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Dynamic Prediction of Landslide Displacement Using Time Series GRU and Incorporating Environmental Variables

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Abstract

Landslide is one of the most common geological disasters globally, which has caused serious impact on human society and natural environment. High-precision prediction of landslide displacement has important effects on prevention and early warning against landslide disasters. Most existing landslide displacement prediction models focus on static model methods and focus minimally on the effects on the external environmental variables of landslide. To solve these problems, this study proposed a time series gate recurrent unit (GRU) dynamic prediction model that considers the effects of environmental variables. First, landslide displacement was decomposed into the trend and periodic term displacements by exponential smoothing. Second, a GRU model was built by considering the influences of external environmental variables on landslide displacement to predict the periodic term displacement. Third, the individual component displacements were aggregated to attain a dynamic forecast of the landslide movement. Lastly, a case study was conducted based on the landslide of Baishui River, China. The effectiveness of the proposed prediction model was verified by comparing with traditional intelligence algorithms (e.g., back propagation (BP) and extreme learning machine (ELM)). Results demonstrate that the proposed model conforms well to the evolution process of landslide displacement with consideration to the influences of external environmental variables on the fluctuation characteristics of periodic term displacement. The memory structural function of the GRU model can automatically adapt to the dynamic variation characteristics of landslide data during landslide prediction. The minimum and maximum prediction errors of the GRU model are 0.01 mm and 12 mm, respectively. The GRU model, compared with the BP and ELM static models, effectively increases the prediction accuracy (RMSE is increased by 6.7 times and the MRE is increased by 3.5 and 7.6 times, respectively). This study provides an important evidence for the prediction, early warning, prevention, and reduction of landslide disasters.

Keywords: Landslide displacement prediction, Environmental variables, Time series, Deep learning, Gate recurrent unit

1. Introduction

Landslide is a type of geological disaster characterized by extensive global distribution, sudden occurrence, and extensive damages. Landslide disasters can cause considerable casualties and property losses and also result in significant damage to resources, the environment, ecology, and other aspects [1-2]. In recent years, the frequency and intensity of landslide occurrence have increased annually as a result of global climate change, rapid industrialization, melting glaciers, and strong rainfalls. Landslides have emerged as a significant threat to the sustainable development of human production and life. Hence, research on the prediction and forecast of landslide has practical significance [3]. Landslide displacement is a macroscopic manifestation of complicated mechanical changes in landslide mass. Numerical prediction of landslide displacement is significant in the study of landslide change mechanisms and prevention of landslide disasters [4]. The analysis of the variation trend of displacement and construction of forecast models based on landslide monitoring data have become effective means to comprehensively control landslide disasters. Existing landslide displacement prediction mainly includes physical [5], statistical [6-8], and intelligence models [9-10]. Given the uncertainty of the rock-soil material parameters, constitutive model, and boundary conditions of landslide, physical models have difficulty in accurately predicting future deformation. Statistical prediction model requires analysis of the internal relationship and development laws of extensive historical monitoring data, and it disregards the constitutive relationship between rock and soils in the landslide mass during prediction. Hence, this model has a poor generalization performance.

Intelligence prediction model learns landslide displacement deformation characteristics aided by computers, such as machine learning or deep learning model [11-12]. Intelligence prediction model is not restricted by complicated physical parameters, such as the geology and hydrology of the study area, during prediction. This model brings new opportunities for the scientific and accurate analysis and prediction of landslide displacement deformation [13-14].

Extensive studies have been conducted on predicting landslide displacement through the application of machine learning techniques. Nevertheless, existing prediction models of landslide deformation mainly focus on the single variable of time or displacement. These models emphasize on data model and algorithm optimization but disregard research on landslide geologic model. Hence, the practical of significance is how to introduce in the new machine learning algorithm under the support of mass multi-source time series monitoring data and the macroscopic deformation track

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information[15] with consideration to the dynamic influence of different action modes of the causes of landslide displacement to realize high-precision prediction. To provide some references to the prediction of landslide deformation, this study built a prediction model based on GRU with consideration of the effects of multiple environmental variables.

2. State of the art

Recently, many scholars have applied machine learning algorithms to landslide prediction. Some of the details of their findings are as follows. Feng *et al*. [16] first proposed the theoretical framework of intelligence rock mechanisms and established the intelligence analytical method of rock mechanics by using the back propagation neural network system. Cao *et al*. [17] studied intelligence landslide prediction based on the improved algorithms of various neural networks from different perspectives, thereby further facilitating the development of intelligence landslide prediction systems. However, they proved various problems of neural networks, such as large sample size, over fitting, difficult convergence, and local optimization. Cortes *et al*. [18] used neural networks as bases to propose the support vector machine (SVM) model. This model mapped linear inseparable data onto a high-dimensional space by introducing kernel function theory, thereby realizing the linear separation of data. The SVM model is theoretically superior to neural networks. Zhao *et al*. [19] studied landslide deformation prediction by using SVM and discovered some of its advantages, including small training sample size, strong generalization performance, and easy acquisition of global optimal solution. Tien Bui *et al*. [20] ranked landslide adjustment factors based on the least square SVM technique and established a hybrid learning algorithm to predict landslide. Their results showed that the least square SVM technique can increase the efficiency of the random gradient decreasing algorithm in landslide space prediction. Thereafter, SVM began to comprehensively succeed neutral networks. Nevertheless, various studies have indicated that the values of the penalty coefficient, kernel function parameters, and relaxation coefficient of SVM are key influencing factors of prediction accuracy. Moreover, a fixed and mature method to select the values of the three parameters is lacking, thereby becoming a hindrance in the extensive application of SVM. To address the considerable influence of the kernel function parameters and penalty factor on the SVM-based prediction process, Shihabudheen *et al*. [21] built a landslide displacement prediction model using extreme learning machine (ELM). Their results proved that ELM has strong extrapolation prediction ability and is superior to BP and SVM in terms of network convergence rate and prediction accuracy.

Swarm intelligence and bionic algorithms have been applied recently to optimize the parameters of the prediction model. Guo *et al*. [22] optimized the neutral network parameters by using the particle swarm and sparrow search algorithms, thereby effectively improving the prediction performances of BP. Wen *et al*. [23] built a hybrid model by combining particle swarm algorithm and SVM. Al-Shabeeb *et al*.[24] optimized the structural parameters of the ELM network by using the genetic algorithm (GA) and studied landslide sensitivity prediction. They found that GA-ELM had relatively high accuracy. Although the improved algorithms can relatively optimize network structural parameters, such as BP, SVM, and ELM, the new optimization algorithms introduced many network parameters, resulting in difficulties in parameter optimization.

Deep learning technologies are being developed continuously. Lecun *et al*. [25] proved from the technical perspective that the effects of local extreme problem on deep network could be disregarded, and deep learning technology has become the most leading machine learning method. Nava *et al*. [26] compared the prediction effects of multilayer perception, convolutional neural network and GRU for landslide masses with different geographic locations and geological background, proving that deep learning model achieved better prediction effects. Liu *et al*. [27] decomposed the “step-type” landslide displacement. They predicted the periodic term displacement by GRU and found that this algorithm could accurately predict the periodic term displacement of landslides by maximizing historical landslide information.

The preceding studies mainly build landslide prediction models based on traditional machine learning algorithms and optimized model parameters. On the one hand, the built models demonstrate overreliance on mathematical fitting and deduction of landslide displacement monitoring but disregard the influence of the internal evolution mechanism of landslides and external environmental variables on landslide displacement. On the other hand, existing prediction models, such as ELM, SVM, and BP belong to typical static networks. With respect to modeling principle, these models transform dynamic time series into static problems appropriate for the algorithms. None of these models have considered the dynamic evolution characteristics of landslide during prediction and are mismatched with the evolution data of landslides, thereby restricting the improvement of the prediction accuracy. To solve these problems, a dynamic prediction model was built by coupling GRU in deep learning and time series analysis with comprehensive consideration of the influencing mechanisms of landslide causes on displacement changes. The present study aims to offer a robust methodology for the dynamic forecasting of landslide displacement.

The remainder of this study is organized as follows. Section 3 constructs the landslide displacement prediction models based on time series neural learning and designs the test schemes of GRU landslide displacement prediction by considering environmental variables. Section 4 investigates the effectiveness of the GRU model prediction based on the monitoring point ZG118 at the Baishui River landslide in China. Lastly, Section 5 presents the conclusions.

3. Methodology

3.1 Time series analysis of landslide displacement

Landslide is controlled by the collaborative effects of internal and external factors. Internal factors mainly include rock properties and the geologic and internal structures of the slope stratum. External factors include movements of surface and ground water, rainfall, artificial slope cutting or loading, vibration, and other factors resulting in the slope losing stability [28-29]. Controlled by internal factors, increments of landslide displacement and time present a monotone increasing function and reflect the variation trend of the long time series of displacement. Influenced by external environmental factors, landslide displacement and time increase in a fluctuating manner and reflect periodic changes caused by external environmental factors. Landslide displacement is decomposed as follows:

$$Y_t = T_t + P_t \tag{1}$$

Where, Y_t is the monitoring value of the displacement, T_t is the trend term displacement of the landslide, and P_t is the periodic term displacement. In this study, the trend term displacement was extracted using the exponential smoothing method. The smoothing formula is as follows:

First-order exponential smoothing method:

$$F_t = \alpha Y_t + (1-\alpha)F_{t-1} \tag{2}$$

Where F_t is the predicted value of data in phase t, Y_t is the original value of data in phase t, and α refers to the smoothing coefficient, where $0 \le \alpha \le 1$ .Based on the first-order exponential smoothing sequence, applying the same smoothing coefficient to the first-order exponential smoothing results in the second-order exponential smoothing.

$$F_t = \alpha Y_t + (1-\alpha)(F_{t-1} + T_{t-1}) \tag{3}$$

$$T_t = \beta(F_t - F_{t-1}) + (1-\beta)T_{t-1} \tag{4}$$

Where, T_t represents the trend value of the phase t , and β denotes the trend coefficient ($0 \le \beta \le 1$).

3.2 GRU model

The Deep learning, gate recurrent neural network has become a strong tool for processing sequence data. GRU is a variant of recurrent neural networks (RNN). RNN, which is different from traditional artificial neural networks (ANN), has connections among adjacent nodes in the hidden layer.

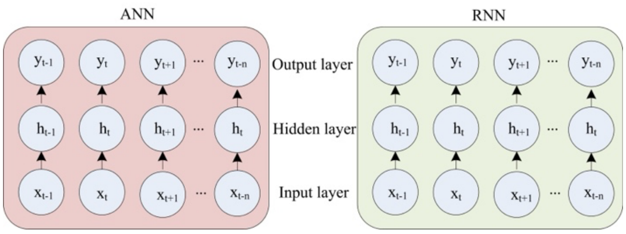

Fig. 1. Comparison of the RNN and ANN structures

Each hidden layer node concurrently receives information from the input layer at the current time step and the information passed from the hidden layer at the previous time step (Fig. 1). Hence, it can keep a memory state during sequence processing, thereby enabling the determination of the internal time series relations of the sequence data [30-31].

GRU combines the input and forget gates of LSTM into an update gate according to different contributions of three gate control structures to the model's learning ability, thereby forming a gate control structure composed of update and reset gates. This situation can decrease the corresponding weight parameters. The Schematic of GRU is shown in Fig. 2.

The update gate controls the ignorance degree of historical information, whereas the reset gate is used to decide the combination degree of input state and historical information. The forward calculation per time is as follows:

$$Z_t = \sigma(W_z \cdot [h_{t-1}, x_t] + b_z) \tag{5}$$

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t] + b_r) \tag{6}$$

$$h_t = \tanh(W_r \cdot [r_t \cdot h_{t-1}, x_t] + b_h) \tag{7}$$

Where, x_t is the input, Z_t is the update gate, r_t is the reset gate, h_t is the output of the current time step, σ is the sigmoid function, h_{t-1} is the output of the previous time step, W_z , W_r , and W_h are the weight matrixes, tanh is a hyperbolic tangent function, b_z , b_r , and b_h are deviation coefficients.

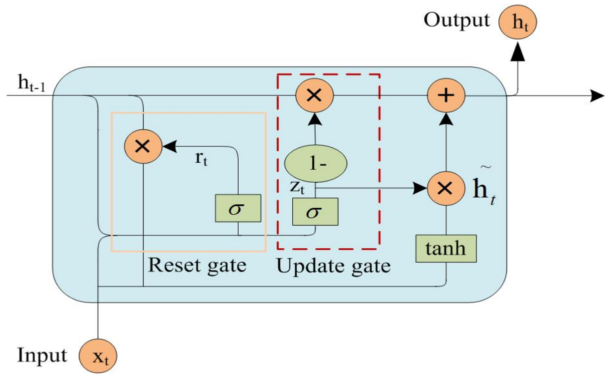

Fig. 2. Schematic of GRU

The basic process of the proposed dynamic landslide displacement prediction model based on time series GRU by considering the effects of environmental variables is shown in Fig. 3.

Model accuracy was evaluated using root-mean-square error (RMSE) and mean relative error (MRE).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{n}} \tag{8}$$

$$MRE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{(\hat{y}_i - y_i)}{y_i}\right| \tag{9}$$

Where, $\hat{y}$ and y represent the forecasted and observed values, respectively, at time i and n refers to the sample size.

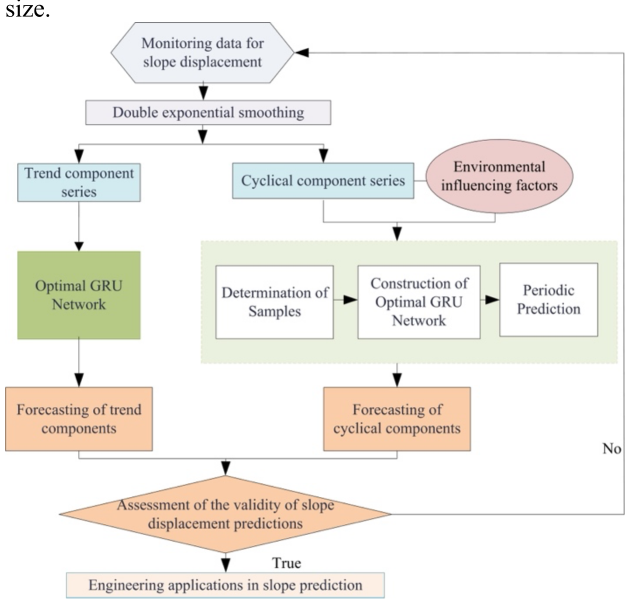

Fig. 3. Process of the prediction model

4. Result Analysis and Discussion

4.1 Landslide monitoring data analysis

The Baishui River landslide is located in Zigui County, China. It has been monitored since June 2003, when the reservoir water level reached 135 m. At present, there are 11 GPS deformation monitoring points in the landslide region, and Point ZG118 is at the middle of the landside mass. ZG118, compared with other monitoring points where data fluctuates substantially, reflects the entire process of displacement evolution. In this study, the ZG118 data at 72 phases from 2007 to 2012 were chosen for analysis (Fig. 4). The monitoring curves of the accumulative displacement, rainfall, and reservoir water level are shown in Figs. 5 and 6. According to the data of the reservoir water level meter, the monitoring curves were divided into two periods for analysis.

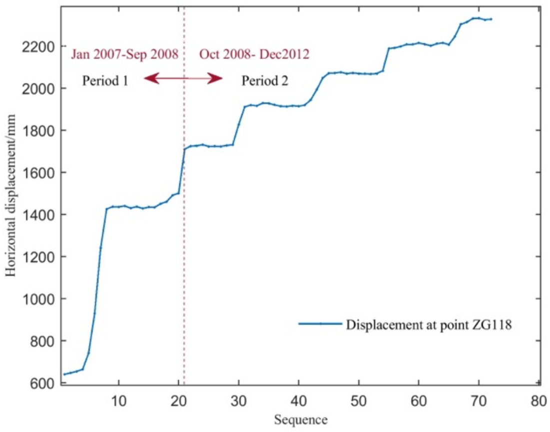

Fig. 4. Displacement curve of the Baishui River landslide(ZG118）

Period 1: The reservoir water level fluctuated within the range of 145-155 m. The accumulative displacement at ZG118 was kept stable in the beginning and the deformation rate began to accelerate thereafter. From January to July 2007, the reservoir water level was lowered to 144.2 m, and the accumulative displacement growth changed suddenly. The maximum displacement growth rate reached 310.9 mm/month (July 2007). From August 2007 to September 2008, the reservoir water level experienced two stages of rising and fluctuation. The accumulative displacement curve presented a stable variation and the maximum displacement growth rate reached 31 mm/month. The preceding variations were caused by the violent changes of external environmental variables (i.e., changes of rainfall and reservoir water level in the flood season).

Period 2: The reservoir water level had periodic fluctuations within the range of 145-174 m. The landslide mass adapts to the regular changes in rainfall and reservoir water level. The accumulative displacement at ZG11 presents a “step-like” growth [14]. From 2009 to 2012, the maximum displacement growth rates were 96, 55, 105, and 59 mm/month, respectively. All maximum displacement growth rates appeared in the period when the reservoir water level lowered and there was concentrated rainfall in the summer.

4.2 Decomposition of displacement and selection of environmental variables

4.2.1 Decomposition of displacement

Displacement at ZG118 was decomposed into the trend and periodic term displacements using the second-order exponential smoothing method (smoothing coefficient is 0.4). The trend and periodic term displacements at ZG118 are shown in Fig. 7.

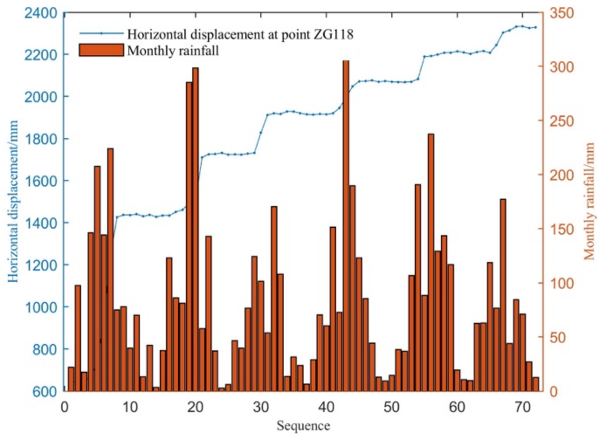

Fig. 5. Accumulative displacement-rainfall monitoring curves

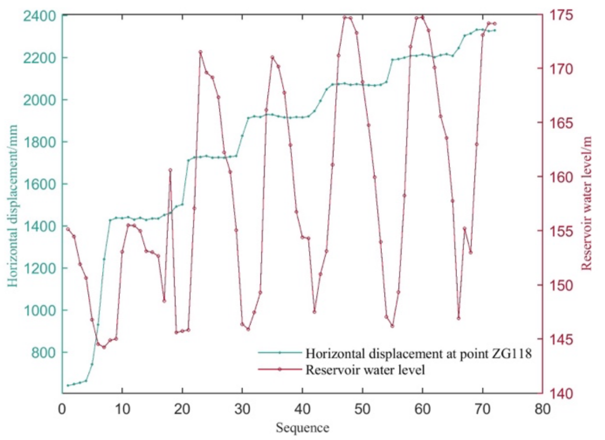

Fig. 6. Accumulative displacement–reservoir water level monitoring curves

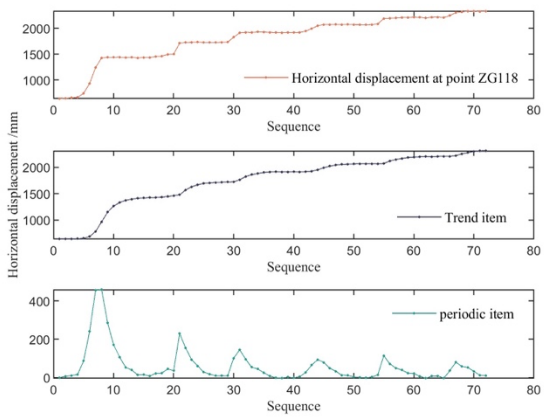

Fig. 7. Trend and periodic term displacements at ZG118

4.2.2 Selection of environmental variables

Selection of environmental variables can significantly influence the landslide displacement prediction accuracy significantly. The accumulative displacement curve at ZG118 presents “step-type” fluctuations. Rainfall and periodic fluctuation of reservoir water level are dominant factors influencing the deformation characteristics at ZG118.

Seasonal rainfall is an important cause of periodic changes of landslide displacement. Landslide soil is wet during rainfall, resulting in soil loss, which influences the stability of the landslide. In addition, rocks crack and ground water level rises upon the entrance of rainwater into rock cracks, resulting in the easy facilitation of landslide. As shown in Fig. 8, the effects of rainfall on periodic term displacement at ZG118 are relatively hysteretic. Every year, the periodic term displacement presents an evident increment trend at one to two months after rainfall increases. The correlation coefficients of periodic term displacement with monthly, bimonthly, and maximum monthly rainfall were calculated as 0.982, 0.993, and 0.992, respectively, using the grey correlation. This finding indicates the close relationship between periodic term displacement and rainfall.

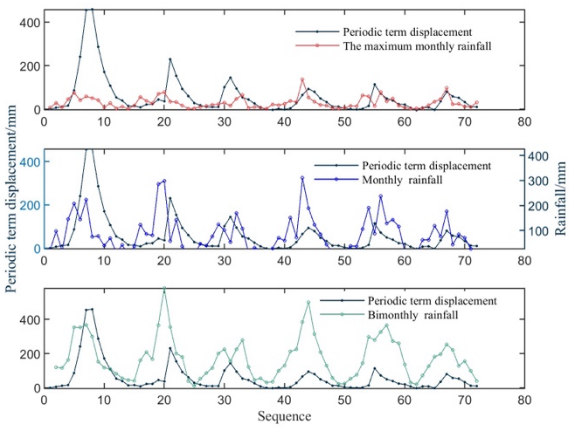

Fig. 8. Relationship between periodic term displacement and rainfall

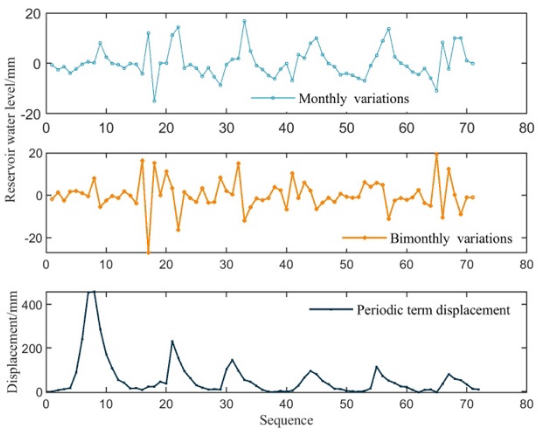

Fig. 9. Relationship between periodic term displacement and reservoir water level

When reservoir water level rises, water pressure may increase, thereby breaking the stress balance of rock and soil and influencing the stability of the landslide. In addition, water infiltration may cause the saturation loss of soil, thereby increasing landslide risks of the reservoir banks. When reservoir water level lowers, stresses on rocks and soils in the landslide will still be influenced. With an increase in water level variation rate, the influence on landslide stability increases and landslide risks also increase. As shown in Fig. 9, reservoir water level significantly influences periodic term displacement at ZG118. Calculation indicates that the grey correlation degrees of periodic term displacement with reservoir water level, monthly variations of reservoir water level, and bimonthly variations of reservoir water level are 0.982, 0.720, and 0.812, respectively, indicating their close relationships in a time series.

Influences of rainfall and reservoir water level are periodic and relatively random. To prevent the adverse effects of randomness on the prediction results, influences of the monthly, bimonthly, and tri-monthly periodic term displacement growths on prediction were considered (Fig. 10).

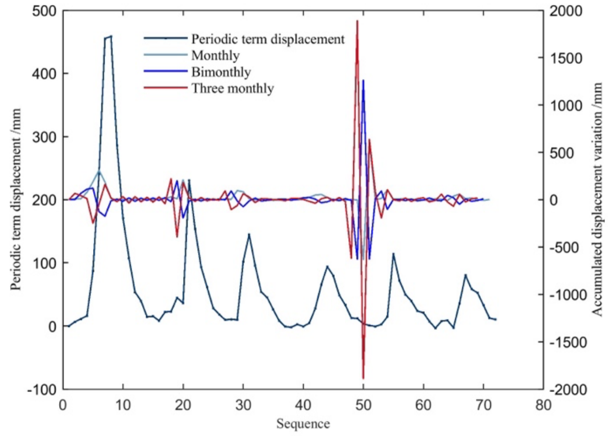

Fig. 10. Relationship between periodic term displacement and reservoir water level

In summary, nine variables were chosen as environmental variables of periodic term displacement at ZG118: monthly rainfall, bimonthly rainfall, maximum monthly rainfall, reservoir water level, monthly variations of reservoir water level, and bimonthly variations of reservoir water level, monthly periodic term displacement growth, bimonthly periodic term displacement growth, and tri-monthly periodic term displacement growth.

4.3 Landslide displacement prediction

4.3.1 The prediction process of landslide displacement

As shown in Fig. 3, the prediction process in this study is as follows:

(1) Decomposition of accumulative displacement. It was divided into the periodic and trend term displacements based on the exponential smooth method by using the original landslide data.

(2) Selection of landslide environmental variables. According to the grey correlation analysis, the nine environmental variables were used as inputs of the periodic term displacement model.

(3) Construction of the data grouping model. Data of the 72 phases from 2007 to 2012 were divided into two groups: 60 groups (2007-2011) before the training dataset and 12 groups (January to December 2012) after the prediction dataset.

(4) Prediction of the trend term displacement. The trend term displacement data were used as the input and the GRU model, thereby obtaining the prediction results. Results were evaluated and compared.

(5) Prediction of the periodic term displacement. The nine influencing factors were used as inputs and the GRU model, thereby obtaining the prediction results. Results were evaluated and compared.

(6) The prediction results of the trend and periodic term displacements were superposed, thereby obtaining the prediction results of the accumulative displacement.

4.3.2 Prediction of trend term displacement

The trend term displacement at ZG118 was predicted using the GRU neural network. Input and output of the GRU network were both 1, and the hidden layer has 200 neurons. The maximum training rounds was 300, gradient threshold was 1, and initial learning rate was 0.005. The staged learning rate adjustment strategy was applied. The attenuation period and attenuation factor of learning rate were 125 and 0.2, respectively. The prediction results are listed in Table 1.

Table 1. Trend term displacement at ZG118 predicted using GRU (mm)

Sequence	Trend term displacement	Prediction results	Residual error
61	2202.44	2202.01	-0.43
62	2205.31	2208.29	2.99
63	2203.90	2211.49	7.59
64	2206.98	2211.76	4.78
65	2210.51	2218.94	8.43
66	2209.39	2227.40	18.01
67	2223.67	2230.03	6.36
68	2255.76	2248.83	-6.94
69	2279.10	2285.57	6.47
70	2300.14	2307.68	7.54
71	2313.20	2323.64	10.43
72	2318.16	2332.94	14.78

Table 1 shows that in 12 phases of trend term displacement at ZG118 predicted using GRU, the maximum and minimum residual errors were 18.01 mm and 0.43 mm, respectively. MRE of prediction is 0.35%, proving the good performances of GRU in predicting trend term displacement at ZG118.

4.3.3 Prediction of periodic term displacement

The periodic term displacement at ZG118 was predicted using the GRU neural network. Inputs of the GRU prediction are monthly rainfall, bimonthly rainfall, monthly maximum rainfall, reservoir water level, monthly variations of reservoir water level, and bimonthly variations of reservoir water level, monthly displacement increment, bimonthly displacement increment, and trimonthly displacement increment. Output was 1, and the hidden layer has 80 neurons. Maximum training rounds were 300, gradient threshold was 1, and initial learning rate was 0.005. The staged learning rate adjustment strategy was utilized. The attenuation period and attenuation factor of learning rate were 125 and 0.2, respectively. The prediction results are listed in Table 2.

Table 2 shows that among the 12 phases of periodic term displacement at ZG118 predicted using GRU, the residual error fluctuates significantly. Maximum and minimum residual errors were 9.78 mm and 0.91mm, respectively. According to the analysis of reasons, rainfall in December 2012 decreased from the peak (177.2 mm) to 12.5 mm, while reservoir water level increased from the minimum to the peak (about 174.1 m). Sudden changes in the external environment influence the prediction performances of GRU.

Table 2. Periodic term displacement at ZG118 predicted using GRU（mm）

Sequence	Periodic term displacement	Prediction results	Residual error
61	7.16	8.89	1.73
62	-3.51	-0.21	3.29
63	7.70	5.52	-2.17
64	8.82	4.16	-4.66
65	-2.81	-4.95	-2.15
66	35.71	29.78	-5.94
67	80.23	79.31	-0.92
68	58.34	59.25	0.91
69	52.60	44.49	-8.11
70	32.66	25.11	-7.55
71	12.40	6.43	-5.97
72	10.24	0.46	-9.78

4.3.4 Prediction of accumulative displacement

The predicted accumulative displacements at ZG118 are listed in Table 3. Table 3 shows that in the 12 phases of accumulation displacement at ZG118 predicted using GRU, the maximum and minimum residual errors were 12.07 mm and 0.01 mm, respectively. MRE of calculation was 0.14%. To further verify the effectiveness of the proposed algorithm, ELM and BP were applied for prediction under the same conditions. Results were compared with the prediction results of GRU (Table 4 and Fig. 11). Accuracy evaluations are shown in Table 5.

Table 3. Accumulative displacement at ZG118 predicted using GRU（mm）

Sequence	Periodic term displacement	Prediction results	Residual error
61	2209.60	2210.90	1.30
62	2201.80	2208.08	6.28
63	2211.60	2217.01	5.41
64	2215.80	2215.92	0.12
65	2207.70	2213.98	6.28
66	2245.10	2257.17	12.07
67	2303.90	2309.34	5.44
68	2314.10	2308.07	-6.03
69	2331.70	2330.06	-1.64
70	2332.80	2332.79	0.01
71	2325.60	2330.07	4.47
72	2328.40	2333.40	5.00

Table 4. Prediction results comparison of GRU with ELM and BP（mm）

Sequence	Displacement	GRU	Residual error	ELM	Residual error	BP	Residual error
61	2209.60	2210.90	1.30	2255.23	45.63	2210.69	1.09
62	2201.80	2208.08	6.28	2155.21	-46.59	2197.53	-4.27
63	2211.60	2217.01	5.41	2185.93	-25.67	2188.70	-22.90
64	2215.80	2215.92	0.12	2229.47	13.67	2212.55	-3.25
65	2207.70	2213.98	6.28	2274.74	67.04	2212.91	5.21
66	2245.10	2257.17	12.07	2205.19	-39.91	2195.10	-50.00
67	2303.90	2309.34	5.44	2277.45	-26.45	2266.36	-37.54
68	2314.10	2308.07	-6.03	2342.46	28.36	2340.61	26.51
69	2331.70	2330.06	-1.64	2365.68	33.98	2310.42	-21.28
70	2332.80	2332.79	-0.01	2374.57	41.77	2331.61	-1.19
71	2325.60	2330.07	4.47	2354.56	28.96	2322.00	-3.60
72	2328.40	2333.40	5.00	2342.35	13.95	2310.99	-17.41

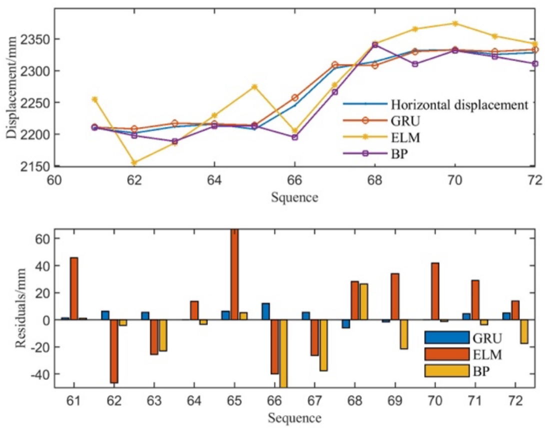

Fig. 11. The comparison chart of GRU with ELM and BP

Table 5. Prediction accuracy comparison of GRU with ELM and BP

Prediction models	RMSE/mm	MRE
BP	37.21	0.71%
ELM	37.22	1.52%
GRU	5.55	0.20%

As shown in Fig. 11 and Table 4, the prediction results of GRU agree the most with the original monitoring value, and residual errors are in relative uniform distribution. The prediction process of BP and ELM can only reflect the overall trend of landslide mass deformation. Residual errors of prediction at some points are relatively high. Maximum residual errors of BP and ELM were 50 mm (Phase 66) and 67.04 mm (Phase 65), respectively. Moreover, residual errors of Phases 61, 62, and 70 were relatively high. Combining with accuracy evaluation indexes in Table 5, RMSE of GRU increased 6.7 times compared with those of BP and ELM. Meanwhile, MRE increased 3.5 times and 7.6 times, respectively. That is, the time series GRU model considering the influences of external environmental variables has high prediction accuracy and stability. Moreover, it substantially conforms to the dynamic characteristics of landslide.

5. Conclusions

To improve the accuracy of landslide prediction, a dynamic prediction model based on time series by considering the effects of environmental variables is proposed. The proposed model is applied to predict the Baishui River landslide in China. Some of the major conclusions are as follows.

(1) Landslide displacement is decomposed into the trend and periodic term displacements. Thereafter, the corresponding mathematical models are built according to their various characteristics to predict the dynamic features conforming to landslide deformation.

(2) Changes in reservoir water level and rainfall can significantly affect the prediction of periodic term displacement. Displacement changes substantially in the period with high reservoir water level and rainfall, but it changes slightly in the period with stable reservoir water level and in non-rainy seasons.

(3) The time series GRU model considering multiple influencing factors can predict landslide displacement substantially, showing high accuracy and stability. The unique memory structure of the GRU model can automatically adapt to the historical information of monitoring points during training, thereby realizing the state feedback of the model and matching with dynamic characteristics of the data.

On the bases of considering the influences of environmental variables, this study realizes the dynamic prediction by combining time series analysis and GRU neural network. This research provides technical references to the prevention and reduction of landslides. This study considers the responses of causes, such as reservoir water level and rainfall, but it still lacks a deep quantitative analysis on the hysteretic responses of causes to landslide. Future studies can predict landslide displacement by considering to the hysteretic responses of causes.

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