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Quantitative Risk Assessment for Landslide Disaster and Some Applications in Chongqing

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Abstract: Chongqing is located in the southwestern China, and geological disasters occur frequently; the number of potential landslide disasters is far greater than the number of landslides that can be managed by government funds; risk assessment for potential landslide disasters is critical. The risk assessment method based on the stability and loss of landslides is restricted by various factors in practical application. It has been simplified to a semi-empirical assessment method, which is influenced by the discrimination factor near the limit value of the determining condition, which is may easily lead to a sudden change in the evaluation result and distort the conclusion. In order to solve this problem, the author proposes a full quantitative risk assessment method based on the probability of landslide damage. A mathematical probability model is used to quantitatively describe the risk assessment impact factors, weaken the boundary impact, and improve the accuracy of landslide risk assessment; and corresponding software was developed to conduct quantitative risk assessments on six landslides in Feng jie County, Chongqing, which verified the accuracy and reliability of the full quantitative risk assessment method, and provided an important reference for judging urban landslide geological disasters.

Keywords: landslide disaster; quantitative risk assessment method; mathematical probability model; landslide risk assessment; project applications.

1. Introduction

Chongqing is located in southwestern China, and geological disasters occur frequently. According to statistics, there are more than 14,000 potential geological disasters in Chongqing, of which landslides account for more than 80%. Obviously, the landslide disaster has become one of the most serious geological environmental problems in the city (Fig. 1). Faced with the contradiction between so many potential geological disasters and the government's limited budget for geological disaster prevention. The key issue is to determine the selection rules for potential landslide geological disaster management projects.

Figure 1. Jiweishan landslide of Chongqing in 2009.

The research on the risk of single landslide disaster focuses on the two elements of disaster: risk and vulnerability. The research of risk includes the study of the probability of disaster damage and the scope of impact; Vulnerability research includes research on the intensity of disasters on disaster-bearing bodies and vulnerability of disaster-bearing bodies (Abedini et al., 2019; Chen et al., 2019b; Hoang et al., 2019; Hong et al., 2019; Nguyen Duc et al., 2020; Niu, 2020). In addition, someone consider that the stable state of the landslide is the key factor in making a choice and take the stability factor as the primary criterion for selection . Others believe that the possible results of landslides are more important than the stability state. Actually, according to research results (Chen et al., 2019c; Dong Van et al., 2020; Hong et al., 2019; Pourghasemi et al., 2020; Shafizadeh-Moghadam et al., 2019; Yan et al., 2019), it has been proved only risk level can be used as a criterion of geological disaster assessment.

Based on the definition of risk, both stability and losses of a landslide may cause have been taken into account in the process of risk assessment of landslide . Although theories of landslide risk assessment are relatively clear, they are not widely used in practical engineering due to the influence of many factors. At present, traditional risk assessment methods of landslide are still mainly based on semi-quantitative risk assessment theory.

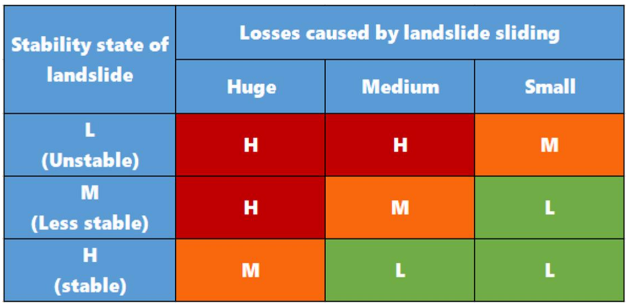
With the continuous needs for landslide risk assessment in practical engineering, Some defects of traditional methods have gradually emerged, especially in accuracy of assessment result. To solve this problem and improve accuracy of landslide risk assessment, a fully quantitative risk assessment method based on failure probability of landslide is proposed in this paper and some applications to practical engineering in Chongqing are also carried out.

2. Traditional methods of risk assessment for landslide hazards

2.1 Qualitative risk assessment for landslide disaster

Based on information collected from geological survey of the landslide site, combining with engineering experience given by experts and geological engineers, a stability state of a landslide is described and a corresponding stable grade is given. Qualitative description about the stability state characteristics of a landslide generally includes the following aspects (Gao et al., 2018; Wu et al., 2017; Yang et al., 2017): (1) Regional geological background of the landslide site; (2) Leading factors and triggering factors of the landslide; (3) Stage and developing trend of the landslide and the possible failure mode. In the meantime, a qualitative stable evaluation of a landslide can be given and corresponding stability grades (high, medium, low) can also be determined according to "Code for geological investigation of landslide prevention" (GB/T 32864-2016) (China, 2016). Similarly, the statistics of possible losses caused by a potential landslide generally include the following aspects: (1) threatened person; (2) economic losses; (3) The importance of objects threatened by landslide (both in social and economic aspect)

Based on the above statistical results, a possible losses caused by a potential landslide can be given and corresponding loss grades (high, medium, low) can also be determined according to "Code for geological investigation of landslide prevention" (GB/T 32864-2016)(China, 2016). Combining stable state and possible losses caused by the landslide, a risk matrix which can be used to judge the risk level of a landslide disaster is formed (Fig. 2).



Stability state of landslide	Losses caused by landslide sliding		
	Huge	Medium	Small
L (Unstable)	H	H	M
M (Less stable)	H	M	L
H (stable)	M	L	L

Figure 2. Risk matrix based on qualitative risk assessment of landslide.

The advantage of qualitative risk assessment of landslide is that it is based on the results of on-site geological survey and does not require technical work such as surveying, mapping, drilling, and testing. It's relatively simple and easy to be applied in practical engineering. But, due to lack of work basis, the determination of risk influencing factors is subjective to a certain extent, and the corresponding risk level evaluation results are rough. Qualitative risk assessment is suitable for preliminary screening and comparison of a large number of landslides, as well as further research or evaluation of landslides with higher risks.

2.2 Semi-quantitative risk assessment of landslide hazard

To improve the accuracy of qualitative risk assessment for landslide, values of quantitative stability factor Fs are introduced, so the corresponding risk matrix is more accurate than that of the qualitative risk assessment.

The classification based on stability factor Fs of a landslide refers to the "code for geological investigation of landslide prevention" (GB/T 32864-2016)(China, 2016) and the specific classification criteria are shown in Table 1. Referring to the same code and according to the statistic result, the value of protecting objects or the possible losses caused by a potential landslide are divided into 3 grades as shown in Table 2.

Table 1. Classification of stable state of landslide.

Stability factor *Fs*	Fs<1.00	1.00≤Fs< 1.05	1.05≤Fs< 1.15	1.15≤Fs
Stability state	Unstable	less stable	almost stable	stable

Table 2. Grade of protecting objects.

Grade of protection	I	II	III
EL(10^4 yuan)	EL≥5000	5000>EL≥500	EL<500
TP	TP≥500	500>TP≥100	TP<100
PI	Very Important	Important	Average

EL=Economic Loss TP= Threatened Person PI=Public Infrastructure
Only one conditions can be defined as the corresponding protection grade

Based on the two tables above, a semi-quantitative risk matrix can be obtained and used to judge the risk level of a landslide disaster.

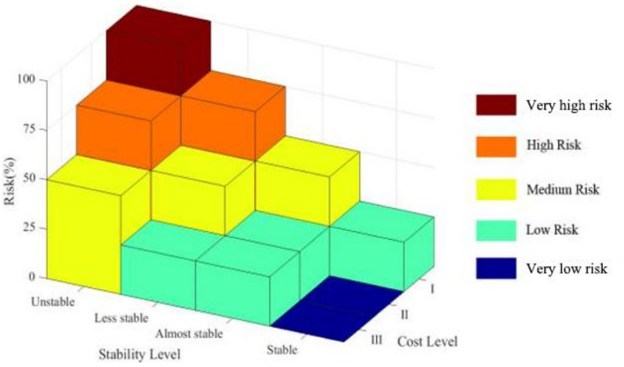


Figure 3. Spatial relationship diagram of semi-empirical risk level and control factors

Fig. 3 shows that semi-quantitative risk assessment gives the specific judging standard and dividing boundary, it is correct in the trend and good in application. But there are still some problems in the application because of the discontinuity of risk interval division. Taking Threatened Person (TP) of a landslide as an example, if the stability state of a landslide keeps unchanged (stability factor Fs is a constant), changes in TP may cause a change in risk level of the landslide as follows.

Table 3 shows that an increase of 2 persons in TP (from 99 to 101 or from 499 to 501) makes an change of risk level (Low to Medium or Medium to High) even if Fs keeps unchanged, but in the same situation of stability, an increase of 398 persons of TP (from 101 to 499) take no change of risk level. This is obviously not a reasonable conclusion. Similarly, taking Economic Loss (EL) as an example and keeping the landslide in the same stable state, changes in EL may cause changes in risk level of the landslide as follows.

Table 3. Change of risk level caused be TP.

stability factor：Fs=1.04		Stability state：Less stable
TP： 99	Grade：III	Risk Level：Low
TP：101	Grade：II	Risk Level：Moderate
TP：499	Grade：II	Risk Level：Moderate
TP：501	Grade：I	Risk Level：High

Table 4. Change of risk level caused be EL.

Stability factor：Fs=1.04		Stability state：Less stable
EL(10^4)： 490	Grade：III	Risk Level：Low
EL(10^4)： 510	Grade：II	Risk Level：Moderate
EL(10^4)： 4990	Grade：II	Risk Level：Moderate
EL(10^4)： 5010	Grade：I	Risk Level：High

Table 4 shows that an increase of 20×104 yuan in EL (from 490×104 to 510×104 or from 4990×104 to 5010×104) make a change of risk level (from Low to Medium or from Medium to High), but in the same situation of stability, an increase of 4480×104 in TP (from 510 to 4990) take no change of risk level (from Moderate to Medium). This is also an unreasonable conclusion. In addition, when the stability factor increase by 0.01 (from 1.04 to 1.05), the stable state changes from less stable to almost stable， while the stability factor increased by 0.1 (from 1.05 to 1.15), the stable state remained unchanged.

Since the classification of both stable states and protection object value of a landslide are based on interval division, there are some characteristics of regional invariance and marginal mutation in the risk matrix, the resulting risk grade classification also has corresponding invariance and mutation. The way to solve this problem is to continuously describe the stable state and protected objects, which means to replace the interval division with continuous assignment to realize the full quantitative analysis of risk assessment.

3. Fully quantitative risk assessment of landslide

The stable state and the potential loss of the landslide must be analyzed quantitatively. Considering the variability of rock strength parameters, the stability factor should be a random variable, and it is more reasonable to use the failure probability (sliding probability) to describe the stable state of the landslide.

According to the definition of stability factor of landslide, *Fs* can be expressed as

$$F_s = R / T \tag{1}$$

Where *R* is anti-sliding force, *T* is sliding force (DB50/5029-2004)(Chongqing, 2004).

If the relevant strength parameters of geotechnical materials are regarded as random variables with normal distribution, the corresponding stability factor *Fs* is also a random variable. For the convenience, the stability factor *Fs* is assumed to be a random variable, which follows normal distribution.

The *PDF* of *Fs* can be expressed as (Sheng Ju, 2018):

$$f(x;\mu,\sigma) = \frac{1}{\sigma\sqrt{2\pi}} \exp(-\frac{(x-\mu)^2}{2\sigma^2}) \tag{2}$$

The *CDF (sliding probability)*_of *Fs* is express as (Dong Van et al., 2020; Nguyen Duc et al., 2020):

$$P(0 < x \le 1) = \frac{1}{\sigma\sqrt{2\pi}} \int_0^1 \exp[-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2]dx \tag{3}$$

In which, $x=Fs, \mu=M_{Fs}, \sigma=\Delta_{Fs}=n \bullet M_{Fs}$

M_{Fs} is the mean of *Fs*, Δ_{Fs} is the standard deviation of *Fs*, *n* is the coefficient of variation of *Fs*.

Because *Fs* and *n* are related to the strength parameters of rock and soil materials, the failure probability (sliding probability) of landslide can be expressed as *P*(*Fs* /*n*), that is, the failure probability of a landslide with a mean of *Fs* and a variation coefficient of *n*.

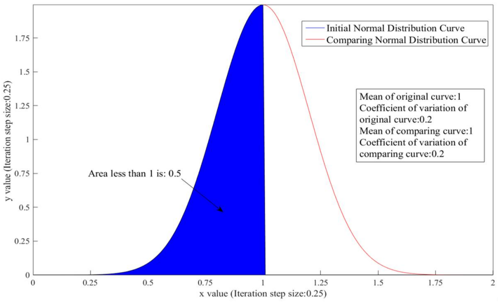
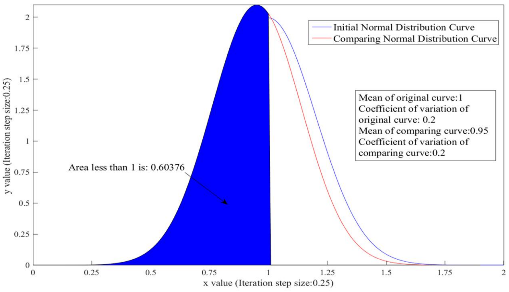
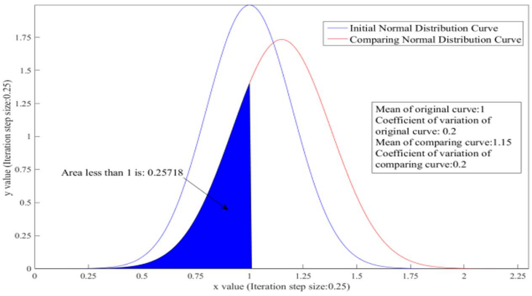


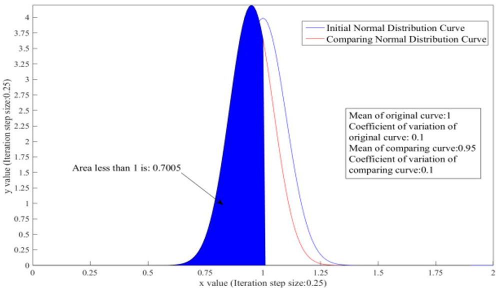
Figure 4. PDF and CDF of Fs (mean=1, n=0.2).



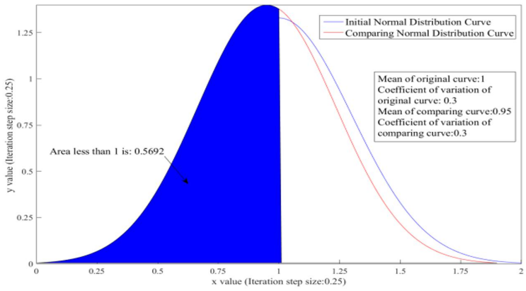
(a) CDF of P (0.95/0.2)



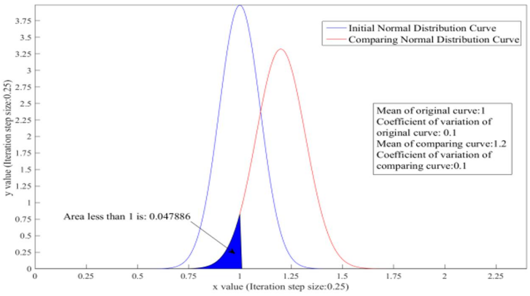
(b) CDF of P (1.15/0.2)



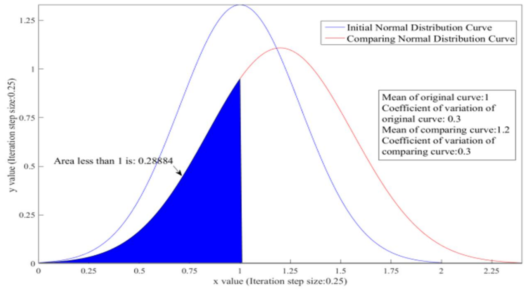
(c) CDF of P (0.95/0.1)



(d) CDF of P (0.95/0.3)



(e) CDF of P (1.20/0.1)



(f) CDF of P (1.20/0.3)

Figure 5. CDF of P (0.95~1.20/0.1~0.3).

To study the change of landslide failure probability with Fs and n, a comparative analysis was done and some results of calculation are shown in Fig. 5.

As can be seen from Fig. 5, Fig 5.(a)~Fig 5.(b) show the failure probability with the same coefficient of variation (n=0.2) but different means of the stability factor (Fs=0.95, 1.15, respectively). Fig 5.(c)~Fig 5.(d) show the failure probability with the same mean of stability factor (Fs=0.95) but different coefficients of variation (n=0.1,0.3, respectively). Fig 5.(e)~Fig 5.(f) show the failure probability with the same mean of stability factor (Fs=1.20) but different coefficients of variation (n=0.1, 0.3, respectively). Results of calculation can also be shown in following tables.

Table 5. Variation range of failure probability with stability factor *Fs* (*n*=0.2).

Fs	0.95	1.0	1.05	1.15
n	0.20	0.20	0.20	0.20
P	60.38%	50.00%	40.59%	25.71

Table 6. Variation range of failure probability with coefficient of variation *n* (*Fs*=0.95).

Fs	0.95	0.95	0.95
n	0.10	0.20	0.30
P	70.05%	60.38%	56.92%

Table 7. Variation range of failure probability with coefficient of variation *n* (*Fs*=1.20).

Fs	1.20	1.20	1.20
n	0.10	0.20	0.30
P	4.78%	20.24%	28.88%

Trend of failure probability *P* changing with mean of *Fs* and coefficient of variation *n* can be obtained and shown in Fig. 6. Trend of failure probability *P* changing with mean of *Fs* and coefficient of variation *n* can be obtained and shown in Fig. 6.

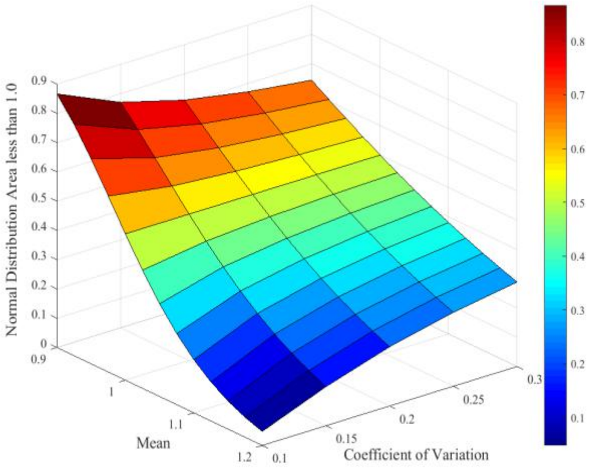


Figure 6. Trend surface of failure probability changing with mean of *Fs* and *n*.

Based on the calculation method of sliding probability (P) mentioned above and considering the statistical results of potential loss (C) of landslide, the risk index (R) of a landslide can be expressed as follows (Chen et al., 2019a; Dieu Tien et al., 2020):

$$R = P \cdot C \tag{4}$$

Then,a technical route of quantitative risk assessment can be established and corresponding computer software can be developed, as shown in Fig. 7.

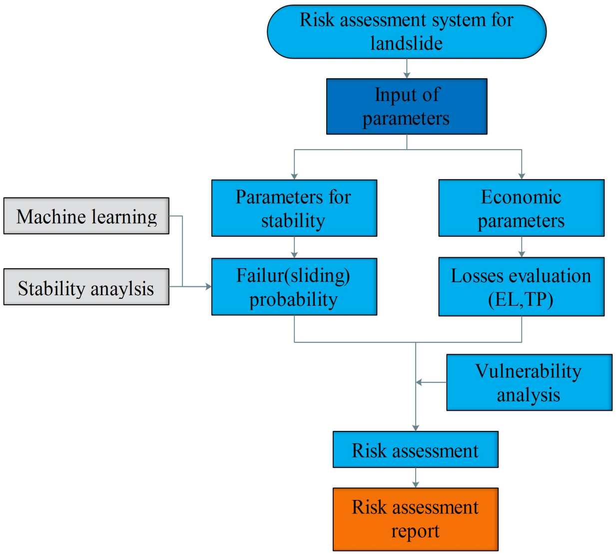


Figure 7.Flowchart of quantitative risk assessment for landslide.

The corresponding full quantitative risk index can be obtained and the variation of risk index with both P and C are shown in Fig. 8.

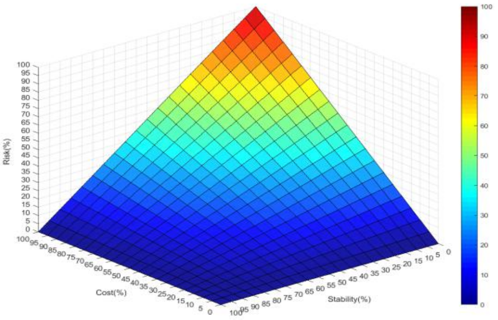


Figure 8. Spatial figure of risk index.

4. Engineering applications of landslide assessment

Based on the geological survey reports of six landslides located at Fengjie county, Chongqing, six quantitative risk assessment reports were carried out by use of quantitative risk assessment software. Six quantitative risk indexes about stability state, threatened person (TP) and economic loss (EL) were obtained and sorted according to the values of the index, as shown in table1 to table 8~ table 9. It is proved that the results of quantitative risk assessment can provide important reference and play important rule for the judgment and management of landslide disaster in the city.

Table 8. Ranking of TP risk of 6 landslides in Fengjie county, Chongqing

Name of landslide	State of analysis	Grade of TP	Stability state	Sliding probability	Risk Index of TP	Ranking of TP risk
Chejiaba landslide	Heavy rain	I	1.075 Almost stable	28.52%	1.5899	1
Huoshiliang Landslide	Heavy rain	II	1.013 Less stable	34.75%	0.7536	2
Wanjiaping landslide	Heavy rain	II	1.037 Less stable	31.18%	0.4334	3
Chenjiagou landslide	Heavy rain High water level	II	1.069 Almost stable	29.16%	0.4124	4
Fangniuping landslide	Heavy rain	II	1.065 Almost stable	29.34%	0.2993	5
Laolingou landslide	Heavy rain	II	1.356 Stable	11.77%	0.2649	6

Table 9. Ranking of EL risk of 6 landslides in Fengjie county, Chongqing

Name of landslide	State of analysis	Grade of TP	Stability state	Sliding probability	Risk Index of EL	Ranking of EL risk
Chejiaba landslide	Heavy rain	I	1.075 Almost stable	28.52%	1.1424	1
Chenjiagou landslide	Heavy rain High water level	II	1.069 Almost stable	29.16%	1.0910	2
Huoshiliang Landslide	Heavy rain	II	1.013 Less stable	34.75%	0.6914	3
Wanjiaping landslide	Heavy rain	II	1.037 Less stable	31.18%	0.5709	4
Fangniuping landslide	Heavy rain	II	1.065 Almost stable	29.34%	0.2934	5
Laolingou landslide	Heavy rain	II	1.356 Stable	11.77%	0.1412	6

5. Conclusions

(1) Based on the failure probability analysis, a quantitative risk assessment method for landslide was proposed.

(2) A technical route of the assessment was established and corresponding computer software was developed. Quantitative risk assessment reports for six landslides located at Fengjie county in Chongqing were carried out by use of the software.

(3) It has been proved that quantitative risk assessment of landslide is better than qualitative or semi-quantitative risk assessment both in theoretical analysis and practical application.

(4) Results of quantitative risk assessment can provide important references for the judgment of landslide disaster and play important rules in management of geological disaster in the city.

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