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1 **VULNERABILITY ASSESSMENT FOR**
2 **EARTHQUAKE-LIQUEFACTION-INDUCED SETTLEMENTS**
3 **OF AN EMBANKMENT USING GAUSSIAN PROCESSES**

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5 **ABSTRACT**

6 The major cause of earthquake damage to an embankment is the liquefaction of the
7 soil foundation that induces ground level deformations. The aim of this paper is to assess
8 numerically the effect of the liquefaction-induced settlement of the soil foundation on an
9 levee due to real earthquakes. The seismic vulnerability is evaluated in terms of analytical
10 fragility curves constructed on the basis of non-linear dynamic Finite Elements (FE) analysis.
11 However, FE analysis can be expensive due to very large number of simulations needed for an
12 accurate assessment of the system failure behaviour. This problem is addressed by building
13 a Gaussian Process (GP) emulator to represent the output of the expensive FE model. A
14 comparison with the FE reference results suggests that the proposed GP model works well
15 and can be successfully used as a predictive tool to compute the induced damage on the
16 levee. Findings also illustrate clearly the importance and the advantages of an adequate
17 definition of the input parameters to build the GP model.

18 **Keywords:** Liquefaction, Damage levels, Gaussian processes, Fragility functions, Performance-
19 based methodology.

20 **INTRODUCTION**

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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 σ^2 is the variance of Z , θ 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 γ -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 (ρ_{bd}) of 2000kg/m³. 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 σ_{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 (Δt) 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 μ_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 γ -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 γ -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) γ -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 $\hat{\alpha}$, $\hat{\beta}$, σ_1 and σ_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 σ_1 and σ_2 values, Table 3).
343 It is noted that a reduction in the σ 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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417 REFERENCES

- 418 Ancheta, T. D., Darragh, R. B., Stewart, J. P., Seyhan, E., Silva, W. J., Chiou, B. S. J., Wooddell,
419 K. E., Graves, R. W., Kottke, A. R., Boore, D. M., Kishida, T., and Donahue, J. L. (2013) PEER
420 NGA-*West2 Database*. PEER Report No. 2013/03, Pacific Earthquake Engineering Research
421 Center, University of California, Berkeley, CA.
- 422 Aoi, S., Obara, K., Hori, S., Kasahara, K., and Okada, Y. (2001). “New Japanese uphole-downhole
423 strong-motion observation network: KiK-net.” *Seismological Research Letters*, 72:239.
- 424 Aubry, D., Chouvet, D., Modaressi, A., and Modaressi, H. (1986). “GEFDyn: Logiciel d’Analyse
425 de Comportement Mécanique des Sols par Eléments Finis avec Prise en Compte du Couplage
426 Sol-Eau-Air.” *Manuel scientifique*, Ecole Centrale Paris, LMSS-Mat.
- 427 Aubry, D., Hujeux, J.-C., Lassoudière, F., and Meimon, Y. (1982). “A double memory model with
428 multiple mechanisms for cyclic soil behaviour.” *International symposium on numerical models in
429 geomechanics*, Balkema, 3–13.
- 430 Aubry, D. and Modaressi, A. (1996). “GEFDyn.” *Manuel scientifique*, Ecole Centrale Paris, LMSS-
431 Mat.
- 432 Baker, J. W. and Cornell, C. A. (2008a). “Uncertainty propagation in probabilistic seismic loss
433 estimation.” *Structural Safety*, 30(3), 236–252.
- 434 Baker, J. W. and Cornell, C. A. (2008b). “Vector-valued Intensity Measures Incorporating Spectral
435 Shape For Prediction of Structural Response.” *Journal of Earthquake Engineering*, 12(4), 534–
436 554.
- 437 Bucher, C. and Most, T. (2008). “A comparison of approximate response functions in structural
438 reliability analysis.” *Probabilistic Engineering Mechanics*, 23(2-3), 154 – 163.
- 439 Byrne, P. M., Park, S.-S., Beaty, M., Sharp, M., Gonzalez, L., and Abdoun, T. (2004). “Numerical

440 modeling of liquefaction and comparison with centrifuge tests.” *Canadian Geotechnical Journal*,
441 41(2), 193–211.

442 Cardoso, J. B., de Almeida, J. R., Dias, J. M., and Coelho, P. G. (2008). “Structural reliability
443 analysis using monte carlo simulation and neural networks.” *Advances in Engineering Software*,
444 39(6), 505 – 513.

445 DiazDelaO, F. A., Adhikari, S., Saavedra Flores, E. I., and Friswell, M. I. (2013). “Stochastic
446 structural dynamic analysis using bayesian emulators.” *Computers & Structures*, 120(1), 24 –
447 32.

448 Dubourg, V., Sudret, B., and Deheeger, F. (2013). “Metamodel-based importance sampling for
449 structural reliability analysis.” *Probabilistic Engineering Mechanics*, 33, 47–57.

450 Ferrario, E., Pedroni, N., Zio, E., and Lopez-Caballero, F. (2017). “Bootstrapped Artificial Neural
451 Networks for the seismic analysis of structural systems.” *Structural Safety*, in-press.

452 Genton, M. G. (2001). “Classes of kernels for machine learning: a statistics perspective.” *Journal*
453 *of Machine Learning Research*, 2(1), 299 – 312.

454 Ghosh, J., Padgett, J. E., and Dueñas-Osorio, L. (2013). “Surrogate modeling and failure sur-
455 face visualization for efficient seismic vulnerability assessment of highway bridges.” *Probabilistic*
456 *Engineering Mechanics*, 34(1), 189 – 199.

457 Gidaris, I., Taflanidis, A. A., and Mavroeidis, G. P. (2015). “Kriging metamodeling in seismic risk
458 assessment based on stochastic ground motion models.” *Earthquake Engineering & Structural*
459 *Dynamics*, 44(14), 2377–2399.

460 Iooss, B., Boussouf, L., Feuillard, V., and Marrel, A. (2010). “Numerical studies of the metamodel
461 fitting and validation processes.” *International Journal On Advances in Systems and Measure-*
462 *ments, IARIA*, 3, 11–21.

463 Juang, C. H., Yuan, H., Li, D. K., Yang, S. H., and Christopher, R. A. (2005). “Estimating severity
464 of liquefaction-induced damage near foundation.” *Soil Dynamics and Earthquake Engineering*,
465 25(5), 403–411.

466 Kawase, H. (2011). “Strong motion characteristics and their damage impact to structures during
467 the Off Pacific Coast of Tohoku earthquake of march 11, 2011; How extraordinary was this
468 M9.0 earthquake?.” *4th IASPEI / IAEE International Symposium: Effects of Surface Geology*

469 *on Seismic Motion, University of California Santa Barbara.*

470 Kayen, R. E. and Mitchell, J. K. (1997). “Assessment of liquefaction potential during earthquakes
471 by arias intensity.” *Journal of Geotechnical and Geoenvironmental Engineering*, 123(12), 1162–
472 1175.

473 Koutsourelakis, S., Prévost, J. H., and Deodatis, G. (2002). “Risk assessment of an interacting
474 structure-soil system due to liquefaction.” *Earthquake Engineering and Structural Dynamics*,
475 31(4), 851–879.

476 Lancieri, M., Renault, M., Berge-Thierry, C., Gueguen, P., Baumont, D., and Perrault, M. (2015).
477 “Strategy for the selection of input ground motion for inelastic structural response analysis based
478 on naïve bayesian classifier.” *Bulletin of Earthquake Engineering*, 13(9), 2517–2546.

479 Lopez-Caballero, F. and Modaressi-Farahmand-Razavi, A. (2008). “Numerical simulation of lique-
480 faction effects on seismic SSI.” *Soil Dynamics and Earthquake Engineering*, 28(2), 85–98.

481 Lopez-Caballero, F. and Modaressi-Farahmand-Razavi, A. (2010). “Assessment of variability and
482 uncertainties effects on the seismic response of a liquefiable soil profile.” *Soil Dynamics and*
483 *Earthquake Engineering*, 30(7), 600–613.

484 Luco, N. and Cornell, C. A. (2007). “Structure-Specific Scalar Intensity Measures for Near-Source
485 and Ordinary Earthquake Ground Motions.” *Earthquake Spectra*, 23(2), 357–392.

486 Matsuo, O. (1996). “Damage to river dikes.” *Soils and Foundations*, 36(1), 235–240.

487 Modaressi, H. and Benzenati, I. (1994). “Paraxial approximation for poroelastic media.” *Soil Dy-*
488 *namics and Earthquake Engineering*, 13(2), 117–129.

489 National Academies of Sciences, Engineering, and Medicine (2016). *State of the Art and Practice*
490 *in the Assessment of Earthquake-Induced Soil Liquefaction and Its Consequences*. The National
491 Academies Press, Washington, DC.

492 Oka, F., Tsai, P., Kimoto, S., and Kato, R. (2012). “Damage patterns of river embankments due to
493 the 2011 off the pacific coast of tohoku earthquake and a numerical modeling of the deformation
494 of river embankments with a clayey subsoil layer.” *Soils and Foundations*, 52(5), 890–909.

495 Okamura, M., Tamamura, S., and Yamamoto, R. (2013). “Seismic stability of embankments sub-
496 jected to pre-deformation due to foundation consolidation.” *Soils and Foundations*, 53(1), 11 –
497 22.

498 Ozutsumi, O., Sawada, S., Iai, S., Takeshima, Y., Sugiyama, W., and Shimazu, T. (2002). “Effective
499 stress analyses of liquefaction-induced deformation in river dikes.” *Soil Dynamics and Earthquake*
500 *Engineering*, 22(9-12), 1075 – 1082.

501 Popescu, R., Prévost, J. H., Deodatis, G., and Chakraborty, P. (2006). “Dynamics of nonlinear
502 porous media with applications to soil liquefaction.” *Soil Dynamics and Earthquake Engineering*,
503 26(6-7), 648–665.

504 Porter, K. A. (2003). “An overview of PEER’s Performance-Based Earthquake Engineering
505 Methodology.” *Ninth International Conference on Applications of Statistics and Probability in*
506 *Civil Engineering (ICASP9) July 6-9, San Francisco*.

507 Rapti, I., Lopez-Caballero, F., Modaressi-Farahmand-Razavi, A., Foucault, A., and Voldoire, F.
508 (2017). “Liquefaction analysis and damage evaluation of embankment-type structures.” *Acta*
509 *Geotechnica*, in-press.

510 Rasmussen, C. E. and Williams, C. K. I. (2006). *Gaussian Processes for Machine Learning*. the
511 MIT Press.

512 Roustant, O., Ginsbourger, D., and Deville, Y. (2012). “DiceKriging, DiceOptim: Two R packages
513 for the analysis of computer experiments by kriging-based metamodeling and optimization.”
514 *Journal of Statistical Software*, 51(1), 1–55.

515 Sacks, J., Welch, W. J., Mitchell, T. J., and Wynn, H. P. (1989). “Design and analysis of computer
516 experiments.” *Statistical Science*, 4(4), 409–423.

517 Saez, E., Lopez-Caballero, F., and Modaressi-Farahmand-Razavi, A. (2011). “Effect of the inelastic
518 dynamic soil-structure interaction on the seismic vulnerability assessment.” *Structural Safety*,
519 33(1), 51–63.

520 Seed, H. B. and Idriss, I. M. (1971). “Simplified procedure for evaluating soil liquefaction potential.”
521 *Journal of Soil Mechanics and Foundations Division - ASCE*, 97(SM9), 1249–1273.

522 Seo, J., Dueñas-Osorio, L., Craig, J. I., and Goodno, B. J. (2012). “Metamodel-based regional vul-
523 nerability estimate of irregular steel moment-frame structures subjected to earthquake events.”
524 *Engineering Structures*, 45(1), 585 – 597.

525 Seyedi, D. M., Gehl, P., Douglas, J., Davenne, L., Mezher, N., and Ghavamian, S. (2010). “De-
526 velopment of seismic fragility surfaces for reinforced concrete buildings by means of nonlinear

527 time-history analysis.” *Earthquake Engineering & Structural Dynamics*, 39(1), 91–108.

528 Sharp, M. K. and Adalier, K. (2006). “Seismic response of earth dam with varying depth of lique-

529 fiable foundation layer.” *Soil Dynamics and Earthquake Engineering*, 26(11), 1028–1037.

530 Shinozuka, M., Feng, Q., Lee, J., and Naganuma, T. (2000). “Statistical analysis of fragility curves.”

531 *Journal of Engineering Mechanics - ASCE*, 126(12), 1224–1231.

532 Stern, R., Song, J., and Work, D. (2017). “Accelerated Monte Carlo system reliability analysis

533 through machine-learning-based surrogate models of network connectivity.” *Reliability Engineer-*

534 *ing & System Safety*, 164(1), 1–9.

535 Strong, M. and Oakley, J. E. (2014). “When is a model good enough? deriving the expected

536 value of model improvement via specifying internal model discrepancies.” *SIAM/ASA Journal*

537 *on Uncertainty Quantification*, 2(1), 106–125.

538 Swaisgood, J. R. (2003). “Embankment dam deformation caused by earthquakes.” *Pacific Confer-*

539 *ence on Earthquake Engineering*, Paper no. 014.

540 Toal, D. J. J., Bressloff, N. W., and Keane, A. J. (2008). “Kriging Hyperparameter Tuning Strate-

541 gies.” *AIAA Journal*, 46(5), 1240–1252.

542 Unjoh, S., Kaneko, M., Kataoka, S., Nagaya, K., and Matsuoka, K. (2012). “Effect of earthquake

543 ground motions on soil liquefaction.” *Soils and Foundations*, 52(5), 830–841.

544 Zentner, I. (2010). “Numerical computation of fragility curves for NPP equipment.” *Nuclear En-*

545 *gineering and Design*, 240(6), 1614 – 1621.

546 Zienkiewicz, O. C. and Shiomi, T. (1984). “Dynamic behaviour of saturated porous media; the

547 generalised biot formulation and its numerical solution.” *International Journal for Numerical*

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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] 2 input param. $N_{LDB}=95$	Q_{VDB}^2 [1] 3 input param. $N_{LDB}=95$
Matérn (3/2)	0.63	0.83
Exponential	0.74	0.94
γ -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				$\sigma_{\text{GPM}}/\sigma_{\text{FEM}}$	
	$\hat{\alpha}$	$\hat{\beta}$	σ_1	σ_2	$\hat{\alpha}$	$\hat{\beta}$	σ_1	σ_2	σ_1	σ_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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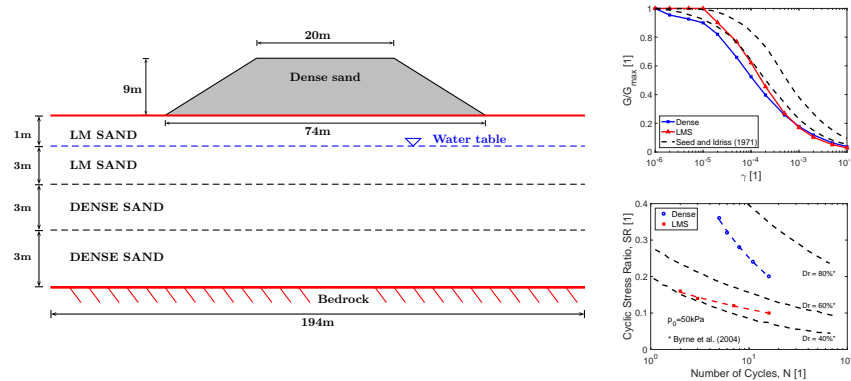
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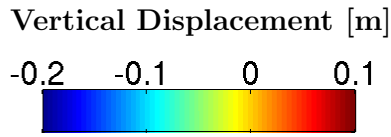
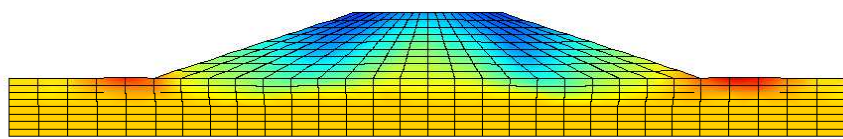
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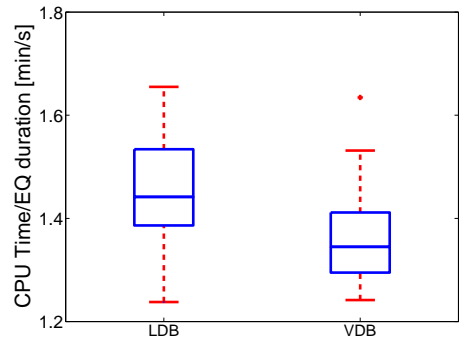
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(a)



(b)



(c)

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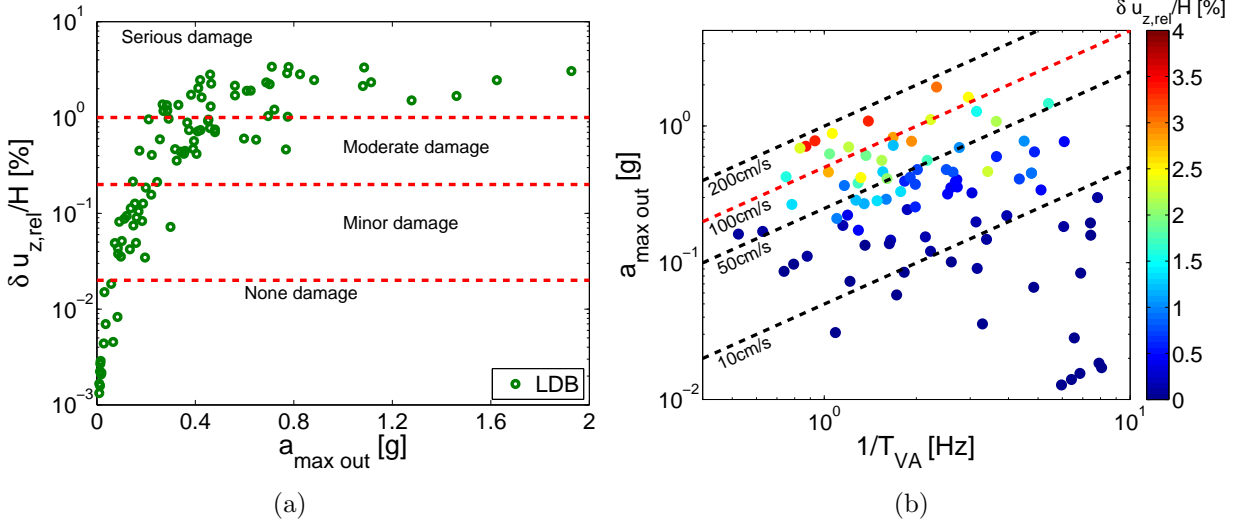


FIG. 2. Scatter plot of crest settlement ratio of the FE model as a function of a) $a_{max\ out}$ and b) $a_{max\ out}$ and $1/T_{VA}$. Case of LDB sets.

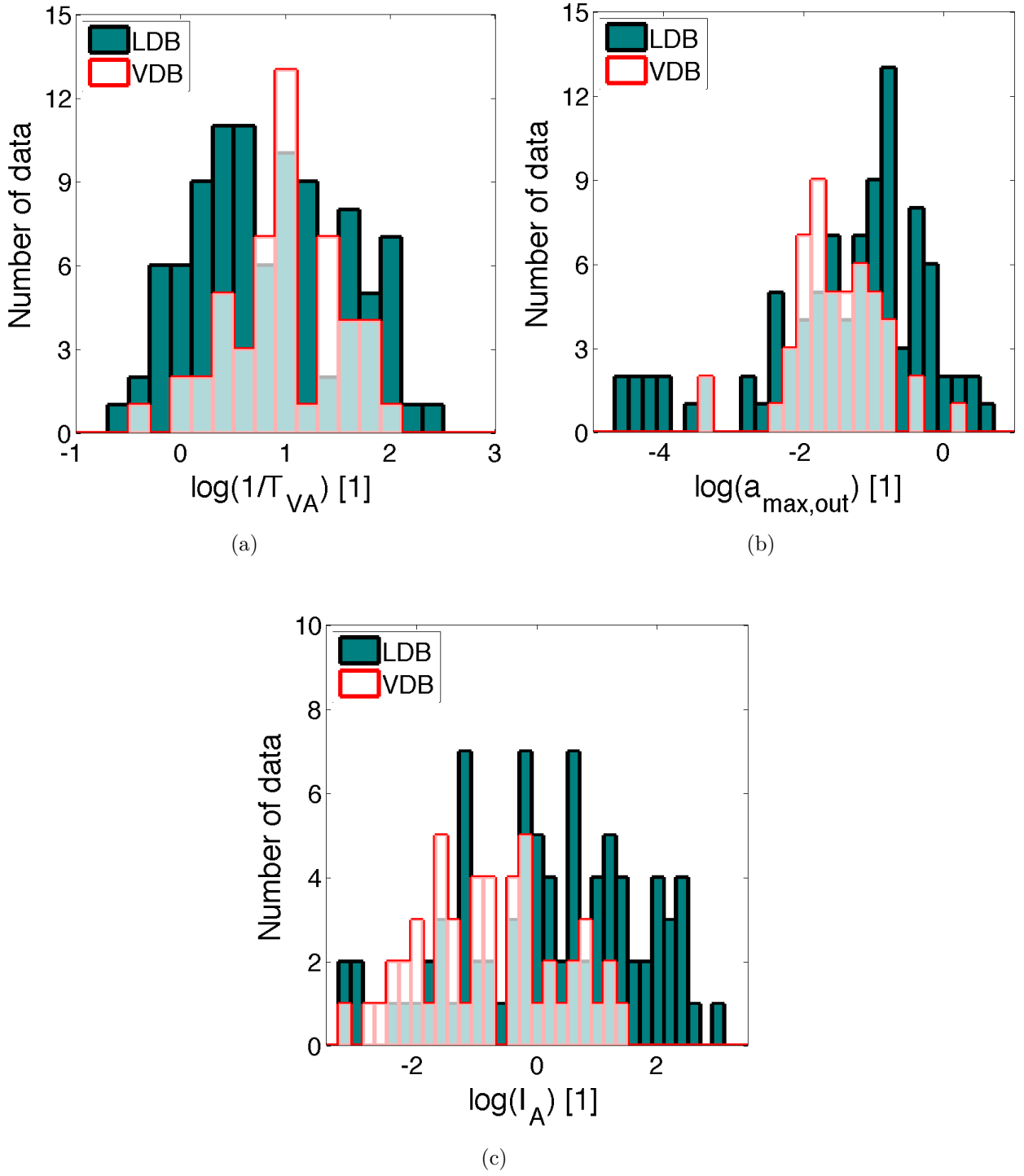


FIG. 3. Comparison of the distribution of the GPM input parameters for LDB and VDB; a) $1/T_{V/A}$; b) $a_{max,out}$ and c) I_A .

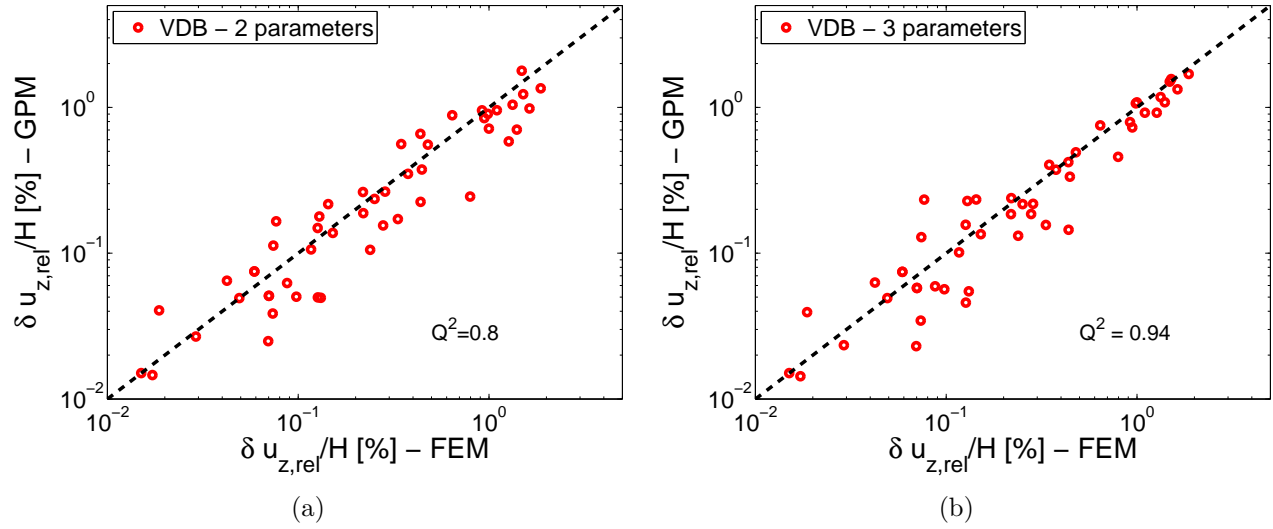


FIG. 4. Comparison of $\delta u_{z,rel}/H$ values obtained with FEM and with GPM approaches. a) γ -exponential GPM with 2 input parameters and b) Exponential GPM with 3 input parameters. Case of VDB sets.

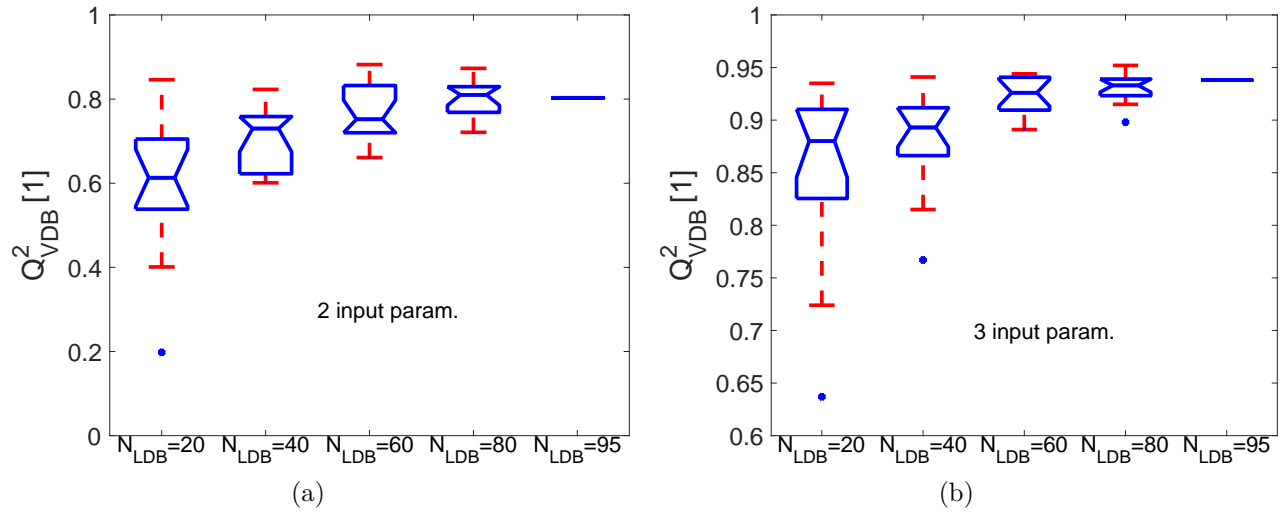


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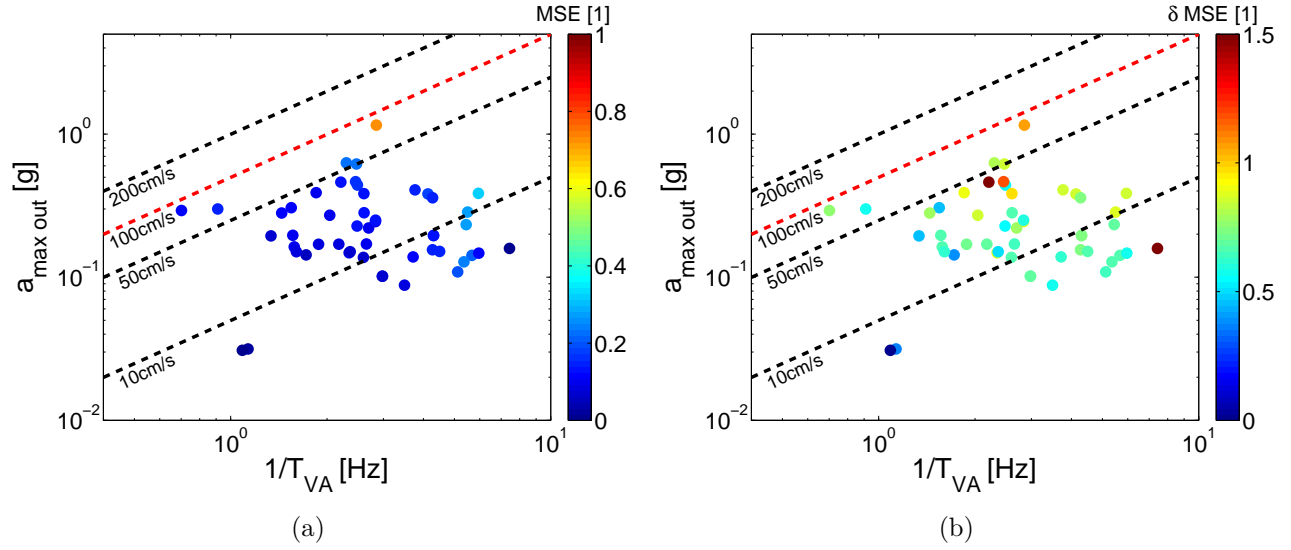


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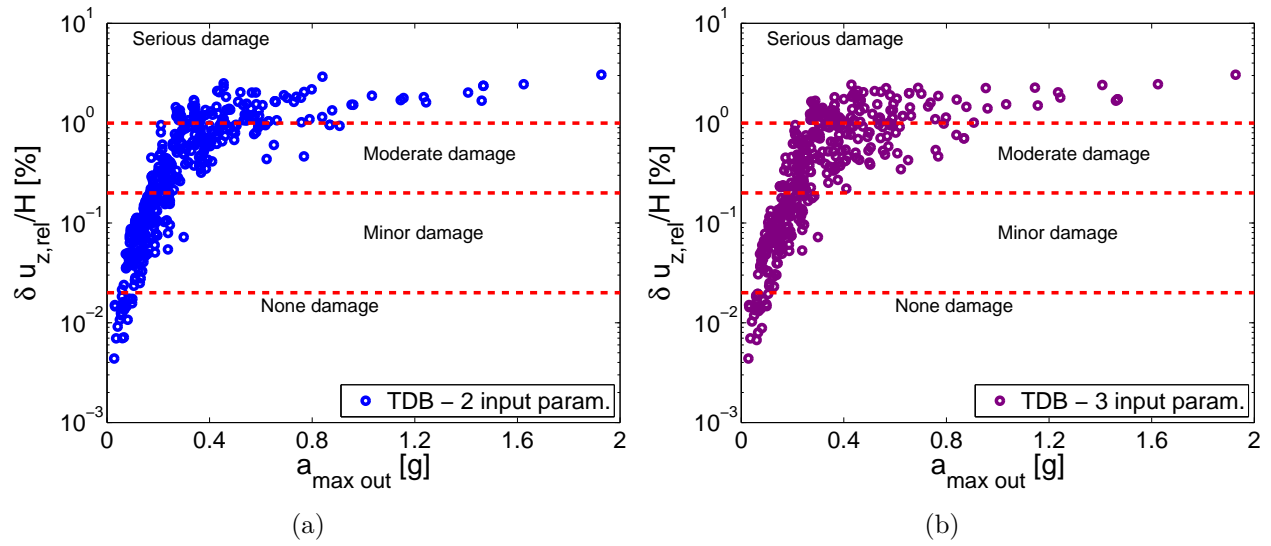


FIG. 7. Mean predicted $\delta u_{z,rel}/H$ as a function of $a_{max\ out}$ obtained with the GPM approach. a) GPM with 2 input parameters and b) GPM with 3 input parameters. Case of TDB sets.

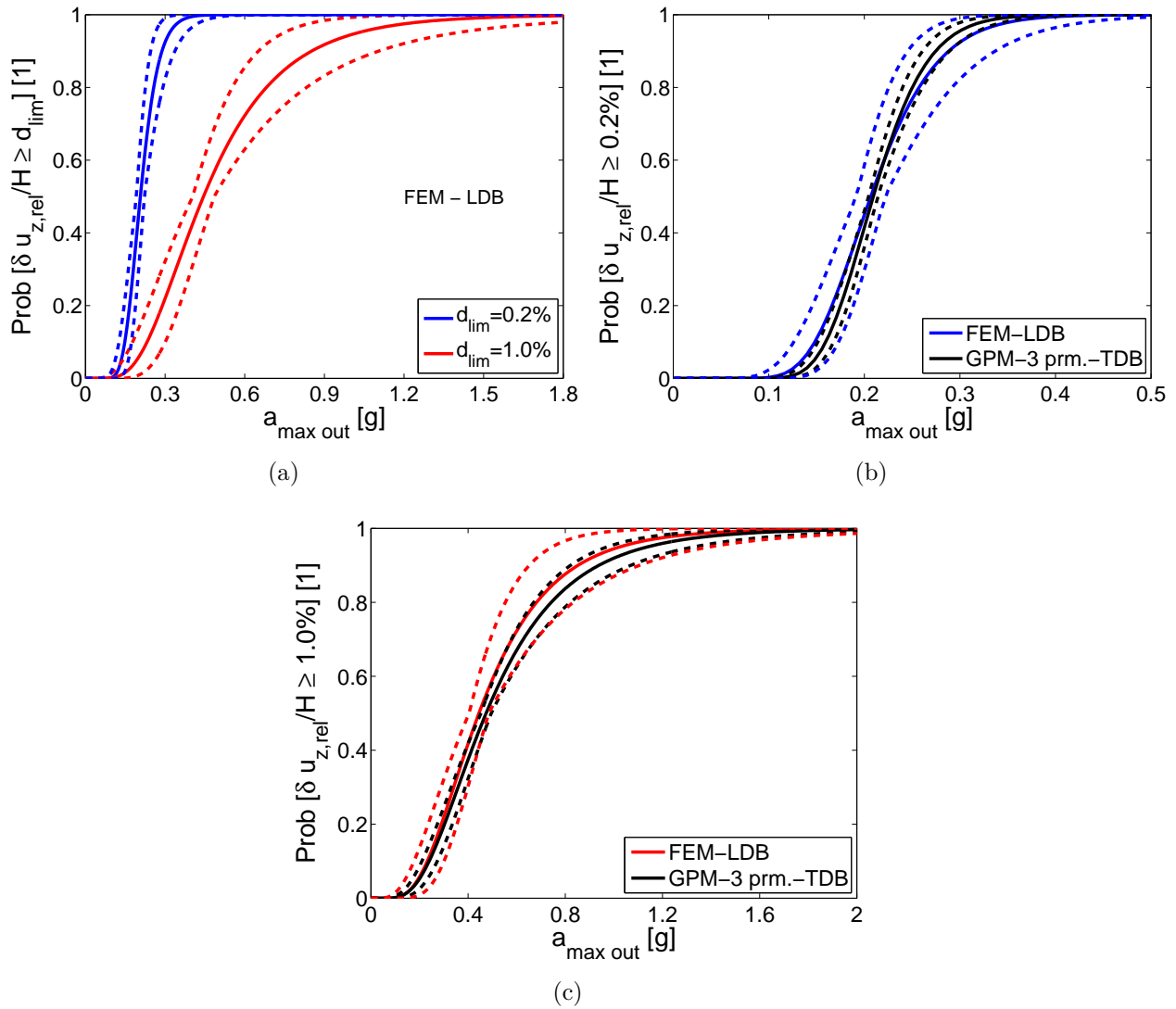


FIG. 8. Computed fragility curves for two damage levels following a) FEM approach; b) and c) FEM and GPM approaches.

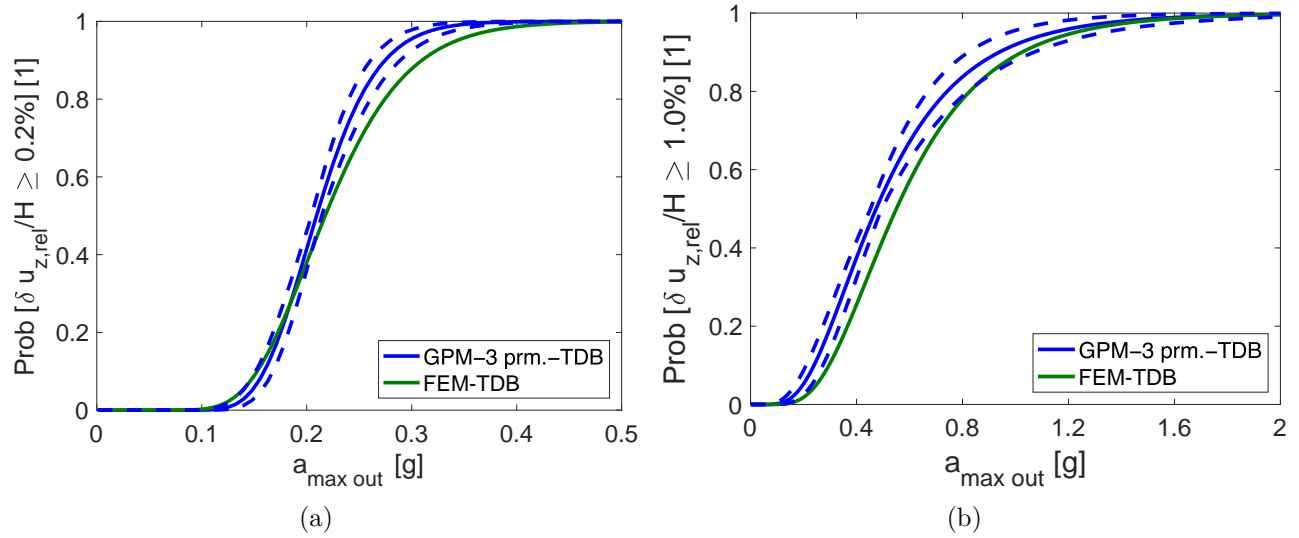


FIG. 9. Computed fragility curves for two damage levels, a) minor to moderate and b) moderate to serious damages. Comparison of responses obtained with FEM and predicted with GPM using the TDB sets.

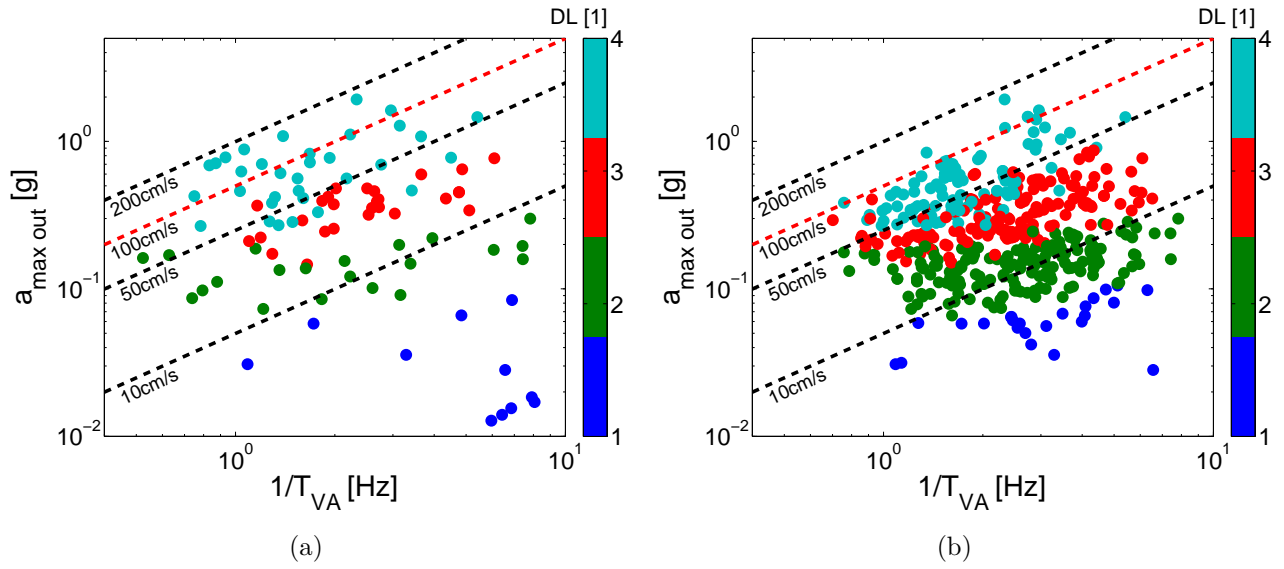


FIG. 10. Two dimensional failure surface, a) FEM with LDB set and b) GPM with TDB set.