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Linking Crack Precursors to Landslide Runout Dynamics via Deep Learning Mapping and SPH Simulation

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Abstract: To investigate the landslide's spatiotemporal evolution and failure mechanisms, a comprehensive field campaign based on multi-source data was conducted. Deep learning models (U-Net and ResU-Net) were applied to UAV orthophotos to automatically extract ground cracks, with ResU-Net achieving the highest accuracy (89.7%). Stability analysis using the limit equilibrium method and Monte Carlo simulations revealed a substantial reduction in the safety factor to 0.822 and a 72.82% increase in failure probability under extreme rainfall conditions. Smoothed Particle Hydrodynamics (SPH) simulations further predicted a 48 s run-out with a peak velocity of 28 m/s. This integrated framework highlights the potential of combining deep learning, probabilistic analysis, and particle-based modeling for quantitative landslide hazard assessment and early warning.

Keywords: ***Deep learning, single- and multi-temporal UAV-based ground-crack mapping, Post-failure kinematics, Smoothed Particle Hydrodynamics (SPH), Spatiotemporal evolution, Kinematic run-out prediction.***

Introduction

Increasingly frequent extreme weather has made rainfall-induced landslides (Lele et al., 2025) a major global geohazard, threatening lives and infrastructure due to their rapid mobility and long runout. Effective risk management requires integrated strategies that couple precursor detection, stability assessment, and kinematic runout prediction. In this study, we develop a comprehensive framework that combines UAV-based photogrammetry, deep learning (U-Net and ResU-Net) for automated crack detection (Daud et al., 2025), the Limit Equilibrium Method (LEM) with Monte Carlo Simulation (MCS) for probabilistic stability analysis, and Smoothed Particle Hydrodynamics (SPH) for runout simulation. Applied to the Tanjiawan (TJW) landslide in China, this approach provides new insights into the landslide's spatiotemporal evolution and failure mechanisms, and supports the development of targeted prevention and mitigation strategies.

Methodology and result

The methodology was structured around an integrated framework to investigate the TJW landslide, comprising four key components: (i) engineering geological modeling, (ii) UAV photogrammetry, (iii) deep learning–based crack identification, and (iv) stability and runout analysis.

First, a comprehensive engineering geological model was established through detailed field surveys and the integration of multi-source data, including regional geological maps, topographic data, lithological profiles, and precipitation records. This model provided the essential geological context for interpreting the landslide mechanism and deformation behavior.

Second, UAV photogrammetry was employed for high-resolution data acquisition. A DJI Phantom 4 Multispectral UAV was used to capture aerial imagery of the landslide area. The imagery was processed using Structure-from-Motion (SfM) techniques to generate Digital Orthophoto Maps (DOMs), Digital Elevation Models (DEMs), and Digital Surface Models (DSMs), which formed the basis for subsequent deformation mapping and crack detection.

Third, deep learning models were implemented for automatic identification of ground cracks, which are critical precursors to slope failure. U-Net and ResU-Net architectures were trained and applied to the high-resolution DOMs to perform semantic segmentation and mapping of crack features. Model performance was quantitatively evaluated using metrics such as overall accuracy and Intersection over Union (IoU), enabling a direct comparison of their effectiveness for crack extraction in this setting.

Finally, the stability and post-failure dynamics of the landslide were analyzed. Slope stability was assessed using both deterministic and probabilistic approaches, primarily the LEM combined with MCS to account for uncertainties in geotechnical parameters (Aminpour et al., 2023) and to estimate the Factor of Safety (FS) and probability of failure (Pf). For runout simulation, the mesh-free SPH method was adopted to model the landslide mass as a fluid-like continuum, predicting key dynamic parameters such as velocity, depositional thickness, and runout extent. Rheological parameters for the SPH model were calibrated through back-analysis of the observed depositional characteristics of the TJW landslide (Figure 1).

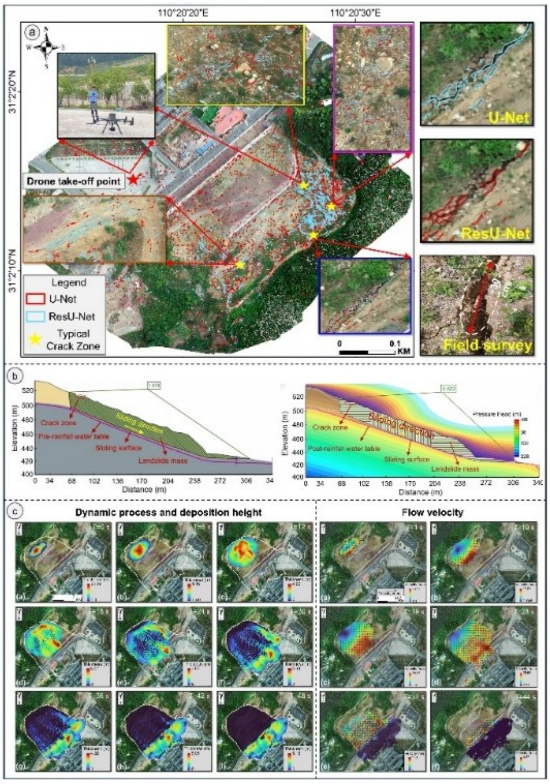

*Figure 1, **(a)** Ground crack automatically recognition; **(b)** Slope stability analysis; **(c)** Landslide post-failure dynamics.*

Conclusion

In July 2020, the TJW landslide experienced significant deformation under extreme rainfall, posing severe threats to local residents and infrastructure. An integrated analysis combining field surveys and multi-source data was conducted to evaluate its hazard potential. The main findings are as follows:

(1) Deformation characteristics: Extensive tensile cracks and plumose fissures were observed at the rear of the landslide. A crack approximately 80 cm long developed in the drainage ditch along the landslide boundary, and the road surface at the front edge experienced uplift with cracks extending to about 3 m. Differential analysis of multi-temporal DSMs showed that the average vertical deformations of the TJW landslide from 2020 to 2024 were −0.3196 m, −0.1764 m, −0.2068 m, and −0.1659 m, respectively, with deformation concentrated mainly in the middle and rear parts of the slope.

(2) Automated crack detection: High-resolution UAV orthophotos were used for automatic detection of ground cracks using ResU-Net and U-Net. Both models identified crack networks primarily along the rear edge and lateral boundaries of the landslide, consistent with field observations. ResU-Net achieved an overall recognition accuracy of 89.7%, outperforming U-Net's 85.9%, demonstrating the superior capability of ResU-Net for landslide crack detection.

(3) Stability under extreme rainfall: Deterministic and probabilistic stability analyses of the TJW landslide were performed using LEM and MCS, respectively. Under extreme rainfall conditions (rainfall intensity = 320 mm/d), the FS decreased markedly from 1.079 to 0.822, while the Pf increased by 72.82%. These results emphasize the critical influence of intense precipitation on the instability of the slope.

(4) Runout behavior and dynamics: The potential runout extent and kinematics of the unstable mass were analyzed using SPH, revealing a dynamic process lasting approximately 48 s. The landslide reached a peak velocity of about 28 m/s at 19 s, after which it decelerated and came to rest, leaving a final deposition thickness of around 5 m. Sensitivity analyses indicated that higher turbulence coefficients and lower basal friction coefficients lead to reduced debris accumulation thickness but increased runout distance.

Future work will focus on incorporating multi-temporal imagery and additional domain-specific information (e.g., stratigraphy and lithology) to further enhance the robustness and generalizability of crack recognition. Moreover, extending the integrated framework of stability assessment and runout simulation to multiple landslide sites will facilitate the development of practical, site-specific disaster risk reduction strategies, including evacuation planning and the formulation of early warning thresholds.

References

Aminpour, M., Alaie, R., Khosravi, S., Kardani, N., Moridpour, S., and Nazem, M. (2023). Slope stability machine learning predictions on spatially variable random fields with and without factor of safety calculations. Computer and Geotechnics,153, 105094. https://doi.org/10.1016/j.compgeo.2022.105094

Daud H., Dou J., Khan N.G., Xu B., Dong S., Dong A., and Ma H. (2025). Tree-based machine learning and flow simulation for debris flow susceptibility, runout propagation, and dynamics in the higher Himalayas. Mathematical Geosciences, 57, 1195-1233. https://doi.org/10.1007/s11004-025-10196-3

Lele Z, Jie D, Zilin X., Huang M., Tang Z., Xu G., Hou S., Yuan F., Peng B., and Liu X. (2025). Spatiotemporal reconstruction and post-failure stability analysis of rainfall-induced landslides via multi-modal SAR-optical data fusion. Catena 259, 109399. https://doi.org/10.1016/j.catena.2025.109399