



# Reliability analysis and risk assessment of a landfill slope failure in spatially variable municipal solid waste

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## Abstract

Quantitative assessment of landfill slope failure risk provides valuable information about slope design and risk reduction. This study presents a reliability-based analysis in which an accurate method is applied to assess slope failure risk using the stochastic finite difference method. This method incorporates the spatial variability of municipal solid waste properties due to anisotropic autocorrelation structures and evaluates the consequence associated with each failure separately. This method was evaluated using the data of the Saravan landfill (Rasht, Iran) and presenting a parametric analysis. Several Monte Carlo simulations were conducted to indicate the heterogeneity of the municipal solid waste, taking into account the shear strength and the unit weight of the municipal solid waste randomly. Finally, the safety factor, probability of failure, and risk were assessed using different analysis cases. Deterministic analysis was also performed for all modes using mean values for various municipal solid waste properties. The results show that spatial variability of municipal solid waste parameters and autocorrelation structures significantly affect the safety factor, probability of failure, and risk. Also, comparing the obtained results revealed that for the given slope, the safety factor values in deterministic analyses are overestimated compared to those of the probabilistic analyses. However, risk shows the opposite behavior.

**Keywords** Landfill slope stability · Probabilistic method · Reliability analysis · Slip mass · Variability

## List of symbols

$c$	Cohesion	$k(x_i)$	A geotechnical property at location $x_i$
$C$	The consequence associated with that failure	$N_f$	The number of landfill slope failures
$C_i$	Consequence associated with every failure	$N_f$	The number of realizations in which the slope is failed
COV	Coefficient of variation	$N_{sim}$	The total number of realizations
COV <sub>FS</sub>	Coefficient of variation of the safety factor	$P_f$	Probability of failure
COV <sub>P</sub>	Coefficient of variation of properties of MSW	$R$	Risk
COV <sub>P(f)</sub>	Coefficient of variation of probability of failure	$\gamma$	Unit weight
$F$	Reduction factor	$\delta$	Autocorrelation distance
FS	Safety factor	$\delta_x$	Auto-correlation distance in the horizontal directions
FS <sub>det</sub>	Deterministic safety factor	$\delta_y$	Auto-correlation distance in the vertical directions
FS <sub>st</sub>	Stochastic safety factor	$\mu$	Mean
$G(x_i)$	A random field with a standard normal distribution	$\sigma$	Standard deviation
		$\tau$	Shear strength
		$\tau_x$	The relative distances of two points in the horizontal direction
		$\tau_z$	The relative distances of two points in the vertical direction
		$\phi$	Internal friction angle

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## Introduction

The increase in municipal solid waste (MSW) production over the past few decades has led to the rapid expansion of MSW management and disposal technologies. Landfilling is still an efficient and common method in many countries because of its excellent performance in cost–benefit analysis (Machado et al. 2010; Karimpour-Fard et al. 2011; Babu et al. 2014; Rajesh et al. 2016; Mehdizadeh et al. 2020). Due to increased MSW production and limited new landfills, the prevailing attitude in most countries is to extend the capacity of existing landfills, which in turn requires increasing their height and area. As a result, the overall slope stability of these landfills should be cautiously considered (Eskandari et al. 2016; Zhang et al. 2020). The instability of landfills can have many adverse effects on the environment and surroundings, including air pollution, water pollution, soil pollution, climate change, fires or explosions, loss of biodiversity, obstruction of drains; landfills can also contaminate drinking water and transmit diseases (Koerner and Soong 2000; Eid et al. 2000; Chang 2005; Chugh et al. 2007; Zhan et al. 2008; Blight 2008; Jahanfar et al. 2017). Although many research has been done on the recycling of waste, the reliance on landfilling remains a prevalent waste management strategy in numerous places (Aziz et al. 2017; Razali et al. 2018a, b; Aziz et al. 2019; Japar et al. 2019).

The slope stability of landfills depends primarily on the shear strength ( $\tau$ ) and unit weight ( $\gamma$ ) of the MSW (Zekkos et al. 2012). The geotechnical properties of the MSW show considerable spatial variability even in a single landfill and a specific layer. These properties depend on various factors, including inherent MSW heterogeneity, different loading conditions, compaction methods, weather conditions, different testing methods, MSW ages, gas and leachate pressure, leachate level, and degradability of MSW due to various physical, chemical, and biological factors (Gharabaghi et al. 2008; Ering and Babu 2015; De Stefano et al. 2016; Jahanfar et al. 2017; Feng et al. 2018). Internal friction angle ( $\phi$ ) and cohesion ( $c$ ) of the MSW have been reported from 10 to 60° and from 0 to 80 kPa, respectively (Babu et al. 2015; Zhan et al. 2008). Based on these factors and the resulting variability, the choice of landfill design parameters in conventional methods is a challenging issue directly related to landfill slope stability.

In slope stability analysis of variable MSWs, since failure slip tends to cross the weakest paths, different failure modes may occur (Mehdizadeh et al. 2020) and the consequence is associated with each failure separately. Therefore, a design engineer not only must thoroughly examine the slope stability of the landfills but must also examine the occurrence of failure damage separately. One

of the techniques to quantify landfill slope failure risk ( $R$ ) is to calculate the probability of failure ( $P_f$ ) and multiply it by the failure occurrence (Huang 2013; Cheng 2018). In this way, the effect of MSW properties variability on the assessment of landfill slope risk can be evaluated by considering different failure modes.

Landfill slope stability assessment is conventionally based on a deterministic approach with a safety factor (FS) that provides limited information about the consequence of landfill slope failure for variable MSWs. This approach tries to deal with uncertainties involved in choosing logical parameters conservatively. However, the same safety factors may be used for different MSW slope conditions, regardless of the uncertainty associated with each condition. Because this is not a very reasonable strategy, many recently conducted studies have systematically developed some methods to address the uncertainties involved. Probabilistic methods provide a good framework for incorporating the MSW variability in the probabilistic slope stability analysis and calculating the involved risk.

Limited studies have been conducted on the probabilistic landfill slope stability. The main purpose of these studies has been to determine the  $P_f$  or reliability index of these slopes. Sia and Dixon (2012) evaluated the interaction of MSW and the lining system in a probabilistic framework. The lining system of a landfill is a protective barrier designed to prevent the leakage or migration of leachate, which is the liquid that forms as water percolates through the waste in a landfill. The primary purpose of the lining system is to contain and control the movement of leachate, preventing it from contaminating surrounding soil and groundwater. Babu et al. (2014) applying a probabilistic finite difference method assessed the landfill slope stability by considering the spatial variability of the MSW's geotechnical properties. Rajesh et al. (2016) investigated the probabilistic stability of a landfill slope using the response surface metamodeling approach. Reddy et al. (2018) evaluated the stability of a bioreactor landfill with a hydro-bio-mechanical model in a probabilistic framework. They also investigated the effect of spatial variability properties on settlement and moisture distribution in the landfill. Mehdizadeh et al. (2020) used probabilistic methods to investigate the effect of variability of shear strength and unit weight of MSW on the stability and  $P_f$  of an MSW landfill slope. For this purpose, they combined the random field theory with the numerical finite difference method (FDM) in the Monte Carlo simulation framework. The results showed that the probabilistic methods have a good ability to incorporate the spatial variability of MSW properties and their effect on the performance and  $P_f$  of landfill slopes. Mehdizadeh et al. (2020) evaluated the reliability of a landfill. For this purpose, they studied the effect of the anisotropic



structure of MSW's random variables, including  $c$ ,  $\varphi$ , and  $\gamma$ , on the mean ( $FS_{st}$ ) and coefficient of variation ( $COV_{FS}$ ) of the safety factor and  $P_f$  using Monte Carlo simulation (MCS). The results showed that the coefficient of variation (COV) of random variables significantly affects the  $FS_{st}$ ,  $COV_{FS}$  and the  $P_f$  of the landfill slope. In addition, it was found that assuming the isotropic structure of random variables leads to an underestimation of the  $P_f$ . Falamaki et al. (2021) studied the static and seismic stability of the failed landfill from a probabilistic perspective. They investigated the effect of uncertainties involved in MSW strength parameters and seismic forces on the landfill slope stability during and after construction. Based on the obtained results, they provided recommendations for building open dumpsites.

Despite numerous studies on the probability of failure in landfill slopes, scarce studies have assessed the risk of landfill slope with some probabilistic methods. For instance, Jahanfar et al. (2017) proposed a new method for risk assessment of landfill slope failure using probability analysis of potential failure scenarios and related losses. The main framework of their method included selecting appropriate statistical distributions for MSW shear strength and rheological properties, probability analysis of slope stability, and determination of waste run-out length, which is ultimately used to calculate the risk of potential losses. Compared to existing slope stability analyses, which are based solely on the probability of slope failure, this method provides a more accurate estimate of the casualty risk due to landfill slope failure. As a result, probabilistic studies performed for landfill slope stability have been limited to calculating  $P_f$  or  $R$  without considering various failure modes resulting from MSW variability. Hence, in order to safely design and reduce the risks of landfill instability, and estimate the  $P_f$  and hazards of consequences associated with landfill slope failure, it is necessary to assess the risk of landfill slope failure by considering the variability of MSW characteristics.

In this paper,  $P_f$  and  $R$  of a landfill are assessed when strength parameters ( $c$  and  $\varphi$ ) and unit weight ( $\gamma$ ) of MSW have spatial variability with anisotropic structure and different correlation lengths. In this method, which is called the random finite difference method (RFDM), FLAC2D code is coupled with the random field theory. Jamshidi and Alaie (2015) and Cheng et al. (2018) used RFDM to study the possibility of soil slope failure. In RFDM, the matrix decomposition method generates random fields of shear strength and unit weight of MSW. Then, the safety factor is calculated using the FLAC2D code, and the critical slip surface and the slip mass are calculated by a Fish program (FLAC2D). Finally, the  $P_f$  and  $R$  are calculated using the MCS. This research was conducted in 2022 in the city of Rasht, Iran.

## Materials and methods

### Random fields

Vanmark (1983) showed that according to stochastic field theory, the spatial variability of a continuous environment could be expressed in terms of mean ( $\mu$ ), COV, and auto-correlation distance ( $\delta$ ). For probabilistic analyses, each of the MSW geotechnical parameters (i.e., cohesion,  $c$ , friction angle,  $\varphi$ , and unit weight,  $\gamma$ ) is modeled as independent random variables using probability density function (pdf) and parameters related to their distribution. Assuming that the geotechnical parameters of the MSW ( $k$ ) have a log-normal distribution, the mean ( $\mu$ ), standard deviation ( $\sigma$ ), and the spatial autocorrelation distance ( $\delta$ ) of the parameter  $k$  are used to simulate random fields using Eq. 1:

$$k(x_i) = \exp \left\{ \mu_{\ln k}(x_i) + \sigma_{\ln k}(x_i) \cdot G(x_i) \right\} \quad (1)$$

where  $k(x_i)$  is a geotechnical property at location  $x_i$  and  $G(x_i)$  is a random field with a standard normal distribution (mean zero and unit variance). The values of  $G(x_i)$  are determined using the method of matrix decomposition and the anisotropic function of single exponential auto-correlation (Baecher and Christian 2003):

$$\rho_k(\tau_x, \tau_y) = \exp \left( -\frac{\tau_x}{\delta_x} - \frac{\tau_y}{\delta_y} \right) \quad (2)$$

where  $\tau_x$  and  $\tau_y$  represent the relative distances of two points in the horizontal and vertical directions, respectively, and  $\delta_x$  and  $\delta_y$  show the auto-correlation distance in the main directions. The complete process of anisotropic random field modeling and its FDM-based implementations have been studied in detail in Jiang and Huang (2018) and Mehdizadeh et al. (2020).

### The probability of failure ( $P_f$ )

After generating random fields for the three parameters  $c$ ,  $\varphi$ , and  $\gamma$ , the safety factor (FS) of each simulation can be calculated, and the  $P_f$  of the desired slope is obtained. In this study, the shear strength reduction method in the FDM-based FLAC2D software was used to calculate FS. Unlike the limit equilibrium methods (LEMs), this method can determine different slip surfaces. Also, in this method, parameters of  $c$  and  $\varphi$  are reduced by the same reduction factor ( $F$ ) using Eq. (3). Next, FS is obtained by selecting different values of  $F$  and replacing the reduced values (i.e.,  $c/F$  and  $\varphi/F$ ) with the initial values, and finally performing various analyses to reach the critical state. The reduction

coefficient that leads to the critical state will be the same as the FS (ITASCA 2015).

$$\begin{aligned} c_F &= c/F \\ \varphi_F &= \arctan(\tan \varphi/F) \end{aligned} \quad (3)$$

The whole process of generating random fields and stability analysis is performed using the FISH language in FLAC2D software. This method obtains an FS for each realization for random fields  $c$ ,  $\varphi$ , and  $\gamma$  using the Monte Carlo sampling method. Thus, the MCS is adapted to generate a sufficient number of realizations for random fields. After determining the stochastic FSs, the probability of slope failure is calculated by Eq. (4):

$$P_f = \frac{N_f}{N_{\text{sim}}} \quad (4)$$

where  $N_{\text{sim}}$  is the total number of realizations and  $N_f$  is the number of realizations in which the slope is failed ( $FS < 1$ ).

### The consequence of failure

In risk quantification, the consequence of each landfill slope failure is estimated using a specific and simple method and taking into account the spatial variability of the shear strength and the unit weight parameters of the MSW. The accurate determination of the consequence of slope failure requires complete data and information about the landfill, facilities, buildings, artificial and natural factors around it, and human factors involved in the landfill site. In the absence of such data, Zhu et al. (2015) suggest that damage due to slope failure is usually directly related to an increase in the volume of the slip mass. In this study, the volume of slip MSW mass due to the landfill slope failure was used as a simple and approximate measure to determine the consequence of any failure. As mentioned earlier, due to the spatial variability of the MSW parameters, different failure modes are formed on the landfill slope, and the volume of the sliding MSW mass depends on the critical surface formed on the slope.

Hicks et al. (2014) proposed a method for calculating the volume of a sliding mass on a slope based on the invariant shear strain on a critical slope. The shear strain invariant is used because it easily combines all the strain components into a single value, thus providing a clear picture of the failure mechanism. After calculating the strain in this method, the critical failure surface is determined using the ridge-finding technique. The ridge-finding technique has two steps: First, a virtual point is selected in the space above the slope toe. Then, the algorithm searches the location of the points along the straight lines that pass through the desired point and has the highest invariant shear strain. Finally, the volume

of the slip mass is calculated as the area above the critical surface. This critical surface is determined by summing the volume of all the failed elements above the critical surface. In this study, this approach was run using the FISH language in FLAC2D software.

According to Cheng et al. (2018), to determine the critical surface, the failed elements along the horizontal direction must be continuous, but the target elements may be discrete in the vertical direction. A very important point in determining the critical shear surface is determining the size of the elements. The smaller the elements, the more accurate the critical slip surface will be. As a result, the volume of the slip surface will be calculated accurately. On the other hand, reducing the size of the elements also affects the simulation time of random fields and their analyses. Therefore, to determine the optimal size for the target elements, a sensitivity analysis was performed to compare the accuracy of the calculated sliding mass volume and computational effort.

### Risk assessment

Conventionally, the risk of slope failure is calculated as the product of the consequence of failure, and the  $P_f$ :

$$R = C \times P_f \quad (5)$$

where  $P_f$  is the probability of slope failure and  $C$  is the consequence associated with that failure. Equation (5) is suitable for systems with a specific failure mode (Huang et al. 2013). In the landfill slopes, due to the spatial variability of the shear strength and the unit weight parameters, there are different failure modes (Mehdizadeh et al. 2020), the consequence of which is different from each other. Huang et al. (2013) presented Eq. (6) to calculate the risk in multiple failure modes:

$$R = \frac{1}{N} \sum_{i=1}^{N_f} C_i \quad (6)$$

where  $N_f$  is the number of landfill slope failures ( $FS < 1$ ) and  $C_i$  is the consequence associated with that failure. Generally, for a fixed number of MCSs, the lower the  $P_f$ , the lower the number of slope failures in the probabilistic analysis will be. As a result, the smaller the number of failure occurrences, the greater the computational error of the risk assessment will be. Therefore, as the  $P_f$  declines, the number of MCSs must be increased to keep the computational accuracy constant. On the other hand, increasing the number of MCS increases the computation time. Thus, it is necessary to compare the accuracy of the calculations and the time spent to select the optimal mode. The accuracy of  $P_f$  estimation is highly dependent on the number of random field samples and is estimated by the  $COV_{P_f}$ :



$$\text{COV}_{P_f} = \sqrt{(1 - P_f) / (N \cdot P_f)} \quad (7)$$

The  $\text{COV}_{P_f}$  decreases gradually by increasing the number of MCS with a convergence rate of  $1/\sqrt{N}$ . In this paper,  $\text{COV}_{P_f}$  is calculated at the end of the MCS analysis and 2000 iterations were performed for cases where the  $P_f$  is greater than 10%. For other cases, more iterations were performed to ensure that the maximum  $P_f$  error was less than 0.01 at the 90% confidence level.

### Implementation of RFDM method

Risk assessment in the probabilistic failure analysis of landfill slope was conducted using the RFDM method through the following steps:

- (1) Determining the landfill slope geometry and statistical parameters related to the variability of MSW properties (statistical information of geotechnical properties such as mean values, standard deviations, probability distribution function, autocorrelation functions, and correlation distances).
- (2) Slope meshing in FLAC2D software and generation of random fields by matrix decomposition method.
- (3) Performing the MCSs, calculating the FSs, calculating the  $P_f$ , determining the  $\text{COV}_{P_f}$ , and finally determining whether the number of iterations satisfies the desired criterion; if the desired criterion is not met, the number of simulations will increase.
- (4) Determining the consequence of each slope failure to calculate risk ( $R$ ).

## Case study of Saravan landfill in Iran

### Landfill configuration

Saravan MSW Landfill is an active landfill site with an approximate area of 13 hectares in northern Iran (Rasht, Guilan Province, Iran). The MSW has been dumped directly into the natural valley since 1984 without installing geosynthetic membranes in the foundation. Also, the MSW is deposited from a small bottom layer in the foundation to a wide top layer at a thickness of 3 m. Since then, the site has become the largest landfill in northern Iran, containing about 10 million cubic meters of MSW. Currently, about 1,000 tons of MSW enters the landfill daily. The depth of the MSW with the valley's topography varies from 40 to 70 m at the highest level. According to Karimpour-Fard (2019), no proper MSW disposal regulations are followed in the Saravan landfill. In addition, there are no proper compression method and no specific working method in this landfill.

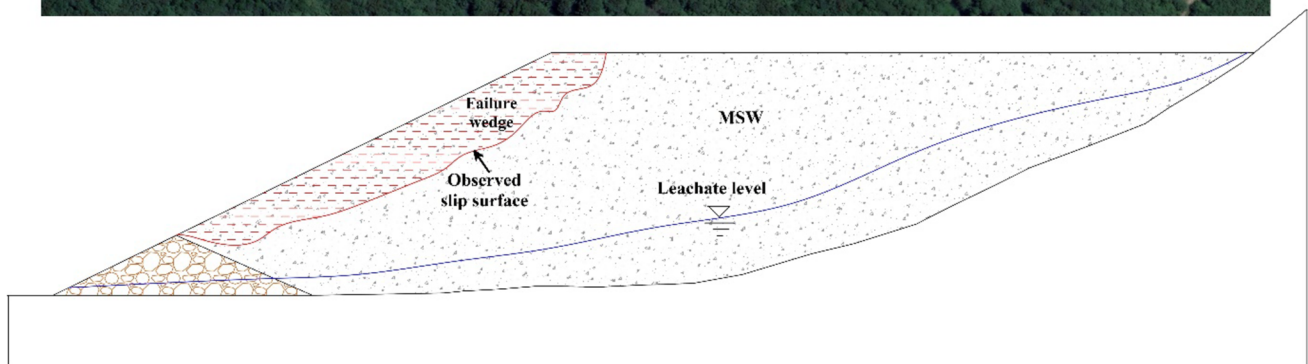
Contrary to designs and field investigations in the stability and safety assessment of the landfill slope, a part of the landfill was failed in 2018, and about 300,000 m<sup>3</sup> of MSW was displaced along the failure surface. Figure 1 presents the aerial view of this failure and its idealized cross section after the failure. The slope of the failed part before the failure was approximately 1V:2.5H (the vertical change to horizontal change). Due to the natural slope of the earth, the leachate surface is always at a certain level. The highest position of this slope is shown in Fig. 1. The failure did not cause any casualties but caused serious damage to existing buildings and the environment around the landfill, leading to extensive economic damage.

### Numerical model and materials properties

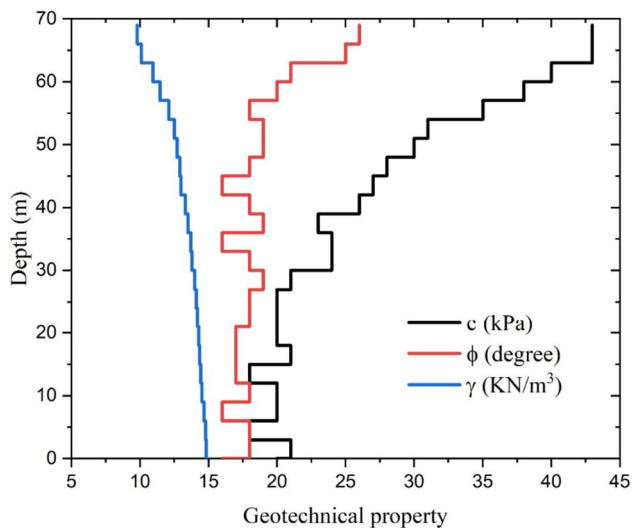
Although the landfill slope is three-dimensional, with a suitable approximation, it can be simulated using a simplified two-dimensional model based on the assumptions of plane strain analysis for the failed part of the landfill. Therefore, a two-dimensional plan strain slope with a width of 250 m and a height of 70 m was created in FLAC2D software for numerical simulations. The geometry of the MSW slope is shown in Fig. 1. In this study, uncertainties related to foundation soil and interaction characteristics were not considered. Landfill foundation soil properties were considered deterministic, and the values of cohesion and angle of friction are equal to 54 kPa and 33°, respectively, and the unit weight is 17.2 kN/m<sup>3</sup> (Karimpour-Fard 2019). As mentioned earlier, the FDM-based FALC2D software was used to perform slope stability analyses. The 4-sided elements with dimensions of 0.5 × 0.5 m were used to model the MSW slope to increase the accuracy of calculations in determining the FS and slip mass of MSW. The MSW behavior was modeled using an elastoplastic model based on the Mohr–Coulomb failure criterion with a non-associated flow rule. The discretized mesh of random fields contains about 52,000 elements.

Before performing the MCSs, it is necessary to determine the mean values ( $\mu$ ), coefficient of variation ( $\text{COV}_p$ ), correlation lengths ( $\delta$ ), and the type of probabilistic distribution of random parameters ( $c$ ,  $\phi$ , and  $\gamma$ ). In this study, the  $\mu$  and  $\text{COV}_p$  of random parameters were determined using the results of studies of Karimpour-Fard (2019) and Karimpour-Fard et al. (2021); they evaluated the mean variations of  $c$ ,  $\phi$ , and  $\gamma$  with depth (per 3 m depth) in this landfill. Figure 2 presents the proposed values for different depths in this landfill. The mean values of  $c$ ,  $\phi$ , and  $\gamma$  are assumed to be the same for MSW in each 3-m layer, and the initial values of these properties are chosen based on Fig. 2. Therefore, the total 70 m height of the slope is divided into 23 layers, each with a thickness of 3 m and a specific degree of degradation. Karimpour-Fard (2019) showed that the  $\text{COV}_p$  of  $c$ ,  $\phi$ , and  $\gamma$  are almost constant with





**Fig. 1** Aerial image and cross section of the failed part of Saravan landfill



**Fig. 2** Variation in geotechnical properties of MSW in Saravan landfill (Iran)

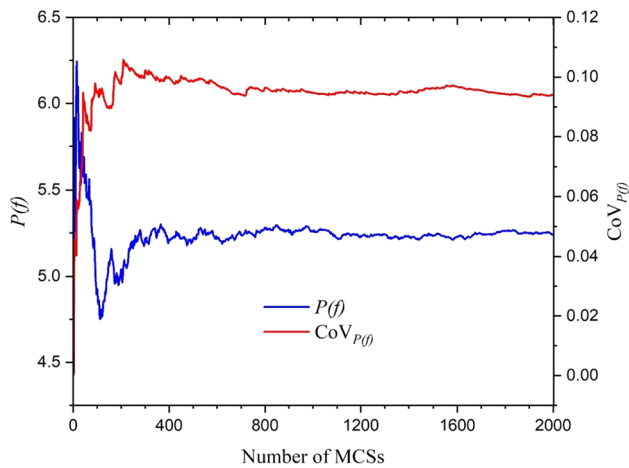
depth and  $COV_p$  obtained for  $c$ ,  $\phi$ , and  $\gamma$  are 49, 26, and 11%, respectively. However, in this study, a wider range of  $COV_p$  was investigated to determine the effect of  $COV_p$  of random parameters on the output results. Due to the lack of sufficient data to determine the CLs of random properties, a wide range of these lengths was selected, followed by investigating their effect on the probability of failure ( $P_f$ ) and risk ( $R$ ).

Table 1 shows the values of the  $COV_p$  and the horizontal and vertical CLs. The statistical range of  $COV_p$  of these parameters was considered by reviewing several studies (Babu et al. 2014; Reddy et al. 2013 and 2018, Sia and Dixon 2012; Rajesh 2016; Mehdizadeh et al. 2020; Falamaki et al. 2021). Finally, normal probability distributions for the random variables of  $\gamma$  and  $\phi$  and lognormal probabilistic distribution for  $c$  were chosen to describe how the data are distributed (Raviteja 2021; Mehdizadeh 2020).



**Table 1**  $CoV_p$  and CLs of geotechnical parameters for probabilistic slope stability analysis of Saravan landfill

Cases	$CoV_p$ (%)			$\delta_v$ (m)	$\delta_h$ (m)
	Unit weight	Cohesion	Friction angle		
1	5	20	15	0.5, 1, 3	0.5,1,3,5,10, 25,50 and 100
2	5	30	20		
3	10	40	25		
4	10	50	30		
5	15	60	35		
6	15	70	40		
7	20	80	45		



**Fig. 3** Variation in the  $P_f$  and  $COV_{P(f)}$  with the number of MCSs (case 1,  $\delta_h=5$  and  $\delta_v=0.5$  m)

## Results and discussion

### Deterministic analysis

Deterministic analysis of landfill slope was performed using the mean values of MSW geotechnical properties in Fig. 2 to consider the effect of MSW degradability over time and overburden pressure. Using the strength reduction method in FLAC2D software, FS was 1.33 in this case, which is less than the minimum value recommended by USACE (1997). Thus, this slope in the deterministic state also has a sliding risk, and its  $P_f$  is high. For a given condition, the critical failure surface is roughly a circular arc that starts at the MSW slope surface and extends to the slope toe. Based on the method mentioned in the previous sections, the critical slip surface has a slip mass of 2218 m<sup>2</sup> per meter length.

### Probabilistic analyses

MCSs were used for probabilistic analyses. The sample size of MCS is a very important criterion in accurately

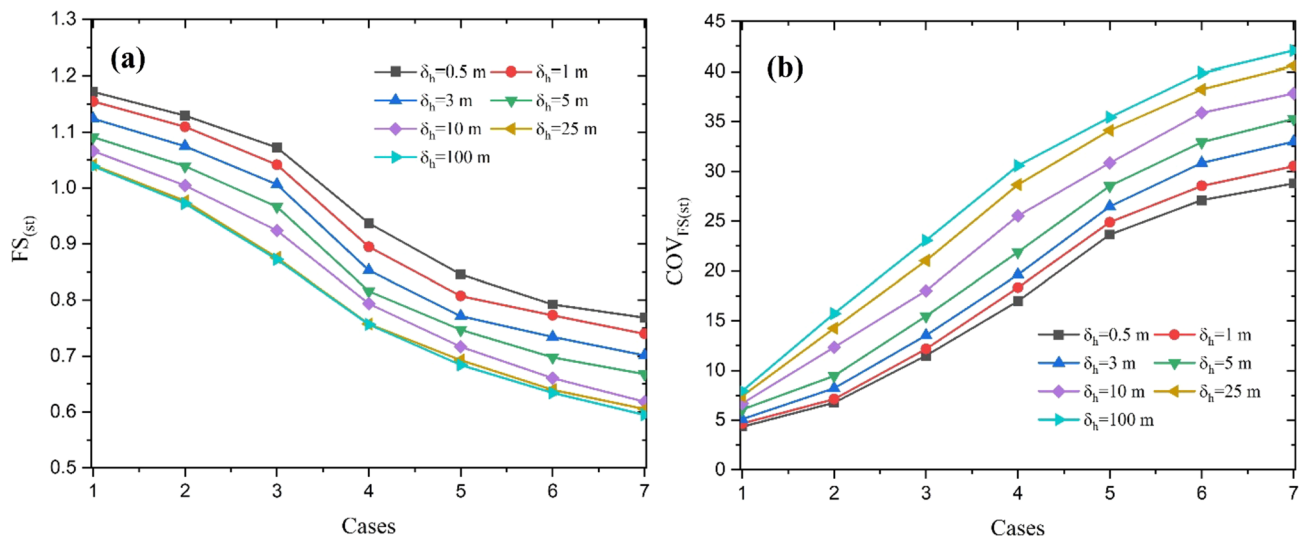
estimating  $P_f$  and  $R$  parameters. The convergence criterion was evaluated by performing the slope stability of each analysis case with specific statistical data with different numbers of MCSs. As mentioned,  $P_f$  is an important factor in assessing the risk and reliability of MSW slopes.

Figure 3 illustrates the variations in, but variations in the  $P_f$  and  $COV_{P(f)}$  for Case 1 of the analyses with  $\delta_h=5$  and  $\delta_v=0.5$  m. The results show that both  $P_f$  and  $COV_{P(f)}$  converge to a relatively constant value at MCS of 2000 after the initial oscillation. The  $COV_{P(f)}$  for this condition is about 0.1, which is sufficient for the accuracy of the study results. This convergence criterion has been performed for other analyses as well. Except for 6 cases of statistical inputs, 2000 iterations of MCSs for each case resulted in a  $COV_{P(f)} < 0.1$ . In the remaining 6 cases, the number of iterations depending on the  $COV_p$  was increased up to 8000. Regarding the computational efforts, it takes about 45 s to complete each realization with a 64-core fast computing system (Intel Xeon SkyLake, Gen 2 Gold, CPU @ 3.9 GHz 64 GB of RAM).

### Effect of $COV_p$ and CLs on $FS_{st}$

Mehdzadeh et al. (2020) showed that the  $COV_p$  of MSW input parameters is the most important factor affecting the stochastic safety factor ( $FS_{st}$ ). In this section, the effect of  $COV_p$  on  $FS_{st}$  is evaluated. Figure 4 shows the  $FS_{st}$  variations for all analysis cases with all  $\delta_h$  and  $\delta_v=1$  m. According to Table 1,  $COV_p$  of MSW increases from cases 1 to 7; Fig. 4 shows that for all  $\delta_h$  values, with increasing  $COV_p$ ,  $FS_{st}$  decreases. Also, for all cases,  $FS_{st}$  is less than the deterministic safety factor ( $FS_{det}$ ). Therefore, not considering the variability in the input parameters leads to an overestimated FS. The reduction rate of  $FS_{st}$  with increasing  $COV_p$  is almost smooth (up to case 3), such that the highest decrease is related to cases 4 and 5 (about 10%). After Case 5, with increasing  $COV_p$ , the reduction rate of  $FS_{st}$  decreases, and the  $FS_{st}$  values tend to a constant value.

The lowest  $FS_{st}$  for  $\delta_v=1$  m corresponds to case 7 of analyses with a value of 0.59. Evaluating  $FS_{st}$  values for  $\delta_v=0.5$  and 3m also showed similar results. The maximum  $FS_{st}$  reduction for all analysis cases is about 60% compared to



**Fig. 4**  $FS_{st}$  statistics of the landfill slope (all cases,  $\delta_v = 1$  m). **a**  $FS_{st}$  versus cases, **b**  $COV_{FS(st)}$  versus cases

$FS_{det}$ , which is for analysis Case 7 with  $\delta_h = 100$  and  $\delta_v = 3$  m. Mehdizadeh et al. (2020) estimated a maximum reduction of about 40% for slope stability analyses. Higher reduction in  $FS_{st}$  in this study is due to the high slope height of landfill and lower mean of MSW parameters. The decrease in  $FS_{st}$  with increasing  $COV_p$  can be explained using Fig. 4b. Figure 4b represents the effect of  $COV_p$  on  $COV_{FS(st)}$  for all analysis cases with all horizontal CLs and  $\delta_v = 1$  m. From cases 1 to 7 of the analysis, the value of  $COV_{FS(st)}$  increases for all horizontal CLs. The results show that the trend of increasing  $COV_{FS(st)}$  up to case 4 is almost linear, and then, this increasing trend becomes smooth, and this is the reason for the low variations in  $FS_{st}$  after case 5. The failure mechanisms based on the shear strength reduction (SSR) method pass through the weakest elements (Mehdizadeh et al. 2020). Thus, with increasing  $COV_p$ , the heterogeneity of random fields increases, and different failure mechanisms form, leading to an increase in  $COV_{FS}$ . On the other hand, since the  $FS_{det}$  of landfill slope with the mean parameters of the MSW properties (Fig. 2) is close to 1 ( $FS_{det} = 1.33$ ), passing the failure mechanism through the weakest elements, whose properties are often lower than the mean values, will result in lower FS values, thereby decreasing the  $FS_{st}$ . Similar results were obtained for vertical CLs of 0.5 and 3 m and the maximum  $COV_{FS(st)}$  (i.e., 45%) is related to analysis case 7 with  $\delta_h = 100$  and  $\delta_v = 3$  m.

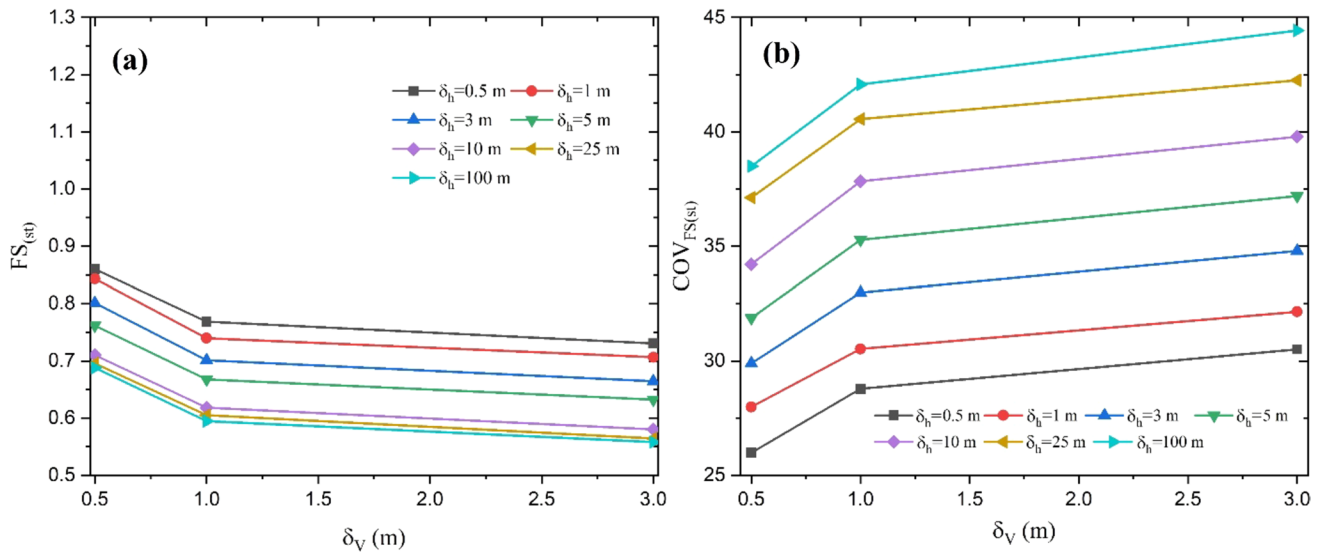
Figure 4a shows that an increase in  $\delta_h$  leads to a decrease in  $FS_{st}$ . The effect of  $\delta_h$  on  $FS_{st}$  is almost the same in all cases. The maximum decrease occurs in the range of 0.5 to 10 m for  $\delta_h$  (about 20%), and after  $\delta_h = 10$  m, the effect of  $\delta_h$  decreases about 5%. The reason for decreasing  $FS_{st}$  with  $\delta_h$  is that in a constant  $\delta_v$ , with increasing  $\delta_h$ , the possibility of forming weak areas (lower shear strength) along the

horizontal direction increases. Moreover, due to the possibility of forming these weak areas in the whole height of the slope and different positions, the possibility of forming multiple failure mechanisms also increases, thereby increasing the  $COV_{FS(st)}$  values. An increase in  $COV_{FS(st)}$  means a greater variability of  $FS_{st}$  and consequently an increased probability of failure ( $FS_{st} < 1$ ). The maximum effect of  $\delta_h$  on  $FS_{st}$  occurs up to  $\delta_h = 10$  m (maximum 40% for analysis case 7 with  $\delta_v = 3$ ), and then, the effect of  $\delta_h$  decreases so that the results for  $\delta_h$  of 25 and 100 m are almost the same. It was also observed that increasing the  $COV_p$  leads to a decrease in the convergence of the results with increasing the  $\delta_h$ . Since both of these two factors ( $COV_p$  and  $\delta_h$ ) reduce  $FS_{st}$ , for all CLs from case 5 onward, most realizations are failed and their FS is less than 1,  $FS < 1$ . Overall, failure occurred in other cases depending on the value of CL; for example, for analysis case 3 with  $\delta_v = 1$  m, cases of  $\delta_h = 0.5$ , 1 and 3 do not fail. However, increasing  $\delta_h$  from 3 to 100 m, all simulations failed. Certainly,  $FS_{st} < 1$  does not necessarily indicate the failure of all MCSs in that analysis case, but the mean of these simulations has an  $FS_{st}$  of less than 1. Therefore, the probability of failure should be assessed to compare these cases better and determine how many MSCs have failed.

Figure 5 shows the effect of  $\delta_v$  on  $FS_{st}$  and  $COV_{FS(st)}$  for analysis case 7. The results show that with increasing  $\delta_v$ , the  $FS_{st}$  decreases for all cases, but  $COV_{FS}$  increases. The decreasing trend of  $FS_{st}$  and increasing  $COV_{FS}$  are almost the same for all cases, and maximum  $FS_{st}$  and  $COV_{FS}$  vary from  $\delta_v = 0.5$  to 1 m (13% reduction and 10% increase for  $FS_{st}$  and  $COV_{FS}$ , respectively). As mentioned, different failure mechanisms are formed in different situations with increasing CLs and increasing  $COV_{FS}$ . This process becomes more







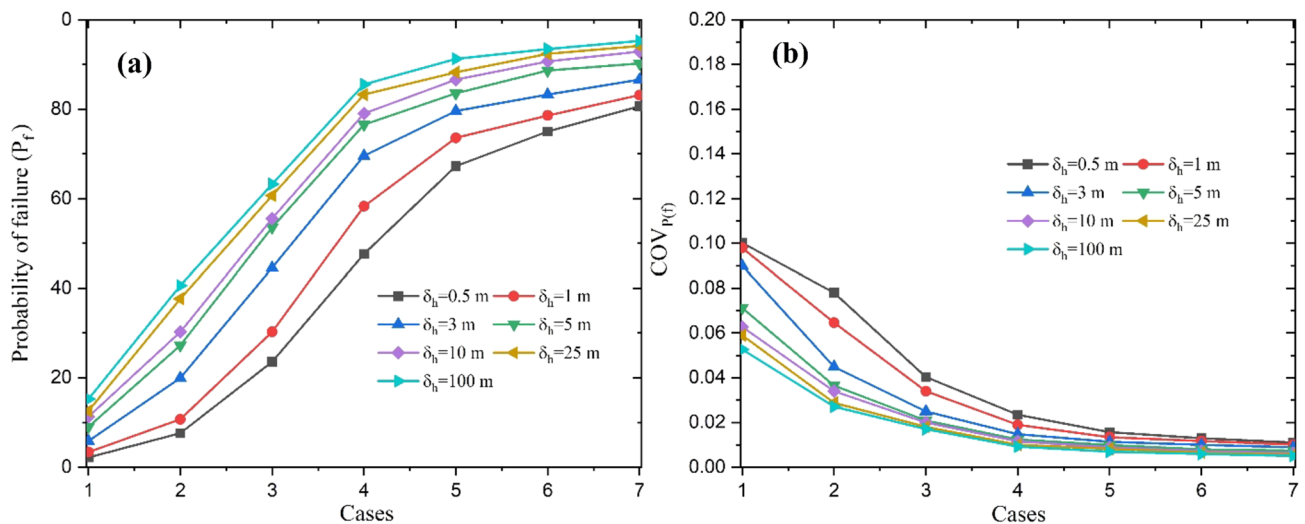
**Fig. 5**  $FS_{st}$  statistics of the landfill slope (case 7). **a**  $FS_{st}$  versus  $\delta_v$ , **b**  $COV_{FS(st)}$  versus  $\delta_v$

apparent with increasing  $COV_p$ .  $FS_{st}$  and  $COV_{FS(st)}$  values show that with increasing  $\delta_v$  values, the effect of  $COV_p$  will increase on the output results. For example, in analysis case 7, with increasing  $\delta_v$  from 0.5 to 3,  $FS_{st}$  decreases by 19%, and  $COV_{FS(st)}$  increases by 15%. Comparing the obtained results shows that the maximum effect on  $COV_{FS(st)}$  is due to  $COV_p$  (with a maximum of 200% increase in  $COV_{FS(st)}$ ), next, the horizontal correlation length (with a maximum of 200% increase in  $COV_{FS(st)}$ ), and finally the vertical correlation length (with a maximum of 200% increase in  $COV_{FS(st)}$ ). The explanation for these results is that FS depends on the spatial average of the strength parameters across the failure zone. For short correlation lengths, the failure mechanism always passes through highly oscillating areas with low

and high shear strengths. As a result, the effect of averaging increases with increasing CLs, and spatial variability decreases. These results are consistent with those of Meh-dizadeh et al. (2020).

**Effect of  $COV_p$  and CLs on  $P_f$**

The  $FS_{st}$  and  $COV_{FS(st)}$  values can be considered as a measure of slope safety. However, these data do not provide any information about  $P_f$  and which analysis cases present higher risks. In this section,  $P_f$  values obtained from different analysis cases are evaluated, and the effect of  $COV_p$  and CLs on the output results is investigated. Figure 6a shows the effect of  $COV_p$  on  $P_f$  of all analysis cases with  $\delta_v = 1m$ . The



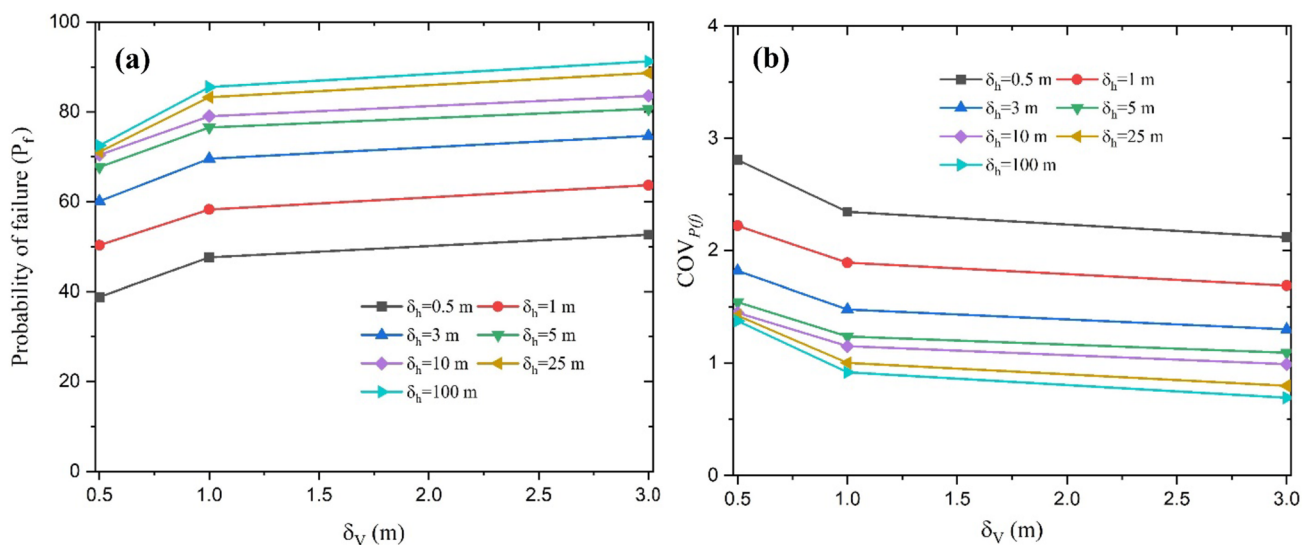
**Fig. 6**  $P_f$  statistics of the landfill slope (all cases,  $\delta_v = 1m$ ). **a**  $P_f$  versus cases, **b**  $COV_{P(f)}$  versus cases

results show that increasing  $COV_p$  leads to increasing  $P_f$  in all cases. The minimum value of  $P_f$  for  $\delta_v = 1$  m is related to analysis case 1 with  $\delta_h = 0.5$  m and is equal to 2.17%. In contrast, the maximum value of  $P_f$  is related to analysis case 7 with  $\delta_h = 100$  m with a value of 95.25%. The results show that up to analysis case 4, the  $P_f$  increase rate with increasing  $COV_p$  is high, and the trend of increasing  $P_f$  decreases after this case.

Figure 6a also shows the effect of  $\delta_h$  on  $P_f$ . As can be seen, increasing  $\delta_h$  leads to an increase in  $P_f$ . In all analysis cases, maximum variations occur up to  $\delta_h = 10$  m, exceeding which the increasing trend of  $P_f$  declines. From analysis cases 1 to 4, the effect of  $\delta_h$  on  $P_f$  increases. For example, for case 4 at  $\delta_v = 0.5$  m and  $\delta_h$  from 0.5 to 100 m, the value of  $P_f$  increases about 86%. In comparison, for analysis cases 5 to 7,  $P_f$  variations with  $\delta_h$  are negligible. These changes are attributed to the effect of  $\delta_h$  on  $FS_{st}$ . According to the  $P_f$  calculation method (in which the number of slope failures is important instead of FS value), from case 4 to case 7, the  $FS_{st}$  value of MCSs is all less than 1, and as  $\delta_h$  increases (which has a reducing effect on  $FS_{st}$ ), the number of simulations whose FS value is less than 1 does not change, and as a result, the effect of  $\delta_h$  decreases. However, from cases 1 to 4, the number of MCSs with  $FS_{st}$  close to 1 increases; as a result, increasing  $\delta_h$  leads to an increase in failed slopes and  $P_f$ . Figure 6a also shows that with increasing  $\delta_h$ , the effect of  $COV_p$  on  $P_f$  increases such that for  $\delta_h$  s of 3–100 m (up to analysis Case 4), the relationship between  $P_f$  and  $COV_p$  is almost linear. Figure 6b shows the effect of  $COV_p$  and  $\delta_h$  on  $COV_{P(f)}$ . As can be seen, with increasing  $COV_p$ ,  $COV_{P(f)}$  decreases. This result is due to the reduction of  $FS_{st}$  below 1 ( $FS_{st} < 1$ ) in MCS analyses, which results in

the failure of most slopes and reduction in  $COV_{P(f)}$  values. According to USACE (1997) recommendations for geotechnical structures, the reliability index ( $\beta$ ) of 1 is equal to hazardous performance, and  $\beta = 2$  is equal to poor performance of structures. Assuming a normal distribution for  $FS_{st}$ , their  $P_f$  is 0.16 and 0.023, respectively. According to Fig. 6b, for all cases, the landfill slope performance is poor, and except for case 1, the performance of all cases is less than hazardous performance. Therefore, landfill slope does not meet the requirements of average performance of geotechnical systems, and  $P_f$  and  $R$  of the slope are high, leading to many human and financial losses. In fact, unlike FS, which does not provide a probabilistic view of the landfill slope failure,  $P_f$  has a good ability to determine the safety level of the slopes. For example, although analysis case 2 has an  $FS_{st} > 1$ . However, its  $P_f$  is high, indicating a hazardous performance level.

Figure 7 presents the effect of  $\delta_v$  on  $P_f$  and  $COV_{P(f)}$  for analysis case 4. As can be seen, the maximum  $P_f$  in all analysis cases is related to  $\delta_v = 3$  and  $\delta_h = 100$  m. Results showed that the maximum increase is related to case 4 and is about 20% between  $\delta_v$  of 0.5 to 1 m. Comparing the obtained results showed that with increasing  $COV_p$ , the effect of  $\delta_v$  increases up to analysis case 4 and then declines. This reduction corresponds to the decrease in the effect of  $COV_p$  on  $FS_{st}$ . Figure 7b also shows the effect of  $\delta_v$  on  $COV_{P(f)}$ . With increasing  $\delta_v$ , the value of  $COV_{P(f)}$  decreases which is due to the increase in  $COV_p$  and, consequently,  $P_f$  increases. With increasing  $P_f$ , the number of failed slopes increases, and  $COV_{P(f)}$  decreases. Moreover, with increasing  $\delta_h$ , the decreasing effect of  $\delta_v$  decreases, and again, the maximum reduction occurs between  $\delta_v$  of 0.5 and 1 m. Comparing these results shows that  $\delta_h$  is a more effective parameter than  $\delta_v$ .



**Fig. 7**  $P_f$  statistics of the landfill slope (case 4). **a**  $P_f$  versus  $\delta_v$ , **b**  $COV_{P(f)}$  versus  $\delta_v$



### Effect of $COV_p$ and CDs on $R$

Considering the spatial variability of the MSW parameters, the  $P_f$  of the landfill slope can be considered a suitable criterion for quantitatively describing the safety and instability in the landfill slope. However, it does not provide any information about the damage level in failed slopes. The presence of multiple failure mechanisms in the variable MSW material leads to the risk of each failure. Consequently, the total risk associated with a set of probabilistic input data is quite different from each other and conventional methods. Thus, as mentioned earlier, the volume of sliding mass was used as a suitable criterion of risk.

Figure 8a presents the effect of  $COV_p$  on  $R$  for all analysis cases with  $\delta_v = 1$ . The results show that increasing the  $COV_p$  increases the  $R$  value for all cases, and increasing the  $COV_p$  has the maximum effect in cases 1–4. For instance, at  $\delta_h = 5$  m, the value of  $R$  increases from 190 to 1546  $m^2$ , which increases about 700%. From cases 4 to 7, the increase rate of  $R$  is low and is approximately the same in cases 6 and 7, suggesting that a further increase in  $COV_p$  does not affect the risk associated with the slope failure and this is the maximum  $P_f$  of landfill slope. Comparing the results of the conventional analysis with probabilistic results shows that the  $R$  is less than the conventional value in all probabilistic analyses (i.e., 2218  $m^2$ ). The maximum  $R$  in the probabilistic analysis is 1834  $m^2$ , which is about 18% less than the conventional method. As a result, unlike the FS, which was overestimated in the conventional method, the  $R$  in the conventional method is higher than the probabilistic method. Nevertheless, the conventional method does not provide any information on the  $P_f$ , safety margin, or slope instability and only shows the most probable failure path, which is different from the actual failure surface.

Also, Fig. 8a represents the effect of  $\delta_h$  on  $R$  for all analysis cases. The results show that an increase in  $\delta_h$  leads to increasing  $R$ . Evaluation of failure mechanisms showed that increasing  $\delta_h$ , on the one hand, leads to increasing the failure paths in the MSW slope and on the other hand leads to a decrease in  $FS_{st}$  values. Thus, the simultaneous effect of these two parameters leads to expanding the failure surface and increasing  $R$ . The effect of  $\delta_h$  on  $R$  increases from case 1 to case 4 and decreases thereafter. When MSW data are highly scattered, and the random fields are highly variable, the failure mechanisms are often deep, the volume of sliding mass is slightly variable, and the increase in  $\delta_h$  does not affect them. Indeed,  $COV_p$  is the controller of the failure mechanisms, rather than  $\delta_h$  and  $\delta_v$ . Maximum variation in  $R$  occurs in the  $\delta_h$  of 0.5 to 10 m, followed by a slight variation in  $R$  with  $\delta_h$ . Figure 8b presents the effect of  $\delta_v$  on  $R$  for analysis case 4. The results show that with increasing  $\delta_v$ ,  $R$  also increases, and the maximum variation in  $R$  occurs in the  $\delta_v$  of 0.5 and 1 m, the maximum of which is about 80% for  $\delta_h = 0.5$  m. All analysis cases showed that the effect of  $\delta_v$  decreases with increasing  $COV_p$ . In this respect, in analysis case 1,  $\delta_v$  has the maximum effect (500% increase in  $R$ ), while in analysis case 7, the maximum increase in  $R$  is about 15%.

Studying failure mechanisms in probabilistic analyses showed that probabilistic failure mechanisms are either nonlinear curves or a combination of curves and several lines. This issue is unlike conventional analyses, in which the failure mechanisms have a specific shape. Due to the random values of the input parameters, the failure mechanism is formed in such a way that it passes through the weakest points (low shear strength), and also the overall strength is minimal on the failure surface. These two

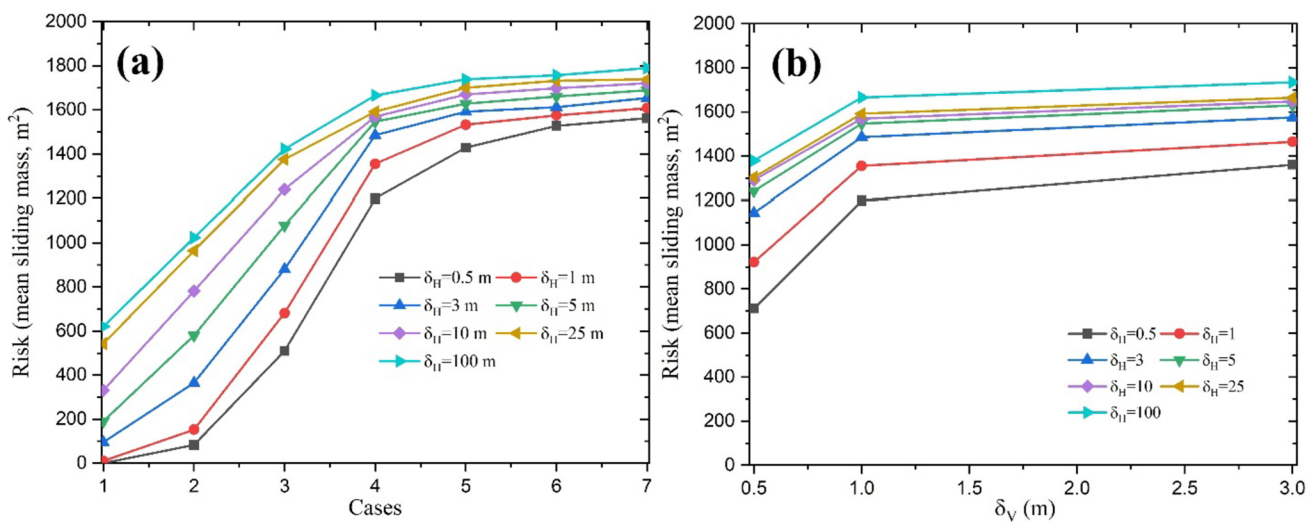
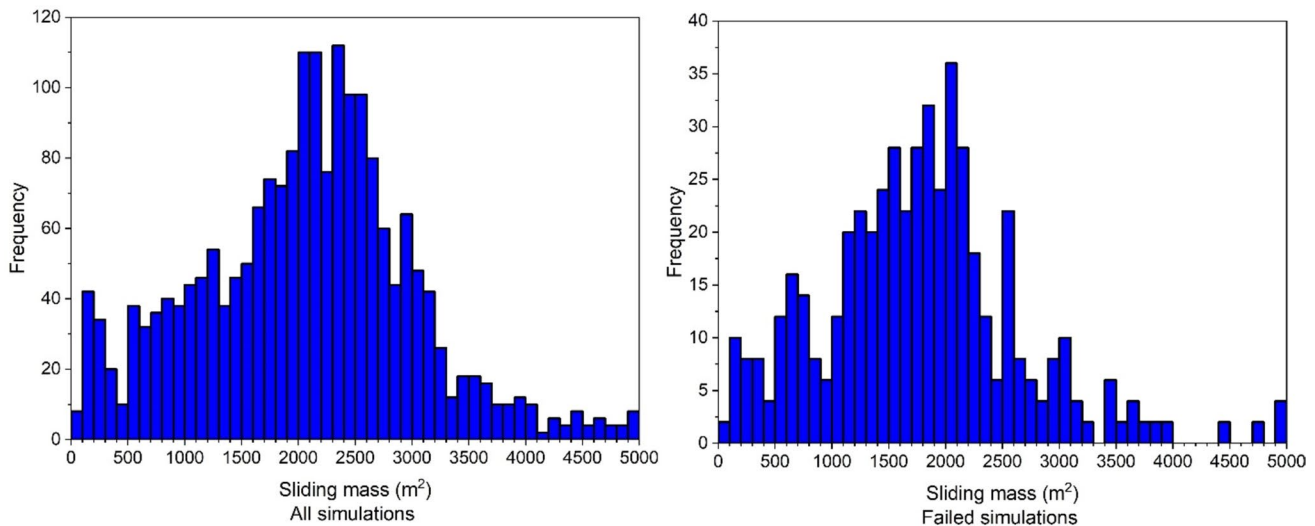


Fig. 8  $R$  statistics of the landfill slope (all cases,  $\delta_v = 1$ ). a  $R$  versus cases, b  $R$  versus  $\delta_v$



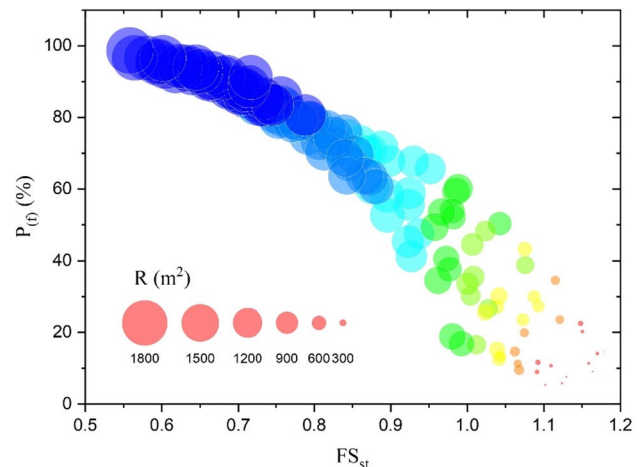
**Fig. 9** Histogram of sliding mass in analysis case 7 ( $\delta_h = 100$  and  $\delta_v = 1m$ )

factors lead to the high effect of CLs on the shape of the failures and, consequently, the risk of landfill slope.

Figure 9 exhibits the sliding mass histogram for 2000 MCSs in case 7 with  $\delta_h = 100$  and  $\delta_v = 1m$ . In Fig., all simulations are included in the left histogram, while the right histogram only includes simulations in which the slope has failed. For all simulations, a continuous range of sliding mass is observed, with the most sliding masses occurring around 2200 (close to the deterministic value) with an average of 2079. However, in the case of slope failure, discontinuity is observed in the volume of sliding mass, and the maximum failure frequency occurs in the range of 1800 (with a mean value of 1789.87 m<sup>2</sup>). In general, the scatter of all simulations (left histogram) is greater than the failed cases. Moreover, the volume of the sliding mass varies over a wide range (i.e., shallow to deep failure mechanisms).

The histogram of failed simulations demonstrates that for failure mechanisms ( $FS < 1$ ), most slip masses are smaller than the deterministic value. In addition, increasing the  $COV_p$  increases the number of simulations with a smaller sliding mass than the deterministic value. This difference is attributed to the formation of shallow and localized failure mechanisms due to the high spatial variability of the input parameters.

Finally, Fig. 10 shows the relationship between the three parameters  $FS_{st}$ ,  $P_f$ , and  $R$  for all probabilistic analyses. The results show that from a probabilistic point of view, if obtained  $FS_{st} > 1.1$ , the  $P_f < 40\%$ , but  $R$  is low ( $< 250$  m<sup>2</sup>). But, for  $1 < FS_{st} < 1.1$ ,  $P_f$  does not change much, while the  $R$  increases sharply (up to about 1200). Also, for  $FS_{st} < 0.9$ ,  $P_f$  increases rapidly, but variations of  $R$  are uniform and ascending. The results showed that the relationship between  $FS_{st}$  and  $P_f$  is almost linear (for  $0.7 < FS_{st} < 1.2$ ), but the



**Fig. 10** Correlation of  $R$  with  $FS_{st}$  and  $P_f$  for probabilistic landfill slope analyses

relationship of  $R$  with  $FS_{st}$  and  $P_f$  is not linear and has a rapid upward trend in the range of  $FS_{st} = 1.2$  to  $FS_{st} = 0.8$ , and for  $FS_{st} < 0.8$ , the increase rate of  $R$  decreases to reach a constant value in the range of  $0.5 < FS_{st} < 0.7$ . In particular, for  $FS_{st} < 0.8$ , the  $R$  is constant for failed slopes, but their  $P_f$  values are different.

## Conclusion

Instability and the risk involved in landfill sites are important issues in the geotechnical design of landfills, especially for those designed without paying attention to engineering considerations. The present study investigates the importance of

incorporating the spatial variability of geotechnical properties of MSW in assessing the stability, probability of failure, and risk of landfill slopes. In this paper, the effect of spatial variability of MSW parameters was evaluated on  $FS_{st}$ ,  $P_f$ , and  $R$ . RFD, an advanced FDM-based probabilistic method that combines random fields with a finite-difference code, was used to perform a landfill risk assessment. The RFD code can accurately determine the critical failure surface by considering multiple failure mechanisms caused by the spatial variability of MSW parameters. Compared to analytical methods, this method does not consider any initial assumptions to determine the mechanism of landfill slope failure. Therefore, this method can be used to assess the landfill slope stability with multiple potential failure mechanisms.

- The results showed that spatial variability has a significant effect on  $FS_{st}$ ,  $P_f$ , and  $R$  in the landfill slope. For all cases, the  $FS_{st}$  value was lower than the  $FS_{det}$ , and not considering the variability in the input parameters of MSW leads to an overestimated FS. Although values of  $FS_{st}$  provide a probabilistic criterion for assessing the stability and safety of landfill slopes, they do not provide any quantitative information about the probability of failure and system performance levels.
- Therefore,  $P_f$  of landfill slopes must be calculated to determine the level of performance of landfill slopes from a geotechnical stability perspective. Calculating the  $P_f$  for all simulations in each case showed that increasing  $COV_p$  leads to increasing  $P_f$  and decreasing  $COV_{P(f)}$ . Evaluations also showed that when  $COV_p$  values are low,  $\delta_h$  and  $\delta_v$  have a great effect on  $P_f$  and their effect decreases with increasing  $COV_p$ . Comparing these results with USAS recommendations showed that for all analyses (except case 1), the performance of all cases was less than hazardous. As a result, contrary to the FS, the  $P_f$  well determines the performance of the landfill slope system and allows comparing the probability of its instability with recommended criteria.
- The results showed that although the  $P_f$  determines the level of performance of landfill slopes, the risk associated with these slopes must be calculated to determine the damage due to the possible failure of landfill slopes. The results indicate that the volume of MSW sliding mass can be considered a measure of risk in each slope; however, the accurate determination of slope failure risk requires complete data and information about the landfill. The results showed that with increasing  $COV_p$ , the value of  $R$  increases for all cases, but the maximum increase occurs in cases 1–4, and a further increase in  $COV_p$  has a low influence on the slope failure risk. Comparing the results of the deterministic analysis with the probabilistic results shows that  $R$  in all proba-

bilistic analyses is less than the deterministic value ( $\approx 2118 \text{ m}^2$ ). However, it should be noted that the deterministic method proposes a failure mechanism with  $FS = 1.26$ . Also, from a conventional point of view, the slope may never fail, and the obtained failure mechanism may be very different from the actual slope failure mechanism. The results show that the autocorrelation structure significantly affects the risk of slope failure, which depends primarily on the  $P_f$  variations.

- Finally, when there is no accurate data on the spatial variability of MSW parameters and their uncertainty is high, reliability-based analyses can predict landfills' performance efficiently and make the risk associated with them more perceivable for geotechnical engineers.

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## Declarations

**Conflict of interest** There is no conflict of interest.

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