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Accurate and Intelligent Early Warning Method of Debris Flow Formation Based on IGWO-LSTM Algorithm

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Abstract: To improve the accuracy of debris flow forecasts and serve as disaster prevention and mitigation, an accurate and intelligent early warning method of debris flow initiation based on the IGWO-LSTM algorithm is proposed. First, the entropy method is employed to screen the early warning indicators. Then, the improved grey wolf algorithm (IGWO) is obtained by optimizing the grey wolf algorithm by combining elite reverse learning and adaptive convergence factors. Finally, the IGWO-LSTM algorithm is obtained by using IGWO to improve the total connection layer weight and bias parameters of LSTM, which takes the screened early warning indicators as input and outputs the early warning results of the debris flow formation risk level. In comparison with the methods introduced in earlier studies, the results demonstrate that the proposed method achieves superior outcomes in terms of assessing a single warning of multiple debris flow gullies, a multi-year warning of a single debris flow gully, and a multi-year warning of multiple debris flow gullies. The mean absolute error and root mean square error of the early warning results of the ANN model and PEEM method show low values, while the early warning hit rate shows high values, surpassing 90%. Also, the other two methods developed in the previous studies show low values of the early warning coverage rate, reaching 90% at most. Moreover, the triggered traffic model and MLPG method show high values in the early warning coverage rate, exceeding 90%, and low values in the early warning hit rate of less than 90%, and the average absolute error and root mean square error are high. On the other hand, the results of the proposed method show that the overall early warning hit rate is higher than 95%, the coverage rate is close to 100%, and the error is less than 1.5. Thus, the comprehensive analysis results show that the proposed method has better performance and higher reliability than other studied methods.

Keywords: LSTM algorithm; debris flow; entropy method; grey wolf algorithm; elite reverse learning; convergence factor



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1. Introduction

Debris flows are very destructive and unpredictable natural processes in mountain regions worldwide. Debris flows are not only responsible for repeated blockage of national highways and rivers but also for loss of life, property damage, and environmental degradation in mountainous regions. Debris flow is a special torrent formed by a large number of solid materials such as mud, sand, stones, and boulders generated by precipitation, heavy rain, glaciers, and snowmelt water in the valley or hillside [1–4]. It has the characteristics of suddenness, fast flow, large flow, large material capacity, and strong destructive power [5,6]. Debris flow formation needs specific natural and/or human factors [7]. Among natural factors, landslides can form mudslides [8], mainly when landslides occur on hillsides or valleys containing many loose deposits, including sand, stones, and boulders. Human

factors such as excessive deforestation, land clearing, construction, and other activities destroy mountains. The instability of a mountain can lead to debris flow. Debris flow poses a severe threat since it can destroy roads, railways, and other traffic facilities, even villages and towns, causing significant losses to people's lives and the economy. Mud and stones in the debris flow can block the downstream rivers and lakes, impacting the ecological environment [9]. Therefore, specific preventive measures should be taken in mountainous areas and other places prone to mudslides, such as planting trees and building protective dikes to reduce the occurrence and harm of mudslides. At the same time, government departments and professional institutions should adopt efficient, intelligent, and accurate early warning means to implement early warning of the risk of debris flow formation in such areas in a timely and effective manner [10].

Several scholars have carried out a great deal of research on debris flow disasters and achieved worthwhile results. The artificial neural network model (ANN) proposed by Lee D.H. et al. was used to predict debris flows. That study had four inducing factors: watershed area, river length, watershed topography fluctuation, and rainfall. Those factors were extracted from many inducing factors by Pearson correlation analysis and used as the input of the trained ANN, and the prediction results were the output [11]. That method exhibited a high early warning coverage rate but also a high early warning error. Bernard, M. et al. studied a trigger flow model early warning system using a rain gauge and radar to predict the debris flow caused by runoff. That early warning method combined rain gauges and radar technology to ensure the accuracy of the obtained data, such as rainfall, and input such high-precision data into the trigger flow model and early warning system to realize the early warning of debris flow. Although that early warning method had high coverage, the accuracy of the early warning results required enhancement [12]. Kovarik K. et al. studied a local meshless method with weighted squares suitable for solving differential equations. A debris flow prediction model was developed based on that information. That method also had high prediction coverage, but the prediction hit rate was slightly lower, resulting in slightly inferior overall accuracy [13]. Franci, A. et al. studied a three-dimensional simulation and prediction method for debris flow disasters based on the particle finite element method (PEEM). PEEM was used to simulate different debris flow and landslide scenes, evaluate the damage caused by different scenes, and predict debris flow disasters according to the evaluation results. That method showed good prediction accuracy and a high hit rate; however, its prediction coverage was limited [14]. In order to reduce the impact of debris flows, numerous methods and techniques have been proposed and tested for an extended period. However, according to the literature and a generalized consensus among experts, debris flow susceptibility zonation and hazard evaluation have become very complicated. The utilization of a rigorous scientific approach has become necessary in order to solve the uncertainties that have arisen during data collection, model selection, and application. In general, predictive models of debris flow hazard analysis can never be easily verified using experiments under controlled conditions. Indeed, the only solution to problems in testing and validating debris flow predictive maps is the collection of field data over time. Additionally, a consensus regarding techniques and methodologies in that field has yet to be achieved. The solutions to this challenging problem will have to come from persistent efforts to cope with societal requirements, hence the importance of this research.

The Long Short-Term Memory (LSTM) neural network is a kind of time-cycling neural network (RNN) that aims to solve the long-term dependence problem of general RNNs [15]. All RNNs have a chain form of repetitive neural network modules. However, LSTM can process sequence data more effectively through careful design, especially long sequence data [16]. LSTM enables the network to learn and decide which information needs to be saved and which information needs to be forgotten by introducing the "gate" structure. Specifically, LSTM has two "gates": the forgetting gate and the input gate. The forgetting gate is responsible for deciding which information should be discarded or kept, while the input gate is responsible for updating the cell state. The forgetting gate operates by

subjecting the input data to a sigmoid function, resulting in the output of a value between 0 and 1 for each time step. This value determines whether the output from the previous time step should be forgotten. Then, the input data pass through a hyperbolic tangent function to generate a new candidate value. Finally, we multiply the output of the sigmoid function with the output of the hyperbolic tangent function to generate a new output. Thus, LSTM can process long-series data, avoid the problem of “gradient disappearance” or “gradient explosion”, learn better, and predict data [17]. The gradient descent method is commonly employed to update the coefficient of LSTM, but it is prone to being trapped in local optimal solutions. Therefore, in order to ensure its accuracy, it is necessary to optimize the weights and bias coefficients between all connected layers. The Grey Wolf Algorithm (GWO) is a swarm intelligence optimization algorithm [18]. This algorithm has three wolves as leaders: the Wolf King, the second leader, and the third leader. These leaders guide other wolves to find prey. The algorithm keeps the best three wolves in the current population in each iteration and then updates the location of other search agents according to their location information. The algorithm has the characteristics of strong convergence, few parameters, and easy implementation, making it suitable for continuous optimization problems that have been initially applied. It is mainly used in parameter optimization of machine learning models, image classification, signal processing, and control system optimization.

This study investigates an accurate and intelligent early warning method for debris flow formation by combining the Grey Wolf algorithm and the LSTM algorithm based on the characteristics of the above algorithms in view of the problems existing in the literature method. The whole research process of this method is as follows:

- (1) Selection of early warning indicators of debris flow formation risk. The entropy method is employed to select high-impact indicators from the early warning indicators of basic debris flow formation risk. The selected indicators serve as follow-up early warning indicators, providing a foundation for accurate early warning by early warning methods.
- (2) Basic LSTM model. The model consists of an input gate, a forgetting gate, an output gate, and a cell state. The sigmoid activation function processes the historical output and current input data, and the basic debris flow early warning model is constructed.
- (3) Basic Grey Wolf Algorithm. Constructing the social hierarchy pyramid of the Grey Wolf Algorithm for debris flow early warning.
- (4) The Grey Wolf Algorithm is based on elite reverse learning and adaptive convergence factors. First, the Improved Grey Wolf Algorithm (IGWO) is obtained by combining elite reverse learning and adaptive convergence factors to improve GWO. Second, IGWO optimizes the key parameters of the whole connection layer of LSTM to obtain the improved LSTM algorithm, namely Improved Grey Wolf Algorithm-Long Short-Term Memory (IGWO-LSTM). Third, the early warning indicators obtained in the previous screening are input into IGWO-LSTM to obtain the output of debris flow early warning results.
- (5) The early warning accuracy, coverage, and hit rate of this method are tested in the experiment, which verifies the accuracy of its early warning results.

2. Accurate and Intelligent Early Warning Method for Debris Flow Formation

2.1. Debris Flow Risk Early Warning Index Selection

It is necessary to select the basic early warning indicators of debris flow [19,20] formation risk and filter out the weak impact indicators to obtain the strong impact indicators. The strong impact indicators are used as the input for the subsequent improvement of the LSTM debris flow early warning method to realize accurate early warning of debris flow formation. This study identifies ten key indicators that serve as fundamental criteria for early warning of the risk of debris flow formation. These indicators include the maximum amount of debris flow, the frequency of debris flow, the basin area, the length of the main ditch, the maximum relative height difference in the basin, the cutting density of the basin, the bending coefficient of the main ditch bed, the length ratio of the mud and sand replenishment section, the maximum rainfall of 24 h, and the population density. The weight of each indicator is calculated by the entropy method [21]. The weak impact indicators with

lower weight are filtered out based on the weight level. The operation process of the index weight based on the entropy method is as follows:

(1) There are objects to be an early warning, and the index data matrix of the early warning index is $A = (a_{ij})_{km}$. With the increase in the difference between the indicator status value a_{ij} of each object for an index j , there is an increase in the significance of the role that the index plays in the comprehensive early warning. Information entropy is a measure of system disorder in information theory, and its expression is:

$$H(a) = \sum_{i=1}^k \phi'(a_i) \ln \phi'(a_i) \quad (1)$$

where a_i represents the i th state value and k states in total; $\phi'(a_i)$ indicates the probability of the i th state value. The greater the difference in the value of an index in the index data matrix A , the smaller the information entropy, and the greater the weight of the index. Therefore, according to the different degrees of each index, the initial given weight of each index is adjusted by using information entropy, and the weight is dynamically weighted by this method.

(2) The process of adjusting weight through information entropy is as follows:
Entropy value b_j of the operational indicators j :

$$b_j = -\delta H(a_{ij}) = -\delta \sum_{i=1}^k \phi(a_{ij}) \ln \phi(a_{ij}) \quad (2)$$

where $b_j \geq 0$, δ is a constant greater than 0; $\phi(a_{ij})$ indicates the weight of the indicator a_{ij} under the indicator j . If a_{ij} for a given j all are equal, then Formula (2) is established.

The difference factor adjusts the weights given by expert groups in relevant fields, as shown by:

$$\begin{aligned} v_j &= d_j \times c_j, j = 1, 2, \dots, m \\ c_j &= -b_j + 1 \end{aligned} \quad (3)$$

where d_j represents the initial index weight given by the expert group in the relevant field. After normalization, the index weight value adjusted by the entropy method can be obtained, namely:

$$\omega_j = \frac{v_j}{\sum_{j=1}^m v_j}, j = 1, 2, \dots, m \quad (4)$$

The weight values of each debris flow formation risk early warning index obtained based on the entropy method are shown in Table 1.

Table 1. Weight value of warning indicators of debris flow formation risk.

Index Number	Index Name	Weighted Value/%
1	Bending coefficient of main trench bed	0.0704
2	Length ratio of mud and sand recharge section	0.0426
3	Population density	0.1128
4	Maximum rainfall in 24 h	0.1201
5	Watershed cut density	0.1007
6	Length of main ditch	0.1221
7	Basin area	0.1012
8	Frequency of debris flow	0.1135
9	Maximum outflow of a debris flow	0.1026
10	Maximum relative height difference in basin	0.1140

Upon eliminating the two indicators with the lowest weight value in Table 1, the ratio of the main gully bed bending coefficient and the length of the silt supply section (the weight of the two indicators is less than 0.10) indicates that the indicators are less important

in the early warning decision-making process and their reference value is low. Therefore, the two indicators are deleted, and the remaining eight are the subsequent early warning indicators. The pre-debris flow data were analyzed, and the warning level threshold was obtained. According to the threshold, each early warning indicator was divided into four levels: low risk, medium risk, high risk, and extremely high risk. See Table 2 for details.

Table 2. Classification of warning indicators of debris flow formation risk.

Parameter Symbol	Index Name	Risk Level			Extremely High Risk
		Low Risk	Medium Risk	High Risk	
X_1	Population density/Person/km ²	[0, 50]	(50, 150]	(150, 250]	(250, ∞]
X_2	Maximum rainfall in 24 h/mm	[0, 25]	(25, 50]	(50, 100]	(100, ∞]
X_3	Watershed cut density/km/km ²	[0, 5]	(5, 10]	(10, 20]	(20, ∞]
X_4	Length of main ditch/km	[0, 1]	(1, 5]	(5, 10]	(10, ∞]
X_5	Basin area/km ²	[0, 0.5]	(0.5, 10]	(10, 35]	(35, ∞]
X_6	Frequency of debris flow/%	[0, 10]	(10, 50]	(50, 100]	(100, ∞]
X_7	Maximum outflow of a debris flow/ $\times 10^4$ m ³	[0, 1]	(1, 10]	(10, 100]	(100, ∞]
X_8	Maximum relative height difference in basin/km	[0, 0.2]	(0.2, 0.5]	(0.5, 1.0]	(1.0, ∞]

2.2. IGWO-LSTM Algorithm

The accurate and intelligent debris flow formation warning method is constructed after identifying the warning index of debris flow formation risk. After adopting elite reverse learning and adaptive convergence factor optimization of the Grey Wolf algorithm (GWO), the optimized Grey Wolf algorithm (IGWO) is obtained. IGWO is used to optimize the initial weight of the LSTM neural network, and the IGWO-LSTM algorithm is obtained, through which the risk of debris flow formation can be intelligently warned.

2.2.1. Basic LSTM Model

The reason for choosing the LSTM model as the core algorithm is that debris flow involves environmental factors and historical data, which have the characteristics of time-series data, and the subsequent design is designed to solve the problem of data classification. The LSTM model is suitable for the analysis of this feature, and it has more advantages in dealing with the problem of time series classification. The neurons of the basic LSTM model [22,23] are mainly composed of the input gate, forgetting gate, output gate, and cell state, as shown in Figure 1.

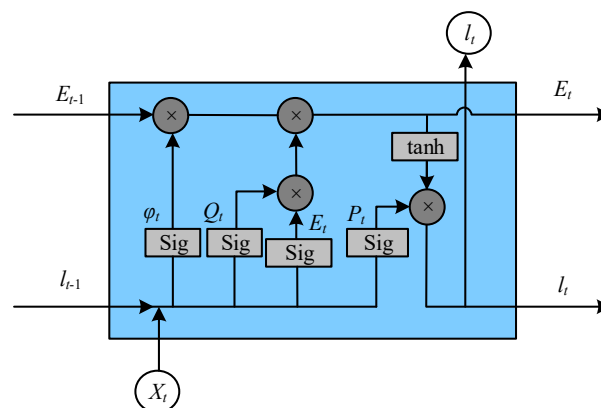


Figure 1. Neuron structure of the basic LSTM model.

E_{t-1} represents the cell state at the last moment of the LSTM model in Figure 1, E_t represents the cell state at the current moment of the LSTM model, l_{t-1} represents the output at the last moment, l_t represents the current output, Sig represents the sigmoid activation function, $\tanh$ represents the tanh activation function, Q_t represents the state value of the input gate, and P_t indicates the status of the output gate.

The operation process mainly includes forgetting, memory, and output stages:

(1) Forgetting stage: The forgetting gate processes historical output and current input data through the sigmoid activation function to determine the cell state at the previous moment E_{t-1} and retain the information up to the current time. A status value of the forgotten door φ_t is:

$$\begin{aligned}\varphi_t &= \varsigma(\eta_\varphi + [l_{t-1}, X_t] \cdot w_\varphi) \\ X_t &\in \{X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8\}\end{aligned}\quad (5)$$

where ς represents the sigmoid activation function; l_{t-1} indicates the output at the last moment; X_t indicates input data; η_φ represents the offset term of the forgetting gate; and w_φ represents the weight matrix of the forgetting gate.

(2) Memory stage: The input gate determines the new input information of the neural network at the current time through the sigmoid activation function. It creates a new candidate vector based on historical output and current input data through the tanh activation function $\dot{E}_t$. Then, the contents of the cell state are updated through the forgetting gate and the input gate. The operation equation at this stage is:

$$\begin{cases} Q_t = \varsigma(\eta_Q + [l_{t-1}, X_t] \cdot w_j) \\ \dot{E}_t = \tanh(\eta_e + [l_{t-1}, X_t] \cdot w_e) \\ E_t = \dot{E}_t * Q_t + E_{t-1} * \varphi_t \end{cases}\quad (6)$$

where Q_t indicates the status value of the input door; E_t indicates the current cell state; w_e is the weight matrix representing the input gate and cell state; η_Q and η_e are the offset terms representing the input gate and cell state, respectively; and $*$ represents the Hadamard product operation.

(3) Output stage: The output gate determines the output information through the sigmoid activation function and calculates the output value of LSTM [24] at the current time based on the updated cell state. The formula of this stage is:

$$\begin{cases} P_t = \varsigma(\eta_P + [l_{t-1}, X_t] \cdot w_P) \\ l_t = \tanh(E_t) * P_t \end{cases}\quad (7)$$

where P_t indicates the status value of the output gate; w_P represents the weight matrix of the output gate; η_P indicates the offset term of the output gate; and l_t indicates the updated hidden layer state.

2.2.2. Basic Grey Wolf Algorithm

The Grey Wolf Algorithm (GWO) is built to establish the foundation for debris flow early warning after building the LSTM debris flow model. GWO is an optimized search method inspired by grey wolf prey hunting activities [25]. The grey wolf is a social animal that is considered a top predator, and the grey wolf population has an average of 5–12 wolves per group, which has a pyramid social hierarchy system, as shown in Figure 2.

According to Figure 2, individuals are divided into different levels: σ wolves, λ wolves, γ wolves, and θ wolves in the grey wolf population. These layers represent different roles and responsibilities. The highest level is σ wolves, who are seen as leaders and are responsible for guiding the behavioral decisions of the entire group. λ wolves are at the second level, acting as the σ wolf's think tank team, providing important decision-making advice. γ wolves are located on the third level and take orders from σ wolves and λ wolves. At the bottom, the θ wolf is responsible for maintaining balance and coordination within the group. This social hierarchy mimics the way grey wolves organize and cooperate in

groups in nature. In the optimization process based on the grey wolf algorithm, the first few individuals representing the optimal solution need to be identified, namely σ wolves, λ wolves, and γ wolves. They act as guide individuals, directing other group members to search for the best goal. θ wolves are the remaining individuals, who update their positions based on σ wolves, λ wolves, or γ wolves. The algorithm randomly generates grey wolf individuals and sets the initial location and initial search range. The fitness value of each individual grey wolf was evaluated according to the predefined fitness function. They also update the corresponding social hierarchy of each individual according to the fitness value and ranking of each grey wolf. Then, depending on the wolf's social rank and fitness, a specific mathematical formula is used to update the location of each wolf and adjust the search scope. The optimization process ends when a predetermined termination condition is reached.

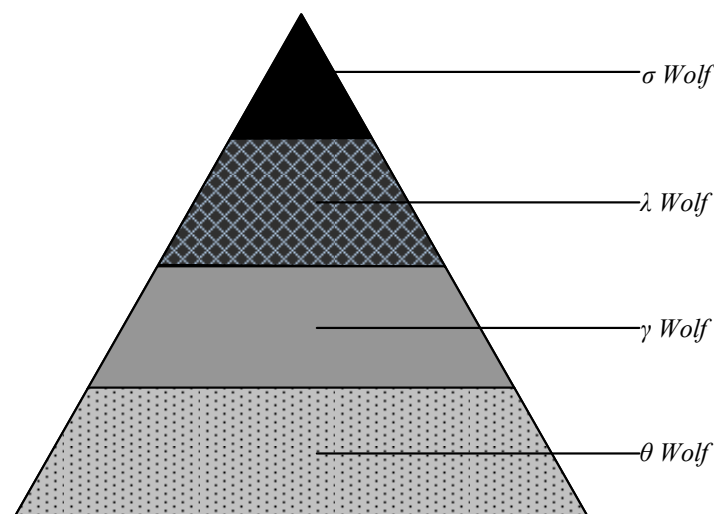


Figure 2. Social hierarchy pyramid of Grey Wolf algorithm.

2.2.3. Grey Wolf Algorithm Based on Elite Reverse Learning and Adaptive Convergence Factor

(1) Optimization of GWO initial population by elite reverse learning.

It is easy to cause the problem that grey wolves are too scattered or gathered in the same area because the initial population generation mode of GWO is randomly initialized, which leads to poor population diversity. It has a great adverse impact on the subsequent iterative optimization [26]. Therefore, the elite reverse learning strategy is selected to initialize the initial population of GWO to expand the search area. The reason for choosing this method is that elite reverse learning is a feasible solution to a problem to find its reverse solution, which expands the search area in this way. The set $y_{jt'}(P_t)$ is a solution for the GWO t' -th iteration. After elite reverse learning, its reverse solution is $\hat{y}(P_t)$, then the inverse solution $\hat{y}_{jt'}(P_t)$ in dimension j -th can be expressed as:

$$\hat{y}_{jt'}(P_t) = \tilde{\kappa}' g_{jt'}^{\max}(P_t) \times \vartheta + g_{jt'}^{\min}(P_t) \times \vartheta - y_{jt'}(P_t)(w_0\sigma + w_1\lambda + w_2\gamma) \quad (8)$$

where ϑ represents a random number and its value range is $0 \leq \vartheta \leq 1$; $g_{jt'}^{\max}(P_t)$ indicates that the decision variable is in the first j upper limit of the dimension; $g_{jt'}^{\min}(P_t)$ indicates the lower limit of the variable in this dimension; $y_{jt'}(P_t)$ indicates the solution of the GWO in the j -th dimension before reverse learning; $\tilde{\kappa}'$ represents the adjusted convergence factor; and w_0, w_1, w_2 represent the weight corresponding to the grey wolf solution. The accuracy, convergence, and results of GWO are closely related to the quality of its initial population. Formula (8) is applied to generate an initial population by GWO randomly. Then, elite reverse learning is applied to the initial population to generate a brand new population

from which several elite grey wolf individuals with the highest fitness rank are selected to form a brand-new optimized grey wolf population.

(2) Optimization of GWO search performance with adaptive adjustment of convergence factor.

The set represents the convergence factor in GWO, which gradually decreases linearly from 2 to 0 with the number of iterations during the algorithm operation. It is necessary to adaptively adjust the convergence factor in the iterative operation of GWO $\tilde{\kappa}'$ in order to optimize and balance the search performance of GWO optimized by elite reverse learning. Adjusted convergence factor $\tilde{\kappa}'$ can be expressed as:

$$\tilde{\kappa}' = \frac{1 - \left(\frac{t'}{T}\right)^2}{1 - \left(\frac{t'}{T}\right)^2 \times v} \quad (9)$$

where v represents the nonlinear modulation index, and its value range is $0 \leq v \leq 3$; t' represents the current iteration times and T represent the total iteration times.

2.3. Intelligent Early Warning of Debris Flow Based on IGWO-LSTM

We consider that the output layer of the basic LSTM model is a fully connected layer after the IGWO algorithm, and the gradient descent method is commonly used to update the coefficient of the LSTM algorithm but the gradient descent method can easily fall into the local optimal solution. Therefore, after the initial training of the basic LSTM model, the IGWO-LSTM model is obtained by using IGWO to optimize the weight and bias coefficient between all connected layers of the basic LSTM model, so as to improve the intelligent early warning accuracy of the LSTM model. On this basis, eight debris flow formation risk warning indicators screened above are used as the input of IGWO-LSTM to complete the intelligent warning of debris flow formation. The warning process of debris flow formation based on IGWO-LSTM is shown in Figure 3.

The specific early warning steps are as follows:

(1) Eight screened early warning indicators of debris flow formation risk and historical debris flow formation data are used as the IGWO-LSTM model's initial input, and the risk grade of debris flow formation is used as its early warning result output. The input data are divided into the training set and the test set. Seventy percent of the data were selected as the training set, and the remaining 30% as the test set. After that, the normalization process is implemented.

(2) After GWO optimization by initializing LSTM model parameters such as the number of neurons, learning rate, hidden layer nodes, and training times, elite reverse learning is combined with adaptive adjustment of the convergence factor, population, and search performance to obtain IGWO and initialize the parameters of IGWO.

(3) The LSTM model is used for initial training, and after the training times are reached, the parameters between all connected layers are taken out. IGWO is used to optimize the extracted parameters of the full connection layer of the LSTM model. It included the bias coefficient and weight. The optimal parameters of the full connection layer of the LSTM model optimized by IGWO are obtained after reaching a certain number of iterations.

(4) The initial full connection layer parameters of the basic LSTM model are replaced with the optimal full connection layer parameters of the LSTM model optimized by IGWO to obtain the IGWO-LSTM model. The test set is input into the IGWO-LSTM model, and it outputs the early warning results of debris flow formation risk level through this model to realize accurate and intelligent early warning of debris flow formation.

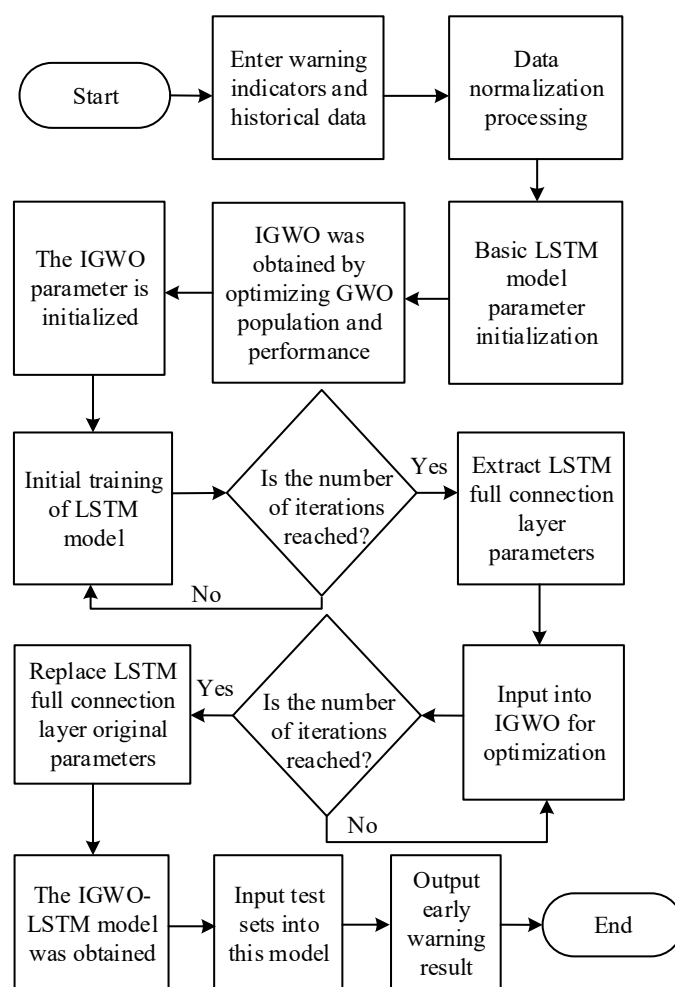


Figure 3. Warning process of debris flow formation based on IGWO-LSTM.

3. Results Analysis

3.1. Experimental Data

Ten typical debris flow gullies (A1~A10) in a certain area are selected as experimental research objects and intelligent early warning of debris flow formation is implemented using the method proposed in this study. The practical application effect of this method is analyzed according to the early warning results. The factors affecting debris flow formation, such as rainfall and topography, are complicated. The experimental dataset adopts the historical data of debris flow formation of the experiment area from 2013 to 2022. During that period, 128 datasets were recorded on extra-large, large, medium, and small debris flows in the experimental area, including 3 extra-large debris flows, 11 large debris flows, 51 medium debris flows, and 63 small debris flows. The dataset mainly includes data types such as population density, rainfall, topography, debris flow occurrence, and time stamp, among which 30% of the data are used as the test set and 70% of the data are used as the training set to test the actual effect of this method. The research object is shown in Figure 4.

The area with red dashed lines in Figure 4 is where the debris flow occurred. The landform of the study area is divided into four categories: middle mountains, low mountains, hills, and valley plains. Mountains and hills account for approximately 80% of the total area of the county, and the terrain slopes from southeast to northwest. The main peak in the study area is Dayang Mountain, which has a peak elevation of 1500.6 m. In the study area, the average annual rainfall is 1637.1 mm, the maximum annual rainfall is 2184.89 mm, and the minimum annual rainfall is 1306.94 mm. During the year, the rainfall is concentrated, and the rainfall from April to September is 1152.8 mm, accounting for 70% of the annual rainfall.

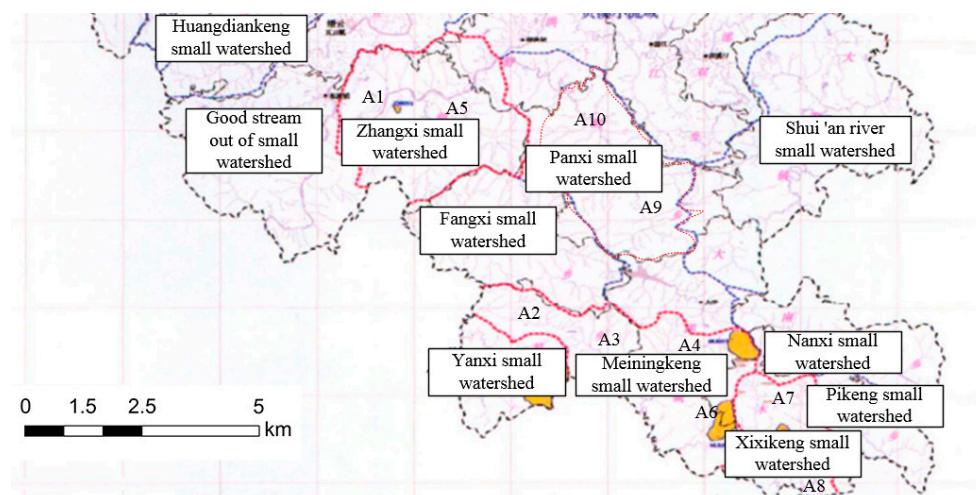


Figure 4. Research objects.

3.2. Experimental Environment and Experimental Parameter Setting

(1) Setting of the experimental environment: The experimental environment mainly includes hardware and software environments. The hardware environment is the NVIDIA Tesla V100 high-performance workstation with GPU, which is selected to accelerate the training and reasoning of the model in this method to ensure the real-time operation of this method and the accuracy of the experiment. The software environment is TensorFlow deep learning framework, with the code written in Python, and data science libraries such as Pandas and NumPy are selected for data processing and visualization.

(2) Setting of the experimental parameters: The LSTM model is the key core model in this method. Setting some superparameters based on the model requirements and manual experience is necessary. However, its learning ability is relatively strong, increasing its optimization speed and classification accuracy. Specific parameter setting requirements are as follows:

The set of experimental parameters is shown in Table 3 based on the above-mentioned parameter setting requirements and experimental requirements.

Table 3. Setting of key experimental parameters.

Parameter Name	Parameter Meaning	Parameter Value
Hidden_Size	Number of hidden layer neurons	480
Keep_Prob	The probability that the neuronal connection will not be severed	0.35
Num_Layers	Network layer number	3
Learning_Rate_Base	Initial value of learning rate	0.9
Learning_Rate_Decay	Learning rate decay rate	0.98
Regularization_Rate	Regularization rate	0.001
Train_Times	Training times	900

The experimental parameters were set according to the values in Table 3 to avoid low model performance due to different parameter values, thus affecting the reliability of the experiment.

3.3. Experimental Indicators

The average absolute error and root-mean-square error are selected as the evaluation indexes of the early warning accuracy, and the accuracy of the method is tested by the indexes. The lower the value of the two errors, the more accurate the early warning result is. At the same time, in order to test the application performance of this method more comprehensively, two indicators of the early warning hit rate and coverage rate are

introduced into the experiment based on the two accuracy indicators mentioned above, and the prediction accuracy index is also set. The calculation method for each indicator is as follows:

(1) The calculation equation for the mean absolute error of Mae is:

$$\begin{cases} Mae^s = \frac{\sum_{t'=1}^T \sum_{i \in N_s}^u |z_i^{t'} - \tilde{z}_i^{t'}|}{T|N_s|} \\ Mae = Mae^s \sum_{s=1}^4 \frac{\sum_{t'=1}^T \sum_{i \in N_s}^u z_i^{t'}}{\sum_{t'=1}^T \sum_{i=1}^u z_i^{t'}} \end{cases} \quad (10)$$

where N_s represents the risk of grade s debris flow formation, and $N_s \in N$ and $N = \{N_1, N_2, N_3, N_4\}$ represent the total risk level; Mae^s represents the average absolute error of the risk of debris formation in grade s ; $z_i^{t'}$ represents the actual risk level of the debris flow ditch in the article i ; $\tilde{z}_i^{t'}$ indicates the risk level of the debris flow gully from early warning; and u indicates the total number of debris flow gullies.

(2) The calculation equation for the root mean square error, $Rmse$, is:

$$Rmse^s = \sqrt{\frac{\sum_{t=1}^8 (P_t^s - P_0^s)^2}{8}} \quad (11)$$

where $Rmse^s$ represents the root mean square error of the formation risk of grade s debris flow.

(3) Early warning hit rate ω is the proportion of debris flow gullies with actual debris flow risk in the debris flow gullies obtained from the early warning. The calculation equation is:

$$\omega = \frac{O_1}{O_2} \quad (12)$$

where O_1 indicates the number of actual early-warning debris flow gullies hit by different methods; O_2 represents the number of risk early-warning debris flow gullies obtained by different methods.

(4) Alert coverage ρ is the proportion of debris flow gullies with actual debris flow risk covered by early warning results obtained by different methods. The calculation equation is:

$$\rho = \frac{O_1}{O_3} \quad (13)$$

where O_3 indicates the number of debris flow gullies with actual debris flow risk.

(5) Prediction accuracy ψ , which represents the proportion of correctly predicted samples in the total number of samples; the calculation equation is:

$$\psi = \frac{O_1}{O_4} \quad (14)$$

where O_4 represents the total number of samples.

The artificial neural network (ANN) model (reference [11]), early warning system triggering traffic model (reference [12]), maximum likelihood parameter generation (MLPG) method (reference [13]), and particle finite element method (PEEM) (reference [14]) are selected as comparison methods. The early warning results of the proposed method are compared with those of each comparison method to test the application performance of this method.

3.4. Test Results

After training the model of the proposed method with the training set of the experimental dataset, the training method and four other comparison methods are used to provide an early warning of the formation risk of a single debris flow in each debris flow ditch of the experimental area. The results of the early warning and the actual occurrence of debris flow are shown in Table 4.

Table 4. Comparison of the warning results of each method with the actual occurrence of debris flow.

Debris Flow Trench Number	The Early Warning Results of the Method in This Paper	Early Warning Results of ANN Model	Trigger the Alert Result of the Traffic Model	Early Warning Results of MLPG Method	Early Warning Results of PEEM Method	The Actual Occurrence of Debris Flow
A1	High risk	High risk	High risk	Extremely high risk	High risk	Occurrence of large debris flow
A2	Low risk	Low risk	Low risk	Medium risk	Low risk	Small debris flow occurs
A3	Extremely high risk	High risk	Extremely high risk	Extremely high risk	Medium risk	A huge mudslide occurred
A4	Medium risk	Medium risk	High risk	Medium risk	Medium risk	Occurrence of medium debris flow
A5	Low risk	Low risk	Low risk	Low risk	Low risk	Small debris flow occurs
A6	High risk	High risk	High risk	High risk	High risk	Occurrence of large debris flow
A7	Low risk	Low risk	Low risk	Low risk	Low risk	Small debris flow occurs
A8	Extremely high risk	Extremely high risk	Extremely high risk	Extremely high risk	Extremely high risk	A huge mudslide occurred
A9	Medium risk	Medium risk	Medium risk	Medium risk	Medium risk	Occurrence of medium debris flow
A10	High risk	High risk	Low risk	High risk	High risk	Occurrence of large debris flow

There is one inaccurate early warning result in the early warning results obtained by the ANN model and PEEM method, specifically for the A3 debris flow gully, according to Table 4. The debris flow gully has a very large debris flow. However, the early warning results of the ANN model show that the debris flow formation risk level of this debris flow gully is high risk, and the early warning results of the PEEM method show that it is medium risk. The early warning results obtained by the trigger flow model and the MLPG method have two error early warning results. The error early warning of the trigger flow model corresponds to the A4 and A10 debris flow gullies, which occur in medium and large debris flows, respectively. However, the trigger flow model classifies the error early warning as high risk and low risk for the A4 and A10 debris flow gullies, respectively. The error warning of the MLPG method corresponds to A1 and A2 debris flow gullies. Large and small debris flows occurred in both gullies, but the warning results obtained by this method show that the risk level is very high and medium in the A1 and A2 debris flow gullies, respectively. There is no wrong early warning information in the early warning results of the single debris flow formation risk of 10 debris flow gullies, and the early warning results obtained are consistent with the actual debris flow occurrence of each debris flow gully.

For example, the early warning results of the single debris flow gully A3 formation risk in the past ten years (2013–2022) are obtained using various methods. Through a unified comparison with the actual debris flow occurrence of this debris flow gully, the early warning performance of each method is further analyzed. The early warning results of each method and the occurrence of debris flow are shown in Figure 5.

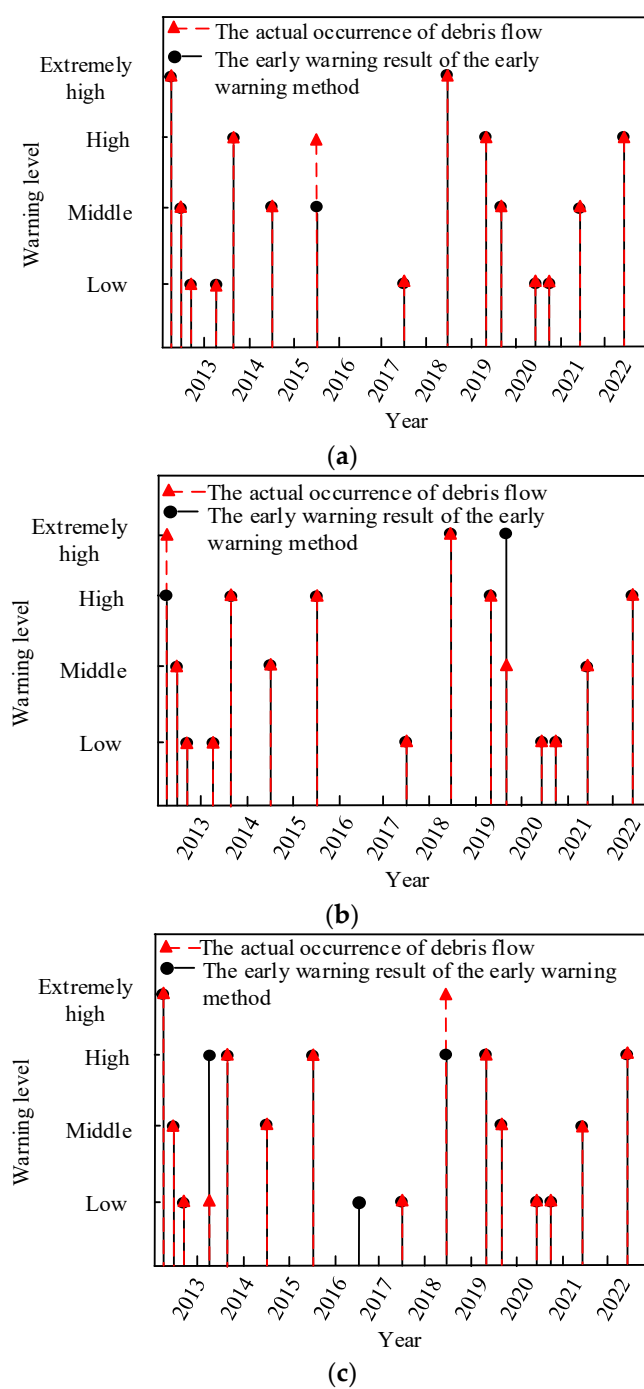


Figure 5. Cont.

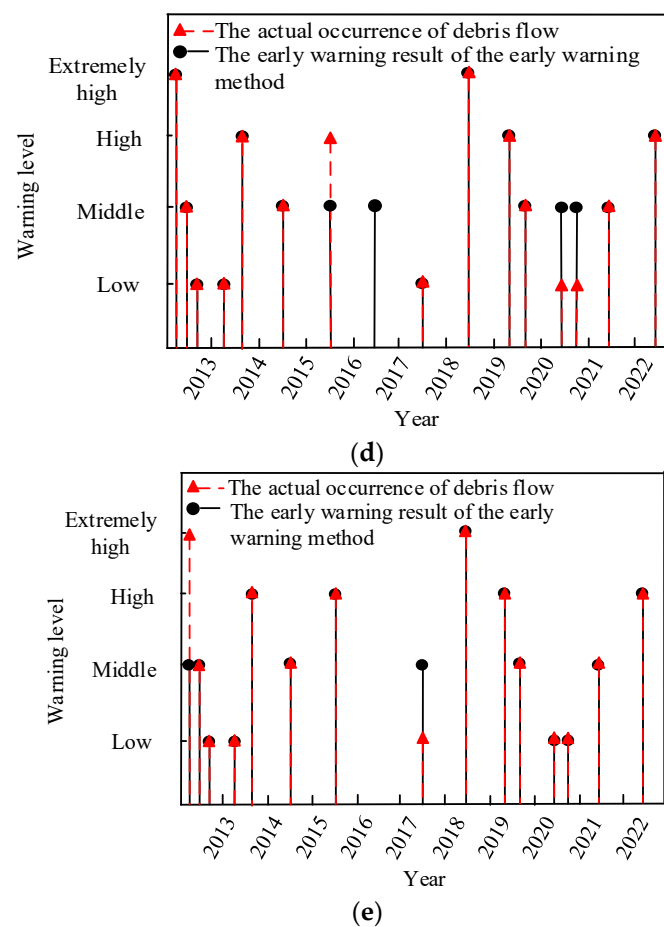


Figure 5. Comparison of warning results and actual situation of debris flow formation risk of A3 rock flow trench in recent 10 years by different methods. (a) This method; (b) ANN model; (c) Trigger traffic model; (d) MLPG method; (e) PEEM method.

4. Discussions

It can be concluded from Figure 5 that among the early warning results of various methods for debris flow formation risk of debris flow gully A3 in the last ten years, the early warning results of this method have been the most consistent with the actual debris flow occurrence, and only a slight deviation occurred in 2015–2016. The early warning results of the ANN model and PEEM method have a slightly larger deviation from the actual situation. In contrast, the early warning results of the trigger flow model and the MLPG method have the most significant deviation from the actual situation. In addition, in the case of no debris flow between 2016 and 2017, the risks of low and medium debris flow formation are mistakenly predicted. At the same time, there are more than two (including two) early warning errors in the multiple warnings of the comparison method. The MLPG method exhibits an early warning deviation that is four times greater. In comparison with the MLPG method, the proposed method effectively reduces the number of early warning errors. Moreover, the experimental results show that the proposed method has more accurate warning results and can effectively alert one to the formation risk of debris flow.

The evaluation indicators selected in the experiment are used further to test the overall early warning accuracy of each method. The early warning results of debris flow formation risk in 10 debris flow gullies from A1 to A10 in the last ten years are obtained through various methods. The average absolute error, root mean square error, early warning hit rate, and early warning coverage index values of the early warning results of various methods are calculated after comparing them with the actual debris flow occurrence. The statistical results are shown in Figure 6.

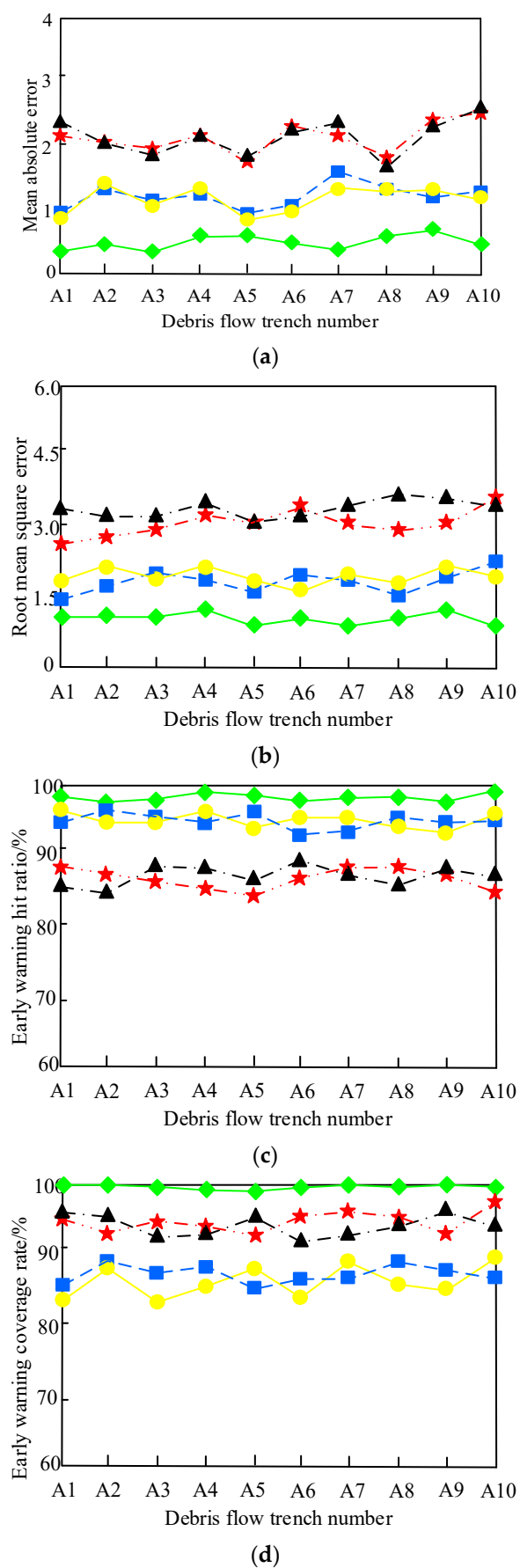


Figure 6. Cont.

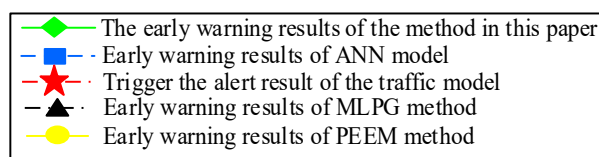


Figure 6. Each evaluation index value of the early warning results of each method. (a) Mean absolute error; (b) root mean square error; (c) alert hit rate; (d) alert coverage.

Figure 6 shows that the average absolute error, root-mean-square error, early-warning hit rate, and early-warning coverage rate of the ANN model, triggered traffic model, MLPG method, PEEM method, and the proposed method are different. The ANN model and PEEM method show the lower average absolute error and root-mean-square error of early-warning results and the highest early-warning hit rate. Both achieve a higher than 90% hit rate, but their early warning coverage rate is lower than 90%. The early warning coverage rate of the triggered traffic model and MLPG method is higher than 90%, but the early warning hit rate of both is lower than 90%, and the average absolute error and root mean square error are higher than 90%. The proposed method's early warning hit rate and coverage rate are higher than 95%, reaching the highest values of 99.1% and 100.0%, respectively. On the other hand, the highest values of the early warning hit rate and coverage rate of the comparison method are only 97.1% and 97.6%. Therefore, regarding the early warning hit rate and coverage rate, the proposed method shows more than 2.0% higher results than the comparison method. The minimum values of the proposed method are 0.25 and 7.5, and the average absolute error and root-mean-square error of other methods are only lower in the ANN model and PEEM method. However, the minimum values of the two methods are also higher than 0.82 and 1.5. It can be seen that the average absolute error and root-mean-square error of the proposed method are lower than those of the comparison method by more than 0.5. It shows that the proposed method can effectively reduce early warning errors and improve the accuracy and coverage of early warning, which shows that it has better accuracy and high reliability of early warning results.

In order to further verify the prediction performance of the proposed method, the prediction accuracy of different methods was analyzed with the prediction accuracy as the measurement index, and the results are shown in Table 5.

Table 5. Prediction accuracy of different methods.

Number of Samples/PCS	The Early Warning Results of the Method in This Paper	Prediction Accuracy			
		Early Warning Results of ANN Model	Trigger the Alert Result of the Traffic Model	Early Warning Results of MLPG Method	Early Warning Results of PEEM Method
1000	0.993	0.981	0.963	0.975	0.980
2000	0.994	0.982	0.982	0.971	0.983
3000	0.995	0.980	0.974	0.969	0.972
4000	0.994	0.979	0.970	0.976	0.979
5000	0.995	0.983	0.963	0.977	0.980

It can be seen from the data in the table that the prediction accuracy of the methods in Table 5 is relatively high, and their values are all above 0.9600. However, detailed analysis shows that when the number of samples is 5000, the early warning results of the method in this paper have the highest prediction accuracy, reaching 0.994. Compared with other methods, only the prediction accuracy of the early warning results of the ANN model and the early warning results of the PEEM method are above 0.980, indicating that the prediction accuracy of the proposed method is more than 0.010 higher than that of the comparison method. This method has better prediction accuracy.

5. Conclusions

The prevention of debris flow plays an important role in the management of debris flow disasters. Therefore, timely and accurate warning of debris flow formation risk has become the focus of research in the field of debris flow management. Based on this premise, an accurate intelligent warning method of debris flow formation based on the improved LSTM algorithm is studied in this paper.

(1) The method first selects the indicators with high influence on the early warning of debris flow formation risk by combining the entropy method, filters out the weak influence indicators, reduces the complexity of the early warning indicators, and simplifies the later calculation process. Then, the improved Grey Wolf algorithm (IGWO) is used to optimize the key parameters of the full connection layer of the basic LSTM model, and the improved LSTM algorithm, namely IGWO-LSTM, is obtained to improve the intelligent early warning accuracy of the LSTM model. The selected early warning indicators are input into the IGWO-LSTM to obtain the early warning output. We achieved accurate and intelligent early warning of debris flow formation.

(2) Among the early warning results of a single debris flow formation risk in 10 debris flow gullies, the results of a single early warning are completely consistent with the actual occurrence of debris flow, while there is only one slight deviation in the early warning results of a random single debris flow gully in the past 10 years, and the early warning coverage rate is close to 100% and the early warning hit rate is higher than 95%. In addition, the average absolute error and root-mean-square error of the early warning results are both lower than 1.5, and the prediction accuracy reaches 0.995, which fully shows that the overall early warning accuracy of the method is high, and the early warning effect is ideal.

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