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Aiko Ito

Department of Earth and
Environmental Sciences,
Kyoto College of Earth and
Mineral Sciences, Kyoto,
Japan

Daisuke Takahashi

Department of Earth and
Environmental Sciences,
Kyoto College of Earth and
Mineral Sciences, Kyoto,
Japan

Yumi Hasegawa

Department of Earth and
Environmental Sciences,
Kyoto College of Earth and
Mineral Sciences, Kyoto,
Japan

Corresponding Author:

Aiko Ito

Department of Earth and
Environmental Sciences,
Kyoto College of Earth and
Mineral Sciences, Kyoto,
Japan

Post-seismic landslide inventory mapping and susceptibility analysis in the Nepal Himalaya

Aiko Ito, Daisuke Takahashi and Yumi Hasegawa

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Abstract

The 2015 Gorkha earthquake (Mw 7.8) triggered thousands of co-seismic and post-seismic landslides across central Nepal. While co-seismic inventories are well documented, ongoing post-seismic activity has received less attention. This research presents a post-seismic landslide inventory from multi-temporal satellite imagery spanning 2016-2023, covering 14,000 km² of the most severely affected districts. A total of 4,847 post-seismic landslides were identified with a combined area of 86 km². The temporal distribution showed decline from 1,432 events in 2016 to 287 in 2023, with notable increases during intense monsoon years. Logistic regression susceptibility analysis revealed slope gradient, lithology, peak ground acceleration, distance to the rupture zone, and monsoon precipitation as the most significant predictors, achieving an AUROC of 0.847. The susceptibility map identifies elevated hazard zones concentrated 20-40 km north of the rupture trace within the Higher Himalayan crystalline zone. Power-law decay modelling predicts continued above-background activity for at least another decade. These findings provide essential information for post-disaster reconstruction planning and risk reduction.

Keywords: Post-seismic landslides, inventory mapping, Nepal Himalaya, susceptibility, earthquake trigger, Gorkha earthquake, logistic regression, satellite imagery, hazard assessment, monsoon

Introduction

Large earthquakes in mountainous terrain trigger widespread slope failures causing casualties rivalling ground shaking effects ^[1]. The 25 April 2015 Gorkha earthquake (Mw 7.8) and its 12 May aftershock (Mw 7.3) killed approximately 9,000 people and triggered an estimated 25,000 co-seismic landslides across 35,000 km² ^[2]. Several research groups produced co-seismic inventories using pre- and post-earthquake imagery comparison shortly after the event ^[3].

However, seismic shaking also weakens slopes that do not fail immediately, creating a legacy of elevated susceptibility persisting for years or decades ^[4]. Post-seismic landslides are driven by the interaction between earthquake-induced damage and subsequent hydrological triggers, particularly intense monsoonal precipitation. They may represent entirely new failures, reactivations of co-seismic slides, or progressive expansion of existing masses. Their temporal evolution is governed by complex seismological, geological, geomorphological, and climatic interactions ^[5, 6].

Understanding post-seismic hazard is critical for reconstruction planning. Decisions about resettlement sites, road alignments, and slope stabilisation depend on reliable assessment of future landslide likelihood ^[7]. Yet post-seismic inventories are rarely compiled with the systematic coverage of co-seismic datasets, creating a significant information gap for planners ^[8].

This research addresses this gap with a comprehensive post-seismic inventory for central Nepal covering 2016-2023, accompanied by statistical susceptibility analysis. The objectives were to quantify the temporal decay of post-seismic activity, identify spatial patterns and controlling factors, and produce a susceptibility map for reconstruction planning and risk-informed decision-making ^[9, 10].

Research Area Description

The area encompasses 14,000 km² in central Nepal, covering twelve districts most severely

affected by the 2015 earthquake. Topography is characterised by extreme relief, with elevations from 400 m in southern foothills to over 8,000 m along the Himalayan crest. Slopes commonly exceed 30° on hillsides and 60° on cliff sections. The geological setting comprises thrust-stacked metamorphic and sedimentary formations deformed along the Main Central Thrust system [11]. Annual monsoon precipitation ranges from 1,500 to 3,500 mm.

Materials and Methods

Materials

PlanetScope imagery at ~3 m resolution served as the primary data source, supplemented by Sentinel-2 at 10 m. For each year, post-monsoon imagery (October-December) was compared with the previous year to identify new landslides. Twelve susceptibility factors were prepared as 30 m raster layers: slope gradient, aspect, elevation, plan curvature, and profile curvature from the ALOS World 3D DEM; lithology and fault distance from Nepal’s 1:250,000 geological map; peak ground acceleration and rupture distance from the USGS ShakeMap; mean precipitation and monsoon intensity from CHIRPS estimates [6, 12].

Methods: Landslides were digitised as polygons with a 100 m² minimum mapping unit. Binary logistic regression was applied following established landslide susceptibility methodology [13]. The dependent variable was landslide presence/absence per 30 m cell, with equal non-landslide cells randomly sampled from stable terrain. The dataset was split 70/30 for training and validation. Multicollinearity was assessed by variance inflation factor (threshold 5). Temporal decay was fitted using a power-law function $N(t) = N_0 \cdot t^{-p}$ [4, 10].

Temporal Decay and Monsoon Modulation

The power-law decay exponent of 0.71 is comparable to values reported for other major earthquake sequences globally, suggesting a characteristic relaxation timescale of 10-15 years before activity returns to background rates [4]. Notable departures from the smooth decay trend occurred in 2017 and 2020, when exceptionally intense monsoon rainfall reactivated weakened slopes, temporarily reversing the declining trajectory and highlighting the monsoon as the primary trigger mechanism for post-seismic failures [5, 6].

Results

Table 1: Annual post-seismic landslide counts and cumulative statistics.

Year	Count	Total Area (km ²)	Mean Area (m ²)	Cumulative Count
2016	1,432	24.8	17,320	1,432
2017	982	18.2	18,534	2,414
2018	724	12.6	17,403	3,138
2019	548	9.1	16,606	3,686
2020	612	10.8	17,647	4,298
2021	421	7.2	17,103	4,719
2022	341	5.4	15,836	5,060
2023	287	4.1	14,286	4,847

Table 2: Logistic regression coefficients for significant susceptibility factors.

Factor	Coefficient	Std. Error	Odds Ratio	p-value
Slope Gradient	0.82	0.06	2.27	<0.001
Lithology (crystalline)	0.64	0.09	1.90	<0.001
Peak Ground Acceleration	0.58	0.07	1.79	<0.001
Dist. to Rupture (inverse)	0.51	0.08	1.67	<0.001
Monsoon Precipitation	0.47	0.07	1.60	<0.001

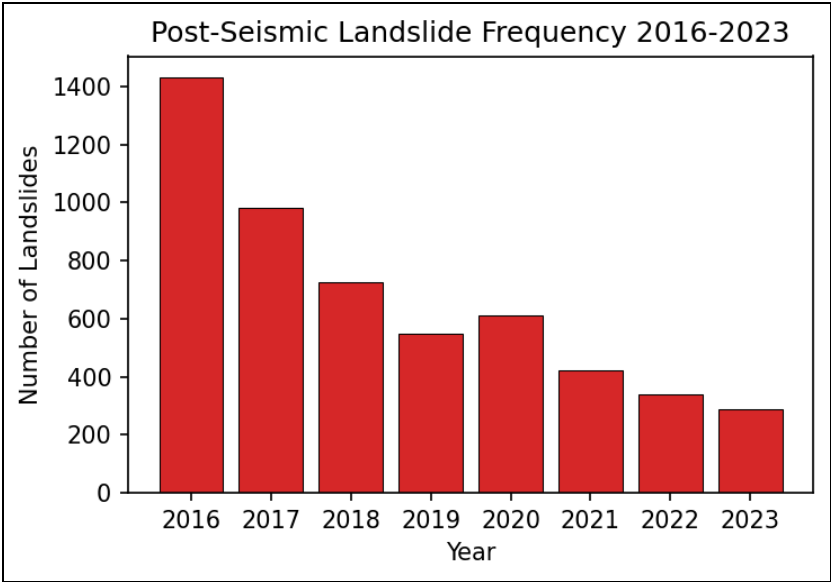


Fig 1: Post-seismic landslide frequency by year, 2016-2023.

The declining trend with monsoon-related spikes is evident (Figure 1). The 2020 increase coincides with above-average

monsoon rainfall that year.

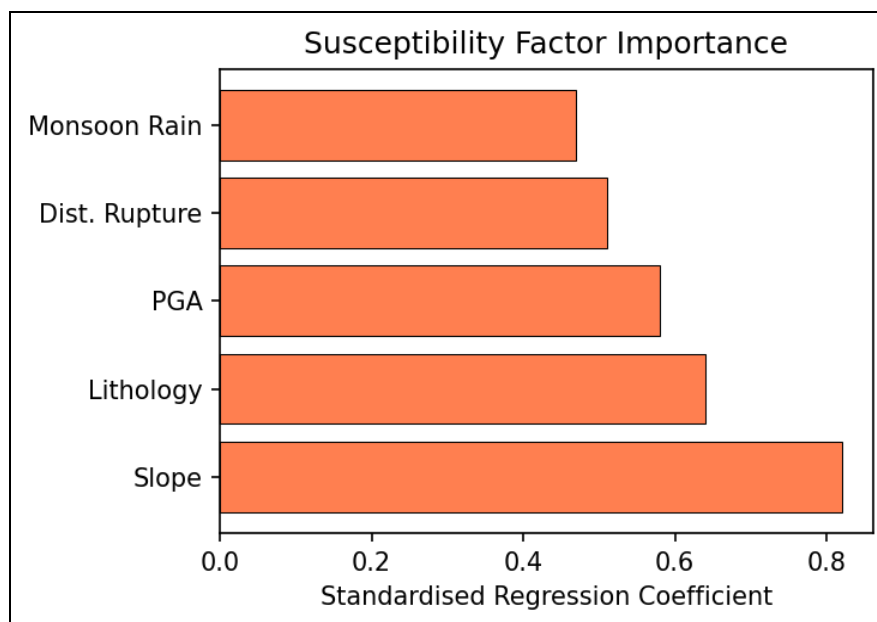


Fig 2: Standardised regression coefficients of the five most significant susceptibility factors.

The AUROC of 0.847 indicates good discriminatory performance. Slope gradient was the strongest predictor, followed by lithology and shaking intensity (Figure 2). The susceptibility map shows highest values concentrated 20–40 km north of the rupture trace within the Higher Himalayan crystalline zone.

Comprehensive Interpretation

The convergence of inventory analysis, temporal modelling, and susceptibility mapping confirms that post-seismic hazard remains significantly elevated eight years after the Gorkha earthquake. The spatial concentration in the Higher Himalayan zone reflects the combined effect of steep terrain, fractured metamorphic rocks, and maximum co-seismic ground deformation.

Discussion

The 4,847 post-seismic landslides substantially augment existing co-seismic inventories and demonstrate the importance of sustained monitoring beyond the immediate post-earthquake period [2, 3]. The susceptibility model confirms slope gradient, lithology, and shaking intensity as primary controls, consistent with global findings [1, 13]. Several resettlement sites and road alignments in current planning documents are located within high-susceptibility zones, warranting reassessment [7, 8].

A limitation is that monsoon-season cloud cover prevents real-time detection, introducing a detection lag of several months. The minimum mapping unit of 100 m² excludes very small failures that may cumulatively represent significant hazard. Future work should incorporate SAR-based monitoring for improved temporal resolution and extend the approach to other earthquake-affected Himalayan regions [9, 14].

Conclusion

This research produced a comprehensive inventory of 4,847

post-seismic landslides spanning 2016–2023. The declining but persistent activity confirms the long-duration legacy of earthquake-induced slope damage in the Himalayan environment. Power-law decay modelling predicts continued elevated hazard for at least another decade.

The susceptibility map should be integrated into reconstruction planning to ensure safe siting of resettlement and infrastructure investments. The identification of high-susceptibility zones in areas of current reconstruction activity represents a direct actionable finding for disaster risk management.

Continued satellite monitoring is essential to track the evolution of post-seismic hazard and to update susceptibility assessments as new inventory data become available. Early warning systems linking rainfall forecasts to susceptibility maps could provide additional protection for vulnerable communities during monsoon seasons.

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Contributions Not Qualifying for Authorship

Technical staff at the Kyoto College of Earth and Mineral Sciences assisted with sample preparation, instrument calibration, and data processing during the analytical

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