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Displacement prediction in colluvial landslides, Three Gorges Reservoir, China

Abstract The prediction of active landslide displacement is a critical component of an early warning system and helps prevent property damage and loss of human lives. For the colluvial landslides in the Three Gorges Reservoir, the monitored displacement, precipitation, and reservoir level indicated that the characteristics of the deformations were closely related to the seasonal fluctuation of rainfall and reservoir level and that the displacement curve versus time showed a stepwise pattern. Besides the geological conditions, landslide displacement also depended on the variation in the influencing factors. Two typical colluvial landslides, the Baishuihe landslide and the Bazimen landslide, were selected for case studies. To analyze the different response components of the total displacement, the accumulated displacement was divided into a trend and a periodic component using a time series model. For the prediction of the periodic displacement, a back-propagation neural network model was adopted with selected factors including (1) the accumulated precipitation during the last 1-month period, (2) the accumulated precipitation over a 2-month period, (3) change of reservoir level during the last 1month, (4) the average elevation of the reservoir level in the current month, and (5) the accumulated displacement increment during 1year. The prediction of the displacement showed a periodic response in the displacement as a function of the variation of the influencing factors. The prediction model provided a good representation of the measured slide displacement behavior at the Baishuihe and the Bazimen sites, which can be adopted for displacement prediction and early warning of colluvial landslides in the Three Gorges Reservoir.

Keywords Landslide · Displacement prediction · Time series · Periodic response · The Three Gorges Reservoir

Introduction

Landslides and floods in Asian countries cause major socio-economic disruptions, extensive property damage, and casualties and are often associated with heavy rainfall and human activities. Although recent research has improved the understanding of landslide mechanisms and mitigation technologies, only a few of the highest-risk landslides receive funding for engineering and environmental studies and remediation.

If slope stabilization is not a viable option, a warning system to avoid property damage and casualties may be an effective method. To function effectively and reliably, warning systems require information on the behavior of the landslide, including the sliding mechanism, the potential triggers, and their thresholds for issuing emergency warnings. Critical parameters for early warning are the velocity of the movement, the magnitude of the displacement, and the accuracy of the prediction of landslide movement Sassa et al. (2009).

Sometimes slope failure can be predicted by monitoring the displacement over time. Translational and rotational movements can display different behaviors, from long-term creep to sudden catastrophic movement, without warning (Petley and Allison 1997). Landslide events can be forecasted from creep theory and the analysis of the displacement before the slope failure, i.e., tertiary creep (Saito 1965), with the Hayashi model (Hayashi et al. 1988) and the general creep model (Federico et al. 2004), or from the linear trend of the inverse displacement rate curve (Voight 1988; Voight 1989; Fukuzono 1990; Petley et al. 2002). Landslide displacements can be predicted by curve fitting techniques, e.g., the Verhulst model, the GM (1, 1) model, the exponential smoothing model (Picarelli et al. 2000; Li et al. 1996; Chen and Wang 1988), and so on.

Dormant landslides may be reactivated and movements in active slides may follow heavy rainfall. Analyses of meteorological data show that landslide displacements were often closely related to seasonal rainfall fluctuations (Corominas and Moya, 1999; Coe et al., 2003). A sharp increase in displacement following heavy rainfall has been noted by Hilley et al. (2004) and He et al. (2005).

For slopes in the reservoirs, fluctuations of the water level can be a significant influencing factor for slopes within a reservoir (Breth 1967; Wang et al. 2005; Liu et al. 2004). The fluctuation of the reservoir water levels may change the water content and seepage conditions in the reservoir slopes. Either one can lead to instability (Chai et al. 2008). On initial impoundment in the Three Gorges Reservoir, when the water level reached 135 m above sea level on June 1, 2003, the Qianjiangping landslide (volume of 14 million m³) was reactivated and caused extensive damages and many casualties (Wang et al. 2004). By November 2008, the reservoir level had risen to 172 m, causing over 60 landslides and resulting to widespread damage in the Hubei Province and the Chongqing Municipality.

Brunsden (2001) indicated that a landscape change (including material transport, morphological evolution, and structural rearrangement) takes place as a process–response function. For active landslides and exposed slopes, a reliable prediction of displacement requires a "dynamic" analysis instead of a classical "static" approach. He recommended that the prediction of landslide displacement should be based on the analysis of the observed displacements as a function of the influencing factors and their dynamic fluctuation.

This paper analyzes two typical colluvial landslides in Three Gorges Reservoir, the Baishuihe and Bazimen landslides, and proposes a displacement prediction model based on the relationship between displacement and key influencing factors. A time series model was adopted to divide the total displacement into trend and periodic components. The displacement trend was predicted by nonlinear regression. To obtain the predicted periodic displacement, influence factors were selected as input in the back-propagation (BP) neural network model. The total forecast displacement was obtained by adding the trend and periodic displacements together.
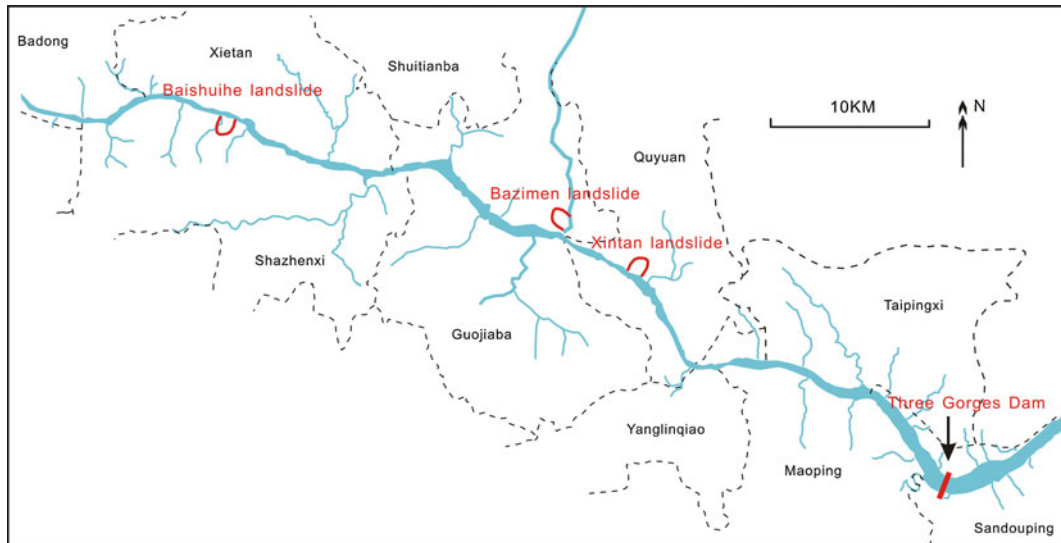
Fig. 1 Location map of the Three Gorges Reservoir landslides mentioned in the paper

Displacements of colluvial landslides in Three Gorges Reservoir

In the Three Gorges Reservoir, the displacement curves of most of the colluvial landslides show a stepwise evolution influenced by precipitation and reservoir level fluctuations. For continuously moving landslides, part of and, at times, the entire displacement curves show alternations of displacement acceleration with, at times, sharp increments. The complexity and randomness are characteristics of the displacement of colluvial landslides in the Three Gorges Reservoir.

The Xintan colluvial landslide in Xintan village, Zigui county, 26 km upstream of the Three Gorges Dam (Fig. 1), occurred on June 12, 1985. The landslide covers an area of over 0.75×10^6 m² and had a volume of 3×10^7 m³. Based on 7-year monitoring data, the accumulated displacement versus time shows both stepwise and continuous increase (Fig. 2). The displacement velocity increased in rainy seasons and decreased in dry seasons (Fig. 3). The deformation history at Xintan can be divided into three periods:

1. 1978 to 1981—Except for the increment in September 1979, the landslide showed stable displacements with small fluctuations.

2. 1982 to March 1985—The velocity showed large fluctuations, with stepwise displacements.
3. April to July 1985—The movement sharply accelerated and the displacement in 1 month reached 2,000 mm at failure.

Factors influencing the displacement include the degradation of the shear strength, stress concentrations, and the sliding mass itself. However, the dominant factors are precipitation and the fluctuation of reservoir levels. Under the changing conditions, the accumulated displacement exhibited a sharp growth. When the rainfall was reduced and the reservoir level steadied, the accumulated displacement remained stable.

Most landslide forecast models predict displacement by curve-fitting of historical displacement data versus time. However, a landslide is a nonlinear dynamic system controlled by geological, climatic, and other conditions (Dong et al. 2007), such as precipitation, earthquake, and human activities. Changes in these conditions play a critical role in the development of the displacement. In many cases, changes in landslide displacements can be directly correlated to visible
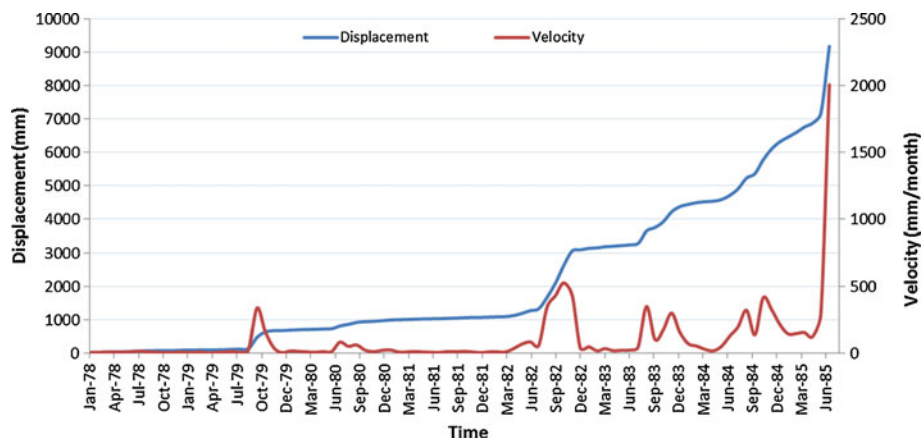

Fig. 2 Accumulated displacement and velocity vs time at Xintan landslide
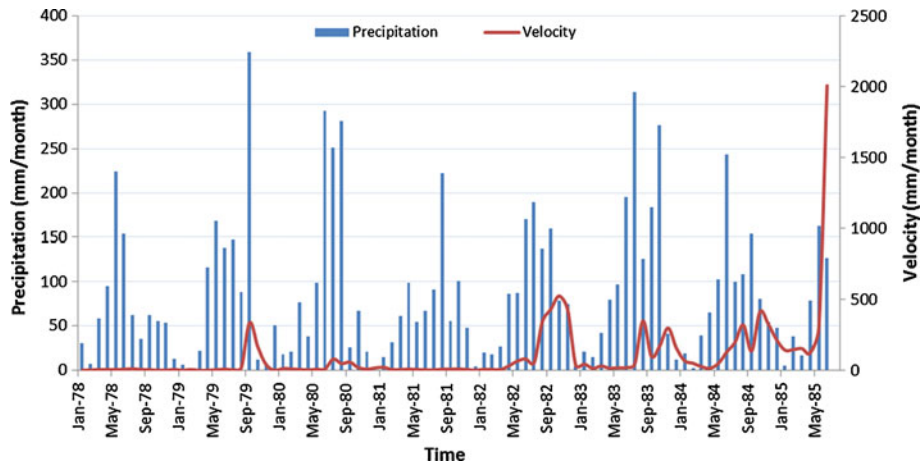
Fig. 3 Precipitation and displacement velocity vs time at Xintan landslide

variations in the influencing factors (He et al. 2005; Chen et al. 2008; Dai and Lee 2001). In the development of a new forecast model for the prediction of landslide displacement, both deformation mechanism and the influencing factors should be considered.

Proposed forecast model

In the proposed model, landslide displacements are associated with the geological, weather, and hydrological conditions and the external influencing factors. The total displacement was divided into two components:

1. Displacement controlled by geological conditions in the long term
2. Displacement dependent on external factors, which fluctuate in the short term

The two components represent the approximately regular and the step-increasing displacements in a landslide (Xu et al. 2008).

In a time series model, the total displacement, A_t, contains four response components as expressed in Eq. 1 (Wang 2003):

$$A_t = t_t + c_t + s_t + \varepsilon_t \tag{1}$$

where t_t, c_t, and s_t are the trend, periodic, and pulsation terms and ε_t is a random variable reflecting the uncertainty.

The trend term represents the tendency of the developing displacement. It is determined by the potential energy and the constraint condition of the slope. The trend term varies as a function of time. The periodic term is the displacement induced by the periodic change of the trigger (s), e.g., diurnal temperature difference and monthly precipitation. The pulsation term is the displacement response caused by a sudden change, e.g., a raise or drop of the reservoir level. In the Three Gorges Reservoir, the main influencing factors are precipitation and the regulation of the reservoir level (Fig. 4). The reservoir level changes regularly on an annual cycle. Precipitation and reservoir regulation could be considered as periodic terms. In this paper, the variables were treated as deterministic (rather than random) variables. Because of the different mechanisms of each of the displacement components, the total displacement measured by the monitoring system should also be divided into trend and

periodic terms, and each can be predicted separately by different methodologies.

Development of the time series component—moving average method

The decomposition of the trend and periodic terms forms the basis of the model. If the period of the time series and influencing factors can be determined accurately, the fluctuation can be smoothed by the moving average method, and the trend term of the displacement can be extracted. The function for the single moving average method is shown in Eq. 2 (Pan 2006):

$$\bar{S}_t^{[1]} = \frac{1}{N}(S_t + S_{t-1} + \cdots + S_{t-N+1}) \qquad (t \geq N) \tag{2}$$

where $\bar{S}_t^{[1]}$ is the single moving average value at the t-th time interval, S_t is the monitored displacement at the t-th time interval, and N is the cycle of the moving average.

To weaken, and even completely eliminate the periodic and irregular fluctuation in the time series, a double moving average method can also be used (Eq. 3) (Pan 2006):

$$\bar{S}_t^{[2]} = \frac{1}{N}\left(\bar{S}_t^{[1]} + \bar{S}_{t-1}^{[1]} + \cdots + \bar{S}_{t-N+1}^{[1]}\right) \qquad (t \geq 2N-1) \tag{3}$$

where $\bar{S}_t^{[2]}$ is the double moving average value at the t-th time interval. However, as the moving average increases with time, the trend term would show hysteresis deviation. A model of higher order than twice moving average is seldom adopted in time series analysis.

Prediction of trend displacement

When a time series contains a trend term only, a nonlinear regression, with the binomial regression model, is one of the more reliable forecast methods:

$$S_t = \alpha_0 + \alpha_1 t + \alpha_2 t^2 + \varepsilon_t \tag{4}$$

where S_t is the trend displacement, α_0, α_1, and α_2 are the indexes of the regression function, which can be calculated by the least square method, and ε_t is the error threshold. A higher-degree nonlinear regression model can be adopted to reduce the error threshold.
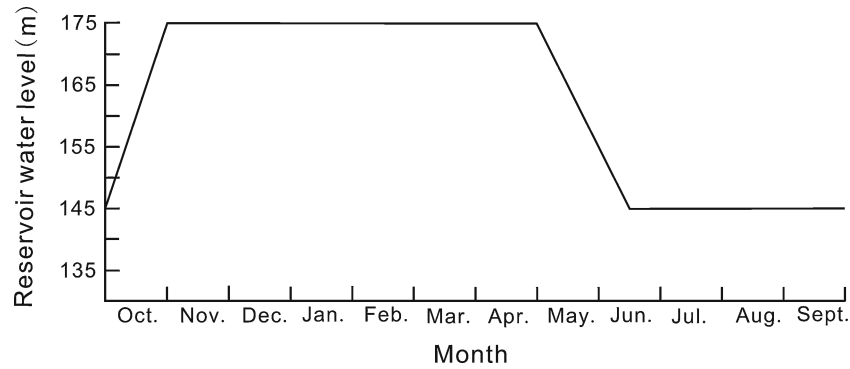
Fig. 4 Water level regulation of the Three Gorges Reservoir

Prediction of periodic displacement

Periodic landslide displacement is influenced by multiple variables and the response relationship is difficult to describe by conventional analytical methods. Neural networks are non-linear statistical data modeling tools, which are usually used to model complex relationships between multi-variables (inputs) and responses (outputs) (Mayoraz and Vulliet 2002; Ran et al. 2010; Pradhan and Buchroithner 2010; Biswajeet and Saro 2010).

BP is a common method of training neural networks. It is learned by example, which consists of some input examples and the known correct output for each case. These input–output examples are used to obtain the bounded mapping function (hidden layer) after the training of network, and the BP algorithm allows the network to adapt with other inputs. In 1989, Robet Hect-Nielsen proved that the three-layer BP neural network model can effectively approximate any function (Hect-Nielsen 1989). In this paper, BP neural network was adopted to forecast the periodic landslide displacement.

Prediction of total displacement

The total forecast displacement can be obtained by adding the trend and periodic terms. Figure 5 describes the analysis process of the forecast model in a flowchart form.

Case studies

Two colluvial landslides in the Three Gorges Reservoir, each with different deformation characteristics, were selected as study cases. With the measured displacements and measured external influencing factors (precipitation and reservoir level), the forecast model was validated for the two landslides.

Case study 1: Bazimen landslide

Geological conditions and deformation characteristics
The Bazimen landslide is located in the Zigui town on the west side of the Xiangxi River (Fig. 1), a major tributary to the Yangtze River. Its boundaries are defined by the interface between bedrock and
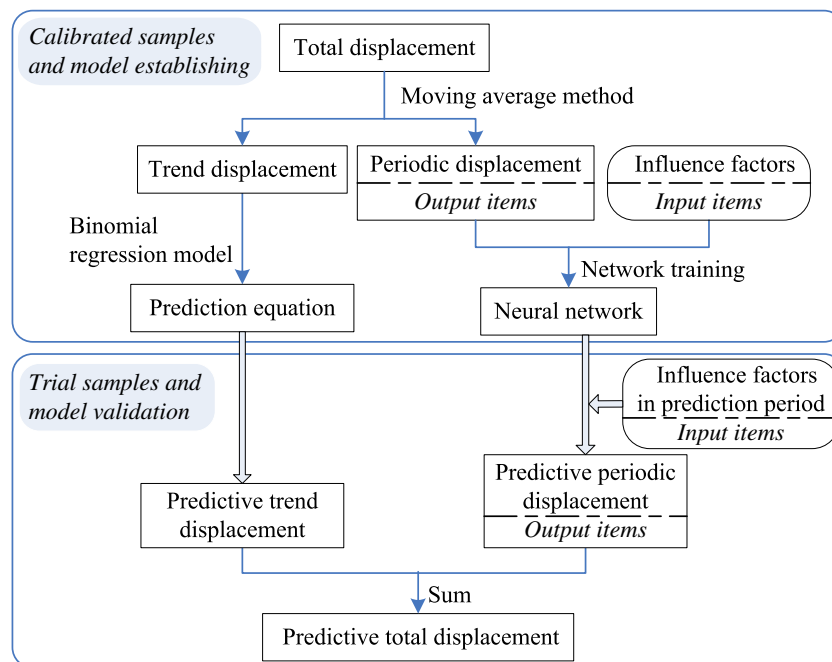

Fig. 5 Analysis flowchart of the proposed forecast model

soil. The landslide has an estimated volume of 2×10^6 m³, with a maximum longitudinal dimension of 380 m and width of 100 to 350 m. The landslide lies at an elevation between 110 and 250 m with most of the landslide mass below the reservoir surface (Figs. 6 and 7).

The landslide slope varies between 10° and 30°. The mobilized material is composed of loose Quaternary deposits and fragmented rubble. Based on the borehole data, two sliding surface levels were found. The lower one was the initial sliding surface at the interface between deposit and bedrock at a depth of 10 to 35 m. The upper sliding surface was a secondary sliding surface at a depth of 6 to 18 m at the top and middle of the sliding mass and at a depth of 27 to 33 m at the bottom. The secondary sliding surface formed after the early deformation phase along the initial sliding surface.

The deformation behavior of the Bazimen landslide was mainly observed at the head and north boundary of the landslide. A road was across the landslide at an elevation of 195 m and subsided 20 to 80 cm. A series of tension cracks, 20 to 25 m in length and 3 to 5 cm in width trending N25E, appeared beside it. The deformation at the north boundary was a series of pinnate shear cracks 5 to 8 m in length and 5 to 7 cm in width in the direction appearing as N50–75E. In the top and middle parts of the landslide, arcuate tension cracks 10 m in length and 5 cm in width appeared in the direction N40–50E.

Monitoring data at Bazimen landslide

The monitoring of surface displacement and displacement within the Bazimen landslide Fig. 8 was made with GPS and inclinometers. Three monitoring points were located in the main cross-section of the landslide (Fig. 6). The displacement data, the precipitation, and the reservoir level between July 2003 and January 2008 are shown in Figs. 9 and 10. The borehole information indicated, as mentioned earlier, two sliding surfaces with most deformation along the secondary sliding surface (e.g., QTZK4 in Fig. 8). The displacement at the top of the landslide (Z111; Fig. 9) was used to establish the forecast model.

Displacement vs time was analyzed and summarized below:

1. Between July 2003 and September 2004: After the first rise of the water level in the Three Gorges Reservoir to 135 m in June 2003, Z111 at the top of the landslide showed the largest
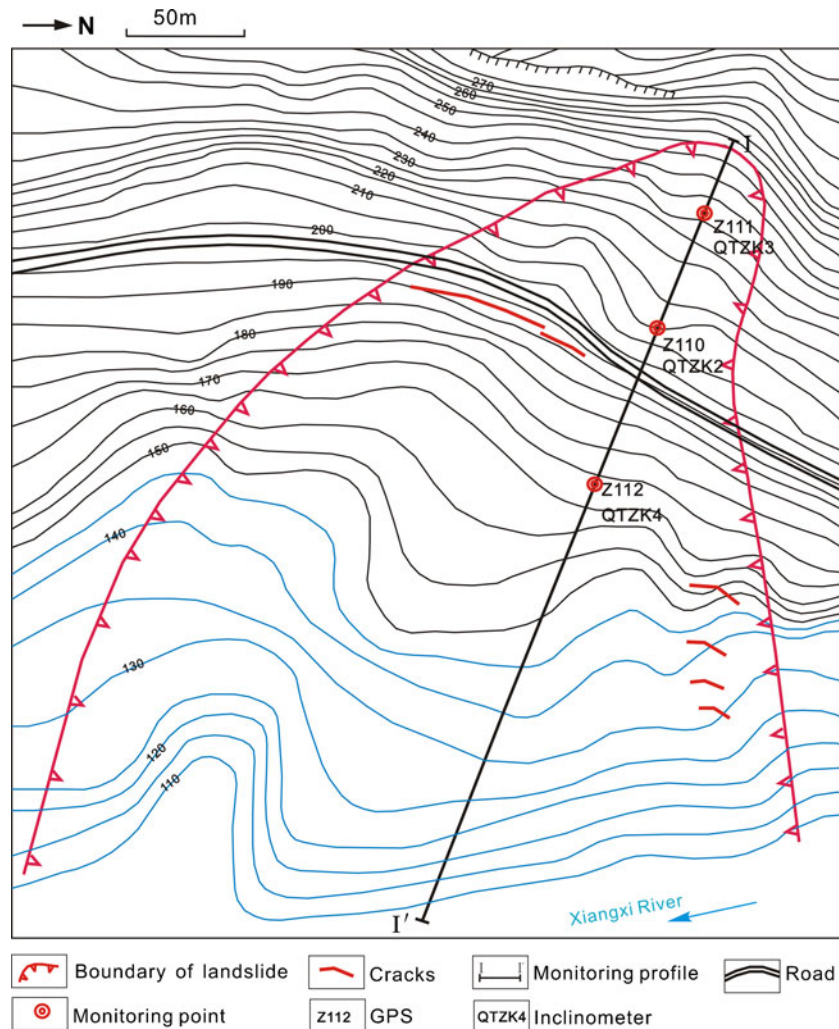

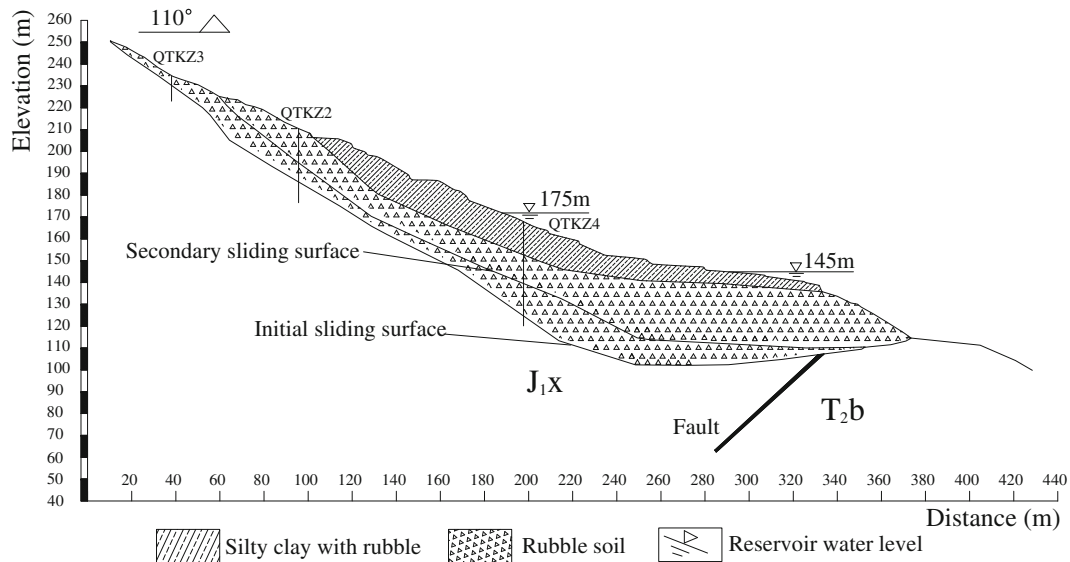**Fig. 6** Topographical map of the Bazimen landslide, with monitoring network

Fig. 7 Schematic geological cross-section of the Bazimen landslide (J_1x is the Xiangxi Formation of Lower Triassic; T_2b is the Badong Formation of Middle Triassic)

displacement. Before the rainy season in May 2004, the displacement grew essentially steadily, indicating that the rise of the water level continued to have an effect on the displacement some time after the first reservoir filling. Between June and September 2004, under stable reservoir level and precipitation of 530.9 mm, the three monitored displacements showed rapid and sustained growth, indicating the strong influence of precipitation.

2. From October 2004 to September 2006: The reservoir level rose by 4 m, with little effect on the displacement. During

Fig. 8 Lateral displacement versus depth from inclinometer QTZK4, Bazimen landslide

the rainy season each year (May to September), the landslide displacement grew. An examination of the displacement increment in each rainy season indicated that the effect of rainfall on the displacement became less as time passed. At point Z111 for example, the accumulated precipitation during the period of May to September from 2004 to 2006 was essentially identical: 635, 640, and 630 mm. The displacement increments were on the other hand 156.6, 131.2, and 49.7, mm respectively. For the Bazimen landslide, precipitation was an early predominant influencing factor, whose effect reduced with time.

3. From October 2006 to January 2009: When the reservoir level rose to 19.4 m in October 2006, the displacements did not increase. The accumulated displacement in the middle and front parts of the landslide even showed a decreasing trend, indicating that the most recent rise of reservoir level has little effect on deformation. Between February and April 2007, the reservoir level dropped down from 156 to 145 m, but the accumulated displacement remained stable. However, under the 606-mm precipitation between May and September 2007, the increment of accumulated displacement of Z111 reached 122.2 mm.
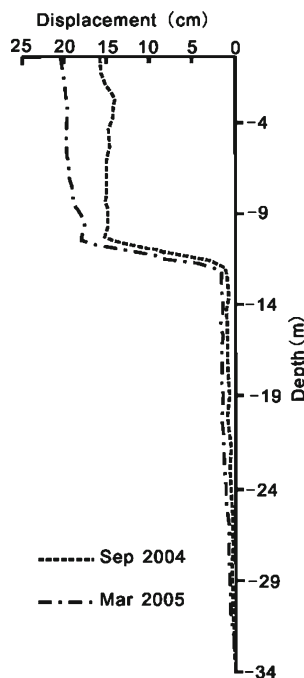
The deformation characteristics of the Bazimen landslide indicate that the movement is an "advancing" type of landslide, meaning that the landslide was initiated from the upper part and developed downwards with increasing displacement. The sliding surface (Figs. 7 and 11) can be divided into two parts: the upper steeper part and the lower flatter part. The lower part of the landslide had larger depth and almost horizontal sliding surface. This helped resist the sliding. The accumulated displacement in the upper part (tension section, Fig. 11) of the landslide was much larger than the displacement in the middle (main sliding section) and lower part (compression section). The displacement at point Z111 showed stepwise increases, whereas at points Z110 and Z112 the displacement exhibited much smoother growth except for the sharp rise between June and April 2004.
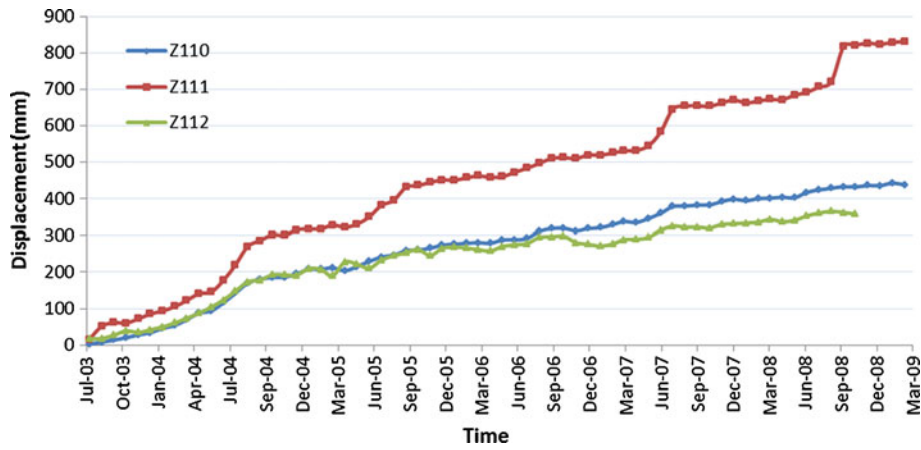
Fig. 9 Displacement at three locations within Bazimen landslide

Precipitation appears to be the dominant factor influencing displacement of the Bazimen landslide. With respect to the fluctuation of the reservoir level, drawdown, rather than filling, represents the major influence on slope stability. The entire deformation history at Bazimen indicated that:

1. The state of deformation may reflect the degree of influence of the different factors to the landslide.
2. Landslide displacement was a function of the precipitation and the rate of the change in the reservoir level.

Prediction of trend displacement
The displacement at Z111 was used to establish the forecast model. The data before January 2008 were used to calibrate the model and the remainder data were used to do the trial predictions. The single moving average method was used to extract the trend displacement, with a moving average cycle of 12 months. The trend and periodic displacements based on the measured values between June 2004 and January 2009 are shown in Figs. 12 and 13. The remaining periodic displacement (after removing the trend) showed cyclic variation characteristics.

The trend displacement was a monotonically increasing series. A binomial regression, with a threshold value of 0.99, was adopted to fit the displacement. A cubic polynomial (Eq. 5) provided the best fit with the observed data. For the forecast result shown in Fig. 12, the largest error between measured and predicted value was 3 %.

$$S_t = 0.0058t^3 - 0.737t^2 + 38.977t - 286.88 \qquad (5)$$

where S_t is the displacement at time t and t is time.

Prediction of periodic displacement
The determination of periodic influence factors is critical for reliable forecasting and reasonable displacement response. Otherwise, noise
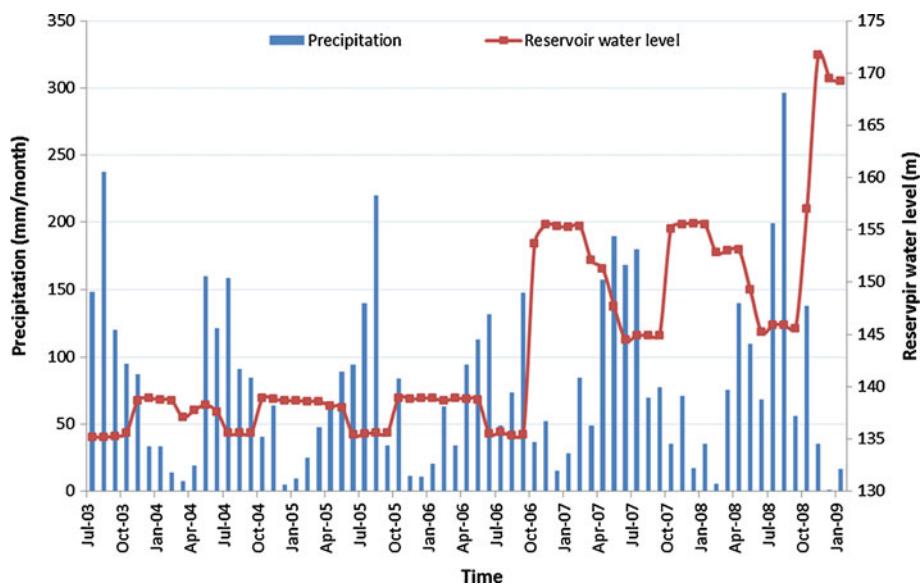

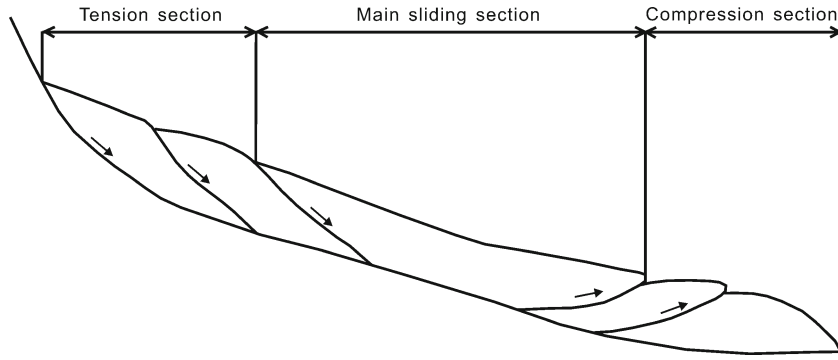**Fig. 10** Rainfall and reservoir level during the period 2003–2008

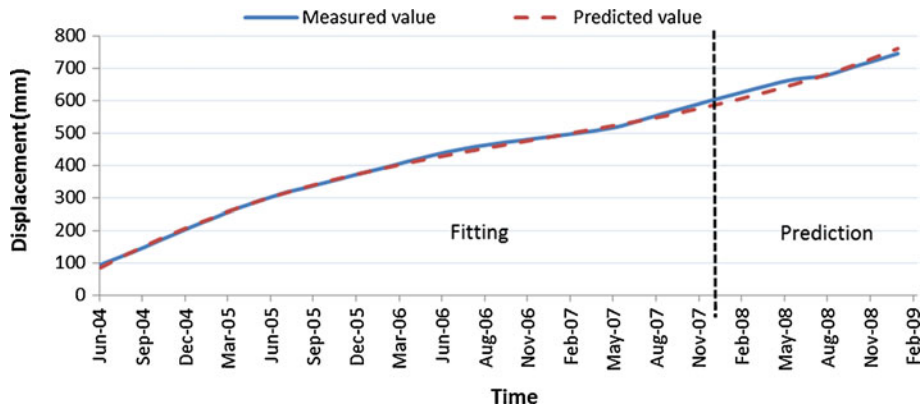**Fig. 11** Sketch of deformation mechanism of advancing landslide at Bazimen

Fig. 12 Measured and predicted trend term of displacement at the Bazimen landslide
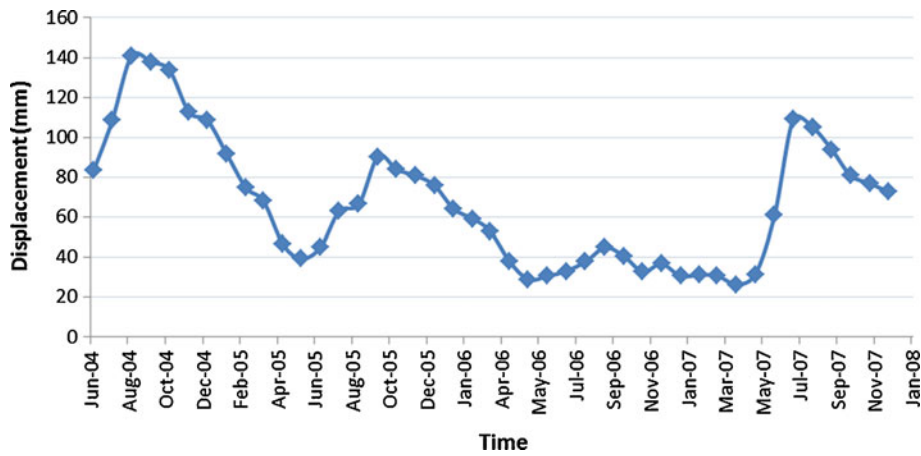

Fig. 13 "Measured" (after removal of trend) periodic displacement with calibrated model, Bazimen landslide

could be introduced and mask the underlying relationship between trigger and response. Based on an analysis of the deformation mechanism, four periodic influence factors were selected:

1. The accumulated precipitation over the past month.
2. The accumulated precipitation over the past 2 months to reflect the influence of rainfall. Keefer et al. (1987) and Zhang (2005) suggested, based on research on the relationship between rainfall and landslide, that the precipitation 1 or 2 months before failure has a strong influence on landslide deformation.
3. Change of reservoir level during the last month to reflect the influence of the rapidity of reservoir level regulation: the analysis assumed that the water level was increased/decreased at constant velocity during 1 month.
4. The increment of accumulated displacement during 1 year: the displacement was accumulated from November in a particular year to October in the next year. For the pattern of rainfall season and water level regulation, a slow displacement period began in November and lasted until May in the next year. This was observed for most of the colluvial landslides in the Three Gorges Reservoir. During this period, the landslide achieved a temporary relatively stable status, with probable adjustment of internal stress distribution, consolidation of looser moving masses, and so on. A new displacement cycle starts with the next rainy season. The different cycles of the periodic displacement are linked through the accumulated displacement, but the trend term and periodic term are independent of each other. In one cycle, the larger the accumulated displacement, the more unstable the landslide will be, and the displacement response will then be larger under the same influencing factors. This, however, would not necessarily be true from one cycle to the other. The displacement was considered separately each year, starting with the onset of the dry season in November each year.

The accumulated precipitation over the past 1 and 2 months, the change of reservoir water level during the last 1 month, and the increment of accumulated displacement during 1 year were used as inputs, and the periodic displacement was the output. Then, BP neural network model was trained to quest the response relationship between the inputs and the output (Table 1). The error was less than 1×10^{-4} after the network training for 2×10^4 times. The neural network was then adopted to predict the periodic displacement.

The predicted periodic displacement can be divided into two parts (Fig. 14):

1. Before October 2008, the predicted value was quite consistent with the measured value, especially under drawdown of the reservoir level in May 2008. During the 496-mm precipitation between June and August 2008, the displacement showed rapid and sustained growth until September 2008.
2. After October 2008, the predicted value differed from the measured value, although the predicted value did reflect the general behavior of the measured displacement.

One reason for this is the following: as the time extends for the displacement predicted by a neural network model, random factors can to some extent affect the prediction, and the past information can disturb the accuracy of the prediction. To establish an improved response, one could gradually delete the earlier information and continuously supplement with new monitoring data.

Total displacement

To obtain the total displacement, the predicted trend and periodic displacement terms are added together. Figure 15 shows that the proposed model provided a very good prediction of the total measured behavior with the maximum error of 4.4 %.

Case study 2: Baishuihe landslide

Geological conditions and deformation characteristics

The Baishuihe landslide occurred in the town of Zigui, on the south side of the Yangtze River, 56 km west of the Three Gorges Dam (Fig. 1). The landslide covers an area of 0.42 km² with an estimated volume of 12,600 m³. The fan-shaped landslide has maximum length of 780 m and width of 700 m. It extends from an elevation of 75 to 390 m and displays superficial cracking and distinct ground displacements as shown in Figs. 16 and 17.

Most of the surface deformation occurs at the boundaries and on the frontal part of the landslide. The largest crack is 300 m in length and the maximum width is 60 cm in the

Table 1 Inputs and output for neural network modeling of periodic displacement in the two study cases

| No.	Name of landslide	Input parameters (influence factors)	Output item
Case 1	Bazimen	1. The accumulated precipitation during the last 1-month period	Periodic displacement
		2. The accumulated precipitation over a 2-month period	
		3. The change of reservoir level during the last 1 month	
		4. The accumulated displacement increment during 1 year	
Case 2	Baishuihe	1. The accumulated precipitation during the last 1-month period	Periodic displacement
		2. The accumulated precipitation over a 2-month period	
		3. The change of reservoir level during the last 1 month	
		4. The accumulated displacement increment during 1 year	
		5. The average elevation of the reservoir level in the current month	
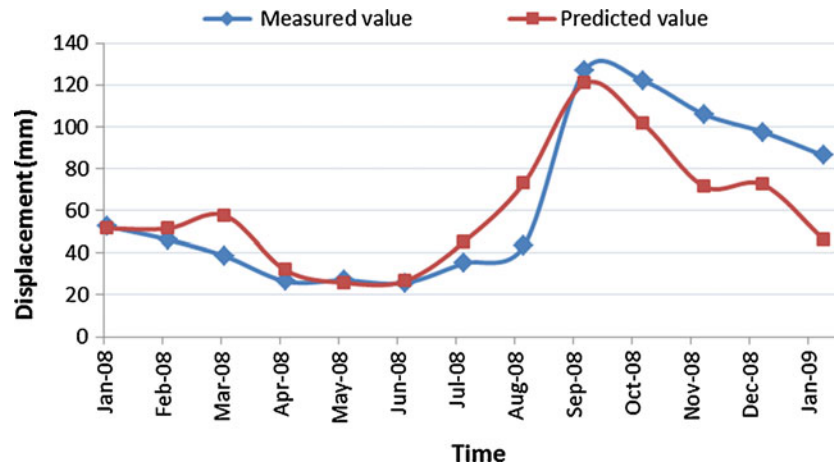
Fig. 14 Comparison between predicted and measured periodic landslide displacement in Bazimen landslide

frontal part of the landslide. It occurred after the first reservoir impoundment in June 2003. During the period August 2005 to August 2006, many transverse cracks appeared on the ground surface. A collapse sector was observed in the upper part of the landslide (Fig. 16), where the moving mass of 10×10^4 m³ slid in June 2007. Inclinometer QZK1 indicated that the main sliding zone lied in the layer of brown silty clay, at a depth varying from 12 to 21.5 m (Fig. 18). The deeper sliding zone had a thickness between 0.6 and 1 m above the siltstone bedrock.

Analysis of displacement data at Baishuihe landslide

Four monitoring profiles and 14 monitoring points were located on the landslide, including 11 GPS monitoring points and three inclinometers (Fig. 16). Monitoring was done at 1-month intervals. Monitoring at GPS points, ZG93 and ZG118, started in June 2003, XD1and XD2 started in May 2005, and XD3 and XD4 started in October 2005. The surface displacement data monitored by the GPS were used to establish the forecast model. The landslide displacement, the precipitation, and the water level of reservoir between 2003 and 2007 are shown in Figs. 19 and 20.

To compare the characteristics of the displacement at different locations, the displacement data were considered for three different periods of time as follows:

1. May 2005 to March 2006: In June 2005, the reservoir water level dropped by 2.53 m fairly rapidly, and the displacement at XD1and XD2, in the middle and forward part of landslide, increased rapidly and continued to increase during July and August. However, the displacement at ZG93 and ZG118 showed only a small increase. The displacement caused by the drawdown of the reservoir level was mainly concentrated in the middle and frontal part of the landslide, and the area in the middle of the slope prevented the transmission of sliding traction forces from the bottom to the top of the landslide. In October 2005, the reservoir level rose by 3.3 m, and the displacement at each monitoring point remained stable. This indicated that the rise of the water level in Three Gorges reservoir had a relatively little effect on the stability of the landslide.

2. April 2006 to September 2006: After the heavy rainfall in April 2006, the measured displacement at each monitoring point showed regular fluctuations corresponding to the
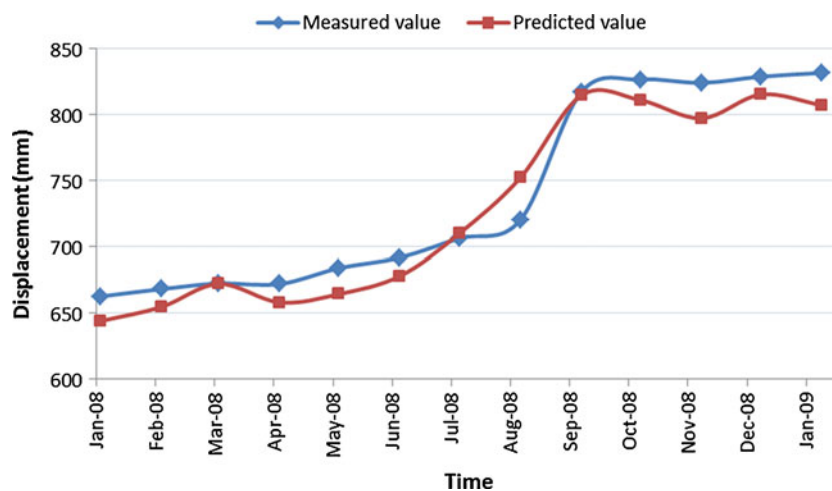

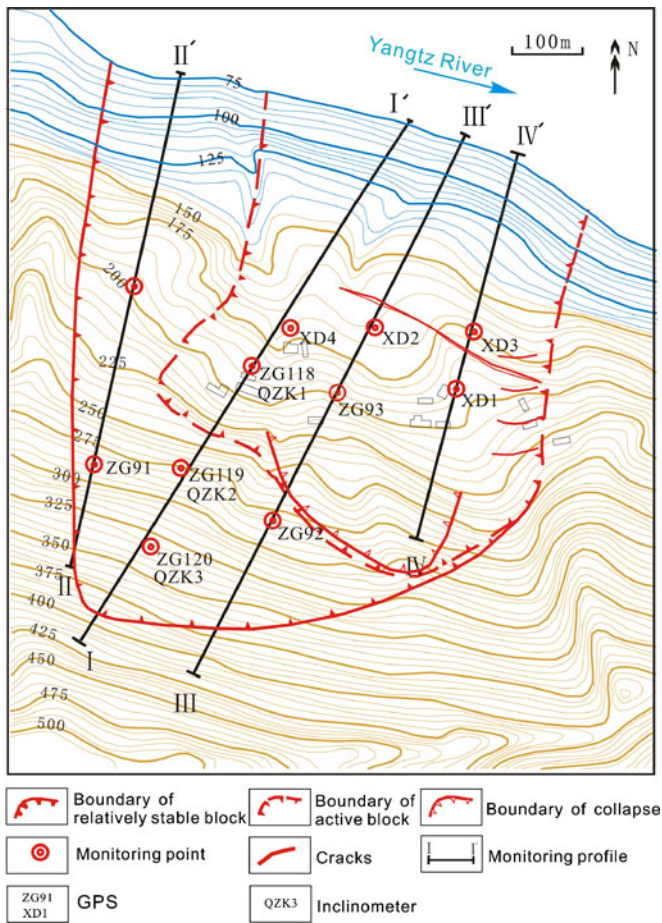**Fig. 15** Comparison between predicted and measured total displacement in Bazimen landslide

Fig. 16 Topographical map of Baishuihe landslide, with observed superficial cracks

Fig. 18 Lateral displacement versus depth from inclinometer QZK1, Baishuihe landslide

precipitation during April to August. In June 2006, the 3.1-m drawdown of the reservoir level had a strong effect on the displacement at point XD3, leading to increased deformation during July and August 2006. It is believed that this area of the landslide separated from the slope and became part of the unstable portion of this landslide.

3. March 2007 to July 2007: After the drawdown of the reservoir level by 2.64 m in March 2007 and 1.82 m in April 2007, the displacement at each monitoring point remained stable, indicating that the slope response to the drawdown of the reservoir level was gradually decreasing. However, under 355-mm rainfall during April and May 2007 and a 2.64-m drawdown of the reservoir level that same May, the displacement at each monitoring point increased rapidly.

In contrast with the Bazimen landslide, the Baishuihe landslide is a typical retrogressive landslide, which means that the failure began from the bottom of the slope. The sliding surface is an approximately straight line and the upper part had a relatively steeper slope and shallower depth (Fig. 21). The displacements
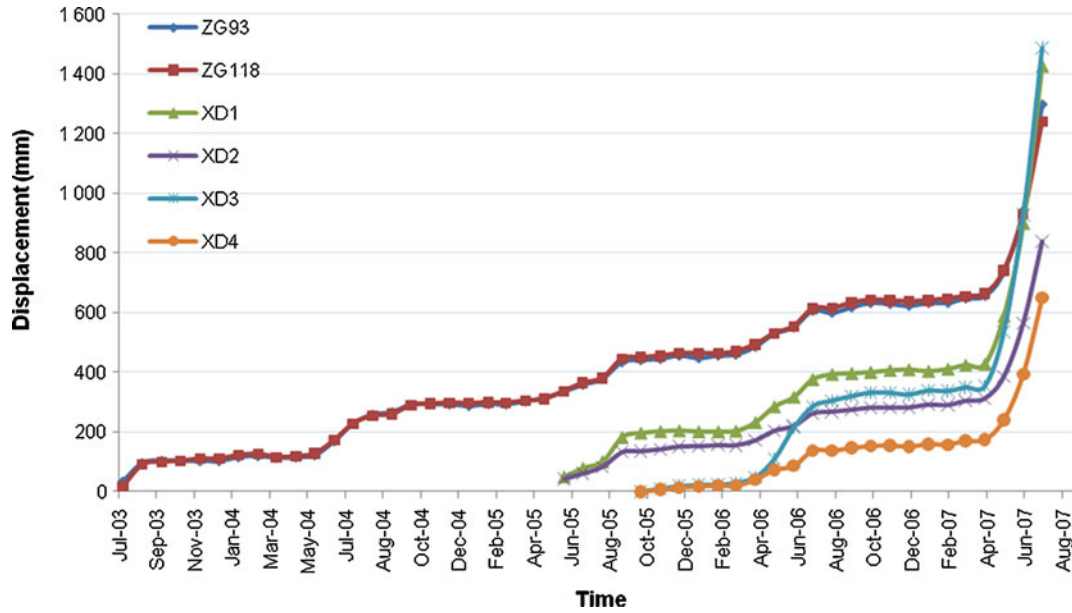

Fig. 17 Schematic cross-section $I - I'$ of the Baishuihe landslide (J_1x is the Xiangxi Formation of Lower Triassic)

Fig. 19 Displacement at six locations within Baishuihe landslide

were mainly concentrated in the area below the elevation at 250 m. Within this area, the displacement increments at the monitoring points in the front part of the landslide (XD2, XD3, and XD4) were much higher than that at ZG93 and ZG118.

Compared with the Bazimen landslide, the Baishuihe landslide proved to be more sensitive to the reservoir drawdown. The combined effect of precipitation and drawdown of the reservoir water level would cause the sliding of the frontal part of the landslide. The monitoring points ZG93 and ZG118 are believed to reflect the displacement characteristics of the entire sliding mass.

Prediction of trend displacement
Based on the above observations, we used the displacement at point ZG93 and the data before August 2006 to calibrate the model, and remaining data were used on the prediction model.

The single moving average method was adopted to extract the trend displacement with a cycle of 12 months (Fig. 22). Using the least squares method, the forecasting function was obtained (Eq. 6). Figure 22 shows the predicted trend displacement.

$$S_t = 0.0056t^3 - 0.2497t^2 + 17.264t + 88.151 \qquad (6)$$

where S_t is the displacement at time t and t is time.

Prediction of periodic displacement
The periodic displacement of the landslide was obtained by subtracting the trend term from the observed total displacement (Fig. 23).

Compared to the Bazimen landslide, the change of reservoir level had a greater influence on the Baishuihe landslide displacement. For
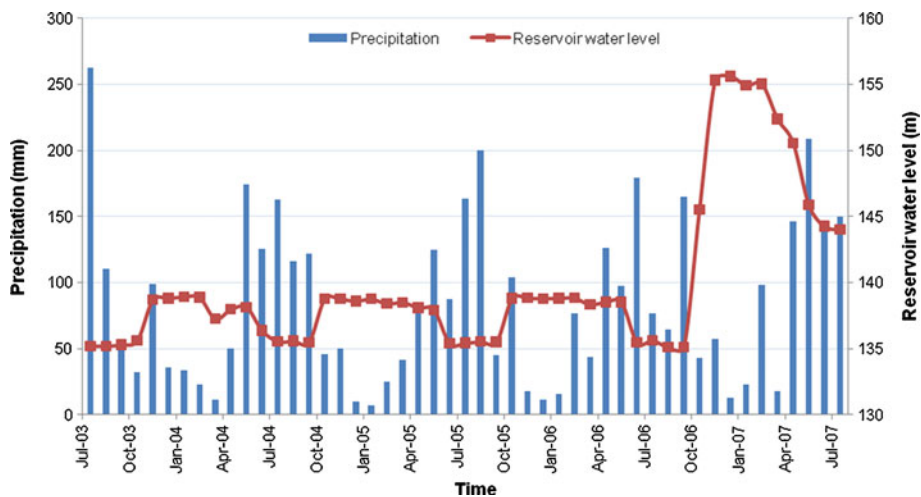

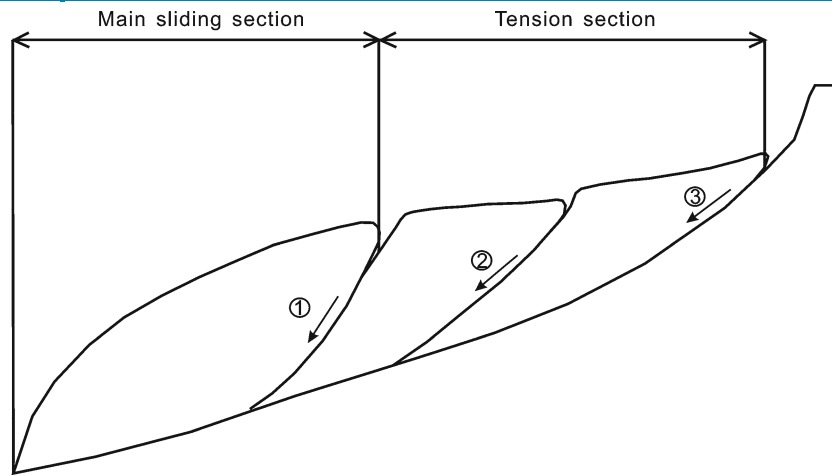**Fig. 20** Rainfall and reservoir level during period 2003-2007

Fig. 21 Sketch map of deformation mechanism of retrogressive landslide at the Baishuihe landslide

this reason, an additional influence factor was included to improve the response (Table 1):

1. The accumulated precipitation during the last 1-month period.
2. The accumulated precipitation over a two-month period.
3. The change of reservoir level during the last month.
4. The average elevation of the reservoir level in the current month.
5. The accumulated displacement increment during 1 year.

The error was less than 1×10^{-4} after the network training for 2,400 times. The neural network was then adopted to predict the observed displacement.

The predicted periodic displacement is shown in Fig. 24. It is noted that, in May 2005, under a 355-mm rainfall in 2 months and a 9-m drawdown of the reservoir water level, the predicted displacement increased rapidly and showed continued growth in July and August. Two portions of the curve show larger discrepancies between predicted and measured displacement: October 2006 and July 2007. The errors were 14.6 and 12.8 % separately. Both were subjected to fluctuation of the reservoir water level. The reason for the differences may be an inadequacy of the neural network approach, which could cause deviation in the predicted relationship between influencing factors and landslide displacement.

Total displacement

To obtain total displacement, the predicted trend and periodic displacement terms were added together. Figure 25 shows that the proposed model provided an excellent prediction of the measured behavior. Comparing Figs. 24 and 25, the periodic displacement is the critical component determinant for the total displacement.

Conclusion

Observations of two typical colluvial landslides in the Three Gorges Reservoir showed both stepwise displacements and alternations of accelerating and decelerating movements, which are attributed to the combined effect of precipitation and fluctuation of the reservoir level.
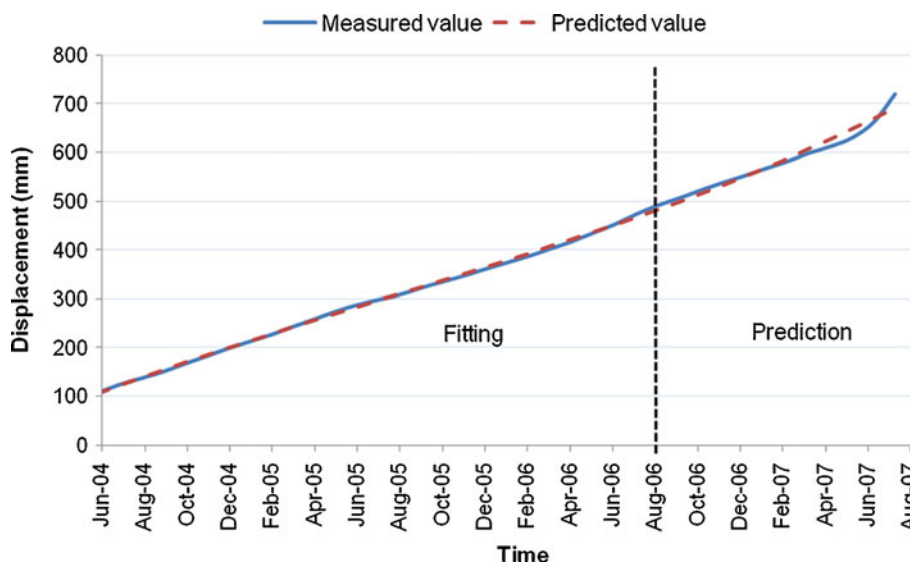

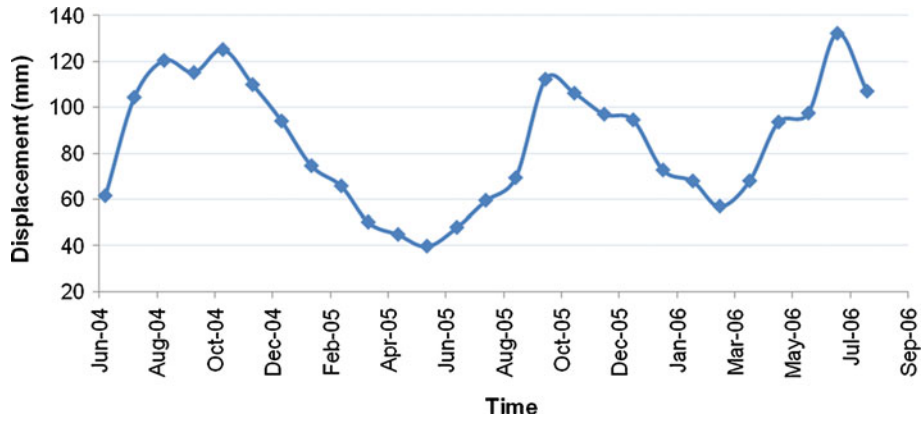**Fig. 22** Measured and predicted trend term of displacement at the Baishuihe landslide

Fig. 23 "Measured" (after removal of trend) periodic displacement with calibrated model, Baishuihe landslide
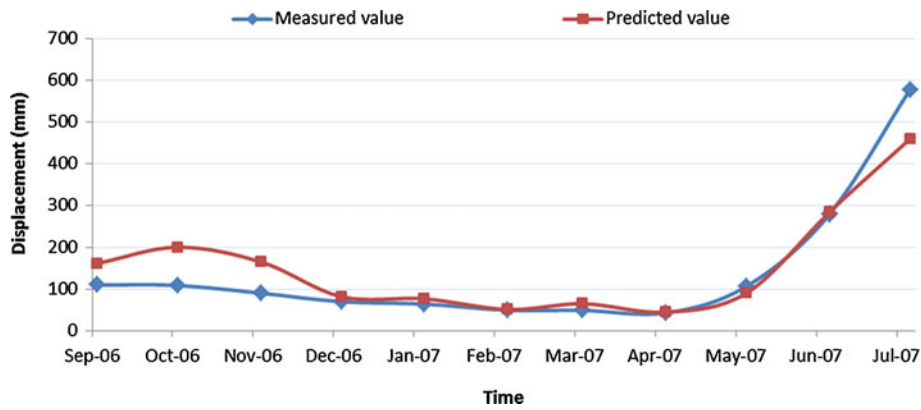

Fig. 24 Comparison between predicted and measured periodic displacement at Baishuihe landslide
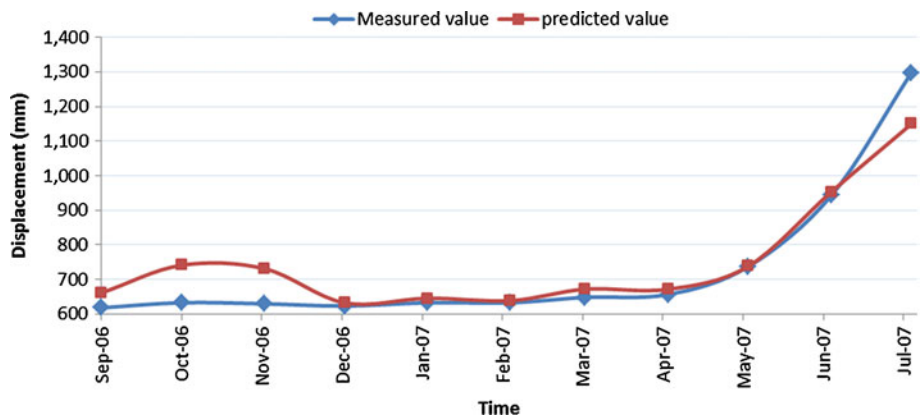

Fig. 25 Comparison between predicted and measured total displacement at Baishuihe landslide

With the time series models, the displacement could be divided into a trend term and a periodic term. A good prediction of the periodic displacement was essential to ensure an accurately predicted total displacement. The prediction should be based on the analysis of the deformation mechanism and the dominant influencing factors.

The analysis of the displacement in two landslides, advancing landslide and retrogressive landslide, required the application of different influence factors in order to establish a reliable prediction of the response. With the characteristics of the multivariate network mapping of a back-propagation neural network model, the results provided an accurate prediction of the measured behavior for two landslides. The average errors were only 1.3 and 3.04 % separately. The analyses showed that it was insufficient to analyze the displacement based only on the observed displacements versus time. It was necessary to establish the relationship between the displacement and each influencing factor and to consider the dominant effect of the periodic variation of the triggers (precipitation and regulation of reservoir) on the periodic displacement. It would be useful to apply this analysis method to other landslides to confirm these conclusions.

In each case, a typical monitoring point was selected for the analysis. A single point is insufficient to describe the deformation characteristics for an entire landslide. To achieve a more comprehensive and more accurate prediction and to further evaluate the proposed forecast model, the deformation characteristics and displacement trend at several monitoring points in different parts of the landslide should be analyzed and compared with the results of the model.

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