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Probabilistic post-failure analysis of landslides using stochastic material point method with non-stationary random fields

Analyse probabiliste post-rupture des glissements de terrain à l'aide de la méthode des points de matériau stochastique non stationnaires

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ABSTRACT: Landslides are a common geological hazard, which cause serious damage to buildings or infrastructure facilities. Accurate prediction of influence zone of landslides, including influence (retrogressive) distance and runout distance, is vital for disaster mitigation. However, reliable post-failure analysis of landslides is particularly challenging due to natural uncertainties that are involved in spatially varying soil properties. The aim of this paper is to propose a probabilistic method informed with non-stationary random fields and material point method, which considers the effects of depth-dependent spatial variability of undrained shear strength of soils and large deformations. With the proposed model, a benchmark example of a heterogeneous clayey slope is simulated. The undrained shear strength of soil profile is modeled as a random variable, and commonly-used stationary random fields and non-stationary random fields are executed and compared to investigate the effects of soil spatial variability on post-failure deformations. The associated influence zone is predicted and discussed, which demonstrated that ignoring the non-stationary characteristics of soil properties will result in overestimation of the soil deformations.

RÉSUMÉ : Les glissements de terrain sont un risque géologique courant, qui causent de graves dommages aux bâtiments ou aux infrastructures. La prédiction précise de la zone d'influence des glissements de terrain, y compris la distance d'influence (régressive) et la distance de faux-ronde, est essentielle pour l'atténuation des catastrophes. Cependant, une analyse fiable après rupture des glissements de terrain est particulièrement difficile en raison des incertitudes naturelles impliquées dans les propriétés spatiales du sol. Le but de cet article est de proposer une méthode probabiliste informée des champs aléatoires non stationnaires et de la méthode des points matériels, qui considère les effets de la variabilité spatiale en fonction de la profondeur de la résistance au cisaillement non drainé des sols et des grandes déformations. Avec le modèle proposé, un exemple de référence de pente argileuse hétérogène est simulé. La résistance au cisaillement non drainée du profil du sol est modélisée comme une variable aléatoire, et des champs aléatoires non stationnaires sont exécutés pour étudier les effets de la variabilité spatiale du sol sur les déformations post-rupture. La zone d'influence associée est prévue et discutée, ce qui a démontré que le fait d'ignorer les caractéristiques non stationnaires des propriétés du sol surestimera la déformation.

KEYWORDS: landslide, stochastic modeling, non-stationary random field, material point method.

1 INTRODUCTION

It is widely admitted that soil properties vary spatially because of geophysical and geological processes. The inherent heterogeneity of soil mass is a major source of uncertainty in geotechnical engineering. It has been approved that the spatial variability of the soil properties notably influences the likelihood of the landslides (Jiang and Huang, 2018), as well as their failure modes (Zhu et al., 2019), and subsequently influences on the post-failure behaviors.

Random field (RF) modeling is commonly used in analyzing uncertainties of geotechnical properties (Mousavi et al., 2011, 2018) and widely integrated with limit equilibrium method (LEM) (e.g., Griffiths and Fenton, 2004; Jiang et al., 2014), and finite element method (FEM) (e.g., Gironacci et al. 2018; Zhang et al., 2018; Masoudian et al., 2019) in a Monte-Carlo (MC) framework to systematically investigate slope failure problems. However, the majority of previous studies primarily focus on pre-failure stage of landslides (i.e., stability, reliability, probability of failure) instead of post-failure stage, which is a secondary consequence of landslides (Ma et al. 2018). Part of the reason is the numerical instability of the classic Lagrangian modeling algorithms due to mesh distortion when simulating large deformation problems. Therefore, limited modeling methods have been developed so far for simulating the uncertainties in post-failure behavior of landslides considering soil spatial variability.

Recent progress in developing particle-based methods, such as material point method (MPM) (Soga et al., 2016), made it possible to avoid excessive mesh distortions issues that emerge in solving the partial differential equations of problems involving large deformations. With respect to probabilistic slope failure analysis, Wang (2017) combined the MPM with stationary RF model to quantify the retrogressive distance (influence distance) from the slope crest at undrained conditions. Liu et al. (2019) utilized the LEM and MPM combined with MC simulations to quantify the failure probability of landslides and predict the slope failure modes. Remmerswaal et al. (2021) evaluated the uncertainties of residual dyke with a stationary RF model. These studies primarily considered slopes with stationary random properties, which means the mean and standard deviation of strength were spatially constant within the region of the RF. However, numerous site-specific data collected from in-situ tests have confirmed that normally consolidated clays regularly display an increasing undrained strength trend with depth because of the effective overburden stresses (Jiang and Huang, 2018). A basic illustration of the non-stationary soil variability with an increasing linear trend along with fluctuation is shown in Fig. 1. Griffiths et al. (2015) and Zhu et al. (2017) introduced the slopes where the mean strength increase linearly with depth from a non-zero value at the ground, and presented examples with non-stationary RFs, which shows a great importance of the non-stationary characteristics of soil properties. Therefore, it is significant to take depth-dependent nature of soil properties in the post-failure analysis of landslides.
In this paper, a stochastic material point method (SMPM) is proposed to evaluate post-failure motion of landslides considering the effects of both spatially varying soil properties and large deformations. Over an example case study with a classic layout of clayey slope, the post-failure process is simulated. The undrained shear strength, $S_u$, of soil profile is modeled as a random variable, both stationary and non-stationary RFs are executed to investigate the effects of soil spatial variability on post-failure motions in terms of influence distance and runout distance.

$$\rho(\tau_x, \tau_y) = \exp[-2(\frac{\tau_x}{\delta_h} + \frac{\tau_y}{\delta_v})]$$  \hspace{1cm} (1)

where, $\rho(\tau)$ is the correlation coefficients, $\tau_x = |x_i - x_j|$ and $\tau_y = |y_i - y_j|$ are the absolute distances between two spatial locations in horizontal and vertical directions, respectively; $\delta_h$ and $\delta_v$ are the scales of fluctuation in horizontal and vertical directions, respectively. The scale of fluctuation $\delta$ is used to determine the distance within which the random quantities are highly correlated. Many researchers (Phoon, 2008; Liu, 2018) studied different approaches of determining the value of $\delta$ for soil properties and suggested that the scale of fluctuation of the undrained shear strength parameter, $S_u$, for clay is typically within the horizontal range of 1.0–92.4 m and the vertical range of 0.1–8.0 m, respectively. In this work, similar values for $S_u$ are used for simulations.

The Cholesky matrix decomposition (CMD) method (Jiang et al., 2014; Liu et al., 2017) is used to generate RFs in this work, which is readily implementable in a computationally efficient manner. Firstly, the domain $\Omega$ is discretized into elements of the RF with the centroid coordinates of the elements specified by $(x_i, y_i)$. The autocorrelation matrix $C_{nn}$, representing the spatial variability of the properties, can be obtained. Then, the $C_{nn}$ can be decomposed as

$$L \cdot L^T = C_{nn}$$  \hspace{1cm} (2)

where, $L$ is the lower triangular matrix with dimension of $n \times n$. Then, a standard Gaussian RF $X^G_i(x,y)$ is derived as

$$X^G_i(x,y) = L \cdot \xi_i \quad (i = 1, 2, ..., N)$$  \hspace{1cm} (3)

where $i$ is the number of standard Gaussian RF, $\xi_i$ is a sample matrix obtained by arranging the vector of $n$ independent standard normal samples as $m$ vectors with dimension of $n$. In this study, the undrained shear strength parameter is considered to be lognormally distributed, the corresponding lognormal RF $X^{L}(x,y)$ can be generated by isoprobabilistic transformation method as

$$X^{L}_i(x,y) = F^{-1} \{ \Phi [X_i(x,y)] \} \quad (i = 1, 2, ..., N)$$  \hspace{1cm} (4)

where the $F^{-1} (\bullet)$ is the inverse function of its corresponding marginal cumulative distribution of the desired undrained shear strength $S_u$, and $\Phi (\bullet)$ is the standard Gaussian cumulative distribution function. The $\Phi (\bullet)$ can rearrange the standard Gaussian RF $X^G_i(x,y)$ into the uniform distribution $U$. At this stage, the stationary lognormal RF $X^{L}(x,y)$ can be generated.

For generating non-stationary RFs, initially let the stationary RF $X^{L}(x,y)$ values assigned to all elements in the domain $\Omega$ to be $\xi_{G_i}$. The mean undrained strength is a linear function as

$$\mu_z = \mu_0 + \rho z$$  \hspace{1cm} (5)

where $\mu_z$ is the mean strength at depth $z$, $\mu_0$ is the mean strength at $z=0$ (ground surface), and $\rho$ is the gradient of mean strength increase with $z$, with typical values from 0 to 3.5 kN/m$^3$ (Zhu et al. 2017; Jiang et al. 2018). The standard deviation of strength is assumed to be proportional to depth with a gradient, which results in a constant coefficient of variation. Then, the element values in a non-stationary RF can be obtained as

$$C_{zi} = C_{G_i}(\mu_0 + \rho z) / \mu_0$$  \hspace{1cm} (6)

Note that if $\rho = 0$, there is no adjustment in Eq. (6), and the stationary RF is retained. For more details of the algorithms refer to Griffiths et al. (2015) and Zhu et al. (2017).

Figure 1. Soil variability with increasing linear trend (modified from Phoon and Kulhawy, 1999)

2 STOCHASTIC MATERIAL POINT METHOD

2.1 GIMP

MPM is a particle-based mesh-free method which was developed on the basis of the particle-in-cell concept (Sulsky et al., 1994) and has been proven as a promising particle-based method for modeling the behavior of different earth structures under the large strain processes (Soga et al., 2016).

MPM consists of two discretizations, including: a) a cluster of material points (Lagrangian particles) representing the continuous material which are allowed to move freely and carry the density, strain, stress, and all state variables of the continuous body, and b) a background Eulerian mesh for solving the governing equations and determining incremental velocities, instead of carrying mechanical parameter information. Note that the deformation of the domain can be tracked by the motion of the material points, while the governing equations are solved on the background mesh which is regularly reset to initial configuration in each calculation step. However, the original MPM has grid-crossing instability, which is caused by the discontinuous gradient of shape functions. This error can be reduced by using generalized interpolation material point method (GIMP) by introducing GIMP grid shape function and particle characteristic function (Bardenhagen, 2002; Tran et al. 2019). This paper uses GIMP and modified update stress last (MUSL) as encoded in the openly available MPM3D code (Zhang et al., 2016) to simulate landslides. The application of the code for landslide analysis has been previously exercised by other researchers (e.g., Liu et al., 2019).

2.2 Non-stationary random field generation

Spatial variability of soil is commonly defined as RFs and prior information from their spatial variability are used to calibrate their statistical features, which are described by a probability density function (PDF) with mean value and coefficient of variation (COV), and an auto-correlation function (Phoon and Kulhawy, 1996; Phoon, 2008; Jiang et al., 2014). In this study, the single exponential function is used as auto-correlation function to characterize the spatial correlation structure between any two points, which can be expressed as

where $\tau_x = |x_i - x_j|$ and $\tau_y = |y_i - y_j|$ are the absolute distances between two spatial locations in horizontal and vertical directions, respectively; $\delta_h$ and $\delta_v$ are the scales of fluctuation in horizontal and vertical directions, respectively. The scale of fluctuation $\delta$ is used to determine the distance within which the random quantities are highly correlated. Many researchers (Phoon, 2008; Liu, 2018) studied different approaches of determining the value of $\delta$ for soil properties and suggested that the scale of fluctuation of the undrained shear strength parameter, $S_u$, for clay is typically within the horizontal range of 1.0–92.4 m and the vertical range of 0.1–8.0 m, respectively. In this work, similar values for $S_u$ are used for simulations.

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Note that if $\rho = 0$, there is no adjustment in Eq. (6), and the stationary RF is retained. For more details of the algorithms refer to Griffiths et al. (2015) and Zhu et al. (2017).
3 ANALYSES AND RESULTS

3.1 Domain and boundary conditions

A simple clayey slope is modeled to verify the SMPM in simulating the landslide failure. The slope is considered to have 5 m height with a length of 25 m and a slope gradient of 45° relative to the horizontal direction. The clay material is also assumed to have a strain-softening behavior. Fig. 2 shows the geometries of the model slope with the corresponding background meshes and material points. The background mesh is extended to 100 m to offer enough space for possible extensive runout distances of the landslide. A frictional contact under the slope base is assumed with frictional coefficient of 0.3 taken from Bandara and Soga (2015) who presented the characteristics of a similar type of soil. A roller boundary condition is set at the left boundary of the domain to allow vertical material points’ movements.

![Figure 2. The initial geometry, boundary conditions, and background mesh of the clay slope](image)

### 3.2 Material properties

The undrained shear strength, $S_u$, of the clay is assumed as the spatially random variable, while the Young’s modulus $E$, Poisson’s ratio $\nu$, and other soil properties are assumed to be constants as it has been found that their contributions on landslide post-failure motions are not significant (Cheuk et al., 2013). Table 1 shows the statistical parameters of $S_u$. The $S_u$ in RFs is interpreted as the peak undrained shear strength $S_{u\infty}$. The properties’ values for the representative clay material are summarized in Table 2, which are consistent with previous literature (e.g., Wang, 2017; Yuan et al., 2020).

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Unit</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean, $\mu_0$</td>
<td>kPa</td>
<td>20</td>
</tr>
<tr>
<td>COV</td>
<td></td>
<td>0.25</td>
</tr>
<tr>
<td>Gradient, $\rho$</td>
<td></td>
<td>2</td>
</tr>
<tr>
<td>Horizontal scale of fluctuation, $\delta_h$</td>
<td>m</td>
<td>1</td>
</tr>
<tr>
<td>Vertical scale of fluctuation, $\delta_v$</td>
<td>m</td>
<td>1</td>
</tr>
</tbody>
</table>

### Table 2. Material properties for the clay slope analysis

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Unit</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Solid grain density, $\gamma$</td>
<td>kN/m$^3$</td>
<td>20</td>
</tr>
<tr>
<td>Young’s modulus, $E$</td>
<td>kPa</td>
<td>0.25</td>
</tr>
<tr>
<td>Poisson’s ratio, $\nu$</td>
<td></td>
<td>0.33</td>
</tr>
<tr>
<td>Peak undrained shear strength, $S_{u\infty}$</td>
<td>kPa</td>
<td>20</td>
</tr>
<tr>
<td>Residual undrained shear strength, $S_r$</td>
<td>kPa</td>
<td>4</td>
</tr>
</tbody>
</table>

As for the model settings, each realization of $S_u$ is generated according to the centroid coordinates $(x_i, y_i)$ at mid-points of the material points in the background mesh with two dimensions, and then they are mapped onto the material points for calculations. The MPM model contains 11224 material points and 26052 cells, with lengths of 0.1 m for each material point and 0.2 × 0.2 m for all four-node quadrilateral background cells, resulting in 4 material points in each cell. The minimum values of the scale of the fluctuation ($\delta_h = \delta_v = 1$ m) are much larger than 2 times of the cell size (0.2×0.2 m), which is consistent with recommendations of Li and Der Kiureghian (1993) to prevent loss of information about the spatial variability of the RF. The landslide is triggered by applying the gravitational loading. The time increment is 7.5 × 10$^{-4}$ s. The total time for the calculation is 15 s, when soil deposits become stable according to kinematic energy and unbalanced forces of the system (Kafaji, 2013).

### 3.3 Deterministic analysis

Fig. 3 shows the final configuration of a homogeneous landslide computed by deterministic MPM modeling. According to the results, several blocks are formed during the failure process and at $t=15.0$ s the landslide is completely deposited with an extensive runout motion and substantial retrogressive failure at a new formed backscarp. The results give failure shapes similar to those predicted in previous works, where the influence distance is close to the finding in Wang (2017) (i.e., 9.2 m), and the corresponding runout distance is close to the results of Yuan et al. (2020) (i.e., 18.57 m).

![Figure 3. Initial and final configuration of landslide by deterministic analysis](image)

### 3.4 Stochastic analysis

For illustration, Fig. 4 shows two typical samples of the $S_u$ variations over the slope domain, where a stationary RF and a non-stationary RF can be seen. In these figures, the red regions denote the larger $S_u$ values, indicating stronger zones, while the blue parts represent the relatively smaller $S_u$ values for weaker zones of the slope. It can be observed that the $S_u$ values increase with depth in the non-stationary RF model (Fig. 4b). In addition, the variation of $S_u$ in the shallow area is relatively small in comparison with the bottom area for the non-stationary case. Comparing the corresponding simulated data with the two cases in depth, it can be found that the mean value of $S_u$ stays constant with depth in the stationary case (Fig. 5a), while the mean value of $S_u$ is linearly increasing with depth (Fig. 5b). Because of the non-stationary characteristics of soil properties, it leads to different distribution of $S_u$ values compared with the stationary case. Both cases are consistent with the descriptions in the work by Lumb (1966).

![Figure 4. Typical samples of the $S_u$ variations over the slope domain](image)
By conducting the GIMP analysis, the corresponding $I$ and $R$ for the stationary RF case is 13.11 m and 25.17 m (Fig. 6a), respectively. While the non-stationary RF case have relatively shorter distance compared with stationary case, in which $I = 5.82$ m and $R = 16.01$ m (Fig. 6b). It can be found that the non-stationary case results in a relatively short influence/runout distance, while the stationary case is prone to form extensive runout motions.

It should be noted that the results of each sample in stationary or non-stationary case may differ due to the distribution of shear strength. Therefore, multiple MC simulations are required to reflect the possible post-failure behaviors of landslides. To analyze the uncertainties of $I$ and $R$ of landslides with non-stationary and stationary RFs, iterative calculations based on MC simulation are conducted. The stationary RF case is adopted to check the convergence criterion, which indicates that the statistical convergence is achieved after around 600 simulations with a variance of 2.24 and 1.75 for $I$ and $R$, respectively. Therefore, 1000 MC simulations can produce reasonably stable results.

Fig. 7 and Fig. 8 respectively show the probability density histograms for $I$ and $R$ from the analyses of the stationary RF and non-stationary RF case. In these figures, the horizontal coordinate represents the calculated influence distance or calculated runout distance, the left vertical coordinate represents the PDF, and the right coordinate represents the cumulative probability. The PDF is obtained by fitting both Normal and Lognormal distribution functions based on the computed values. It is seen that both distributions could reasonably fit the histogram. According to the Chi-square goodness of fit test, it is confirmed that the Normal distribution could be adopted to characterize the influence distance for all the involved cases at a 5% level of significance. As such, the Normal distribution function will be used to approximate the PDF of the computed distance.

Fig. 7a shows that the estimated mean value of $I$ for the stationary RF case is 10.15 m. In comparison, the deterministic analysis underestimates the influence distance with 9.32 m, giving an unconservative estimation of the potential retrogressive failure. This is a notable discrepancy in post-failure motions between the homogeneous landslide and the heterogeneous landslide. Because of the spatial variability in soil strength, the values for the influence distance mostly vary from 6 m to 14 m, and the maximum influence distance can reach up to 17.3 m. Similar with the computed $I$, the values for the computed $R$ also vary notably, which is mostly in the range of 17 m to 24 m; the minimum runout distance is 15.08 m, and the maximum runout distance can reach up to 27.00 m (as shown in Fig. 7b). The estimated mean value of the computed $R$ is 20.08 m. Comparing with the homogeneous case, the deterministic analysis particularly underestimates the runout distance with 18.82 m, which may give a nonconservative estimation of the potential risks for the structures located in the vicinity of slopes. However, as for non-stationary case, it shows totally different characteristics with the stationary case. Fig. 8a shows that the
estimated mean value of $I$ for the non-stationary RF case is 7.88 m, and the maximum influence distance can reach up to 12.4 m, the minimum value is 4.3 m. For runout distance as shown in Fig. 8b, the minimum runout distance is 13.78 m, and the maximum runout distance can reach up to 21.50 m. The estimated mean value of the computed $R$ is 17.03 m. Based on the results from the non-stationary case, the deterministic analysis gave an overestimation for both $I$ and $R$. This could be explained by the distribution of $S_u$ in the non-stationary RF, where the $S_u$ is increasing with the depth, it leads to the weaker layers distribution in the shallower depths, while the stronger soils are distributed in the bottom areas. Therefore, the stronger deposit at bottom side in the slope tends to be stable which leads to small failure scale.

To distinguish the non-stationary characteristics of $S_u$, Fig. 9 compares the PDF curves of calculated $I$ and $R$ for stationary and non-stationary RF models. It can be seen that the PDF curve for the non-stationary RF is much narrower and taller than that for the stationary RF, which indicates that the variation of $I$ and $R$ for the non-stationary RF is notably smaller than the stationary case. That may be attributed to the characteristics of spatial distribution of strength in soil mass. As can be seen from the typical sample in Fig. 5b, the variation of $S_u$ in the shallow area (depth < 1 m) is relatively small in comparison with the deep area (depth = 5 m) for the non-stationary case. Meanwhile, as typical samples shown in Fig. 4, the variation of $S_u$ in the shallow area for the non-stationary case is smaller than that of the stationary RF, which leads to a small variation of post-failure deformation with the non-stationary RF. Additionally, it can be seen from the Fig. 5 that, $S_u$ linearly increasing with depth leads to the increase in overall strength of the slope, which further results to a low variability in $I$ and $R$ for the non-stationary RF. This is consistent with studies conducted by Li et al. (2015), who indicated that the commonly-used stationary RF would overestimate the variations in deformation. If the deterministic result is considered as a limit of safety, the exceedance probability (influence distance > 9.32 m) is about 63% for the stationary RF model and 13% for the non-stationary RF model. As for runout distance, the exceedance probability (runout distance > 18.82 m) is about 75% for the stationary RF model and 6.7% for the non-stationary RF model. Based on the above analysis, it is demonstrated that the rationale assumption should be clarified when using stationary or non-stationary RF models because these soil uncertainties can directly influence the post-failure behavior of landslides.

This paper has investigated the effect of spatially variable undrained shear strength on post-failure motions of landslides with SMPM, in which non-stationary RFs and MPM are integrated. The proposed model considers the effects of depth-dependent spatial variability of undrained shear strength of soils and large deformations. MC simulations are conducted to evaluate the statistics of influence distance and runout distance.

### Figure 8. Histograms and PDFs of the (a) influence distance and (b) runout distance for the non-stationary RF

![Figure 8](image_url)

### Figure 9. Comparison of PDF curves for stationary and non-stationary RF cases (a) influence distance and (b) runout distance

#### 4 CONCLUSIONS

This paper has investigated the effect of spatially variable undrained shear strength on post-failure motions of landslides with SMPM, in which non-stationary RFs and MPM are integrated. The proposed model considers the effects of depth-dependent spatial variability of undrained shear strength of soils and large deformations. MC simulations are conducted to evaluate the statistics of influence distance and runout distance,
which are compared with the results for deterministic analysis and commonly-used stationary RF model. The main conclusions obtained from the analyses can be summarized as follows:

1. The spatial variability of $\sigma_n$ notably influences the failure mode of the landslide and consequently its post-failure behavior.

2. The statistics of the influence zone are considerably influenced by the non-stationary characteristics of $\sigma_n$. Compared with the non-stationary RF model, stationary RF model may overestimate the variations in influence zone of landslides.

3. The rationale of assumption should be clarified when using stationary or non-stationary RF models because these soil uncertainties can directly influence the post-failure behavior of landslides.

6 REFERENCES


Jiang SH and Huang J. 2018. Modeling of non-stationary random field of undrained shear strength of soil for slope reliability analysis. Soils found 58(1), 185-198


