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Geostatistical models for the assessment of the influence of shear wave velocity uncertainty and variability on ground response analyses

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ABSTRACT: A robust assessment of the influence of epistemic uncertainties and aleatory variabilities on ground response analyses is a fundamental requirement for modern probabilistic seismic hazard analyses. The study of epistemic uncertainties and aleatory variabilities should follow three sequential steps: identification, quantification, and management (IQM procedure). A fundamental input for ground response analyses is the shear-wave velocity (V_S) profile. The V_S profile can be obtained via various types of geophysical tests. Each test has specific characteristics. For these reasons, a consistent IQM procedure must be established to assess the type and amount of uncertainties involved in the measurements, also addressing the peculiarities of the investigated site. We propose a geostatistical model for the management of the uncertainties included in the V_S profiles obtained with surface wave tests. The model is based on the separate randomization of travel times and layer thicknesses. It generates profiles that are consistent with the measured "site signatures" such as the Rayleigh wave dispersion curve and the predominant site period. The model can be easily generalized for other geophysical tests.

1 INTRODUCTION

The estimation of the seismic risk is of primary interest in a comprehensive design and infrastructure management framework that encompasses tools ranging from earthquake engineering to civil protection. An important step is to provide an accurate prediction of the seismic hazard at a site by means of numerical simulations and/or analysis of recorded data. In this context, the performance of hazard-consistent Ground Response Analyses (GRAs) represents one of the most challenging aspects (Stewart et al. 2014). Both Epistemic Uncertainties (EUs) and Aleatory Variabilities (AVs) have to be identified, quantified and managed (i.e., IQM procedure) along this process (Passeri 2019). This operation is essential for rigorous consistency with the probabilistic seismic hazard analysis methodology (Cornell 1968). The epistemic uncertainties result from incomplete knowledge of the physics of the process and/or from insufficient and/or inadequate experimental data and models. They can, in principle, be reduced by the collection of additional and higher quality information and can be managed with advanced models. Aleatory variability refers to the intrinsic randomness of natural systems. It can be quantified, but it cannot be reduced using multiple experimental measurements.

The shear-wave velocity (V_S) profile is the parameter that controls the elastic behavior of the soil deposit. The V_S profiles are estimated by seismic (i.e., geophysical) tests that are often divided into two broad categories: invasive or non-invasive methods (Foti 2000). The use of non-invasive tests increasingly spread in standard practice because of their time and cost-effectiveness.

The identification of EUs and AVs in shear-wave velocity profiles should be performed by expert analysts, explicitly accounting for the geophysical theory that underlies each test. In particular, each seismic test shows typical sources of uncertainties and variabilities. The identification of EUs mainly depends on the adopted test and its configuration. The identification of AVs is a more complicated process and should account for the combination of the spatial resolution of the test and the site characteristics.

The quantification of EUs and AVs for shear-wave velocity profiles should evaluate the global engineering perspective of the case study and the spatial scale of the specific problem. Different geophysical methods are associated with a typical amount of EUs and AVs that strongly depend on the characteristics of the performed test (e.g., equipment used, external conditions) and investigated volume (e.g., the geological environment in addition to the site characteristics). Note that the amount of AVs depends on the dimensions of the studied area and/or the structure under design (e.g., a single building, a bridge, a motorway, or a tunnel).

The management of epistemic uncertainties and aleatory variabilities in shear-wave velocity profiles still represents an open issue (Stewart et al. 2014). For these purposes, two methods are presented in the Electric Power Research Institute (EPRI) guidelines and are usually adopted for scientific and technical applications (EPRI 2013). The first is referred to as alternative (upper-range and lower-range) method and is suggested for the management of epistemic uncertainties. The second is described in Toro (1995) as a geostatistical randomization model for the management of aleatory variabilities. Many authors demonstrated various limits of these methods in reproducing a consistent "picture" of uncertainties and variabilities. In particular, the upper-lower range profiles lead to a distorted response of the soil profile, mainly due to the scaling procedure (Griffiths et al. 2016, Teague & Cox 2016, Passeri et al. 2019). Similarly, the pioneering work by Toro generates shear-wave velocity models that are incompatible with the experimental evidence (i.e., the site signatures) (Griffiths et al. 2016, Teague et al. 2018, Passeri 2019). This is mainly due to the inadequate randomization approach that uses the interval velocity.

This paper proposes a new geostatistical model for the management of EUs and AVs in shear-wave velocity profiles specifically obtained by surface wave tests. The model can overcome the limitations of the usual methods adopted for scientific and technical applications.

2 THE GEOSTATISTICAL MODEL

2.1 *General characteristics*

The proposed geostatistical model has been developed for the management of the epistemic uncertainties and aleatory variabilities in V_S profiles obtained from active (i.e., Multistation Analysis of Surface Waves, MASW) and passive (i.e., Microtremor Array Measurement, MAM) surface wave methods (Passeri 2019). The model has four main general characteristics that are summarized in the following.

The geostatistical model is calibrated with a high-quality database of experimental measurements. It is based on the specifically compiled Polito Shear Wave velocity Database (PSWD). Each dataset has been reinterpreted with the same inversion approach to ensure the consistency of the results.

Usually, the randomization of the V_S profiles is based on the assumption of interval velocities (i.e., a stack of horizontal, parallel layers with constant V_S). The inadequacies of this scheme are extensively demonstrated in Passeri (2019). The interval velocity is only an engineering simplification adopted in GRA models. On the other hand, the proposed geostatistical model assumes a neat separation between the fundamental physical quantities of space and time. Indeed, it accounts for sources of EUs and AVs avoiding the generation of artificial uncertainties, which results from models that randomize separately the interval velocity and the depth of interfaces (i.e., layer thicknesses), as proposed in Toro (1995).

The new geostatistical model is test- and site-specific. This allows reproducing realistic (i.e., experimentally based) characteristics regarding both EUs and AVs. An in-depth study of the peculiarities of each geophysical test is essential for the development of a model that randomizes realistic V_S profiles. These randomized profiles must be consistent with the type and amount of uncertainties that are specific for each adopted test. In this paper, the model is calibrated for MASW and MAM tests. Also, the model reproduces the specific characteristics of the case study in terms of geological complexity included in the investigated volume. Indeed, the dimensions of the soil volume are fundamental for the IQM procedure.

Finally, the new geostatistical model is flexible for further improvements (e.g., an extension of applicability to other geophysical tests, such as Down-Hole tests). The "core" of the model remains fixed, whereas additional components can be introduced to specialize the model.

2.2 *Model "architecture"*

The general characteristics of the model summarized in Section 2.1 agree with the specific mathematical architecture described in Passeri (2019) and recalled here. We refer to the sequence of layers modeled in GRAs as the *column*. On the other side, we refer to the last layer with no thickness in the model as *halfspace*. Note that these definitions are disconnected from the usual definitions of *soil deposit* and *bedrock* based on the materials stiffness because the depth of characterization in surface wave tests may include stiff material within the soil column, or in some cases may not reach a stiff layer at depth. An inferential process conducted on the PSWD gave the essential information for the explicit development of the model separating the *column* and the *halfspace*.

The interval velocity can be instead expressed as a function of travel-time versus depth. Note that these independent parameters can be seen together as harmonic average velocity function with depth ($V_{S,z}$ (z)). For this purpose, an interval velocity profile can be converted in a harmonic average profile using Equation 1:

$$V_{S,z}(z) = \frac{z}{\sum_{i=1}^{n}\left(\frac{h_i}{V_{S,i}}\right)} = \frac{z}{tt_S(z)} \tag{1}$$

where z is the depth, n the number of layers of the interval velocity profile, h_i the thickness of the layer i, and $V_{S,i}$ is the velocity of the layer i. Note that the $V_{S,30}$ usually adopted for soil or rock classifications is only a particular value of this function. The harmonic average profile is closer to the real physics of the problem than the interval velocity profile as it is obtained dividing a length (i.e., depth) by the cumulated travel time tt_S. This last contribution is indeed the time that the wave spends to travel from the depth z to the surface and it is assumed log-normally distributed for the *column*. In addition, the randomization model uses a first-order auto-regressive model (AR1) for the inter-layer correlation of the *column*. Differently from Toro (1995), the correlation factor is applied to the cumulated travel times.

The model chosen for the spatial random variable of the *column* (i.e., the interfaces position with depth) is the Non-Homogenous Poisson model also adopted by Toro (1995). The Non-Homogeneous Poisson process is a Markovian and non-stationary process. The model is described by the Poisson exponential formulation:

$$f(h, z) = e^{-\lambda(z)h} \tag{2}$$

where $\lambda(z)$ is the depth-dependence occurrence rate, which can be modelled by a power-law model:

$$\lambda(z) = a(z + b)^c \tag{3}$$

The parameters (a, b, and c) can be site-specific (i.e., obtained from a regression based on experimental data, preferred choice) or generic, as proposed in Toro (1995). Two specific modifications are introduced to the basic formulation of the Non-Homogeneous Poisson's model. The first modification is to propose limits on the (z) resulting from the randomization process. The second modification is an acceptance or refusal criterion for the generated layering distributions. The refusal criterion is consistent with the depth resolution of the surface wave tests. This last improvement is essential to generate a layering compatible with the data included in the Experimental Dispersion Curve (EDC) as Rayleigh phase velocity (V_R) vs. frequency (f). The procedure follows a methodology discussed in Socco et al. (2017) that demonstrated the possible transformation of the EDC from V_R-wavelength to the harmonic average profile $V_{S,z}$ with depth. This linear transformation is termed “wavelength-depth” transformation.

The velocity of the *halfspace* can be modeled without separating length and time random variables, as it has not a spatial dimension (i.e., no thickness). The lognormal distribution can also be used for the *halfspace* shear-wave velocity. Similarly, the distribution of the *halfspace* depths can be approximated by the lognormal distribution. Also, the geostatistical model includes a correlation structure between the *halfspace* velocity and depth. As expected, if the *halfspace* depth increases, the V_S should increase to be consistent with the EDC.

3 APPLICATION

This section shows the main characteristics of the geostatistical model through an example of an application at the site of Accumoli (Italy). This validation exercise evaluates the model capability to reproduce the known solution obtained after the inversion of the experimental data. The statistical sample of V_S profiles obtained from the inversion represents the experimental “picture” of the uncertainties propagated on the final result (Foti et al. 2009, Comina et al. 2011). For further details, the reader can refer to Passeri (2019).

First, the input data for the randomization model are presented (Figure 1):

- Experimental dispersion curve of the Rayleigh waves phase velocity and Rayleigh waves phase velocity standard deviation (σ_{VR});
- Single (i.e., deterministic) interval velocity V_S profile (i.e., base-case profile).

Figure 1 shows the visual output of the model implemented in MATLAB® for the input parameters. It presents the base-case V_S profile in terms of interval and harmonic average profiles. Figure 1 also includes the EDC proposed as V_R-wavelength. The wavelength-depth linear transformation applied to the EDC shows the transformed EDC that is in excellent agreement with the $V_{S,z}$ profile of the base-case.

The geostatistical model is designed to be as independent as possible. The user has the initial control of the randomization, but each operation is conducted in automatic mode (if possible). One example is the regression of the model parameters for the Non-Homogeneous Poisson’s model presented in Figure 2a. At the same time, the model automatically limits the layering generations according to the user’s choice. This operation is conducted with an iterative process, and the result is illustrated in Figure 2a for the Accumoli’s example. Each point in

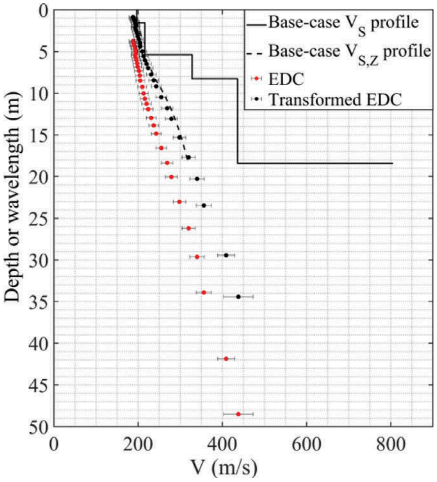

Figure 1. Input parameters for the geostatistical model as velocity profile and experimental dispersion curve associated with the base-case (Accumoli).

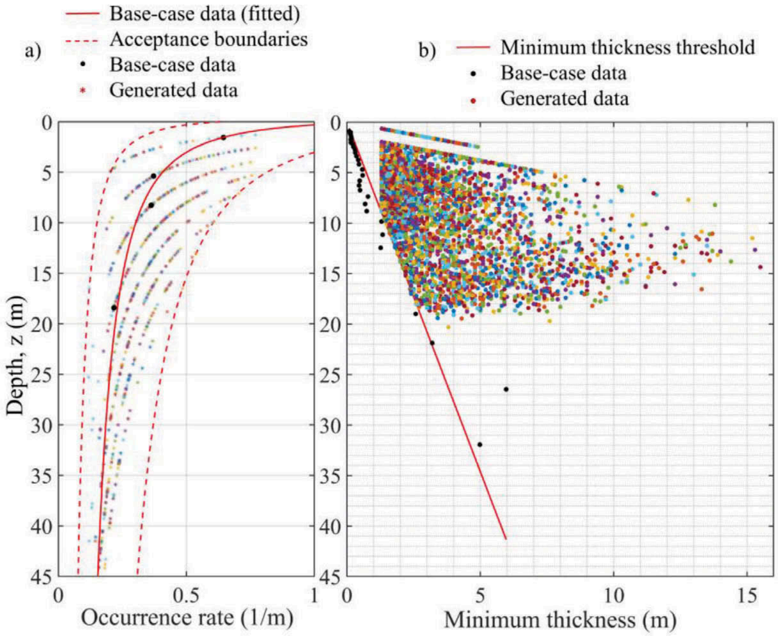

Figure 2. Layering generation for the example of Accumoli, a) occurrence rate of the base-case profile fitted and generated for the randomized profiles and b) minimum thickness limitation according to the experimental resolution with depth.

Figure 2a represents a generated value of occurrence rate (λ) within the user-defined boundaries. The different curves (i.e., exponential laws) are associated with a different number of layers generated by the model.

The layering generation is then limited according to the test resolution with depth. Figure 2b shows the generated points that respect the prescribed minimum thickness that is automatically calculated by a regression of the experimental data. Also, the user can select the minimum thickness of the first layer as 1/2 or 1/3 of the minimum experimental wavelength (in this case equal to 1.25 m) (Foti et al. 2018).

Once the layering distributions have been generated, the time randomization of the *column* is performed. The chosen model parameters for this example are suggested in Passeri (2019). Figure 3 shows the results of the randomization for Accumoli in terms of cumulated travel-times and harmonic average profiles (i.e., complete *column* randomization). Figure 3 confirms the accordance of the randomized profiles with the fundamental physical quantities of the problem. In particular, Figure 3b demonstrates that the $V_{S,z}$ and $V_{P,z}$ values calculated at the bottom of each generated layer are included in a restricted area.

Figure 4 illustrates the randomization of the base-case profile. Figure 4a shows the interval velocity profiles after the assembly of the layering (i.e., space) and time variables (Figure 3). Also, the velocity of the *halfspace* is merged into the interval velocity V_S and V_P profile as the last interface. Figure 4b shows the semi-independent randomization obtained exclusively for the *halfspace* regarding velocity and depth (the colors illustrate the points' density). These values are merged into the *column* preserving the layering previously generated with the Non-Homogenous Poisson's model (Passeri 2019).

The verification of the goodness of randomization is illustrated in Figure 5 in terms of Theoretical Dispersion Curves (TDCs, Figure 5a) and Theoretical Transfer Functions (TTFs, Figure 5b). The comparison shown in Figure 5a is not entirely adequate, as the TDC also depends on the Poisson's ratio (or, equivalently, V_P). In any case, the generated profiles are associated with consistent TDCs with respect to the TDC of the base-case profile. Figure 5a shows a significant improvement if compared with the solutions obtained by the Toro model

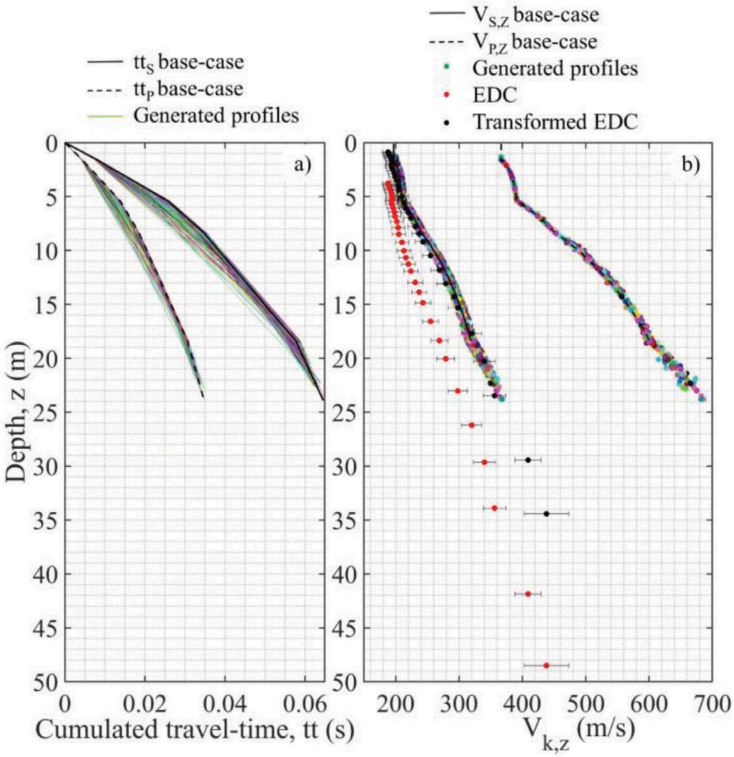

Figure 3. Results of the randomization for Accumoli. a) Randomized cumulated travel-times (for P- and S-waves) and b) randomized harmonic average profiles (for P- and S-waves).

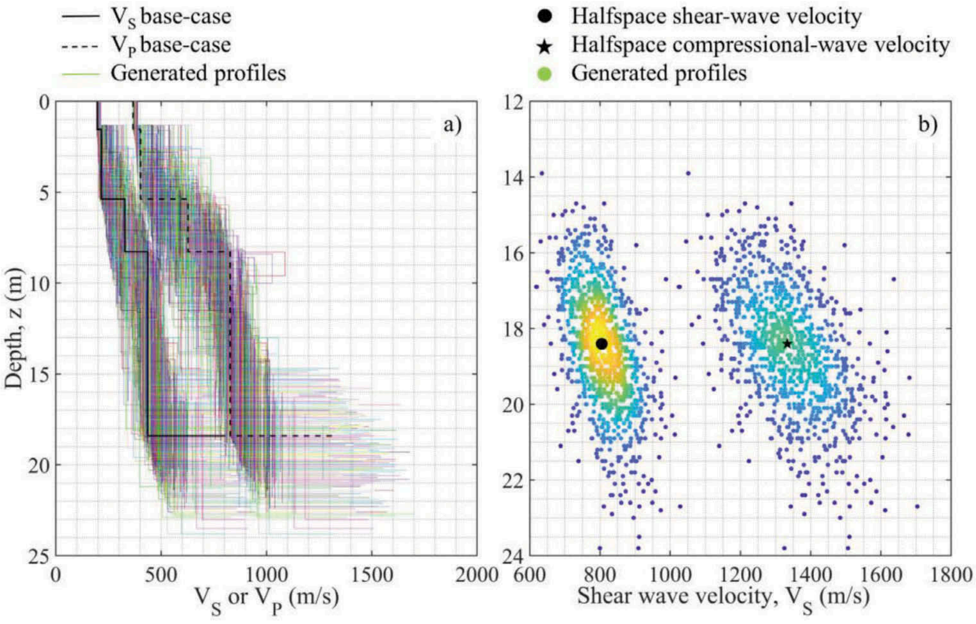

Figure 4. Complete Accumoli profile randomization. a) Reassembled interval velocity profiles for the column and b) Depth and velocity randomization of the halfspace.

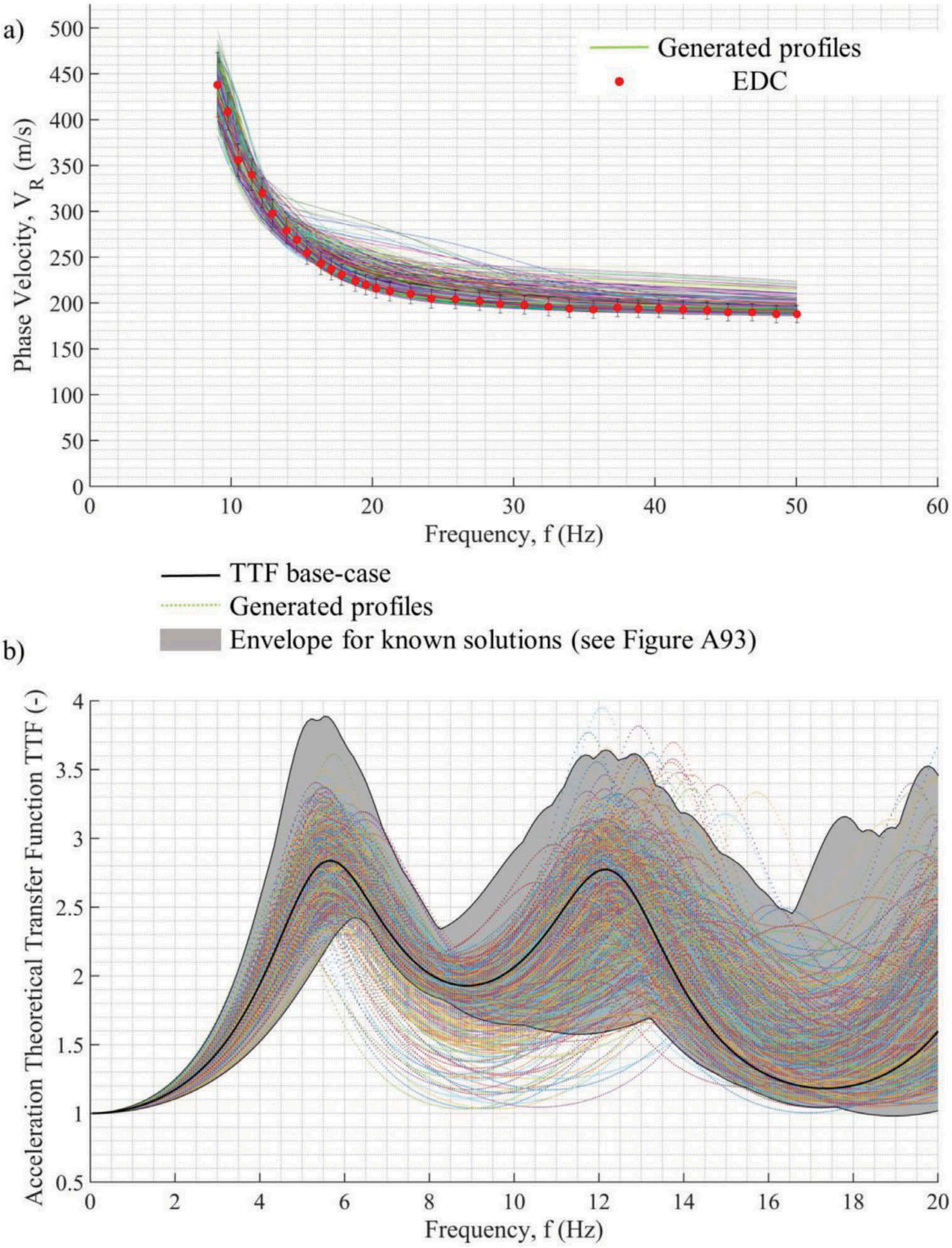

Figure 5. Validation of the randomization performed for the site of accumoli, a) Comparison as theoretical dispersion curves, and b) Comparison as theoretical transfer functions.

in Teague and Cox (2016), Griffiths et al. (2016), and Teague et al. (2018). Only small differences are identifiable at Figure 3. Results of the randomization for Accumoli. a) Randomized cumulated travel-times (for P- and S-waves) and b) randomized harmonic average profiles (for P- and S-waves).

high frequencies due to the generation of thicker, shallower layers that should have higher velocity to be consistent with the $V_{S,z}$ profile.

Figure 5b shows the excellent agreement between the TTFs of the generated profiles and the TTF of the base-case profile. In this regard, the geostatistical model respects the site signature in terms of both amplitudes and resonant frequencies. Figure 5b also shows (i.e., gray background) the envelope of the TTFs calculated from the equivalent profiles obtained after the inversion. It is clear that the geostatistical model reproduces well the variabilities obtained after the inversion process.

4 CONCLUSIONS

This paper focuses on the development of a new geostatistical model for the management of Epistemic Uncertainties (EUs) and Aleatory Variabilities (AVs) in shear-wave velocity profiles (V_S) obtained with surface wave methods. The new randomization model fits into the broad process of Identification, Quantification, and Management (IQM procedure) of EUs and AVs. This procedure represents a vital part of hazard-consistent probabilistic analyses conducted by means of Ground Response Analyses (GRAs). Various authors demonstrated the inadequacy of the methods proposed in EPRI (2013) for the management of EUs and AVs in V_S profiles. The geostatistical model overcomes the drawbacks of the methods usually adopted for scientific and technical applications, mostly thanks to the information gathered within the Polito Shear Wave velocity Database (PSWD). The essential characteristics of the proposed geostatistical model are the calibration with a high-quality database (PSWD), the separation of the physical primary random variables, the test- and site-specific features and the flexibility.

Validation of the proposed geostatistical model for surface wave testing methods is reported for a site included in the PSWD (Accumoli). In this case, the results are in agreement with the solutions obtained by the inversion process accounting for the geophysical equivalence (Foti et al. 2009). The comparison is performed for the Theoretical Transfer Functions (TTFs) that controls the dynamic small-strains behavior of the profile.

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