

Application of a two-step cluster analysis and the Apriori algorithm to classify the deformation states of two typical colluvial landslides in the Three Gorges, China

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Abstract Several extensive landslides have occurred in the vicinity of the Three Gorges Reservoir since its initial impoundment in June 2003. A reduction of the landslide risk is essential for the safety and security of lives and property in the region. This study analyses the deformation states of two typical colluvial landslides (the Baijiabao and Laoshewo landslides) using 6 years of monitoring data, a two-step cluster analysis, and the Apriori algorithm. The landslide displacement versus time curves exhibit step-like patterns, and the landslide deformation is highly correlated with fluctuations in the reservoir level and seasonal precipitation. To determine different types of landslide deformation, the monthly displacement curves of the colluvial landslides are classified into three types using a two-step cluster analysis: initial deformation, constant deformation, and rapid deformation. Five driving factors were selected as the antecedents for the Apriori algorithm to obtain rules that describe the relationships between the landslide deformation and the influential parameters. These factors include the cumulative precipitation over the previous month, the maximum daily precipitation during the

current month, changes in the reservoir level over the previous month, cumulative increases in the reservoir level and the average reservoir level during the current month. The analytical results were validated by comparing them with observed landslide deformation characteristics using three measurement standards: support, confidence and lift. The results show that the combined method of a two-step cluster analysis with the Apriori algorithm can effectively model the landslide deformation states that are associated with the Baijiabao and Laoshewo landslides. Moreover, this method may serve as a potential reference for deformation analyses of colluvial landslides in the Three Gorges.

Keywords Landslides · Deformation · Apriori algorithm · Two-step cluster · Three Gorges Reservoir

Introduction

The Three Gorges Dam on the Yangtze River in western Hubei Province, China, is the largest hydroelectricity project in the world, and it has a designated maximum reservoir level of 175 m. The geomorphology of the Three Gorges is characterized by rugged topography with hills that range in elevation from 800 to 2000 m. The Yangtze River generally crosses the study area in the NWW–SEE direction. The supracrustal Sinian–Jurassic sedimentary cover is widespread in the region and is mainly composed of marly limestone, mudstone, shale, sandstone and siltstone, and these units are highly susceptible to landslides. In addition, the study area is located on the NE flank of the Zigui syncline, which has a NNE–SSW trending axis. The numerous fault zones that follow the NE–SW orientation of the fold systems tend to

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form weaker zones of tectonically stressed rock with high landslide susceptibility (Fourniadis et al. 2007; Wu et al. 2013). The reservoir is located in a subtropical monsoonal climate, which typically experiences hot and humid summers and cold and dry winters, and the annual average rainfall is 1006 mm. Because the environment is topographically, geologically, and climatically conducive to the formation of landslides, the Three Gorges Reservoir suffers from frequent landslides that directly affect the dam's operations and navigability as well as the safety of human lives and property.

Colluvial landslides are landslides that occur in Quaternary deposits or in unconsolidated deposits from before the Quaternary period, which are generally characterized by a loose composition, high porosity and permeability, and significant viscoplastic deformations (He et al. 2008). Moreover, colluvial landslides are the most common form of reservoir-induced landslides in the region; they account for 52.82 % of the landslides in the Three Gorges and present a substantial risk. The number of catastrophic colluvial landslides is rapidly increasing because of the high reservoir storage, long durations of water exposure, reservoir level fluctuations and seasonal precipitation of approximately 30 m. Several pre-existing colluvial landslides, including the Baijiabao, Laoshewo, Shuping, Baishuihe, Xintan and Bazimen landslides, have recently reactivated or begun deforming (Wang et al. 2008; Xia et al. 2013). These landslides are located along both sides of the Yangtze River and its tributaries. Reservoir-induced colluvial landslides are closely related to fluctuations in the reservoir level and seasonal precipitation (Miao et al. 2014; Jiao et al. 2014). The intensity of rainfall events and the paths of the centres of the rainstorms greatly influence the occurrence of landslides. Rainfall, especially in the form of rainstorms, is the dominant factor that is responsible for inducing landslides (Zhou et al. 2002; Pradhan and Lee 2010; Liu et al. 2011; Lian et al. 2014). The infiltration of rainfall reduces the shear strength at the slip surface by increasing the pore water pressure, which results in greater landslide displacement. Therefore, significantly increased displacements often follow heavy rainfall events. Field investigations in the Three Gorges region have shown that continuous rainfall is a contributing factor to landslide hazards. During continuous rainfall, the sloped surfaces become partially saturated (Jian et al. 2014). Several physical similarity models have been developed to analyse changes in the seepage field and their effects on landslide stability in relation to fluctuations in reservoir level (Van Asch et al. 1996; Huang et al. 2014). Several factors that are related to the reservoir level have been used to assess landslide susceptibility and predict landslide displacements (Zhang et al. 2005; Du et al. 2013; Ren et al. 2015; Wang et al. 2014), including the cumulative displacement, the

maximum continuous drawdown, and the average reservoir levels during the current month.

Predicting active colluvial landslide deformation is important for an early warning system because the extent of these potential disasters can be minimized if the sliding mechanism is understood and the potential triggers are determined (Pradhan 2010a). The need for this type of study in the Three Gorges has attracted the attention of the Chinese government, engineers, and planners that are involved in investigating landslide hazards, and monitoring and countermeasure projects for disaster mitigation have been developed for several typical landslides. To mitigate future disasters, we applied a method that incorporates 6 years of monitoring data, a two-step cluster analysis, and the Apriori algorithm to determine the states of deformation for the Baijiabao and Laoshewo landslides in the Three Gorges Reservoir.

Landslide deformation analyses are considered to be a critical initial step for landslide hazard mitigation and management. Landslide displacement is a typical characteristic of landslide deformation behaviour, and predictions of this type of displacement can be expressed as the probability of landslide deformation that is associated with a set of geo-environmental conditions. However, because of the complexity and random characteristics of landslide displacement, generating reliable predictions of landslide displacement is not easy. Therefore, several studies have focused on predicting landslide displacements. There are three basic types of predictive methods: deterministic models, statistical models and computational intelligence models (Li et al. 2012; Pradhan 2013). Deterministic models use general creep theory, large-scale laboratory experiments and field-monitored physical parameters and are good tools for predicting landslide events (Helmstetter et al. 2004; Mufundirwa et al. 2010). The early warning criteria that were developed for the Yuhuangge colluvial landslide based on comprehensive monitoring data and landslide monitoring of the Three Gorges Reservoir area provide an example of a deterministic model (Yin et al. 2010). These models have proven to be suitable for several landslides and can provide an objective physical explanation of the processes. Statistical models that utilize definite equations have also been widely applied to predict landslides. These approaches are primarily valid for landslides with similar deformation characteristics (Randall 2007; Pradhan et al. 2011). In recent years, computational intelligence methods have been successfully developed to determine the underlying rules and features in uncertain, nonlinear landslide systems (Pradhan et al. 2010; Liu et al. 2014). Artificial neural networks (ANNs) and support vector machines (SVMs) are commonly used to explore the complex nonlinear relationships between landslide displacements and associated causal factors. However, these

methods cannot extract information or provide association rules for landslide deformation (Matías et al. 2010; Pradhan 2010b; Lv and Liu 2012; Chen and Zeng 2013; Zhu and Hu 2013; Li and Kong 2014; Niu et al. 2014). The Gauss process can also be used to predict landslide displacements; it was used to analyse a series of displacement monitoring data for the New Wolong Temple landslide (Liu et al. 2012). Apriori algorithms are also widely employed to determine association rules in nonlinear modelling problems and have been successfully applied to wind speed forecasts and oral cancer operations (Tang et al. 2013; Guo et al. 2014). An effective and reliable early warning and assessment system for landslides requires deformation-related features, including the evolution mechanisms, major driving factors, and specific thresholds. Here, the Apriori algorithm is used to identify the deformation states of the Baijiabao and Laoshewo landslides in the Three Gorges Reservoir.

Correlating the movement of active landslides with environmental factors is important for understanding the complex characteristics of landslide deformation. The Baijiabao and Laoshewo landslides were selected as typical colluvial landslides in the Three Gorges Reservoir to explore the relationships between deformation and the major driving factors. The cumulative displacement versus time and the macroscopic deformation characteristics are analysed to extract the influential factors, and a two-step cluster analysis is adopted to convert the continuous displacement and conditioning factors into categorical variables. The deformation phases and influencing factors are used as the consequents and antecedents, respectively, for the Apriori algorithm to determine the association rules. The analytical results are then validated through a comparison with known landslide deformation characteristics using the three standards: support, confidence and lift. The software packages ArcGIS 10, SPSS 21 (a statistical programme), and MATLAB 2010b are used as analytical tools to manage and manipulate the data.

Methods

The deformation of an active landslide involves dynamic responses and a nonlinear evolution. A reliable deformation state analysis for colluvial landslides should be represented as association rules between the landslide deformations and the major driving factors. In this study, a hybrid method that involves a two-step cluster analysis and the Apriori algorithm is used to classify the deformation states of two typical colluvial landslides that are adjacent to the Three Gorges Reservoir. Based on the deformation characteristics of the landslides, the monthly displacements are divided into three deformation phases using the two-

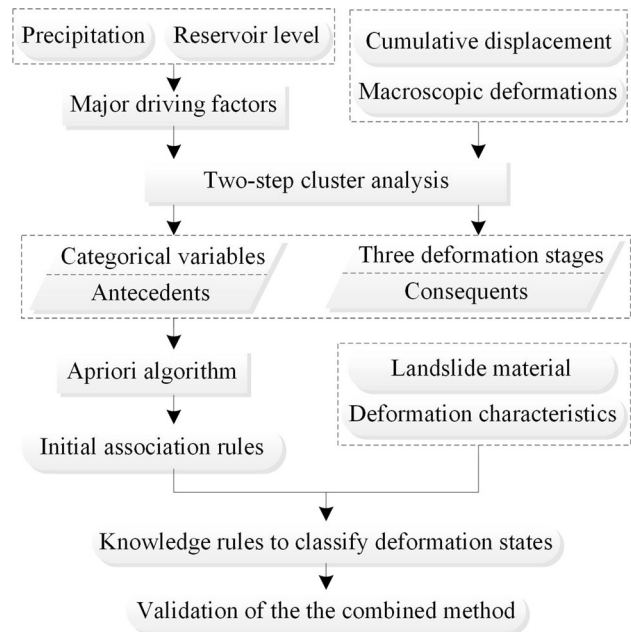


Fig. 1 Methodological flowchart of the research process

step cluster analysis, and the major influential factors are used as antecedent variables in the Apriori algorithm to determine the associations between these categorical factors and landslide deformation. Figure 1 presents a flowchart of the processes that are involved in this research.

Two-step cluster analysis

Clustering is a widely used technique in data mining applications for identifying patterns in datasets. The two-step cluster analysis procedure is an exploratory tool that was designed to reveal natural clusters within a dataset that would otherwise not be apparent. A two-step cluster analysis has several advantages compared with the *k*-means and balanced iterative reducing and clustering using hierarchies (BIRCH) clustering methods, including its ability to manage categorical and continuous variables and automatically select specific cluster numbers as well as its scalability (Chiu et al. 2001). This method is highly effective at identifying tolerant genotypes in biomedical studies (Martínez et al. 2006; Babic et al. 2012). Two-step cluster analysis is used to classify the monthly displacements and the major conditioning factors into categorical attributes, which are then used as the corresponding antecedents and consequents of the Apriori algorithm.

The two-step cluster analysis is a scalable cluster analysis algorithm that was designed to manage large datasets, such as time-series monitoring data of colluvial landslides. The analysis is composed of two steps: (1) the monitoring data are pre-clustered into many small sub-clusters, and (2) the sub-clusters that result from the pre-clustering step are

used as inputs and are clustered into the final number of clusters. In both the pre-clustering and clustering steps, a distance measurement determines how to calculate the similarity between the two clusters. To manage both continuous and categorical variables, the log-likelihood function is used to derive the distance measurement. The likelihood measurement places a probability distribution on the variables, which are all assumed to be independent. Continuous variables are assumed to be normally distributed, whereas categorical variables are assumed to be multinomial.

Apriori algorithm

The association rule algorithm is commonly used to identify relationships between items or features that occur synchronously in a database. The Apriori algorithm (Agrawal and Srikant 1994) is widely used to mine frequent item sets and learning association rules in a data-mining field. It seeks to generate the desired rules from large item sets and then uses these association rules as a reference during the decision-making process. Hence, the Apriori algorithm is employed in this study to explore the correlation between the landslide deformation types and the major environmental factors.

The problem for learning association rules can be defined as follows. Let $I = \{i_1, i_2, \dots, i_m\}$ be a set of literals called items and D be a set of transactions, where each transaction T is a set of items such that $T \subseteq I$. An association rule is represented as an implication form $(X \subset T) \Rightarrow (Y \subset T)$ and $X \cap Y \neq \emptyset$. Various measures of significance can be used to select effective rules from the set of all possible rules. The best-known constraints are minimum thresholds for the support and confidence. The rule $X \Rightarrow Y$ holds in the transaction set with *confidence* c if $c\%$ of the transactions in D contain both X and Y . The rule $X \Rightarrow Y$ has support s in the transaction set D if $s\%$ of the transactions in D contain $X \cup Y$. In addition, *lift* ($X \rightarrow Y$), which is calculated as the confidence of the rule divided by the support of the right-hand side, can be used to evaluate the resulting rules. The lift represents the probability ratio. If the lift is equal to 1, X and Y are independent. The more the lift is above 1, the more likely that X and Y will occur together in a transaction because of a relationship between them and not because of a random occurrence.

The Apriori algorithm is usually divided into two separate steps. First, minimum support is applied to find all of the frequent item sets in a database. Second, these frequent item sets and the minimum confidence constraint are used to form rules. The Apriori algorithm uses a bottom-up approach in which frequent subsets are extended one item

at a time, and groups of candidates are tested against the data. The algorithm terminates when no further successful extensions are found. The pseudocode of the Apriori algorithm is as follows:

Procedure Apriori (T , *minsupport*) { // T is the database, and *minsupport* is the minimum support

$L_1 = \{\text{frequent items}\};$

for ($k = 2; L_{k-1} \neq \emptyset; k++$) {

$C_k =$ candidates generated from L_{k-1} ; // is the Cartesian product $L_{k-1} \times$

L_{k-1} and //eliminates any $k-1$ size item set that is not common.

for each transaction t in database do {

Increase the count of all candidates in C_k that are contained in t ;

$L_k =$ candidates in C_k with *minsupport*; } // end for each

} // end for

return $\cup_k L_k$; }

Case studies

Colluvial landslides in the Three Gorges Reservoir are triggered by the combined effects of reservoir level fluctuations and seasonal precipitation. The reservoir is located in western Hubei Province, which experiences heavy rainfall. The average annual precipitation is 1100 mm. Rainfall is generally concentrated in the summer, and the maximum daily precipitation is between 150 and 240 mm. Several landslides have been reactivated because of the high water level associated with the impoundment of the reservoir. The Baijiabao and Laoshewo landslides (Fig. 2), which are two typical colluvial landslides, are selected as case studies to identify the association rules between landslide deformation characteristics and the major driving factors of the landslides.

Baijiabao landslide

Geological background

The Baijiabao landslide occurred in the village of Xiangjiadian in Zigui County on the right bank of the Xiangxi River ($30^{\circ}58'59.9''\text{N}$, $110^{\circ}45'33.4''\text{E}$) approximately 2.5 km upstream from the Xiangxi estuary (Fig. 2). Figure 3 shows a photograph of the Baijiabao landslide

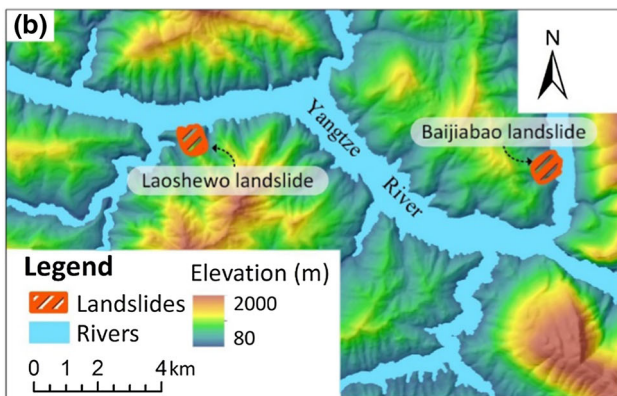
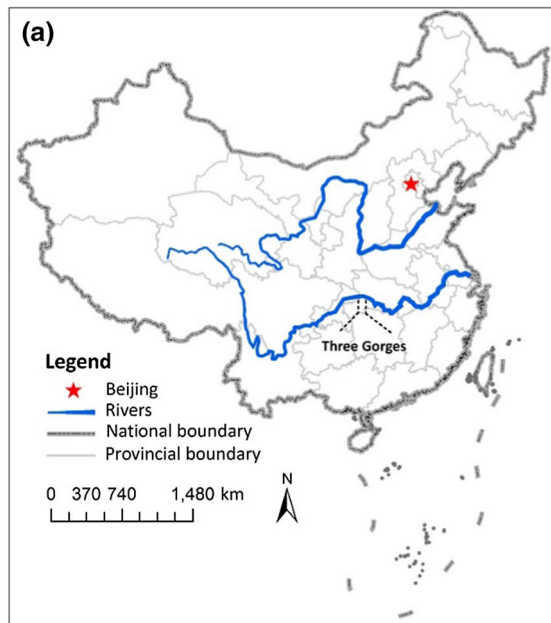


Fig. 2 Location of the Three Gorges and the Baijiabao and Laoshewo landslides in China: **a** map of China, **b** map showing the location of the Baijiabao and Laoshewo landslides

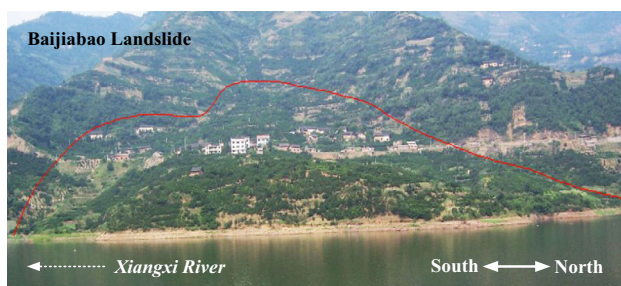


Fig. 3 Photograph of the Baijiabao landslide from the opposite bank of the Xiangxi River

that was taken from the opposite bank of the Xiangxi River. The landslide extends to the Xiangxi River, and the elevation of the toe rupture surface varies between 125 and 135 m. The landslide’s upper boundary is defined by the

bedrock at an elevation of 265 m. The Triassic Badong Formation underlies much of this landslide and is highly susceptible to landslides. The sliding bed is primarily composed of feldspar–quartz sandstone and mudstone, and Quaternary deposits and soil are found only at the frontal section of the sliding bed. The dip of the strata is approximately 30°, and the dip direction is approximately 285°, which is typical of anclinal slopes. The sliding mass mainly consists of interbedded greyish-yellow to brownish-yellow silty clay, fragmented rubble and debris soil. The short tongue-shaped landslide covers an area of 0.22 km² and has a maximum width of 500 m and a length of 550 m. Borehole monitoring data indicate that the deeper sliding mass has an average thickness of approximately 45 m and an estimated volume of 9.9 × 10⁶ m³, and the shallow sliding mass has an average thickness of 30 m and an estimated volume of 6.6 × 10⁶ m³. The Baijiabao landslide was induced by precipitation and the high level of the water that was impounded in the Three Gorges Reservoir, and a series of surface deformations have been observed on the ground.

Deformation characteristics

The Baijiabao landslide is one of the key monitored landslides in the study area. From June to July 2007, ground cracking became increasingly severe; in particular, two arc-shaped tension cracks developed at the head of the landslide (Fig. 4a). These cracks were 160 m long and 10 cm deep, and the right crack was 1–3 cm wide, whereas the left crack was 1–5 cm wide. Additional tension cracks formed along the road in the middle part of the landslide and severely damaged the road surface (Fig. 4b). Between April and June 2008, a sudden drawdown in the reservoir level accelerated the landslide deformation, and heavy rainfall in July and August then caused relatively rapid displacements. After 6 days of continuous rainfall in May 2009, cracks developed along the road in the right frontal part of the landslide on May 27, 2009. A rapidly deforming zone formed in the left frontal part of the landslide at an elevation of 200 m on June 13, 2009. Figure 5a shows the ground cracks along the road; they trend N20E and are 15 cm wide and 25 cm deep. Figure 5b shows the arcuate collapse at an elevation of 160 m, which is 30 m long and 30 cm deep. In June 2011, ground cracks, particularly cracks along Zixing Road, formed mainly in the middle part of the landslide; they were triggered by a drawdown in the reservoir level and heavy rainfall (Fig. 6). In June 2012, tension cracks that were induced by heavy rainfall and a drawdown in the reservoir level were observed mainly along the northern and southern boundaries of the landslide (Fig. 7).

Fig. 4 Tension cracks in the upper and middle parts of the landslide

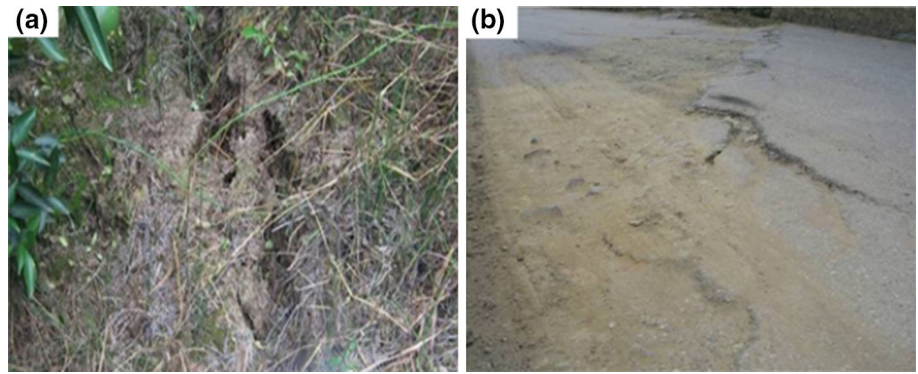


Fig. 5 Ground cracks along the road and the arcuate collapse in the left frontal part of the landslide

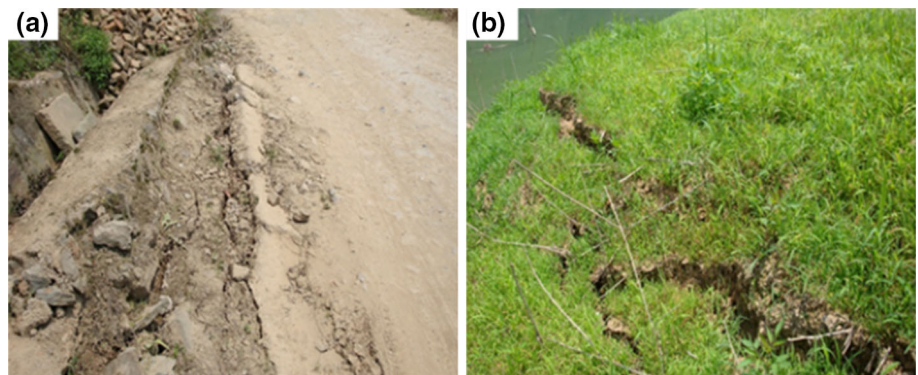


Fig. 6 Damage along Zixing Road in the middle part of the landslide

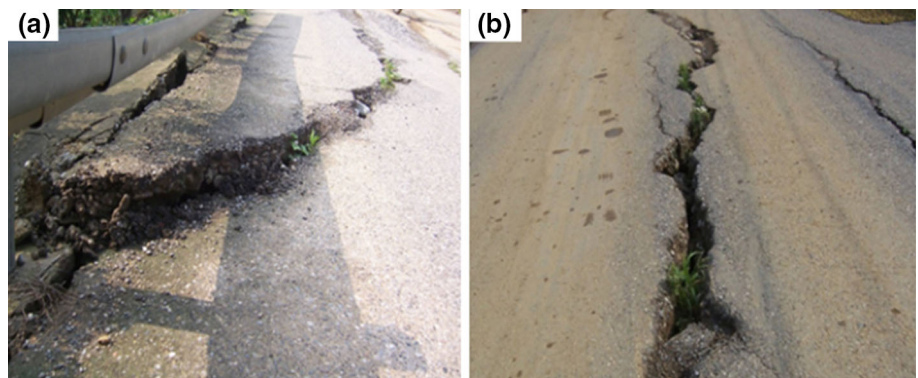
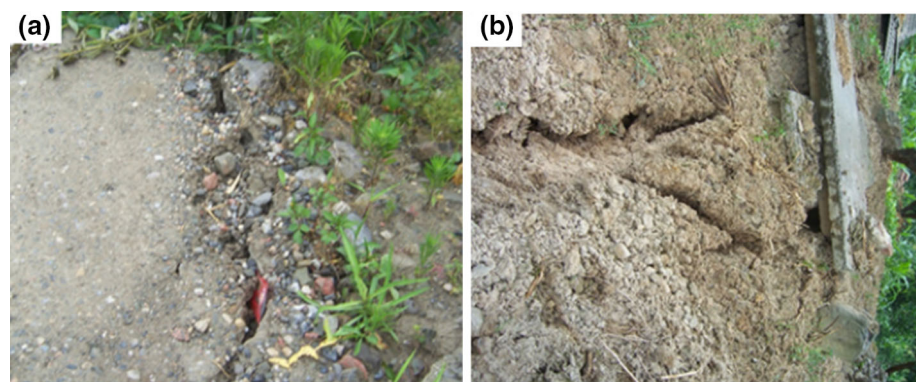


Fig. 7 Tension cracks along the northern and southern boundaries of the landslide



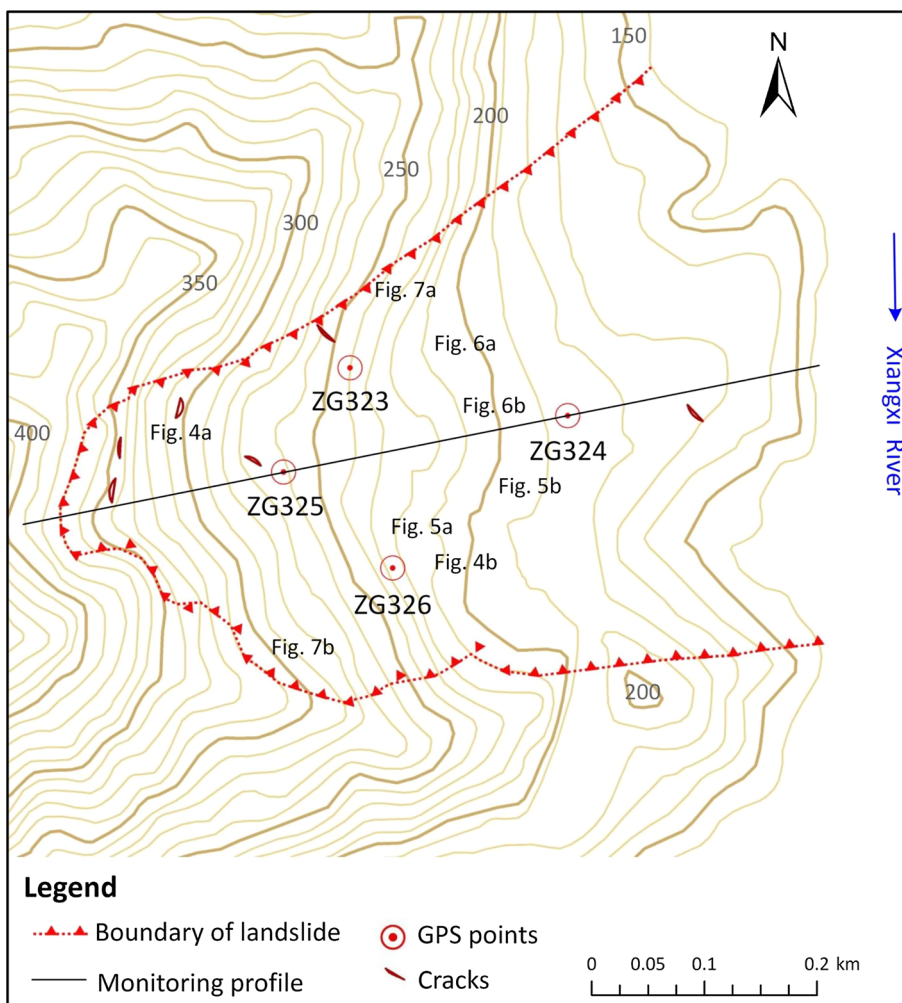
Deformation state analysis

The deformation characteristics of the Baijiabao landslide indicate that the tension cracks in the middle part of the landslide are more common and severe than those in other parts of the landslide. To analyse the factors that influence the landslide and assess the landslide’s deformation tendencies and types, a professional monitoring system was established in November 2006. Figure 8 shows the arrangement of four Global Positioning System (GPS) monitoring points as well as the locations of Figs. 4, 5, 6 and 7. GPS monitoring points ZG323 and ZG326 were installed in the middle part of the landslide, and the monitoring results from points ZG323 and ZG326 are at least qualitatively consistent with the observed ground deformation, including the ground cracks. There are 74 groups of displacement data for the period November 2006 to December 2012. Each time step represents 1 month. Considering the completeness of the data for the monitoring points and the deformation characteristics, the monitoring

data from these two points are used to analyse the deformation behaviour of the Baijiabao landslide. Plots of the cumulative displacement, monthly precipitation, and fluctuations in the reservoir level versus time for monitoring points ZG323 and ZG326 are shown in Fig. 9. The landslide deformation exhibits a step-like pattern during the monitoring period; the abrupt increases in the landslide displacement may have been triggered by intense rainfall and fluctuations in the reservoir level, especially when the reservoir level rose or fell suddenly.

The Baijiabao landslide is located along the right bank of the Xiangxi River and represents a typical reservoir-induced colluvial landslide. Figure 9 shows that the Three Gorges Reservoir went through three impoundment phases during the study period, including fluctuations in the reservoir level between elevations of 145 and 156 m from November 2006 to September 2008, 145 and 172 m from October 2008 to September 2010, and 145 and 175 m from October 2010 to December 2012. Reservoir level fluctuations were the most important influencing factor from

Fig. 8 Contour map of the Baijiabao landslide showing the locations of the monitoring points and the observed surficial cracks. The locations of Figs. 4, 5, 6 and 7 are marked



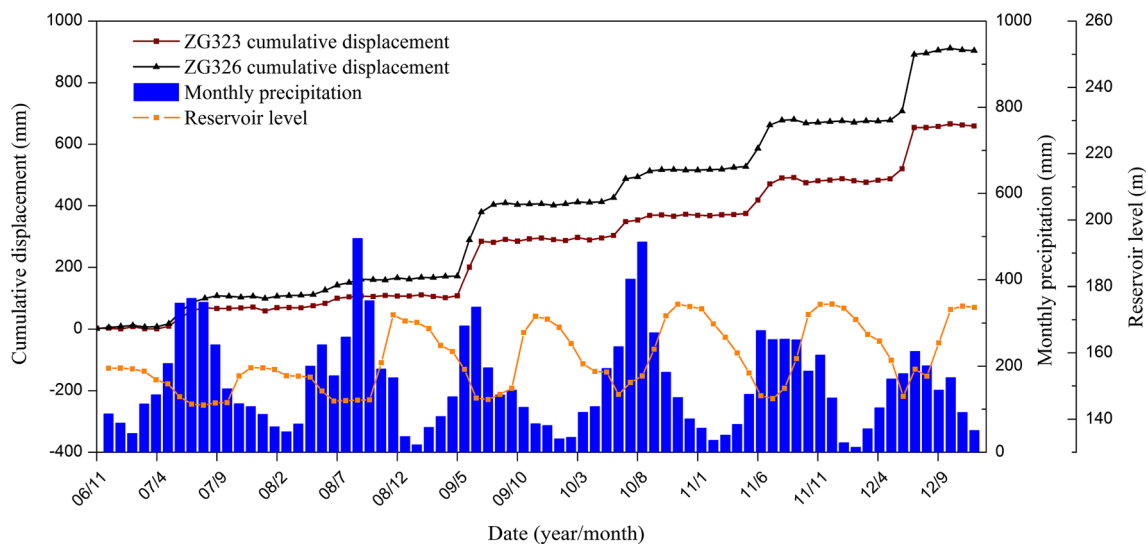


Fig. 9 Cumulative displacements for points ZG323 and ZG326 between 2006 and 2012; the monthly precipitation and fluctuations in the level of the Three Gorges Reservoir are also shown

November 2006 to December 2012. The landslide deformation was more severe during the increases and decreases in the reservoir level and particularly when the reservoir level dropped significantly over consecutive days. Although monthly precipitation is not completely proportional to the increase in cumulative displacement, precipitation was the second most important triggering factor and is positively correlated with the displacement rate, and the peaks in the monthly rainfall coincide with the sharp increases in the monthly displacement. Therefore, based on the deformation characteristic and the dynamic response relationship between the monthly displacement and reservoir level fluctuations and seasonal precipitation, the monthly displacements at monitoring points ZG323 and ZG326 are classified into three deformation phases using two-step cluster analysis: initial, constant, and rapid deformation phases (Table 6), and five factors that contribute to landslide deformation are selected as input variables to determine the deformation states of colluvial landslides. These factors are the cumulative precipitation over the previous month (CPPM), the maximum daily precipitation during the current month (MDPM), the change in reservoir level over the previous month (RLCM), the cumulative increase in the reservoir level (CIRL) and the average reservoir level during the current month (ARLM). A two-step cluster analysis is adopted to classify these five factors into categorical attributes. The corresponding categorical results are listed in Tables 1, 2, 3, 4 and 5.

Three deformation phases and five categorical factors are used as the consequents and antecedents, respectively, for the Apriori algorithm to determine the association rules between the landslide deformation and these driving

Table 1 Results of the two-step cluster procedure performed on the cumulative precipitation over the previous month

Clusters	Cumulative precipitation (mm)
Low	1.3–81.3
Moderate	84.5–170.4
High	177.2–311.0

Table 2 Results of the two-step cluster procedure performed on the maximum daily precipitation during the current month

Clusters	Maximum daily precipitation (mm)
Very low	0.8–9.3
Low	10.1–33.3
Moderate	34.3–64.0
High	66.1–136.8

Table 3 Results of the two-step cluster procedure performed on the changes in reservoir level over the previous month

Clusters	Reservoir level change rate (m/day)
Slow	0.001–0.090
Ordinary	0.103–0.319
Fast	0.381–0.621

factors. For the training models, 80 % of the dataset is randomly selected as training samples, and the remaining 20 % is used for validation testing. The Apriori algorithm with the optimal parameters is trained and used to determine the association rules for points ZG323 and ZG326. The values of the minimum antecedent support (%) and the

Table 4 Results of the two-step cluster procedure performed on the cumulative increase in the reservoir level during the current month

Clusters	Cumulative increments (m)
Slow	0.00–5.00
Ordinary	5.80–13.90
Fast	14.20–22.38

Table 5 Results of the two-step cluster procedure performed on the average reservoir level during the current month

Cluster	Average reservoir level (m)
Low	144.24–151.07
Moderate	151.93–163.00
High	163.57–174.73

Table 6 Results of the two-step cluster procedure performed on the monthly cumulative displacements

Deformation phases	Monthly displacement (mm)	
	ZG323	ZG326
Initial deformation	<5.02	<8.13
Constant deformation	5.03–14.84	8.14–19.08
Rapid deformation	>14.85	>19.09

minimum rule confidence (%) are set to 1.0 and 75, respectively. The representative association rules for the three deformation phases at GPS monitoring points ZG323 and ZG326 are shown in Tables 7 and 8, respectively.

To illustrate the meanings of these rules, three of the rules at different deformation states are provided as examples. IF ARLM is low (from 144.24 to 151.07 m), RLCM is fast (from 0.381 to 0.621 m/day), and MDPM is moderate (from 34.3 to 64.0 mm), THEN the landslide is in

a state of rapid deformation with support, confidence and lift of 8.00, 100 and 1.39, respectively. This rule suggests that the moderate MDPM supplements and increases the groundwater level, ARLM is low, and the reservoir level is increasing rapidly, but the groundwater level of the landslide is still higher than the reservoir level, which causes dynamic water pressure and accelerates the landslide deformation. IF MDPM is moderate (from 34.3 to 64.0 mm), CPPM is moderate (from 84.5 to 170.4 mm), RLCM is normal (from 0.103 to 0.319 m/day), and CIRL is slow (from 0.00 to 5.00 m), THEN the landslide is in a state of constant deformation with support, confidence and lift of 4.00, 100 and 3.13, respectively. This rule suggests that the rate that precipitation increases the groundwater level is slower than in the rapid deformation stage, so the difference between the reservoir level and the groundwater level decreases, the dynamic water pressure of the landslide decreases, and the rate of deformation is slower than in the rapid deformation stage. IF MDPM is very low (from 0.8 to 9.3 mm), CPPM is low (from 1.3 to 81.3 mm), ARLM is moderate (from 151.93 to 163.00 m), and CIRL is slow (from 0.00 to 5.00 m), THEN the landslide is in a state of initial deformation with support, confidence and lift of 5.33, 100 and 1.39, respectively. This rule suggests that the precipitation is very low and supplements the groundwater level only slightly, and the reservoir is at a medium level and is equal to or higher than the groundwater level, which generates hydrostatic pressure and slows the landslide deformation.

Laoshewo landslide

Geological background

The Laoshewo landslide is located in the village of Huangjincun in Zigui County on the right bank of the

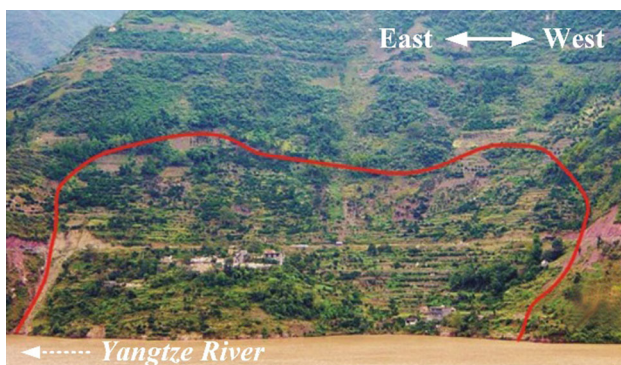
Table 7 Association rules for the landslide deformation types at GPS monitoring point ZG323

Consequent	Antecedent	Support (%)	Confidence (%)	Lift
Rapid deformation	CPPM = high, RLCM = fast and CIRL = ordinary	6.67	80	2.50
Rapid deformation	CPPM = high, MDPM = moderate and ARLM = low	12.00	78	1.58
Rapid deformation	MDPM = moderate, ARLM = low, RLCM = fast and CIRL = slow	5.33	75	4.33
Constant deformation	MDPM = moderate, CPPM = moderate, RLCM = ordinary and CIRL = slow	4.00	100	3.13
Constant deformation	MDPM = moderate, CPPM = moderate, RLCM = ordinary and ARLM = moderate	5.33	75	2.34
Constant deformation	MDPM = moderate, CIRL = slow, RLCM = ordinary and ARLM = moderate	5.33	75	2.34
Constant deformation	CPPM = moderate, RLCM = slow, MDPM = low and CIRL = slow	5.33	75	2.34
Initial deformation	ARLM = high, RLCM = ordinary, MDPM = low, CIRL = slow and MDPM = low	9.33	86	1.74
Initial deformation	MDPM = very low, ARLM = moderate and RLCM = slow	8.00	83	1.69
Initial deformation	MDPM = very low, ARLM = moderate and CIRL = slow	5.33	75	1.52
Initial deformation	MDPM = very low, ARLM = moderate, RLCM = slow and CIRL = slow	5.33	75	1.52

Table 8 Association rules for the landslide deformation types at GPS monitoring point ZG326

Consequent	Antecedent	Support (%)	Confidence (%)	Lift
Rapid deformation	CPPM = high, MDPM = moderate and ARLM = low	8.00	100	1.39
Rapid deformation	CPPM = high, ARLM = low and RLCM = ordinary	13.33	100	1.39
Rapid deformation	CPPM = high, RLCM = fast and CIRL = slow	9.33	100	1.39
Rapid deformation	ARLM = low, RLCM = fast and MDPM = moderate	8.00	100	1.39
Constant deformation	ARLM = low, RLCM = ordinary and CIRL = slow	76.00	79	1.10
Constant deformation	ARLM = low, RLCM = slow and MDPM = low	42.67	78	1.09
Constant deformation	ARLM = low, CPPM = moderate, RLCM = slow and MDPM = low	40.00	77	1.06
Constant deformation	ARLM = low, CPPM = moderate, MDPM = low and CIRL = slow	5.33	75	5.63
Initial deformation	MDPM = very low, ARLM = moderate and RLCM = slow	5.33	100	1.39
Initial deformation	MDPM = very low, ARLM = moderate, CPPM = low and CIRL = slow	5.33	100	1.39
Initial deformation	RLCM = slow, CPPM = low and MDPM = low	18.67	100	1.39
Initial deformation	CPPM = low, MDPM = low and CIRL = slow	28.00	100	1.39

Yangtze River (30°59'30.2"N, 110°35'27.4"E) 47 km upstream of the Three Gorges Dam (Fig. 2). As shown in Fig. 10, the armchair-shaped landslide covers an area of $1.2 \times 10^4 \text{ m}^2$ and has an estimated length of 320 m in the north–south direction and an estimated width of 400 m in the east–west direction. The landslide extends to the Yangtze River, the elevation of the upper rupture surface is approximately 270 m, and the eastern and western boundaries are defined by bedrock. The deeper sliding mass has an average thickness of approximately 25 m and an estimated volume of $3.0 \times 10^6 \text{ m}^3$. The landslide's slope gradient varies between 35° and 45°, and the main slip direction is approximately 342°. The sliding body is the contact zone between the bedrock and the colluvial soil and is mainly composed of gravel soils. The sliding bed is composed of thick clay, argillaceous siltstone, and fine siltstone layers. Deformation behaviour is mainly observed in the middle part of the landslide.

**Fig. 10** Photograph of the Laoshewo landslide from the opposite bank of the Yangtze River

Deformation characteristics

The Laoshewo landslide is an active colluvial landslide and is a key monitored landslide in the study area. From April to June 2007, many ground cracks that were associated with fluctuations in the reservoir level and rainfall formed on the ground surface. A crack formed and expanded in the middle-upper part of the landslide, and it reached a width of 12 cm, a length of 50 m, and a visible depth of 15 cm (Fig. 11a). A 20-m-long and 3-m-wide section collapsed in the middle part of the landslide and blocked the rural road (Fig. 11b). A series of ground cracks gradually developed in 2009, and the ground clearly settled in several places, particularly in the middle-rear section. Figure 12a shows 2- to 10-mm-wide tension cracks in the upper eastern flank of the landslide. Figure 12b shows a local slope collapse, which was primarily triggered by rainfall, along the road in the middle part of the landslide. This collapse has a total volume of 1–5 m³. During June 2012, the pre-existing cracks gradually expanded, and additional cracks appeared at the toe of the landslide. These new cracks had a dip direction of 230°, lengths of 1–2 m, and widths of 3–6 mm (Fig. 13a). An additional crack formed along the village road on the left part of the landslide; this crack had a dip direction from 115° to 135°, a length of 20 m, and a width of 1–3 cm (Fig. 13b).

Deformation state analysis

The macroscopic deformation characteristics of the Laoshewo landslide indicate that the deformation in the upper middle part of the eastern active block is much greater than the deformation in the frontal part. In the western active block, the deformation in the lower frontal part is more significant than in the upper rear part.

Fig. 11 Cracked and collapsed sections of the middle-upper and middle parts of the landslide

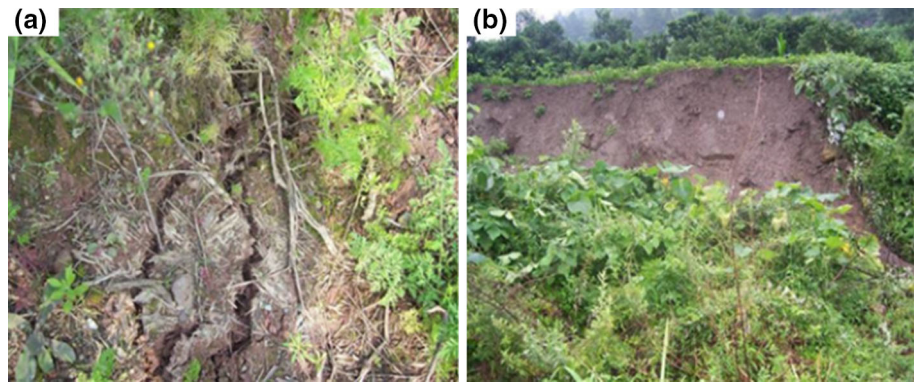


Fig. 12 Tension cracks and local slope collapse in the upper and middle parts of the landslide

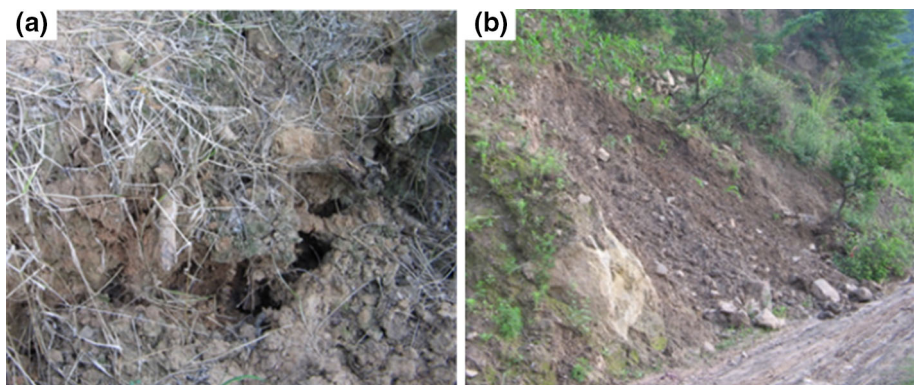


Fig. 13 Ground cracks at the toe and left sides of the landslide

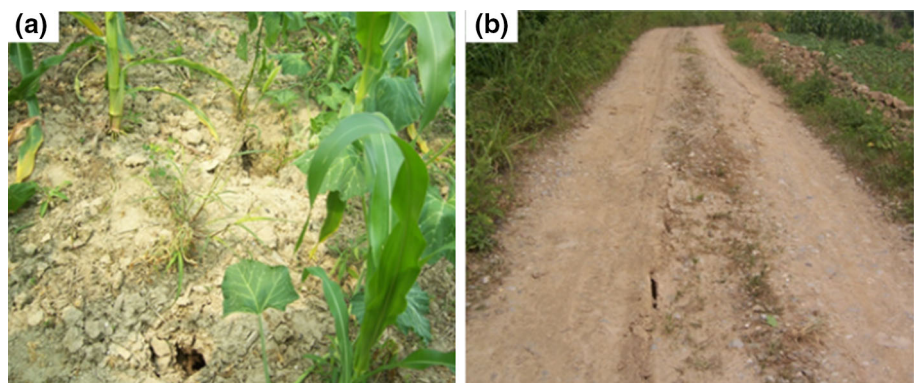


Figure 14 shows two monitoring profiles and four monitoring points that were installed on the landslide in October 2006 as well as the locations of Figs. 11, 12 and 13. GPS monitoring points ZG265 and ZG268 are located in the upper middle part of the eastern active block and in the lower frontal part of the western active block, respectively, and the monitoring results from these points are at least qualitatively consistent with the observed ground deformation, including ground cracks. There are 75 groups of displacement data for the period October 2006 to December 2012. Because of the completeness of the data of the monitoring points and the deformation characteristics, the monitoring data from these two points are used to analyse

the deformation behaviour of the Laoshewo landslide. Figure 15 shows plots of the cumulative displacements, monthly precipitation, and fluctuations in the reservoir level versus time at monitoring points ZG265 and ZG268. The landslide deformation exhibits a step-like pattern during the monitoring period, and the abrupt increases may have been triggered by changes in the reservoir level and rainfall.

The Laoshewo landslide is a typical reservoir-induced colluvial landslide. Figure 15 shows that the Three Gorges Reservoir went through three impoundment phases during the study period, including reservoir level fluctuations between elevations of 145 and 156 m from October 2006

Fig. 14 Contour map of the Laoshewo landslide showing the locations of the monitoring points and observed surficial cracks as well as the locations of Figs. 11, 12 and 13

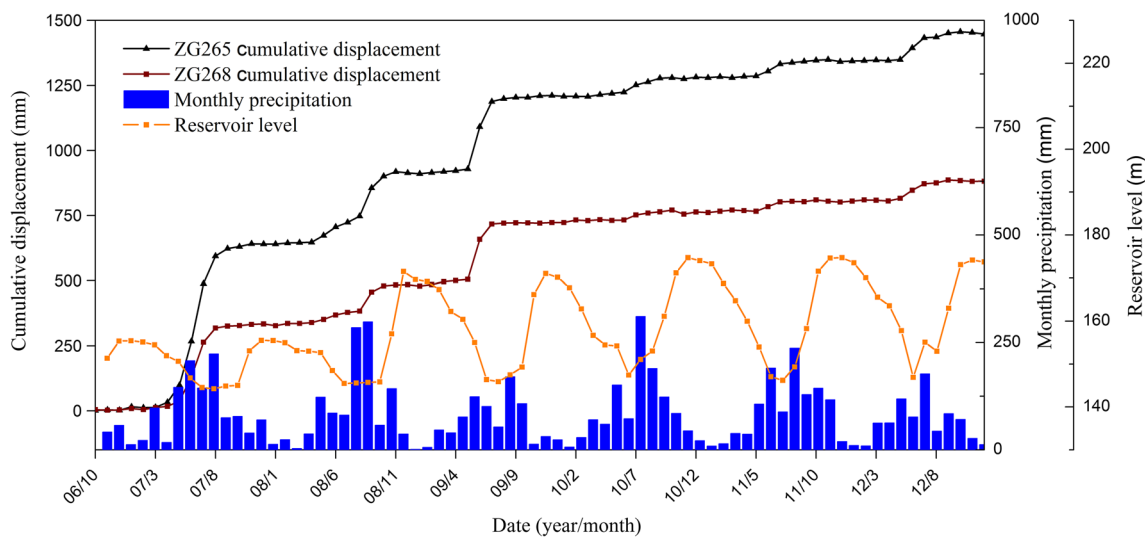
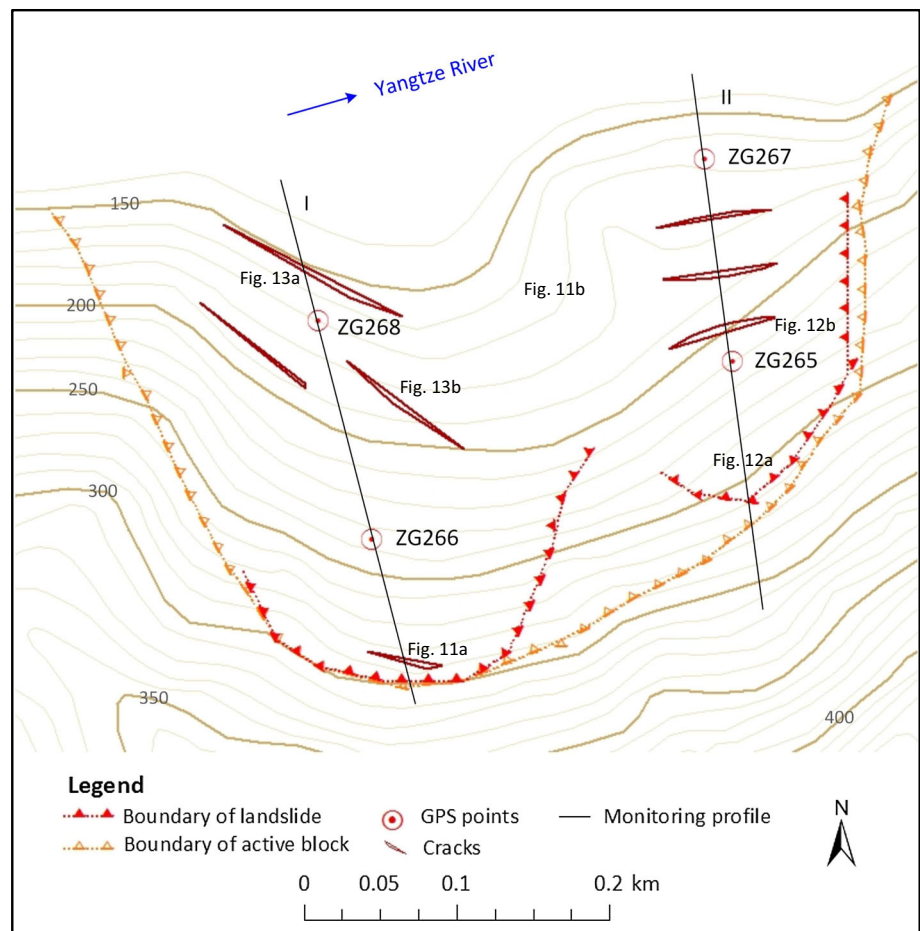


Fig. 15 Cumulative displacements at ZG265 and ZG268 between 2006 and 2012 and the monthly precipitation and reservoir level in the Three Gorges Reservoir

to September 2008, 145 and 172 m from October 2008 to September 2010, and 145 and 175 m from October 2010 to December 2012. After the first impoundment phase, GPS

monitoring point ZG268 was covered by the Yangtze River. Reservoir level fluctuations were the most important influencing factor in each year from October 2006 to

Table 9 Results of the two-step cluster procedure performed on the monthly cumulative displacements

Deformation phases	Monthly displacement (mm)	
	ZG265	ZG268
Initial deformation	<7.98	<4.38
Constant deformation	7.99–23.58	4.39–31.01
Rapid deformation	>23.59	>31.02

August 2009. During the first three fluctuations of the reservoir level, the landslide displacement increased during changes in the reservoir level and particularly when the reservoir level decreased. Precipitation was another important factor that influenced landslide deformation during this period. The loading of the landslide decreased after the first three large displacements, and the landslide was relatively stable from September 2009 to December

2012. Although the fluctuations in reservoir level and monthly precipitation are not completely proportional to the increase in cumulative displacement, a positive correlation was observed between the reservoir level fluctuations and landslide deformation, and the peaks in the monthly rainfall coincide with the sharp increases in the monthly displacement. The two-step cluster analysis is applied to group the monthly displacements of monitoring points ZG265 and ZG268 into three types: initial deformation, constant deformation, and rapid deformation (Table 9). The three deformation phases and five categorical factors are used as the consequents and antecedents, respectively, in the Apriori algorithm to determine the association rules between the landslide deformation and these driving factors. The Apriori algorithm with the optimal parameters is trained and used to determine the association rules for points ZG265 and ZG268. The values of the minimum antecedent support (%) and the minimum

Table 10 Association rules for the landslide deformation types at GPS monitoring point ZG265

Consequent	Antecedent	Support (%)	Confidence (%)	Lift
Rapid deformation	MDPM = high, ARLM = low, RLCM = ordinary and CIRL = slow	5.33	100	5.00
Rapid deformation	CPPM = high, ARLM = low, RLCM = ordinary and CIRL = slow	4.00	100	5.00
Rapid deformation	ARLM = low, RLCM = ordinary and CIRL = ordinary	9.33	86	4.29
Rapid deformation	MDPM = moderate, CPPM = moderate, ARLM = low and CIRL = slow	5.33	75	3.75
Constant deformation	CIRL = ordinary, MDPM = moderate and RLCM = ordinary	6.67	80	1.22
Constant deformation	MDPM = moderate, ARLM = low and CIRL = slow	6.67	80	1.22
Constant deformation	CIRL = ordinary, ARLM = low and RLCM = ordinary	18.67	79	1.20
Constant deformation	MDPM = moderate, CPPM = moderate, ARLM = low and CIRL = slow	18.67	79	1.20
Initial deformation	CPPM = moderate, ARLM = moderate and CIRL = slow	40.00	77	1.17
Initial deformation	ARLM = high, MDPM = low, RLCM = slow, CPPM = low and CIRL = slow	6.67	100	1.53
Initial deformation	MDPM = low, CPPM = low and CIRL = slow	28.00	86	1.31
Initial deformation	MDPM = very low, ARLM = moderate, RLCM = slow, CPPM = low and CIRL = slow	8.00	83	1.28

Table 11 Association rules for the landslide deformation types at GPS monitoring point ZG268

Consequent	Antecedent	Support (%)	Confidence (%)	Lift
Rapid deformation	MDPM = high, ARLM = low, RLCM = slow and CPPM = high	4.00	100	2.03
Rapid deformation	MDPM = high, ARLM = low, RLCM = ordinary and CIRL = slow	4.00	100	2.03
Rapid deformation	MDPM = moderate, RLCM = fast and CPPM = high	4.00	100	2.03
Constant deformation	MDPM = moderate, ARLM = moderate and CIRL = slow	4.00	100	2.03
Constant deformation	CIRL = ordinary, ARLM = moderate and MDPM = low	4.00	100	2.03
Constant deformation	RLCM = ordinary, CPPM = moderate and MDPM = low	4.00	100	2.03
Constant deformation	MDPM = moderate, CPPM = moderate, ARLM = low and CIRL = slow	5.33	75	1.52
Initial deformation	MDPM = very low, ARLM = high and RLCM = slow	8.00	83	1.95
Initial deformation	MDPM = very low, ARLM = high, RLCM = slow and CIRL = slow	8.00	83	1.95
Initial deformation	MDPM = very low, ARLM = high, RLCM = slow, CPPM = low and CIRL = slow	8.00	83	1.95
Initial deformation	CPPM = low, RLCM = ordinary, ARLM = moderate and CIRL = slow	5.33	75	1.76

rule confidence (%) are set to 1.0 and 75, respectively. The representative association rules for the three deformation phases of GPS monitoring points ZG265 and ZG268 are shown in Tables 10 and 11, respectively.

To illustrate the meanings of these rules, three of the rules at different deformation states are provided as examples. IF MDPM is high (from 66.1 to 136.8 mm), the ARLM is low (from 144.24 to 151.07 m), RLCM is normal (from 0.103 to 0.319 m/day), and CIRL is slow (from 0 to 5.00 m), THEN the landslide is in a state of rapid deformation with support, confidence and lift of 5.33, 100 and 5.00, respectively. This rule suggests that the reservoir level is low, precipitation greatly recharges and increases the groundwater level, and the difference between the reservoir level increases further, which increases the dynamic water pressure and accelerates the landslide deformation. IF MDPM is low (from 10.1 to 33.3 mm), ARLM is moderate (from 151.93 to 163.00 m), and CIRL is normal (from 5.80 to 13.90 m), THEN the landslide is in a state of constant deformation with support, confidence and lift of 4.00, 100 and 2.03, respectively. This rule suggests that the reservoir is at a medium level and fluctuates slowly, the precipitation is low, and the difference between the groundwater level and the reservoir level is not clear; therefore, the dynamic water pressure decreases, and the deformation slows. IF MDPM is very low (from 0.8 to 9.3 mm), ARLM is high (from 163.57 to 174.73 m), RLCM is slow (from 0.001 to 0.090 m/day), and CIRL is slow (from 0.00 to 5.00 m), THEN the landslide is in a state of initial deformation with support, confidence and lift of 8.00, 83 and 1.95, respectively. This rule suggests that the reservoir level is high, precipitation is low and contributes little to the groundwater, the difference between the reservoir level and the groundwater level decreases, and the former is equal to or higher than the latter, so hydrostatic pressure will form and decrease the deformation.

Conclusions

The Baijiabao and Laoshewo landslides are two typical active colluvial landslides in the Three Gorges, and the potential risks that are posed by this type of landslide are substantial. Therefore, determining the deformation states is an important task for landslide early warning systems. This paper presents an approach for analysing the deformation states of two typical colluvial landslides using 6 years of time-series monitoring data, a two-step cluster analysis, and the Apriori algorithm.

The observed ground deformations demonstrate that tension cracks and collapses occur in association with heavy rainfall and sharp increases or decreases in the

reservoir level. The cumulative displacement versus time curves exhibit step-like increasing patterns, and the sharp increases in the curves are caused by fluctuations in the reservoir level and changes in precipitation during the rainy season. A two-step cluster analysis indicates that the landslide deformation process can be divided into initial, constant, and rapid deformation phases, which correspond to a decreasing rate, steady rate, and increasing rate of deformation with time, respectively. The association rules for landslide deformation are obtained using the three deformation phases and five reservoir level and rainfall factors as consequents and antecedents in the Apriori algorithm. The support, confidence and lift measurement standards are applied to select reliable and representative knowledge rules, and the analytical results are generally consistent with the observed ground deformations. The results suggest that the deformations of the Baijiabao and Laoshewo landslides are mainly influenced by fluctuations in the reservoir level followed by rainfall. Due to the poor permeability of the frontal sections of the sliding beds, when the reservoir level drops below the groundwater level, dynamic water pressure will form and accelerate the landslide deformation. Simultaneously, increases in rainfall will raise the groundwater level, which will further increase the dynamic water pressure and accelerate landslide deformation. The Laoshewo landslide is a colluvial bedding landslide, and its groundwater discharge is higher than that of the Baijiabao landslide. Therefore, at the same reservoir level, rainfall has a smaller effect on the Laoshewo landslide than on the Baijiabao landslide.

The association rules that were extracted from these two typical colluvial landslides may serve as useful references for assessing the level of deformation of similar colluvial landslides in the region, and the combined method of a two-step cluster analysis with the Apriori algorithm that was proposed in this study can be applied to analyse the deformation conditions of other types of landslides with clear response factors. Nevertheless, fluctuations in the reservoir level and rainfall are the only important inducing factors for analyses of the deformation and evolution of colluvial landslides. Future work will consider interior factors that indicate landslide mechanisms.

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