Landslide risk assessment based on combination weighting-improved TOPSIS

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Abstract. Landslide risk assessment is of great significance to landslide disaster monitoring and prevention. A landslide hazard evaluation method based on combination weighting and improved TOPSIS method is proposed. TOPSIS based on grey correlation degree is applied to landslide hazard evaluation, and a new closeness degree is constructed to evaluate landslide hazard level. The subjective and objective weights of evaluation indexes are obtained by G1 method and entropy weight method, which improves the accuracy of TOPSIS evaluation results. The case analysis shows that the method has high accuracy, certain rationality and effectiveness, and can provide a reference for landslide disaster prevention.

1. Introduction
Landslide is a natural phenomenon that the soil or rock mass on the slope slides down as a whole or dispersedly along a certain weak surface or weak belt under the action of gravity, which is affected by river erosion, groundwater activity, earthquake and artificial slope cutting (Wu and Sidle 1995; Tien Bui et al. 2015). In addition, the activity of fault zone and seismic vibration will destroy the structure of rock and soil, and the dynamic load or horizontal seismic force reduces the normal pressure of the landslide on the potential slip surface and increases the sliding force, thereby inducing landslide (Xue et al. 2020). Landslides often cause significant losses to industrial and agricultural production and people’s lives and property (Fell et al. 2008; Pradhan and Lee 2010). Therefore, it is necessary to monitor and control landslide disasters, and landslide risk assessment has essential reference value for disaster monitoring and prevention.

To evaluate the risk of landslide, scholars at home and abroad have done a lot of research. (Fan et al. 2004) used the analytic hierarchy process (AHP) to establish the evaluation index system of landslide risk and determine the landslides risk levels. (Wang et al. 2007) used the weight of evidence method to evaluate each factor’s influence on landslide development quantitatively, and carried out the selection of landslide risk evaluation factors and quantitative evaluation of landslide risk. (Li et al. 2013) used the combination weighting-unascertained measure theory coupling evaluation model to evaluate the landslide risk, and obtained each landslide risk grade. (Xu et al. 2015) selected four-factor groups comprising ten separate subfactors of landslide-related data layers to establish a susceptibility evaluation model based on the back-propagation neural network included slope. (Abay et al. 2019) used the AHP method to assign weight and rating and then applied the weighted -linear combination (WLC) technique to calculate the landslide susceptibility index (LSI). Ten landslide conditioning factors were determined.
as the inputs to assess the landslide susceptibility for the study area. The above studies provide references for landslide risk analysis and evaluation.

The occurrence of a landslide is controlled by multiple factors with randomness, uncertainty and fuzziness. In the landslide hazard evaluation, the original data information is often not fully utilized, and the calculation process of the evaluation method is complex. This paper combines the combination weighting and TOPSIS method based on grey correlation analysis to determine the index weight value and the landslide risk level. This method is suitable for multi-objective evaluation and decision-making and provides a theoretical basis for landslide hazard evaluation.

2. Combination weighting method

2.1. $G_1$ method

For the evaluation index set $Y = \{y_1, y_2, ..., y_n\}$, the order relationship is determined according to the relative importance of indexes, which is denoted as $y_1 > y_2 > ... > y_n$.

The ratio of relative importance between the adjacent index $y_{k-1}$ and $y_k$ is given, namely, weight evaluation scale:

$$r_k = \frac{\beta_{k-1}}{\beta_k}, \ k = n, n - 1, ..., 2$$

(1)

The assignment of $r_k$ based on the exponential scale can be referred to Table 1.

| $r_k$ | Explanation |
|------|-------------|
| 1    | The index $x_{k-1}$ is just as important as the index $x_k$ |
| $a=1.316$ | The index $x_{k-1}$ is slightly more important than the index $x_k$ |
| $a^2=1.732$ | The index $x_{k-1}$ is more important than the index $x_k$ |
| $a^3=3$ | The index $x_{k-1}$ is much more important than the index $x_k$ |
| $a^4=9$ | The index $x_{k-1}$ is extremely more important than the index $x_k$ |

Using Equations (2)-(3) to obtain the weight of the index:

$$\beta_n = \left(1 + \sum_{k=2}^{n} \prod_{i=k}^{n} r_i \right)^{-1}$$

(2)

$$\beta_{k-1} = r_k \beta_k, \ k = n, n - 1, ..., 2$$

(3)

The specific calculation steps of $G_1$ method can be referred to other studies (Chang and Chen 2013).

2.2. Entropy weight method

If the evaluation system includes $m$ items to be evaluated, and the index system includes $n$ evaluation indicators, the information entropy of the $j$-th index is:
where, the constant $k$ can be taken as $1/\ln m$, and $0 \leq e_j \leq 1$.

The coefficient of the difference of the $j$-th index:

$$ g_j = 1 - e_j, \ j = 1, 2, ..., n $$

The weight of the $j$-th index:

$$ \omega_j = \frac{1 - e_j}{\sum_{j=1}^{n} (1 - e_j)}, \ j = 1, 2, ..., n $$

The specific calculation steps of entropy weight method can be referred to other studies (Li et al. 2019).

### 2.3. Combination weighting method

In this paper, combined with $G_1$ method and entropy weight method, the combination weight is obtained by Equation (7). Both the subjective experience of experts and the objective information of data are considered, which can fully reflect the importance of evaluation indicators (Xue et al. 2019). The subjective weight is denoted as $\beta_j$, the objective weight is denoted as $\omega_j$, and the combined weight is denoted as $\varphi_j$. The combined weight of the $j$-th index is:

$$ \varphi_j = \frac{(\beta_j \omega_j)^{1/2}}{\sum_{j=1}^{n} (\beta_j \omega_j)^{1/2}} $$

### 3. Improved TOPSIS

TOPSIS is a multi-attribute decision-making method with a simple calculation, reliable results and wide application. However, the traditional TOPSIS method has certain defects. When the two evaluation objects are located on the vertical line of positive and negative ideal solutions, their Euclidean distance to the positive ideal solution may be equal to that to the negative ideal solution, which makes it difficult to judge the pros and cons of the evaluation objects (Zheng and Li 2014; Li et al. 2015). Grey correlation analysis is an important part of grey system theory. It can consider the nonlinear relationship between sequences and has been widely used in engineering problems (Zhou et al. 2020). Therefore, this paper adopts the TOPSIS method based on grey relational analysis, which comprehensively considers the Euclidean distance and the grey relational degree to make the evaluation result more credible. The basic steps are as follows.

#### 3.1. Calculating the weighted normalization matrix

When evaluating the system, it is necessary to standardize the evaluation indexes and evaluation standards to obtain the standardized decision matrix. The positive index refers to the index that the greater the value is, the higher the landslide hazard is. The negative index refers to the index that the greater the value is, the lower the landslide hazard is. The standardization of positive and negative indicators is processed according to equations (8)-(9).

Positive index:
The combination weight vector $\hat{\varphi}=(\varphi_1, \varphi_2, \ldots, \varphi_n)$ of the evaluation index set is multiplied by each column of the standardized evaluation index matrix and the standardized evaluation standard matrix. The weighted standardized matrix (Tripathy and Tripathy 2016) is obtained:

$$Z^* = (z_{ij})_{mn} = (\varphi_j x_{ij})_{mn} \tag{10}$$

### 3.2. Calculating grey correlation degree and Euclidean distance

Determining the positive and negative ideal solutions of the weighted normalized matrix:

$$Z^+_0 = \max_i Z_i(j) = (z^+_0(1), z^+_0(2), \ldots, z^+_0(n)) \tag{11}$$

$$Z^-_0 = \min_i Z_i(j) = (z^-_0(1), z^-_0(2), \ldots, z^-_0(n)) \tag{12}$$

Calculating grey relation coefficients between evaluation objects and positive and negative ideal solutions (Kirubakaran and IlangoKumar 2016; Yang and Wu 2019):

$$s^+_i = \frac{\Delta^+_i(j) + \rho \Delta^+_i(j)}{\Delta^+_i(j) + \rho \Delta^+_i(j)} \tag{13}$$

$$s^-_i = \frac{\Delta^-_i(j) + \rho \Delta^-_i(j)}{\Delta^-_i(j) + \rho \Delta^-_i(j)} \tag{14}$$

Where, $\Delta^+_i(j)$ and $\Delta^-_i(j)$ are the absolute difference between the sample and the positive ideal solution and the negative ideal solution, respectively. $\Delta^+_i(j) = \max_j \left| z^+_i(j) - z^-_i(j) \right|$; $\Delta^-_i(j) = \min_j \left| z^+_i(j) - z^-_i(j) \right|$. $\rho$ is the resolution coefficient, $\rho \in [0,1]$, and generally takes the value 0.5.

Calculating grey correlation degree $r_i^+$ and $r_i^-$ between each evaluation object and positive and negative ideal solutions:

$$r_i^+ = \frac{1}{n} \sum_{j=1}^{n} s^+_i, r_i^- = \frac{1}{n} \sum_{j=1}^{n} s^-_i \tag{15}$$

Calculating Euclidean distance $d_i^*$ and $d_i^-$ between each evaluation object and positive and negative ideal solutions:
3.3. Calculating closeness degree

The grey correlation degree and Euclidean distance are respectively non-dimensionalized according to Equation (17).

\[ d^+_i = \sqrt{\sum_{j=1}^{n} (z_{ij} - z^+_j)^2}, d^-_i = \sqrt{\sum_{j=1}^{n} (z_{ij} - z^-_j)^2} \] (16)

Combining grey correlation degree and Euclidean distance according to Equation (18).

\[ R^{(+)}_i = \frac{r^{(+)}_i}{\max r^{(+)}_i}, D^{(+)}_i = \frac{d^{(+)}_i}{\max d^{(+)}_i} \] (17)

\[ T^+_i = aR^+_i + bD^+_i, T^-_i = aR^-_i + bD^-_i \] (18)

where, a and b reflect the preference of decision-makers for position and shape, and satisfy \( a + b = 1 \), and \( a, b \in [0,1] \). Decision-makers can determine their values according to their preferences. In this paper, \( a=b=0.5 \).

Calculating relative closeness \( C^+_i \) of each evaluation object to ideal solution:

\[ C^+_i = \frac{T^+_i}{T^+_i + T^-_i} \] (19)

Converting the relative closeness into a range of 0-1:

\[ C_i = \frac{C^+_i - C_{i_{\text{min}}}}{C_{i_{\text{max}}} - C_{i_{\text{min}}}} \] (20)

4. Case analysis

4.1. Evaluation index and grading standard of landslide hazard

Factors inducing landslides are complex, including rock and soil types, geological structure conditions, topography and geomorphology conditions, hydrogeological conditions and human activities that violate natural laws and destroy slope stability conditions (Guzzetti et al. 1999b; van Westen et al. 2008). The selected evaluation indicators should be comprehensive and representative. Based on existing references (Varnes 1984; Song et al. 2014), landslide risk is divided into four grades: I (low risk), II (medium risk), III (high risk), IV (very high risk). Considering the causes and spatial distribution characteristics of landslide, nine evaluation indexes were selected, including slope weathering degree, stratum lithology, distance from slope to fault, slope inclination, vegetation coverage, slope gradient, slope height, landslide volume and immersion ratio after normal water storage. The slope weathering degree and stratum lithology are qualitative indexes, and the evaluation criteria are given by assignment. The slope weathering degree is divided into four levels: full weathering (0.75-1), strong weathering (0.50-0.75), weak weathering (0.25-0.50), and light weathering (0-0.25). Stratum lithology is divided into four levels: hard rock (0-0.25), hard rock with soft rock (0.25-0.50), soft rock with hard rock (0.50-0.75), soft rock and loose body (0.75-1). The classification standards are shown in Table 2. The data in Table 2 are standardized, as shown in Table 3.
The above method is used to analyze the risk of landslides in the study area in the literature (Song et al. 2014). Yansangshu Hydropower Station is located on the mainstream downstream of the Nu River in Baoshan City, Yunnan Province. The project area extends upstream to Sandadi Manhai Bridge (Nujiang Bridge) and downstream to Sanjiangkou. There are 22 potential landslides on both banks of the reservoir area. This paper selects landslides 1-10 for risk analysis, and the data of nine evaluation indicators are shown in Table 4. The data in Table 4 are standardized, as shown in Table 5.

### Table 2. Landslide risk assessment standard

| evaluation indicators               | risk grade |
|-------------------------------------|------------|
|                                     | I         | II        | III       | IV        |
| Slope weathering degree $Y_1$       | 0.75-1    | 0.50-0.75 | 0.25-0.50 | 0-0.25    |
| Stratum lithology $Y_2$             | 0.75-1    | 0.50-0.75 | 0.25-0.50 | 0-0.25    |
| Distance from slope to fault $Y_3$/m| <0        | 0-100     | 100-500   | 500-2000  |
| Slope inclination $Y_4/°$           | 135-180   | 90-135    | 45-90     | 0-45      |
| Vegetation coverage $Y_5/°$         | 180-225   | 225-270   | 270-315   | 315-360   |
| Slope gradient $Y_6/°$              | 0-25      | 25-50     | 50-75     | 75-100    |
| Slope height $Y_7$/m                | 40-50     | 30-40     | 20-30     | 0-20      |
| Landslide volume $Y_8/(10^3$m³)     | 300-1000  | 200-300   | 100-200   | 0-100     |
| Immersion ratio after normal water storage $Y_9/%$ | 100-1500 | 10-100    | 1-10      | 0-1       |

| evaluation indicators               | risk grade |
|-------------------------------------|------------|
|                                     | I         | II        | III       | IV        |
| Slope weathering degree $Y_1$       | 0-0.25    | 0.25-0.50 | 0.50-0.75 | 0.75-1    |
| Stratum lithology $Y_2$             | 0-0.25    | 0.25-0.50 | 0.50-0.75 | 0.75-1    |
| Distance from slope to fault $Y_3$/m| 0-0.75    | 0.75-0.95 | 0.95-1    | >1        |
| Slope inclination $Y_4/°$           | 0-0.25    | 0.25-0.5  | 0.5-0.75  | 0.75-1    |
| Vegetation coverage $Y_5/°$         | 0-0.25    | 0.25-0.5  | 0.5-0.75  | 0.75-1    |
| Slope gradient $Y_6/°$              | 0-0.4     | 0.4-0.6   | 0.6-0.8   | 0.8-1.0   |
| Slope height $Y_7$/m                | 0-0.1     | 0.1-0.2   | 0.2-0.3   | 0.3-1     |
| Landslide volume $Y_8/(10^3$m³)     | 0.0007-   | 0.0067-   | 0.0667-   | 0.6667-   |
| Immersion ratio after normal water storage $Y_9/%$ | <0        | 0-0.3     | 0.3-0.6   | 0.6-1     |

The above method is used to analyze the risk of landslides in the study area in the literature (Song et al. 2014). Yansangshu Hydropower Station is located on the mainstream downstream of the Nu River in Baoshan City, Yunnan Province. The project area extends upstream to Sandadi Manhai Bridge (Nujiang Bridge) and downstream to Sanjiangkou. There are 22 potential landslides on both banks of the reservoir area. This paper selects landslides 1-10 for risk analysis, and the data of nine evaluation indicators are shown in Table 4. The data in Table 4 are standardized, as shown in Table 5.
Table 5. Landslide evaluation indicator values (standardization)

| Landslide | Y₁ | Y₂ | Y₃ | Y₄ | Y₅ | Y₆ | Y₇ | Y₈ | Y₉ |
|-----------|----|----|----|----|----|----|----|----|----|
| 1         | 0.625 | 0.625 | 0.96 | 0.75 | 0.1 | 0.14 | 0.032 | 0.0333 | 0 |
| 2         | 0.375 | 0.375 | 1 | 0.9278 | 0.5 | 0.2 | 0.029 | 0.0022 | 0 |
| 3         | 0.375 | 0.375 | 0.9925 | 0.9278 | 0.4 | 0.74 | 0.268 | 0.0111 | 0.04 |
| 4         | 0.375 | 0.375 | 0.8875 | 0.7444 | 0.3 | 0.8 | 0.389 | 0.0007 | 0 |
| 5         | 0.625 | 0.375 | 1 | 0.9722 | 0.2 | 0.24 | 0.708 | 0.136 | 0.027 |
| 6         | 0.500 | 0.375 | 1 | 0.4667 | 0.3 | 0.74 | 0.122 | 0.0175 | 0.38 |
| 7         | 0.500 | 0.375 | 0.8365 | 0.4833 | 0.2 | 0.86 | 0.430 | 0.0077 | 0.10 |
| 8         | 0.375 | 0.375 | 0.2365 | 0.3889 | 0.3 | 0.68 | 0.185 | 0.0201 | 0.23 |
| 9         | 0.375 | 0.375 | 0.6 | 0.2889 | 0.3 | 0.6 | 0.435 | 0.0111 | 0.115 |
| 10        | 0.375 | 0.375 | 1 | 0.3611 | 0.1 | 0.8 | 0.285 | 0.0019 | 0.175 |

4.2. Calculating combination weight of landslide hazard evaluation index
The subjective weight of each index is calculated based on G₁-method. The objective weight of each evaluation index is determined by entropy weight method. The combined weight is calculated using Equation (7). The results of subjective weight, objective weight and combined weight are shown in Table 6. Landslide 1 is taken as an example to calculate its risk level.

Table 6. Results of the indexes weight

| Index layer | G₁ method | Entropy weight method | combined weight |
|-------------|-----------|-----------------------|-----------------|
| Y₁          | 0.1992    | 0.1810                | 0.1927          |
| Y₂          | 0.1513    | 0.1250                | 0.1395          |
| Y₃          | 0.0575    | 0.0682                | 0.0636          |
| Y₄          | 0.0871    | 0.1304                | 0.1082          |
| Y₅          | 0.0413    | 0.0745                | 0.0563          |
| Y₆          | 0.1472    | 0.1118                | 0.1302          |
| Y₇          | 0.0372    | 0.0906                | 0.0589          |
| Y₈          | 0.1319    | 0.1061                | 0.1201          |
| Y₉          | 0.1472    | 0.1123                | 0.1305          |

4.3. Calculating weighted normalization matrix
The weighted normalization matrix is obtained from Equation (10):

\[
Z = \begin{pmatrix}
0 & 0.0482 & 0.0349 & 0.0477 & 0.0271 & 0.0141 & 0.0521 & 0.0059 & 0.0001 & 0 \\
0.0482 & 0.0349 & 0.0477 & 0.0271 & 0.0141 & 0.0521 & 0.0059 & 0.0001 & 0 \\
0.0964 & 0.0698 & 0.0604 & 0.0541 & 0.0282 & 0.0781 & 0.0118 & 0.0008 & 0.0391 \\
0.0964 & 0.0698 & 0.0604 & 0.0541 & 0.0282 & 0.0781 & 0.0118 & 0.0008 & 0.0391 \\
0.1445 & 0.1046 & 0.0636 & 0.0811 & 0.0422 & 0.1042 & 0.0177 & 0.0080 & 0.0783 \\
0.1445 & 0.1046 & 0.0636 & 0.0811 & 0.0422 & 0.1042 & 0.0177 & 0.0080 & 0.0783 \\
0.1927 & 0.1395 & 0.0636 & 0.1082 & 0.0563 & 0.1302 & 0.0589 & 0.1201 & 0.1305 \\
0.1204 & 0.0872 & 0.0611 & 0.0811 & 0.0056 & 0.0182 & 0.0019 & 0.0040 & 0
\end{pmatrix}
\] (21)

4.4. Calculating grey correlation degree and Euclidean distance
The positive and negative ideal solutions are obtained from Equation (11)-(12):

\[
Z^*_0 = (0.1927, 0.1395, 0.0636, 0.1082, 0.0563, 0.1302, 0.0589, 0.1201, 0.1305)
\] (22)
According to Equations (13)-(16), the grey correlation degree and Euclidean distance between each evaluation object and the positive and negative ideal solutions are calculated. According to Equation (17), the grey correlation degree and Euclidean distance are dimensionless. The calculation results are shown in Table 7.

### Table 7. Grey correlation degree and Euclidean distance

| evaluation object | I     | II    | III   | IV    | Landslide 1 | Landslide 2 |
|-------------------|-------|-------|-------|-------|--------------|--------------|
| $r_i^+$           | 0.484 | 0.560 | 0.560 | 0.638 | 0.739        | 0.739        |
|                   | 7     | 4     | 4     | 1     | 2            | 2            |
| $r_i^-$           | 1.000 | 0.812 | 0.812 | 0.695 | 0.613        | 0.484        |
| $d_i^+$           | 0.356 | 0.284 | 0.284 | 0.213 | 0.148        | 0.148        |
|                   | 9     | 3     | 3     | 0     | 8            | 8            |
| $d_i^-$           | 0.097 | 0.097 | 0.171 | 0.171 | 0.248        | 0.248        |

### 4.5. Calculating relative closeness

According to the Equations (18)-(19), the relative closeness is calculated. Finally, Using Equation (20) to transform relative closeness into the range of 0-1, and obtaining the membership of each grade:

$$C_1=(0.0000−0.2396), \ C_2=(0.2396−0.4407), \ C_3=(0.4407−0.6345), \ C_4=(0.6345−1.0000)$$

The evaluation results of landslide 1-10 are shown in Table 8.

### Table 8. Landslide hazard evaluation results

| Landslide | Closeness degree | Improved TOPSIS | Catastrophe theory | Actual situation |
|-----------|------------------|-----------------|--------------------|------------------|
| 1         | 0.4028           | II              | medium             | medium           |
| 2         | 0.3596           | II              | medium             | medium           |
| 3         | 0.4307           | II              | medium             | medium           |
| 4         | 0.4092           | II              | medium             | medium           |
| 5         | 0.4522           | III             | medium             | medium           |
| 6         | 0.4410           | III             | high               | high             |
| 7         | 0.4258           | II              | medium             | medium           |
| 8         | 0.3424           | II              | medium             | medium           |
| 9         | 0.3357           | II              | medium             | medium           |
| 10        | 0.3871           | II              | medium             | medium           |
4.6. Results analysis

It can be seen from Table 8 that the evaluation results of improved TOPSIS are basically consistent with the evaluation results of mutation theory in the literature (Song et al. 2014), and are basically consistent with the actual investigation. In this paper, the discrimination level of landslide 5 is III (high risk), and the actual investigation risk is medium (II). It can be seen that the discrimination level of this paper is relatively high. Since landslide disasters are controlled by multiple factors, and the evaluation system is relatively complex, the selected evaluation indexes and their accuracy will affect the evaluation results, so it is reasonable to have certain errors. In addition, for landslide disasters, the high level of discrimination indicates that the evaluation results are safer, which is beneficial to improve the awareness of disaster prevention. Therefore, the evaluation method proposed in this paper is still feasible.

5. Discussion and conclusion

TOPSIS method is an effective multi-attribute decision-making method with simple principle and convenient calculation. The traditional TOPSIS method uses Euclidean distance to measure the proximity between evaluation objects and targets. This paper adopts the TOPSIS method based on grey correlation degree and considers the nonlinear relationship between sequences. A landslide risk evaluation model is established. The comprehensive closeness is calculated by combining the Euclidean distance from the evaluation object to the ideal solution and the grey correlation degree, making the evaluation result more reasonable.

In this paper, G1 method, entropy weight method and TOPSIS method based on grey correlation degree are combined to establish a combined weighting-improved TOPSIS method to evaluate the risk of landslide 1-10 in the literature (Song et al. 2014). The subjective weight and objective weight of each index are obtained by using G1 method and entropy weight method, and then the combined weight is obtained. The improved TOPSIS method is used to evaluate the landslide risk, and good evaluation results are obtained. Compared with the catastrophe theory method and field survey results in the literature, the feasibility of the evaluation method is verified, which provides a reference for landslide risk assessment.

The combination weight-improved TOPSIS method proposed in this paper comprehensively considers the subjective experience of decision-makers and objective data information, making the weight results more reliable and making full use of the original data information to evaluate the landslide risk. However, the accuracy of the evaluation index value will affect the weight value, thus affecting the evaluation results, so it is necessary to ensure the accuracy of the data.

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