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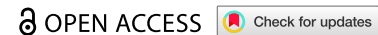


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RESEARCH ARTICLE



Exacerbating landslide risks under future climate change and land use scenarios: evidence from the Western Himalayas in Pakistan

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ABSTRACT

Landslides are exacerbating in the climate-sensitive Western Himalayas, threatening populations, infrastructure, and ecosystems. This study develops a dynamic risk assessment framework using static stressors and dynamic drivers, including climate projections from CMIP6, land use forecasts via CA-Markov, and Shared Socioeconomic Pathways (SSP1–2.6, SSP2–4.5, SSP5–8.5). Landslide susceptibility was modeled using an integrated Frequency Ratio–Analytic Hierarchy Process approach, validated through ROC analysis and Seed Cell Area Index. Population exposure used gridded SSP datasets, while vulnerability was assessed using the static Global Relative Deprivation Index due to limited future socioeconomic data. Results show extreme precipitation dominates the risk at high elevations, while land-use change intensifies in peri-urban corridors. Landslide risk areas are projected to expand under all SSPs, with a significant increase from 5.34% in 2020 to 9.04% by 2060 under SSP2–4.5, a relative change of 69.3%. Hotspot transition analysis reveals that moderate-risk zones in 2020 will evolve into high-risk areas by 2060, mainly near expanding infrastructure on steep slopes. ~61% population resides in vulnerable zones, highlighting the urgency for targeted adaptation. The framework offers insights into slope zoning, early warning systems, and resilient infrastructure, supporting the UNDRR's 'Early Warning for All' initiative and IPCC adaptation goals.

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Landslide risk; geospatial modeling; climate projections; land use forecasting; disaster risk reduction

1. Introduction

Landslides have accounted for 10%–15% of global disasters and 5%–10% of related fatalities over the past two decades (UNISDR-CRED 2015; UNDRR 2020, 2023). These hazards present widespread risks to human life, infrastructure, and economies, with annual damages nearing US\$20 billion globally (Klose et al. 2016). Landslides result from a complex interaction of static stressors, including geological structures, topography, and geomorphic conditions, as well as dynamic stressors such as climate change and land cover shifts (Dai et al. 2023; Sharma and Sandhu 2024). Anthropogenic alterations through urbanization, deforestation, agriculture, and industrialization further exacerbate risks by altering natural landscapes (Alcántara-Ayala 2025). The current decade is the warmest on record, with Asia being most affected by climate-related disasters (IPCC 2023; WMO 2024). Climate change intensifies extreme rainfall events,

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thereby escalating landslide hazards, especially in mountainous regions. In areas like the Western Himalayas, rapid and unplanned urban expansion compounds this effect, significantly destabilizing slopes. Thus, integrating climate and urbanization stressors within disaster risk frameworks, such as UNDRR's recent 'Early Warning for All' initiative, is urgently needed (UNDRR 2023).

Although machine learning and geospatial approaches have become common for landslide susceptibility mapping (Liu et al. 2023; Agboola et al. 2024), relatively few studies have adopted integrated risk frameworks that dynamically combine susceptibility, exposure, and vulnerability across future climate and land-use scenarios (Gariano and Guzzetti 2016). Many regional studies remain descriptive, lacking anticipatory modeling that incorporates evolving land use land cover (LULC) and climate scenarios (Tyagi et al. 2023). While dynamic approaches to landslide risk are becoming common globally (Alcántara-Ayala 2025), their application at finer resolutions remains limited, especially within South Asian contexts characterized by complex monsoonal climates and rapid urbanization.

Most fatal landslides occur in tropical and monsoon-prone areas, notably South Asia, where seasonal rainfall frequently triggers disasters (Froude and Petley 2018; Kirschbaum et al. 2020; Burrows et al. 2023). Recent studies in the eastern and northern Hindu Kush have highlighted how urban expansion interacts with local geo-environmental conditions, significantly increasing landslide susceptibility (Rahman et al. 2022; Rusk et al. 2022). Similarly, research in the northwestern Himalayas indicates that landscape disturbances resulting from urban encroachment substantially elevate slope instability (Riaz et al. 2018; Rehman et al. 2022). Collectively, these studies underscore an important gap: while global efforts have advanced dynamic exposure and risk modeling, the spatial interplay of projected urban expansion, climate-induced stressors, and terrain instability remains poorly understood in Pakistan, despite it being a climate change hotspot with accelerating urban development and recurrent landslide disasters (Riaz et al. 2024). This gap in spatially explicit, scenario-informed risk assessments is especially critical for proactive planning in a terrain characterized by steep slopes, weak lithology, and increasingly exposed communities.

To bridge this gap, simulating future LULC scenarios alongside climate projections offers essential insights for proactive landslide risk management. This dynamic is especially pronounced in Murree, where unregulated urban expansion, tourism-related infrastructure, and road construction increasingly interact with intensifying monsoon patterns and geologically fragile slopes. These combined pressures amplify the likelihood and severity of future landslide events yet remain underexplored in scenario-based spatial models. Effective landslide risk reduction requires frameworks that integrate projected climate scenarios, urbanization trends, and local terrain characteristics (Capobianco et al. 2025). Thus, this study proposes an integrated framework designed to assess the spatio-temporal dynamics of landslide risk under future climate and land-use scenarios in Pakistan's Western Himalayas. The framework systematically: (1) evaluates future LULC scenarios for short- (2040) and mid-term (2060) periods using a Cellular Automata-Markov (CA-Markov) model under projections from three Shared Socioeconomic Pathways (SSPs) – SSP1–2.6, SSP2–4.5, and SSP5–8.5; (2) assesses projected precipitation and temperature changes using an ensemble of CMIP6 General Circulation Models (GCMs); (3) examines how evolving susceptibility influences vulnerability and exposure; and (4) analyzes the resulting shifts in landslide risk. The multi-scenario approach captures optimistic (SSP1–2.6), intermediate (SSP2–4.5), and high-risk pathways (SSP5–8.5), enhancing robustness and practical policy relevance. Additionally, dynamic population and exposure projections identify emerging risk hotspots, aiding proactive resilience planning. By explicitly linking climate–urban interactions with risk transitions, this study provides a comprehensive understanding of landslide risk dynamics, directly supporting the Sendai Framework (2015–2030) and initiatives such as UNDRR's 'Early Warning for All'.

2. Study area characteristics

The study area comprises the Murree Hills in Punjab Province, Pakistan, located on the southern slopes of the Western Himalayan foothills, approximately 50 km northeast of Islamabad (73°10'00"–73°33'00" E; 33°44'00"–34°05'00" N), covering an area of 382 km² (Figure 1). The region features steep and rugged topography (471–2231 m elevation) and a subtropical highland climate (Cfb). With a population of ~260,538 and a density of 682 persons/km² (PBS 2017), human settlements are concentrated along roads and newly urbanized slopes. Geologically, ~80% of the area is underlain by the Murree Formation (Miocene age), composed of alternating sandstone, shale, and mudstone. These interbedded weak and strong lithologies

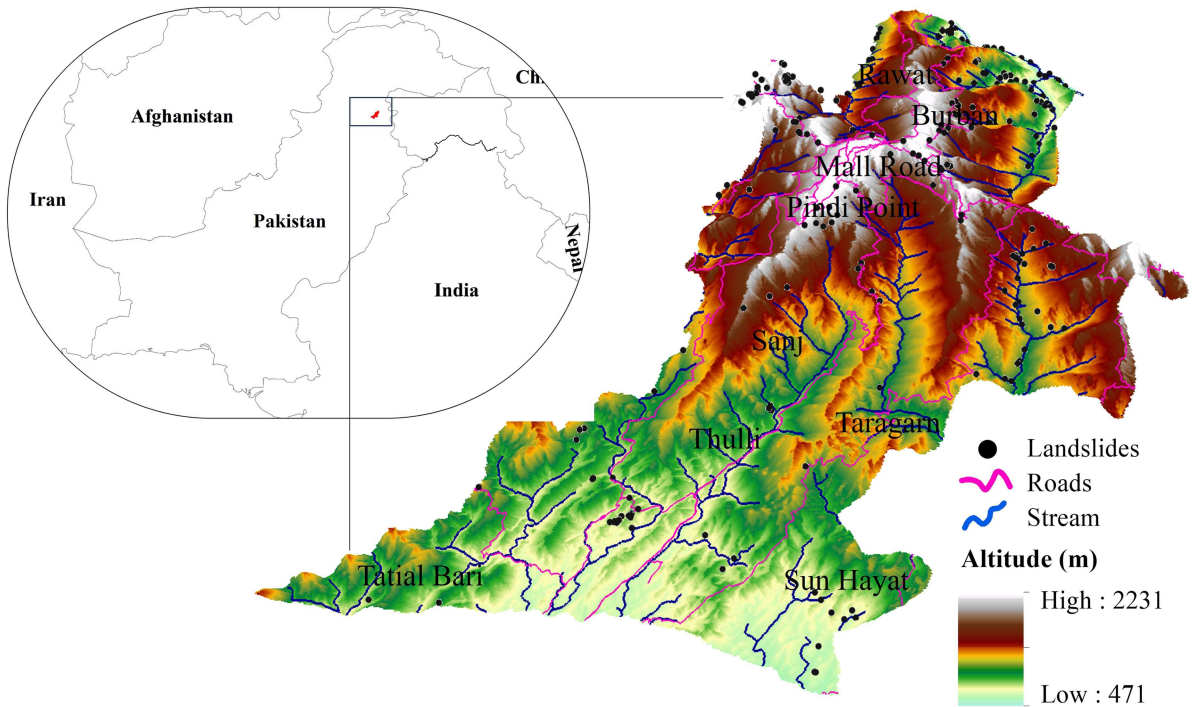


Figure 1. Geographical location and landslide inventory of Murree: the left panel shows the location of Murree in Pakistan (Source: ESRI online resources). The right panel illustrates the topography of Murree, marking major tourist destinations alongside an inventory of landslide occurrences from 2001 to 2023.

influence slope failure behavior, with sandstone units typically experiencing block-type failures along joints, while the softer shale and mudstone are prone to translational or rotational slides during saturation (Riaz et al. 2024). These geological features are incorporated into susceptibility modeling as a categorical lithological stressor. The remaining formations (Palaeocene to Pleistocene) include limestone and alluvium deposits, which are moderately stable but destabilize under anthropogenic or hydrological disturbance.

Murree receives ~1789 mm of annual precipitation, primarily during the June–August monsoon, along with heavy winter snowfall (~62.6 inches/year) (Shaw 2014). Intense rainfall and snowmelt increase pore pressure, triggering both shallow and deep-seated failures, especially on deforested or road-cut slopes. Between 2001 and 2024, multiple rainfall-triggered landslides have occurred, including the catastrophic 2005 event, which resulted in over 50 fatalities (Khan et al. 2011). Similar disasters occurred in 2010 (resulting in 20+ deaths), 2015 and 2017 (25 fatalities along the Murree Expressway), and more recently in 2022 (30 deaths) and 2023 (Khajut landslide: five deaths and evacuations) (Zaheer et al. 2020; Qasim et al. 2021; Ahmed et al. 2023). These events highlight the region's sensitivity to climate-induced landslide hazards, underscoring its suitability for this study's dynamic landslide susceptibility and risk modeling framework.

3. Data and methodology

Figure 2 presents the methodological framework employed in this study, with detailed descriptions of each step provided in the subsequent sections. The process begins with the development of a landslide inventory, followed by the evaluation of relevant stressors. Subsequently, landslide susceptibility, vulnerability, and exposure are assessed, and risk is quantified under multiple future scenarios. Finally, spatio-temporal analyses are conducted to identify short- and medium-term transitions in landslide risk hotspots.

3.1. Landslide inventory database development

The historical record of landslides, also known as the inventory, is crucial to understanding the relationship between landslides and their causative stressors. Due to the absence of centralized or publicly

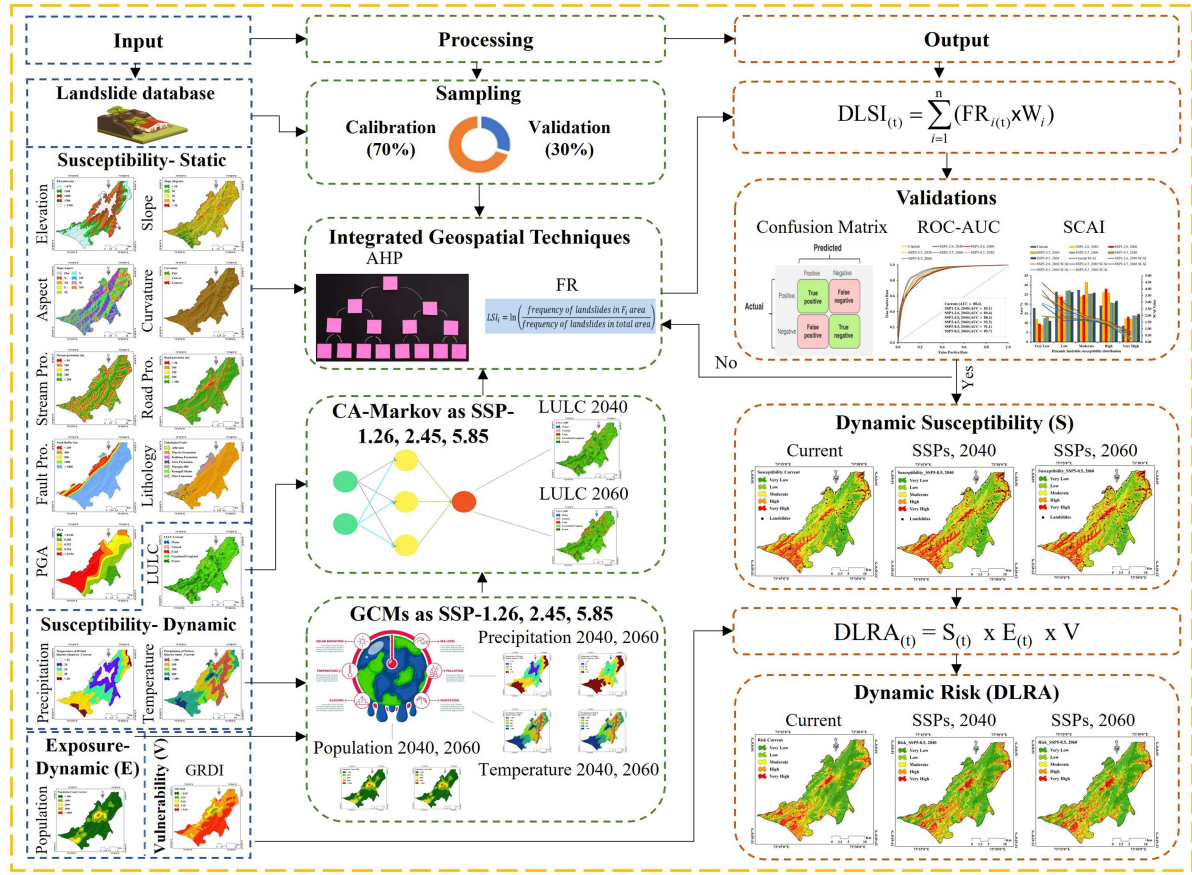


Figure 2. The methodological framework adopted for dynamic landslide risk assessment in this study.

accessible landslide databases in Pakistan, we developed a new inventory using a multi-source visual interpretation approach. This included remote sensing datasets such as Google Earth Pro, Landsat, and Sentinel-2 imagery, complemented by field visits conducted between 2020 and 2023. A 500×500 -meter fishnet grid was created in ArcGIS and imported into Google Earth Pro, where the time-slider tool was used to inspect imagery from 2001 to 2023. Landslides were identified, particularly following the monsoon season, when imagery allowed clear post-event comparison. Where annual Google Earth updates were missing, we utilized Landsat (16-day revisit, 2001–2013) and Sentinel imagery (6–12-day revisit, 2014–2023) as supplementary sources. To enhance positional accuracy and reduce subjective bias, a cross-verification procedure was implemented using overlay analysis across multiple years and platforms. Ambiguous cases, especially those concealed by vegetation or cloud cover, were excluded. The final inventory includes 230 landslide events, each represented as both a point (scarp) and a polygon (body) feature (Figures 1 and 3).

Approximately 20% of the landslides were field verified using handheld GPS devices during field visits (Figure 3a and d). Ten additional landslides were validated during our 2023 field survey (Figure 3b, c, e and f). The overall mapping accuracy was estimated at 92%. Due to image resolution constraints and limited ground-truthing resources, temporal stratification and landslide type classification (shallow slides, debris flows, and rockfalls) were not formally implemented and grouped under the term ‘landslides’. The final inventory was split into a 70:30 ratio for model training and testing, respectively.

3.2. Susceptibility stressor screening via multicollinearity

To ensure the reliability and interpretability of landslide susceptibility modeling, multicollinearity among predictor stressors was assessed before model development. Strong correlations between variables can bias coefficient estimates and reduce predictive accuracy (Hong et al. 2018). We first applied Pearson's

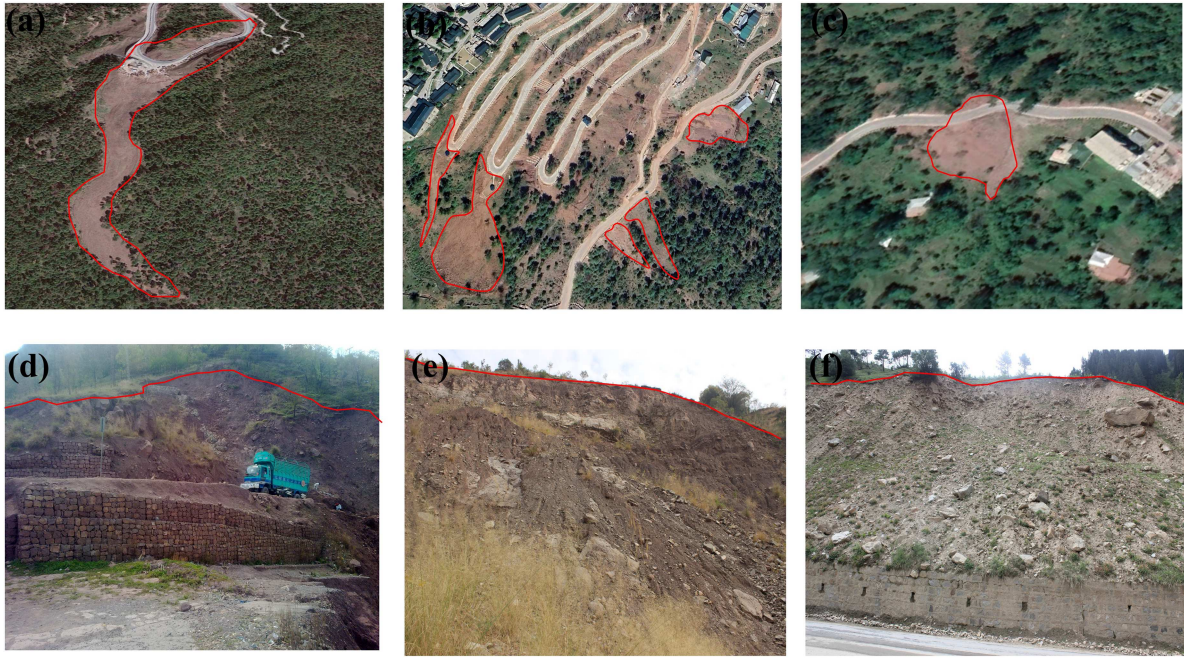


Figure 3. Landslides database development. The upper panel (a–c) shows landslide identification via high-resolution remote sensing images (Google Earth Pro), and the lower panel (d–f) shows the same identified landslides via field visits. The red polygons in the upper panels mark the landslide body, whereas the red line in the lower panels marks the scarp lines.

correlation coefficient (PCC) to assess linear associations between all stressors, using a threshold of $|r| \geq 0.70$ to identify highly correlated pairs (Huang and Chen 2024). To further verify stressors' independence, the Variance Inflation Factor (VIF) was computed using an Ordinary Least Squares (OLS) model. Variables with VIF values exceeding 5.0 were excluded, while those below 3.0 were retained for the final susceptibility assessment (Arabameri et al. 2020). A stepwise regression with bidirectional selection was then performed to evaluate how including or excluding collinear variables affected the model's performance and simplicity. The refined stressor set ensured both statistical validity and physical relevance under future land use and climate conditions.

3.3. Dynamic landslide risk assessment (DLRA) framework

DLRA is a comprehensive approach that accounts for all risk components. A key step is determining susceptibility weights, which are essential for hazard mapping and mitigation planning. Susceptibility assessments can be performed using machine learning (ML), deep learning (DL), or multi-criteria decision-making (MCDM) methods. While ML and DL offer high accuracy, they require extensive data and computational resources. In contrast, simpler methods such as frequency ratio (FR) and analytic hierarchy process (AHP) are more practical in data-scarce regions due to their simplicity and reliability (Fatah et al. 2024). Based on the study area's characteristics and research goals, we adopted an integrated FR–AHP approach to assess landslide susceptibility under both current and future scenarios.

The Frequency Ratio (FR) method is employed to quantify the relationship between landslide occurrences and various stressors, as presented in Table 1. The underlying principle of this method is that certain stressor classes are more susceptible to landslides than others. By comparing the frequency of landslides within each stressor class to the corresponding land area in the same class, the FR method indicates the strength of association between each stressor and landslide occurrences. The FR for each stressor class is calculated using Equation 1:

$$FR = \frac{L_i/L}{A_i/A} \quad (1)$$

Table 1. Details of the data source used for dynamic landslide risk assessment.

Risk component	Stressor	Source	Spatial, temporal resolution	Format
Susceptibility-static	Elevation, slope, aspect, curvature	www.asf.alaska.edu	12.5 m, 2006–2011	Raster
	Proximity to roads	www.openstreetmap.org	2024	Vector
	Lithology, proximity to streams and faults	https://gsp.gov.pk/	1:50,000, 1983 and 2004	Thematic
Susceptibility-dynamic	PGA	https://doi.org/10.5281/zenodo.8409647	1 km, 2023	Raster
	LULC	www.earthexplorer.usgs.gov	30 m, 2000–2020	Raster
	Precipitation, Temperature	www.worldclim.org	1 km, 1970–2060	Raster
Exposure-dynamic	Population	(Wang et al. 2022), www.sedac.ciesin.columbia.edu	1 km, 2000–2060	Raster
Vulnerability	GRDI	www.sedac.ciesin.columbia.edu	1 km, 2010–2020	Raster

L_i represents the number of landslide occurrences within a stressor subclass i . L is the total number of landslides across the entire study area. A_i is the area of stressor within subclass i , and A is the total study area.

To reduce subjectivity in the AHP weighting process, the FR-derived rank values were used to inform the construction of the pairwise comparison matrix. This hybrid FR–AHP integration allows the incorporation of empirical statistical relationships into the subjective structure of AHP, thereby enhancing consistency and reducing bias. The AHP, developed by Saaty (1980), assigns subjective weights to stressors through expert-based pairwise comparison matrices. The matrix reflects the relative prioritization of each stressor, and the weights of the stressor are determined by deriving the eigenvector corresponding to the largest eigenvalue of the matrix. The normalized weight of each stressor can be calculated using Equation 2.

$$w_i = \frac{1}{n} \sum_{j=1}^n \left(\frac{a_{ij}}{\sum_{k=1}^n a_{kj}} \right) \quad (2)$$

$$CI = \frac{\lambda_{\max} - n}{n - 1} \quad (3)$$

$$CR = \frac{CI}{RI} \quad (4)$$

where n represents the total number of stressors (in our case, 11), and the term a_{ij} denotes the relative importance of stressor i compared to stressor j . To normalize these comparisons, the inner sum $\sum_{k=1}^n a_{kj}$ calculates the sum of all elements in column j of the pairwise comparison matrix. Equations (3) and 4 denote the consistency of all the calculated weights, which should be <0.1 . To produce the dynamic landslide susceptibility Index (DLSI), we integrate the FR values with the AHP-derived weights using Equation 5 by adding $f(t)$. This integration is achieved by multiplying the FR of each stressor class i (assigned rank values based on the FR) by its corresponding fixed AHP weight (W_i) and then summing the weighted products for all stressors. The current DLSI is a composite index reflecting the current landslide susceptibility ($t = 0$), whereas, for future projections ($t > 0$), we replaced the dynamic stressors to calculate short-term ($t = 1$ for 2040) and medium-term ($t = 2$ for 2060) susceptibility for all SSPs.

$$DLSI_{(t)} = \sum_{i=1}^n (FR_{i(t)} \times W_i) \quad (5)$$

Model validation was performed using the ROC curve and Seed Cell Area Index (SCAI). The ROC calculates the DLSI area percentage on the y-axis and the landslide occurrence percentage on the x-axis on a scatter plot. It utilizes the area under the curve (AUC) method to validate the DLSI – the more area under the curve, the higher the validation. In contrast, the SCAI denotes the higher values in the lower DLSI. After validating the current DLSI, we extend it by incorporating dynamic stressors to assess short- and mid-term DLSI under all SSPs.

DLRA is important for understanding landslide consequences and informing risk management strategies. As defined by the IPCC and UNDRR, the risk framework calculates risk as the product of hazard (susceptibility (S)), exposure (E), and vulnerability (V). However, due to the absence of hazard intensity and severity, we simplify the risk equation by focusing on relative risk assessment, considering the hazard component as susceptibility. Exposure refers to the population and infrastructure that landslides could affect (Emberson et al. 2020). Vulnerability quantifies the susceptibility of these assets to landslide hazards (Bayes 2021). Additionally, we revised the risk equation by implementing the $f(t)$ as shown in Equation 6. The current landslide risk is calculated using the baseline susceptibility, exposure, and vulnerability components, considering a time of $t = 0$.

$$DLRA_{(t)} = S_{(t)} \times E_{(t)} \times V \quad (6)$$

For dynamic risk assessment, projections of dynamic susceptibility stressors (such as land use and climate change) and exposure (such as changes in population distribution) are incorporated utilizing the $t = 1$ for short-term (2040) and $t = 2$ for mid-term (2060). It is worth mentioning that the vulnerability component is assumed to be constant for dynamic risk assessments, as no projections for future vulnerability are available for the study area.

3.3.1. Dynamic landslide susceptibility stressors

Comprehensive data were compiled from various topographic, environmental, and meteorological sources to assess landslide susceptibility (Table 1). It is worth noting that static stressors, such as morphology, require significantly more time to change their characteristics. In contrast, dynamic stressors, such as climatic stressors, exhibit higher variability over short time scales. Therefore, we assume topographic and geological factors as static stressors, and climate-related factors are categorized as dynamic stressors, incorporating future projections for climate and LULC changes, which justifies the used terminologies and underscores the importance of addressing temporal variability in risk assessment. Geospatial data for static stressors, including elevation, slope, aspect, and curvature, were derived from the SRTM-derived DEM. Road networks were sourced from OpenStreetMap (OSM), while lithology, faults, and streams were obtained from the Geological Survey of Pakistan (GSP) maps. Peak Ground Acceleration (PGA) data were acquired from the USGS global seismic hazard map.

We utilized bioclimatic variables from the ‘WorldClim’ data archives (30 arc-second resolution) to evaluate the dynamic stressors affecting landslide susceptibility. This includes historical climate records (1970–2000) and future projections based on the Coupled Model Intercomparison Project Phase 6 (CMIP6) (Eyring et al. 2016). To enhance projection reliability and address model uncertainty, we employed an ensemble of four GCMs: ACCESS-CM2, HadGEM3-GC31-LL, IPSL-CM6A-LR, and MIROC6, given their strong performance in mountainous and monsoonal regions (Abbas et al. 2022). Each raw model was bias-corrected using quantile mapping (Equation 7) and calibrated against observed data to improve the realism of rainfall and temperature distributions at local scales (Ngai et al. 2017).

$$X_{\text{corrected}} = F_{\text{obs}}^{-1}(F_{\text{model}}(X_{\text{raw}})) \quad (7)$$

where F_{model} is the cumulative distribution function (CDF) of the raw model data, and F_{obs}^{-1} is the inverse CDF (quantile function) of observed data. Ensemble weights were derived from historical performance (R^2 -based), and spatial uncertainty layers were calculated using the inter-model standard deviation. This multi-model ensemble (MME) approach mitigates the over-reliance on a single model and improves the credibility of downscaled datasets (30-meter resolution) used in risk simulations. Further details on the ensemble weights, quantile mapping diagnostics (e.g. Q-Q plots and CDF shifts), and spatial uncertainty are provided in the Supplementary Materials (Figure S1). This improved approach ensures that the dynamic susceptibility stressors for 2040 and 2060 under all SSPs reflect the aggregated results from MME rather than a single trajectory, making the results more generalizable.

To analyze LULC changes, Landsat 5 (2000, 2010) and Landsat 8 (2020) imagery were classified using the Random Forest algorithm, capturing key transformations, such as urban expansion, deforestation, and agricultural expansion (Waleed et al. 2024). These changes were integrated with scenario-specific

projections of future climate and population data corresponding to SSP1–2.6, SSP2–4.5, and SSP5–8.5, along with static drivers, to simulate land change dynamics for 2040 and 2060. The Cellular Automata-Markov (CA-Markov) model was employed to project future LULC distributions by analyzing historical transitions and applying probabilistic and spatial rules. Each LULC map was calibrated with its respective SSPs to ensure consistency between climate stressors and socio-economic trends. The core computation of the Markov chain model estimates the probability of transitioning from one land use class i to another class j using the transition probability matrix P_{ij} , where each element satisfies $0 < P_{ij} < 1$, ensuring a total probability distribution across all LULC classes (Hamad et al. 2018). The future land use transitional probability is predicted using Equation 8 by implementing the $f(t)$ as:

$$L_{(t)} = p_{ij}xL \quad (8)$$

where L represents the current land use status at time $t = 0$, while $t = 1$ and $t = 2$ represent the simulations for short-term (2040) and mid-term (2060). This formulation enables the CA-Markov model to account for both the likelihood of land use transitions and the impact of spatial neighborhoods. The MOLUSE plugin in QGIS was used for simulation implementation. These SSP-informed LULC projections were then integrated as dynamic stressors into the landslide susceptibility modeling, enhancing the accuracy of future risk assessments by capturing how anthropogenic and climatic stressors jointly affect slope stability.

3.3.2. Dynamic exposure assessment

Exposure in landslide risk assessment refers to the presence of population and assets located within areas vulnerable to landslides (Pellicani et al. 2014). To evaluate this component, we carried out both a baseline (2020) and future (2040 and 2060) population-based exposure assessment using gridded datasets under multiple SSPs. Baseline population exposure was derived from the Gridded Population of the World version 4 (GPWv4) dataset (CIESIN 2016), which provides global population counts at a 1 km spatial resolution. To ensure spatial compatibility with other 30-m resolution raster layers (e.g. landslide susceptibility and LULC), the GPWv4 dataset was resampled using bilinear interpolation. This resampling was performed solely for raster overlay operations and does not imply a gain in the spatial accuracy of the original data. We considered this downscaling as redistributed proxies rather than precise fine-scale demographic estimates.

For future exposure assessment, we utilized population projection datasets under SSP1–2.6, SSP2–4.5, and SSP5–8.5, sourced from Wang et al. (2022). These datasets provide gridded population counts at a 1 km resolution, updated every 5 years, from 2020 to 2100. Projections for the target years 2040 and 2060 were extracted and resampled. The same resampling rationale applies, wherein the downscaled data were used to maintain spatial correspondence during analysis, but do not represent actual high-resolution demographic patterns. All population layers were overlaid with the corresponding landslide susceptibility maps using raster-based spatial intersection. This process enabled us to quantify population exposure across multiple timeframes and SSP-based development scenarios, allowing for dynamic modeling of future exposure patterns under varying socio-economic trajectories.

3.3.3. Vulnerability assessment

Vulnerability in landslide risk assessments refers to the degree to which a community or infrastructure is susceptible to harm from a hazard event, given its exposure to such hazards (Dai et al. 2002). Socioeconomic conditions and preparedness factors influence vulnerability (Sajjad et al. 2018). We employed the Global Gridded Relative Deprivation Index Version 1 (GRDIv1) to quantify vulnerability (CIESIN 2022). GRDIv1 assesses deprivation at a 1 km resolution using sociodemographic and satellite data on income, education, health, and living conditions. GRDIv1 is expressed on a scale from 0 to 100, where 100 signifies the highest level of deprivation, and 0 indicates the lowest. The GRDIv1 data was the primary instrument for assessing current vulnerability, reflecting the socioeconomic conditions that influence a community's capacity to withstand and recover from landslide events. However, we acknowledge that GRDIv1 represents a static and does not capture evolving vulnerability dynamics under different SSPs. This is primarily due to the lack of high-resolution, spatially explicit projections of future socioeconomic indicators (e.g. income, education, housing access) for Pakistan. Existing SSP datasets, such as SSP-RCP-linked projections, provide coarse national trends but lack spatial disaggregation below the

provincial level, thereby limiting their integration into sub-district analyses. Moreover, government infrastructure and development plans are often non-digitized or lack consistent geographic coverage. Therefore, we used GRDIv1 as the best available proxy for vulnerability.

3.4. Spatial change detection of landslide risk hotspots

The spatial transitions in landslide-prone areas over time were generated by binary raster layers, which represented very high-risk (VHR) zones for each period (2020, 2040, 2060) and scenario (SSP1–2.6, SSP2–4.5, SSP5–8.5). The rasters were compared with the baseline (2020) using raster overlay analysis (cell-by-cell logic) to identify key transition areas where VHR status changed from lost to gained or remained persistent. Each pair overlaid to produce change maps with four classes: not VHR, lost VHR (previously VHR in 2020 but not in the future), gained VHR (newly classified as VHR in the future), and persistent VHR (remained VHR in both periods). The area of each transition was calculated using Equation 9:

$$A_i = n_i x \left(\frac{r^2}{10^6} \right) \quad (9)$$

where A_i is the area of transition class i , n_i is the number of raster pixels in that class, and r is the spatial resolution of the raster. This standard raster-based area estimation approach allowed quantification of transition dynamics in terms of spatial extent. The outputs were visualized as categorical raster maps of all SSPs.

4. Results

4.1. Multicollinearity analysis

Multicollinearity analysis was conducted to identify statistically independent stressors in the susceptibility assessment. The correlation matrix (Figure 4) revealed a strong negative linear relationship between elevation and temperature ($r = -0.98$), indicating severe collinearity. Similarly, slope, PGA, and fault proximity exhibited moderate associations, suggesting potential redundancy. To quantify this collinearity,

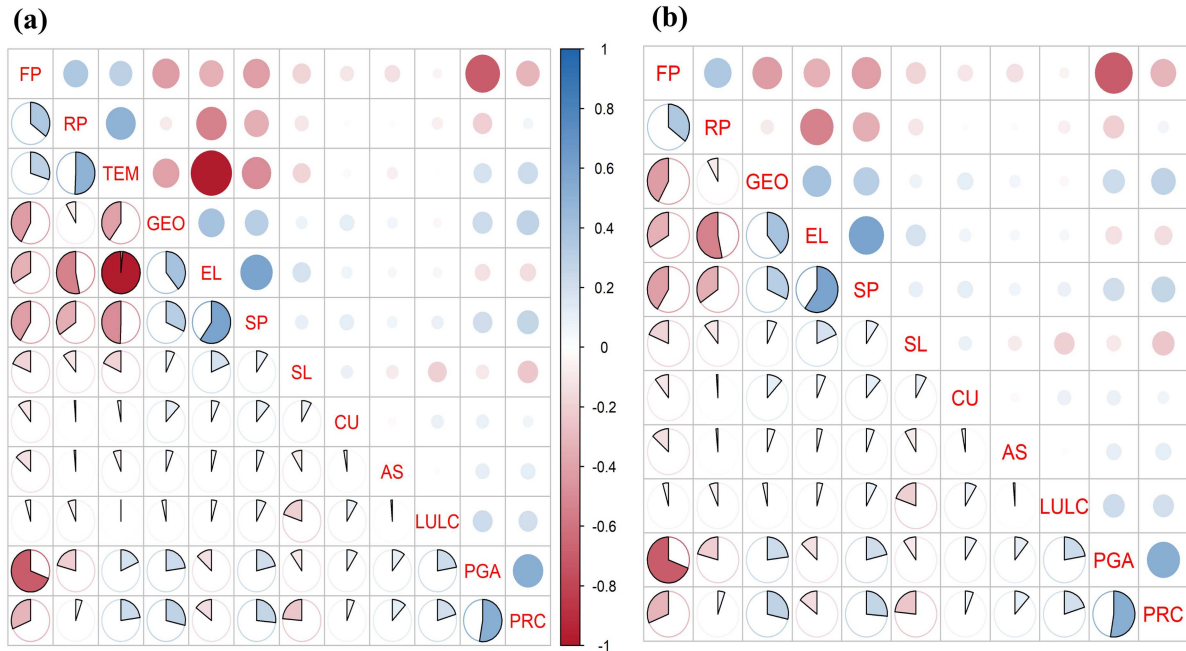


Figure 4. Pearson correlation matrix showing pairwise linear relationships among all susceptibility stressors: (a) full model including temperature; (b) reduced model after temperature exclusion. Abbreviations: FP = fault proximity, RP = road proximity, TEM = temperature, GEO = lithology, EL = elevation, SP = stream proximity, SL = slope, CU = curvature, AS = aspect, LULC = land use/land cover, PGA = peak ground acceleration, PRC = precipitation.

we computed Variance Inflation Factors (VIFs) for all stressors. While all variables were below the exclusionary threshold of 5.0, temperature (VIF = 3.53), fault proximity (VIF = 3.67), and PGA (VIF = 3.58) showed elevated values. These findings reinforced the importance of further stressor selection. Therefore, we performed a stepwise regression analysis to evaluate the model's sensitivity to variable inclusion. The full model, which included temperature, achieved a high adjusted R^2 of 0.9876 but was overly dominated by a single predictor ($\beta_{\text{temperature}} = -193.0$, $p < 0.001$), suggesting potential overfitting. After removing temperature, the revised model retained satisfactory explanatory power (adjusted $R^2 = 0.729$) and revealed slope, PGA, lithology, and road proximity as statistically significant (see Supplementary Tables S1 and S2 for complete regression outputs and VIF diagnostics). The reduced model's VIFs fell below 3.0 across all stressors, confirming improved independence and reduced redundancy. The final stressor maps are presented in Figures 5 and 6.

4.2. Dynamic landslide susceptibility assessment

The FR-AHP analysis revealed spatial and temporal dynamics of landslide susceptibility under current and future conditions. Among static stressors, the Lora and Murree formations are strongly associated with landslide occurrence (Table 2). Slope steepness above 32° was also highly significant (FR = 1.62), followed by road proximity (FR = 2.37 for 0–50 m buffer) and stream proximity (FR = 1.76). Regarding dynamic factors,

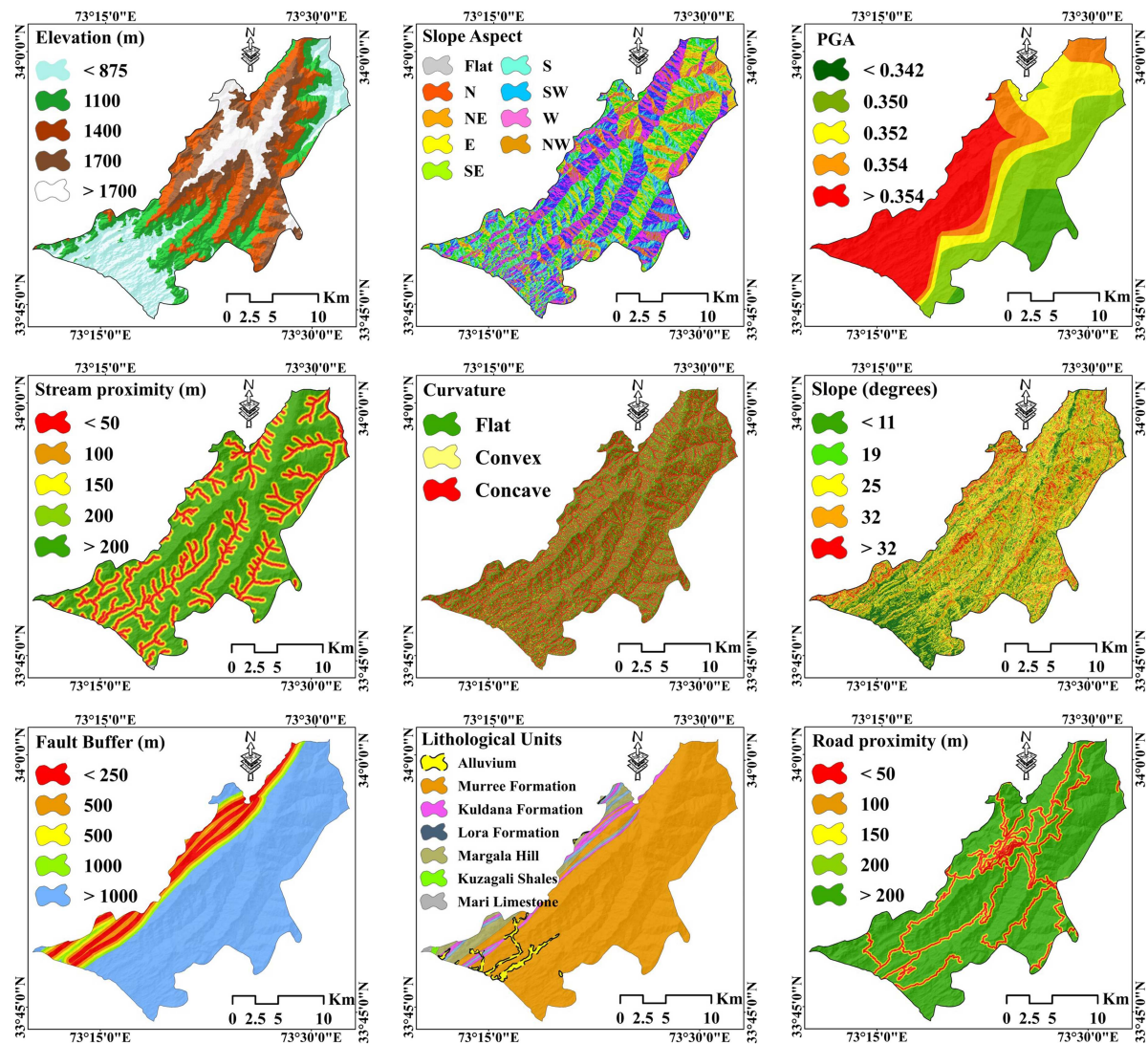


Figure 5. Static stressors for landslide susceptibility assessment.

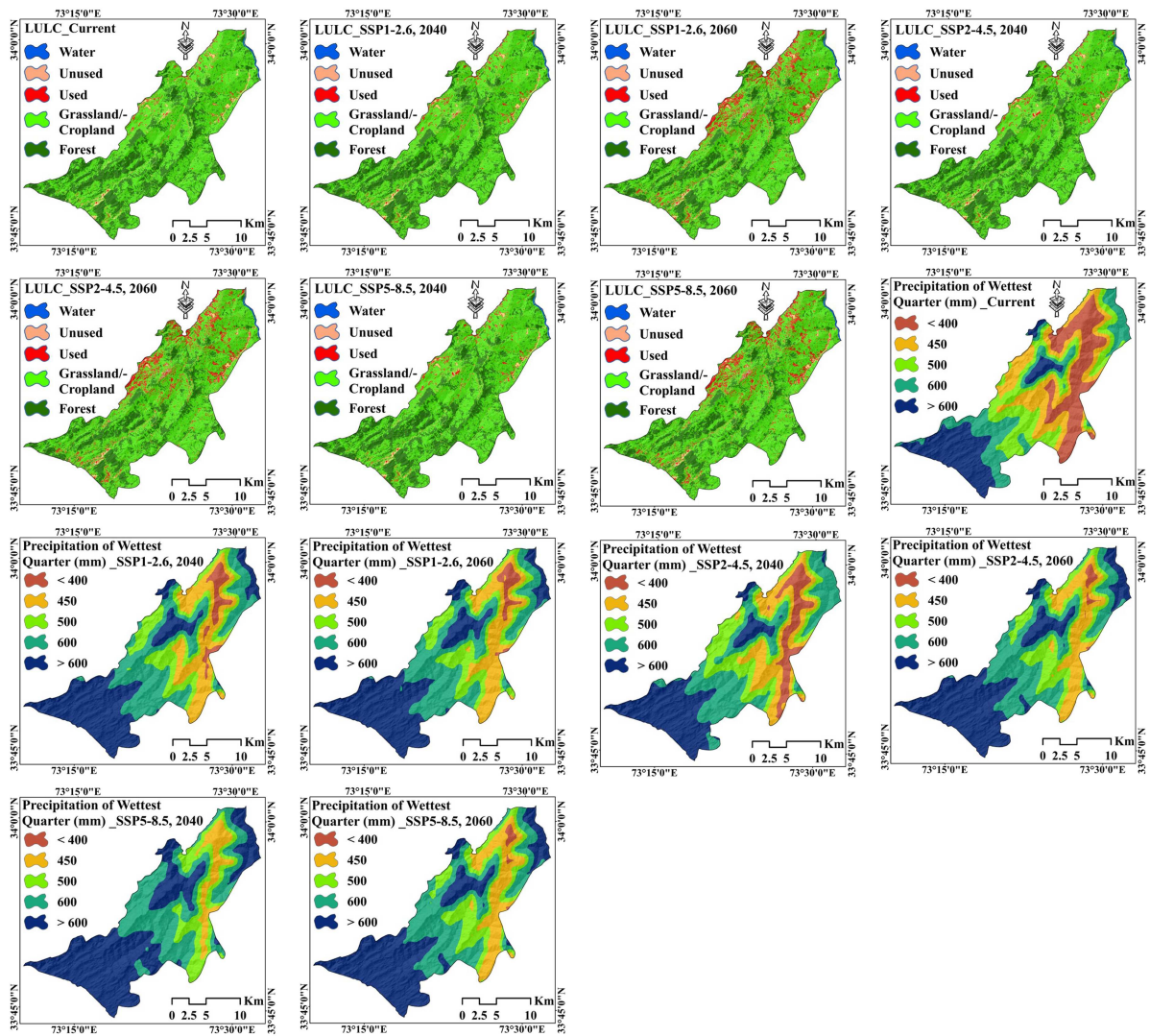


Figure 6. Dynamic stressors for landslide susceptibility assessment.

LULC types such as deforested and urbanized zones exhibited a FR of 2.22 (the LULC changes and accuracy assessment results are presented in the supplementary Tables S4 and Figure S2), while precipitation emerged as a key climatic driver (FR = 1.79), especially in areas with loose material and steep terrain. The AHP matrix results further corroborated these findings, assigning the highest weights to precipitation (21.1%) and lithology (19.1%), underscoring their dominant role in slope instability (Figure 7, Supplementary Table S2). Curvature and aspect had minimal influence, with weights of 2.3% and 3.1%, respectively. The consistency ratio (CR = 0.04) confirmed the robustness of the pairwise comparison matrix.

The susceptibility classes were assigned using the Jenks optimization classification scheme to minimize intra-class variance and improve spatial stratification. The resulting maps (Figure 8) revealed substantial temporal shifts in landslide-prone areas across all scenarios. In the current year (2020), most of the areas fell within the moderate (27.56%) and low (26.56%) susceptibility classes, with only 8.63% classified as very high susceptibility. However, under the high-emissions scenario (SSP5–8.5), the area of very high susceptibility increased to 14.82% by 2060, representing a relative rise of 71.7% compared to the baseline. The corresponding reduction in very low and low susceptibility zones suggests a progressive expansion of hazard-prone terrain (see bar chart in Figure 8, lower right panel). SSP1–2.6 yielded a more moderate rise in high-risk areas. The very high susceptibility zone increased from 8.63% in 2020 to 13.3% by 2060, reflecting a 54.1% relative increase. High-susceptibility classes expanded under all three SSPs, while very low zones consistently shrank. Overall, SSP5–8.5 showed the most prominent shift toward high and very high susceptibility zones, followed by SSP2–4.5 and SSP1–2.6. This pattern highlights the compound

Table 2. Integrated AHP matrix-based weights and FR-based assigned rank value.

	Weight %	Class	Area (%)	Landslides (%)	FR	Objective rank
Lithology	19.1	Murree formation	86.7	77.6	0.89	4
		Kuldana formation	4	7.7	1.92	4
		Margala hill limestone	4.7	7.7	1.62	4
		Alluvial and stream deposits	2.4	1.6	0.68	3
		Lora formation	1.9	4.9	2.59	5
		Mari limestone	0.1	0	0.00	1
		Kuzagali shale	0.1	0	0.00	1
Fault proximity (meters)	15.2	0–250	8.1	10.9	1.35	5
		250–500	6.2	4.4	0.71	4
		500–750	3.6	2.2	0.61	2
		750–1000	3.1	0.5	0.16	1
		>1000	79	82	1.04	4
LULC	7.2	Water bodies	0.1	0.2	1.64	3
		unused	4.0	6.5	1.65	4
		Used	5.0	11.2	2.22	5
		Grass/Cropland	58.9	57.0	0.97	2
		Forest	32.0	24.8	0.77	1
Slope (degrees)	10.3	0–11	19.7	14.2	0.78	1
		11–19	20.6	15.3	0.84	2
		19–25	20.1	12.6	1.01	3
		25–32	20.3	24	1.26	4
		>32	19.3	33.9	1.62	5
Stream proximity (meters)	7.4	0–50	13.7	24	1.76	5
		50–100	12.6	9.8	0.78	4
		100–150	12.2	7.7	0.65	3
		150–200	11.1	7.1	0.62	2
		>200	50.5	50.3	1	4
Road proximity (meters)	6.6	0–50	7.6	18	2.37	5
		50–100	5.6	6	1.07	4
		100–150	5.5	4.9	0.89	3
		150–200	4.4	3.3	0.75	2
		>200	76.9	67.8	0.88	3
Aspect	3.1	Flat	0.1	0	0	1
		N	4.7	0.5	0.11	1
		NE	7.7	7.1	0.92	3
		E	12.9	13.1	1.02	4
		SE	17.2	31.1	1.81	5
		S	12.8	19.7	1.54	5
		SW	10.2	11.5	1.13	4
		W	14	13.1	0.94	3
		NW	15	3.3	0.22	2
		N	5.5	0.5	0.09	1
Elevation (meters)	1.7	471–649	3.7	6.6	1.78	4
		649–1039	32.1	37.2	1.16	3
		1039–1429	32.2	18.6	0.58	1
		1429–1819	23.2	15.3	0.66	2
		1819–2231	8.8	22.4	2.55	5
Precipitation (mm)	21.1	<400	24.4	13.0	0.53	1
		450	19.7	11.8	0.60	2
		500	15.9	15.4	0.97	3
		600	33.8	48.7	1.44	4
		>600	6.2	11.1	1.79	5
PGA	5.1	<0.342	10.0	11.4	1.1	4
		0.35	23.9	18.8	0.8	2
		0.352	19.6	26.6	1.4	3
		0.354	13.1	22.7	1.7	5
		>0.352	33.5	20.5	0.6	1
Curvature	2.3	Flat	39.4	41.9	1.1	3
		Convex	21.1	16.2	0.8	2
		Concave	39.5	41.9	1.1	5

impact of intensified precipitation and anthropogenic pressures (e.g. deforestation and infrastructure development) under high-emissions scenarios. Areas on the southeastern and central ridgelines that are already prone to instability are projected to experience the highest susceptibility amplification.

4.3. Dynamic exposure assessment

Population exposure to landslide was assessed for 2020 (current), 2040, and 2060 under the SSP1–2.6, SSP2–4.5, and SSP5–8.5 scenarios, as presented in [Figure 9](#). The current year's results show most of the

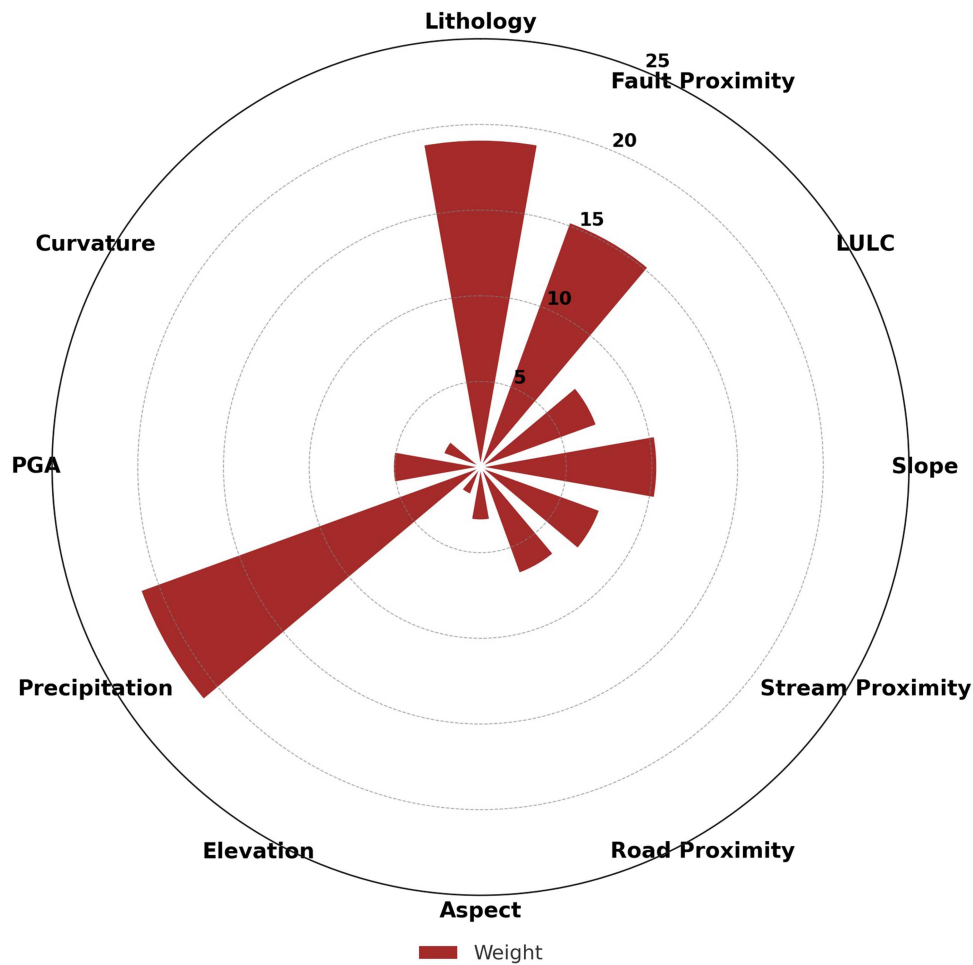


Figure 7. AHP-based weights contribution for all the landslide susceptibility stressors.

population concentrated in very low (83.1%) and low (13.0%) exposure zones, with only 0.9% and 0.4% residing in high and very high exposure zones, respectively. By 2040, high- and very high-exposure zones are expected to have expanded under all scenarios. SSP2–4.5 showed notable increases (high: 1.5%, very high: 1.4%), followed by SSP5–8.5 (1.4% and 0.8%) and SSP1–2.6 (1.4% and 0.7%). The trend continued through 2060, with SSP2–4.5 reaching the highest exposure levels (high: 2.0%, very high: 2.3%), reflecting a more than fivefold increase in very high exposure compared to 2020. SSP5–8.5 and SSP1–2.6 showed smaller but consistent increases. Spatially, high-exposure clusters appear predominantly along the south-eastern urban fringes, and central settlements are expanding along major roads. These patterns are most pronounced under SSP2–4.5 and SSP5–8.5, due to stronger growth assumptions and associated land-use pressures. The findings show that while very low exposure zones remain dominant (exceeding 76% across all scenarios), a gradual increase in population concentration is consistent in moderate-to-high exposure areas.

4.4. Vulnerability assessment (base year 2020)

Figure 10 shows the current vulnerability using the GRDIv1 index. The results reveal that a significant portion of the population is highly vulnerable to landslides, with 60.9% falling into the high and very high vulnerability classes, primarily due to limited resources and high multidimensional deprivation. Low income, education, and access to healthcare reduce community resilience to landslides. Meanwhile, moderate vulnerability areas comprise 27.8% of the population, showing partial resilience but continued risk exposure. Only a small proportion of the population is in low (9.3%) or very low (2%) vulnerability

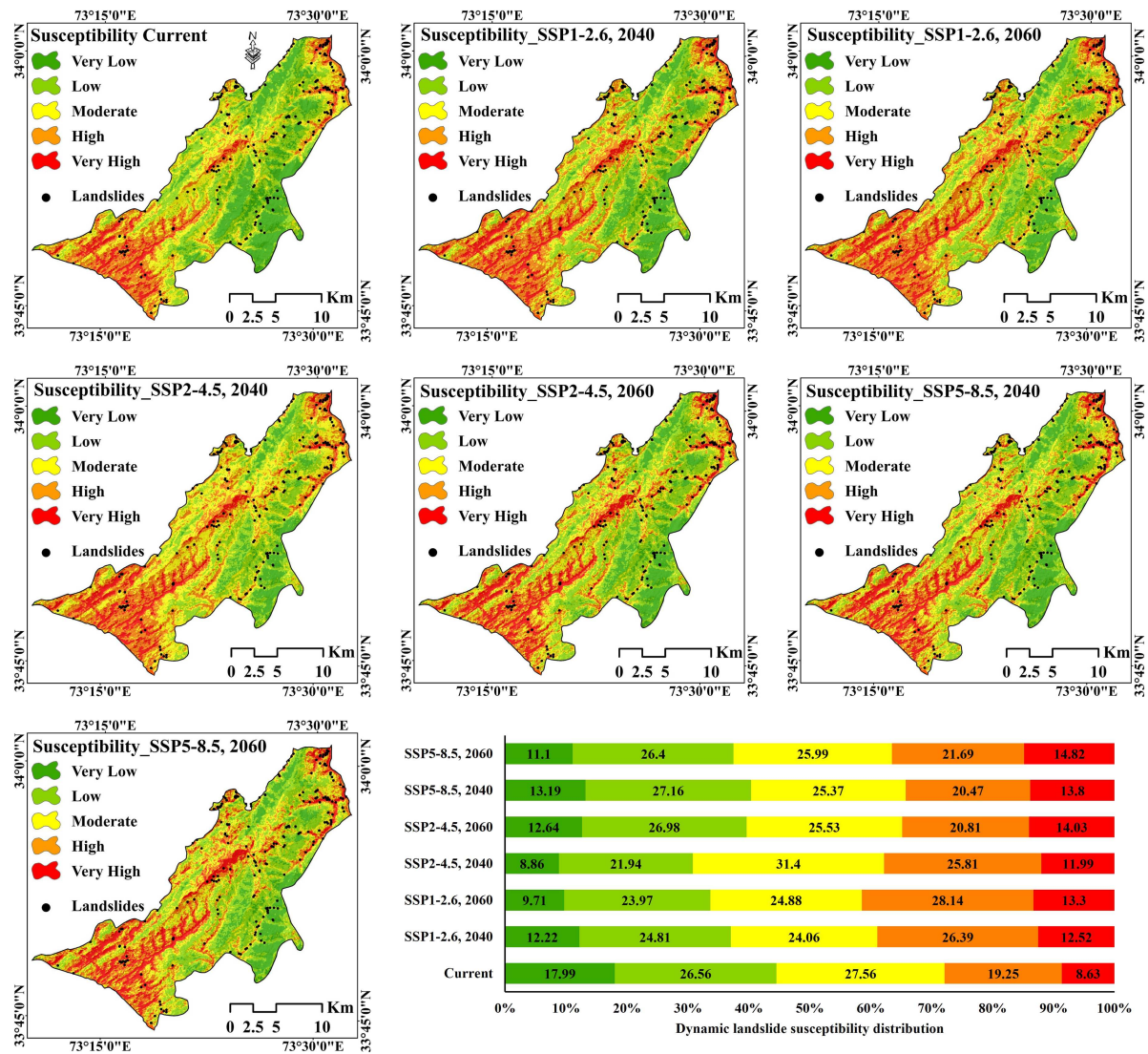


Figure 8. Dynamic landslide susceptibility maps for the current year (2020) and future projections for 2040 and 2060 under SSP1-2.6, SSP2-4.5, and SSP5-8.5 scenarios. The bar chart summarizes the percentage distribution of each susceptibility class under all scenarios and time frames.

classes, indicating a stronger capacity to cope with landslides. Future vulnerability may worsen due to climate change and land use shifts, likely to intensify landslide risks and strain resilience.

4.5. Dynamic landslide risk assessment

DLRA integrates susceptibility, exposure, and vulnerability to assess how landslide risk evolves under various climate and land-use scenarios. Figure 11 presents risk maps for the base year (current) and projections for 2040 and 2060 under SSP1-2.6, SSP2-4.5, and SSP5-8.5. The risk distribution in the base year is relatively low across most of the region, with 38.7% of the area classified as very low risk and 19.3% as low. Only 5.34% of the region is classified as a very high-risk zone, primarily confined to central areas along steep slopes and fault zones, where high susceptibility overlaps with socioeconomically vulnerable populations. By 2040, risk intensifies across all SSPs. Under SSP2-4.5, the very high-risk area expands to 7.97%, and high-risk zones rise to 17.8%. SSP5-8.5 shows a similar trend, though slightly less pronounced. This trend continues into 2060, with SSP2-4.5 exhibiting the most dominant shift: very high-risk zones reach 9.04%, and moderate-to-high-risk areas collectively account for over 45% of the region (Figure 11, lower right panel). In comparison, SSP1-2.6 and SSP5-8.5 stabilise at approximately 6.3% and 6.2%,

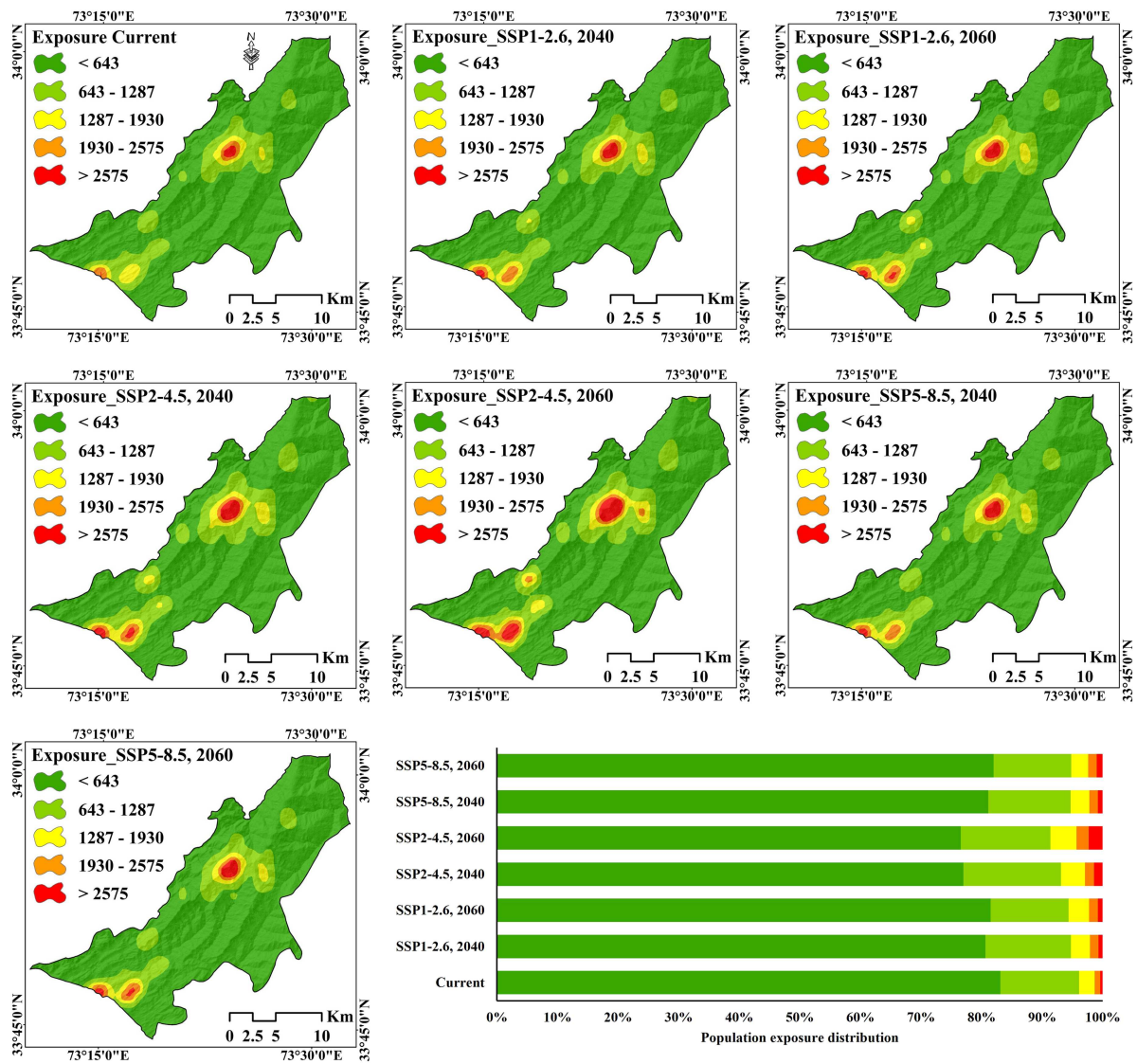


Figure 9. Dynamic exposure maps for 2020 and projections for 2040 and 2060 under SSP1–2.6, SSP2–4.5, and SSP5–8.5 scenarios. The lower panel shows the percentage distribution of population exposure classes across all scenarios.

respectively, for very high risk. These changes are driven mainly by compounded effects of LULC conversion (e.g. deforestation and settlement expansion), dynamic susceptibility under climate extremes, and persistent vulnerability in rural communities.

Spatially, the most elevated risk zones are concentrated along the Murree town, Srinagar highway, Kashmir Road, and the lower Jhika Gali road, where the expansion of road infrastructure and settlements exacerbates the combination of steep slopes and lithological fragility. These areas are tectonically active near the Jhelum Fault zone and adjoining valleys, where urban sprawl interacts with unstable terrain and deforested slopes. These high-risk zones are consistent across short- and long-term projections, particularly under SSP2–4.5, highlighting its intermediate emissions and development pressures as a critical driver of future instability. In relatively vegetated east-west zones, risk remains consistently low, emphasizing the spatial heterogeneity of risk interactions. These results emphasized that even moderate emission trajectories can yield substantial future risk.

4.6. Validation and accuracy assessment

The classification accuracy and predictive performance of the ensemble FR–AHP model were evaluated using ROC–AUC and SCAI metrics. The ROC–AUC analysis (Figure 12a) shows strong model validity

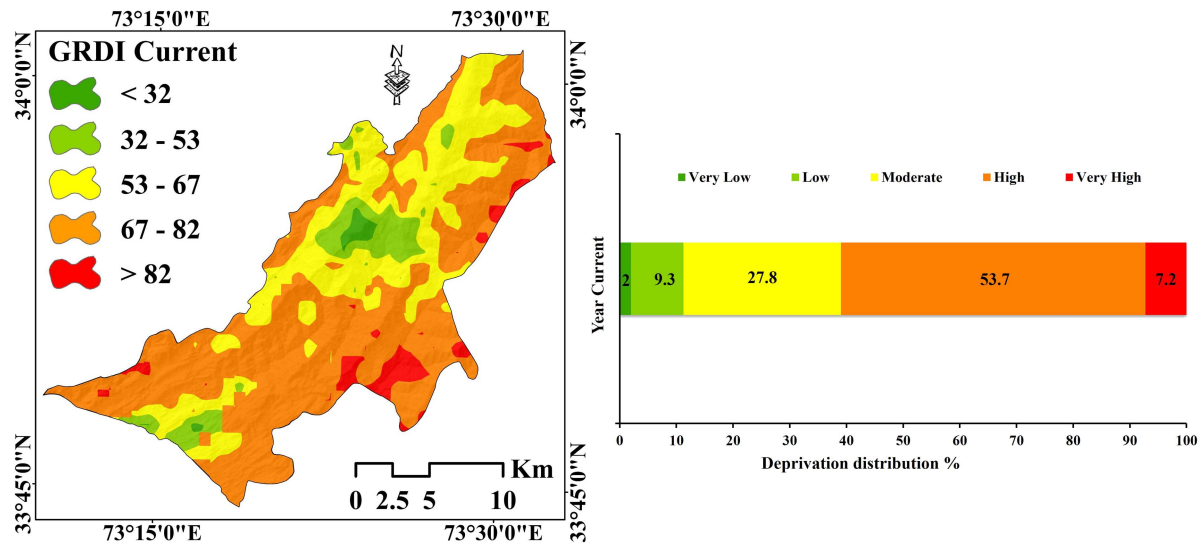


Figure 10. Illustrate the current vulnerability map. The right panel shows the percentage distribution of the vulnerable population.

across the current year and all future scenarios. The AUC for the current scenario reached 88.6%, while future projections ranged from 85.1% (SSP1–2.6, 2040) to 92.5% (SSP2–4.5, 2060). The results reveal a positive accuracy trend under moderate to high emission scenarios, particularly under SSP2–4.5 (2060) and SSP5–8.5 (2040), suggesting an increased susceptibility correspondence under more dynamic climate and land-use stressors.

The SCAI method was further applied to validate the spatial correspondence of predicted susceptibility zones (Figure 12b). The results indicate that the percentage of seed cells was highest in the very low and low susceptibility classes, decreasing gradually in the higher classes. This inverse relationship between SCAI and DLSA classes confirms the robustness of the model, as higher seed densities align with lower susceptibility zones. Collectively, these two metrics demonstrate that the ensemble model is reliable for both current and projected landslide susceptibility patterns under varying future conditions.

4.7. Emerging landslide hotspots under future scenarios

The policy-oriented decision requires careful attention, as it can benefit people within a limited budget. Therefore, we further expand the result to map the spatial transitions in areas of very high risk (VHR) under future scenarios. Figure 13 presents a comparative hotspot transition map, classifying the landscape into four categories: Not VHR, Lost VHR, Gained VHR, and Persistent VHR. The persistent VHR hotspots are mainly concentrated along the central densely settled urban fringes, such as southern Murree and northeastern Patriata, Lower Topa-Kohala road, and along the Srinagar Highway (E–75). These areas consistently exhibit high-risk conditions under all scenarios. In contrast, the gained VHR zones that were not previously high-risk but projected to show rapid expansion (4.39%) under SSP2–4.5 and SSP5–8.5 by 2060, particularly in the northwest and southeast. These shifts can be attributed to a combination of expanding peri-urban settlements and intensifying precipitation patterns under medium- to high-emission pathways. Meanwhile, the lost VHR zones remain limited across all scenarios (0.69%–1.15%), implying that once an area becomes a VHR hotspot, it rarely de-escalates unless major environmental or land-use reversals occur. These findings underscore the transition dynamics of landslide risk in core zones, while also highlighting emerging hotspots driven by dynamic land-use and climate interactions.

5. Discussion

Effective risk management and land use planning require a comprehensive assessment of hazard-prone areas. The complex interaction of climate variability, land-use changes, and socioeconomic factors is

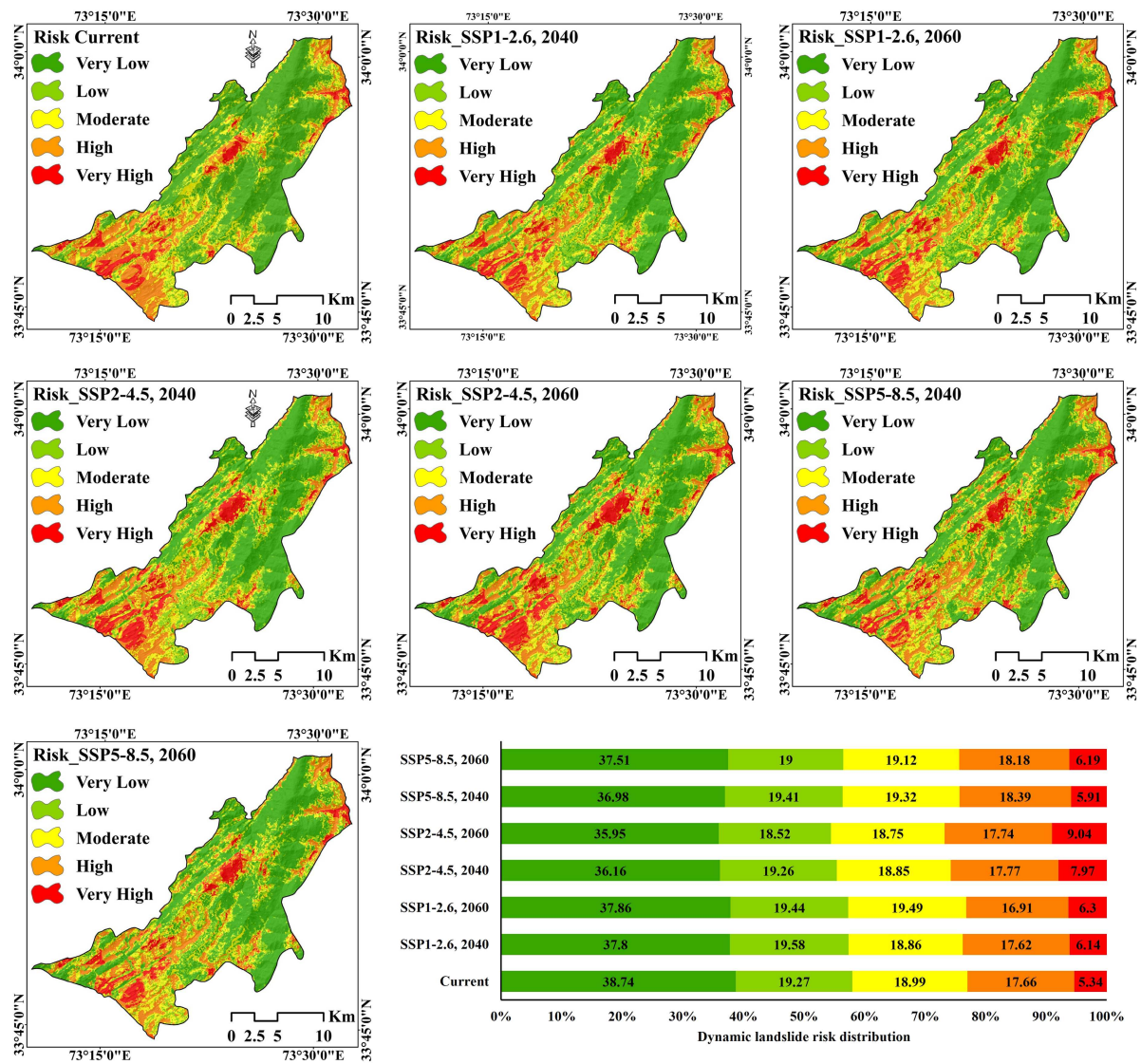


Figure 11. Dynamic landslide risk maps for the current year (2020) and future projections for 2040 and 2060 under SSP1–2.6, SSP2–4.5, and SSP5–8.5 scenarios. The lower panel displays the percentage distribution of each risk class across all scenarios and time frames.

increasingly influencing landslide risk in mountainous regions (Hürlimann et al. 2022; Ullah et al. 2024a; Alcántara-Ayala 2025). As climatic and human-induced stressors accelerate, risk patterns no longer remain static or isolated but are constantly changing over time and space. The present study assesses landslide risk dynamics by combining susceptibility, exposure, and vulnerability under future climate and land use scenarios. This integrated approach is vital for promoting sustainable development and disaster risk reduction in the Western Himalayas, where risk is no longer driven solely by topography but by cumulative social and environmental stressors. Notably, most landslide-prone regions in data-scarce countries like ours suffer from fragmented or outdated inventories, which restrict effective disaster risk reduction strategies. Existing global-level databases such as the Global Landslide Catalog (Kirschbaum et al. 2010), the Global Fatal Landslide Database (Froude and Petley 2018), COOLR, and the USGS Landslide Inventory (Felsberg et al. 2022) remain constrained by coarse resolution and underreporting. The present study advances the field by constructing a high-resolution landslide inventory using freely available remote sensing (RS) and field data.

One of the critical aspects of this study lies in its DLRA framework, which first accounts for the uncertainty inherent in both climate modeling and land-use simulation. Projections from different GCMs often vary substantially, especially at local scales, due to differences in topography and downscaling

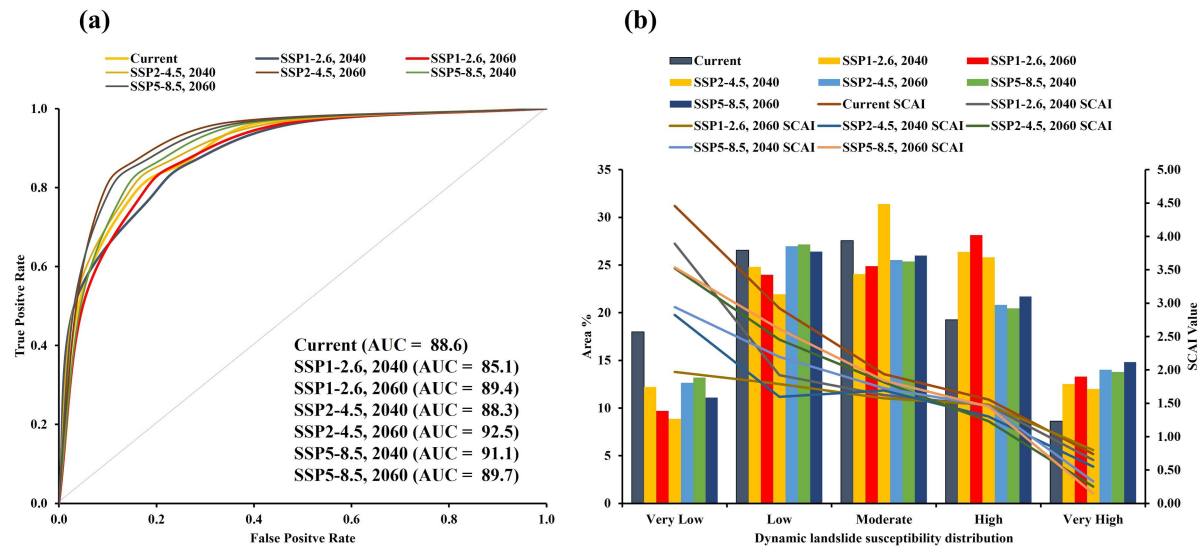


Figure 12. Validation of the ensemble FR-AHP model using (a) ROC-AUC curves across current and future SSP scenarios and (b) SCAI bar plots showing the spatial correspondence between susceptibility classes and observed seed cells.

approaches (Bulti and Yutura 2025). To address this, we selected four well-performing GCMs based on regional validation studies. We employed a multi-model ensemble (MME) strategy, utilizing quantile mapping and cumulative distribution function (CDF) corrections, to reduce bias. This ensemble-based correction approach enhances robustness and enables the generation of more accurate scenario outputs (Wang et al. 2023; Lamichhane et al. 2024). Secondly, the landslide susceptibility classification thresholds can significantly influence spatial risk outputs. We adopted a junk-based optimization method combined with two well-established validation metrics (ROC-AUC and SCAI) to minimize intra-class variability. This dual validation strategy helps reduce overprediction and minimize false positives, which are common challenges in susceptibility modeling, particularly in highly heterogeneous mountainous terrain (Atok and Chai 2025; Rehman et al. 2025). Compared to previous susceptibility studies in similar mountainous regions, our integrated FR-AHP model demonstrated notably higher predictive performance, with ROC-AUC scores ranging from 85.1% to 94.5% (Rehman et al. 2022; Ullah et al. 2024a, 2024b).

The spatial change detection revealed that landslide risk hotspots are not only expanding geographically under all SSPs but also becoming demographically more significant due to population growth and urban expansion. This supports earlier findings by Dodman et al. (2022) and Alcántara-Ayala (2025), who highlighted the amplifying role of land pressure in mountainous hazard zones. The persistent VHR zones represent long-standing landslide hotspots driven by geophysical constraints (e.g. slope, lithology), while newly gained VHR zones emerge in areas subject to dynamic pressures, including deforestation and urban sprawl. This finding is consistent with earlier studies that have shown human-driven land alterations accelerate shallow landslide occurrences (Kaushal et al. 2025). A critical insight from our findings is that certain high-susceptibility zones persist even under low-emission scenarios (SSP1-2.6), suggesting that terrain degradation and infrastructure pressure may lead to irreversible instability. These findings underscore the fact that climate mitigation alone may not be sufficient to reverse risk trends in regions where geophysical fragility is already exacerbated by unregulated development. The overlap of expanding VHR zones with densely populated areas underlines the growing exposure dimension of landslide risk, especially in rapidly urbanizing regions like southeastern Murree. This disproportionate increase in population exposure compared to changes in susceptibility indicates that human settlement trends are outpacing natural hazard controls. This is particularly concerning in peri-urban growth corridors where deforestation, tourism infrastructure, and road expansion intersect with slope-sensitive zones. As noted by Ziegler et al. (2023), such mismatches between human development and environmental thresholds can quickly transform moderate hazards into high-risk events.

From a policy perspective, the outputs of this study offer direct spatial and strategic value for local governments and planning authorities. First, persistent VHR zones identified across all scenarios should be

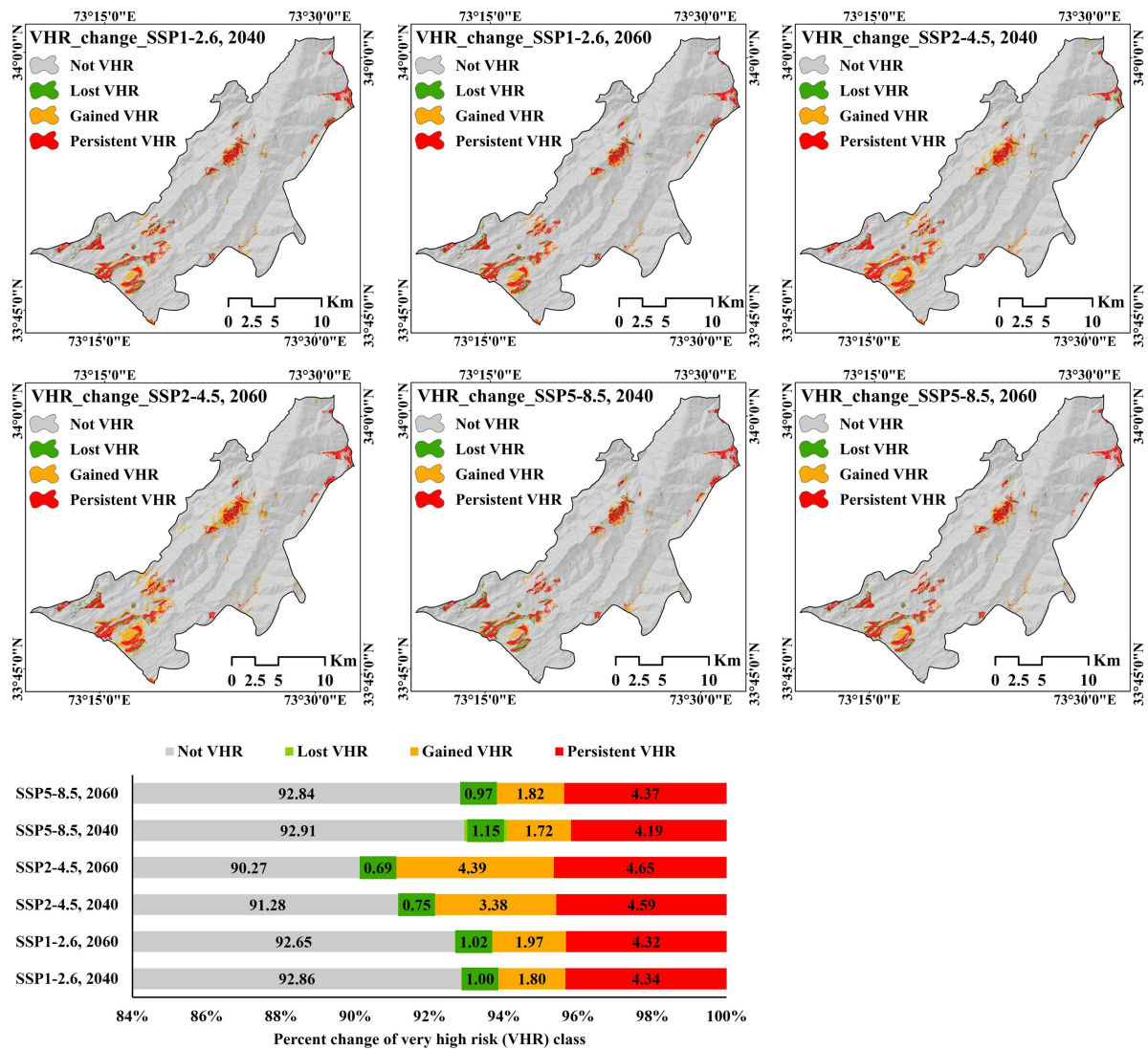


Figure 13. Spatial hotspot transition maps and percentage-based bar plots showing changes in very high risk (VHR) zones for future periods (2040, 2060) under three SSP scenarios.

designated as high-priority zones where geotechnical investigation should be conducted prior to any developmental activities. Second, newly emerging hotspots along urban edges must be prioritized for slope stabilization, vegetation restoration, and the implementation of risk zoning regulations. These interventions should be integrated into land use master plans and enforced through building codes that account for slope sensitivity and hydrological vulnerability. Third, our exposure maps can inform the development of risk communication systems in tourism-sensitive corridors, where seasonal influxes exacerbate vulnerability. Moreover, the DLRA framework supports anticipatory governance, a key priority of the Sendai Framework for Disaster Risk Reduction (UNDRR, 2015), by integrating future-oriented data into actionable zoning, investment, and policy design. It encourages a shift from reactive hazard mapping to proactive, scenario-informed planning that accounts for both physical and human drivers of change. This is especially important in data-scarce contexts where real-time monitoring is limited but spatial foresight can still shape adaptive decisions.

5.1. Limitations and the way forward

This study was initiated to map the actual DLSA; however, due to limited data on landslide magnitude and severity, we shifted our focus to mapping relative DLSA by combining rockfalls, debris flows, and shallow

landslides. However, we acknowledge that these phenomena may not always behave similarly, as their size, shape, and material composition can influence their characteristics and impacts. This simplification was necessary because there is no comprehensive landslide database in Pakistan for our analysis scale. Another limitation of this work is treating vulnerability as a static component. While the study introduces DSA and DEA layers, future research should incorporate dynamic socioeconomic scenario modeling or participatory mapping to account for changes in deprivation, infrastructure, and resilience over time. This will foster a more comprehensive understanding of vulnerability that evolves in response to the socio-environmental context.

Additionally, the current study assumes consistent relationships between static stressors and landslide susceptibility, but these relationships may change due to unexpected environmental or geological shifts, such as seismic activity. This assumption was based on the region's seismically active nature, exemplified by the 2005 earthquake (7.6 Mw), which triggered numerous landslides. Given these uncertainties, future research should incorporate dynamic environmental data, like real-time monitoring and advanced machine learning algorithms, to improve susceptibility and exposure assessments. To further enhance the model's accuracy, applying machine learning thresholds or ensemble calibration could improve spatial precision and reduce the risk of overprediction or false positives, a common issue in empirical and expert-based models. Although our validation with ROC-AUC and SCAI showed strong predictive performance, integrating more advanced machine learning techniques could increase predictive reliability.

6. Conclusion

This study details the DLRA framework that integrates static topographic stressors with dynamic climate and land use changes under three SSPs (SSP1–2.6, SSP2–4.5, and SSP5–8.5). The integrated FR-AHP model, supported by multicollinearity diagnostics and validated using ROC-AUC and SCAI, was used to assess DSA. The results highlight that increasing precipitation extremes and urban expansion are the primary stressors of future landslide risk, with climate-induced rainfall having a greater influence in high-elevation areas and land-use change having a stronger impact in peri-urban corridors. Scenario-based modeling revealed a 59.3% increase in VHR zones by 2060 under SSP2–4.5, while SSP1–2.6 and SSP5–8.5 showed similar increases in risk. Exposure analysis indicated that although very high exposure areas are relatively small, their spatial distribution extends across all SSPs, particularly in the southeastern urban fringes and central settlements along major roads. The GRDIv1 index confirmed that more than half of the population resides in high-vulnerability zones. The hotspot transition analysis further concluded that many moderate-risk areas in 2020 are expected to evolve into high-risk zones by 2060, mainly near expanding infrastructure on steep slopes. These findings are crucial for identifying spatial priority zones for slope stabilization, deploying early warning systems, and risk-informed land use planning. Despite the assumption of static vulnerability in the DLRA framework, the results still demonstrate a strong relative predictive capability, providing actionable foresight for risk planning. The findings from this study support a range of policy applications, including zoning laws and building codes for unstable terrains, integration of dynamic risk maps into local early warning systems, and climate-sensitive infrastructure planning. These recommendations align with the Sendai Framework Priority 1 and the UNDRR's 'Early Warning for All' initiative, offering decision-makers a robust, scenario-informed tool for proactive disaster risk management.

This study also serves as a road map for identifying and scaling down persistent and emerging high-risk hotspots for more detailed evaluation in the Western Himalayas and other landslide-prone mountainous regions. In the wake of climate change and anticipated land-use transformations, the DLRA approach offers a scalable and transferable solution for climate-resilient spatial planning, particularly in data-scarce and hazard-prone regions. Dynamic socioeconomic projections, compound hazard interactions, and the integration of higher temporal resolution data are recommended for upcoming studies.

Author contribution

Adnanul Rehman: Conceptualization, Methodology, Software, Formal analysis, Writing – Original Draft, Visualization. Muhammad Sajjad: Conceptualization, Methodology, Software, Formal analysis, Writing – Review & Editing, Visualization. Heli Lu: Supervision, Funding acquisition, Writing – Review & Editing,

Visualization. Siqi Lu: Writing – Review & Editing, Visualization. Liang Cao: Writing – Review & Editing, Visualization. Zongran Han: Writing – Review & Editing, Visualization. Wanfu Feng: Writing – Review & Editing, Visualization. Shuo Qi: Formal Analysis, Investigation. Yali Zhang: Investigation, Software. Jingyi Wang: Visualization, Validation. Muhammad Tayyab Riaz: Data Curation, Writing – Review & Editing. Sohail Abbas: Review & Editing.

Disclosure statement

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Data availability statement

Data will be available on request from the corresponding author.

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