Physics-Informed Deep Learning for Robust Landslide Detection: A Dual-Stream Architecture With Geomorphological Constraints

Qu, Tiger (Zheyuan) (School: Oregon Episcopal School)

Landslides are a kind of major natural disaster that causes huge economic and life losses globally. And visual detection using satellite imagery is critical for disaster response. Landform, or topography, is vital in the landslide process. However, current AI models treat physical context merely as an input channel, leading to false alarms and low accuracy. This study suggests a physics-informed deep learning model to improve the robustness for landslide detection. First, to make the model more physics-aware, we extract the Topographical Positional Indices to capture relative topography, along with the slope channel, the physical information dynamically calibrates model’s activation using a Feature-wise Linear Modulation layer. Then, in order to suppress physically inconsistent outputs, we propose a hard gate to block false alarms according to the slope data. Rather than using an if-else logic (which would cut off the gradient flow in backpropagation), we made it differentiable so that it can discover the safety boundary in the training process. The final evaluation result shows our model improves the main metric, landslide intersection-over-union, from 0.54 to 0.59 compared to a strong ResNet50 baseline. By integrating physical laws into the model, our architecture suggests a robust, lightweight, and more interpretable solution for landslide detection.

Awards Won: