Early Warning of Abrupt Displacement Change at the Yemaomian Landslide of the Three Gorge Region, China

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Abstract: Like most natural systems, landslides also have critical points at which a great change in displacement occurs. The displacement may recover increasingly slowly from small perturbations when landslides approach an abrupt change. The Yemaomian Landslide, located in the Three Gorge Region, China, is studied. A time series of displacement is modeled using an autoregressive (AR) model and a detrended fluctuation analysis (DFA) method. The coefficient and variance of AR(1) and the scaling exponent of DFA are estimated using a slide window. The results show that the DFA scaling exponent can indicate the abrupt change in displacement. The DFA scaling exponent increases when an abrupt change is approaching. If the variation in displacements is small, the scaling exponent declines accordingly. The variance of AR(1) may also indicate the displacement fluctuation. These early-warning signals are extracted directly from the observations. They can be used to detect abrupt changes in real time series. They have the potential to be used as early-warning signals for a wide range of landslides.

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Introduction

Landslides are the most common geological disaster in China (as per the China Geological Environment Information Site, National Geological Hazards Briefing in 2013). Each year, landslides cause the loss of many lives and billions of dollars. Landslides occur when the slope condition changes from stable to unstable. Factors that trigger landslides include geological, morphological, and physical factors as well as human activities. For a given landslide, it is usually possible to identify one main cause. The two main triggers for landslides in China are (1) intense rainfall, and (2) changes in river water levels [especially along the banks of Yangtze River, China (Du et al. 2013)].

Early warnings are feasible for landslides that are induced by precipitation, or water level changes (Baum and Godt 2010). Understanding the landslide initiation process, precipitation thresholds for landslide occurrence, and real-time monitoring have provided the technical basis for early warnings. Early warning systems (EWSs) are considered a cost-effective means to reduce risk and mitigate the damage (Intrieri et al. 2012). The EWSs include monitoring, forecasting, warning, and people response activities. The National Oceanic and Atmospheric Administration (NOAA) and the USGS have established a demonstration flash flood and debris flow EWS in southern California. A landslide early-warning system prototype was established to provide early warning to railroads in Japan (Thiebes 2012). Several landslide EWSs are located along the lake created by the Three Gorges Dam (Thiebes 2012). However, resident awareness has been found to be one of the most effective ways to avoid landslide damage in the Three Gorges Reservoir area. Although rainfall is a triggering factor, displacement directly indicates whether the landslide surface shifts. Displacement is a critical issue in design and implementation of EWS (Intrieri et al. 2012).

Various techniques are employed to monitor the surface movements of landslides. The spatial displacement monitoring techniques are divided into two parts, i.e., (1) area surveying, and (2) point target sensing. Area surveying techniques employ synthetic aperture radar (SAR) images [Envisat SAR images (Liu et al. 2013) and ground-based SAR interferometer (Leva et al. 2003)] or light detection and ranging (LIDAR) data (Glenn et al. 2006) to monitor landslide movement. Point target sensing means that one point is surveyed. Sensors used for this method are primarily point target sensing devices, such as three-axis acceleration sensors, two-axis inclination sensors, pluviometers, displacement meters, and so on. These sensors are deployed on the landslide surface or shallowly embedded into the landslide. They directly sense the change in slope, rainfall, water table level, and other factors. Wireless data transmission allows wireless sensor networks (WSNs) to be used for landslide observation (Azzam et al. 2010). Through wireless transmission techniques, such as wifi, Zigbee, or general packet radio service (GPRS), WSNs can be remotely controlled from the web. The WSNs have become the first choices for measuring geophysical (Oden et al. 2008), atmospheric, hydrodynamic (Pérez et al. 2011), and soil factors that are related to landslides. The time series obtained from different types of sensors are important resources for the study of the movements of landslides.

Both the geographic information systems (GIS) and time series are essential for predicting where and when the landslides may occur. Spatial prediction is usually performed before the analysis of the time series data. The aim of spatial prediction is to identify areas that are susceptible to landslide based on GIS (Pradhan et al. 2010), past landslide events, terrain parameters, geological attributes, and...
other factors. The accuracy and effectiveness of the estimating methods, such as deterministic prediction model, statistical forecasting models, and nonlinear prediction models, have been demonstrated (Li and Li 2012). However, prediction of the landslide occurrence time is a problem worldwide. Early warning is an effective alternative for individuals to react to the upcoming threat in sufficient time.

Early warning is widely studied by scientists. Because a number of landslides are induced by rainfall, the triggering threshold of rainfall intensity/duration has been set as an early-warning signal for landslides in the United States (Baum and Godt 2010; Khabarov et al. 2011). The value of the threshold is obtained according to the history data or empirical parameters. To set an effective threshold requires large antecedent data training. Moreover, the thresholds may change with location and time (Lagomarsino et al. 2013). Thus, the early warning based on the precipitation threshold is restricted to specific regions. Because landslide displacement indicates the stability of a slope more directly, it is an essential signal for early warning. A wide range of different sensor data related to landslide displacement will be obtained with state-of-the-art technology. Interpreting the sensor data for early warning is a challenge. Multiple methods for data interpretation have been proposed. For example, predicting the landslide displacement in Three Gorges Reservoir Area, China by support vector machine (SVM) regression has been proposed (Zhu and Hu 2012). In addition, a novel neural network technique called ensemble of extreme learning machine was introduced to investigate different triggering factors that affect the evolution of landslides (Lian et al. 2014). However, these methods require large amounts of data for training. The time interval between the collection of the training data and the observed landslide displacement may be 1 year or more because not only the data but also the conditions, such as season, regional rainfall or water table level, must agree. This long time interval may not represent current conditions, potentially resulting in a false alarm.

Marten Scheffer and others have noted that many complex systems have critical thresholds called tipping points, at which the system shifts abruptly from one state to another (Scheffer et al. 2009). Critical thresholds for such transitions correspond to bifurcations. Although predicting where critical thresholds may occur is typically inaccurate, whether a system is near a bifurcation is related to a phenomenon known in dynamical systems theory as critical slowing down. This phenomenon leads to three possible early-warning signals when a dynamic system approaches a bifurcation, as follows: (1) slower recovery from perturbations, (2) increased autocorrelation, and (3) increased variance.

The fluctuations with repeated disturbance have primarily been modeled by autoregressive models (AR) or detrended fluctuation analysis (DFA) for studying time series (Held and Kleinen 2004; Livina and Lenton 2007; Peng et al. 1994). The scaling exponent of DFA or the AR model coefficient may indicate whether a natural system is approaching to a bifurcation. When the dynamic system is close to the critical threshold, the autocorrelation of the lag-1 autocorrelation [AR(1)] model tends to 1 and the variance tends to infinity (Scheffer et al. 2009). The DFA is more suited to quantify long-range correlations in nonstationary signals than power spectrum and correlation analysis. The optimal scale range for the DFA performance method is given by Cimatoribus et al. (2013). The two models [i.e., (1) AR, and (2) DFA] have been widely used for detecting bifurcation in ecosystems, financial markets, and climate (Lenton et al. 2012; Hu et al. 2001).

Four-year displacements have been obtained for several points on the Yemaomian Landslide in the Three Gorge Region, China. These data reflect the changes in displacements with time. The AR and DFA models are employed for the analysis of the displacement series. The objective is to detect the early-warning signal of abrupt displacement changes. Early-warning signals are extracted directly from the observed time series. The displacement change may be predicted using the previous sequence. Early warning of landslide displacement will have application for a large range of landslide types.

The paper is organized as described next. The time series model of landslide displacement is first described. The landslide and the data source are then introduced. The computation results and their analysis are then presented. The work is then summarized.

## Models of Landslide Displacement Series

It is hypothesized that the displacement of Yemaomian Landslide may relate to change in the water level in the Yangtze River. Water levels change seasonally. However, the water level fluctuates randomly over a short time scale. This short period fluctuation appears to be stationary. The landslide displacement fluctuations are assumed to be a stationary random process on short time scale, such as 2 or 3 months. This short-term process is modeled by the AR model and the DFA model. The idea that the coefficient and variance of AR(1) or the scaling exponent of DFA are indicative of abrupt changes in landslide displacement is tested in the next section.

### Autoregressive Model

Autoregressive models describe time-varying random processes in nature. An AR model is a special type of an autoregressive moving average process (ARMA). An AR model specifies that the output variable depends linearly on its own previous value. The simplest autoregressive model is
defined by the linear first-order AR process

\[
y_{n+1} = c + \alpha y_n + v_n
\]

where \(y_n = \) displacement sampled at time \(n\); \(v_n = \) white noise process, with zero mean \(E(v_n) = 0\) and constant variance \(\sigma_v^2\); \(c = \) constant; and \(\alpha = \) autocorrelation coefficient. The expectation of AR(1) process is

\[
E(y_n) = c + \alpha E(y_n) + E(v_n) \Rightarrow \mu = c + \alpha \mu \Rightarrow \mu = \frac{c}{1-\alpha}
\]

(2)

If \(|\alpha| < 1\), the process of displacement is broadly stationary. If \(c = 0\), then the mean of the process is zero. The variance (VAR) is

\[
\text{VAR}(y_{n+1}) = \alpha^2 \text{VAR}(y_n) + \sigma_v^2 \Rightarrow \text{VAR}(y_n) = \frac{\sigma_v^2}{1-\alpha^2}
\]

(3)

If \(\alpha = 1\), \(y_n\) has infinite variance and is not broadly stationary; \(\sigma_v^2\) is the variance of white noise \(v_n\).

According to Scheffer et al. (2009), the autocorrelation and variance of the displacement fluctuation may tend to increase when the landslide approaches a bifurcation. Close to a transition, the speed of return to equilibrium decreases, which implies that the autocorrelation tends to 1. Thus, the variance tends to infinity. The autocorrelation reflects the ratio between the time scale of dynamics and the frequency of the measurements. The autocorrelation and the variance of AR(1) model may predict the trend of displacement or indicate whether the landslide displacement is close to a bifurcation point. However, the effectiveness may not be consistent with the expectation because AR(1) is sensitive to noise.
Detrended Fluctuation Analysis

The DFA is a scaling analysis method providing a simple scaling exponent to represent the correlation properties of a signal. The DFA was proposed as an independent measure of long-term correlations embedded in a seemingly variable time series, complementary to spectral analysis (Buldyrev et al. 1995). The DFA was employed to measure the fluctuation of the window size \( N \). The DFA procedure consists of the following four steps:

1. The profile of time series \( x(j) \) is determined

\[
x(j) = \sum_{i=1}^{j} (y_i - \mu_s)
\]

where \( \mu_s = (1/N) \cdot \sum_{i=1}^{N} y_i, j = 1, \ldots, N \).

2. The window is divided into nonoverlapping boxes of equal size \( s \). In each box, the best polynomial fit of a chosen order is calculated. The determined variance between the polynomial and profile function is evaluated

\[
F^2(s, v) = \frac{1}{s} \sum_{i=1}^{s} \{ x[(v-1)s + i] - X_v(i) \}^2
\]

where \( X_v(i) = \) fitting polynomial; and \( v \in [1, N_s], N_s = \text{int}(N/s) \).

3. The \( q \)-th order fluctuation function is obtained by averaging over all boxes

\[
F_q(s) = \left( \frac{1}{N_s} \sum_{i=1}^{N_s} F^2(s, v)^{q/2} \right)^{1/q}
\]

4. The expected DFA scaling exponent \( \beta \) is evaluated by analyzing \( F_q(s) \) versus \( s \) for different \( q \) in terms of the power law

\[
F(s) \propto s^{\beta}
\]

Compared with the AR model, DFA is not a director indicator. The trend in the time series is eliminated. The DFA scaling exponent may indicate the range in the fluctuation of the landslide displacement. For self-uncorrelated series, \( \beta < 0.5 \), whereas for self-correlated series, \( \beta > 0.5 \). When the scaling exponent \( \beta \) increases, large changes in displacement will occur. When the scaling exponent decreases, the range of fluctuation will decrease.

Data Acquisition

Landslide

The Yemaomian Landslide is located within Zigui County, near the Three Gorges region of the Yangtze River, China. It is on the north bank of the Yangtze River, 3-km upstream of the Three Gorge Dam. The Yangtze River is narrowest at the site of the Yemaomian Landslide. Thus, the stability of the landslide is essential to the safety of Three Gorges Dam.

The Yemaomian Landslide is on the eastern gravelly slope of the Chanzi Cliff (Sun et al. 2004). The Yangtze River flows past it to the south. The two main rock types are (1) limestone, and (2) dolostone. The rocks strike north–northwest (NNE), north–northwest (NNW), southeast (SE), and northeast (NE). The dip angles of the landslide scarp are between 70 and 80°. Unloading joints grow along the scarp. Fractures, faults, and unloading joints crosscutting each other will lead to the rock falls.

The front edge of the landslide, which is near the Yangtze River, is arcuate in shape and is 700 m in width. The lowest elevation is 25-m high. All elevations in this paper refer to the Year 1956 Yellow Sea height data of China. The width of the cliff from the front edge is 170 m and the elevation varies from 430–450 m. There is one gully in the west and another in the east. The longitudinal length of the gully is approximately 1,100 m. In general, the inclination of the landslide is towards the south, as observed in Fig. 1 of Sun et al. (2004). The front part of the landslide, which is along the river, is steep, but it is not steep at the back of the landslide. In plane view, the Yemaomian Landslide is wide in the front but narrow at the back. The area is estimated to be approximately 0.343 km², the volume is approximately \( 1.7 \times 10^6 \) m³.

The Yemaomian Landslide is located in a subtropical zone with a humid monsoon climate; it is drier in winter with more rainfall in summer. The most rainfall occurs between May and October each year. According to records, the average annual rainfall is 1,025 mm. The maximum annual rainfall of 1,430 mm occurred in Year 1963. The maximum daily rainfall of 358 mm occurred on August 8, 1975.

The water level in the Yangtze River is adjusted regularly each year. In the dry season, the river width at the Yemaomian Landslide is approximately 250–300 m. When the water level is 175-m deep, the river width is correspondingly increased to 500–600 m. When the water level rises, a high proportion of the landslide is submerged. During the decline of water level, seepage flow may lead to landslide movement. Therefore, the change of water level is considered to be a key factor for the stability of the Yemaomian Landslide (Liu 2003).

Data Sources

The survey of the deformation is divided into two parts (Yang et al. 2012), i.e., (1) surface displacement surveying, and (2) underground deformation monitoring. The surface displacement surveying consists of horizontal and vertical displacement monitoring. The horizontal displacements refer to the collimating line that is established perpendicularly to the trend of the landslide. The horizontal displacements are key parameters because they directly indicate the surface deformation and the landslide stability. The underground monitoring instrument is a drilled inclinometer. The water level measured using the underground piezometer reflects the level of underwater in the body of the landslide, which is an important parameter for the landslide research. The piezometers were set at ZK14 and ZK19.

Collimating line and resection measurement methods are used to measure the horizontal displacement. Fig. 1 shows the locations of the horizontal displacement observation points. Each point represents a pillar. Prisms are embedded on the top of each pillar. The displacement is measured by a total station. The monitoring network is composed of nine points [(1) TN01, (2) TN02, (3) TN03, (4) TN04-1, (5) TN05, (6) TN06-1, (7) TN07, (8) TN08, and (9) TN09]. There are three collimating lines [(1) Line A, (2) Line B, and (3) Line C]. Line A consists of two basic work points [(1) TN06-1, and (2) TN07] and three observation points [(1) TN06, (2) AL01, and (3) AL02]. Line B includes two basic work points [(1) TN04-1, and (2) TN05] and three observation points [(1) AL03, (2) AL04, and (3) AL05]. Line C also has two basic work points [(1) TN08, and (2) TN09] and two observation points [(1) AL16, and (2) AL17]. Four horizontal displacement observation points [(1) TP06, (2) TP07, (3) TP08, and (4) TP09] are located on the landslide surface. The resection method is employed to measure the displacements of TP06–TP09 using total stations.

According to long-term observation, the displacement at TP06 is larger than those at the other observation points. Three years of displacement data were analyzed for TP06 using both AR(1) model and DFA method.
Computing Results

A technician measured the displacements of the observation points two times per month. The sparse data were not sufficient for either AR(1) model or the DFA method. The data were scaled using a cubic spline function. For example, when the DFA scaling exponent on February 26, 2010, was computed, the point values within a sliding window were interpolated through the observed values from November 27, 2009 to February 26, 2010. The length of the sliding window was extended by interpolation due to the requirement of the AR(1) model or DFA analysis. To estimate the DFA scaling exponent, the length of each window segment was changed through interpolation. In both AR and DFA analysis, 25% of the data was varied between two successive sliding windows. It was assumed that each observed displacement correlated with the displacements previous 2 or 3 months. The computed results show the effectiveness of the two models for abrupt displacement change warning.

Fig. 2 shows the AR(1) coefficients in 2010. The results of two other years [(1) 2011, and (2) 2012] are similar to those of 2010 and thus are not presented in this paper. The AR(1) model coefficients are higher than 0.9, which may mean that the landslide is unstable. However, the coefficients cannot be used as an early indicator for abrupt changes in landslide displacement because the fluctuation of the coefficients is small. The variances in the AR(1) for each year are shown in Figs. 3–5, respectively. When the displacement variation grows, the variance increases accordingly. When the displacement fluctuation decreases, the variance becomes lower. The variance in the AR(1) model may indicate the range of fluctuation. The difference between the successive variance sometimes indicates the future trend of the displacement although it may not be right.

Figs. 6–8 shows the DFA scaling exponents for 2010, 2011, and 2012, respectively. The results are encouraging. When a large change of displacement is approaching, the scaling exponent increases sharply. If the variation in successive displacements is small, the scaling exponent is accordingly low. It can be concluded that in most cases, the DFA scaling exponent is an early warning of
Fig. 3. (Color) Standard deviation of AR(1) model from July 2009 to December 2010

Fig. 4. (Color) Standard deviation of AR(1) model from July 2010 to December 2011
Fig. 5. (Color) Standard deviation of AR(1) model from July 2011 to December 2012

Fig. 6. (Color) Scaling exponent of DFA from July 2009 to December 2010 with $q = 2$
Fig. 7. (Color) Scaling exponent of DFA from July 2010 to December 2011 with $q = 2$

Fig. 8. (Color) Scaling exponent of DFA from July 2011 to December 2012 with $q = 2$
abrupt changes in displacements in the Yemaomian Landslide. However, the scaling exponent cannot be used to predict whether the subsequent displacement will increase or decrease. Combining the AR(1) variance and the DFA scaling exponent may roughly estimate the range and the direction of change.

The length of the sliding window affects the DFA computation results. The data within 2 or 3 months are beneficial for DFA analysis. If the window size is 4 months or more, the magnitude of the scaling exponent near the abrupt change may decline. The choice of $q$th-order fluctuation function affects the computational results. Different $q$th values were tried, i.e., $q = -2, -1, 1, or 2$. Figs. 6–8 are the best results from the different $q$th values. The method for the choice of $q$th value will be studied in the future.

**Conclusion**

Displacement usually increases when rockfalls, rock topples, or debris flows occur. The abrupt change in displacement is considered to be a transition point. Like most natural systems, when a landslide approaches such critical points, it recovers increasingly slowly from small perturbations. The Yemaomian Landslide was selected for studying early-warning signals for abrupt changes in displacement. The displacement time series were modeled by an AR model. The time series were also processed with the DFA algorithm. The coefficients and variance of the AR(1) model and the DFA scaling exponents were computed within a sliding window. The computation results show that the DFA scaling exponents usually increase when an abrupt change is approaching. The DFA scaling exponents decrease, when the displacement fluctuation becomes small. The coefficients of AR(1) do not indicate changes in displacements, but the variance of AR(1) may indicate a change in displacement direction with limited accuracy. Combining the DFA scaling exponent and the AR(1) variance may estimate the range and direction of change. These early-warning signals are extracted directly from the sequence of landslide displacement. The advantage of this approach is that no training data are required, meaning that it can be used in processing real-time monitoring data. The abrupt change in displacement may be detected in time evacuation or deployment of other damage mitigation. The early-warning signals may be applicable in a wide variety of landslides.

A wireless sensor network has been deployed on the Yemaomian Landslide to monitor the displacement. The time series will be also analyzed by the AR model and DFA algorithm. The results will be compared to those obtained from surveying data. The effectiveness of the AR model and DFA method will be further verified.

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