

A Case Study on the Effects of 3D Visualized Engineering Geological Model Uncertainty on Dip-Slope Stability

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Abstract: Dip-slope failures often threaten infrastructure stability, and discrepancies between predicted and observed slope behavior frequently arise due to geological model uncertainty. This study presents a case-based workflow, developed from a real dip-slope failure, integrating borehole interpretation, Gaussian Process Regression (GPR), and Monte Carlo simulation to assess the influence of geological uncertainty on slope stability. Potential sliding surfaces were generated by sampling weak-layer intervals from borehole data and modeling their spatial variability using GPR with a radial basis function (RBF) kernel. The results indicate that geometric uncertainty in sliding surfaces significantly affects stability conditions, particularly regarding slope orientation and depth. A 3D visualization workflow using open-source tools (PyVista, VTK) integrates multiple simulated surfaces within a GIS framework, allowing intuitive identification of zones with high geological uncertainty. The proposed approach provides a reproducible and data-driven framework that bridges geological interpretation and uncertainty visualization, supporting more proactive slope management decisions.

Keywords: *Engineering geological model, Uncertainty quantification, Visualization.*

Introduction

Dip-slope failures frequently occur and pose serious threats to infrastructure and human safety. However, discrepancies between predicted and actual stabilization performance often arise due to geological uncertainties, making the reliability of engineering geological models a key challenge in slope risk management. (Stead and Wolter, 2015; Einstein and Baecher, 1983).

This study establishes a workflow for quantifying geological model uncertainty by integrating borehole data, Gaussian Process Regression (GPR), and Monte Carlo simulation. The proposed method further investigates the spatial variability of potential sliding surface exposure under geological uncertainty. Visualization techniques are further employed to present uncertainty information, helping decision-makers better understand the spatial distribution of geological risks and improve management precision.

Methodology

In 2022, a dip-slope failure occurred at chainage 10.1 K on the southbound section of National Freeway No. 1 (Figure 1). The slope, located on the northern bank of the Keelung River, was a cut slope formed during highway construction. Following the failure, twelve boreholes were drilled in the affected area—eight within and four outside the sliding mass.



Figure 1, Dip-slope failure near national freeway no. 1 (Source: Geological survey and mining management agency).

Engineering geologists interpreted borehole data to identify lithological boundaries and weak layers, while borehole elevations were measured using RTK surveying to ensure consistency with the digital terrain model. The positions of the potential sliding surface and sliding mass were delineated through integration of pre- and post-failure high-resolution topographic datasets. Calcareous sandstone was recognized as a marker bed for stratigraphic correlation, whereas the red interval in Figure 2 indicates the sandy mudstone layer that weakens upon water exposure.

In dip-slope stability analysis, the spatial position of potential sliding surfaces has a significant influence on the analytical results. Therefore, identifying these potential surfaces is a key issue in evaluating slope stability. This study proposes a method that determines a group of potential sliding surfaces by interpreting weak-layer intervals from borehole data, thereby capturing the variability in stability results caused by

geological uncertainty. Figure 2 shows the distribution range of weak layers outside the post-failure sliding mass, suggesting that the potential sliding surface most likely developed within this interval. The weak layer exhibits good continuity, extending approximately 150 m from north to south. Based on these interpreted weak-layer intervals, a quantitative simulation of potential sliding surfaces was performed as described below.

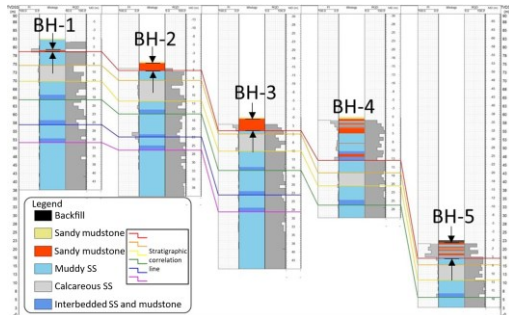


Figure 2, Borehole interpretation and stratigraphic correlation. BH-1, BH-2, BH-3, and BH-5 are outside the sliding mass; the red zone indicates water-sensitive sandy mudstone.

Figure 3 illustrates the workflow for quantifying the uncertainty of potential sliding surfaces. The procedure consists of the following steps: (1) defining weak-layer intervals within boreholes; (2) uniformly sampling within these weak-layer intervals; (3) simulating potential sliding surfaces using Gaussian Process Regression (GPR); and (4) repeating steps (2) and (3) n times to generate ‘n’ realizations of sliding surfaces.

In the generation of sliding surface samples, the radial basis function (RBF) kernel was adopted. The model parameters—length scale and signal variance—were optimized by maximizing the log marginal likelihood (LML) following Rasmussen and Williams (2006). This ensures that each simulated surface passes through all sampled points while preserving its unique spatial variability characteristics.

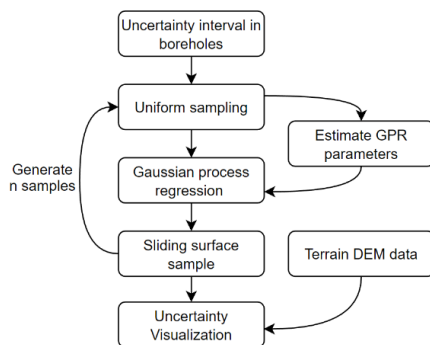


Figure 3, Workflow of uncertainty quantification based on Gaussian process regression.

Figure 4 illustrates that multiple geological model hypotheses were established and compared through visualization. This approach enables early identification of potential high-risk zones and helps avoid bias caused by a single interpretation. This multi-model comparative approach enables decision-makers to recognize the range of geological uncertainty at the early planning

stage, improving both reliability and flexibility in overall slope management.

Moreover, during the monitoring design phase, visualized models provide effective guidance for monitoring instrument placement. When potential sliding surfaces from different models overlap in certain areas such as the western part of the slope shown in Figure 4. These regions often indicate zones of higher instability risk. The western side also exhibits lower uncertainty than the eastern side, suggesting that deformation anomalies are more likely to manifest there. Installing instruments in low-uncertainty zones improves sensitivity and enables early detection. Furthermore, the evident discrepancy between the pre-failure geological model and the actual post-failure sliding surface indicates that monitoring layout decisions are strongly influenced by the assumed geological model.

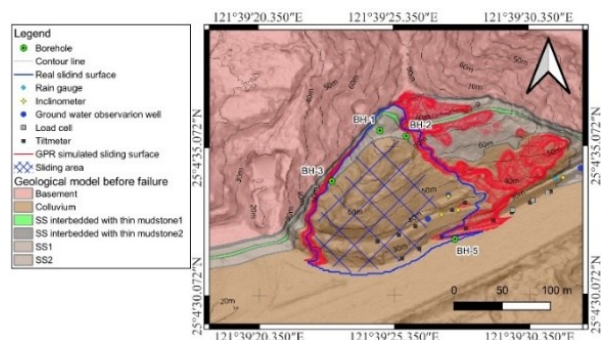


Figure 4, Illustration of multi-model assumptions for potential sliding surfaces. The red line indicates the weak layer interpreted from nearby borehole cores, with the surface trace derived from RBF and Gaussian process regression. The blue line represents the actual sliding surface observed after failure.

Conclusion

Using borehole data and Gaussian Process Regression (GPR), multiple realizations of potential sliding surfaces were generated, capturing spatial variability in stratigraphic orientation and depth. GIS visualization highlights zones of high geological uncertainty and potential exposure, supporting monitoring and reinforcement planning.

References

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