*Proc. of the 9th International Symposium on Geotechnical Safety and Risk (ISGSR)*
*Edited by* Zhongqiang Liu, Jian Dai and Kate Robinson
*Published by* Research Publishing, Singapore. 
doi: 10.3850/GRF-25280825_isgsr-237-P385-cd

# A NOVEL APPROACH TO DETERMINING ANNUAL FAILURE PROBABILITY OF LANDSLIDE BASED ON TIME-SERIES INSAR AND ITS APPLICATION IN LANDSLIDE RISK ASSESSMENT

Fumeng Zhao[a], Yaming Tang[a]*, YalinNan[b], Fan Feng[a], Wei Feng[c], BoHong[c]

*([a]Institute of Earth Environment, Chinese Academy of Sciences, China. E-mail: zhaofumeng@ieecas.cn; tangyaming@ieecas.cn; 384488166@qq.com; [b]China DK Comprehensive Engineering Investigation and Design Research lnstitute Co., Ltd, nan.yalin@dky53.com; [c]Xi'an Center of China Geological Survey, fwei@mail.cgs.gov.cn, hongbo01@mail.cgs.gov.cn.)*

Abstracts:Quantitative landslide risk assessment is a critical step in hazard prevention and mitigation, as well as in informing government decision-making. However, the complexity involved in determining the annual failure probability poses substantial challenges in assessing both individual and societal risks in landslide areas. This study proposes a new method for estimating the annual failure probability based on time-series InSAR deformation data and modified inverse velocity analysis. The ground deformations and deformation velocity time series are first studied with Interferometric Synthetic Aperture Radar (InSAR); then, the onset of acceleration creep and the time of failure are determined through the time series deformation curve and the modified inverse velocity analysis; as such, the annual failure probability can be estimated based on the time of failure; finally, the individual and societal landslide risks are quantified through analyses of the elements at risk and the *F-N* curve. To illustrate the effectiveness of the proposed method, the risk assessment of the Bailing landslide in Xiangning County, China, is conducted. It was observed that the Bailing landslide has exhibited a general deformation trend since early 2020, primarily due to the influence of surrounding coal mining activities. The estimated annual failure probability of the Bailing landslide is 0.1, with an individual risk of $4\times10^{-4}$ per year. The societal risk associated with landslide failure falls within an unacceptable range according to the *F-N* standard established by Hong Kong. Considering the impact of coal mining activities on the stability of the Bailing landslide, it is essential to implement more comprehensive and frequent deformation monitoring in the future.

*Keywords*: InSAR, Slope annual failure probability, Landslide risk quantitative assessment.

## 1. Introduction

Landslides are among the most frequent natural hazards, causing extensive damage and posing significant threats to human lives and infrastructure. The concept of landslide risk encompasses both the consequences of landslides and their probability of occurrence. In this context, the determination of the annual failure probability of landslides is a key indicator in risk assessment. The annual failure probability of a specific slope is usually estimated using statistical analyses of historical slope failure events within a region (Dai et al., 2002). Statistical analysis of historical landslide records over an extended period facilitates the estimation of the temporal probability of landslide occurrence. However, this approach requires a substantial volume of reliable historical data, which may not always be available. Note that the annual probability of slope failure is closely related to the time of slope failure (Intrieri et al., 2019). Thus, an alternative indirect method utilizing the time of failure has been proposed to estimate the temporal probability of landslides. Saito (1969) introduced an empirical and graphical method to divide the temporal behavior of landslide creeping deformation into three stages based on the three-stage creep theory. Fukuzono (1985) developed the widely recognized inverse velocity method, linking velocity and acceleration during slope failure to estimate failure timing by identifying when the reciprocal of slope velocity approaches zero.

Note that the time-series displacements are directly related to the stability conditions of the moving mass; thus, the time-series slope movement rate can be directly used to predict the time of failure (Intrieri et al., 2019; Roy et al., 2022). Modern technology provides plenty of proficient instruments to monitor them accurately in realtime. Particularly, with the development of remote sensing, time-series Interferometric Synthetic Aperture Radar (InSAR) has become an important method for long-term monitoring of ground deformations caused by slope instability, owing to its advantages of all-weather capability, wide monitoring coverage, high accuracy, and immunity to weather conditions. Although SAR remote sensing has been successfully applied in landslide monitoring for many years, its potential for identifying precursors to catastrophic slope failure remained largely overlooked until recent studies.

## 2. Methodology

As illustrated in Figure 1, there exist four steps in estimating annual failure probability and quantitatively assessing landslide risk. The methodologies of these key components, in terms of the ground deformation analysis through time-series InSAR technology, annual failure probability determination through time-series deformations, individual landslide risk assessment, and societal landslide risk assessment, are detailed below.

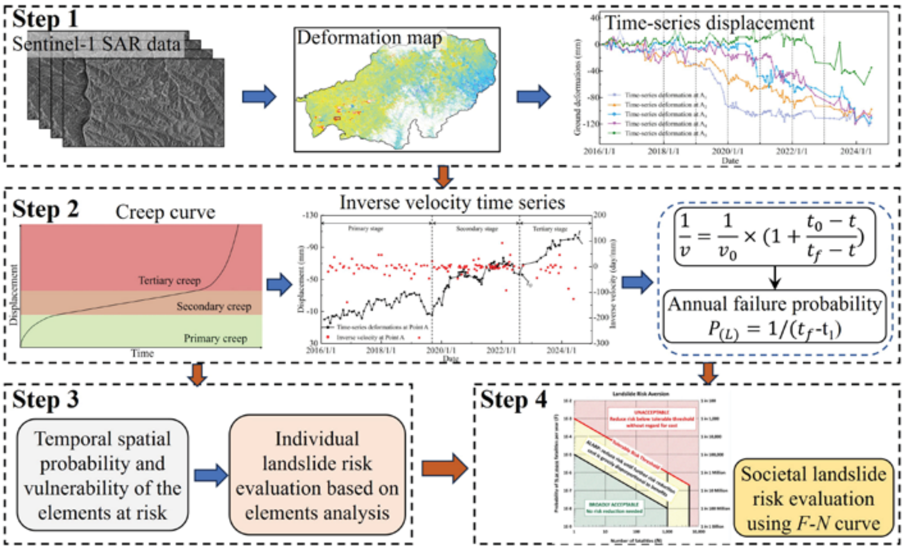

Figure 1. Flowchart for determining the landslide annual failure probability and quantifying landslide risk

### 2.1*Ground deformation analysis through time-series InSAR technology*

This study employs the Small Baseline Subset InSAR (SBAS-InSAR) method to obtain time-series surface deformation results. The technique involves setting an appropriate baseline threshold to group SAR images covering the same study area into several subsets, which are then processed through interferometry to form interferograms. Finally, the least squares method and matrix singular value decomposition are performed to obtain high-precision time-series cumulative deformation and annual average deformation rates along the radar line-of-sight.

### 2.2 *Annual failure probability determination through time-series deformations*

In this study, the annual failure probability was converted into estimating the time of failure of the specific landslide. Based on creep theory, the ideal landslide deformation-time curve exhibits three distinct phases: primary deformation, secondary deformation, and tertiary deformation. Thus, the deformation measurement points through InSAR analysis also encompass at least three types of points with distinct dynamic behaviors: stable points, points with linear variation, and accelerating points. Among these, accelerating points are particularly valuable for detecting slope instability, as they can be directly associated with signals of slope destabilization. Acceleration typically precedes slope failure, providing a means for predicting the timing of slope instability. Based on the derived time-series ground deformation and velocity information, this study utilizes the modified inverse velocity method to estimate the time of failure. The estimated velocity time series is converted into the inverse velocity time series with respect to the observation days. The time of failure ($t_f$) was deterministically estimated using the following mathematical formulation (Roy et al., 2022):

$$\frac{1}{v} = \frac{1}{v_0} \times (1 + \frac{t_0 - t}{t_f - t}) \qquad (1)$$

where $t_0$ is the day of onset of acceleration (OOA), which can be determined from the change in the trend of the displacement-time graph. From the displacement-time curve, $t_0$ is observed as the penultimate change in the trend of the displacement time series prior to failure (Roy et al., 2022), and the inverse velocity estimated by calculating the reciprocal of the velocity value corresponding to $t_0$ is marked as $1/v_0$. The value of $t$ and corresponding $v$ is taken to be the day of the last observation of the time series. The predicted time difference • $t$ (unit: year) corresponds to the duration between the deformation occurs and the ultimate failure time of the landslide (i.e., $t_f$); as such, the annual failure probability is estimated as 1/• $t$.

### 2.3*Individual landslide risk assessment*

Individual risk refers to the probability of a specific individual experiencing fatality due to a landslide. Fell et al. (2005) defined the annual landslide risk for property as follows:

$$R_{(prop)} = P_{(L)} \times P_{(T:L)} \times P_{(S:T)} \times V_{(prop:S)} \times E \qquad (2)$$

where $R_{(prob)}$is the annual loss of property value; $P_{(L)}$ is the frequency of the landslide (i.e., landslide annual failure probability); $P_{(T:L)}$is the probability of the landslide reaching the elements at risk; $P_{(S:T)}$ is the temporal-spatial probability of the elements at risk; $V_{(prob:S)}$ is the vulnerability of the component at risk to the landslide event. $E$ is the element at risk (e.g., the value or net present value of the property).

To estimate the annual loss associated with individual life risk, $E$ in Eq (2) can be represented as the number of individuals at risk. Accordingly, similar to the calculation of the annual loss of property value, the annual probability of a specific individual losing their life can be determined using the following expression:

$$P_{(LOL)} = P_{(L)} \times P_{(T:L)} \times P_{(S:T)} \times V_{(D:T)} \quad (3)$$

where $P_{(LOL)}$ is the annual probability of loss of life; $V_{(D:T)}$ is the vulnerability of the person to the landslide event.

### 2.4 *Societal landslide risk assessment*

Risk to a group of people is commonly referred to as societal risk. Societal risk can be expressed using an f-N curve, F-N curve, or probable life loss (PLL). The $x$-axis of an f-N curve represents the number of fatalities (N) in a particular landslide risk scenario. The $y$-axis represents the probability (f) of the landslide scenario. Each risk scenario is plotted as a point on the f-N curve to display its relative importance. The product of probability (f) and number of fatalities (N) yield probable life loss (PLL). PLL describes the expected number of deaths over a period of time. An F-N curve displays the probability of N or more fatalities. Risk scenarios are combined to form a single curve that is a complementary cumulative distribution function.

## 3. An application: Landslide risk assessment of the Bailing landslide in Shanxi, China

### 3.1 *Study area and dataset*

The study area is located along the Yaohuang highway in the Bailing Village of Xiangning County, Shanxi Province (see Figure 2). Frequent coal mining activities characterize the study area. In this study,118 scenes of ascending Sentinel-1 data from February 2016 to June 2024 are acquired to analyze the time series ground deformation and velocity information through the time-series InSAR technique.

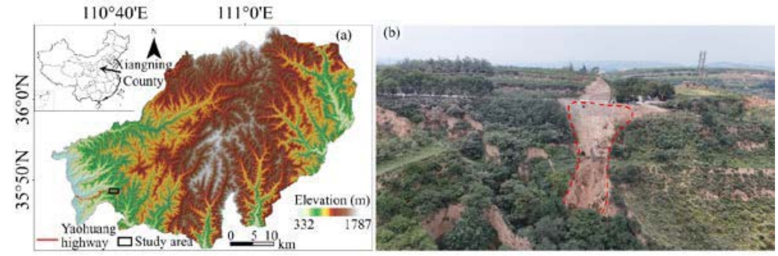


Figure2.Location of the study area: (a) Location of the study area; (b) Overview of the Bailing landslide

### 3.2 *Results of the annual failure probability and risks for the Bailing landslide*

#### 3.2.1 *Time-series ground deformation results for the Bailing landslide*

Figure.3(a) illustrates the ground deformation rates and the maximum ground deformation rate reached -75 mm/year, occurring near the 32105coalface. Figure 3(b) shows the deformation signs of the Bailing landslide.

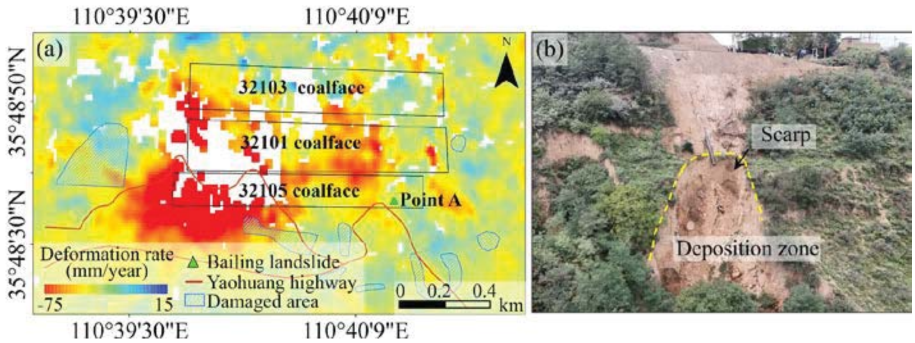


Figure3.Ground deformation rate in the study area: (a) Ground deformation rate in the study area; (b) Deformation signs of the Bailing landslide

#### 3.2.2 *Annual failure probability for the Baling landslide*

Shown in Figure4 is the time-series ground deformation of Point A, which is located in the Bailing landslide. It can be seen that the time-series ground deformation can be divided into three stages: the primary stage, the secondary stage, and the tertiary stage. The $t_0$ was the onset of acceleration (i.e., August 1, 2022). In this study, the coal mining in this area started on January 1, 2019 (day 0). The last observation date of the time series is

June 15, 2024, corresponding to 1992 days. The failure time $t_f$ is calculated as 3648 days using Eq. (1). The annual failure probability of the Bailing landslide is therefore estimated as 0.1.

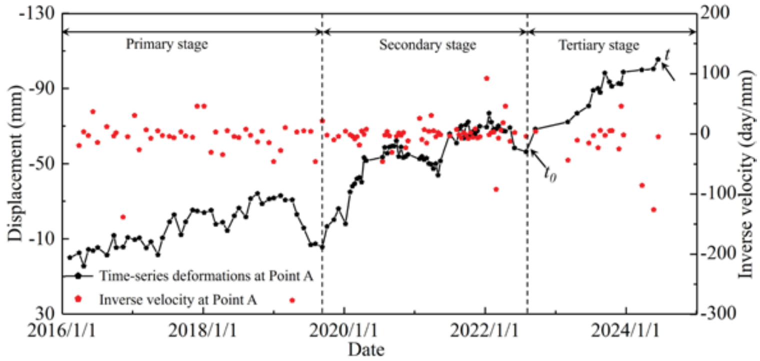


Figure4. Time-series ground deformations of Bailing landslide represented by Point A

### 3.2.3 *Individual risk results for the Bailing landslide*

In this case, $P_{(T:L)}$is 1. $P_{(S:T)}$ is calculated as 0.02 according to Fell et al. (2005). $V_{(prop:S)}$ is estimated to be 0.6. $E$ represents the property value of the elements at risk, and the average economic value per vehicle is estimated at 500,000 *Yuan*. The Bailing landslide spans a length of 45 m, suggesting that up to 4.5 vehicles could be at risk in the event of a landslide failure, based on an average vehicle length of 10 m. Therefore, $E$ is calculated as $2.25\times10^6$*Yuan*. Thus, the estimated annual property loss is 27000 *Yuan*/year, according to Eq. (2).

Individual risk is calculated using Eq. (3). $V_{(D:T)}$ represents the vulnerability of individuals to landslide failure, which is also the probability of individual fatality in the event of the landslide. For this case, $V_{(D:T)}$ is assumed to be 0.2. Thus, the estimated individual risk $R_{(LOL)}$ is $4\times10^{-4}$/year, according to Eq. (3).

### 3.2.4 *Societal risk results for the Bailing landslide*

In this case, assuming an average of two persons per vehicle, the number of individuals at risk (N) is calculated as nine people. This case indicates that the risk lies within the unacceptable zone. This result shows that the Bailing landslide poses a significant societal risk in terms of potential fatalities, making it unnecessary to perform further cost-benefit analysis. Instead, immediate implementation of risk mitigation measures is required.

## 4. Conclusions

This study proposes a method for calculating the landslide annual failure probability based on the time-series InSAR deformation curve and the modified inverse velocity method. The case study of the Bailing landslideshows that the method proposed was effective in the studies conducted. However,this method is based on the following two assumptions: 1) the primary trigger for slope failure is the coal mining activities; 2) the coal mining-induced deformations follow the three-stage creep behavior. As a result, the proposed method is particularly applicable to determine the landslide annual failure probability and risk assessment caused by coal mining activities. Future studies should aim to integrate more complex factors, such as variable rainfall patterns and heterogeneous geological conditions, to improve the robustness and broaden the applicability of the proposed method.

**Acknowledgment**

This study was supported by the National Key R&D Program of China (No. 2023YFC3008405) and the Technology Innovation Team Project of Shaanxi Province (No. 2023-CX-TD-33).

**References**

1. Dai, F. C., Lee, C. F., and Ngai, Y. Y. (2002). “Landslide risk assessment and management: an overview.”Eng Geol. 64(1): 65-87.
2. Fell, R., Ho, K. K., Lacasse, S., and Leroi, E. (2005). “A framework for landslide risk assessment and management.” In Landslide risk management, pp. 13-36. CRC Press.
3. Fukuzono T. (1985). “A method to predict the time of slope failure caused by rainfall using the inverse number of velocity of surface displacement.” Landslides 22(2): 8-13-1.
4. Intrieri, E., Carlà, T., and Gigli, G. (2019). “Forecasting the time of failure of landslides at slope-scale: A literature review.”Earth Sci. Rev. 193: 333-349.
5. Roy, P., Martha, T. R., Khanna, K., Jain, N., and Kumar, K. V. (2022). “Time and path prediction of landslides using InSAR and flow model.”Remote Sens Environ. 271: 112899.
6. Saito, M. (1969). “Forecasting time of slope failure by tertiary creep.” In: Proceedings of the 7th International Conference on Soil Mechanics and Foundation Engineering, Mexico City. pp. 677-683.