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Influence of 2D heterogeneous elastic soil properties on surface ground motion spatial variability

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26 variability is mainly controlled by the V_s coefficient of variation. A comparison between 2D and 1D ground
27 motion probabilistic modeling shows that the 1D probabilistic approach may correctly reproduce average
28 fundamental resonance frequencies and corresponding amplification. However, the 1D approach significantly
29 under-predicts both ground motion amplification at higher frequencies and related variabilities, as well as Arias
30 intensities and inferred durations, which are all controlled by the generation of locally diffracted surface waves.

31 Key words: Seismic response, spatial variability, probabilistic modeling.

32 **1. Introduction**

33 Spatial variation of earthquake ground motion (SVEGM) refers to the differences in amplitude and phase
34 between recordings of the same earthquake at different locations. This variation is mainly caused by seismic
35 source rupturing heterogeneities, regional wave propagation scattering and modification of ground motion by
36 surface geology, most often referred as site effects (Harichandran, 1999). One of the key factor controlling site
37 effects is the presence of soft deposits overlying a more rigid geological formation. In sedimentary structures
38 like valleys, soft surficial deposits may exhibit lateral variation in thickness, which lead to significant changes in
39 surface ground motion even at close distance (e.g. Moczo and Bard, 1993; Field et al., 1996; Graves et al., 1998;
40 Pagliaroli et al., 2014b). At local scale (tens to hundreds of meters), the spatial heterogeneity of near-surface
41 material results from the surface natural processes of erosion and sedimentation (Einsele, 2000) and human
42 activities (construction, mining, ...) generating anthropogenic deposits that can reach more than 10 m (e.g.
43 Jongmans and Campillo, 1990; Pagliaroli et al., 2014a). Additionally, intrinsic variation in properties within the
44 soil layer contributes to the spatial variability (Jenny, 1941; Burrough, 1993). The soil heterogeneity at various
45 spatial scales may then have a significant effect on SVGEM, as frequently pointed out by the damage studies
46 after earthquakes, especially on long-span structures such as dams, bridges and lifeline facilities (Ariman et al.,
47 1981; Anagnostopoulos, 1988; Trifunac et al., 1997; Trifunac, 2009; Bradley et al., 2011; for a summary of
48 historic observations, refer to Kozák, 2009). In particular, SVGEM has been put forward to explain the damage
49 to the high rise buildings during the San Fernando earthquake in 1971 (Hart et al., 1975) and to the bridges
50 during the earthquake of Loma Prieta in 1989 (Kiureghian et al. 1992), of Northridge in 1994 (Hall et al., 1994)
51 and Christchurch in 2011 (Chouw and Hao, 2012).

52 There is therefore a need to quantify the soil parameter spatial variability and uncertainty for predicting
53 SVGEM. To address this issue, probabilistic modeling approaches using random fields (Popescu, 1995) have
54 been widely used in geotechnical engineering. In particular, such studies have been made on soil liquefaction

55 (Lopez-Caballero and Modaressi, 2010), on the stability of soil dams and slopes (Fenton and Griffiths, 1996;
56 Abdellah et al., 2000; Griffiths and Fenton, 2004), on the analysis of shallow foundations (Youssef Abdel
57 Massih and Soubra, 2008; Soubra and Youssef Abdel Massih, 2010; Al-bittar and Soubra, 2013 and Al-bittar
58 and Soubra 2017) and on the analysis of equipartition time and diffusion regime in random heterogeneous media
59 (Khazaie et al., 2016 and 2017). In contrast, these techniques have aroused only limited interest among the
60 seismological community, probably because of the difficulty of measuring small spatial scale variation in soil
61 mechanical properties (Pagliaroli, 2014a; Salloum et al., 2014). The few 2D probabilistic approaches performed
62 so far in earthquake engineering (Assimaki et al. , 2003; Nour et al. , 2003; Thompson et al., 2009; Pagliaroli et
63 al., 2014a) have highlighted the influence of the spatial variability of the soil properties on the surface ground
64 motion. However, these papers mix effect of variable input ground motion with variability of linear and/or non-
65 linear soil properties on different surface ground motion indicators (spectral response, Peak Ground
66 Acceleration, amplification, Housner intensity), making thus difficult the understanding of the respective impact
67 of source of variability (input ground motion, linear and non-linear soil spatial variability) on SVGEM.

68 This paper aims at numerically studying the effect of the 2D soil spatial variability on SVGEM in the linear
69 domain for a model consisting of one variable soil layer overlying an elastic bedrock, derived from a well-
70 known site (alluvial plain of Beirut, Lebanon). The chosen random soil parameter is the shear-wave velocity
71 (V_s), the spatial variability being discretized by random fields using the Expansion Optimal Linear Estimation
72 method (EOLE) (Li et Der Kiureghian, 1993). Synthetic seismograms at surface receivers are then computed
73 using the FLAC2D Finite difference code. First, the effect of the 2D spatial variability of V_s at a single surface
74 receiver is evaluated on the following scalar indicators: resonance frequency, corresponding amplification, as
75 well as Arias based intensity and duration. Second, impact of spatially variable ground structure on the spatial
76 correlation of surface ground motion is studied. Since some authors (Rahtje et al., 2010; Rodriguez-Marek et al.,
77 2014; Haji-Soltani et al., 2017) chose to replace the 2D spatially variable seismic velocity profiles by 1D
78 spatially variable ones for site-specific hazard assessment, we also compare surface ground motion indicators
79 and related variability inferred from 2D and 1D modelling by using 1D V_s profiles extracted from the 2D V_s
80 model.

81

82 **2. Introducing ground structure spatial variability in wave propagation modeling**

83 2.1. Strategy

84 Spatial variability of soil properties can be modeled by using the random field theory (Vanmarcke, 2010),
85 defined by two functions (1) a Probability Density Function (*pdf*), which is usually positive-skewed and non-
86 Gaussian in soils (Popescu, 1995), and (2) an autocorrelation function $\rho(x,z)$. In this paper, the 2D shear-wave
87 velocity structure, $V_s(x,z)$, is modeled as a random field with μ_{V_s} and σ_{V_s} being the mean and the standard
88 deviation of the *PDF*, respectively. The coefficient of variation, $COV = \mu_{V_s}/\sigma_{V_s}$, quantifies the range of dispersion
89 of V_s around the mean. The autocorrelation function is defined by its spatial fluctuation scale described by the
90 correlation distances θ_x and θ_z along the horizontal and vertical directions, respectively, which are the distances
91 over which the soil property values are not correlated any more.

92 A number n of discretized 2D V_s models (called realizations) are generated using the probability density
93 function and then used to simulate seismic wave propagation. Like any probabilistic modeling, n should be large
94 enough to ensure the statistical convergence of the surface ground motion indicators (resonance frequency,
95 spectral amplification, Arias intensity, duration ...) in terms of average value and standard deviation. Among the
96 numerous methods of random field discretization (Sudret et al., 2000), the Expansion Optimal Linear Estimation
97 method (EOLE) belonging to the family of the series expansion methods (Li and Der Kiureghian, 1993) is used
98 in this study. The main reason is that the convergence of ground motion indicators is reached after a lower
99 number of seismic wave propagation simulations, compared to traditional Monte Carlo approaches (Sudret et
100 al., 2000).

101 In order to understand near-surface spatial V_s variation effects on surface ground motion, we focus on a
102 parametric sensitivity study for a simple case of a spatially variable soil layer overlying a bedrock with constant
103 elastic properties. The V_s structure of the alluvial plain in Beirut (Lebanon) is chosen as a test site since detailed
104 geotechnical and geophysical campaigns carried out at this site have allowed to image spatial variation of the
105 underground geological structure (Saloum et al., 2014; Salloum, 2015).

106 2.2. Soil statistical parameters

107 In the approach adopted in this paper, the three statistical parameters describing the soil spatial variability are
108 the coefficient of variation COV and the two autocorrelation distances θ_x and θ_z . Numerous studies attempted to
109 determine these parameters from geotechnical laboratory or in situ tests (for a recent synthesis, see Salloum,

110 2015). In contrast, very few studies were made on the quantification of the V_s variability. This probably results
111 from the difficulty to obtain reliable V_s values through in situ tests.

112 In geotechnics, penetration tests (SPT – Standard penetration Tests or CPT – Cone penetration Tests) are widely
113 used for soil investigation (Cornforth, 2005). They provide resistance parameters (N : number of blows for SPT;
114 q_c : cone resistance for CPT) that, like V_s , mainly increase with soil density or compactness if the effect of the
115 effective stress due to overburden pressure is removed (Karray et al., 2011). For these two parameters, the
116 coefficient of variation was found to cover a wide range between 5 and 43% (e.g Phoon and Kulhawy, 1999;
117 Srivastava and Babu, 2009; Zhao et al., 2018). For getting the coefficient of variation (COV) of V_s , Thomson et
118 al. (2007) compiled results of V_s measurements using different techniques (down-hole tests, seismic cone tests)
119 in various geologic units (Holzer et al, 2005; Wills and Clahan, 2006; Moss, 2008). They found that COV
120 values are generally contained within the interval from 14 to 46% for V_s measurements in the same geologic
121 unit. COV values in a similar range are also reported by Haji-Soltani and Penscheck (2017) for a very soft
122 sediment (5 to 15%) and by Rodriguez-Marek et al. (2014) for very hard rock site (10 to 25%). Making use of
123 the Electric Power Research Institute (EPRI, 1993) V_s profile database, Toro (1995) found COV ranging
124 between about 30% and 45% for various NEHRP site classes.

125

126 *Table 1: Properties in the two layers (soil and bedrock) for the probabilistic modeling. The bedrock properties*
127 *are fixed, as well as the density ρ and the P-wave velocity V_p in the soil layer. The soil S-wave velocity is*
128 *considered as a random field and characterized by four statistical parameters (μ_{Vs} , COV, θ_x , θ_z). Nine models*
129 *are defined with various COV, θ_x and θ_z (see text for details). The so-called deterministic model is defined by*
130 *the values shown in italics in the Table.*

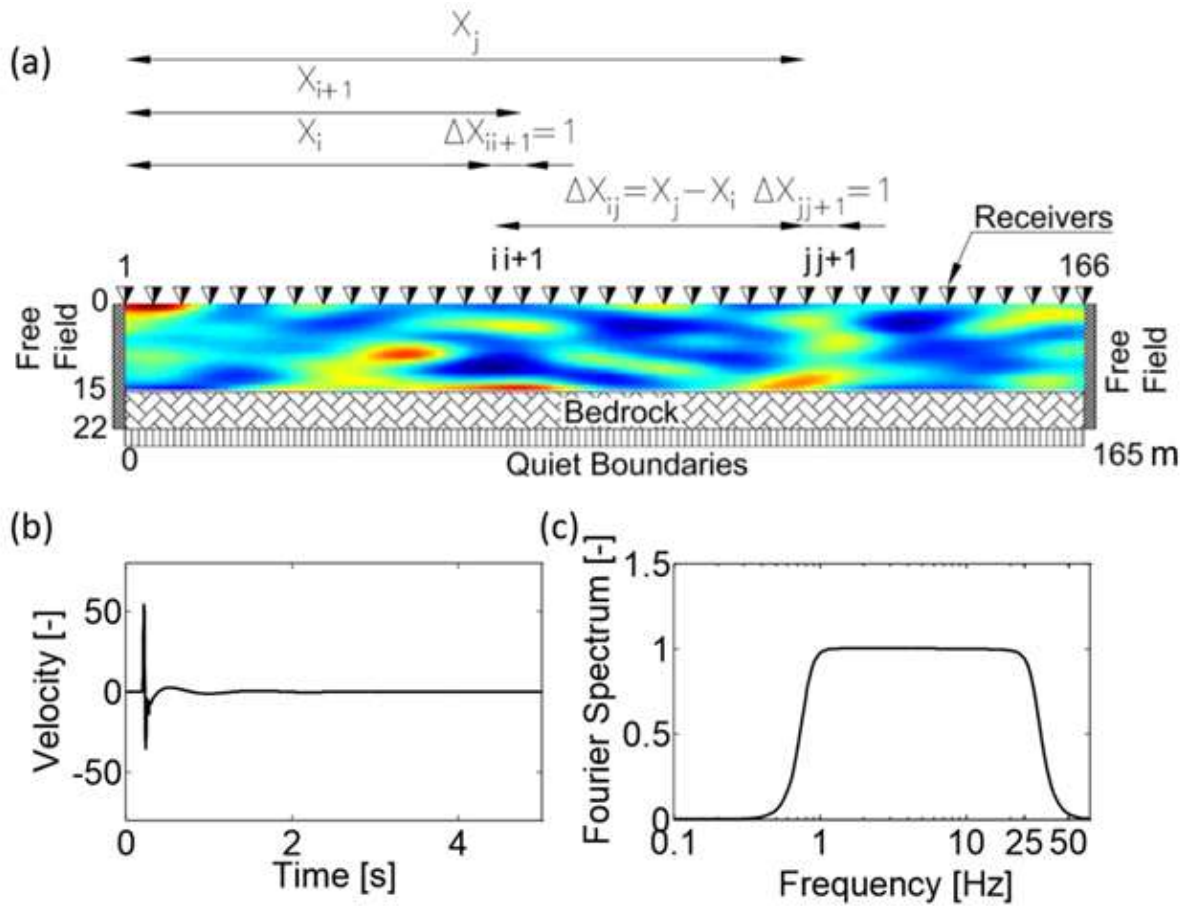
Layers	Properties						Model #		
	ρ (Kg/m ³)	V_p (m/s)	μ_{Vs} (m/s)	COV (%)	θ_x (m)	θ_y (m)			
Soil with a thickness of 15.5 m	1600	1500	220	5	5	2	1		
					10	2	2		
				20	5	2	3		
					10	1	4		
						2	5		
					20	2	6		
					40	5	2	7	
				10		1	8		
									2
				Bedrock	2500	3000	1000	---	---

131

132 The autocorrelation parameters in a soil layer θ_x and θ_z can be estimated by using several methods (e.g. Popescu,
133 1995; Assimaki et al., 2003; Thomson et al., 2009), depending on the available data and the chosen
134 autocorrelation function. As most sedimentary layers are characterized by a strong anisotropy resulting from
135 depositional processes, the horizontal autocorrelation distances are expected to be greater than vertical ones. In-
136 situ geotechnical and V_s tests are usually performed along vertical profiles and most of the available information
137 is on the vertical autocorrelation distance θ_z . Thus, θ_x is usually poorly constrained. Penetration test analyses
138 provide a relatively wide range for the vertical autocorrelation distances, from a few cm to a few m, while the
139 horizontal distances were estimated from around 1 m to more than 100 m (e.g., Alonso et al., 1975; Phoon and
140 Kulhawy, 1996; Fenton, 1999; Jaksa et al., 1997; Assimaki et al., 2003; see Salloum, 2015 for a synthesis).

141 Using suspension log slowness data, Thomson et al. (2009) determined a maximum θ_z value of about 5 m; θ_x
142 was estimated to 50 m to 100 m, assuming an anisotropy factor of 10 to 20. These results illustrate the wide
143 scattering of soil statistical parameter values, resulting from the wide variety in geological depositional contexts
144 (marine, lake, glacial, alluvial sediments), and from the large uncertainty on the horizontal autocorrelation
145 distance quantification.

146 As our parametric study is built on the alluvial plain of the river Nahr Beirut (Beirut, Lebanon), the statistical
147 parameters determined from the extensive near-surface geotechnical (borehole measurements, SPT, laboratory
148 measurements) and geophysical (seismic, resistivity) campaigns (Salloum et al. , 2014; Salloum, 2015) are used
149 hereafter. These experiments showed the presence of interbedded Quaternary layers of pebble, gravel, sand and
150 clay overlying marly limestone of Tertiary age, with strong vertical and horizontal variability. The typical soil
151 column is, from the surface to depth: (1) a 7.5 m thick gravel layer with $V_s=350$ m/s, (2) a softer clay layer of 8
152 m in thickness with $V_s=150$ m/s and (3) weathered limestone ($V_s>400$ m/s). Fitting a theoretical lognormal
153 probability density function on down-hole tests data led to a V_s coefficient of variation (COV) of 13% and 44%
154 in the clay and gravel layers, respectively (Salloum, 2015). The vertical autocorrelation distance θ_z was found to
155 vary between 0.5 m and 2 m in the soil layers, using the same data. ERT (Electrical Resistivity Tomography)
156 profiles were used to evaluate the horizontal autocorrelation distance θ_x , which was bracketed between 3.8 and
157 10.6 m (Salloum, 2015), assuming that the variability is the same for the two geophysical parameters (shear
158 wave velocity and electrical resistivity).



159

160 *Figure 1: (a) Two-layered ground model composed of a 15,5m thick soil layer overlying bedrock ($V_s=1000$*
 161 *m/s). The V_s distribution in the soil layer was computed using the EOLE method with the following statistical*
 162 *parameters: $\mu V_s = 220$ m/s; $COV = 40\%$; $\theta_x = 10$ m; $\theta_z = 2$ m (model # 9 in Table 1). X_i refers to the distance of*
 163 *the receiver i from the left side of the model. ΔX_{ij} refers to the distance between receiver i and j . Synthetic*
 164 *velocities are computed at 166 surface receivers 1 m apart (some locations are shown with black triangles). (b)*
 165 *Horizontal input signal (particle velocity) applied at the model base. (c) Fourier amplitude Spectrum of the*
 166 *input signal.*

167

168 For the purpose of simplifying the 2D modeling, the two soil layers were merged into a unique 15.5 m thick
 169 bed with a mean value $\mu_{V_s} = 220$ m/s overlying a homogeneous sound bedrock ($V_s = 1000$ m/s) (Figure 1a). The
 170 statistical parameters in the sedimentary layer are chosen in a range covering the values found during the survey
 171 and in the literature ($5\% < COV < 40\%$; $5 < \theta_x < 20$ m; $1 < \theta_z < 2$ m). The 9 probabilistic models used for the
 172 sensitivity analysis are given in Table 1. No attenuation or damping is considered in the analysis in order to

173 focus only on the effects of elastic properties variability. The fundamental resonance frequency of the soil layer
 174 for the mean V_s is $f_{0D} = 3.54$ Hz, with a theoretical amplification $AF_{D=}$ 7.1 at the resonance frequency. This case
 175 will be referred to as the deterministic model in the following.

176 2.3. Random field discretization method

177 The Expansion Optimal Linear Estimation method (EOLE), originally proposed by Li and Der Kiureghian
 178 (1993) is used herein to discretize the random field of $V_s(x,z)$. It is described by a lognormal *probability density*
 179 *function* $f(V_s)$ (Eq. 1):

$$f(V_s) = \frac{1}{V_s \sigma_{\ln} \sqrt{2\pi}} \exp\left(-\frac{(\ln(V_s) - \mu_{\ln})^2}{2\sigma_{\ln}^2}\right) \quad (1)$$

180 where μ_{\ln} and σ_{\ln} are the mean and the standard deviation of V_s natural logarithm, respectively, and by an
 181 anisotropic square exponential autocorrelation function $\rho[(x, z), (x', z')]$ (Eq. 2), which gives the values of the
 182 correlation function between two arbitrary points (x, z) and (x', z') :

$$\rho[(x, z), (x', z')] = \exp\left(-\frac{|x - x'|^2}{\theta_x} - \frac{|z - z'|^2}{\theta_z}\right) \quad (2)$$

183 where θ_x and θ_z are the autocorrelation distances along x and z , respectively.

184 In this discretization method, one should first define a stochastic mesh composed of Nq grid points (or nodes)
 185 and determine the autocorrelation matrix $\sum_{\mathcal{X};\mathcal{X}}$ that gives the correlation between each grid point of the
 186 stochastic mesh and the other grid points using Eq. 2. The stochastic mesh dimensions (D_X, D_Y) are taken equal
 187 to half of the autocorrelation distance of the model in each direction ($D_X = \theta_x/2, D_Z = \theta_z/2$). The random field
 188 $V_s(x,z)$ at any point is estimated by the following equation, using the autocorrelation matrix :

$$\tilde{V}_s(x, z) = \mu + \sigma \sum_{i=1}^s \frac{\xi_i}{\sqrt{\lambda_i}} (\phi_j)^T \sum_{V_s(x,z);\mathcal{X}} \quad i = 1 \dots s \quad (3)$$

189 where $\tilde{V}_s(x, z)$ is the approximate of the random field, μ and σ are the mean and standard deviation values of
 190 V_s , ξ_j is the vector of independent standard gaussian random variables, λ_j and ϕ_j are the eigenvalues and
 191 eigenvectors of the autocorrelation matrix $\sum_{\mathcal{X};\mathcal{X}}$, $\sum_{V_s(x,z);\mathcal{X}}$ is the correlation vector between the values of the
 192 random field at the different nodes of the stochastic grid and its value at the arbitrary point (x, z) as obtained
 193 using Eq. 2. The series of Eq. 3 is truncated to a number of terms s (expansion order), which is smaller than the

194 number of grid points, after sorting the eigenvalues λ_j ($j=1 \dots S$) in a descending order. This number should
 195 ensure that the variance of the error is smaller than a prescribed tolerance (10% in our study). The variance of
 196 the error on the random field in the EOLE method is given by (Li and Derkiureghian, 1993):

$$Var[V_s(x, z) - \tilde{V}_s(x, z)] = \sigma_{V_s}^2 - \sum_{i=1}^N \frac{1}{\lambda_i} \left((\phi_j)^T \sum_{V_s(x); \chi} \right)^2 \quad (4)$$

197 where $V_s(x, z)$ and $\tilde{V}_s(x, z)$ are the exact and the approximate values of the random fields at a given point (x, z) ,
 198 respectively.

199 Each vector of standard Gaussian random variables ξ_j ($j=1 \dots S$) provides (when substituted into Eqs. 3.3 and
 200 3.4) spatial variations in V_s that fulfill the correlation structure of this field and are called V_s realizations. This is
 201 performed by computing, for this vector, the values of V_s at the centroids and the nodes of the different elements
 202 of the stochastic mesh. For each Since the finite difference mesh of FLAC^{2D} used to simulate wave propagation
 203 is much smaller than the stochastic mesh, the kriging method (Sacks et al. 1989) is used for determining V_s at
 204 the centre of each finite difference mesh. In this study, the ordinary kriging and an anisotropic square
 205 exponential function for the correlation function are used. For each model (Table 1), the autocorrelation
 206 distances used for the kriging method are similar to the ones defined in the EOLE method. The lower and upper
 207 boundaries of the autocorrelation distances were taken equal to 0.5 m and 100 m, respectively. Thus, in both
 208 directions, 5 V_s are determined within one autocorrelation distance using the EOLE method and the others are
 209 extrapolated using the ordinary kriging method. By the combination of these two discretization methods,
 210 Figures 2d and 2h show example of one V_s realization for the 2 models #5 and #9 (Table 1), which have the
 211 same correlation distances ($\theta_x=10$ m and $\theta_z=2$ m) and differ by the *COV* value (20% and 40%, respectively). In
 212 order to check the accuracy of the generated 2D V_s realizations, the average shear wave velocity (μ_{V_s}) and the
 213 coefficient of variation (*COV*) are calculated for the two examples. The autocorrelation distances θ_x and θ_z are
 214 then evaluated respectively for the horizontal and vertical 1D samples extracted from the 2D realizations (refer
 215 to the black dashed rectangles in Figures 2d and 2h). The re-estimated statistical parameters are summarized in
 216 Table 2. The results show that the generated 2D realizations have about the same statistical parameters initially
 217 introduced during the random field discretization phase.

218

219 *Table 2: Statistical parameters: the average shear wave velocity (μ_{Vs}), the coefficient of variation (COV) and*
 220 *the autocorrelation distances (θ_x , θ_z) computed for the two V_s realizations shown in Figures 2d and 2h. For*
 221 *each realization, θ_x and θ_z are estimated, respectively, for the horizontal and vertical rectangle of each figure.*

Statistical parameters	Model #5	Model #9
μ_{Vs} (m/s)	222	217
COV (%)	20.93	38.81
θ_x (m)	11.09	10.85
θ_z (m)	1.91	1.98

222

223 2.4. Wave propagation simulation

224 The finite difference code FLAC^{2D} is used to propagate seismic waves in the 2D V_s structures (Bouckovalas et
 225 al., 2005; Pagliaroli, 2006; Stamatopoulos et al., 2007 & 2009). After discretizing V_s for all the models listed in
 226 Table 1, the minimum value of V_s is found to be 50 m/s and the maximum value is 750 m/s. An example of one
 227 realization of the V_s structure obtained for model #9 (Table 1) is shown in Figure 1a. The source time function
 228 is a pseudo-Dirac having a flat Fourier amplitude spectrum between 1 and 25 Hz (Figures 1b and 1c). According
 229 to the frequency and V_s ranges, the minimum and maximum wavelengths in the sediment layer are 2 m and 750
 230 m, respectively. The mesh size Δl is chosen less than one tenth of the minimum wavelength to avoid numerical
 231 dispersion phenomena (Eq. 5) (Kuhlemeyer, R. L. and Lysmer, 1973):

$$\Delta l_{\max} \leq \frac{\lambda_{\min}}{10} = \frac{V_{s_{\min}}}{10 \cdot f_{\max}} \quad (5)$$

232 where Δl_{\max} is the maximum size of the finite difference mesh, λ_{\min} is the minimum wave length, $V_{s_{\min}}$ is the
 233 minimum shear wave velocity, and f_{\max} is the maximum wave frequency.

234 With the parameters of this study, the maximum mesh size, Δl_{\max} , is 0.2 m ($\Delta l_{\max} \leq \frac{50}{10 \cdot 25}$).

235 Zero horizontal displacements are applied along lateral boundaries of the model, while the horizontal and
 236 vertical movements are fixed at its base. Free field boundaries are applied to the side edges of the model. A
 237 quiet boundary (absorbing effect defined in FLAC^{2D} (Itasca, 2011)), is applied to the model base in order to
 238 model a flexible base that absorbs the energy emitted by the waves reflected on the surface and arriving to the
 239 model base. After initializing the stresses, a seismic shear stress excitation consisting of a vertically incident
 240 plane SV-type wave is applied to the base of the model:

$$\sigma_s = 2 \cdot (\rho \cdot V_s) \cdot v_s \quad (6)$$

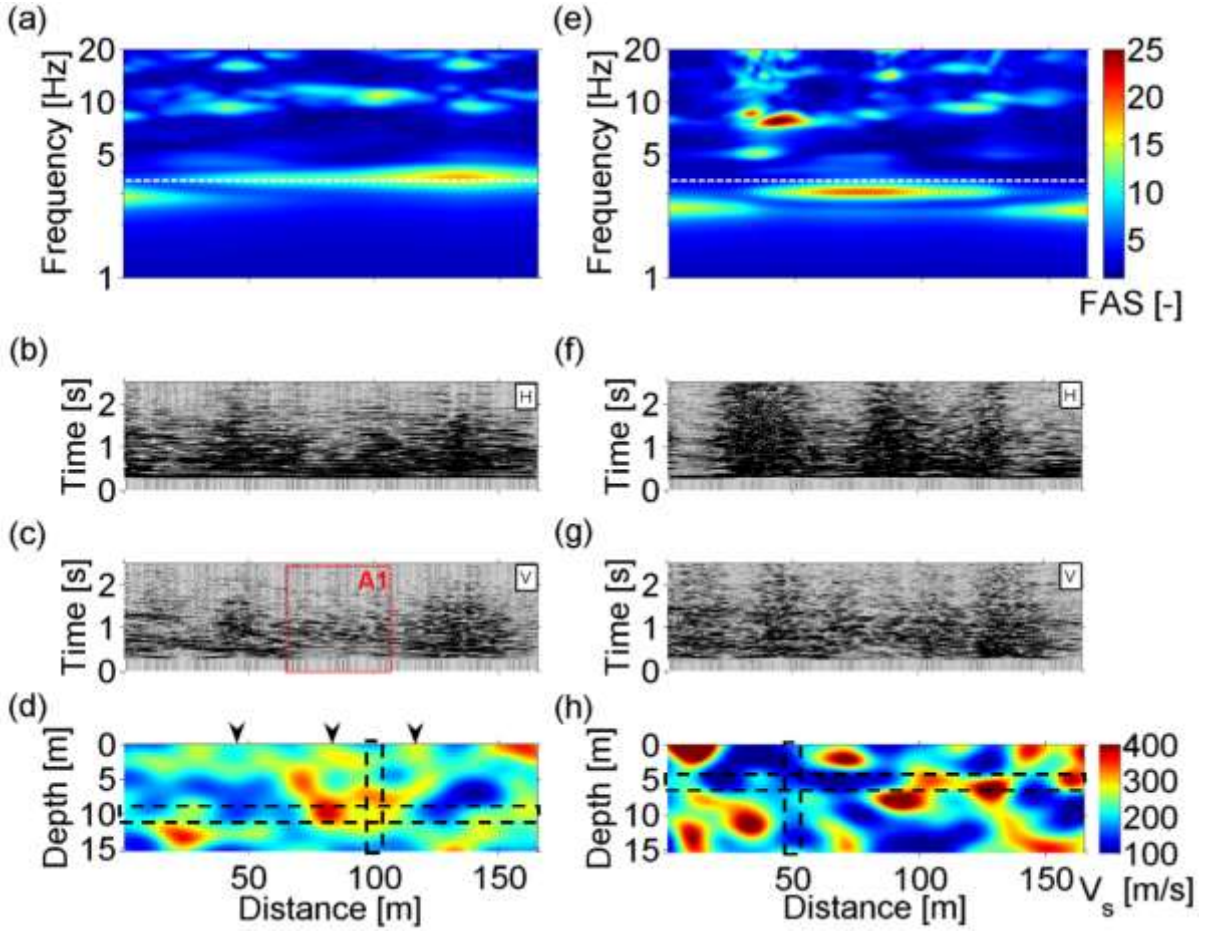
241 Where σ_s is the applied shear stress, ρ is the soil density, V_s is the medium shear wave velocity and v_s is the
242 horizontal component of the velocity signal.

243 The 2D soil structure used in the simulation is a 22 m x 165 m model. The width of the model is relatively small
244 compared to the maximum wavelength of 750 m. Therefore, in order to check that the boundary conditions are
245 efficient and that such a model size does not affect the wave propagation, we compared seismograms computed
246 for two different model sizes (750 m and 165 m wide) keeping fixed all the other parameters. The simulations
247 performed over a duration of 2 seconds show similar results (Appendix 1). Finally, the computation time for one
248 simulation and 10-second seismograms is around 5 hours on a single processor and a PC having an i7-core and
249 2.4 Hz CPU frequency, leading to a total computation time of about 4500 hours for all models.

250 **3. Characterization of the ground motion spatial variability**

251 In this section, we present an analysis of the synthetic seismograms computed for two probabilistic models (one
252 realization), discuss the probabilistic simulation stability and provide the definition of the ground motion
253 indicators extracted from the seismograms.

254



255

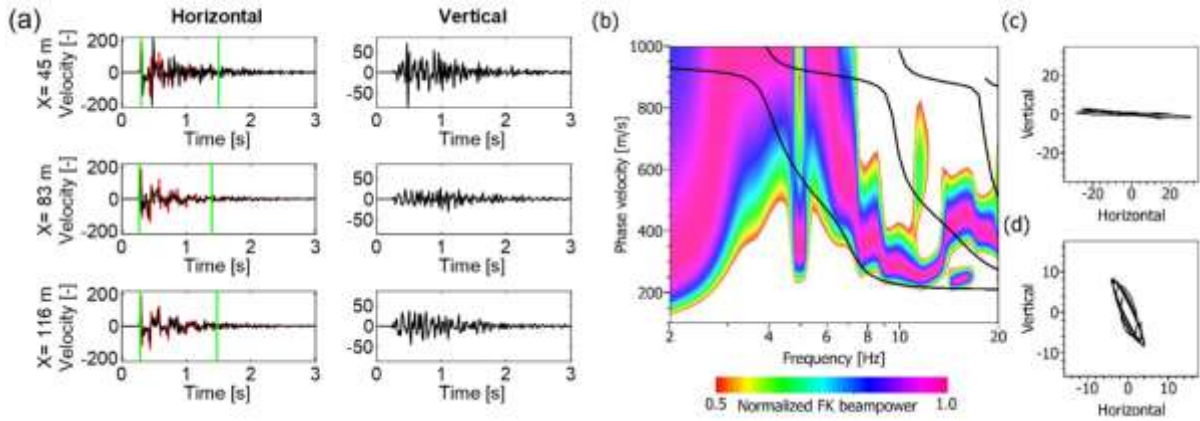
256 *Figure 2: Seismic responses for the two V_s realizations of models #5 (left column) and #9 (right column). (a)*
 257 *and (e) Fourier amplitude spectra (FAS) for the horizontal velocity seismograms shown in (b) and (f); (b) and*
 258 *(f) 3-second horizontal seismograms (H) computed for the V_s realizations shown in (d) and (h), respectively. (c)*
 259 *and (g) 3-second vertical seismograms (V) ; (d) and (h) V_s realizations for models #5 ($COV=20\%$ $\theta_x=10m$*
 260 *and $\theta_z=2m$) and #9 ($COV=40\%$ $\theta_x=10m$ and $\theta_z=2m$) (see Table 1). The white dashed lines in (a) and (e)*
 261 *correspond to the fundamental frequency of the deterministic model, f_{oD} .*

262 **3.1. Ground motion synthetics and probabilistic simulation stability**

263 **3.1.1. Ground motion synthetics**

264 Figure 2 shows the simulation results of one V_s realization for the 2 models #5 and #9 (Table 1). For each case,
 265 the V_s model, the vertical and horizontal surface velocity signals, and the Fourier amplitude spectra of the
 266 horizontal seismograms are shown. The increase in COV (40%) is clearly visible on the V_s model #9 (figure 2h),
 267 which exhibits larger velocity contrasts than model #5 (Figure 2d; $COV= 20\%$). The V_s spatial variation turned
 268 out to have a strong influence on the surface ground motion characteristics: seismograms exhibit larger
 269 amplitude and longer duration at receivers located over near-surface low velocity zones (see Figures 2b, c, f and

270 g), especially for the horizontal seismograms and for $COV=40\%$. The Fourier amplitude spectra (Figures 2a and
 271 2e) show that the amplification at the fundamental resonance frequency occurs at or a little lower the
 272 deterministic 1D resonance frequency ($f_0=3.54$ Hz), with lateral variations resulting from the surface wave
 273 propagation. Amplification at higher frequencies are also spatially variable (Figure 2e).



274

275 *Figure 3: (a) 3-second seismograms (horizontal and vertical velocities) simulated for the V_s model shown in*
 276 *Figure 2d at 3 different locations spotted by black arrows in Figure 2d (curves in black). Seismograms*
 277 *computed for the deterministic model are indicated in red. The vertical green lines represent the duration*
 278 *corresponding to 5 and 95% of the total energy calculated for the seismograms computed for the probabilistic*
 279 *model (see text for details). (b) Dispersion curves for the vertical component of the synthetic ground motion*
 280 *obtained for distance between 65 and 115 m between $t=0$ s and 8 s (refer to rectangle A1 in Figure 2c); the*
 281 *theoretical dispersion curves for the first three modes of the deterministic model are shown in black. (c) Particle*
 282 *motion of the 1-5 Hz band-pass filtered velocities recorded at $X= 83$ m between $t=0.1$ s and $t=0.8$ s (top) and 7-*
 283 *11 Hz band-pass filtered velocities recorded at $X= 83$ m between $t=1$ s and 1.8s (bottom).*

284

285 Figure 3a shows the first three seconds of the ground surface seismograms (horizontal and vertical components)
 286 calculated for the model #5 at three distances indicated in Figure 2d. The horizontal signals are compared with
 287 the ones computed for the deterministic model considering no variability in the soil properties ($\mu_{V_s} = 220$ m/s;
 288 $\sigma_{V_s}=0$). Figure 3a illustrates the motion spatial variability generated by the 2D probabilistic models in terms of
 289 amplitude of the first arrivals (e.g. see the signals at 45 m and 116m) and generation of strong later seismic
 290 waves (e.g. at 45 m) both on the horizontal and vertical components.

291 In order to determine the wave types, the particle motions are plotted in Figures 3c and 3d within two time
 292 windows (0.1-0.8s) and (1-1.8s), respectively. As expected, the early seismic waves are horizontally polarized
 293 shear waves, while elliptical motion of the late waves indicate presence of Rayleigh waves. By using the f-k
 294 method (Lacoss et al., 1969), the dispersion characteristics of the surface waves were calculated by using
 295 vertical seismograms recorded at receivers located between 65 m and 115 m. The dispersion diagram shown in
 296 Figure 3b indicates two branches of dispersion curves between 4Hz and 20 Hz, while the image is blurred below
 297 4 Hz. This results from the high-pass filtering of the soil layer (Scherbaum et al. 2003), which leads the energy
 298 vanishing below the soil fundamental frequency (see also the Fourier amplitude spectrum in Figure 2a).
 299 Although the theoretical curves from the deterministic model (first three modes, black curves) do not perfectly
 300 match the dispersion maxima caused by V_s differences between the 2D and the deterministic cases, the
 301 comparison suggests that the first two Rayleigh wave modes have been excited in the 2D probabilistic model.

302 3.1.2. Convergence of probabilistic ground motion simulations

303 Probabilistic modeling approaches require simulating ground motion for a large enough number of realizations
 304 of discretized V_s models to ensure the statistical convergence of the average and standard deviation estimators
 305 of any surface ground motion parameter. We define the convergence of a ground motion parameter α as a
 306 fraction of the relative variation of α between realization i and realization $i+1$:

$$\text{CONV}(\alpha) = \frac{|\alpha_i - \alpha_{i+1}|}{|\alpha_i|} \quad (7)$$

307 The convergence is considered to be reached when $\text{CONV}(\alpha) < 5\%$ (Haldar et al., 2008). For both the average
 308 and standard deviation estimators, the convergence was tested on both surface ground motion parameters in time
 309 (Arias Intensity and duration) and frequency (Fourier amplitude spectra, site fundamental frequency and
 310 corresponding amplification) (see section 3.2 for definition). As an example, the convergence for the Fourier
 311 amplitude spectra (horizontal component) at different frequencies and the duration are shown in Appendix 2 for
 312 model #9 that exhibits the largest V_s range. According to the defined criterion, the convergence is reached after
 313 86 realizations for all frequencies for Fourier amplitude spectra and after 82 realizations for the duration. All the
 314 tests performed on other indicators showed that 100 realizations ensure the convergence. Finally, due to the
 315 presence of absorbent boundaries, receivers located less than 30 m from the borders were omitted in the
 316 analysis.

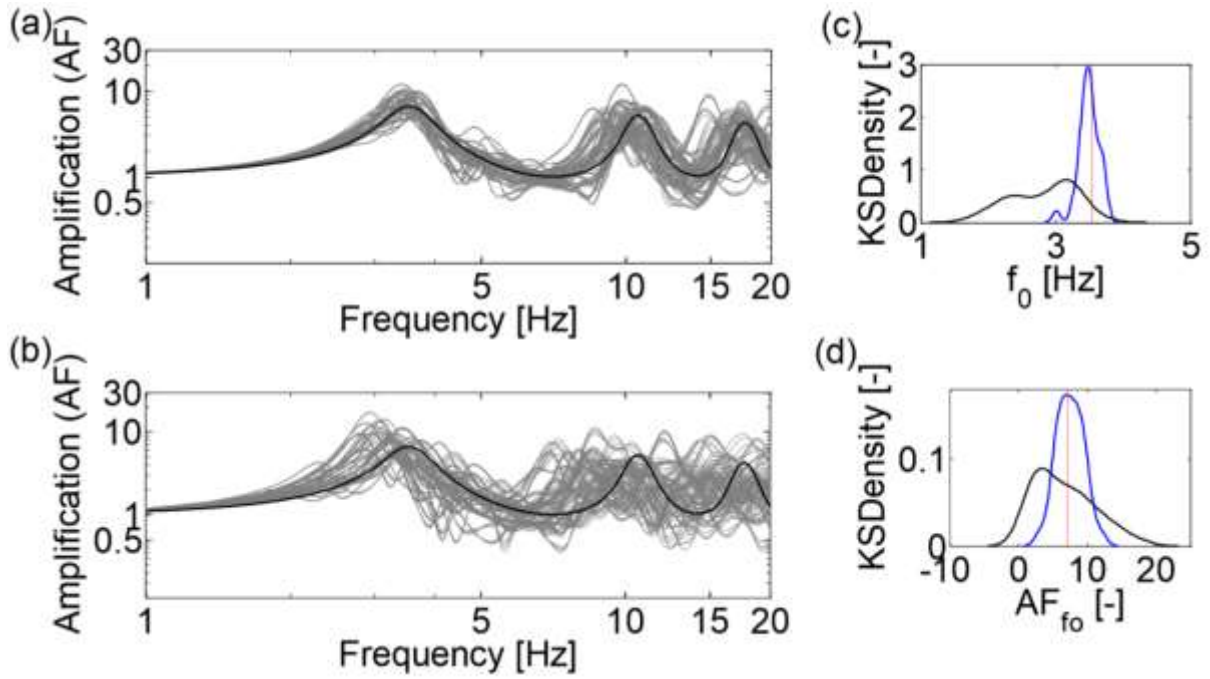
317 3.2. Surface ground motion indicators

318 In this paper, we consider surface ground motion indicators in time and frequency domain, as described
319 hereafter. In the frequency domain, the spectral amplification $AF(f)$ is defined as the ratio between the Fourier
320 amplitude spectra of the signals recorded at the soil surface and at the outcropping bedrock. For vertically
321 incident waves, this latter is 2 times the spectrum shown in Figure 1c. Two parameters are extracted from the
322 spectral amplification: the fundamental frequency f_0 and the corresponding amplification, AF_{f_0} . In the time
323 domain, we consider the Arias based intensity parameter (A_bI) that provides a measure of the shaking intensity
324 (Arias, 1970), here defined as the integral of the square surface horizontal velocity as function of time. The
325 second time parameter is the effective duration (D_{AbI}) defined as the difference between the time where 5% and
326 95% of the total A_bI is reached. The durations inferred for models #5 are indicated in Figure 3a.

327 **4. Influence of ground structure variability on surface ground motion indicators at a single** 328 **station**

329 4.1. Resonance frequency and related amplification

330 The amplification AF was calculated at the central receiver (located at $x=83$ m) for all models (Table 1) from the
331 10-second seismograms after smoothing the Fourier amplitude spectra by using the Konno and Ohmachi
332 algorithm with $b=50$ (Konno and Ohmachi, 1998). Spectral amplifications for the 100 simulations are shown in
333 Figures 4a and 4b for models #5 ($COV=20\%$) and #9 ($COV=40\%$), respectively. The variability of the
334 amplification curves increases with COV , both in terms of maximum amplification and corresponding
335 frequency. We computed the probability density functions of f_0 and AF_{f_0} (Figures 4c and 4d) using the non-
336 parametric kernel density estimation technique (Rosenblatt, 1956; Parzen, 1962). Compared to the deterministic
337 fundamental frequency f_{0D} (dashed red line), the probabilistic f_0 values tend to be lower than f_{0D} by about 2% and
338 20% for $COV=20\%$ and 40%, respectively (Figure 4c). The distribution of amplifications at the fundamental
339 resonance frequency peaks (AF_{f_0}) (Figure 4d) is slightly higher by about 6.7% than the deterministic one ($AF_{f_{0D}}$)
340 for $COV = 20\%$, with AF_{f_0} values ranging between 3.15 and 12.0, while it is significantly shifted to a lower
341 amplification values for $COV=40\%$ with AF_{f_0} values ranging between 1.6 and 17.2.

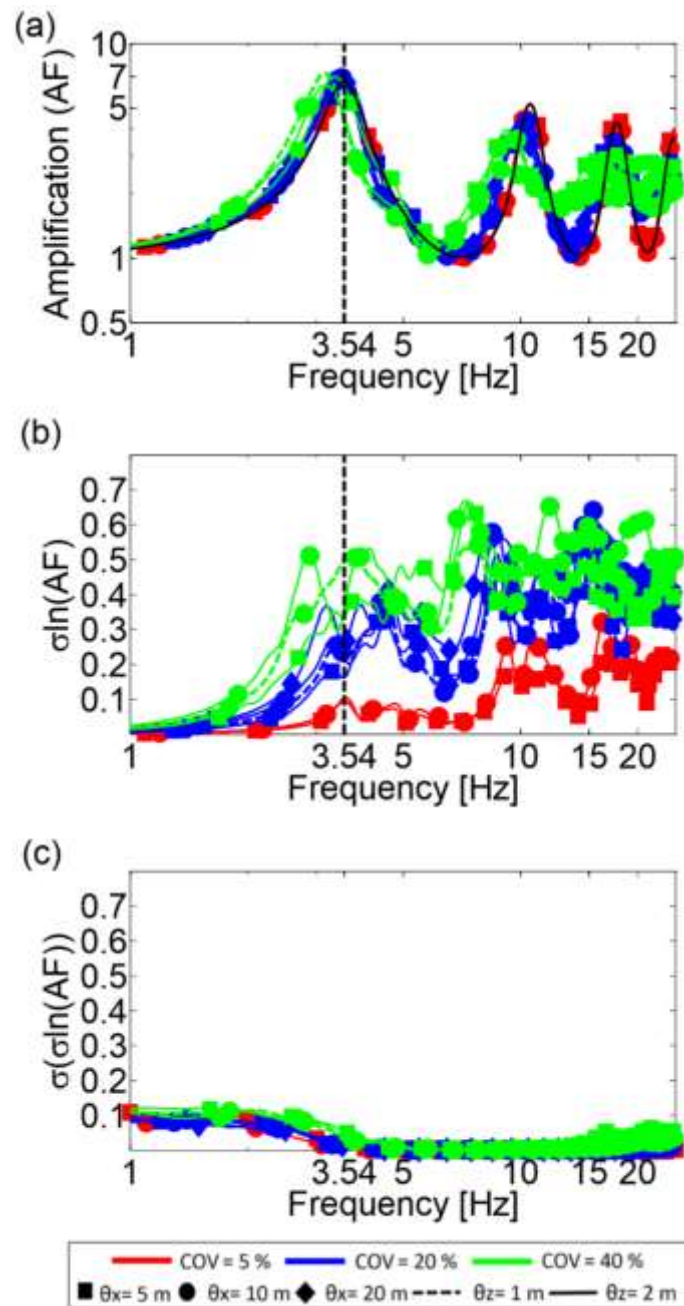


342

343 *Figure 4 : Amplification functions at the central receiver. (a) and (b) Amplification curves (100 realizations in*
 344 *grey) for parameter set #5 (COV=20% $\theta_x=10m$ and $\theta_z=2m$) and for the parameter set #9 (COV=40% $\theta_x=10m$*
 345 *and $\theta_z=2m$), respectively. The black curve is the theoretical transfer function for the deterministic model*
 346 *($V_s=220$ m/s). (c) KSdensity of the fundamental resonance frequency f_0 computed by considering all*
 347 *realizations for parameter set #5 (in blue) and #9 (in black). The red dashed line indicates the fundamental*
 348 *resonance frequency f_{0D} of the deterministic model. (d) KSdensity of the amplification AF_{f_0} at the fundamental*
 349 *resonance frequency for parameter set #5 (in blue) and #9 (in black). The red dashed line indicates the*
 350 *amplification AF_{f_0D} for the deterministic model.*

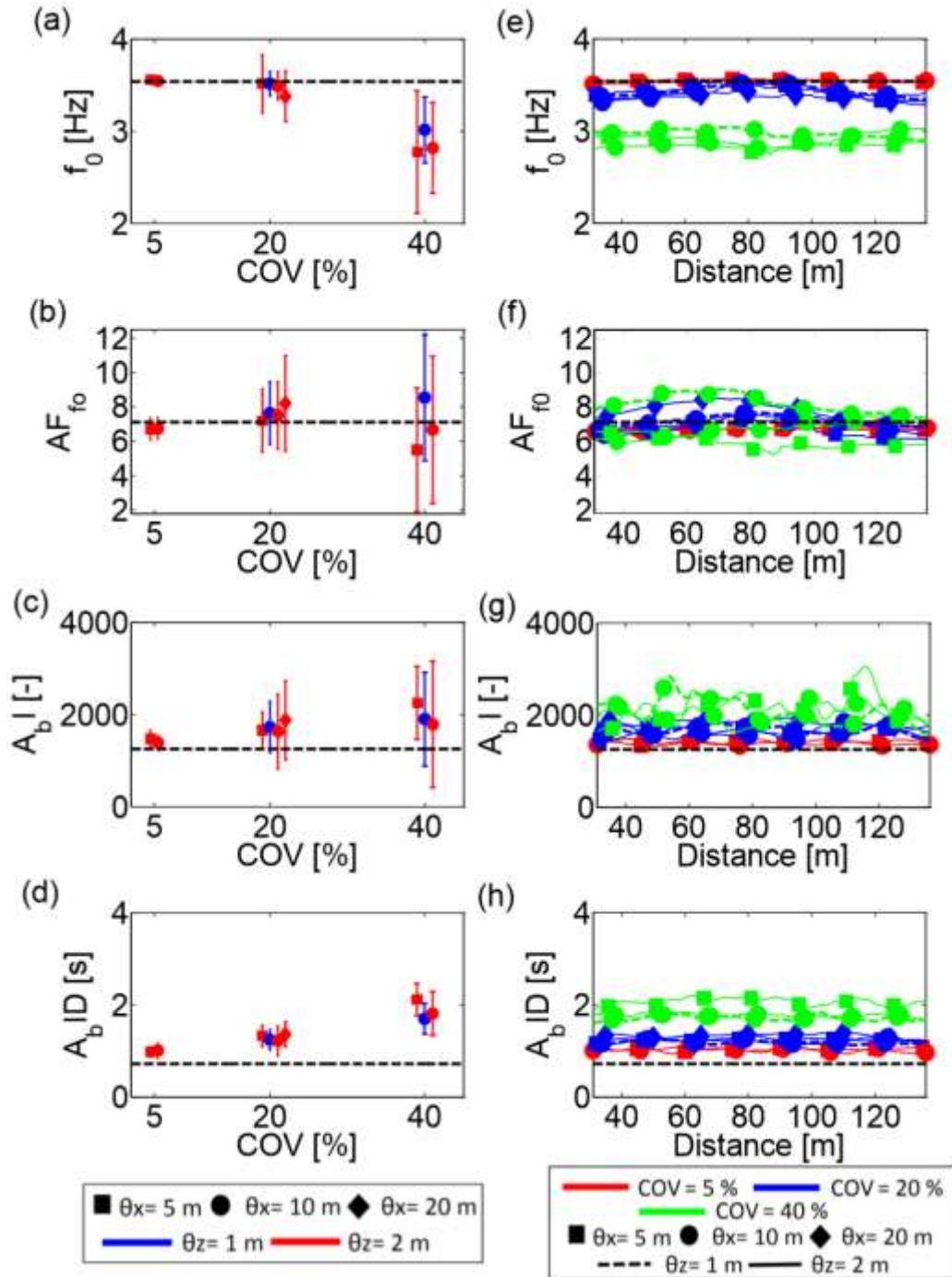
351 The average amplification and the standard deviation computed on the natural logarithm of amplifications at the
 352 central receiver ($x= 83$ m) are shown for all models in Figures 5a and 5b, respectively. The average AF curves
 353 provide fundamental resonance frequencies close to the deterministic one, except for the higher COV (40%). For
 354 that COV , the fundamental frequency f_0 is shifted down to values around 3 Hz, as already highlighted in Figure
 355 4c. At frequencies equal or over f_0 , standard deviations increase with frequency, the higher standard deviation
 356 being found for larger COV values as a consequence of stronger scattering of the AF curves (Figure 5b), which
 357 in turns leads to a decrease in average amplification values at frequencies larger than f_0 (Figure 5a).

358



360

361 *Figure 5 : (a) Average amplification at the central receiver ($X=83$ m) for different values of COV, θ_x and θ_z*
 362 *obtained by computing the geometric mean of the transfer functions for the 100 realizations. The amplification*
 363 *and the fundamental frequency for the deterministic model are shown by the black curve and black dashed line,*
 364 *respectively. (b) Standard deviation of the natural logarithm of the Amplification ($\sigma_{\ln}(AF)$) at the central*
 365 *receiver. (c) Standard deviation of $\sigma_{\ln}(AF)$ obtained by considering all receivers location. The values of COV,*
 366 *θ_x and θ_z are shown with different colors, symbols and lines, respectively.*



367

368 *Figure 6: Synthesis of simulation results for the 9 parameter sets. Left panel: Average values and error bars (+-*
 369 *one standard deviation) for the four spectral and temporal parameters at the central receiver: (a) average*
 370 *fundamental frequency (f_0), (b) average amplification at the fundamental frequency (AF_{f_0}), (c) average of the*
 371 *Arias based intensity (AbI) and (d) average of the Arias based duration ($AbID$). The black dashed lines indicate*
 372 *values of f_0 , AF_{f_0} , AbI and the related duration of the deterministic model. Right panel: (a) average f_0 , (b)*
 373 *average AF_{f_0} , (c) average AbI and (d) duration at different locations on the surface for the 100 simulations. The*
 374 *values of COV, θ_x and θ_z are shown with different colors, symbols and lines, respectively.*

375

376 In order to evaluate the effect of the receiver position on amplification, we calculated the standard deviation
377 $\sigma(\ln(AF))$ for all receiver locations. The curves are presented in Figure 5c at the same scale as the ones in Figure
378 5b. The standard deviation is slightly affected by the receiver location at frequencies higher than 15 Hz for the
379 greatest *COV* (40%). The main impact of considering all receivers is however observed for frequencies lower
380 than f_0 , a range for which the standard deviation is significantly greater, whatever the *COV* value. Such increase
381 results from the filtering effect of the sedimentary layer, which yields little energy below the fundamental
382 frequency (Scherbaum et al., 2003) and greater variability in amplification. Moreover, Appendix 3 compares the
383 standard deviation of $\ln(AF)$ computed by considering, firstly, all the receivers of all the realizations (in dashed
384 lines) and secondly, the central receiver of each realization (in continuous lines) for the model #6 having
385 $COV=20\%$, $\theta_z=2m$ and $\theta_x=10m$ and model #9 having $COV=40\%$, $\theta_z=2m$ and $\theta_x=10m$. The standard
386 deviations calculated by the two methods are very similar. This observation emphasizes the stationarity of $\ln(AF)$
387 due to the stationary random field generated by the *EOLE* discretization method.

388 The simulation results are synthesized for the 9 probabilistic models in Figure 6. First, the average f_0 values
389 along with error bars for all parameter sets are shown as a function of *COV* at the center receiver in Figure 6a.
390 As already evidenced in Figure 4 for two models, the average f_0 at the central receiver is close to the
391 deterministic value $f_{0D}=3.54$ Hz for low *COV* but sharply decreases to around 2.8-3 Hz for $COV=40\%$. The two
392 other probabilistic parameters (θ_x and θ_z) do not seem to significantly influence neither the average nor the
393 dispersion of f_0 . This significant influence of *COV* on average f_0 values is observed at all receivers (Figure 6e),
394 θ_x and θ_z having little effect. The variations in f_0 over distance are small and remain below 10%.

395 The same kind of analysis are presented for the average amplification AF_{f_0} in Figures 6b and f. At the central
396 receiver (Figure 6b), the average amplification is close to the deterministic value AF_D and, again, θ_x and θ_z seem
397 to have little influence. However, the average amplification variability increases largely for $COV=40\%$ with
398 values being higher or lower than AF_D , depending on the combination of θ_x and θ_z . Figure 6f shows that, in
399 contrast to f_0 , AF_{f_0} is spatially variable, especially for $COV=40\%$. Such spatial variation is due to large lateral
400 V_s variation and/or to the presence of a double amplification peak close to the fundamental resonance frequency
401 on the AF curve at some receiver location. The second peak generated by low V_s superficial zones may exhibit
402 an amplitude higher than the first one identified as the amplification at the fundamental resonance frequency
403 (see Figure 2e for receivers located between $X=30$ m and $X=120$ m).

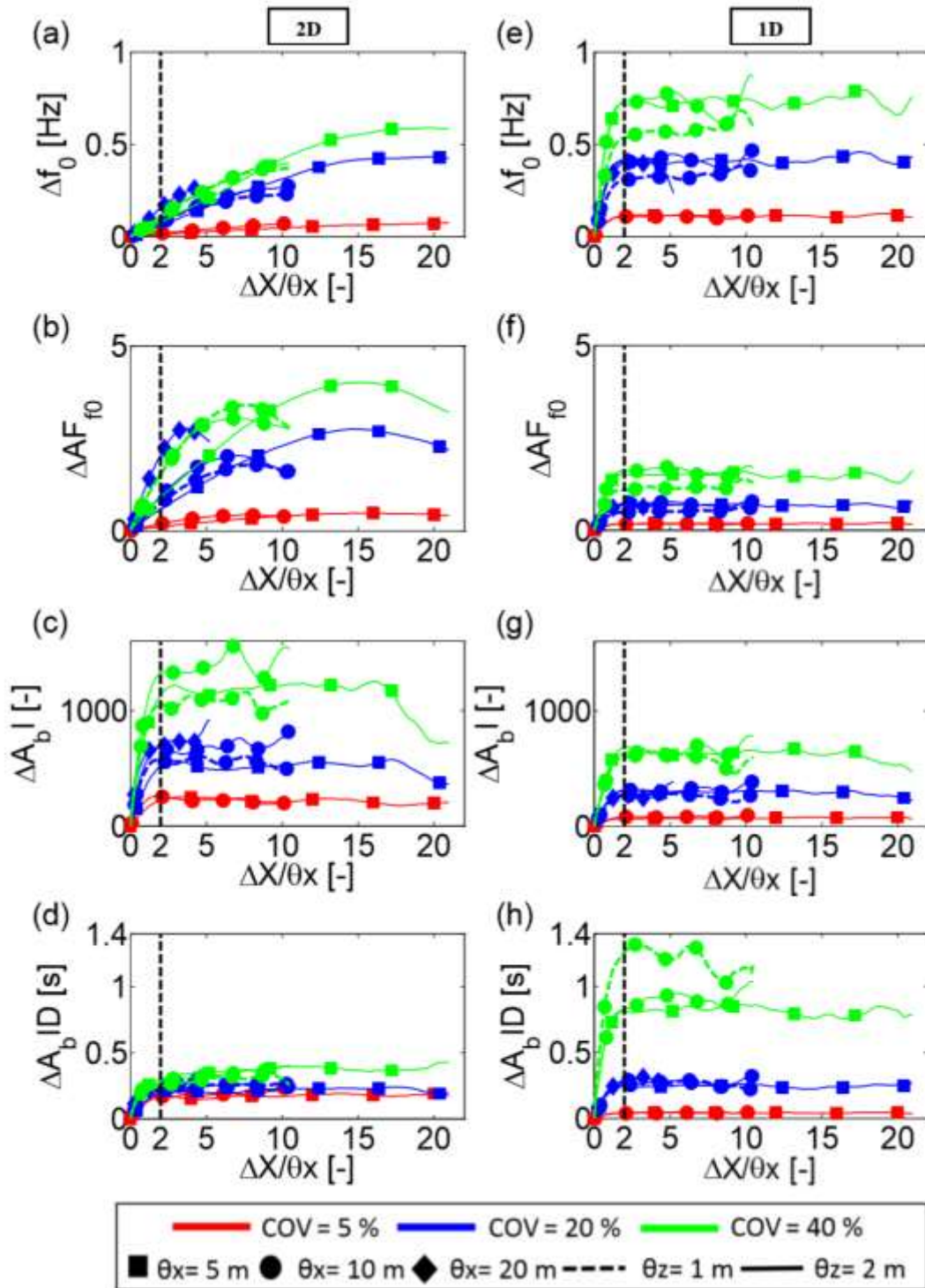
4.2. Arias based intensity and duration

404 Similarly to the spectral parameters, the results for temporal parameters (Arias intensity A_bI and duration A_bID)
405 are synthesized in Figure 6c, d, g and h. The average Arias intensity and duration (Figures 6c and 6d,
406 respectively) are systematically larger than those corresponding to the deterministic V_s structure, and increase
407 with COV , as well as the standard deviations. This effect is particularly clear for A_bID (Figure 6d), which may
408 reach values two to three times higher than the deterministic one for $COV=20\%$ and 40% , respectively. Also,
409 these two temporal parameters seem to be slightly influenced by the receiver location, as shown in Figures 6g
410 and 6h, except A_bI for $COV=40\%$. In this case, large lateral variations of 50% can be observed over short
411 distances.
412

413 In summary, this study outlines the predominant influence of COV on the surface ground motion indicators in
414 terms of average and standard deviation compared to the correlation distances. However, for the largest COV
415 (40%), ground motion average indicators related to the amplitude of seismic signals (amplification AF_{f_0} , Arias
416 intensity A_bI) exhibit larger variation over distance for $\theta_x=5$ m and $\theta_z=2$ m suggesting then an influence of the
417 size of the heterogeneity, while the average fundamental frequency f_0 and duration A_bID turned out to be
418 spatially independent, whatever the COV value.
419

5. Effects of spatial ground variability on spatial correlation of indicators

421 In previous sections, the variability of indicators was analyzed at a single station. However, studying the impact
422 of spatial ground variations on the spatial correlation of ground motion is also of interest for understanding or
423 predicting damage to long-span civil engineering structures (e.g. Abrahamson et al., 1990; Schneider et al.,
424 1992; Ancheta et al., 2011; Goda and Atkinson, 2008; Liu and Hong, 2015; Koufoudi et al., 2018). Here, we
425 focus on investigating the spatial correlation of the four ground motion scalar indicators defined in section 4
426 (resonance frequency and corresponding amplification, Arias based intensity and duration) and one frequency-
427 dependent indicator (Fourier amplitude spectrum). We estimated the spatial correlation by computing the
428 absolute differences of indicators between two receivers separated by a distance ΔX , ΔX spanning all possible
429 inter-receiver distances and being normalized by the horizontal correlation distance θ_x .



430

431 *Figure 7: Spatial variability of the four scalar indicators as a function of the receiver spacing normalized by the*
 432 *horizontal autocorrelation distance $\Delta X/\theta_x$. (a), (b), (c) and (d), Variation of the differences in fundamental*
 433 *resonance frequency f_0 , related amplification AF, Arias based Intensity $A_b I$ and Arias based Intensity duration*
 434 *$A_b ID$ using 2D ground motion synthetics. (e), (f), (g) and (h), the same for 1D ground motion synthetics. The*
 435 *values of COV, θ_x and θ_z are shown with different colors, symbols and lines, respectively.*

436

437 5.1. Scalar indicators

438 We first computed the mean spatial correlation of the 4 scalar indicators for the 100 V_s realizations. Figures 7a,
439 7b, 7c and 7d display the spatial correlation of the resonance frequency (Δf_0), the corresponding amplification
440 ($\Delta A f_0$), the Arias based intensity ($\Delta A_b I$) and the Arias based intensity duration ($\Delta A_b I D$), respectively, as a
441 function of $\Delta X/\theta_x$ for all the models (Table 1).

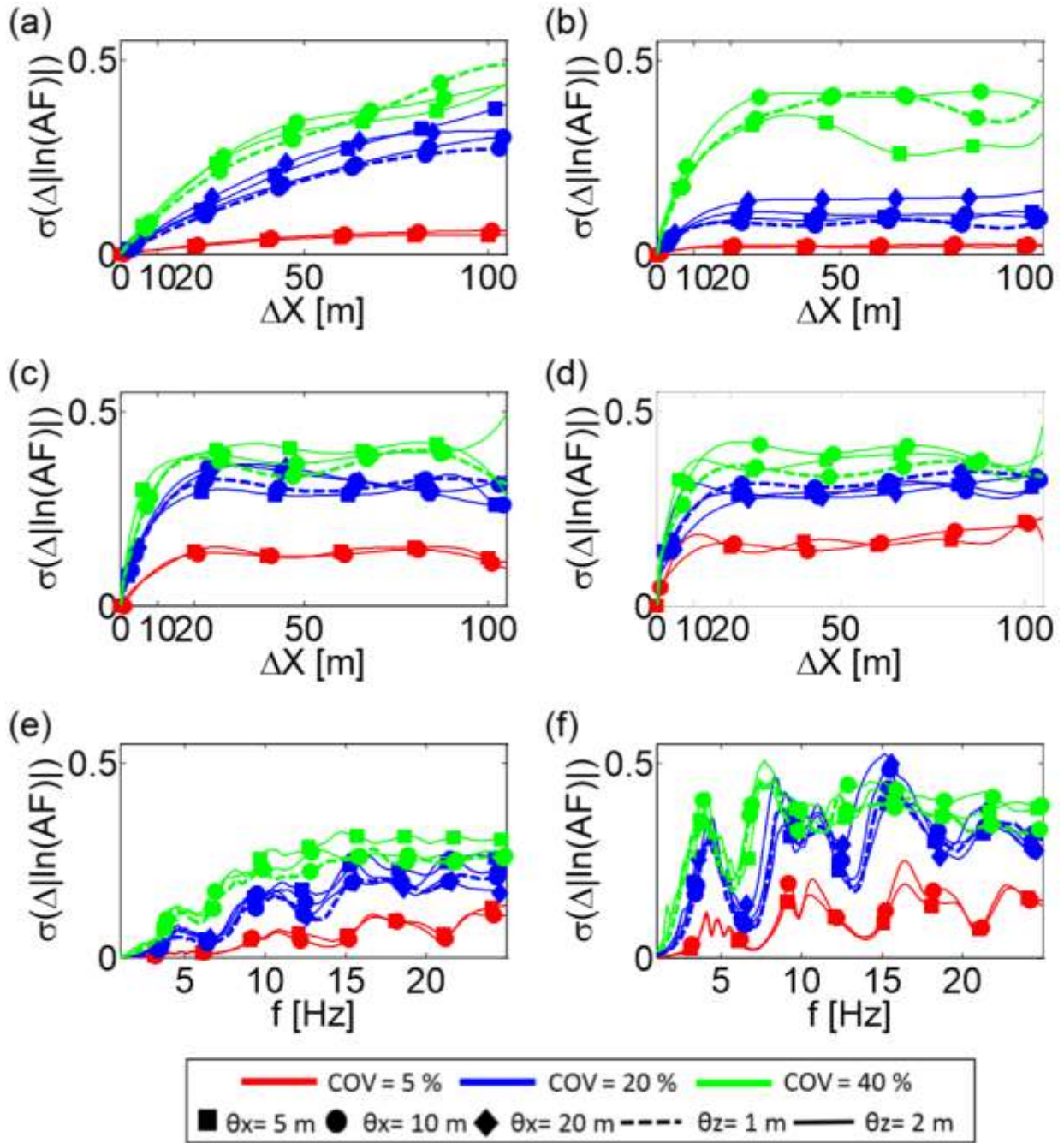
442 The variability of $\Delta A_b I$ and $\Delta A_b I D$ increases linearly until reaching a constant value for ΔX larger than $2\theta_x$, a
443 larger variability being systematically observed for larger COV values. This general trend is explained by the
444 random field discretization in V_s (see section 2). For a given realization, the V_s vertical profiles below receivers
445 located at $X\pm\theta_x$ are correlated, leading to close seismic responses at the surface. In contrast, the seismic
446 responses at two receivers with a spacing larger than $2\theta_x$ are not expected to be similar. Thus, the seismic
447 indicators ($A_b I$ and $A_b I D$) that are strongly controlled by the most energetic seismic phase (the incident SV wave
448 (Figure 3a), mostly itself influenced by the locally 1D V_s structure) will lead to indicator differences not
449 correlated anymore for ΔX larger than $2\theta_x$ and thus constant whatever the receiver spacing.

450 The spatial correlation of the fundamental resonance frequency (Δf_0) and the corresponding amplification
451 ($\Delta A f_0$) (Figures 7a, 7b and Appendix 4) indicates an increase in variability with distance, reaching constant or
452 maximum values for $\Delta X/\theta_x$ ranging between 2.5 and 4 for $\theta_x=20$ m, between 6 and 8 for $\theta_x=10$ m and between
453 13 and 16 for $\theta_x=5$ m. These ratios correspond to an absolute value ΔX ranging between 50 and 80 m, i.e. close
454 to the wavelength at the fundamental resonance frequency for the deterministic V_s structure ($\lambda=62$ m). As for
455 other indicators, the f_0 and $A f_0$ variability increases with COV and their convergence seems to be independent
456 of θ_x like the time domain parameters (see also Appendix 4 where results are plotted in terms of non-normalized
457 ΔX).

458 5.2. Frequency-dependent indicator

459 Following Abrahamson et al. (1990) and Schneider et al. (1992), we computed the standard deviation of the
460 absolute difference of the natural logarithms of the Fourier amplitude spectra ($\sigma(\Delta|\ln(AF)|)$). Figures 8a, 8b, 8c
461 and 8d display $\sigma(\Delta|\ln(AF)|)$ versus the receiver spacing ΔX for four frequencies (3.54 Hz, 7 Hz, 10 Hz and 24
462 Hz, respectively), while Figures 8e and 8f show $\sigma(\Delta|\ln(AF)|)$ as a function of frequency for two receiver
463 spacing values (5 and 50 m, respectively). The lowest frequency (3.54 Hz) corresponds to the fundamental
464 resonance frequency f_{0D} previously defined. For all frequencies, $\sigma(\Delta|\ln(AF)|)$ increases with ΔX until reaching a

465 constant value that significantly increases with COV (Figures 8a to 8d). For small frequencies ($<f_{0D}$), the
466 wavelengths are much larger than θ_x (5 and 10 m) and θ_z (1 and 2 m) and the analyzed inter-receivers distances
467 (ΔX). Then, $\sigma(\Delta \ln(AF))$ increases with the increase of ΔX and no convergences is observed with ΔX in the range
468 between 0 and 100m. The correlation distances θ_x and θ_z appear to have little influence on the variability, except
469 for one frequency (7 Hz) for $COV=40\%$. The spatial amplitude variability with frequency shows a different
470 picture depending on the receiver spacing ΔX (Figures 8e and 8f). For $\Delta X = 5$ m, the variability is weak at low
471 frequency and progressively increases with frequency (see for instance the curve for $COV=40\%$). This shows
472 the effect of the wavelength. Indeed, for $COV=40\%$, V_s varies from 50 to 750 m/s, corresponding to minimum
473 wavelengths of 2, 5, 7 and 14 m for $V_s = 50$ m/s and at 24, 10, 7 and 3.54 Hz, respectively. For wavelengths
474 much larger than the size of the heterogeneity (i.e. at low frequency) the amplitude variability is low, while
475 maximum when wavelength is about the size of the heterogeneity. It could explain that maximum variability is
476 observed for $\theta_x=5$ m at high frequency (Figure 8e). For large spacing ($\Delta X = 50$ m $>$ θ_x), the V_s structure below
477 the receivers is not correlated anymore and $\sigma(\Delta \ln(AF))$ is maximum at the resonance frequencies (f_{0D} , $3 f_{0D}$ and
478 $5 f_{0D}$), with no clear dependency on θ_x (Figure 8f).



479

480 *Figure 8: Frequency-dependent indicator variability computed from 2D ground motion synthetics. The standard*
 481 *deviation of the absolute difference of natural logarithm of Fourier amplitude spectra ($\sigma(\Delta \ln(AF))$) as a function*
 482 *of receiver spacing at frequencies equal to (a) 3.54 Hz, (b) 7 Hz, (c) 10 Hz and (d) 24 Hz. $\sigma(\Delta \ln(AF))$ as a*
 483 *function of frequency for two receiver spacing values (d) $\Delta X=5$ m and (f) $\Delta X=50$ m. The values of COV, θ_x and*
 484 *θ_z are shown with different colors, symbols and lines, respectively.*

485

486 **6. Can 2D modeling be replaced by 1D modeling?**

487 In order to evaluate the importance of accounting for 2D wave propagation on surface ground motion for site
488 specific hazard assessment compared to alternative modelling approaches that simplify the 2D spatial variation
489 of ground structure into a suite of 1D variable soil profiles (e.g. Rahtje et al., 2010; Rodriguez-Marek et al.,
490 2014; Haji-Soltani et al., 2017), we extracted 100 1D soil columns at each receiver from the V_s 2D
491 discretization. 1D wave propagation simulation was performed and spectral amplification, Arias based intensity
492 and duration are computed at each receiver and compared to the values obtained from 2D wave propagation
493 modeling. The 1D and 2D modeling results are compared from various perspectives in Figures 9, 10 and 11,
494 showing the parameter ratios and standard deviation differences for all realizations at the central receiver, the
495 spatial evolution of the four parameters along the profile for one given realization, and the average and standard
496 deviation of 2D/1D ratio for all realizations, respectively

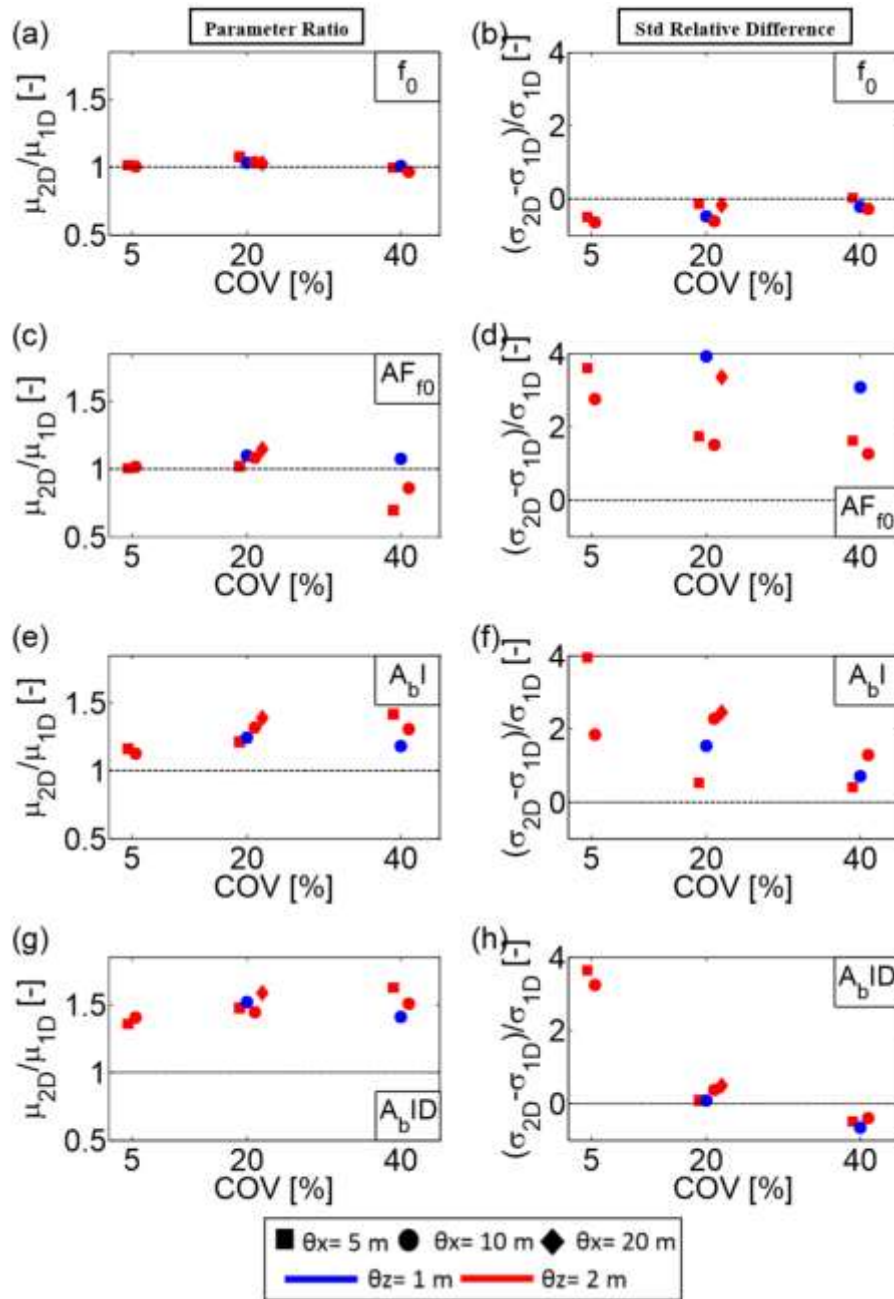
497 **6.1. Fundamental frequency, corresponding amplification and spectral amplification**

498 Figure 6.1a and b compare in terms of ratio the average fundamental resonance frequency and amplification
499 together with related standard deviation derived from 1D and 2D modeling approaches. Average resonance
500 frequencies are very similar for both modeling types (Figure 9a), while standard deviation is larger for 1D
501 modelling (Figure 9b). Such higher standard deviation comes from 1D resonance frequencies being only
502 controlled by SH body waves propagating through locally 1D soil profiles, while 2D wave propagation
503 modeling also incorporates locally diffracted surface waves that sample larger underground volume and lead to
504 homogenize seismic response. Figure 10a illustrates, for the ground model realization shown in Figure 2d,
505 differences between spatial distribution of resonance frequency derived from 1D and 2D wave propagation
506 modeling. The resonance frequency computed from the 2D ground motion synthetics is very weakly sensitive to
507 the spatial variation of ground velocity structure compared to that computed from 1D synthetics, except when
508 strong lateral discontinuities of V_s occur (e.g. at $X=65$ m in Figure 10e). Although average amplification
509 computed from 1D and 2D ground motion synthetics are very similar, especially for COV of 5% and 20%,
510 standard deviation of amplification computed from 2D synthetics are significantly larger (by 15% to 40%) than
511 the one inferred from 1D synthetics, whatever the COV value. Such a large increase in standard deviation is
512 easily explained when looking at the spatial variation of 2D amplification for a single V_s realization (Figure
513 10b). Amplification variation is either due to large lateral V_s variation prone to efficiently generate (or not)
514 surface waves (Figures 2b and 10b) or the presence at some receivers of a double amplification peak close to the

515 resonance frequency, leading in most cases to an amplitude at the fundamental resonance frequency much lower
516 than the one at the secondary peak (see Figure 2e for receivers located between $X=30$ m and $X=120$ m).

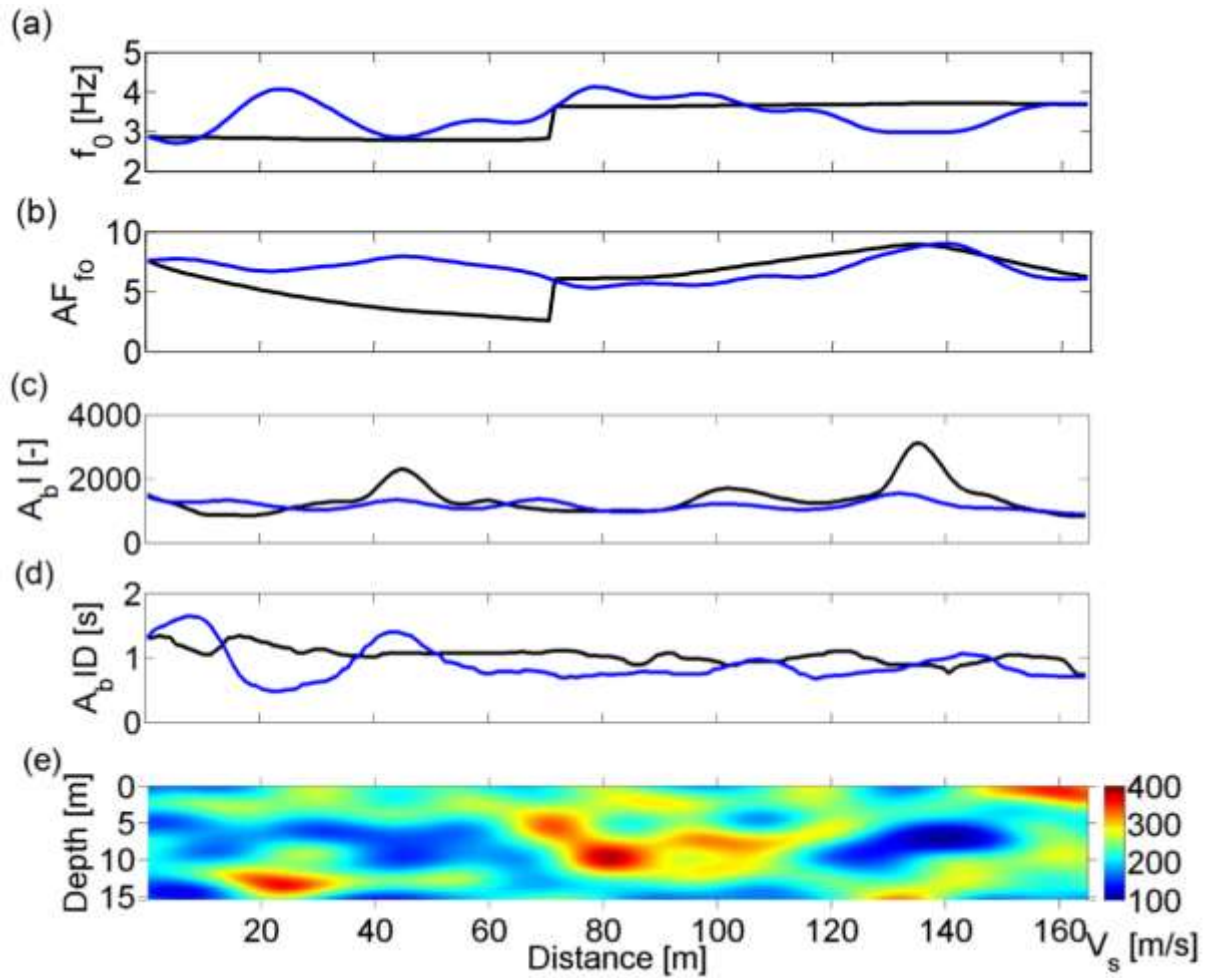
517 In order to analyze the effect of 2D wave propagation modeling approach compared to the 1D one over the
518 whole frequency range from 1 Hz to 25 Hz, we computed the ratio between Fourier amplitude spectra obtained
519 from 2D and 1D ground motion synthetics. Accounting for 2D wave propagation modeling in spatially variable
520 V_s structure obviously leads to larger amplification at frequencies higher than the fundamental resonance
521 frequency of the probabilistic model, except for the frequency range in-between the fundamental and first
522 higher mode (Figure 11a). This increase in amplification, especially significant for $COV=20\%$ and $COV=40\%$
523 (Figure 11a), is also associated with a higher variability (Figure 11b), which increases with COV .

524 These observations clearly outline that, although the 1D probabilistic approach may correctly reproduce average
525 fundamental resonance frequencies and corresponding amplification, it under-predicts ground motion
526 amplification at high frequencies and related variabilities whose origin relates to the presence of locally
527 diffracted surface waves.



528

529 *Figure 9: Ratio between the parameter extracted from 2D wave propagation modeling and 1D ones at the*
 530 *central receiver (left column), and the relative difference between standard deviation of this parameter inferred*
 531 *from 1D and 2D wave propagation modelling (right column): (a) and (b), average fundamental resonance*
 532 *frequency (c) and (d) average amplification at the fundamental resonance frequency, (e) and (f) average of the*
 533 *Arias based intensity, (g) and (h) average of Arias based duration.: (e) fundamental resonance frequency, (f)*
 534 *average amplification at the fundamental resonance frequency, (d) average of the Arias based intensity, e)*
 535 *average of Arias based duration. The values of COV, θ_x and θ_z are shown with different colors, symbols and*
 536 *lines, respectively.*



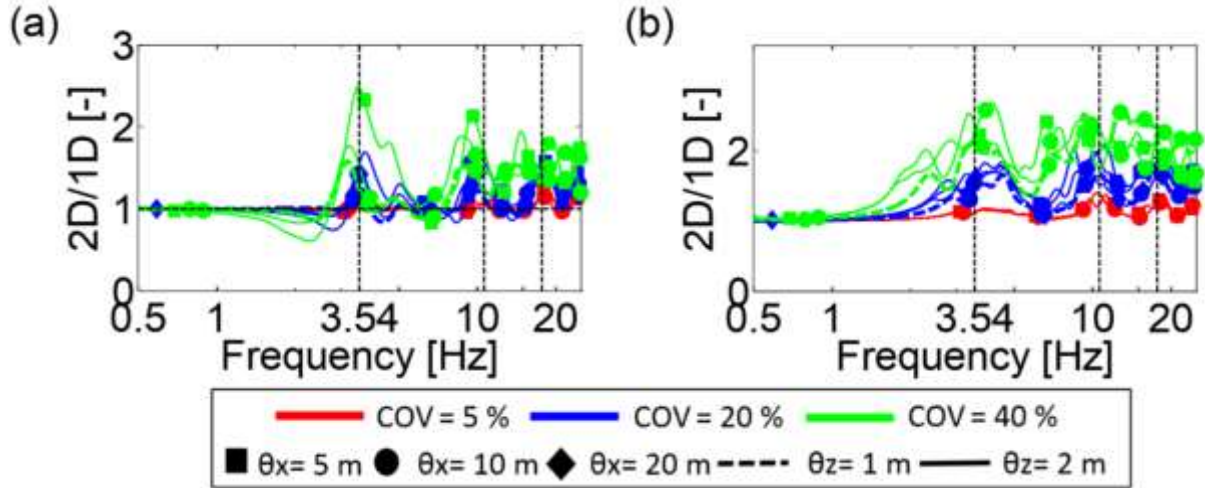
537

538 *Figure 10: Comparison of 2D (black line) and 1D modeling (blue line) results for the V_s realization shown in*
 539 *(e). (a) Fundamental resonance frequency (f_0), (b) amplification at f_0 (AF_{f_0}), (c) Arias based Intensity ($A_b I$) and*
 540 *(d) Arias based Duration. The test parameter is #5 in Table 1 ($COV=20\%$ $\theta_x=10m$ and $\theta_z=2m$).*

541 **6.2. Arias based intensity and duration**

542 Average Arias based intensity and duration inferred from 2D ground motion synthetics are systematically higher
 543 than the ones inferred from 1D synthetics, by a factor of 1.2 to 1.6, whatever the considered COV and
 544 autocorrelation distances (Figures 9c and 9d). The increase in intensity and duration for 2D modeling is simply
 545 explained by the presence of the locally generated surface waves that contaminates the strongest S-wave phase
 546 used in the computation (e.g. see Figure 2b for receivers close to $X = 50$ m, $X = 100$ m and $X = 130$ m and the
 547 corresponding Arias intensity increase intensity in Figure 10c). As a consequence, standard deviation of Arias
 548 based intensity is larger for 2D synthetics compared to 1D ones. Interestingly however, the relative difference
 549 between standard deviation of duration is decreasing with COV , reaching values below one for $COV=40\%$. This
 550 feature is explained by the increase of the duration standard deviation in 1D modelling due to the presence of

551 overall very stiff or very soft 1D V_s profiles leading to significant change in the duration of S-wave main pulse
 552 at the surface. This is illustrated in Figure 10d with duration derived from 1D synthetics being short above
 553 overall stiff areas while large above overall soft areas (e.g. at receivers located at $X = 10$ m or $X = 45$ m).



554

555 *Figure 11: Ratio between the Fourier amplitude spectra computed on 2D and 1D probabilistic ground motion*
 556 *synthetics: (a) average ratio and (b) standard deviation. Colors and symbols refer to the different test*
 557 *parameters (Table 1).*

558 6.3. Spatial correlation of indicators

559 Spatial correlation of scalar indicators for the 100 V_s realizations using 1D motion synthetics have been
 560 computed. Figures 7e, 7f, 7g and 7h display the spatial correlation of the resonance frequency (Δf_o), the
 561 corresponding amplification ($\Delta A f_o$), the Arias based intensity ($\Delta A_b I$) and the Arias based intensity duration
 562 ($\Delta A_b I D$), respectively, as a function of $\Delta X/\theta_x$ for all models (Table 1). The variability of all indicators increases
 563 linearly until reaching a constant value for ΔX larger than $2\theta_x$, over which correlation between signals does not
 564 exist anymore. The larger variability is systematically observed for larger COV values. This is consistent with
 565 the control of 1D ground motion synthetics by the locally 1D V_s structures. The 1D f_o variability for all COV
 566 values is larger than that computed for 2D synthetics (compare Figures 7a and 7e) in the range $\Delta X/\theta_x < 10$. This
 567 is due to the presence of surface waves in the 2D seismograms, which are little sensitive to short scale variations
 568 of locally 1D velocity structure but rather to the homogenized ground structure elastic properties. In contrast, the
 569 variability in $A f_o$ is smaller than that observed for 2D synthetics (compare Figures 7b and 7f) for $\Delta X/\theta_x > 2$,
 570 whatever the value of COV . This could be related to energetic diffracted surface waves and the double
 571 amplification peak close to the resonance frequency, as already mentioned in section 4.1. For $\Delta X > 2\theta_x$, the

572 spatial variability in A_bI computed from 2D synthetics is greater than the one derived from 1D synthetics, while
573 the opposite is observed for A_bID . The larger variability in A_bI (Figure 7c) results from the presence of body and
574 surface waves diffracted at near-surface heterogeneities in the early seismic phase (see Figure 3a). The lower
575 variability in $AbID$ (Figure 7d) most probably results from the presence of diffracted surface waves in the
576 analysis time window leading to large duration as shown in Figure 7d.

577

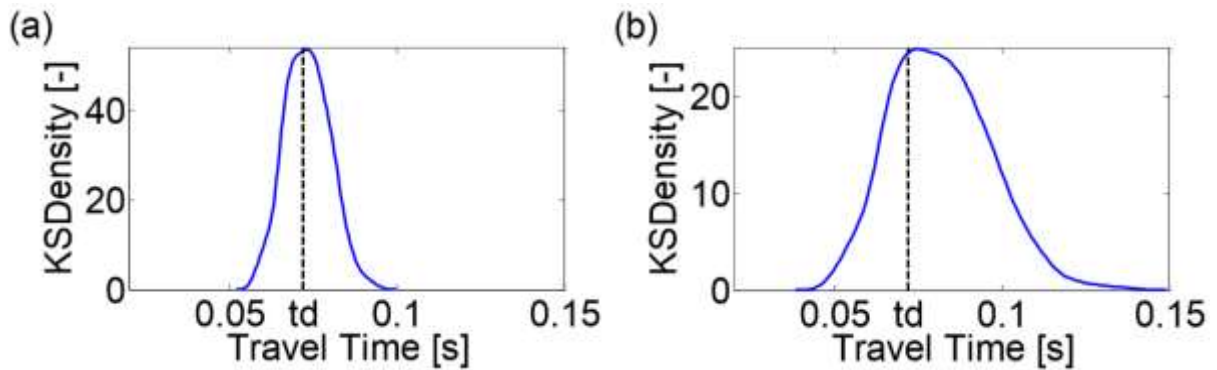
578 **7. Discussion and conclusion**

579 In this paper, the effect of the V_s spatial variability on the surface ground motion is assessed through a set of
580 numerical computations. A simple elastic 2D velocity structure is used for surface ground motion simulations in
581 order to solely focus on the effects of V_s variability. V_s is modeled as a random field, considering the coefficient
582 of variation (COV) and the horizontal and vertical autocorrelation distances (θ_x and θ_z , respectively) as
583 parameters.

584 We show that spatial variation of shear-wave velocity structure efficiently generate locally diffracted surface
585 waves. Hence, the fundamental resonance frequency is only very weakly sensitive to the local V_s heterogeneities
586 while the Arias Intensity and derived duration are clearly increased due to the locally diffracted body and
587 surface waves that contaminate the most energetic phase. Analysis of synthetic seismograms at a single station
588 clearly outlines that the coefficient of variation on the shear-wave velocity (COV) mostly controls the variability
589 of the four ground motion indicators (resonance frequency and corresponding amplification, Arias intensity and
590 duration), as compared to the horizontal and vertical correlation distances.

591

592



593

594 *Figure 12. Travel-time distribution (blue thick line) in the soil column below the central receiver for the 100*
595 *realizations for (a) model #5 (COV=20%) and (b) model #9 (COV=40%) listed in Table 1. The travel time*
596 *computed from the deterministic model ($t_d=0.0705$ s) is shown a black dashed line.*

597 As regards spectral amplifications, considering shear-wave spatial variability in the modeling leads to reduce
598 mean amplification, and conversely to increase variability, at frequencies higher than the site fundamental
599 resonance frequency, as also observed in Assimaki et al. (2003). A striking result is the 20% decrease in mean
600 fundamental resonance frequency (f_0) for $COV = 40\%$ (Figures 5a and 6a) compared to the resonance frequency
601 of the deterministic model. This reduction of f_0 , similarly observed on 1D and 2D ground motion probabilistic
602 modeling, is related to the V_s random field discretization. Indeed, we calculated the SV waves travel time for the
603 1D soil columns extracted from 2D V_s realizations for two parameter sets with $COV = 20\%$ and $COV=40\%$,
604 respectively (probabilistic models #5 and #9, Table 1). The SV wave travel time for the deterministic
605 sedimentary layer is $t_d= 0.0705$ s. The travel time for the parameter set having a $COV= 20\%$ (Figure 12a) is
606 found to be almost normally distributed around t_d , while log-normally distributed for the parameter set with
607 $COV = 40\%$ (Figure 12b). In this latter case, a larger number of realizations has travel times exceeding the t_d ,
608 leading to a reduction of the mean fundamental resonance frequency for the 1D ground motion synthetics.
609 Although the calculation of travel times for heterogeneous 2D soil models from 1D soil columns is approximate,
610 these results suggest that long travel times in 2D realizations with $COV=40\%$ may be the cause of the resonance
611 frequency drop. Like other authors for 2D probabilistic modeling (Assimaki et al., 2003; Nour et al.; 2003;
612 Thompson et al., 2009) or 1D modeling (Li and Assimaki, 2010; Rathje et al., 2010; Rodriguez-Marek et al.,
613 2014; Haji-Soltani et al., 2017), we discretized V_s because it is the physical parameter that can be measured in
614 the field. Considering however that seismic wave propagation is primarily controlled by travel time, random

615 field discretization on travel time would be the most natural and relevant choice. Although such discretization is
616 easily achievable for 1D body or surface wave propagation modeling (e.g. Pilz and Parolai, 2014; Teague and
617 Cox, 2016; Pilz and Fäh, 2017; Teague et al., 2018), it remains more complex for body and surface wave
618 propagation in 2D heterogeneous medium.

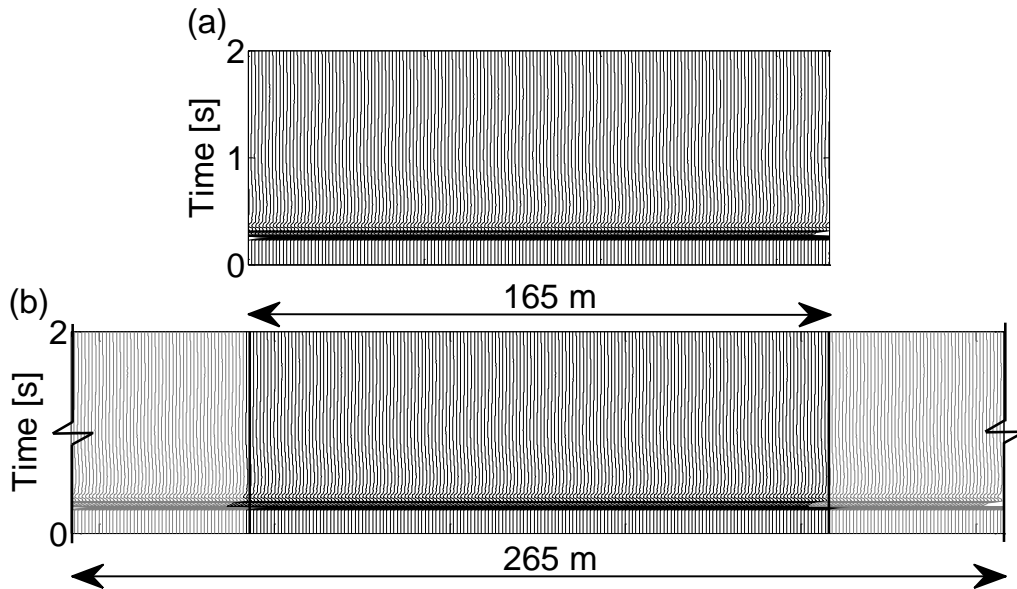
619 Comparison between spectral amplification obtained from 2D and 1D probabilistic modeling synthetics clearly
620 outlines that, although both modeling approaches predict similar mean fundamental resonance frequency and
621 corresponding amplification, 2D wave propagation modeling leads to larger amplification and related variability
622 at frequencies higher than the fundamental resonance frequencies, especially for large *COV*, compared to 1D
623 wave propagation probabilistic modeling approach (Figures 9 and 11). This increase in amplification and
624 standard deviation is definitely caused by the presence of locally diffracted surface waves in 2D wave
625 propagation modeling and, hence, questions the reliability of using a population of 1D *V_s* profiles to account for
626 spatial variability of the seismic properties as proposed for site-specific hazard assessment (Rathje et al., 2010;
627 Rodriguez-Marek et al., 2014; Haji-Soltani et al., 2017).

628 Our results also indicate that the indicator spatial variability increases linearly until reaching a constant value,
629 with greater variability being systematically observed for larger *COV*. Effect of horizontal correlation distance,
630 θx , is only observed for frequency dependent (and thus wavelength dependent) indicators (Fourier amplitude
631 spectra) when receiver spacing, wavelength and lateral size of heterogeneity (θx) are of the same order.
632 Interestingly, ground motion indicators (Arias Intensity and derived duration) computed on the strongest seismic
633 phase dominated by S waves are not anymore spatially correlated for receiver spacing larger than two times the
634 horizontal correlation distance. This opens up interesting perspectives in measuring horizontal autocorrelation
635 distances from available seismological recordings at dense array data. Maximum of the spatial correlation of the
636 natural logarithms of the Fourier amplitude spectra obtained on real data (Abrahamson et al., 1990; Schneider et
637 al., 1992; Ancheta et al., 2011; Goda and Atkinson, 2008; Liu and Hong, 2015; Koufoudi et al., 2018) is close to
638 1 whatever the site condition, i.e. larger than the constant value obtained in our numerical simulations. This may
639 be due to the fact that our modeling is not accounting for 3D wave propagation, attenuation and broadband
640 seismograms.

641 To sum up, our study clearly outlines the main control of *COV* on the spatial variability of surface ground
642 motion indicators and that stochastic ground motion modeling by using 1D variable soil profiles to account for
643 spatial variation of ground structure properties will underestimate surface ground motion spatial variability as

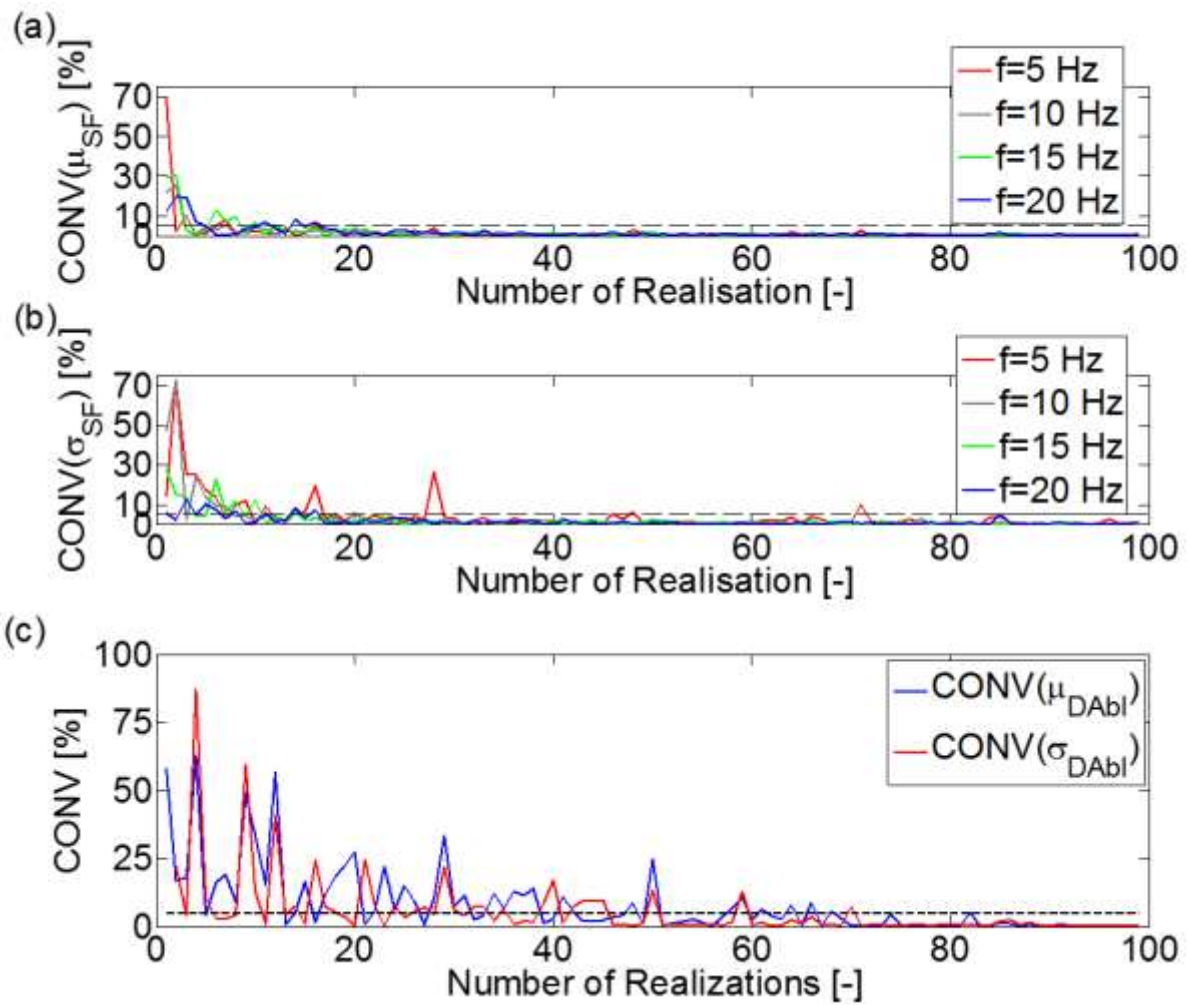
644 compared to full 2D/3D wave propagation modeling. However, the simple case of a sedimentary layer over a
645 bedrock does not represent the real site conditions. To confirm our results, further numerical simulations should
646 be carried out for a set of typical ground structure, considering also attenuation and non-linear soil behavior.

647 **8. Appendices**



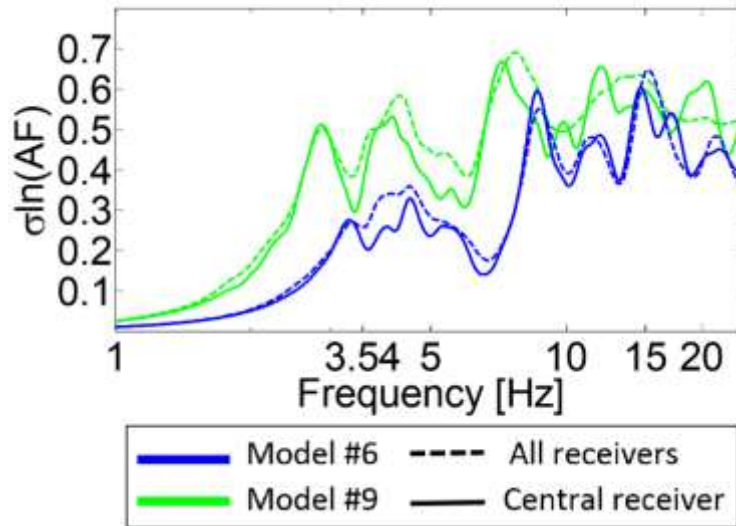
648

649 *Appendix 1 : Synthetic horizontal surface obtained for a homogeneous layer over a half-space for a vertically*
650 *incident SV plane wave excitation at the base of the homogeneous layer. Source time function is a delta-like with*
651 *flat Fourier amplitude spectrum between 1 and 25 Hz. Shear-wave velocity in the homogeneous layer is 750*
652 *m/s and 1000 m/s in the halfspace. The computational model is 15.5 m along depth axis and (a) 165 m and (b)*
653 *750 m width along the horizontal direction. In (b), the computed seismograms are only shown for the 265*
654 *central receivers out of 750 receivers.*



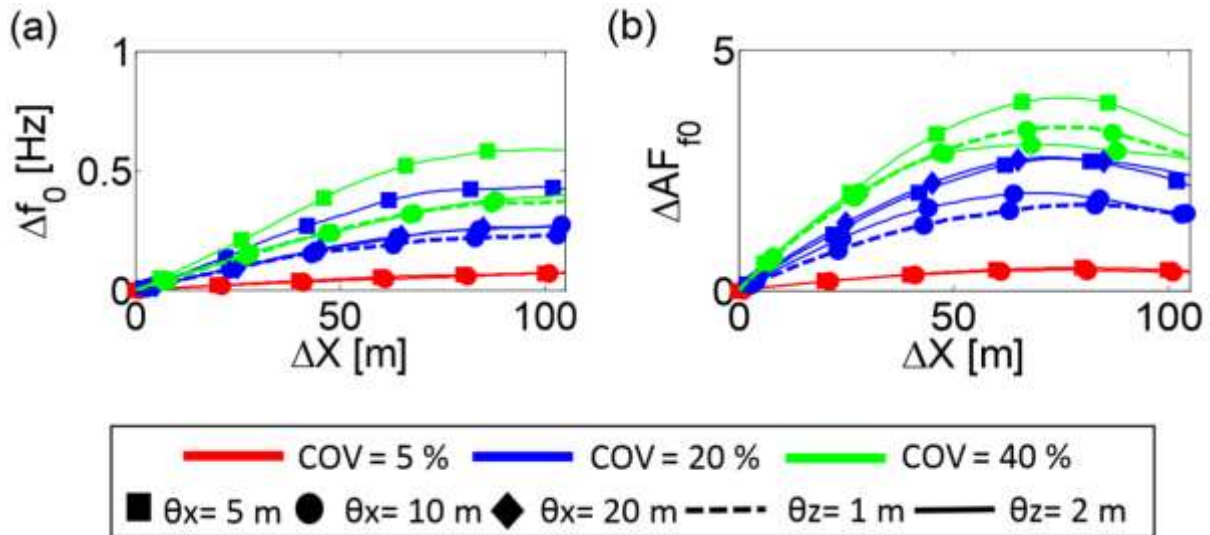
655

656 Appendix 2 : Convergence of (a) the average, (b) standard deviation of the Fourier amplitude spectra at various
 657 frequencies and (c) the average (in blue) and standard deviation (in red) of the duration as a function of the
 658 number of realizations for the horizontal velocity for model #9 with a COV=40% $\theta_x=10$ m and $\theta_z=2$ m. The
 659 dashed black line shows the 5% convergence criteria.



660

661 Appendix 3 : The standard deviation of $\ln(AF)$ obtained by considering all the receivers locations (dashed line)
 662 and the central receiver of each realization (continuous line) for the model #6 (in blue) having $COV=20\%$,
 663 $\theta_z=2m$ and $\theta_x=10m$ and the model #9 (in green) having $COV=40\%$, $\theta_z=2m$ and $\theta_x=10m$.



664

665 Appendix 4 : Spatial variation of the two scalar indicators as a function of the receiver spacing ΔX . (a) and (b),
 666 Variation of the differences in fundamental resonance frequency f_0 and the related amplification AF using 2D
 667 ground motion synthetics. The values of COV , θ_x and θ_z are shown with different colors, symbols and lines,
 668 respectively.

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