Educational Administration: Theory and Practice
2024, 30(4), 9767-9772
ISSN: 2148-2403
https://kuey.net/
Research Article

Developing a Model for the Identification of Onset of Failure of Slopes in Surface Mines

Basavaraja Simpi [1], K. Raghu [2], Lavanya Hegde [3], G Satish Kumar [4], R.T.Swamy [5] and Anilkumar [6*] and Prashant Sunagar[7]

[1] Assistant professor, Department of Geology, Government Engineering College, Hassan 573201, India
[2] Assistant professor, Department of Civil Engineering, Government Engineering College, Hassan 573201
[3] Assistant professor, Department of Geology, Government SKSJTI, Bengaluru 580001
[4] Assistant professor, Department of Geology, Government Engineering College Chamarajanagar 571313
[5] Assistant professor, Department of Geology, Government Engineering College, Huvinahadagali, Vijayanagara (District)
[6*] Assistant professor, Department of Civil Engineering, Government Engineering College, Raichur
[7] Associate Professor, Department of Civil Engineering, Sandip Institute of Technology and Research Centre, Nashik, Maharashtra - 422213, Savitribai Phule Pune University, Pune.

*** Corresponding author:** Anilkumar
*E-mail address: anilkumarsahukar@gmail.com

Citation: Anilkumar (2024) Developing a Model for the Identification of Onset of Failure of Slopes in Surface Mines, *Educational Administration: Theory and Practice, 30(4),* 9767-9772
Doi: 10.53555/kuey.v30i4.5285

ARTICLE INFO | **ABSTRACT**

Mine slope failures are a grave issue, leading to loss of life and substantial harm to infrastructure and equipment. Although they are intricate, most of these slope characteristics can be anticipated. Global mining companies have devoted significant efforts to mitigating mine slope failures due to the risk of human and material losses. Consequently, multiple inquiries and research have been conducted to gain a deeper understanding of these occurrences and their growth. This study presents the development of an automated technique for monitoring displacement data and detecting the initiation of slope failure, which coincides with the onset of acceleration. A specific dataset is processed using a five-step methodology. If the analysis yields a positive outcome for a certain set of slope monitoring data, it indicates that the slope is experiencing acceleration. It assists us in identifying the commencement of the acceleration of the slope. The produced result can serve as an advanced alert system that predicts slope collapses in order to prevent potentially disastrous slope incidents, enhancing overall mining efficiency and safety protocols.

Keywords: Mine slope, slope monitoring; slope stability radar; onset-of-failure; early warning; prediction.

Introduction

Slope failures present a multifaceted challenge, requiring thorough evaluation and proactive measures to mitigate potential damage to equipment, structures, and most importantly, human lives. Employing advanced technologies like Slope Stability Radar (SSR) alongside traditional methods enhances our ability to detect early warning signs in unstable terrain. The severity, timing, and speed of a slope collapse significantly influence its impact, underscoring the importance of comprehensive risk management strategies.
Geological risk management employs several techniques to ascertain the moment of failure, which poses a significant obstacle. Throughout the years, numerous researchers have extensively examined and implemented different theories and methodologies. Among these, the creep theory has emerged as a widely favoured approach for effectively elucidating slope behaviour.2 to 5. Fukuzono introduced the Inverse Velocity Method (IVM) as a means of predicting failures, as documented in the literature6. The results were predominantly favourable.7.8. The challenge of accurately forecasting when slope breakdowns would occur in mines remains unresolved despite extensive study and thorough investigations conducted over many years. Precise prediction necessitates a profound understanding of the dataset employed to track the temporal variation in a gradient. Determining the exact start of acceleration is crucial for properly utilising slope behaviour and predicting failure.

Copyright © 2024 by Author/s and Licensed by Kuey. This is an open access article distributed under the Creative Commons Attribution License which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

The use of human procedures has been widespread, but the absence of automation has impeded the ability to evaluate slope behaviour and predict failures in real-time. Although manual approaches yield certain outcomes, they are not the optimal alternative when prompt notification or response is required. Various research on landslides and structural collapses have utilised a combination of short-term and long-term moving averages to validate the behaviour of the raw data11. Despite extensive research on landslides and other natural and human-made structures, there is still no universally accepted approach for identifying the initiation of the tertiary creep phase. This phase marks the beginnings of collapse in the majority of slope failure situations.

The utilisation of the tertiary creep concept may aid in the prediction of slope instability. The accuracy of the forecast is significantly impacted by the assumption that the data should exclusively consist of accelerating displacements. Therefore, it is necessary to use large sample rates and automated collecting systems in order to monitor and control this. Due to the low sample rate, which is insufficient to accurately record the extended acceleration phase lasting several hours, manual data gathering is not suited for early warning purposes. Identifying the acceleration phase can be straightforward when performed manually by a skilled operator. However, the matter becomes more intricate when dealing with near-real-time or real-time acceleration, since the software needs to autonomously confirm the advancement of an accelerating phase and the initiation of acceleration. There are also concerns regarding the increasing use of automated instruments that can detect multiple slopes at the same time. Due to their exorbitant cost and demanding computational needs, very intricate models cannot be incorporated into the second scenario.

The issue of mine slope failures is a serious concern, with the potential for significant loss of life and damage to vital infrastructure and machinery. While these events may seem complex, many of their behaviors can be predicted with careful attention. Major mining corporations have made substantial efforts to address mine slope failures, recognizing the grave risks they pose to both human lives and material assets. Consequently, extensive research and investigations have been undertaken to deepen our understanding of these phenomena and their progression.
This study introduces an innovative approach to monitor displacement data automatically, aiming to detect the onset of slope failure, which often coincides with the initial acceleration phase. Through a detailed five-step methodology, a specific dataset is analyzed to identify instances of slope monitoring data indicative of acceleration. This analysis serves as an early warning system, alerting us to the initiation of slope acceleration. Such insights can significantly improve our ability to predict slope failures, thereby preventing potential disasters and bolstering overall safety measures and operational efficiency in the mining industry.

2.0 Methodology

We present a model that predicts the occurrence of slope failure by detecting a progressive increase in velocity (rate of displacement) data. The model is extremely beneficial when automated. Terminating the model if one condition is not met accelerates time analysis. The significance of this decision is little in a study that just involves one dataset, but it becomes essential in several high-sampling rate systems. The model may use conditional tolerance levels as part of its multi-step methodology. Any potential equipment for measuring slope displacement may employ this technique. The model consists of five sequential steps, and the moment at which acceleration or failure occurs is identified after the final step yields a positive result.

Step 1: Displacement values ($d^{33333}0$)
It is imperative that all displacement values are greater than or equal to zero in order to ensure the accuracy of the data recorded by the monitoring equipment.

Step 2: Rate of displacement ($v>0$)
This stage involves evaluating the rate of displacement. The subsequent tasks may only be carried out if four consecutive positive velocities are acquired. To initiate this step, a dataset containing four velocity values (specifically, five positive values of d) is required.

Step 3: Velocity increase ($vi > vi–1$)
we utilize data analysis techniques to evaluate the intervals between measurements, aiming to determine if there is a discernible upward trend in velocity. If three out of the four velocity values within the dataset meet this criterion, it is considered to be met. The main purpose of setting this tolerance level is to minimize the impact of outliers present in the monitoring data. While the occurrence of a negative output at this stage may seem inconsequential compared to the broader trend of slope movement, a model trained under the assumption that all validation conditions within the dataset would result in a positive outcome might halt its process at this juncture.

Step 4: Analysis of the displacement rate trend

Velocities that are accelerated should exhibit a non-linear behaviour. By fitting a curve to the data of displacement vs. time, we have validated our theory regarding the behaviour of slope deformation rate. The velocity data was analysed using a power law to precisely determine the creep stages of potentially unstable slopes. Although the power law function was extensively validated and calibrated with numerous data sets using different random dataset windows, it did not exhibit a high correlation with the raw data. The technique extrapolated a broad trend, but the power law function only accounted for subsequent variations in slope. A parabolic function is employed to discern whether there are upward or downward trends by examining the concavity.

The primary goal of step 4 is to determine the concavity of the interpolating curve by calculating the coefficient 'a' in the general equation of the parabola (y=ax2+bx+c). The concavity direction, represented by the parameter 'a', is determined by fitting a parabolic curve to the velocity data by interpolation. The concavity of a curve is oriented upwards when there is positive acceleration (a>0) and downwards when there is negative acceleration (a<0). The model depends on monitoring the presence of a positive 'a' value in order to detect acceleration. Step 4 has been finished, and additional analysis can be carried out if the condition a>0 is true for at least 75% of the data.

Step 5: Concavity check

At this stage, the change in the coefficient 'a' is assessed between two measurements to determine the significant concavity orientation in the monitoring data curve. In other words, the acceleration reduces or increases depending on whether there is a downward or upward direction. A lack of change in the variable 'a' indicates that the curve is becoming more linear, resulting in a decrease in the magnitude of slope fluctuations. Step 5 commences if at least three out of four data items are precise. If this condition is met, it may initiate an accelerating phase, and the 'i' value of time represents the rate of acceleration of the slope. The model's validation is conducted using a parametric analysis on various datasets obtained from the field.

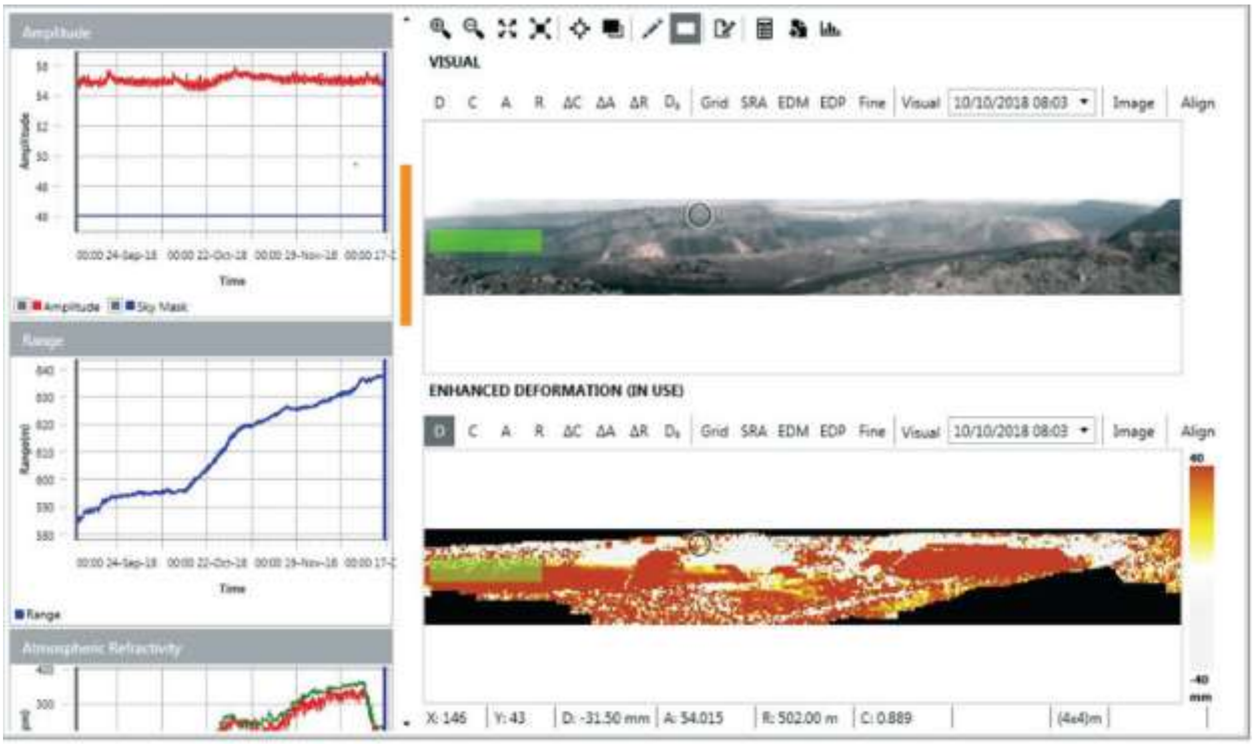


Figure 1: SSR Viewer screen showing the image of the wall/slope, the scanned area, the selection, and the heat map, SECL India

3.0 Case Studies and Validation of the Proposed Approach

The commencement of failure in our model is identified using data from the mines of South Eastern Coalfields Limited, Bilaspur (SECL). The slope stability radar, often known as SSR, was used to monitor slopes in all three mines. The data included measurements of displacement, velocity, and inverse velocity, as well as information about the amplitude, range, and coherence associated with the time values. Figure 1 illustrates the process of collecting SSR data in the SSR viewer. SSR establishes connections between various computers, so forming a comprehensive monitoring system. MATLAB is utilised to examine the data from the SSR viewer and generate a multi-step model. By following the multi-step approach described earlier, it is possible to extract potentially hazardous acceleration patterns from displacement data for real-time monitoring. The method emulates a real-time capture despite the fact that all the monitoring data displayed here is derived from previous instances.At this stage, we assess the change in the coefficient 'a' between two measurements to determine the significant concavity orientation in the curve of the monitoring data. In other words, we determine whether the acceleration reduces or increases when the curve has a downhill or upward orientation. A lack of variation in the variable 'a' indicates that the curve is becoming more linear, resulting in a decrease in the magnitude of slope fluctuations. Step 5 commences if at least three out of four data items are accurate. If this requirement is met, an accelerating phase can be initiated, and the value of 'i' for time shows the acceleration of the slope. The model is validated using a parametric analysis conducted on several datasets obtained from the field.

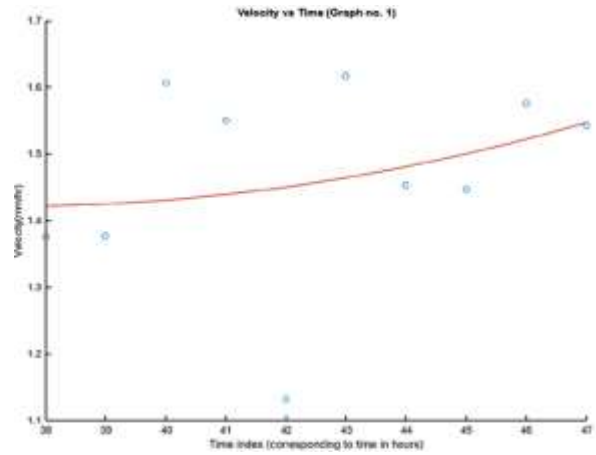
Case Study 1

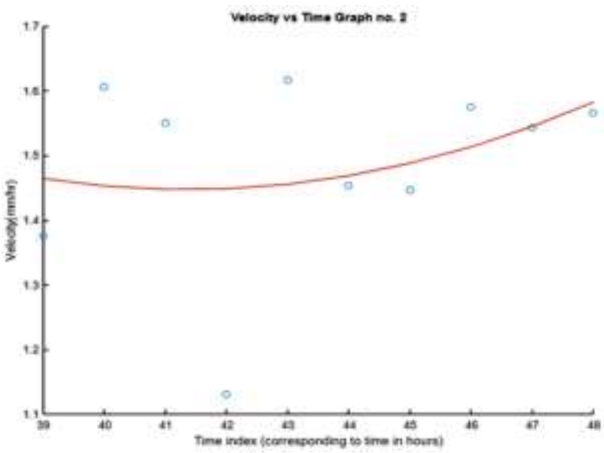
The presented case study originates from an undisclosed SECL mine site. Illustrated in Figure 2 is a visual depiction of the monitored slope face. Analysis of SSR displacement data revealed a consistent acceleration pattern, indicating that the creep had advanced into its third stage. Identifying the initiation of slope failure involves pinpointing the moment when the first acceleration increase occurs, leading ultimately to slope collapse. Despite initial challenges, the model effectively detected the onset of either acceleration or failure. Additionally, the tolerance levels integrated into the model operated with precision. On August 16, 2017, a slope failure incident occurred at an SECL-operated mine. The collapse could have been triggered by nearby excavation activities or significant rainfall. Interestingly, the SSR had been relocated to this area several days before the failure, yet failed to detect any movement on the seemingly unstable slope.

Figure 2: Image of the face/wall/slope being monitored, SECL India

Case Study 2

SSR monitoring of one location in a SECL mine revealed consistent activity. After noise removal, displacement data revealed a constant rise. The displacement and other relevant





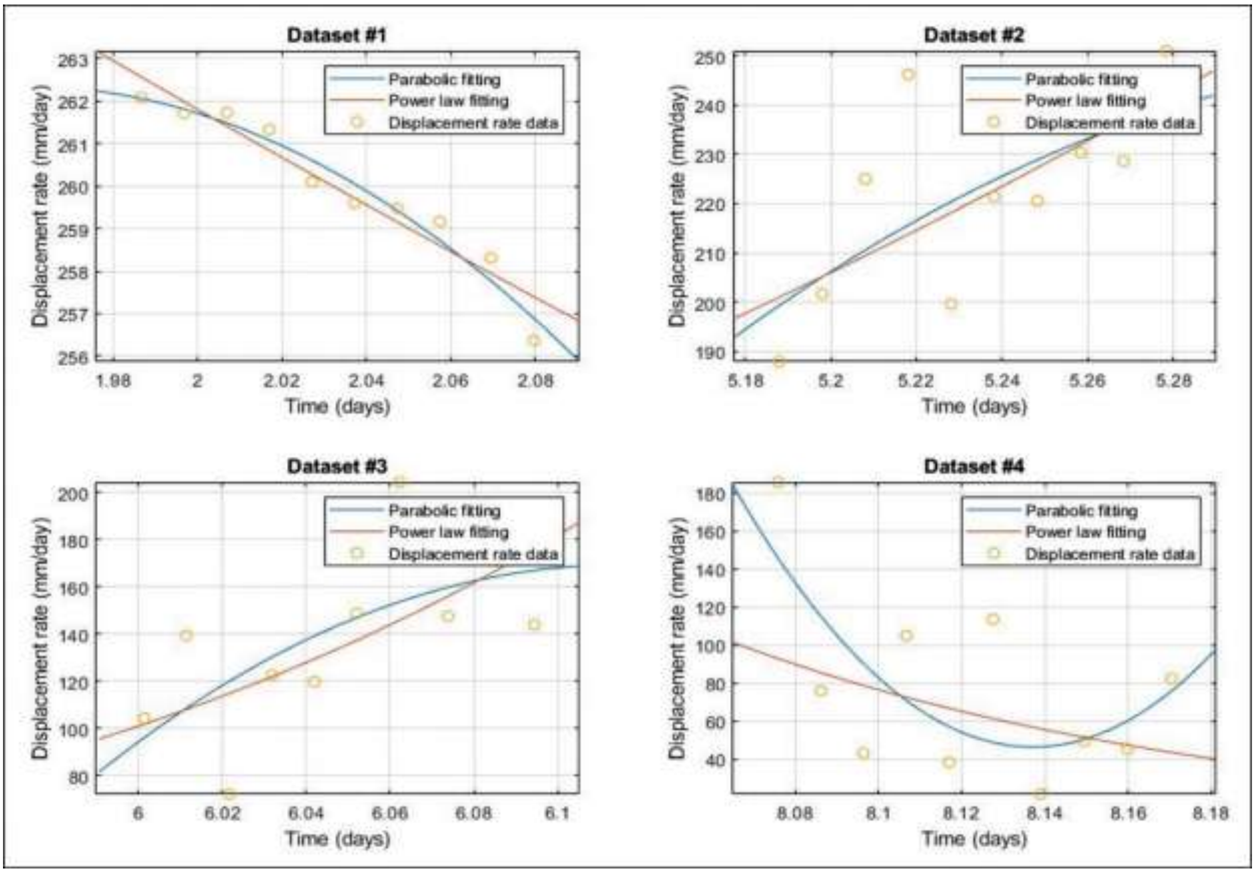


Fig. 4. Trend analysis using MATLAB, Case Study 2

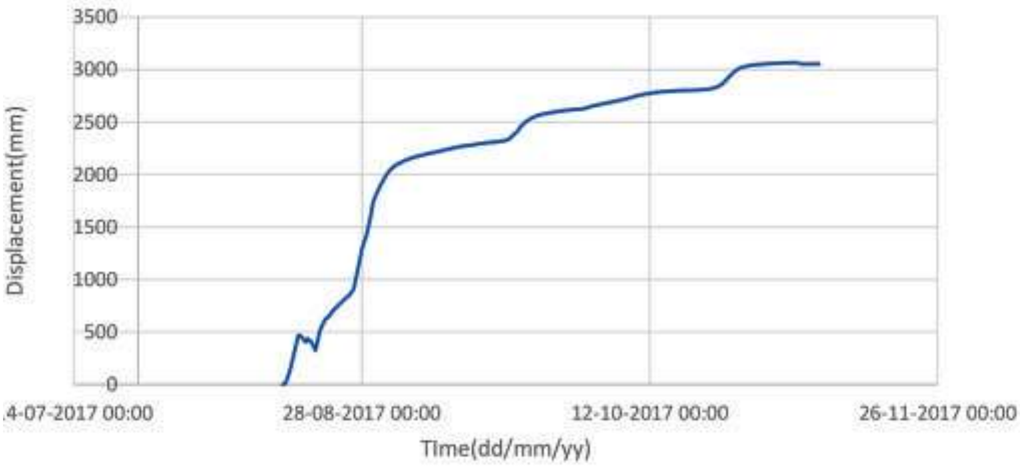


Fig 5. Displacement vs. Time plot for a SECL mine slope, Case Study 2

At present, there are no indications of a slope collapse, and it seems to be maintaining its stability. We utilized Microsoft Excel to confirm the acceleration phases and the curvature of the velocity curve, serving as validation measures for our model. The results obtained from Excel and MATLAB were consistent and aligned.

Filtering and smoothing the raw monitoring data has the potential to enhance data analysis in all scenarios and datasets. Incorporating supplementary data analysis techniques into the proposed strategy could potentially lead to improved results. Nevertheless, it is important to highlight that false alarms can often be easily recognised when future datasets fail to meet one of the model's step requirements, even within the specified tolerance limits.

The case study originates from an unknown SECL mine. Figure 2 depicts a visual representation of the slope face under surveillance. The SSR displacement data indicated a consistent increase in acceleration, indicating that the creep had progressed into the third stage of development. The initiation of slope failure can be determined by calculating the time when the first increase in acceleration occurs, ultimately resulting in the collapse of the slope. Despite numerous initial attempts, the model successfully recognised the onset of acceleration or failure. Furthermore, the tolerance levels included in the model were operating accurately. An incident of slope failure occurred on August 16, 2017, at a mine operated by SECL. The collapse may have been triggered by the proximate excavation activity or the substantial rainfall. This was the location where the SSR was relocated several days prior to its failure to detect any movement on the apparently unstable slope.

4.0 Conclusion

In recent years, there have been advancements in slope monitoring devices that have resulted in increased efficiency, reliability, and accuracy. An early warning system could greatly benefit from the use of automated data collection, signal processing, and distribution. A method that focuses on detecting significant events, such as a rise in velocities, may offer advantages in terms of risk management and prevention. Although extensive research has been conducted on failure-predicting models, there is a scarcity of models that specifically focus on early detection of acceleration or failure. Inaccuracies arise in predictions due to the oversight of a crucial event in slope failure. Our primary objective is to develop a sophisticated system that can autonomously identify emerging patterns in displacement monitoring data through a series of steps. This method also reveals unique characteristics of slopes. This work aims to fulfil a crucial research requirement in mining engineering by facilitating more precise predictions of slope collapse. Furthermore, the crucial parameters of the model were adjusted through a sequence of parametric evaluations. The paper showcases exemplar research that effectively reproduces a live data gathering process during a collapse, hence substantiating the soundness of the offered methodologies. Through the analysis of displacement data, it was established that the mining slope had two separate stages of growth. Moreover, the model facilitates a direct juxtaposition of the anticipated onset of acceleration with the actual acceleration profiles observed. We are harnessing data collected from diverse locations and timeframes to scrutinize our intricate methodology. Presently, we are in the process of crafting a system that leverages this model to track and record alterations in slope dynamics over time. Furthermore, our objective is to harness this model to devise an advanced, intuitive early warning mechanism tailored for mines, capable of accurately forecasting slope failures and alerting mining personnel to imminent collapses.

5.0 References

1. Intrieri E, Carlà T, Gigli G. (2019): Forecasting the time of failure of landslides at slope-scale: A literature review. Earth-Science Reviews [Internet]. 193:333–49. Available from: https://www.sciencedirect.com/science/article/pii/S001282521830518X
2. Saito M. (1969): Forecasting time of slope failure by tertiary creep. In: Proc 7th Int Conf on Soil Mechanics and Foundation Engineering, Mexico City. Citeseer; p. 677–83
3. Barry V. (1989): A Relation to Describe Rate- Dependent Material Failure. Science [Internet]. Jan 13; 243(4888):200-3. Available from: https://doi.org/ 10.1126/science.243.4888.200
4. Crosta GB, Agliardi F. (2003): Failure forecast for large rock slides by surface displacement measurements. *Canadian Geotechnical Journal* [Internet]. Feb 1;40(1):176–91. Available from: https://doi.org/10.1139/t02-085
5. Xue L, Qin S, Li P, Li G, AdewuyiOyediran I, Pan X. (2014): New quantitative displacement criteria for slope deformation process: From the onset of the accelerating creep to brittle rupture and final failure.