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Article

Multiclassification Method of Landslide Risk Assessment in Consideration of Disaster Levels: A Case Study of Xianyang City, Shaanxi Province

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Abstract: Geological disaster risk assessment can quantitatively assess the risk of disasters to hazard-bearing bodies. Visualizing the risk of geological disasters can provide scientific references for regional engineering construction, urban planning, and disaster prevention and mitigation. There are some problems in the current binary classification landslide risk assessment model, such as a single sample type, slow multiclass classification speed, large differences in the number of positive and negative samples, and large errors in classification results. This paper introduces multilevel landslide hazard scale samples, selects multiple types of samples according to the divided multilevel landslide hazard scale grade, and proposes a landslide hazard assessment model based on a multiclass support vector machine (SVM). Due to the objective limitations of the single weighting method, the combined weights are used to determine the vulnerability of the landslide hazard-bearing body, and the analytic hierarchy process (AHP) and entropy method are combined to construct a landslide vulnerability assessment model that considers subjective and objective weights. This paper takes landslide disasters in Xianyang City, Shaanxi Province, as the research object. Based on the landslide hazard assessment model and the landslide vulnerability assessment model, a landslide risk assessment experiment is carried out. It generates the landslide risk assessment zoning map and summarizes the risk characteristics of landslides in various towns. The experimental results verify the feasibility and effectiveness of the proposed model and provide important decision support for decision makers in Xianyang City.

Keywords: landslide disaster; hazard assessment; risk assessment; multiclass SVM

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1. Introduction

In recent years, disasters have occurred frequently worldwide, destroying human property and socioeconomic activities [1–3]. The potential risks faced by human beings and society are increasing, and disasters have gradually attracted much attention. As one of the largest countries in the world, China has a complex and diverse topography. With the expansion of the scope of human engineering activities, many natural disasters frequently occur [4]. In 2020, according to statistics from the Geological Environment Monitoring Institute of the Geological Survey of China, the number of perennial disaster-affected people in China reached 200 million, and socioeconomic losses exceeded 1 trillion. There were 7840 geological disasters nationwide with a direct economic loss of CNY 5.02 billion, 139 deaths or missing persons, and 58 injuries. Among the Chinese geological disasters, there were 4810 landslides, 1797 collapses, 183 ground collapses, 899 mudslides, 8 instances of ground subsidence, and 143 ground fissures events. The situation of geological disaster prevention and control remains severe in China.

Despite the increasingly severe disaster situation and the shortage of land resources [5,6], disaster prevention and mitigation work are gradually progressing [7]. It is critical to establish a correct and effective geological disaster risk assessment system and analyze the magnitude of disaster risk for effective disaster prevention and mitigation. In 1991, the United Nations Humanitarian Department defined the natural disaster risk calculation and proposed the expression "risk = function (hazard, vulnerability)". This calculation method has been recognized by most researchers, marking the transformation of disaster risk assessment from qualitative to quantitative research [8]. With the in-depth study of geological disasters, machine learning has been widely used in landslide risk assessment. In the selection of evaluation factors and calculation of weights [9–21], Lee et al. analyzed the relationship between landslides and various influencing factors, and achieved the risk zoning [22]. Zhao et al. used the Shannon entropy theory, a fuzzy comprehensive method, and an analytic hierarchy process (AHP) to assess landslide sensitivity [23]. In the process of landslide hazard assessment [24–32], Yu et al. combined the geographically weighted regression, particle swarm optimization (PSO), and support vector machine (SVM) to map the landslide sensitivity in the Three Gorges Reservoir of Wanzhou District [33]. Xu et al. integrated the entropy index into an SVM to realize landslide susceptibility assessment in Shaanxi Province [34]. In the process of landslide risk assessment [35–43], Xiao et al. combined the random forest model and the deterministic coefficient model to evaluate the risk of landslides in Wanzhou District [43]. Pradhan et al. discussed the application of the BP neural network model in landslide risk assessment [44]. The research results of geological disaster risk assessment are fruitful. The evaluation methods are being increasingly perfected, and the accuracy of the evaluation is gradually improving.

However, the existing classification models used in landslide risk assessments are mostly binary classification models. The impact of different landslide disaster scales on disaster risk assessment is not considered, and there is a lack of multiclassification studies on landslide disaster scales. When using the binary classification model for multiclassification tasks, there is a problem of slow classification speed. The sample classification error is large due to the large difference between the numbers of positive and negative samples. Therefore, it is necessary to establish a geological disaster risk assessment system based on the scale of landslide disasters, identify multicategory geological disaster risk assessment models, and carry out quantitative research on the scale of various disasters [45].

This paper combines landslide hazard assessment based on multiclass SVM and landslide vulnerability assessment with subjective and objective weights, and proposes a landslide risk assessment that combines multiclass SVM and combined weights. The main contributions are summarized as follows:

(1) Nine evaluation factors are selected from the four aspects of terrain features, meteorological features, human influence, and historical geological disasters to construct the landslide hazard evaluation index system: elevation, slope, aspect, normalized difference vegetation index (NDVI), distance from rivers, accumulated rainfall, distance from roads, lithology, and landforms. Using the idea of multiclassification, a landslide hazard assessment model based on a multiclass SVM is proposed. This method selects multitype samples according to the scale of divided multilevel landslide hazards, improves the sample types of landslide classification and is beneficial to the hazard assessment of multilevel landslide disasters.

(2) Four evaluation factors for landslide vulnerability are selected from the three aspects of population vulnerability, economic vulnerability, and material vulnerability to construct a landslide vulnerability evaluation index system: population density, arable land density, GDP density, and road density. Combining the AHP and the entropy method, a landslide vulnerability assessment model that considers the subjective and objective weights is proposed. This paper evaluates the vulnerability of landslides by combining subjective and objective weighting calculation methods, combines the advantages of subjective and objective methods, and avoids the objective limitations caused by a single weighting method.

(3) Taking the landslide in Xianyang city of Shaanxi Province as the research object and taking the towns as the evaluation unit, the landslide risk assessment is carried out based on the landslide hazard assessment model and the landslide vulnerability assessment model. This paper generates the landslide risk assessment zoning map of the study area, analyzes the results by using the existing risk levels of landslide points, summarizes the risk characteristics of landslides in various towns, and provides a scientific basis for the implementation of regional disaster prevention and mitigation.

2. Research Area and Data

2.1. Research Area

Xianyang City, Shaanxi Province is located between 107°38′ E–109°10′ E and 34°9′ N–35°34′ N. It is in the central part of the Guanzhong Basin, with a total area of approximately 9543.6 km^2. The terrain is higher in the north and lower in the south, leaning from north to south in a stepped shape. The northwest is the Weibei Loess Plateau, with an altitude of 1000–1800 m, and the terrain is mostly a semiarid gully area. The southeast is the Weihe Basin, and the terrain is flat and open, with an altitude of 400–800 m. The annual rainfall is mainly concentrated between July and October. The average annual precipitation is 537–650 mm. The river level is greatly affected by precipitation. There are more than 5400 large and small rivers and channels, and the river network density reaches 0.86 km/km^2. The rainfall in the territory is more in the south and less in the north, with obvious monsoon characteristics, and the annual average rainfall changes greatly. As a result, the seasonal changes in river runoff are great, and the changes in flood and dry flow are obvious. The remote sensing image of Xianyang City, Shaanxi Province is shown in Figure 1.

Figure 1. Xianyang City, Shaanxi Province.

Xianyang City has complex geological and geomorphic conditions and strong new geological tectonic activities. It belongs to an area prone to geological disasters. With the development of the social economy, the scale of human engineering activities has gradually expanded, and the hidden dangers of geological disasters have increased significantly. There are six major types of geological disasters in the city: landslides, mudslides, collapses, ground fissures, unstable slopes, and ground subsidence [46,47].

2.2. Data

Landslide risk assessment is jointly determined by natural and social attributes. Natural attributes can reflect disaster intensity, activity scale, incubation conditions, and predisposing factors, which are mainly reflected in the hazard of geological disasters. Social attributes refer to the degree of loss related to social characteristics such as life, engineering activities, and economic level, which are closely related to geological disasters [9]; that is, the vulnerability of disaster-bearing bodies. Therefore, in this paper, based on the "Spatial Distribution Data of Geological Disaster Points", "Spatial Distribution Data of Geological Lithology in China", and "Spatial Interpolation Dataset of Annual Precipitation in China since 1980" from the Chinese Academy of Sciences' Data Center for Resource and Environmental Sciences, DEM data from China's first national geoinformation survey, public road data and water system data provided by OSM, considering three aspects of basic environmental factors, predisposing factors and historical geological disasters, a total of nine evaluation factors in four categories were selected as natural attribute data for landslide hazard assessment. They were terrain characteristic factors (elevation slope, aspect, NDVI, distance from rivers), meteorological characteristic factors (accumulated rainfall), human influence factors (distance from roads), and historical geological disasters (lithology, landforms). The details are shown in Figures 2 and 3. According to "China's geographical situation monitoring data", from the three aspects of population vulnerability, economic vulnerability, and material vulnerability, four types of spatial distribution maps were extracted from Xianyang City in 2018 as social attribute data. They were population density, arable land density, GDP density, and road density, as shown in Figure 4. To facilitate statistics and analysis, regular grid units were selected as the risk assessment units of the study area, and the study area was divided into 30 m $\times$ 30 m grid units, including 5639 columns, 6098 rows, and 17,059,135 grid units.

The disaster data in this paper were derived from the "Spatial Distribution Data of Geological Hazard Points" from the Data Center for Resources and Environmental Science of the Chinese Academy of Sciences. The data format was Microsoft Excel and vector shape files, including landslides, mudslides, collapses, ground fissures, unstable slopes, and ground subsidence, with a total of 637 disaster points.

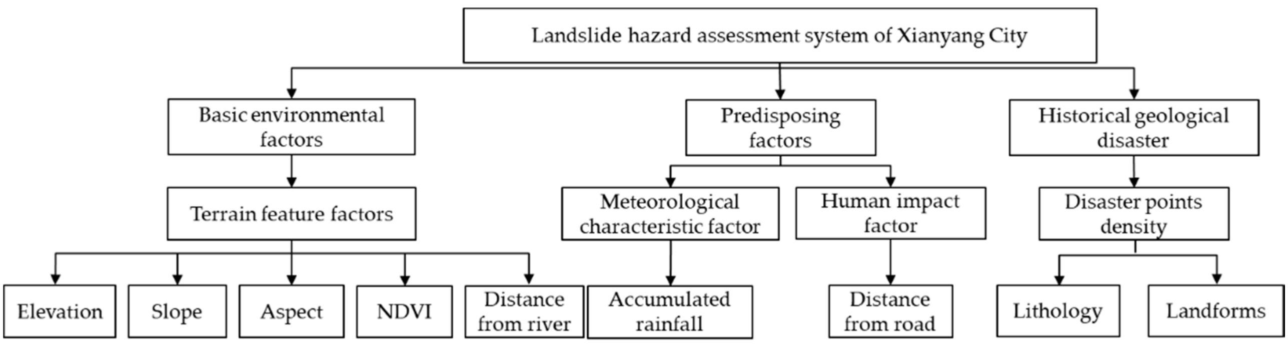

Figure 2. The landslide hazard evaluation index system.

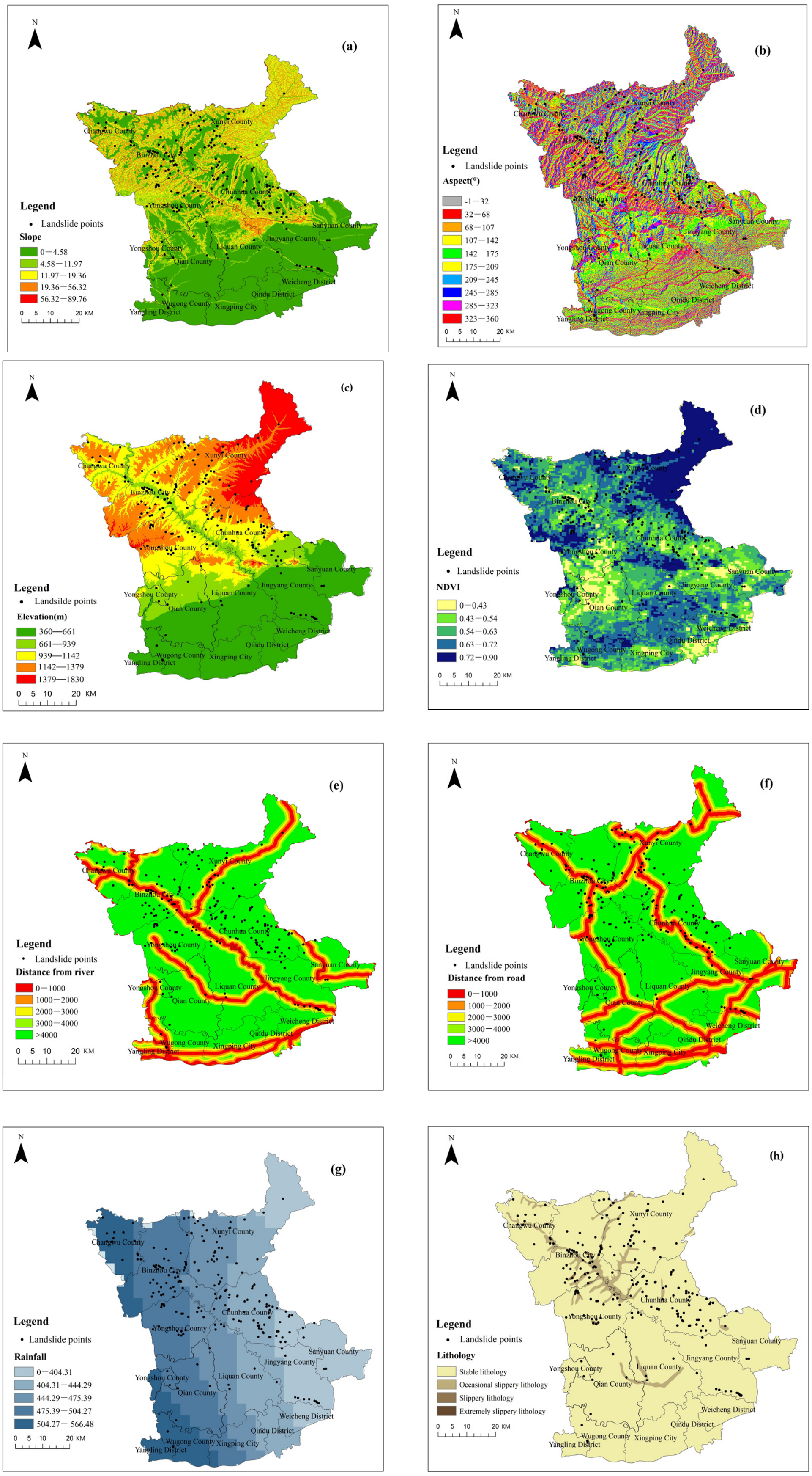

Figure 3. *Cont.*

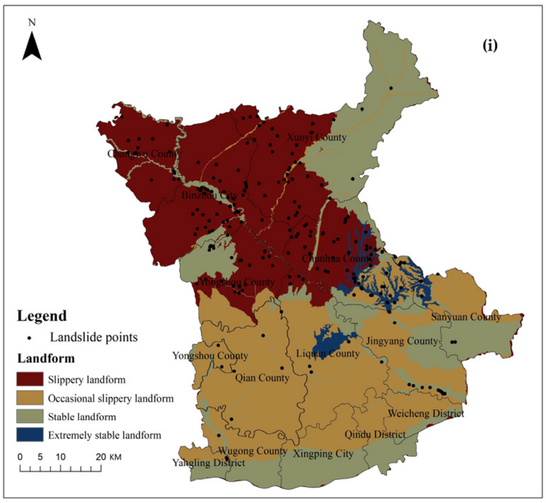

Figure 3. Landslide hazard assessment factors: (**a**) slope; (**b**) aspect; (**c**) elevation; (**d**) NDVI; (**e**) distance from rivers; (**f**) distance from roads; (**g**) rainfall; (**h**) lithology; (**i**) landforms.

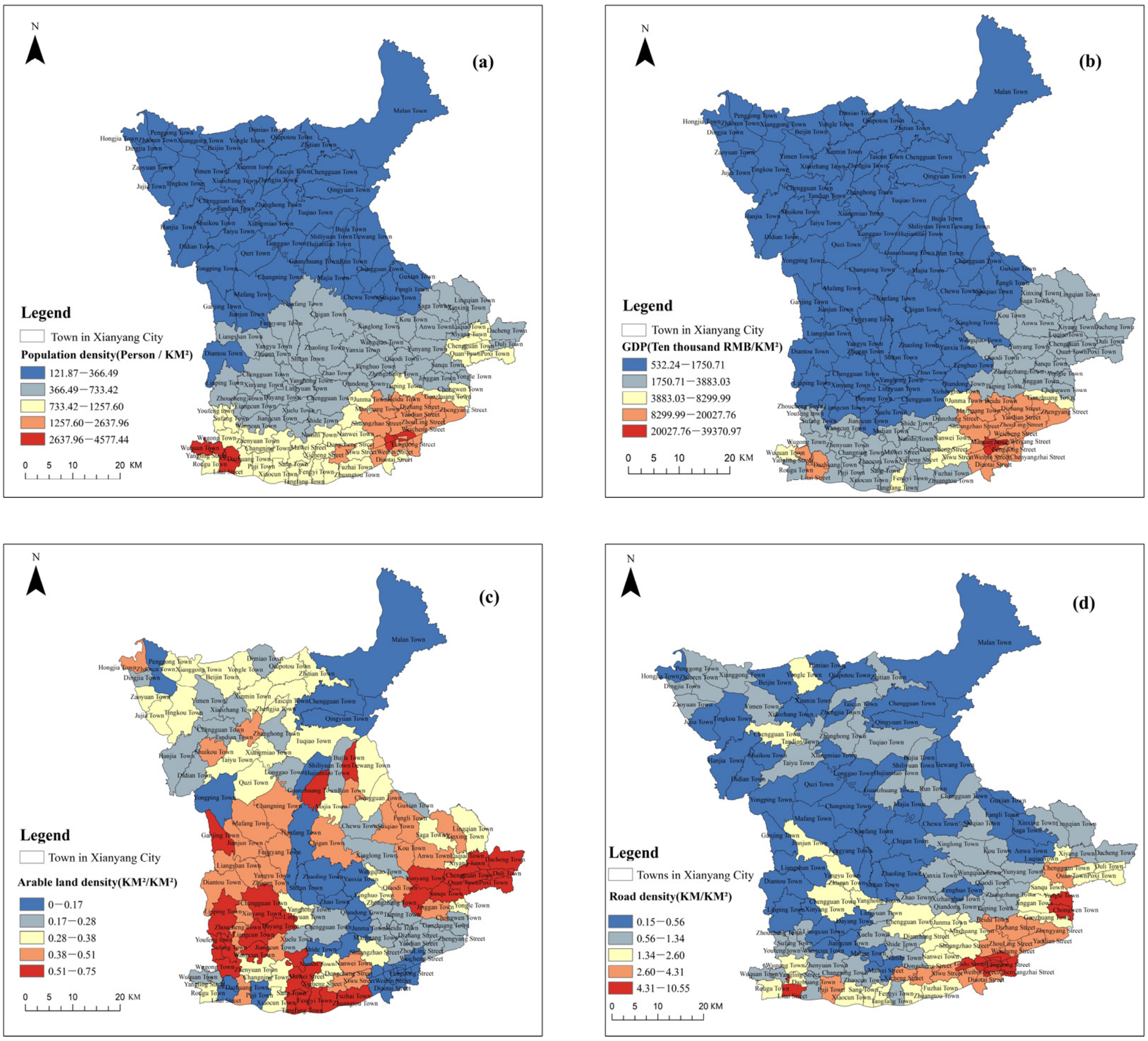

Figure 4. Landslide vulnerability assessment factors: (**a**) population density; (**b**) GDP density; (**c**) arable land density; (**d**) road density.

3. Landslide Risk Assessment Method

This section shows the classification standard of the geological disaster scale and classification standard of geological disasters, and introduces the multiclass SVM landslide hazard assessment model and landslide vulnerability assessment model, which consider the subjective and objective weights to carry out landslide risk assessment.

3.1. Classification of Geological Disaster Scale

According to the "Basic Requirements for Geological Disaster Investigation and Zoning of Counties (Cities)" compiled by the Ministry of Land and Resources of China, the disaster scale and risk level of Xianyang City are divided. The geological disaster scale grade is a classification of geological disasters according to indicators such as geological disaster intensity or influence range [48,49]. Generally, the larger the disaster intensity, the greater the hazard of geological disasters and the more disaster-affected objects. According to China's geological disaster prevention and management measures, the scale of geological disasters is generally divided into four levels: low, medium, high, and extremely high hazard. The classification standards of different geological disasters are shown in Table 1. According to the loss or potential threat caused by geological disasters, the risk degree of geological disasters was divided into four levels: low risk, medium risk, high risk, and extremely high risk, as shown in Table 2.

Table 1. Classification standards of geological disaster scale.

Level	Landslide (10^4 m^3)	Collapse (10^4 m^3)	Mudslide (10^4 m^3)	Ground Collapse (km^2)
Extremely high hazard	≥1000	≥100	≥50	≥10
High hazard	100~1000	10~100	20~50	1~10
Medium hazard	10~100	1~10	2~20	0.1~1
Low hazard	<10	<1	<2	<0.1

Table 2. Classification standards of geological disasters.

Level	Death Toll (People)	Number of Threats (People)	Direct Economic Loss (Ten Thousand)	Potential Economic Loss (Ten Thousand)
Extremely high risk	≥30	≥1000	≥1000	≥10,000
High risk	10~30	100~1000	500~1000	5000~10,000
Medium risk	3~10	10~100	100~500	500~5000
Low risk	<3	<10	<100	<500

3.2. Landslide Hazard Assessment Model Based on Multiclass SVM

3.2.1. Multiclass SVM

SVM is based on the principle of structured risk minimization, and was proposed by a Bell Labs research group led by Vapnik in 1963. It has two types: linear and nonlinear [24]. Its basic idea is to find the optimal hyperplane in the sample or feature space to maximize the space between different categories, especially in solving the more common nonlinear high-dimensional multiclassification problems in practical applications. Multiclassification is a given dataset containing N samples, $X = \{(x_1, y_1), (x_2, y_2), \ldots\ldots (x_N, y_N)\}$, and class labels $y_n = (1, 2, \ldots\ldots, M), n = 1, 2, \ldots\ldots N$, and the dataset has a total of M classes. According to the decision function $y = f(x)$, we predicted the categories of N sample data. The multiclass SVM could convert the nonlinear problem in the multiclass samples into the linear separable problem in the high-dimensional feature space, find an optimal hyperplane between every two classes, and divide the N samples into M classes for output.

In the sample space, hyperplane h can be expressed as:

$$w^T x + b = 0 \tag{1}$$

where w is the normal vector, which determines the direction of hyperplane h; x is the training sample; and b is the displacement term, which is the distance between the hyperplane and the origin. When w and b are optimal, it means that the optimal hyperplane is found so that the distance between positive and negative samples is the largest.

For the nonlinear classification problem, it is necessary to transform the nonlinear problem in the multiclass samples into the high-dimensional feature space [25] and to find the linear hyperplane in the high-dimensional space to classify the samples. $\phi(x)$ represents the feature vector after sample x is transformed into a high-dimensional space; then, the model corresponding to hyperplane h in the feature space is:

$$f(x) = w^T \phi(x) + b \tag{2}$$

The corresponding objective function is:

$$\min\left(\frac{\|w\|^2}{2}\right) \tag{3}$$

$$s.t. y_i(w^T \phi(x) + b) \geq 1, i = 1, 2, 3, \ldots n \tag{4}$$

By using the Lagrangian multiplier α_i, under the constraints of $\sum_i a_i y_i = 0$ and $0 \leq \alpha_i \leq \mathrm{C}$, the following relationship is obtained:

$$\max : \sum_i \alpha_i - \frac{1}{2} \sum_i \sum_j \alpha_i \alpha_j y_i y_j x_i^T x_j \tag{5}$$

$$s.t. \sum_{i=1}^{n} \alpha_i y_i = 0, i = 1, 2, 3, \ldots n \tag{6}$$

where $j = 1, 2, 3, \ldots m$, and $i \neq j$; to calculate the above formula, a kernel function $K(x_i, y_j)$ is introduced to reduce the error rate of sample classification. Sample x is converted from low-dimensional space to $\phi(x)$ in high-dimensional space.

$$K(x_i, y_j) = \phi(x_i)^T \phi(y_j) \tag{7}$$

By inserting $K(x_i, y_j)$ into Equation (5), and after solving, the decision function of the SVM model is obtained:

$$f(x) = w^T \phi(x) + b = sign\left(\sum_{i=1}^{n} y_i \alpha_i K(x_i, y_j) + b\right) \tag{8}$$

The classification accuracy of SVM depends on the selection of the kernel function and the setting of related parameters. The kernel function can be selected according to application conditions and sample characteristics. At present, the commonly used kernel functions are the linear kernel function (LN), polynomial kernel function (PL), radial basis function (RBF), and sigmoid kernel function (SIG).

3.2.2. Algorithm Flow

Multitype sample selection based on divided multilevel landslide hazard scale grade can increase the number of disaster classification samples, solve the problem of a single sample type, and improve the classification accuracy of multilevel landslide disasters. Therefore, a multiclass SVM landslide risk assessment model was proposed by combining with the multilevel landslide hazard scale grade. Therefore, the accuracy and reliability of landslide hazard assessment results could be improved. The specific algorithm flow is shown in Figure 5.

The algorithm process was as follows:

(1) Construction of the landslide hazard assessment index: nine index factors were selected from three aspects to construct the landslide hazard assessment index system in the study area.
(2) Construction of the sample dataset: units with the same number of landslide hazard points were randomly selected as nongeological hazard units, and the two were combined as the sample dataset.
(3) Sample point classification: according to the classification standard of the landslide disaster scale, the landslide hazard sample points in the study area were classified by hazard level, and 80% of all samples were selected as the training sample and 20% as the test sample.
(4) Parameter optimization: the radial basis function was selected for multiclassification of nonlinear samples, and the optimal parameters c and g were selected by the cross-validation method.
(5) Landslide hazard zoning map: the natural discontinuity method was used to divide landslide hazard grades into four categories.

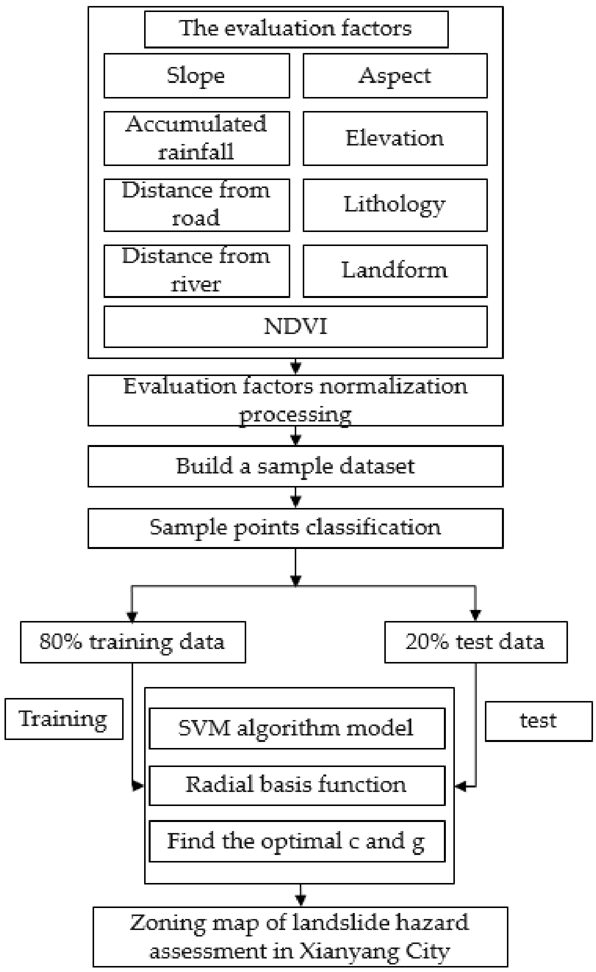

Figure 5. Flowchart of landslide hazard assessment in Xianyang City.

3.3. Landslide Vulnerability Assessment Model Considering Subjective and Objective Weights

3.3.1. Combined Weights

There are three main methods for calculating the weights of evaluation factors: the subjective weighting method, objective weighting method, and combined weights [10]. The subjective weighting method is mainly obtained by experts based on subjective judgments and experience, with strong subjectivity. The objective weighting method is obtained through a mathematical model by quantitatively calculate the relationship between the research index value and the geological hazard. The accuracy of the calculation results is mostly determined by the measured data and is too dependent on the data. The combined weights integrate the advantages of subjective and objective methods and avoid the objective limitations of a single weighting method, so they are widely used in many fields.

(1) Subjective weighting method

AHP is a combination of quantitative and qualitative analysis. Experts subjectively analyze the relative importance of each evaluation index based on experience and give the relative index value. The operation is simple and convenient; however, the subjectivity is strong. The specific process is shown in Figure 6. Among them, the method of constructing the judgment matrix is the 1–9 scale method proposed by Saaty [13]. As shown in Table 3, this method could avoid the difficulty of comparing different qualitative evaluation factors, and it had strong operability. The consistency test is usually measured by the consistency ratio (CR). It is generally believed that when the CR < 0.1, the inconsistency degree of the matrix is within the allowable range, and the consistency of the judgment matrix meets the requirements.

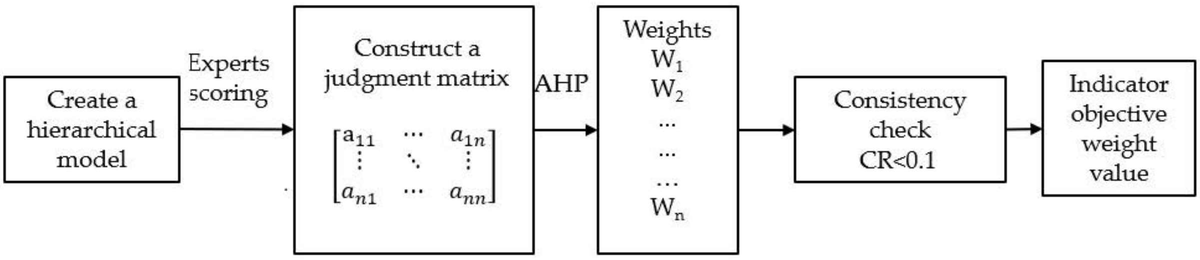

Figure 6. Flowchart of AHP.

Table 3. Standards and meanings of judgment matrix.

Standards	Meanings
1	When two factors are compared, they have the same importance
3	When two factors are compared, the former is slightly more important than the latter
5	When two factors are compared, the former is obviously more important than the latter
7	When two factors are compared, the former is more important than the latter
9	When two factors are compared, the former is extremely more important than the latter
2,4,6,8	The adjacent middle value of the above
$1/i$ (i = 1, 2 . . . 9)	The above situation is reversed

(2) Objective weighting method

The entropy method is one of the methods for calculating objective weights. Its principle is to calculate the indicator weights according to the information provided by the indicator data. The calculation result entirely depends on the objective data, and the objectivity is strong. In the entropy method, the size of entropy is negatively related to the amount of information provided by objective data. There is no specific requirement for the number of evaluation indicators, and it is widely used and easy to understand. Compared with the AHP, although it cannot reflect the evaluator's understanding of the importance of each index, it can guarantee the objectivity of the evaluation and reduce the shortcomings of the excessive subjectivity of the AHP. The entropy method process is shown in Figure 7.

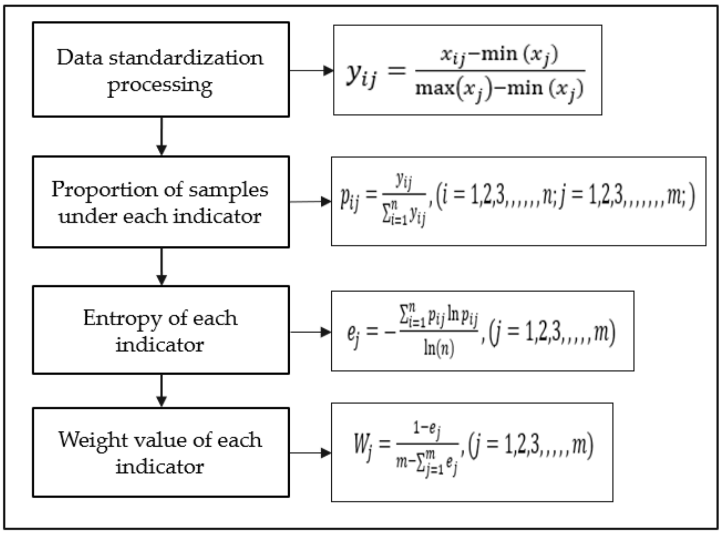

Figure 7. Flowchart of the entropy method.

(3) Combined weights

This study applied combined weights in the landslide vulnerability assessment. This could combine the advantages of subjective and objective evaluations to make the evaluation results more accurate. In this paper, the distance function [11,12] was used to combine subjective and objective weights to achieve ideal and reasonable weights. The formula is:

$$W = \mu W_1 + \gamma W_2 \tag{9}$$

where μ is the subjective weighting coefficient, and γ is the objective weighting coefficient.

From Formula (9), determining the subjective and objective weighting coefficients is the key to calculating the comprehensive weight. This study completed the distribution of subjective and objective weighting coefficients according to the calculation principle of the distance function [14,35]. The specific method is as follows.

Suppose the subjective and objective weights are W_1 and W_2, respectively. The distance function of W_1,W_2 is $d(W_1, W_2)$:

$$d(W_1, W_2) = \sqrt{\frac{\sum_{i=1}^{n} (W_1 - W_2)^2}{2}}, i = 1, 2, 3, 4; \tag{10}$$

$$d(W_1, W_2)^2 = (\mu - \gamma)^2 \tag{11}$$

$$\mu + \gamma = 1 \tag{12}$$

According to the above formula, the subjective and objective weighting coefficients μ and γ were calculated. Finally, the comprehensive weight was calculated according to the distance function formula.

3.3.2. Algorithm Flow

The subjective and objective combined weights were used to determine the weight of the vulnerability evaluation factor of the hazard-bearing body. This method had the advantage of considering decision makers' subjective understanding of the degree of loss caused by geological disasters. At the same time, the amount of information provided by objective indicators on the vulnerability of geological disasters is considered, which increases the reliability of the vulnerability of disaster-bearing bodies. Therefore, this study combined the AHP and entropy method and adopted the comprehensive vulnerability evaluation index model based on combined weights to evaluate the landslide vulnerability in the study area. The specific process is shown in Figure 8. The principle of the comprehensive vulnerability index evaluation model is shown in Formula (13):

$$F_i = \sum_{j=1}^{m} P_j \times W_j \tag{13}$$

where F_i is the comprehensive vulnerability index of each evaluation unit, i represents the evaluation unit, P_j represents the normalized weight of the j-th evaluation index of the i-th evaluation unit, and W_j represents the weight of the j-th evaluation index of the i-th evaluation unit.

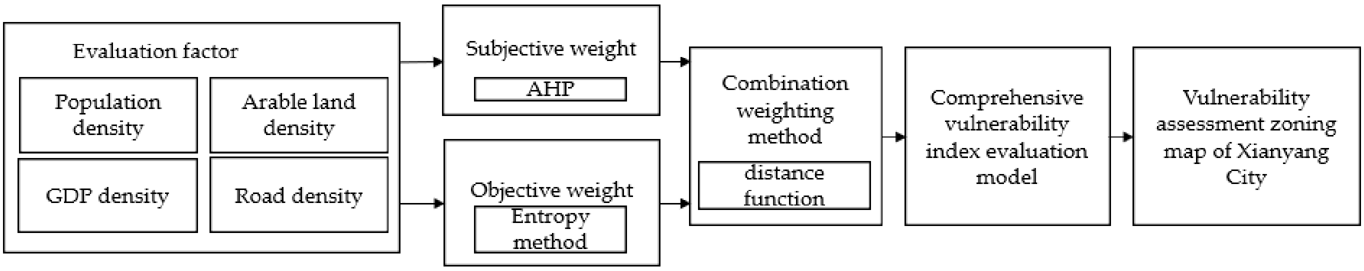

Figure 8. Flowchart of the disaster vulnerability assessment.

4. Experiment and Analysis

This section presents the classification of geological disaster types and levels, combined with the methods introduced in Section 3, and tests and analyzes the hazard, vulnerability, and risk of landslides.

4.1. Classification of Geological Disaster Types and Levels in the Study Area

According to the scale-grade standard of geological disasters, the scale of geological disasters in Xianyang City was divided into four levels: low, medium, high and extremely high hazards. Among them, there were two extremely high-hazard geological disaster points, accounting for 0.314% of the total number of geological disaster points. There were 45 high-hazard geological disaster points, accounting for 7.064% of the total. There were 106 medium-hazard geological disaster points, accounting for 16.641% of the total, and there were 484 low-hazard geological disaster points, accounting for 75.981% of the total. The specific distribution is shown in Table 4. The distribution of disaster intensity levels in each geological disaster type is shown in Table 5.

Table 4. Statistical table of geological disaster intensity level.

Disaster Intensity Level	Count (Piece)	Proportion (%)
Extremely high hazard	2	0.314
High hazard	45	7.064
Medium hazard	106	16.641
Low hazard	484	75.981

Table 5. Statistical table of disaster intensity level in different types of disasters.

Types of Disaster	Extremely High Hazard	High Hazard	Medium Hazard	Low Hazard
Landslide	2	27	67	119
Collapse	0	18	35	242
Surface collapse	0	0	4	36
Mudslide	0	0	0	3
Ground fissure	0	0	0	83
Unstable slope	0	0	0	1

4.2. Landslide Hazard Assessment Based on Multiclass SVM

In this paper, the same number of units as the landslide disaster points in Xianyang City was randomly selected as nongeological disaster units, and the two samples were combined into one sample dataset, for a total of 415 sample points. In the selection of nongeological disaster points, to improve the accuracy of nondisaster point extraction, the distance from the disaster point was used as the constraint condition. The greater the distance from the disaster point, the less affected the disaster, and the accuracy of nondisaster point selection in the area was relatively high. Therefore, based on comprehensive factors such as the size of the area and the density of disaster points in Xianyang City, this paper selected a distance of 2 km from the disaster points and a distance greater than 1 km between nondisaster points as the constraint conditions, so the nondisaster units were randomly selected. Subsequently, based on the divided multilevel landslide disaster points in Xianyang City, the sample points were selected in the ratio of nondisaster points:low-risk points:medium-risk points:high-risk points = 6:4:2:1.

The landslide hazard assessment model outputted four discrete values, representing the four levels of extremely-low-hazard, low-hazard, medium-hazard and high-hazard areas, and each output grid cell had a hazard degree value. Based on the predicted landslide hazard values of Xianyang City, the zoning of each hazard level was carried out to obtain the zoning map of landslide hazards in Xianyang City, as shown in Figure 9. The area and proportion of each hazard area were statistically analyzed, as shown in Table 6.

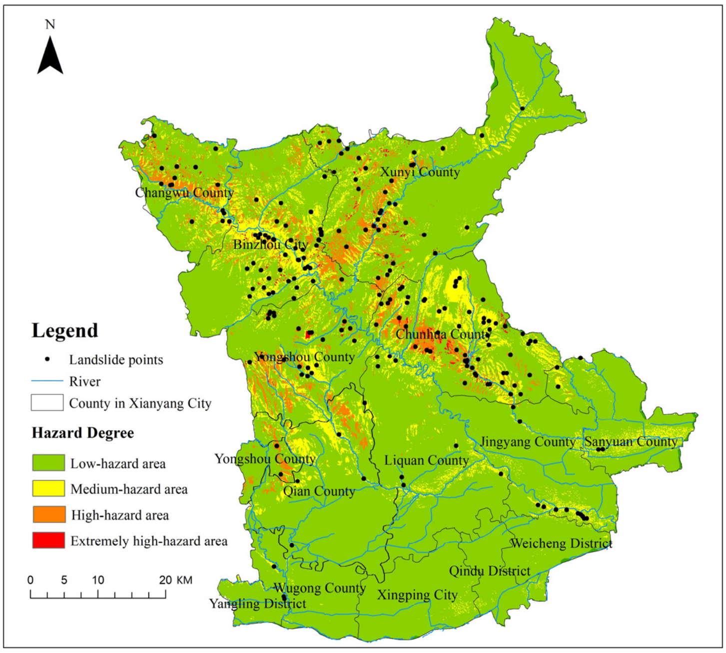

Figure 9. Landslide hazard assessment zoning map of Xianyang City.

Table 6. Area and proportion of each dangerous zone.

Dangerousness	Area (km^2)	Proportion
Extremely low-hazard area	8036.952	84.21%
Low-hazard area	1008.186	10.56%
Medium-hazard area	456.471	4.78%
High-hazard area	41.991	0.44%

4.3. Landslide Vulnerability Assessment Considering Subjective and Objective Weights

The combined weights of the vulnerability evaluation factors of Xianyang's population density, arable land density, GDP density, and road density were calculated, and the results are shown in Tables 7–9:

Table 7. Subjective weights and maximum eigenvalues of vulnerability assessment factors.

Evaluation Factor	Population Density	Road Density	Arable Land Density	GDP Density	CR	λ_{max}
Weights	0.5860	0.2418	0.1149	0.0573	0.0804	4.217

Table 8. Calculation results of objective weights of vulnerability assessment factors.

Evaluation Factor	Population Density	Road Density	Arable Land Density	GDP Density
Weights	0.2467	0.2649	0.0850	0.4033

Table 9. Calculation results of objective weights of vulnerability assessment factors.

Evaluation Factor	Population Density	Road Density	Arable land Density	GDP Density
Comprehensive weights	0.474703	0.24936	0.105094	0.170843

Based on the combined weights, the four vulnerability evaluation factors were normalized, and the comprehensive vulnerability index of Xianyang City was using by Formula (13). The calculation result is shown in Figure 10. According to the Jenks method, this paper carried out the vulnerability zoning of Xianyang City, divides the vulnerability degree of Xianyang City into four levels of extremely low vulnerability, low vulnerability, medium vulnerability, and high vulnerability. The vulnerability assessment zoning map of Xianyang City is shown in Figure 11. Since there are 149 towns in Xianyang City in the study area, this paper used the administrative town as a unit to carry out quantitative statistics of the carrier. It was convenient to provide a scientific basis for the implementation of disaster prevention and mitigation decision-making and engineering activities by township governments.

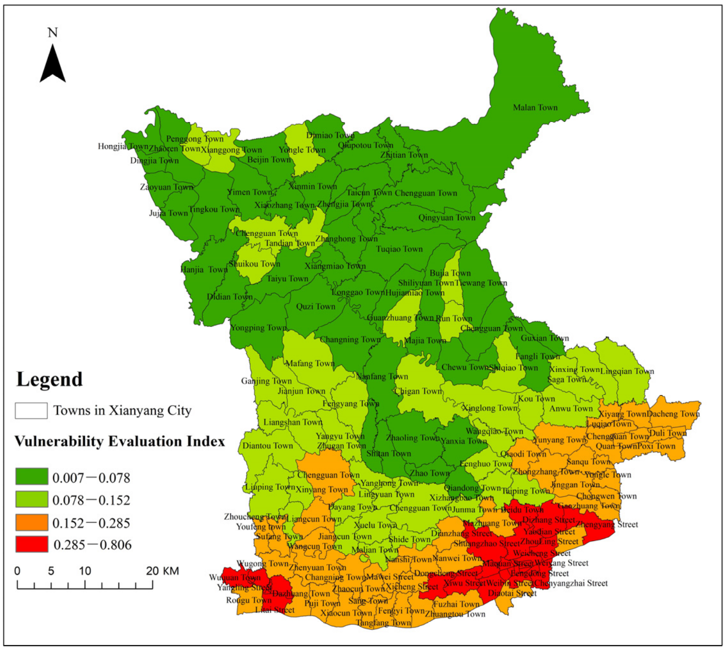

Figure 10. Landslide vulnerability evaluation index of Xianyang City.

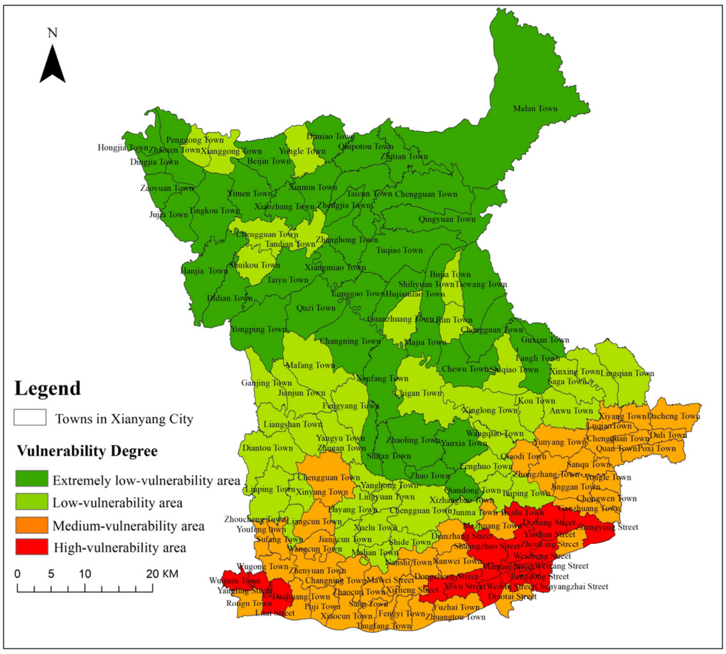

Figure 11. Landslide vulnerability assessment zoning map of Xianyang City.

The results showed that the vulnerability of the northern part of Xianyang City was generally low, while the vulnerability of the southern part was relatively high, especially the area around the Xianyang urban area. This was because the area is close to the Xianyang urban area, with rapid economic development and densely distribution of population and roads. If geological disasters occur, there will be many affected objects, and the vulnerability of the bearing body will be large.

4.4. Landslide Risk Assessment

Risk emphasizes the threat of a certain hazard to an object, and has the characteristics of uncertainty, objectivity, and sociality. Geological disaster risk assessment is a quantitative assessment of the losses caused by geological disasters. Combining the topographic and geological characteristics of Xianyang City and the development characteristics of landslide disasters, this paper adopted the evaluation model method of "risk = function (hazard, vulnerability)" proposed by the United Nations Humanitarian Business Department (UNDHA) in 1991. The standardization treatment was carried out based on the results of landslide hazard and vulnerability assessments in Xianyang City. It quantitatively represented four extremely low-risk (extremely low vulnerability), low-risk (low vulnerability), medium-risk (medium vulnerability), and high-risk (high vulnerability) risk levels or vulnerability levels in numerical form, and calculated the risk value of landslides in Xianyang City. The results are shown in Figure 12. According to the calculation results, the Jenks method was used to partition the landslide risk in Xianyang City. The partition standards are shown in Table 10:

Xianyang City is divided into four research areas: lower-risk areas, low-risk areas, medium-risk areas, and high-risk areas, according to the landslide risk using the Jenks method. The area of each study area and the distribution characteristics of landslide disaster points are summarized in Figure 13 and Table 11. The risk was researched and analyzed by combining the various characteristics of each area.

Table 10. Risk zoning standards of the study area.

Risk Zoning	Lower-Risk Area	Low-Risk Area	Medium-Risk Area	High-Risk Area
Value at risk	(0,1)	(1,3)	(3,4)	(4,9)

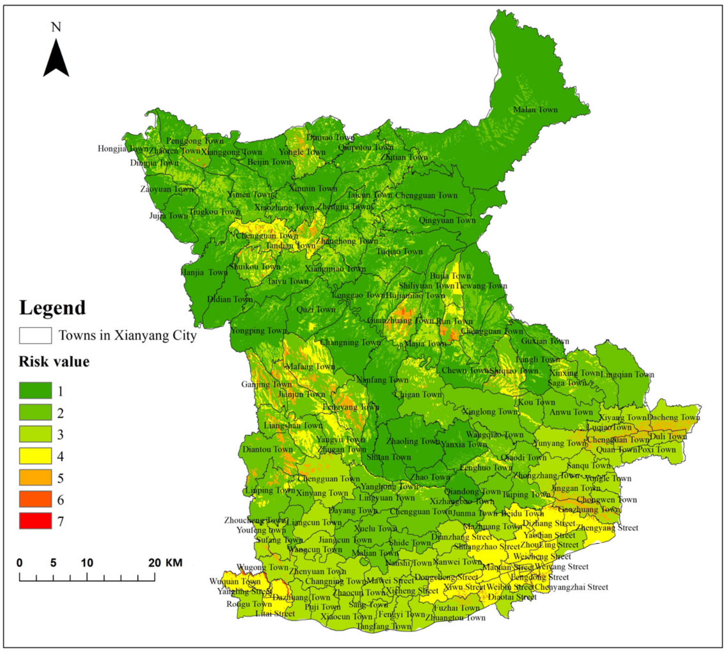

Figure 12. Landslide risk values in Xianyang City.

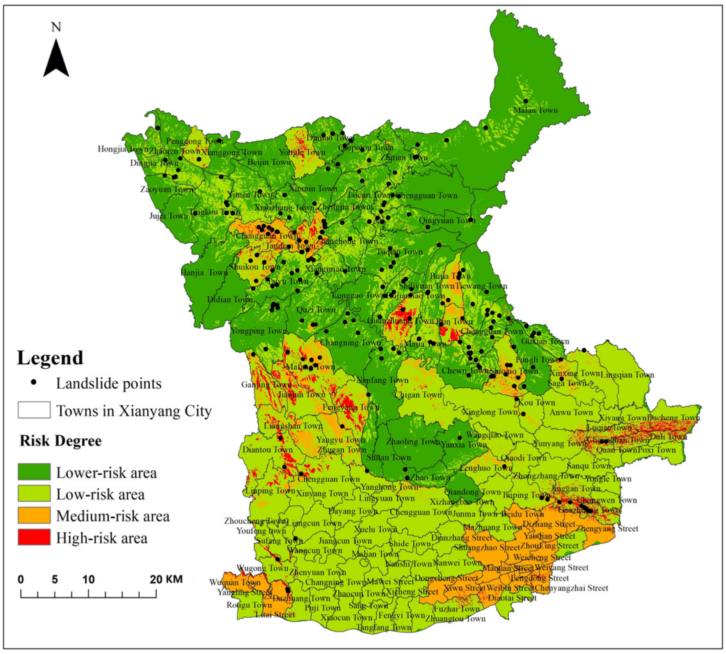

Figure 13. Landslide risk assessment zoning map in Xianyang City.

Table 11. Area and proportion of each risk area.

Degree of Risk	Area (km^2)	Percentage
Lower-risk area	3693.954	38.706%
Low-risk area	4711.729	49.370%
Medium-risk area	896.870	9.398%
High-risk area	241.047	2.526%

(1) Lower-risk areas were mainly distributed in Changwu County, Binzhou City, Xunyi County, Yongshou County, Chunhua County, Liquan County, etc. There were three landslide disaster points in this area, accounting for 1.40% of the total landslide disaster points. There were few geological disasters in this area, a low density of disaster points, and low landslide risk. In addition, the area had low urbanization, sparse population, low economic development, and low landslide risk.
(2) Low-risk areas were mainly distributed in Wugong County, Jingyang County, Sanyuan County, Qianxian County, Xingping City, and other parts of southern Xianyang City. However, there were a small number of distributions in Changwu County, Binzhou City, Xunyi County, Yongshou County, Liquan County, and Chunhua County. There were 122 landslide disaster points in this area, accounting for 46.744% of the total. There were many geological disasters in this area, but the disaster level was relatively low. The economic development and population density of the area increased compared with lower-risk areas, human activities were moderate, and the risk of landslides was relatively low.
(3) Medium-risk areas were mainly distributed in Yongshou County, Yangling District, Weicheng District, Qindu District, etc. There were 64 landslide disaster points, accounting for 29.767% of the total. The density of disaster points in this area was not high. However, most landslide hazard levels were medium-hazard points, the urbanization in the area was relatively high, the population density was relatively high, and the transportation network was relatively developed, so the landslide risk was medium.
(4) High-risk areas were mainly distributed in Yongle Town, Tandian Town, Run Town, Guanzhuang Town, Mafang Town, Jianjun Town, Ganjing Town, Dantou Town, Fengyang Town, etc. There were 26 landslide disaster points, accounting for 12.093% of the total number of landslide disaster points. The geological hazards of landslides in this area were mostly high-risk points, and the risk was greatly affected by the hazard level. In addition, the terrain in this area had a high slope, poor geological stability, fully developed landslide hazards, a relatively high population density, and strong human activities. The occurrence of landslide disasters caused greater vulnerability and greater risk.

5. Conclusions

Landslide disasters have the characteristics of a large scope of influence, high threat number, and serious disaster results. It is critical to perform landslide risk assessment and analyze the magnitude of landslide risk to reduce disaster loss and effectively prevent landslide disasters [50]. In August 2019, landslides occurred in Yiping Township, Ebian County, Leshan City; and Fengyan Village, Shangzhou Town, Xuzhou District, Yibin City. Due to real time monitoring of high-risk areas, a landslide was found at hidden points of unstable slopes. The disaster-prevention plan was activated in time, and personnel in the danger zone were transferred in advance, successfully avoiding casualties.

This paper took Xianyang City landslide geological disasters as the research object. According to the arrangement and analysis of the collected multicategory landslide disaster point scale and risk data, the disaster scale and risk level of Xianyang city were divided. Based on the nine selected landslide hazard evaluation factors and four hazard-bearing-body vulnerability evaluation factors, the landslide hazard assessment model of multiclass SVM and the landslide vulnerability assessment model based on combined weights were constructed to perform the landslide risk assessment of Xianyang City. Experimental results provided a scientific reference for the disaster prevention and mitigation of various landslide risk levels and improved the efficiency of landslide disaster monitoring in Xianyang City. In this paper, exploratory landslide hazard, vulnerability and risk assessments were carried out. In follow-up studies, to further improve the accuracy and reliability of landslide risk assessments, landslide hazard assessments should consider factors such as strata, soil moisture content, and river runoff. Landslide vulnerability assessments should be combined with accurate spatial data of disaster prevention and mitigation projects, population, and economy in the study area.

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