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Seismic Newtonian-noise cancellation for the Einstein Telescope

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Program

Workflow

Prior

1. Obtain information on geology, topography, and perform numerical simulations of seismic correlations in 3D

↓

Likelihood

2. Observe seismic correlations with seismometer arrays

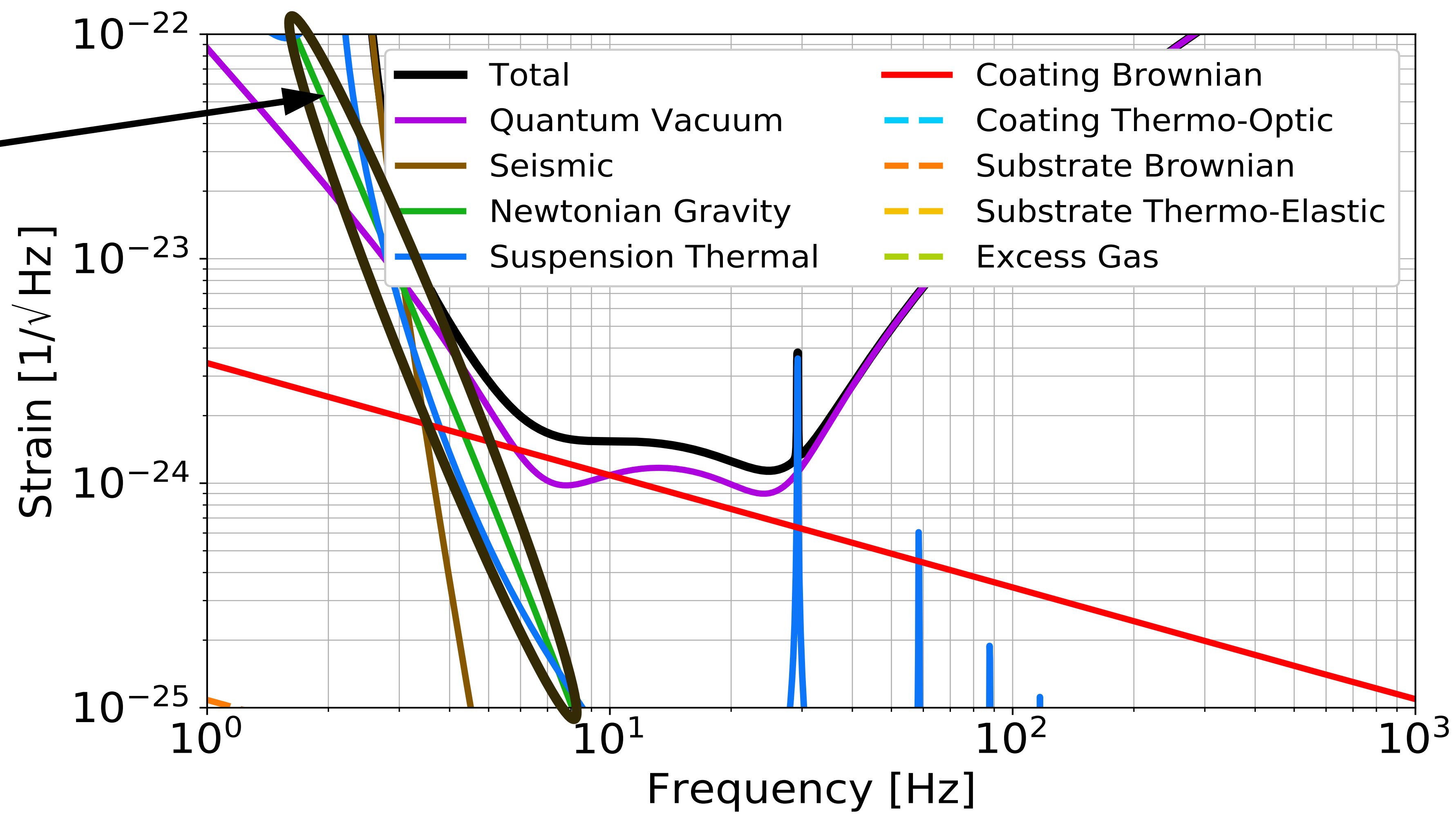
↓

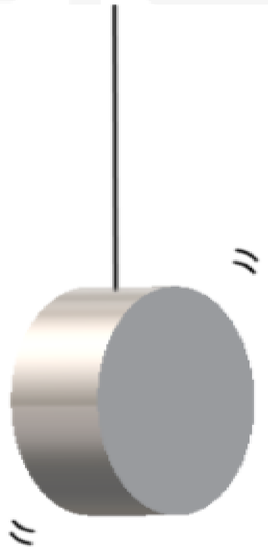
Posterior

3. Use Bayesian surrogate models of Wiener filters (obtained using GPR) for array optimization in 3D

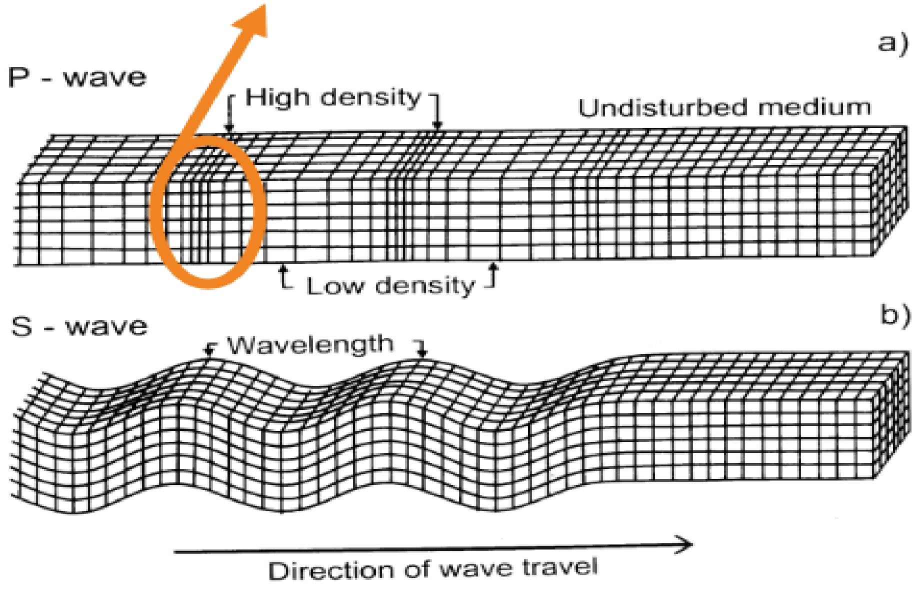
Introduction

- Seismic Newtonian noise:
  1. Seismic surface displacement
  2. (De)compression of rock
  3. Displacement of underground cavern walls

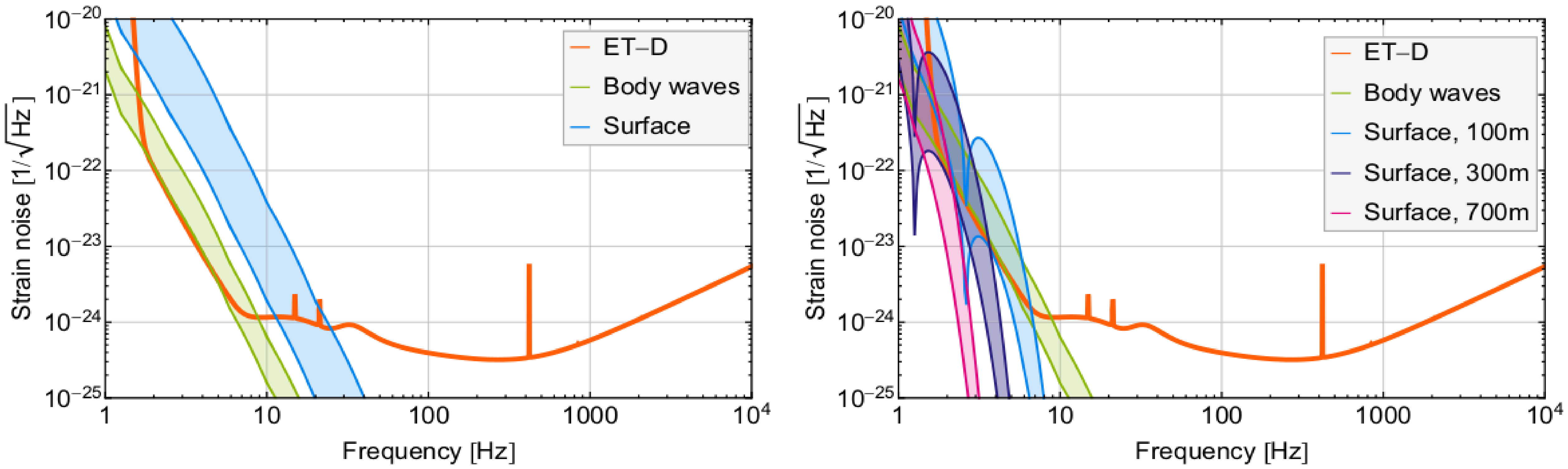




$$\delta\rho \rightarrow NN$$



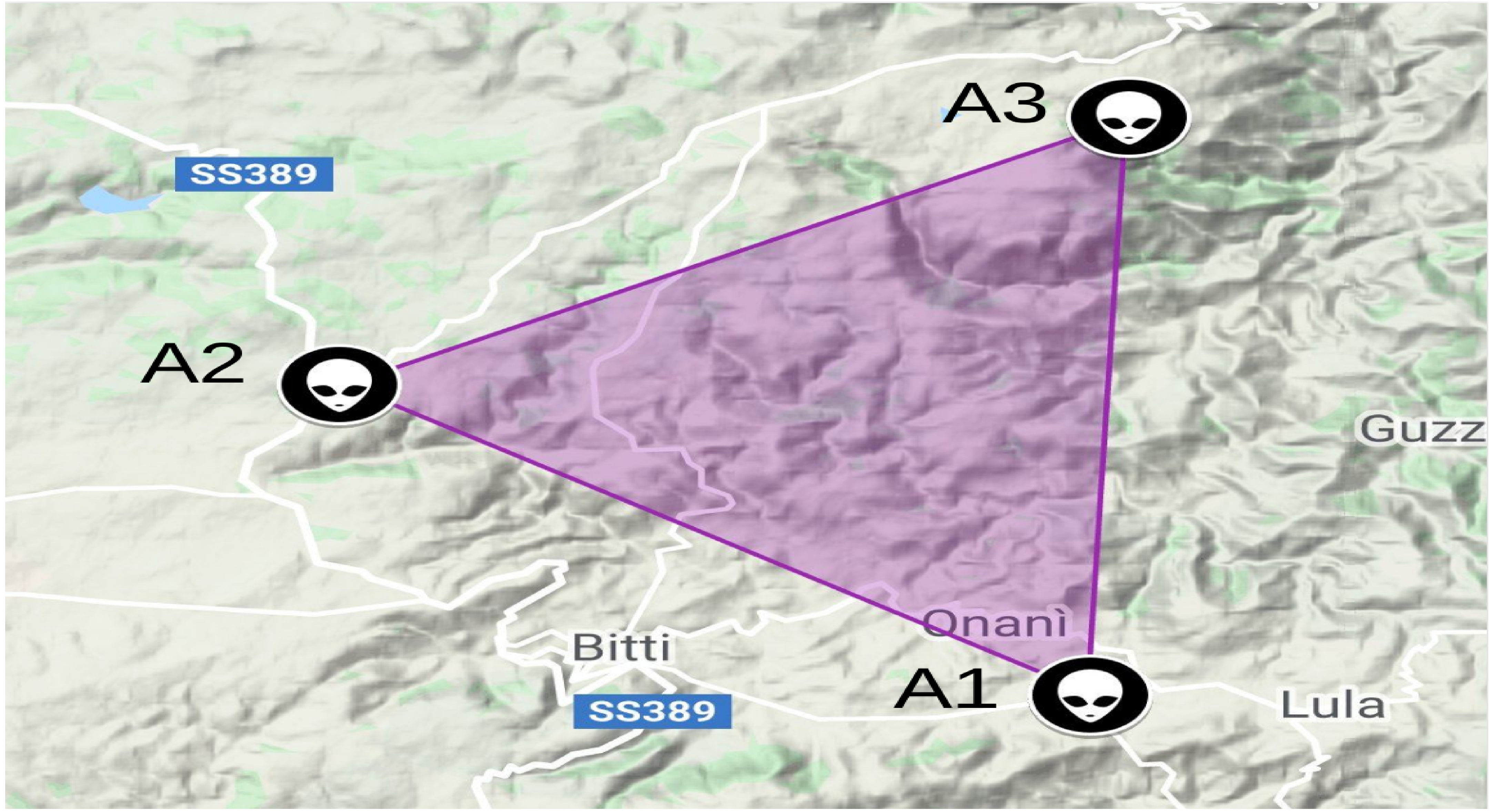
- Surface and underground locations of ET

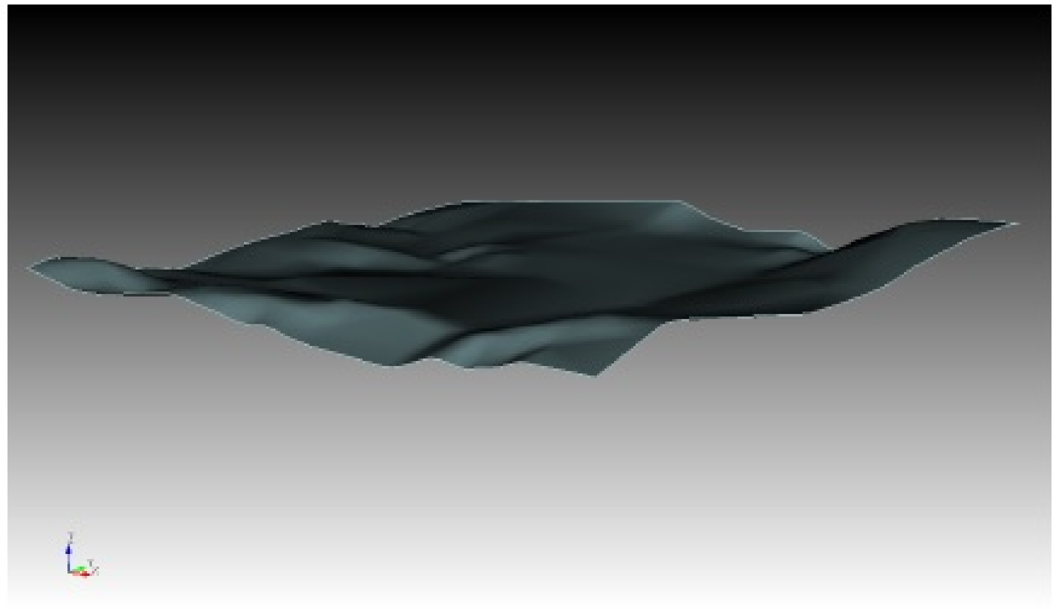


F Badaracco and J Harms 2019 Class. Quantum Grav. 36 145006

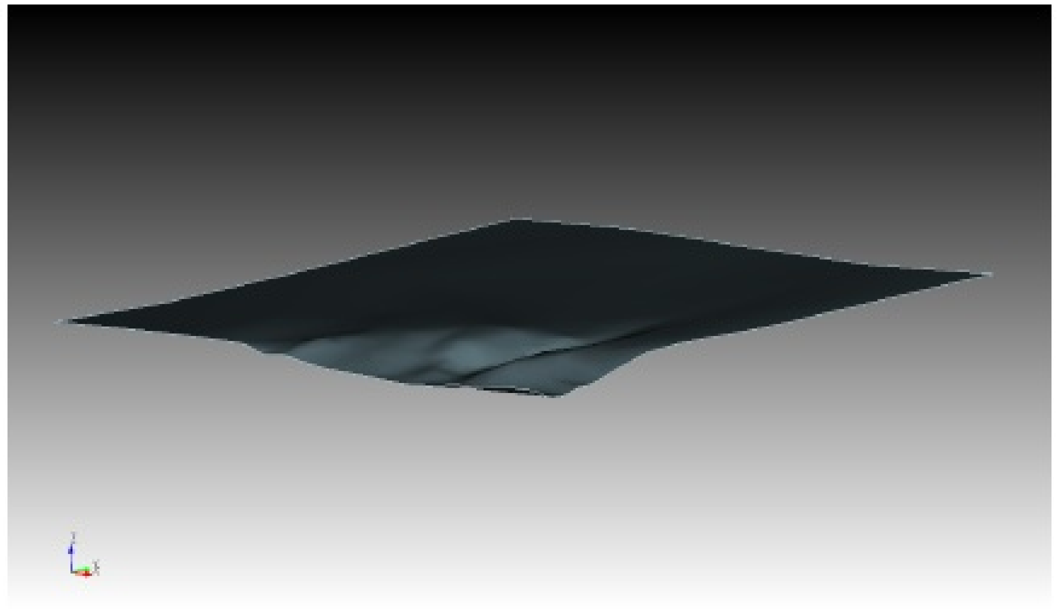
Sardinia site

- Topographic scattering
- Vertex A3

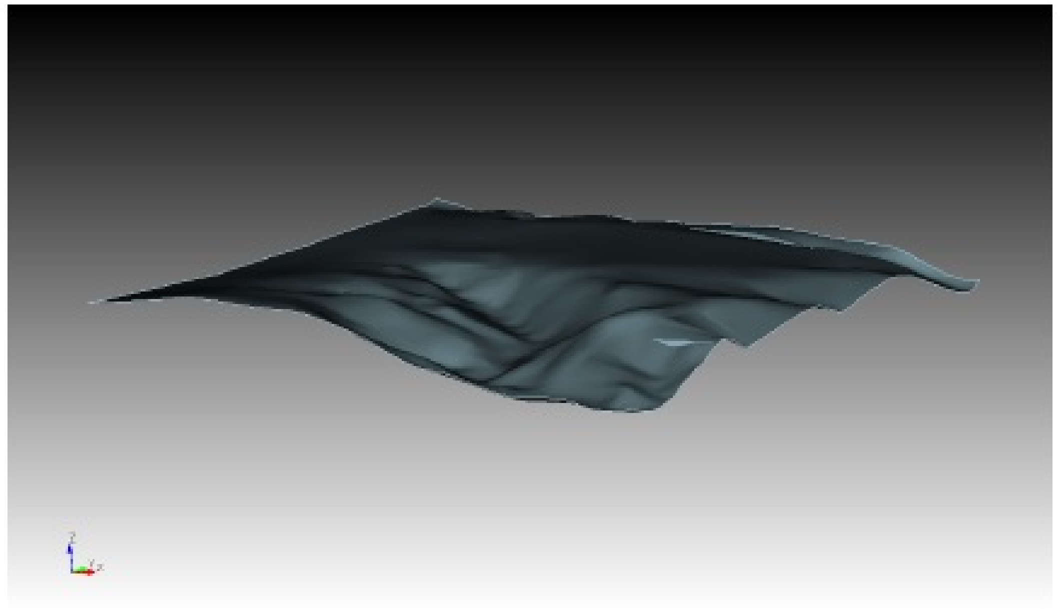




(a) Vertex A1



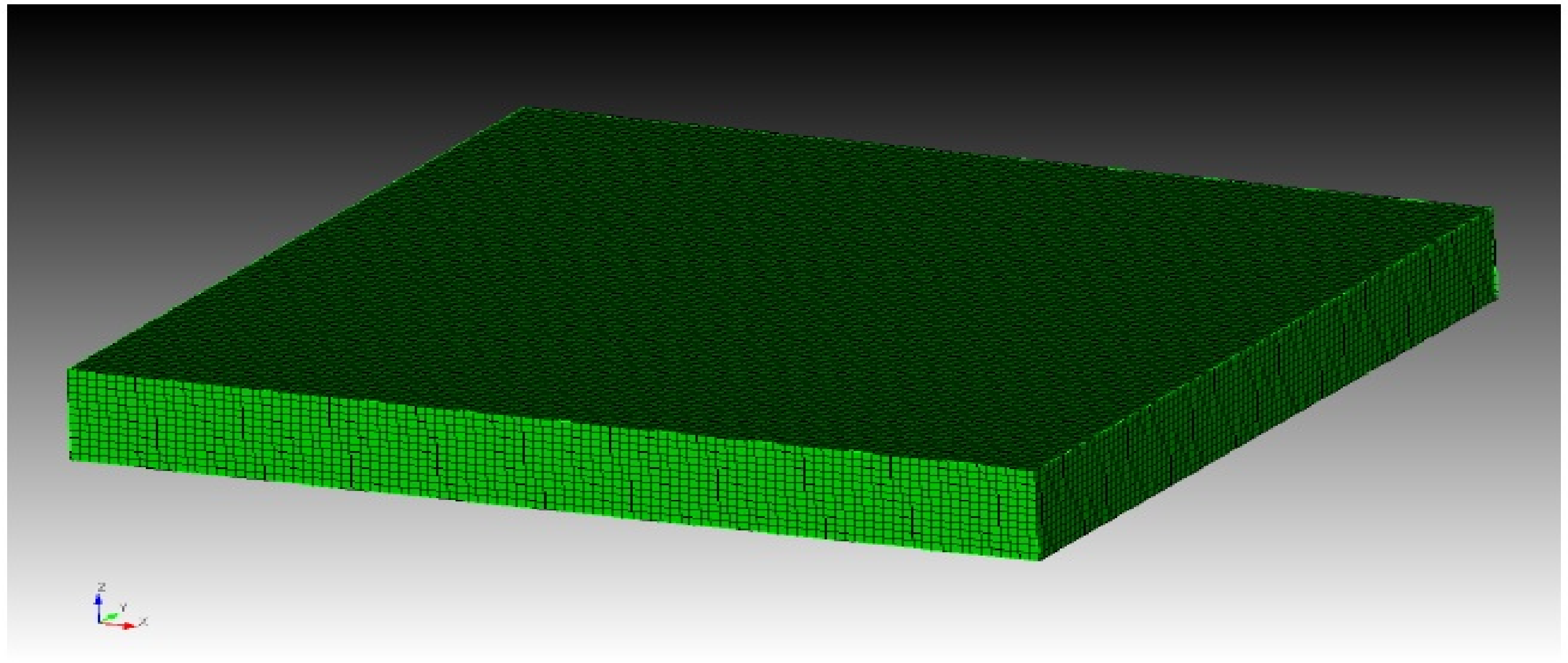
(b) Vertex A2



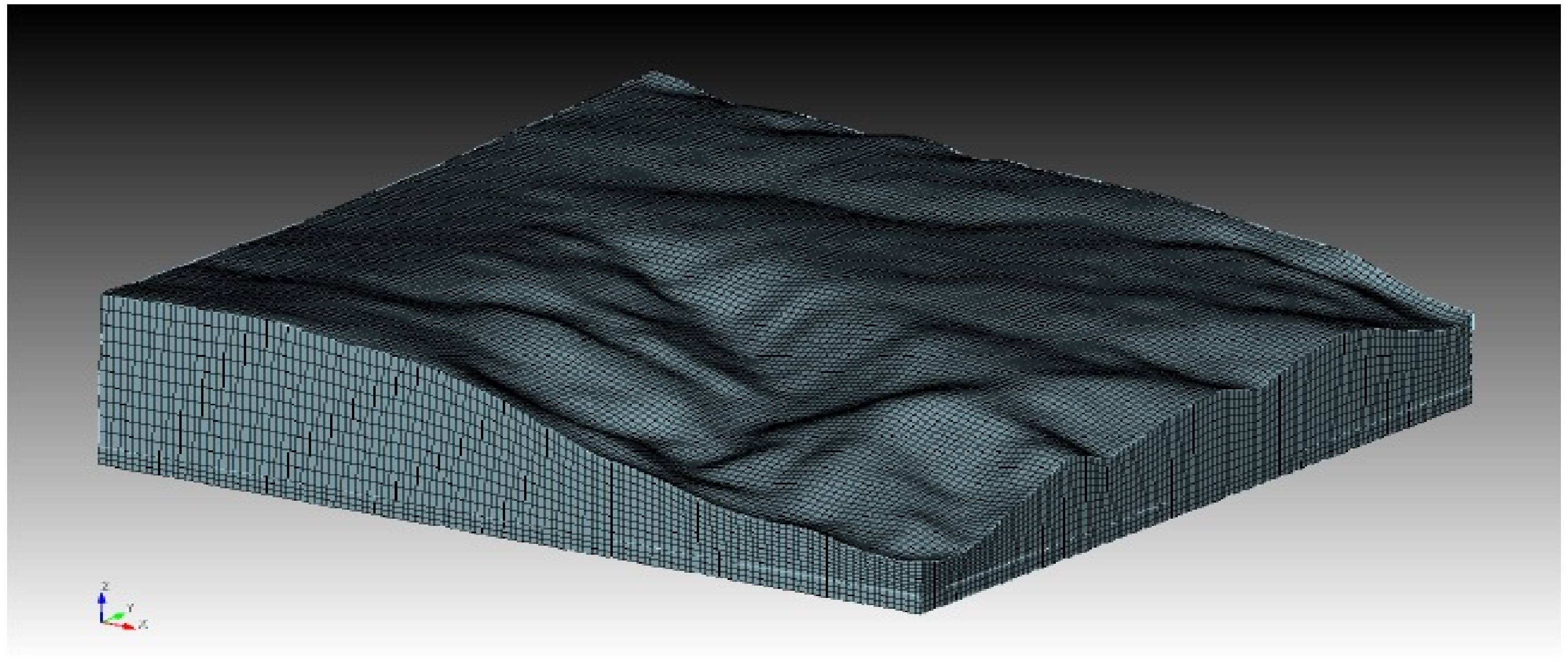
(c) Vertex A3

Finite-element simulations

- Trelis
- SPECFEM3D Cartesian
- Convolutional perfectly matched layer (C-PML)

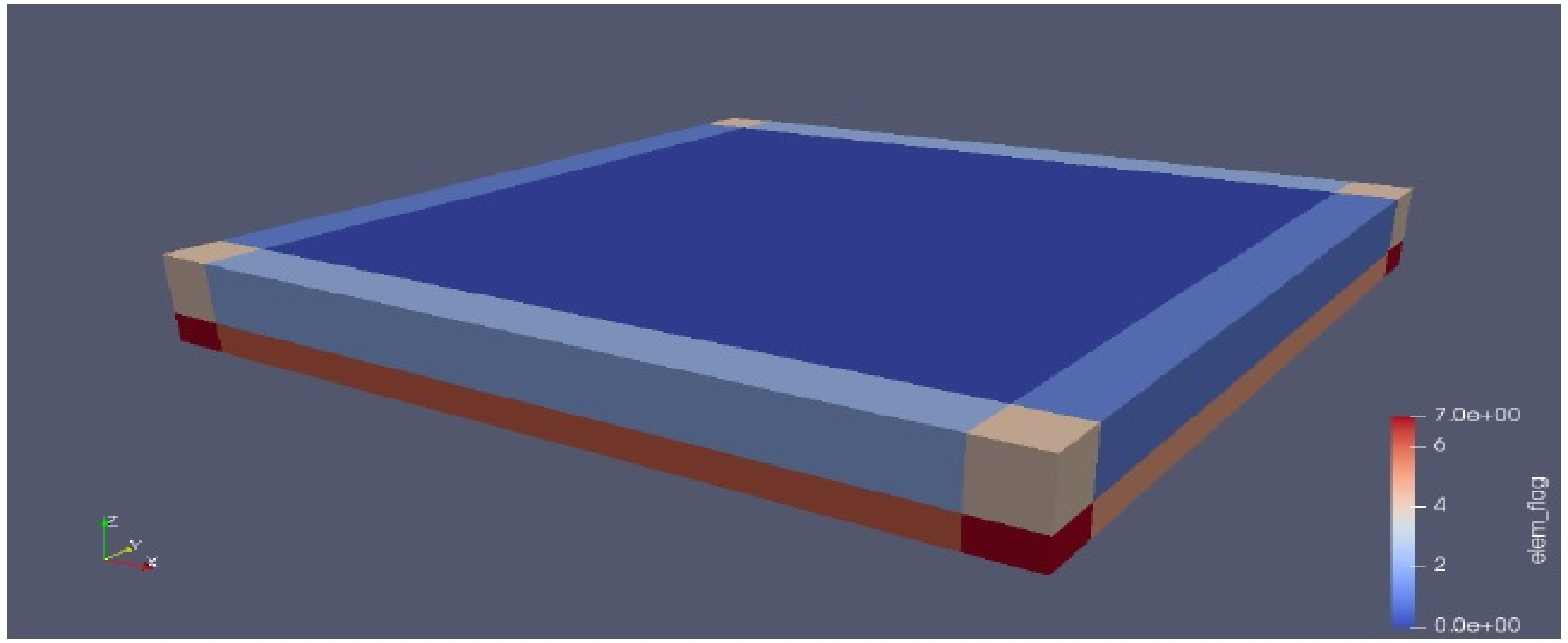


(a) Flat

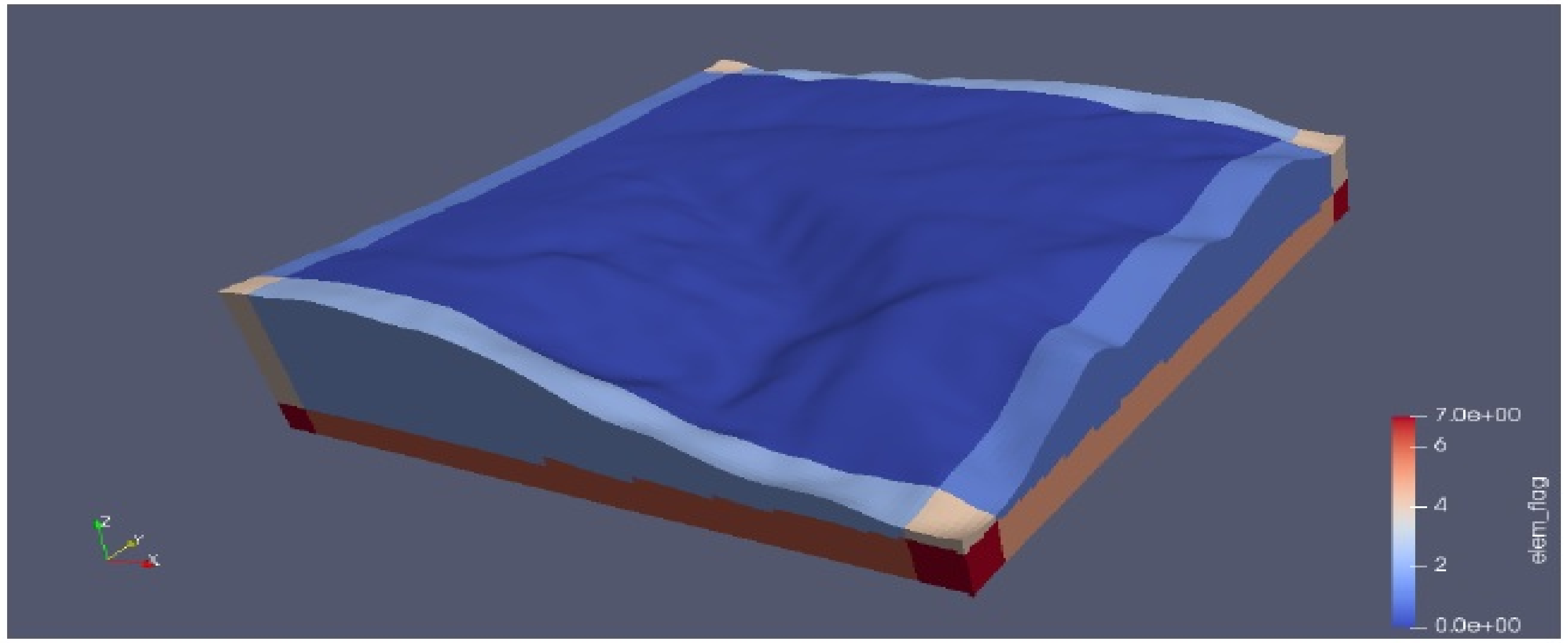


(b) Topography

Meshed models



(a) Flat

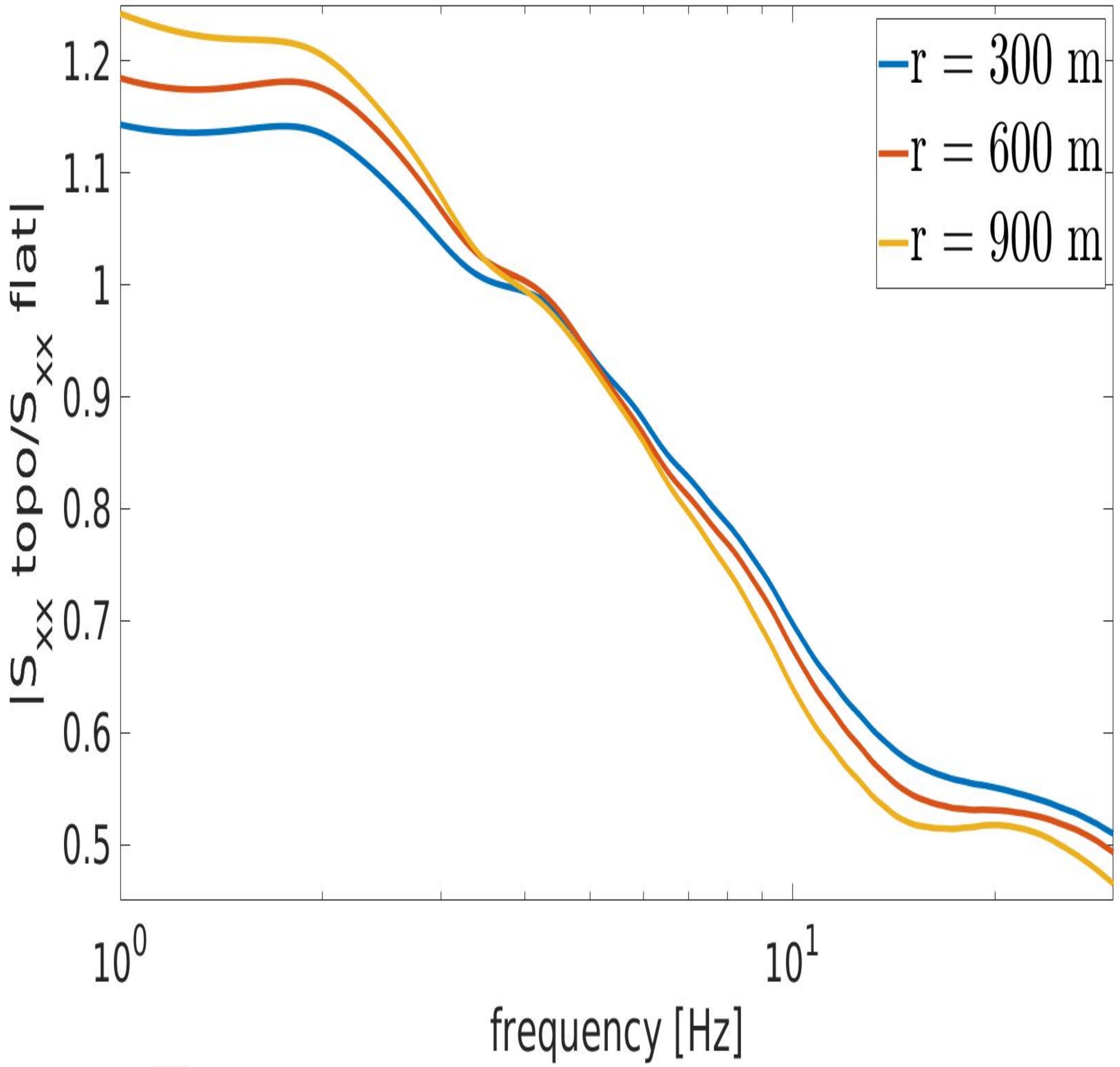


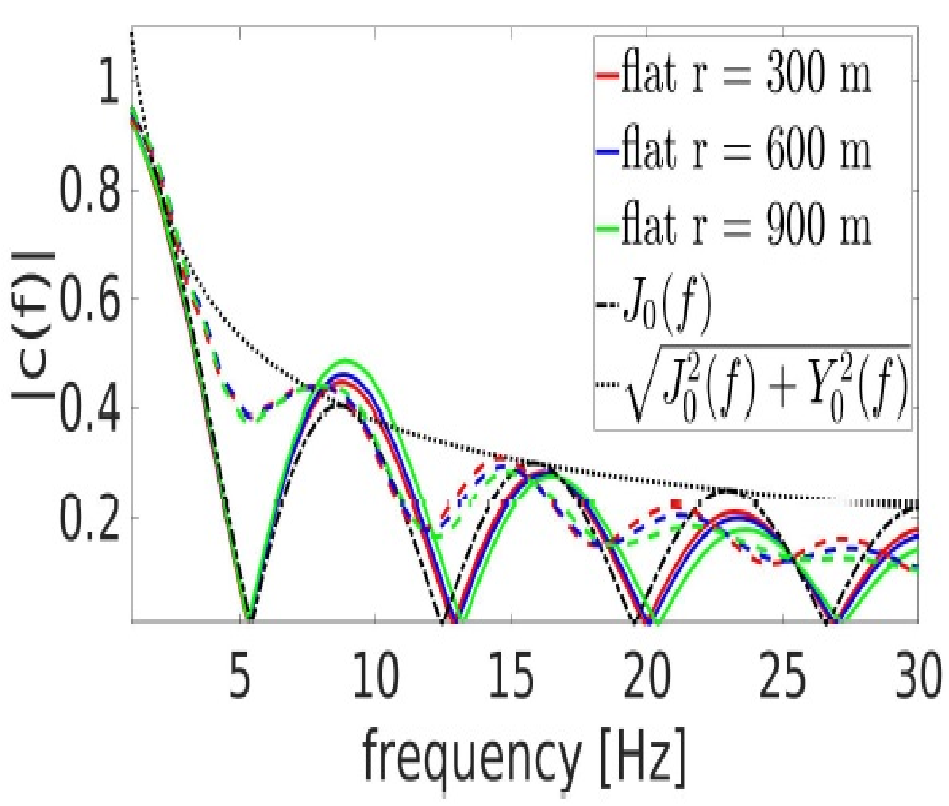
(b) Topography (A3)

Models with C-PML

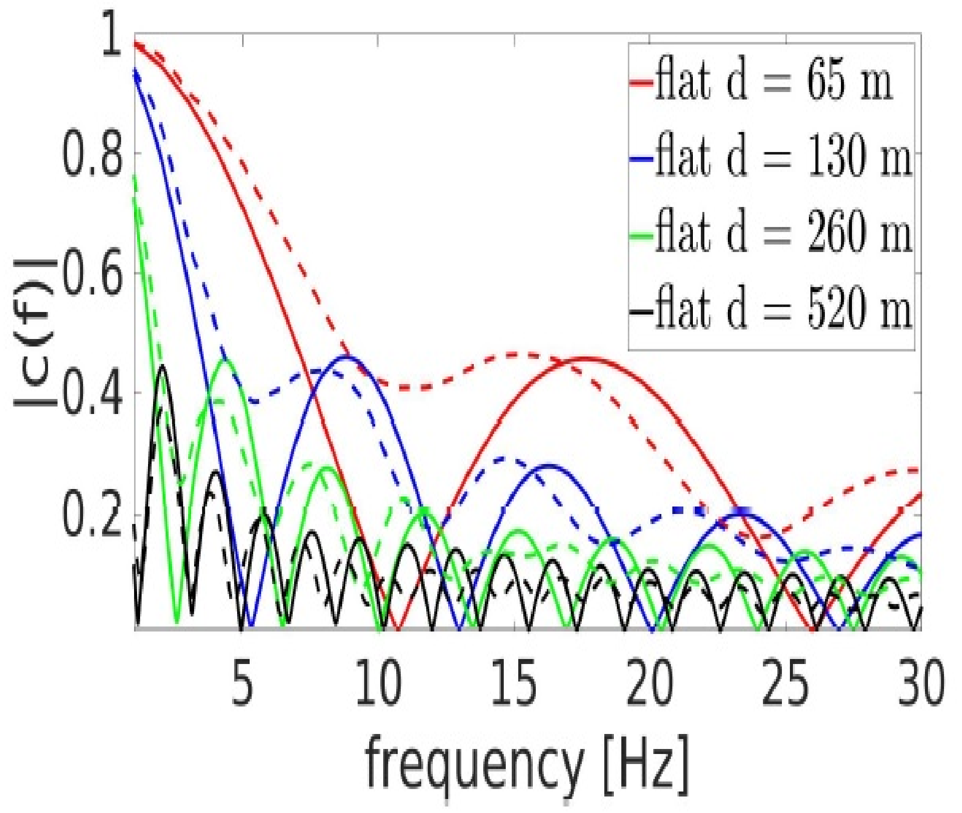
Results

- Seismic coherence $$c_{ij}(f) = \frac{S_{ij}(f)}{\sqrt{S_i(f)S_j(f)}}$$

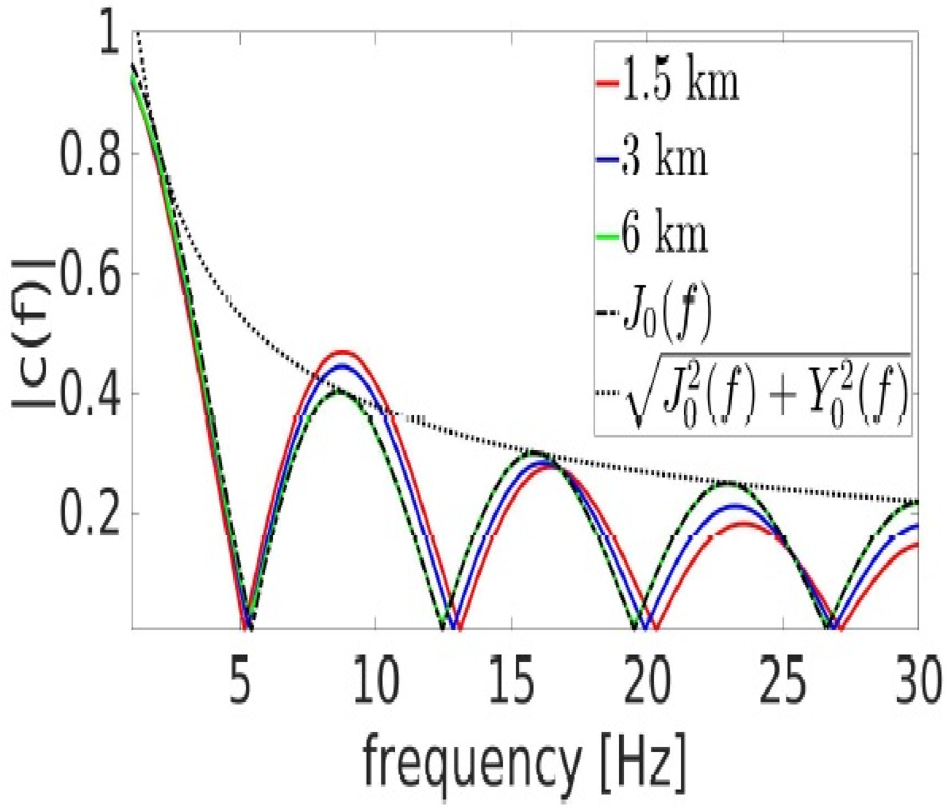




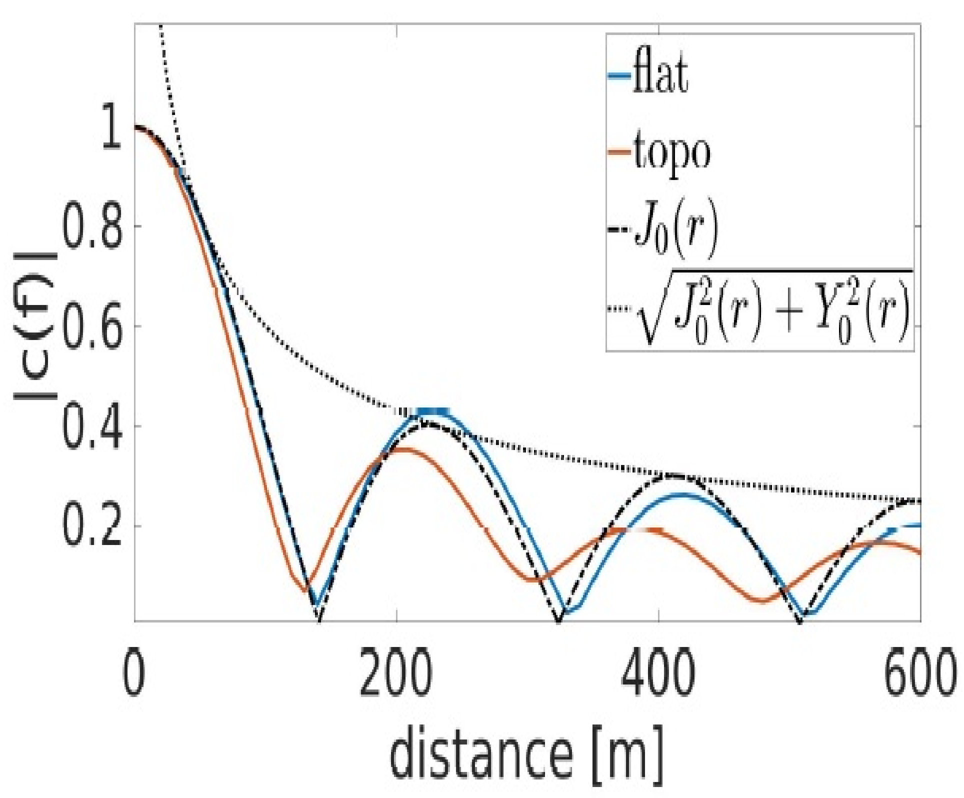
(a) Varying sizes of source-exclusion zones.



(b) Varying distances between receivers.



(c) Varying FEM sizes.

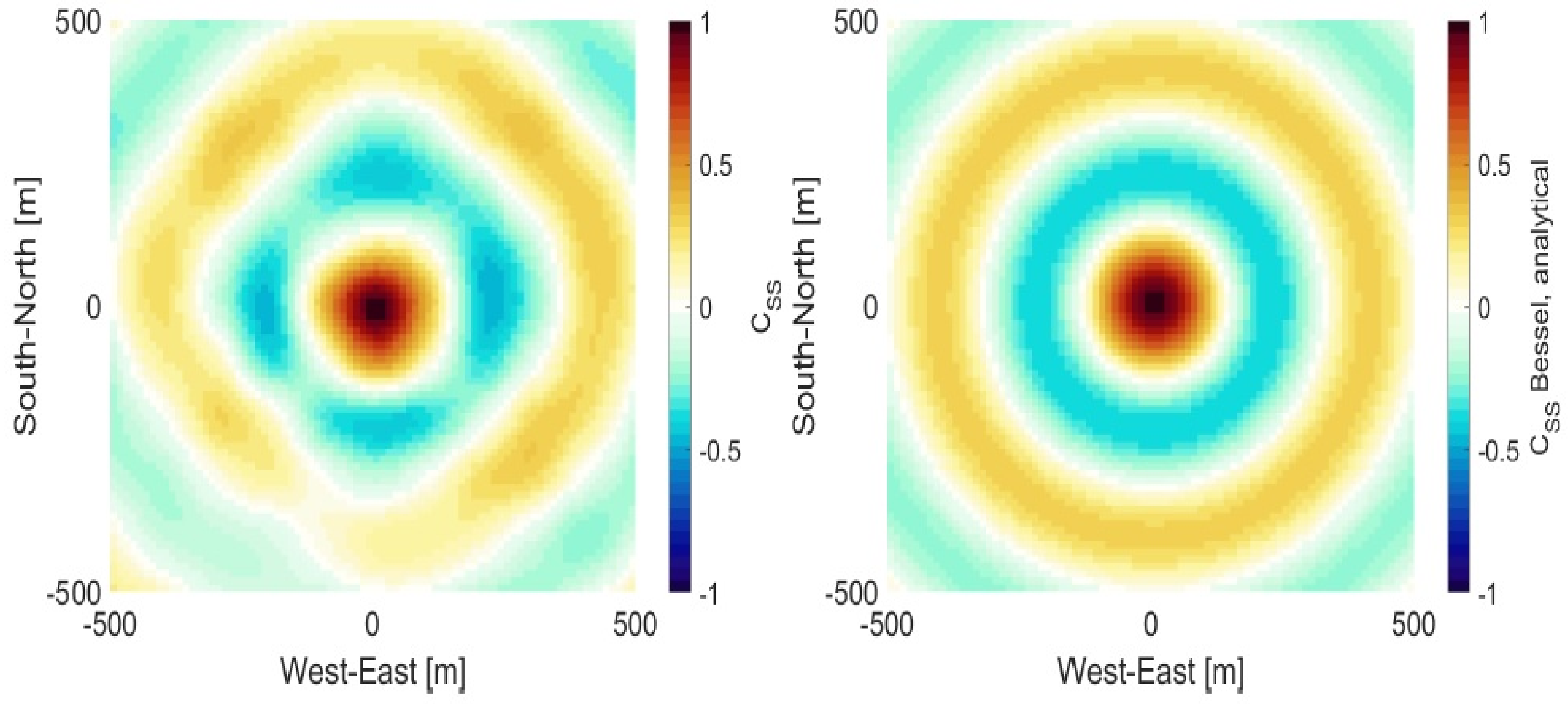


(d) As a function of distance at 5 Hz.

Results

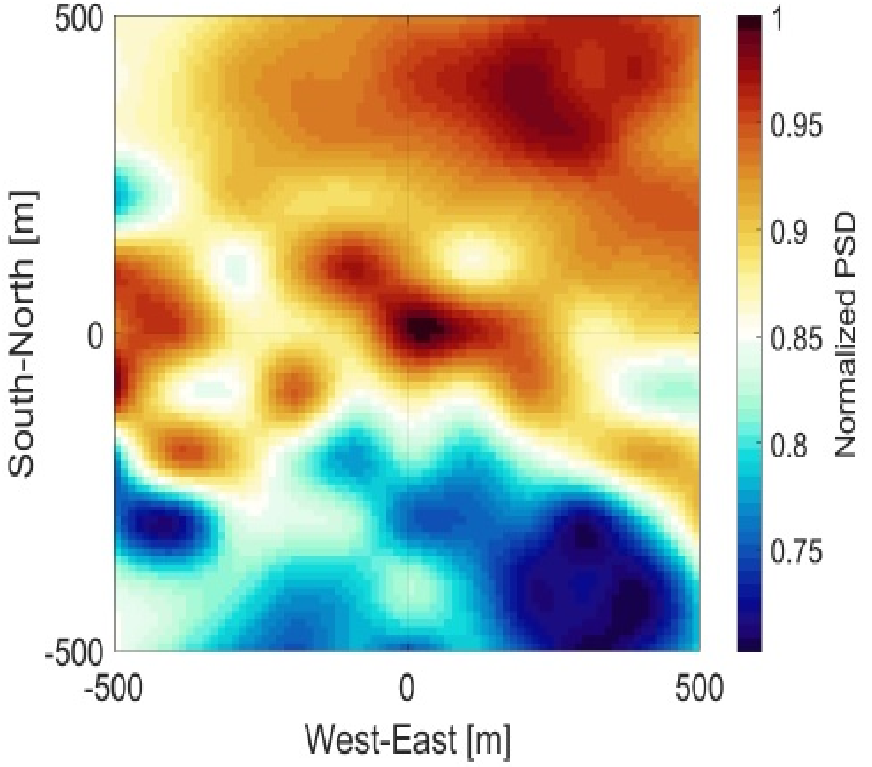
$$\text{Posterior probability} \propto \text{Likelihood} \times \text{Prior probability}$$

- Seismic correlations



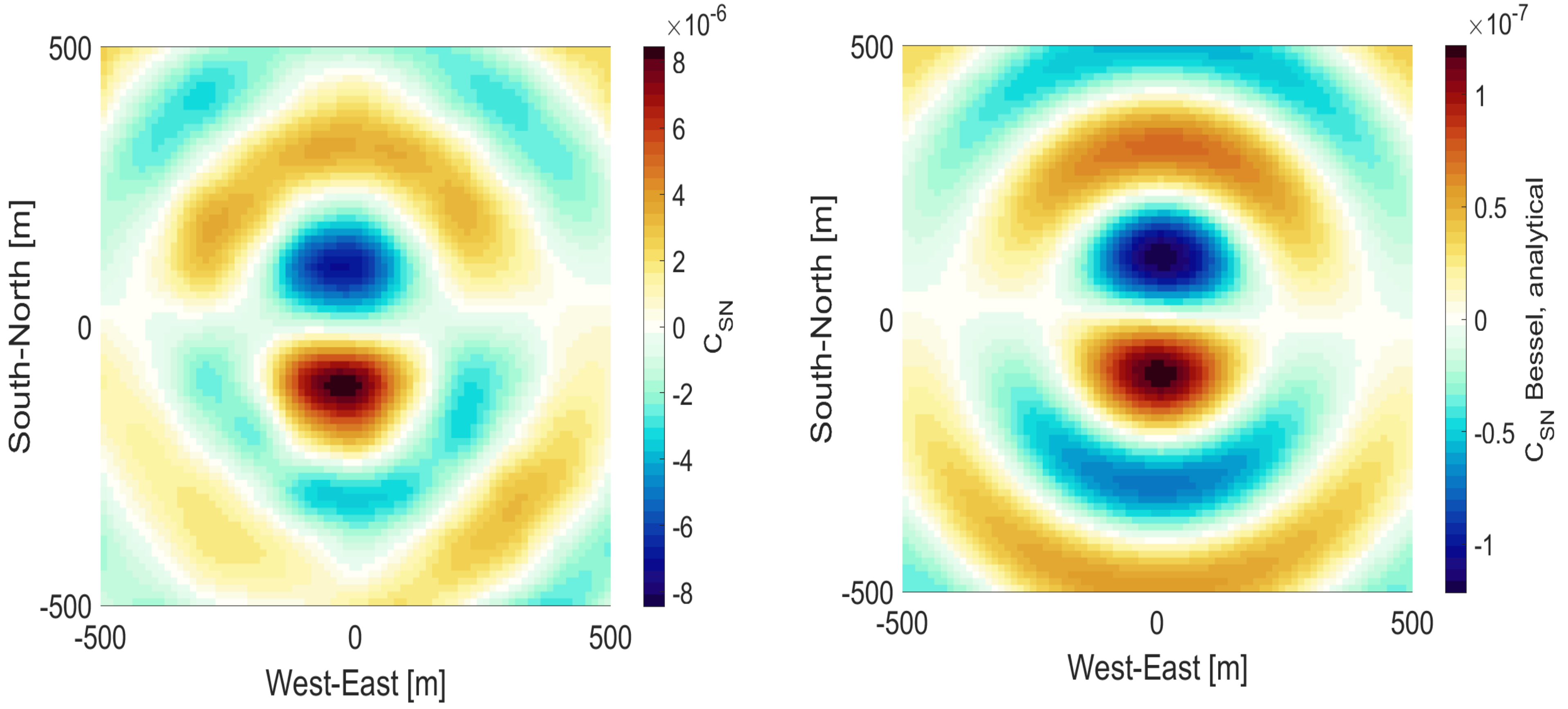
(a) SPECFEM3D simulation.

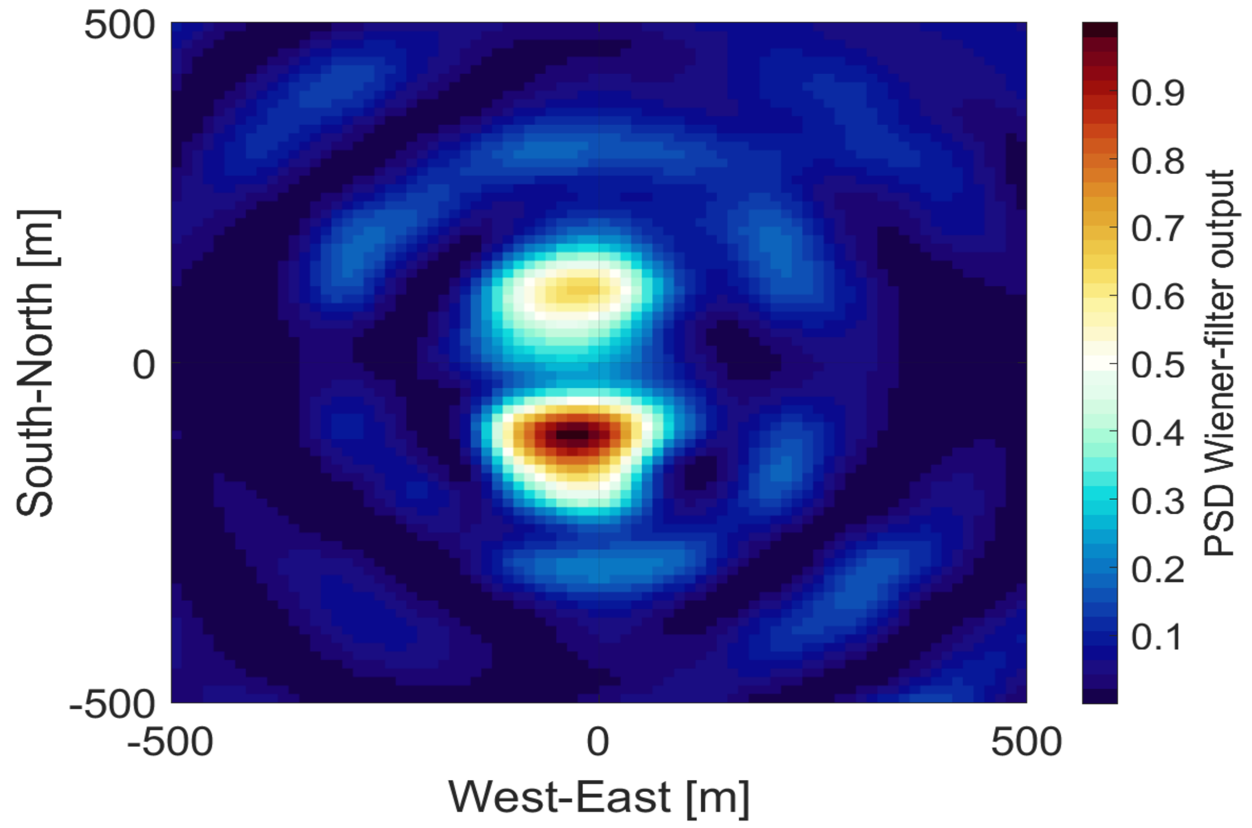
(b) Flat-surface, isotropic.



(c) Simulated vertical seismic displacement.

- Gravity-displacement correlations





Significance

- Estimates of gravitoelastic correlations – optimization of surface arrays
- Effects of topography on correlations and NN cancellation
- Important milestone, but one step in a series of tasks (include the remaining two contributions in simulations of seismic correlations)
- Importance of simulations: we cannot hope to have all the important seismic measurements (seismic displacements at all caverns, underground measurements)

JGR Solid Earth

Research Article

Simulations of gravitoelastic correlations for the Sardinian candidate site of the Einstein Telescope

Tomislav Andric, Jan Harms

First published: 28 September 2020 | https://doi.org/10.1029/2020JB020401

Abstract

Gravity fluctuations produced by ambient seismic fields are predicted to limit the sensitivity of the next-generation, gravitational-wave detector Einstein Telescope at frequencies below 20 Hz. The detector will be hosted in an underground infrastructure to reduce seismic disturbances and associated gravity fluctuations. Additional mitigation might be required by monitoring the seismic field and using the data to estimate the associated gravity fluctuations and to subtract the estimate from the detector data, a technique called coherent noise cancellation. In this paper, we present a calculation of correlations between surface displacement of a seismic field and the associated gravitational fluctuations using the spectral-element SPECFEM3D Cartesian software. The model takes into account the local topography at a candidate site of the Einstein Telescope at Sardinia. This paper is a first demonstration of SPECFEM3D's capabilities to provide estimates of gravitoelastic correlations, which are required for an optimized deployment of seismometers for gravity-noise cancellation.

https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2020JB020401

https://www.essoar.org/doi/abs/10.1002/essoar.10503439.2

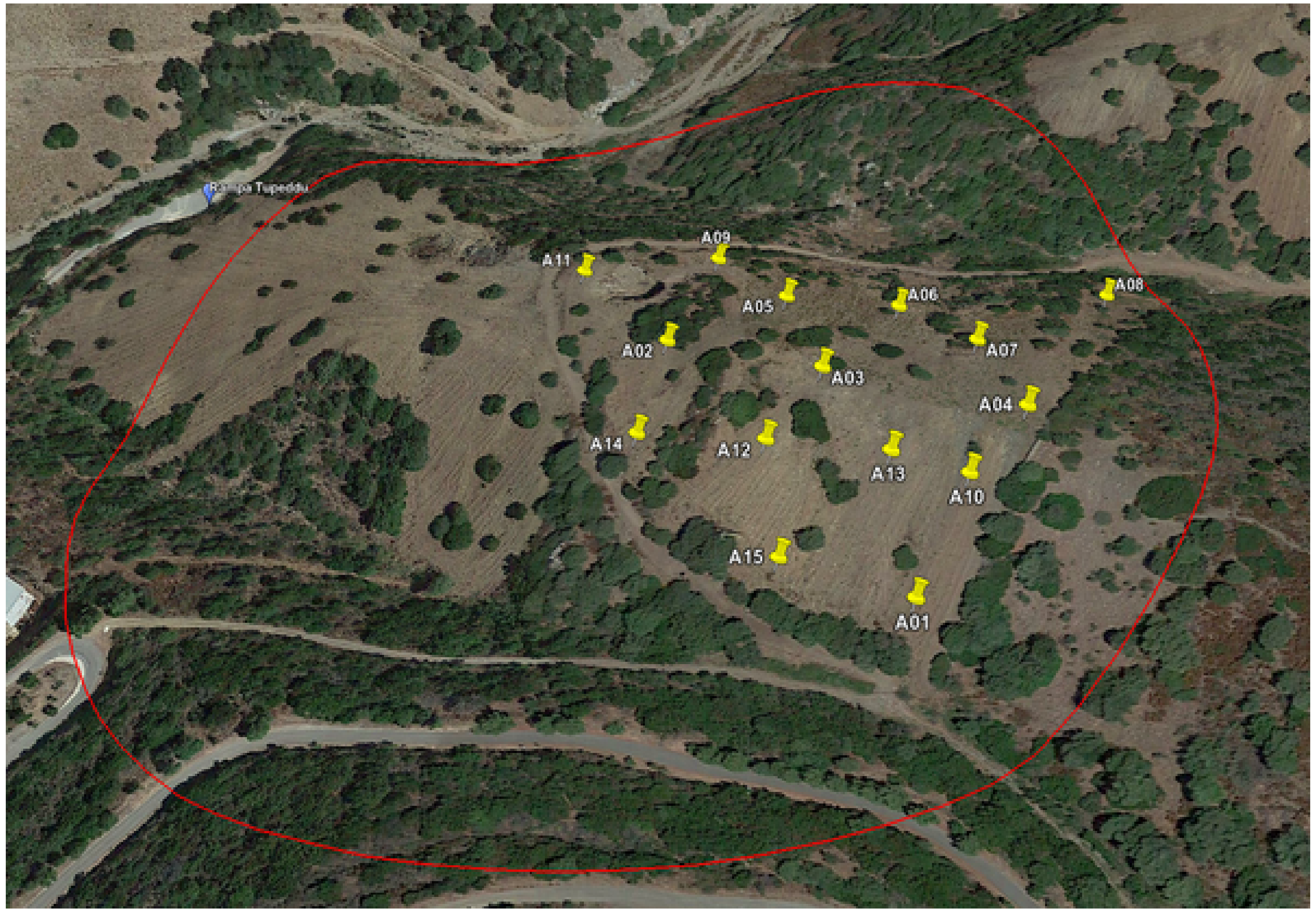
Observation of seismic correlations

Posterior probability ∝ Likelihood × Prior probability

- Trilium 120
- 2 Hz geophones (Sercel L-4A)
- 40 of 5 Hz geophones
- At least 7 days of continuous recording

- Vertex-by-vertex site characterization campaign
- Provides the likelihood for the GPR

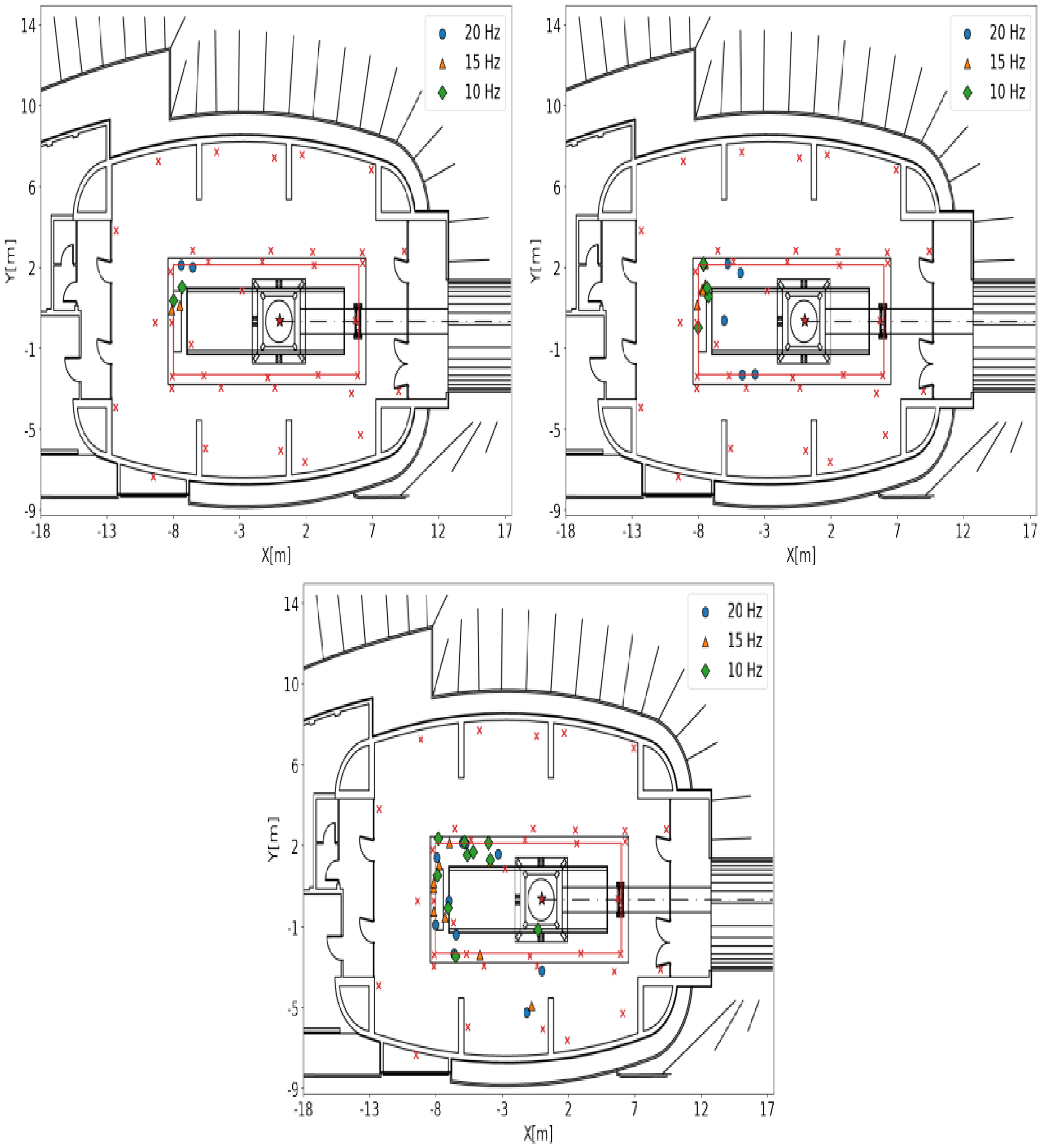
- We can observe at lower frequencies
- Tremornet sensors – target frequency is beyond 5 Hz
- The configuration is not decided yet



Bayesian surrogate model of Wiener filters

$$\text{Posterior probability} \propto \text{Likelihood} \times \text{Prior probability}$$

- Numerical results to define priors for a Gaussian Process Regression
- Combine priors and observed seismic correlations for a Bayesian inference of seismic correlations everywhere in the medium – forms the basis of the optimization algorithm



Machine learning for gravitational-wave detection: surrogate Wiener filtering for the prediction and optimized cancellation of Newtonian noise at Virgo

F Badaracco[8,1,2], J Harms[1,2], A Bertolini[3], T Bulik[4], I Fiori[5], B Idzkowski[4], A Kutynia[4], K Nikliborc[4], F Paoletti[6], A Paoli[5] + Show full author list

Published 10 September 2020 • © 2020 IOP Publishing Ltd
Classical and Quantum Gravity, Volume 37, Number 19

+ Article information

Abstract

The cancellation of noise from terrestrial gravity fluctuations, also known as Newtonian noise (NN), in gravitational-wave detectors is a formidable challenge. Gravity fluctuations result from density perturbations associated with environmental fields, e.g., seismic and acoustic fields, which are characterized by complex spatial correlations. Measurements of these fields necessarily provide incomplete information, and the question is how to make optimal use of available information for the design of a noise-cancellation system. In this paper, we present a machine-learning approach to calculate a surrogate model of a Wiener filter. The model is used to calculate optimal configurations of seismometer arrays for a varying number of sensors, which is the missing keystone for the design of NN cancellation systems. The optimization results indicate that efficient noise cancellation can be achieved even for complex seismic fields with relatively few seismometers provided that they are deployed in optimal configurations. In the form presented here, the optimization method can be applied to all current and future gravitational-wave detectors located at the surface and with minor modifications also to future underground detectors.

https://iopscience.iop.org/article/10.1088/1361-6382/abab64

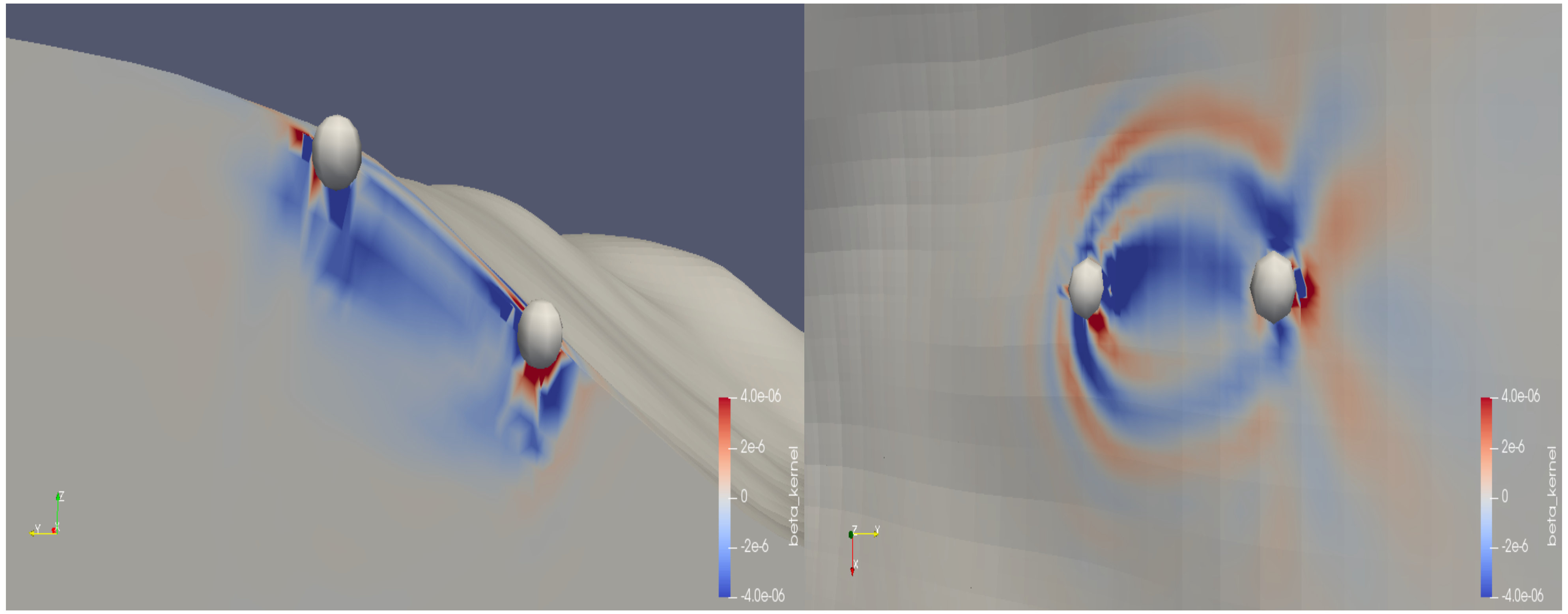
Summary - Significance

- Simulation + measurement – to improve the estimation of seismic correlations everywhere in the medium
- Wiener surrogate model allows to calculate the Wiener filter for an arbitrary number of seismometers placed at arbitrary locations

- Calculation of optimal sensor locations – array optimization in 3D (Bayesian seismic-array design)
- Allows us to change the positions of seismometers to maximize NN cancellation via Wiener filtering (using multi-sensor numerical optimization routines)

- Important advantages – where to put sensors for more robust estimates (at which locations we should put other seismometers during site-characterization campaigns to achieve a better overall estimate of the field of seismic correlations) – tells us where it becomes too model dependent

- Other important remarks:
  1. Calculations including optimization will come with a great request for computational resources
  2. Investigate what type of seismic sensor helps most for efficient NN cancellation
  3. SPECFEM3D can also tell us where we should improve our knowledge of geology (sensitivity kernels)



- Importance:
  1. Decrease the required effort and therefore cost of a NN mitigation system
  2. Optimal arrays for the best NN reduction – increased sensitivity of ET

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Thank you for your attention

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Backup

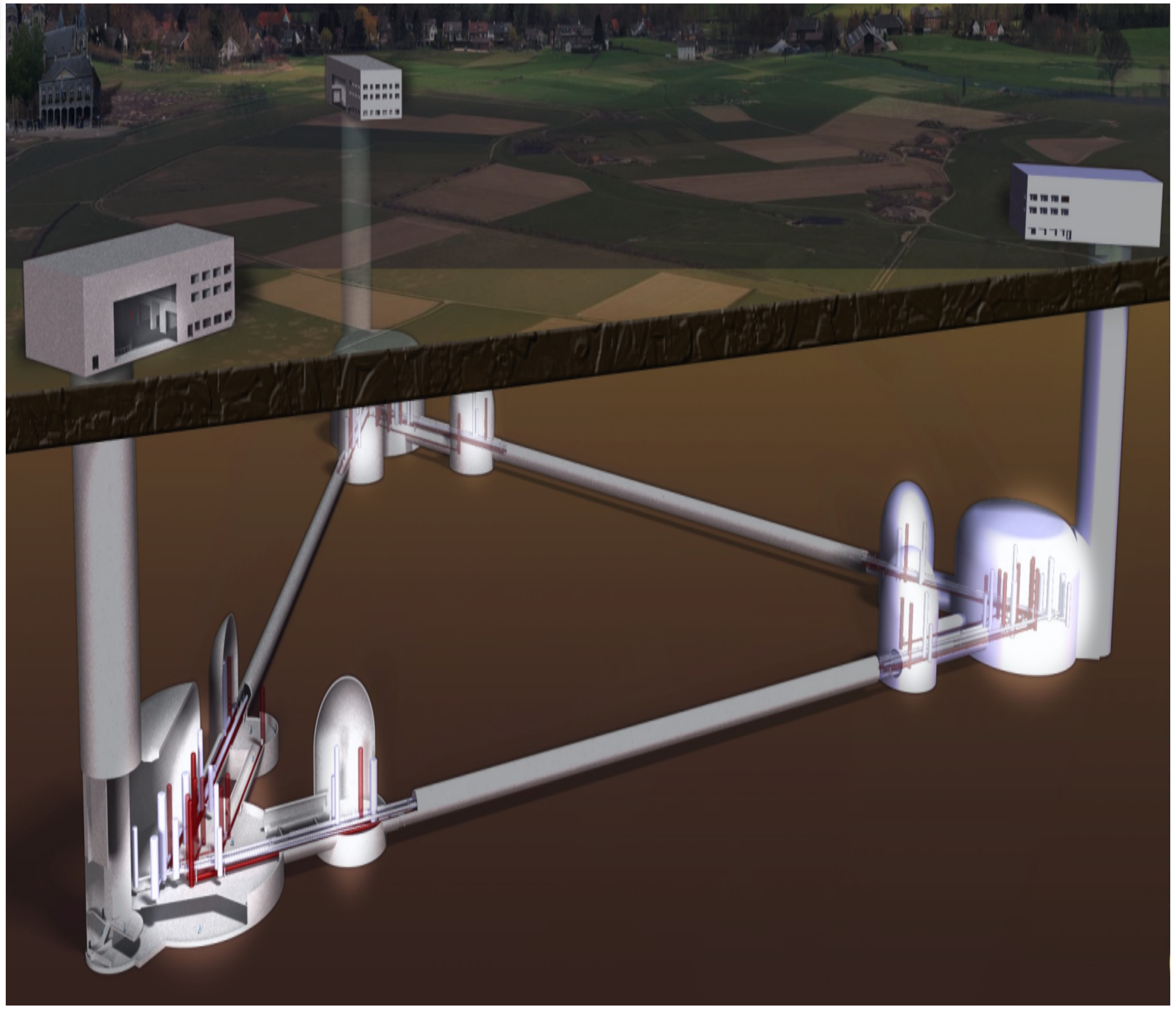
It uses a mesh of hexahedral finite elements on which the wave field is represented in terms of high-degree Lagrange polynomials on Gauss–Lobatto–Legendre interpolation points.

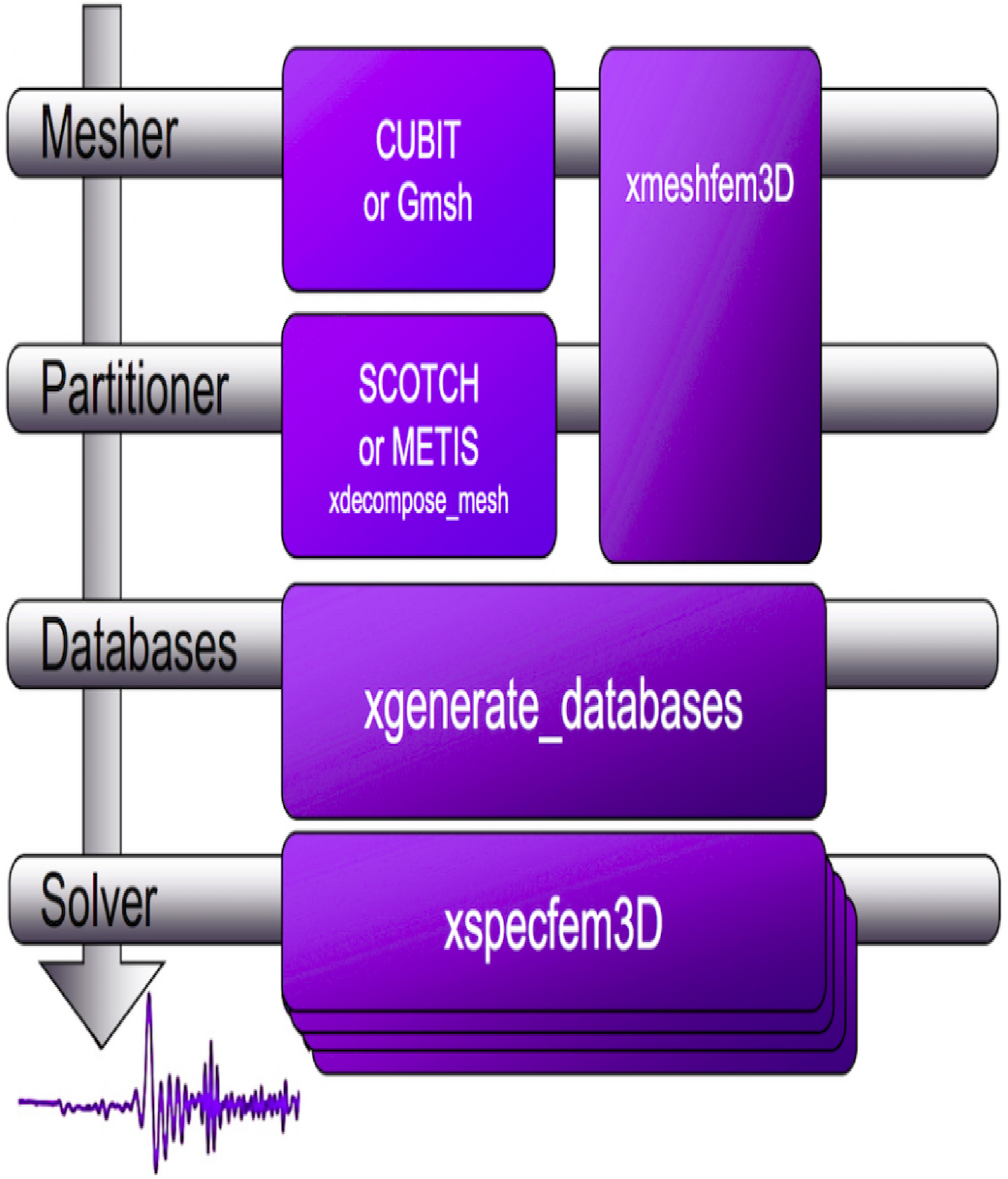
For cross-correlation simulations, the distribution of noise sources in SPECFEM3D Cartesian is constrained to the surface, which is not a major drawback since the most relevant seismic sources in the NN band are expected to be surface sources.

The source-time function of the generating wavefield is obtained using the spectrum of the ensemble-averaged noise, and it is narrowly concentrated around zero time. We use a source-time function shown in figure 6a representing a frequency-independent seismic spectrum in the interesting frequency range (1 – 30 Hz), since the absolute values of the seismic spectrum are not relevant for this paper. Generally, results in frequency domain can be rescaled using realistic / observed seismic spectra when needed.

We used Trelis for the creation of models and their exporting into a SPECFEM3D Cartesian file format. Trelis is a full-featured software for generation of two- and three-dimensional finite-element grids (meshes) and geometry preparation

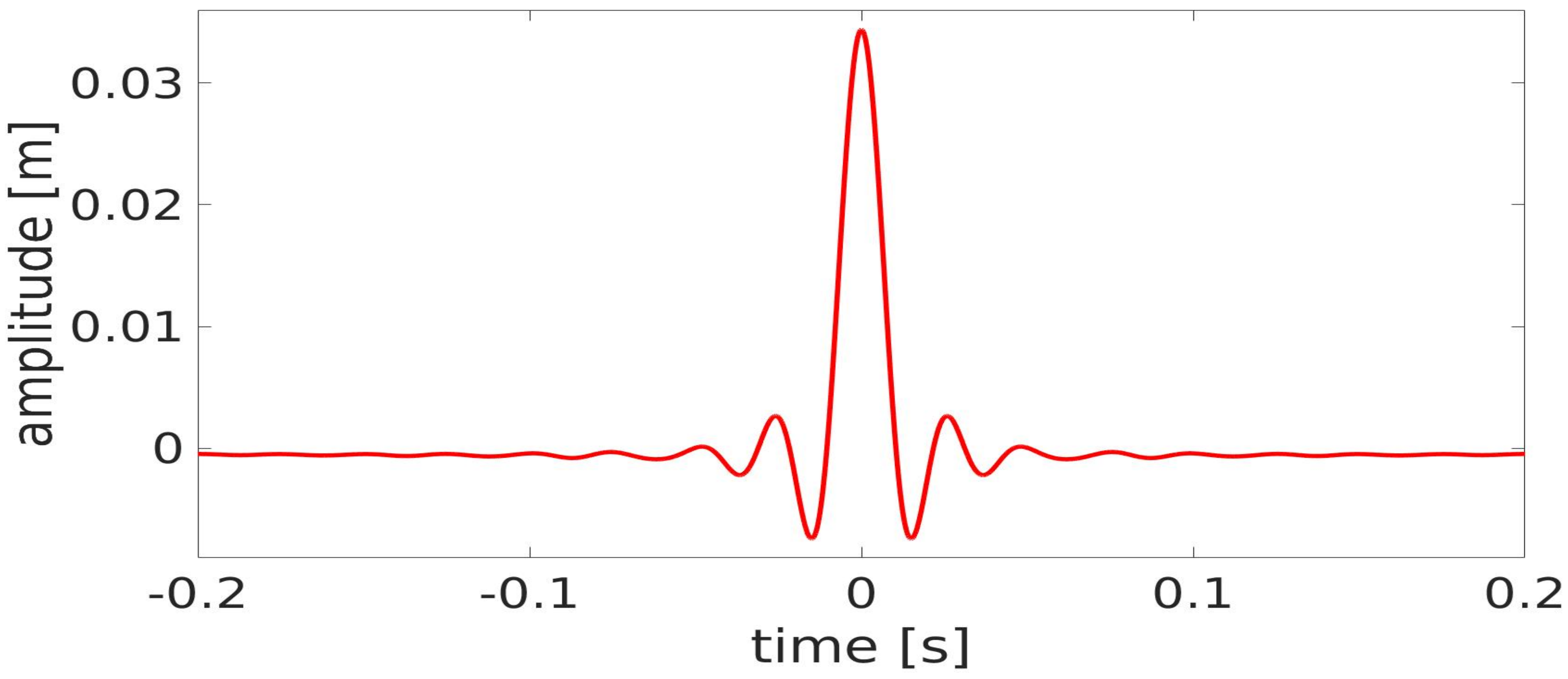
One of the most important data-processing techniques in all of the ambient-noise seismology is ensemble averaging, allowing to reduce the effects of a set of scatterers and sources randomly distributed in time and space to those of a diffuse wavefield

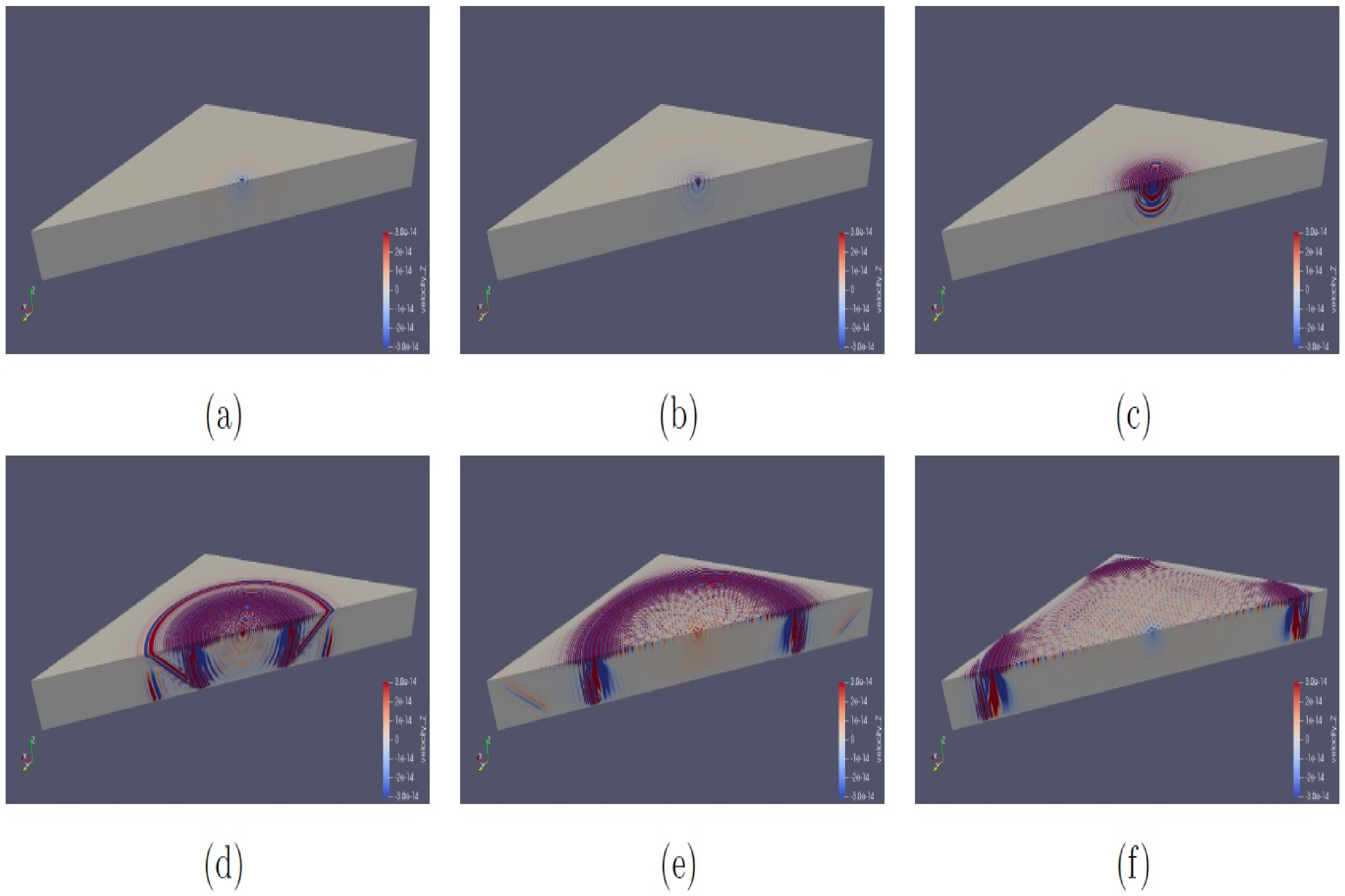


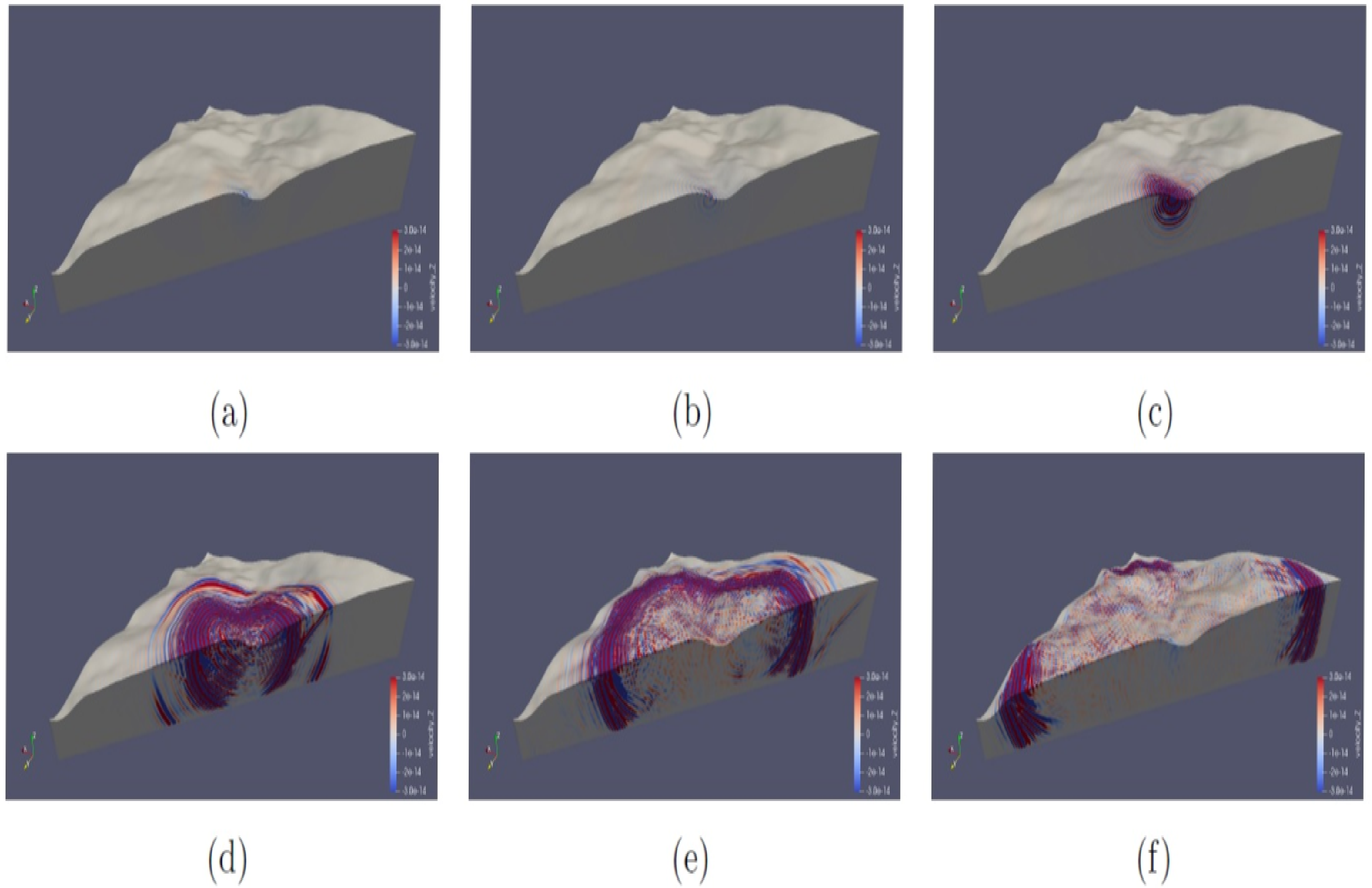


Noise cross-correlation simulations

- Two steps of simulations:
    1. Injection
    2. Noise emission







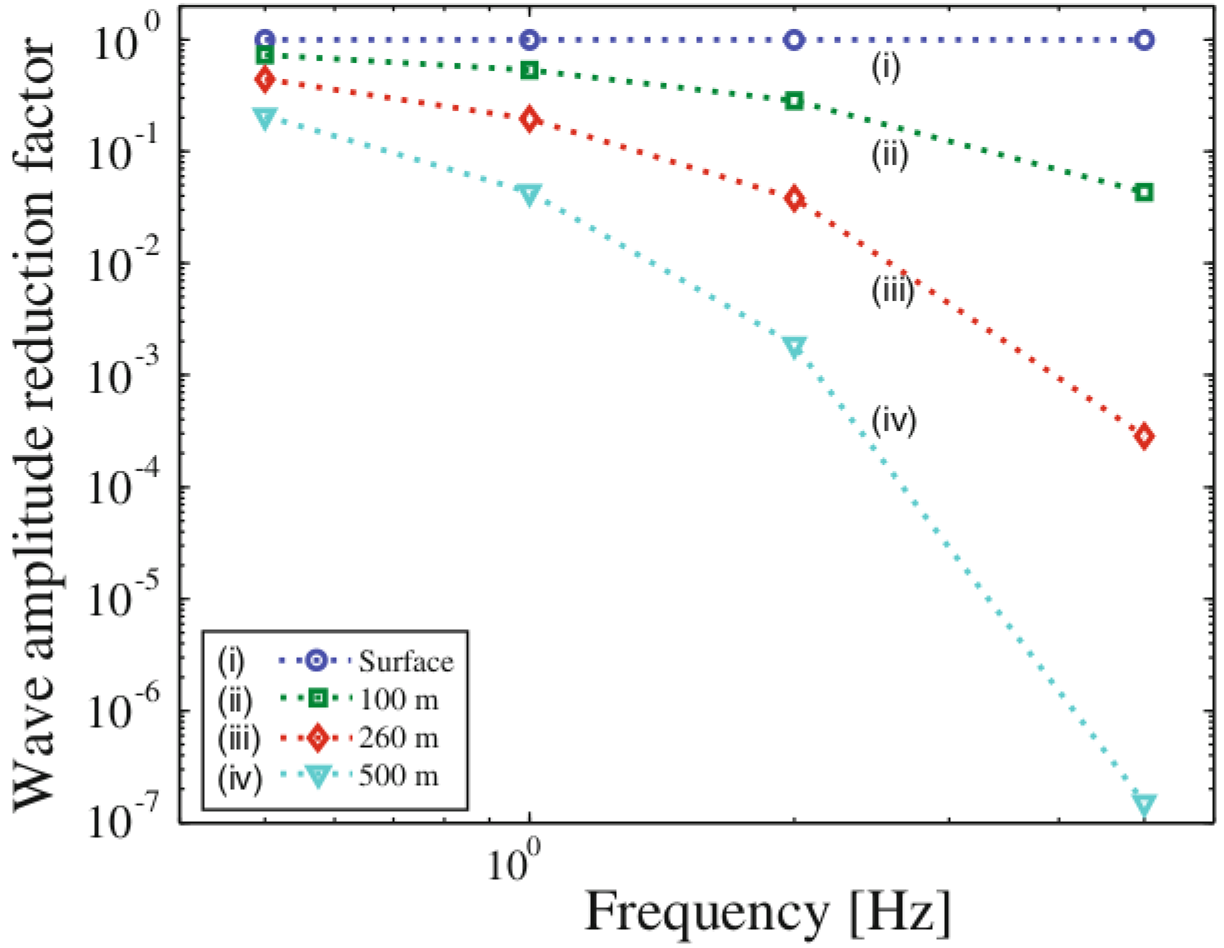
Further mitigation of NN can be achieved by noise cancellation using an extensive monitoring system of the ambient seismic field (Harms, 2019). The idea is to pass seismic data through a filter such that its output can be understood as a coherent estimate of seismic NN and be subtracted from the GW data (Cella, 2000)

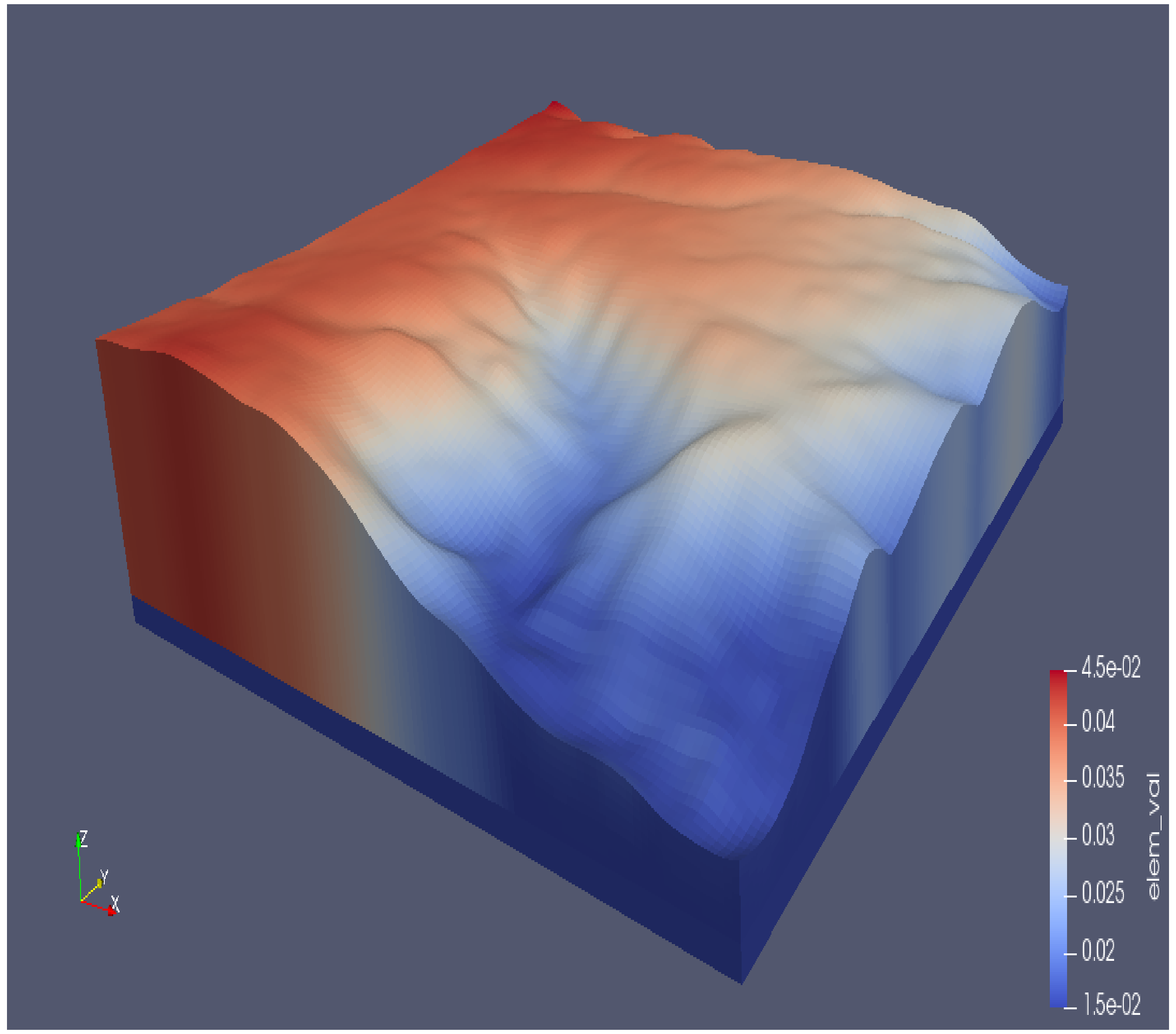
Nonetheless, the quantities required for such a multi-sensor optimization are provided by SPECFEM3D. They need to be used in numerical optimization routines. What we in fact propose is to use the correlation results from numerical analysis as presented in this paper to define priors for a Gaussian Process Regression, which then combines priors and observed seismic correlations for a Bayesian inference of seismic correlations everywhere in the medium, which forms the basis of the optimization algorithm

As a consequence, and as a first step, we attempt to model the gravitational coupling between seismic surface fields and underground gravitational perturbations.

With the A3-topographic model, |c ij (f)| does not vanish at any frequency, which is likely due to a mixed wave content with Rayleigh waves and scattered waves of different wavelengths

$$C\left(\delta a_{\mathrm{arm}}(\boldsymbol{r}_0), \xi_z(\boldsymbol{r}); f\right) = G\rho_0 \int \mathrm{d}^2\boldsymbol{r}' C\left(\xi_n(\boldsymbol{r}'), \xi_z(\boldsymbol{r}); f\right) \frac{(\boldsymbol{r}' - \boldsymbol{r}_0)\cdot \boldsymbol{e}_{\mathrm{arm}}}{|\boldsymbol{r}' - \boldsymbol{r}_0|^3}$$

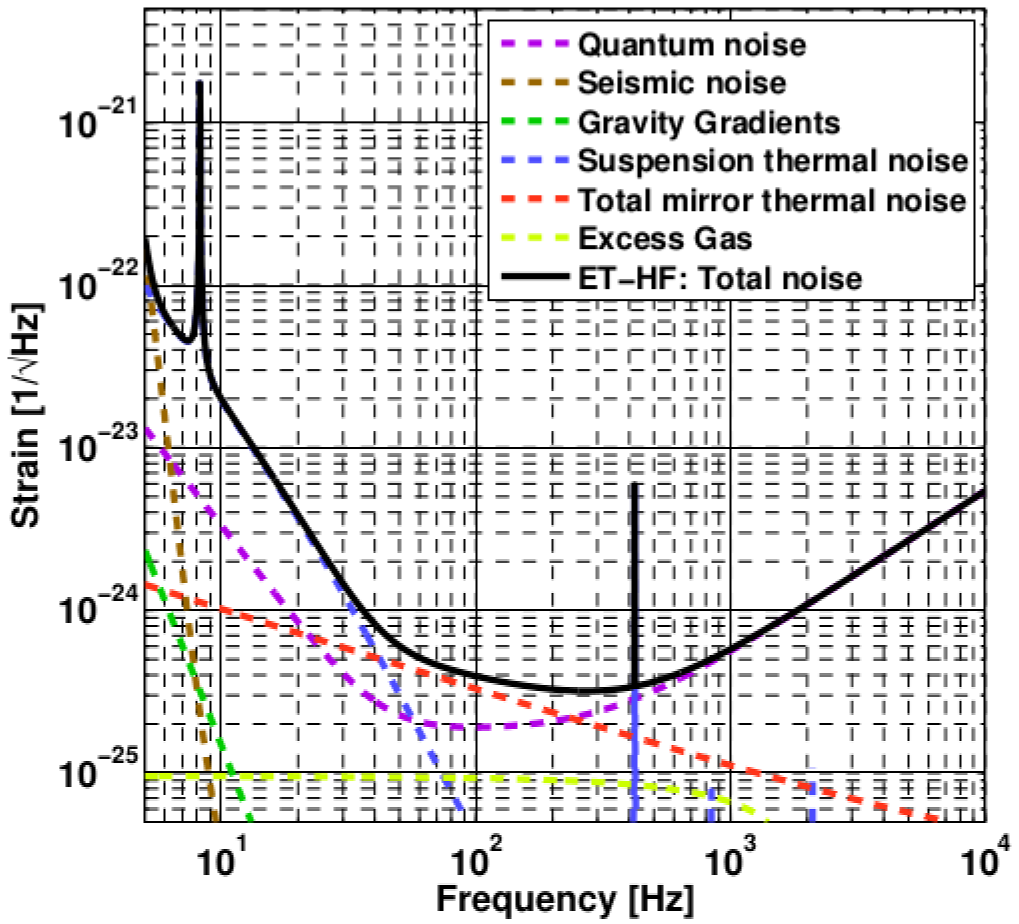


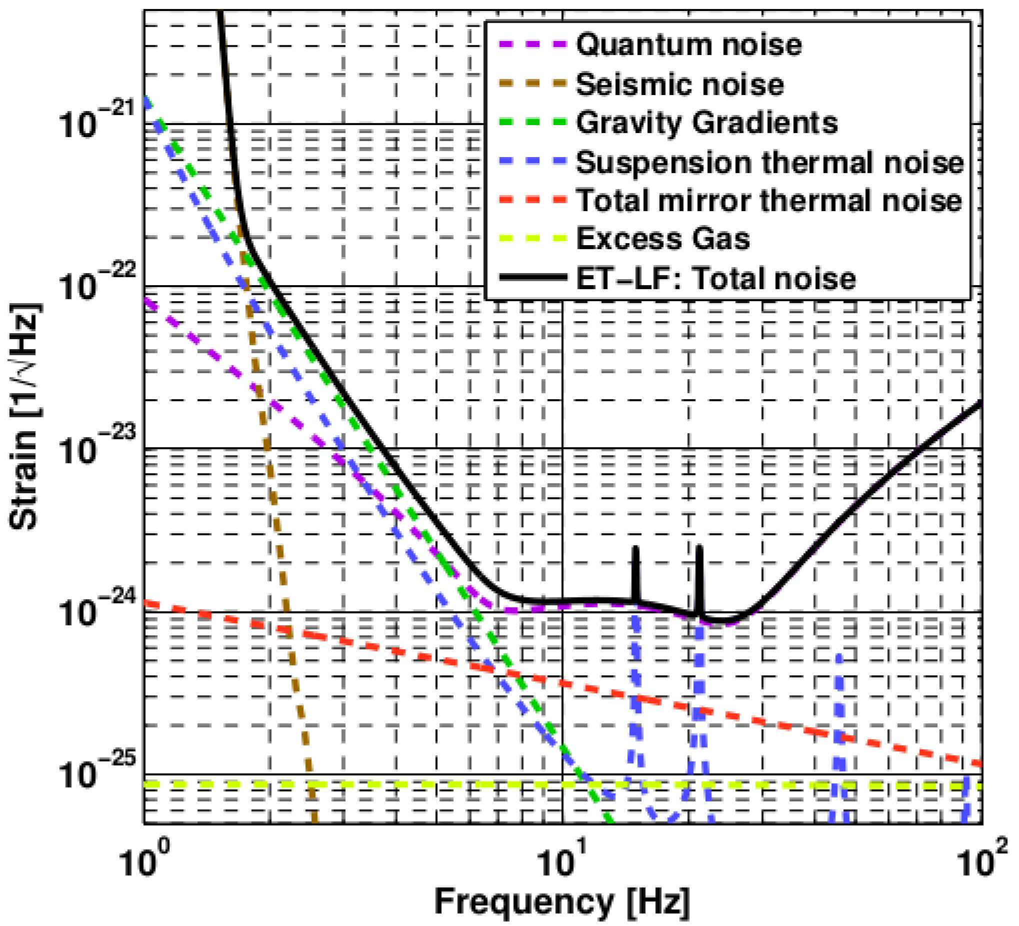


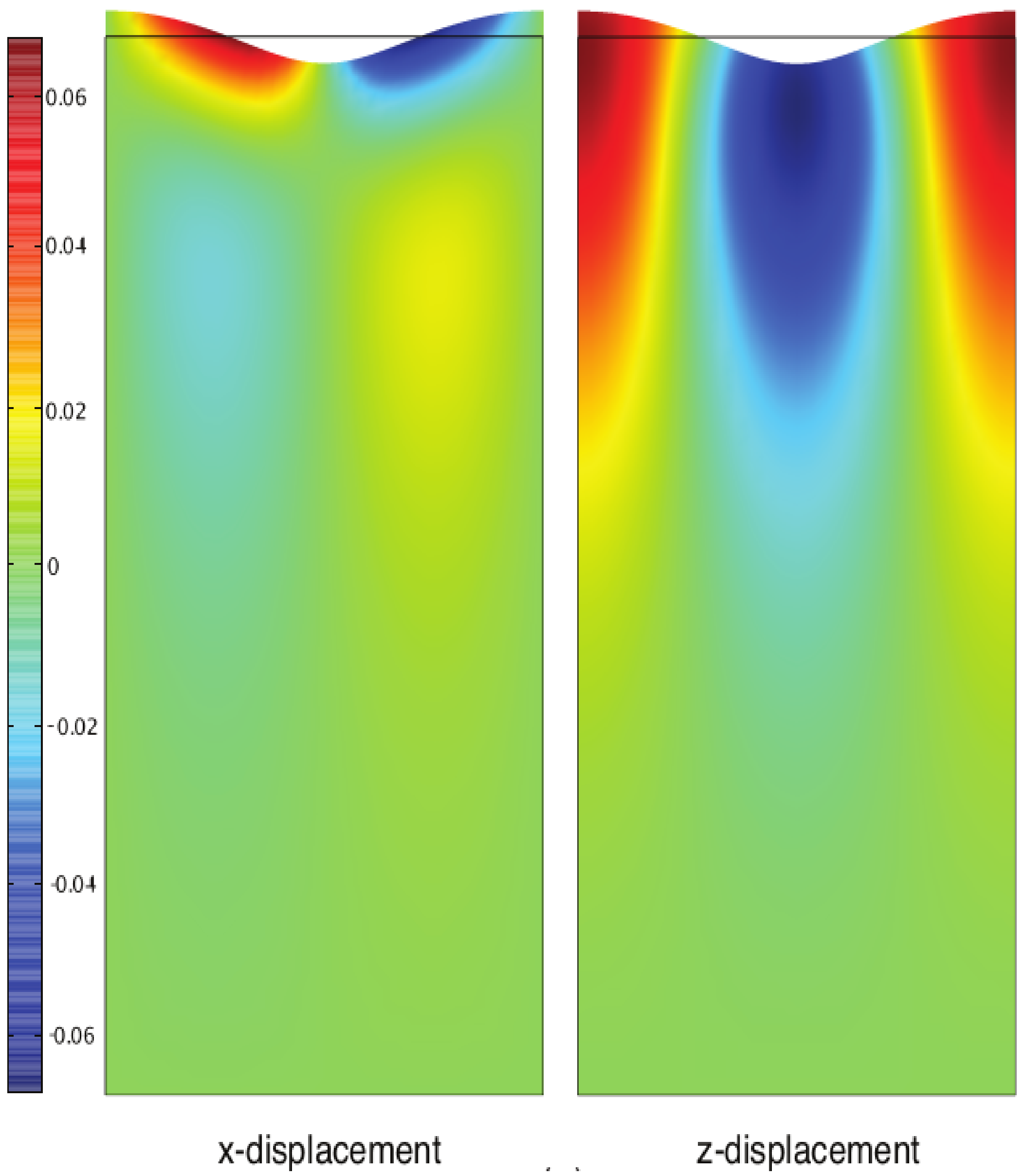
$$C\left(\delta a_{\mathrm{arm}}(0), \xi_z(\boldsymbol{r}); f\right) = 2\pi G\rho_0 S\left(\xi_z; f\right) \mathrm{e}^{-hk(f)} \cos(\phi) J_1\left(k(f) r\right),$$

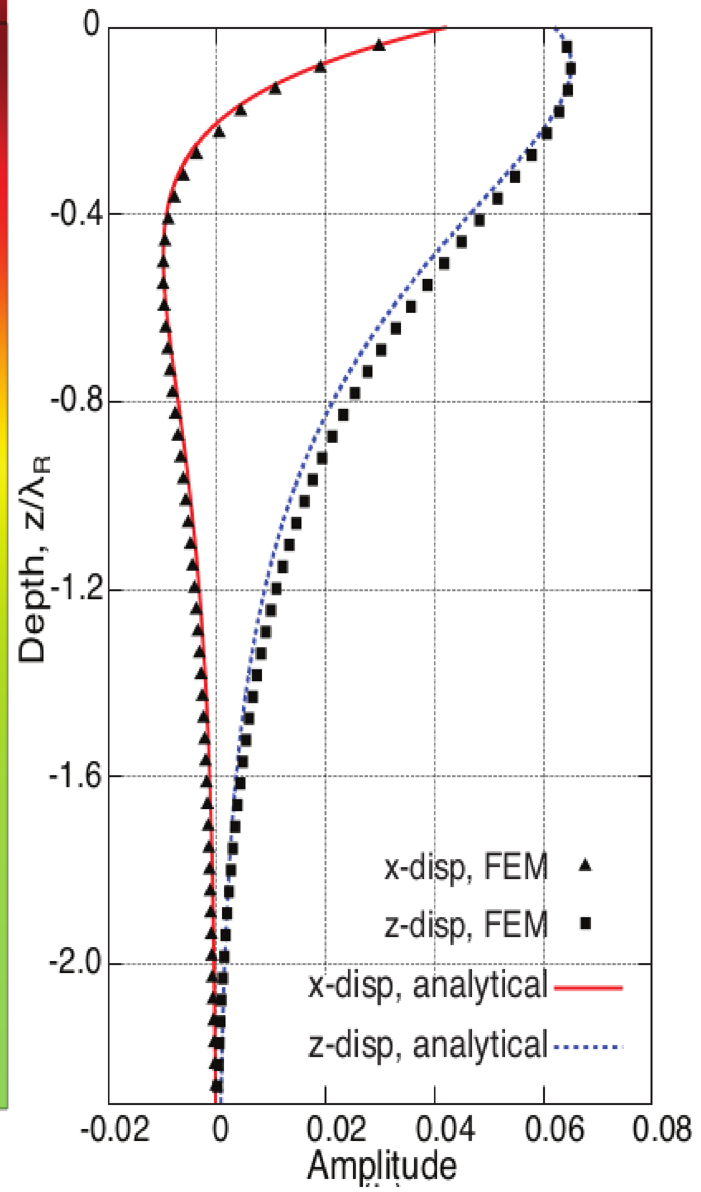
$$S(w; f) = \left|C\left(\delta a_{\mathrm{arm}}(\boldsymbol{r}_0), \xi_z(\boldsymbol{r}); f\right)\right|^2 / C\left(\xi_z(\boldsymbol{r}), \xi_z(\boldsymbol{r}); f\right)$$

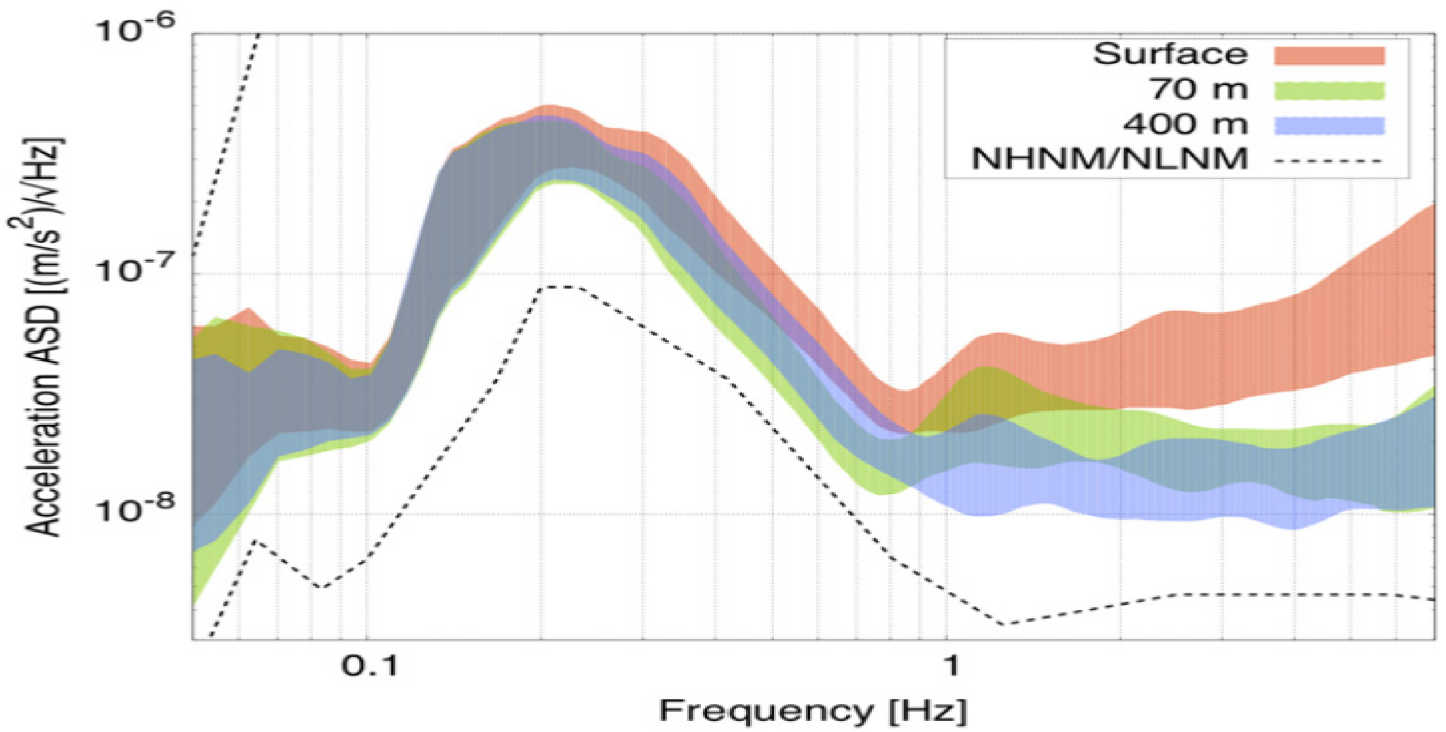
GSSI

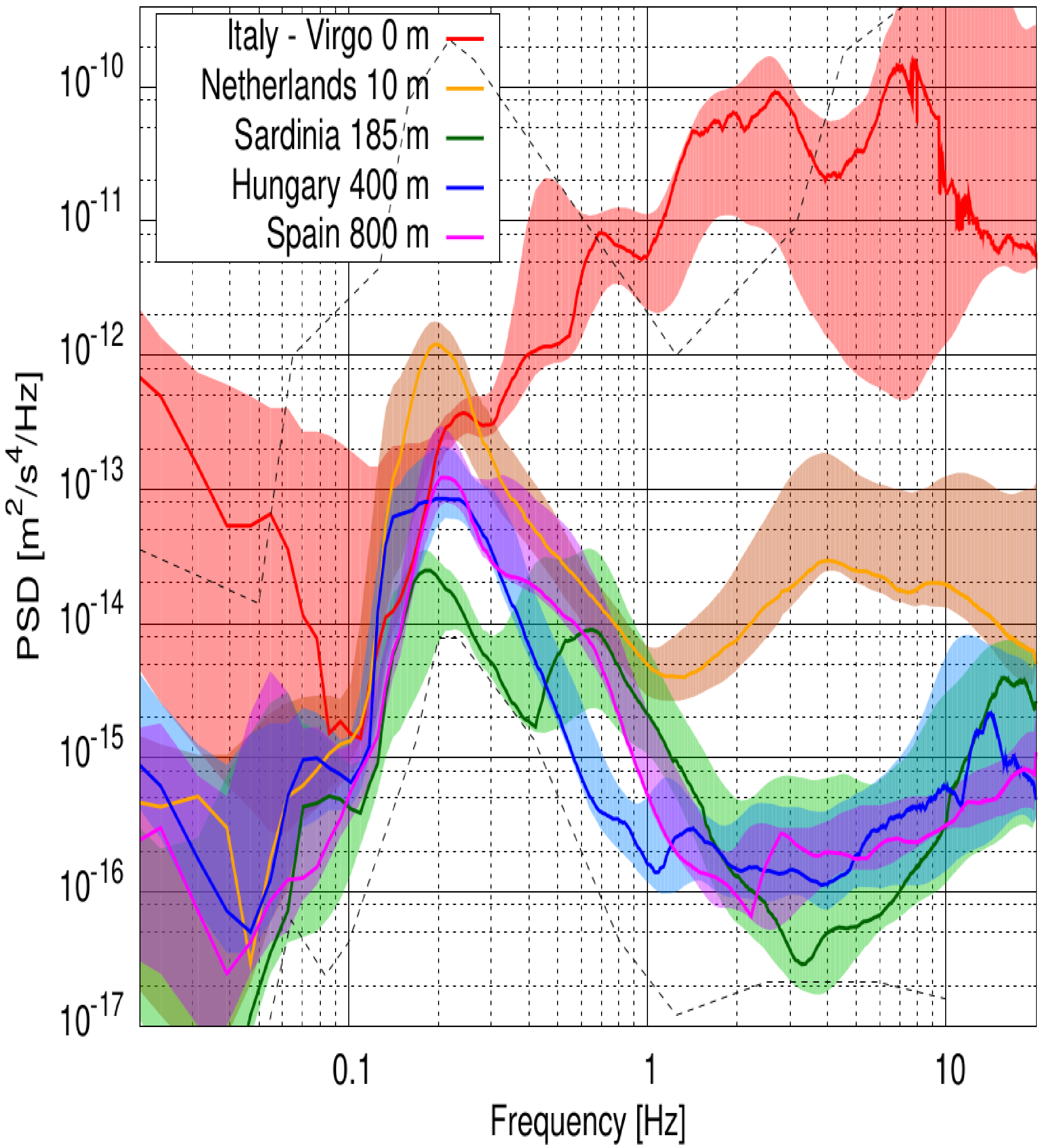

Quantum noise
Seismic noise
Gravity Gradients
Suspension thermal noise
Total mirror thermal noise
Excess Gas
ET–HF: Total noise
Strain [1/√Hz]
Frequency [Hz]


Quantum noise
Seismic noise
Gravity Gradients
Suspension thermal noise
Total mirror thermal noise
Excess Gas
ET–LF: Total noise
Strain [1/√Hz]
Frequency [Hz]


x-displacement
z-displacement


Depth, z/λR
Amplitude
x-disp, FEM
z-disp, FEM
x-disp, analytical
z-disp, analytical


Surface
70 m
400 m
NHNM/NLNM
Acceleration ASD [(m/s2)/√Hz]
Frequency [Hz]



Ensemble averaging is the fundamental data-processing technique in all of ambient-noise seismology, allowing to reduce the effects of a set of sources and scatterers randomly distributed in space and time to those of a diffuse wavefield. It consists essentially of subdividing a long (e.g., one year) continuous seismic record into shorter intervals; whitening the records so that the effects of possible earthquake signals are minimized; cross-correlating simultaneous records from different stations, and finally stacking the results for each station pair over the entire year [e.g., Bensen et al., 2007; Boschi et al., 2012].

$$c_{ij}(f) = J_0(2\pi f|\vec{r}_j - \vec{r}_i|/c)$$

Bayesian surrogate model

Posterior probability ∝ Likelihood × Prior probability

optimized seismometer arrays for each ET vertex location
Once the field of seismic correlations is modeled in this way, one can use it as surrogate model for array optimization as explained in the first publication. However, for ET, the calculations including optimization will come with a great request for computational resources, which we don't have readily available now (we could request time on some large clusters).
Another interesting result of the Gaussian Process Regression is that it also tells us at which locations we should put other seismometers during site-characterization campaigns to achieve a better overall estimate of the field of seismic correlations, and SPECFEM3D can tell us where we should improve our knowledge of geology

- Maximization of NN cancellation via Wiener filtering
- Where to put sensors for more robust estimates
- Tells where things become too model dependent
- Great request for computational resources (need to request time on some large clusters)
- Investigate what type of seismic sensor helps most for efficient NN cancellation

A GPR requires priors (in our case in form of a modeled seismic correlation, and then uses data to improve the estimation of seismic correlations everywhere (not only where measured). The importance of the simulations (i.e., of the priors) is that we cannot hope to have all the important seismic measurements (e.g., you need to measure seismic displacements at all caverns and with 3D arrays throughout the medium as well). We might only have a handful of underground measurements in the end, and more detailed surface measurements.

Bayesian surrogate model - significance

$$\text{Posterior probability} \propto \text{Likelihood} \times \text{Prior probability}$$

The importance of the simulations (i.e., of the priors) is that we cannot hope to have all the important seismic measurements (e.g., you need to measure seismic displacements at all caverns and with 3D arrays throughout the medium as well). We might only have a handful of underground measurements in the end, and more detailed surface measurements.

- Modeled seismic correlations can be used as surrogate model for array optimization in 3D
- Allowed to change the positions of seismometers to maximize cancellation via Wiener filtering

optimized seismometer arrays for each ET vertex location

Once the field of seismic correlations is modeled in this way, one can use it as surrogate model for array optimization as explained in the first publication. However, for ET, the calculations including optimization will come with a great request for computational resources, which we don't have readily available now (we could request time on some large clusters).
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Gaussian process regression

$$\text{Posterior probability} \propto \text{Likelihood} \times \text{Prior probability}$$

- Gaussian processes
- For a proper regression – infer the values of the hyperparameters from the data
- Relying on the Bayesian framework