

## PREDICTION OF LANDSLIDE DISPLACEMENT USING BP NEURAL NETWORK MODEL: A CASE STUDY IN GANSU, CHINA

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**Abstracts:** Landslides pose significant threats to the human living environment and severely endanger the life and property safety of surrounding residents. Therefore, conducting landslide displacement prediction and implementing corresponding prevention and control measures are crucial for mitigating such losses. In this study, taking the Beishan Landslide in Gansu Province as a case study, we established a landslide displacement prediction model based on a backpropagation (BP) neural network. We compared the prediction accuracy of two models: a cumulative displacement prediction model that considers only the deformation trend of previous cumulative displacement, and a multi-source data prediction model that integrates rainfall meteorological conditions with previous displacement data. The results demonstrate that the multi-source data prediction model achieves higher accuracy and precision. Specifically, its relative prediction error is less than 0.5%, and it exhibits high prediction effectiveness for linear, concave-down, and concave-up deformation curves.

**Keywords:** Landslide displacement prediction, BP neural network, cumulative displacement prediction model, multi-source data prediction model.

### 1. Introduction

It is well established that the property changes of slope mass represent a highly nonlinear process characterized by complexity and uncertainty. When the stability of a slope transitions from a stable to an unstable condition, the slope mass undergoes instability and initiates sliding. Such changes in slope stability may be triggered by various factors acting individually or in combination. With the increasing diversification of monitoring indicators and means, the acquired monitoring data have become more comprehensive and effective (Liu et al., 2020). However, when dealing with complex and variable landslide data, relying solely on historical deformation data to establish a prediction model has certain limitations. Independent analyses of single-source monitoring data can lead to discrepancies in analysis results. To improve the reliability of landslide monitoring data and enhance the utilization rate of such data, multi-source heterogeneous data fusion technology has gradually emerged as an important tool for landslide deformation data analysis. By integrating multi-source heterogeneous data, including historical deformation data and external environmental impact factors, the deformation and failure characteristics, as well as the evolution laws of landslide masses, can be more effectively studied.

The backpropagation (BP) neural network is renowned for its strong adaptability and nonlinear mapping capabilities, making it one of the most widely used neural network models today. By leveraging data sample information, the BP neural network can effectively capture the feature distributions of the data. This algorithm is particularly well-suited for addressing complex internal mechanism problems and achieving high-precision prediction results (Zhu et al., 2020).

The objective of this study is to focus on the Beishan Landslide in Zhouqu Town, Gansu Province. Utilizing the BP neural network algorithm, we have established two distinct models: a cumulative displacement model and a multi-source data model. These models are employed to predict the displacement variation of future landslide deformation.

### 2. Case Study Area

The Beishan landslide is an ancient landslide situated on the north bank of the Bailong River in Zhouqu Town, with a volume of  $2.4 \times 10^6 \text{ m}^3$ . It comprises several old and new landslides (Fig. 1). The engineering geological conditions and characteristics of the landslide were obtained through remote sensing interpretation and field investigations (Feng et al., 2024). Based on the landslide properties, deformation and failure characteristics, stratigraphic distribution, and sliding direction, the landslide is divided into two levels, encompassing eight sliding blocks in total. The upper-level landslide (H1) primarily encompasses the area of the old landslide, which has not yet undergone overall sliding. The lower-level landslide mainly consists of landslides H2 to H7, which display

obvious damage and significant deformation. The lithology of the slope primarily includes exposures of phyllite, slate, limestone, and Quaternary unconsolidated sediments. The landslide poses a threat to the village on the slope and the town at the foot of the slope, and there is a risk of it blocking the river.

The Beishan landslide has been undergoing creeping deformation for an extended period, with shallow slides and collapses occurring continuously in localized slope masses. Since 1979, the landslide has exhibited reactivation and deformation. In August 2020, a large-scale slide occurred and transformed into a debris flow that surged into the Bailong River. In January 2021, the deformation further intensified, with numerous cracks and displacements appearing across the slope. Following the significant damage caused by the landslide, relevant departments undertook slope clearing and reinforcement of the upper-level landslide (H1). However, the lower-level landslide remained in a state of progressive sliding. The areas experiencing the most severe deformation were primarily concentrated in the H2, H3, H4, and H5 areas at the front edge of the landslide. This study is primarily based on GNSS deformation data and meteorological data collected from the actively deforming area of the landslide.

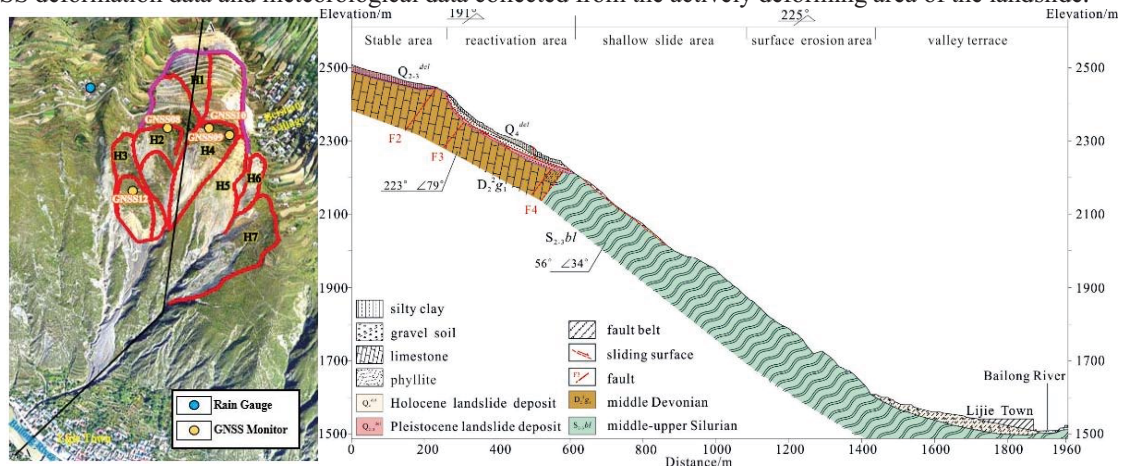


Fig. 1. Overview of the Beishan Landslide. Fig. 2. Engineering-geological Profile of A-A'.

### 3. Data and methods

#### 3.1.1. Relationships among multi-source environmental factors

The construction of a multi-source data prediction model requires the selection of environmental factors that are related to deformation but not correlated with each other. This approach can eliminate information overlap among the environmental factors, thereby enhancing model accuracy (Chen et al., 2021). The correlation test results are shown in Fig. 3. Considering the lag effect of previous rainfall on the current displacement, the correlation coefficients between the previous rainfall and the displacement were calculated. Specifically, 0Day denotes the rainfall on the current day, 1Day represents the rainfall from the previous day, and 4Day\_Total indicates the cumulative rainfall over the preceding 4 days, with similar notations used for other time intervals. In addition to rainfall, other meteorological factors considered include the current monitoring values of temperature (Temp) and wind force (Wind).

As can be seen in Fig. 3, the correlation between the rainfall on the n-th day before and the current deformation first increases and then decreases. the correlation between the cumulative rainfall and the current deformation increased gradually with the increase of the cumulative number of days. The correlation between the current rainfall and the current deformation is relatively low. Although the temperature shows a moderate correlation with the current deformation, it has a weak correlation with the rainfall environmental factor, so this factor should be discarded. Since wind speed shows no correlation with displacement changes, it is thus excluded.

0.02	-0.10	-0.06	-0.03	0.10	0.08	0.01	0.04	0.10	0.18	0.11	0.13	0.14	0.12	0.15	-0.04	0.01	0.08	0.14	0.17	0.45	0.00	Wind
0.17	0.17	0.21	0.23	0.23	0.22	0.20	0.20	0.22	0.24	0.23	0.25	0.27	0.27	0.26	0.27	0.40	0.45	0.51	0.55	0.00	0.45	Temp
0.06	0.12	0.04	0.04	0.05	0.05	0.08	0.05	0.04	0.12	0.22	0.20	0.20	0.13	0.10	0.10	0.12	0.14	0.20	0.21	0.43	0.04	Disp
0Day	1Day	2Day	3Day	4Day	5Day	6Day	7Day	8Day	9Day	10Day	11Day	12Day	13Day	14Day	4Day_Total	7Day_Total	10Day_Total	12Day_Total	14Day_Total	Temp	Wind	

Fig. 3. Pearson correlation results.

### 3.1.2. Displacement prediction model

This study investigates the displacement prediction model of the Lijie Beishan Landslide based on the BP neural network algorithm. By analyzing the historical displacement monitoring data from existing GNSS displacement monitoring points on the landslide mass and the monitoring data of meteorological environmental factors, two models were established: a cumulative displacement prediction model based solely on historical GNSS displacement monitoring data and a multi-source data prediction model based on both historical GNSS displacement monitoring data and meteorological environmental factors monitoring data are established respectively. The flowchart of the model establishment process is shown in Fig.4.

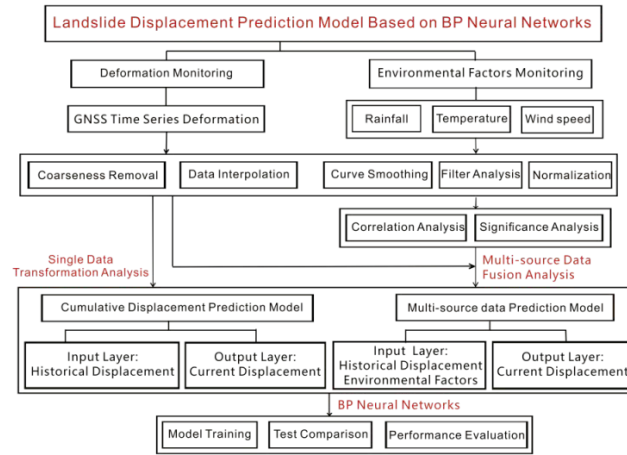


Fig. 4. Framework of the proposed model for landslide displacement prediction.

Currently, landslide displacement prediction primarily focuses on short-term and imminent forecasts, which infer the displacement and deformation for the current day or the next few days based on the historical deformation characteristics, as well as the progressive trends of the landslide. In this study, we analyze the cumulative deformation over the first 150 days of the monitoring period of the Beishan Landslide to predict the daily cumulative deformation values for the subsequent 40 days.

The BP model adopts a three-layer network structure. The cumulative displacement prediction model takes the cumulative displacement of the first 10 consecutive days in the historical displacement time series ( $y_{i,t-10} \sim y_{i,t-1}$ ) as the input layer, and the cumulative displacement value of the day as the output layer. While the multi-source data prediction model takes the first 10 consecutive days ( $y_{i,t-10} \sim y_{i,t-1}$ ), the current rainfall ( $r_{i,t}$ ), the rainfall of the previous 1st day ( $r_{i,t-1}$ ), the rainfall of the previous 10th day ( $r_{i,t-10}$ ) and the cumulative rainfall of the previous 12 days ( $\sum r_{i,12}$ ) as the input layer. The necessary parameters used in the BP neural network are shown in Table. 1.

Table 1. The main parameters of the BP neural network.

Training function	Error function	Maximum epochs	Learning rate ( $\mu$ )	Allowable error
trainglm	mean square error (MSE)	10000	0.001	$10^{-10}$

### 3.1.3. Evaluation of prediction model accuracy

To evaluate the prediction accuracy of the landslide displacement prediction model, three criteria are employed: average relative error (ARE), mean absolute error (MAE), and root mean square error (RMSE). These criteria are defined in Equations (1) to (3). Lower values of ARE, MAE, and RMSE indicate smaller errors between the predicted and monitored values, thereby indicating a better prediction effect of the model.

$$ARE = \frac{1}{n} \sum_{k=1}^n \left| \frac{y_k - y_k'}{y_k} \right| \quad (1)$$

$$MAE = \frac{1}{n} \sum_{k=1}^n |y_k - y_k'| \quad (2)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{k=1}^n (y_k - y_k')^2} \quad (3)$$

where  $y_k$  and  $y_k'$  represent the actual monitored displacement value and the predicted displacement value, respectively.

#### 4. Results and discussion

The prediction performance of the GNSS monitoring points on the Beishan landslide is illustrated in Fig. 5. Both the cumulative displacement prediction model and the multi-source data prediction model, based on the BP neural network, have achieved outstanding prediction results. The predicted deformation trends closely align with the actual deformation trends, and the ARE between the measured and predicted values is consistently within 3%.

In comparison, the displacement prediction curve generated by the multi-source data prediction model more accurately and realistically reflects the overall deformation trend of the landslide, with predicted values that are closer to the actual monitored values. The ARE between the measured and predicted values for this model is less than 0.5%, representing a significant reduction in prediction error by 23.45% to 89.20% compared to the cumulative displacement prediction model.

When comparing the displacement prediction effects with the deformation characteristics, it is evident that the multi-source data prediction model demonstrates excellent predictive performance for deformation points characterized by linear curves, concave-downward curves, and concave-upward curves. In contrast, the cumulative displacement prediction model exhibits good predictive results only for linear and concave-downward deformations.

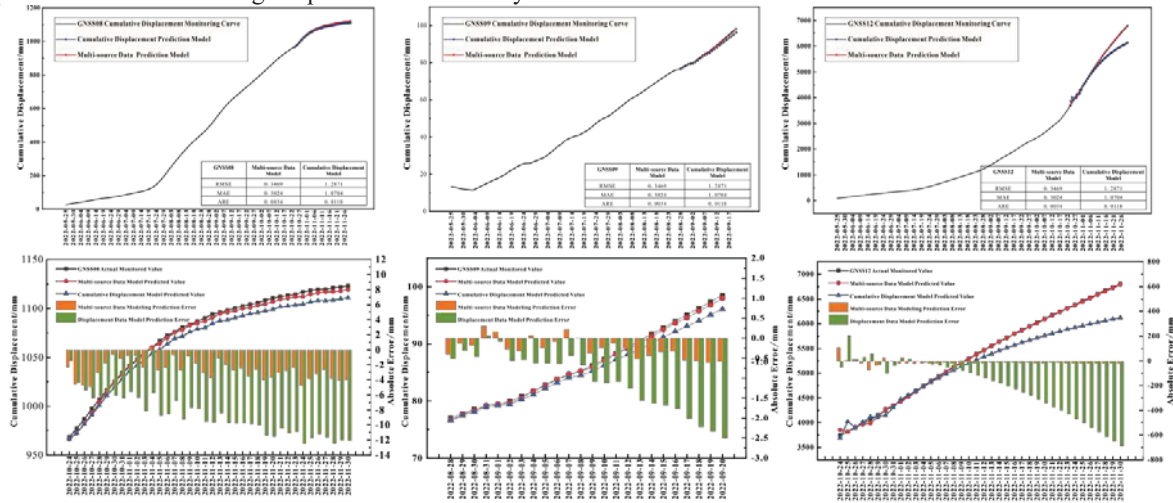


Fig. 5. Displacement prediction results and errors based on different prediction methods.

#### 5. Conclusions

To enhance the accuracy of short-term and imminent predictions of landslide displacement, a landslide displacement prediction model based on the BP neural network was proposed. The results indicate that the multi-source data prediction model offers a significant advantage in highly accurate prediction of landslide displacement. The predicted values obtained from this model, which integrates rainfall data and historical displacement data, more accurately reflect the actual deformation trend. Compared with the cumulative displacement prediction model, the prediction error is reduced by 23.45% to 89.20%. The effectiveness of this data fusion method for landslide deformation analysis and prediction has been verified.

#### Acknowledgement

This research was funded by the Open Fund of Observation and Research Station of Geological Disaster in Lanzhou (grant numbers: ORSGD-202403), Joint Research Fund of Gansu Province (grant numbers: 24JRRA814).

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