

Postprint: Deformation Monitoring and Prediction of the Xijitan Giant Landslide Based on SBAS-InSAR Technology and LSTM Neural Network

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Date: 2025-07-14T11:39:32+00:00

Abstract

To investigate the surface deformation characteristics and deformation prediction of giant landslides on both banks of the upper Yellow River from Longyangxia to Jishixia, this study selected the Xijitan giant landslide in the Guide area of the upper Yellow River as the research area. The Small Baseline Subset Interferometric SyntheticAperture Rader (SBAS-InSAR) technique was utilized to conduct surface deformation monitoring of the Xijitan giant landslide, and the landslide surface deformation rates and their variation characteristics from 2019 to 2022 were discussed. The results indicate: (1) The maximum surface deformation rate of the landslide body in the study area is $-96 \text{ mm} \cdot \text{a}^{-1}$, the maximum cumulative deformation is 464.71 mm, and obvious deformation zones exist at the front and rear edges of the landslide body, with surface deformation rates ranging from -96 to $16 \text{ mm} \cdot \text{a}^{-1}$. (2) Based on the SBAS-InSAR technique, the cumulative deformation of feature points deployed on the landslide surface in the study area was obtained, with a maximum cumulative deformation of -140.50 mm . (3) The Long Short-Term Memory (LSTM) neural network model was adopted to predict the cumulative deformation of feature points and compared with Support Vector Machine (SVM) and Back Propagation (BP) neural network models. The prediction results calculated by the LSTM neural network model reflect relatively high prediction accuracy, with an absolute error within 5.00 mm and a goodness-of-fit (R^2) higher than 0.8, demonstrating the effectiveness of applying the LSTM neural network model to the prediction of cumulative surface deformation of landslide bodies. The research results can provide data support and practical guidance for further surface deformation monitoring of giant landslides and early identification of potential landslides in the upper Yellow River.

Full Text

Deformation Monitoring and Prediction of the Xijitan Giant Landslide Based on SBAS-InSAR Technology and LSTM Neural Network

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Abstract

To investigate the surface deformation characteristics and deformation prediction of giant landslides along both banks of the upper Yellow River between Longyang Gorge and Jishi Gorge, this study selected the Xijitan giant landslide in the Guide region as the research area. Small Baseline Subset Interferometric Synthetic Aperture Radar (SBAS-InSAR) technology was employed to monitor surface deformation of the Xijitan giant landslide and analyze its deformation rates and variation characteristics from 2019 to 2022. The results demonstrate that: (1) The maximum surface deformation rate of the landslide body reached $96 \text{ mm} \cdot \text{a}^{-1}$, with a maximum cumulative deformation of 464.71 mm. Distinct deformation zones were identified at the front and rear edges of the landslide, with surface deformation rates ranging from -96 to $16 \text{ mm} \cdot \text{a}^{-1}$. (2) The cumulative deformation at characteristic points, derived from SBAS-InSAR technology, showed a maximum cumulative deformation of 140.50 mm. (3) The Long Short-Term Memory (LSTM) neural network model was utilized to predict the cumulative deformation at these characteristic points, with results compared against Support Vector Machine (SVM) and Back Propagation (BP) neural network models. The LSTM model achieved relatively high prediction accuracy, with absolute errors within 5 mm and goodness-of-fit (R^2) values exceeding 0.8, confirming the effectiveness of the LSTM neural network model for predicting cumulative surface deformation of landslide bodies. These findings provide data support and practical guidance for enhanced surface deformation monitoring of giant landslides and early identification of potential landslides in the upper Yellow River region.

Keywords: upper Yellow River; Longyang Gorge to Jishi Gorge Basin; Xijitan giant landslide; LSTM neural network; SBAS-InSAR; surface deformation monitoring; prediction of surface cumulative deformation

1. Introduction

The upper Yellow River region, located at the transition zone between China's first and second topographic steps, has experienced multi-stage erosion terraces and associated geological hazards including collapses, landslides, and debris flows throughout its geological evolution, with particularly significant development of super-large landslides. Previous research indicates that the Lagan Gorge-Sigou Gorge section of the upper Yellow River hosts a high density of super-large landslides, representing a high-incidence area for geological hazards. Historical evolution of landslides along the main stream of the upper Yellow River has resulted in numerous accumulation platforms, such as the Xiazangtan giant paleo-landslide in the Jianzha area, which caused severe damage to the Makang Highway, power transmission lines, and water pipelines, with direct economic losses of approximately 6 billion yuan, posing serious threats to local residents' lives, property, and economic development. Furthermore, partial instability of the Jungong giant paleo-landslide along the Yellow River main stream in Maqin County's Lajia Town in 2021 caused highway traffic disruption, endangering local residents' lives and property. Consequently, surface deformation monitoring of giant paleo-landslide distribution areas in the upper Yellow River, combined with Long Short-Term Memory (LSTM) neural network models for landslide deformation prediction, yields results of significant importance for deformation monitoring and early identification of local instability in giant ancient landslides distributed along both banks of the upper Yellow River.

With the development of space geodesy, Interferometric Synthetic Aperture Radar (InSAR) technology has been widely applied in surface deformation monitoring research due to its all-weather, all-day capabilities. SBAS-InSAR technology has been used to monitor historical deformation characteristics of the Moli landslide on the Tibetan Plateau, revealing continuous deformation at the landslide's rear edge with rates of -35 to $35 \text{ mm} \cdot \text{a}^{-1}$ during the monitoring period. Yue et al. applied InSAR technology to monitor the Xiazangtan giant paleo-landslide in the upper Yellow River, demonstrating through comparison with field monitoring data that InSAR technology can effectively monitor landslide deformation. Other studies have applied InSAR technology to analyze surface deformation of the Yongsheng landslide in Leshan, Sichuan, identifying long-term creep deformation with maximum surface deformation rates of $-43 \text{ mm} \cdot \text{a}^{-1}$.

Existing research on landslide deformation prediction primarily relies on surface deformation data obtained through traditional ground monitoring methods. However, with the advancement of artificial intelligence and emerging information technologies, machine learning and non-linear prediction models have been widely applied to landslide deformation prediction. For instance, Xu et al. combined InSAR time-series data with Back Propagation (BP) neural network models to monitor the Fanjiaping landslide in the Three Gorges Reservoir area, achieving correlation coefficients of 0.91 between predicted and monitored results. Chang et al. evaluated landslide susceptibility in the Yichang section

of the Yangtze River basin using integrated deep learning algorithms, reporting an identification accuracy of 96.29%. Chen et al. applied LSTM models to predict ground deformation in the Nanjing section of the Yangtze River, with prediction results showing high consistency with InSAR monitoring results and maximum absolute errors of 6.94 mm. Liu et al. integrated SBAS-InSAR with LSTM for time-series analysis and prediction of ground subsidence in mining areas, demonstrating that the model's spatial distribution of prediction results was relatively consistent with actual conditions.

In summary, previous research on giant landslides in the upper Yellow River has primarily focused on formation mechanisms, development characteristics, and geomorphic evolution. However, studies on surface deformation monitoring and prediction for these landslides remain limited, with existing research mainly concentrating on InSAR-based extraction and monitoring of surface deformation along both banks, while integrated applications of neural network models for landslide deformation monitoring and prediction are relatively scarce. Therefore, this study selected the Xijitan giant landslide as the research area, employing SBAS-InSAR technology to extract and analyze annual surface deformation information from 2019 to 2022, examining the spatial distribution characteristics of surface deformation in the landslide area. Based on these results, the LSTM neural network model was applied to conduct time-series analysis of deformation trends at representative characteristic points on the landslide body.

1.1 Study Area Overview

This study selected the Xijitan giant landslide, located in the Longyang Gorge to Jishi Gorge section of the upper Yellow River on the northeastern margin of the Tibetan Plateau, as the research area. The landslide is situated on the north bank of the Yellow River within the Guide Basin in Qinghai Province, with geographic coordinates of $36^{\circ}02'51''$ $-36^{\circ}07'48.2''$ N , $101^{\circ}24'2.1''$ $-101^{\circ}29'1.8''$ E . The highest elevation on the south bank of the Yellow River is 3,150 m, with the landslide front extending to the riverbank at approximately 2,220 m elevation, representing a relative height difference exceeding 900 m. The landslide body currently measures 6,500 m in length, with a relatively gentle middle section at approximately 2,460–2,640 m elevation. The Xijitan landslide area features a typical plateau continental climate characterized by long winters, short summers, extended sunshine hours, strong solar radiation, relatively low average temperatures, and arid conditions with low precipitation. The average annual temperature is $9.03^{\circ}C$, with an average annual precipitation of 254.80 mm and annual sunshine duration reaching 59%–67%.

As shown in Figure 1, the landslide boundary and development stages are based on studies by Wang et al., with modifications for this research. The Xijitan giant landslide is primarily divided into three development stages, with Stage III being the largest. Stage I landslide deposits are approximately 7,200 m long, featuring short sliding distances, large widths, and steep rear walls. The eastern portion of Stage I landslide body was cut and covered by Stage II deposits, while

the western portion remains preserved. Stage III represents the main body of the Xijitan giant landslide, with the largest deposit volume and area. Stage II landslide deposits formed after the disintegration of Stage I, and despite being covered by Stage III deposits, the original steep scarps remain clearly visible, providing free surfaces for Stage III development. Stage III landslide occurred at the front edge of Stage II deposits at the intersection with the Yellow River floodplain, manifesting as several modern small-scale landslides.

1.2 Data Sources and Processing

This study utilized Sentinel-1A satellite data from the European Space Agency, comprising 74 ascending-orbit images acquired between March 2019 and December 2022. The imagery parameters are detailed in Table 1. Additionally, ASTER GDEM data were employed to eliminate topographic phase effects in InSAR processing, while Precise Orbit Ephemerides data were used to correct orbital information and remove systematic errors caused by orbital inaccuracies.

1.3 Research Methods

1.3.1 SBAS-InSAR Processing Workflow To obtain the surface deformation rate of the landslide body, SBAS-InSAR technology was applied by dividing the Sentinel-1A imagery into multiple small baseline subsets. The least squares method was used to derive surface deformation for each subset, followed by singular value decomposition (SVD) to jointly solve multiple subsets. Atmospheric phase components were then estimated and removed to obtain time-series deformation information. The basic processing workflow includes: data import and cropping, connection graph generation, interferometric processing, orbital refinement and re-flattening, rate inversion, and geocoding, ultimately yielding the surface deformation rate map of the study area. Input imagery data were paired based on temporal and spatial baseline thresholds, generating 205 image pairs with connection characteristics shown in Figure 4.

1.3.2 LSTM Neural Network Model The LSTM neural network model is a special type of recurrent neural network (RNN). Compared with traditional RNN models, LSTM introduces memory cells and three gating mechanisms (input gate, forget gate, and output gate), providing better adaptability for processing and predicting time-series tasks with long intervals. The forget gate determines whether information in memory cells should be discarded based on the previous hidden state h_{t-1} and current input x_t through a sigmoid activation function, outputting vector f_t (with each dimension value between 0 and 1, where 1 represents complete retention and 0 represents complete discarding). This vector is then multiplied with the single-cell state C_{t-1} . The forget gate output f_t is calculated as:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

where f_t is the forget gate output, $\sigma(\cdot)$ is the logistic function, W_f is the weight matrix of the forget gate, h_{t-1} is the hidden layer output vector at time $t-1$, x_t is the input vector at time t , and b_f is the bias term.

The input gate determines whether current input information should be written into memory cells, comprising two parts. The first part takes the previous hidden state h_{t-1} and current input x_t to obtain candidate information $\tilde{C}_t$ at time t . The second part outputs a control vector i_t that is multiplied with the first part result. The input gate control vector i_t and candidate information vector $\tilde{C}_t$ are calculated as:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

To obtain the new memory cell state C_t at time t , the old cell state C_{t-1} is multiplied with f_t to remove information designated for forgetting, then added with $i_t \cdot \tilde{C}_t$ to incorporate new information. The new memory cell state C_t is calculated as:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t$$

where i_t is the input gate control vector at time t , $\tilde{C}_t$ is the candidate information vector, C_t is the hidden layer cell state at time t , W_i and W_C are weight matrices, and b_i and b_C are bias terms.

The output gate determines whether to output information from memory cells. A sigmoid function determines the proportion of cell state information to output, while the current cell state C_t is processed through a $\tanh$ activation function to obtain the state information to be output. These are multiplied to obtain the final output h_t at time t . The output gate control vector o_t and final output h_t are calculated as:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

$$h_t = o_t \cdot \tanh(C_t)$$

where o_t is the output gate control vector at time t , W_o is the weight matrix, and b_o is the bias term.

In summary, the LSTM model exhibits superior capability in learning long-term dependencies and effectively preserving and updating historical information, making it particularly suitable for processing prediction time-series with long intervals in recurrent neural networks.

1.3.3 Prediction Model Accuracy Evaluation Metrics The accuracy of cumulative deformation prediction models for characteristic points in the Xijitan landslide area was evaluated using Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and goodness-of-fit (R^2). MAE enables comparison of stability between different models, RMSE directly measures differences between predicted and actual values, and R^2 assesses the fitting degree between neural network predictions and actual values. An R^2 value approaching 1 indicates better model fitting of deformation data, while an R^2 near zero suggests weaker explanatory power and poorer fitting between predicted and actual values. The calculation formulas are:

$$MAE = \frac{1}{N} \sum_{i=1}^N |A_t - F_t|$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (A_t - F_t)^2}$$

where N is the sample size, A_t represents actual values, and F_t represents predicted values.

2. Results and Analysis

2.1 Deformation Rate Characteristics of the Xijitan Landslide

The SBAS-InSAR technique revealed that the Xijitan giant landslide had an average annual surface deformation rate of -96 to 16 $\text{mm} \cdot \text{a}^{-1}$ during the monitoring period, with significant deformation concentrated at the front and rear edges. The maximum deformation rate at the front edge reached -96 $\text{mm} \cdot \text{a}^{-1}$, while the central portion of the landslide body exhibited relatively stable deformation rates of -10 to 10 $\text{mm} \cdot \text{a}^{-1}$. This result is consistent with findings from Wang et al. and Zhao et al., confirming that areas with relatively intense surface deformation rate changes are located at the front and rear edges of the landslide body.

Field investigations identified three distinct deformation zones (H1, H2, H3) in areas with significant deformation. The H1 zone, located at the landslide front edge on Stage III deposits, showed deformation rates of -96 to -70 $\text{mm} \cdot \text{a}^{-1}$, with deformation rates gradually decreasing from the center to the edges. The central portion of this zone exhibited a concave topography with surface slumping, large-scale gullies, and multiple tension cracks. The H2 zone, situated on Stage III deposits at the rear edge, displayed deformation rates of -70 to -50 $\text{mm} \cdot \text{a}^{-1}$, with widespread slumping, multi-level tension cracks extending backward, and a large north-south oriented gully traversing the main landslide body. The H3 zone, located on Stage II deposits at the rear edge, showed deformation rates of -70 to -50 $\text{mm} \cdot \text{a}^{-1}$, with stepped topography, tension cracks of small aperture

at the rear, and multi-level collapse and secondary landslide phenomena in the central area.

2.2 Time-Series Cumulative Deformation Results

To further analyze deformation trends of the Xijitan giant landslide, characteristic points (P1, P2, P3, P4) were selected in areas with obvious deformation. Combined with monthly cumulative rainfall data within the landslide area during the monitoring period, the relationship curves between cumulative deformation, monthly cumulative rainfall, and time were plotted (Figure 9). The deformation trends at characteristic points P1, P2, and P4 were relatively stable, with cumulative deformations of -140.5 mm, -109.7 mm, and -76.8 mm, respectively. Notably, increased rainfall showed significant correlation with landslide surface deformation, particularly during periods of high rainfall when landslide surface deformation rates increased markedly. Between June and September 2021, the landslide surface deformation rate accelerated, with cumulative deformation at each characteristic point exceeding 88.6 mm. The deformation rate 突变 occurred in July 2021, corresponding to a monthly cumulative rainfall of 134.5 mm. Similarly, in July 2022, the deformation rate 突变 corresponded to a monthly cumulative rainfall of 88.6 mm. These results demonstrate a close relationship between deformation at the landslide's front and rear edges and rainfall, indicating that precipitation is a significant factor driving increased landslide surface deformation.

2.3 Cumulative Surface Deformation Prediction Based on Different Neural Network Models

To validate the applicability of the LSTM neural network model for predicting cumulative deformation at characteristic points in the Xijitan giant landslide, time-series deformation data from March 2019 to December 2022 for characteristic points P1, P2, and P4 at the landslide's front and rear edges were used as experimental parameters for the prediction model. The LSTM model was configured with 4 input layer nodes, 1 output layer node, 50 hidden layer nodes, 2 layers, and a time step of 4. After parameter configuration, the cumulative deformation data obtained from InSAR were used as the dataset, partitioned into training and testing sets at a 7:3 ratio. This partitioning ensures sufficient data for model training while providing adequate testing data.

The LSTM model predictions for characteristic points P1, P2, and P4 are shown in Figure 10. The cumulative deformation trends at these points were consistent, with all characteristic points achieving R^2 values greater than 0.8, indicating high fitting degrees between predicted and actual values (Table 2). The absolute errors between predicted and actual values for all three characteristic points were less than 5 mm, demonstrating the effectiveness of the LSTM model for predicting cumulative deformation at characteristic points. Characteristic point P2 showed the highest fitting degree ($R^2 = 0.91$), with an average absolute error of 1.93 mm between predicted and actual values.

For comparative analysis, SVM and BP neural network models were also applied to predict the time-series deformation of the giant landslide. The SVM model predictions (Figure 11) showed maximum absolute errors of 5.87 mm, 6.94 mm, and 4.50 mm for characteristic points P1, P2, and P4, respectively, with error ranges controlled within 10 mm. The BP neural network model predictions (Figure 12) yielded R^2 values of 0.88, 0.91, and 0.90 for P1, P2, and P4, respectively.

Comparative analysis of the three models (Table 3) reveals that the LSTM neural network model achieved the smallest average absolute error (1.82 mm) and highest prediction accuracy. The LSTM model's R^2 values for all characteristic points exceeded those of the SVM model (maximum $R^2 = 0.88$), and its prediction accuracy was slightly higher than that of the BP model. The maximum absolute errors for the LSTM model predictions were 4.50 mm, 3.06 mm, and 1.60 mm for P1, P2, and P4, respectively, all within 5 mm. These results confirm that the LSTM neural network model provides highly accurate and effective predictions of cumulative deformation at characteristic points on the landslide surface.

3. Conclusions

- 1) This study processed Sentinel-1A imagery using SBAS-InSAR technology to obtain the average annual surface deformation rate of the Xijitan giant landslide. The landslide exhibited an average annual deformation rate of -96 to $16 \text{ mm} \cdot \text{a}^{-1}$, with the central portion showing relatively stable rates of -10 to $10 \text{ mm} \cdot \text{a}^{-1}$. Localized areas at the landslide's front and rear edges demonstrated significant deformation, with maximum annual rates reaching $-96 \text{ mm} \cdot \text{a}^{-1}$.
- 2) The cumulative deformation at characteristic points on the Xijitan giant landslide's front and rear edges was obtained through SBAS-InSAR monitoring. Characteristic points P1, P2, and P4 showed maximum cumulative deformations of -140.5 mm , -109.7 mm , and -76.8 mm , respectively, indicating relatively significant surface deformation at the landslide's front and rear edges.
- 3) The LSTM neural network model was applied to predict cumulative deformation at characteristic points on the landslide surface. For the front-edge characteristic point P1, the maximum absolute error was 4.50 mm; for the rear-edge characteristic point P4, the maximum absolute error was 1.60 mm. These results demonstrate the effectiveness of the LSTM neural network model for predicting cumulative deformation at characteristic points, providing valuable technical support for surface deformation monitoring and early identification of potential landslides in the upper Yellow River region.

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