EGU26-10764, updated on 08 Nov 2026
https://doi.org/10.5194/egusphere-egu26-10764
EGU General Assembly 2026
© Author(s) 2026. This work is distributed under
the Creative Commons Attribution 4.0 License.

From Physics-Aware AI to Digital Twins: Generating Photorealistic Satellite Imagery of Future Landslides for Predictive Hazard Scenarios

Omid Ghorbanzadeh[1] and Alessandro Crivellari[2]
[1]Department of Geoinformatics—Z_GIS, University of Salzburg, Salzburg, Austria (omid.ghorbanzadeh@plus.ac.at)
[2]Department of Geography, National Taiwan University, Taipei, Taiwan (alessandrocr@ntu.edu.tw)

Digital Twins of the Earth are required to represent future scenario- and trajectory-based hazards that obey physical laws and realistic dynamics in an interpretable and actionable manner, understandable not only by experts but also by non-expert stakeholders and local authorities, to support efficient decision-making, adaptation planning, and emergency management. Machine learning has substantially advanced generating landslide susceptibility maps (LSM). However, LSMs typically provide static, abstract, expert-oriented snapshots that are difficult for non-expert audiences to interpret and are poorly aligned with the interactive, immersive visualization needs of Digital Twin and Augmented Reality (AR)/Virtual Reality (VR) environments, thereby limiting their effectiveness for anticipatory risk communication and decision support.

We present a physics-aware generative framework that transforms predictive landslide modeling into photorealistic satellite imagery of *future* events, enabling intuitive “what-if” hazard exploration within Digital Twin architectures.

Our approach integrates Landslide Physics-Aware Neural Networks (LPANNs) with conditional Generative Adversarial Networks (GANs) to generate synthetic, post-event satellite images. These generate synthetic images conditioned on multi-attribute probability maps (physics-informed predictions) resulting from embedding geotechnical, hydrological, geomorphological, and geometric constraints, ensuring physical plausibility. Our developed conditional GAN is trained based on pre- and post-event real images, with annotated landslide areas. Different supervised and self-supervised deep learning are used for large-scale landslide detection.

By conditioning generative part of the approach on physics-informed predictions, the proposed Digital Twin component mitigates hallucinations typical of generative AI and synthetic images and trustworthy hazard visualizations. The resulting synthetic imagery is scenario-consistent and bridges the gap between numerical susceptibility outputs and human-centered decision support, enhancing interpretability for policymakers, emergency managers, and non-expert stakeholders.