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# Vulnerability assessment for earthquake-liquefaction-induced settlements of an embankment using gaussian processes

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21 Earthquakes are the most natural phenomenon that cause damage to the soil and to  
22 the structures, in addition to other losses such as human and economic. Liquefaction phe-  
23 nomenon is considered as one of the most devastating and complex behaviours that affect the  
24 soil due to earthquake loading. It was observed that geotechnical structures, such as river  
25 dikes, highway embankments, and earth dams, founded on saturated loose sandy ground  
26 have been frequently damaged during past major earthquakes (Matsuo 1996; Ozutsumi et al.  
27 2002; Unjoh et al. 2012; Okamura et al. 2013). According to the state of the art in the  
28 assessment of earthquake-induced soil liquefaction performed by the National Academies of  
29 Sciences, Engineering, and Medicine (2016), it is necessary *to refine, develop, and implement*  
30 *performance-based approaches to evaluating liquefaction, including triggering, the geotech-*  
31 *nical consequence of triggering, structural damage, and economic loss models to facilitate*  
32 *performance-based evaluation and design.* The Pacific Earthquake Engineering Research  
33 Center (PEER)'s performance-based earthquake engineering methodology deals with four  
34 stages: the hazard analysis in which an intensity measure (*IM*) parameter is identified, the  
35 structural analysis in which the response to the earthquake is represented by the engineering  
36 demand parameter (*EDP*), the damage analysis in which the probability of failure is quan-  
37 tified and the final stage is the loss analysis which requires the estimation of the decision  
38 based on the cost and maintenance of the project (Porter 2003; Baker and Cornell 2008a).  
39 The present work would be dealing with two stages of this methodology: the structural and  
40 the damage analyses. The dynamic structural analysis requires a deterministic approach to  
41 calculate the used parameters of the study. As the final objective is to evaluate expected  
42 losses, it is necessary to perform a large number of non-linear calculations, providing suffi-  
43 cient details about the damage state and with an acceptable computational cost. Previous  
44 works have used such approach to study the apparition of soil liquefaction and their effects  
45 on the response of the structures or dams (Koutsourelakis et al. 2002; Juang et al. 2005;  
46 Popescu et al. 2006; Lopez-Caballero and Modaressi-Farahmand-Razavi 2010).

47 The aim of this work is to assess numerically the effect of soil liquefaction-induced failure

48 to a levee due to real earthquakes. A deterministic study to quantify a failure way of a  
49 levee (crest settlement) and a probabilistic study to find the probability of exceedance of a  
50 certain level of performance, took place. As a first approach, only the aspects concerning  
51 the uncertainties in the seismic ground motion are addressed. Fragility functions were drawn  
52 for this purpose. The Finite Element (FE) calculations were performed using the *GEFDyn*  
53 code and the numerical model was inspired from the one proposed by Rapti et al. (2017).  
54 Consequently, a database including a great number of ground motions is required to provide  
55 enough information to estimate in a reliable way the parameters defining the fragility curves  
56 (Luco and Cornell 2007; Saez et al. 2011).

57 However, due to the high computational cost to perform the numerous non-linear dynamic  
58 calculations, it is no feasible to explore a large design space using the complex proposed Finite  
59 Element model (FEM). In this context, fast-running models, also called surrogate models  
60 could be implemented by means of input-output data sets to approximate the response of the  
61 original FEM. Several kinds of surrogate models (e.g. Linear regression, Neural networks,  
62 Chaos polynomials, support vector machines among others) have been implemented to assess  
63 the damage of non linear structures or networks under earthquake loading (Bucher and Most  
64 2008; Cardoso et al. 2008; Seo et al. 2012; Ghosh et al. 2013; Gidaris et al. 2015; Ferrario  
65 et al. 2017; Stern et al. 2017). Hence, in this work a Gaussian Process model (GPM) was  
66 used as a surrogate model for the levee-foundation system, so as to reduce the computation  
67 time associated keeping an accurate prediction (Sacks et al. 1989; Toal et al. 2008). The  
68 GPM was built using input model parameters that are relevant to represent system response  
69 of the inelastic transient FE analysis. Once the GPM was trained and validated, it is applied  
70 to quantify the effect of soil liquefaction-induced failure on a levee subject to a large variety  
71 of earthquake events. In particular, the maximal induced crest settlement is computed and  
72 the corresponding fragility curves for a given damage threshold are estimated. Although  
73 Gaussian process emulators have been used in other disciplines, there is no knowledge of it  
74 having been implemented in the framework of performance-based approaches to evaluating

75 liquefaction induced damage of dams or embankments.

76 In the next section, a brief description of a construction of Gaussian process model is  
77 given. In the third section, a synthetic description of the Finite Element model used to  
78 simulate the levee is provided. Next, the main results of the analysis with the FEM are  
79 presented. In the the fifth section, the choice of the input parameters and the validation of  
80 the GPM in terms of its capability of prediction are shown. In the last section, intensive  
81 simulations are performed with the GPM in order to estimate the fragility curves for a given  
82 levee damage threshold. Finally, conclusions summarizing the obtained results and future  
83 developments of this work are provided.

## 84 GAUSSIAN PROCESS EMULATOR

85 A meta-model or surrogate model is an analytical function used to provide rapid approx-  
86 imations of more expensive models (e.g. an analytical model or a finite element numerical  
87 model). In the Gaussian process (GP), the responses and input values are combined statis-  
88 tically to create functional relationships in a non-intrusive approach (i.e. the original model  
89 is considered as a black box). One of the advantages of Gaussian processes is that they  
90 are flexible enough to represent a wide variety of complex models using a limited number  
91 of parameters. In contrast to other kind of meta-models (e.g. Linear regression, Neural  
92 networks, Chaos polynomials among others), GP provides a function that does not depend  
93 on the probabilistic model for the input data.

94 Let us consider a non-linear computer model response, that could be represented by  
95 a multivariate function  $\mathbf{y} = f(\mathbf{x})$ ; where  $\mathbf{x}$  is a  $d$ -dimensional vector describing the input  
96 parameters of the model and  $\mathbf{y}$  is a vector of  $n$  observed outputs. Usually,  $f(\mathbf{x})$  is deter-  
97 ministic whenever the same input ( $\mathbf{x}$ ) results in the same output ( $\mathbf{y}$ ). It is also assumed  
98 that evaluation of  $f(\mathbf{x})$  is computationally expensive, thus, only limited function evaluations  
99  $\mathbf{y}_1 = f(\mathbf{x}_1), \dots, \mathbf{y}_n = f(\mathbf{x}_n)$  are available. These evaluations are called experimental design  
100 (ED) and they are used as a database for training or learning the meta-model (i.e. the  
101 learning database LDB). The purpose of the meta-model is therefore to predict the response

102 ( $\mathbf{y} = f(\mathbf{x}^*)$ ) for a new data set where only the input  $\mathbf{x}^*$  are known (i.e. the test database,  
 103 TDB) (Sacks et al. 1989; Rasmussen and Williams 2006; DiazDelaO et al. 2013; Dubourg  
 104 et al. 2013; Strong and Oakley 2014). Hence, it is possible to obtain a statistical approxima-  
 105 tion to the output of a numerical model after evaluating a small number  $n$  of design points  
 106 if  $f(\mathbf{x})$  is modelled as a Gaussian process (GP). A GP is a collection of random variables,  
 107 which have a joint multivariate Gaussian distribution. The GP model will be separated in  
 108 mean and covariance functions :

$$109 \quad f(\mathbf{x}) = \mathbf{h}(\mathbf{x})^T \boldsymbol{\beta} + Z(\mathbf{x}) \quad (1)$$

110 where  $\mathbf{h}(\mathbf{x})^T \boldsymbol{\beta}$  is the mean function (usually modelled as a generalized linear model and  
 111 sometimes times assumed to be zero),  $\mathbf{h}(\mathbf{x})$  is a vector of known functions and  $\boldsymbol{\beta}$  is a vector of  
 112 unknown coefficients. The function  $Z(\cdot)$  is a Gaussian process with mean zero and covariance  
 113 function  $\text{Cov}(Z(\mathbf{x}), Z(\mathbf{x}') | \sigma^2, \theta)$  between output points corresponding to input points  $\mathbf{x}$  and  
 114  $\mathbf{x}'$  :

$$115 \quad \text{Cov}(Z(\mathbf{x}), Z(\mathbf{x}') | \sigma^2, \theta) = \sigma^2 \cdot c_\theta(\mathbf{x}, \mathbf{x}') \quad (2)$$

116 where  $\sigma^2$  is the variance of  $Z$ ,  $\theta$  the range parameter and  $c_\theta(\cdot, \cdot)$  its correlation function. The  
 117 GP assumes that the correlation between  $Z(\mathbf{x})$  and  $Z(\mathbf{x}')$  is a function of the “*distance*”  
 118 between  $\mathbf{x}$  and  $\mathbf{x}'$ . The covariance can be any function having the property of generating  
 119 a positive definite covariance matrix (Rasmussen and Williams 2006; Iooss et al. 2010). A  
 120 wide variety of covariance functions could be used in the Gaussian process framework, thus,  
 121 in this work three common correlation functions were used, namely, exponential (equation

122 3), Matérn (3/2) (equation 4) and  $\gamma$ -exponential (equation 5).

$$123 \quad c_{\theta}(\mathbf{x}, \mathbf{x}') = \exp \left\{ - \sum_{i=1}^d \frac{|x_i - x'_i|}{\theta_i} \right\} \quad (3)$$

$$124 \quad c_{\theta}(\mathbf{x}, \mathbf{x}') = \left( 1 + \frac{\sqrt{3}}{\theta} \|\mathbf{x} - \mathbf{x}'\| \right) \exp \left( - \frac{\sqrt{3}}{\theta} \|\mathbf{x} - \mathbf{x}'\| \right) \quad (4)$$

$$125 \quad c_{\theta}(\mathbf{x}, \mathbf{x}') = \exp \left\{ - \sum_{i=1}^d \left( \frac{x_i - x'_i}{\theta_i} \right)^{\gamma} \right\} \quad (5)$$

126 for  $\mathbf{x} = (x_1, \dots, x_d)$ . Note that equation 4 is parametrized as in Genton (2001). The hyper-  
 127 parameters involved in each covariance function are estimated by likelihood maximization.  
 128 Finally, the predictor and the variance of the GP for the new input  $\mathbf{x}^*$  are estimated as  
 129 follows:

$$130 \quad \mathbf{E}(f(\mathbf{x}^*)) = \mathbf{h}(\mathbf{x}^*)^T \boldsymbol{\beta} + \mathbf{k}(\mathbf{x}^*)^T \boldsymbol{\Sigma}^{-1} (f(\mathbf{x}) - \mathbf{h}(\mathbf{x})^T \boldsymbol{\beta}) \quad (6)$$

$$131 \quad \text{Var}(f(\mathbf{x}^*)) = \sigma^2 - \mathbf{k}(\mathbf{x}^*)^T \boldsymbol{\Sigma}^{-1} \mathbf{k}(\mathbf{x}^*) \quad (7)$$

$$132 \quad \mathbf{k}(\mathbf{x}^*) = \sigma^2 [c_{\theta}(\mathbf{x}_1, \mathbf{x}^*), \dots, c_{\theta}(\mathbf{x}_n, \mathbf{x}^*)]^T \quad (8)$$

$$133 \quad \boldsymbol{\Sigma} = \sigma^2 (c_{\theta}(\mathbf{x}_i, \mathbf{x}_j))_{i=1 \dots n, j=1 \dots n} \quad (9)$$

134 where  $\boldsymbol{\Sigma}$  is the covariance matrix. Refer to Sacks et al. (1989), Rasmussen and Williams  
 135 (2006) or Iooss et al. (2010) among others for further details about the GP meta-model.

## 136 **SELECTED LEVEE CASE STUDY**

137 The geometry of the model, as shown in Figure 1(a), consists of an embankment of 9m  
 138 high composed of dry dense sand. The soil foundation is composed of a liquefiable loose-to-  
 139 medium sand (*LMS*) of 4m at the top of a saturated dense sand of 6m. The bedrock at the  
 140 bottom of the dense sand has a shear wave velocity ( $V_s$ ) equal to 1000m/s and a mass density  
 141 ( $\rho_{bd}$ ) of 2000kg/m<sup>3</sup>. The water table is situated at 1m below the base of the embankment  
 142 and it was kept dry. The levee's inclination is a slope of 1:3 (vertical: horizontal). The  
 143 geometry used in the FEM was inspired from the one proposed by Rapti et al. (2017).

144 All computations were conducted with GEFD $_{yn}$  FE code (Aubry et al. 1986; Aubry and  
145 Modaressi 1996). The elastoplastic multi-mechanism model briefly described below is used  
146 to represent the soil behaviour (Figure 1(a)). For the bedrock representing a half-space, an  
147 isotropic linear elastic behaviour was assumed. The model length is 194m.

148 A 2D coupled dynamic approach derived from the  $\underline{u} - p_w$  version of the Biot's generalized  
149 consolidation theory (Zienkiewicz and Shiomi 1984) was adopted for the soil. The so-called  
150  $\underline{u} - p_w$  formulation, consists of neglecting fluid acceleration terms and convective terms  
151 of this acceleration so that the unknown variables remain the displacement of the solid  
152  $\underline{u}$  and the pressure of the water  $p_w$ . The saturated soil was modelled using quadrilateral  
153 isoparametric elements with eight nodes for both solid displacements and fluid pressures.  
154 The size of elements is 0.5m $\times$ 0.5m. It was chosen in order to have 8 to 10 elements per  
155 wavelength which are sufficient to prevent numerical dispersion. A plane-strain condition  
156 was assumed in the finite element model. In the analysis, only vertically incident shear waves  
157 are introduced into the domain and as the response of an infinite semi-space is modelled,  
158 equivalent boundaries have been imposed on the nodes of lateral boundaries (i.e. the normal  
159 stress on these boundaries remains constant and the displacements of nodes at the same depth  
160 in two opposite lateral boundaries are the same in all directions). The model is 194m wide  
161 so as to ensure that the effect of the boundaries on the model response can be neglected  
162 and also to satisfy the free field condition at the lateral boundaries. For the half-space  
163 bedrock's boundary condition, paraxial elements simulating "*deformable unbounded elastic*  
164 *bedrock*" have been used (Modaressi and Benzenati 1994). The incident waves, defined at  
165 the outcropping bedrock are introduced into the base of the model after deconvolution.

166 The elastoplastic multi-mechanism model developed at *Ecole Centrale Paris* (ECP)  
167 (Aubry et al. 1982) is used to represent the soil behaviour. This model can take into  
168 account the soil behaviour in a large range of deformations. The model is written in terms of  
169 effective stress. The representation of all irreversible phenomena is made by four coupled el-  
170 elementary plastic mechanisms: three plane-strain deviatoric plastic deformation mechanisms



171 in three orthogonal planes and an isotropic one. The model uses a Coulomb-type failure  
172 criterion and the critical state concept. The evolution of hardening is based on the plastic  
173 strain (deviatoric and volumetric strain for the deviatoric mechanisms and volumetric strain  
174 for the isotropic one). To take into account the cyclic behaviour a kinematical hardening  
175 based on the state variables at the last load reversal is used. The soil behaviour is decom-  
176 posed into pseudo-elastic, hysteretic and mobilized domains. Refer to Aubry et al. (1982),  
177 Lopez-Caballero and Modaressi-Farahmand-Razavi (2008) among others for further details  
178 about the ECP model. The obtained curves of cyclic stress ratio ( $SR = \sigma_{v-cyc}/(2 \cdot p'_o)$ ), with  
179  $\sigma_{v-cyc}$  the cyclic vertical stress applied in the cyclic loading) as a function of the number of  
180 loading cycles to produce liquefaction ( $N$ ) and  $G/G_{max} - \gamma$  curves are given in Figure 1(a).  
181 As qualitative comparison, the modelled test results are compared with the experimentally  
182 obtained curves given by Byrne et al. (2004) for Nevada sand at different densities (i.e.  $D_r$   
183 = 40% and 60%) and with the reference curves given by Seed and Idriss (1971).

## 184 **Input earthquake motion**

185 The selection of input motions for geotechnical earthquake engineering problems is im-  
186 portant as it is strongly related to the non-linear dynamic analyses. So as to obtain analytical  
187 fragility curves, it is necessary to analyse the embankment response to a wide range of ground  
188 motions. In addition, when dealing with surrogate models, it is required to have a repre-  
189 sentative set of data to train, to validate and to test the proposed meta-model. A total of  
190 540 unscaled records were chosen from the Pacific Earthquake Engineering Research Center  
191 (PEER) database (Ancheta et al. 2013), the Center for Engineering Strong Motion Data  
192 and the Kiban Kyoshin strong-motion network (KIK-NET) (Aoi et al. 2001). The events  
193 range between 5.2 and 7.6 in magnitude and the recordings have site-to-source distances  
194 from 15 to 50km and concern dense-to-firm soil conditions (i.e.  $360\text{m/s} < V_{s\ 30m} < 800\text{m/s}$ ).  
195 All input signals have a baseline correction, a sampling time ( $\Delta t$ ) equal to 0.005s and they  
196 are filtered using a *non-causal* 4th-order Butterworth bandpass filter (i.e. Zero-phase digital  
197 filtering), between 0.1-25Hz.

198 The database was split as follows : 95 signals concern the learning database (LDB),  
199 50 ground-motions are used for the validation set (VDB) and the test database (TDB) is  
200 composed of 395 unscaled records. The statistics on some input earthquake characteristics  
201 obtained for each database are summarized in Table 1. These earthquake characteristics are  
202 maximal outcropping acceleration ( $a_{max\ out}$ ), Arias intensity ( $I_A$ ), mean period ( $T_m$ ), peak  
203 ground velocity ( $PGV$ ), period of equivalent harmonic wave ( $T_{V/A} = \alpha \cdot PGV/a_{max\ out}$ , with  
204  $\alpha=4.89$ ) and significant duration from 5% to 95% Arias intensity ( $D_{5-95}$ ).

## 205 **RESULTS WITH THE LEARNING DATABASE SET (LDB)**

206 For embankments placed in seismic zones, it has been shown that the widespread damage  
207 to such embankments occurred mainly due to the liquefaction of foundation soil, resulting  
208 in excessive settlements, lateral spreading and slope instability (Sharp and Adalier 2006;  
209 Oka et al. 2012; Okamura et al. 2013). Thus, in this study, the crest settlement is chosen  
210 to be the mode of failure because it is a quantifiable measurement. Figure 1(b) shows a  
211 zoomed view of the typical response of vertical displacement contours in the levee after the  
212 earthquake loading. The computed deformed shape is characterized by a crest settlement  
213 due to soil liquefaction in the foundation and associated with lateral spread in foundation  
214 soil. In addition, Figure 1(c) shows a box plot of the ratio of CPU time per earthquake  
215 duration spent to perform the computations using LDB and VDB sets. It is noted that for  
216 the used FE model, CPU time varies between 1.2 and 1.7 minutes per second of earthquake  
217 duration. It means that a single FEM run for an earthquake with a typical duration of 30s,  
218 takes approximatively 35 to 55 minutes.

219 Even if the earthquake loading applied to the soil-levee system is very complex, it is  
220 necessary to select few strong-motion intensity parameters that can be accurately represent  
221 the levee behaviour. Swaisgood (2003) analysed a historical database on the performance  
222 of dams during earthquakes and found that the crest settlement is directly related to some  
223 input ground motion characteristics (i.e. the peak ground acceleration and magnitude). In  
224 addition, he proposes four damage levels according to the induced crest settlement. Following

225 Swaisgood’s proposition, in this work the obtained percentage crest settlement ( $\delta u_{z,rel}/H$ ,  
226 where  $u_{z,rel}$  is the crest settlement,  $H$  is the height of the dam and the foundation which is  
227 19m as seen in Figure 1(a)) is compared to the peak ground acceleration at the outcropping  
228 bedrock ( $a_{max\ out}$ ). To take into account all the signals in the LDB set, the crest settlement  
229 was calculated accordingly and was drawn as function of  $a_{max\ out}$  (Figure 2(a)). It is interest-  
230 ing to note that, as expected, the calculated crest settlement increases when the acceleration  
231 at the outcrop increases.

232 On the other hand, it is also noticed that two motions with very different  $a_{max\ out}$  values  
233 could provide the same crest settlement ratio (i.e. damage level), which implies that not  
234 only the amplitude of a motion controls the levee response. Hence, Kawase (2011) proposes  
235 to use the equivalent predominant frequency ( $1/T_{V/A}$ ), the maximum velocity ( $PGV$ ) and  
236 acceleration of the ground motion to represent the earthquake loading. Figure 2(b) displays  
237 the variation of crest settlement ratio of the FE model as a function of  $a_{max\ out}$  and  $1/T_{V/A}$ . It  
238 is observed that the values of increasing crest settlements of the FE models follow the lines of  
239 increasing velocity. In addition, according to Kayen and Mitchell (1997) and Koutsourelakis  
240 et al. (2002) among others, the liquefaction induced seismic settlement on structures is also  
241 well correlated with the Arias intensity value, which represents the input seismic energy.

## 242 **NONLINEAR SYSTEM IDENTIFICATION USING GPM**

243 One of the problem of calibrating or training a surrogate model (GPM) to observations  
244 from the numerical model (FEM) deals with finding input values such that the GPM outputs  
245 match the observed data as closely as possible. According to the previous section, several  
246 strong-motion intensity parameters have a great influence on the levee response, e.g.  $a_{max\ out}$ ,  
247  $1/T_{V/A}$  and  $I_A$  among others. Thus, it means that the proposed GPM will be a multiple-  
248 input single-output one. Other aspect concerns the correlation function defining the Gaussian  
249 process itself (i.e. found the unknown hyperparameters). As recalled before, three common  
250 correlation functions will be tested in this section, equations 3 to 5. The hyperparameters  
251 for those models are estimated with the R-code packages for the Analysis of Computer

252 Experiments developed by Roustant et al. (2012). Once the GPM was trained with the  
 253 LDB set, the possible models are validated, hence, a comparison of all responses in terms  
 254 of  $\delta u_{z,rel}/H$  obtained with FEM and predicted by GPM using the VDB set will be done.  
 255 Further, the selected GP model is tested on a database (TDB) that is similar in structure  
 256 to the database which was used for training, but was not used to built the surrogate model.

257 Figure 3 displays a comparison of the distribution of the GPM input parameters used as  
 258 training set (LDB) and the set which is used to validate the predictions of the model on new  
 259 data (VDB). It concerns three possible input parameters, namely,  $1/T_{V/A}$ ,  $a_{max\ out}$  and  $I_A$ .  
 260 It is important to note the great variance of those distributions and the overlap between the  
 261 training data and the validation one.

262 In order to assess how well the GP model has been trained (i.e. Validation phase) a com-  
 263 parison between the  $\delta u_{z,rel}/H$  values obtained with the FEM and the mean predicted ones  
 264 by the GPM using the VDB set is done (Figure 4). Thus, the relative error or discrepancy  
 265 between the GPM predictions ( $y_i^{pred}$ ) with the FEM computations ( $y_i$ ) is calculated with the  
 266 predictive squared correlation coefficient ( $Q^2$ ) :

$$267 \quad Q^2(y_i, y_i^{pred}) = 1 - \frac{\sum_{i=1}^N (y_i^{pred} - y_i)^2}{\sum_{i=1}^N (y_i - \mu_y)^2} \quad (10)$$

268 where  $\mu_y$  is the mean of the  $N$  observations (i.e. FEM computations). It ranges between 0  
 269 and 1. The results of the performed parametric study are summarized in Table 2 for a size of  
 270 the learning sample ( $N_{LDB}$ ) equal to 95. For the sake of brevity, only the two better responses  
 271 are displayed in Figure 4. It is noted that, the best fit to the FEM data is given for the  
 272 case when three input parameters are used and the exponential and  $\gamma$ -exponential covariance  
 273 functions seem to provide the best predictions. When only 2 input parameters ( $1/T_{V/A}$  and  
 274  $a_{max\ out}$ ) are used to train the GPM, the best fit is obtained with the  $\gamma$ -exponential covariance  
 275 function.

276 In addition, it is well know that the choice and the size of the learning samples are key

277 issues on the quality of the GPM predictions. Thus, in order to study the evolution of the  
 278 estimated  $Q_{VDB}^2$  criteria as a function of the size of the learning sample ( $N_{LDB}$ ) the following  
 279 procedure was used: For both, a fixed  $N_{LDB}$  value (ranging from 20 to 95) and for a GPM  
 280 type, the 95 signals from the learning database are permuted randomly and the first  $N_{LDB}$   
 281 samples are used to construct the GPM. Then, the accuracy of the prediction of the obtained  
 282 GPM is evaluated using the  $Q_{VDB}^2$  criteria. This procedure is repeated 20 times for each  
 283 fixed  $N_{LDB}$  value and the obtained median value is used to define the accuracy of the GPM.  
 284 As example, Figure 5 displays the boxplots of the obtained  $Q_{VDB}^2$  evolution as a function  
 285 of the learning sample size ( $N_{LDB}$ ) for a)  $\gamma$ -exponential GPM with 2 input parameters and  
 286 b) Exponential GPM with 3 input parameters. It is observed that in the case when three  
 287 input parameters ( $1/T_{V/A}$ ,  $a_{max\ out}$  and  $I_A$ ) are adopted the variation of the estimated median  
 288  $Q_{VDB}^2$  value with  $N_{LDB}$  is very small.

289 Concerning the variance of the GPM, Figure 6(a) displays the obtained mean squared  
 290 error (MSE) of predictions as a function of  $1/T_{V/A}$  and  $a_{max\ out}$  using the model with 3 input  
 291 parameters. It is noted that the obtained MSE values are in general less than 0.2 for the  
 292 cases when  $a_{max\ out} < 1g$ . On the other hand, it is important to note that for the same input  
 293 values, a reduction in the MSE values is found with respect to the ones obtained when the  
 294 GPM with 2 input parameters is used (Figure 6(b)). This figure shows the ratio between the  
 295 MSE for 3 input parameters and the one for 2 input parameters ( $\delta MSE = MSE_{3pr} / MSE_{2pr}$ ).

296 Finally, the GPM with 2 input parameters and with 3 input ones that provided the best  
 297 fits are now used to simulate other earthquake scenarios (i.e. TDB with 445 signals). The  
 298 mean  $\delta u_{z,rel} / H$  values predicted by the two GPM are shown in Figure 7. It can be noted  
 299 that both GP models selected for this study show a reasonable capability to reproduce the  
 300 variation of  $\delta u_{z,rel} / H$  as a function of  $a_{max\ out}$ . However, visually a less dispersion in the  
 301 predicted values seems to be obtained using the 2 input parameters model for  $a_{max\ out}$  values  
 302 between 0.4 and 0.6g.

## 303 EVALUATION OF LEVEE VULNERABILITY USING GPM

304 In the context of the PBEE, the damage analysis, which is the third stage of this method-  
 305 ology, is a procedure to quantify the structural damage. It consists of setting fragility func-  
 306 tions in order to find the conditional probability of the design to exceed a certain level of  
 307 performance for a given seismic input motion parameter. Usually, fragility curves are con-  
 308 structed by using a single parameter to relate the level of shaking to the expected damage  
 309 (Koutsourelakis et al. 2002; Baker and Cornell 2008a; Zentner 2010). So as to derive analyt-  
 310 ical fragility functions, it is necessary to define damage states in terms of some mechanical  
 311 parameters that can be directly obtained from the analysis (e.g.  $\delta u_{z,rel}/H$ ). The damage  
 312 states limits or the performance levels of the levee are those proposed by Swaisgood (2003).  
 313 The three damage levels thresholds are superposed in Figures 2(a) and 7. They correspond  
 314 to  $\delta u_{z,rel}/H=0.02, 0.2$  and  $1.0\%$ . In this work, the fragility curves are constructed following  
 315 the methodology proposed by Shinozuka et al. (2000), i.e. the maximum likelihood method  
 316 is used to compute numerical values of the estimators  $\hat{\alpha}$  and  $\hat{\beta}$  of Log-normal distribution.

317 The obtained fragility curves for the third and fourth state damages (i.e. minor to  
 318 moderate and moderate to serious damages) are shown in Figure 8. These curves are drawn  
 319 as solid lines whereas the statistical confidence of the derived fragility curves are drawn as  
 320 dashed lines (i.e.  $\{\hat{\alpha} \hat{\beta}\} \pm \{\sigma_1 \sigma_2\}$ ). This confidence is a function of the information provided  
 321 by the size of motion database over the parameters  $\hat{\alpha}$  and  $\hat{\beta}$  describing the shape of each  
 322 curve and it is computed via the Fisher information matrix (Saez et al. 2011). Figure 8(a)  
 323 presents fitted fragility functions obtained for two damage levels with respect to  $a_{max out}$  using  
 324 the FEM and the training dataset (LDB) (Figure 2(a)). These curves are used as reference  
 325 case study. The obtained  $\hat{\alpha}$ ,  $\hat{\beta}$ ,  $\sigma_1$  and  $\sigma_2$  values at which the levee reaches the threshold of  
 326 the minor to moderate and moderate to serious damages are provided in Table 3. According  
 327 to Figure 8(a), it is clear that, for this database size, no enough information is available  
 328 to develop a fragility curve for moderate to serious damages. It includes less information  
 329 regarding statistical confidence of parameters. For a given value of  $a_{max out}$ , the probability  
 330 of exceeding the damage threshold varies up to  $\pm 15\%$ . Consequently, a database including

331 a great number of ground motions is required to provide enough information to estimate in a  
332 reliable way the parameters defining the fragility curve (Luco and Cornell 2007; Seyed et al.  
333 2010; Lancieri et al. 2015). Due to the high computational cost to perform the numerous  
334 non-linear dynamic calculations of the TDB set with the FEM (Figure 1(c)), the proposed  
335 GPM with 3 input parameters was used. A comparison of the fragility curves obtained using  
336 the GPM and the FEM is displayed in Figure 8(b) and 8(c). This comparison is done for  
337 two damage levels (i.e. minor to moderate and moderate to serious damages) with respect to  
338  $a_{max\ out}$ . GPM curves displayed in these figures have been derived using 445 ground motions  
339 (i.e. VDB and TDB set).

340 According to this comparison, the benefit of using a surrogate model appears principally  
341 in the reduction of the statistical confidence of the derived fragility curves for both damage  
342 levels by increasing the size of tested motions (i.e. the obtained  $\sigma_1$  and  $\sigma_2$  values, Table 3).  
343 It is noted that a reduction in the  $\sigma$  values for each fragility curve is obtained when the GPM  
344 predictions are used. A reduction of 70% for the case of minor to moderate damage and  
345 50% for the moderate to serious damage. However, concerning the mean values, for the case  
346 of minor to moderate damage (Figure 8(b)), both  $\hat{\alpha}$  and  $\hat{\beta}$  estimators have similar values  
347 independent of the used database. On the contrary, for the moderate to serious damage  
348 (Figure 8(c)), it is noted that the fragility curve shifts slightly to higher acceleration values  
349 when the GPM is used. It means that for the same  $a_{max\ out}$  input value a lower probability  
350 of exceedance is found. Finally, it is important to note that both curves obtained with the  
351 GPM are placed inside the statistical confidence of the derived FEM fragility curves. This  
352 parametric study confirms that the use of a well constructed surrogate models allows to  
353 obtain fragility curves with a reasonable accuracy and with a manageable computational  
354 effort.

355 Moreover, so as to assess the performance of the obtained GPM, a comparison between  
356 the computed fragility curves using the predicted values from the GPM and the obtained  
357 ones with FEM employing the TDB set is performed (Figure 9). It is noted that the curves

358 obtained using the two approaches are comparable. For the case of minor to moderate  
359 damage level (Figure 9(a)), some differences for higher acceleration values are remarked and  
360 on the contrary, for the moderate to serious damage level case the discrepancies are found for  
361 lower acceleration values (Figure 9(b)). These results confirm that for this particular case,  
362 the mean predicted GP values provide a good approximation to the FE outputs. However,  
363 it is clear that those differences could be reduced if the LDB is enriched with more input  
364 data in the regions where the variance is maximum (see Figure 6(a)).

365 Coming back to Figure 2(b), the response of the levee is a function of  $a_{max\ out}$  and  $1/T_{V/A}$ ,  
366 thus, the induced damage must be also related with a vector composed by various input  
367 motion parameters, characterizing different aspects of the shaking (Baker and Cornell 2008b;  
368 Seyedi et al. 2010). Hence, a comparison of the obtained distribution of the induced damage  
369 levels in the levee as two dimensional failure surfaces is provided in Figure 10. Figures 10(a)  
370 and 10(b) show the distribution obtained with the FEM using the LDB and with the GPM  
371 using the TDB respectively. It is remarked that the boundaries between each damage level  
372 are well defined for both studied cases and only few responses (i.e. a vector of  $1/T_{V/A}$ ,  $a_{max\ out}$   
373 and DL) are overlapped. It is also noted the shape similarity between the observed surface  
374 (FEM-LDB) and the predicted one (GPM-TDB), which confirms again the applicability of  
375 the proposed metamodel to approximate the induced settlement and damage level in the  
376 levee for the range of parameters considered. Again from Figure 10, those results imply that  
377 instead of use fragility curves, fragility surfaces must be used to improve the representation  
378 of the strong ground motion in the damage assessment of the studied non-linear system  
379 (Seyedi et al. 2010). Nevertheless, this aspect is out of the scope of the present work but  
380 further researches will be done in this direction.

## 381 CONCLUSIONS

382 A FE analysis and a meta-model were used to investigate the soil liquefaction induced  
383 settlement and associated damage for an levee due to real earthquakes. Fragility functions  
384 were obtained for that purpose. The main conclusions drawn from this study are as follows:



385 Seismic demand fragility evaluation is one of the basic elements in the framework of  
386 performance-based earthquake engineering (PBEE). For solving the absence of sufficient  
387 Finite Element responses to obtain fragility curves with a reasonable accuracy, a Gaussian  
388 process model was build to mimic the FEM and used to increase the number of levee model  
389 evaluations reducing the computational time.

390 The predictive capability of the adopted GPM was assessed comparing the obtained levee  
391 settlements and induced damage levels with the ones simulated with the FEM. With respect  
392 to the case study considered, the GPM has shown a good capability of approximating the  
393 non-linear FEM response.

394 Results reveal that a GPM with three inputs parameters (i.e.  $1/T_{V/A}$ ,  $a_{max out}$  and  $I_A$ )  
395 to describe the liquefaction induced settlement of a levee, provides the most accurate esti-  
396 mates. Further investigations in this direction will be needed in order to obtain more general  
397 conclusions for diverse structure and soil typologies.

398 Based on these analyses, it is concluded that the proposed Gaussian process model is  
399 accurate enough for practical purposes and represents an important economy in CPU con-  
400 sumption time. It is confirmed by the comparison between the fragility curves obtained by  
401 the two methods on the test data set.

402 Further research can be done to ameliorate the results as to account for a better way  
403 to select the input parameters and to minimize the number of FEM computations so as to  
404 reduce discrepancies between both models (i.e. FEM and GPM).

405 Finally, it was found that fragility surfaces must be used to improve the representation  
406 of the strong ground motion in the damage assessment of the studied non-linear system.  
407 Further researches will be done in this direction.

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**TABLE 1. Statistics characteristics for the selected earthquakes in each database (DB)**

Parameter	LDB Range	VDB Range	TDB Range
$a_{max\ out}$ [g]	0.01 – 1.93	0.03 – 1.16	0.03 – 1.93
$T_m$ [s]	0.12 – 1.69	0.17 – 1.69	0.17 – 1.81
$T_{V/A}$ [s]	0.09 – 1.91	0.13 – 1.42	0.13 – 1.32
$I_A$ [m/s]	0.001 – 20.64	0.04 – 4.13	0.004 – 20.64
$D_{5-95}$ [s]	2.26 – 69.84	2.96 – 42.77	2.26 – 47.36
$PGV$ [cm/s]	0.23 – 167.6	4.27 – 83.58	0.86 – 166.1
DB Size	95	50	395



**TABLE 2. Relative error between the GPM predictions and the FEM computations. Case of VDB set.**

Covariance Function	$Q_{VDB}^2$ [1]	$Q_{VDB}^2$ [1]
	2 input param. $N_{LDB}=95$	3 input param. $N_{LDB}=95$
Matérn (3/2)	0.63	0.83
Exponential	0.74	0.94
$\gamma$ -exponential ( $\gamma = 2$ )	0.80	0.93

**TABLE 3. Fragility curve parameters from the mean GPM predictions (TDB set) and the FEM computations (LDB set).**

Damage state	FEM				GPM				$\sigma_{\text{GPM}}/\sigma_{\text{FEM}}$	
	$\hat{\alpha}$	$\hat{\beta}$	$\sigma_1$	$\sigma_2$	$\hat{\alpha}$	$\hat{\beta}$	$\sigma_1$	$\sigma_2$	$\sigma_1$	$\sigma_2$
DL III	0.21	0.26	0.015	0.067	0.21	0.21	0.005	0.023	0.33	0.34
DL IV	0.45	0.51	0.041	0.135	0.47	0.53	0.021	0.068	0.51	0.50

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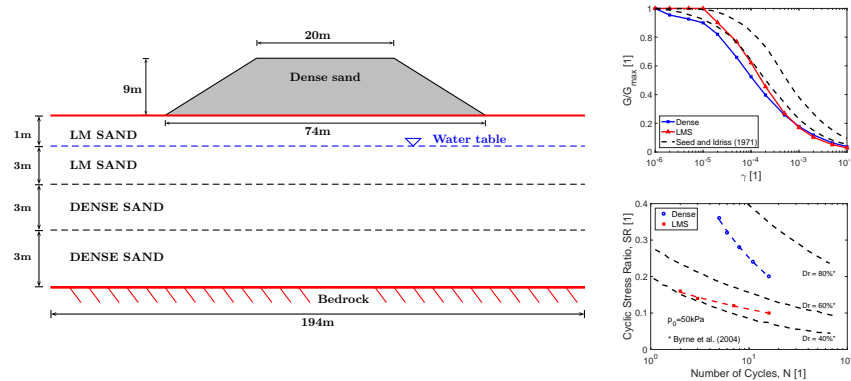
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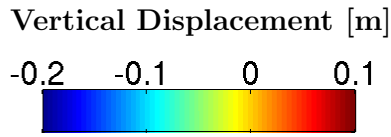
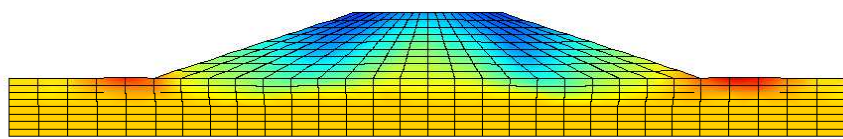
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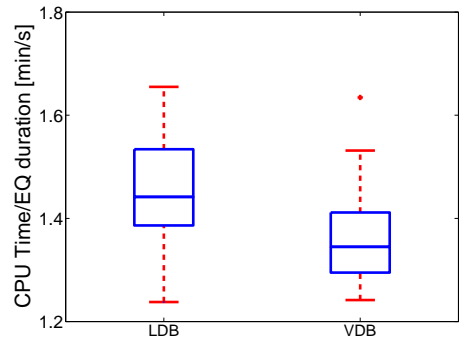
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(a)



(b)



(c)

**FIG. 1. a) Geometry and behaviour of soils used in the numerical model; b) Enlarged view of typical vertical co-seismic displacement contours at the end of the shaking and c) box plot of the ratio of CPU time per earthquake duration spent to perform the computations using LDB and VDB sets.**

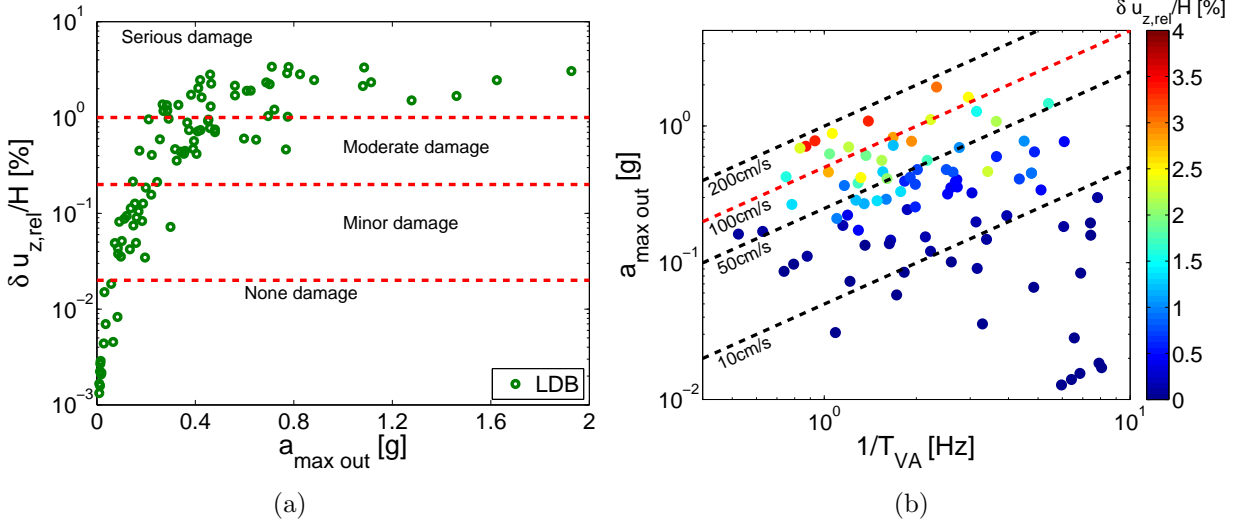


FIG. 2. Scatter plot of crest settlement ratio of the FE model as a function of a)  $a_{max\ out}$  and b)  $a_{max\ out}$  and  $1/T_{VA}$ . Case of LDB sets.

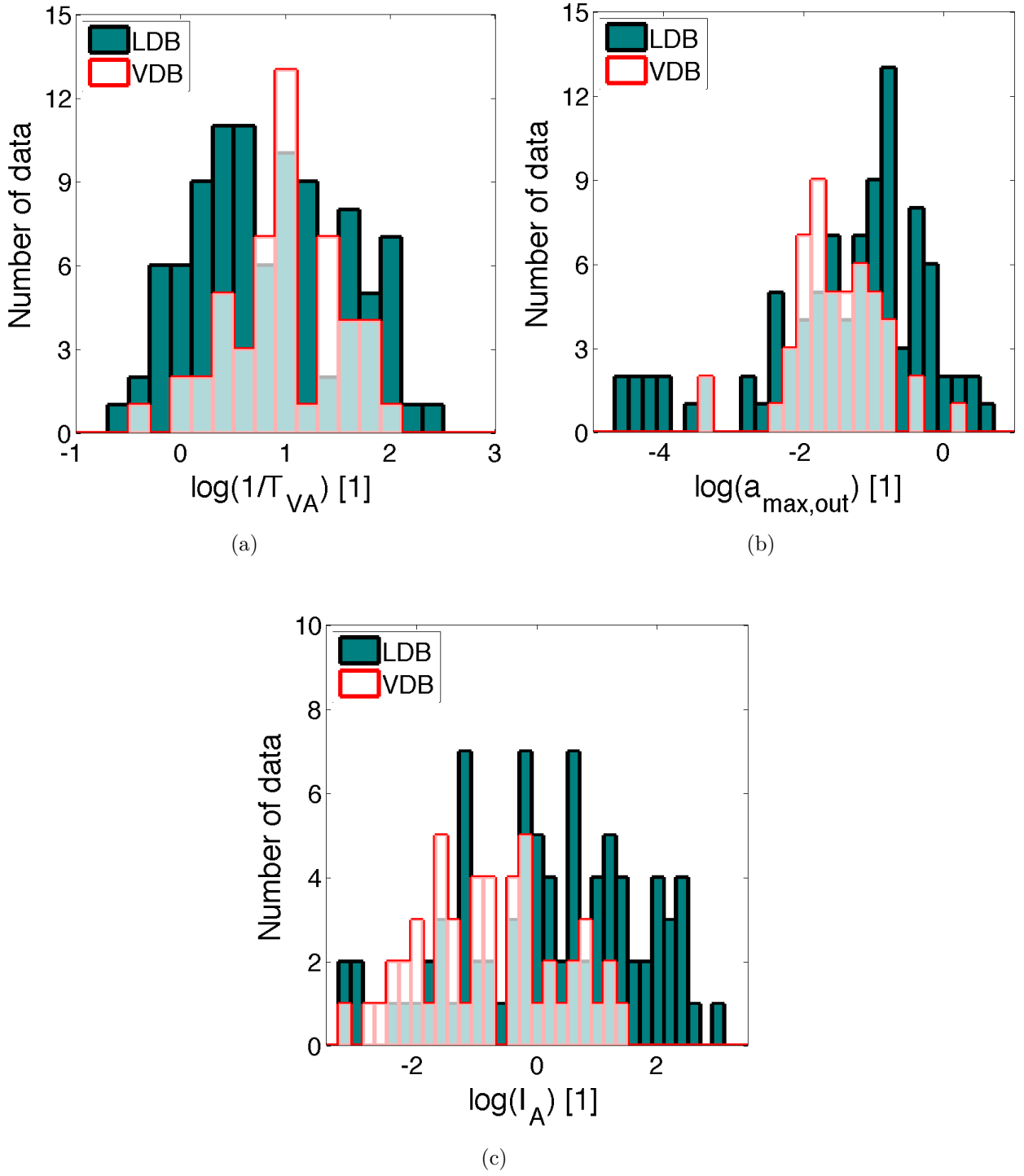
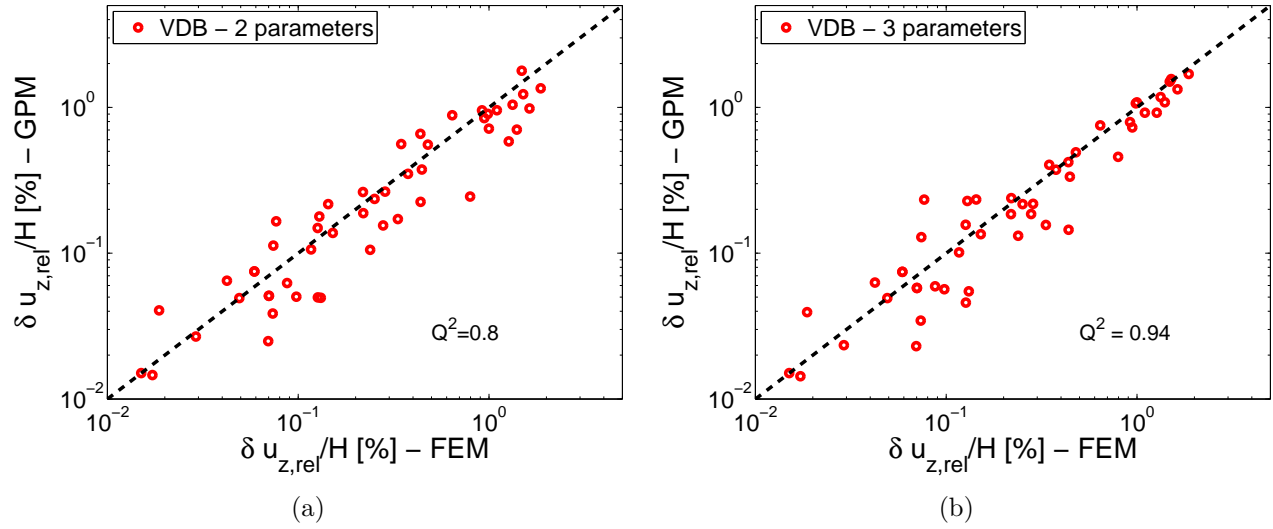
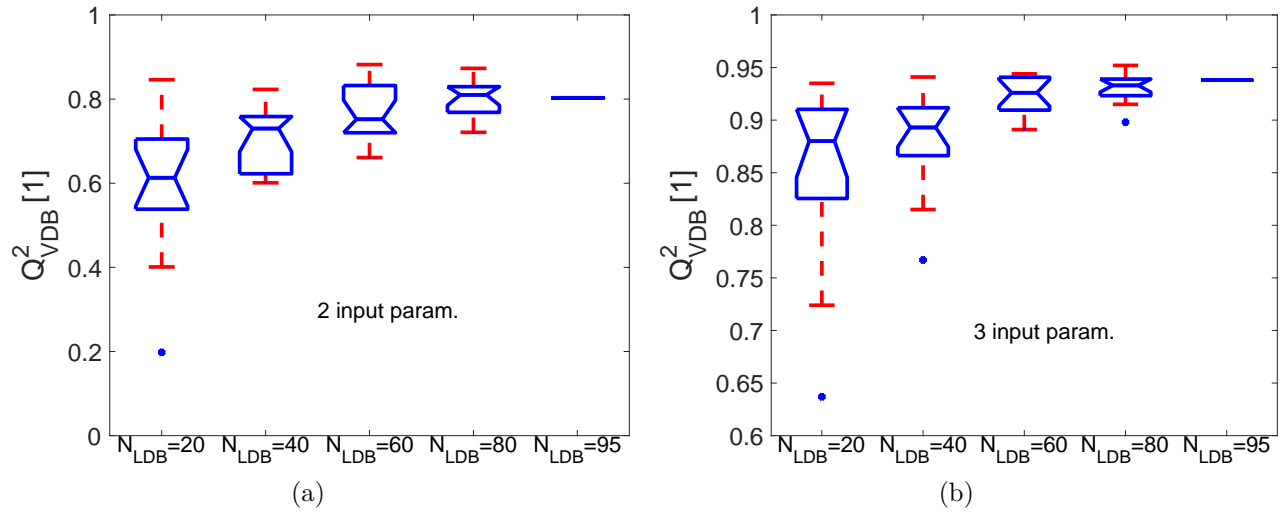


FIG. 3. Comparison of the distribution of the GPM input parameters for LDB and VDB; a)  $1/T_{V/A}$ ; b)  $a_{max,out}$  and c)  $I_A$ .

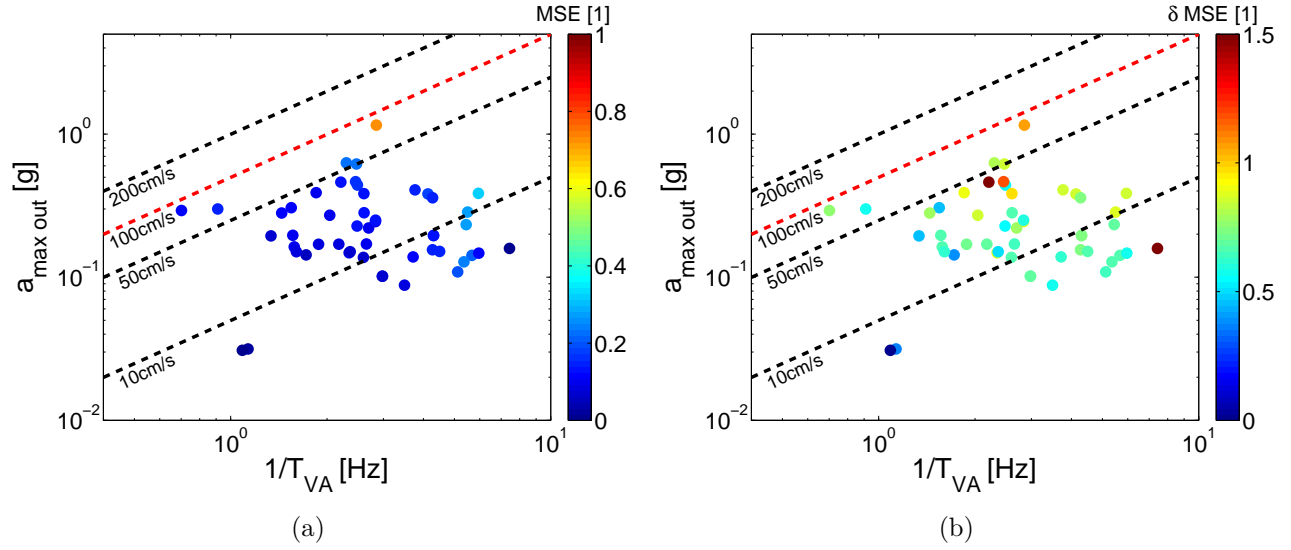


**FIG. 4. Comparison of  $\delta u_{z,rel}/H$  values obtained with FEM and with GPM approaches. a)  $\gamma$ -exponential GPM with 2 input parameters and b) Exponential GPM with 3 input parameters. Case of VDB sets.**

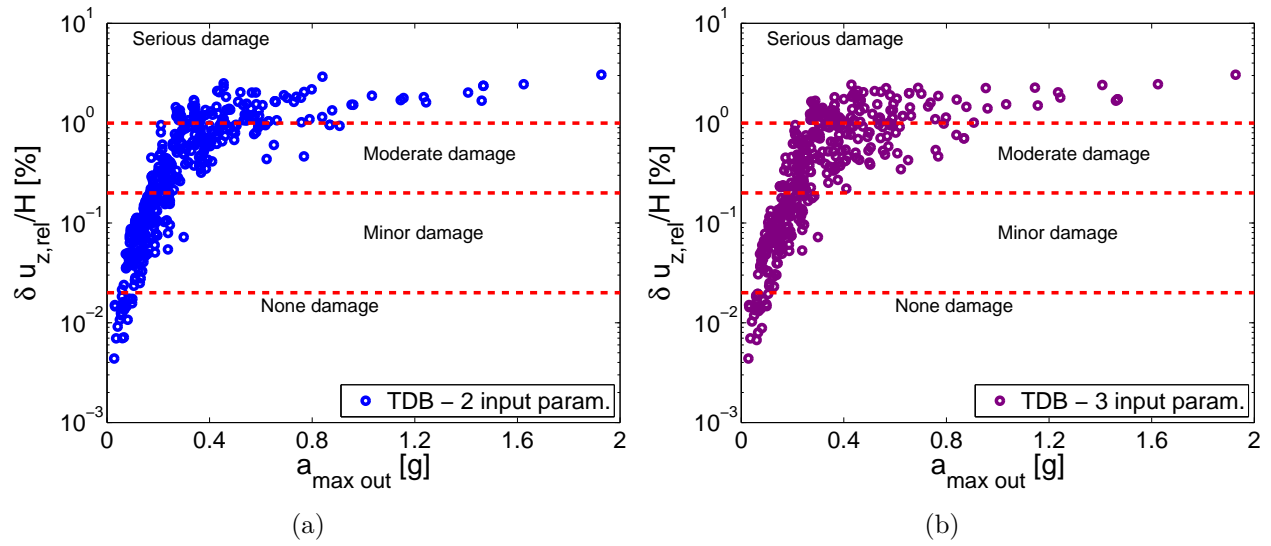




**FIG. 5.** Estimated  $Q^2_{VDB}$  evolution as a function of the learning sample size ( $N_{LDB}$ ) for a)  $\gamma$ -exponential GPM with 2 input parameters and b) Exponential GPM with 3 input parameters. Case of VDB sets.



**FIG. 6.** a) Obtained mean squared error (MSE) in the prediction of  $\delta u_{z,rel}/H$  values obtained using GPM with 3 input parameters and b) Ratio between the obtained MSE for 3 input parameters and the MSE for 2 input parameters ( $\delta MSE = MSE_{3pr} / MSE_{2pr}$ ). Case of VDB sets.



**FIG. 7.** Mean predicted  $\delta u_{z,rel}/H$  as a function of  $a_{\max out}$  obtained with the GPM approach. a) GPM with 2 input parameters and b) GPM with 3 input parameters. Case of TDB sets.

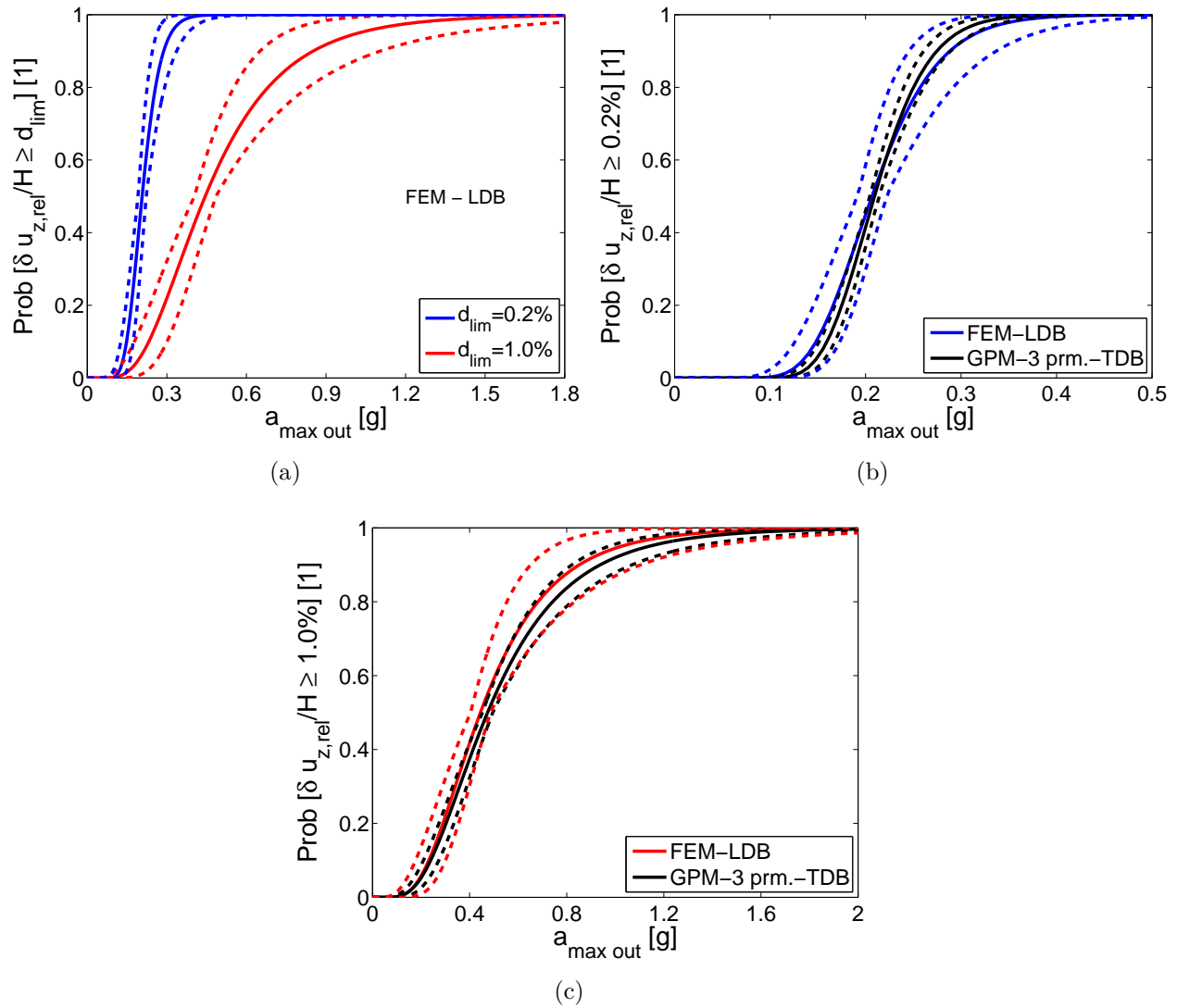
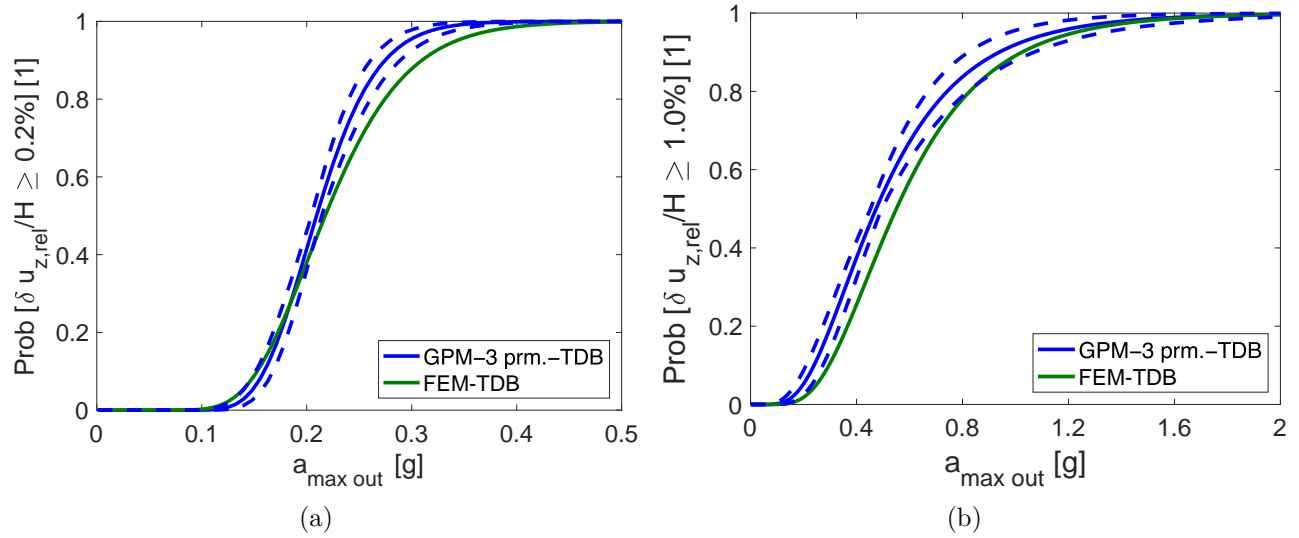


FIG. 8. Computed fragility curves for two damage levels following a) FEM approach; b) and c) FEM and GPM approaches.



**FIG. 9. Computed fragility curves for two damage levels, a) minor to moderate and b) moderate to serious damages. Comparison of responses obtained with FEM and predicted with GPM using the TDB sets.**

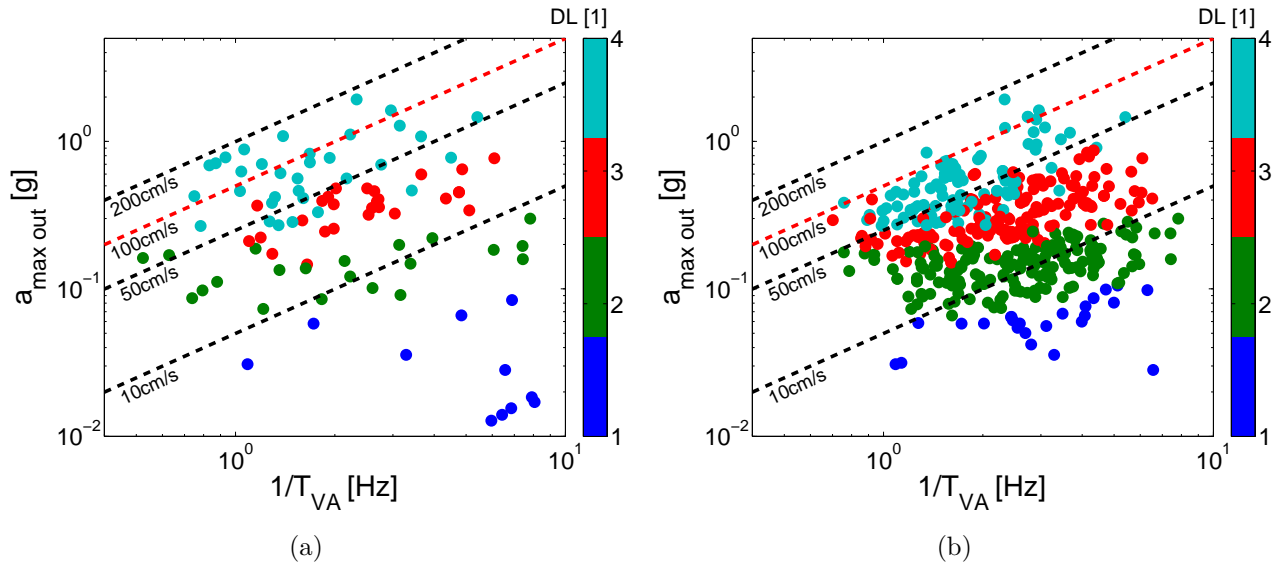


FIG. 10. Two dimensional failure surface, a) FEM with LDB set and b) GPM with TDB set.