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Construction of a Computer-Aided Dual-Parameter Landslide Prediction Method

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Abstract: **-** This study focuses on the typical geological region of granitic weathered soil in the hilly areas of southern China, integrating computer-assisted statistical methods and intelligent computing techniques to analyze geological disaster data and hourly precipitation data from 2016 to 2022. The research indicates that in the study area, geological disasters triggered by precipitation generally occur within 48 hours following the precipitation event. For 90% of the events, the average rainfall intensity is concentrated between 1.2 to 27.7 mm/h, with 72% having an average rainfall intensity of less than 10 mm/h, and only 13% exceeding 20 mm/h. The influence of prior precipitation mainly depends on the cumulative effect of effective rainfall over the previous 11 days. Based on these findings, this paper constructs a meteorological risk prediction model for geological disasters using two parameters: the average rainfall intensity (I) and the duration of rainfall (D). After comparing the prediction results with 62 test samples from 2022, it is noted that the method's TS score is superior to other prediction methods, significantly reducing the false alarm and missed alarm rates for meteorological forecasts in the granitic weathered soil geological region. Moreover, the computer implementation of this model demonstrates its efficiency and reliability in handling large-scale geological data, providing strong computational support for geological disaster risk assessment.

Keywords: Landslide Forecasting; Granitic Weathered Soil; Dual-Parameter Approach; Computer Simulation; Statistical Analysis.

I. Introduction

In the field of geological disaster prediction, the application of computer technology has become a key factor in improving the accuracy and efficiency of predictions. Traditional geological risk assessment methods often rely on human experience and qualitative analysis, while modern intelligent computing technologies, such as machine learning and deep learning[1], offer new possibilities for quantitative analysis of geological data. This study delves into computational geology research on the risk of geological disasters in the granitic weathered soil region by introducing mathematical statistics and big data analysis techniques, aiming to develop a more precise and reliable landslide risk prediction model.

In the southern part of China, the terrain is characterized by more mountains and less flat land. The region frequently experiences small-scale geological disasters such as landslides and collapses[2]. Notably, a vast area of South China is covered with weathered granite soil[3]. The soil here has poor mechanical stability. Coupled with frequent human-engineering slope-cutting activities in recent years, it becomes highly susceptible to precipitation. Once the soil's superficial moisture content reaches a certain level, geological disasters like landslides, collapses, and terrain subsidence occur. Particularly, landslides, characterized by their short reaction times, small scales, and high frequencies, result in severe consequences[4-5]. They are the most common and typical geological disaster in South China.

Precipitation, as the primary external factor inducing landslides[6], has long been the focal point of geological disaster warning and prediction. Numerous studies primarily focus on exploring and establishing early warning models for landslides in different geological environments. These include the dynamic risk assessment early warning model (using prior effective rainfall, superimposed forecasted rainfall to assess the susceptibility of geological disasters)[7], the dynamic early warning model (a slope dynamic model involving meteorological,

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hydrological, and geological coupling)[8], machine learning early warning models, and critical rainfall judgment models. Among them, the latter has been most extensively researched and applied in practice. Studies on the critical rainfall judgment model can be categorized into three types: The first type establishes the relationship between rainfall and geological disasters using statistical methods. For instance, Dong et al.[9], Zeng et al.[10] initially constructed the meteorological forecast relationship for geological disasters in Guangxi based on individual disaster cases and daily precipitation. Li et al.[2] divided the country into nine regions, constructing a disaster probability fitting equation based on disaster samples and prior effective precipitation within those regions. The second type relates the rainfall intensity of the current event to geological disasters. Liao et al.[11] concluded that the critical precipitation amounts causing geological disasters in Lingshan County are 80 mm/d and 140 mm/d. Liang[12] selected the critical precipitation thresholds for landslides and collapses in the karst geological region of Northwest Guangxi as 50 mm/d and 120 mm/d. As research deepened, the influence of prior effective rainfall inducing geological disasters began to gain attention[13], leading to the development of the third common type: the dual-parameter (prior rainfall + current rainfall) forecast model. For instance, Wang et al.[14] believed that the correlation between the cumulative precipitation of the previous seven days and the occurrence of geological disasters was strongest. Yang ＆ Mao[15] proposed using the sum of the day's precipitation and the cumulative precipitation of the previous five days as the triggering threshold for geological disasters. Li ＆ Li .[16] introduced a combination model of regional critical daily rainfall and prior rainfall inducing landslides. Wen et al.[17] presented a linear relationship and critical precipitation threshold between the number of geological disasters in Longsheng County and the day's rainfall and the rainfall of the previous three days.

Landslides, influenced by varying geological conditions, arise from complex and varied factors. When combined with the main inducing factor, precipitation, landslide warning and forecasting models differ significantly across regions. Although China has established a unified county-level meteorological risk early warning system for geological disasters, there's still a need to enhance and optimize localized warning models to meet the requirements of detailed disaster prevention and mitigation. This paper primarily focuses on researching the meteorological early warning model for typical granitic weathered soil landslides in the South China region. Wuzhou City, located at the junction of central Guangdong and Guangxi in South China, is selected as the representative study area. Building on previous studies and based on hourly precipitation and historical landslide event data, this research analyzes the impact of prior effective rainfall and the day's rainfall, establishing a regional landslide meteorological risk forecast model. This enriched and refined work provides a scientific basis and reference for predicting rainfall-induced landslides in similar soil regions.

II. Data and Methods

A. Data

The landslide data of weathered granite soil used in this study comes from the Wuzhou City Geological Environment Monitoring Station. It consists of landslide records registered by technicians through field surveys between 2016 and 2022. To ensure data quality, this study excluded the landslide events that lacked specific occurrence dates, latitude and longitude, had no precipitation information for three days before and after, or were clearly caused directly by human engineering activities. Ultimately, we obtained 155 landslide case samples. Using the spherical nearest distance method[17], the distance between the landslide occurrence point and the nearest surrounding meteorological station was calculated. It was found that 86% of the landslide occurrences were less than 5 km away from the nearest automated meteorological station, which is also less than the average distance between automated meteorological stations in Wuzhou City (5.2 km). Therefore, the rainfall data from the nearby automated meteorological stations can closely reflect the precipitation conditions at the landslide occurrence points.

B. Methods

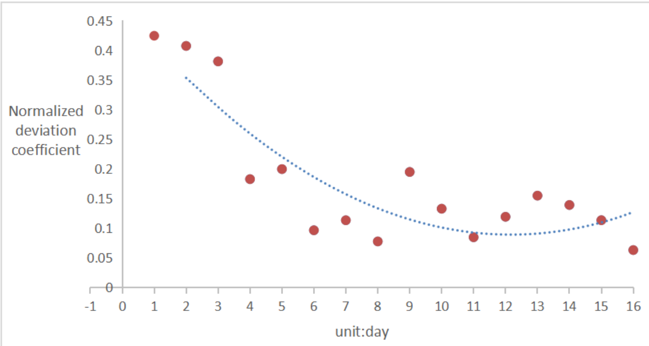
1) Precipitation Calculation Method and Parameter Optimization: Firstly, statistical modeling was carried out using 124 sample data from 2016-2021, and then the model's reliability was tested using 31 sample data from 2022. A two-parameter landslide forecasting model was established, which involves pre-event effective precipitation and the average rainfall intensity of the current event. The calculation formula for pre-event effective precipitation[2] is:

$$E_r = \sum_{k=1}^{n} 0.8^k r_k \tag{1}$$

Where E_r represents the effective precipitation in mm; n is the total number of days of precipitation before the landslide; r_k is the daily precipitation in mm, with r_1, r_2, ...r_n being the precipitation on the day of the landslide, 1 day before, 2 days before, and so on up to n days before the landslide.

Most scholars in the past did not differentiate between precipitation areas when determining the value of n for pre-event effective precipitation. They uniformly used daily precipitation for the 15 days (i.e., n=15) before the disaster. The study area belongs to the rainy region of South China. From April to September each year is the main flood season. During this period, the occurrence of landslides coincides with the temporal and spatial features of frequent and high rainfall[18]. Given the uneven distribution of rainfall in the area, there's a need to further localize the optimization of the total number of days for pre-event effective precipitation.

To facilitate the comparison of the proportion of daily rainfall in the previous 15 days during different rainfall intensities, the daily accumulated rainfall values of each landslide case in the previous 15 days were standardized[19]. Then, the average standardized rainfall values for all cases over the previous n days were calculated. This resulted in the daily distribution of the standardized deviation coefficients of rainfall for all landslide samples over the previous 15 days (Figure 1). Polynomial functions were used to fit these values, resulting in a distribution curve for the rainfall standard deviation coefficients. As can be seen from Figure 1, the fitting curve exhibits a nearly monotonic decreasing distribution. The curve reaches its minimum value of standardized deviation on the 11th day, indicating that the effective pre-event precipitation in Wuzhou City is mainly concentrated within the first 11 days. Thus, when using formula (1) to calculate the effective pre-event precipitation in this area, the number of rainy days n can be optimized to 11.



Standardized Deviation Coefficient
Unit: Day

Figure 1: Average State Curve of Pre-event Rainfall

2) Calculation of Average Rainfall Intensity for the Current Event: Another parameter involved in the landslide forecast is the calculation of the average rainfall intensity. Statistical analysis of the rainfall characteristics in the study area revealed that the duration of local rainfall does not exceed 72 hours. The contributions of rainfall over continuous 6-hour and 12-hour periods to the daily rainfall amount are 69.24% and 78.52%, respectively. This indicates that the precipitation in the study area is mainly influenced either individually or in combination by mesoscale weather systems with a lifespan of 6-12 hours.

Therefore, when calculating the average rainfall intensity, start by sliding backwards from the time of the landslide to calculate the continuous duration (within 72 hours) of accumulated rainfall ≥10mm over 12 hours. If there exists a continuous rainfall process, i.e., the accumulated rainfall over several consecutive 12-hour periods is all ≥10mm, then the starting time of the first 12-hour accumulated rainfall ≥10mm is considered the end time of this rainfall event, and the starting time of the last 12-hour accumulated rainfall ≥10mm is considered the beginning of this rainfall event. From this, the duration D of the rainfall can be determined as D=end time−start time (unit: h). Next, calculate the total rainfall amount SR for the current event, which is the sum of hourly rainfall within the duration of the current rainfall event (unit: mm). Finally, the average rainfall intensity I for the current event is the ratio of the accumulated rainfall to its duration, i.e., $I = SR/D$ (unit: mm/h).

Using this method to back-calculate the rainfall data for the landslide cases, it was found that the rainfall duration triggering landslides ranged from 1 to 48 hours. Among them, events with a rainfall duration of 1 hour accounted for about 32%, and those with a duration of up to 6 hours accounted for about 47%. The average rainfall intensity ranged from 0.2 to 55.4 mm/h. Specifically, cases with an average rainfall intensity between 1.2 and 27.7 mm/h accounted for 90%, those with an average intensity <10 mm/h accounted for 72%, and only 13% had an average intensity ≥20 mm/h.

III. Establishment of Meteorological Risk Forecasting Model for Landslides

Caine[20] proposed a fitting model for the average rainfall intensity (I) and duration (D) of the current rainfall event, which has been widely applied in landslide research and forecasting. The calculation formula is:

$$I = aD^{-b}+c \tag{2}$$

Where I is the average rainfall intensity of the current event, D is the duration of the current rainfall, and a,b,c are the to-be-estimated parameters of the rainfall threshold curve.

During data processing of individual cases, first sort the rainfall sample data by average rainfall intensity, eliminate the top and bottom 5% of samples, and then sort the remaining samples by prior effective rainfall. Take the median value (i.e., R_C =64.6mm) as the dividing value for prior effective rainfall E_r, and separate the rainfall sample data into two situations based on $E_r \geq R_C$ and $E_r < R_C$ for prior effective precipitation threshold R_C. These represent continuous heavy rainfall processes (Type I) and non-continuous heavy rainfall processes (Type II). Construct the $I-D$ relationship curve for each sample set (Figure 2). Since the same rainfall duration may have multiple average intensities, the average value of average rainfall intensities for landslide samples with the same rainfall duration is taken as the average rainfall intensity for that duration. The upper and lower profiles in Figure 2 represent the highest and lowest average rainfall intensities that could lead to a landslide for any rainfall duration in the area. As can be seen from the figure, as the duration of rainfall increases, the average rainfall intensity noticeably decreases. The rainfall duration for non-continuous heavy rainfall processes (Type II) is concentrated between 5-20h, with an average rainfall intensity between 2-4mm/h. The rainfall duration for continuous heavy rainfall processes (Type I) is concentrated between 10-30h, with the longest reaching up to 50h, and a slightly stronger average rainfall intensity concentrated between 2.5-5mm/h.

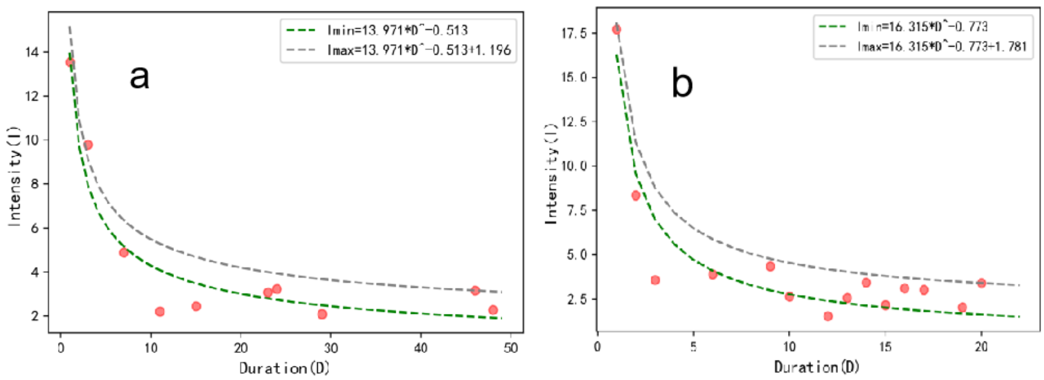


Figure 2: I-D threshold curve and fitting equation

a:Type I E_r ≥64.6mm; b : Type II E_r <64.6mm

Based on the above I-D distribution relationship, establish the landslide occurrence probability formula:

$$p_i = (I_{iD} - I_{minD})/(I_{max_D} - I_{minD}) \tag{3}$$

Where Pi is the landslide occurrence probability for the i-th forecast point, indicating the ratio of the forecasted average rainfall intensity I_i when the rainfall duration for the $i-$th forecast point is D_i to the range of average rainfall intensities in the rainfall threshold model. According to the landslide occurrence probability p_i, values ≤10% are considered low risk, 15%-50% are medium risk, 50%-90% are high risk, and over 90% are extremely high risk. The meteorological disaster risk warning for landslides is divided into four grade intervals.

During calculation, based on the actual measured rainfall before the forecast is issued, calculate the effective rainfall value. Determine the threshold model to be used (Type I or Type II) by comparing it with the boundary threshold. Then, in conjunction with early warning service requirements, input the grid rainfall forecast product (QPF) released daily/hourly for any future period into equation (3) to obtain the meteorological risk level forecast conclusion for landslides for any future period.

IV. Forecast Verification

To verify the forecasting efficacy of the model, the TS score method was adopted. Using 31 landslide records from 2022 and another 31 rainfall events near the dates of those records where no landslides occurred (a total of 62 data points) as verification samples. Landslide meteorological risk levels were calculated using the "Dual-parameter Method" from this study, the "Prior Rainfall Fitting Method" (QX/T487-2019)[21], and the "Current Rainfall Threshold Method". A comparative analysis was conducted against the results of these three methods and the empirical threshold method of the local environmental monitoring department (using daily rainfall intensities of 60mm and 120mm as the critical rainfall thresholds for landslides). It's evident that the "Dual-parameter Method" had the highest TS score among the four forecasting models (Table 1), effectively reducing the high false alarm rates found in the "Prior Rainfall Fitting Method" and "Empirical Threshold Method". Compared to the "Current Rainfall Threshold Method", the "Dual-parameter Method" could to some extent reduce the likelihood of under-predictions.

Table 1: Accuracy of landslide forecasting by various methods

Evaluation Indicator / Method	Correct Forecasts	Over-predictions	Under-predictions	TS Score	Hit Rate	False alarmt rate	Under-prediction Rate
Dual-parameter Method	42	5	15	67.7%	73.7%	8.1%	24.2%
Prior Rainfall Fitting Method	31	31	0	50%	100%	50%	0
Current Rainfall Threshold Method	38	0	24	61%	61%	0	39%
Geological Department's Empirical Threshold Method	31	31	0	50%	100%	50%	0

V. CONCLUSION

This research is based on the landslide records of the Wuzhou City Geological Environmental Monitoring Station and hourly rainfall data from meteorological automatic observation stations from 2016 to 2022.Considering the impact of prior effective rainfall accumulation, a meteorological risk forecasting model suitable for this type of geological landslide was constructed using the current rainfall intensity (I) and duration (D) parameters. The computer-aided dual-parameter landslide prediction method proposed in this study has not only made significant progress in prediction accuracy but also adapts to the requirements of the big data era in terms of computational efficiency. The main conclusions are:

Landslides occurring in the weathered rock and soil regions of granite in the South China region are closely related to prior effective rainfall and current rainfall. The cumulative effect of rainfall over the 11 days preceding a landslide event has the greatest impact. The duration of the current rainfall process generally ranges from 1 to 48 hours. The rainfall volume over a continuous 12-hour period contributes 78.52% to the daily rainfall volume, with 90% of cases having an average rainfall intensity between 1.2~27.7mm/h, 72% of cases with an average rainfall intensity <10mm/h, and only 13% of cases with an average rainfall intensity ≥20mm/h.

In the verification analysis of 62 landslide event samples from 2022, compared to other forecasting methods, the dual-parameter landslide meteorological risk level forecasting model based on the threshold of prior effective rainfall had the highest TS score and the lowest false alarm rate. However, there were still cases of under-predicted landslides. In the future, it will be necessary to integrate local rainfall characteristics, geological properties, types of geological disasters, etc., to construct a more refined meteorological risk forecasting model that's better tailored to the local region.

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