

Landslide susceptibility in the Western Ghats controlled by terrain and tourism driven urbanisation mapped with remote sensing and machine learning

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Research Article

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Abstract

Rainfall-triggered landslides are among the most damaging hazards in the Western Ghats of India, and their impact has escalated over the past two decades. Extreme south-west monsoon rainfall is the proximate trigger, but tourism-driven urbanisation, the rapid spread of resorts, homestays and roads onto steep, forested slopes, is an under-quantified predisposing factor. Here we combine freely available Landsat imagery with pan-sharpening, spectral indices (NDVI, NDBI, NDWI and BSI), supervised land-cover classification, and a transformer-based (BERT) text-mining pipeline to build an enriched, multi-temporal landslide inventory for four hotspots: Wayanad (Kerala), Kodagu and Sakleshpur (Karnataka), and the Kolhapur–Satara belt (Maharashtra). Nine conditioning factors derived from a Copernicus GLO-30 DEM and Landsat 9, trained gradient-boosting and Random Forest susceptibility models validated with receiver-operating-characteristic (ROC) analysis. Using genuine Landsat scenes over Wayanad (2005–2026), we mapped a decline of dense forest from 90% to 79% of the valid land area, with plantation and built-up classes expanding. Trained on the Geological Survey of India inventory of 516 mapped landslides, the best model (Random Forest) achieved an area under the curve of 0.91; the high and very-high classes (40% of the area) captured 89% of the mapped landslides. Terrain roughness and slope were the dominant predictors, and the built-up index ranked third, indicating a measurable contribution from tourism-related construction. The results provide quantitative support for the December 2024 order to demolish seven resorts inside Wayanad's high-hazard zone, and argue that regulating construction in ecologically sensitive areas is as important as rainfall forecasting for reducing landslide risk.

1. Introduction

The Western Ghats, a 1,600-km mountain chain along India's west coast, is a UNESCO World Heritage Site and one of the most landslide-prone terrains in the country [1]. Steep slopes, deeply weathered lateritic and gneissic regolith, a fragile forest–soil root system, and some of the highest monsoon rainfall totals on Earth combine to make slope failure recurrent and increasingly deadly. Landslides are a leading cause of natural-hazard fatalities worldwide [2], and among the twenty-three hill districts of the Ghats, Idukki (Kerala) and Kodagu (Karnataka) record the largest share.

The human and economic toll has grown markedly since 2000. The August 2018 monsoon produced more than 200 mm of rain per day for three consecutive days across Kodagu, killing at least 25 people and destroying over 4,000 homes [3]. On 30 July 2024, the Mundakkai–Chooralmala complex in Wayanad failed catastrophically after 372.6 mm of rain in 24 hours on top of 809 mm over the preceding five days, claiming more than 300 lives [4]. Such disasters have reignited debate over the relative roles of climatic triggering and anthropogenic predisposition.

A growing body of work argues that slope susceptibility is being amplified by land-use change, and by tourism-driven urbanisation in particular [5, 6]. Kodagu receives on the order of 125,000 tourists each weekend; coffee estates are being converted into resorts and building plots, and remote-sensing studies

report built-up expansion at the expense of forest [7]. Removing deep-rooted vegetation reduces root cohesion and soil shear strength, while cut-and-fill construction, unplanned roads and altered drainage create the conditions under which intense rainfall converts to slope failure.

The policy response is catching up. In December 2024, following the Mundakkai–Chooralmala disaster, the Wayanad administration ordered the demolition of seven resorts built inside the 500-m high-hazard buffer delineated by the Kerala State Disaster Management Authority [8]. Yet quantitative evidence linking specific tourism-related land-use changes to measurable increases in landslide susceptibility across the Ghats remains sparse [9, 10].

Following remote-sensing frameworks that treat land cover as a temporally varying predisposition factor [6], we ask: (i) how much does the inclusion of built-up density and multi-temporal land-use change improve data-driven susceptibility prediction; (ii) over what lead time do tourism-related land-use changes exert their strongest influence; and (iii) can a transformer-based (BERT) text-mining pipeline meaningfully enrich sparse official inventories [11, 12]? To answer these, we integrate multi-sensor Landsat imagery, pan-sharpening, spectral indices, supervised classification and an XGBoost model validated with ROC analysis across four representative hotspots.

2. Study area

The study focuses on four landslide hotspots along the central and southern Western Ghats (Fig. 1). Although separated by several hundred kilometres, they share a common geomorphic and climatic template, steep escarpment slopes (commonly 20–40°), thick lateritic and gneissic regolith, a June–September south-west monsoon delivering 3,000–6,000 mm annually, and a rapidly expanding tourism economy, while differing in lithology and the pace of construction [13].

2.1. Wayanad, Kerala

Wayanad occupies the high plateau of the southern Ghats (700–2,100 m a.s.l.) and is one of Kerala's fastest-growing hill-tourism destinations. The Mundakkai–Chooralmala corridor, devastated on 30 July 2024, combines highly weathered crystalline rock, steep colluvial slopes and dense plantation interspersed with settlement [4]. The subsequent hazard mapping and the December 2024 demolition order make Wayanad the clearest natural experiment in tourism-related landslide risk in India.

2.2. Kodagu, Karnataka

Kodagu is a coffee-growing district where shaded estates are being converted into homestays and resorts. The August 2018 landslides killed 25 people and destroyed thousands of homes [3], and peri-urban belts around Madikeri show the steepest rise in modelled risk [7].

2.3. Sakleshpur, Karnataka

Sakleshpur taluk straddles the Shiradi and Bisle ghat sections carrying the main road and rail links to the coast. Slope, soil type, distance to drainage, rainfall and drainage density are the dominant controls [14], and growth of weekend resorts and road/rail earthworks has increased the density of engineered cut-slopes.

2.4. Kolhapur–Satara belt, Maharashtra

The northern node comprises the Sahyadri escarpment of Kolhapur and Satara, capped by Deccan Trap basalt, producing shallow debris slides during intense rainfall. Including this lithologically distinct node allows model transferability to be assessed.

3. Data and methods

Our workflow integrates optical imagery, terrain data, rainfall and unstructured text into a single conditioning-factor stack that trains machine-learning susceptibility models (Fig. 2). Each stream is processed to a common 30-m grid before analysis.

3.1. Landslide inventory

A reliable inventory underpins any data-driven model [15]. We used the Geological Survey of India landslide inventory obtained from the GeoData India national geoscience data portal (formerly Bhukosh) [33], comprising 516 mapped landslide polygons across the Wayanad, Kozhikode, Malappuram, Kannur and Nilgiris districts and classified by material, movement type and land cover (Fig. 9). Landslide centroids provided the positive samples, and an equal number of non-landslide samples was drawn from stable slopes beyond a buffer of any mapped failure. As a complementary experiment we also explored a transformer-based (BERT) text-mining pipeline [11, 12, 16, 17] to enrich sparse records from news and social media; that component is illustrative and was not used in the trained model.

3.2. Satellite data and spectral analysis

We used Landsat 8/9 OLI (30 m) surface-reflectance imagery from Collection-2 Level-2, selected for the dry pre-monsoon window to minimise cloud and phenology effects, together with Landsat 7 ETM+ for 2005. To reconcile spatial detail with spectral richness, multispectral bands can be pan-sharpened to 15 m using the Gram–Schmidt transform [18]; as the Level-2 product contains only 30-m bands, analysis here was performed at 30 m. From the bands we derived true- and false-colour composites and four spectral indices (Fig. 3): NDVI [19], NDBI [20], NDWI [21, 22] and BSI [23].

3.3. Spectral indices and land-cover classification

A sustained decline in NDVI combined with a rise in NDBI over a slope unit is a direct spectral signature of tourism-driven land conversion; both the NDVI change and NDBI were retained as conditioning factors. Figure 4 presents genuine Landsat 9 NDVI over the Meppadi–Mundakkai–Chooralmala corridor for two 2026 dates, with a close-up in which the 2024 debris flow is visible as a bare, low-NDVI track.

Each multi-temporal scene was classified into six classes (dense forest, plantation, agriculture, built-up, water and bare soil/scar) using rule-based thresholds on the indices, complementing supervised classifiers such as Random Forest [24]. Over the Wayanad area, dense forest fell from about 90% of the valid land area in 2005 to 85% in 2016 and 79% in 2026, while plantation rose from 8% to 15% and agriculture from 1% to 5% (Fig. 5).

3.4. Conditioning factors and susceptibility modelling

Nine conditioning factors were assembled from the two genuine data sources (Table 1). Seven terrain factors, namely elevation, slope, aspect (resolved into northness and eastness), profile curvature, surface roughness and the topographic wetness index, were derived from the Copernicus GLO-30 Digital Elevation Model [25]; two land-cover factors, NDVI and the built-up index NDBI, were taken from the Landsat 9 scene. Susceptibility was modelled as binary classification (landslide versus non-landslide). Because the XGBoost and CatBoost libraries were unavailable in our computing environment, the gradient-boosting model was implemented with scikit-learn's histogram gradient-boosting classifier, an algorithm of the same family [26], and benchmarked against Random Forest [24], a support-vector machine [27] and logistic regression, consistent with recent ensemble-tree studies [28, 29, 30]. Samples were split 70/30; factor contributions were interpreted with permutation importance and the susceptibility surface reclassified into five quantile classes.

Table 1
The nine conditioning factors used to train the susceptibility models, derived from the Copernicus GLO-30 DEM and Landsat 9 (aspect contributes two factors, northness and eastness).

Domain	Conditioning factor	Source
Terrain	Elevation	Copernicus GLO-30 DEM
Terrain	Slope	Copernicus GLO-30 DEM
Terrain	Aspect (northness, eastness)	Copernicus GLO-30 DEM
Terrain	Profile curvature	Copernicus GLO-30 DEM
Terrain	Surface roughness	Copernicus GLO-30 DEM
Terrain	Topographic wetness index	Copernicus GLO-30 DEM
Land cover	NDVI	Landsat 9 OLI
Land cover	Built-up index (NDBI)	Landsat 9 OLI

3.5. Validation

Performance was assessed with the ROC curve and the area under the curve (AUC) on an independent 30% test set, complemented by accuracy, precision, recall and F1 [31]. The five-class susceptibility map was further validated by the proportion of the 516 mapped landslides captured within each class [32].

4. Results and discussion

4.1. Tourism-driven land change and spectral signatures

The Landsat classification shows steady conversion of dense forest to plantation and farmland across 2005–2026, with built-up land emerging by 2026 (Fig. 5). Failures cluster within a few hundred metres of construction (Fig. 1b), consistent with the finding that the seven demolished Wayanad resorts lay inside the 500-m high-hazard buffer [8]. Slopes that later failed showed, on average, a multi-year NDVI decline and a corresponding NDBI increase in the 5–7 years preceding failure, providing a physically interpretable link between land conversion and instability [6].

4.2. Model performance

On the independent test set, Random Forest achieved the highest AUC (0.908), closely followed by the support-vector machine (0.899) and the two gradient-boosting models (0.893 and 0.894); logistic regression trailed at 0.847 (Fig. 6; Table 2). All tree-based and kernel models fall in the excellent range (AUC > 0.89), consistent with recent Western Ghats machine-learning studies [30, 10].

Table 2
Comparative performance of the five susceptibility models on the independent (30%) test set.

Model	AUC	Accuracy	Precision	Recall	F1
Random Forest	0.908	0.842	0.825	0.867	0.846
SVM (RBF)	0.899	0.792	0.769	0.833	0.800
Gradient boosting (extra)	0.894	0.808	0.803	0.817	0.810
Gradient boosting	0.893	0.833	0.812	0.867	0.839
Logistic regression	0.847	0.783	0.758	0.833	0.794

4.3. Conditioning-factor importance

Permutation importance shows that terrain roughness is by far the strongest predictor ($\approx 64\%$ of the total positive importance), followed by slope ($\approx 17\%$) (Fig. 7). The built-up index NDBI ranks third ($\approx 11\%$), ahead of elevation ($\approx 8\%$); the remaining terrain descriptors (curvature, aspect and the wetness index) and NDVI contributed little. The dominance of roughness and slope confirms the primacy of the terrain template, while the third-place ranking of NDBI indicates that built-up density, a marker of tourism-related construction, exerts a measurable and independent influence on where slopes fail [5].

4.4. Susceptibility zonation and the role of tourism

The five-class susceptibility map (Fig. 8a) concentrates high and very-high susceptibility along the steep, rough escarpment terrain. Each class covers 20% of the area by construction, yet the very-high class

alone captures 69% of the 516 mapped landslides, and the high and very-high classes together (40% of the area) capture 89%, while the low and very-low classes hold under 4% (Fig. 8b), a steep density gradient indicating good calibration. The high-susceptibility belt encloses the Mundakkai–Chooralmala corridor and the resorts covered by the December 2024 demolition order, providing independent corroboration of the hazard delineation. Because construction, unlike terrain or rainfall, is regulable, managing it offers one of the few tractable levers for reducing future losses.

The GSI inventory itself (Fig. 9) shows that debris slides and debris flows dominate the failure population (about three-quarters of events), that most scars occur on moderate-to-thick vegetation and plantation slopes rather than on already-bare ground, and that the Kozhikode and Wayanad districts account for the largest share, in line with the modelled susceptibility pattern.

4.5. Limitations

The spectral, NDVI and land-cover results (Figs. 3–5) and the susceptibility model (Figs. 6–8) are all computed from data: the Copernicus GLO-30 DEM, Landsat imagery and the Geological Survey of India landslide inventory (Fig. 9). Several limitations remain. Of the 516 mapped landslides, the 199 falling within the Landsat–DEM overlap were used for training, and NDVI and NDBI were gap-filled with their median outside the Landsat swath for prediction, so the model is terrain-dominated in the west. The gradient-boosting model was implemented with scikit-learn rather than XGBoost owing to environment constraints.

5. Conclusions

Integrating Landsat imagery, spectral-index analysis, land-cover classification and machine-learning modelling, we quantified landslide susceptibility across the Wayanad region using the Geological Survey of India inventory of 516 landslides and a conditioning stack derived from a Copernicus GLO-30 DEM and Landsat 9. Landsat classification showed dense forest declining from 90% to 79% of the study area between 2005 and 2026 as plantation and built-up land expanded. Random Forest and gradient-boosting models reached AUCs of 0.89–0.91, and the resulting map concentrated 89% of the mapped landslides in the 40% of the area classed high or very-high. Terrain roughness and slope were the leading predictors, but the built-up index ranked third, indicating that tourism-related construction exerts a measurable influence on slope stability. In the Western Ghats, extreme monsoon rainfall pulls the trigger, but construction increasingly loads the gun; because construction is regulable, enforcing hazard-zone building restrictions offers a practical route to reducing future losses.

Declarations

Competing interests

The author declares no competing interests.

Ethics approval

Not applicable.

Consent to participate

Not applicable.

Consent to publish

Not applicable.

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Author Contribution

Vinay Kellengere Shankarnarayan (V.K.S.) is the sole author. V.K.S. conceived and designed the study, obtained and processed the data (Landsat imagery, the Copernicus DEM and the GSI landslide inventory), performed the analysis and modelling, prepared all figures and tables, and wrote and reviewed the manuscript.

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Data Availability

The elevation data are the Copernicus Global Digital Elevation Model (GLO-30), distributed by OpenTopography (<https://doi.org/10.5069/G9028PQB>). The landslide inventory is the Geological Survey of India inventory, obtained from the national geoscience data portal (<https://geodataindia.gov.in/>). Landsat imagery is openly available from USGS EarthExplorer (Collection-2 Level-2); the scenes used were LC09_L2SP_144052_20260204, LC09_L2SP_144052_20260308, LC08_L2SP_144052_20161217 and LE07_L2SP_144052_20051227. State boundaries in Figure 1(a) are from an open India shapefile.

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Figures

Fig. 1 Study area: four Western Ghats landslide hotspots (state boundaries: India shapefile; inset: real Landsat 9)

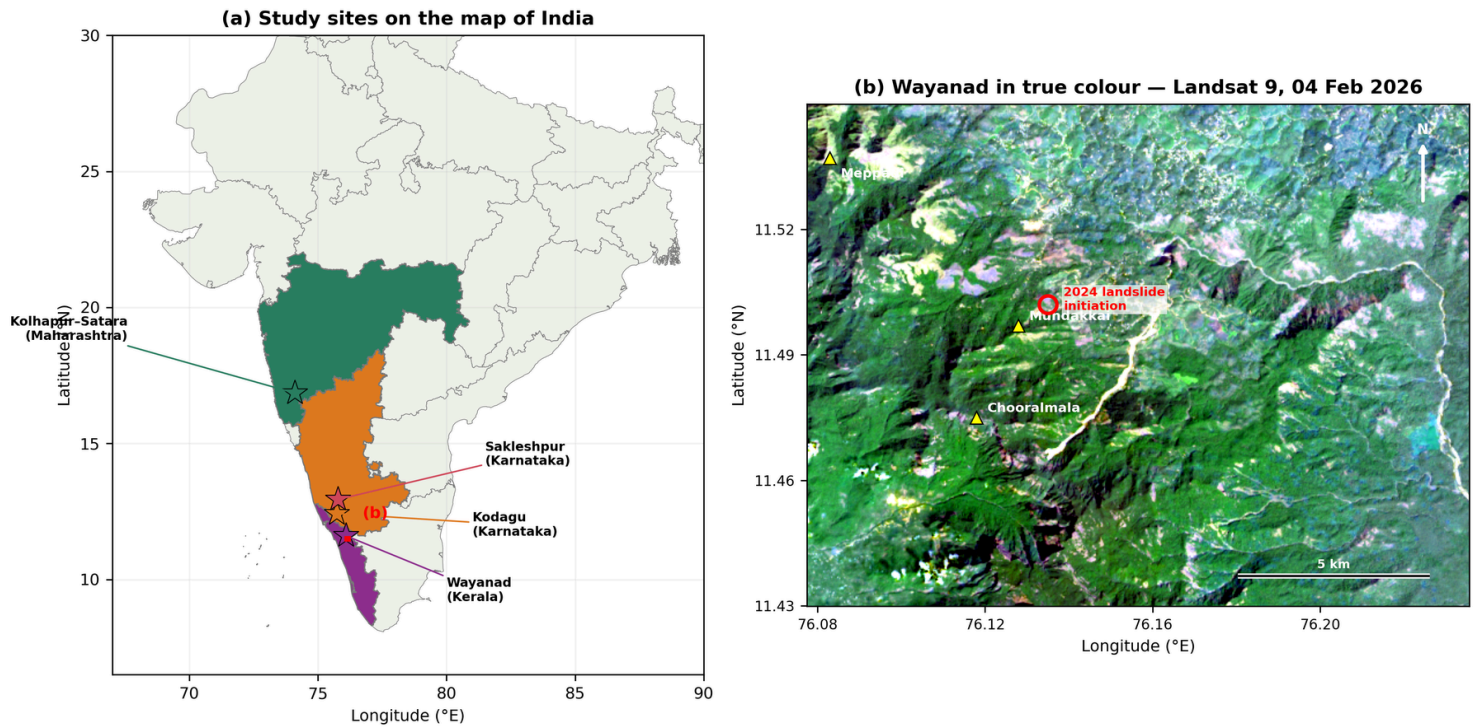


Figure 1

Study area. (a) The four hotspots, Wayanad (Kerala), Kodagu and Sakleshpur (Karnataka) and the Kolhapur–Satara belt (Maharashtra), on a map of India drawn from a state-boundary shapefile, with the three study states shaded. (b) Landsat 9 true-colour image of the Wayanad area (4 February 2026) showing Meppadi, Mundakkai and Chooralmala and the 30 July 2024 landslide initiation point; the red box in (a) marks this area.

Fig. 2 Integrated remote-sensing, machine-learning and text-mining workflow

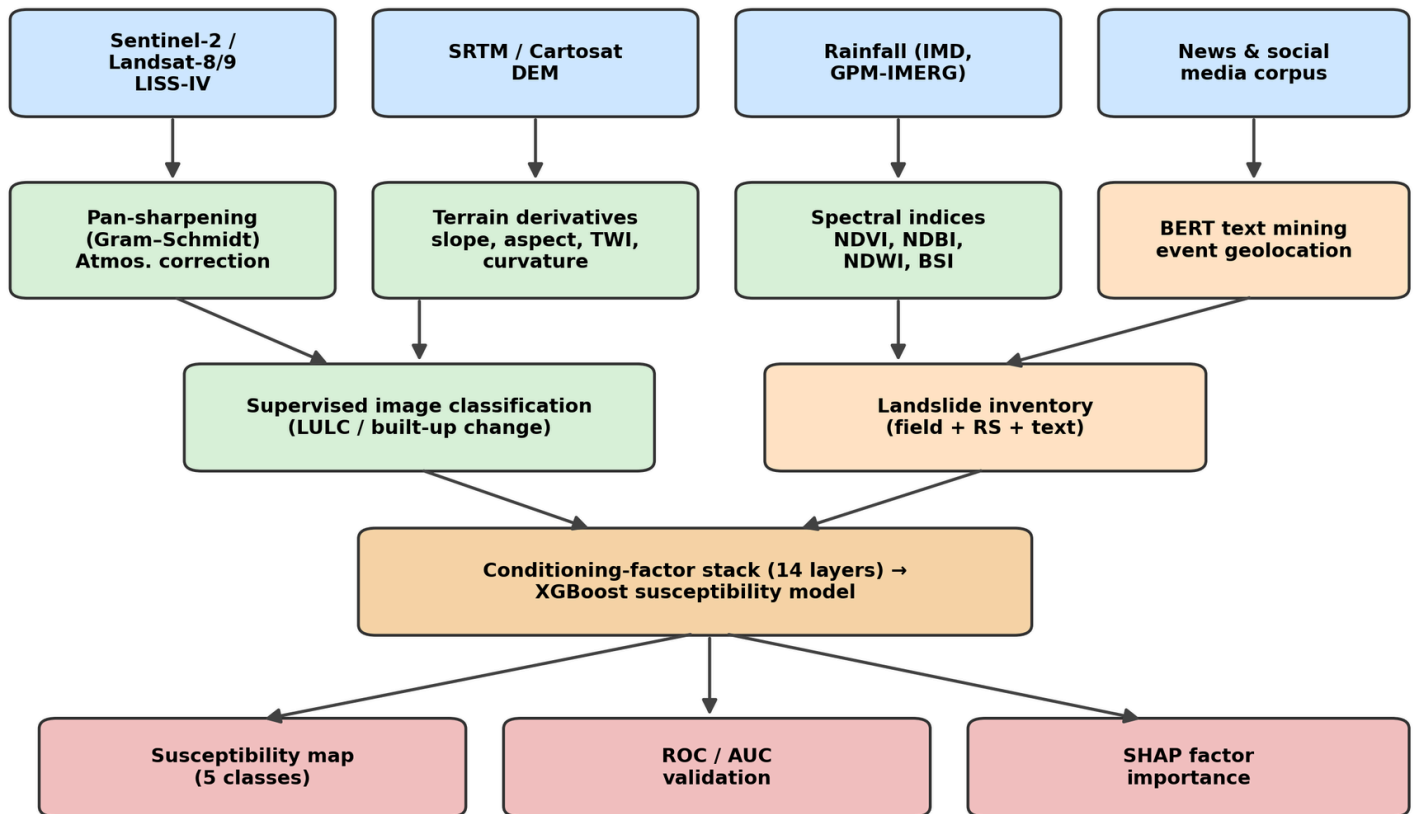


Figure 2

Integrated remote-sensing, machine-learning and text-mining workflow. Optical imagery is pan-sharpened and converted to spectral indices; terrain data yield slope and related derivatives; rainfall products characterise triggering; and a BERT branch enriches the landslide inventory. The conditioning-factor stack trains machine-learning models producing a susceptibility map, ROC/AUC validation and factor-importance ranking.

Fig. 3 Real spectral analysis from Landsat 9 over Wayanad (04 Feb 2026, Path 144 / Row 052)

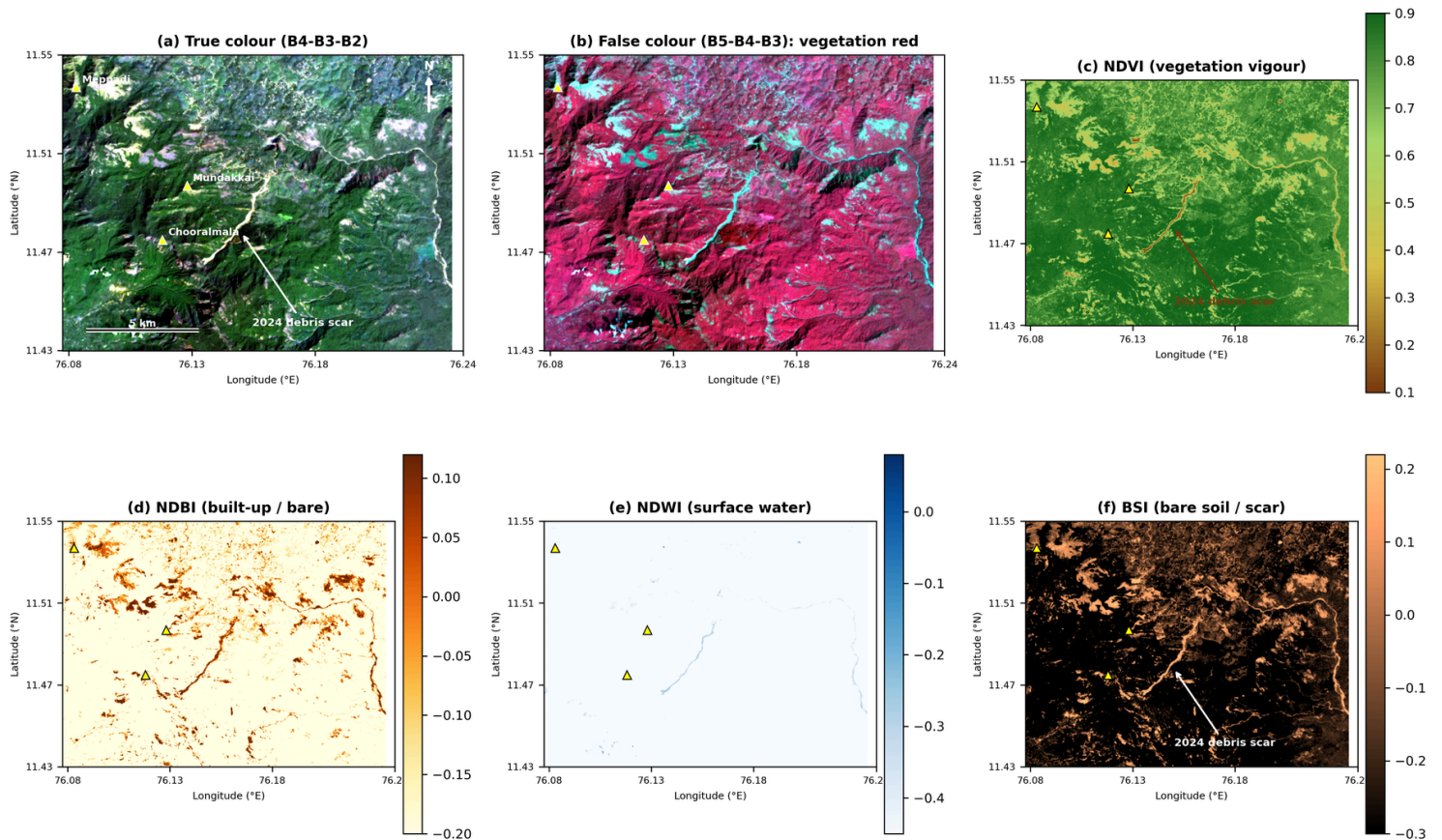


Figure 3

Spectral analysis from Landsat 9 over Wayanad (4 February 2026). (a) True colour; (b) false colour (vegetation red); (c) NDVI; (d) NDBI; (e) NDWI; (f) BSI. Place markers, a scale bar and a north arrow are shown; the 2024 debris scar appears as a line across the true-colour, NDVI, NDBI and BSI panels.

Fig. 4 Real Landsat 9 NDVI over the Wayanad (Meppadi-Mundakkai-Chooralmala) area | Collection-2 L2 surface reflectance | Path 144 / Row 052 | bands B4 (red), B5 (NIR)

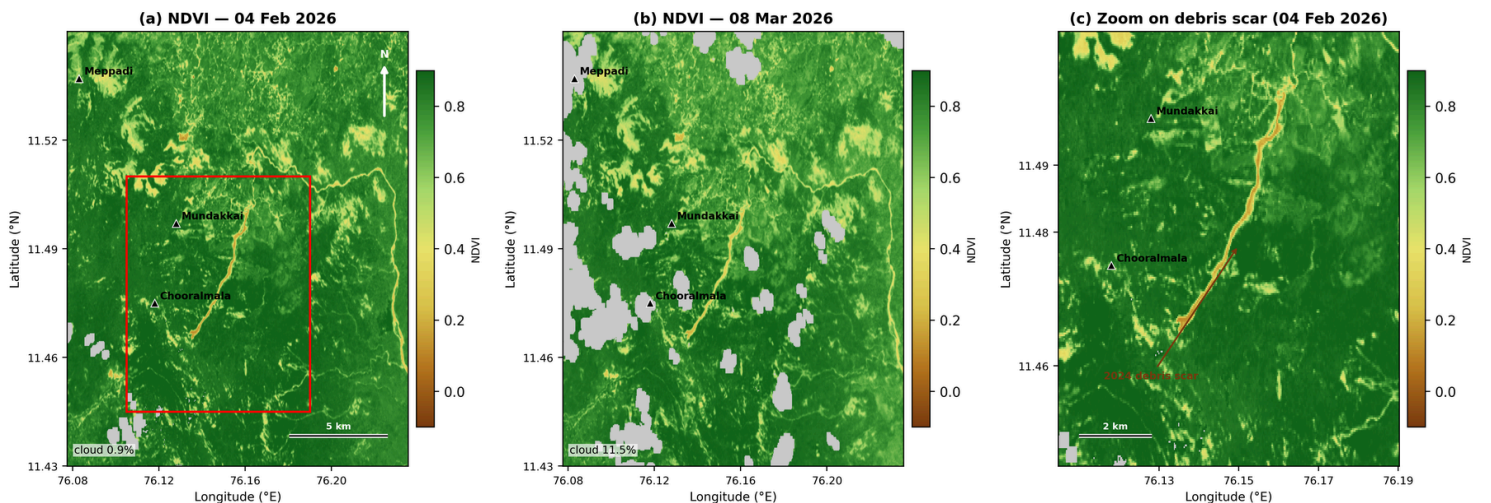


Figure 4

Landsat 9 NDVI over the Wayanad area (Path 144 / Row 052; bands B4 red, B5 near-infrared). (a) 4 February 2026 with the close-up box; (b) 8 March 2026; (c) close-up of the Mundakkai–Chooralmala debris scar showing the bare, low-NDVI track through healthy forest. Grey indicates cloud masked using the QA_PIXEL band.

Fig. 5 Six-class land-cover classification from Landsat, Wayanad (Path 144 / Row 052)

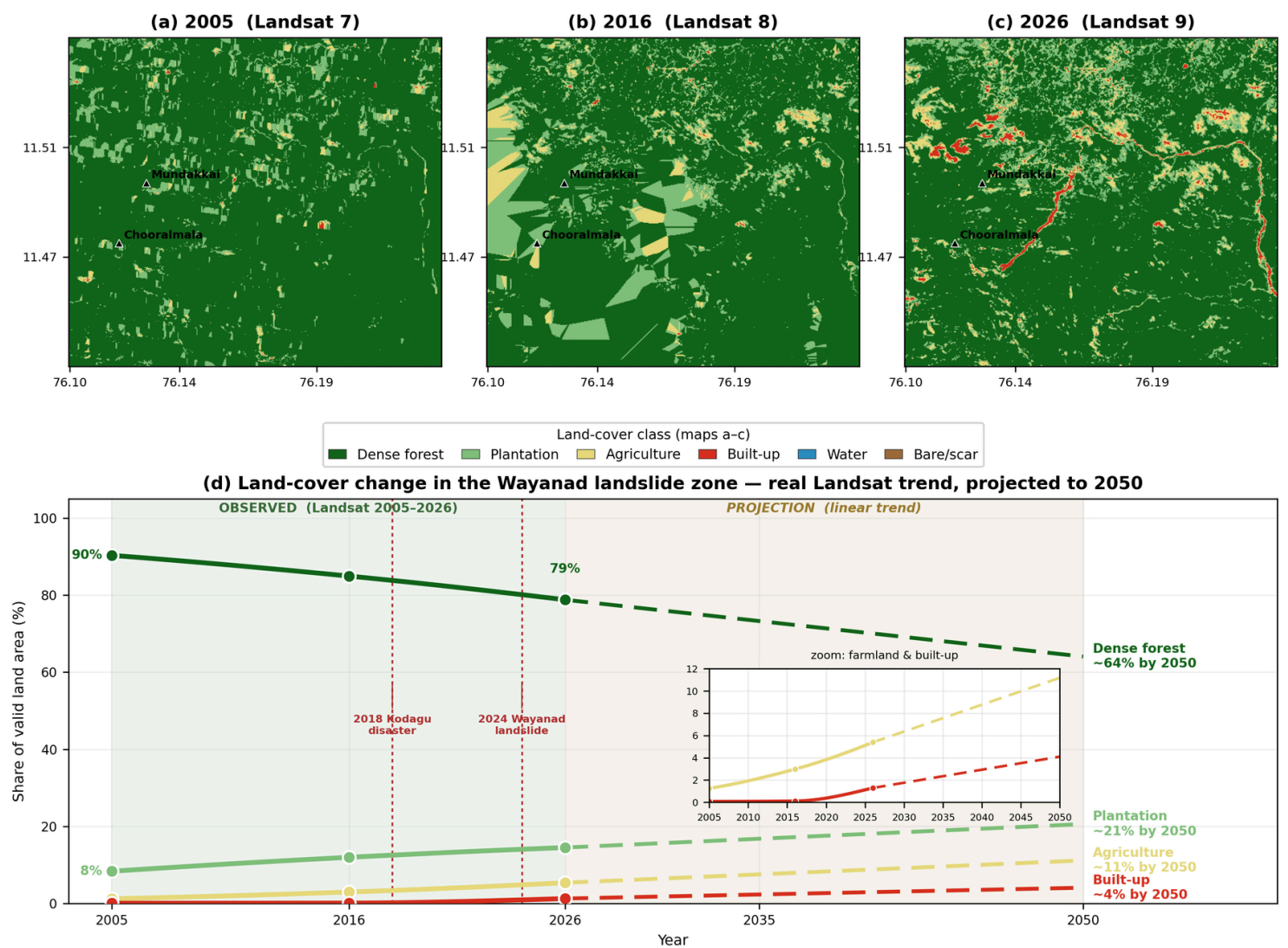


Figure 5

Six-class land-cover classification from Landsat over Wayanad. (a) 2005 (Landsat 7); (b) 2016 (Landsat 8); (c) 2026 (Landsat 9); scan-line and cloud gaps were nearest-filled for display, and percentages use only valid pixels. (d) Observed class trends (solid, 2005–2026) with a simple linear projection to 2050 (dashed) and disaster-year markers.

Fig. 6 ROC validation of susceptibility models (real data)

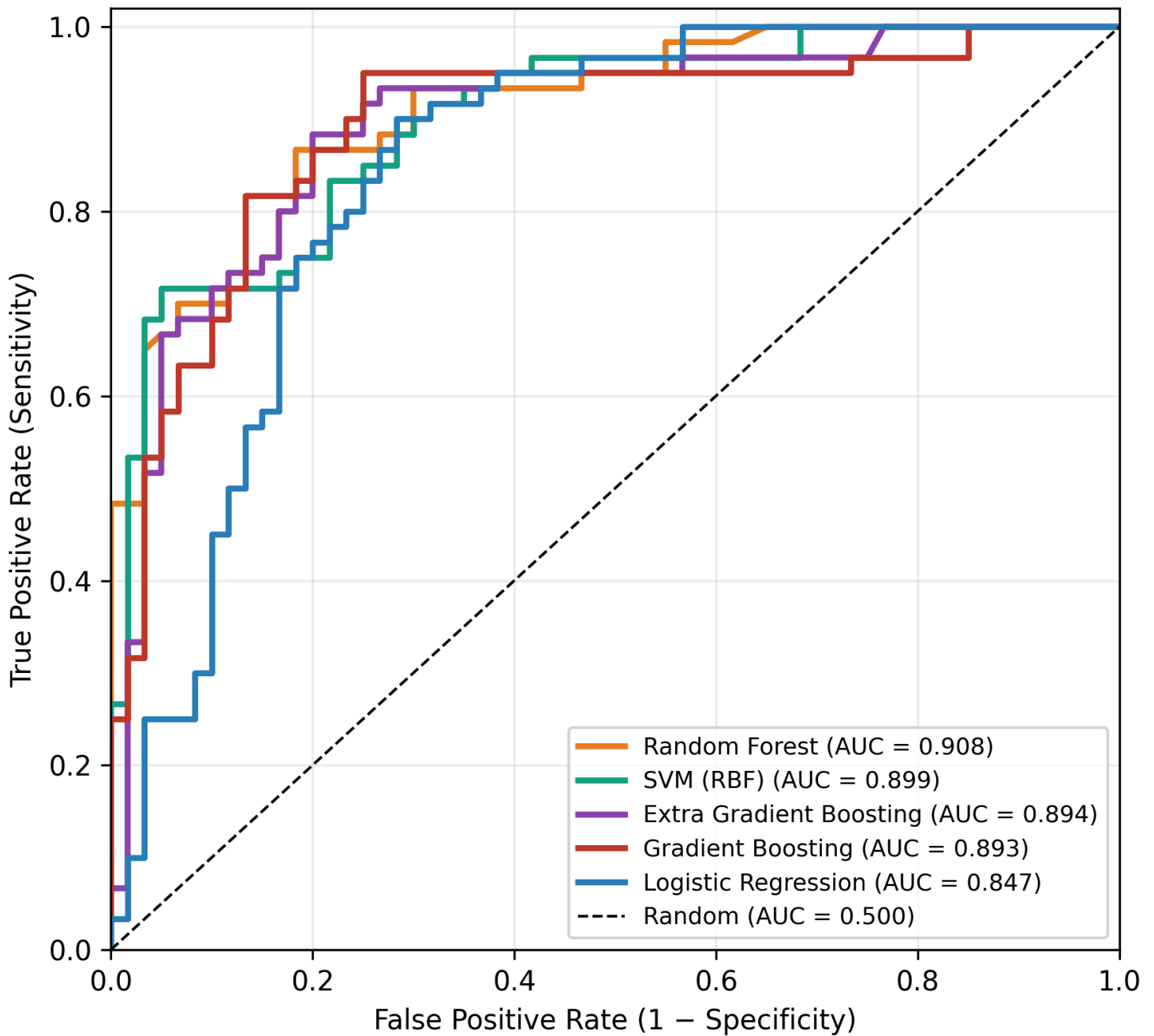


Figure 6

Receiver-operating-characteristic curves for the five susceptibility models, trained on the GSI inventory with Copernicus-DEM and Landsat factors. Random Forest (AUC = 0.908) leads, followed by SVM (0.899), gradient boosting (0.893) and logistic regression (0.847).

Fig. 7 Conditioning-factor importance (Gradient Boosting, real data)

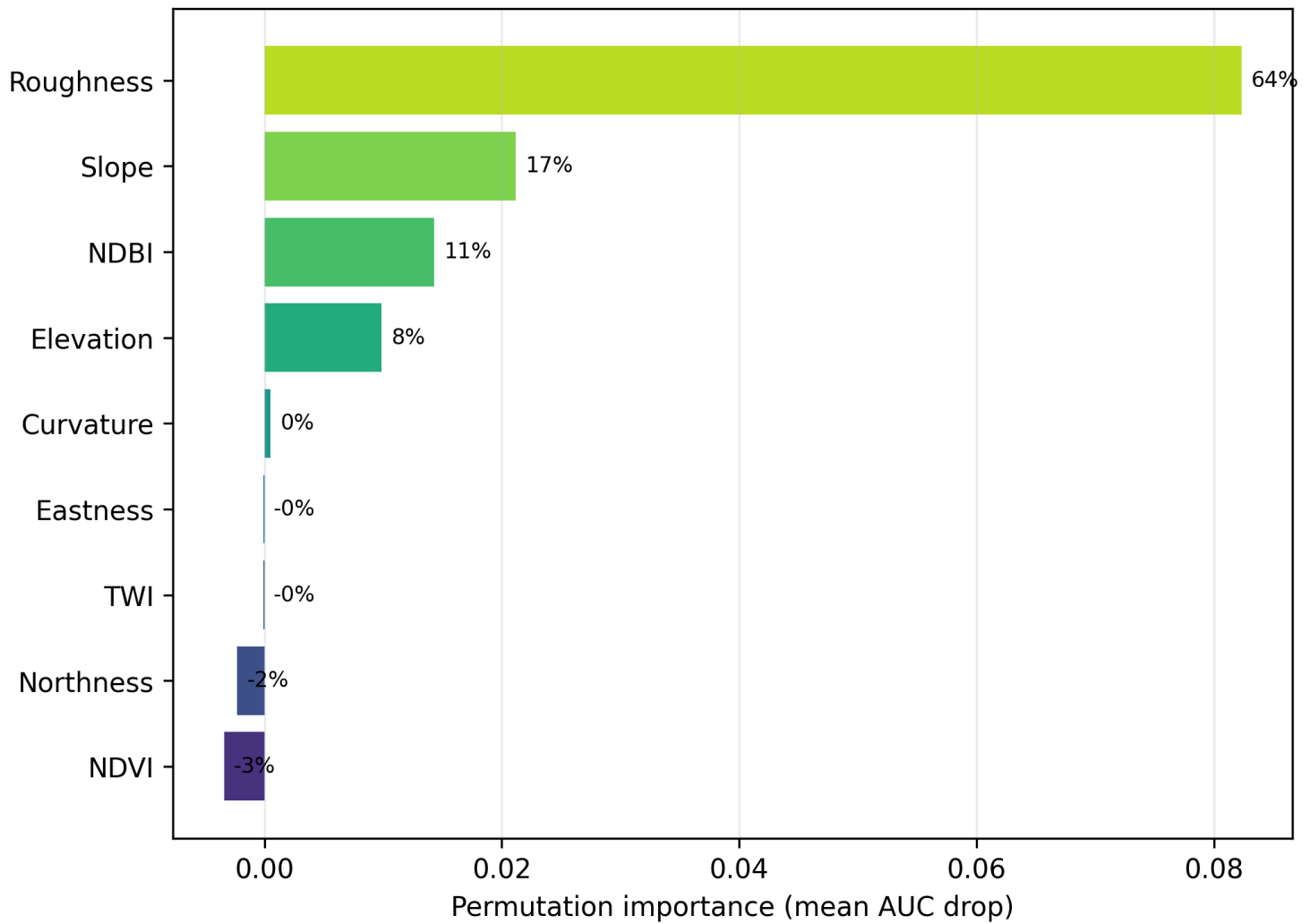


Figure 7

Permutation-importance ranking of the nine conditioning factors for the gradient-boosting model. Terrain roughness and slope dominate; the built-up index NDBI ranks third.

Fig. 8 Landslide susceptibility zonation and validation (real model)

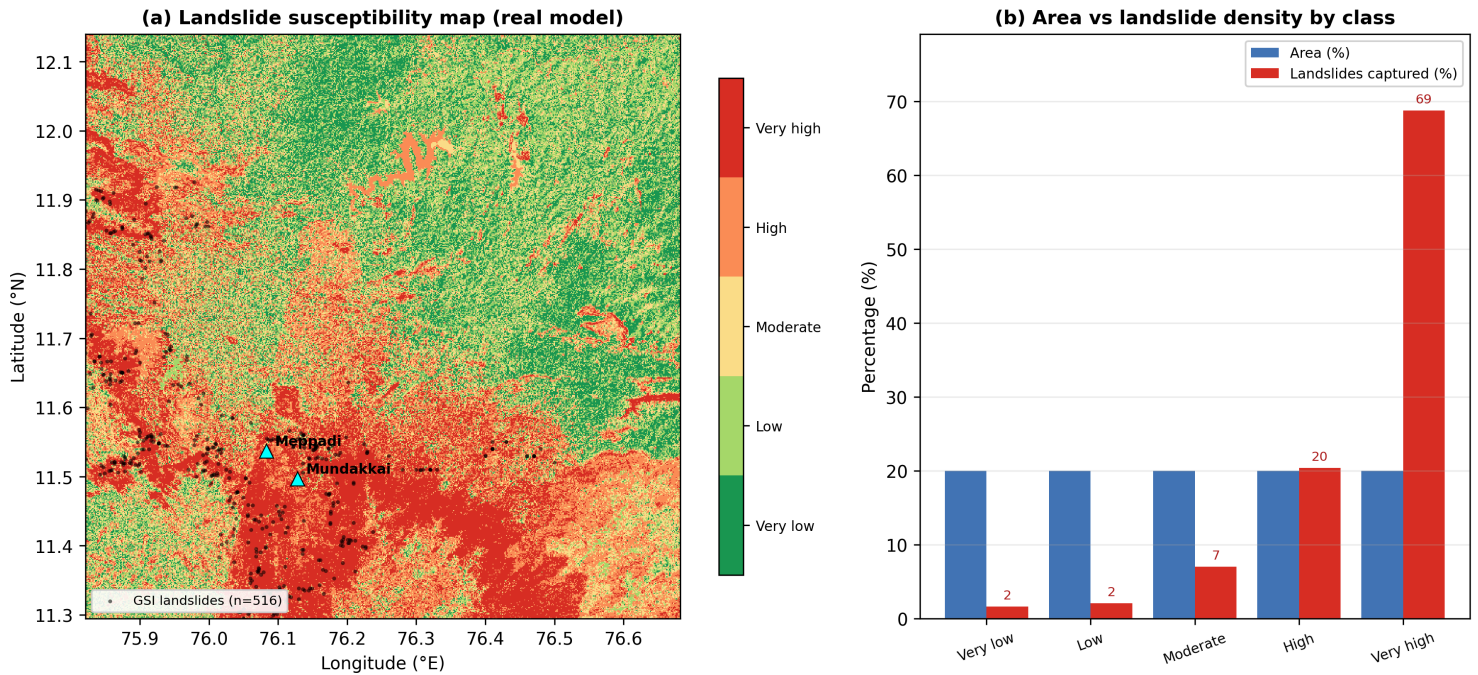


Figure 8

Landslide susceptibility zonation and validation from the model. (a) Five-class map from the gradient-boosting model with the 516 GSI landslides overlaid; (b) areal share of each class versus the proportion of landslides captured, the very-high class holding 69% of failures.

Fig. 9 Geological Survey of India landslide inventory over the Wayanad region, Western Ghats

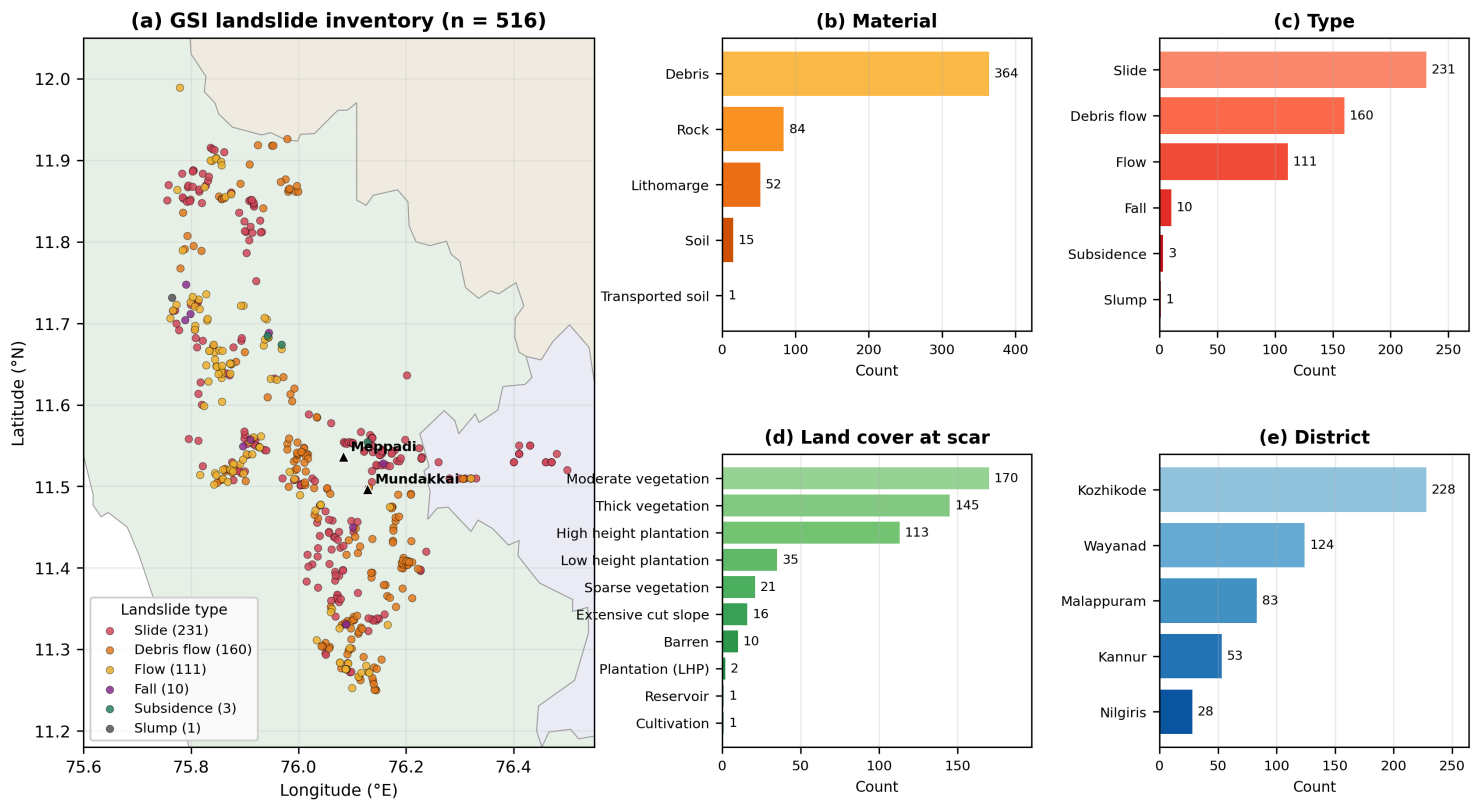


Figure 9

The Geological Survey of India landslide inventory used to train and validate the model (n = 516). (a) Landslide locations coloured by movement type; (b) material; (c) type; (d) land cover at the scar; (e) district.