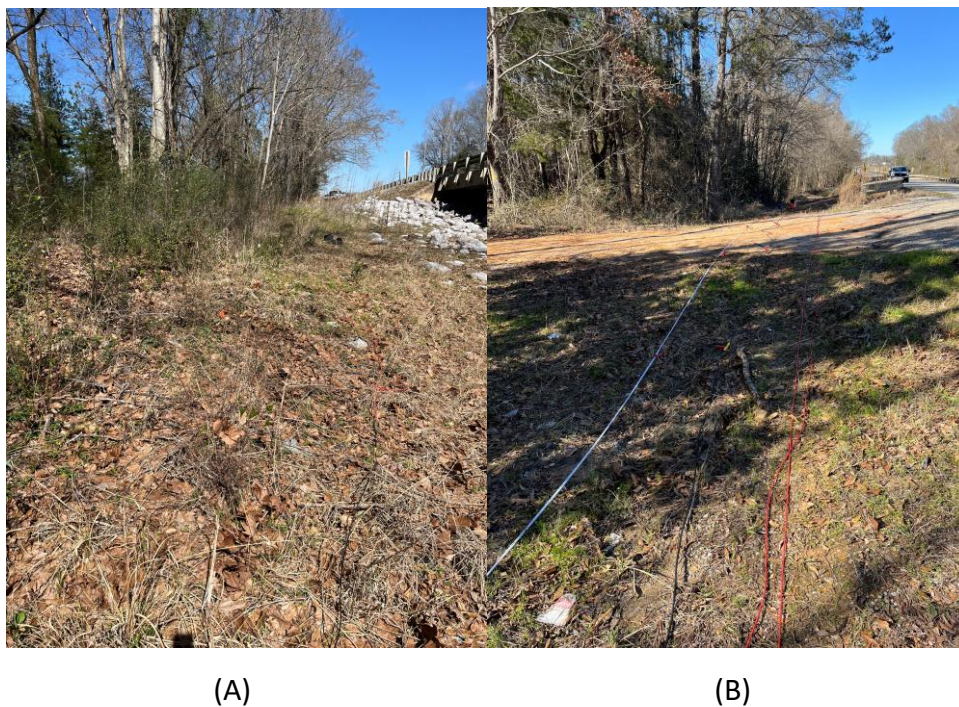


Figure 4-4: MASW survey locations for (A) Line 1 and (B) Line 2 for Beaver Creek surveys

The site is primarily underlain by alluvium and lower terrace deposits of the Holocene series (Osborne et al., 1989). From boring logs, soils encountered are primarily clays with varying degrees of stiffness and some interbedded loose sands.

Data Collection

Two active MASW surveys were performed at the site. For the first active survey, 24 4.5 Hz natural frequency geophones were used at a spacing of 1.5 meters for a total spread length of 34.5 meters. For the second active survey, 24 4.5 Hz natural frequency geophones were used at a spacing of 3 meters for a spread length of 69 meters. Data for both surveys were recorded with the same settings with a sampling frequency of 2000 Hz, a recording length of 1.5 seconds, an offset of 0 seconds, and a delay of -0.1 seconds. No acquisition filters were used. Energy sources for both active surveys were placed at multiple locations along the spread, with off-end, end on, and split-spread shots being used.

MASW Results

An example dispersion curve alongside the 10 best fit inverted ground profiles for the first MASW survey line are shown in Figure 4-5. Considering the profile with the minimum value of misfit, results indicate that a soft layer to a depth of 5 meters (16 feet) with a V_s of 134 m/s (440 ft/s) underlain by a stiffer layer with a V_s of 356 m/s (1168 ft/s) that extends to a depth of 18 meters (59 feet). Below this layer a very stiff layer of clay is encountered with a V_s of 950 m/s (3116 ft/s) that is observed to a depth of 30 meters (98 feet) where the extent of the survey is reached. This minimum misfit V_s profile provides the site with a V_{s30} of 349 m/s (1145 ft/s) which places the site into class C/D. When considering the exponential distribution of the full suite of inverted ground profiles, the median V_{s30} value is 312 m/s (1023 ft/s) which places the site into class C/D.

An example dispersion curve alongside the 10 best fit inverted ground profiles for the second MASW survey line are shown in Figure 4-6. The shallowest layer underlying the second survey line is stiffer in comparison to the first survey line, having a V_s of 174 m/s (571 ft/s) also extending to a depth of approximately 5 meters (16 feet). The underlying layers below are, however, softer than those underlying the first survey line. A layer of soft soil extending to a depth of 14.7 meters (48 feet) with a V_s of 306 m/s (1004 ft/s) is encountered. This layer is underlain by a stiffer layer of clay with a V_s of 486 m/s (1594 ft/s). This minimum misfit V_s profile gives the site a V_{s30} of 321 m/s (1053 ft/s) which places the site into the lower bound of

class C/D. When considering the exponential distribution of the entire suite of inverted ground profiles, the median V_{S30} value is 325 m/s (1066 ft/s) which places the site into class C/D.

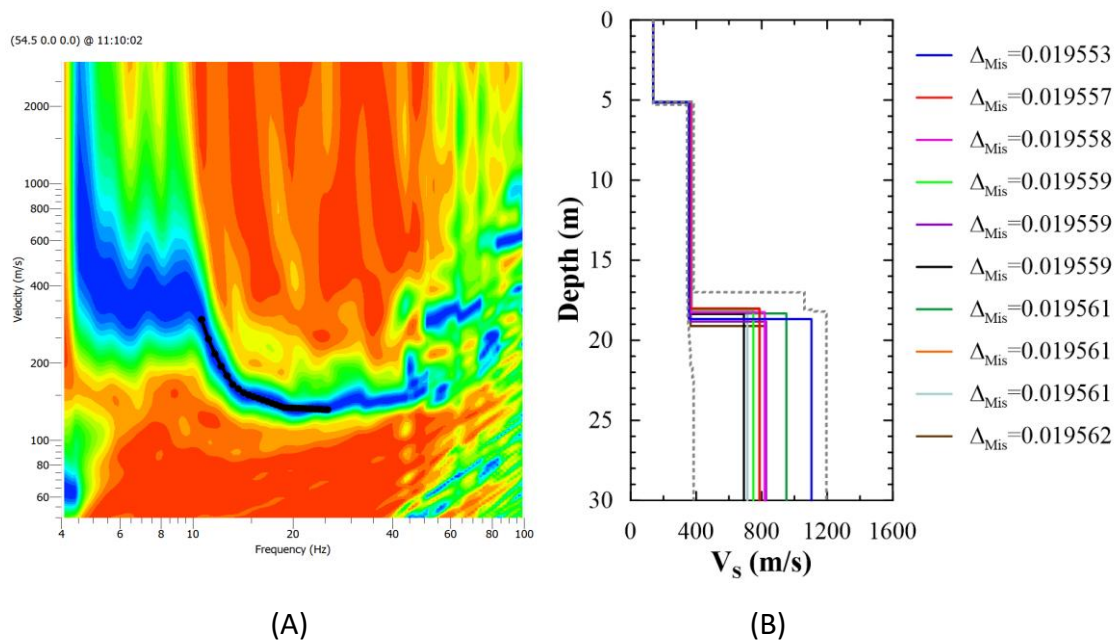


Figure 4-5: Results of first MASW survey conducted at Beaver Creek site showing (A) dispersion and (B) the 10 best fit inverted ground profiles along with the range of V_s values taken from the best 1000 profiles

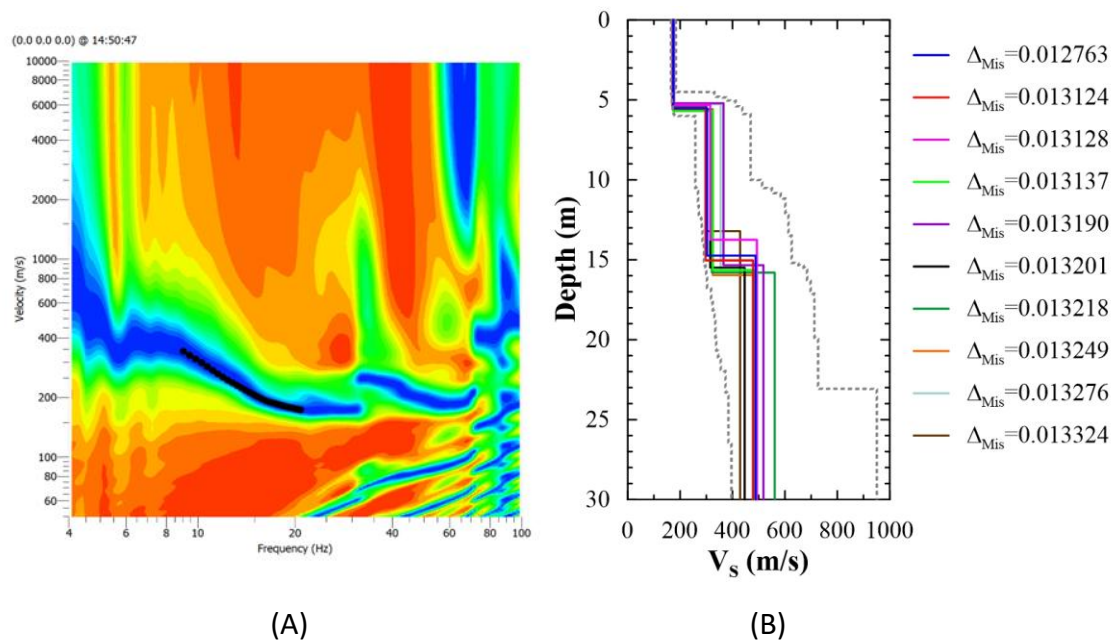


Figure 4-6: Results of second MASW survey conducted at Beaver Creek site showing (A) dispersion and (B) the 10 best fit inverted ground profiles along with the range of V_s values taken from the best 1000 profiles

4.3.2 Big Prairie Creek Site

Location and Geology

The Big Prairie Creek site is located adjacent to a bridge on Highway 69 in Prairieville Alabama (32.54165, -87.68057). Geophysical surveys were conducted on February 20, 2025. Topography of the site is relatively flat with minimal vegetation at the location of the seismic survey as shown in Figure 4-7.



Figure 4-7: Big Prairie Creek seismic survey line

The site is primarily underlain by alluvium and lower terrace deposits of the Holocene series (Osborne et al., 1989). From boring logs, soils encountered are primarily interbedded silty and clayey sands with some sandy clay overlying a layer of elastic silt.

Data Collection

A single active MASW survey was conducted at the site. The survey used 24 4.5 Hz natural frequency geophones spaced at 1.5 meters for a total spread length of 34.5 meters. Data were recorded with a sampling frequency of 2000 Hz, a recording length of 1.5 seconds, an offset of 0 seconds, and a delay of -0.1 seconds. No acquisition filters were used. Energy sources

were placed at multiple locations along the spread, with off-end, end on, and split-spread shots being used.

MASW Results

An example dispersion curve alongside the 10 best fit inverted ground profiles for the MASW survey are shown in Figure 4-8. The V_s profile is divided into three layers. The first layer extends to a depth of 4m (13ft) and has a V_s of 124 m/s (407 ft/s). This layer corresponds with the softer sands and clays near the surface. The next layer extends to a depth of 12m (39ft) and has a V_s of 261 m/s (856 ft/s). This layer corresponds with the denser silty and clayey sands encountered at the site. The last layer observed has a V_s of 1000 m/s (3280 ft/s). This layer corresponds with the hard clay and elastic silt encountered in the SPT boring. This minimum misfit V_s profile provides the site with a V_{s30} of 359 m/s (1178 ft/s) which places the site into class C/D. When considering the exponential distribution of the entire suite of inverted ground profiles, the median V_{s30} value is 315 m/s (1033 ft/s) which places the site into class C/D.

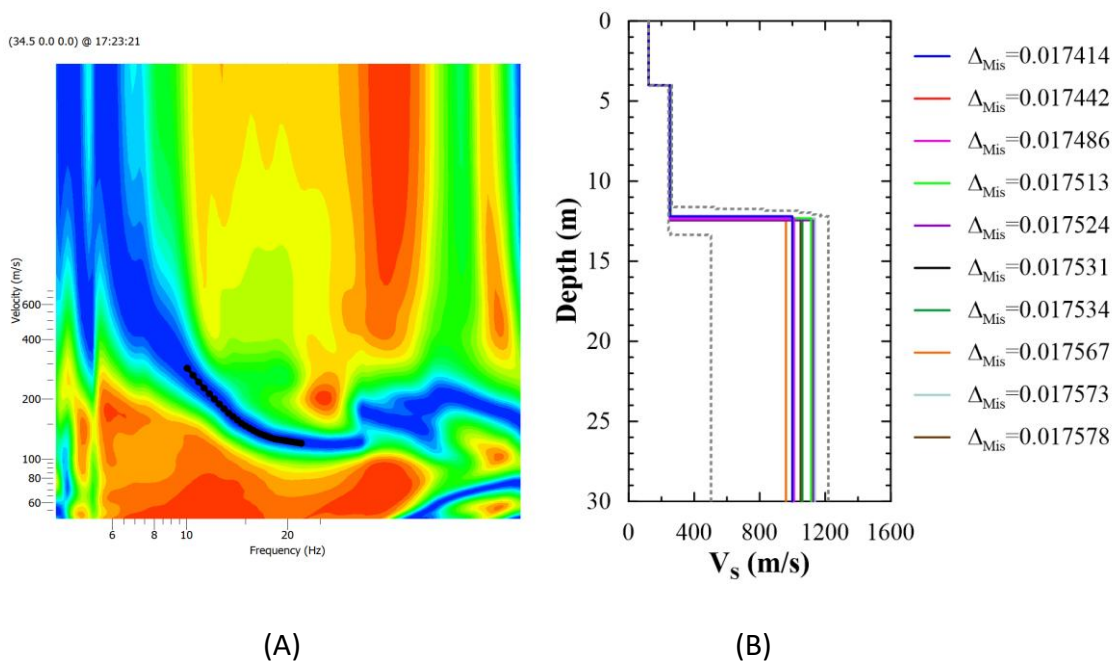


Figure 4-8: Results of MASW survey conducted at Big Prairie Creek site showing (A) dispersion and (B) the 10 best fit inverted ground profiles along with the range of V_s values taken from the best 1000 profiles

4.3.3 Coldwell Creek Site

Location and Geology

The Coldwell Creek site is located south of Raven Road outside of Greensboro, AL (32.72850, -87.60641). Geophysical surveys were conducted on February 21, 2025. Topography of the site is flat and vegetation at the ground level was minimal at the time of the survey. The seismic survey line is shown in Figure 4-9.



Figure 4-9: Coldwell Creek seismic survey line

The site is underlain by the Eutaw formation which is characterized by gray to greenish-gray fine to medium grained glauconitic sand cross bedded with dark clay (Osborne et al., 1989). Soils encountered in a SPT boring at the site are primarily clayey sands with a layer of fat clay with varying amounts of sand.

Data Collection

A single active MASW survey was conducted at the site. The survey used 24 4.5 Hz natural frequency geophones spaced at 1.5 meters for a total spread length of 34.5 meters. Data were recorded with a sampling frequency of 2000 Hz, a recording length of 1.5 seconds, an offset of 0 seconds, and a delay of -0.1 seconds. No acquisition filters were used. Energy sources were placed at multiple locations along the spread, with off-end, end on, and split-spread shots being used.

MASW Results

An example dispersion curve alongside the 10 best fit inverted ground profiles for the MASW survey are shown in Figure 4-10. The first layer encountered extends to a depth of approximately 4m (13ft) and has a V_s of 142 m/s (466 ft/s). This layer corresponds with the loose sands near the ground surface and the underlying fat clay. The next layer that can be observed below extends to a depth of 14m (46ft) and has a V_s of 333 m/s (1092 ft/s). This layer corresponds with the silty sand encountered in the boring log. Underlying this layer there is more uncertainty in the inverted models and there is variation in the number of layers and magnitude of V_s . This layer has extends to a depth of 30m and has a V_s of 671 m/s (2200 ft/s). This layer corresponds with the dense silty sands encountered at these depths in the boring. The minimum misfit V_s profile provides the site with a V_{s30} of 363 m/s (1190 ft/s) which places the site into class C/D. When considering the exponential distribution of the full suite of inverted ground profiles, the median value of V_{s30} is 334 m/s (1096 ft/s) which places the site into class C/D.

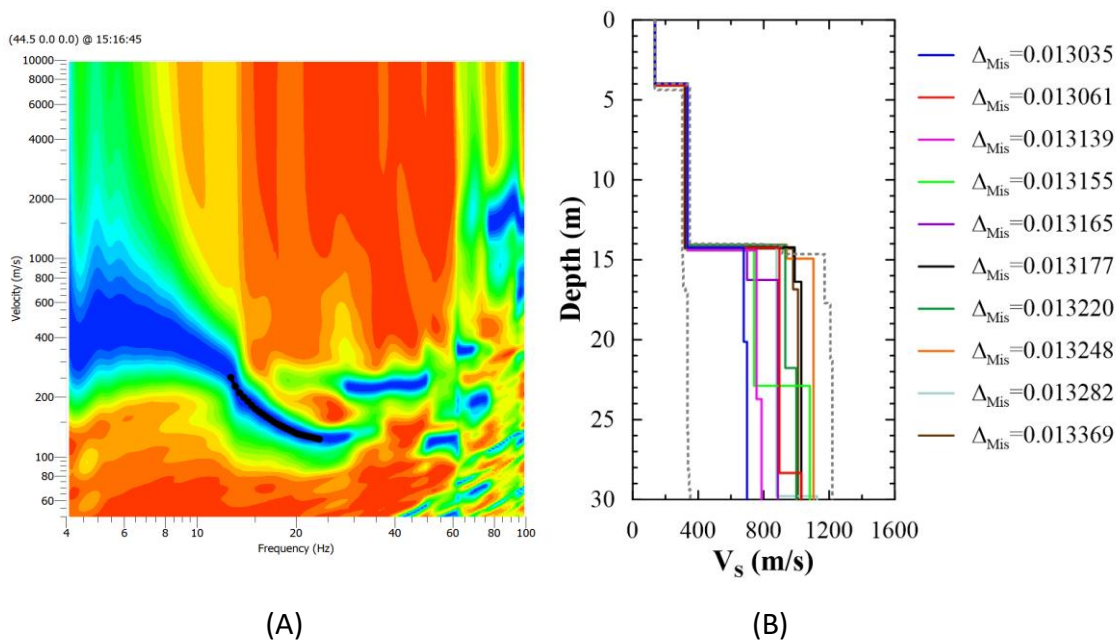


Figure 4-10: Results of MASW survey conducted at Coldwell Creek site showing (A) dispersion and (B) the 10 best fit inverted ground profiles along with the range of V_s values taken from the best 1000 profiles

4.3.4 Moundville, AL Site

Location and Geology

The Moundville site is located along Alabama Highway 69 in Moundville, AL (32.84110, -87.61017). Geophysical surveys were conducted on February 20, 2025. Terrain was flat in topography. The site is primarily wooded with access roads that were used to lay out survey lines. Seismic survey lines are presented in Figure 4-11.

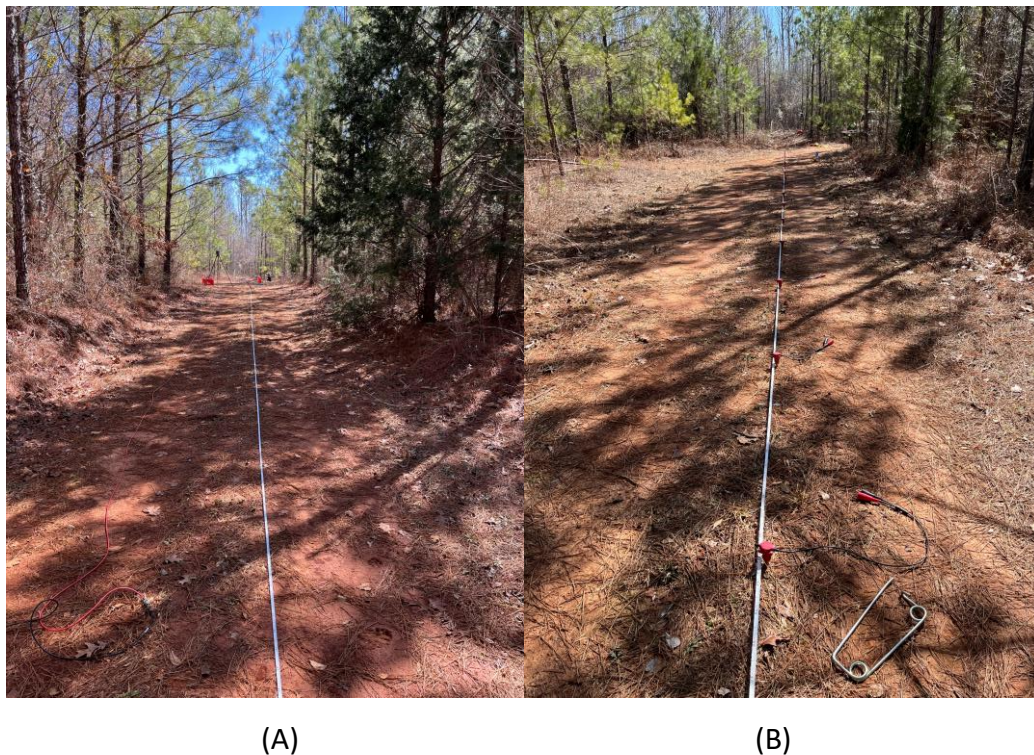


Figure 4-11: Moundville seismic survey line (A) 1 and (B) 2

The site is underlain by the Eutaw formation which is characterized by light greenish gray to yellowish-gray cross-bedded, well-sorted micaceous, fine to medium quartz sand that contains beds of greenish gray silty clay and medium dark gray carbonaceous clay (Osborne et al., 1989). SPT borings were drilled to a depth of 100 feet and primarily encountered sandy soils overlying clays and a layer of elastic silt with fat clays being encountered prior to termination of the borings.

Data Collection

Two active MASW surveys were conducted at the site. The surveys used 24 4.5 Hz natural frequency geophones spaced at 1.5 meters for a total spread length of 34.5 meters. Data were recorded with a sampling frequency of 2000 Hz, a recording length of 1.5 seconds, an offset of 0 seconds, and a delay of -0.1 seconds. No acquisition filters were used. Energy sources were placed at multiple locations along the spread, with off-end, end on, and split-spread shots being used.

MASW Results

An example dispersion curve alongside the 10 best fit inverted ground profiles for the first MASW survey are shown in Figure 4-12. The first layer encountered extends to a depth of 1m (3.3ft) with a V_s of 196 m/s (643 ft/s). This layer corresponds with the sandy lean clay encountered near the ground surface. The next layer encountered extends to a depth of approximately 2.4m (8ft) and has a V_s of 253 m/s (830 ft/s). This corresponds with the upper portion of the layer of silty sand encountered in the SPT boring. The next layer extends to a depth of approximately 20.5m (67ft) and has a V_s of 411 m/s (1348 ft/s). This spans multiple soil layering boundaries and encompasses sands, silts, and clays. The final layer observed has a V_s of 1120 m/s (3674 ft/s) and is subject to more uncertainty than the layers lying above. The minimum misfit V_s profile gives the site a V_{s30} of 326 m/s (1069 ft/s) which places it into the lower bound of class C/D. When considering the exponential distribution of the full ensemble of inverted ground profiles, the median V_{s30} value is 302 m/s (991 ft/s) which places the site into class D

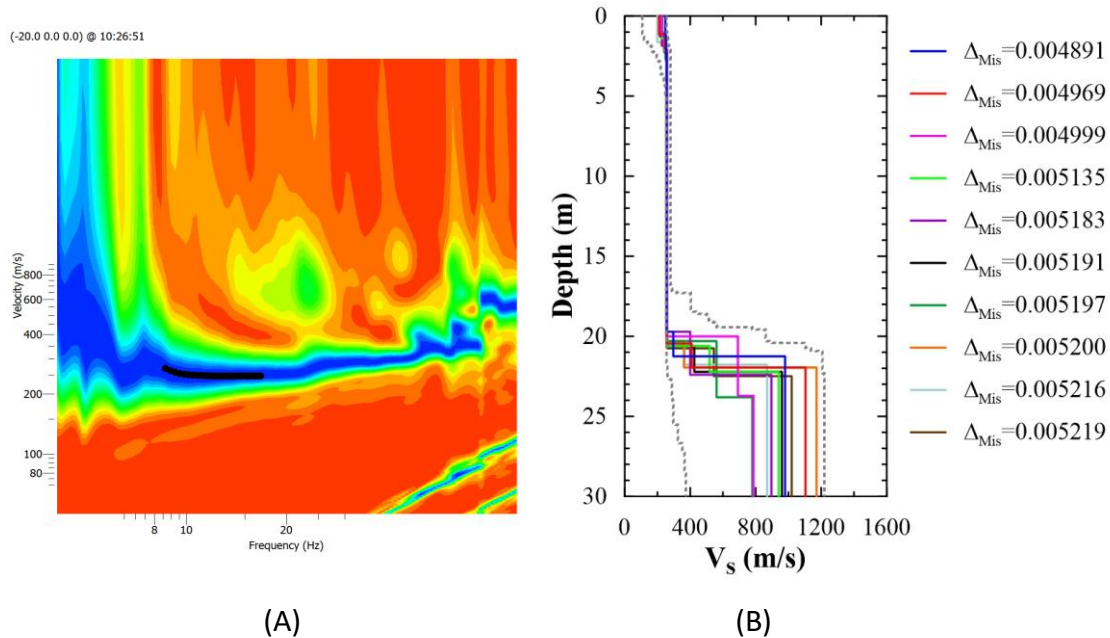


Figure 4-12: Results of first MASW survey conducted at Moundville site showing (A) dispersion and (B) the 10 best fit inverted ground profiles along with the range of V_s values taken from the best 1000 profiles

An example dispersion curve alongside the 10 best fit inverted ground profiles for the second MASW survey are shown in Figure 4-13. Near the ground surface in the inverted models, there are three layers with shear wave velocities that are all very close in magnitude. Those layers can be considered as a singular layer in analysis with a V_s of approximately 270 m/s (886 ft/s) that extends to a depth of approximately 23.7m (78ft). This singular layer would span multiple soil types, encompassing sands and clays with varying degrees of sand content. The next layers that can be observed from inverted ground profiles are subject to more uncertainty, but it can be observed that there are 2 layers that extend to depths of approximately 26.7 and 30m respectively (88 and 100ft). These layers have shear wave velocities of 994 and 1130 m/s (3260 and 3706 ft/s). The minimum misfit V_s profile provides the site with a V_{s30} of 313 m/s (1027 ft/s) which places the site into the lower bound of class C/D. When considering the exponential distribution of the full ensemble of inverted ground profiles, the median V_{s30} value is 290 m/s (951 m/s) which places the site into class D.

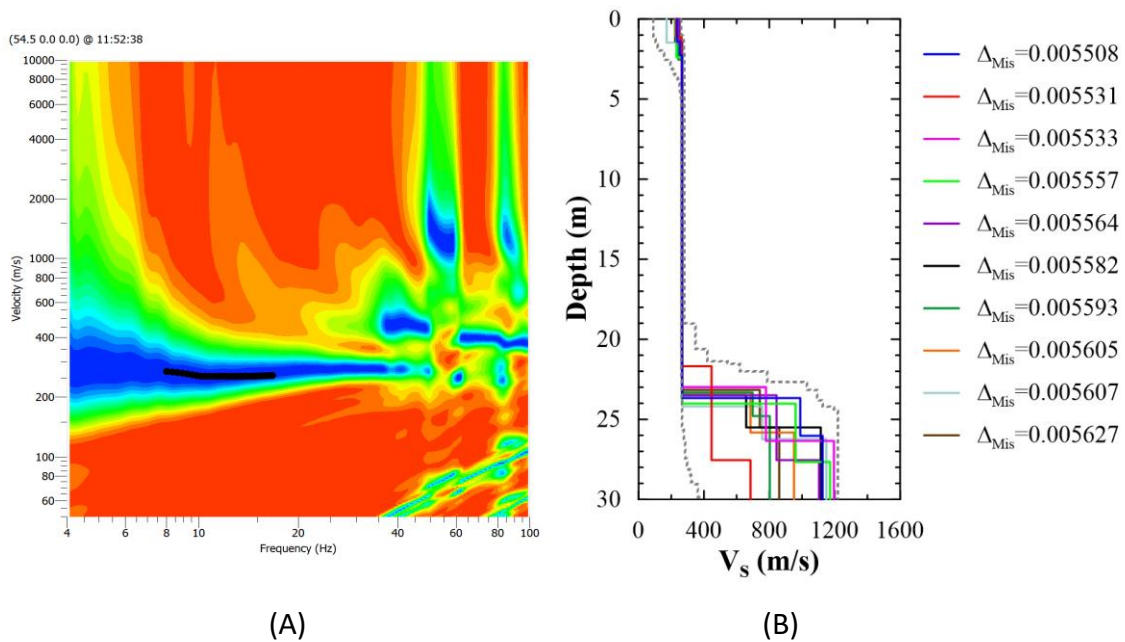


Figure 4-13: Results of second MASW survey conducted at Moundville site showing (A) dispersion and (B) the 10 best fit inverted ground profiles along with the range of V_s values taken from the best 1000 profiles

4.3.5 Greensboro, AL Site

Location and Geology

The Greensboro site is located alongside AL-69 in Greensboro, AL (32.76450, -87.58517). Geophysical surveys were conducted on February 21, 2025. Topography of the site is mildly sloped with minimal vegetation. The seismic survey line is presented in Figure 4-14.



Figure 4-14: Greensboro seismic survey line

The site is underlain by alluvial, coastal, and low terrace deposits of the Holocene series which are characterized by fine to coarse quartz sand containing clay lenses and gravel in places (Osborne et al., 1989). Soils encountered during a SPT boring local to the survey line are primarily sands with varying contents of fines and sandy lean clays.

Data Collection

A single active MASW survey was conducted at the site. The survey used 24 4.5 Hz natural frequency geophones spaced at 1.5 meters for a total spread length of 34.5 meters. Data were recorded with a sampling frequency of 2000 Hz, a recording length of 1.5 seconds, and an offset of 0 seconds, and a delay of -0.1 seconds. No acquisition filters were used. Energy sources were placed at multiple locations along the spread, with off-end, end on, and split-spread shots being used.

MASW Results

An example dispersion curve alongside the 10 best fit inverted ground profiles for the MASW survey are shown in Figure 4-15. The first layer observed from the inverted ground

profiles has a V_s of approximately 146 m/s (479 ft/s) and extends to a depth of 7.4m (24ft). This layer corresponds with the layers of sand with varying fines contents. The next layer that can be observed from inverted ground profiles extends to a depth of 11m (36ft) and has a V_s of 215 m/s (705 ft/s). This layer corresponds with the layer of lean clay observed in the boring. The next layer encountered extends to a depth of 23m (75ft) and has a V_s of 306 m/s (1004 ft/s) This layer corresponds with silty sand observed in the SPT boring. The final layer that extends down to a depth of 30m (100ft) has a V_s of 466 m/s (1528 ft/s). This layer is also in the same layer of silty sand. The minimum misfit V_s profile provides the site with a V_{s30} of 245 m/s (804 ft/s) which places the site into class D. When considering the exponential distribution of the full ensemble of inverted ground profiles, the median value of V_{s30} is 256 m/s (840 ft/s) which places the site into class D.

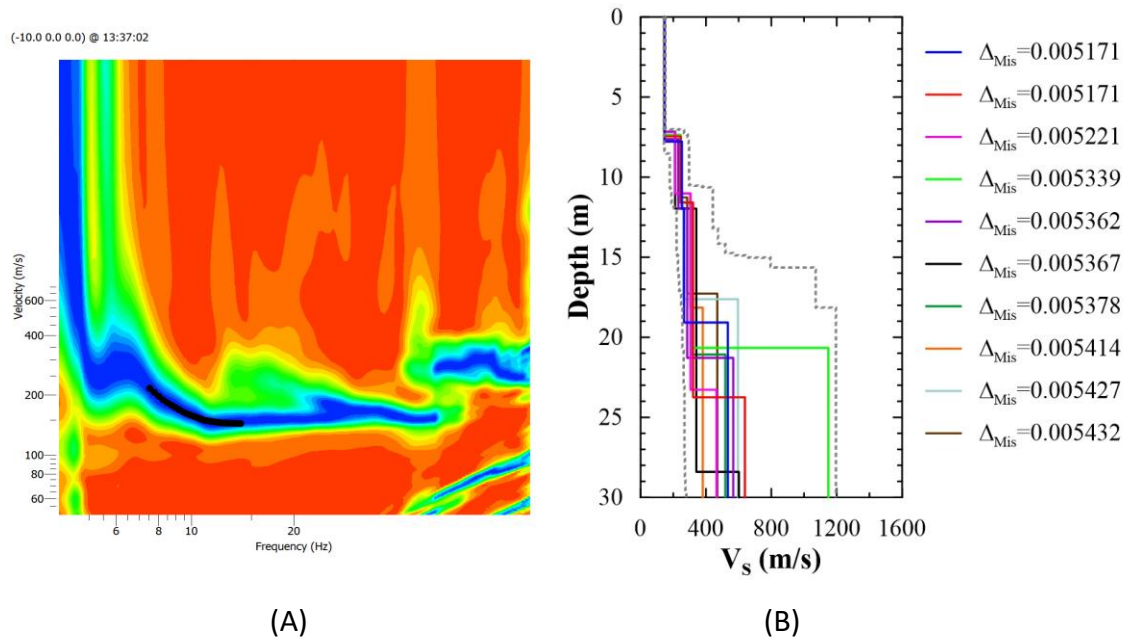


Figure 4-15: Results of MASW survey conducted at Greensboro site showing (A) dispersion and (B) the 10 best fit inverted ground profiles along with the range of V_s values taken from the best 1000 profiles

4.4 Northwest Alabama Surveys

The second aggregated group of sites is the Northwest Alabama Group. Sites selected for the Northwest Alabama surveys were selected due to availability of SPT borings. The MASW technique was used for sites with a greater depth to rock while refraction was used for sites when rock was encountered shallower to the ground surface. SPT borings for the sites in the Northwest Alabama group have a varying degree of depths, ranging from 23.5 ft to 102.1 ft (7.2 m to 31.1 m) so extrapolation of some deeper layers may be required in interpretation of results. HVSr surveys were performed alongside active surveys at these sites and results are presented in Chapter 5 of this work.

4.4.1 Duck River Site

Location and Geology

The first site in the Northwest Alabama group is located along Duck River in Hanceville, AL (34.09289, -86.72132). Geophysical surveys were conducted on May 6, 2025. Terrain at the site is flat with minimal vegetation at the time of the survey. The seismic survey line is shown in Figure 4-16.



Figure 4-16: Seismic survey line at Duck River site

The site is underlain by the lower part of the Pottsville formation, which is characterized by light gray, thick bedded to massive pebbly quartzose sandstone with varying amounts of interbedded shale, siltstone, and coal (Osborne et al., 1989). Boring logs of the site indicate that depth to rock is approximately 18.5 feet (5.6 meters) however visual inspection of the site indicates that rock is to be encountered shallower to the ground surface at the locality of the seismic survey line.

Data Collection

Due to the presence of shallower rock at the site the seismic refraction technique was used. A single active refraction survey was conducted at the site. The survey used 24 14 Hz natural frequency geophones spaced at 3 meters for a total spread length of 69 meters. Data were recorded with a sampling frequency of 16000 Hz, a recording length of 1.5 seconds, an offset of 0 seconds, and a delay of -0.1 seconds. No acquisition filters were used. Energy sources were placed at multiple locations along the spread, with off-end and end on shots being used. A minimum of 5 shots were taken at each location for stacking to increase signal to noise ratio.

Refraction Results

Traveltime curves presented in Figure 4-17 indicate a two layered system. Inversion analysis was performed and the compressional wave velocity model was calculated as presented in Figure 4-18. V_P/V_S ratios of 0.4 and 0.6 were used to calculate the probable range of V_S for the site and are presented in Table 4-2. Extending the lower layer to a depth of 30m and using a median value of V_S from the probable range provides the site with a V_{S30} of 1209 m/s which places the site into class B.

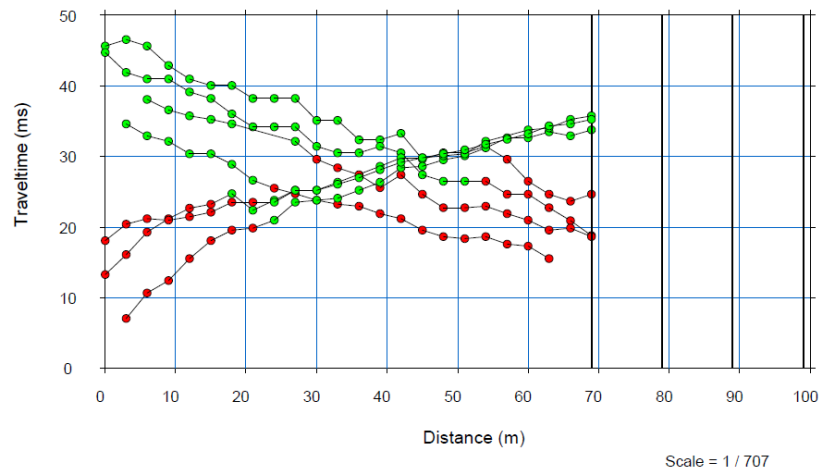
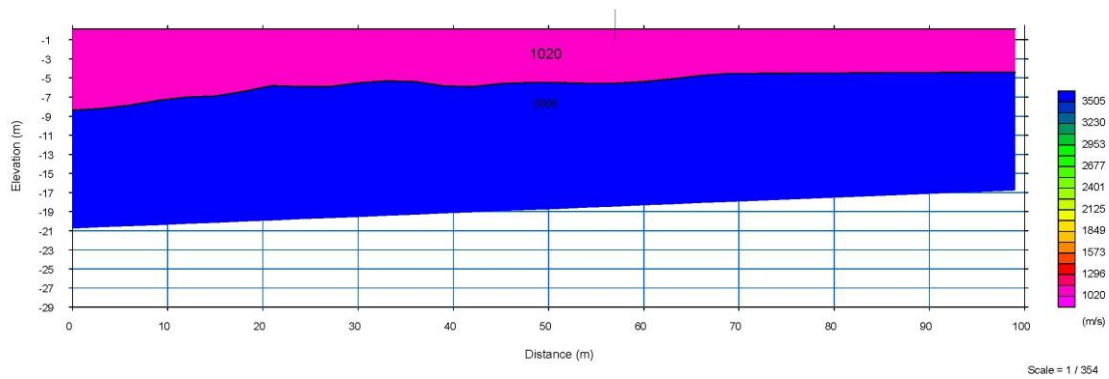


Figure 4-17: Appended traveltime curves for Duck River site

Figure 4-18: V_p model for Duck River siteTable 4-2: Calculated range of V_s profile for Duck River site

Parameter	Layer 1	Layer 2
Compressional wave velocity (m/s)	1020	3506
Shear wave velocity (lower bound, m/s)	408	1402.4
Shear wave velocity (upper bound, m/s)	612	2103.6

4.4.2 Russellville High School Site

Location and Geology

The Russellville High School site is located at Russellville High School in Russellville AL (34.52492, -87.73752). Geophysical surveys were conducted on March 27, 2025. Topography of the site is flat with minimal vegetation at the time of the survey.

The site is underlain by the Gordo formation which is characterized by massive beds of cross-bedded sand, gravelly sand, and lenticular beds of locally carbonaceous partly mottled moderate red and pale red purple clay (Osborne et al., 1989). SPT borings were performed prior to additions on the school in 2020.

Data Collection

Two active MASW surveys were conducted at the site. The surveys used 24 4.5 Hz natural frequency geophones spaced at 1.5 meters for a total spread length of 34.5 meters. Data were recorded with a sampling frequency of 2000 Hz, a recording length of 1.5 seconds, an offset of 0 seconds, and a delay of -0.1 seconds. No acquisition filters were used. Energy sources were placed at multiple locations along the spread, with off-end, end on, and split-spread shots being used.

MASW Results

An example dispersion curve alongside the 10 best fit inverted ground profiles for the first MASW survey are shown in Figure 4-20. Results of inversion analysis indicate that there are 5 layers present. The first layer extends to a depth of approximately 0.9m (3ft) and has a V_s of 110 m/s (361 ft/s). This corresponds with the layer of soft sandy lean clay present directly below the ground surface. The second layer extends to a depth of 2.4m (8ft) and has a V_s of 146 m/s (479 ft/s). This layer corresponds with the layer of sandy silty clay directly underlying the previous layer of sandy lean clay. The next layer extends to a depth of 3.9m (13ft) and has a V_s of 285 m/s (935 ft/s). This layer corresponds with the layer of clayey gravel encountered in the SPT boring. The next layer extends to a depth of 5.4m (18ft) and has a V_s of 500 m/s (1640 ft/s). This corresponds with the layer of sandy fat clay encountered in the SPT boring. The final layer extends to a depth of 30m from the inverted ground profiles but can only be directly compared to the SPT boring to a depth of 7.6m (25ft) where the boring was terminated. This layer is subject to more uncertainty than shallower layers, but all profiles agree that it is stiffer than the shallower layers. The V_s of this layer is 677 m/s (2221 ft/s) and corresponds with a layer of clayey gravel encountered in the SPT boring. The minimum misfit V_s profile provides the site with a V_{s30} of 486 m/s (1594 ft/s) and places the site into class C. When considering the

exponential distribution of the full ensemble of inverted ground profiles, the median value of V_{S30} is 348 m/s (1141 ft/s) which places the site into class C/D.

An example dispersion curve alongside the 10 best fit inverted ground profiles for the second MASW survey are shown in Figure 4-20. Inverted ground profiles indicate that there are two layers present as opposed to the 5 for the first survey line. SPT boring logs agree with the results of these inverted ground models only showing a layer of sandy lean clay overlying a layer of fat clay. The layer of sandy lean clay extends to a depth of 4.75m (16ft) and has a V_s of 236 m/s (774 ft/s). The underlying fat clay extends to a depth of 7.6m (25ft) in the SPT boring while the inverted ground profile extends to a depth of 30m (100ft). This layer has a V_s of 492 m/s (1614 ft/s). This ground profile is subject to more uncertainty as the value of misfit of the inverted model is greater than those of survey line 1. The minimum misfit V_s profile provides the site with a V_{S30} of 427 m/s (1400 ft/s) which places the site into class C/D. When considering the exponential distribution of the full ensemble of inverted ground profiles, the median V_{S30} value is 420 m/s (1378 ft/s) which places the site into class C/D.

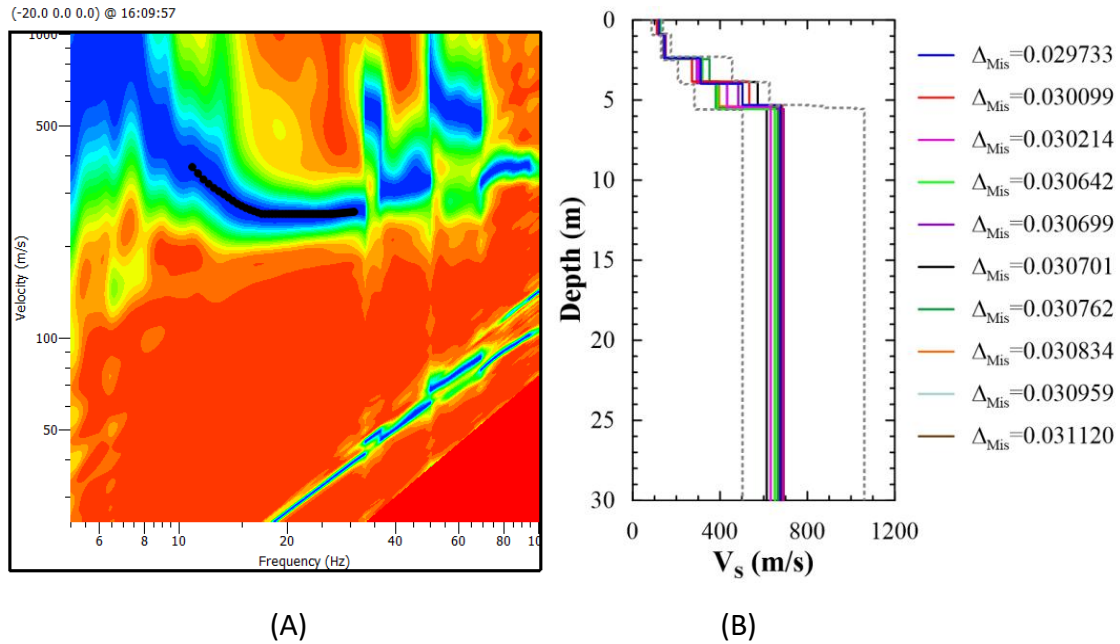


Figure 4-19: Results of first MASW survey conducted at Russellville High School site showing (A) dispersion and (B) the 10 best fit inverted ground profiles along with the range of V_s values taken from the best 1000 profiles

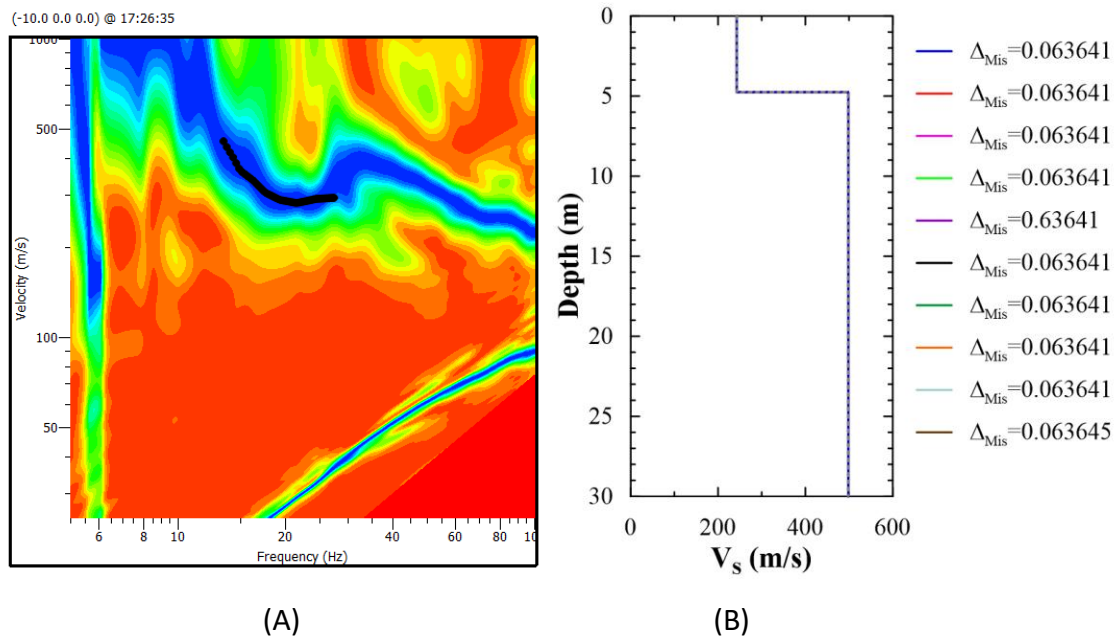


Figure 4-20: Results of second MASW survey conducted at Russellville High School site showing (A) dispersion and (B) the 10 best fit inverted ground profiles along with the range of V_s values taken from the best 1000 profiles

4.4.3 Bluewater Creek Site

Location and Geology

The Bluewater creek site located near a bridge over the Bluewater creek along State Route 2 in Lauderdale County Alabama (34.85717, -87.41544). Geophysical surveys were conducted on March 27, 2025. Topography of the site is relatively flat with little vegetation at the time of the survey.

The site is located within the Fort Payne Chert formation which is characterized by light gray medium to finely crystalized limestone (Osborne et al., 1989). Rock was encountered at a shallow depth around 10 ft (3 m), and in some areas in the site a thin layer of limestone is encountered that is overlying clay. Rock coring was performed on the underlying limestone and RQD ranges from as low as 36% up to 97%.

Data Collection

MASW was selected as the survey technique for this site due to proximity to State Route 2. A single active MASW survey was conducted at the site. The survey used 24 14 Hz natural frequency geophones spaced at 1.5 meters for a total spread length of 34.5 meters. Data were recorded with a sampling frequency of 2000 Hz, a recording length of 1.5 seconds, an offset of 0 seconds, and a delay of -0.1 seconds. No acquisition filters were used. Energy sources were placed at multiple locations along the spread, with off-end, end on, and split-spread shots being used.

MASW Results

An example dispersion curve alongside the 10 best fit inverted ground profiles for the MASW survey are shown in Figure 4-21. From inversion analysis, 4 layers can be seen in the inverted ground profile. The first layer extends to a depth of 0.9m (3ft) and has a V_s of 250 m/s (820 ft/s). This layer corresponds with the layer of lean clay observed near the ground surface. The next layer observed extends to a depth of 3.1m (10ft) and has a V_s of 259 m/s (850 ft/s). This corresponds with the layer of clayey sand with gravel observed in the boring. These two layers are very close in magnitude of V_s and also have SPT blowcounts that are close in magnitude (11

and 12 respectively). The next layer extends to a depth of 7.3m (24ft) and has a V_s of 417 m/s (1368 ft/s). This layer corresponds with the layer of clayey sand with gravel observed in the SPT boring. The final layer has a V_s of 1220 m/s (4002 ft/s). This layer likely corresponds with limestone encountered at the site though inversion analysis indicates that it is encountered at a shallower depth as compared to the locations where borings were performed. The minimum misfit V_s profile gives the site a V_{S30} of 735 m/s (2411 ft/s) which places the site into class B/C. When considering the exponential distribution of the full ensemble of inverted ground profiles, the median value of V_{S30} is 679 m/s (2227 ft/s) which places the site into class B/C.

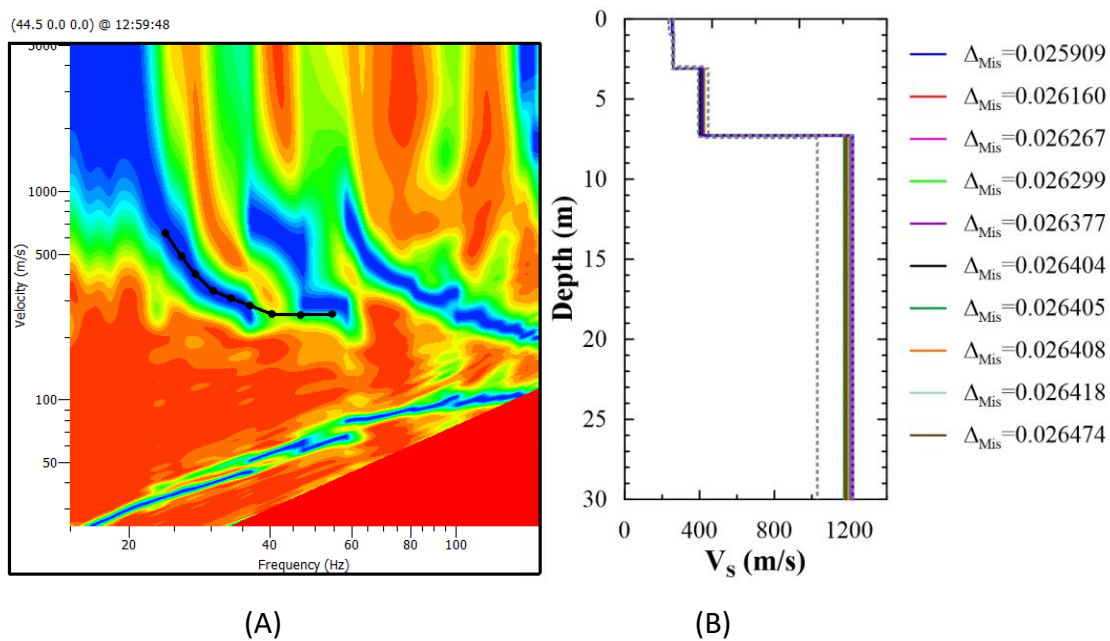


Figure 4-21: Results of MASW survey conducted at Bluewater Creek site showing (A) dispersion and (B) the 10 best fit inverted ground profiles along with the range of V_s values taken from the best 1000 profiles

4.4.4 Lauderdale County Site

Location and Geology

The Lauderdale County site is located alongside County Road 8 in Florence Alabama near a bridge overpass (34.95055, -87.69541). Geophysical surveys were conducted on March 28, 2025. Topography at the site is flat with minimal vegetation. The site is open and access to locations of borings on both sides of the bridge is possible. Due to the ease of access, two survey lines are laid out at the site. The first survey line is located approximately 100 meters (328 feet) from Lauderdale County Road 8 into a large clearing in the wooded area local to the site. The second survey line is located approximately 10 meters (33 feet) off of the road. Survey line 1 is shown in Figure 4-22.



Figure 4-22: Seismic refraction survey line at Lauderdale County site

The Lauderdale County site is underlain by the Fort Payne Chert formation which is characterized by light gray medium to finely crystalized limestone. Boring logs from the immediate area indicate that depth to rock is relatively shallow, 9 feet (2.65 meters) in depth at the shallowest.

Data Collection.

MASW and refraction surveys were used at this site. The MASW surveys used 24 14 Hz natural frequency geophones spaced at 1.5 meters for a total spread length of 34.5 meters. Data were recorded with a sampling frequency of 2000 Hz, a recording length of 1.5 seconds, an offset of 0 seconds, and a delay of -0.1 seconds. The refraction surveys used 24 14 Hz natural frequency geophones spaced at 1.5 meters for a total spread length of 34.5 meters. Data were recorded with a sampling frequency of 16000 Hz, a recording length of 1.5 seconds, an offset of 0 seconds, and a delay of -0.1 seconds. No acquisition filters were used. Energy sources were placed at multiple locations along the spread, with off-end, end on, and split-spread shots being used.

Refraction Results

Results of refraction surveys were only reliable from the first survey location. Travel time curves presented in **Error! Reference source not found.** indicate a two layered system. Inversion analysis was performed to calculate the compressional wave velocity model presented in **Error! Reference source not found.** V_P/V_S ratios of 0.4 to 0.6 were used to calculate the probable range of V_S for the site and are presented in Table 4-3 **Error! Reference source not found.**

MASW Results

MASW results were only reliable for the second survey line. An example dispersion curve alongside the 10 best fit inverted ground profiles for the second MASW survey are shown in Figure 4-27. Two layers can be observed from the inverted ground profiles. The first layer extends to a depth of 4m (13ft) and has a V_S of 412 m/s (1351 ft/s). This layer corresponds with the layer of clay encountered in the SPT boring. The second layer has a V_S of 1086 m/s (3562 ft/s). At this layer in the SPT boring, fragments of chert begin appearing in the clay before limestone is encountered but a clear transition to rock is not observed in the inverted ground profiles. The minimum misfit V_S profile provides the site with a V_{S30} of 886 m/s (2906 ft/s) which places the site into class B/C. When considering the exponential distribution of the full

ensemble of inverted ground profiles, the median value of V_{S30} is 878 m/s (2880 ft/s) which places the site into class B/C.

4.4.5 Blount County Site

Location and Geology

The Blount County site is located alongside US Highway 231 in Oneonta Alabama

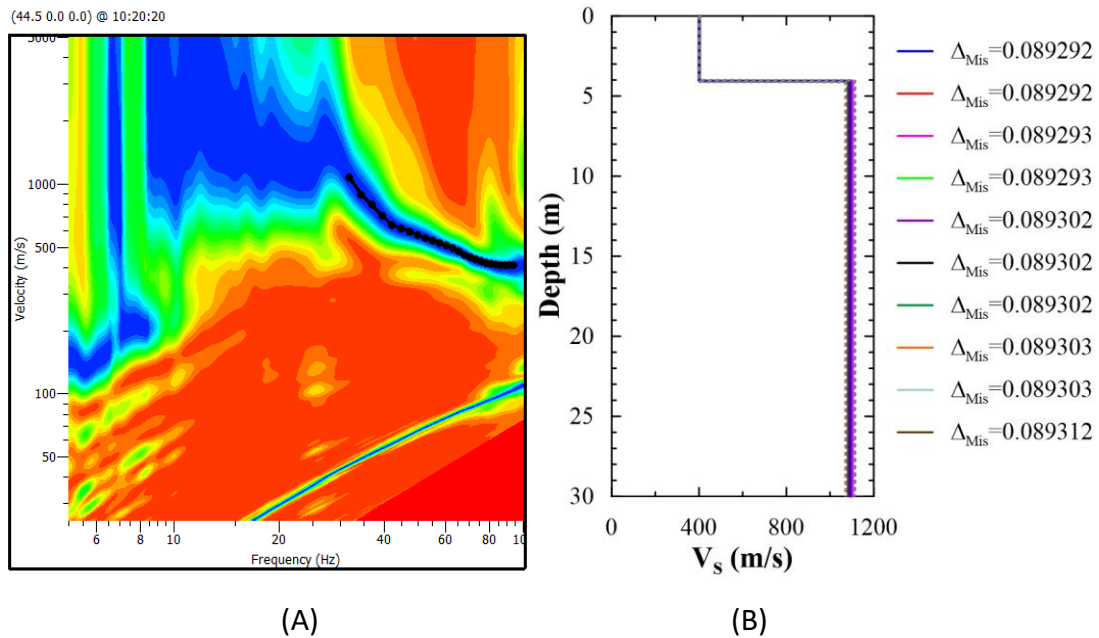


Figure 4-23: Results of MASW survey conducted at Lauderdale County site showing (A) dispersion and (B) the 10 best fit inverted ground profiles along with the range of V_s values taken from the best 1000 profiles

(33.93987, -86.39477). Geophysical surveys were performed on May 6, 2025. Topography of the site is flat with minimal vegetation at the time of the survey.

The site is underlain by the lower portion of the Pottsville formation which is characterized by light gray thin to thick bedded quartzose sandstone and conglomerate containing interbedded dark gray shale, siltstone, and coal. Boring logs from the site indicate that soils to be encountered are clayey and the water table is relatively shallow. Sandstone was encountered at a shallow depth in all of the borings performed at the site.

Data Collection

Due to the presence of shallower rock at the site the seismic refraction technique was used. A single active refraction survey was conducted at the site. The survey used 24 14 Hz natural frequency geophones spaced at 3 meters for a total spread length of 69 meters. Data were recorded with a sampling frequency of 16000 Hz, a recording length of 1.5 seconds, an offset of 0 seconds, and a delay of -0.1 seconds. No acquisition filters were used. Energy sources were placed at multiple locations along the spread, with off-end and end on shots being used. A minimum of 5 shots were taken at each location for stacking to increase signal to noise ratio.

Refraction Results

Travel time curves presented in Figure 4-28 indicate a two layered system. Inversion analysis was performed to calculate the compressional wave velocity model presented in Figure 4-29. V_p/V_s ratios of 0.4 and 0.6 were used to calculate the probable range of V_s for the site and are presented in Table 4-4. Extending the lower layer to a depth of 30m and using a median value of V_s from the probable range provides the site with a V_{s30} of 1178 m/s which places the site into class B.

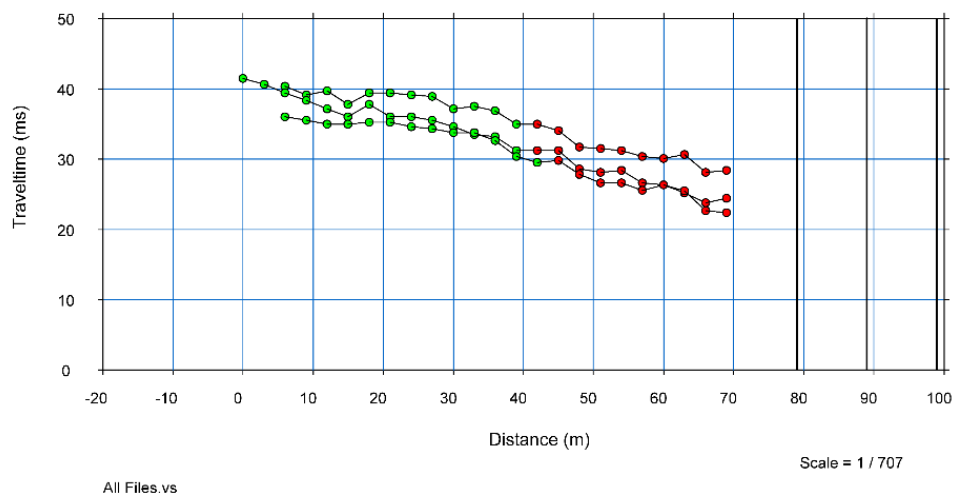
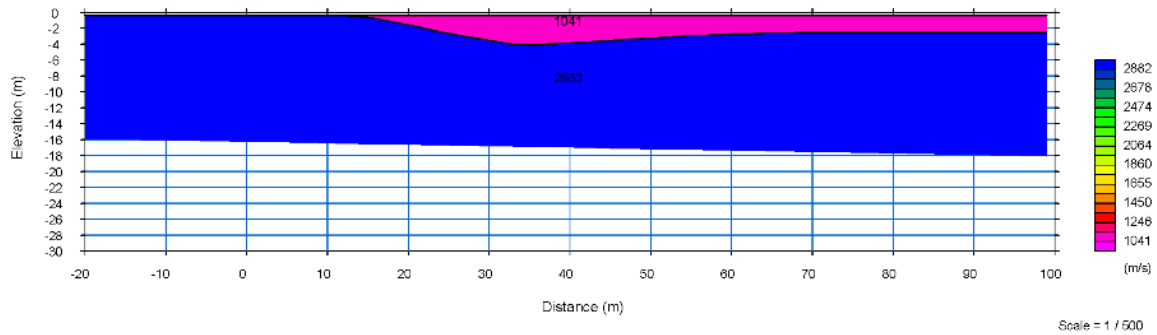


Figure 4-25: Appended traveltimes curves for Blount County Site

Figure 4-26: V_P model for Blount County siteTable 4-3: Calculated range of V_S profile for Blount County site

Parameter	Layer 1	Layer 2
Compressional wave velocity (m/s)	1041	2883
Shear wave velocity (lower bound, m/s)	416.4	1153.2
Shear wave velocity (upper bound, m/s)	624.6	1729.8

4.5 Summary

Field surveys were conducted to obtain quality direct measurements of V_S using either MASW or seismic refraction. Sites within the West Alabama group all had borings drilled to a depth of 100 ft (30 m) with no rock encountered so these sites were excellent candidates for the MASW technique. All sites used the same equipment and recording parameters. Dispersion curves were picked within Geopsy and then inverted in DINVER. A subset of the best 1000 profiles were selected to provide some measure of uncertainty within the inversion process. Additionally, a probabilistic distribution of V_{S30} values from the entire suite of provisional models was used to determine the most likely value of V_{S30} and site class.

Sites within the Northwest Alabama group had borings drilled to various depths with all encountering rock at a shallow depth with the exception of the Russellville High School site. Refraction surveys were chosen for sites where a quality dispersion curve could not be picked due to interference from higher modes. Refraction and MASW surveys used nearly identical

equipment with some MASW surveys using the same 14 Hz geophones as refraction surveys. Following data collection files from common shot locations were stacked to increase the signal to noise ratio then first arrivals were picked. All travel time curves were appended for use in inversion. Inversion produces a two-dimensional model of V_P that is then converted to V_S using known ratios.

Chapter 5: Results of Indirect Methods

5.1 Introduction

The results for V_s and V_{s30} correlations from the methods presented in Chapter 2 are presented in this chapter. This chapter is divided into three main sections. The first section presents the results of boring based correlations containing results of SPT and RQD based V_s correlations. The second section presents the results of passive HVSr surveys conducted at each of the sites along with results of HVSr based correlations to V_{s30} . The third section presents the results of geospatial correlations to V_{s30} applied to the sites from this study as well as sites presented in Carcamo (2022).

5.2 Results of Boring Based Methods

Boring based methods include SPT and RQD based correlations to V_s previously presented in Chapter 2. Correlations were applied to boring log data using a spreadsheet tool previously described in Chapter 3. Correlated values of V_s are plotted alongside the inverted ground profile with the minimum value of misfit for each site where MASW was used to measure V_s , and against the probable range of V_s values for sites where refraction surveys were used to measure V_s . As discussed in Chapter 3, SPT blowcounts were capped at a max value of 100, but these capped values were not used when evaluating the SPT based correlations. RQD based correlations were applied at the appropriate sites with no special considerations for any values of RQD. Table 5-1 presents abbreviations used in presenting results of boring based estimation methods.

Table 5-1: Abbreviations for boring based correlations

Correlation	Abbreviation
Ohta and Goto (1978)	O&G-78
Imai and Tonouchi (1982)	I&T-82
Seed et al. (1983)	S-83
Jinan (1987)	J-87
Lee (1992) equations for individual soil types	L-92 In.
Lee (1992) combined clay and silt equation	L-92 Cmb.
Hasancebi and Ulusay (2007) individual soils, uncorrected blowcount	H-07 IN-N
Hasancebi and Ulusay (2007) individual soils, uncorrected blowcount	H-07 ALL-N
Hasancebi and Ulusay (2007) all soils, corrected blowcount	H-07 IN-N60
Hasancebi and Ulusay (2007) all soils, corrected blowcount	H-07 ALL-N60
Wair et al. (2012) all soils equation	W-12 ALL
Wair et al. (2012) individual soils	W-12 IN
Fatehnia et al. (2015)	F-15
Anbazhagan et al. (2016) including N=100	A-16 100
Anbazhagan et al. (2016) excluding N=100	A-16 No 100
El-Naqua (1996)	EN-96
Biringen and Davie (2013) Ft. Thompson	B&D-13 FT
Biringen and Davie (2013) Key Largo	B&D-13 KL

5.2.1 Cedar Bluff Site

Results of boring based correlations applied to boring BR-0273 B-04 are plotted against the minimum misfit V_s profile in Figure 5-1. Estimated V_s values from SPT based correlations are generally close in agreement with the measured profile to a depth of approximately 7 meters, which is located within the layer of silty gravel encountered in the boring. Below this depth, V_s values increase significantly indicating that rock is encountered at a shallower depth at the locality of the survey as compared to the boring log. V_s values estimated using both SPT and RQD based correlations significantly underpredict V_s . In the rock layer encountered in the boring, estimated values of V_s reach a maximum of nearly 2000 m/s while the measured profile

indicates that V_s is approximately 4053 m/s at these depths. This value of 2000 m/s is also below the boundaries of the best 1000 profiles. Boring BR-0273 B-04 indicates that soils continue to a depth of 14 meters, however measured V_s at these depths is higher than is possible for sands and clays (Oldenberg et al. 2017). Estimates of V_s using SPT based methods below 7.61 meters in depth will not be considered in analysis.

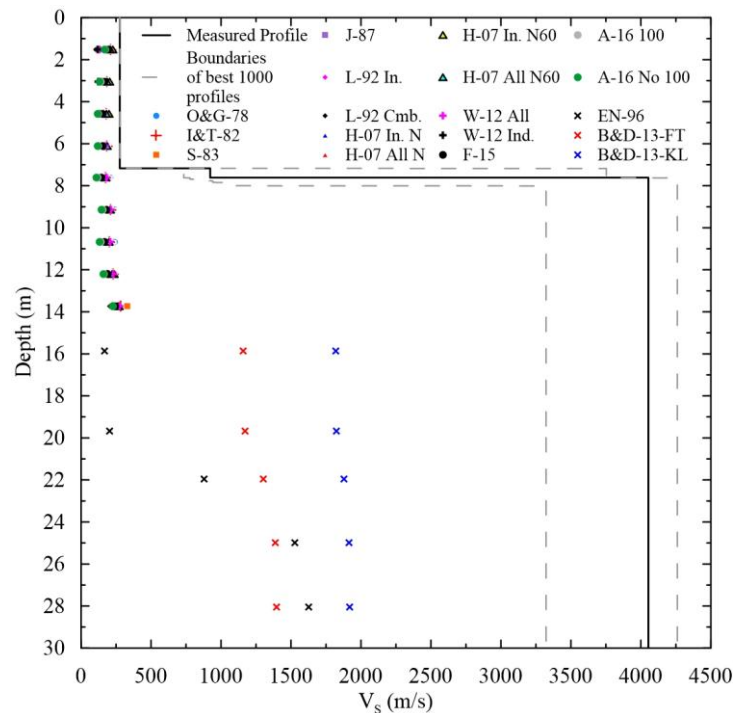


Figure 5-1: Boring based estimates plotted alongside the measured profile for Cedar Bluff site. Boundaries of the best 1000 inverted ground profiles are shown by dashed lines. Refer to Table 5-1 for acronym definitions.

5.2.2 West Alabama Sites

At sites within the West Alabama group, borings were all drilled to a depth of approximately 100 feet (30m) with no rock being encountered. V_s was measured at all sites using the MASW technique. Soils primarily consisted of clays of varying degrees of plasticity with some interbedded sands. A limited amount of silts were encountered at the Moundville and Big Prairie Creek sites.

Beaver Creek Site

Results of boring based correlations applied to Boring 4-BR1767L are plotted alongside the minimum misfit V_s profile from survey line 1 in

Figure 5-2. Correlated values of V_s tend to be in agreement with each other and are centered around the measured profile up to a depth of approximately 3 meters. To a depth of approximately 19 meters, correlated values tend to be lower than the measured profile but are generally close in value to the minimum V_s value from the best 1000 profiles. From depths of 19 to 30 meters, the correlated values of V_s tend to underpredict as compared to the measured profile with only the correlation equation from Imai and Tonouchi (1982) providing estimates that are close in value to the minimum value of V_s from the best 1000 profiles.

Results for Boring 4-BR1762AL are plotted alongside the minimum misfit V_s profile from survey line 2 in Figure 5-3. There is more scatter at depths below 5 meters and all correlations tend to underpredict V_s . Blowcounts for these shallower depths are low due to the use of a hollow stem auger in proximity to the water table (NASEM 2017). From 5 meters to 19 meters in depth, the equations presented in Imai and Tonouchi (1982) and the sand equation using an energy corrected blowcount presented in Hasancebi and Ulusay (2007) most closely match the measured profile and are within the range of V_s values from the best 1000 profiles. From 5 to 19 meters in depth all other correlations underpredict V_s . At depths below 19 meters all correlations underpredict V_s and fall below the boundaries of the best 1000 profiles.

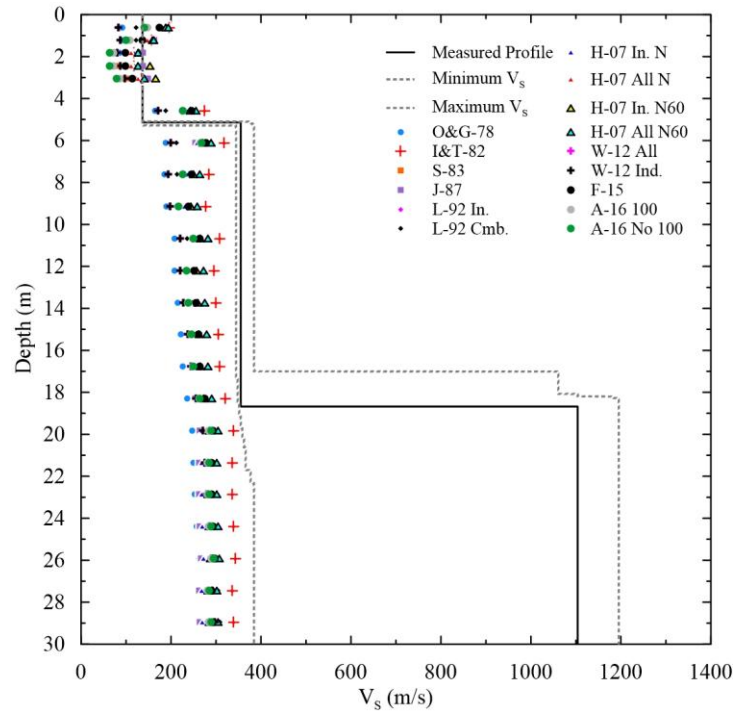


Figure 5-2: Boring based estimates plotted alongside the measured profile for Beaver Creek survey line 1. Boundaries of the best 1000 inverted ground profiles are shown by dashed lines. Refer to Table 5-1 for acronym definitions.

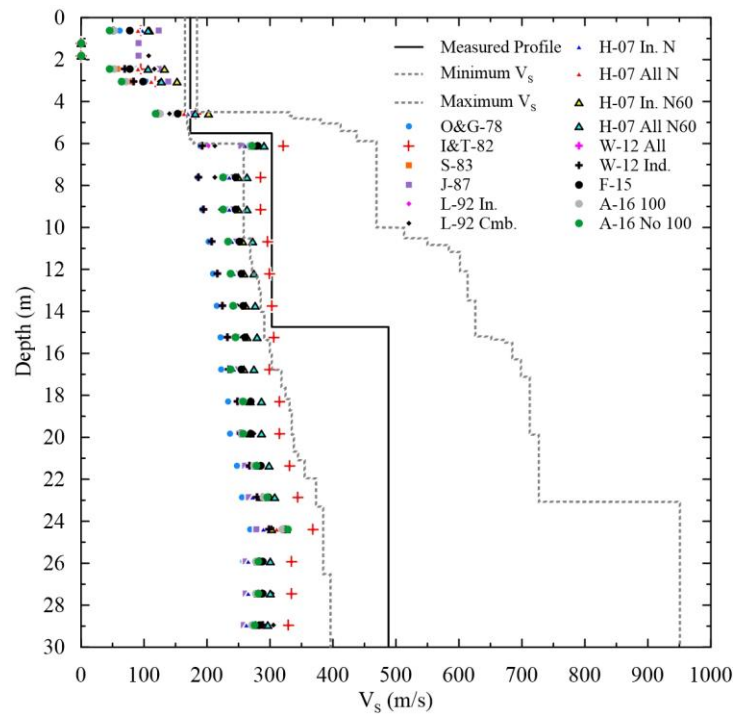


Figure 5-3: Boring based estimates plotted alongside the measured profile for Beaver Creek survey line 2. Boundaries of the best 1000 inverted ground profiles are shown by dashed lines. Refer to Table 5-1 for acronym definitions.

Big Prairie Creek Site

Results of SPT based correlations applied to Boring 8-BR3385R-2 located nearest to the MASW survey line are plotted alongside the minimum misfit V_s profile in Figure 5-4. At depths of less than 4 meters, the correlated values of V_s are distributed around the measured profile with a slight bias towards overestimating V_s . To a depth of 12 meters, V_s values are initially all lower than the measured profile but begin to overestimate at approximately 8 meters in depth. From 12 meters to the full depth of 30 meters in the boring, all correlations underestimate V_s with no estimates being within the range of possible V_s values from the best 1000 profiles.

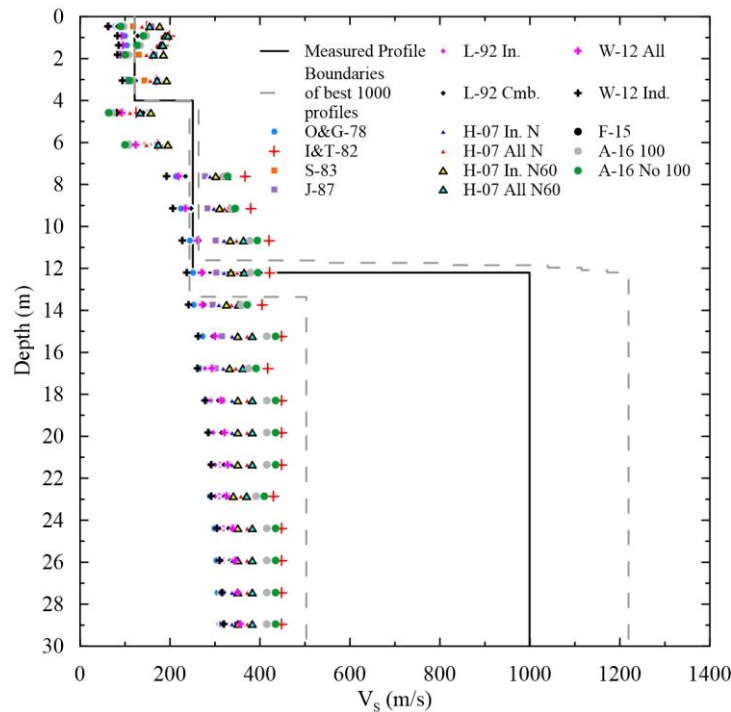


Figure 5-4: Boring based estimates plotted alongside the measured profile for Big Prairie Creek site. Boundaries of the best 1000 inverted ground profiles are shown by dashed lines. Refer to Table 5-1 for acronym definitions.

Coldwell Creek Site

Results of SPT based correlations applied to Boring 10-BR4135 located nearest to the active MASW survey line are plotted alongside the minimum misfit V_s profile in Figure 5-5. At all depths most of the correlations tend to underpredict V_s . The correlation equation presented in Seed et al. (1983) tends to overpredict at shallower depths but is the only correlation to capture

the higher velocity sand layers below 14 meters in the boring. The correlation equation presented in Imai and Tonouchi (1982) tends to match the minimum misfit profile well up to 14 meters in depth. Below depths of 14 meters, the range of possible V_s values is wide and most estimates are within the boundaries of the best 1000 profiles to the full depth of the boring.

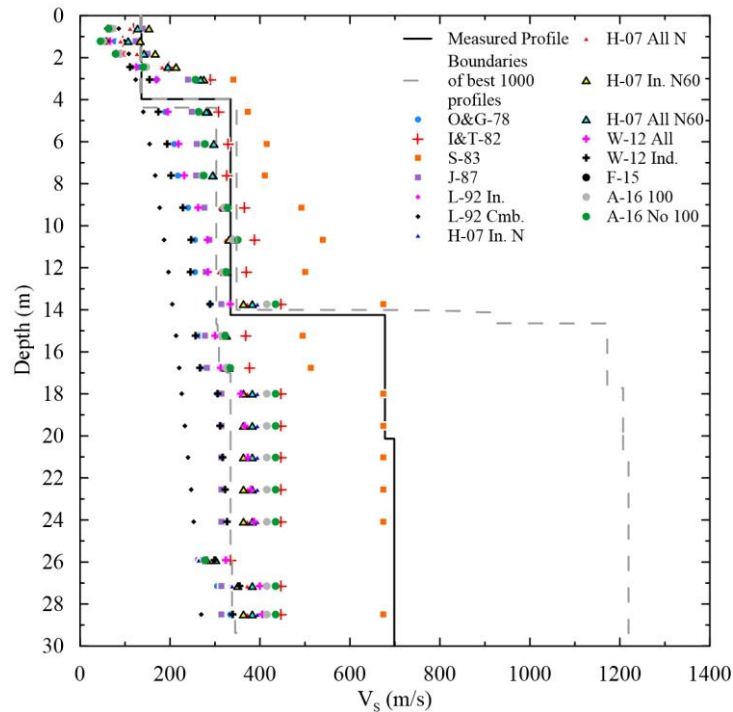


Figure 5-5: Boring based estimates plotted alongside the measured profile for Coldwell Creek site. Boundaries of the best 1000 inverted ground profiles are shown by dashed lines. Refer to Table 5-1 for acronym definitions.

Moundville Site

Results of SPT based correlations applied to Boring 11-4588L located nearest to survey line 1 are plotted alongside the minimum misfit V_s profile in Figure 5-6. At depths below 3 meters there is significant scatter in correlated values of V_s . Below that depth correlated values tend to increase and match the measured profile well until a depth of 21 meters where measured V_s increases significantly to 1104 m/s. None of the presented correlations approach the minimum misfit profile below this depth but are within the range of V_s values taken from the best 1000 profiles

Results of SPT based correlations applied to Boring 11-4590L located nearest to survey line 2 are plotted alongside the minimum misfit V_s profile in Figure 5-7. At depths below 3 meters all presented correlations underestimate V_s as compared to the measured profile. Similarly to survey line 1 for Moundville, correlated values tend to increase with depth and match the minimum misfit profile well until a depth of approximately 24 meters where the minimum misfit profile increases significantly. None of the presented correlations approach the minimum misfit profile below this depth but are within the possible range of V_s values taken from the best 1000 profiles.

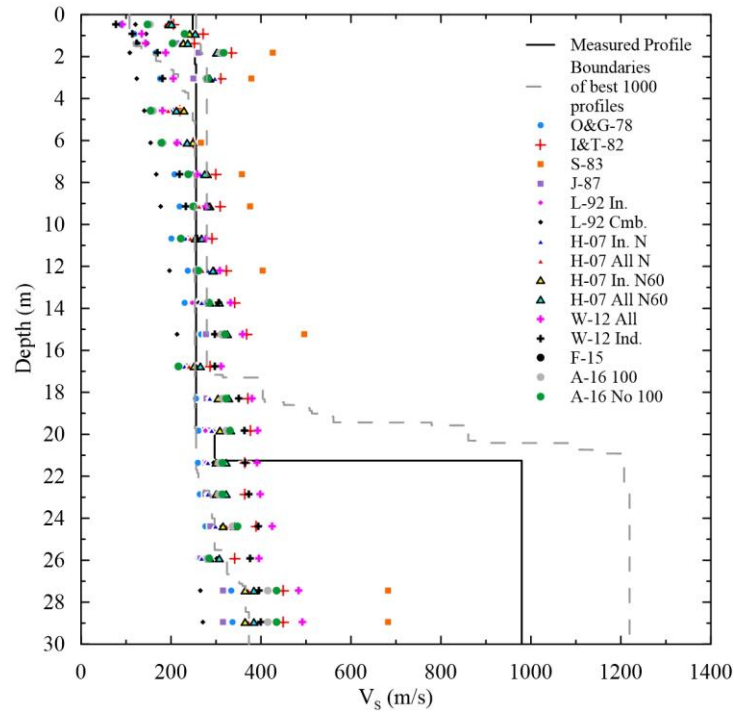


Figure 5-6: Boring based estimates plotted alongside the measured profile for Moundville survey line 1. Boundaries of the best 1000 inverted ground profiles are shown by dashed lines. Refer to Table 5-1 for acronym definitions.

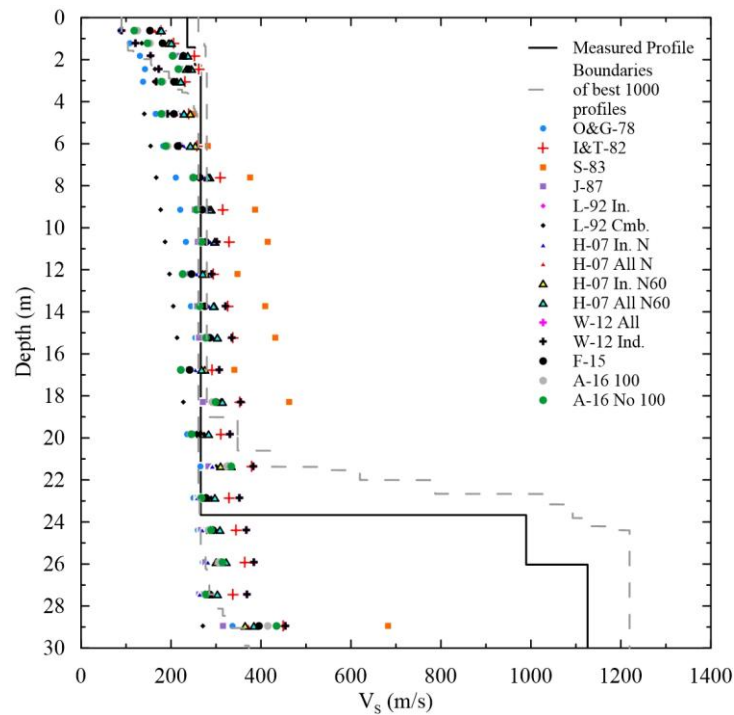


Figure 5-7: Boring based estimates plotted alongside the measured profile for Moundville survey line 2. Boundaries of the best 1000 inverted ground profiles are shown by dashed lines. Refer to Table 5-1 for acronym definitions.

Greensboro Site

Results of SPT based correlations applied to Boring 11-BR4292L located nearest to the active MASW survey line are plotted alongside the minimum misfit V_s profile survey in Figure 5-8. At shallower depths of less than 2 meters, correlated values are scattered around the measured profile to a depth of 8 meters. Between 8 and 19 meters in depth, estimated values tend to overpredict relative to the minimum misfit profile but generally are within the boundaries of the best 1000 profiles. At a depth of 19 meters, the measured profile increases in velocity significantly and is underestimated by all correlations with the exception of the correlation presented in Seed et al. (1983) that overestimates relative to the minimum misfit profile. The boundaries of the best 1000 profiles are broad at these depths so all estimated results are within the boundaries with the exception of the Lee (1992) equations.

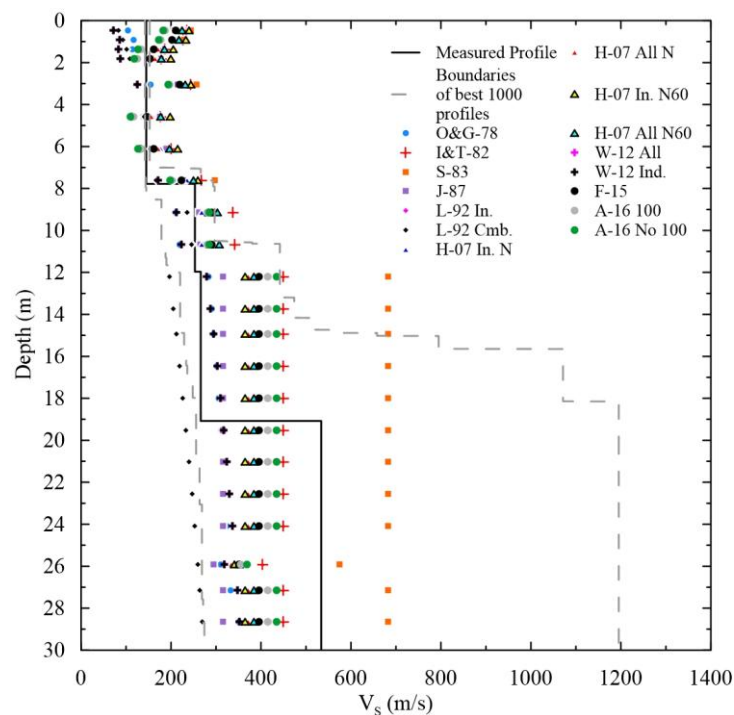


Figure 5-8: Boring based estimates plotted alongside the measured profile for Greensboro site. Boundaries of the best 1000 inverted ground profiles are shown by dashed lines. Refer to Table 5-1 for acronym definitions.

5.2.3 Northwest Alabama Sites

Sites within the Northwest Alabama group have borings drilled to varying depths with rock being encountered at all sites with the exception of the site at Russellville High School. Borings are drilled to a depth of 25 feet (7.6m) at Russellville High School and rock was not encountered at that depth. Rock encountered at these sites is all sedimentary, being either sandstone, limestone, or shale. Soils encountered are primarily clays and sands with some inclusions of gravel at the Russellville High School site.

Duck River Site

Results of boring based correlations applied to the Duck River site are presented in Figure 5-9 alongside the median V_s profile from a refraction survey. Additionally, the probable range of measured V_s values are plotted as dotted lines. At depths of less than 4m layers of sand were encountered with all SPT based correlations tending to underpredict V_s at those depths while the correlation presented in Seed et al. (1983) overpredicts V_s from the median profile but still within the probable range. Below the layer of sands, sandstone was encountered in the boring log with RQD values ranging from 27 to 79. RQD based correlations are more scattered than SPT based correlations with only the Biringen and Davie (2013) Key Largo equation providing estimates close to the measured profile.

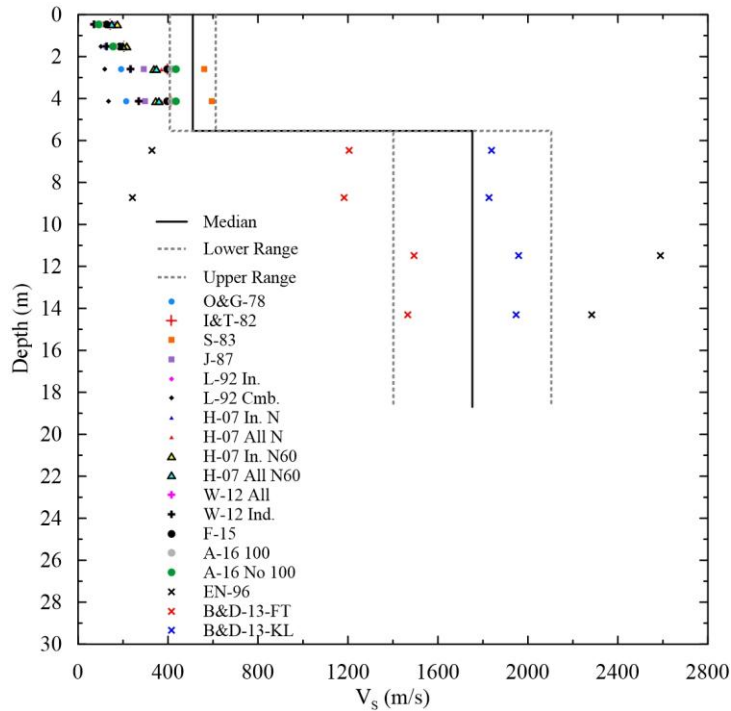


Figure 5-9: Boring based estimates plotted alongside the measured profile for Duck River site. Dashed lines represent the probable range of V_s values from a refraction survey. Refer to Table 5-1 for acronym definitions.

Russellville High School Site

Results of boring based correlations applied to the first active survey location at Russellville High School are plotted alongside the minimum misfit V_s profile in Figure 5-10 while results for the second survey line are presented in Figure 5-11.

Both borings drilled at the Russellville High School sites located nearest the active survey lines were both drilled to a depth of only 25 feet (7.62 meters). For these shallower depths there is more scatter as compared to correlated results of other borings. At depths of less than 2 meters for the first active survey, estimated values are the closest to the minimum misfit profile. Below this depth the estimated values lie below the minimum misfit profile but are generally within the boundaries of the best 1000 profiles.

For the second survey line estimated values are generally scattered about the measured profile to a depth of approximately 5 meters where estimated values then all fall below the

measured profile. At a depth of approximately 1 meter sampler refusal was met with a capped blowcount of 100 being used in correlation.

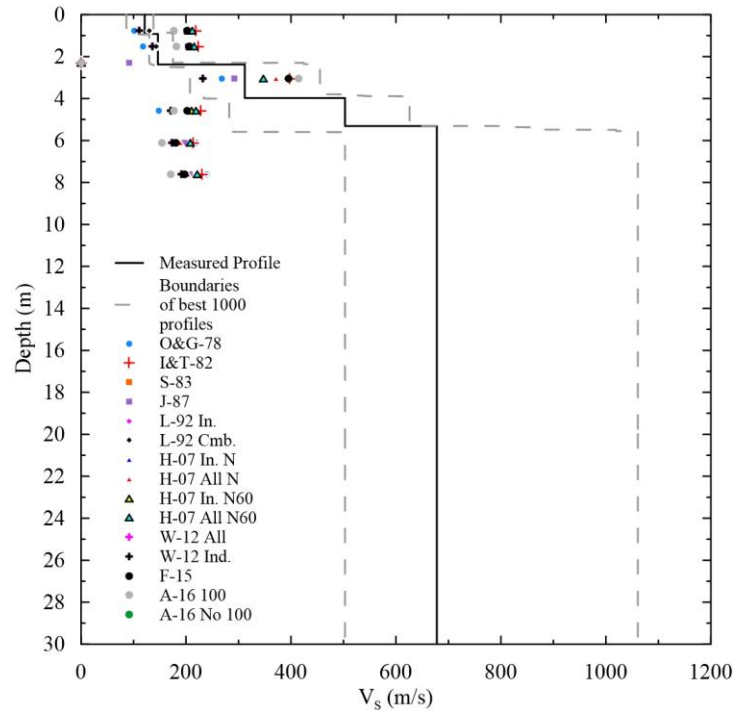


Figure 5-10: Boring based estimates plotted alongside the measured profile for Russellville High School survey line 1. Boundaries of the best 1000 inverted ground profiles are shown by dashed lines. Refer to Table 5-1 for acronym definitions.

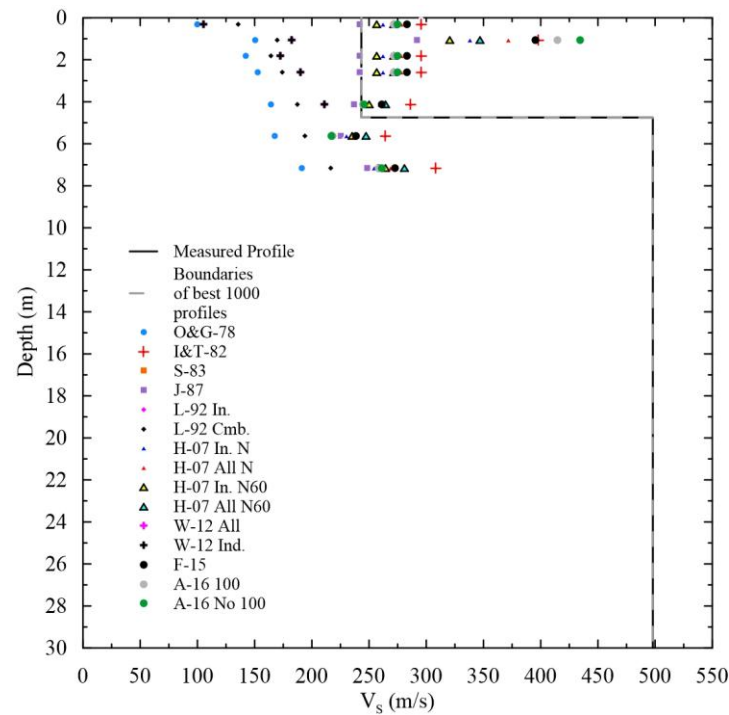


Figure 5-11: Boring based estimates plotted alongside the measured profile for Russellville High School survey line 2. Boundaries of the best 1000 inverted ground profiles are shown by dashed lines. Refer to Table 5-1 for acronym definitions.

Lauderdale County Site

Results of boring based correlations applied to the refraction survey line at the Lauderdale County Site are shown in Figure 5-12 alongside the median V_s profile from a refraction survey. Additionally, the probable range of measured V_s values are plotted as dotted lines. A single SPT was performed at this location prior to rock coring to a depth of 10.47 meters. SPT based correlations all give a similar value for V_s . Results of RQD correlations are more scattered and all overestimate the V_s of the rock layer in the depths that the refraction survey was able to measure.

Results of boring based correlations applied to the MASW survey line at the Lauderdale County Site are shown in Figure 5-13 where estimated values of V_s are plotted alongside the minimum misfit V_s profile. At this location rock was encountered at a depth of 8 meters, deeper than at the location of the refraction survey. For the SPT based correlations applied, they all provide similar V_s values and tend to underestimate V_s at all depths. RQD based correlations applied to rock encountered generally overestimate V_s in the rock layers. The Key Largo equation presented in Biringen and Davie (2013) provides the closest estimate however it is still an overestimate. The equation derived from the one presented in El-Naqua (1996) provides the least reliable results, both over and under predicting V_s within the rock layer.

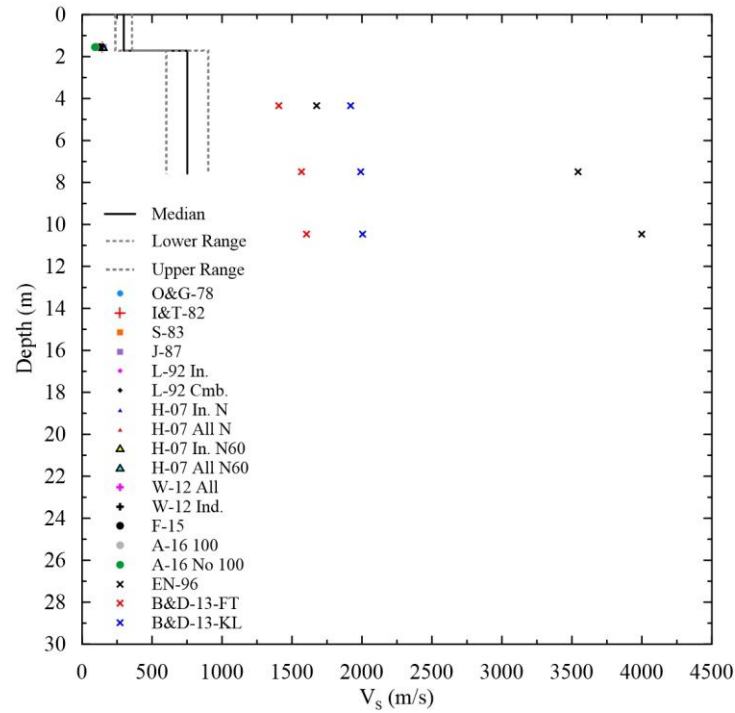


Figure 5-12: Boring based estimates plotted alongside the measured profile for Lauderdale County Refraction survey. Dashed lines represent the probable range of V_s values. Refer to Table 5-1 for acronym definitions.

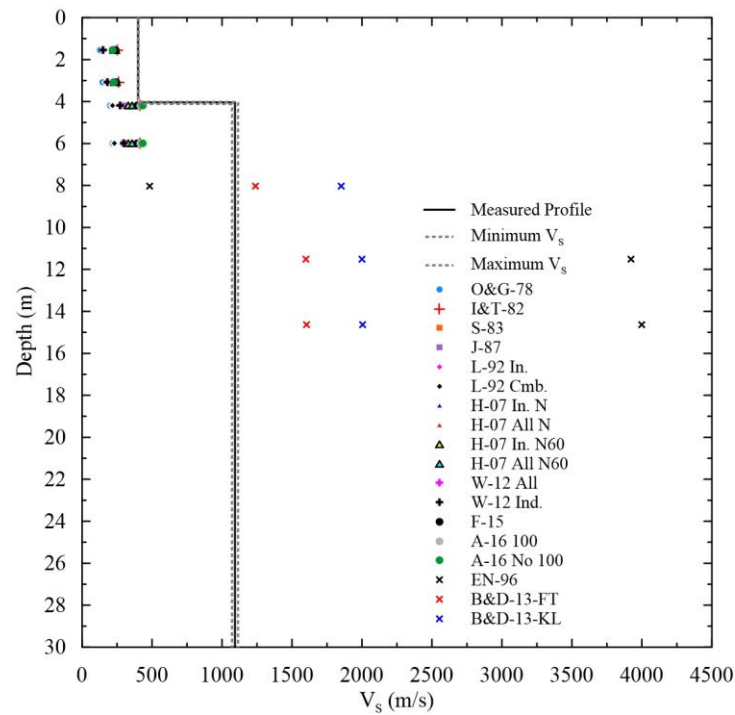


Figure 5-13: Boring based estimates plotted alongside the measured profile for Lauderdale County MASW survey. Boundaries of the best 1000 inverted ground profiles are shown by dashed lines. Refer to Table 5-1 for acronym definitions.

Bluewater Creek Site

Results of boring based correlations applied to the active survey line at the Bluewater Creek Site are shown in Figure 5-14 median V_s profile from a refraction survey. Additionally, the probable range of measured V_s values are plotted as dotted lines. At shallower depths than where rock was encountered at 4 meters, SPT based correlations all tend to underestimate V_s and are generally close in value. In the rock layer encountered, RQD based correlations provide similar performance as they do with other rock sites in this study. All of the RQD based correlations generally overpredict V_s with the Fort Thompson equation presented in Biringer and Davie (2013) providing the closest estimate.

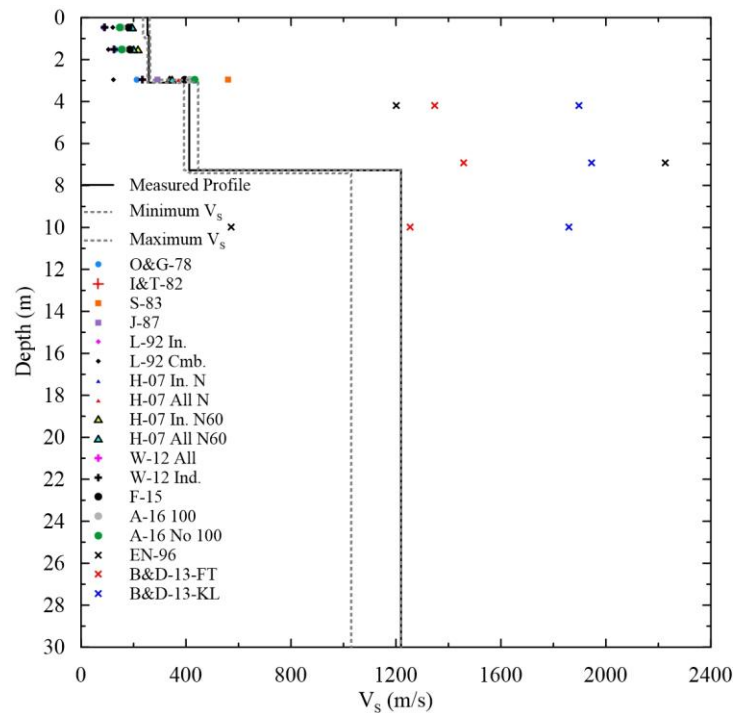


Figure 5-14: Boring based estimates plotted alongside the measured profile for Bluewater Creek site. Boundaries of the best 1000 inverted ground profiles are shown by dashed lines. Refer to Table 5-1 for acronym definitions.

Blount County Site

Results of boring based correlations applied to the active survey line at the Blount County Site are shown in Figure 5-15 median V_s profile from a refraction survey. Additionally, the probable range of measured V_s values are plotted as dotted lines. Rock was encountered at

a depth of 4 meters at this site. SPT based correlation results all give a similar value for V_s and all underestimate as compared to the measured profile. RQD based correlations again perform in a similar manner at this site as compared to others. RQD based correlations generally overestimate V_s at all sites with the Fort Thompson equation presented in Biringen and Davie (2013) providing the closest estimate. At this site the Fort Thompson equation provides a much closer estimate compared to the measured profile than other sites with all estimated values falling within the probable range of V_s .

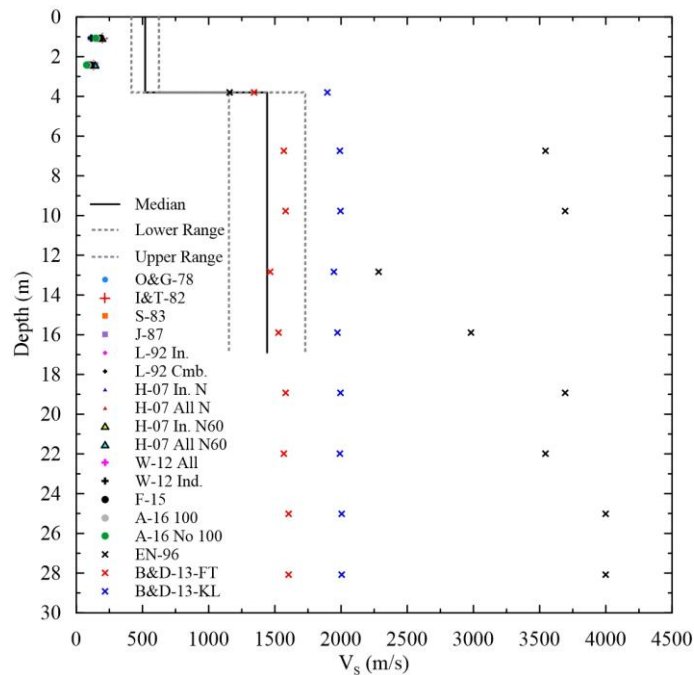


Figure 5-15: Boring based estimates plotted alongside the measured profile for Blount County Refraction survey. Dashed lines represent the probable range of V_s values. Refer to Table 5-1 for acronym definitions.

5.3 HVSR Results

Passive HVSR surveys were conducted at all of the sites visited as a part of this study. A total of 47 unique HVSR curves were able to be calculated from the collected data with only 4 curves failing to pass SESAME reliability standards. Of the 43 reliable curves, only 13 pass SESAME checks for peak clarity. A clear peak was defined by SESAME (2004) as a single dominant peak with an amplitude greater than 2, narrow bandwidth, minimal secondary peaks, and stability across multiple time windows. Sites with deeper sediments tend to produce flatter

HVSR curves due to a likely absence of impedance at depth (SESAME 2004). All of the sites within the West Alabama group had sediments of a minimum thickness of 30 meters making this a likely reason for unclear peaks at these sites. For the Russellville High School sites, anthropogenic noise was present due to power lines and an electronic sign within a few hundred meters of survey locations. The following sections will present an example of data processing for a HVSR curve with a clear and reliable peak and for an unreliable curve, results of HVSR surveys, and estimates of V_{S30} from the methods discussed in Chapter 2.

For the first example of data processing, the Pasi Gemini sensor at the Lauderdale County site's second survey location was selected. Figure 5-16 presents the three-component noise recording. The HVSR analysis of this recording produced a peak at a frequency of 26.383 Hz with a corresponding peak amplitude of 3.3. The analysis was conducted over a frequency range of 1 to 90 Hz using a 120-second window length, with 10 accepted windows contributing to the final mean HVSR curve. The variability in the peak frequency, represented by a log standard deviation ($\sigma_{\log}$) of 0.335 Hz, falls within acceptable limits for stable peak identification and does satisfy both the clarity and reliability criteria defined by the SESAME (2004) guidelines.

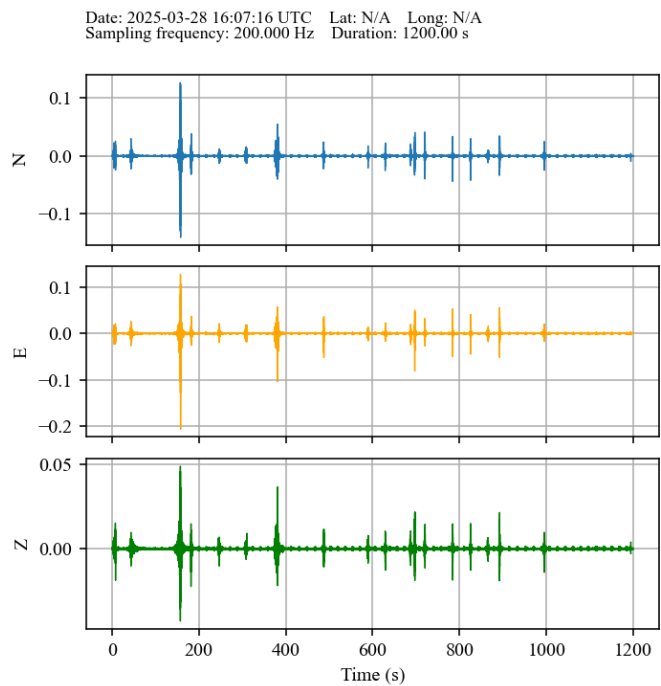


Figure 5-16: Three-component ambient noise recording measured by the PASI Gemini sensor at the Lauderdale County site’s second survey location

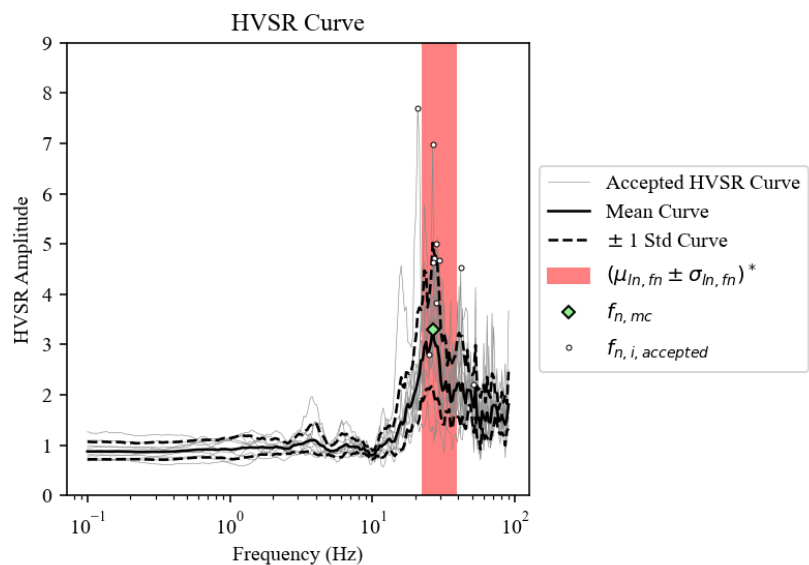


Figure 5-17: HVSR curves for Lauderdale County second survey location as measured by PASI Gemini sensor

For the second example of data processing, the Geotiny 21 sensor at the Cedar Bluff site was selected. Figure 5-18 presents the three-component noise recording measured by the Geotiny 21 sensor at the Cedar Bluff site. The HVSr analysis of this recording produced a peak at a frequency of 10.1 Hz with a corresponding peak amplitude of 4.2. The analysis was conducted over a frequency range of 1 to 50 Hz using a 120-second window length, with 26 accepted windows contributing to the final mean HVSr curve. The variability in the peak frequency, represented by a log standard deviation ($\sigma_{\log}$) of 0.915 Hz, does not fall within acceptable limits for stable peak identification and does not satisfy both the clarity and reliability criteria defined by the SESAME (2004) guidelines.

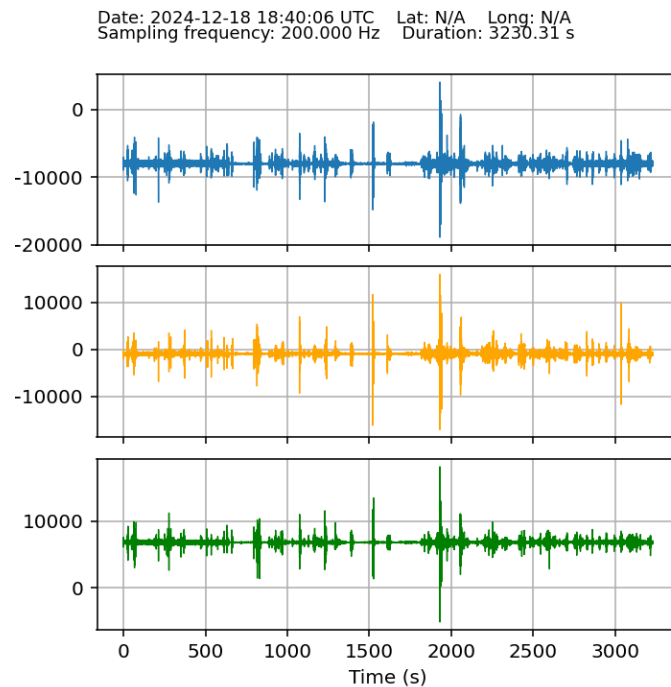


Figure 5-18: Three-component ambient noise recording measured by the Geotiny 21 sensor at the Cedar Bluff site

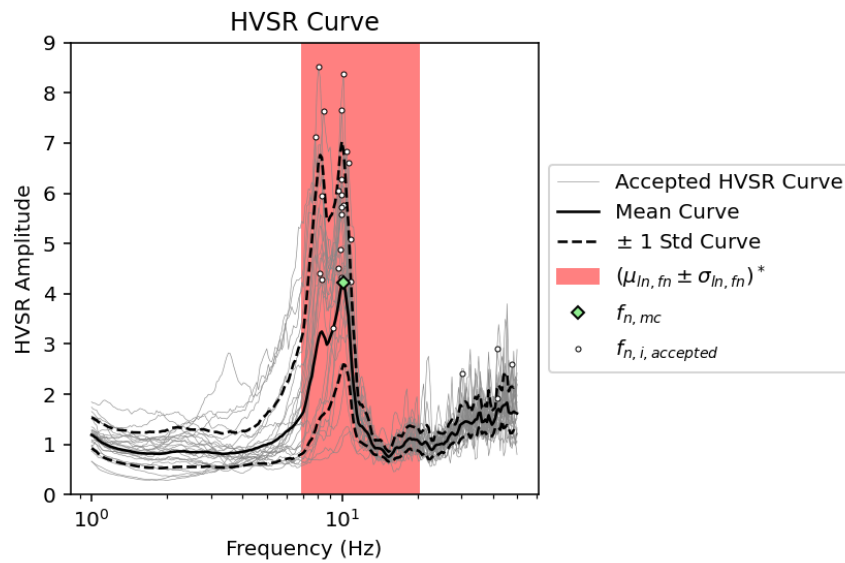


Figure 5-19: HVSR curves for Cedar Bluff site as measured by Geotiny 21 sensor

For brevity, the other 45 unique curves and 3-component signal files are attached in the appendix of this document. Table 5-2 contains the full set of results of HVSR surveys. The presented results include the fundamental frequencies along with a range of plus and minus one standard deviation, the peak amplitude and its respective standard deviation along with results of clarity and reliability checks.

HVSR-based correlations presented in Chapter 2: were then applied to provide estimates of V_{S30} . For each correlation, V_{S30} was calculated using the mean fundamental frequency along with a value of plus and minus one standard deviation. For some of the correlations presented, the authors developed the equations to provide results as a range of V_{S30} values. For those correlations the range was extended by using plus and minus one standard deviation values for the “high” and “low” sides of the correlation. Estimated values using HVSR-based correlations are presented in the following sections.

Table 5-2: Results of HVSr surveys

Site	Instrument	f_0 (Hz)	$f_0 - \sigma_{\log}$ (Hz)	$f_0 + \sigma_{\log}$ (Hz)	A_0	σ_A	Reliable	Clear
Cedar Bluff	GTN21	10.1	4.1	25.3	4.2	1.8	x	x
Cedar Bluff	GTN30	9.2	3.0	28.7	3.1	1.7	✓	x
Cedar Bluff	PASI	10.0	4.4	22.9	3.8	3.0	x	x
Beaver Creek Line 1	GTN21	3.9	2.6	6.0	3.7	1.7	x	x
Beaver Creek Line 1	PASI	6.9	5.4	8.7	3.3	1.6	✓	x
Beaver Creek Line 2	GTN21	7.3	5.1	10.6	1.9	0.9	✓	x
Beaver Creek Line 2	GTN30	7.3	5.3	9.9	1.8	0.8	✓	x
Beaver Creek Line 2	PASI	6.6	5.9	7.4	2.1	0.6	✓	✓
Big Prairie Creek Line 1	GTN21	6.2	3.1	12.5	2.8	1.4	✓	x
Big Prairie Creek Line 1	GTN21_B	6.6	4.0	10.9	3.6	1.9	✓	x
Big Prairie Creek Line 1	GTN30	6.6	6.3	7.0	5.0	1.8	✓	✓
Big Prairie Creek Line 1	GTN30_B	6.5	5.0	8.5	4.5	1.6	✓	x
Big Prairie Creek Line 1	PASI	6.2	3.6	10.8	2.5	1.2	✓	x
Big Prairie Creek Line 2	GTN21	7.2	6.6	8.0	7.9	1.4	✓	✓
Big Prairie Creek Line 2	GTN30	6.9	6.4	7.5	8.8	1.2	✓	x
Big Prairie Creek Line 2	GTN30_B	6.5	4.6	9.3	4.1	1.6	✓	x
Coldwell Creek Line 1	GTN21	0.9	0.2	4.8	2.0	0.2	✓	x
Coldwell Creek Line 1	PASI	5.6	2.7	11.7	1.7	0.4	✓	x
Coldwell Creek Line 2	GTN30	0.8	0.2	3.2	2.0	0.4	✓	x
Moundville Line 1	GTN21	0.6	0.5	0.7	4.7	1.6	✓	✓
Moundville Line 1	PASI	1.0	0.1	9.5	1.6	0.7	✓	x
Moundville Line 2	GTN21	0.6	0.5	0.7	4.1	1.2	✓	✓
Moundville Line 2	GTN30	0.6	0.5	0.7	4.8	1.3	✓	✓
Moundville Line 2	PASI	0.4	0.0	5.9	1.4	0.4	✓	x
Greensboro	GTN21	3.6	0.8	16.7	2.8	1.5	✓	x
Greensboro	PASI	3.5	1.1	10.9	2.1	0.6	✓	x
Duck River	GTN21	18.0	17.0	19.0	4.8	2.1	✓	✓
Duck River	GTN30	18.0	12.1	26.7	4.6	1.6	✓	✓
Duck River	PASI	18.0	14.1	22.9	3.9	2.1	✓	x
RHS Line 1	GTN21	5.7	3.8	8.6	2.6	0.5	✓	x
RHS Line 1	GTN30	6.4	1.6	25.0	2.6	0.8	✓	x
RHS Line 1	PASI	6.6	2.2	19.5	1.8	1.4	✓	x
RHS Line 2	GTN21	7.0	5.2	9.5	2.4	0.9	✓	x
RHS Line 2	GTN30	7.0	5.3	9.3	3.0	0.7	✓	x
RHS Line 2	PASI	7.9	5.1	12.3	0.8	0.2	✓	x
Lauderdale County Line 1	GTN21	24.6	13.3	45.3	1.9	0.8	✓	x
Lauderdale County Line 1	GTN30	24.3	20.1	29.5	2.0	0.8	✓	x
Lauderdale County Line 1	PASI	26.2	21.2	32.4	1.4	0.4	✓	x
Lauderdale County Line 2	GTN21	24.4	12.8	46.3	4.8	2.2	✓	✓
Lauderdale County Line 2	GTN30	26.4	14.6	47.7	7.0	4.5	x	x
Lauderdale County Line 2	PASI	26.4	18.9	36.9	3.3	1.7	✓	✓
Blewater Creek	GTN21	24.1	15.3	37.8	4.6	2.4	✓	✓
Blewater Creek	GTN30	50.3	39.9	63.4	2.6	0.4	✓	✓
Blewater Creek	PASI	19.8	16.5	23.8	1.8	0.5	✓	x
Blount County	GTN21	15.1	12.8	17.9	8.4	3.5	✓	x
Blount County	GTN30	15.1	12.6	18.3	9.2	3.4	✓	✓
Blount County	PASI	18.0	14.7	21.9	6.2	3.4	✓	x

Ghofrani and Atkinson (2014)

Table 5-3 presents V_{S30} estimates using the Ghofrani and Atkinson (2014) model. The authors present a range of uncertainty in the model using $\pm$ values within the constants in the model. For these results the mean f_0 and A_0 along with values of plus and minus one standard deviation values were used in the high end and low end of the model.

The model is only intended for use at sites with a clear peak frequency according to SESAME standards with cells highlighted in green representing results from HVSR curves with clear peaks. The model is not applicable for fundamental frequencies of less than 1Hz with dashed lines representing locations where the model was not able to be applied.

Table 5-3: V_{S30} estimates using Ghofrani and Atkinson (2014) model. Cells highlighted in green indicate estimates from HVSr curves with clear peaks while dashed lines indicate locations where the model was not able to be applied.

Site	Sensor	Mean Value (m/s), High End	-1 σ (m/s), High End	+1 σ (m/s), High End	Mean Value (m/s), Low End	-1 σ (m/s), Low End	+1 σ (m/s), Low End
Cedar Bluff	GTN30	545	679	529	486	604	464
Beaver Creek Line 1	PASI	499	683	421	452	601	387
Beaver Creek Line 1	GTN21	676	903	585	591	770	516
Beaver Creek Line 1	GTN30	692	901	600	604	768	529
Beaver Creek Line 2	PASI	630	738	563	557	642	503
Big Prairie Creek Line 1	GTN21	533	689	485	480	612	436
Big Prairie Creek Line 1	GTN21_B	471	642	412	430	572	378
Big Prairie Creek Line 1	GTN30	397	500	340	370	454	322
Big Prairie Creek Line 1	GTN30_B	416	496	373	385	453	348
Big Prairie Creek Line 1	PASI	563	721	505	504	635	453
Big Prairie Creek Line 2	GTN21	315	343	294	300	325	282
Big Prairie Creek Line 2	GTN30	296	316	280	285	302	271
Big Prairie Creek Line 2	GTN30_B	441	541	393	406	490	364
Coldwell Creek Line 1	GTN21	---	---	578	---	---	519
Coldwell Creek Line 1	PASI	677	678	695	595	605	601
Coldwell Creek Line 2	GTN30	---	---	512	---	---	470
Moundville Line 1	GTN21	---	---	---	---	---	---
Moundville Line 1	PASI	514	---	643	482	---	563
Moundville Line 2	GTN21	---	---	---	---	---	---
Moundville Line 2	GTN30	---	---	---	---	---	---
Moundville Line 2	PASI	---	---	675	---	---	593
Greensboro	GTN21	483	---	510	445	---	453
Greensboro	PASI	553	528	600	502	493	528
Duck River	GTN21	482	641	404	431	555	367
Duck River	GTN30	497	577	457	442	509	408
Duck River	PASI	537	763	448	474	650	402
RHS Line 1	GTN21	546	571	533	492	516	478
RHS Line 1	GTN30	560	530	623	502	491	537
RHS Line 1	PASI	670	1179	603	588	991	524
RHS Line 2	GTN21	584	709	521	520	621	467
RHS Line 2	GTN30	521	568	492	470	510	444
RHS Line 2	PASI	1067	1146	1027	885	951	848
Lauderdale County Line 1	GTN21	829	975	774	692	809	643
Lauderdale County Line 1	GTN30	817	1032	709	683	843	600
Lauderdale County Line 1	PASI	1015	1156	928	827	932	761
Lauderdale County Line 2	GTN21	513	630	473	453	550	415
Lauderdale County Line 2	PASI	632	863	541	544	721	470
Bluewater Creek	GTN21	525	726	453	461	621	402
Bluewater Creek	GTN30	812	858	779	670	707	643
Bluewater Creek	PASI	818	927	749	687	770	633
Blount County	GTN21	350	453	299	325	410	282
Blount County	GTN30	333	410	292	311	375	276
Blount County	PASI	421	614	347	382	535	320

McNamara et al. (2015)

Table 5-4 presents V_{S30} estimates using the McNamara et al. (2015) model. The authors do not state any limitations on the use of their model outside of requiring a clear peak frequency. The model was developed using a total of 21 data pairs of HVSR and V_{S30} measurements with peak frequencies ranging from 0.7 to 10 Hz. The authors chose a linear least squares regression in development of their model. For sites with higher peak frequencies, the model provides estimates with a larger magnitude with the GTN30 sensor at the Bluewater Creek site recording a peak frequency of 50.3 Hz.

Table 5-4: V_{s30} estimates using McNamara et al. (2015) model. Cells highlighted in green indicate estimates from HVSR curves with clear peaks.

Site	Sensor	Mean Value (m/s)	-1 σ (m/s)	+1 σ (m/s)
Cedar Bluff	GTN30	735	409	1746
Beaver Creek Line 1	PASI	612	537	708
Beaver Creek Line 1	GTN21	636	519	803
Beaver Creek Line 1	GTN30	632	531	771
Beaver Creek Line 2	PASI	600	563	641
Big Prairie Creek Line 1	GTN21	575	414	902
Big Prairie Creek Line 1	GTN21_B	599	463	823
Big Prairie Creek Line 1	GTN30	600	581	620
Big Prairie Creek Line 1	GTN30_B	593	514	696
Big Prairie Creek Line 1	PASI	579	442	816
Big Prairie Creek Line 2	GTN21	630	595	668
Big Prairie Creek Line 2	GTN30	614	587	645
Big Prairie Creek Line 2	GTN30_B	593	492	736
Coldwell Creek Line 1	GTN21	299	263	506
Coldwell Creek Line 1	PASI	544	393	860
Coldwell Creek Line 2	GTN30	298	266	420
Moundville Line 1	GTN21	287	283	291
Moundville Line 1	PASI	307	260	748
Moundville Line 2	GTN21	287	283	291
Moundville Line 2	GTN30	286	283	290
Moundville Line 2	PASI	275	256	562
Greensboro	GTN21	443	296	1122
Greensboro	PASI	437	313	820
Duck River	GTN21	1187	1137	1240
Duck River	GTN30	1187	881	1642
Duck River	PASI	1187	988	1441
RHS Line 1	GTN21	551	453	699
RHS Line 1	GTN30	585	339	1551
RHS Line 1	PASI	598	371	1268
RHS Line 2	GTN21	619	525	746
RHS Line 2	GTN30	619	530	737
RHS Line 2	PASI	665	519	892
Lauderdale County Line 1	GTN21	1529	945	2608
Lauderdale County Line 1	GTN30	1518	1298	1786
Lauderdale County Line 1	PASI	1616	1356	1938
Lauderdale County Line 2	GTN21	1519	919	2659
Lauderdale County Line 2	PASI	1624	1234	2169
Bluewater Creek	GTN21	1504	1051	2215
Bluewater Creek	GTN30	2864	2324	3546
Bluewater Creek	PASI	1283	1109	1492
Blount County	GTN21	1041	921	1182
Blount County	GTN30	1041	906	1203
Blount County	PASI	1187	1020	1391

Hassani and Atkinson (2016)

Table 5-5 presents V_{S30} estimates using the Hassani and Atkinson (2016) model. Similarly to the Ghofrani and Atkinson (2014) model, a range of uncertainty is included in the model using $\pm$ values within the constants in calculation. For these results the mean f_0 and A_0 along with values of plus and minus one standard deviation values were used in the high end and low end of the model.

Similar to the last two models, the Hassani and Atkinson (2016) model is only intended for use on clear peak frequencies, represented by cells highlighted in green. For peak frequencies of 2 Hz and lower, the model provides a blanket estimate of 250 m/s as documented in (14). With no limit on the upper end of frequencies that the model can be applied to, it returns estimates that would place sites into classes B and A.

Table 5-5: V_{s30} estimates using Hassani and Atkinson (2016) model. Cells highlighted in green indicate estimates from HVSR curves with clear peaks.

Site	Sensor	Mean Value (m/s), High End	-1 σ (m/s), High End	+1 σ (m/s), High End	Mean Value (m/s), Low End	-1 σ (m/s), Low End	+1 σ (m/s), Low End
Cedar Bluff	GTN30	807	369	1763	514	269	980
Beaver Creek Line 1	PASI	658	559	775	434	379	497
Beaver Creek Line 1	GTN21	688	535	884	450	366	554
Beaver Creek Line 1	GTN30	683	551	848	448	375	535
Beaver Creek Line 2	PASI	642	594	695	426	399	454
Big Prairie Creek Line 1	GTN21	610	376	991	408	273	609
Big Prairie Creek Line 1	GTN21_B	641	453	906	425	319	565
Big Prairie Creek Line 1	GTN30	642	617	668	426	412	440
Big Prairie Creek Line 1	GTN30_B	633	527	761	421	361	490
Big Prairie Creek Line 1	PASI	615	422	898	411	301	561
Big Prairie Creek Line 2	GTN21	680	636	728	446	422	472
Big Prairie Creek Line 2	GTN30	661	625	699	436	416	456
Big Prairie Creek Line 2	GTN30_B	633	496	808	421	344	514
Coldwell Creek Line 1	GTN21	250	250	516	250	250	355
Coldwell Creek Line 1	PASI	569	342	947	385	253	586
Coldwell Creek Line 2	GTN30	250	250	387	250	250	280
Moundville Line 1	GTN21	250	250	250	250	250	250
Moundville Line 1	PASI	250	250	821	250	250	521
Moundville Line 2	GTN21	250	250	250	250	250	250
Moundville Line 2	GTN30	250	250	250	250	250	250
Moundville Line 2	PASI	250	250	593	250	250	398
Greensboro	GTN21	423	250	1213	301	250	720
Greensboro	PASI	413	250	903	296	250	564
Duck River	GTN21	1275	1228	1324	750	727	774
Duck River	GTN30	1275	969	1678	750	598	941
Duck River	PASI	1275	1080	1505	750	654	860
RHS Line 1	GTN21	578	437	765	390	310	492
RHS Line 1	GTN30	623	250	1601	415	250	905
RHS Line 1	PASI	640	303	1351	424	229	787
RHS Line 2	GTN21	667	542	819	439	370	520
RHS Line 2	GTN30	667	549	809	439	374	515
RHS Line 2	PASI	724	534	981	470	365	604
Lauderdale County Line 1	GTN21	1582	1036	2415	896	632	1271
Lauderdale County Line 1	GTN30	1573	1378	1795	892	799	995
Lauderdale County Line 1	PASI	1656	1431	1916	931	825	1050
Lauderdale County Line 2	GTN21	1573	1009	2452	892	618	1287
Lauderdale County Line 2	PASI	1662	1319	2095	934	771	1130
Bluewater Creek	GTN21	1560	1143	2129	886	685	1145
Bluewater Creek	GTN30	2594	2210	3044	1348	1181	1539
Bluewater Creek	PASI	1364	1200	1550	793	713	881
Blount County	GTN21	1134	1011	1270	680	619	748
Blount County	GTN30	1134	996	1291	680	611	757
Blount County	PASI	1275	1113	1461	750	670	839

Stanko and Markušić (2020)

Table 5-6 presents V_{S30} estimates using the Stanko and Markušić (2020) model. Similarly to the Ghofrani and Atkinson (2014) and Hassani and Atkinson (2016) models, a range of uncertainty is included in the model using $\pm$ values within the constants in calculation. For these results the mean f_0 and A_0 along with values of plus and minus one standard deviation values were used in the high end and low end of the model.

The model is only applicable to clear peak frequencies of up to 30 Hz. Cells containing dashes represent HVSr curves with peak frequencies of greater than 30 Hz, where the model was not able to be applied. For peak frequencies of less than 1 Hz, the model returns values of 188 and 228 m/s for the low and high end of the model respectively. The model has a wider bound of uncertainty included than the Ghofrani and Atkinson (2014) and Hassani and Atkinson (2016) models. Values between the low and high ends of the model can differ greatly for those intermediate frequencies between 1 and 10 Hz. For frequencies greater than 10 Hz but less than 30 Hz, the model returns values of 58 and 620 m/s for the low and high end of the model respectively. Due to the large range of uncertainty included in the model, values of V_{S30} for intermediate frequencies can be larger or smaller than the values assigned to the ends of the model.

Table 5-6: V_{S30} estimates using Stanko and *Markušić* (2020) model. Cells highlighted in green indicate estimates from HVSr curves with clear peaks while dashed lines indicate locations where the model was not able to be applied.

Site	Sensor	Mean Value (m/s), High End	-1 σ (m/s), High End	+1 σ (m/s), High End	Mean Value (m/s), Low End	-1 σ (m/s), Low End	+1 σ (m/s), Low End
Cedar Bluff	GTN30	1992	998	680	169	119	520
Beaver Creek Line 1	PASI	1665	1441	1924	154	143	166
Beaver Creek Line 1	GTN21	1730	1385	680	157	140	520
Beaver Creek Line 1	GTN30	1721	1422	2082	157	142	173
Beaver Creek Line 2	PASI	1629	1520	1746	153	147	158
Big Prairie Creek Line 1	GTN21	1557	1015	680	149	120	520
Big Prairie Creek Line 1	GTN21_B	1626	1197	680	152	130	520
Big Prairie Creek Line 1	GTN30	1629	1573	1687	153	150	155
Big Prairie Creek Line 1	GTN30_B	1608	1367	1893	152	139	165
Big Prairie Creek Line 1	PASI	1568	1123	680	150	126	520
Big Prairie Creek Line 2	GTN21	1714	1614	1819	157	152	161
Big Prairie Creek Line 2	GTN30	1671	1591	1755	154	151	158
Big Prairie Creek Line 2	GTN30_B	1608	1297	1995	152	136	169
Coldwell Creek Line 1	GTN21	228	228	1343	188	188	138
Coldwell Creek Line 1	PASI	1463	933	680	144	115	520
Coldwell Creek Line 2	GTN30	228	228	1041	188	188	121
Moundville Line 1	GTN21	228	228	228	188	188	188
Moundville Line 1	PASI	513	228	2024	85	188	170
Moundville Line 2	GTN21	228	228	228	188	188	188
Moundville Line 2	GTN30	228	228	228	188	188	188
Moundville Line 2	PASI	228	228	1517	188	188	147
Greensboro	GTN21	1126	228	680	126	188	520
Greensboro	PASI	1103	553	680	125	88	520
Duck River	GTN21	680	680	680	520	520	520
Duck River	GTN30	680	680	680	520	520	520
Duck River	PASI	680	680	680	520	520	520
RHS Line 1	GTN21	1485	1160	1901	146	128	165
RHS Line 1	GTN30	1585	688	680	150	98	520
RHS Line 1	PASI	1624	839	680	152	109	520
RHS Line 2	GTN21	1683	1403	2020	155	141	170
RHS Line 2	GTN30	1683	1418	1999	155	142	169
RHS Line 2	PASI	1810	1384	680	161	140	520
Lauderdale County Line 1	GTN21	680	680	---	520	520	---
Lauderdale County Line 1	GTN30	680	680	680	520	520	520
Lauderdale County Line 1	PASI	680	680	---	520	520	---
Lauderdale County Line 2	GTN21	680	680	---	520	520	---
Lauderdale County Line 2	PASI	680	680	---	520	520	---
Bluewater Creek	GTN21	680	680	---	520	520	---
Bluewater Creek	GTN30	---	---	---	---	---	---
Bluewater Creek	PASI	680	680	680	520	520	520
Blount County	GTN21	680	680	680	520	520	520
Blount County	GTN30	680	680	680	520	520	520
Blount County	PASI	680	680	680	520	520	520

Sharma Wagle et al. (2026)

Sharma Wagle et al. (2026) presents four unique models for use that will be evaluated separately. The low dimensional models are intended to be used on clear peak frequencies, limiting the dataset to a sample size of 13 for evaluation. The high dimensional models were developed to consider the entire area under the HVSR curve, therefore not requiring clear peak frequencies.

Low dimensional models

Table 5-7 presents estimated V_{S30} values using the random forest model. As the model is only applicable to clear peak frequencies, only estimated values from those sites will be used for evaluation. The model in general provides lower estimates of V_{S30} than previous models and is applicable to peak frequencies of less than 2 Hz. Table 5-8 presents estimated V_{S30} values using the gradient boosted trees model. Estimates using the gradient boosted trees model are generally lower than those using the random forest model.

Table 5-7: V_{s30} estimates using Sharma Wagle et al. (2026) random forest model. Cells highlighted in green indicate estimates from HVSR curves with clear peaks.

Site	Sensor	Mean Value (m/s)	-1 σ (m/s)	+1 σ (m/s)
Cedar Bluff	GTN30	228	248	583
Beaver Creek Line 1	PASI	425	229	560
Beaver Creek Line 1	GTN21	226	235	245
Beaver Creek Line 1	GTN30	227	235	224
Beaver Creek Line 2	PASI	395	202	546
Big Prairie Creek Line 1	GTN21	492	226	265
Big Prairie Creek Line 1	GTN21_B	479	241	616
Big Prairie Creek Line 1	GTN30	495	465	554
Big Prairie Creek Line 1	GTN30_B	500	404	556
Big Prairie Creek Line 1	PASI	425	202	600
Big Prairie Creek Line 2	GTN21	514	459	578
Big Prairie Creek Line 2	GTN30	486	420	551
Big Prairie Creek Line 2	GTN30_B	471	408	551
Coldwell Creek Line 1	GTN21	246	243	235
Coldwell Creek Line 1	PASI	231	236	474
Coldwell Creek Line 2	GTN30	233	243	259
Moundville Line 1	GTN21	254	255	254
Moundville Line 1	PASI	273	261	641
Moundville Line 2	GTN21	276	271	498
Moundville Line 2	GTN30	276	284	276
Moundville Line 2	PASI	245	281	539
Greensboro	GTN21	198	232	453
Greensboro	PASI	207	253	272
Duck River	GTN21	496	510	638
Duck River	GTN30	434	252	614
Duck River	PASI	539	239	565
RHS Line 1	GTN21	258	240	455
RHS Line 1	GTN30	247	243	253
RHS Line 1	PASI	207	240	595
RHS Line 2	GTN21	230	230	233
RHS Line 2	GTN30	226	235	412
RHS Line 2	PASI	267	240	420
Lauderdale County Line 1	GTN21	208	240	624
Lauderdale County Line 1	GTN30	433	222	611
Lauderdale County Line 1	PASI	458	266	359
Lauderdale County Line 2	GTN21	206	228	626
Lauderdale County Line 2	PASI	549	233	324
Bluewater Creek	GTN21	206	228	626
Bluewater Creek	GTN30	233	242	257
Bluewater Creek	PASI	504	456	468
Blount County	GTN21	621	621	599
Blount County	GTN30	616	616	593
Blount County	PASI	601	630	586

Table 5-8: V_{s30} estimates using Sharma Wagle et al. (2026) gradient boosted trees model. Cells highlighted in green indicate estimates from HVSR curves with clear peaks.

Site	Sensor	Mean Value (m/s)	-1 σ (m/s)	+1 σ (m/s)
Cedar Bluff	GTN30	209	237	475
Beaver Creek Line 1	PASI	389	242	506
Beaver Creek Line 1	GTN21	221	242	249
Beaver Creek Line 1	GTN30	233	242	213
Beaver Creek Line 2	PASI	369	224	475
Big Prairie Creek Line 1	GTN21	476	224	328
Big Prairie Creek Line 1	GTN21_B	434	250	496
Big Prairie Creek Line 1	GTN30	487	474	496
Big Prairie Creek Line 1	GTN30_B	439	387	492
Big Prairie Creek Line 1	PASI	416	222	493
Big Prairie Creek Line 2	GTN21	481	418	488
Big Prairie Creek Line 2	GTN30	408	373	486
Big Prairie Creek Line 2	GTN30_B	440	370	494
Coldwell Creek Line 1	GTN21	263	257	255
Coldwell Creek Line 1	PASI	253	264	477
Coldwell Creek Line 2	GTN30	240	251	274
Moundville Line 1	GTN21	219	231	224
Moundville Line 1	PASI	295	257	533
Moundville Line 2	GTN21	251	254	492
Moundville Line 2	GTN30	272	290	276
Moundville Line 2	PASI	263	261	516
Greensboro	GTN21	205	241	370
Greensboro	PASI	240	265	270
Duck River	GTN21	501	508	455
Duck River	GTN30	414	268	452
Duck River	PASI	500	261	453
RHS Line 1	GTN21	260	264	359
RHS Line 1	GTN30	249	253	259
RHS Line 1	PASI	248	264	406
RHS Line 2	GTN21	232	234	239
RHS Line 2	GTN30	228	235	372
RHS Line 2	PASI	266	264	384
Lauderdale County Line 1	GTN21	243	263	485
Lauderdale County Line 1	GTN30	408	254	397
Lauderdale County Line 1	PASI	425	256	357
Lauderdale County Line 2	GTN21	248	253	489
Lauderdale County Line 2	PASI	508	257	358
Bluewater Creek	GTN21	248	253	491
Bluewater Creek	GTN30	255	262	264
Bluewater Creek	PASI	510	459	460
Blount County	GTN21	502	502	483
Blount County	GTN30	504	504	484
Blount County	PASI	504	507	443

High Dimensional Models

Unlike the low dimensional models and the other previously discussed models, a clear peak is not required as the models consider the area under the entire HVSR curve. Along with the HVSR curve, the dual mode artificial neural network model considers topography of the area around the station in correlation.

Table 5-9 presents estimated V_{S30} values using the single mode artificial neural network model. The model considers the entire area under the HVSR curve and does not consider topographical data. In some instances the model provides estimates that are lower using a peak frequency minus one standard deviation than estimates using the peak frequency plus one standard deviation. As the measured data from this study is different than the database used to develop the model, these are likely errors within the model. Table 5-10 presents estimated V_{S30} values using the dual mode artificial neural network model. The model failed to provide estimates for multiple sites and provided unreasonable estimates that are ignored in evaluation of the model.

Table 5-9: V_{S30} estimates using Sharma Wagle et al. (2026) single mode artificial neural network model

Site	Sensor	Mean Value (m/s)	-1 σ (m/s)	+1 σ (m/s)
Cedar Bluff	GTN30	423	733	548
Beaver Creek Line 1	PASI	435	462	444
Beaver Creek Line 1	GTN21	441	638	509
Beaver Creek Line 1	GTN30	403	681	414
Beaver Creek Line 2	PASI	447	674	383
Big Prairie Creek Line 1	GTN21	162	464	147
Big Prairie Creek Line 1	GTN21_B	167	153	614
Big Prairie Creek Line 1	GTN30	348	151	277
Big Prairie Creek Line 1	GTN30_B	343	304	115
Big Prairie Creek Line 1	PASI	137	457	421
Big Prairie Creek Line 2	GTN21	576	562	154
Big Prairie Creek Line 2	GTN30	563	543	554
Big Prairie Creek Line 2	GTN30_B	145	313	131
Coldwell Creek Line 1	GTN21	478	470	459
Coldwell Creek Line 1	PASI	498	546	456
Coldwell Creek Line 2	GTN30	277	398	286
Moundville Line 1	GTN21	296	864	265
Moundville Line 1	PASI	220	556	273
Moundville Line 2	GTN21	806	644	373
Moundville Line 2	GTN30	211	816	266
Moundville Line 2	PASI	445	852	168
Greensboro	GTN21	301	212	355
Greensboro	PASI	305	274	382
Duck River	GTN21	663	742	383
Duck River	GTN30	399	745	380
Duck River	PASI	518	705	445
RHS Line 1	GTN21	455	451	467
RHS Line 1	GTN30	537	315	506
RHS Line 1	PASI	583	490	542
RHS Line 2	GTN21	306	240	469
RHS Line 2	GTN30	238	399	335
RHS Line 2	PASI	811	922	753
Lauderdale County Line 1	GTN21	414	512	352
Lauderdale County Line 1	GTN30	521	518	533
Lauderdale County Line 1	PASI	548	144	494
Lauderdale County Line 2	GTN21	434	398	402
Lauderdale County Line 2	PASI	363	435	314
Bluewater Creek	GTN21	467	404	418
Bluewater Creek	GTN30	390	214	605
Bluewater Creek	PASI	651	696	627
Blount County	GTN21	376	645	452
Blount County	GTN30	674	652	530
Blount County	PASI	600	500	671

Table 5-10: V_{s30} estimates using Sharma Wagle et al. (2026) dual mode artificial neural network model.
Dashes indicate where the model could not provide an estimate

Site	Sensor	Mean Value (m/s)	-1 σ (m/s)	+1 σ (m/s)
Cedar Bluff	GTN30	514	532	465
Beaver Creek Line 1	PASI	427	394	461
Beaver Creek Line 1	GTN21	526	526	535
Beaver Creek Line 1	GTN30	488	594	474
Beaver Creek Line 2	PASI	450	664	380
Big Prairie Creek Line 1	GTN21	---	405	---
Big Prairie Creek Line 1	GTN21_B	---	3083	---
Big Prairie Creek Line 1	GTN30	428	---	278
Big Prairie Creek Line 1	GTN30_B	423	316	636
Big Prairie Creek Line 1	PASI	---	437	---
Big Prairie Creek Line 2	GTN21	601	620	409
Big Prairie Creek Line 2	GTN30	606	618	591
Big Prairie Creek Line 2	GTN30_B	541	386	---
Coldwell Creek Line 1	GTN21	390	412	397
Coldwell Creek Line 1	PASI	501	627	411
Coldwell Creek Line 2	GTN30	286	305	270
Moundville Line 1	GTN21	306	341	300
Moundville Line 1	PASI	295	305	305
Moundville Line 2	GTN21	331	442	385
Moundville Line 2	GTN30	267	266	311
Moundville Line 2	PASI	396	442	671
Greensboro	GTN21	265	250	299
Greensboro	PASI	334	319	369
Duck River	GTN21	705	688	560
Duck River	GTN30	609	628	401
Duck River	PASI	563	664	444
RHS Line 1	GTN21	535	473	597
RHS Line 1	GTN30	471	358	495
RHS Line 1	PASI	580	400	636
RHS Line 2	GTN21	393	391	445
RHS Line 2	GTN30	400	424	419
RHS Line 2	PASI	274	240	308
Lauderdale County Line 1	GTN21	609	576	413
Lauderdale County Line 1	GTN30	660	523	582
Lauderdale County Line 1	PASI	702	255	462
Lauderdale County Line 2	GTN21	289	303	283
Lauderdale County Line 2	PASI	297	312	290
Blewater Creek	GTN21	300	309	292
Blewater Creek	GTN30	270	244	370
Blewater Creek	PASI	338	284	407
Blount County	GTN21	328	433	319
Blount County	GTN30	514	532	465
Blount County	PASI	427	394	461

5.4 Geospatial Methods

Geospatial based correlations were applied to all of the sites from this study as well as sites presented in Carcamo (2022) following the methodology presented in Section 3.3.3. Values of V_{S30} estimated by the geospatial methods considered in this study are presented in Table 5-11.

The correlation presented in Gann-Phillips et al. (2024) was only able to be applied to sites located within the Coastal Plains province within the state. The model presented in Yong et al. (2012) was not able to be applied to the Big Prairie Creek site as the site was classified into terrain class 13, the single class without a median V_{S30} value assigned to it.

Values of V_{S30} between the Wald and Allen and Yong et al. models are generally in agreement with each other and are consistently lower than values estimated using the Parker et al. and Geyin and Maurer models. For sites where the Gann-Phillips et al. model is able to be applied, values are generally lower than the other models but are higher than estimates from the Parker et al. model at some sites. This is due to the minimum V_{S30} estimate category from the Parker et al. model being lower than the minimum category for the Gann-Phillips model. Repeated values of V_{S30} are due the Yong et al., Parker et al., and Gann-Phillips et al. models being categorical as opposed to raster based models like those presented in Wald and Allen (2007) and Geyin and Maurer (2023).

Table 5-11: Results of geospatial correlations

Site	Wald and Allen (2007) V_{S30} (m/s)	Yong et al. (2012) V_{S30} (m/s)	Parker et al. (2017) V_{S30} (m/s)	Geyin & Maurer (2023) V_{S30} (m/s)	Gann-Phillips et al. (2024) V_{S30} (m/s)
Cedar Bluff	359	402	684	373	---
Beaver Creek L1	256	497	210	438	237
Beaver Creek L2	256	497	210	438	237
Big Prairie Creek	326	---	210	288	237
Coldwell Creek	381	497	822	477	331
Moundville L1	486	402	822	615	331
Moundville L2	486	402	822	615	331
Greensboro	388	497	210	348	237
Duck River	339	497	684	514	---
RHS L1	452	388	822	340	---
RHS L2	452	388	822	340	---
Bluewater Creek	409	497	822	760	---
Lauderdale County L1	372	497	822	566	---
Lauderdale County L2	372	497	822	605	---
Blount County	302	363	822	567	---
ASEL Site	503	402	699	391	331
TU01	254	402	210	339	237
SR-21 site	319	402	684	597	---
SR-219	672	328	822	399	331
AN01	547	388	684	697	---
X50B	782	402	684	523	---
S1AL	478	497	315	368	299
S2AL	339	328	210	295	237
Y47A	436	402	210	276	237
X48A	332	328	684	296	---
B01X	341	402	684	412	---
BLF1	390	497	684	1040	---
AFBM	219	363	210	302	237

5.5 Summary

Boring based estimation methods were applied to boring logs from all sites. SPT methods generally performed best at shallower depths and would underestimate V_s at depths below approximately 50 feet. At lower measured velocities the correlations tended to produce more residuals that were within the AASHTO uncertainty boundaries. Correlations that consider an energy corrected SPT blowcount tended to agree with the minimum misfit profile more. RQD based estimates were scattered and generally overestimated V_s .

A total of 47 unique HVSR curves were able to be calculated from recordings of ambient noise taken at all of the sites. Of the 47 presented curves, 4 fail to meet SESAME reliability criteria. 13 of the presented curves are able to meet both reliability and clarity checks. This

limits the database for all HVSR models with the exception of the high dimensional models presented in Sharma Wagle et al. (2026).

Geospatial estimation methods were applied to sites from this study along with sites presented in Carcamo (2022). Categorical models provided repeated values of V_{S30} while raster based models provided unique estimates for each site.

Chapter 6: Evaluation of Approaches for Estimating V_s

This chapter presents comparisons between measured and estimated data using the previously presented estimation methods. A total of 10 sites were visited with 15 direct measurements being taken to use as a basis for comparisons to be made. A total of 15 SPT-based correlations, three RQD-based correlations, and 9 HVSR-based correlations were applied to the sites visited as a part of this study. five geospatial correlations were applied to all sites from this study as well as to sites presented in Carcamo (2022). Correlations were evaluated on their fit to measured data using multiple statistical measures.

All statistical measures were calculated using measured and estimated values in natural log units to provide more equal weight between estimation error at lower and higher velocities. Mean squared error was considered first when evaluating the performance of a correlation. Values of MSE closer to zero indicate better fit of the estimated data to the measured data and is a measure of general model fit. Secondly Thiel's Index was considered. Thiel's Index more heavily penalizes outliers than mean squared error will, with values closer to zero having less entropy between measured and estimated data pairs. Third, mean absolute deviation was considered, which considers the absolute distance between measured and estimated data pairs. Lastly the Gini Index was considered when comparing correlations from the same category when they are applied to the same sample size. Values closer to zero indicate greater equity between measured and estimated data.

Using natural log units for statistical measures helps improve the comparisons across a range of velocity magnitudes, but does have the potential to suppress outliers. To examine this, Theil's Index was calculated in both natural log and arithmetic units. Values of Theil's Index when using natural log units all had a greater magnitude than those calculated using arithmetic units indicating that suppression of outliers is not of concern when using natural log units. Correlations with the lowest values of Theil's Index in natural log units also had the lowest values when calculated in arithmetic units.

In addition to evaluating performance of correlations for providing accurate and equitable estimates, the overall performance of the best fit correlations were evaluated for

their performance in determining site class. Direct measurements were used to determine the mean site class along with the site class for V_{S30} values of plus and minus one standard deviation. Estimates from each of the best fit correlations from each category (i.e., boring based, HVSR based, and geospatial) were used to estimate site class using median values as well as with an upper and lower bound calculated using a $\pm 30\%$ value of V_{S30} or with $\pm$ one standard deviation V_{S30} value for HVSR correlations. Each method was evaluated based on the rate of occurrence of overpredictions of site class. The rate of overpredictions was considered as a conservative bias (i.e., lower V_{S30} predictions) is desirable as it will lead to more conservative seismic design requirements. Recommendations were made based on methods that provide the most reasonable estimates with a conservative bias.

6.1 Comparison of Boring Based Estimation Methods

This section compares results of boring based estimation methods against direct measurements taken at the sites visited as a part of this study. Estimates are evaluated against the minimum misfit inverted V_S profile by plotting residuals of V_S against measured V_S along with calculating the presented statistical measures.

6.1.1 Comparison of SPT Based Estimation Methods

For the presented SPT based estimation methods, residuals in natural log units are plotted against the measured V_S along with 1:1 plots of measured versus estimated. The following section presents the plots for the individual correlations and statistical measures for each soil type and for all soils are presented.

Ohta and Goto (1978)

Figure 6-1 plots residuals against the measured V_S using the Ohta and Goto (1978) equation alongside a 1:1 comparison plot of measured versus estimated V_S . The majority of residuals are positive meaning that the correlation equation underpredicts V_S more often than it overpredicts. At measured velocities of approximately 150 to 300 m/s there are negative residuals meaning the correlation equation overpredicts the measured V_S in this range. Overpredictions of V_S are primarily observed in sands and clays but not in silts. Due to the small

sample size of silts (only 8 data pairs of a SPT blowcount and an estimated V_s value) a conclusion on the overall behavior of the correlation equation on silts cannot be drawn.

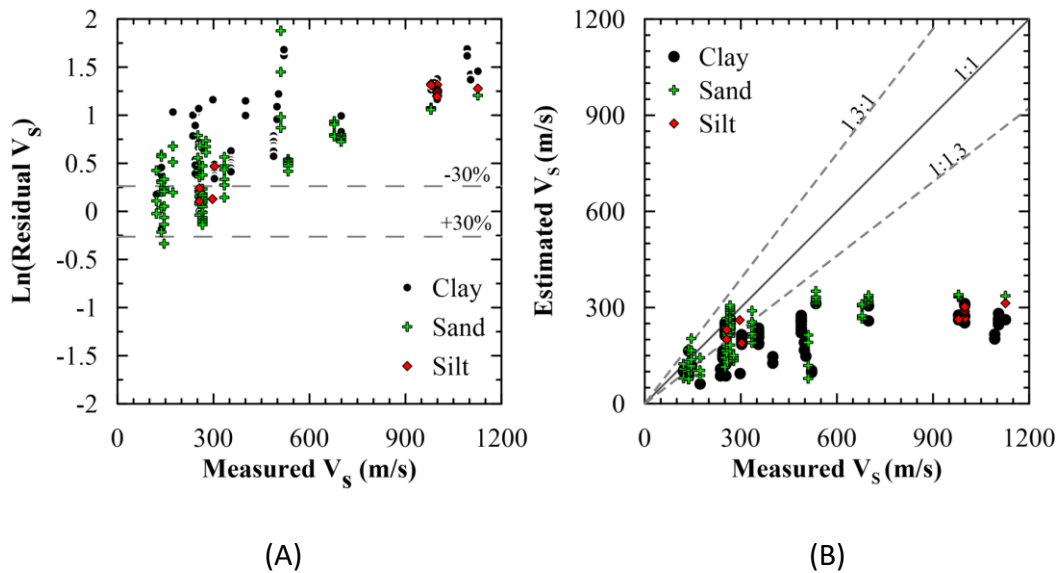


Figure 6-1: Plot of (A) residuals against measured V_s for all soil types with a range of $\pm 30\%$ bars overlain and (B) 1:1 plot of measured versus estimated V_s for Ohta and Goto (1978) correlation

Imai and Tonouchi (1982)

Figure 6-2 plots residuals against the measured V_s using the Imai and Tonouchi (1982) equation alongside a 1:1 comparison plot of measured versus estimated V_s . At velocities of less than 500 m/s, many residuals lie between the $\pm 30\%$ range recommended by AASHTO with a greater number of residuals falling below the $+30\%$ boundary. As compared to the correlation equation presented in Ohta and Goto (1978), the correlation equation overpredicts V_s more at lower velocities but does produce more estimates that are within 30% of the measured velocity. At velocities greater than 500 m/s, the residuals are smaller than those from the Ohta and Goto correlation indicating estimates are closer to the measured values.

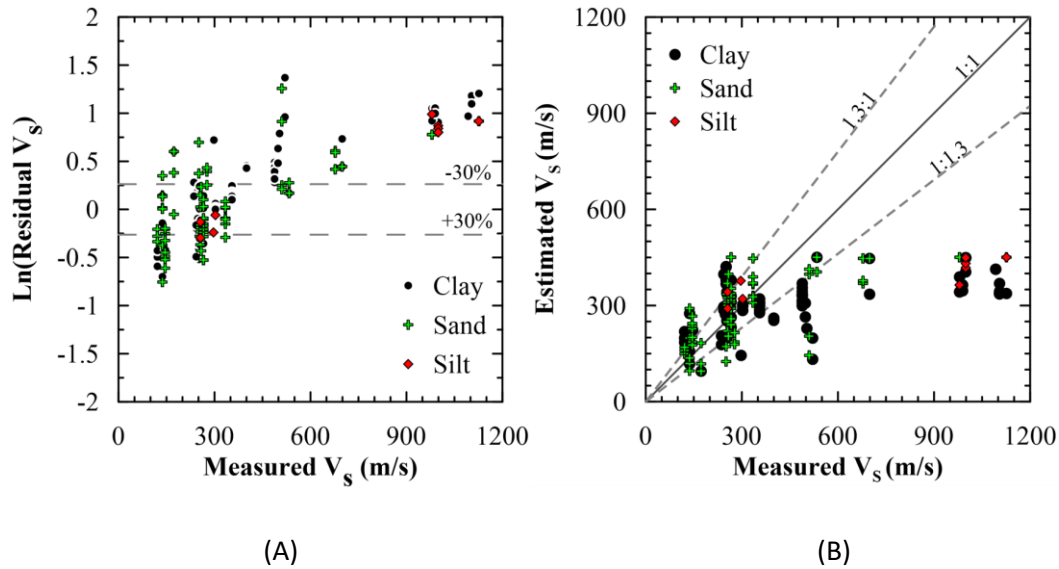


Figure 6-2: Plot of (A) residuals against measured V_s for all soil types with a range of $\pm 30\%$ bars overlain and (B) 1:1 plot of measured versus estimated V_s for Imai and Tonouchi (1982) correlation

Seed et al. (1983)

Figure 6-3 plots residuals against the measured V_s using the Seed et al. (1983) equation alongside a 1:1 comparison plot of measured versus estimated V_s . As the equation is only applicable to sands, there are no estimated values for clays or silts. At velocities of less than 750 m/s the correlation equation does provide estimates that lie within the $\pm 30\%$ boundary with more of a tendency to overpredict V_s at lower velocities than the previous two equations. At velocities of less than 500 m/s, there is more scatter present with both positive and negative residuals having a greater magnitude than those from the Imai and Tonouchi correlation equation.

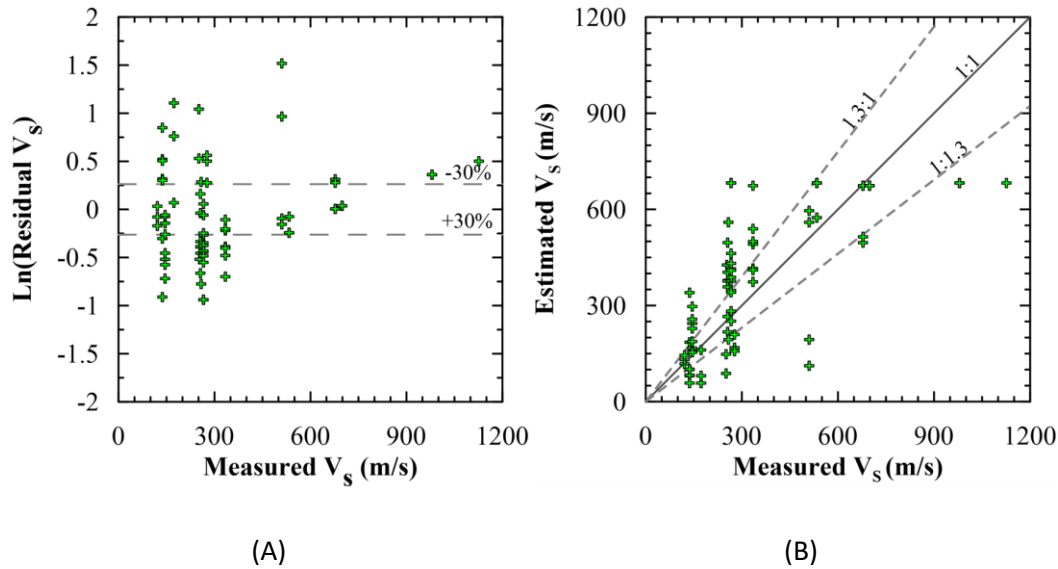


Figure 6-3: Plot of (A) residuals against measured V_s for all soil types with a range of $\pm 30\%$ bars overlain and (B) 1:1 plot of measured versus estimated V_s for Seed et al. (1983) correlation equation

Jinan (1987)

Figure 6-4 plots residuals against the measured V_s using the Jinan (1987) equation alongside a 1:1 comparison plot of measured versus estimated V_s . At measured velocities of less than 400 m/s, many residuals lie within the boundaries of $\pm 30\%$ of the measured V_s with a tendency to overpredict at measured velocities of approximately 150 m/s. At measured velocities between 150 and 400 m/s the tendency is to underpredict V_s with the majority of residuals being positive. At measured velocities of greater than 400 m/s, the correlation equation tends to underestimate V_s with no residuals falling within the AASHTO range. These same trends are able to be observed in Figure 6-4 (B) where measured and estimated values of V_s are plotted against each other on an arithmetic scale.

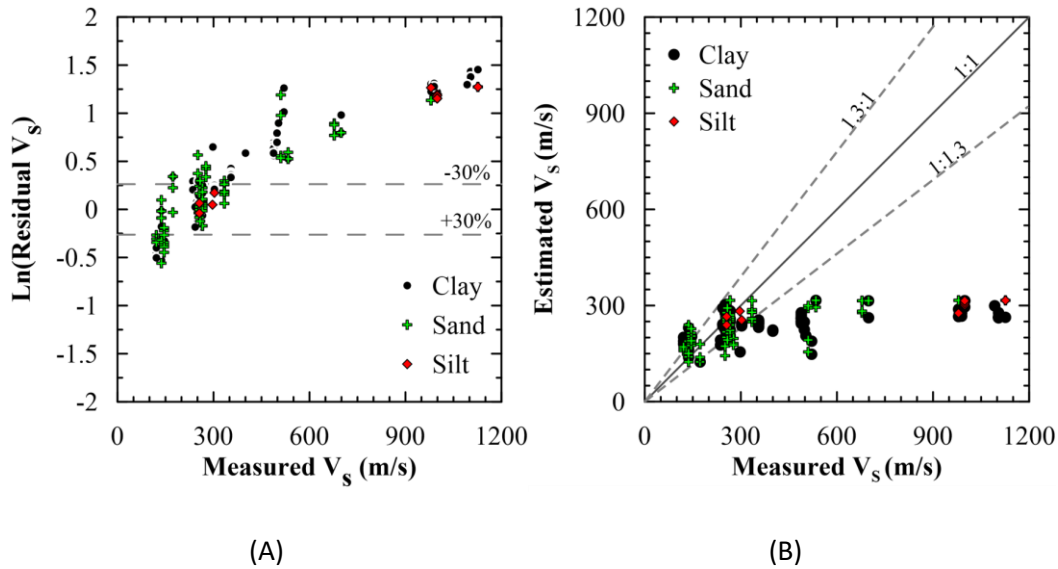


Figure 6-4: Plot of (A) residuals against measured V_s for all soil types with a range of $\pm 30\%$ bars overlain and (B) 1:1 plot of measured versus estimated V_s for Jinan (1987) correlation equation

Lee (1992)

Figure 6-5 plots residuals against the measured V_s using the Lee (1992) equations alongside a 1:1 comparison plot of measured versus estimated V_s . When considering the individual soils equations presented in parts A and B of Figure 6-5, for measured velocities of 300 m/s and below, the correlation equations do provide estimates that are within the $\pm 30\%$ boundaries with a tendency to underpredict V_s . Between different soil types sands tend to have more accurate V_s estimates with the majority of residuals between the boundaries being those from estimates using the sand equation. At measured velocities of greater than 300 m/s all residuals are positive indicating underestimation of V_s . Additionally to the individual soils equations presented the authors developed an equation for use on clays and silts. Residuals and a plot of measured versus estimated V_s on an arithmetic scale are documented in Figure 6-5 (C) and (D). Only residuals for clays and silts are plotted as the equation was not intended for use on sands. The combined clay and silt equation performs very similarly to the individual clay and silt equations with a limited number of estimates being within $\pm 30\%$ at measured velocities of

less than 300 m/s. At measured velocities of greater than 300 m/s, the combined equation also does not yield any estimates that are within the boundaries.

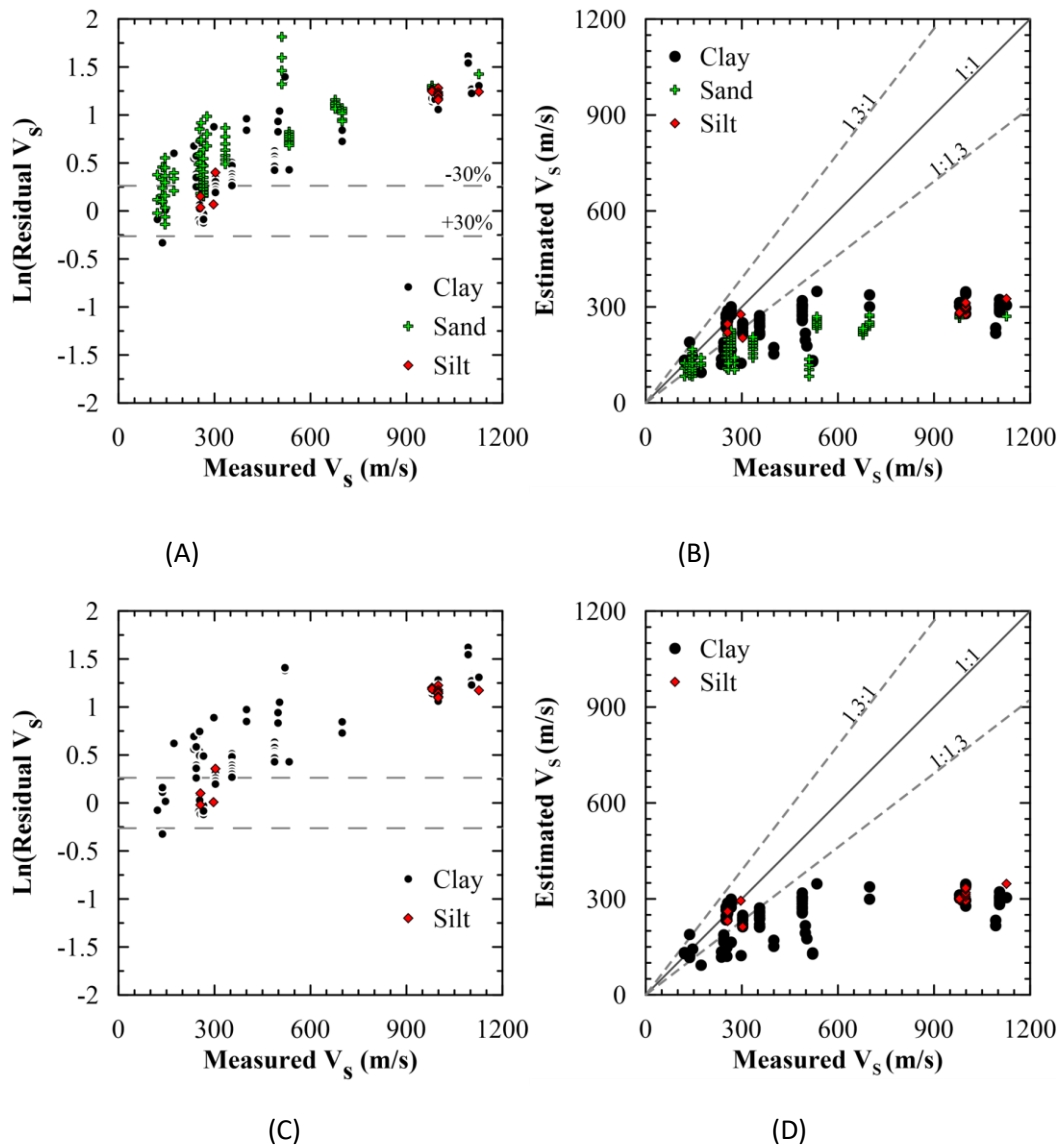


Figure 6-5: Plots of residuals and direct comparisons of Lee (1992) correlation equations (A) residual and (B) direct comparison plots for the individual soil type equations and (C) residual and (D) direct comparison plots for the combined clay and silt equation

Hasancebi and Ulusay (2007)

Figure 6-6 plots residuals against the measured V_s using the uncorrected blowcount equations from Hasancebi and Ulusay (2007) alongside a 1:1 comparison plots of measured

versus estimated V_s . Performance is similar for both sets of equations with an overall tendency to underestimate V_s . At measured velocities of less than 400 m/s both sets of equations yield residuals that lie within the $\pm 30\%$ range with some slight tendency to overestimate at measured velocities of 150 m/s. The individual sand equation does underpredict slightly less than the all soils equation applied to sands indicated by residuals with a lesser magnitude. At higher measured velocities both sets of equations do not provide accurate estimates and underpredict V_s .

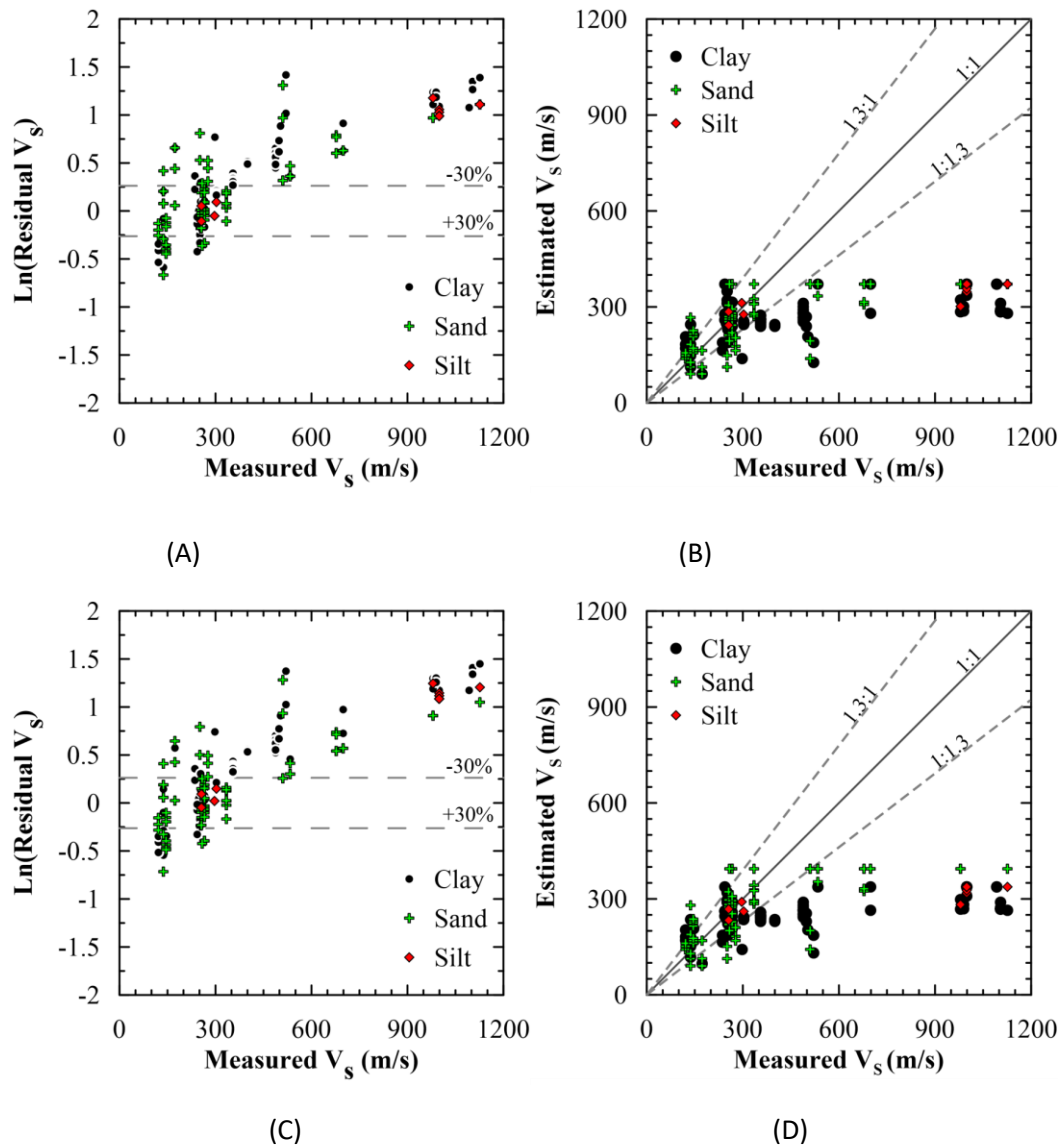


Figure 6-6: Plots of residuals and direct comparisons of Hasancebi and Ulusay (2007) correlation equations using an uncorrected SPT blowcount showing (A) residual and (B) direct comparison plots for the all soils equation and (C) residual and (D) direct comparison plots for the individual soil types equations

Figure 6-7 plots residuals against the measured V_s using the energy corrected blowcount equations from Hasancebi and Ulusay (2007) alongside 1:1 comparison plots of measured versus estimated V_s . Performance is similar for both sets of equations with an overall tendency to underestimate V_s . At measured velocities of less than 400 m/s both sets of equations yield residuals that lie within the $\pm 30\%$ range with a tendency to overestimate at measured velocities

of 150 m/s. The individual sand equation does underpredict slightly less than the all soils equation applied to sands indicated by residuals with a lesser magnitude. At higher measured velocities both sets of equations do not provide accurate estimates and underpredict V_s .

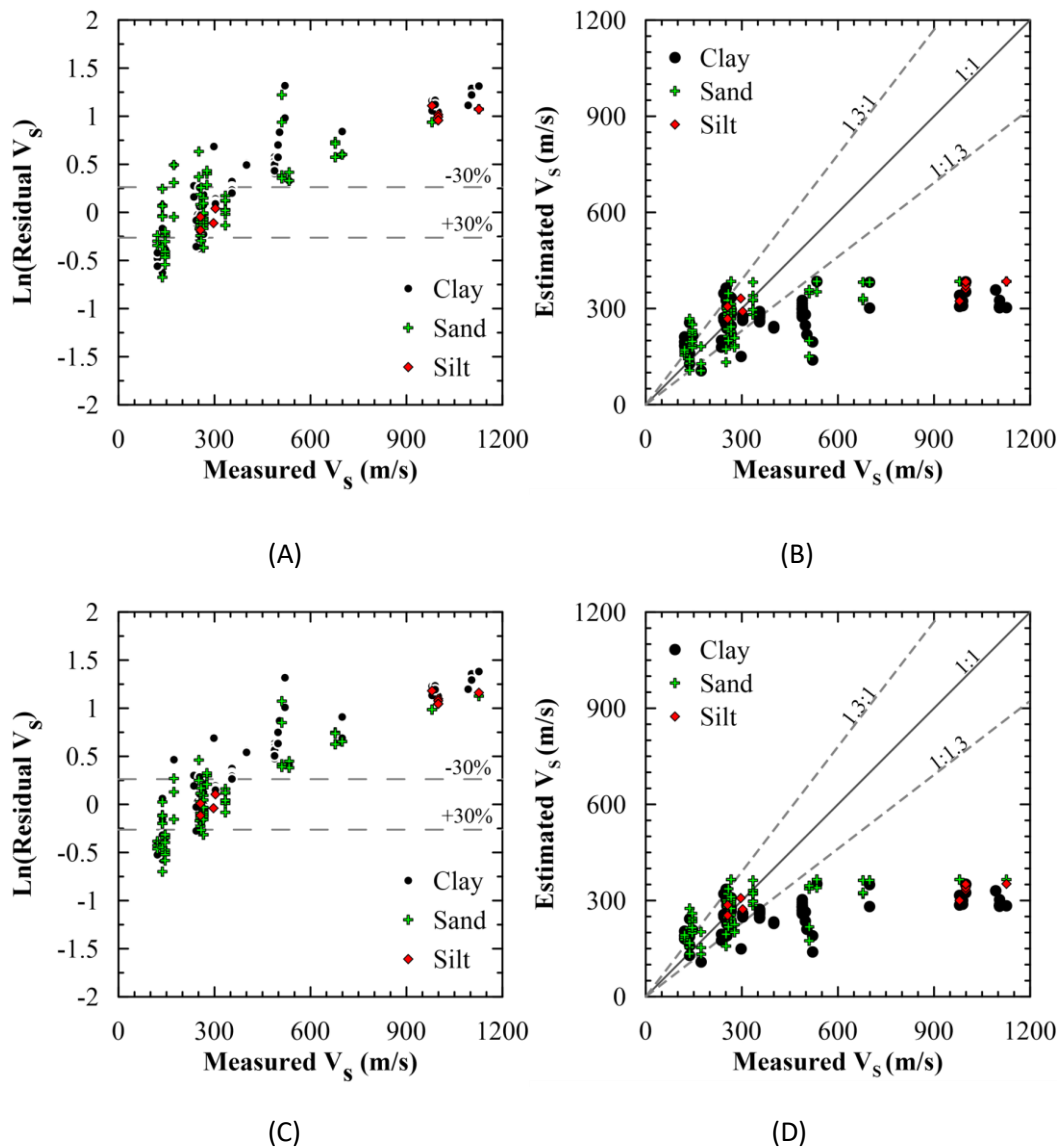


Figure 6-7: Plots of residuals and direct comparisons of Hasancebi and Ulusay (2007) correlation equations using an energy corrected SPT blowcount showing (A) residual and (B) direct comparison plots for the all soils equation and (C) residual and (D) direct comparison plots for the individual soil types equations

Wair et al. (2012)

Figure 6-8 plots residuals against the measured V_s using the Wair et al. (2012) equations alongside 1:1 comparisons plot of measured versus estimated V_s . From the residual plot for the all soils equation presented in Figure 6-8 (A), across the entire range of measured V_s the equation tends to produce positive residuals, meaning underprediction of V_s . At values of measured V_s of up to approximately 350 m/s, the equation does provide residuals that lie within the ± 30 boundary with few overpredictions between measured V_s values of 150 and 250 m/s. From the residual plot for the individual soils equations presented in Figure 6-8 (C), performance is very similar to the all soils equation but with more of a tendency to underpredict as reflected by positive residuals with a greater magnitude.

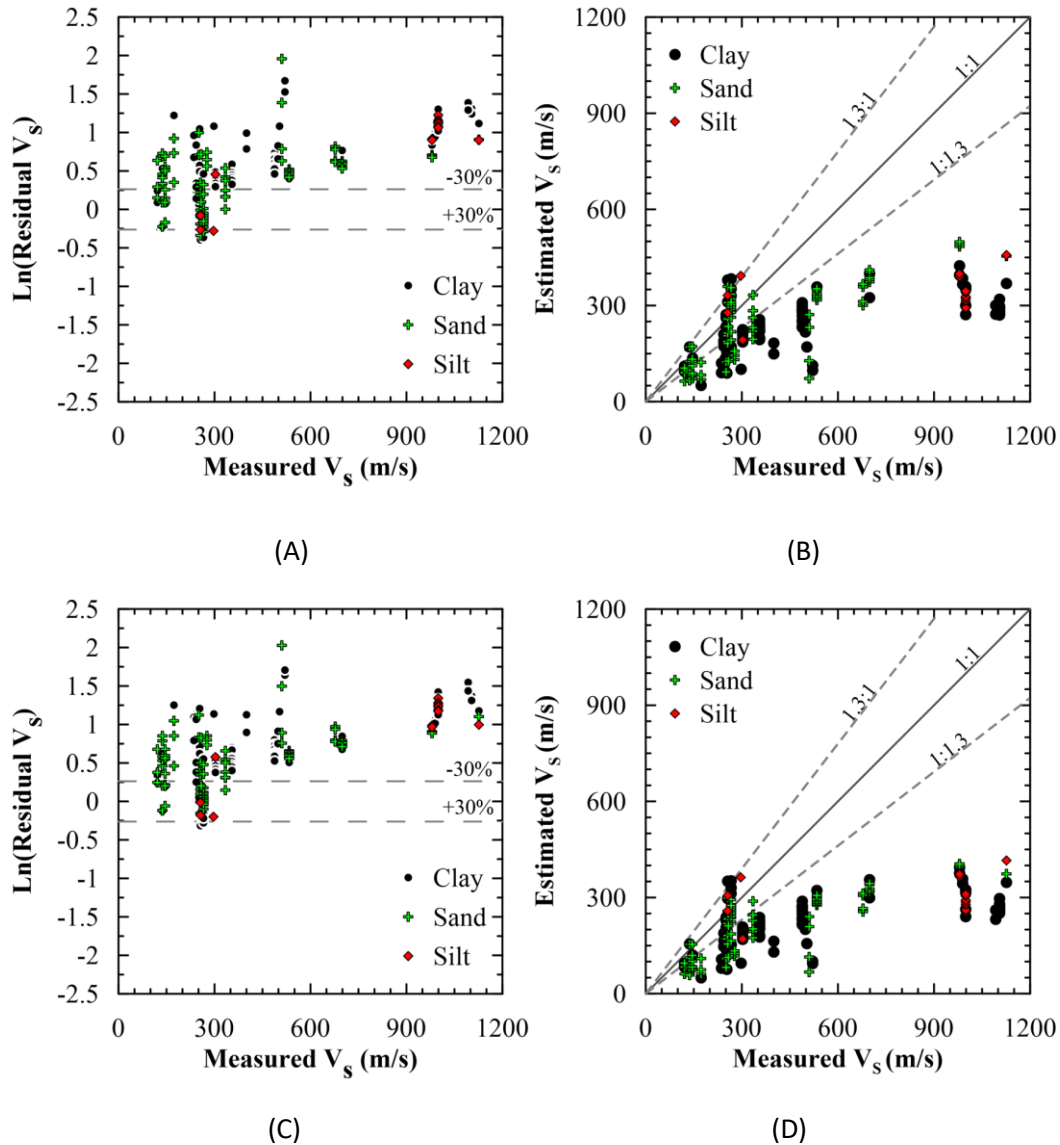


Figure 6-8: Plots of (A) residuals and (B) direct comparison for the Wair et al. (2012) all soils equation and (C) residuals and (D) direct comparison plot for the individual soils equations

Fatehnia et al. (2015)

Figure 6-9 plots residuals against the measured V_s using the Fatehnia et al. (2015) equation alongside a 1:1 comparison plot of measured versus estimated V_s . At velocities of less than 400 m/s, many residuals lie between the $\pm 30\%$ range with some tendency to overestimate up to a measured value of 300 m/s. At measured velocities higher than 400 m/s only two estimated values for sand fall within the $\pm 30\%$ boundary with all others lying above the -30%

boundary. These same trends can be observed in the direct comparison plot presented in Figure 6-9 (B) where a maximum value of estimated V_s of approximately 400 m/s can be observed.

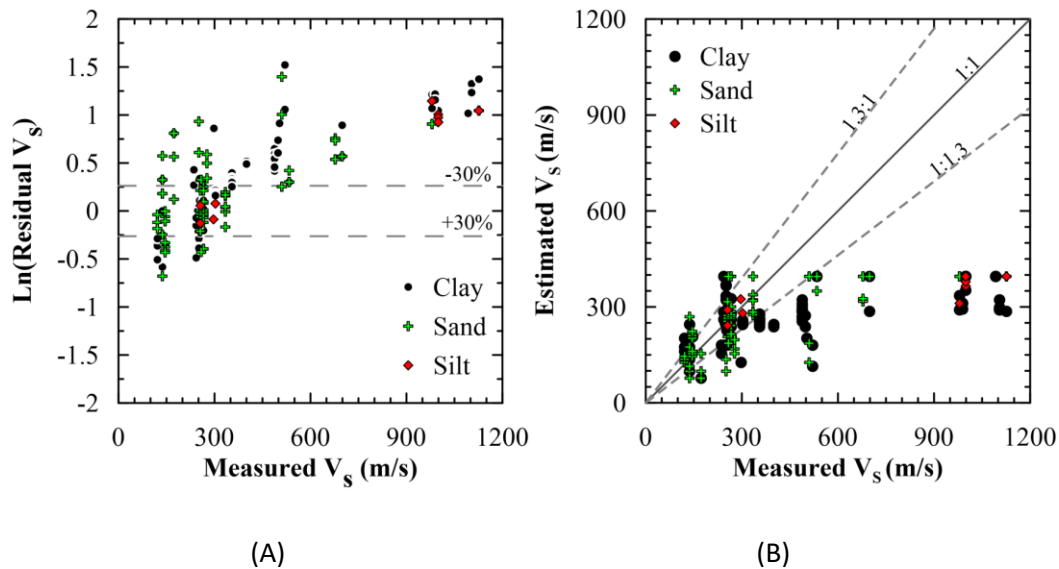


Figure 6-9: Plot of (A) residuals against measured V_s with a range of $\pm 30\%$ overlain and (B) direct comparison plot for Fatehnia et al. (2015) correlation equation

Anbazhagan et al. (2016)

Figure 6-10 presents residuals from the correlation equations presented in Anbazhagan et al. (2016). At velocities of less than 400 m/s, many residuals lie between the $\pm 30\%$ range with some tendency to overestimate up to a measured value of 300 m/s. At measured velocities higher than 400 m/s only two estimated values for sand fall within the $\pm 30\%$ boundary with all others lying above the -30% boundary. These same trends can be observed in the direct comparison plot presented in Figure 6-9 (B) where a maximum value of estimated V_s of approximately 400 m/s can be observed for both correlation equations.

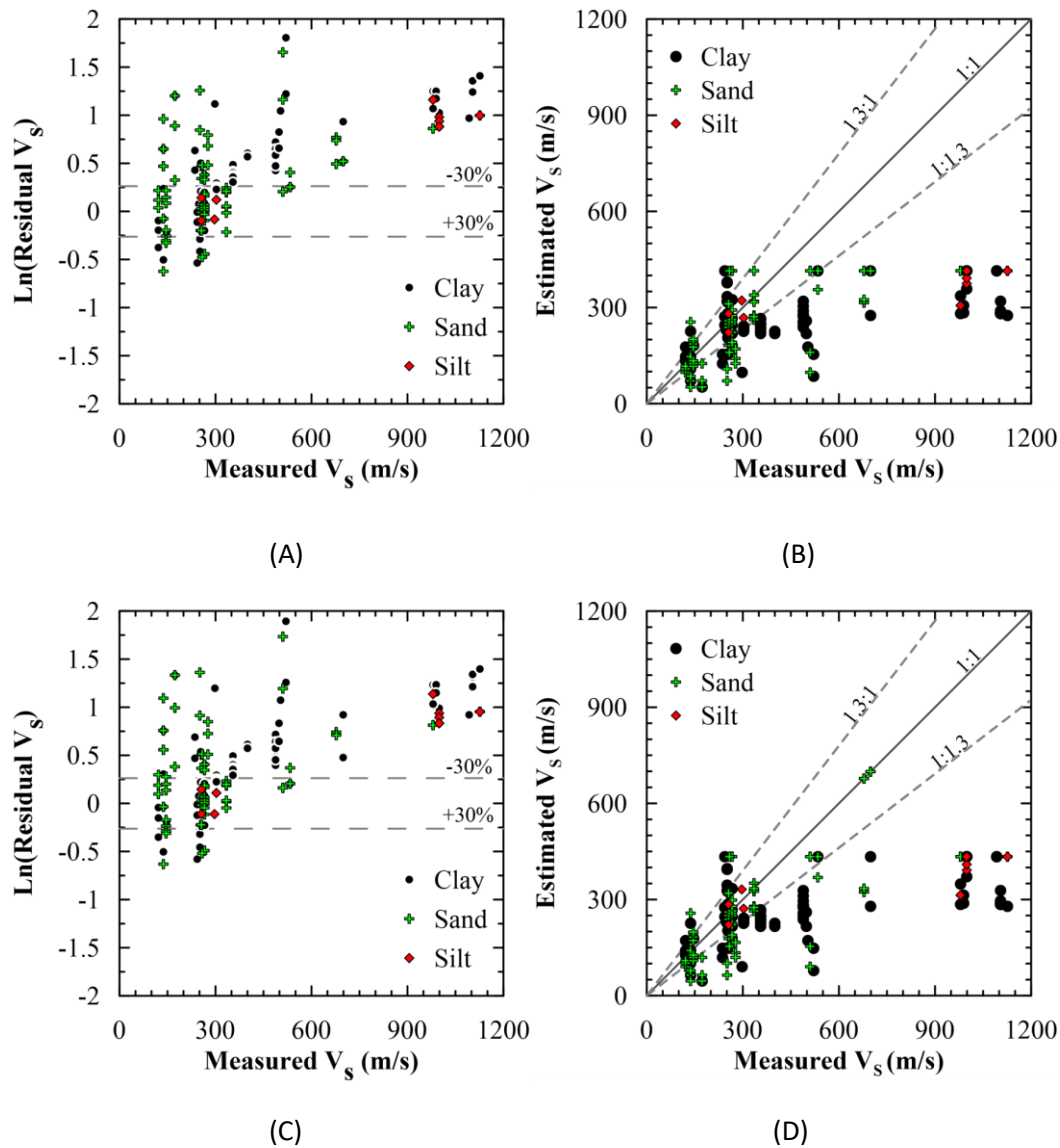


Figure 6-10: Plots of (A) residuals and (B) direct comparison for the Anbazhagan et al. (2016) correlation equation including SPT blowcounts of 100 and (C) residuals and (D) direct comparison plot for the correlation equation excluding SPT blowcounts of 100

Statistical Measures

To allow for direct comparisons between the different correlations, statistical measures were calculated for all soil types as well as for the entire dataset. Table 6-1 presents the calculated statistical measures for clays. Values of mean square error above 0.5 indicate a

greater degree of variation between the estimated and measured data. The Imai and Tonouchi correlation has the lowest value of mean squared error which indicates the least amount of variation between measured and estimated data for clays. This conclusion is also supported by the low value of percent root mean squared error. Values of Theil's Inequality are low for all equations indicate a minimal amount of entropy between measured and estimated data with the lowest value being for the Imai and Tonouchi correlation. Values of mean absolute deviation indicate that all correlations have a moderate amount of variability between measured and estimated data with the exception of the Imai and Tonouchi correlation having lower absolute variability between measured and estimated values. All Gini Index values are low indicating minimal inequality between measured and estimated data with the minimal amount of inequality being the Imai and Tonouchi correlation.

Overall the best performing correlations all correct for hammer efficiency for SPT blowcounts. Without energy corrections there is no way to ensure that SPT blowcounts are equivalent between the datasets used to develop these correlations and the SPT blowcounts that are used for correlation. Correlations that apply a factor for geologic age do not work as well as those that do not correct for age. The highest values of mean squared error, Theil's Index, mean absolute deviation, and Gini Index come from the Ohta and Goto and the Wair et al. correlations. While these correlations were effective in the geologic units the authors intended for these correlations to be used in, they do not match well to the dataset from this study.

Table 6-1: Calculated statistical measures for clays. Bolded values indicate best performing correlations for each statistical measure

Correlation	Mean Squared Error	Theil's Inequality	Mean Absolute Deviation	Gini Index
Ohta and Goto (1978)	0.733	0.0767	0.723	0.000547
Imai and Tonouchi (1982)	0.352	0.0511	0.461	0.000349
Jinan (1987)	0.503	0.0621	0.544	0.000411
Lee (1992) individual equations	0.507	0.0628	0.571	0.000432
Lee (1992) combined clay and silt	0.515	0.0633	0.577	0.000436
Hasancebi and Ulusay (2007) individual equations with uncorrected blowcounts	0.499	0.0618	0.549	0.000415
Hasancebi and Ulusay (2007) all soils equation with uncorrected blowcounts	0.457	0.0590	0.528	0.000400
Hasancebi and Ulusay (2007) individual equations with energy corrected blowcounts	0.451	0.0585	0.517	0.000391
Hasancebi and Ulusay (2007) all soils equation with energy corrected blowcounts	0.406	0.0553	0.493	0.000373
Wair et al. (2012) all soils equation	0.580	0.0675	0.647	0.000490
Wair et al. (2012) individual equations	0.696	0.0745	0.726	0.000549
Fatehnia et al. (2015)	0.455	0.0588	0.531	0.000402
Anbazhagan et al. (2016) equation including blowcounts of 100	0.529	0.0639	0.581	0.000440
Anbazhagan et al. (2016) equation excluding blowcounts of 100	0.537	0.0643	0.586	0.000444

Table 6-2 presents the calculated statistical measures for sands. Overall, all measures are lower than their counterparts for clays with similar trends of energy corrected blowcounts providing more accurate estimates. The poorest performing equations for sands are those that consider geologic age and the Lee (1992) sand equation. Due to the author's criteria for avoiding multicollinearity the equation does not consider SPT blowcounts and only uses depth as a variable. Unlike clays, the best performing correlation is not the one presented in Imai and Tonouchi, although it does perform well reflected by the low values of all statistical measures. The best performing correlation is the sand equation using an energy corrected blowcount from Hasancebi and Ulusay (2007). Low values of all measures demonstrate that the correlation provides the best fit to the measured data evidenced by values of MSE and Thiel's Index. The

correlation does have a higher degree of absolute magnitude of error between measured and estimated data than the Jinan (1987) or the all soils equation using an energy corrected blowcount from the same source, but values are generally very close. Additionally the correlation does not provide the most equity between the measured and estimated data, but does provide a comparable amount of equity to the Jinan (1987) correlation.

Table 6-2: Calculated statistical measures for sands. Bolded values indicate best performing correlations for each statistical measure

Correlation	Mean Squared Error	Theil's Inequality	Mean Absolute Deviation	Gini Index
Ohta and Goto (1978)	0.267	0.0490	0.390	0.000447
Imai and Tonouchi (1982)	0.143	0.0347	0.292	0.000335
Seed et al. (1983)	0.258	0.0464	0.412	0.000472
Jinan (1987)	0.135	0.0340	0.266	0.000304
Lee (1992) sand equation	0.370	0.0584	0.490	0.000561
Hasancebi and Ulusay (2007) individual equations with uncorrected blowcounts	0.145	0.0352	0.278	0.000318
Hasancebi and Ulusay (2007) all soils equation with uncorrected blowcounts	0.150	0.0359	0.279	0.000320
Hasancebi and Ulusay (2007) individual equations with energy corrected blowcounts	0.126	0.0325	0.268	0.000307
Hasancebi and Ulusay (2007) all soils equation with energy corrected blowcounts	0.131	0.0333	0.266	0.000305
Wair et al. (2012) all soils equation	0.305	0.0523	0.428	0.000491
Wair et al. (2012) individual equations	0.396	0.0603	0.497	0.000569
Fatehnia et al. (2015)	0.172	0.0385	0.295	0.000338
Anbazhagan et al. (2016) equation including blowcounts of 100	0.277	0.0495	0.376	0.000430
Anbazhagan et al. (2016) equation excluding blowcounts of 100	0.320	0.0533	0.405	0.000464

Table 6-3 presents the statistical measures for clays and silts. When compared to the measures calculated for clays exclusively, all measures increase in value indicating that the models are a poorer fit when considering silts along with clays. Still the Imai and Tonouchi correlation provides a moderately well fit to the measured data reflected by the values of mean squared error, percent root mean squared error, Theil's Inequality, and mean absolute deviation. The Gini Index for the clays and silts category is lower than for clays exclusively. This is partially

due to the increase in sample size when including silts as the measure divides by the square of the sample size in its calculation. Estimations for clays and silts combined provide a lesser degree of inequality compared to estimates solely for clays.

Table 6-3: Calculated statistical measures for clays and silts. Bolded values indicate best performing correlations for each statistical measure

Correlation	Mean Squared Error	Theil's Inequality	Mean Absolute Deviation	Gini Index
Ohta and Goto (1978)	0.747	0.0770	0.727	0.000498
Imai and Tonouchi (1982)	0.361	0.0515	0.469	0.000322
Jinan (1987)	0.526	0.0633	0.554	0.000379
Lee (1992) individual equations	0.533	0.0642	0.583	0.000399
Lee (1992) combined clay and silt	0.533	0.0642	0.584	0.000400
Hasancebi and Ulusay (2007) individual equations with uncorrected blowcounts	0.518	0.0628	0.557	0.000381
Hasancebi and Ulusay (2007) all soils equation with uncorrected blowcounts	0.471	0.0596	0.534	0.000366
Hasancebi and Ulusay (2007) individual equations with energy corrected blowcounts	0.469	0.0594	0.525	0.000359
Hasancebi and Ulusay (2007) all soils equation with energy corrected blowcounts	0.420	0.0560	0.501	0.000343
Wair et al. (2012) all soils equation	0.582	0.0672	0.648	0.000444
Wair et al. (2012) individual equations	0.697	0.0741	0.723	0.000495
Fatehnia et al. (2015)	0.466	0.0593	0.535	0.000367
Anbazhagan et al. (2016) equation including blowcounts of 100	0.533	0.0638	0.582	0.000399
Anbazhagan et al. (2016) equation excluding blowcounts of 100	0.537	0.0640	0.585	0.000401

Table 6-4 presents statistical measures calculated for the entire dataset of SPT based estimates. The inclusion of sands better the fit compared to the clays and silts category. Compared to sands exclusively, the fit is not as good with values of all statistical measures with the exception of the Gini Index increasing. Mean squared error values for the Imai and Tonouchi correlation nearly double in value while values for the Hasancebi and Ulusay energy corrected blowcount correlations more than double. Values of percent root mean square error and Theil's Inequality are comparable between the entire dataset and for clays. Values of mean absolute

deviation increase in the same manner indicating that the absolute distance between measured and estimated data are larger. The Gini Index decreases in value when considering the entire dataset as sample size is increased.

If the goal of the engineer is to obtain a conservative estimate with minimal risk for an overprediction, the all soils equation presented in Wair et al. (2012) performs the best. Conservatism is a necessary part of design, but overly conservative estimates may falsely inflate project costs. When applying this work, a balance of risk tolerance and project costs need to be considered.

Table 6-4: Calculated statistical measures for all soils. Bolded values indicate best performing correlations for each statistical measure

Correlation	Mean Squared Error	Theil's Inequality	Mean Absolute Deviation	Gini Index
Ohta and Goto (1978)	0.562	0.0683	0.597	0.000256
Imai and Tonouchi (1982)	0.277	0.0462	0.401	0.000172
Jinan (1987)	0.375	0.0546	0.442	0.000190
Lee (1992) individual equations	0.470	0.0622	0.547	0.000235
Lee (1992) combined clay and silt	0.470	0.0623	0.547	0.000235
Hasancebi and Ulusay (2007) individual equations with uncorrected blowcounts	0.374	0.0545	0.449	0.000192
Hasancebi and Ulusay (2007) all soils equation with uncorrected blowcounts	0.347	0.0524	0.436	0.000187
Hasancebi and Ulusay (2007) individual equations with energy corrected blowcounts	0.336	0.0513	0.426	0.000182
Hasancebi and Ulusay (2007) all soils equation with energy corrected blowcounts	0.309	0.0492	0.410	0.000176
Wair et al. (2012) all soils equation	0.475	0.0623	0.563	0.000241
Wair et al. (2012) individual equations	0.581	0.0696	0.635	0.000272
Fatehnia et al. (2015)	0.352	0.0529	0.442	0.000190
Anbazhagan et al. (2016) equation including blowcounts of 100	0.434	0.0592	0.502	0.000215
Anbazhagan et al. (2016) equation excluding blowcounts of 100	0.453	0.0605	0.515	0.000221

SPT based estimation methods provide more accurate estimates for sands than for the other categories presented. Values of mean squared error are lower indicating that estimates fit

measured data better and their values are more equal to the measured data. Values of the Gini Index are higher for sands due to the smaller sample size. All correlations that provide the best fit to the measured data all correct SPT blowcounts to a common energy percentage.

Correlations that include a term for geologic age do not provide a better fit for this dataset, positive residuals tend to increase compared to other correlations indicating that the inclusion of geologic age produces more underestimates compared to other correlations. For the entire dataset, correlations designed for use on all soil types provide the best estimates for this dataset. When considering the entire dataset and using individual equations for each soil type, poor performance on clays and silts reduces the level of agreement between the measured and estimated data for the entire dataset compared to all soils equations. The individual soil types equations work best for sands, but their fit is worsened due to poorer performance on clays and silts.

In application of these correlations, they are most effective in sands at shallower depths. The most accurate SPT based correlation presented in this study is the Hasancebi and Ulusay sand equation using an energy corrected blow count. The correlation has the lowest values of mean squared error, percent root mean squared error, and a low value of mean absolute deviation. For clays and silts and for all soils, the Imai and Tonouchi correlation will provide the most accurate estimates and is most effective at shallower depths. For every correlation, estimates are most accurate at shallower depths and underpredict for deeper and stiffer soils. In the dataset analyzed, no SPT blowcounts greater than 81 were used for analysis. For very stiff layers of soil where samplers met termination, no blowcounts were able to be used as the true value was not known. SPT in general may not be the best method to correlate with stiffer soils.

6.1.2 RQD Based Estimation Methods

RQD based estimation methods are evaluated in the same manner as SPT based estimation methods. Residuals are calculated in natural log units to provide more equal weight to estimation error at low and high velocities. Statistical measures are then calculated for each of the estimation methods to allow for direct comparison.

El-Naqua (1996)

Figure 6-11 presents residuals of the El-Naqua (1996) correlation along with a direct comparison plot of measured and estimated V_s . For the entire range of measured velocities the correlation produces residuals with a greater magnitude on both the positive and negative sides compared to any SPT based correlation. Fit for measured to estimated data is poor with a single datapoint within the AASHTO uncertainty range. The correlation was not intended for use in Alabama and was retrofit to provide V_s estimates so this performance is not unexpected. Geology within Alabama is not the same as in Jordan, where the correlation was intended for use.

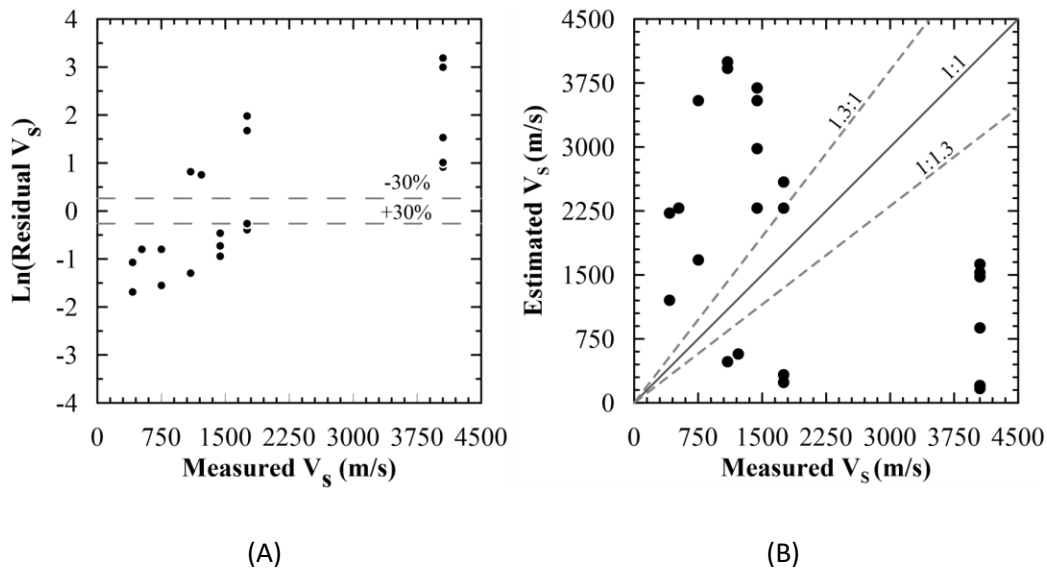


Figure 6-11: Plot of (A) residuals against measured V_s for all soil types with a range of $\pm 30\%$ bars overlain and (B) 1:1 plot of measured versus estimated V_s overlain by site class bins for El-Naqua (1996) correlation equation

Biringen and Davie (2013)

Figure 6-12 presents residuals and 1:1 comparison plots for the two sedimentary rock correlations presented in Biringen and Davie (2013).

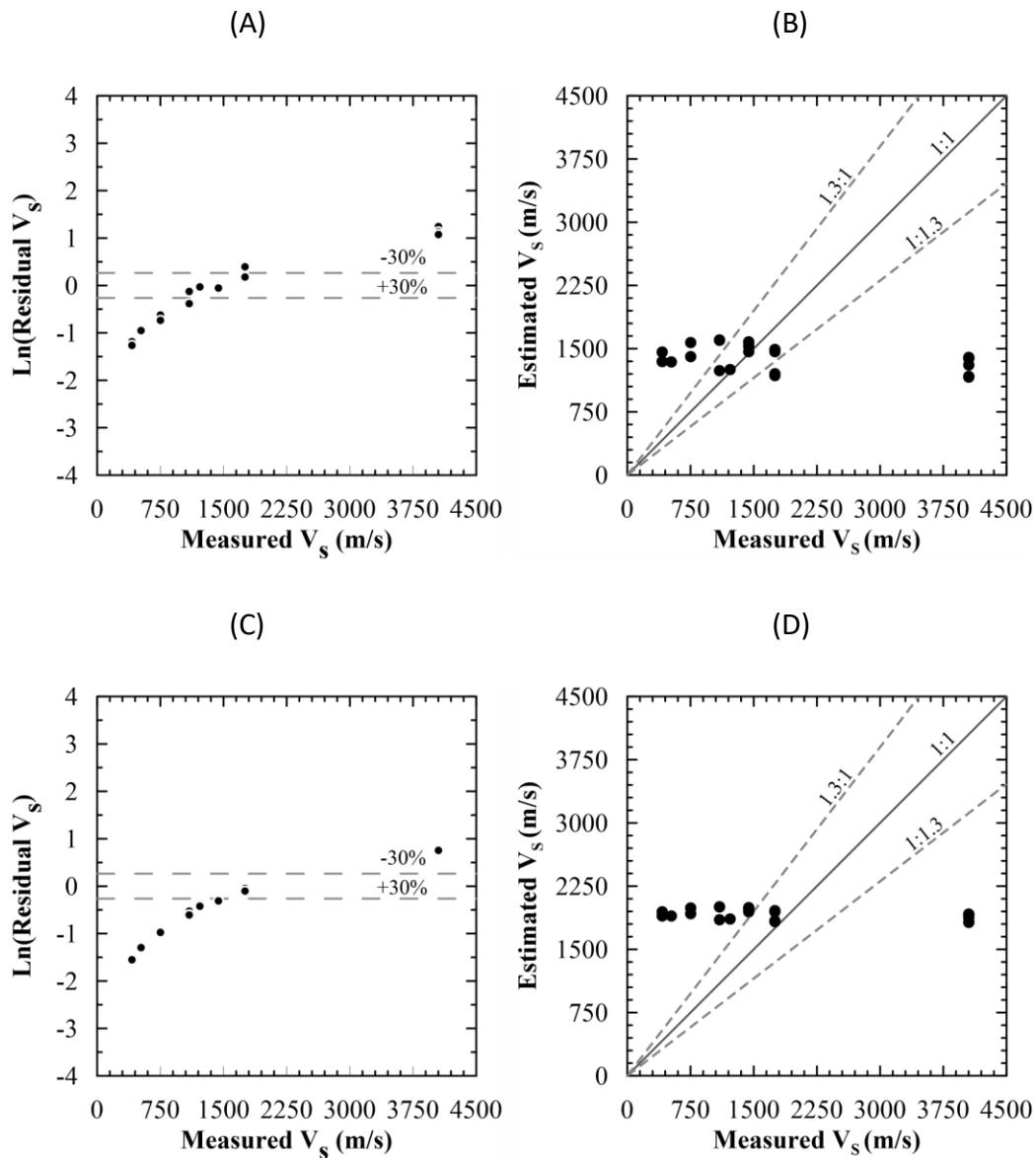


Figure 6-12: Plot of (A) residuals against measured V_s for all soil types with a range of $\pm 30\%$ bars overlain and (B) 1:1 plot of measured versus estimated V_s for Biringen and Davie (2013) Ft. Thompson correlation and (C) residuals against measured V_s for all soil types with a range of $\pm 30\%$ bars overlain and (D) 1:1 plot of measured versus estimated V_s for Biringen and Davie (2013)

Table 6-5 presents statistical measures for RQD based correlations. The high value of mean squared error for the El-Naqua correlation indicates a large degree of variability between measured and estimated data. This is not unexpected as the correlation was never intended for use in Alabama which has different geology than Jordan. Additionally, the correlation was retrofitted to predict V_s using known ratios of V_p to V_s so poor performance in Alabama is not the fault of the correlation itself, it is a byproduct of being applied outside the area of intended use. The two Biringen and Davie equations return similar results with measures indicating the Fort Thompson equation is a better fit to the modeled data and estimates are more equal to measured results. The Ft. Thompson does have a higher value of Theil's Index as compared to the Key Largo equation, indicating poorer performance due to outliers. The equations are a linear fit to their respective datasets with a constant to provide minimum estimates of 1055 and 1755 m/s for the Fort Thompson and Key Largo correlations. These constants do allow for the correlations to provide a better fit in more competent rock but do not match well with estimated data for more fractured and weathered rock.

Table 6-5: Calculated statistical measures for RQD based estimation methods. Bolded values indicate best performing correlations for each statistical measure

Correlation Equation	Mean Squared Error	Theil's Inequality	Mean Absolute Deviation	Gini Index
El-Naqua (1996)	1.996	0.137	1.174	0.00361
Biringen and Davie (2013) Ft. Thompson	0.580	0.074	0.556	0.00179
Biringen and Davie (2013) Key Largo	0.583	0.072	0.603	0.00189

Overall RQD based correlations do not provide the best fit to the dataset for this study. All three correlations were applied outside of their intended areas of use with Alabama geology differing from Jordan and Florida geology. The correlations are a poor fit for more weathered and fractured rock and will overestimate the V_s of these layers. In more competent rock performance is better with values closer to the measured values. The number of available

correlations is limited at the time of this study and none of the presented correlations were developed with Alabama geologic units in mind.

6.2 Comparison of HVSR Methods

Figure 6-13 presents 1:1 comparison plots of measured versus estimated V_{S30} using the Ghofrani and Atkinson (2014), McNamara et al. (2015), Hassani and Atkinson (2016), and Stanko and Markušić (2020) models. All models provide estimates using clear peak frequencies are most often within 30% of the measured V_{S30} within site class C/D. The Hassani and Atkinson (2016) model performs better than the other three in site class C with both data pairs of measured and estimated V_{S30} being within the uncertainty boundaries. Both the McNamara et al. (2015) and Hassani and Atkinson (2016) models provide an outlier to the dataset from the Bluewater Creek site measured by the Geotiny 30 sensor.

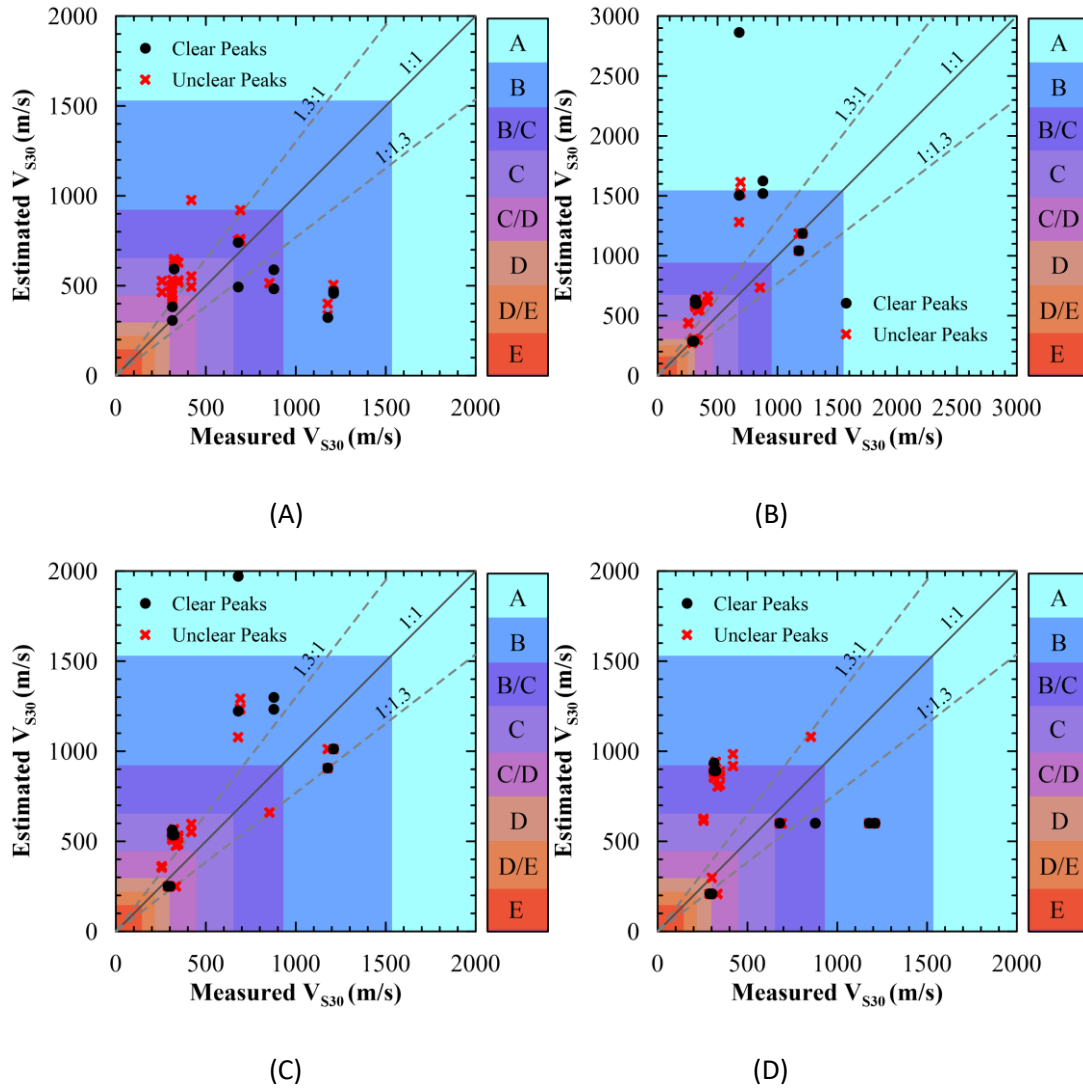


Figure 6-13: 1:1 comparison plots of measured versus estimated V_{s30} for (A) Ghofrani and Atkinson (2014), (B) McNamara et al. (2015), (C) Hassani and Atkinson (2016), and (D) Stanko and Markušić (2020) models. Estimates using clear peak frequencies are represented by black dots while estimates using unclear peak frequencies are represented by a red x.

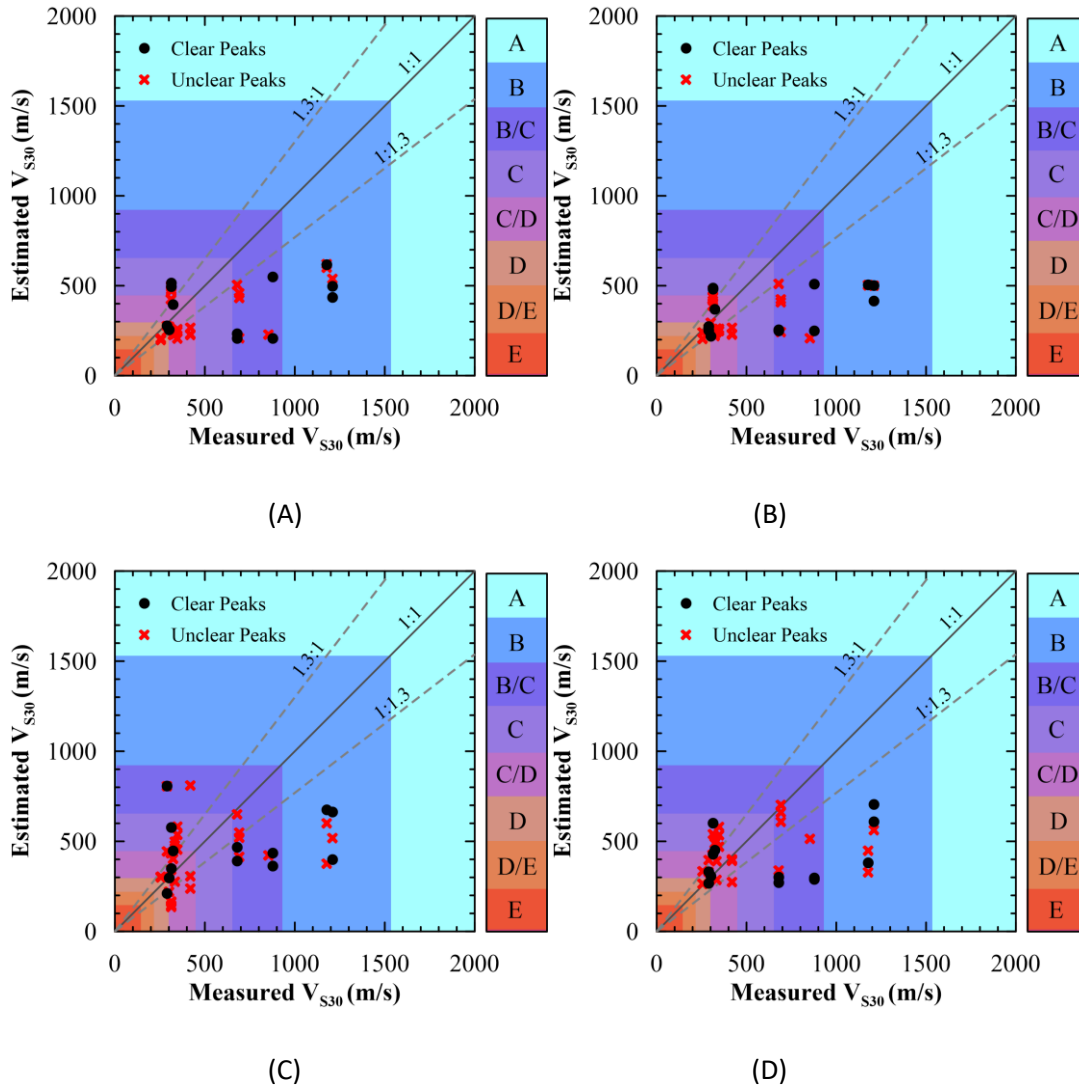


Figure 6-14: 1:1 comparison plots of measured versus estimated V_{s30} for Sharma Wagle et al. (2026) (A) random forest model (2014), gradient boosted trees model, (C) single mode artificial neural network, and (D) dual mode artificial neural network models. Estimates using clear peak frequencies are represented by black dots while estimates using unclear peak frequencies are represented by a red x.

6.2.1 Statistical Measures for HVSR Based Estimation Methods

Table 6-6 presents the calculated statistical measures for HVSR based methods. For the models that require a clear peak, measures were only calculated for estimated results using a clear HVSR peak frequency. The high dimensional models presented in Sharma Wagle et al.

(2026) were able to be applied to the entire dataset so measures were calculated for the entire dataset along with only for unclear peaks.

For sites with clear peaks the Hassani and Atkinson (2016) model provides the most accurate estimates. Low values of mean squared error, percent root mean square error, and mean absolute deviation indicate a good fit to the measured data. The model does produce estimates outside of the AASHTO uncertainty range, but these datapoints are closer to the 1:1 line compared to the other models. The value of Theil's Inequality indicate that the model has the least entropy between measured and estimated data for the clear peak models. Of the clear peak models, the Hassani and Atkinson model has the lowest value of the Gini Index indicating that its estimates are more equal to the measured data.

For the entire dataset, the single mode artificial neural network provides the most accurate estimates while when only considering sites with unclear peaks, the dual mode artificial neural network model performs the best.

Table 6-6: Calculated statistical measures for HVSR based estimation methods. Bolded values indicate best performance for each statistical measure

HVSR Model	Mean Squared Error	Theil's Inequality	Mean Absolute Deviation	Gini Index
Ghofrani and Atkinson (2014)	0.456	0.0532	0.545	0.00425
McNamara et al. (2015)	0.389	0.0476	0.430	0.00621
Hassani and Atkinson (2016)	0.234	0.0374	0.392	0.00238
Stanko and Markušić (2020)	0.480	0.0550	0.595	0.00393
Sharma Wagle et al. (2026) Random Forests Model	0.640	0.0654	0.628	0.00382
Sharma Wagle et al. (2026) Gradient Boosted Trees Model	0.585	0.0626	0.625	0.00380
Sharma Wagle et al. (2026) Single Mode Artificial Neural Network Model (Entire Dataset)	0.311	0.0460	0.484	0.000918
Sharma Wagle et al. (2026) Dual Mode Artificial Neural Network Model (Entire Dataset)	0.323	0.0465	0.451	0.000914
Sharma Wagle et al. (2026) Single Mode Artificial Neural Network Model (Unclear Peaks)	0.236	0.0406	0.431	0.00125
Sharma Wagle et al. (2026) Dual Mode Artificial Neural Network Model (Unclear Peaks)	0.181	0.0349	0.344	0.00101

6.3 Comparison of Geospatial Methods

Figure 6-15 shows the 1:1 direct comparison plots with site class bins overlain for all five geospatial models evaluated for this study. Alongside the 1:1 line of a perfect estimate, a range of $\pm 30\%$ is plotted as dashed lines.

The model presented in Wald and Allen (2007) produced 12 out of 27 estimates that fall between the range of $\pm 30\%$ of the measured value. The model performs best for site classes C and lower but can produce overestimates for softer sites. For stiffer site classes than C, the model does not perform well with all estimates being below the -30% boundary with the exception of the X50B site. The model was not developed with any data from Alabama so this behavior is not unexpected.

The model presented in Yong et al. (2012) is most effective for site class C/D as all estimates within the $\pm 30\%$ boundaries are within this site class. The model is categorical and for terrain types encountered in Alabama does not capture the behavior of stiffer sites in the northern part of the state. The terrain classifications are coarse so variations within the classes are not able to be captured. Additionally no data from Alabama was used in development of the model so failure to capture the behavior of stiffer sites in the northern part of the state is not unexpected.

The model presented in Parker et al. (2017) does capture some of the behavior of stiffer sites unlike the Yong et al. (2012) model. This model, however, does overestimate V_{S30} more often than the Yong et al. (2012) model. Despite the model being developed specifically for CENA, the model did not consider any data for the state. Like the Yong et al. (2012) model, the geologic classes are too coarse to capture regional variations within the same geologic class.

The model presented in Geyin and Maurer (2023) provides the best estimates for site class C. The model does capture more of the behavior of stiffer sites with more estimates in class B and B/C being within the boundaries of $\pm 30\%$. At these stiffer sites the model underestimates V_{S30} but to a lesser magnitude than the Wald and Allen (2007) and the Yong et al. (2012) models. The model is also less likely to overestimate V_{S30} than the Parker et al. (2017)

model. Overall the model is effective compared to the measured dataset with a tendency to provide more conservative estimates of V_{S30} at stiffer sites.

The model presented in Gann-Phillips et al (2024) is only applicable to one province of the states but is the most effective geospatial method analyzed in this study. The model can overpredict V_{S30} but does not do so outside of the +30% bound. For the softer sites that the model is applicable towards it performs better than any of the previously discussed models.

To allow for more direct comparison between the five models, statistical measures were calculated. Table 6-7 presents statistical measures for the geospatial estimation methods. For all of the model fit statistics, the Gann-Phillips model provides the best fit to the measured data. Lower values of mean square error and percent root mean squared error indicate that the model fits to the measured data better than the other geospatial methods and better than any of the boring based estimation methods. The value of Theil's Inequality for the Gann-Phillips et al. (2024) model indicates minimal entropy between measured and estimated data reflected by the low value. Additionally, the model has the lowest value of mean absolute deviation indicating that estimates have the lowest absolute deviation from the measured data. The model however does not have the lowest value of the Gini Index. Since the model is not applicable to all regions of the state, the model that provides the best estimates for the entire state is the one presented in Geyin and Maurer (2023). The model has the second lowest inequality statistics indicating that the model is most accurate to the entire measured dataset for all sites. The model has the lowest Gini Index of any of the geospatial models meaning that the measured and estimated data are more equal than the other models.

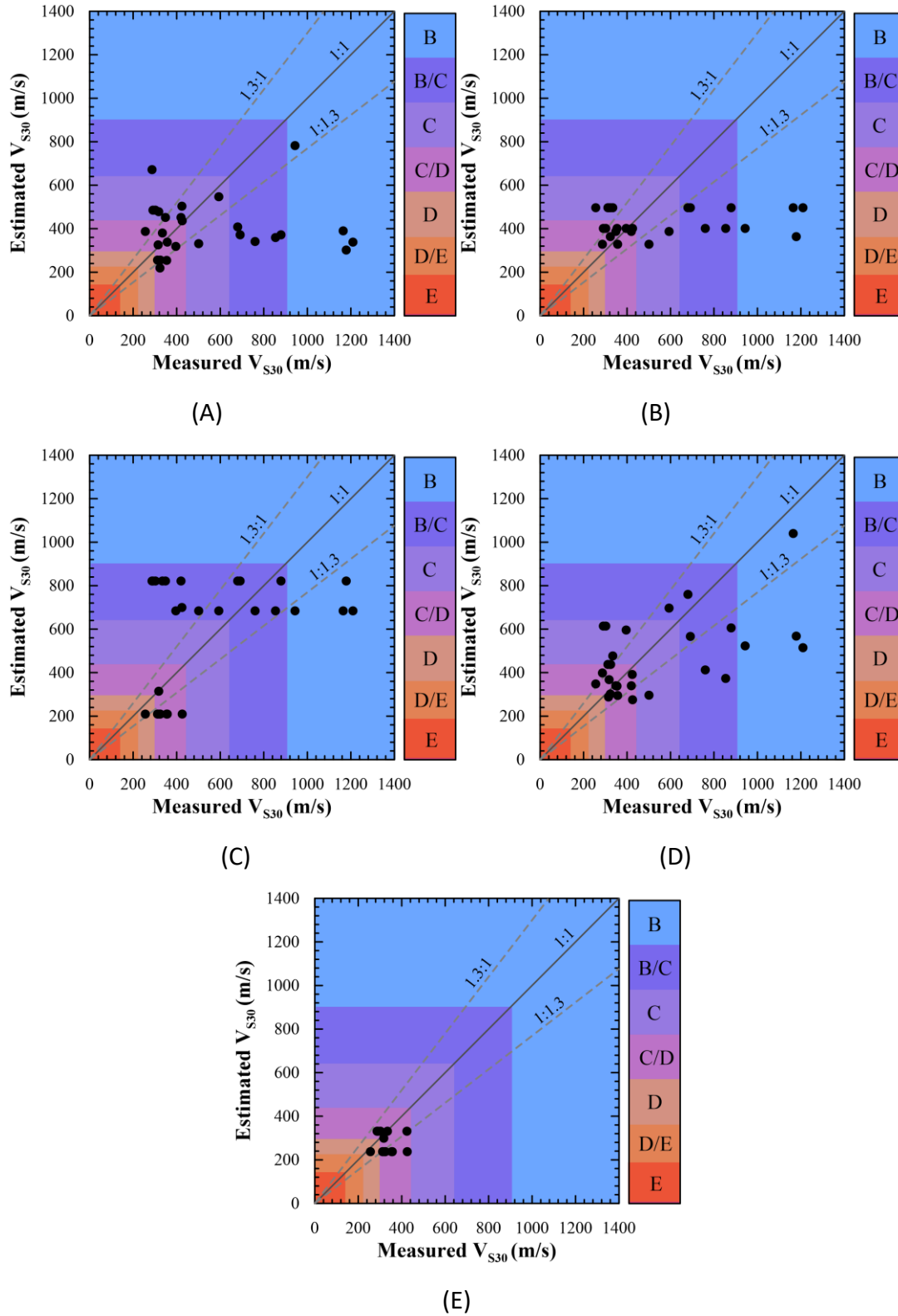


Figure 6-15: 1:1 comparison plots of (A) Wald and Allen (2007) model, (B) Yong et al. (2012) model, (C) Parker et al. (2017) model, (D) Geyin and Maurer (2023) model, and (E) Gann-Phillips et al. (2024) model

Table 6-7: Calculated statistical measures for geospatial estimation methods. Bolded values indicate best performance for each statistical measure

Geospatial Estimation Method	Mean Squared Error	Theil's Inequality	Mean Absolute Deviation	Gini Index
Wald and Allen (2007)	0.348	0.0485	0.459	0.00132
Yong et al. (2012)	0.258	0.0414	0.408	0.00122
Parker et al. (2017)	0.308	0.0446	0.471	0.00136
Geyin and Maurer (2023)	0.188	0.0352	0.353	0.00100
Gann-Phillips et al. (2024) (Coastal Plains)	0.081	0.0250	0.239	0.00147

6.4 Effect on Determining Site Class

For all sites visited as a part of this study, site class was determined using direct measurements and the best fit estimation methods from each category. Uncertainty was considered using either the standard deviation of the correlation or the AASHTO range of $\pm 30\%$. AASHTO requires considering all three values and selecting the most conservative case, which is site class D for Alabama. For direct measurements, the probabilistic distribution of the full ensemble of inverted ground profiles was used to provide a standard deviation. Table 6-8 presents site class determined by direct measurements and SPT methods while Table 6-9 presents site class determined by HVSr and geospatial methods. Cells where site class is underestimated compared to the mean value of V_{S30} are highlighted in orange while cells where site class is overestimated are highlighted in red.

When considering the range of uncertainty, 24% and 49% of V_{S30} estimates using the Imai and Tonouchi (1982) and Wair et al. (2012) all soils correlation respectively assigned a site class lower than the range of direct measurements. The two correlations provided a site class higher than from the range of direct measurements 16 and 4% of the time. Estimates at the softer alluvial sites in the West Alabama group tended to be more conservative with the majority of underestimates occurring at these sites. At the Northwest Alabama sites where rock was encountered in boring logs as well as the Cedar Bluff site, the correlations tended to

overestimate site class with all but three overestimates occurring at these sites. This is due to the necessity of including estimates for rock which tended to be greater than measured values.

HVSR based methods provided both conservative and unconservative estimates simultaneously. When considering the full range, the correlations overestimated site class 28% of the time while they underestimated site class 23% of the time. The majority of these overestimates all occurred at sites in the West Alabama group, which represent the critical soft alluvial sites from this study. Overestimation at these sites is undesirable as they represent the greatest seismic hazard.

Geospatial models provide the most reasonable estimates of site class of the presented methods. Using both the Gann-Phillips et al. (2024) and Geyin and Maurer (2023) correlations in conjunction provided estimates that were lower than the range from direct measurements 36% of the time while overestimating site class 7% of the time. While the correlations have a slightly greater chance of overprediction relative to the Wair et al. (2012) all soils correlation, the methods underpredicted site class less than the Wair et al. (2012) correlation. Due to the lack of need for boring logs and not being sensitive to the presence of rock, these methods provide the most reliable estimates with a bias towards conservatism.

Table 6-8: Range of site classes for sites visited in this study along with estimated site classes using the best fit estimation methods from each category. Both boring based estimation methods apply the Biringer and Davie (2013) Ft. Thompson correlation when applicable. Site classes highlighted in yellow indicate underestimation of site class while cells highlighted in red indicate an overestimation of site class.

Site	Direct -1 σ	Direct Mean	Direct +1 σ	I&T82 Lower Bound	I&T82	I&T82 Upper Bound	Lower Bound W12 All	W12 All	W12 All Upper Bound
Cedar Bluff	B/C	B/C	B	C/D	C	C	C/D	C/D	C
Beaver Creek Line 1	D	C/D	C/D	D	D	C/D	D/E	D/E	D
Beaver Creek Line 2	D	C/D	C/D	D	C/D	C	D/E	D	C/D
Big Prairie Creek	D	C/D	C/D	D	C/D	C/D	D/E	D/E	D
Coldwell Creek	D	C/D	C/D	D	C/D	C/D	D/E	D	C/D
Moundville Line 1	D	D	C/D	D	C/D	C/D	D	D	C/D
Moundville Line 2	D	D	C/D	D	C/D	C/D	D/E	D	C/D
Greensboro	D	D	D	D	C/D	C/D	D/E	D/E	D
Duck River	B	B	B	B/C	B/C	B	C	B/C	B/C
RHS Line 1	D	C/D	C/D	D/E	D/E	D	D/E	D/E	D
RHS Line 2	C/D	C/D	C	D	C/D	C/D	D	C/D	C/D
Lauderdale County Line 1	C	B/C	B/C	B/C	B	B	B/C	B/C	B
Lauderdale County Line 2	B/C	B/C	B	B/C	B/C	B	C	B/C	B/C
Bluewater Creek	C	B/C	B/C	B/C	B	B	C	B/C	B
Blount County	B	B	B	B/C	B/C	B	C	B/C	B

Table 6-9: Range of site classes for sites visited in this study determined by HVSR and Geospatial estimation methods. Cells highlighted in yellow indicate indirect methods underestimate site class while cells highlighted in red indicate indirect methods overestimate site class. Dashes represent where the dual mode artificial neural network model did not provide an estimate.

Site	HVSR -1σ	HVSR Mean	HVSR $+1\sigma$	Geospatial Lower Bound	Geospatial	Geospatial Upper Bound
Cedar Bluff	C	C	C	D	C/D	C
Beaver Creek Line 1	C/D	C/D	C	D/E	D	C/D
Beaver Creek Line 2	C	C	C	D/E	D	C/D
Big Prairie Creek Line 1	C/D	C/D	---	D/E	D	C/D
Big Prairie Creek Line 2	C	C	C	D/E	D	C/D
Coldwell Creek Line 1	C	C	C/D	D	C/D	C/D
Coldwell Creek Line 2	C/D	D	D	D	C/D	C/D
Moundville Line 1	D/E	D/E	D/E	D	C/D	C/D
Moundville Line 2	D/E	D/E	D/E	D	C/D	C/D
Greensboro	D	D	C/D	D/E	D	C/D
Duck River	B/C	B	B	C/D	C	B/C
RHS Line 1	C/D	C	C	D	C/D	C
RHS Line 2	C/D	C/D	C/D	D	C/D	C
Lauderdale County Line 1	C	B/C	C	C	B/C	B
Lauderdale County Line 2	B	B	A	C/D	C	B/C
Bluewater Creek	B	A	A	C	C	B/C
Blount County	B/C	B/C	B	C/D	C	B/C

6.5 Summary

Statistical measures were computed to allow for direct comparison between the presented estimation methods presented in this study. Comparisons were made between the presented estimation methods for each category presented. All measures were calculated in natural log units to allow for more equal weight between estimation errors at low and high velocities. Statistical measures calculated in natural log units were compared to those calculated using arithmetic units and did not indicate any differences in conclusions.

SPT correlations that use energy corrected SPT blowcounts perform better than those that use uncorrected blowcounts. Correlations that include a term for geologic age provide estimates that are consistently lower than correlations that do not consider geologic age. Alabama's geology is different than in the regions where these correlations were developed so a mismatch between the two is not unexpected. Comparisons between individual soil types indicated that SPT correlations in general performed better when applied to sands versus clays or the combination of clays and silts. Silts could not be individually evaluated due to the low sample size of this study. The best performing SPT correlation for clays and the combination of clays and silts is the Imai and Tonouchi (1982) correlation. For sands the Hasancebi and Ulusay (2007) sand equation using energy corrected blowcounts provides the best fit to the measured data. When considering performance for all soils, the Imai and Tonouchi (1982) correlation provides the best fit to the measured data. If conservative estimates of V_s are desired, the Wair et al. (2012) all soils equations provides reasonably conservative estimates.

RQD based correlations are more limited in number than SPT based correlations. Of the limited number of RQD based correlations presented in this study, only correlations intended for use on sedimentary rock were able to be applied as all rock encountered in this study is sedimentary in nature. RQD based correlations do not provide as good of a fit to the measured data as compared to SPT based correlations. Geology at the sites where these correlations were applied is different than the geology of the areas of intended use for these correlations, so a

poorer fit is not an unexpected result. Of the presented correlations, the Fort Thompson equation presented in Biringen and Davie (2013) provides the best fit to the measured data.

Due to the limited number of HVSR curves that comply with SESAME standards for clarity of the peak, conclusive trends were not able to be observed. For the curves with clear peaks, the Hassani and Atkinson (2016) provides the best fit to the measured data, but the sample size needs to be increased to determine if this trend is representative of the entire state. The two high-dimensional models presented in Sharma Wagle et al. (2026) are able to be applied to HVSR curves without a clear peak, so they can effectively be validated for the whole state. When applied to the entire database, including clear and unclear peaks, the single mode artificial neural network model provides the best fit to the measured data. When only considering HVSR curves lacking a clear peak, the dual mode artificial neural network model provides the best fit with statistical measures with values less than those for the single mode artificial neural network model when applied to the entire dataset.

Geospatial models provide a better fit to the dataset of measured V_{S30} values than HVSR models as indicated by lower values of mean squared error. The most accurate geospatial method is the model presented in Gann-Phillips et al. (2024) but is only applicable to sites within the coastal plains province of the state. The Geyin and Maurer (2023) model provides the best fit when considering the entire dataset of V_{S30} measurements across the state. The model provides more accurate estimates at sites with a higher measured V_{S30} than the other presented methods and should be used in conjunction with the Gann-Phillips et al. (2024) model to provide reasonable estimates across the state.

Chapter 7: Conclusions and Recommendations

7.1 Summary

In order to provide a basis for evaluating estimation methods for shear wave velocity at sites within Alabama, direct measurements were taken at 10 sites with 15 direct measurements taken. Direct methods used for this study are seismic refraction and multichannel analysis of surface waves. For MASW sites, a full ensemble inversion was performed to provide some measure of uncertainty in V_{S30} measurement along with presentation of the best 1000 profiles to provide an estimate of uncertainty for V_S profiles. Refraction surveys provide a two-dimensional model of compressional wave velocity for sites that is converted to shear wave velocity using known ratios of V_P to V_S .

Correlations to V_S from results of common in-situ tests, ambient seismic noise recordings, and to geospatial features of a site were then applied for all of the sites visited as a part of this study. Correlations to common in-situ testing results included SPT and RQD based correlations. Correlations to ambient noise recordings considered the HVSR curve and its peak frequency. Geospatial correlations considered topographic slope, surface geology, terrain classification, and a number of other geospatial factors. To allow for comparisons between measured and estimated data to be made, statistical measures were needed to provide quantitative values of fit. Statistical measures included mean squared error, Theil's Index, mean absolute deviation, and the Gini Index. Statistical measures were all calculated in natural log units to give more equal weight to estimation error at lower and higher velocities.

Lastly, recommendations based on the conclusions from this study are provided in the following sections. Evaluation criteria previously presented in Chapter 6 were used to determine the best performing correlation from each category. Best performing correlations from each category were then used to determine site class and were compared against each other.

7.2 Conclusions

Overall SPT based estimation methods tend to underpredict V_S for stiffer soils and are more scattered for softer soils. Of the presented SPT based estimation methods, the correlation equation that has the best fit when considering all soils is the one presented in Imai and

Tonouchi (1982). The correlation presented in Imai and Tonouchi (1982) also provides the best fit for clays and silts although the sample size for silts is not large enough to adequately determine a trend. The correlation equation that provides the best fit for sands is the sand equation using an energy corrected blowcount presented in Hasancebi and Ulusay (2007). If a conservative estimate is desired, the all soils equation presented in Wair et al. (2026) provides estimates that are not overly conservative with minimal risk for overestimation. If V_s of discrete soil layers is desired then the Imai and Tonouchi and Hasancebi and Ulusay corrected blowcount equations can provide the most reasonable estimates. SPT based correlations are most effective for sands at depths of less than approximately 15 meters. Estimates for clays and silts are more likely to be more conservative than estimates for sand. The correlations are most effective in shallower depths of less than approximately 15 meters. For deeper layers all correlations do not capture the behavior of higher velocity layers and will underestimate V_s . With all estimates uncertainty needs to be considered by providing a range of values for the estimate with either a standard deviation or blanket multipliers to give high and low estimates. The consequence of each case should be considered when making engineering decisions with estimated values of V_s .

Correlations to RQD were more limited in number than correlations to SPT blowcounts. Some selected correlations are to compressional wave velocity and can be converted to shear wave velocity using known ratios in the same manner as for refraction surveys. RQD based correlations evaluated in this study all provide a poorer fit to the measured data than the SPT based estimation methods and tend to overestimate V_s at lower measured velocities, which are more critical for this study.

Passive HVSR surveys produced 47 unique HVSR curves and of the 47 calculated curves, 43 met SESAME reliability criteria. Of the 43 reliable curves, 13 also met peak clarity criteria. HVSR peak frequencies ranged from less than 1 Hz to 50.3 Hz. Correlations intended for use on clear peak frequencies were only able to be applied to the results of these 13 HVSR surveys. Due to the small sample size trends within this dataset may not be indicative of overall behavior. Despite this limitation, the model presented in Hassani and Atkinson (2016) fits the measured data for clear peaks moderately well. The dual mode artificial neural network model presented

in Sharma Wagle et al. (2026) provides a good fit to exclusively curves with an unclear peak. The two models can be used in tandem by applying the Hassani and Atkinson (2016) model at sites with a clear peak, and the Sharma Wagle et al. (2026) model at sites lacking a clear peak. Since the dataset to evaluate the Hassani and Atkinson model is limited caution should be taken when using results and additional sources of data should be used to verify if estimates are reasonable for the desired site.

Geospatial estimation methods generally work best for lower velocity sites in class C/D and lower. Of the presented geospatial methods presented the one that provides the best fit is the model presented in Gann-Phillips et al. (2024). The model has the lowest values of mean squared error, percent root mean squared error, Theil's Inequality, and mean absolute deviation of all the estimation methods evaluated as a part of this study. As the model is only applicable to sites within the coastal plain province of the state, it is not suitable for every possible site. The method that provides the most accurate estimates for the whole state is the model presented in Geyin and Maurer (2023) which provides the second best fit to the measured data and minimum inequality determined by the Gini Index for geospatial methods.

7.3 Recommendations

This study serves to provide a comprehensive set of recommendations for estimating V_s in Alabama. Results of this study indicate that the models presented in Gann-Phillips et al. (2024) and Geyin and Maurer (2023) provide the most accurate estimates as evidenced by values of mean squared error, Thiel's Index, and mean absolute deviation. Additionally from evaluations of performance in determining site class, the models provide the most reasonable estimates of site class with less of a tendency to overpredict as compared to boring based or HVSR based correlations. Geospatial correlations can be used as a preliminary tool as a part of a desk survey prior to a site visit. An initial estimate of V_{s30} with an associated range of values due to uncertainty inherent in estimating V_s can provide engineers with critical information for determining the level of attention to seismic design required for the project. If initial estimates indicate that the site is within a risk category that requires seismic design, it will likely be economically feasible for a direct measurement to be taken. Design costs alone when including

seismic design provisions for bridges will likely increase the cost significantly and the additional cost to collect direct measurements will likely be a small fraction of this.. If the direct measurement were to confirm that the project will require seismic design considerations, then the information collected by direct measurement will be critical to design.

Boring based methods can also provide reasonable estimates of V_s for sites within the state, but have a greater tendency to overpredict site class at softer sites, as evidenced by performance on sites within the West Alabama group. Overprediction of site class for sites within the Northwest Alabama group is of lesser consequence as many of those sites are not in the critical soft alluvial regions that dominate seismic hazard throughout the state. The presented methods have a greater risk to provide an estimate of site class that could artificially decrease seismic risk and potentially cause unconservative design of sensitive structures. Despite their ability to provide reasonable estimates of site class, they should be considered less than geospatial methods due to their tendency to overpredict site class.

SPT based methods can be used to estimate V_s for discrete soil layers. The methods are most effective for sands at shallower depths but reasonable estimates can be made for clays and silts as well. V_s is a crucial property for seismic design and is also directly related to the shear modulus. V_s can be determined by a SPT based estimate for preliminary calculations and modeling prior to a more expensive active or passive survey. SPT based methods are likely to underestimate V_s so the consequences of an underestimate need to be considered. RQD-based correlations are generally not recommended for use.

7.4 Future Research

This study considered multiple sites with boring logs but lacked much data for silty soils. Silts were encountered at some sites within the West Alabama group but were mostly encountered at depth where sampler refusal was met. Adding more SPT and V_s data pairs will allow for better evaluation of SPT based estimation methods.

Correlations to RQD were limited in number and do not accurately estimate V_s at the sites visited as a part of this study. There is a clear need for correlations for estimating V_s in

rock. RQD may not be the best measure for correlation, and future work should consider correlation to rock type, effective stress, and potentially compressive strength.

Seismic refraction surveys from this study were all compressional wave based and were not able to reach a full depth of 30 meters. Additional work in the state should consider the use of shear wave-based refraction surveys to reduce the uncertainty inherent in converting compressional wave to shear wave velocity along with using larger energy sources. Larger energy sources would allow for a higher signal to noise ratio, which would allow for more confident selection of first arrivals at geophones farther away from the energy source. This would allow for refraction surveys to reach greater depths.

Comparisons with HVSR estimation methods were limited in this study by the lack of sites with clear peak frequencies. Additional surveys should aim to isolate sensors from anthropogenic noise and other sources of error in measurement.

Future studies should also consider more alluvial sites within the northern part of the state. Soft alluvial sites in the northern part of the state represent the greatest seismic hazard as they have a greater potential for seismic activity to occur and are softer compared to shallow rock sites commonly found in the region. More data is needed to properly evaluate models requiring a clear peak frequency in their application.

Future studies could consider seasonal changes to V_{S30} due to changes in groundwater. As the groundwater table rises, soils are to get softer and potentially decrease in V_S . Studies with a temporal aspect of V_{S30} could serve to be beneficial in determining critical risk cases. Additionally future studies could consider additional sources of geophysical data to determine V_S . Fiber optic networks could be used to allow for more high resolution mapping of V_{S30} (Yust et al. 2024).

References

- AASHTO (American Association of State Highway and Transportation Officials). 2023. *AASHTO LRFD Bridge Design Specifications, 10th Edition*. Washington, D.C.: AASHTO.
- Abrahamson, N., Atkinson, G., Boore, D., Bozorgnia, Y., Campbell, K., Chiou, B., Idriss, I. M., Silva, W., & Youngs, R. 2008. "Comparisons of the NGA Ground-Motion Relations." *Earthquake Spectra*, 24(1), 45-66. <https://doi.org/10.1193/1.2924363>
- Allen, T. I., & Wald, D. J. 2009. "On the use of high-resolution topographic data as a proxy for seismic site conditions (VS 30)." *Bulletin of the Seismological Society of America*, 99(2A), 935-943.
- Amatulli, G., Domisch, S., Tuanmu, M. N., Parmentier, B., Ranipeta, A., Malczyk, J., and Jetz, W. 2018. "A suite of global, cross-scale topographic variables for environmental and biodiversity modeling." *Sci. Data* 5, no. 1, 1–15.
- Anbazhagan, P., Bajaj, K., Reddy, G. R., Phanikanth, V. S., & Yadav, D. N. 2016. "Quantitative assessment of shear wave velocity correlations in the shallow bedrock sites." *Indian Geotechnical Journal*, 46(4), 381–397. <https://doi.org/10.1007/s40098-016-0181-y>
- Andrus, R. D., Mohanan, N. P., Piratheepan, P., Ellis, B. S., and Holzer, T. L. 2007. "Predicting shear-wave velocity from cone penetration resistance." *Proc., 4th Inter. Conf. on Earthq. Geotech. Eng.*, Thessaloniki, Greece.
- ASCE/SEI (American Society of Civil Engineers). 2022. *ASCE/SEI 7-22 Minimum Design Loads and Associated Criteria for Buildings and Other Structures* (Vol. 1) <https://www.asce.org/publications-and-news/asce-7>
- ASTM. 2011. *Standard Test Method for Standard Penetration Test (SPT) and Split-Barrel Sampling of Soils*. ASTM D1586-11. West Conshohocken, PA: ASTM.

- ASTM. 2014. *Standard Practice for Rock Core Drilling and Sampling of Rock for Site Investigation*. ASTM D 2113-14. West Conshohocken, PA: ASTM.
- ASTM. 2017. *Standard Test Method for Determining Rock Quality Designation (RQD) of Rock Core*. ASTM D 6032-17. West Conshohocken, PA: ASTM.
- ASTM. 2020. *Standard Test Method for Electronic Friction Cone and Piezocone Penetration Testing of Soils*. ASTM D 5778-20. West Conshohocken, PA: ASTM.
- Baldi, G., Bellotti, R. Ghionna, V. N., Jamiolkowski, M., and LoPresti, D. C. F. 1989. "Modulus of sands from CPTs and DMTs." *Proc., 12th Inter. Conf. Soil Mech. and Foundation Eng.*, Vol. 1, Rio de Janeiro, pp. 165–170.
- Ballard, R. F. 1976. "Method for Crosshole Seismic Testing." *Journal of the Geotechnical Engineering Division*, 102(12), 1261-1273. <https://doi.org/10.1061/AJGEB6.0000355>
- Bard, P. Y., and Participants, S. E. S. A. M. E. 2004. "The SESAME project: an overview and main results." *In Proc. of 13th World Conf. on Earthquake Engineering*, Vancouver, BC, Canada, August (pp. 1-6).
- Beresnev, I., and Atkinson, G. 1997. "Shear-Wave Velocity Survey of Seismographic Sites in Eastern Canada: Calibration of Empirical Regression Method of Estimating Site Response." *Seismological Research Letters* 68:6, 981-987.
- Biringen, E. and Davie, J. 2013. "Correlation Between VS and RQD for Different Rock Types" *International Conference on Case Histories in Geotechnical Engineering*. 11. https://scholarsmine.mst.edu/icchge/7icchge/session_06/11
- Bowles, J. E., & Guo, Y. 1996. *Foundation analysis and design*. New York: McGraw-hill.
- Butler, D. K., and Curro, J. R. 1981. "Crosshole seismic testing—Procedures and Pitfalls." *Geophysics*, 46(1), 23-29. <https://doi.org/10.1190/1.1441134>
- Campanella, R. G., Robertson, P. K., and Gillespie, D. 1986. "Seismic Cone Penetration Test." 116-130. [Seismic Cone Penetration Test by Campanella et al.](#)

- Carcamo, P. 2022. "Application of Methods to Characterize V_{S30} in Alabama." (Ph.D. Dissertation, Dept. of Civil and Environmental Engineering, Auburn University).
- El-Naqa, A. 1996. "Assessment of geomechanical characterization of a rock mass using a seismic geophysical technique." *Geotech Geol Eng* 14, 291–305.
<https://doi.org/10.1007/BF00421945>
- Fan, Y., Li H., and Miguez-Macho, G. 2020. "RE: Updated dataset for global patterns of groundwater table depth." *Science* 339, no. 6122, 940–943, doi: 10.1126/science.1229881.
- Farr, T. G., & Kobrick, M. 2000. "Shuttle Radar Topography Mission produces a wealth of data." *Eos, Transactions American Geophysical Union*, 81(48), 583-585.
- Fatehnia, M., Hayden, M. and Landschoot, M. 2015. "Correlation between Shear Wave Velocity and SPT-N Values for North Florida Soils." *EJGE*. 20. 12421-12430.
- Gann-Phillips, C., Cabas, A., Ji, C., Cramer, C., Kaklamanos, J., & Boyd, O. 2024. "Regional seismic velocity model for the US Atlantic and Gulf Coastal Plains based on measured shear wave velocity, sediment thickness, and surface geology." *Earthquake Spectra*, 40(2), 1269-1300.
- GEObit Instruments. 2023. *GEOtinyMK3 Low Power Compact Digital Seismometer: User Manual, Revision 12.6, Firmware Version 13.0.0*. GEObit Instruments.
- Geometrics, I. 2009. *SeisImager/2D Seismic Refraction Data Analysis Software Manual and Examples Booklet* (ver 3.3).
- Geyin, M., and Maurer, B.W. 2023. "U.S. National VS30 Models and Maps Informed by Remote Sensing and Machine Learning." *Seismol. Res. Lett.* 94, 1467–1477, doi: 10.1785/0220220181.
- Gomberg, G. Waldron, B., Schweig, E., Hwang, H. Webbers, A., Van Arsdale, R., Tucker, K. Williams, R., Street, R., Mayne, P., Stephenson, W., Odum, J., Cramer, C., Updike, R.,

- Hutson, S., and Bradley, M. 2003. "Lithology and Shear-Wave Velocity in Memphis, Tennessee." *Bulletin Seismological Society of America* 93:3, 986-997.
- Goulet, C. A., Kishida, T., Ancheta, T. D., Cramer, C. H., Darragh, R. B., Silva, W. J., & Youngs, R. R. 2021. "PEER NGA-east database." *Earthquake Spectra*, 37(1_suppl), 1331-1353.
- Green, R. 1974. "The seismic refraction method—a review." *Geoexploration*, 12(4), 259-284.
- Grelle, G., and Guadagno, F. M. 2009. "Seismic refraction methodology for groundwater level determination: "Water seismic index"." *Journal of Applied Geophysics*, 68(3), 301-320.
<https://doi.org/10.1016/j.jappgeo.2009.02.001>
- Hasancebi, N., and Ulusay, R. 2007. "Empirical correlations between shear wave velocity and penetration resistance for ground shaking assessments." *Bull. Eng. Geology and the Environment*, 66:203–213.
- Hassani, B., & Atkinson, G. M. 2016. "Applicability of the site fundamental frequency as a VS 30 proxy for central and eastern North America." *Bulletin of the Seismological Society of America*, 106(2), 653-664.
- Heath, D. C., Wald, D. J., Worden, C. B., Thompson, E. M., and Smoczyk, G. M. 2020a. "A global hybrid VS30 map with a topographic slope–based default and regional map insets." *Earthq. Spectra* 36, no. 3, 1570–1584.
- Hegazy, Y. A., and Mayne, P. W. 1995. "Statistical correlations between VS and cone penetration data for different soil types." *Proc., Inter. Symp. on Cone Penetration Testing, CPT '95*, Linköping, Sweden, Vol. 2, pp. 173–178.
- Hepton, P. 1988. "Shear wave velocity measurements during penetration testing." *Penetration Testing in the UK*. Thomas Telford, London, 275-278.
- Herath, P., Stern, T., Savage, M., Bassett, D., Henrys, S., Barker, D., Avendonk, H. V., Bangs, N., Arnulf, A., Arai, R., Kodaira, S., and Mochizuki, K. 2020. "Using P- to S- wave conversions from controlled sources to determine the shear-wave velocity structure along Hikurangi

- Margin Forearc, New Zealand (N.° EGU2020-11940)." *EGU2020. Copernicus Meetings*.
<https://doi.org/10.5194/egusphere-egu2020-11940>
- Holzer, T., Noce, T, and Bennett, M. 2010. "Maps and Documentation of Seismic CPT Soundings in the Central, Eastern, and Western United States." USGS OFR 2010-1136.
- Horton, J. D., San Juan, C.A., and Stoeser, D.B. 2017. "The State Geologic Map Compilation (SGMC) geodatabase of the conterminous United States (ver. 1.1, August 2017)" U.S. Geol. Surv. Data Release, doi: 10.5066/F7WH2N65.
- ICC (International Code Council). 2015. *IBC: International Building Code (3rd ed., Vol. 1-2)*. Country Club Hills, IL: ICC.
- Imai, T. and Tonouchi, K. 1982. "Correlation of N-value with S-wave velocity and shear modulus." *Proc. 2nd European Symp. Of Penetration Testing (Amsterdam)*, 57–72.
- Iwahashi, J., and Pike, R. J. 2007. "Automated classifications of topography from DEMs by an unsupervised nested-means algorithm and a three-part geometric signature." *Geomorphology* 86, 409–440.
- Jinan, Z. 1987. "Correlation between seismic wave velocity and the number of blow of SPT and depth." *Selected Papers from the Chinese J. Geotech. Eng.*, ASCE, pp. 92–100.
- Kahraman, S. 2001 "A Correlation Between P-wave Velocity, Number of Joints and Schmidt Hammer Rebound Number." *International Journal of Rock Mechanics and Mining Sciences*, 38(5), pp.729–733.
- Kaneko, F., Kanemori, T., and Tonouchi, K. 1990. "Low-Frequency Shear Wave Logging in Unconsolidated Formations for Geotechnical Applications." *ASTM Special Technical Publication* 1101, ASTM, 79-98.
- Kottke, A. R., Hashash, Y. M., Stewart, J. P., Moss, C. J., Nikolaou, S., & Rathje, E. M. 2012. "Development of geologic site classes for seismic site amplification for central and eastern North America". *UCLA: Civil and Environmental Engineering*. Retrieved from <https://escholarship.org/uc/item/8374p3d3>

- Kovacs, W. D., Evans, J. C, and Griffith, A. H. 1977. "Towards a More Standardized SPT," *Proceedings of the Ninth International Conference on Soil Mechanics and Foundation Engineering*, Tokyo, Japan.
- Kovacs, W. D. 1978. "Velocity Measurement of a Free-Fall Hammer."
- Kramer, S. L., and Stewart, J. P., 2025. *Geotechnical Earthquake Engineering Second Edition*. Upper Saddle River, New Jersey. Prentice-Hall.
- LaMondia, J. J., Blackmar, C. E., and Bhat, C. R. 2010. "Comparing Transit Accessibility Measures: A Case Study of Access to Healthcare Facilities." *Transport Research Board 2011 Annual Meeting*. Washington, DC. 2010.
- Liu, L., and Zoback, M. D. 1997. "Lithospheric strength and intraplate seismicity in the New Madrid seismic zone." *Tectonics*, 16(4), 585-595. <https://doi.org/10.1029/97TC01467>
- Lee, S. H. H. 1992. "Analysis of the multicollinearity of regression equations of shear wave velocities." *Soils and Foundations*, 32(1):205–214.
- Lehner, B., and Grill, G. 2013. "Global river hydrography and network routing: Baseline data and new approaches to study the world's large river systems." *Hydrol. Process.* 27, no. 15, 2171–2186.
- Lermo, J., and Chávez-García, F. J. 1993. "Site effect evaluation using spectral ratios with only one station." *Bulletin of the seismological society of America*, 83(5), 1574-1594.
- Lo Pinto, V. J. 1966. "Discussion of Standard Penetration Test: Its uses and abuses, by G.F.A. Fletcher" *Journal Soil Mechanics and Foundations Division*, ASCE, Vol 92 No.SM1 pp. 195–196.
- Mayne, P. W. 2006. "In situ test calibrations for evaluating soil parameters." *Proc., Characterization and Engineering Properties of Natural Soils II*, Singapore.
- Mayne, P. W., and Rix, G. J. 1995. "Correlations between shear wave velocity and cone tip resistance in natural clays." *Soils and Foundations*, 35(2):107–110.

- McDonald, F. J., Angona, F. A., Mills, R. L., Sengbush, R. L., Van Nostrand, R. G., & White, J.E. 1958. "Attenuation of Shear and Compressional Waves in Pierre Shale." 23(3), 421-439.
- McNamara, D. E., Stephenson, W. J., Odum, J. K., Williams, R. A., & Gee, L. 2015. "Site response in the eastern United States: A comparison of Vs30 measurements with estimates from horizontal:vertical spectral ratios", The 2011 Mineral, Virginia, Earthquake, and Its Significance for Seismic Hazards in Eastern North America, J. Wright Horton, Jr., Martin C. Chapman, Russell A. Green
- Miller, R. D., Pullan, S. E., Waldner, J. S. and Haeni, F. P. 1986. "Field comparison of shallow seismic sources." *Geophysics*, 51: 2067–2092.
- Miller, R. D., Pullan, S. E., Steeples, D. W. and Hunter, J. A. 1992. "Field comparison of shallow seismic sources near Chino, California." *Geophysics*, 57: 693–709.
- Miller, R. D., Pullan, S. E., Steeples, D. W. and Hunter, J. A. 1994. "Field comparison of shallow P-wave seismic sources near Houston, Texas." *Geophysics*, 59: 1713–1728.
- Mohanan, N., Fairbanks, C., Andrus, R., Camp, W., Cleary, T., Casey, T., and Wright, W. 2006. "Electronic Files of Shear Wave Velocity and Cone Penetration Test Measurements from the Greater Charleston Area, South Carolina." US Geological Survey, Final Technical Report No. 05HQGR0037.
- Motazedian, D. and Hunter, J. Pugin, A., and Crow, H. 2011. "Development of a Vs30 (NEHRP) map for the city of Ottawa, Ontario." *Canada Canadian Geotechnical Journal* 48:3, 458-472.
- Mousa, A., & Hussein, M. 2022. "Prediction of shear wave velocity in fine-grained soils from cone penetration test data: toward a global approach." *Transportation Research Record*, 2676(6), 565-582.
- Mucciarelli, M., and Gallipoli, M. R. 2001. "A critical review of 10 years of microtremor HVSr technique." *Boll. Geof. Teor. Appl*, 42(3-4), 255-266.

- Murphy, C. 2003. "Near-surface Characterization and Estimated Site Response at POLARIS Seismograph Stations in Southern Ontario, Canada." M.Sc. Thesis, University of Western Ontario, London, Ontario, Canada.
- Mussett, A.E., and Khan, M.A. 2000. "Looking into The Earth: An Introduction to Geological Geophysics." New York, Cambridge University Press, 470 p
- Nakamura, Y. 1989. "A method for dynamic characteristics estimation of subsurface using microtremor on the ground surface". *Railway Technical Research Institute, Quarterly Reports*, 30(1).
- Nakamura, Y. 2009." Basic Structure of QTS (HVSr) and Examples of Applications." In: Mucciarelli, M., Herak, M., Cassidy, J. (eds) *Increasing Seismic Safety by Combining Engineering Technologies and Seismological Data*. NATO Science for Peace and Security Series C: Environmental Security. Springer, Dordrecht. https://doi.org/10.1007/978-1-4020-9196-4_4
- Nakamura, Y. 2019. "What Is the Nakamura Method?" *Seismological Research Letters*. <https://doi.org/10.1785/0220180376>
- National Academies of Sciences, Engineering, and Medicine. 2021. *State of the Art and Practice in the Assessment of Earthquake-Induced Soil Liquefaction and Its Consequences*. Washington, DC: The National Academies Press. <https://doi.org/10.17226/23474>.
- Ohta, Y, and Goto, N. 1978." Empirical shear wave velocity equations in terms of characteristic soil indexes." *Earthquake Engineering and Structural Dynamics*, 6:167–187.
- Ohya, S., Ogura, K., and Imai, T. 1984) "The Suspension PS Velocity Logging System." *Offshore Technology Conference*. <https://doi.org/10.4043/4680-MS>
- Oldenberg, D., Capriotti, J., Kang, S., Devriese, S., Astic, T., Cockett, R., Heagy, L., & Jones, F. 2017. *Seismic velocities of rocks and various materials*.
- Osborne, W. E., Szabo, E. W., Copeland, C. W., Jr., and Neathery, T. L. 1989. Geologic map of Alabama: Special Map 221. Geological Survey of Alabama.

- Park, S., and Elrick, S. 1998. "Predictions of shear-wave velocities in southern California using surface geology." *Bull. Seism. Soc. Am.* 88, 677–685.
- Park, C. B., Miller, R. D., and Xia, J. 1999. "Multichannel analysis of surface waves (MASW)." *Geophysics*, 64, 800-808.
- Parker, G. A., Harmon, J. A., Stewart, J. P., Hashash, Y. M., Kottke, A. R., Rathje, E. M., & Campbell, K. W. 2017. "Proxy-based VS 30 estimation in central and eastern North America." *Bulletin of the Seismological Society of America*, 107(1), 117-131.
- PASI. 2013. *HVSR Data Acquisition Unit GEMINI-2: User Manual, 2013 Edition, Revision 2.0.1*. P.A.S.I. srl, Torino, Italy.
- Pickett, G. R. 1963. "Acoustic Character Logs and their Applications in Formation Evaluation." *Journal of Petroleum Technology*, 15, 659-667.
- Pilz, M., Parolai, S., Leyton, F., Campos, J., and Zschau, J. 2009. "A comparison of site response techniques using earthquake data and ambient seismic noise analysis in the large urban areas of Santiago de Chile." *Geophysical Journal International*, Volume 178, Issue 2, August 2009, Pages 713–728, <https://doi.org/10.1111/j.1365-246X.2009.04195.x>
- Piratheepan, P. 2002. "Estimating Shear-Wave Velocity from SPT and CPT Data." M. S. thesis, Dept. of Civil Engineering, Clemson University.
- Raikes, S. A., and White, R. E. 1984. "Measurements of Earth Attenuation from Downhole and Surface Seismic Recordings." *Geophysical Prospecting*, 32(5), 892-919.
<https://doi.org/10.1111/j.1365-2478.1984.tb00745.x>
- Reynolds, J. M. 2011. *An Introduction to Applied and Environmental Geophysics*. John Wiley & Sons.
- Riggs, C. O., 1986. "North American Standard Penetration Test Practice: An Essay in Use of in Situ Tests in Geotechnical Engineering." *ASCE Geotechnical Special Publication No. 6*

- Robertson, P. K. 2009. "Interpretation of cone penetration tests – a unified approach." *Canadian Geotech. J.*, 46(11):1337–1355.
- Robertson, P. K., Campanella, R. G., Gillespie, D., and Rice, A. 1986. "Seismic CPT to Measure in Situ Shear Wave Velocity." 112(8), 791-803.
- Rogers, J. D. 2006. "Subsurface exploration using the standard penetration test and the cone penetrometer test". *Environmental & Engineering Geoscience*, 12(2), 161-179.
- Rosenblad, B., Bailey, J., Csontos, R., and Van Arsdale, R. (2010). Shear Wave Velocities of Mississippi Embayment Soils from Low Frequency Surface Wave Measurements. *Soil Dynamics and Earthquake Engineering* 30:8, 691-701.
- Salaamah, A. F., Fathani, T. F., & Wilopo, W. 2019. "Correlation of P-wave velocity with rock quality designation (RQD) in Volcanic Rocks." *Journal of Applied Geology*, 3(2), 11. <https://doi.org/10.22146/jag.48594>
- Schmertmann, J. H., and Palacios, A. 1979. "Energy dynamics of SPT." *Journal of the Geotechnical Engineering Division*, 105(8), 909-926.
- Seed, H. B., Idriss, I. M., and Arango, I. 1983. "Evaluation of Liquefaction Potential Using Field Performance Data." *J. Geotech. Eng.*, 109(3):458–482.
- Seed, H. B., Tokimatsu, K., Harder, L. F., and Chung, R. M. 1985. "Influence of SPT procedures in soil liquefaction resistance evaluations." *Journal of geotechnical engineering*, 111(12), 1425-1445.
- SESAME 2004. "Guidelines for the Implementation of the H/V Spectral Ratio Technique on Ambient Vibrations: Measurements, Processing and Interpretation." SESAME European Research Project WP12.
- Sexton, J. L., and Jones, P. B. 1986. Evidence for recurrent faulting in the New Madrid seismic zone from Mini-Sosie high-resolution reflection data. *Geophysics*, 1760-1788.
- Shangguan, W., Hengl, T., de Jesus, J. M., Yuan, H., & Dai, Y. 2017. "Mapping the global depth to bedrock for land surface modeling." *J. Adv. Model. Earth Syst.* 9, no. 1, 65–88.

- Sharma Wagle, K., Vantassel, J. P., Rodriguez-Marek, A., & Anbazhagan, B. (2026). "A Set of Data-Driven Models to Predict VS 30 from the Horizontal-to-Vertical Spectral Ratio of Microtremors." *Bulletin of the Seismological Society of America*. Stanko, D., and Markušić, S. 2020. "An empirical relationship between resonance frequency, bedrock depth and Vs30 for Croatia based on HVSR forward modelling." *Natural Hazards*, 103(3), 3715-3743. <https://doi.org/10.1007/s11069-020-04152-z>
- Sheriff, R. E., Geldart, L.P. 1995. "Seismic velocity. In: Exploration Seismology." Cambridge University Press; 107-144.
- Siddiqi, J. and Atkinson, G. 2002. "Ground-Motion Amplification at Rock Sites across Canada as Determined from the Horizontal-to-Vertical Component Ratio." *Bulletin of the Seismological Society of America* 92:2, 877-884.
- Skempton, A. W. 1986. "Standard penetration test procedures and the effects in sands of overburden pressure, relative density, particle size, ageing and overconsolidation." *Geotechnique*, 36(3), 425-447.
- Stümpel, H., Kähler, S., Meissner, R., and Milkereit, B. 1984. "The Use of Seismic Shear Waves and Compressional Waves for Lithological Problems of Shallow Sediments." *Geophysical Prospecting*, 32(4), 662-675. <https://doi.org/10.1111/j.1365-2478.1984.tb01712.x>
- Sykora, D. E., and Stokoe, K. H. 1983. "Correlations of in-situ measurements in sands of shear wave velocity." *Soil Dynamics and Earthquake Engineering*, 20:125–36.
- Teague, D., Cox, B. 2016. "Site response implications associated with using non-unique Vs profiles from surface wave inversion in comparison with other commonly used methods of accounting for Vs uncertainty." *Soil Dynamics and Earthquake Engineering*, 91:87-103, <https://doi.org/10.1016/j.soildyn.2016.07.028>.
- Theodulidis, N., Roumelioti, Z., Panou, A. 2006. "Retrospective Prediction of Macroseismic Intensities Using Strong Ground Motion Simulation: The Case of the 1978 Thessaloniki (Greece) Earthquake (M6.5)." *Bull Earthquake Eng* 4, 101–130. <https://doi.org/10.1007/s10518-006-9001-6>

- Tuttle, M. P., Schweig, E. S., Sims, J. D., Lafferty, R. H., Wolf, L. W., & Haynes, M. L. 2002. The Earthquake Potential of the New Madrid Seismic Zone. *Bulletin of the Seismological Society of America*, 92(6), 2080-2089. <https://doi.org/10.1785/0120010227>
- Vantassel, J. P. 2025. "hvsrpy: An Open-Source Python Package for Microtremor and Earthquake Horizontal-to-Vertical Spectral Ratio Processing." *Seismological Research Letters*. 96 (4): 2671–2682, <https://doi.org/10.1785/0220240395>
- Verdin, K. L. 2017." Hydrologic Derivatives for Modeling and Applications (HDMA) database." U.S. Geol. Surv. Data Release, doi: 10.5066/F7S180ZP.
- Wair, B. R., DeJong, J. T., & Shantz, T. 2012. "Guidelines for Estimation of Shear Wave Velocity Profiles." Berkley, California: Pacific Earthquake Engineering Research Center.
- Wald, D. J., and Allen, T. I. 2007. "Topographic slope as a proxy for seismic site conditions and amplification." *Bull. Seismol. Soc. Am.* 97, no. 5, 1379–1395.
- Wathelet, M., Jongmans, D., and Ohrnberger, M. (2004). Surface-wave inversion using a direct search algorithm and its application to ambient vibration measurements. *Near Surface Geophysics*, 2(4), 211–221.
- Wathelet, M. 2005. Array recordings of ambient vibrations: Surface-wave inversion (Ph.D. Thesis).
- Wathelet, M., Jongmans, D., and Ohrnberger, M. (2005). Direct inversion of spatial autocorrelation curves with the neighborhood algorithm. *Bulletin of the Seismological Society of America*, 95(5), 1787–1800.
- Wathelet, M. 2008. "An improved neighborhood algorithm: Parameter conditions and dynamic scaling." *Geophysical Research Letters* 35(9), L09301. <https://doi.org/10.1029/2008GL033256>
- Wathelet, M., Chatelain, J., Cornou, C., Giulio, G. D., Guillier, B., Ohrnberger, M., & Savvaidis, A. 2020a. "Geopsy: A User-Friendly Open-Source Tool Set for Ambient Vibration

- Processing." *Seismological Research Letters*, 91(3), 1878-1889.
<https://doi.org/10.1785/0220190360>
- Wills, C. J., Petersen, M., Bryant, W. A., Reichle, M., Saucedo, G. J., Tan, S., Taylor, G., and Treiman, J. 2000. "A site-conditions map for California based on geology and shear-wave velocity." *Bull. Seismol. Soc. Am.* 90, no. 6B, S187–S208.
- Yong, A., Hough, S. E., Iwahashi, J., & Braverman, A. 2012." A Terrain-Based Site-Conditions Map of California with Implications for the Contiguous United States." *Bulletin of the Seismological Society of America*, 102(1), 114-128. <https://doi.org/10.1785/0120100262>
- Yust, M. B., Cox, B. R., Vantassel, J. P., & Hubbard, P. G. (2024). DAS for 2-D MASW imaging: a case study on the benefits of flexible subarray processing. *Geophysical Journal International*, 237(3), 1609-1623.

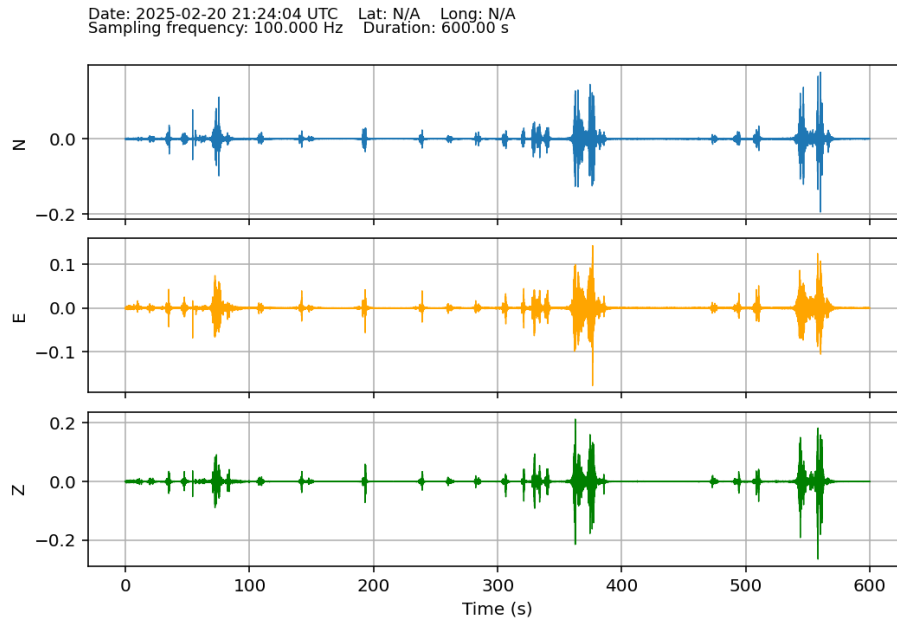
Appendix: HVSR Signal Files and Curves

The following section shows signal files along with computed HVSR curves from the surveys conducted as a part of this study. A total of 47 unique HVSR curves were able to be calculated and are classified based on the reliability of the curve and the clarity of the peak frequency. From the results, 13 calculated curves are reliable with a clear peak, 30 curves are reliable but do not have a clear peak, and 4 curves are unreliable without a clear peak.

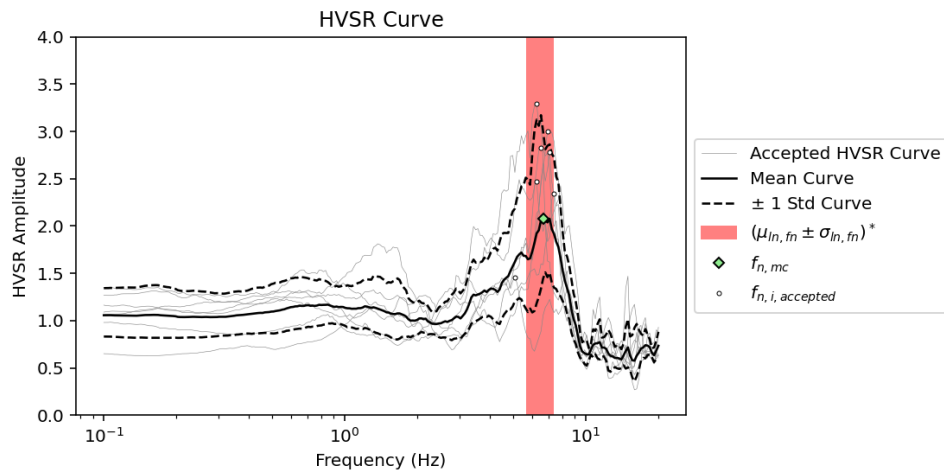
Reliable HVSR Curves with a Clear Peak

Sensors that provided a clear peak with a reliable curve are presented in Figure A-1 through Figure A-12. For an HVSR curve to be reliable it must meet all three SESAME reliability criteria while to have a clear peak only five out of the six clarity criteria must be met. All of the following curves have satisfied these requirements.

Generally the reliable curves with a clear peak show one distinct peak frequency. However, some curves display less prominent peaks at higher and lower frequencies, notably in the curves calculated from data collected at the Duck River, Bluewater Creek, and Lauderdale County sites. All curves with the exception of those calculated from data collected at the Moundville, AL site have peak frequencies of greater than 1 Hz with all 3 of the subsequent curves from the Moundville site having a peak frequency of 0.6 Hz. Stations with a singular significant peak show a large impedance contrast. If the amplitude of the peak frequency is greater than 4 it is certain that a large impedance contrast exists which causes a sharp discontinuity (SESAME 2004). Higher peak frequencies, such as those observed at the Bluewater Creek site could indicate shallower stiff structures.

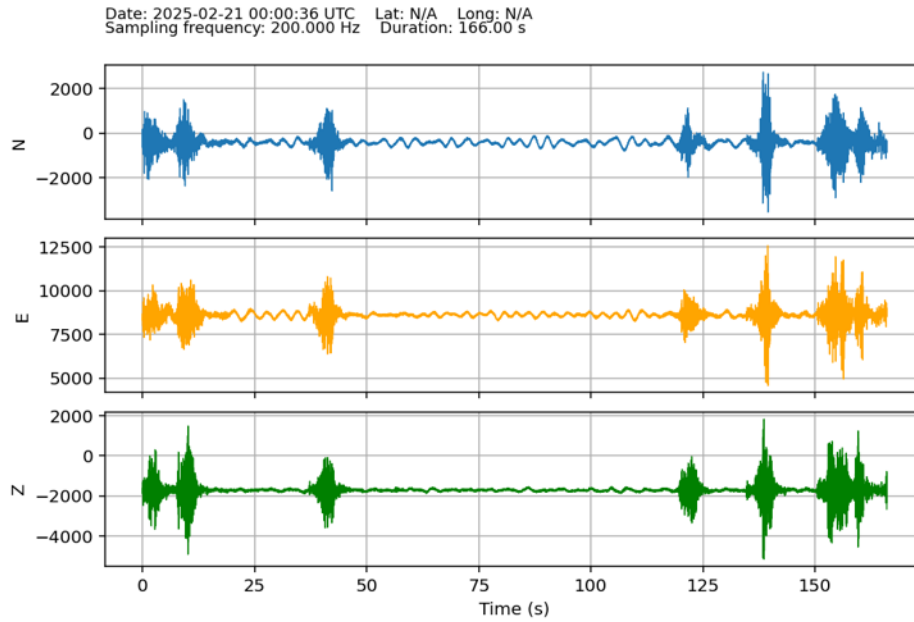


(A)

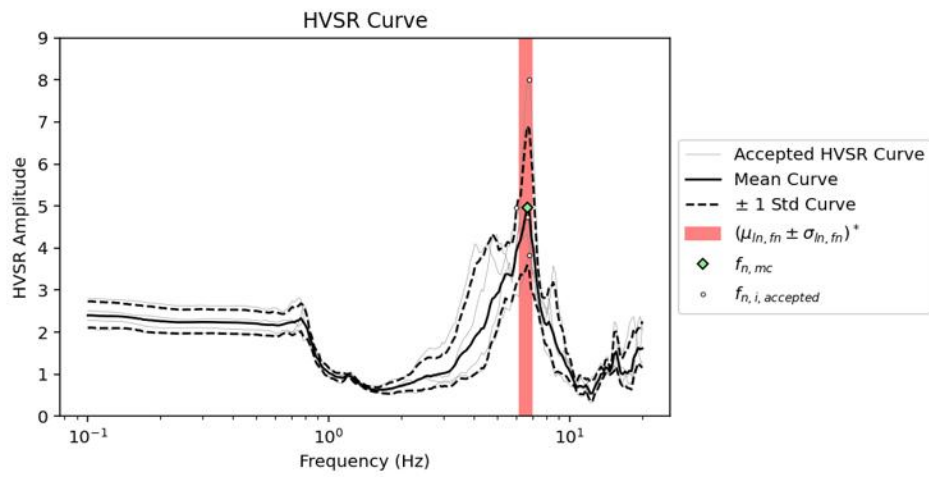


(B)

Figure A-1: (A) 3-component signal file and (B) HVSR curve for Beaver Creek survey line 2 measured by PASI Gemini sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

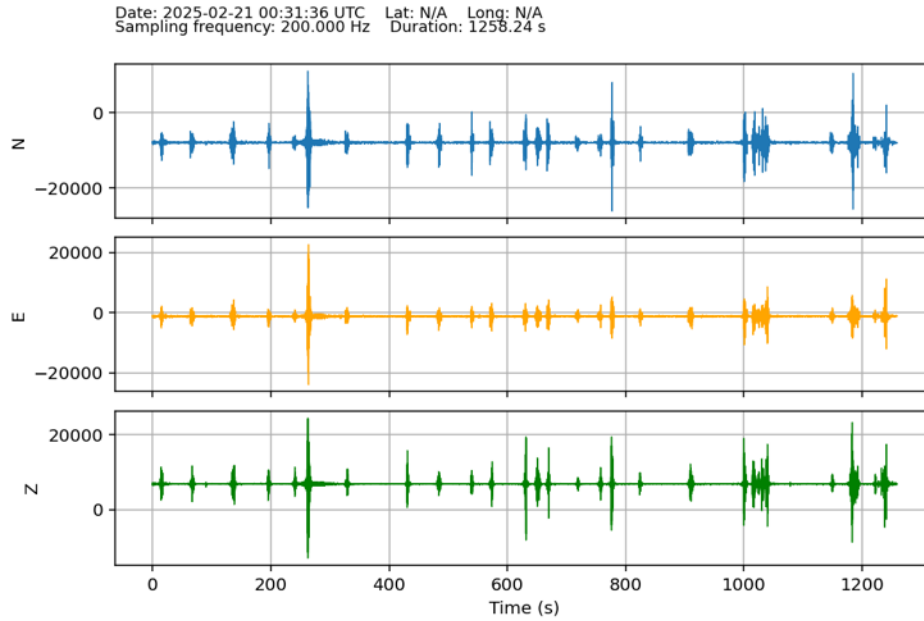


(A)

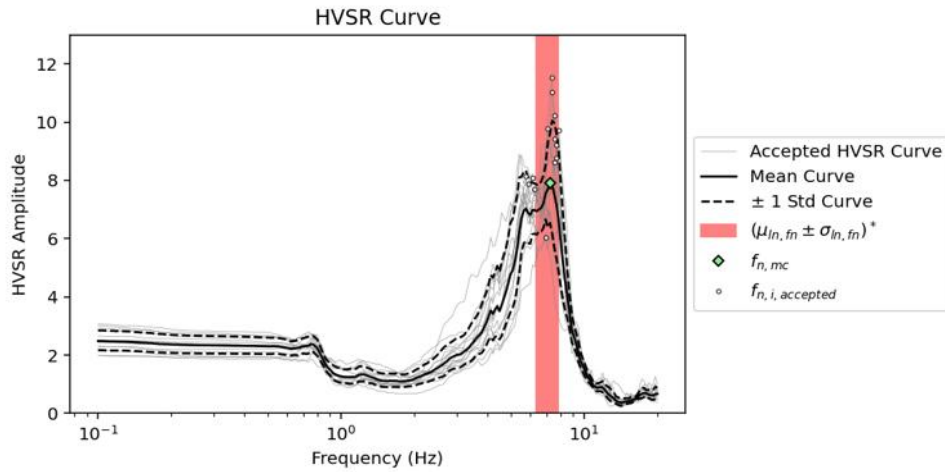


(B)

Figure A-2: (A) 3-component signal file and (B) HVSR curve for Big Prairie Creek survey line 1 measured by GTN30 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

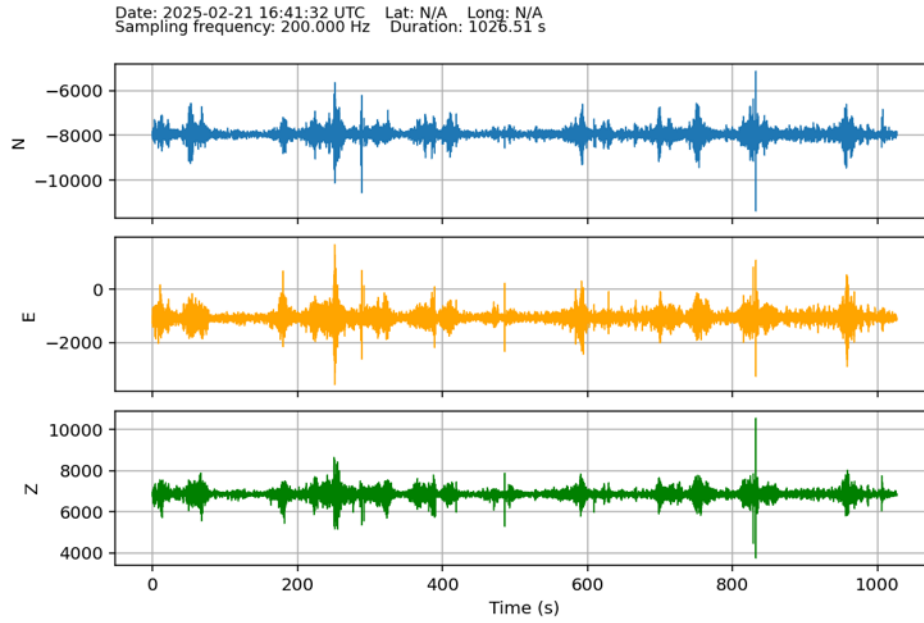


(A)

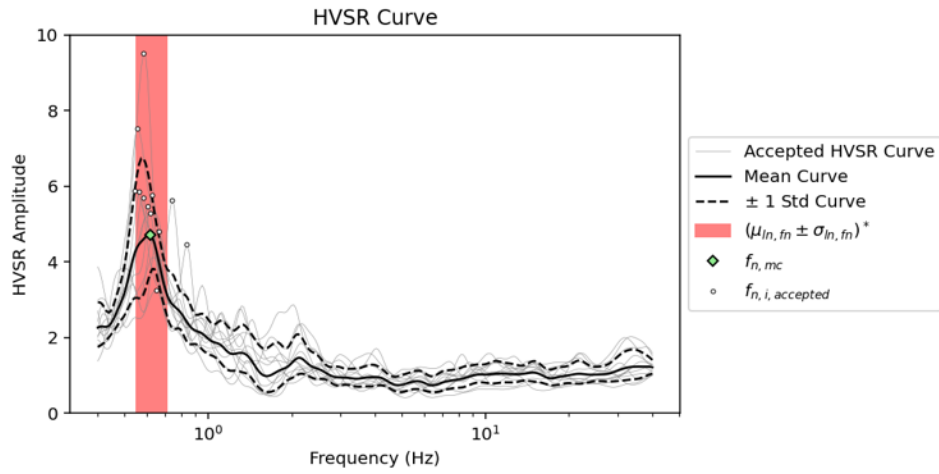


(B)

Figure A-3: (A) 3-component signal file and (B) HVSR curve for Big Prairie Creek survey line 2 measured by GTN21 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

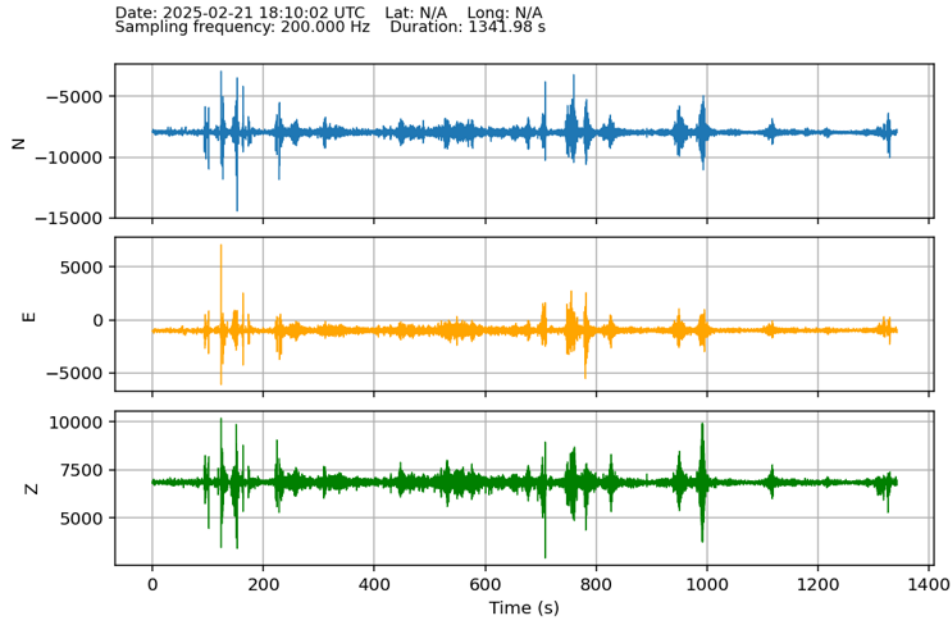


(A)

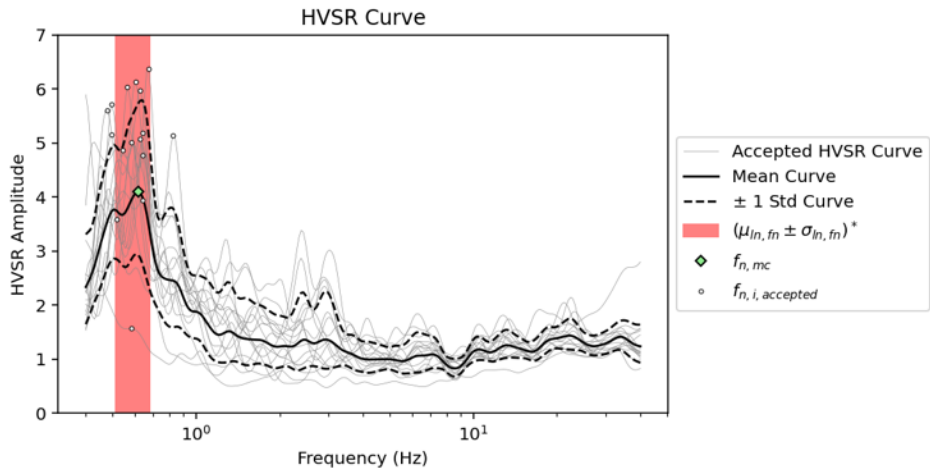


(B)

Figure A-4 : (A) 3-component signal file and (B) HVSR curve for Moundville survey line 1 measured by GTN21 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

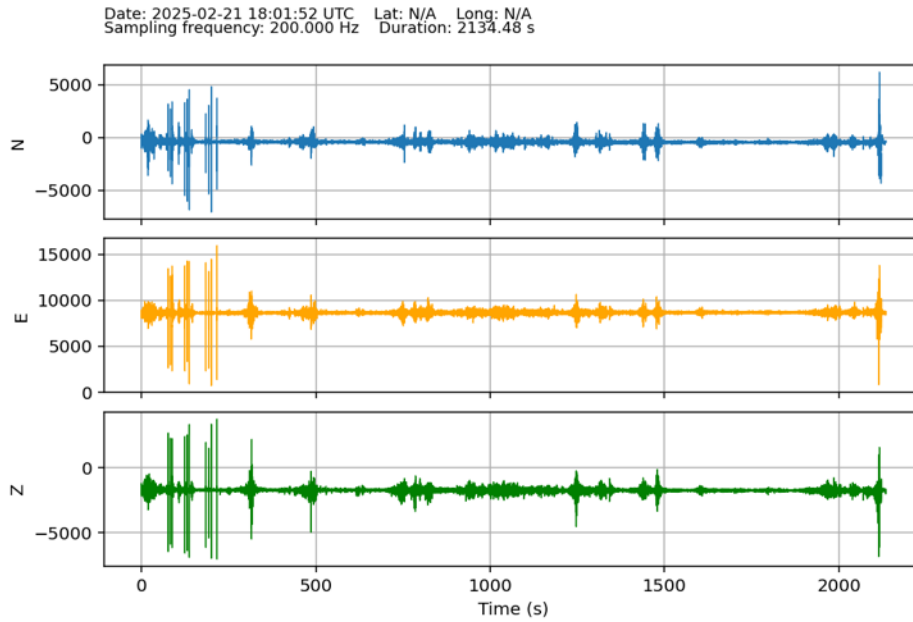


(A)

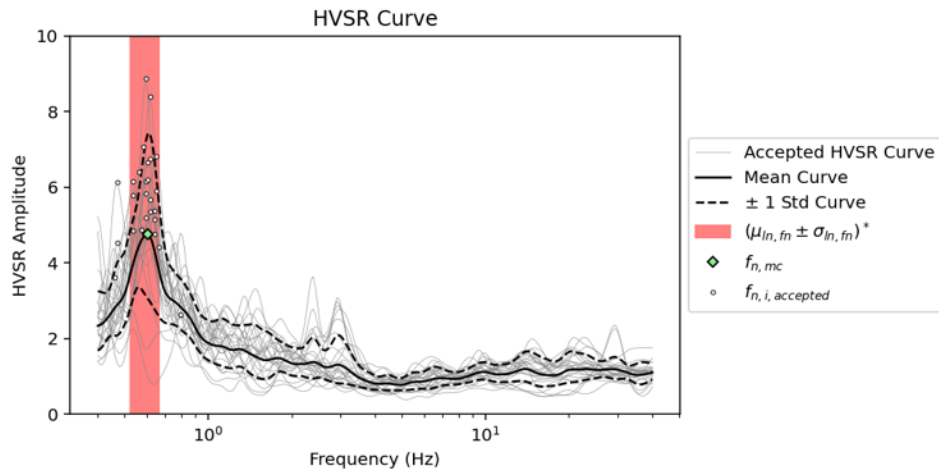


(B)

Figure A-5: (A) 3-component signal file and (B) HVSR curve for Moundville survey line 2 measured by GTN21 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

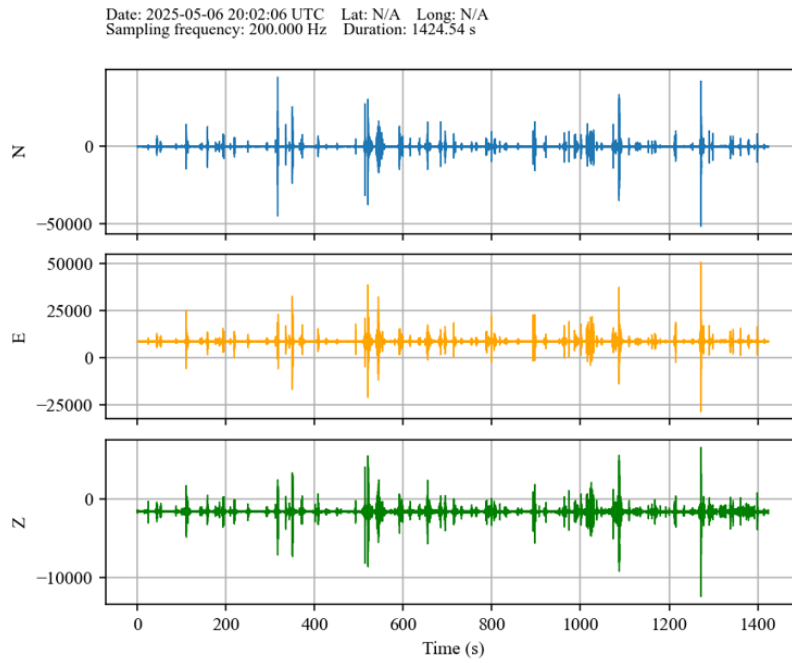


(A)

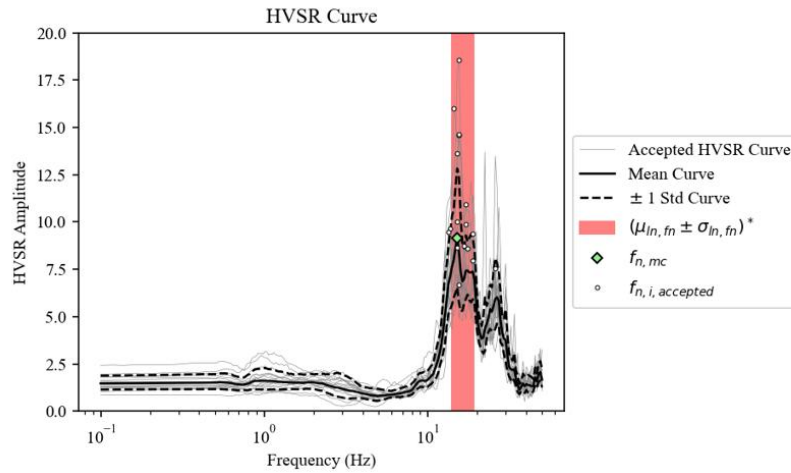


(B)

Figure A-6: (A) 3-component signal file and (B) HVSR curve for Moundville survey line 2 measured by GTN30 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

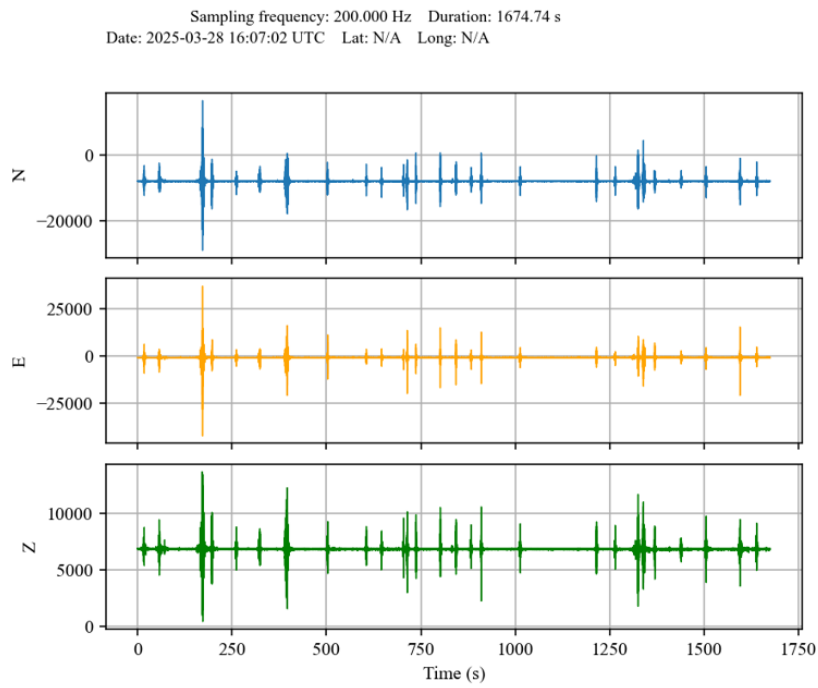


(A)

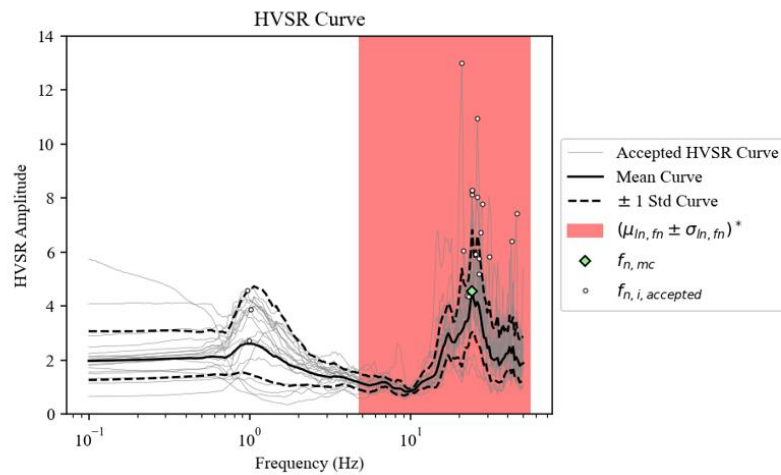


(B)

Figure A-7: (A) 3-component signal file and (B) HVSr curve for Blount County measured by GTN30 sensor. Peak frequency is denoted by a green point. Mean HVSr curve is solid black line while plus and minus one standard deviation curves are dashed lines.

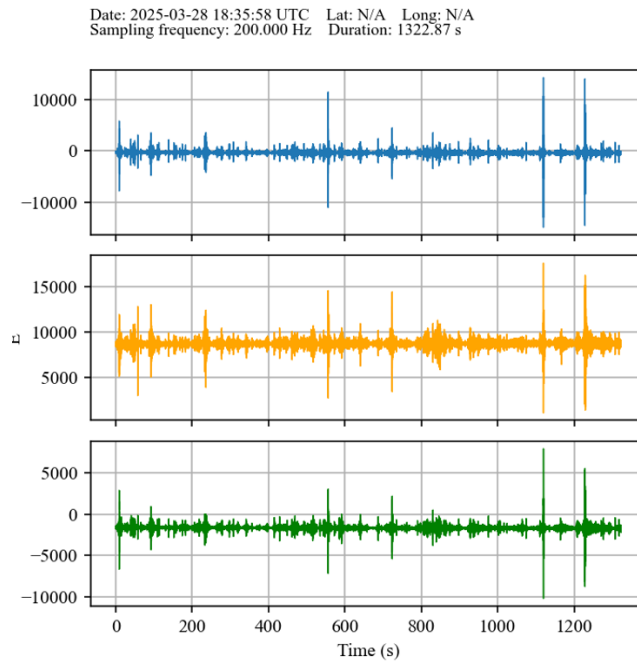


(A)

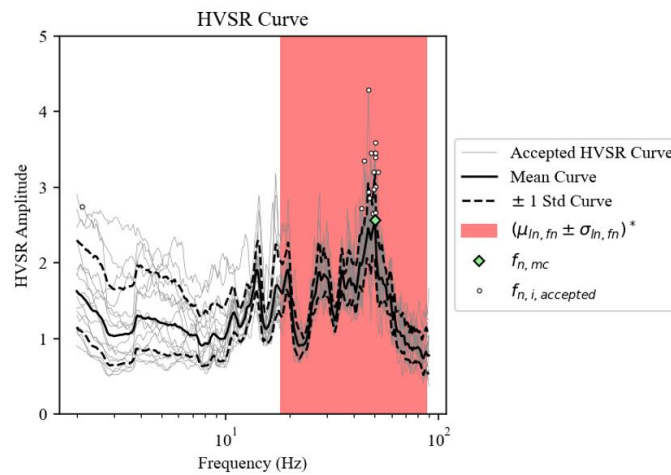


(B)

Figure A-8: (A) 3-component signal file and (B) HVSR curve for Bluewater Creek measured by GTN21 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

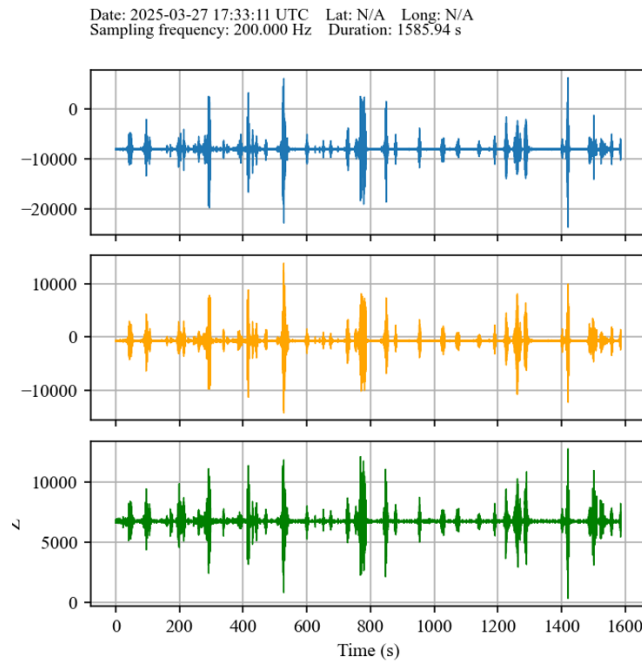


(A)

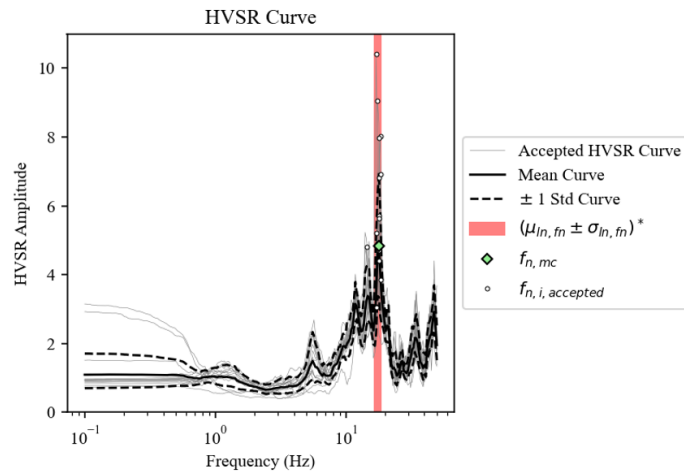


(B)

Figure A-9: (A) 3-component signal file and (B) HVSR curve for Bluewater Creek measured by GTN30 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

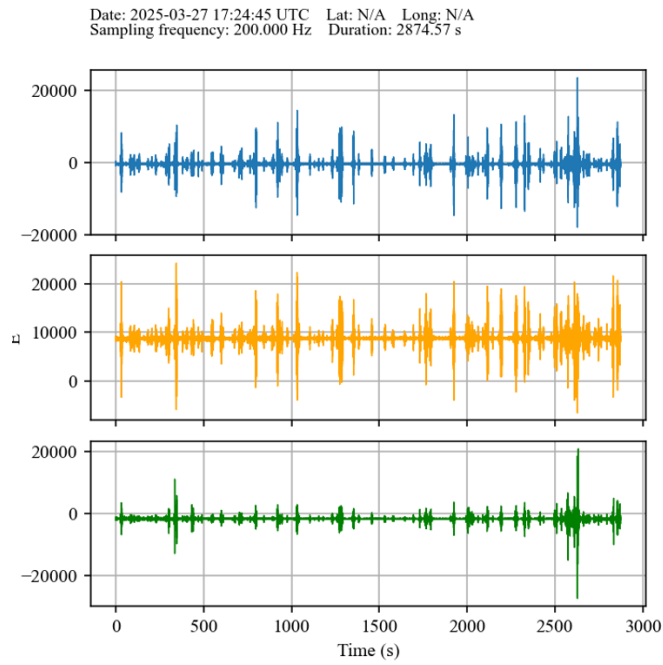


(A)

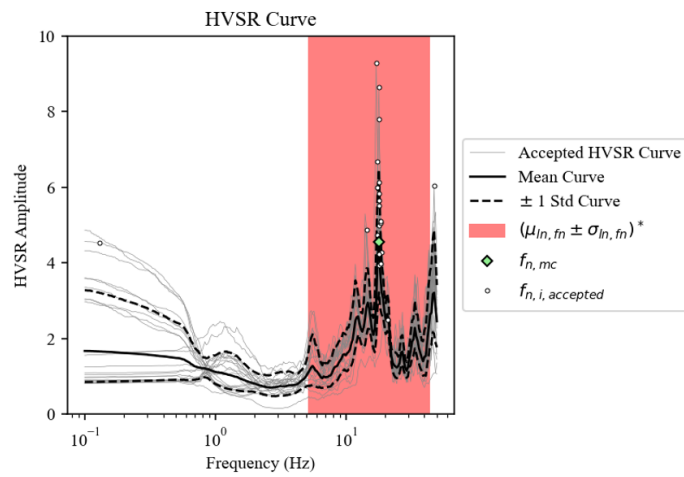


(B)

Figure A-10: (A) 3-component signal file and (B) HVSR curve for Duck River measured by GTN21 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

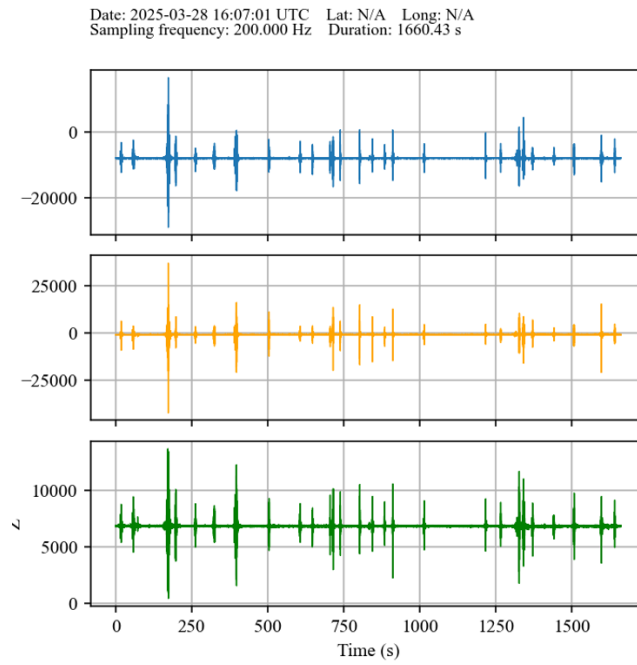


(A)

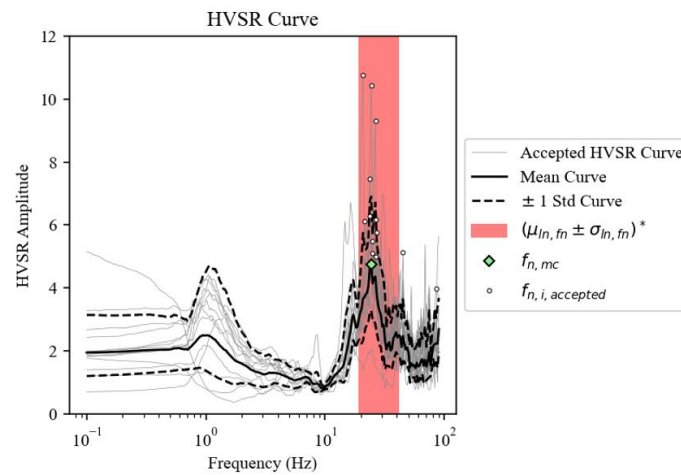


(B)

Figure A-11: (A) 3-component signal file and (B) HVSR curve for Duck River measured by GTN30 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.



(A)

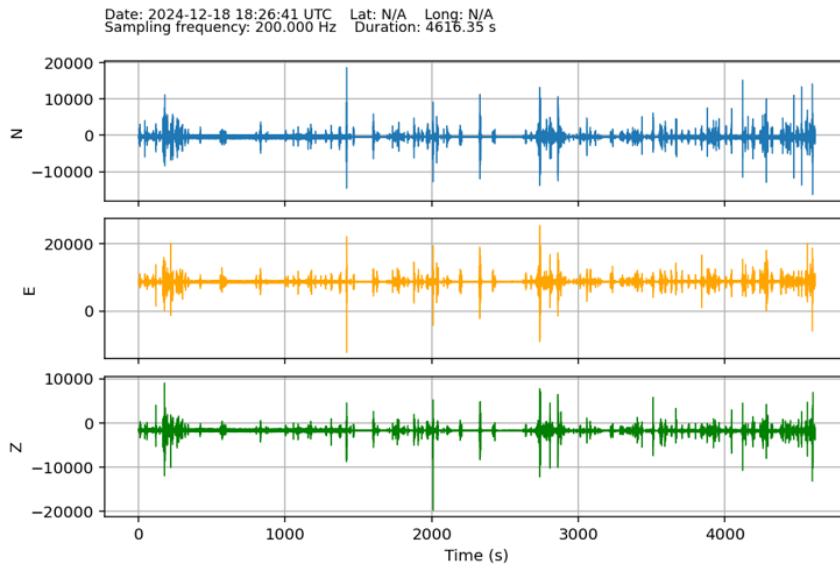


(B)

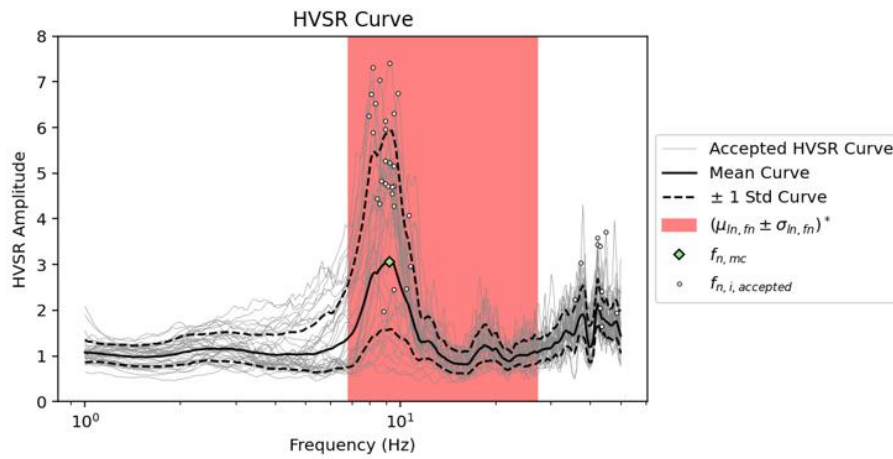
Figure A-12: (A) 3-component signal file and (B) HVSR curve for Lauderdale County survey line 2 measured by GTN21 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

Reliable HVSR Curves without a Clear Peak

Sensors that provided a reliable HVSR curve without a clear peak are presented in Figure A-14 to Figure A-42. Most curves do not meet clarity checks 3 through 6 with a few not meeting clarity checks 1 and 2. Curves that do not meet either set of criteria are presented in Figure A-43 to Figure A-45.

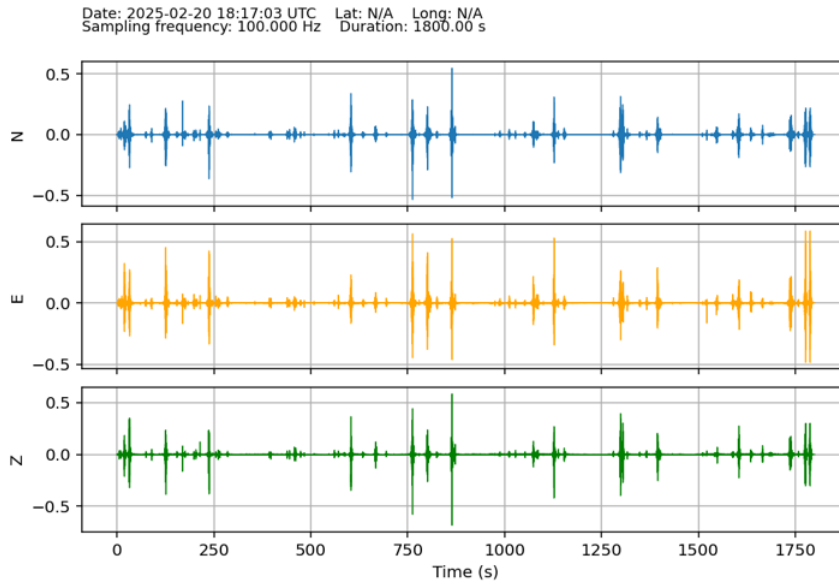


(A)

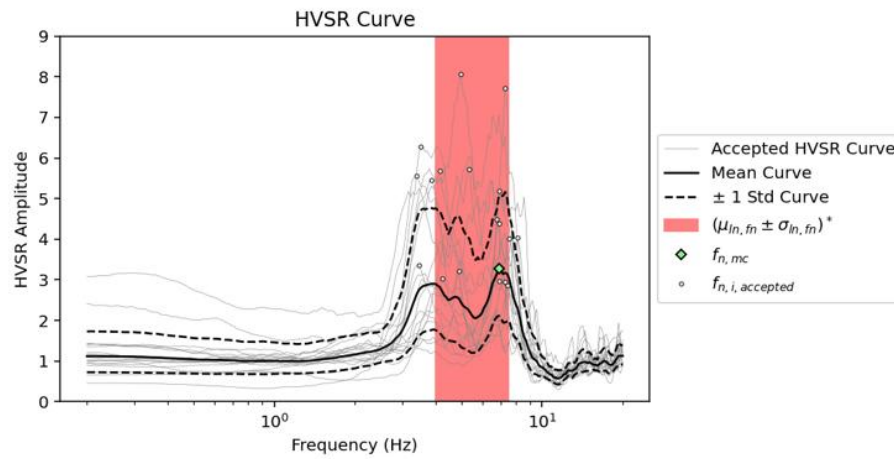


(B)

Figure A-13: (A) 3-component signal file and (B) HVSR curve for Cedar Bluff site measured by GTN30 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

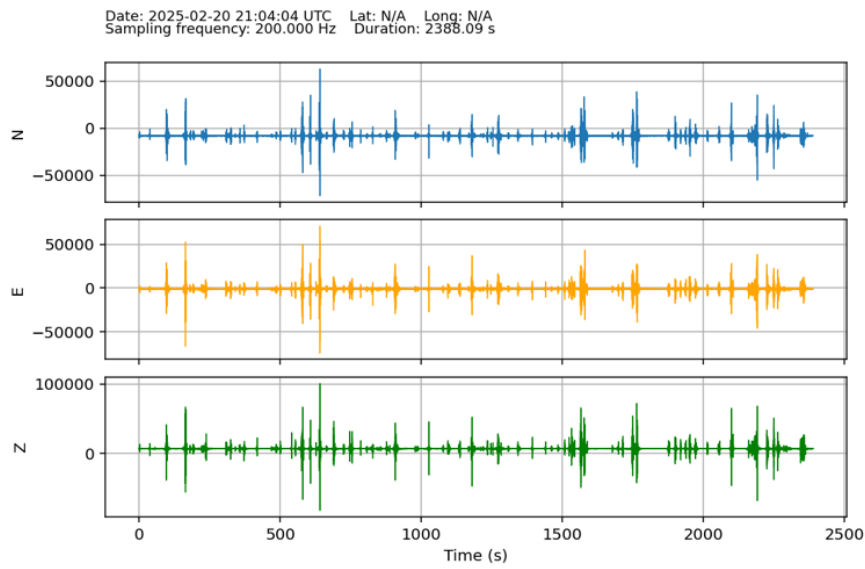


(A)

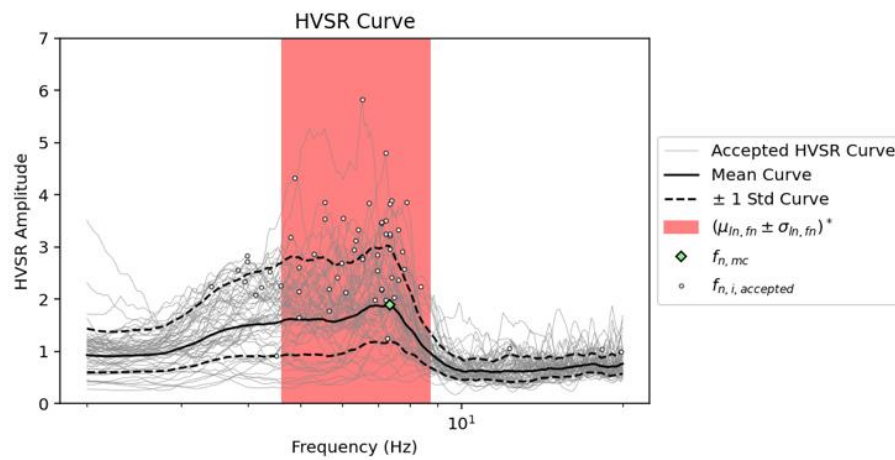


(B)

Figure A-14: (A) 3-component signal file and (B) HVSR curve for Beaver Creek survey line 1 measured by PASI Gemini sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

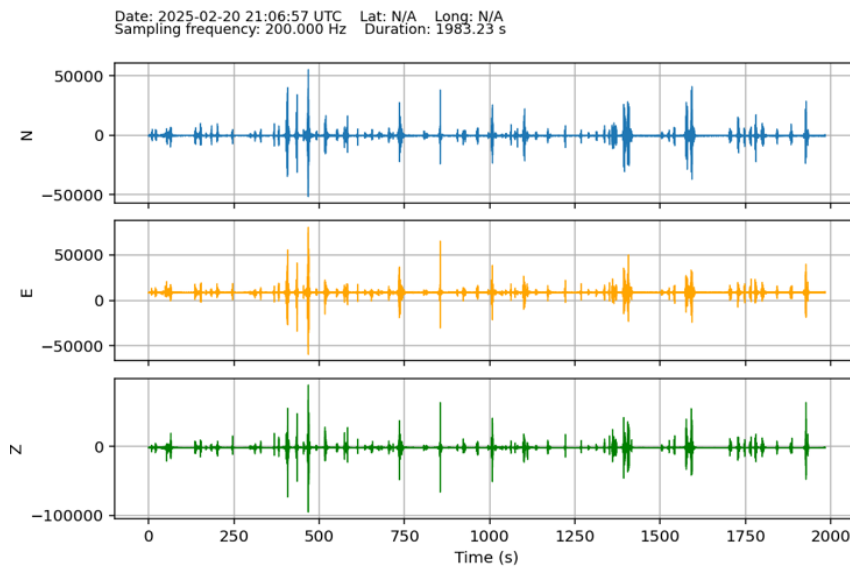


(A)

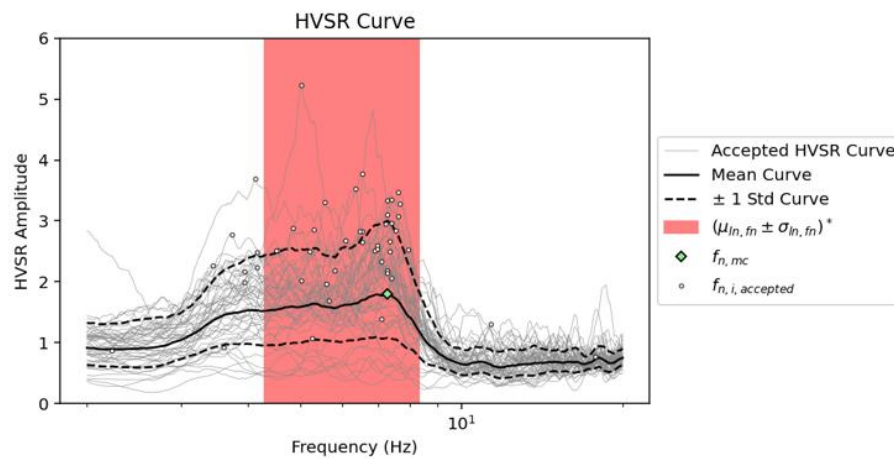


(B)

Figure A-15: (A) 3-component signal file and (B) HVSR curve for Beaver Creek survey line 2 measured by GTN21 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

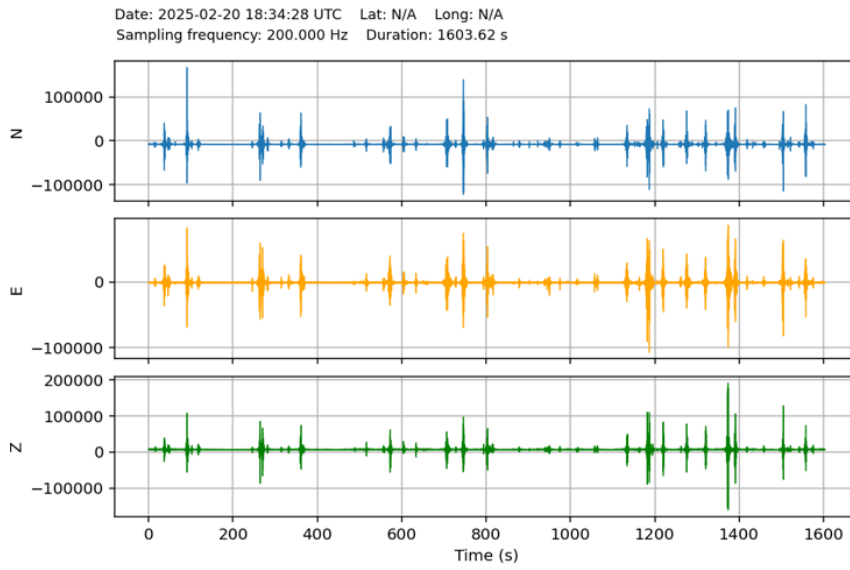


(A)

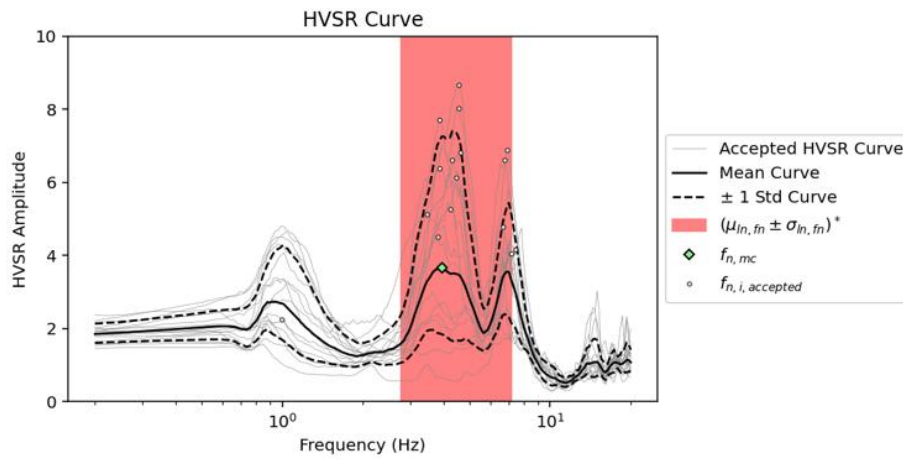


(B)

Figure A-16: (A) 3-component signal file and (B) HVSR curve for Beaver Creek survey line 2 measured by GTN30 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

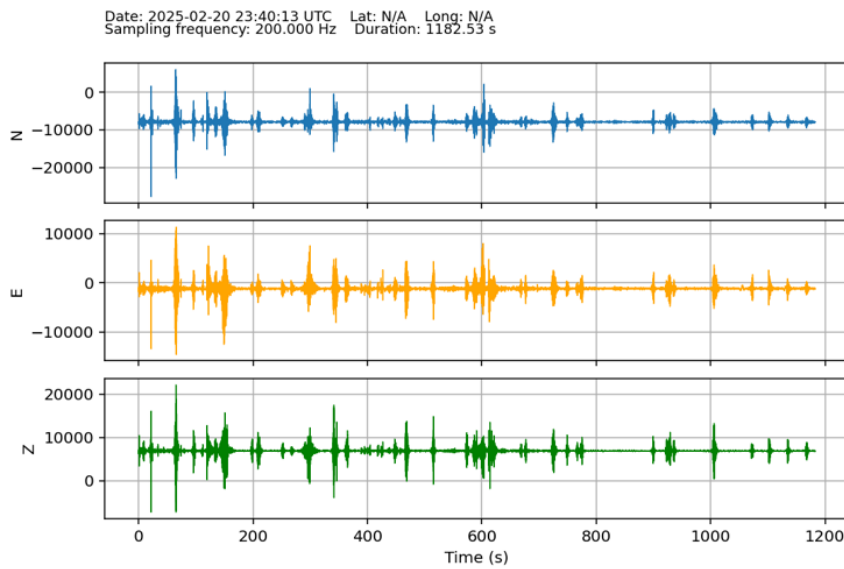


(A)

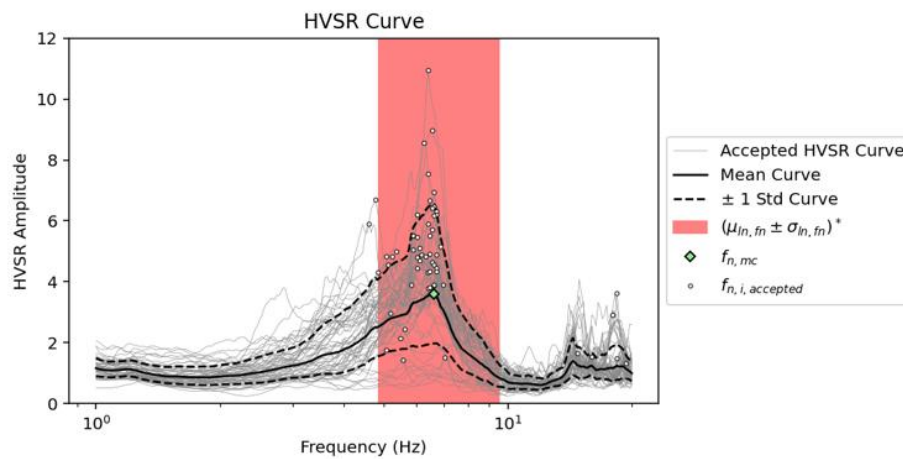


(B)

Figure A-17: (A) 3-component signal file and (B) HVSR curve for Big Prairie Creek survey line 1 measured by GTN21 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

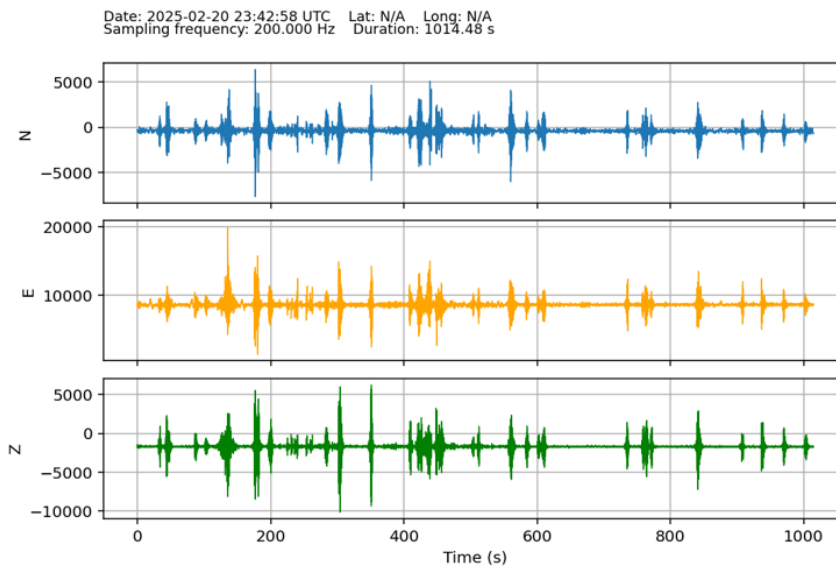


(A)

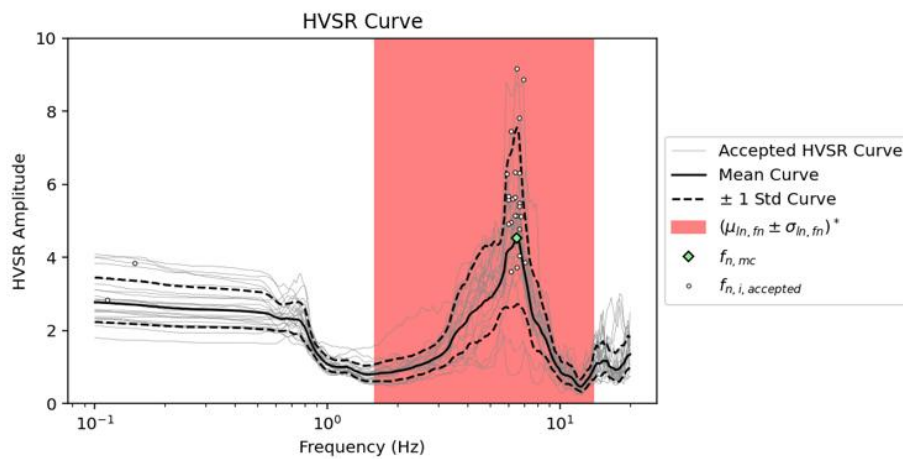


(B)

Figure A-18: (A) 3-component signal file and (B) HVSR curve for Big Prairie Creek survey line 1 measured by GTN21_B sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

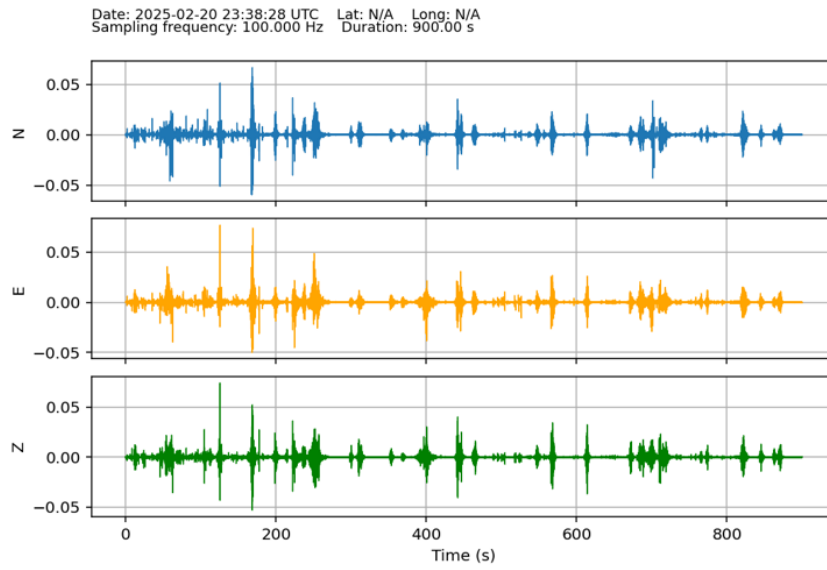


(A)

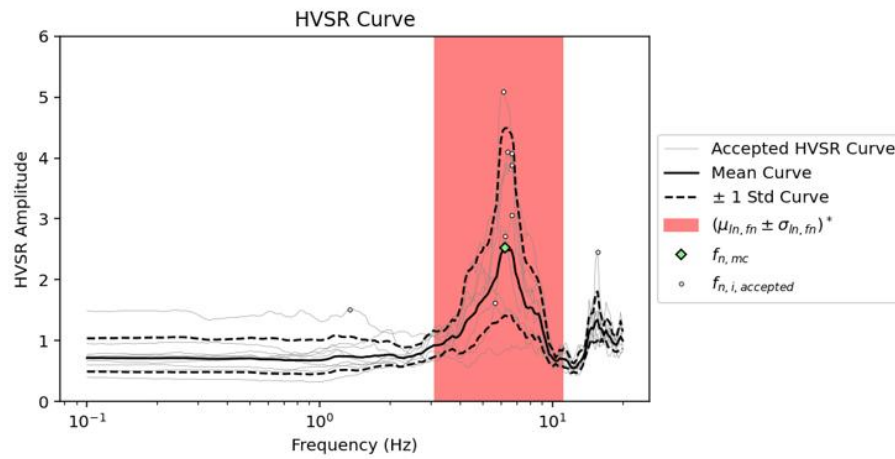


(B)

Figure A-19: (A) 3-component signal file and (B) HVSR curve for Big Prairie Creek survey line 1 measured by GTN30_B sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

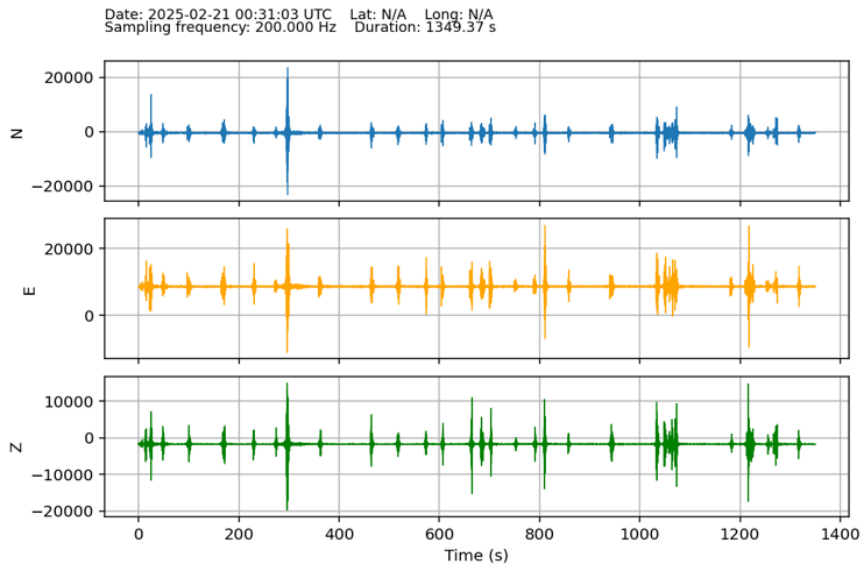


(A)

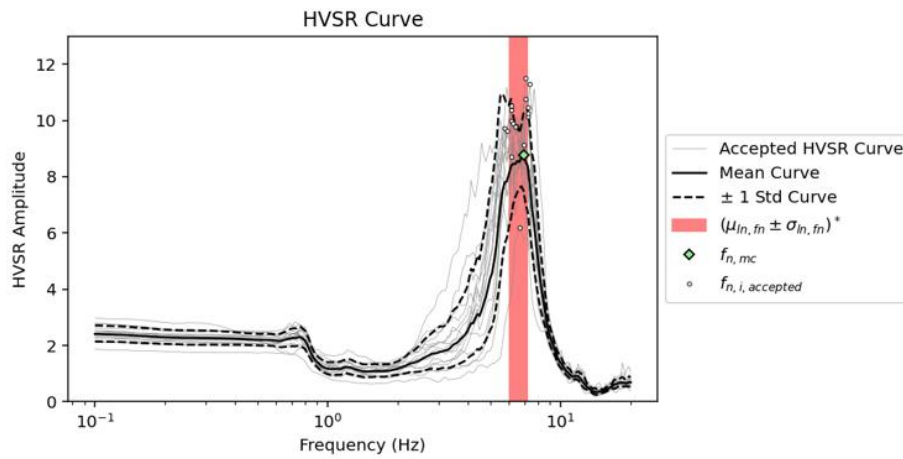


(B)

Figure A-20: (A) 3-component signal file and (B) HVSR curve for Big Prairie Creek survey line 1 measured by PASI Gemini sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

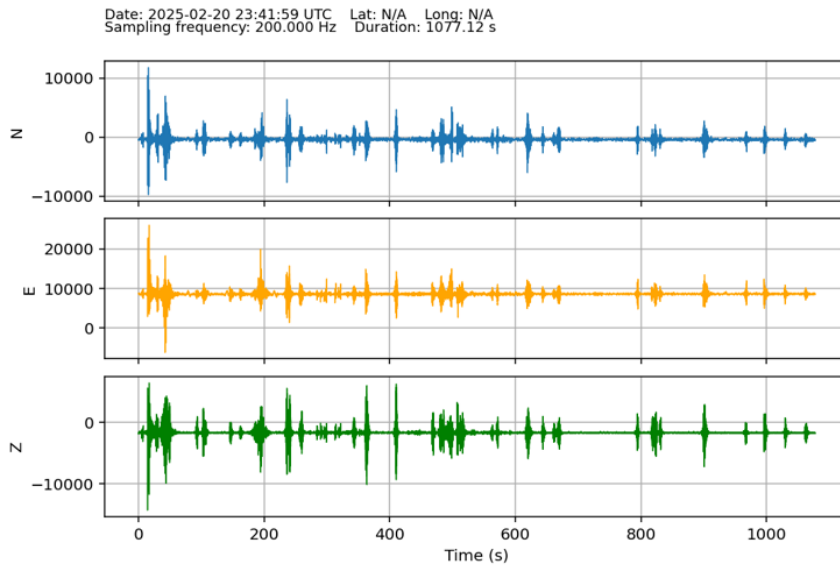


(A)

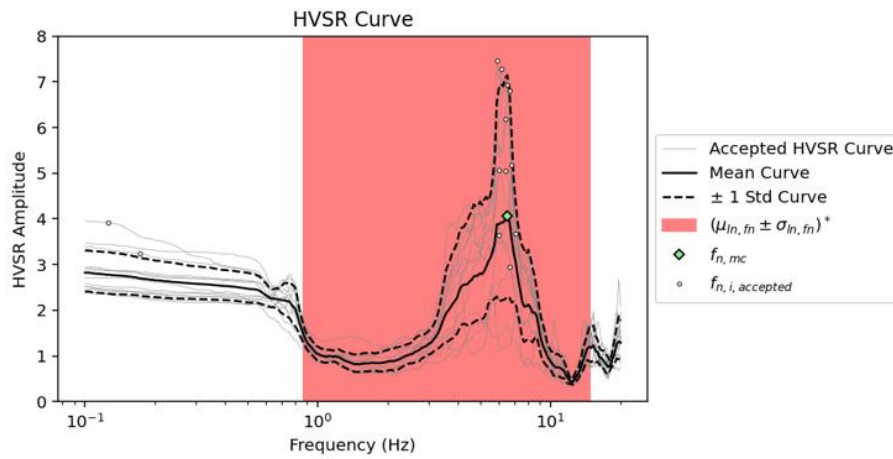


(B)

Figure A-21: (A) 3-component signal file and (B) HVSR curve for Big Prairie Creek survey line 2 measured by GTN30 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

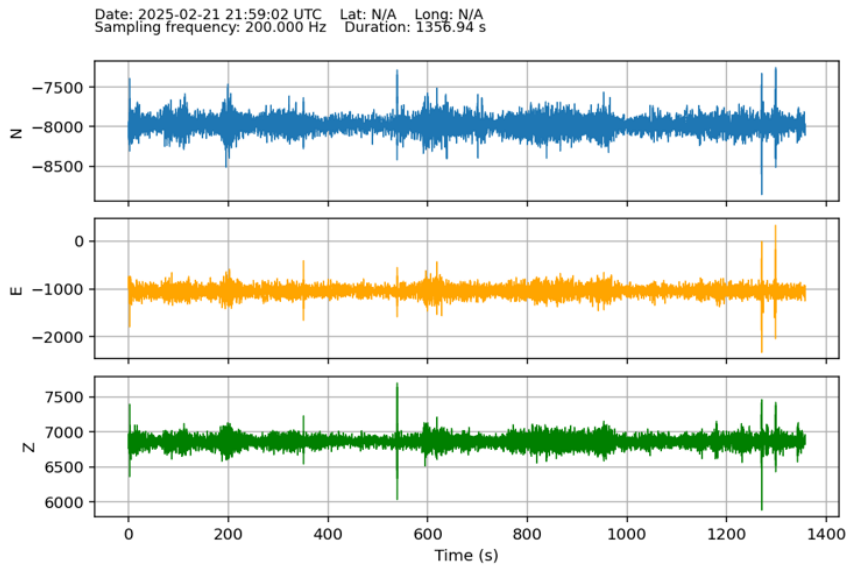


(A)

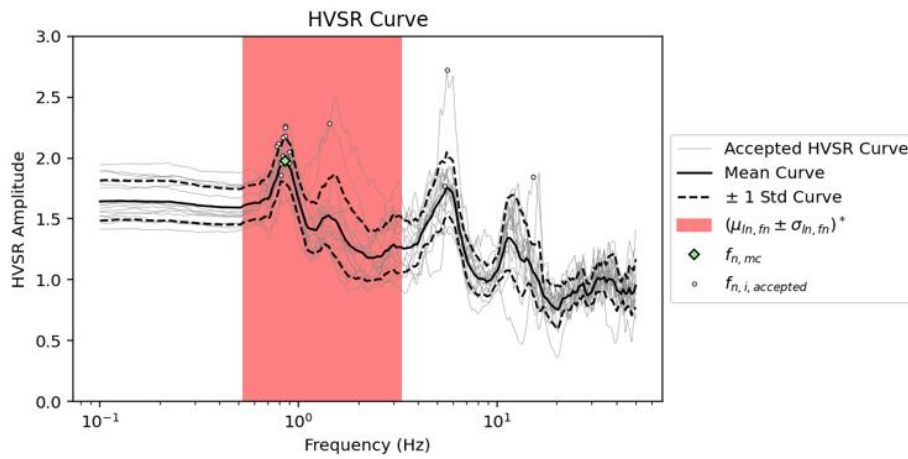


(B)

Figure A-22: (A) 3-component signal file and (B) HVSr curve for Big Prairie Creek survey line 2 measured by GTN30_B sensor. Peak frequency is denoted by a green point. Mean HVSr curve is solid black line while plus and minus one standard deviation curves are dashed lines.

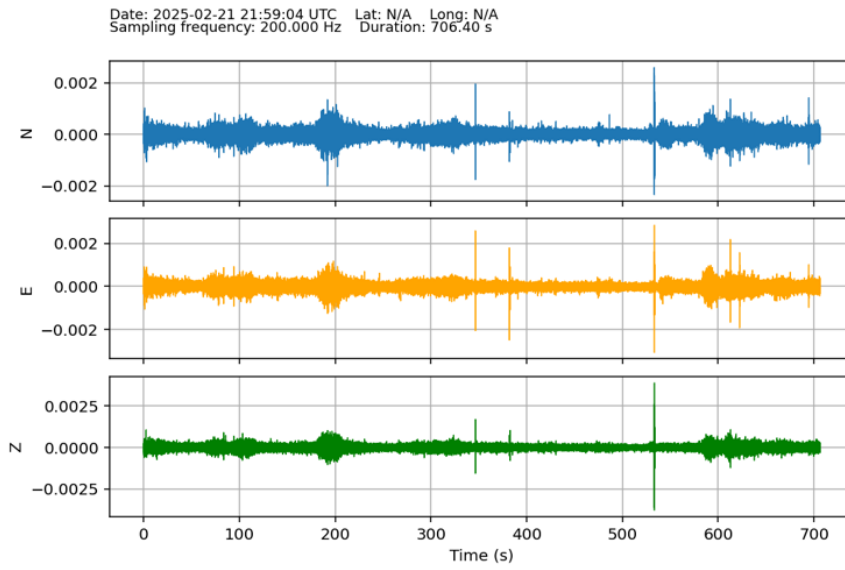


(A)

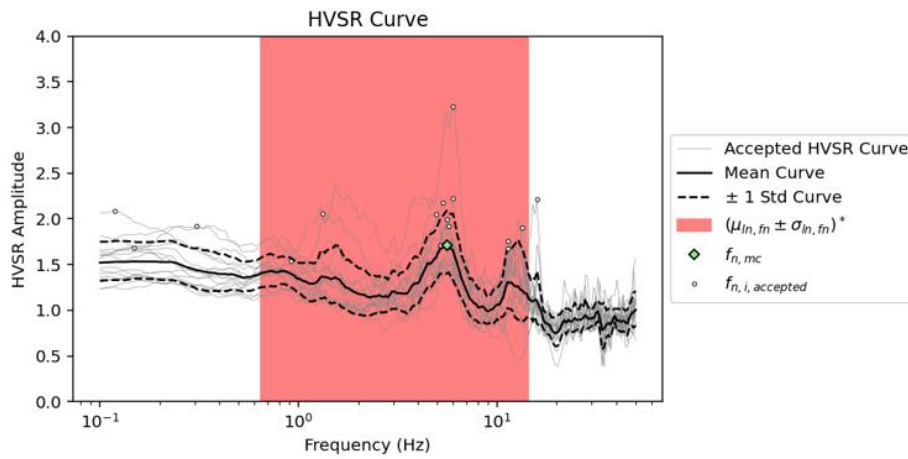


(B)

Figure A-23: (A) 3-component signal file and (B) HVSR curve for Coldwell Creek survey line 1 measured by GTN21 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

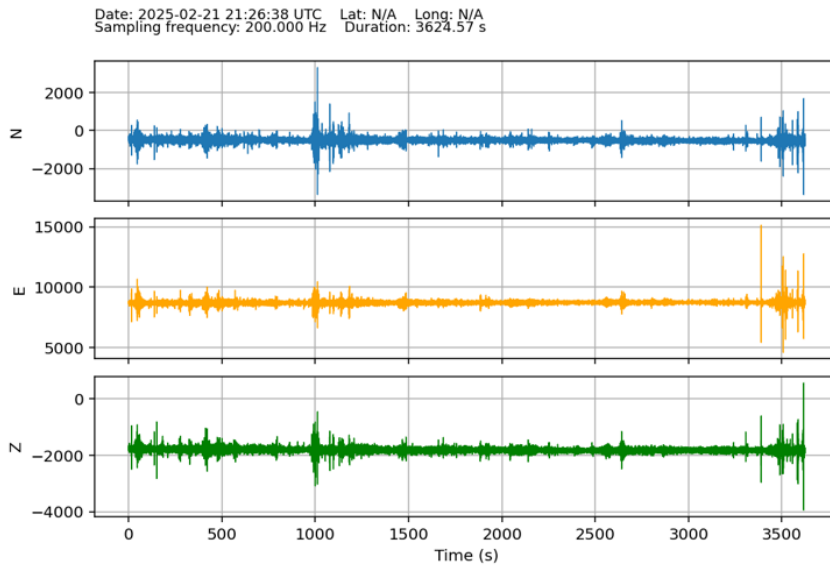


(A)

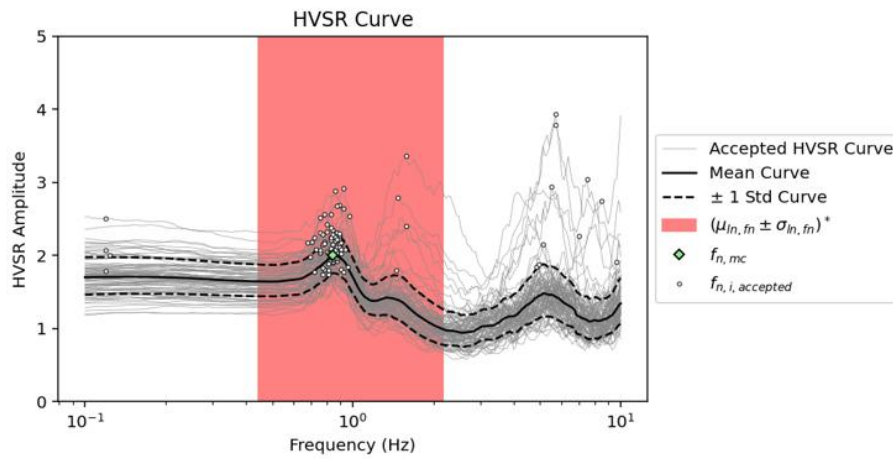


(B)

Figure A-24: (A) 3-component signal file and (B) HVSR curve for Coldwell Creek survey line 1 measured by PASI Gemini sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

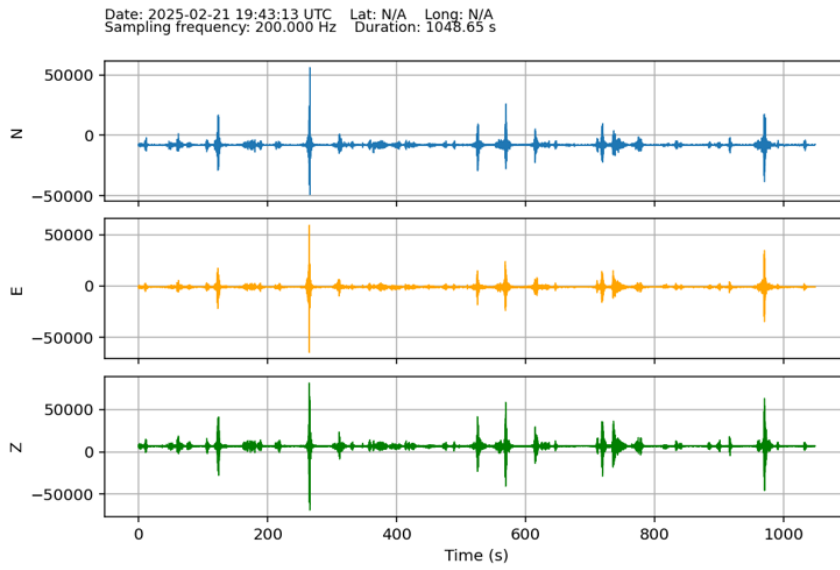


(A)

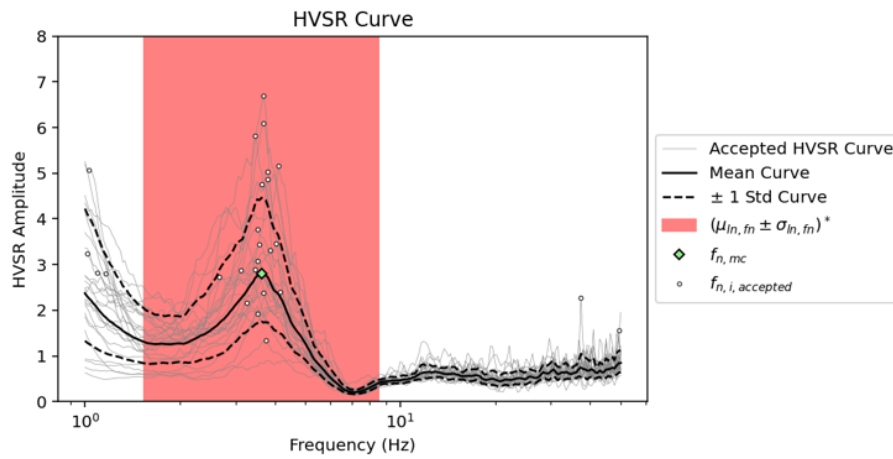


(B)

Figure A-25: (A) 3-component signal file and (B) HVSR curve for Coldwell Creek survey line 2 measured by GTN30 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

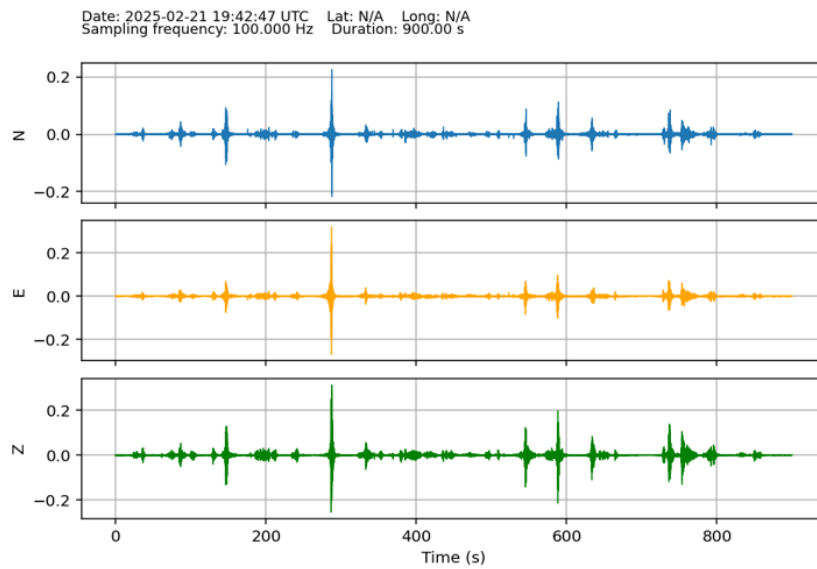


(A)

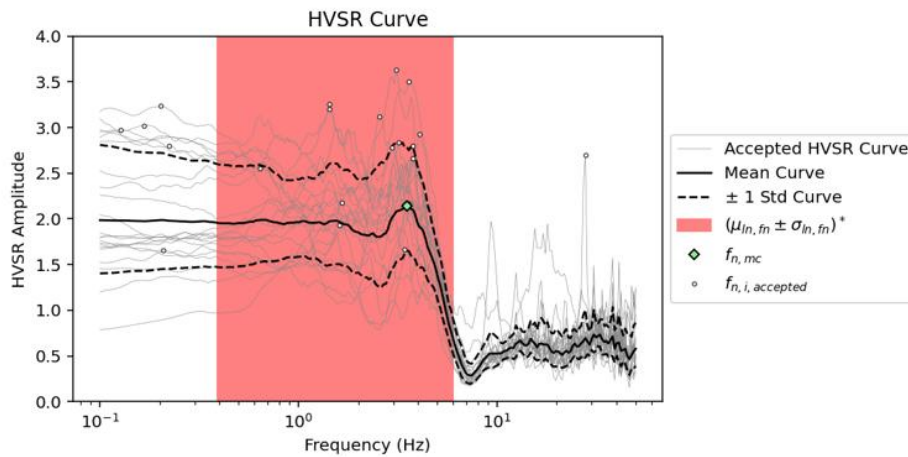


(B)

Figure A-26: (A) 3-component signal file and (B) HVSR curve for Greensboro site measured by GTN21 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

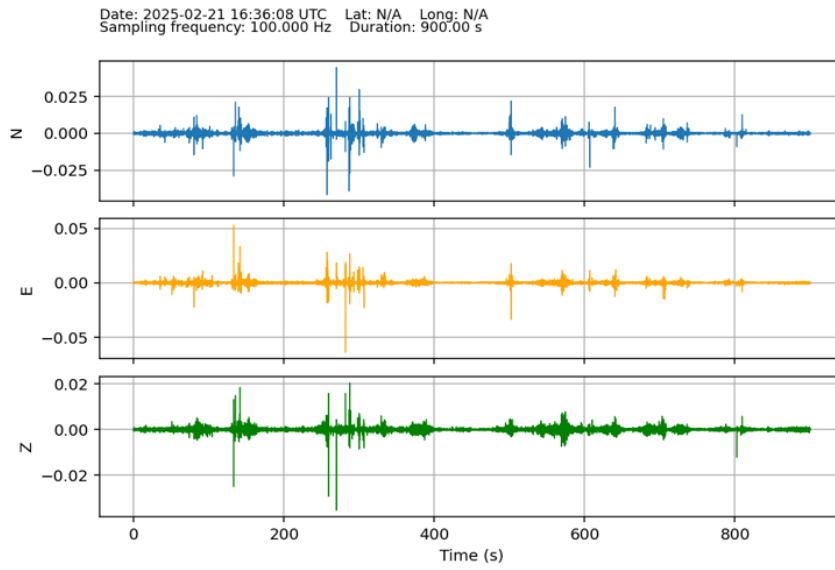


(A)

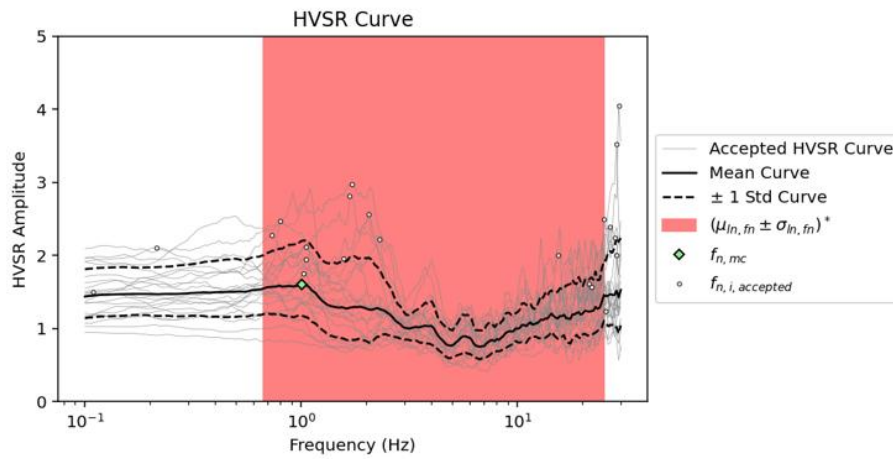


(B)

Figure A-27: (A) 3-component signal file and (B) HVSR curve for Greensboro site measured by PASI Gemini sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

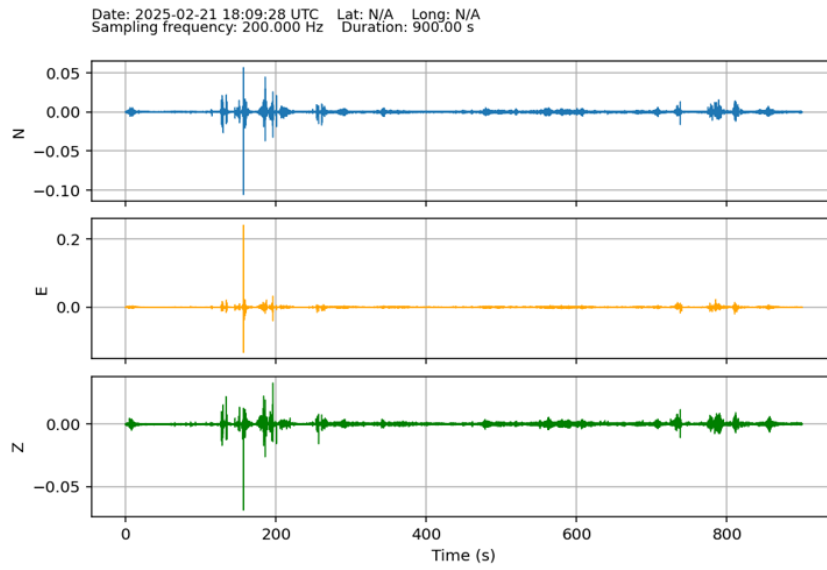


(A)

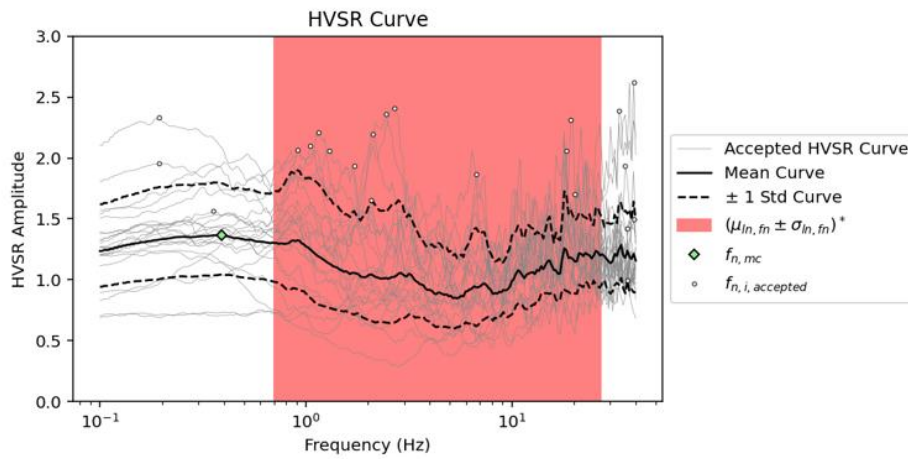


(B)

Figure A-28: (A) 3-component signal file and (B) HVSr curve for Moundville survey line 1 measured by PASI Gemini sensor. Peak frequency is denoted by a green point. Mean HVSr curve is solid black line while plus and minus one standard deviation curves are dashed lines.

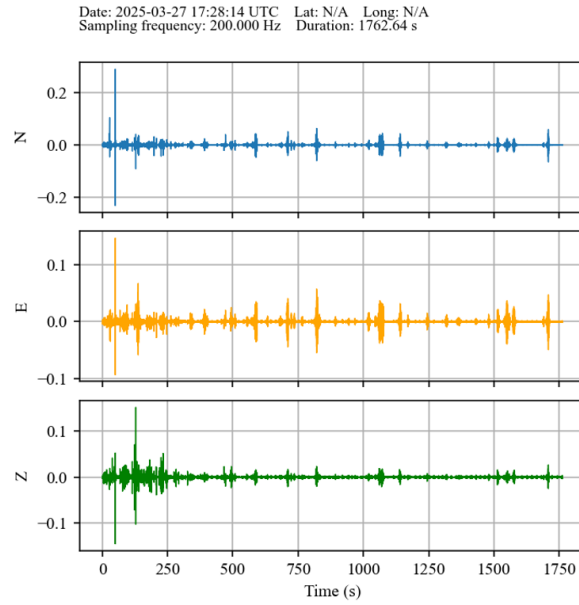


(A)

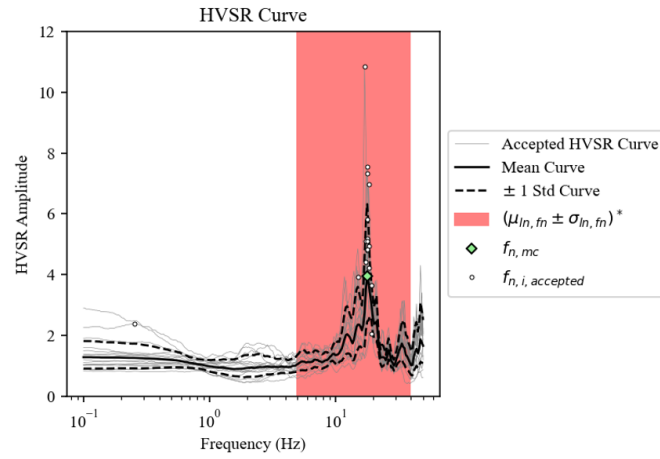


(B)

Figure A-29: (A) 3-component signal file and (B) HVSR curve for Moundville survey line 2 measured by PASI Gemini sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

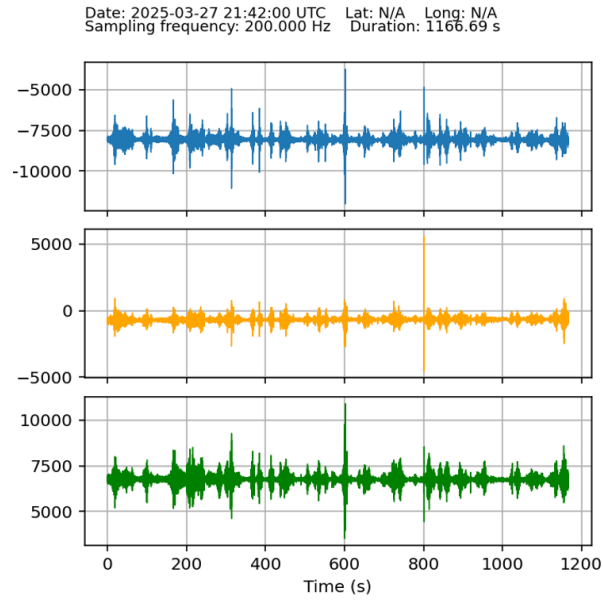


(A)

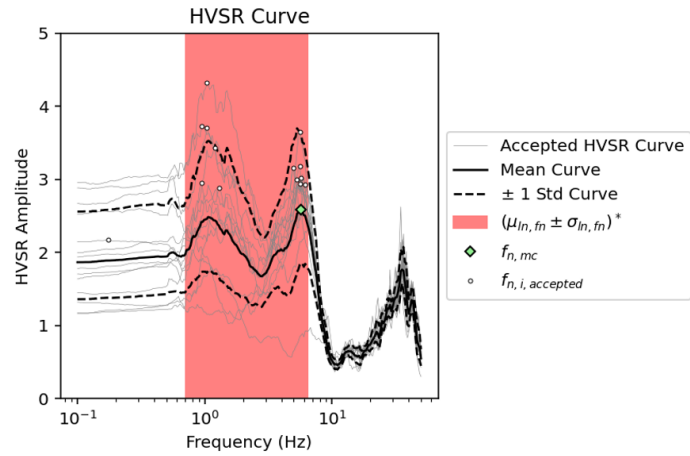


(B)

Figure A-30: (A) 3-component signal file and (B) HVSR curve for Duck River survey line 1 measured by PASI Gemini sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

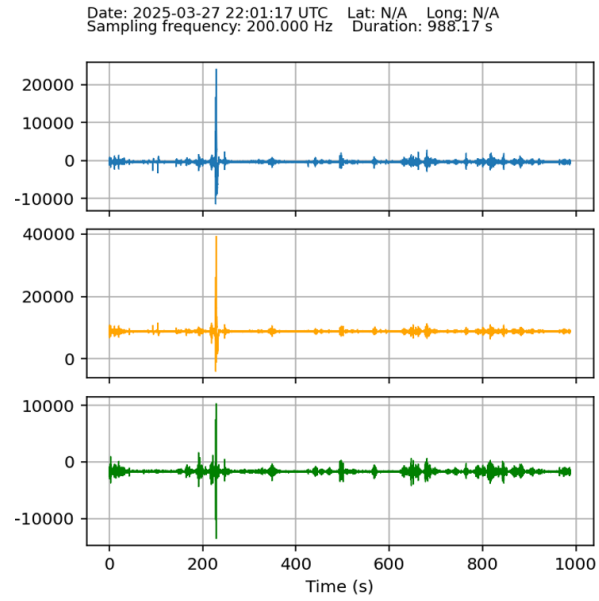


(A)

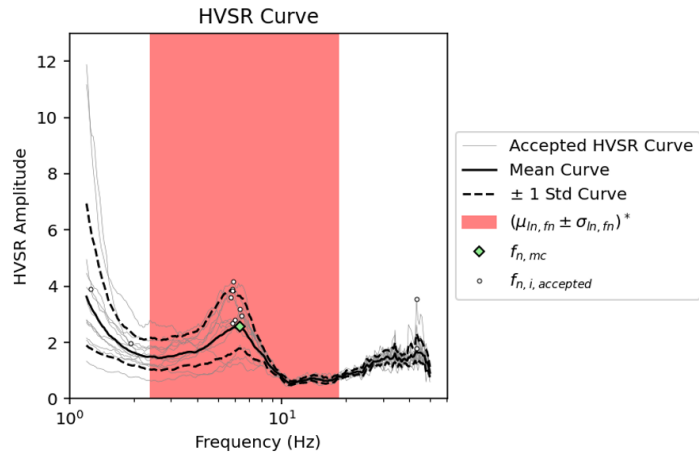


(B)

Figure A-31: (A) 3-component signal file and (B) HVSR curve for Russellville High School survey line 1 measured by GTN21 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

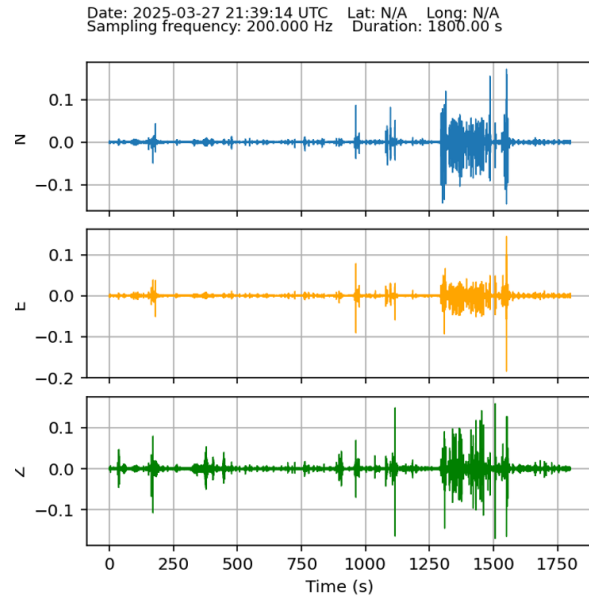


(A)

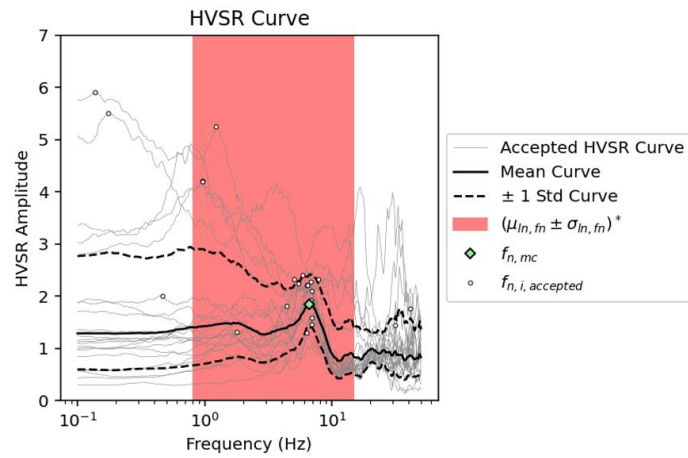


(B)

Figure A-32: (A) 3-component signal file and (B) HVSR curve for Russellville High School survey line 1 measured by GTN30 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

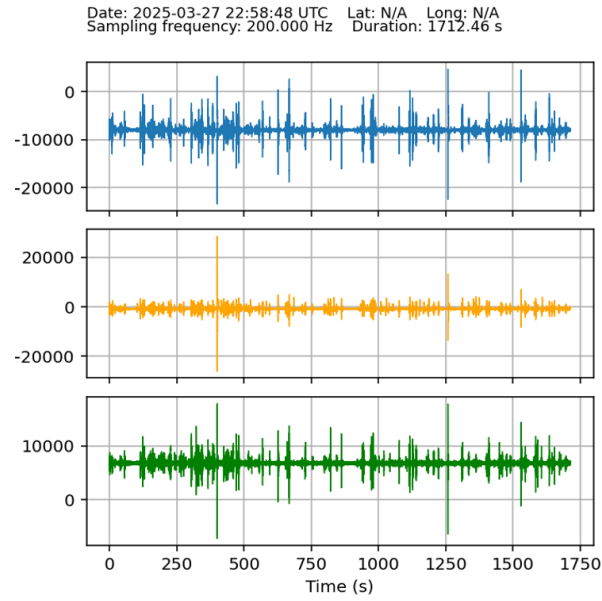


(A)

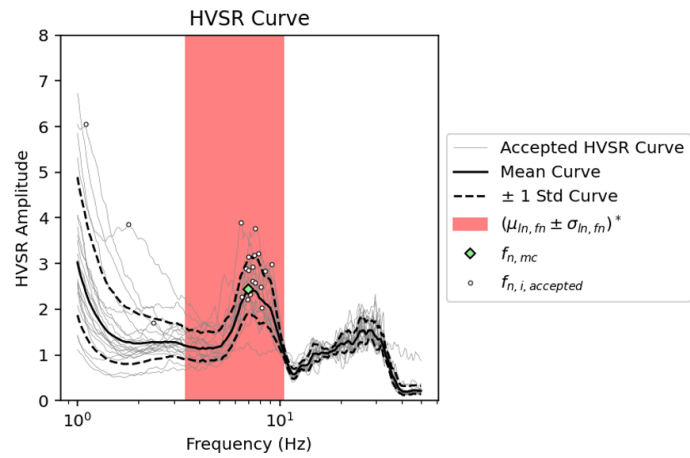


(B)

Figure A-33: (A) 3-component signal file and (B) HVSR curve for Russellville High School survey line 1 measured by PASI Gemini sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

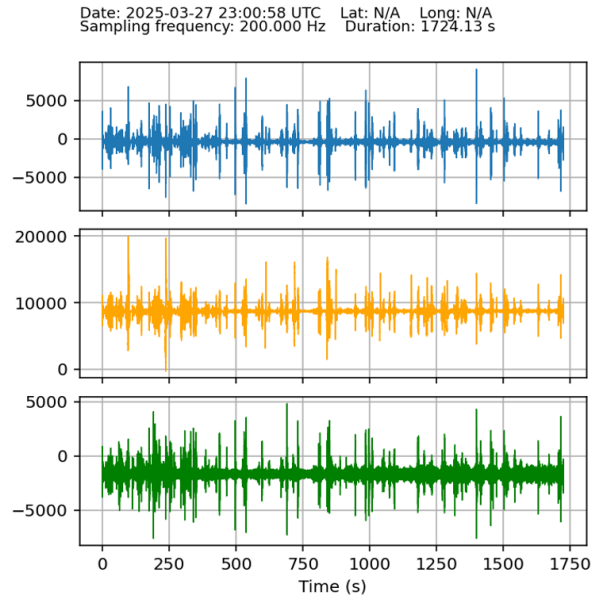


(A)

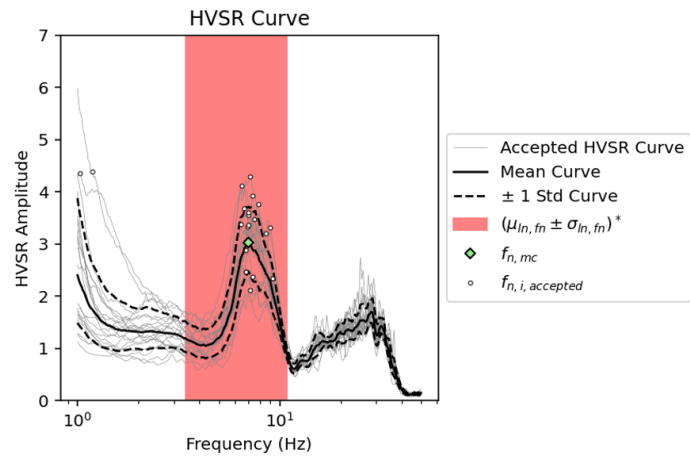


(B)

Figure A-34: (A) 3-component signal file and (B) HVSR curve for Russellville High School survey line 2 measured by GTN21 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

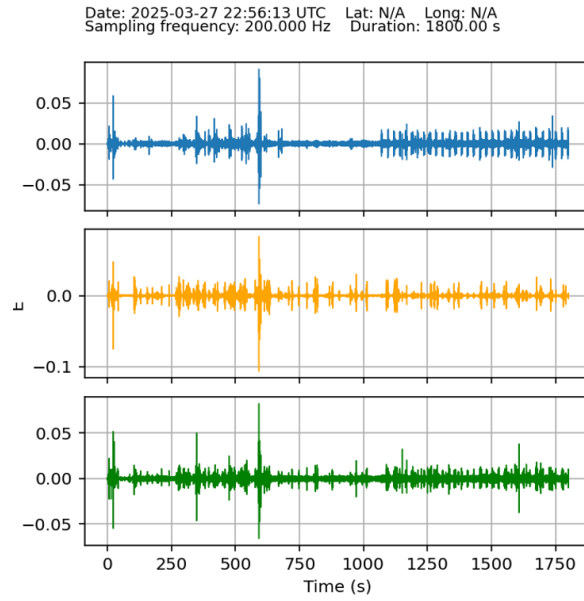


(A)

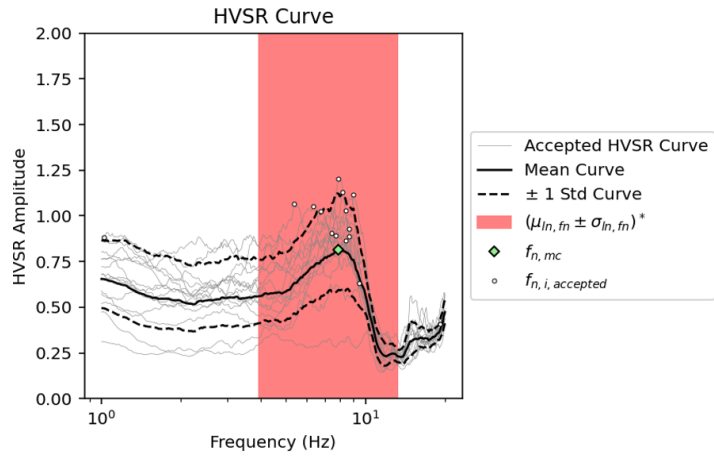


(B)

Figure A-35: (A) 3-component signal file and (B) HVSR curve for Russellville High School survey line 2 measured by GTN30 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

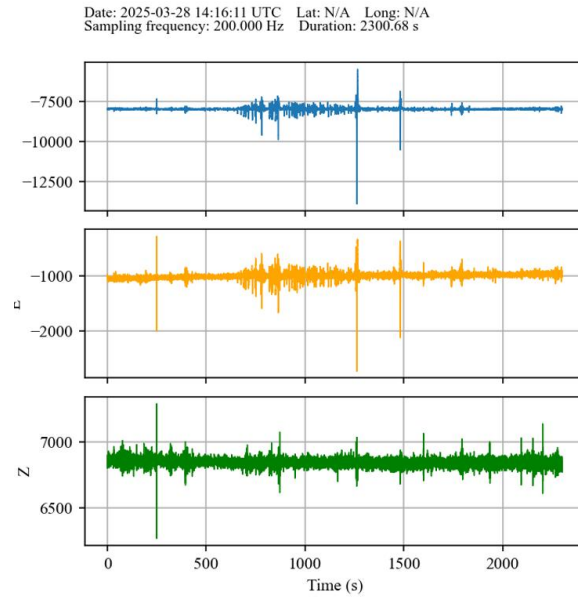


(A)

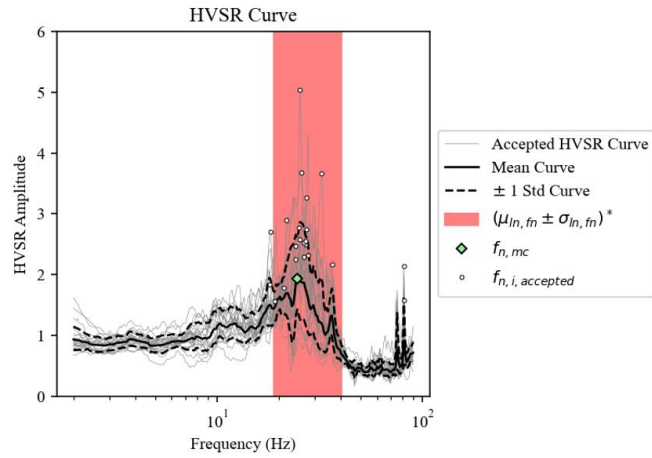


(B)

Figure A-36: (A) 3-component signal file and (B) HVSR curve for Russellville High School survey line 2 measured by PASI Gemini sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

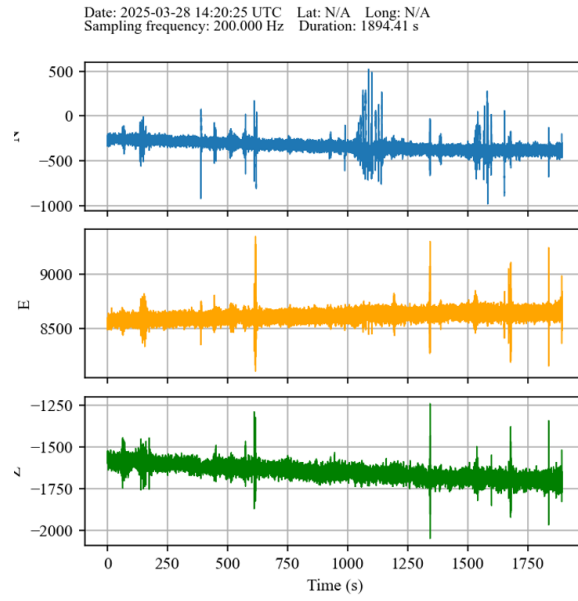


(A)

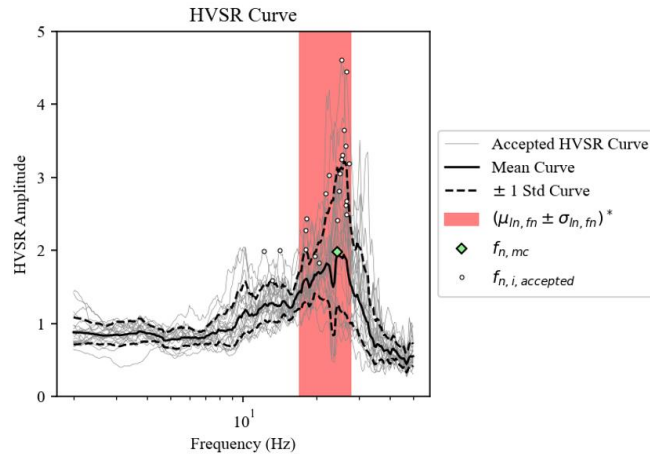


(B)

Figure A-37: (A) 3-component signal file and (B) HVSR curve for Lauderdale County survey line 1 measured by GTN21 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

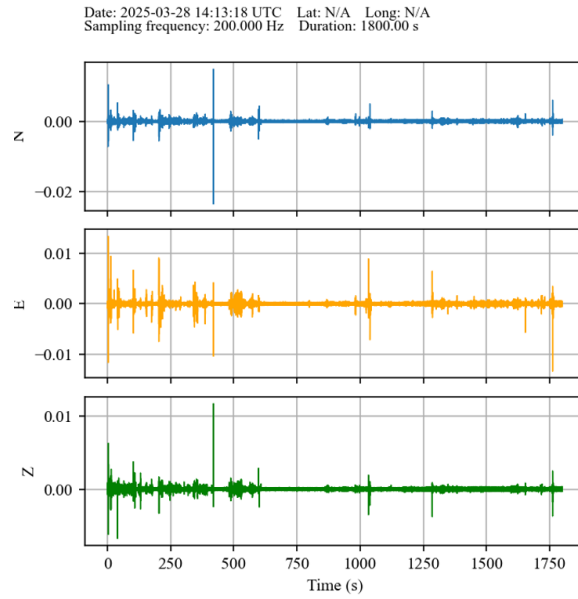


(A)

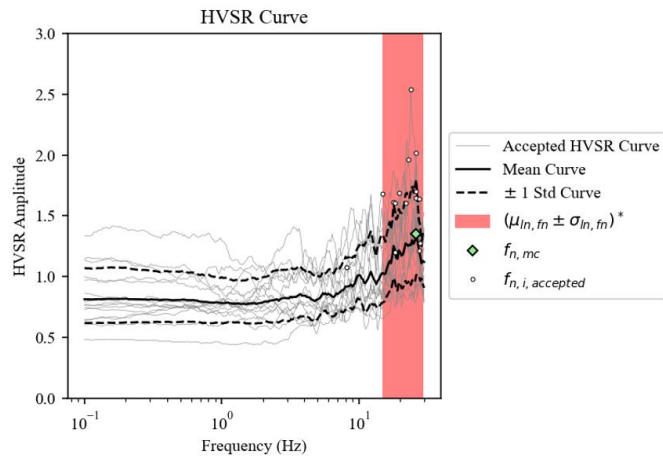


(B)

Figure A-38: (A) 3-component signal file and (B) HVSR curve for Lauderdale County survey line 1 measured by GTN30 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

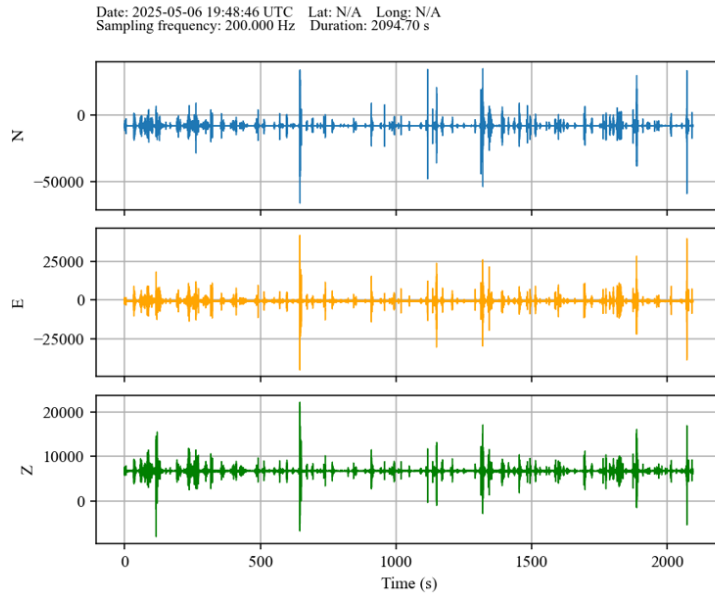


(A)

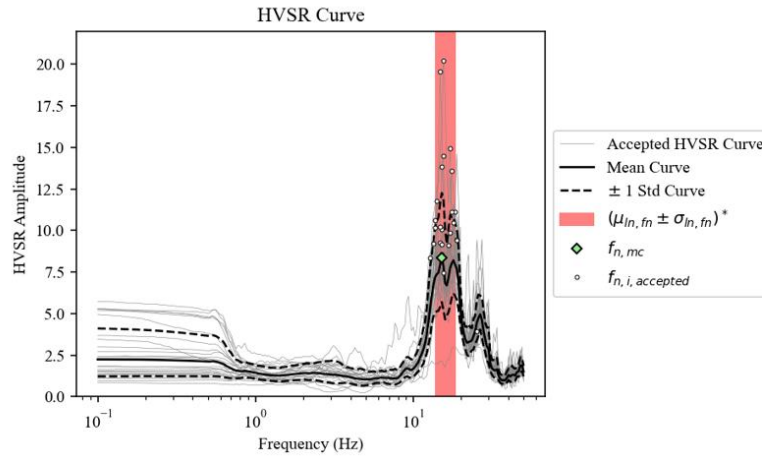


(B)

Figure A-39: (A) 3-component signal file and (B) HVSR curve for Lauderdale County survey line 1 measured by PASI Gemini sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

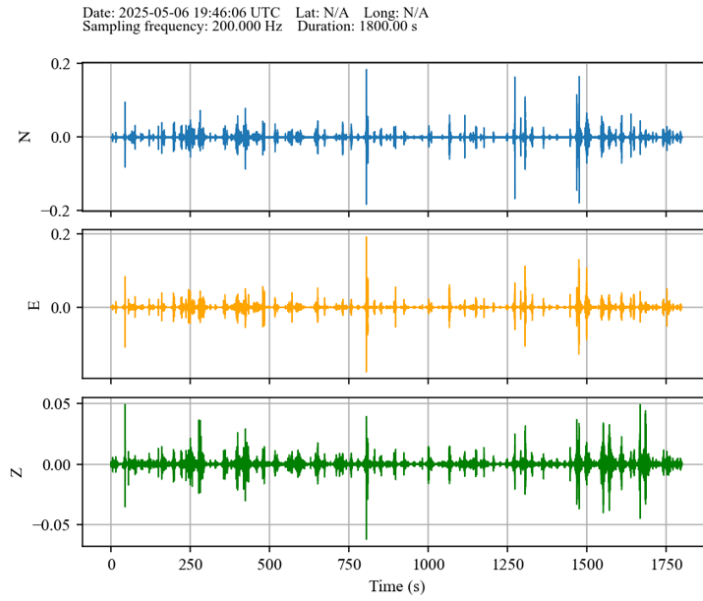


(A)

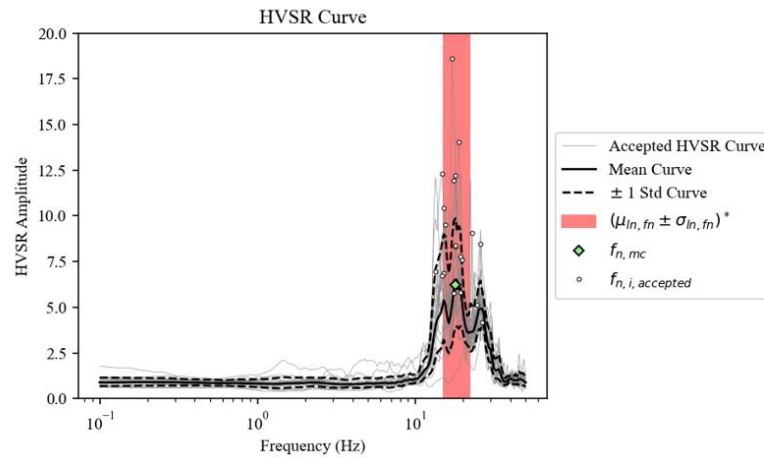


(B)

Figure A-40: (A) 3-component signal file and (B) HVSr curve for Blount County site measured by GTN21 sensor. Peak frequency is denoted by a green point. Mean HVSr curve is solid black line while plus and minus one standard deviation curves are dashed lines.

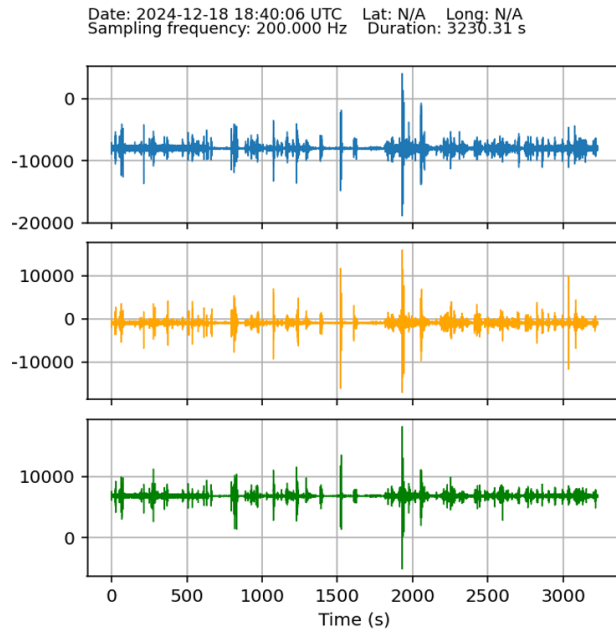


(A)

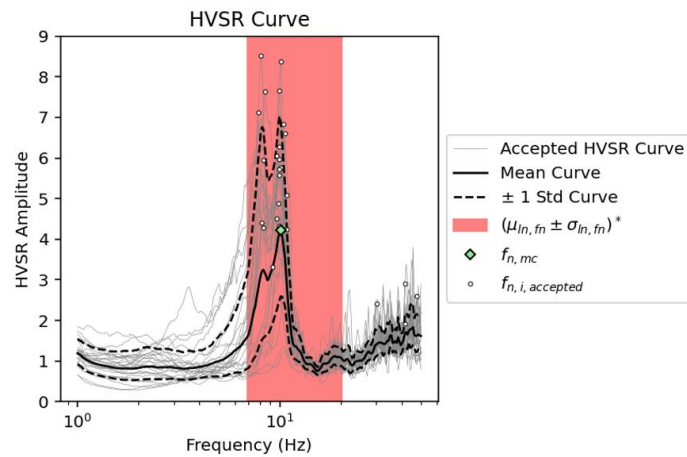


(B)

Figure A-41: (A) 3-component signal file and (B) HVSR curve for Blount County site measured by PASI Gemini sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

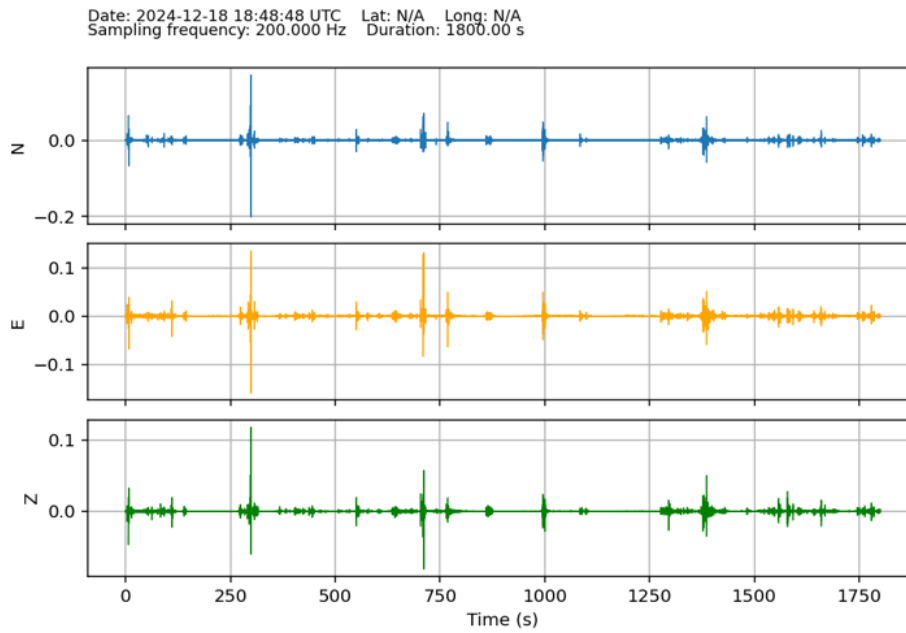


(A)

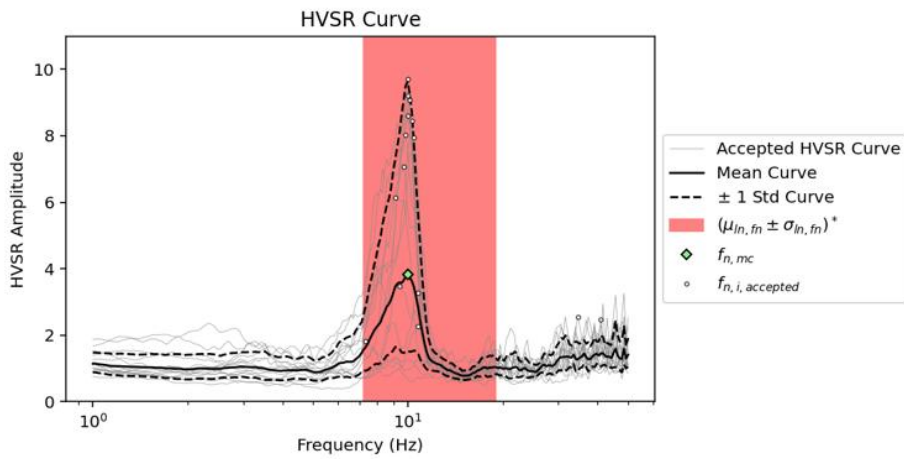


(B)

Figure A-42: (A) 3-component signal file and (B) HVSR curve for Cedar Bluff site measured by GTN30 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.

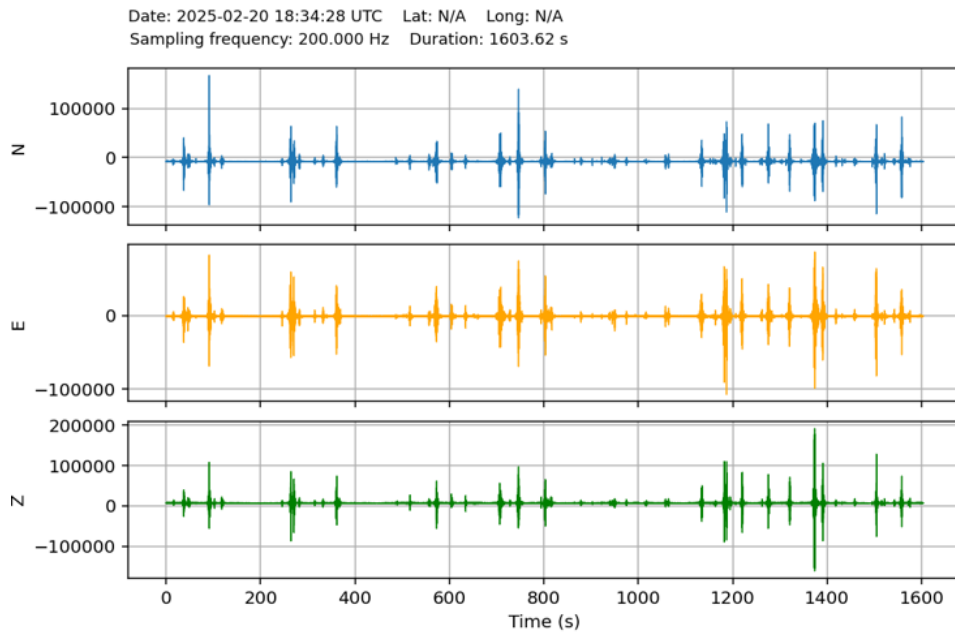


(A)

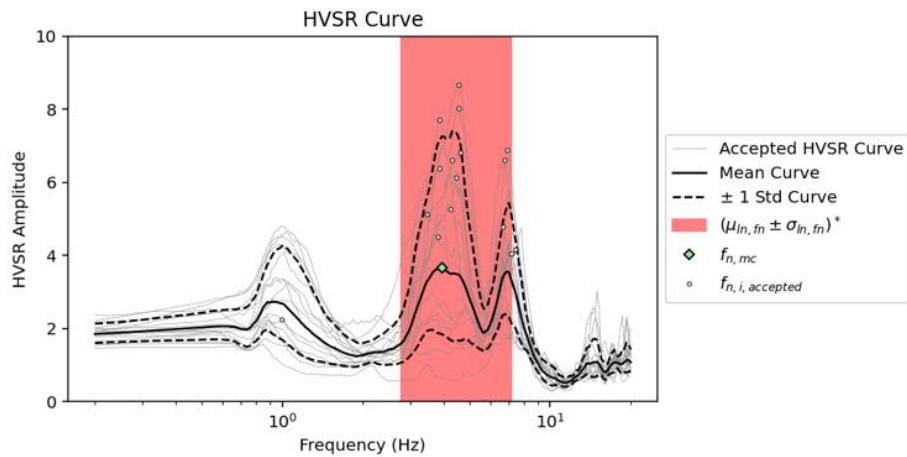


(B)

Figure A-43: (A) 3-component signal file and (B) HVSr curve for Cedar Bluff site measured by PASI Gemini sensor. Peak frequency is denoted by a green point. Mean HVSr curve is solid black line while plus and minus one standard deviation curves are dashed lines.

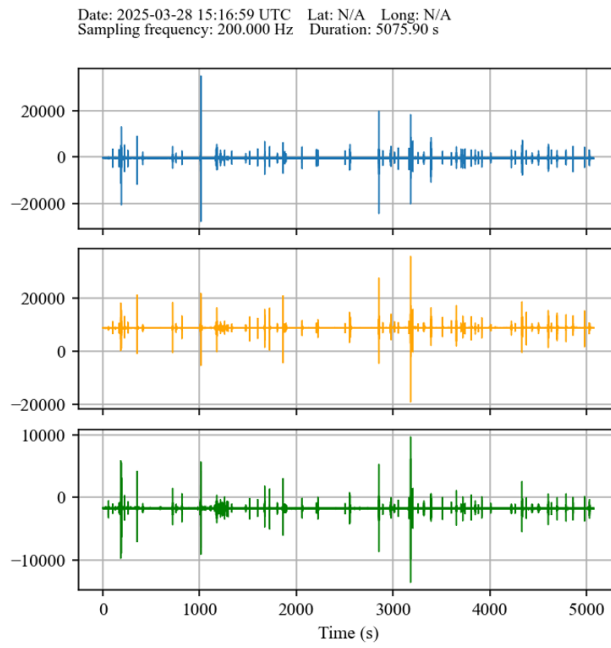


(A)

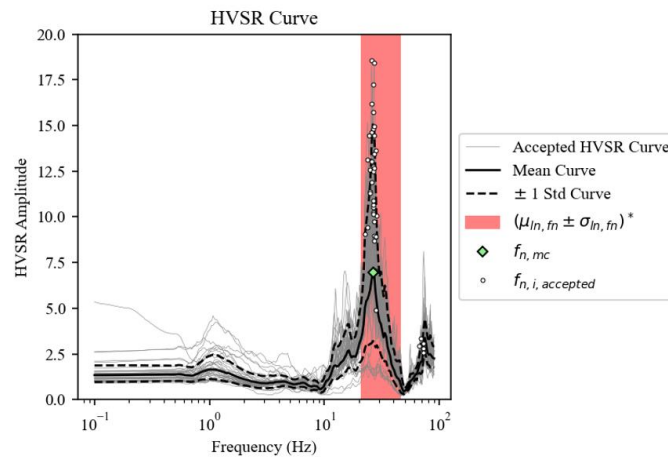


(B)

Figure A-44: (A) 3-component signal file and (B) HVSr curve for Beaver Creek survey line 1 measured by GTN21 sensor. Peak frequency is denoted by a green point. Mean HVSr curve is solid black line while plus and minus one standard deviation curves are dashed lines.



(A)



(B)

Figure A-45: (A) 3-component signal file and (B) HVSR curve for Lauderdale County survey line 2 measured by GTN30 sensor. Peak frequency is denoted by a green point. Mean HVSR curve is solid black line while plus and minus one standard deviation curves are dashed lines.