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How DEM Resolution and Sample Selection Variability Influence Deep Learning Susceptibility Models for Debris Flows

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Abstract: Debris-flow susceptibility mapping requires precise topographic representation and balanced sampling strategies to ensure model robustness, predictive reliability, and generalizability. This study comprehensively 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-dimensional and two dimensional convolutional neural networks (CNN1D and CNN2D), recurrent neural networks (RNN), and long short term memory (LSTM) models. A field-verified debris-flow inventory consisting of 108 catchments and thirteen conditioning factors derived from multi-resolution DEMs and remote-sensing datasets was used for model development and validation. To evaluate sampling uncertainty and improve model stability, one hundred symmetrical iterations of debris flow and non-debris-flow samples were executed, resulting in a 6.7–10.5% increase in mean prediction accuracy through optimized sample selection. Factor-importance analyses derived from Random Forest and Frequency Ratio methods identified rainfall as the dominant controlling factor influencing debris-flow occurrence in the study area. Model performance was evaluated using multiple statistical metrics, including accuracy and area under the curve (AUC), which demonstrated that the LSTM model consistently outperformed the other DL architectures. The highest predictive performance was achieved at 12.5 m DEM resolution, with a maximum accuracy of 0.929 and an AUC value of 0.973. The proposed framework provides a reproducible, reliable, and scalable approach for multiresolution debris-flow susceptibility mapping (DFSM) and for quantifying sampling-related uncertainty in complex mountainous terrain and hazard-prone regions.

Keywords: ***Debris flow, Deep learning, Sampling strategies.***

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, elevation and drainage density, which are critical in capturing terrain variability and controlling surface runoff and flow behavior in mountainous regions (Saleem et al., 2019). Yet, the influence of DEM resolution on debris-flow susceptibility mapping (DFSM) remains uncertain in complex terrain settings. Previous studies have produced inconsistent findings, indicating that optimal DEM resolution depends on terrain complexity, landslide scale, and data quality conditions (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 debris-flow susceptibility mapping (DFSM) research, particularly in complex mountainous environments where terrain variability further increases model uncertainty and affects predictive reliability and overall model performance.

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, and RNN) using 108 field-verified debris-flow catchments across the study area. A symmetrical sampling experiment and Flow-R simulations were performed to quantify uncertainty and assess terrain-resolution effects on debris-flow propagation, thereby establishing a reproducible and scalable framework for multi-resolution debris-flow susceptibility mapping (DFSM) in complex mountainous 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, thereby providing a robust foundation for model calibration and validation. 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 spatial variations in topography, hydrology, and land cover characteristics. All datasets were standardized to a common grid framework, while debris-flow and non-debris-flow points were symmetrically sampled to minimize class imbalance and improve model reliability, consistency, and predictive performance during analysis and validation procedures.

Four deep-learning architectures, i.e., CNN-1D, CNN-2D, RNN, and LSTM, were implemented to comprehensively evaluate the influence of DEM resolution and sampling uncertainty on predictive performance. Model evaluation employed multiple statistical metrics, while Random Forest and Frequency Ratio analyses quantified relative factor importance. Flow-R simulations further assessed the effect of DEM scale on debris-flow runout behavior in a systematic and rigorous quantitative manner.

Influence of DEM scale and sampling strategy

Model performance exhibited clear sensitivity to both DEM resolution and data sampling strategy factors. Finer DEMs (6.5 m–12.5 m) significantly enhanced terrain representation, improving the extraction of key topographic variables such as slope, curvature, and drainage density. Across all architectures, balanced sampling substantially improved overall model stability.

The 100 symmetrical iterations effectively 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 clearly demonstrated that sampling uncertainty can strongly 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, whereas coarser grids underestimated channelized debris-flow propagation, as illustrated in 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).

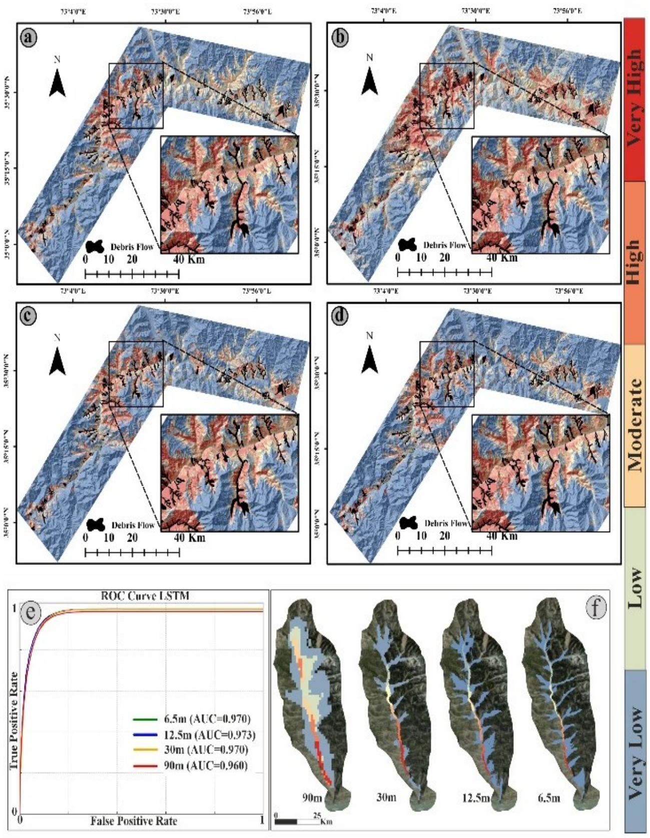

*Figure 1, Debris-flow susceptibility maps from **(a-d)** 6.5-90 m DEMs using LSTM; **(e)** ROC curves; **(f)** Runout simulations across resolutions.*

Equally important, the symmetrical sampling approach significantly reduced class imbalance, clearly confirming that predictive reliability is not only a function of data quality but also of data distribution characteristics (Huang et al., 2023, 2024; Shirzadi et al., 2019; Zhang et al., 2024). This highlights the critical need for systematic uncertainty quantification rather than single-sample validation approaches in advanced predictive modeling studies.

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, strongly supporting the integration of data-driven and physically based models.

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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