Landslide Susceptibility Prediction Based on the Information Value-Logistic Regression Model and Geographic Information System

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Abstract: The landslide susceptibility prediction (LSP) is generally implemented using certain types of single models; however, certain drawbacks exist in the single models; e.g., it is difficult to clearly reflect the weights of landslide-related environmental factors if only the information value (IV) model is adopted. To overcome these limitations, this study proposes an IV-logistic regression (IV-LR) model for LSP. The landslides that occurred in the southern part of Chongyi County, China, are used as study cases. Nine environmental factors—elevation, slope, plane curvature, profile curvature, relief amplitude, distance to river, lithology, normalized difference vegetable index, and normalized difference built-up index—are adopted based on remote sensing and geographic information system. Certain landslide grid units and the same number of non-landslide grid units are used as the output variables of these models. The IV, LR, and IV-LR models are used to implement the LSP in the southern part of Chongyi County. The predicted landslides susceptibility in Chongyi County mostly occurred in areas with low elevations, close distance to rivers, carbonate lithology, low vegetation coverage rate, and densely populated areas. The results show that the prediction rate of the IV-LR model (80.4%) is higher than that of the LR model (76.8%), followed by the IV model (72.8%); they further demonstrate that the IV-LR model has its unique superiority and rationality compared with the IV and LR models.

1. Introduction
A landslide is a type of geological disaster in which shear failure and slippage of slope mass occur along a certain soft surface, causing considerable losses to industrial and agricultural production, as well as losses of peoples’ lives and properties [1–3]. Landslide susceptibility prediction (LSP) is adopted by many researchers to determine potentially high-risk areas to reduce these losses [4–5].

According to the different environmental factors of each study area, it is significant to construct an LSP model matching the study area for improving the LSP accuracy. Marjanovic et al. [6] classified the LSP models into several different types—probabilistic models [7], heuristic models [8], deterministic models [9], mathematical statistics models [10], and machine learning models [11–13]. Among them, the mathematical statistics models are built based on statistical theory to calculate potential relationships between various environmental factors and the occurrence probability of landslides [14].

In applying a single mathematical statistics model for LSP, Xu et al. [15] used the information value (IV) model to predict landslide susceptibility indexes (LSIs), and Zhang et al. [16] used the IV model to predict the LSIs in the areas along the New Jing-Zhang high-speed railway. Moreover, Xu et
al. used the logistic regression (LR) model to predict the landslide susceptibility induced by rainfall processes [17–19]. Although the LSP results of both the IV and LR models are generally satisfying, they still have certain limitations. For the IV model, although the corresponding IVs can reflect whether each subinterval of environmental factors is conducive to the evolution of landslides or not, they cannot demonstrate the contribution weight of each environmental factor to the landslide. Furthermore, the LR model is built based on the multivariate statistical analysis between independent and dependent variables, which can reflect the differences of influence degrees of different environmental factors on landslides. Nevertheless, the LR model cannot indicate the correlations between the subintervals of each environmental factor and landslides from the perspective of space.

To summarize, there are certain disadvantages in adopting a single IV or LR model. Fortunately, a novel model combining the IV and LR models, namely, IV-LR model, can overcome these disadvantages and can yield additional predictive results. Therefore, considering Chongyi County in Jiangxi province of China as a study area, the IV-LR model is built to predict landslide susceptibility. The corresponding LSP results are compared with those predicted by the single IV and LR models.

2. Methods
The primary modeling steps of the IV-LR model are as follows: 1) reasonable environmental factors should be selected based on the evolution characteristics and geological conditions of the landslides in the study area; 2) the IVs of all environmental factors should be calculated based on the landslide inventory map and the landslide-related environmental factors; 3) the LR model is constructed with the IVs as the input variables; 4) landslide susceptibility map of the study area is produced by the IV-LR model with related accuracy assessment; and 5) the single IV and LR models are used to predict the landslides susceptibility for comparisons.

2.1. IV model
The IV model is extensively used for LSP. In practical modeling processes, the IV corresponding to each sub-class in the environmental factor is first calculated, and then a total IV is obtained by adding up the IVs of all sub-classes. In general, the larger the total IVs, the higher the LSIs [20–24]. The calculation formulas of the IV model are as follows:

\[
I_{(A_{j,k})} = \ln \frac{n_{j-k} l_{j-k}}{n / s} \quad (j = 1, 2, 3, \cdots, m; k = 1, 2, 3, \cdots, n) \\
I = \sum_{j=1}^{m} I_{A_{j,k}} = \sum_{j=1}^{m} (I_{A_{j,1}}, I_{A_{j,2}}, \cdots, I_{A_{j,m}})
\]

(1)

(2)

where \(n_{j-k}\) and \(s_{j-k}\) are the landslide and study areas in the \(kth\) sub-class of the \(jth\) environmental factor, respectively; \(n\) and \(s\) are the total areas of landslides and Congyi County, respectively; and \(I_{(A_{j,k})}\) and \(I\) are the IV of a single environmental factor and total IV, respectively. These IVs can be classified as positive and negative values, which mean constructive and conducive to the occurrence of landslides, respectively.

2.2. LR model
The LR model is extensively used for LSP because of its simplicity and excellent performance. In this study, the frequency ratio (FR) values of each environmental factor are selected as the independent variables, and the occurrence probabilities of landslides are considered as the dependent variable. Then, the whole grid units with related FR values are predicted using the constructed LR model. The calculation formula of LR is shown in Eq. (3), and the Logit function is done to \(P\), as shown in Eq. (4):

\[
\text{Logit}P = a_0 + a_1 x_1 + a_2 x_2 + \cdots + a_n x_n
\]

(3)
\[
P = \frac{\exp(a_0 + a_1x_1 + a_2x_2 + \cdots + a_nx_n)}{1 + \exp(a_0 + a_1x_1 + a_2x_2 + \cdots + a_nx_n)}
\]

where \(x_1, x_2, x_3, \ldots, x_n\) represent environmental factors, \(\text{LogitP}\) is the landslide occurrence probability, \(a_0\) is the constant value representing the logarithm of the probability ratio of occurrence and non-occurrence of landslides under all environmental factors [25], and \(a_i\) is the coefficient value corresponding to \(i\).

2.3. IV-LR model

For the LSP modeling of the IV-LR model, the landslide grid units and the same number of randomly selected non-landslide grid units are used to extract the IVs of all the environmental factors to construct the LR equation. In this manner, both the contribution weights of different environmental factors to the occurrence of landslides and the space features of the sub-classes of each environmental factor are considered. The calculation equation of the IV-LR model is as follows:

\[
\text{Logit}P = b_0 + b_1(I_{A_{h_1}}, I_{A_{h_2}}, \ldots, I_{A_{h_n}}) + \cdots + b_m(I_{A_{h_1}}, I_{A_{h_2}}, \ldots, I_{A_{h_m}})
\]

\[
= b_0 + b_1 \left( \frac{n_{11}}{n/s}, \frac{n_{12}}{n/s}, \ldots, \frac{n_{1s}}{n/s} \right) + \cdots + b_m \left( \frac{n_{m1}}{n/s}, \frac{n_{m2}}{n/s}, \ldots, \frac{n_{ms}}{n/s} \right)
\]

where \(b_1, b_2, b_3, \ldots, b_m\) are the LR coefficients, and \(I_{A_{h_1}}, I_{A_{h_2}}, \ldots, I_{A_{h_m}}\) are the IVs of sub-classes of each environmental factor calculated by Eq. (1).

3. Materials

The materials employed in this study include natural and geological environments and a landslide inventory map of Congyi County.

3.1. Study area and landslide inventory map

Chongyi County is located in the southwest border of Jiangxi Province, with its position at \(113^\circ 55' - 114^\circ 38'\)E and \(25^\circ 24' - 25^\circ 55'\)N, and a total area of 2206 km\(^2\); its elevation approximately ranges from 154 to 1410 m. The topography of the whole study area is dominated by the mountain and low mountain of the eroded structure, and a few are formed by the karst and erosion accumulation. There are a number of rainfall and water resources in Chongyi County. The spatial variation of engineering rock mass characteristics are complex, which leads to frequent local landslides occurrence. A total of 289 landslide locations are determined according to the survey report of the land and resources department and the field investigation, as shown in the landslide inventory map (Figure 1). These landslides primarily comprise the quaternary deposits of silty clay interspersed with broken stones. The thickness of these landslides vary between 2 and 8 m, and their average area is \(~5000\) m\(^2\). Their evolution features can be analyzed as follows: landslides occur more frequently in the low mountainous and hilly areas with high population density and tend to be induced by rainstorm season and unreasonable human engineering.
3.2. Landslide spatial datasets

3.2.1. Division of mapping units. The primary mapping units of the LSP include grid, slope, sub-basin, unique condition, and other units [26]. Among them, grid and slope units are extensively used. The slope unit is obtained by dividing the real landscape into ridge and valley lines. Although there is clear geological significance in slope units, the production of the slope units highly depends on the subsequent manual correction, resulting in time consumption and low accuracy [27]. The grid unit can be quickly divided and is efficient in the LSP modeling [28]. Therefore, the grid unit with a spatial resolution of 30 m is used as a mapping unit.

3.2.2. Data sources. The data sources are as follows: 1) landslide inventory map and field investigation data; 2) digital elevation model (DEM) with a resolution of 30 m, used to extract slope, topographic relief, and other terrain factors; 3) 1:100000 scale geological map, used to extract stratigraphic lithology information; 4) Landsat TM remote sensing image of Chongyi County, used to extract normalized difference vegetable index (NDVI), and normalized difference built-up index (NDBI).

3.2.3. Selection and correlation analysis of environmental factors. There has been no consensus on the selection of the most suitable environmental factors for the LSP. Generally, factors closely related to landslides, such as terrain, hydrology, basic geology, and vegetation cover, are considered. In this study, based on the landslide evolution characteristics and commonly used environmental factors in Chongyi County, ten environmental factors—elevation, slope, slope structure, plane curvature, profile curvature, relief amplitude, distance to rivers, lithology, NDVI, and NDBI—are selected to form LSP factors (Figure 2) [29]. The continuous environmental factors are divided into six sub-classes using the Jenks natural breaks method; then, Table 1 lists the FR values and IVs of sub-classes in each environmental factor.

Table 1. FR values and IVs of all environmental factors

| Environmental factors | Value (m)   | FR value | IV  | Environmental factors | Value (m) | FR value | IV  |
|----------------------|------------|----------|-----|-----------------------|-----------|----------|-----|
| Elevation            | 140.4−353.9| 1.932    | 0.658| Relief                | 0−44.0    | 1.622    | 0.484|
|                      | 353.9−515.9| 0.954    | −0.047| amplitude            | 44.0−70.1 | 1.197    | 0.180|
|                      | 515.9−699.9| 0.759    | −0.276|                       | 70.1−94.8 | 0.969    | −0.031|
| Slope (°) | Distance to rivers (m) | Lithology          | NDVI      | NDBI    |
|----------|------------------------|---------------------|-----------|---------|
| 0–8      | 0.964 0.036            | 0.685 0.378        | 0.657 0.421| 0.373 0.985|
| 8.0–14.3 | 1.305 0.266            | 0.458 0.781        | 1.074 0.072| 1.399 0.336|
| 14.3–20.0| 1.105 0.100            | 1.576 0.455        | 6.808 1.918| 1.485 0.395|
| 20.0–25.7| 0.967 0.034            | 0.624 0.472        | 1.108 0.103| 0.839 0.175|
| 25.7–32.4| 0.250 1.388            |                    |          |         |
| 32.4–66.1| 0.000 0.000            |                    |          |         |
| Convex slope | 1.33 0.285 |                    |          |         |
| Linear slope | 0.458 0.781 |                    |          |         |
| Compound slope | 1.576 0.455 |                    |          |         |
| Concave slope | 0.685 0.378 |                    |          |         |
| Plan curvature (m⁻¹) | 0.51–2.97 |                    |          |         |
| Profile curvature (m⁻¹) | 0.79–4.33 |                    |          |         |

| Distance to rivers (m) | NDBI | NDVI |
|------------------------|------|------|
| 0–250                  | 0.594 0.521 |
| 250–500                | 0.978 0.023 |
| 500–750                | 0.594 0.521 |
| >750                   | 0.978 0.023 |

| Lithology          | NDVI | NDBI |
|--------------------|------|------|
| Hard rock          | 1.108 0.103 | 0.373 0.985 |
| Magmatite          | 0.657 0.421 | 1.399 0.336 |
| Clasolite          | 1.074 0.072 | 0.839 0.175 |
| Carbonate          | 6.808 1.918 | 1.485 0.395 |
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Figure 2 Classification of environmental factors: (a) elevation, (b) slope, (c) plane curvature, (d) profile curvature, (e) relief amplitude, (f) distance to rivers, (g) lithology, (h) NDVI, and (i) NDBI (slope structure is not present)

(1) Topographic factors

As shown in Figure 2, the correlations between environmental factors and landslides are primarily reflected by the corresponding landslide density and IVs of sub-classes in each environmental factor. According to Figures 2 (a) and (b), the landslides mainly occur in the area with an elevation of 140–353 m and a slope of 8.03°–19.96°. The types of slope structure are primarily divided into concave, convex, linear, and composite slopes. The composite and convex slopes are conducive to the occurrence of landslides, as shown in Figure 2 (c). The plane and profile curvatures reflect the convergence and acceleration of terrain to surface water flow, respectively. When the plane and profile curvatures range from −0.3 to 0.19 and from −0.27 to 0.79, respectively, the landslides are more likely to occur, as shown in Figures 2 (d) and (e), respectively. Furthermore, when the relief amplitude (Figure 2 (f)) varies between 0 and 70 m, it is constructive to landslide occurrence.

(2) Hydrologic environment factors

The river system refers to the water reticulation network comprising all rivers, lakes, and other water bodies [30, 31]. In this study, the distance to rivers can be extracted by the function of hydrological analysis in ArcGIS 10.2 as follows. Firstly, the DEM is filled, and the flow direction and accumulation are calculated. Then, the river networks can be obtained through vector treatment. Lastly, the distances to rivers are extracted through the multiple ring buffer analysis function, as shown in Figure 2 (g). When the distance from a grid unit to a corresponding river is within 500 m, the IV is greater than 0, indicating that the grid unit closer to the river system is more prone to landslides.

(3) Lithology and land cover factors

Lithology [32] is a paramount environmental factor of landslide occurrence (Figure 2 (h)). The structures of hard, clasolite, and carbonate rocks are relatively weak, and their corresponding IVs are >0, which are conducive to the occurrence of landslides. The NDVI and NDBI are used to
represent the relative ratio of vegetation coverage and surface construction degree, as shown in Figures 2 (i) and (j), respectively. The areas with NDVI of <0.345 and NDBI of >0.483 are conducive to the occurrence of landslides.

4. LSP

4.1. LSP using IV model
In this study, 7618 recorded landslide grid units and 7618 randomly selected non-landslide grid units are used to extract the IVs of each environmental factor, and Eq. (2) is used to predict the LSIs of Congyi County. Then, the generated landslide susceptibility map is divided into five levels by the Jenks natural breaks method—very low, low, moderate, high, and very high susceptible levels (Figure 3 (a)).

4.2. LSP using LR model
The FR values of environmental factors are used as the independent variables of the LR model. The landslide grid units are denoted by 1 and non-landslide grid units are denoted by 0, and they are considered as dependent variables. In the modeling processes, SPSS 24.0 is used to perform binary LR analysis, and the LR coefficient value of each environmental factor is calculated. The results show that the significance test values of all environmental factors are <0.05, thereby suggesting that the LR model is of statistical significance. Eq. (6) is the obtained LR fitting equation, which suggests that elevation, distance to rivers, lithology, NDVI, NDBI, and other environmental factors play paramount roles in the occurrence of landslides. The landslide susceptibility map (Figure 3 (b)) is produced in ArcGIS10.2.

\[
\text{Logit}\, P = -3.856 + 0.594 \times \text{Elevation} + 0.352 \times \text{Slope} + 0.391 \times \text{Slope structure} \\
+ 0.382 \times \text{Plane curvature} + 0.406 \times \text{Profile curvature} - 0.295 \times \text{Relief amplitude} \\
+ 0.531 \times \text{Distance to the rivers} + 0.426 \times \text{Lithology} + 0.544 \times \text{NDVI} + 0.611 \times \text{NDBI}
\]  \tag{6}

4.3. LSP using IV-LR model
In this study, the IVs of the sub-classes in the environmental factors are used as the input variables of the IV-LR model, and the landslides and non-landslides (set as 1 and 0) are used as output variables. As in the single LR model, the significance test levels of the LR coefficient values of all environmental factors are <0.05, indicating that the IV-LR model is of statistical significance. The LR fitting equation of the above IV-LR model is shown as Eq. (7), suggesting that the environmental factors of elevation, distance to rivers, NDVI, and NDBI play paramount roles in the evolution of landslides. Furthermore, Figure 3 (c) shows the landslide susceptibility map produced by the IV-LR model. From Figure 3 (c), the prediction results of the IV-LR model are highly consistent with the actual landslide occurrence conditions.

\[
\text{Logit}\, P = -0.014 + 0.635 \times \text{Elevation} + 0.098 \times \text{Slope} + 0.304 \times \text{Slope structure} \\
+ 0.345 \times \text{Plane curvature} + 0.289 \times \text{Profile curvature} + 0.002 \times \text{Relief amplitude} \\
+ 0.530 \times \text{Distance to the rivers} + 0.323 \times \text{Lithology} + 0.557 \times \text{NDVI} + 0.728 \times \text{NDBI}
\]  \tag{7}
Figure 3. Landslide susceptibility map of each model

4.4. Accuracy evaluation and LSP results analysis

The prediction rate is used to evaluate the accuracies of the IV, LR, and IV-LR models. The prediction rate curve can express the relationship between the measured data and test results. The larger the area under the prediction rate curve, the higher the prediction accuracy of the model. Figure 4 shows that the prediction rate of the IV-LR model (80.4%) is significantly higher than that of the IV (72.8%) and the LR models (76.8%). The distribution rules of landslides in the landslide susceptibility maps are similar to each other.

(1) The statistical results in Table 2 show that the areas with very high susceptible levels account for ~11.56% of the total study area. Table 2 also shows that, compared to the 30.67% for the IV model and the 19.54% for the LR model, 40.93% of the whole landslide grids units fall in the very high susceptible areas for the IV-LR model. Furthermore, 33.84% of the whole landslide grid units are located in the high susceptible area for the IV-LR model (34.94% for IV and 31.47% for LR).

(2) The very high and high susceptible levels are concentrated in the areas with relatively low elevation, close distance to the river system, carbonate structure, low vegetation coverage, and relatively dense engineering. Among them, water can reduce the shear strength of rocks and soils and increase the probability of landslides by eroding and softening the slope masses.

(3) The distribution of the high and very high susceptible areas of the IV model is the most scattered, compared to the LR and IV-LR models. The distribution of the high and very high susceptible areas of the LR model is excessively concentrated along the river system. However, the IV-LR model overcomes the limitations that existed in the IV and LR models, thereby showing the trend of concentration along the river system with a certain degree of dispersion. This phenomenon shows the superiority of the IV-LR model over the other two models.

![Figure 4. Prediction rate curves of all models](image)

Table 3. Landslide distribution in the susceptibility levels of each model

| Levels    | IV-LR model | IV model | LR model |
|-----------|-------------|----------|----------|
|           | Pixels in domain | Landslide Percentage (%) | Pixels in domain | Landslide Percentage (%) | Pixels in domain | Landslide Percentage (%) |
| Very low  | 0.05—0.22   | 32384    | 1.56     | 20356    | 50487    | 6.01     |

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5. Conclusion

As the study area, the southern part of Chongyi County in China is used. The IV, LR, and IV-LR models are proposed to predict landslide susceptibility in the study area. It can be concluded that:

(1) Overall, all three models have reliable LSP results, among which the prediction performance of the IV-LR model is higher than that of the IV and LR models.

(2) The high and very high landslide susceptible levels are primarily concentrated in the areas with low elevation, close distance to the river system, carbonate structure, low vegetation coverage, and dense engineering. Among all the environmental factors, elevation, distance to rivers, lithology, NDVI, and NDBI play the most paramount roles in the landslides occurrence.

(3) The landslide susceptibility map produced by the IV-LR model is more consistent with the distribution of recorded landslides in Chongyi County than those produced by the single IV and LR models. In conclusion, the LSP results of the IV-LR model can provide theoretical guidance for the landslide risk assessment in Chongyi County and other similar areas.

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