Landslide Susceptibility Assessment Using a Physics-Informed Deep Learning Model

Ho-Hong-Duy Nguyen[1], Thanh-Nhan Nguyen[1], Chang-Ho Song[1], Yun-Tae Kim[1*]

[1]Ocean Engineering Department, Pukyong National University, Busan, 48513, Republic of Korea

(*Corresponding E-mail: yuntkim@pknu.ac.kr)

Abstract: While deep learning techniques have demonstrated considerable potential in modeling complex, nonlinear relationships among environmental and geological variables, their application often neglects the incorporation of physical principles, thereby limiting interpretability and compromising the reliability of negative sample selection. To address this limitation, the present study introduces a physics-informed deep learning framework that integrates a physically based slope stability model with a one-dimensional convolutional neural network (1D-CNN). In contrast to conventional approaches that rely on randomly selected negative samples, the proposed method utilizes a physically justified criterion extracting non-landslide samples from areas exhibiting low probability. The model is applied to the 2018 landslide event in Hiroshima, Japan, to evaluate its effectiveness. The results reveal that the physics-informed framework yields a substantial improvement in predictive performance, as evidenced by an increase in the Area Under the Receiver Operating Characteristic Curve (AUC) from 91.0% to 93.3%, relative to standard data-driven approaches. These findings highlight the advantages of integrating domain knowledge into deep learning models to enhance the accuracy of landslide susceptibility assessments.

Keywords: ***Physics-informed, Susceptibility, Deep learning, Landslide.***

Introduction

Landslides represent one of the most frequent and damaging natural hazards globally, often resulting in significant human, economic, and environmental losses (Nguyen et al., 2025). As such, accurate landslide susceptibility mapping has become a crucial aspect of geohazard assessment and disaster risk reduction, supporting land-use planning, infrastructure development, and early warning systems.

Traditionally, negative samples in landslide susceptibility modeling are selected randomly from areas where no landslide occurrences have been recorded. While this approach is convenient, it introduces a significant degree of uncertainty, as it does not account for the underlying stability conditions of those areas. Specifically, randomly selected locations may include slopes that are currently stable but possess marginal stability, making them susceptible to failure under slightly altered environmental conditions. Consequently, the inclusion of such conditionally unstable areas as negative samples can compromise model reliability, skew predictive performance, and reduce generalizability.

To mitigate these issues, recent studies have emphasized the importance of incorporating physics-informed criteria into the sample selection process (Liu et al., 2023). Methods based on slope stability analysis, such as those utilizing Factor of Safety (FS) computations, provide a more objective and theoretically grounded means of distinguishing truly stable terrain from potentially unstable regions. By integrating physically meaningful thresholds e.g., selecting negative samples exclusively from areas with high FS values models can achieve greater interpretability, more accurate representation of the stability landscape, and improved classification performance. This physics-guided strategy not only enhances the scientific validity of the modeling framework but also facilitates its application in real-world hazard management and decision-making contexts.

In this study, we propose a physics-informed deep learning (DL) framework that integrates a physically based model with a one-dimensional convolutional neural network (1D-CNN). The framework utilizes physically based model with Monte Carlo simulation to calculate the probability of failure and identify stable areas for reliable negative sample selection. Then, 1D-CNN model is developed to predict landslide susceptibility. The proposed method is applied to the 2018 landslide event in Hiroshima, Japan, to evaluate its effectiveness.

Study Area

A representative area in Hiroshima Prefecture, Japan, as illustrated in Figure 1a, was selected to evaluate the performance of the proposed model. This region includes a digital elevation model (DEM) along with 475 documented landslide occurrences. The geological characteristics of the study area are depicted in Figure 1b, which highlights five major geological units: H_sad, comprising valley floors, intermountain basins, and river/coastal plain deposits from the Quaternary Holocene; K21_vas_ai, representing dacite-rhyolite intrusive rocks of the Late Cretaceous; K21_vas_ap, referring to large-scale dacite-rhyolite pyroclastic flows of the same period; Pg3_sns, consisting of non-marine sandstone or sandstone-mudstone from the Paleogene Oligocene; and K21_snc, a non-marine conglomerate also dating to the Late Cretaceous. Figure 1c presents rainfall data associated with the 2018 landslide event, with the maximum hourly rainfall reaching 52.5 mm/h, a key triggering factor for slope failures in the region.

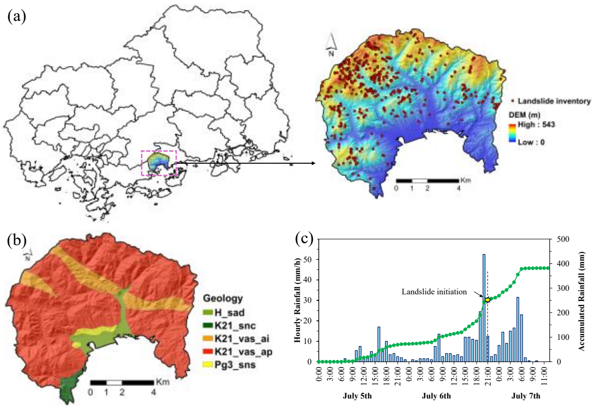

Figure 1, (a) Study area, (b) geology map, (c) Hourly rainfall data.

Methodology

Figure 2 presents a physics-informed deep learning framework for landslide susceptibility mapping. The approach integrates probabilistic slope stability analysis with a one-dimensional convolutional neural network (1D-CNN). Input parameters such as rainfall, slope, soil properties, and hydraulic conductivity are processed through an infinite slope model combined with Monte Carlo simulation. This analysis identifies low-probability areas, which are considered non-landslide samples. Various conditioning factors, including DEM, curvature, TRI, geology, aspect, and vegetation, are collected as predictive inputs. The dataset is divided into 70% for training and 30% for testing. The 1D-CNN model is trained using these inputs and probabilistic data. It produces a spatial probability map showing landslide susceptibility levels. Finally, the model's performance is evaluated for accuracy and interpretability.

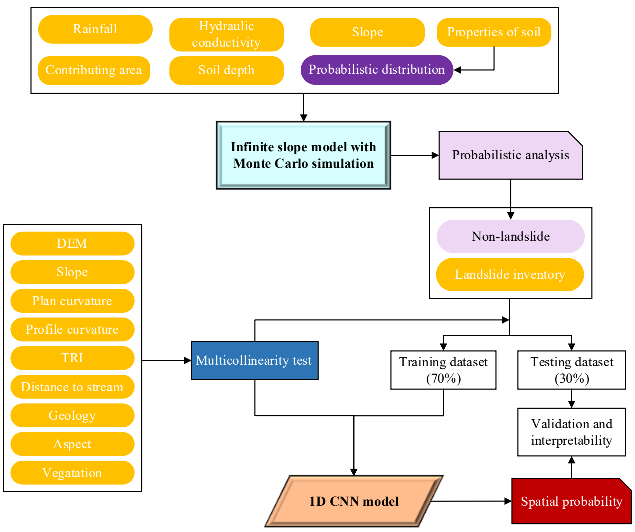

Figure 2, Methodology used in this study.

Results and Discussion

Figure 3 compares landslide susceptibility maps from a physically based model, a conventional 1D-CNN, and a physics-informed (hybrid) 1D-CNN. The hybrid model, which uses physically guided negative sample selection, aligns better with observed landslides and reduces overprediction. ROC analysis shows its superior performance, with the highest AUC values (98.9% training, 93.3% testing), highlighting the advantage of integrating physical knowledge into deep learning for improved prediction.

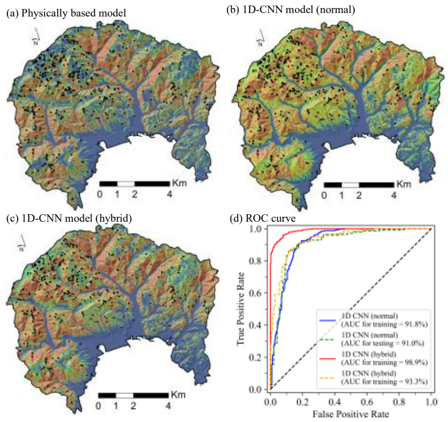

Figure 3, (a) physically based model, (b) 1D-CNN model (normal), (c) 1D-CNN model (hybrid), (d) ROC curve.

Conclusion

This study shows that integrating physical principles into deep learning improves landslide susceptibility mapping. Using slope stability analysis to guide negative sample selection, the physics-informed 1D-CNN outperforms traditional data-driven and physically based models, enhancing predictive accuracy and reliability.

Acknowledgement

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