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Near-field effects on the in-situ estimation of shear-wave velocity and damping ratio from MASW tests

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Abstract

Multichannel Analysis of Surface Waves (MASW) is a viable approach for *in situ* estimation of shear wave velocity and damping ratio. However, conventional processing techniques assume that the recorded wavefield consists only of surface waves, and the presence of body waves leads to detrimental consequences on the reliability of the estimate, referred to as near-field effects. The latter typically induce oscillations in the estimated phase velocity at low frequencies, while little is known about their effect on phase attenuation. This study investigates the influence of near-field effects on the estimated phase velocity and phase attenuation on a synthetic dataset. The results show that the phase attenuation is far more sensitive to body waves than the phase velocity. Furthermore, the findings suggest that near-field effects can be mitigated by selecting the experimental data with Normalized Array Center Distance (NACD; i.e., the ratio between the average offset of the receivers and the Rayleigh wavelength) greater than 2-3. While phase velocity estimates are reliable at NACD values as low as 1, the requirement for $NACD > 2-3$ is mainly driven by phase attenuation and its higher sensitivity to near-field effects. However, this threshold should be adjusted based on the noise level, especially when few receivers are used. The proposed criterion has been applied to the characterization of a real site in Italy, demonstrating that the inclusion of data affected by near-field effects leads to an overestimation of the shear wave damping ratio and significant variability in the estimated profiles.

Keywords

MASW, near-field effects, noise, shear-wave velocity, damping ratio

Introduction

Among the techniques for the *in situ* estimation of the shear-wave velocity V_s and damping ratio D_s , the Multichannel Analysis of Surface Waves (MASW) is becoming increasingly popular due to the cost-effectiveness and ease of use. Typical interpretation requires two main steps (e.g., Foti et al., 2014): (1) estimation of the propagation parameters of the surface waves (typically, Rayleigh or R-waves), i.e. dispersion and attenuation curves, which describe the

30 dependence of the phase velocity V_R and phase attenuation α_R on the frequency; (2) inversion of the experimental data
31 to obtain profiles of V_S and D_S . It should be noted that the propagation of R-waves in linear viscoelastic media is
32 described by a complex wavenumber, with the real part being linked to V_R and the imaginary part corresponding to α_R
33 (e.g., Foti et al., 2014). Estimating V_R and α_R typically assumes only R-waves are present, but recorded data include both
34 surface and body waves, causing near-field effects. This discrepancy typically leads to underestimation and/or
35 oscillations in V_R at low frequencies (e.g., Zywicki and Rix, 2005; Rahimi et al., 2021). Recommendations to minimize
36 near-field errors include adjustments in acquisition layout and processing, with criteria based on statistical tests
37 (Strobbia and Foti, 2006) or wavelength-based normalized offsets (e.g., Tokimatsu, 1995; Yoon and Rix, 2009; Rahimi et
38 al., 2022). However, most research focused on V_R , while few studies investigated α_R (e.g., Yoon, 2005), without reaching
39 effective ways to reduce such effects for α_R .

40 This paper provides insight into the influence of near-field effects on the estimated R-wave parameters, with a focus on
41 phase attenuation. For this purpose, several MASW surveys with different acquisition layouts are simulated. The
42 synthetic dataset is also corrupted by incoherent noise to address the joint influence of body waves and signal quality.
43 The second part describes an application to a real site, highlighting the consequences of the inclusion of data influenced
44 by near-field effects on the estimated V_S and D_S profiles.

45 **Synthetic wavefield**

46 The synthetic wavefield (hereafter referred to as “SW”) represents the response of a homogeneous half-space to a
47 vertical harmonic force of unit amplitude applied to the free surface with a frequency of 5 Hz. The mechanical properties
48 of the medium are the following: V_S is 336 m/s, D_S is equal to 0.015, the Poisson ratio is 0.33, the mass density is 2,000
49 kg/m³, and the P-wave damping ratio is equal to D_S . Vertical displacements at the free surface were computed using the
50 direct stiffness approach (Kausel and Roësset, 1981), as implemented in the EDT software (Schevenels et al., 2009). The
51 wavefield is the combination of both body and Rayleigh waves. For simplicity, this study focuses only on the
52 displacement field harmonics at 5 Hz (i.e., the excitation frequency). The selected frequency represents the lower bound
53 of the typical range used in MASW testing. However, in homogeneous media, the specific frequency does not affect the
54 body wave component, as this depends solely on the distance compared to the wavelength (Tokimatsu, 1995). The
55 corresponding theoretical R-wave wavenumber k_t is 0.1 rad/m, and attenuation α_t is 0.0015 rad/m, as obtained from
56 the solution of the Rayleigh eigenvalue problem.

57 A parametric study simulated the wavefield in various uniformly spaced sensor arrays to assess the impact of near-field
58 effects on R-wave parameters. The geometry can be described by the number of sensors N , the inter-receiver spacing

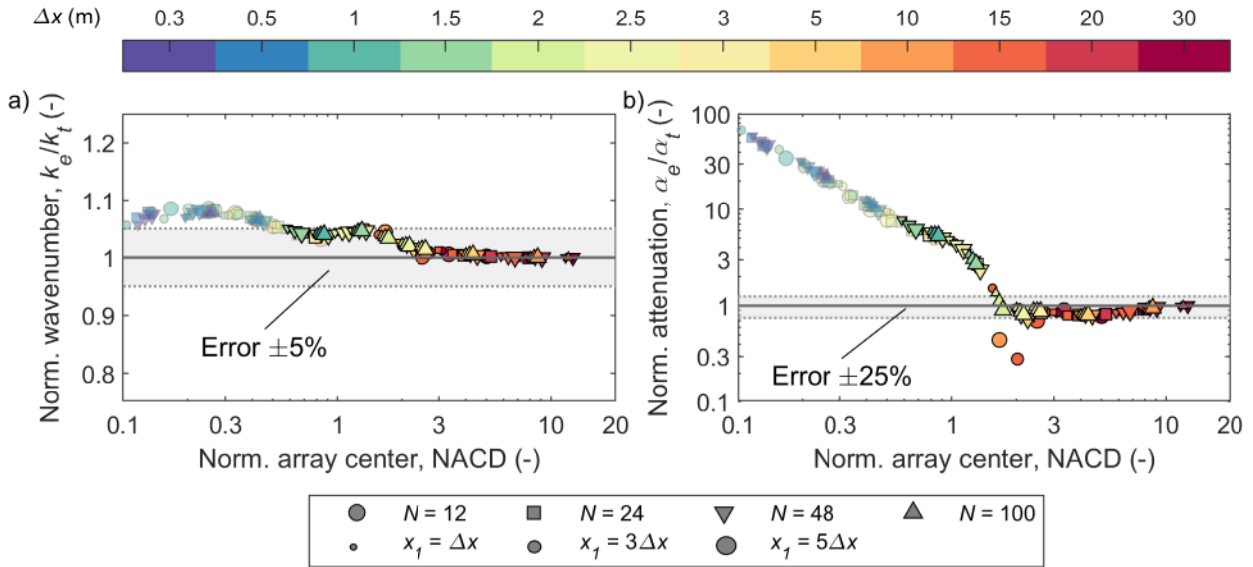
59 Δx , and the offset between the source and the closest receiver x_1 . N was assumed equal to 12, 24, 48, and 100; Δx was
60 set as equal to 0.3 m, 0.5 m, 1 m, 1.5 m, 2 m, 2.5 m, 3 m, 5 m, 10 m, 15 m, 20 m, and 30 m; and x_1 was set as equal to 1,
61 3, and 5 times Δx . A total of 144 acquisition geometries were modeled, each of which described in terms of the
62 Normalized Array Center Distance (NACD; Yoon and Rix, 2009). This quantity is defined as the ratio between the array
63 center (i.e., the average between the sensors' distances from the source x_i) and the investigated R-wave wavelength λ_R
64 (in this case, equal to 62.8 m):

$$NACD = \frac{1}{N} \frac{\sum_{i=1}^N x_i}{\lambda_R} \quad (1)$$

66 The NACD combines information about both the acquisition geometry and the target R-wave. It is effective in describing
67 discrepancies due to near-field effects (Yoon and Rix, 2009). The investigated NACD ranges 0.1 and 15, that are typical
68 values covered in MASW surveys and explored in past studies (e.g., Yoon and Rix, 2009; Rahimi et al., 2022).

69 ***Influence of body waves***

70 For each acquisition setup, the synthetic data were processed with the CFDBFa algorithm (Aimar et al., 2024a), which is
71 a transform-based approach for the combined estimation of V_R (or, alternatively, the wavenumber k_R) and α_R , including
72 explicit modeling of the cylindric shape of the Rayleigh wavefront. To address the influence of body waves, we calculated
73 the ratio between the estimated R-wave parameters (i.e., k_e and α_e) and the corresponding theoretical values (i.e., k_t
74 and α_t ; Yoon and Rix, 2009). Fig. 1 summarizes the results of the parametric analysis, showing the normalized wave
75 parameters as a function of the NACD. The datapoints with a transparent layer correspond to rather short arrays
76 compared to λ_R (i.e., $NACD < 0.5$), that are not typically used in MASW surveys due to the limited wavenumber resolution
77 (Foti et al., 2002).



78

79 Fig. 1. Results of the parametric analysis on SW: a) k_e/k_t vs. NACD; b) α_e/α_t vs. NACD. Each data point corresponds to a
 80 specific acquisition geometry, described in terms of N , Δx , and x_1 . The horizontal bands correspond to an estimation
 81 error of $\pm 5\%$ for k_R and of $\pm 25\%$ for α_R .

82

83 The CFDBFa provides reliable estimates of the wavenumber and the attenuation when the NACD is large, i.e., when the
 84 acquisition is performed at large distances from the source. As for the wavenumber (Fig. 1a), it is slightly overpredicted
 85 (hence, there is a small underestimation of V_R) as the NACD decreases, although the estimation error is less than 10%
 86 and it becomes negligible (i.e., less than 5%) at NACD > 1-2. This behavior in the estimated V_R is a direct effect of body
 87 waves, as confirmed by various in-situ observations (Yoon and Rix, 2009; Rahimi et al., 2021). Instead, the attenuation
 88 is strongly overpredicted at short NACDs, with α_e being even 10-100 times larger than α_t . For this reason, the vertical
 89 axis of Fig. 1b is plotted on a logarithmic scale. The error in α_e is relevant even at moderately large distances, and it
 90 becomes less than 25% only at NACD > 2. Notably, the 25% threshold error for phase attenuation in Fig. 1b is larger than
 91 that used for the wavenumber (5%; e.g., Yoon and Rix, 2009). This is due to the greater uncertainty associated with
 92 phase attenuation compared to phase velocity, as well as its generally less influential role in the inversion process (e.g.,
 93 Verachtert, 2018; Bergamo et al., 2023). Moreover, the 25% threshold represents a practical compromise between
 94 estimation accuracy and the need to preserve low-frequency data, as further discussed in the "Discussion" section. Also,
 95 α_e is quite sensitive to the number of sensors of the acquisition layout, with a higher tendency to drift when N is small.
 96 There are two outliers with a significant underestimation of α_t around NACD = 1.5-2. A possible explanation could be
 97 mutual interference between body waves and surface waves, which have comparable amplitudes in this distance-to-

98 wavelength range (e.g., Tokimatsu, 1995), leading to anomalous α_e values. However, this behavior only occurs for $N =$
99 12, which represents an acquisition setup less commonly used in ordinary near-surface site characterization. Other
100 acquisition setups do not exhibit similar anomalies.

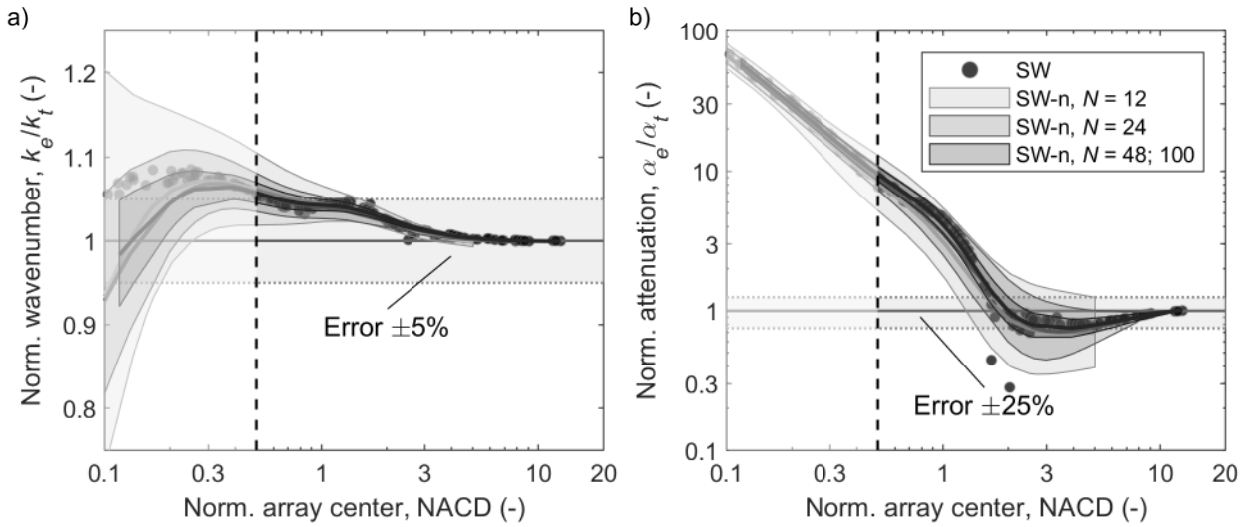
101 ***Influence of incoherent noise***

102 The presence of incoherent noise was modeled through a Monte Carlo procedure, in which white Gaussian noise (e.g.,
103 O'Neill, 2003; Bergamo et al., 2023; Mukherjee et al., 2025) was added to SW to generate a new wavefield, hereafter
104 labelled as “SW-n”. Specifically, 50 independent realizations of white Gaussian noise were generated for each location
105 and superimposed onto the original physics-based signal. This process resulted in 50 noisy signals at each simulated
106 array. The amplitude of the noise signal was constant for all receivers of each simulated array and was calibrated so that
107 the signal-to-noise ratio (SNR) at the farthest receiver was equal to 10 dB. This SNR is consistent with that commonly
108 suggested for MASW testing (Wood and Cox, 2012; Foti et al., 2018). The waveform data were processed using the
109 CFDBFa algorithm (Aimar et al., 2024a), obtaining a distribution of normalized wavenumber k_e/k_t and of normalized
110 attenuation α_e/α_t , for each simulated array.

111 Fig. 2 reports the normalized wave parameters as a function of the NACD, in which the statistical distribution is
112 synthetically described by a region centered at the median value and with an extent equal to the logarithmic standard
113 deviation σ_{\ln} . Indeed, the variability of the estimated wave parameters due to incoherent noise can be modeled through
114 a lognormal distribution (Aimar, 2022). In this case, different regions are defined to address the influence of the number
115 of sensors N on k_e and α_e .

116 As for the wavenumber, there is a good degree of matching over the whole investigated NACD range. Besides, the
117 variability is generally small (i.e., σ_{\ln} less than 0.10). However, for rather small NACDs, the CFDBFa tends to
118 underestimate it, differently from what is observed for the dataset SW. On the other hand, this anomaly occurs only at
119 $\text{NACD} < 0.3$, which is not involved in the usual MASW testing (Foti et al., 2002).

120 Focusing on the attenuation, the distribution of α_e/α_t follows a trend consistent with the one obtained from the dataset
121 SW (i.e., including only body waves). However, the variability is an order of magnitude larger than the corresponding σ_{\ln}
122 for k_e . Specifically, it tends to increase with the NACD, with a maximum at $\text{NACD} = 1.5-2$, exactly in correspondence with
123 the transition region where the body waves start to become less relevant. Then, it decreases at larger NACDs. Notably,
124 the trend of σ_{\ln} is strongly dependent on N . Arrays with few receivers return more variable estimates of α_e , with σ_{\ln} up
125 to 1 at $\text{NACD} = 2$. Instead, using a large number of sensors (i.e., $N = 48$ or 100) allows the variability to decrease
126 significantly, with σ_{\ln} being now limited to 0.3.



127

128 Fig. 2. Results of the parametric analysis on SW-n: a) k_e/k_t vs. NACD; b) α_e/α_t vs. NACD. The transparent layer at NACD <
 129 0.5 highlights the region not typically used in MASW surveys due to the limited wavenumber resolution (Foti et al.,
 130 2002). The horizontal bands correspond to an estimation error of $\pm 5\%$ for k_R and of $\pm 25\%$ for α_R .

131 **Discussion**

132 The results for datasets SW and SW-n highlight that the influence of body waves (and of incoherent noise) is adequately
 133 mitigated for NACD $\geq 2-3$, for both V_R and α_R . It should be noted that this NACD threshold is mostly dictated by the
 134 influence of near-field effects on α_R rather than on V_R . Indeed, the estimation error on V_R is negligible (quantitatively,
 135 less than 5%) for NACD > 1, consistently with the results of Yoon and Rix (2009) and Rahimi et al. (2022). On the other
 136 hand, for NACD $\geq 2-3$, the estimation error for α_R is less than 20-25% on average. This error seems large, but a 10% error
 137 can be achieved only at NACDs larger than 8. This would imply the massive discarding of low-frequency data (with the
 138 consequent strong reduction of the investigated depth) and/or the need of using very long arrays with large
 139 spacing/number of receivers, which is not suitable for ordinary applications. Furthermore, arrays with fewer sensors
 140 are more sensitive to incoherent noise, as the variability of the estimates is larger. At NACD = 2-3, the statistical upper
 141 boundary of the error (corresponding to the median and one logarithmic standard deviation) can increase up to 35%,
 142 50%, and 65%, for N equal to 48-100, 24 and 12, respectively. On the other hand, these variability estimates are obtained
 143 from synthetic data with the conservative (albeit realistic) assumption of SNR = 10dB at the farthest receiver. Indeed,
 144 many MASW surveys are characterized by larger SNR levels.

145 In summary, in the presence of a MASW survey, near-field effects on the estimated V_R and α_R can be mitigated by
 146 considering only those experimental data whose NACD exceeds 2-3.

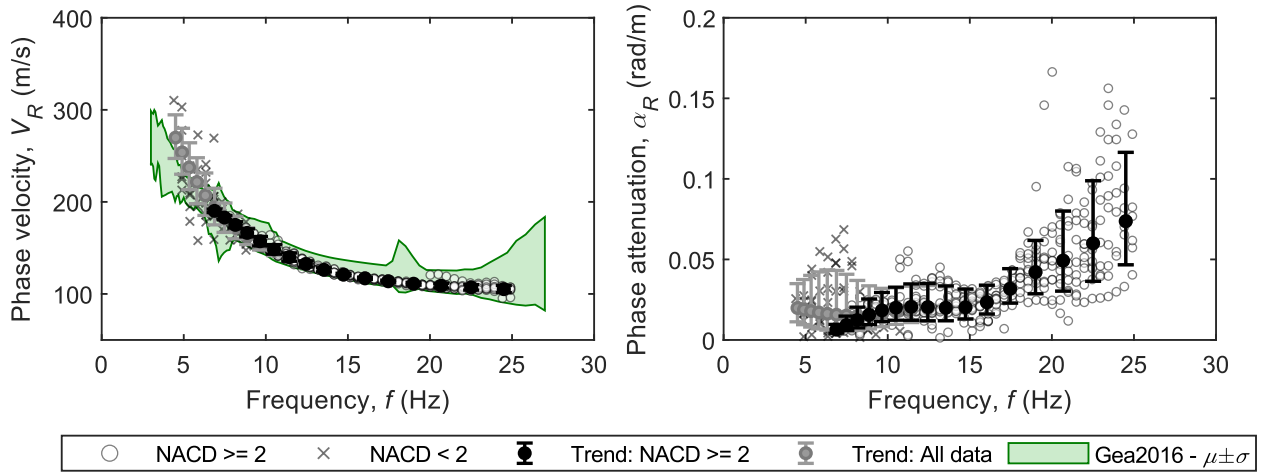
147 Application on a real site

148 The proposed NACD criterion was applied for the interpretation of the MASW data collected at the Mirandola site (Italy)
149 during the InterPACIFIC project (Garofalo et al., 2016b). This site is characterized by alternating layers of fine sands and
150 clays, overlying a rock-like formation at depths between 50 m and 150 m (Garofalo et al., 2016a). Due to the complex
151 stratigraphy, this site represents an appealing case study to gain preliminary insight into the effectiveness of the
152 proposed NACD criterion. The site characterization involved two linear arrays of 48 vertical 4.5-Hz geophones, with Δx
153 equal to 1 m and 2 m, respectively. In both cases, the wavefield was generated by a sledgehammer, with source point
154 offsets of 2.5 m, 3 m, and 15 m. The experimental data were interpreted using the CFDBFa algorithm (Aimar et al.,
155 2024a), over a frequency band between 2 Hz and 25 Hz, with a focus on the R-wave fundamental mode, which is
156 dominant in this range.

157 Fig. 3 reports the estimated V_R and α_R versus frequency, showing data with NACD below or above the threshold NACD
158 = 2 with different marker types. This threshold corresponds to the lower limit of the proposed NACD criterion (i.e., 2-3),
159 being the data SNR larger than 20 in the frequency band of interest. Specifically, two data clusters are identified: (1) a
160 set with all the data points, and (2) a subset with $\text{NACD} \geq 2$, which should not be affected by near-field effects. These
161 data clusters are labeled as “All data” and “ $\text{NACD} \geq 2$ ”, respectively. For each cluster, the distribution of the experimental
162 data is described by the median and the logarithmic standard deviation ($\sigma_{\ln V}$ and $\sigma_{\ln \alpha}$, respectively), calculated over a
163 set of log-spaced frequency bins, and it is represented through error bar plots. Besides, the data in Fig. 3a are overlaid
164 onto the distribution of the V_R estimates for the Mirandola site reported in Garofalo et al. (2016b), represented in terms
165 of intervals given by one logarithmic standard deviation around the median value and labelled as “Gea2016 - $\mu \pm \sigma$ ”. This
166 dataset is an effective benchmark for assessing the reliability of the V_R estimates, since it includes data from ambient
167 noise measurements, which are unlikely to be affected by near-field effects.

168 As for V_R , the two trends of the experimental data are in good agreement, although the “All data” set is affected by a
169 larger variability at low frequencies. Furthermore, this set shows noticeable deviations at low frequencies, sometimes
170 underestimating and at other times overestimating the V_R reported in Garofalo et al. (2016b). Indeed, it is important to
171 note that near-field effects may also cause overestimation of the theoretical V_R in layered media (e.g., Yoon and Rix,
172 2009). Conversely, both the individual data points and the statistical distribution of the “ $\text{NACD} \geq 2$ ” are consistent with
173 Garofalo et al. (2016b), thus corroborating the validity of the proposed NACD threshold. As for α_R , the inclusion of all
174 the data would induce a strong increase in the median α_R , with a clear drift from the “ $\text{NACD} \geq 2$ ” trend at frequencies
175 below 7 Hz. Also, $\sigma_{\ln \alpha}$ increases dramatically up to 1.0 for the “All data” set at low frequencies, while it ranges between

176 0.3-0.5 for the other dataset at all the frequencies. This difference is a consequence of the erratic distribution of the α_R
 177 data points at low frequencies in the “All data” set. This is a clear indication of the influence of body waves and of
 178 incoherent noise, that results in a dramatic increase in the α_R and $\sigma_{In\alpha}$. On the other hand, their influence on V_R seems
 179 less relevant.



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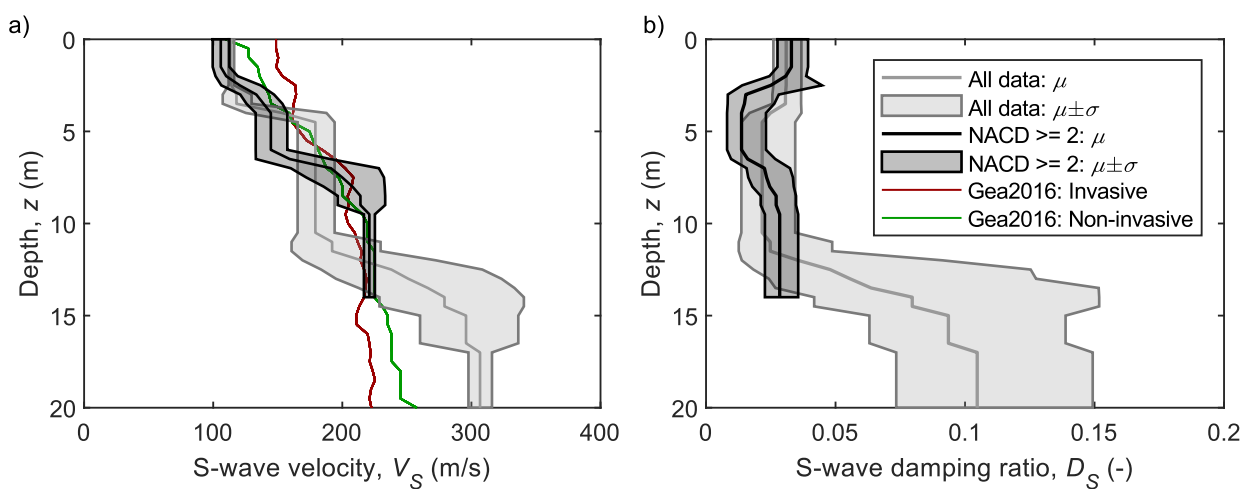
181 Fig. 3. Application of the proposed NACD criterion to the Mirandola dataset: a) Estimated V_R versus frequency; b)
 182 Estimated α_R versus frequency. The figure includes the distribution of the V_R estimates reported in Garofalo et al.
 183 (2016b), for comparison purposes.

184

185 Finally, an inversion of the two experimental datasets was performed to obtain the V_S and D_S profiles at the site. This
 186 provides insight into the consequences of an incorrect separation of near-field effects on V_S and D_S . The inversion was
 187 performed using a Monte Carlo joint inversion method (Aimar et al., 2024b). The inversion involved 10,000 trial ground
 188 models for each dataset, assuming a three-layer profile. The trial models covered a comprehensive range of layer
 189 thicknesses, V_S , and D_S values. Typical values of the mass density and the Poisson ratio were adopted, based on the
 190 available geological information (Foti et al., 2018), whereas the P-wave damping ratio was assumed as equal to D_S .

191 Fig. 4 represents the statistical distribution of the 10 best-fitting V_S and D_S profiles (i.e., those with the smallest deviation
 192 between the theoretical V_R and α_R versus frequency curves and the experimental ones), computed under the
 193 assumption of lognormal distribution for V_S and D_S (e.g., Schevenels, 2007; Li and Assimaki, 2010). Note that this
 194 representation does not provide a rigorous picture of model uncertainties, as it describes the variability of a subset of
 195 the collection of profiles consistent with the experimental data, and it assumes that the true model has three layers –
 196 hence, the uncertainty due to inversion parameterization is neglected. However, this simplified representation is used

197 to better understand the impact of near-field effects on the estimated ground models. Profiles of the “NACD ≥ 2 ” dataset
 198 are truncated at $z = \lambda_{max}/2 = 14$ m (with λ_{max} being the maximum experimental wavelength), which corresponds to the
 199 maximum investigable depth that can be achieved from the corresponding V_R data. The corresponding value for the “All
 200 data” dataset is $z = 26$ m; however, the depth axis is limited at $z = 20$ m because no layer interface was identified beneath
 201 it. Fig. S1 in the Electronic Supplement represents the resulting profiles, together with the comparison between the
 202 theoretical curves with the experimental ones, for both datasets. Besides, V_S profiles in Fig. 4a are compared with the
 203 median profiles obtained from the invasive and the non-invasive tests reported in Garofalo et al. (2016a), labelled as
 204 “Gea2016: Invasive” and “Gea2016: Non-invasive”, respectively.



205

206 Fig. 4. Statistical distribution of a) V_S profiles and b) D_S profiles for the “All data” and “NACD ≥ 2 ” datasets. The regions
 207 indicate the interval defined by the median and one logarithmic standard deviation, at each depth. The figure includes
 208 median V_S profiles obtained from the invasive and the non-invasive tests reported in Garofalo et al. (2016a), for
 209 comparison purposes.

210

211 Fig. 4a shows a good match between the “NACD ≥ 2 ” dataset and the V_S profiles reported in Garofalo et al. (2016a),
 212 proving the reliability of the corresponding estimated profiles, especially at greater depths. As for D_S , the resulting
 213 profiles from the “All data” dataset show two main differences compared to those obtained from “NACD ≥ 2 ”. On the
 214 one hand, the “All data” dataset results in a large D_S at depths larger than 10 m. Also, it increases up to 10-15% for
 215 depths larger than 15 m (i.e., beyond the maximum investigable depth of the “NACD ≥ 2 ” dataset), due to the large
 216 median α_R of the “All data” dataset at low frequencies. These estimates are rather large compared to the expected
 217 values for D_S of fine-grained soils, which typically range between 1% and 3% (e.g., Darendeli, 2001). This even

218 overestimates other effects such as wave scattering, as the corresponding “equivalent” damping ratio is generally
219 around 1-3% (e.g., Wu, 1982; Kurita et al., 1996). Furthermore, the variability of the estimated D_s profiles is larger at z
220 > 5 m, with even greater variability at deeper depths, since the “All data” dataset is affected by large variability in the
221 experimental α_R at low frequencies. This partially prevents an effective constraint on the inverted profiles, resulting in
222 highly scattered D_s profiles, whereas the “NACD ≥ 2 ” dataset gives a clear trend at all depths for both V_s and D_s .

223 **Conclusions**

224 This study investigated the influence of near-field effects and incoherent noise on the estimated R-wave phase velocity
225 and phase attenuation from MASW tests. A parametric analysis over a synthetic surface wave dataset demonstrated
226 that they induce a slight underestimation of the phase velocity, whereas the phase attenuation is strongly
227 overestimated for small NACD values. Furthermore, the data variability induced by incoherent noise is large when the
228 spatial sampling density is reduced. However, near-field effects can be mitigated by selecting experimental data with
229 NACD larger than 2-3. The proposed criterion has been applied for the characterization of the Mirandola site in Italy,
230 highlighting that the inclusion of data affected by near-field effects leads to a significant increase in the estimated
231 damping ratio and its variability at large depths.

232 This study demonstrated the higher sensitivity of phase attenuation to body waves and incoherent noise compared to
233 phase velocity. Therefore, a more conservative NACD threshold should be enforced for the joint estimation of S-wave
234 velocity and damping ratio, compared to previous studies that focused only on soil stiffness characterization. The
235 proposed threshold of NACD = 2-3 can be considered as a good guideline, although further studies are needed to
236 understand the impact of near-field effects on layered media with complex wave patterns (e.g., higher modes) and
237 different noise scenarios. These findings will contribute to a robust estimation of soil dissipation parameters at large
238 depths.

239 **Acknowledgements**

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241 **Data availability**

242 Synthetic data will be made available upon request. Data at the Mirandola site were extracted from the InterPacific
243 Project and are available at <http://interpacific.geopsy.org/>.

244 **Supplemental Materials**

245 Fig. S1 is available online in the ASCE Library (ascelibrary.org).

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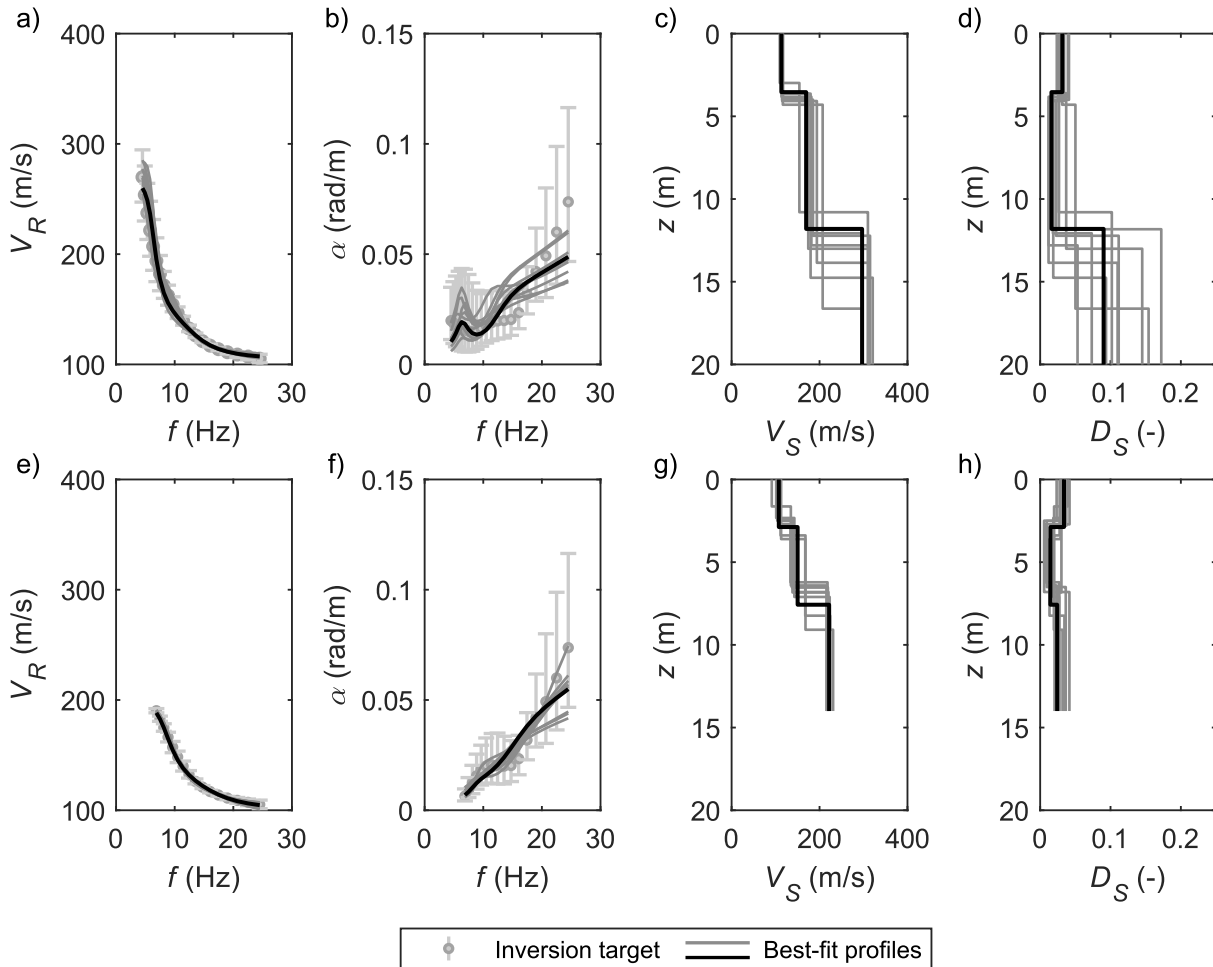
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Electronic Supplement to “Near-field effects on the in-situ estimation of shear-wave velocity and damping ratio
from MASW tests”

Mauro Aimar and Sebastiano Foti



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307 Fig. S1. Best fitting ground models to the “All data” (top row) and “NACD ≥ 2 ” (bottom row) datasets. Each row shows
308 the comparison between theoretical vs. experimental data, for the phase velocity V_R (a and e) and phase attenuation α_R
309 (b and f); the resulting S-wave velocity V_S (c and g) and damping ratio D_S (d and h) profiles. The black line represents the
310 best-fit model (that is, the one with the smallest difference between theoretical and experimental V_R and α_R , as a
311 reference. Profiles of the “NACD ≥ 2 ” dataset are truncated at $z = \lambda_{max}/2 = 14$ m (with λ_{max} being the maximum
312 experimental wavelength), which corresponds to the maximum investigable depth that can be achieved from the
313 corresponding V_R data. The corresponding value for the “All data” dataset is $z = 26$ m; however, the depth axis is limited
314 at $z = 20$ m because no layer interface was identified beneath it.

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