

Effects of DEM Resolution and Sampling Strategy on Deep-Learning Debris-Flow Susceptibility Models

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Abstract: Debris-flow susceptibility mapping requires precise topographic representation and balanced sampling strategies to ensure model robustness and generalizability. This study thoroughly quantifies the influence of digital elevation model (DEM) resolution (6.5, 12.5, 30, and 90 m) and sampling-strategy uncertainty on the predictive performance of advanced deep-learning (DL) architectures, including one and two-dimensional convolutional neural networks (CNN1D, CNN2D), recurrent neural networks (RNN), and long short-term memory (LSTM) models. A field-verified debris-flow inventory comprising 108 catchments and thirteen conditioning factors derived from multi-resolution DEMs and remote-sensing datasets was used for model construction. To evaluate sampling uncertainty, hundred symmetrical iterations of debris-flow and non-debris-flow samples were executed, resulting in a 6.7-10.5 % increase in mean accuracy with optimized sample selection. Factor importance derived from Random Forest and Frequency Ratio analyses identified rainfall as the dominant control on debris-flow occurrence. Model performance, assessed through multiple statistical metrics, revealed that the LSTM consistently outperformed other architectures, achieving a maximum accuracy of 0.929 and AUC of 0.973 at 12.5 m resolution. The proposed framework provides a reproducible and scalable approach for multi-resolution DFSM and quantification of sampling-related uncertainty in complex mountainous terrain.

Keywords: Debris flow, Deep learning, Sampling strategies, DEM resolution, Susceptibility mapping, LSTM.

Introduction

Debris flows are rapid, gravity-driven mixtures of sediment, rock, and water that reshape mountain landscapes and pose severe threats to settlements and infrastructure (Daud et al., 2024, 2025; Khalid et al., 2025; Wei et al., 2018; Xu et al., 2012). Accurate prediction of their spatial occurrence requires reliable topographic representation and balanced sampling strategies. Digital elevation models (DEMs) provide the basis for most conditioning factors, such as slope, curvature, and drainage density. Yet, the influence of

DEM resolution on debris-flow susceptibility mapping (DFSM) remains uncertain. Previous studies have produced inconsistent findings, indicating that optimal resolution depends on terrain complexity, landslide scale, and data quality (Dong et al., 2024).

In addition to topographic uncertainty, sample imbalance often degrades the performance of data-driven models, as non-landslide samples are frequently overrepresented. These methodological limitations, together with the limited evaluation of DEM effects in deep-learning frameworks, highlight persistent gaps in DFSM research.

This study investigates the combined impact of DEM resolution (6.5-90 m) and sampling-strategy uncertainty on four deep-learning architectures (CNN-1D, CNN-2D, LSTM, RNN) using 108 field-verified debris-flow catchments. A symmetrical sampling experiment and Flow-R simulations were performed to quantify uncertainty and assess terrain-resolution effects on debris-flow propagation, establishing a reproducible framework for multi-resolution DFSM in complex mountain regions.

Study area and methodology

The study was conducted in the Besham–Chilas corridor of the western Himalayas, a region characterized by steep relief, fractured lithologies, and intense monsoonal rainfall. These conditions create favorable settings for debris-flow initiation and rapid downstream propagation. Field verification identified 108 debris-flow watersheds representing diverse lithological and geomorphic conditions, providing a robust foundation for model calibration. Thirteen conditioning factors were derived from multi-resolution digital elevation models (6.5 m, 12.5 m, 30 m, and 90 m) and remote-sensing datasets, capturing variations in topography, hydrology, and land cover. Datasets were standardized to a common grid framework, and debris-

flow and non-debris-flow points were symmetrically sampled to mitigate class imbalance.

Four deep-learning architectures, i.e., CNN-1D, CNN-2D, RNN, and LSTM, were implemented to evaluate the influence of DEM resolution and sampling uncertainty on predictive performance. Model performance was assessed using multiple statistical metrics, while Random Forest and Frequency Ratio methods were applied to quantify the relative importance of conditioning factors. In addition, Flow-R simulations were conducted to examine how DEM resolution influences debris-flow runout patterns, enabling integration of data-driven predictions with physically based process understanding.

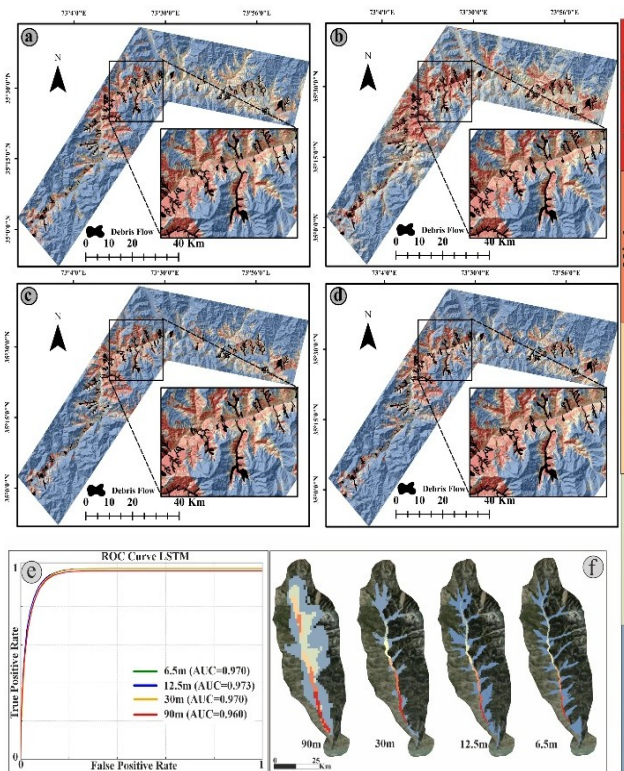


Figure 1, Debris-flow susceptibility maps from (a-d) 6.5-90 m DEMs using LSTM; (e) ROC curves; (f) Runout simulations across resolutions.

Influence of DEM scale and sampling strategy

Model performance exhibited clear sensitivity to both DEM resolution and data sampling strategy. Finer DEMs (6.5m-12.5m) enhanced terrain representation, improving the extraction of topographic variables such as slope, curvature, and drainage density. Across all architectures, balanced sampling substantially improved model stability. The 100 symmetrical iterations reduced classification bias between debris-flow and non-debris-flow points, yielding a 6.7-10.5% increase in mean accuracy compared with unbalanced datasets. These repeated tests demonstrated that sampling uncertainty can influence performance as strongly as DEM resolution.

Among the deep-learning models, the LSTM achieved the best predictive capability, with 0.929 accuracy and 0.973 AUC at 12.5 m resolution, followed by CNN-2D and CNN-1D (as shown in Figure 1 (a-e)). Random Forest and Frequency Ratio analyses identified rainfall, slope, and curvature as the most influential variables. Flow-R simulations further revealed that finer DEMs reproduced more realistic runout paths, while coarser grids underestimated channelized flow Figure 1 (f).

Effects of resolution and sampling on model reliability

The relationship between DEM resolution, sampling strategy, and model reliability underscores the complexity of debris-flow prediction. The observed improvement with finer DEMs suggests that terrain-driven parameters, especially slope and curvature, require sufficient spatial detail to represent local relief variations that govern flow initiation. However, the diminishing gain beyond 12.5 m implies that higher resolution does not always translate into better accuracy, as noise and redundancy may offset precision, a pattern consistent with previous studies (Cama et al., 2016; Cavazzi et al., 2013). This highlights the importance of optimizing DEM resolution based on watershed scale and computational efficiency, ensuring a balance between detail capture and model robustness while avoiding overfitting to minor topographic irregularities that may not influence debris-flow dynamics.

Equally important, the symmetrical sampling approach significantly reduced class imbalance, confirming that predictive reliability is not only a function of data quality but also of data distribution (Huang et al., 2023, 2024; Shirzadi et al., 2019; Zhang et al., 2024). This highlights the need for systematic uncertainty quantification rather than single-sample validation. Incorporating multiple sampling strategies, cross-validation techniques, and ensemble predictions can further enhance model robustness, minimize overfitting, and provide a more comprehensive understanding of model sensitivity. Such practices ensure that predictive outputs accurately reflect the variability inherent in hydro-geomorphic processes, ultimately improving decision-making for hazard management and mitigation planning.

The superior performance of LSTM indicates that temporal dependency and sequential feature learning are essential for modelling complex hydro-geomorphic processes (Ngo et al., 2021). Furthermore, Flow-R results emphasize that DEM scale influences runout geometry and deposition patterns, supporting the integration of data-driven and physically based models. These findings suggest that combining sequential learning approaches with high-resolution topographic inputs can improve predictive accuracy, capture nuanced flow dynamics, and provide more reliable hazard assessments, particularly in areas with complex

terrain and variable triggering conditions, ultimately enhancing risk mitigation and early-warning capabilities for debris-flow-prone regions.

Future perspectives and conclusion

This research demonstrates a reproducible approach for debris-flow susceptibility assessment through integration of multi-resolution DEMs, deep-learning architectures, and controlled sampling design. Beyond achieving high predictive accuracy, the study establishes a methodological foundation for handling spatial and sampling uncertainties that often limit model transferability.

Future advances should prioritize dynamic modelling that links rainfall variability, terrain change, and monitoring data within adaptive learning frameworks. Coupling data-driven prediction with physically based flow simulation will enable process-oriented interpretation and improve hazard forecasting. Expanding this framework to near-real-time systems, supported by UAV and InSAR observations, could transform susceptibility mapping into an operational early-warning tool.

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