

1 **RANDOM FINITE ELEMENT AND LIMIT EQUILIBRIUM METHODS BASED**  
2 **PROBABILISTIC STABILITY ANALYSES OF A CUT SLOPE**

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26

27 **Abstract**

28 This paper elucidates the efficacy of advanced Random Finite Element Method (RFEM) to assess  
29 the excavation induced slope instability over the conventional Limit Equilibrium Method (LEM).  
30 Both the studies have been carried out in a probabilistic framework in which the shear strength  
31 parameters of the slope material are considered as random variables. While the probabilistic LEM  
32 is used for the conventional one-dimensional (1-D) spatial variation with pre-assumed failure  
33 surfaces, the adopted probabilistic RFEM incorporates a more realistic two-dimensional (2-D)  
34 spatial variation of soil properties with the evolution of failure surfaces during the progress of the  
35 analysis. In absence of any previous studies employing RFEM to investigate the toe-excavation  
36 induced hillslope instability, the present study illustrates the importance of considering uncertainty  
37 and two-dimensional spatial variability in soil properties for a safe and economical cut slope design  
38 for hill-road constructions. The outcomes suggest that the chances of a cut-slope failure are  
39 strongly influenced by the coefficient of variation (CoV), cross-correlation coefficient between the  
40 shear strength parameters ( $\rho_{c\phi}$ ), and the non-dimensional correlation length ( $\Theta$ ) governing the  
41 spatial variability of soil properties. For a specific  $\rho_{c\phi} = +0.5$  and CoV varying between 0.2-0.4,  
42 the probability of failure ( $P_f$ ) of the cut slope exhibits a variation of approximately 6%. Based on  
43 the various possible correlation types exhibited by the soil parameters ( $\rho_{c\phi}$ : -0.5, 0, +0.5), for a  
44 specific CoV=0.4, a similar variation in  $P_f$  of approximately 6% is observed. Based on comparative  
45 study with 2-D RFEM-based spatial variability, it is deciphered that adoption of 1-D LEM-based  
46 spatial variability can significantly undermine the failure probability of the cut-slope, especially

47 when the  $\Theta$  ranges in 0.5-0.7. In this range, a cut slope section may even be adjudged safe ('above  
48 average' performance level) through 1-D spatial variability, while in reality the slope may have  
49 substantially higher chances of failure with a 'poor' performance level. The outcomes of the  
50 reported study indicate the inadvertent requirement of obtaining an appropriate site-specific spatial  
51 variation of soil parameters for the successfully assessing the probabilistic failure of cut slopes.

52 **Keywords:** Cut slope instability; Probabilistic analysis; Limit equilibrium method; Random finite  
53 element method; Coefficient of variation; Correlation coefficient; Correlation length

54

## 55 **1. Introduction**

56 In the hilly terrains of India, cutting of hillslopes for construction of roadways is a common  
57 practice. The growing necessity for establishing proper means of communication for rapidly  
58 developing urbanization in the hills has increased the requirement manifold. Stability assessment  
59 of such cut slopes in the hills are of prime importance, as their failure and collapse would have  
60 extremely serious social and economic consequences [1-7]. Several literatures have elucidated the  
61 reasons and consequences of such failures, thereby highlighting the necessity of a rigorous and  
62 thorough stability analysis of cut slopes. A landslide induced disaster to a habitation in San  
63 Francisco bay area, USA was reported by Stark et al. [3], wherein the slope cutting operation for  
64 broadening of the highway triggered the instability. As reported by Umrao et al. [8], various  
65 locations of the Rudraprayag District, Uttarakhand, India, along the NH-109, were significantly  
66 affected by rock slope failures triggered by slope cutting. The degradation of dry stable basaltic  
67 hillslopes with lateritic shear seams in Mahabaleshwar, India was reported by Kainthola et al.  
68 [9,10], wherein subsequent excavations triggered widespread failure of the saturated slopes. The  
69 repeated failures along the Highway G212, China was illustrated by Zhang et al. [11], which was

70 initiated as a result of the toe-excavation of slopes, thereby subsequently exposing the weak  
71 bedding planes. A finite element based stability analysis was conducted by Mahanta et al. [12] to  
72 identify the deformation mechanisms of the vulnerable cut slopes in Kullu, Himachal Pradesh,  
73 India. Depending on the slope geometry and properties of the hillslope material, the influence of  
74 hydrogeological and seismic parameters on the stability of cut slopes was reported by Chakraborty  
75 and Dey [13], wherein the safe thresholds of toe excavations were proposed that would not  
76 jeopardize the hillslope stability.

77

78 All the above-mentioned studies adopted a deterministic approach to interpret the stability of cut  
79 slopes. However, because of the uncertainties in the slope geometry and geotechnical properties,  
80 the deterministic factor of safety can be hardly appreciated to be a very good interpreter of slope  
81 stability. Several factors contribute towards the uncertainties in the outcomes from the analyses,  
82 namely the geological anomalies, limited investigations in difficult terrains, spatial variability of  
83 soil characteristics, uncertainty in slope failure mechanisms and, lastly, adopting simplifying  
84 presumptions in geotechnical modeling. Nonetheless, very less attention is given to integrate the  
85 geotechnical uncertainties for authentic risk assessment of slope instability in hilly areas. Although  
86 probabilistic concepts have been applied in various geotechnical problems in the last few decades,  
87 there still exists an inhibition in applying such necessary techniques in practical considerations and  
88 economic road constructions involving hill cutting. Recently, through a comparative study  
89 between LEM-based deterministic and probabilistic slope stability analyses, the importance of  
90 probabilistic analysis in assessing the stability of cut slopes was also reported by Chakraborty and  
91 Dey [14]. The probabilistic study was further extended to assess the seismic response of a toe-  
92 excavated hillslope retained by sheet pile anchor system [15].

93 This article illustrates the assessment of cut slope instability by incorporating one-dimensional (1-  
94 D) spatial variation of soil shear strength parameters in a limit equilibrium method (LEM) based  
95 probabilistic framework. Further, the influences of a more realistic two-dimensional (2-D) spatial  
96 variation of soil shear strength parameters are investigated in a random finite element method  
97 (RFEM) based probabilistic framework developed by Griffiths and Fenton [16, 17]. While the  
98 former approach employs a presumed failure surface, the advantage in the latter approach lies in  
99 the evolution of failure surface during the analysis. The results obtained from both the approaches  
100 are compared, and the influence of the coefficient of variation (CoV), cross-correlation coefficient  
101 between the shear strength parameters ( $\rho_{c\phi}$ ) and the non-dimensional correlation length ( $\Theta$ ) on the  
102 probability of cut slope failure are illustrated.

103

## 104 **2. Probabilistic Approach for Slope Stability Study**

105 Deterministic slope stability analysis is based on presumed characteristic values of soil properties  
106 without incorporating any associated uncertainty. Probabilistic analysis renders a more pragmatic  
107 approach to assess the cut slope stability as it is capable to explicitly incorporate the uncertainty  
108 and variability in soil properties [14]. Unlike deterministic analysis, which provides a single  
109 measure of factor of safety (FoS), the probabilistic approach delivers a more rational measure in  
110 terms of the probability of failure ( $P_f$ ). Several earlier studies have adopted probabilistic  
111 approaches to assess the stability of slopes [16-25]. However, none of the earlier studies addressed  
112 the probabilistic analysis of the to-excavation induced slope failure.

113

114 In this paper, two different probabilistic approaches are utilized to include the uncertainties  
115 associated with the soil shear strength parameters in assessing cut slope stability. The first

116 approach utilizes a LEM-based slope stability analysis within a probabilistic framework that has  
117 been conducted using the Slope/W module of Geostudio v2018. However, this approach carries  
118 the inherent limitations of LEM in presuming the shape and location of the failure plane [14].  
119 Furthermore, Slope/W is incapable of incorporating the 2-D spatial variation in soil properties  
120 [14]. The second approach is based on advanced RFEM that has been conducted using a computer  
121 model *Rslope2D* developed by Griffiths and Fenton [16, 17]. This approach can incorporate the  
122 spatial variation of soil properties in both horizontal and vertical directions, as well as it does not  
123 presume the shape or location of the failure surface [16, 17]. The failure plane is allowed to develop  
124 through the soil elements in which the shear strength is less than the applied shear stresses.

125

126 The former method, even though having its own inherent trade-offs, is yet very popular due to its  
127 simplicity in modelling and analysis. The latter method, although more pragmatic, demands the  
128 knowledge of RFEM, for which the expertise might not be always available. Nonetheless, for both  
129 the approaches, the framework of computing the probability of cut slope failure approximately  
130 remains the same, which are listed as follows:

- 131 1. A spatially variable 1-D or 2-D random field (RF) for the selected soil properties is  
132 simulated based on the specified statistical parameters.
- 133 2. Limit equilibrium (LE) or random finite element (RFE) based slope stability analysis is  
134 conducted for the simulated model to ascertain the stability of slope against the specified  
135 soil properties and slope geometry.
- 136 3. The steps 1 and 2 are repeated using the Monte Carlo simulation (MCS) process to estimate  
137 the probability of failure,  $P_f$ .

138

139 There are mainly two categorical approaches for probabilistic slope stability analyses. The first  
140 approach pertains to the approximate methods such as first order reliability method (FORM) [26],  
141 the mean value first order second-moment reliability method (MVFOSM) [27] and the second  
142 order reliability method (SORM) [28]. In the field of structural reliability, the Hasofer–Lind  
143 reliability index and the First Order Reliability index are commonly used for approximating the  
144 probability of failure [29, 30]. However, it is worth mentioning at this point that the ‘Approximate  
145 Methods’ are not able to incorporate the spatial variation of soil properties in the analysis, thereby  
146 resulting in either over-estimation or under-estimation of the probability of slope failure under  
147 different conditions [31]. This pitfall can be overcome through the second categorical approach  
148 that adopts the Monte Carlo Simulation (MCS) based methods [31, 32]. For the present study,  
149 Direct Simulation Monte Carlo, or DSMC, [33] has been used. It is a classical technique, wherein  
150 MCS generates a set of trial values of the random variable within a user-specified range that can  
151 be defined based on the site-specific investigations or recommendations from available literature  
152 [34, 35]. For each trial value, the random variable estimates the *limit state function*, which is a  
153 mathematical quantification of system failure and is usually represented by  $g(x)$ . A system is  
154 ascertained safe if  $g(x) > 0$ , and in the otherwise case, it is specified to be in a state of failure. From  
155 all the simulations conducted using the trial values of the random variable, the total number of  
156 system failures are counted, and the failure probability is estimated as  $P_f = \frac{n_f}{N}$ , where,  $n_f$  is the  
157 number of failures that occurred in total  $N$  number of trials.

158

159 In the present study, Monte Carlo technique has been used with both LEM and RFEM-based  
160 approaches. For both the cases, MCS have been used to draw the magnitudes of shear strength  
161 parameters from their respective distributions. In a conventional MCS-based probabilistic slope

162 stability analysis, from each draw, the magnitudes of the random variables are selected for a single  
163 simulation of the slope stability analysis. Thus, for each of the MCS-based analysis, the chosen  
164 magnitude of the random variable still represents a homogeneous slope. Hence, at the end of the  
165 MCS-based analyses, the probability of failure is estimated through a set of homogeneous slope  
166 stability analysis. However, in reality, the hillslope material would comprise materials having  
167 spatially varying properties. In such case, it is important to simulate the spatial variability through  
168 1-D or 2-D random field modelling, as has been done in this study with the aid of amalgamation  
169 of MCS and LEM or RFEM, respectively. In such case, for each MCS simulation, a random field  
170 of the shear strength parameter would be generated. Based on the correlation coefficient, the  
171 random field would generate spatially variable shear strength properties along the entire domain  
172 of the slope. Thus, in this approach, the MCS is still used to draw the parameter magnitudes, but  
173 the spatial variability of the parameters is controlled by the 1-D or 2-D random field. Thus, this  
174 procedure is advantageous in modelling the spatial variability of parameter more realistically.

175

### 176 **3. Numerical Model for Present Study**

177 For obtaining more carriageway width during a road construction in a hilly terrain, vertical or near  
178 vertical excavations are commonly carried out in the hillside slope. Due to the presence of lateritic  
179 soils, the hillslopes in the north-eastern, and similar other regions, of India can withstand near-  
180 vertical cuts (even in the tune of 80°-90° slope inclinations) that are generally carried out at the site  
181 during the dry periods of the year. A vertical cut in a soil slope is clearly considered as the worst  
182 case of excavation scenario in hillslopes, and hence, only the stability of vertical cut slopes is  
183 addressed in this study.

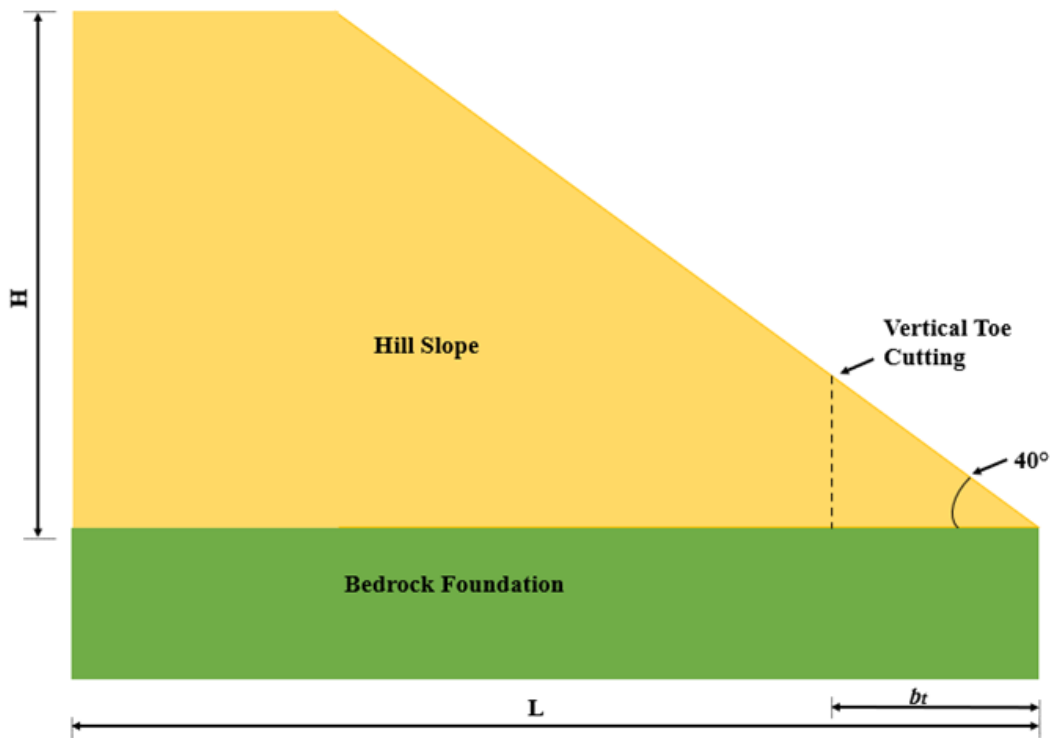


184 As commonly encountered in the hilly terrains of north-east India, Fig. 1 shows a typical 40 m  
185 high slope having a gradient of 2H:1V. A vertical cut is presumed to be carried out at the toe of  
186 the slope, such that a carriageway width ( $b_i$ ) of 10 m can be developed. The shear strength  
187 parameters (cohesion,  $c$ , and angle of internal friction,  $\phi$ ) of the hillslope soil material are  
188 considered as random variables, and are assumed to have their mean values as 40 kPa and 27.5°,  
189 respectively, while both of them are assumed having the coefficient of variation (CoV) as 0.4. The  
190 parameter magnitudes of both the random variables are fetched from a ‘Rectified Normal  
191 distribution’ that has zero as the lower bound. The chosen CoV falls within the typical ranges for  
192 cohesion (0.05-0.5) and internal friction angles (0.02-0.56) as can be found from the literature [34].  
193 It may be noted that for both the LEM-based and the RFEM-based slope stability analysis  
194 conducted for this study, the primary strength-related input parameters are cohesion ( $c$ ), friction  
195 angle ( $\phi$ ) and the soil unit weight ( $\gamma$ ). As the variability of soil unit weight ( $\gamma$ ) is generally less as  
196 compared to the shear strength parameters [35-39], it has little influence in probabilistic slope  
197 stability study. Hence the unit weight of hillslope material is considered deterministic for the  
198 present study, having a constant magnitude of 20 kN/m<sup>3</sup>. The other parameters necessary to  
199 conduct the slope stability analysis are the elastic parameters (Young’s Modulus  $E_s$  and Poisson’s  
200 ratio  $\nu$ ) and the dilation angle ( $\psi$ ). It is reported in literature that the dilation angle and the elastic  
201 parameters have little influence on the predicted stability of a slope [40]. It is also worth  
202 mentioning that the uncertainties in slope geometry and water table location within the slope also  
203 affects the toe-excavation induced slope stability, and the same has been highlighted in earlier  
204 literature [41-43]. However, the primary aim of the reported study is to assess the influence of the  
205 variability in shear strength parameters on the slope stability assessment of cut slopes through both  
206 LEM and RFEM-based methods and subsequently find out their efficacy of assessment. Hence,

207 for the present study, only the variability in the shear strength parameters  $c$  and  $\varphi$  are considered,  
208 and, thus, the same are characterised as random fields.

209

210



211

212

**Fig. 1** Schematic diagram of cut slope geometry

213

#### 214 **4. LEM-based Probabilistic Analysis for Cut Slope**

215 This section reports the failure probability of the chosen slope section estimated through LEM-

216 based probabilistic approach whose details can be found in very recent literatures [14, 15]. In this

217 part of the study, the spatial variation of  $c$  and  $\varphi$  is considered only in horizontal direction

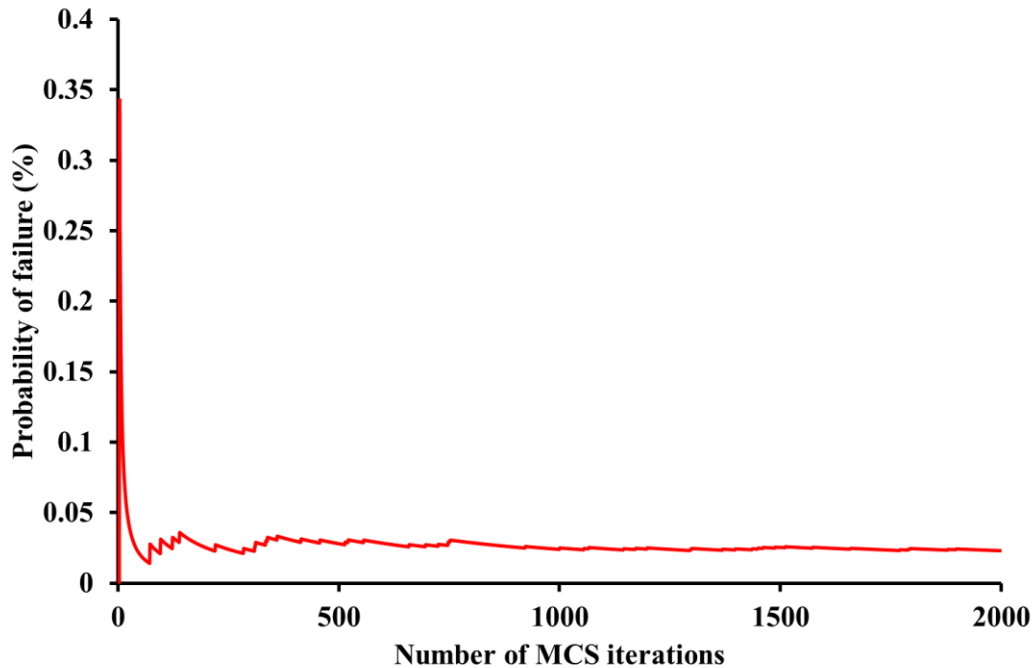
218 (represented by one-dimensional random field). The analyses are conducted using Morgenstern-

219 Price LEM in Slope/W to assess the probability of failure. In such approach, it is necessary to

220 identify the minimum numbers of MCS trials that would be required to generate a consistent

221 estimate. Further increase in number of simulations beyond that required does not lead to  
222 significant refinement in the result, rather unfavourably increase the computational time. As shown  
223 in Fig. 2, it is understood that 2000 MCS trials is adequate to produce a consistent estimate of  
224 failure probability for the chosen problem, and the same is adopted for rest of the study.

225



226

227 **Fig. 2** Variation in the probability of failure with numbers of MCS iterations for  $\Theta = 1$

228

## 229 **5. RFEM-based Probabilistic Analysis for Cut Slope**

230 RFEM was developed in the 1990s [15, 44] and has proven to be a more appropriate tool for  
231 probabilistic analysis in geotechnical engineering, as it can comfortably incorporate the spatial  
232 variation of soil properties. However, the application of this advanced technique in regularly  
233 assessing the stability of cut slopes has yet not gained impetus. There are several instances of cut  
234 slope failure even after being designed using conventional tools. In this regard, this section  
235 attempts to highlight the importance of including RFEM as an effective measure of assessing the

236 cut slope stability by duly incorporating the spatial variability of soil commonly encountered in  
237 hillslopes, thereby paving the possible way of safe and economical design.

238

239 In RFEM analysis, a soil property is considered to be a continuous random variable that is  
240 characterised using a probability density function (pdf) and is correlated with other random  
241 variables at adjoining locations. The set of random variables is characterised by the joint  
242 probability density function and is represented as a random field (RF). RFEM amalgamates the  
243 random field theory with the nonlinear FEM problem. In RFEM, a finite element mesh is overlaid  
244 by a random field and, thus, each mesh element (with its defined soil properties) behaves as a  
245 random variable. The random field is generated by Local average subdivision (LAS) technique  
246 that considers the spatial correlation among the random variables and also adopt a local averaging  
247 scheme. The spatial correlation between various soil properties (considered as random variables)  
248 is expressed by a spatial autocorrelation function. Based on a standard normal distribution function  
249 (i.e., having zero mean and unit variance) and a spatial correlation function, the LAS method  
250 generates correlated local averages of the soil property [45, 46]. Hence, the variance of any  
251 geotechnical property, spatially averaged over a particular soil domain, is lower than the variance  
252 at discrete locations. The variance decreases with an increase in the extent of the soil domain over  
253 which the property is averaged [16, 46-48]. For a random field whose mean and covariance is  
254 spatially varying, for mathematical convenience, it becomes essential to assume the random field  
255 to be statistically homogeneous or stationary whose characterising joint pdf is spatially invariant,  
256 i.e., its mean, variance and all the higher order moments remain constant at any location within the  
257 random field remains same. The correlation between any two random variables entirely depends  
258 on their separation distance, and not on their absolute locations. In order to characterize a stationary

259 random field, it is important to have an a-priori knowledge of its mean, variance and the pattern of  
260 spatial variability characterized using correlation length.

261

### 262 **5.1. Simulation of Random Field in *Rslope2D***

263 To simulate the spatial variation in a chosen slope domain, *Rslope2D* uses the random field theory  
264 developed by Vanmarcke [49, 50]. To conduct the elastoplastic FE slope stability analysis,  
265 *Rslope2D* uses various input parameters such as cohesion ( $c$ ), friction angle ( $\phi$ ), dilation angle ( $\psi$ ),  
266 Young's Modulus ( $E_s$ ), Poisson's ratio ( $\nu$ ), and the soil unit weight ( $\gamma$ ). For the present study, as  
267 explained earlier, only the shear strength parameters  $c$  and  $\phi$  are considered random variables that  
268 are represented through a transformed log-normal pdf. The remaining input parameters are  
269 considered constant ( $\gamma = 20 \text{ kN/m}^3$ ,  $E_s = 100 \text{ MPa}$ ,  $\nu = 0.3$  and  $\psi = 0$ ). In this part of the study, the  
270 slope geometry as well the mean and CoV of shear strength parameters are considered same as in  
271 the earlier discussed LEM-based probabilistic study. Subsequently, a two-dimensional random  
272 field for  $c$  and  $\phi$  are assigned to the chosen slope section for the RFEM analysis. At this stage, for  
273 simplicity of the analyses, the cross-correlation coefficient between  $c$  and  $\phi$  is considered zero, i.e.  
274 there is no correlation between the shear strength parameters. In this study, the two-dimensional  
275 spatial variation of the soil properties in the slope is characterized by an exponentially decaying  
276 (Markovian) correlation function, which implies that the covariance between two points decays  
277 exponentially with absolute separation distance between the points in the field.

278

### 279 **5.2. Estimation of Deterministic FoS and Probability of Failure**

280 In the next stage, the random fields for  $c$  and  $\phi$  are mapped onto the FE mesh of the slope geometry.

281 To develop the FE model of the slope geometry, proper boundary conditions need to be assigned.

282 In this regard, for the FE models developed in *Rslope2D*, the bottom boundary of the slope is  
283 considered completely fixed from deformation in any direction. The vertical boundaries of the  
284 model are allowed to deform in the vertical direction, while the lateral deformation is restrained.  
285 Further, following a mesh convergence study, the FE model of the slope is optimally discretized  
286 into elements of size of  $1 \text{ m} \times 1 \text{ m}$ . The finite elements used in the model are represented by 8-  
287 noded quadrilateral elements with reduced integration for addressing various phases of the  
288 algorithm including generation of gravity loads, stiffness matrix evaluation and stress  
289 redistribution analyses [40, 48, 51, 52]. For plane strain FE modelling in *Rslope2D*, the constitutive  
290 behaviour of soil is represented through an elastic-perfectly plastic stress-strain law enveloped by  
291 a Mohr-Coulomb failure criterion. With the mean values of shear strength parameters ( $c$  and  $\phi$ ),  
292 the FE algorithm in *Rslope2D* utilizes strength reduction technique to estimate the deterministic  
293 FoS [53] that is defined as factor by which the original shear strength parameters need to be  
294 reduced for generating marginal stability condition for failure [54].

295

296 In the next stage of analysis, the probability of failure is estimated using MCS approach. As shown  
297 in Fig. 2, the consistency of the computed probability of failure ( $P_f$ ) has a strong dependency on  
298 the number of MCS conducted. It was reported by Griffiths and Fenton [17] that 1000 numbers of  
299 MCS are sufficient for a 2H:1V undrained clay slope to generate converged estimates of  $P_f$ .  
300 However, based on several studies, it has been recommended to use 4000 number of MCS for a  
301 drained  $c$ - $\phi$  soil slope (soil) while using the *Rslope2D* computer model [48], and the same is  
302 adopted in the present study to estimate the probability of cut slope failure for various correlation  
303 lengths. For generalization, the correlation length is presented with a dimensionless correlation

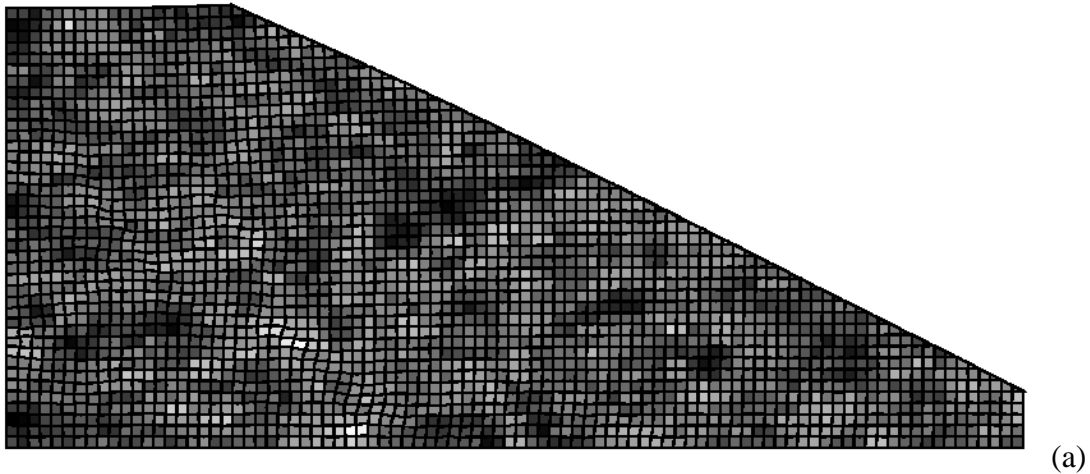
304 length ( $\Theta$ ) that is obtained by dividing the absolute correlation length ( $\theta$ ) by the width of the  
305 excavated cut slope ( $L-b_t$ ), and is expressed as  $\Theta = \theta/(L-b_t)$ .

306

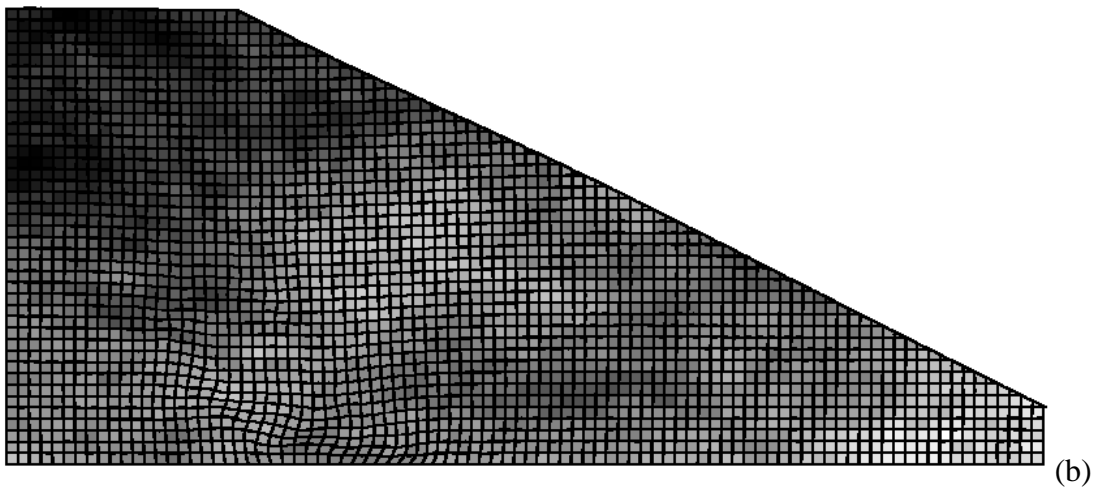
307 Figure 3 shows the typical random fields for cohesion assigned over the discretized soil domain  
308 for two different correlation lengths. Accordingly, the magnitudes of cohesion are assigned to each  
309 of the mesh element that behaves as a random variable for the probabilistic assessment of cut slope  
310 stability through an MCS approach. In Fig. 3, the light greyish cells represent relatively weaker  
311 sections of the slope comprising lesser cohesion values, whereas the darker cells represent the  
312 mesh elements with higher magnitudes of cohesion. Figure 3a represents a comparatively smaller  
313 correlation length ( $\Theta = 0.05$ ), while Fig. 3b represents a larger correlation length ( $\Theta = 1$ ). It should  
314 be noted that both the cohesion distributions are extracted from the same log-normal distribution  
315 assigned to the property, and only the spatial correlation length is different. Figure 3 clearly  
316 highlights that with the change in the correlation length, the initial distribution of the shear strength  
317 parameters might vary significantly, thereby resulting in recognizable difference in the failure  
318 probabilities. Indirectly, this figure also indicates the sheer importance of conducting a thorough  
319 field survey to capture the spatial variation in the soil properties to the best possible detail.

320

321



322



323 **Fig. 3** Typical two-dimensional random field for cohesion magnitudes extracted from the same  
324 lognormal pdf using the dimensionless correlation length of (a)  $\Theta = 0.05$  and (b)  $\Theta = 1$

325

## 326 **6. Comparison of LEM and RFEM-based Analyses**

327 The deterministic study conducted on the chosen slope section using LEM in Slope/W and FEM  
328 in *Rslope2D* resulted in a FoS value of 1.63 and 2, respectively. Therefore, as per the deterministic  
329 analysis, for the chosen slope section, a 10 m wide toe cut can be recommended without  
330 jeopardizing the safety of the resulting vertical face of the cut slope. For different correlation  
331 lengths, Figure 4 presents the comparison of failure probabilities of the chosen slope section ( $b_t =$   
332 10 m) obtained by 1-D random field modeling (using LEM-based probabilistic approach) with that



333 from the 2-D random field modeling (from RFEM-based analyses). The study shows that the LEM-  
334 based probabilistic study predicts the chosen slope section to be safe up to  $\Theta = 0.7$ , with a low  
335 probability of failure and having a performance level 'above average' [14]. However, on the  
336 contrary, the RFEM analysis exhibits the same feature up to  $\Theta = 0.5$ . Therefore, it is noticed that  
337 LEM-based approach considering 1-D random field underestimates the failure probabilities as  
338 compared to RFEM. *Rslope2D* can simulate the field uncertainty more realistically than the 1-D  
339 spatial variation, thereby increasing the failure probability. Moreover, LEM-based deterministic  
340 approach presumes the failure slip plane, whereas the RFEM allows the failure slip plane to  
341 generate along the best possible weakest plane in the soil domain in each realization which is  
342 governed by the local perturbations in the shear strength properties.

343

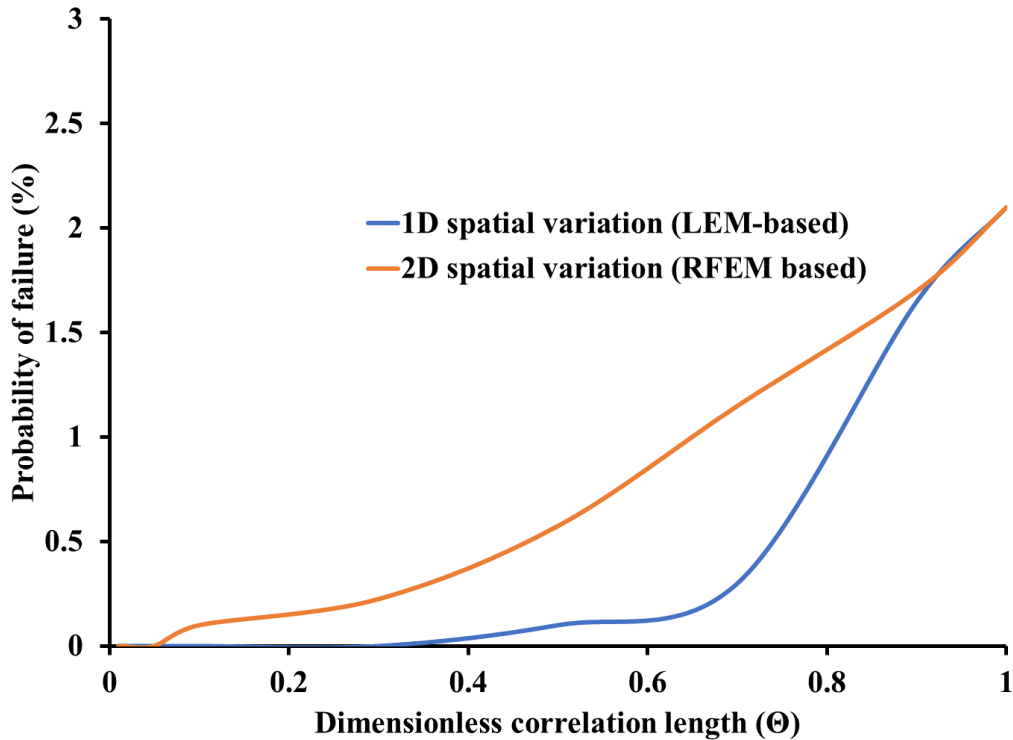
344 It is also noticed that estimation of probability of cut slope failure, in both the methods, are highly  
345 influenced by the spatial variation of the shear strength properties within the soil domain. For small  
346 correlation length, the failure probability is essentially zero; while for intermediate correlation  
347 lengths, the failure probability increases rapidly. For very small value of correlation length, the  
348 local averaging gets maximized. Therefore, in case of small correlation lengths, the random  
349 variables tend to attract values very near to their mean values and, thus, for each and every  
350 realization, the soil domain become essentially homogeneous. As the mean values provide a safe  
351 slope (FoS value is more than one for this particular slope geometry under specified soil  
352 properties), the failure probability is always zero. In case of large correlation lengths (as  $\Theta$   
353 approaches to 1), the entire soil domain becomes highly correlated. Therefore, the slope becomes  
354 essentially homogeneous within each realization, but different from one realization to the next. As  
355 a result, the probability of failure values for both the approaches considered in present study

356 coincides for large correlation lengths (Fig. 4). However, for intermediate values of correlation  
357 lengths, the slope domain reflects heterogeneity in shear strength of soil and, thus, the estimation  
358 of failure probability is governed by the spatial variation characterized using correlation length.

359

360 The study reveals that, in both the approaches, the probability of cut slope failure is very sensitive  
361 to the choice of correlation length characterizing the spatial correlation model that is used to  
362 simulate the in-situ spatial variation of the soil shear strength parameters. Given the inherent  
363 heterogeneity of soil and spatial variation of soil properties, very small correlation lengths or large  
364 correlation lengths are of mere mathematical interest, which have very little practical importance.  
365 Geotechnical engineers are most likely to encounter intermediate correlation lengths, and the study  
366 shows that  $P_f$  changes rapidly in this intermediate range. It is also noteworthy that in this  
367 intermediate range of dimensionless correlation length, the two different approaches predict  
368 noticeably different probabilities of failure. Hence, it highlights the importance of ascertaining a  
369 proper and reliable spatial variation model for a particular site before designing an engineered cut  
370 slope. This realization calls for the necessity to conduct reasonable numbers of field investigations  
371 to ideate the in-situ spatial variation of the desired properties that can be suitably transpired to the  
372 realistic slope stability analysis of cut-slopes.

373



374

375 **Fig. 4** Comparison of the probability of failure for various dimensionless correlation length ( $\Theta$ )  
 376 for the slope section chosen

377

378 **7. Effect of Coefficient of Variation (CoV) and Cross-Correlation Coefficient in RFEM**  
 379 **analysis**

380 This section reports the influence of the coefficient of variation (CoV) and cross-correlation  
 381 between the soil shear strength properties (cohesion,  $c$ , and angle of internal friction,  $\varphi$ ) on the  
 382 failure probability of the chosen slope section ( $H = 40$  m,  $b_t = 10$  m). The study is carried out by  
 383 using RFEM in *Rslope2D*, wherein cross-correlation coefficient ( $\rho_{c\varphi}$ ) between  $c$  and  $\varphi$  is  
 384 implemented by ‘covariance matrix decomposition’ method [55].

385

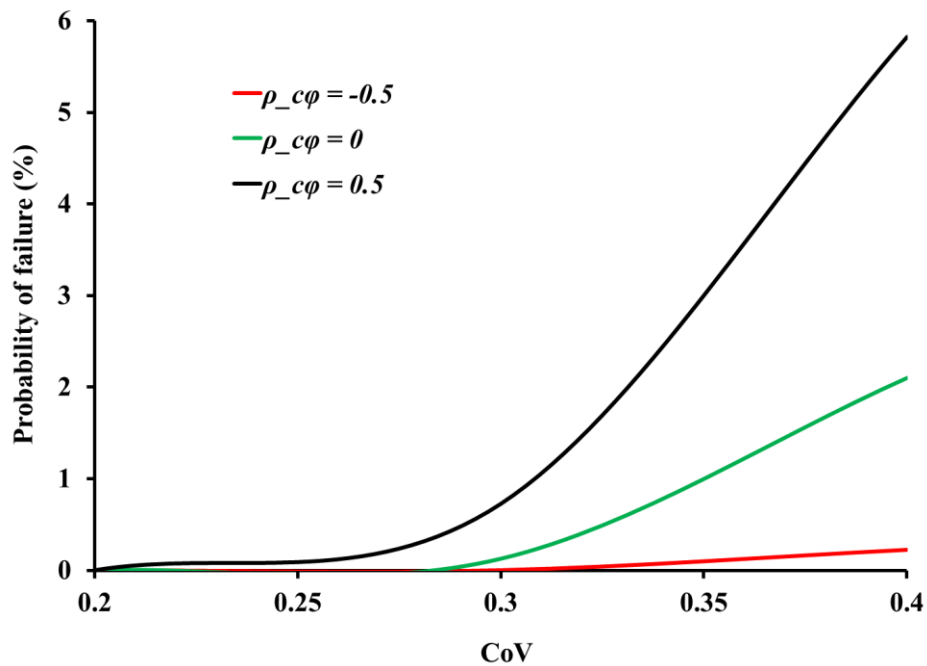
386 To seek out the influence of CoV, the different values considered are 0.2, 0.3 and 0.4. The different  
387 magnitudes of the cross-correlation coefficient between the shear strength parameters of soil ( $c$   
388 and  $\varphi$ ) are considered as -0.5, 0 and +0.5, which indicates that the chosen parameters are negatively  
389 correlated, uncorrelated or positively correlated, respectively. All these forms of correlations can  
390 possibly exist between the shear strength parameters over a region [56]. A negative correlation  
391 coefficient indicates that as  $c$  draws a higher magnitude from its distribution,  $\varphi$  would draw a lower  
392 value; whereas a positive correlation coefficient indicates that both  $c$  and  $\varphi$  would simultaneously  
393 draw higher or lower values from the distribution. If the parameters are uncorrelated, they can  
394 draw any values from their corresponding distribution. The significance of the different correlation  
395 coefficients is well explained in standard literature [34, 47, 56]. The choice of these three  $\rho_{c\varphi}$   
396 values, as adopted in the present study, covers the broad spectrum of correlation coefficients that  
397 can possibly exist between the shear strength parameters, and is helpful to develop a notional  
398 understanding of their effects on the probability of failure.

399

400 For a particular value of dimensionless correlation length ( $\Theta = 1$ ), the results are presented in Fig.  
401 5. Considering a cross-correlation coefficient of 0.5, the probabilities of failure ( $P_f$ ) of the cut slope  
402 with  $b_t = 10$  m are estimated as zero, 0.73% and 5.83% for CoV values of 0.2, 0.3 and 0.4,  
403 respectively. Hence, it is seen that the probability of failure augments with the increase in CoV  
404 value. A higher CoV indicates that the  $c$  and  $\varphi$  values become more dispersed from their mean,  
405 thereby resulting in the increased  $P_f$  values. For the same cut slope section, considering a CoV of  
406 0.4, Fig. 5 shows that the probabilities of failure ( $P_f$ ) are estimated as 0.23%, 2.1% and 5.83% for  
407 cross-correlation coefficient values of -0.5, 0 and +0.5, respectively. It is seen that the probability  
408 of failure of the cut slope decreases when the shear strength parameters are either not correlated or

409 becomes negatively correlated. The observation is in consent with the findings from the LEM-  
410 based probabilistic analysis available in literature [14]. Therefore, a slope with negative or no  
411 correlation between the shear strength parameters is likely to be more stable as compared to a slope  
412 having a positive correlation between  $c$  and  $\phi$ . Therefore, the RFEM analysis conducted on the cut  
413 slope section shows that the probability of failure is highly sensitive to the selection of CoV and  
414 cross-correlation coefficient value of the random variables (in this case the shear strength  
415 parameters). Hence, it can be realised that a proper selection of CoV and cross-correlation  
416 coefficient value is required for estimation of probability of failure of cut slope using random finite  
417 element method.

418



419

420 **Fig. 5** Variation of probability of failure with CoV for various cross-correlation coefficients

421

422

## 423 8. Conclusions

424 This paper reports the contrast between the random finite element method (RFEM) and limit  
425 equilibrium method (LEM) based probabilistic stability analysis of a cut slope. The study shows  
426 that the estimated failure probability is highly governed by the spatial correlation length. The  
427 reported LEM-based probabilistic ignores the spatial variation of shear strength parameters in  
428 vertical direction and also presumes the critical failure surface. On the other hand, RFEM is  
429 capable of simulating spatial variation in both the directions and also allows the slip surface to  
430 generate along the weakest path. It is concluded that in comparison to 2-D spatial variation,  
431 considering 1-D spatial variation of shear strength parameters underestimates the failure  
432 probability of the cut slope in the intermediate ranges of correlation length. Thus, consideration of  
433 2-D spatial variability in the soil shear strength parameters using RFEM approach proves to be  
434 more realistic. It is noted that for LEM and RFEM-based probabilistic study, a slope section is  
435 adjudged safe having a low value of probability of failure (defined by a performance level 'above  
436 average') for a dimensionless correlation length ( $\Theta$ ) up to 0.7 and 0.5, respectively. Any higher  
437 value of correlation length would result in an unsafe cut slope with higher probabilities of failure.

438 The RFEM-based analysis highlighted that the selection of CoV and cross-correlation coefficient  
439 have significant influence on computed failure probability. It is highlighted that increase in CoV  
440 results in an increment of failure probability. Furthermore, positively correlated shear strength  
441 parameters increases the probability of failure of a cut slope. For a cross-correlation coefficient of  
442 +0.5,  $P_f$  of the cut slope varies from zero to 5.83% for CoV ranging from 0.2 to 0.4. For a CoV of  
443 0.4, the  $P_f$  of the cut slope varies 0.23% to 5.83% for the cross-correlation coefficient values  
444 ranging from -0.5 to +0.5, respectively. In a nutshell, the study reveals the importance of  
445 conducting a detailed site specific investigation to assess the spatial variability of the soil shear

446 strength parameter. However, in case a 2-D spatial variability is not readily available based on  
447 limited site investigation, standard literature may be referred for generating synthetic yet  
448 reasonable spatial variabilities, and the same can be used for various probabilistic analysis for  
449 unsupported or retained slopes.

450

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