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Research Article

Keywords: Landslide risk, Environmental exposure, Principal Component Analysis, Socio-economic disadvantage, Institutional access, Structural stability

Posted Date: September 28th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10886972/v1>

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Additional Declarations: No competing interests reported.

Multidimensional Landslide Vulnerability and Risk Assessment Using Principal Component Analysis in Lumbini Province, Nepal

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Abstract

Landslides are a major hazard in Nepal, causing recurrent loss of life, infrastructure damage, and livelihood disruption. This study presents an integrated ward-level assessment of landslide susceptibility, physical exposure, multidimensional vulnerability, and risk across Lumbini Province. Landslide susceptibility was modelled using the Weight of Evidence (WoE) approach based on a multi-temporal landslide inventory and conditioning factors, while physical exposure incorporated buildings and roads. Principal Component Analysis (PCA) was used to derive vulnerability dimensions and indicator weights. The resulting hazard, exposure, and vulnerability indices were integrated to generate a relative ward-level risk index. The susceptibility model achieved AUC values of 0.892 for training (2000–2021) and 0.805 for independent validation (2022–2025). More than 19.6 % of the Province was classified as highly or very highly susceptible. PCA identified four vulnerability dimensions: socio-economic vulnerability, environmental and livelihood exposure, institutional and infrastructure access, and structural and economic stability. Environmental and livelihood exposure accounted for the largest relative contribution (44.89%) to overall vulnerability. High and very high risk encompassed 16.2% of wards, concentrated mainly in Rolpa, Rukum East, Pyuthan, Gulmi, and Palpa. ANOVA revealed a marked transition from strong physiographic control of susceptibility (41.0% of variance) to greater district-level differentiation of risk (22.0%), demonstrating that high susceptibility alone does not determine high risk. The integrated framework highlights how physical hazard interacts with asset exposure, livelihood dependence, socio-economic conditions, and institutional accessibility, providing a practical basis for ward-level risk prioritization and targeted disaster risk reduction

Key words: Landslide risk; Environmental exposure; Principal Component Analysis; Socio-economic disadvantage; Institutional access; Structural stability

1 Background

The Nepal Himalaya is inherently prone to landslides due to a combination of factors, including active tectonic activity, fragile and varied geology, and rugged terrain. The region also experiences erratic and intense rainfall, which further increases the likelihood of landslides. Human activities have intensified the risk, such as the rapid construction of rural roads without adequate engineering or environmental assessments (1,2). Settlement expansion in high-risk areas, driven by the pursuit of economic opportunities, reflects a willingness to accept the danger (3). Additionally, poor land-use practices, such as irrigating areas susceptible to land movement and farming on steep slopes, further contribute to the region's vulnerability to landslides.

Understanding the spatial distribution of landslide risk is essential for prioritizing risk-reduction investments because addressing every potentially unstable slope across the Himalaya is neither technically nor financially feasible. The scale of assessment is particularly important in translating scientific information into practical risk management (4,5). Site-specific assessments are appropriate for individual landslides or relatively small areas (6,7), whereas provincial planning requires a spatial unit that can aggregate complex hazard information while retaining sufficient local detail for intervention. In Nepal, the ward represents the lowest administrative planning unit and therefore provides an appropriate scale for translating continuous susceptibility information into actionable risk information. Pixel-based susceptibility maps alone can be difficult for administrative authorities to interpret and integrate into development planning (8,9). Converting such information into ward-level estimates of susceptibility, exposure, vulnerability, and risk can consequently strengthen spatial prioritization and facilitate its use by local and provincial governments.

This need is particularly relevant under Nepal's federal disaster governance system. The Constitution of Nepal, the Disaster Risk Reduction and Management Act 2017 (10), and related disaster risk management strategies (11–13), mandates all three tiers of government: local, provincial, and federal, to collaborate on disaster risk management. Lumbini Province provides an important setting for operationalizing this approach because of its pronounced physiographic diversity, extending from the higher mountain and middle-hill landscapes in the north through the fragile Chure belt to the Tarai plains in the south. These contrasting environments are accompanied by substantial differences in settlement patterns, infrastructure, livelihoods, accessibility, and socio-economic conditions. Consequently, landslide susceptibility and its potential consequences are unlikely to be spatially coincident, requiring an assessment framework capable of distinguishing where landslides are more likely from where their occurrence may generate greater consequences.

Many landslide studies in Nepal have concentrated primarily on susceptibility or hazard mapping using topographic, geological, hydrological, climatic, and land-cover factors. While such assessments are fundamental for identifying unstable terrain, susceptibility alone does not represent risk. Contemporary disaster-risk frameworks conceptualize risk through the interaction of susceptibility, exposure, and vulnerability (5,14). Accordingly, areas of high susceptibility may have relatively limited risk where few people or assets are exposed, whereas moderate susceptibility may translate into substantial risk where settlements, infrastructure, and vulnerable

liveliness systems are concentrated. An integrated assessment must therefore explicitly distinguish the physical propensity for landslide occurrence from the location of exposed elements and the conditions that influence their sensitivity and capacity to cope and recover.

Vulnerability represents a particular methodological challenge because it is multidimensional and context dependent. Nepalese studies have employed diverse combinations of demographic, socio-economic, livelihood, environmental, structural, and institutional indicators (15–18), resulting in considerable variation in indicator selection and weighting. This divergence highlights the need for a more standardized and context-specific approach to vulnerability assessment in landslide risk studies in Nepal.

Within this context, Principal Component Analysis (PCA) provides a data-driven means of addressing this multidimensionality by identifying underlying structures among correlated vulnerability indicators and reducing dependence on purely subjective weighting (19,20). When combined with spatially explicit susceptibility and exposure information, PCA-derived vulnerability dimensions can provide a more systematic basis for evaluating how environmental/livelihood, socio-economic, institutional/infrastructural, and structural/economic conditions contribute to spatial differences in vulnerability. Such integration is particularly useful for regional assessments where detailed empirical loss functions are unavailable but comparative prioritization among administrative units is required.

The novelty of this study lies in integrating temporally validated landslide susceptibility, asset-based physical exposure, and statistically derived multidimensional vulnerability within a common ward-level framework across the contrasting physiographic environments of Lumbini Province. Rather than treating susceptibility as synonymous with risk, the study explicitly evaluates how the relative spatial controls change from physical susceptibility to exposure, vulnerability, and integrated risk. Landslide susceptibility is modelled using the Weight of Evidence (WoE) approach and independently evaluated using temporally separated landslide inventories; physical exposure is represented by buildings and roads intersecting susceptible terrain; and vulnerability is derived from multiple indicators using PCA. The framework further examines how district, physiography, and their interaction differentiate susceptibility, exposure, vulnerability, and risk, thereby linking continuous geospatial information with administrative units directly relevant to disaster-risk planning.

2 Methodologies

2.1 Study Area

Lumbini Province is situated in the southwestern part of Nepal, sharing the borders with Gandaki Province to the north, Karnali Province to the northwest, Sudurpashchim Province to the west, and India to the south (Fig. 1). Spanning approximately 19,391 square kilometers, Lumbini Province features diverse topography that includes the Tarai plains, the Chure (Siwalik) range, Middle Mountain, and High mountain, with a relief varying from 90 to 7,246 masl.

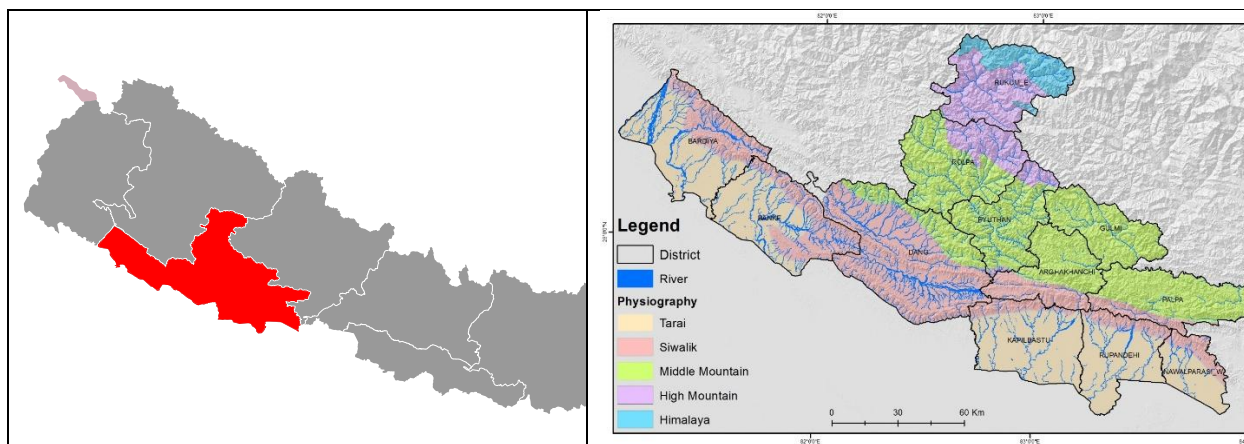


Fig. 1: Study area, Lumbini Province

The province is divided into 12 districts: Arghakhanchi, Banke, Bardiya, Dang, Eastern Rukum, Gulmi, Kapilvastu, Nawalparasi (West), Palpa, Pyuthan, Rolpa, and Rupandehi (Fig. 1). The climatic condition of Lumbini Province is very diverse ranging from sub-tropical in the Tarai to alpine in the High Mountain. The physiography of Lumbini extends to all five physiographic zones in Nepal: 3.1% of its area is covered by high mountains, 9.1% by high hills, 32.2% by mid-hills, 27.9% by Siwalik and 27.6% by Tarai.

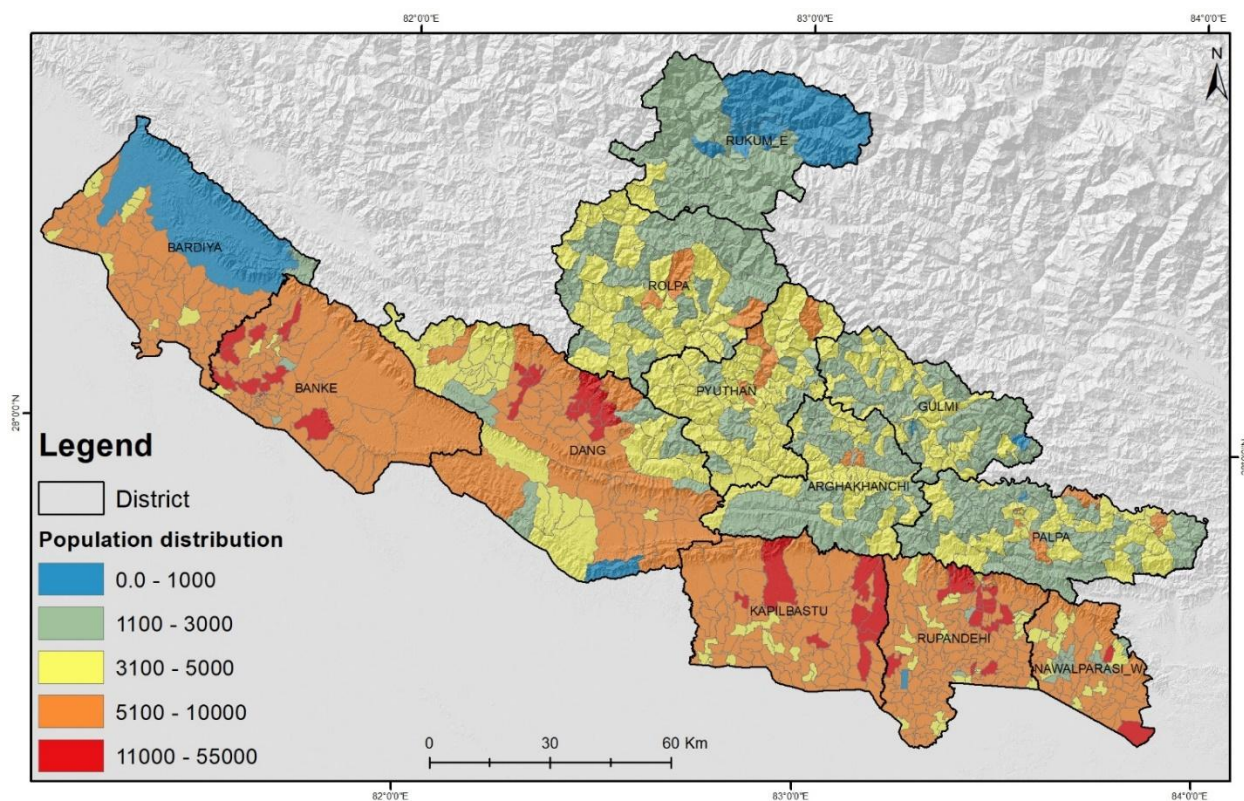


Fig. 2: Population distribution of Lumbini Province

Lumbini Province has a population of 5,124,225, which accounts for 17.6% of Nepal's total population (21). The Tarai region densely populated, whereas, the mid hill and higher mountain and the protected area have moderate to low density (Fig. 2).

Lumbini Province lies within the central Himalayan belt and preserves a well-developed tectonostratigraphic succession extending from the Indo-Gangetic Plain to the Higher Himalayan Crystalline zone (22). The region is structurally controlled by major south-verging thrust systems, including the Himalayan Frontal Thrust, Main Boundary Thrust, and Main Central Thrust, which divide the Himalaya into distinct lithotectonic belts. These structures influence stratigraphy, geomorphology, and active deformation. The southern foreland basin contains unconsolidated alluvial deposits, while the Siwalik formations exhibit fragile slopes prone to erosion and landslides (23). Northward, the Lesser Himalaya comprises folded sedimentary and metamorphic rocks, with low- to medium-grade rocks, including sandstone, shale, quartzite, limestone, dolomite, phyllite, and slate (24), whereas, the Higher Himalayan Crystalline forms the metamorphic core, consisting of high-grade gneiss, quartzite, marble, migmatite, and granite gneiss from deep crustal metamorphism (Fig. 3).

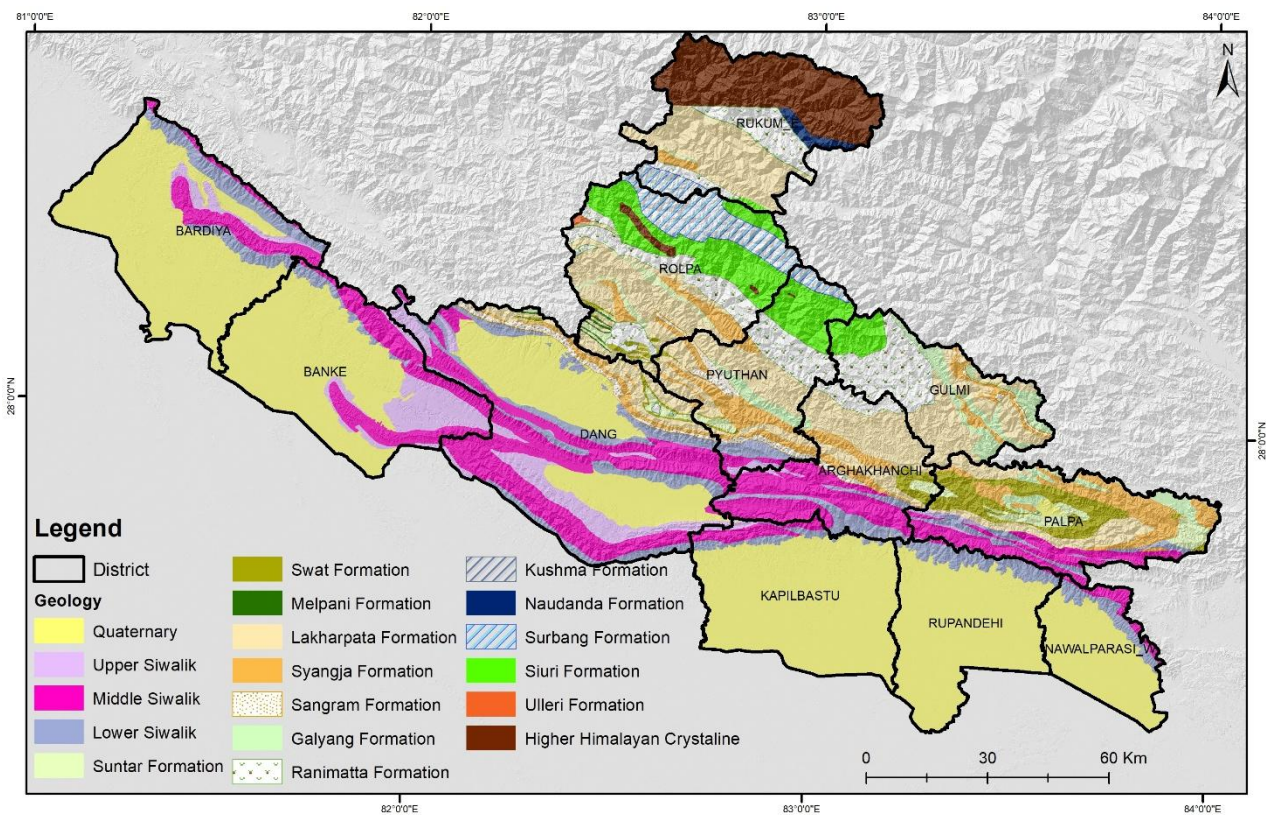


Fig. 3: Geological Map of Lumbini Province

2.2 Risk assessment framework

Landslide risk was conceptualized as the interaction of susceptibility, exposure and vulnerability and represented using a normalized multiplicative index, $\text{Risk} = \text{Susceptibility} \times \text{Exposure} \times \text{Vulnerability}$. This formulation is consistent with established disaster-risk frameworks, which define risk through the interaction of susceptibility with exposed elements and their vulnerability (25,26), and with landslide-risk assessment approaches that combine the physical vulnerability (susceptibility and exposure) and social vulnerability (27).

A stepwise methodology was followed, as described in the subsequent section, while the conceptual framework is illustrated in Fig. 4. In this study, hazard was operationalized as the ward-level mean of the Landslide Susceptibility Index (LSI) derived using the Weight of Evidence (WoE) approach. The LSI represents the spatial likelihood of landslide occurrence based on terrain and environmental conditioning

factors and was therefore used as a proxy for hazard. It does not account for temporal probability, event frequency, or return periods. The LSI, together with exposure and social vulnerability, was aggregated to the ward level using ArcGIS zonal statistics and related spatial functions, and subsequently combined to derive the relative risk index. Thus, the resulting risk values represent relative spatial risk for comparison and prioritization among wards, rather than absolute probabilities of landslide occurrence or estimates of expected loss. This operationalization is appropriate for regional-scale assessments where reliable temporal landslide-frequency data are limited, while providing risk information at Nepal's lowest administrative planning unit to support practical local-level planning and risk management.

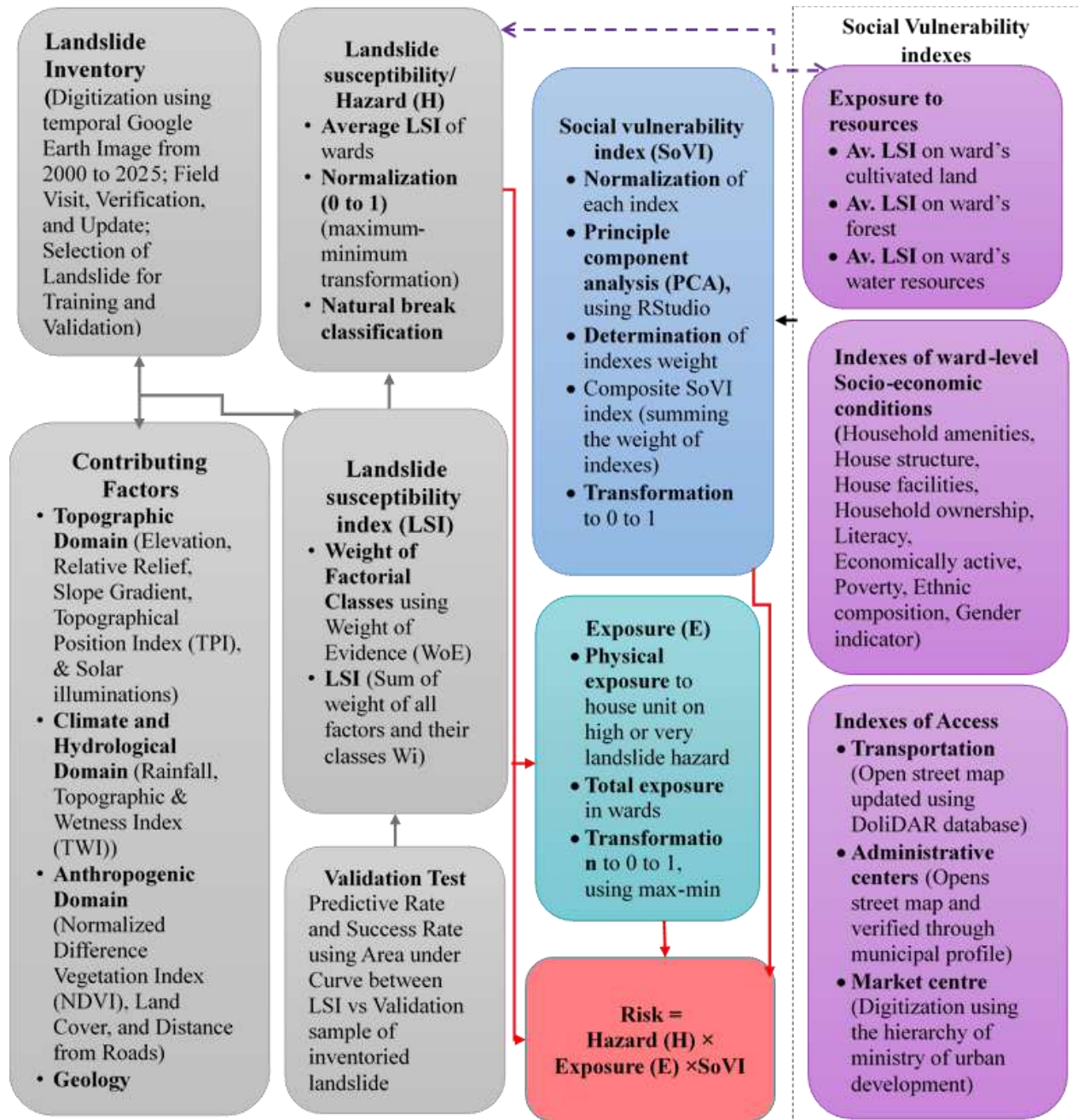


Fig. 4: Conceptual framework

2.2.1 Landslide susceptibility assessment

Landslide inventory and training-validation dataset

The landslide inventory was developed through visual interpretation of multi-temporal, high-resolution Google Earth imagery covering 2000–2025 (approximately 0.5–1 m spatial resolution), using identifiable scarps, displaced terrain, deposits, flow signatures, and other geomorphic indicators. The preliminary inventory was field-verified and refined through visits to 250 individual landslides, including detailed mapping of 50 landslides, with particular attention to landslides with potential direct impacts on settlements. Examples of field-visited landslides and detailed observations are provided in Supplementary Material 1. Field observations were incorporated into the final inventory to improve positional accuracy, process classification, and interpretation of mapped landslide features.

A total of 3,483 landslides were subsequently divided into temporally independent training and validation datasets. The 2,784 landslides from 2000–2021 were used to derive WoE values for the conditioning-factor classes, while 699 landslides from 2022–2025 were retained for independent validation (Fig. 5).

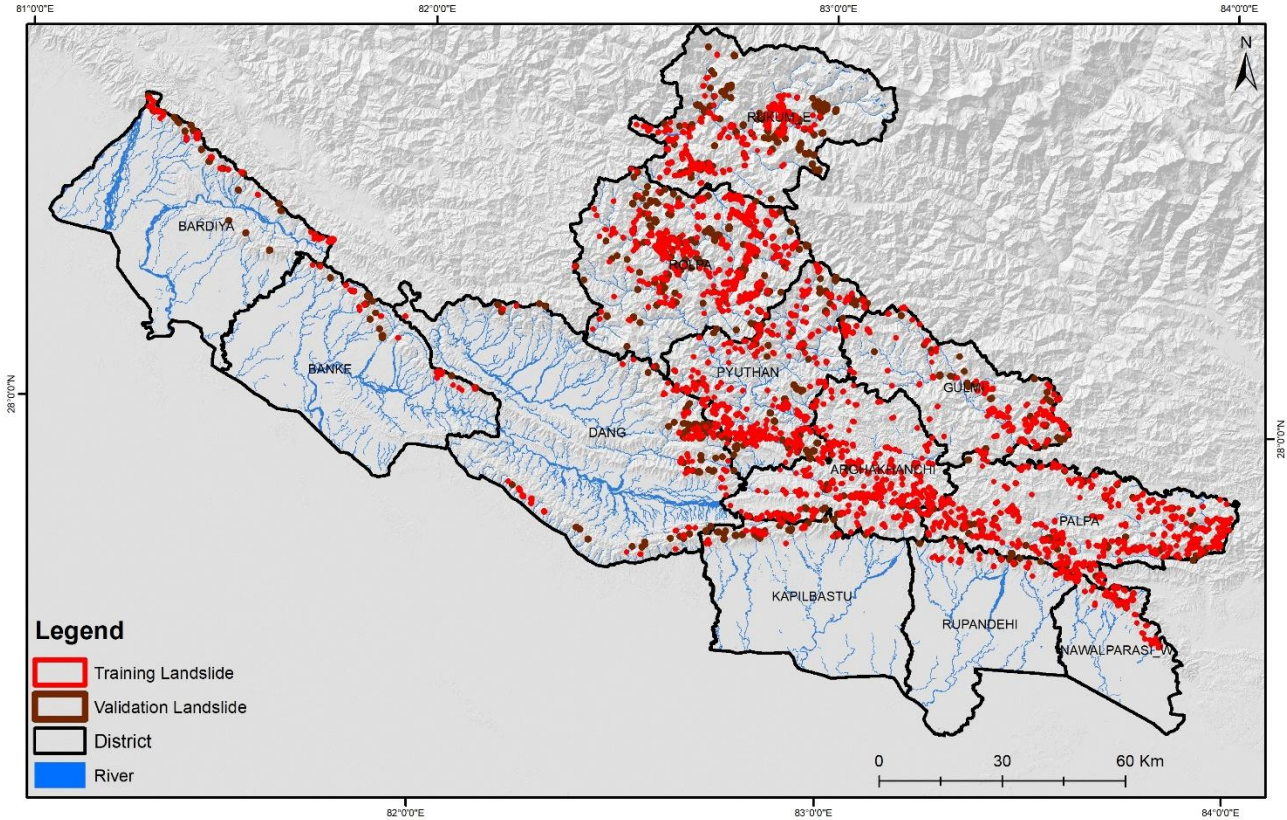


Fig. 5: Inventoried landslide

The training and validation inventories were broadly comparable in process composition, although their mapped-area contributions varied among process types (Table 1).

Table 1: Composition and mapped-area characteristics of the landslide inventories used for WoE modelling and independent validation

Landslide process	Training: 2000–2021		Validation: 2022–2025	
	Number (%)	Area (%)	Number (%)	Area (%)
Landscape creeping	0.7	2.6	0.3	0.7
Complex slope failure	11.5	48.2	10.9	37.8
Debris flow	60.1	30.5	64.2	44.3
Landslide	27	17.4	24.3	16.8
Rock fall	0.6	1.1	0.3	0.4
Number of landslides	2,784	—	699	—
Mean area (m ²)	10,115	—	5,980	—
SD (m ²)	29,218	—	11,643	—
Minimum area (m ²)	84	—	124	—
Maximum area (m ²)	540,320	—	184,665	—
Total area (m ²)	28160596		4179932	

Landslide susceptibility mapping

Landslide susceptibility was assessed through the Weight of Evidence methods (28), using the factors of Table 2.

Table 2: Landslide susceptibility mapping parameters

Theme / Domain	Parameters/ Variables	Data Sources, year	Resolution	Processing
Topographical	Slope Aspect	Digital Elevation Model (DEM), ALOS World 3D-30m (AW3D30), 2020 (29)	30 m	Surface analysis Aspect (N, NE, E, SE, S, SW, W, NW)
	Ground Elevation			Attitudinal (m): <1000, 1000-2000, 2000-3000, 3000-4000, and >4000
	Slope gradient			Slope (degree): <10, 10-20, 20-30, 30-40, and >40
	Relief range			Relative relief (m/100m): < 20, 20 - 40, 40 - 60, 60 - 80 and > 80
	Topographical position index			Valley, Foothill Slope, Mid Slope, Upper Slope and Ridge
	Solar illuminations			Solar radiation (kWh/m ² /day): <3, 3-4, 4-5, 5-6, and >6
Hydrological	Topographic wetness index	Department of Hydrology and Meteorology/GoN of Nepal, 2017 (30)	100m, Resampled to 30 m	Topographic Wetness Index (TWI): < 2, 2-4, 4-6, 6-8, 8-10 and > 10
	Annual average rainfall			Rainfall distribution (mm): <1600, 1600-1800, 1800-2000, 2000-2200, and >2200

Theme / Domain	Parameters/ Variables	Data Sources, year	Resolution	Processing
Anthropogenic domain	Normalized difference vegetation index (NDVI)	Image analysis of Landsat 8, 2020	15 m; Resampled to 30 m	NDVI = (nir - red) / (nir + red); Class: <0.15, 0.15-0.3, 0.3-0.45, 0.45-0.6, and >0.6
	Landuse/ Landcover	Land cover (31)	30 m	Landcover: Agriculture, Forest, Built-up, Other wood land, Grassland, Bare soil/rock, Snow/Glacier, Waterbodies
	Road distance	Update using Google Earth image add-on in QGIS (32)	Euclidian distance (30m)	Road network (m): < 500, 500 - 1000, 1000 - 1500, 1500 - 2000, 2000 - 2500, 2500 - 3000 and > 3000
Geology	Geological formation	Department of Mines and Geology/GoN, field observation and update (22)	Polygon to raster (30m)	Lithological classes (Fig. 3)

The WoE method calculates the statistical association between landslide occurrence area (training sample) and each predictor variable class using the following formulation:

For each predictor class, positive weight (W^+) and negative weight (W^-) are calculated as:

$$W^+ = \ln [P(\text{class/presence}) / P(\text{class/absence})]$$

$$W^- = \ln [P(\text{not class/presence}) / P(\text{not class/absence})]$$

The contrast ($C = W^+ - W^-$) measures the overall predictive power of the predictor class, with positive values indicating positive association and negative values indicating negative association. The continuous LSI map was then classified into very low, low, moderate, high, and very high susceptibility classes. Class thresholds were determined iteratively based on the success- and prediction-rate curves, selecting the scheme that maximized the AUC while maintaining meaningful separation among the five classes.

Validation: The susceptibility model was evaluated using area under the curve (AUC) based on cumulative success- and prediction-rate curves. The susceptibility map was cross-tabulated with the landslide inventories, and the cumulative percentage of mapped landslides was plotted against the cumulative percentage of area from low to high LSI classes (33). The training inventory was used to derive the success-rate curve, while the independent validation inventory was used to generate the prediction-rate curve. The resulting AUC values were 0.892 (89.2%) for the training dataset and 0.805 (80.5%) for the independent validation dataset, indicating that the susceptibility model retained substantial predictive discrimination when evaluated against landslides occurring outside the modelling period.

2.2.2 Exposure analysis

Exposure was assessed for physical assets within landslide-prone areas and aggregated at the ward level. Houses were treated as discrete (binary) assets, classified as exposed when located within high or very high susceptibility zones, whereas roads were treated as linear assets; therefore, their exposure was represented by the mean landslide susceptibility intersecting each road segment, calculated using zonal statistics. The resulting exposure variables were normalized to a 0–1 scale before integration. A composite exposure index was calculated as:

Exposure (E) = $1 \times$ houses in very high susceptibility zones + $0.75 \times$ houses in high susceptibility zones + $0.5 \times$ road exposure to landslides.

House units and road networks were extracted from OpenStreetMap (OSM) and verified and updated using high-resolution Google Earth satellite imagery accessed through QGIS. OSM building completeness was assessed in 15 randomly selected wards by comparing mapped buildings with the imagery, yielding 88–99.7% completeness (mean = $95.0 \pm 3.6\%$). The weights (1.0, 0.75, and 0.5) were assigned through expert judgement, reflecting the greater potential consequences of house exposure for human life, household assets, and livelihoods, particularly in very-high susceptibility zones, while roads represent important but spatially continuous infrastructure exposure.

The resulting exposure index represents the overall physical exposure of each ward to landslide susceptibility and was classified into very low, low, moderate, high, and very high categories using the natural-breaks method.

2.2.3 Vulnerability assessment

2.2.3.1 Selection of the vulnerability parameters

Vulnerability is the degree to which a system, community, or individual is likely to experience harm due to exposure to a landslide susceptibility. In this study, we selected vulnerability indicators based on three criteria: (i) theoretical grounding in established vulnerability frameworks (MOVE, IPCC) (34,35), (ii) contextual relevance to landslide risk in rural Nepal, and (iii) data availability at the ward level. Accordingly, indicators were organized into environmental/livelihood, socio-economic/structural, and institutional/access dimensions, representing conditions that influence sensitivity and the capacity to cope with and recover from landslide impacts.

A distinction was maintained between physical exposure and livelihood vulnerability to avoid conceptual overlap. Houses and roads were included in the exposure component because their location within susceptible areas represents direct exposure of people, assets, and critical access infrastructure. In contrast, dependence on agriculture, forests, and water resources was incorporated into vulnerability as livelihood sensitivity, reflecting the extent to which disruption or loss of these resources can affect food security, income, and longer-term recovery. Thus, although both components incorporate spatial susceptibility information, physical exposure measures the presence of assets within susceptibility-prone areas, whereas livelihood vulnerability captures dependence on potentially affected resources. This distinction is consistent with multidimensional vulnerability frameworks and Nepal-based assessments that distinguish physical exposure from agricultural and natural-resource dependence (15,18).

Socio-economic and structural indicators, including literacy, poverty, gender, housing quality, and economic activity, capture differences in household sensitivity and coping capacity, while distance to administrative centres, markets, and transportation represents constraints on access to services, emergency response, resource mobilization, and recovery. Together, these dimensions characterize the livelihood, socio-economic, and institutional conditions that may amplify or reduce landslide impacts and provide a basis for ward-level risk-reduction planning (35,36). In the context of Nepal, addressing these vulnerabilities requires a multi-sectoral approach that combines environmental conservation, socio-economic development, and institutional strengthening to build resilience against landslides (Table 3).

Table 3: Vulnerability parameters and respective methods

Index; Transformation if non-normal	Formulas	Justification
Agriculture exposure $x' = \log(1+x)/\log(1+x_{\max})$	(Agriculture of wards exposed to (veryhigh $\times 1$ +high $\times 0.75$ +moderate $\times 0.5$ + low $\times 0.2$ +very low $\times 0.1$))/Total Ag in ward	Agricultural exposure increases vulnerability as communities rely on slope-based farming for livelihoods. Communities dependent on farming face food insecurity, income loss, and reduced recovery capacity when productive land is disrupted (37).
Forest/Grassland exposure $x' = \log(1+x)/\log(1+x_{\max})$	(Forest of wards exposed to (very high $\times 1$ +high $\times 0.75$ + moderate $\times 0.5$ +low $\times 0.2$ + very low $\times 0.1$))/Total Forest in ward	Forest/grassland exposure influences vulnerability as communities depend on these resources for fodder, fuelwood, and livelihoods. Landslides disrupt ecosystem services and resource access, increasing livelihood insecurity and environmental stress (38).
Water resources exposure $x' = (x^{\lambda}-1)/\lambda$	(Surface water of wards exposed to (very high $\times 1$ +high $\times 0.75$ + moderate $\times 0.5$ +low $\times 0.2$ +very low $\times 0.1$))/Total surface water in ward	Water resource exposure can damage springs, streams, and irrigation systems. Disruptions to water supply affect drinking water, agriculture, and sanitation, increasing livelihood stress and community vulnerability (39).
Previous loss and damaged	Loss and damaged (http://www.drrportal.gov.np/)	Past landslide losses show higher vulnerability in Nepal, as repeated damage weakens infrastructure, depletes resources, and leaves communities more exposed and slower to recover (40).
Household amenities (HA); $x' = (x^{\lambda}-1)/\lambda$; $\lambda=0.5$	Household Without any amenities/Total household at ward	Access to communication and transport reduces disaster vulnerability; lacking these increases risk, delays response, and weakens landslide resilience (41).
House structure (HS); $x'=x^{1.5}$	(Wood pillar or Other $\times 1$ +Mud bound $\times 0.75$ + Cement bonded $\times 0.3$ + Reinforced Cement Concrete with pillars $\times 0.1$)/ Total household	Mud-bonded and wooden houses increase landslide vulnerability, while cement and RCC structures provide stability, safety, and resilience (42,43).
House facilities (HF); $x' = (x^{\lambda}-1)/\lambda$; $\lambda=0.5$	(Others or Kerosene $\times 1$ + Biogas $\times 0.5$ +Solar $\times 0.3$ + Electricity $\times 0.1$)/ Total household	Reliable energy reduces disaster vulnerability through better communication and response; unstable or kerosene-based energy increases risk (44).
Household ownership (HO); $x'=x^{0.5}$	Total household/House owned	Household ownership reduces vulnerability by enabling safer construction and maintenance, while rented or temporary housing increases risk and displacement (45)
Literacy	Literacy rate	Higher literacy reduces landslide vulnerability by improving warning comprehension, preparedness, communication, and informed decision-making during disasters (46).

Economically active	Non active population/Total population	Economic activity lowers landslide vulnerability by enabling safer housing, preparedness, and faster recovery, while inactivity increases exposure and slows recovery (47).
Communication Access (proxy measurement of poverty); $x' = (x^\lambda - 1)/\lambda$; $\lambda=0.25$	Total Household/Household with Smart phone	Low smartphone ownership signals poverty, limiting information access, preparedness, warning response, and recovery, thereby increasing social vulnerability to disasters (48).
Ethnic composition	(Dalit*1+0.75*Jangati/indigenous group)/Total population	Ethnic composition affects landslide vulnerability in Nepal, as marginalized groups often face limited resources, services, and representation, increasing exposure, reducing preparedness, and slowing recovery (18).
Female Educational Disadvantage $x' = \log x$	Female Literacy rate	Gender influences vulnerability in Nepal, as unequal roles, resources, and decision-making power can limit women's access to information, mobility, and recovery support, increasing risk and impacts (49).
Transportation	Ward score $S = \min(1, 0.1 \times [d])$; d = distance (km) from Highway / Feeder Road / District Road	Limited transport access increases landslide vulnerability by delaying response, evacuation, and aid, while well-connected areas recover faster due to rapid resource mobilization (50).
Access to Governments	Ward score $S = \min(1, 0.1 \times [d])$; d = distance from Headquarter of Local government, District, and Province	Proximity to government headquarters reduces landslide vulnerability in Nepal by enabling faster coordination, aid, and decisions, while remote areas face delayed support and recovery, increasing risk (51).
Proximity to market center	Ward score $S = \min(1, 0.1 \times [d])$; d = distance from primary, secondary and tertiary market	Market access reduces vulnerability by supporting income, supplies, and recovery, while isolated areas face shortages, losses, and greater long-term risk.

Where

$$S = \begin{cases} 1.0 & (d \geq 10), \\ 0.9 & (9 \leq d < 10), \\ 0.8 & (8 \leq d < 9), \\ 0.7 & (7 \leq d < 8), \\ 0.6 & (6 \leq d < 7), \\ 0.5 & (5 \leq d < 6), \\ 0.4 & (4 \leq d < 5), \\ 0.3 & (3 \leq d < 4), \\ 0.2 & (2 \leq d < 3), \\ 0.1 & (0 \leq d < 1), \end{cases}$$

d = distance (km) from Highway / Feeder Road / District Road

S = assigned score

Access indicators (distance to administrative centers, markets, and transportation networks) were scored using a step function with 1-km increments, capped at 10 km. This scheme was adopted based on three considerations. First, distance-based accessibility is a well-established proxy for emergency response capacity and recovery potential in disaster vulnerability assessments (52). Second, the 10-km threshold reflects the sparse service distribution and motorized transport context of rural hill districts in Nepal, where distances to local government headquarters frequently exceed 10 km. Third, the 1-km increment provides sufficient granularity to differentiate wards while avoiding spurious precision. This operationalization is consistent with context-specific

adaptations of accessibility thresholds in developing regions, where fixed thresholds from developed-country contexts are inappropriate.

The exposure of agriculture, forest, and water resources to landslide hazard was assessed through spatial cross-tabulation of high and very susceptibility layers with thematic land-use layers updated using high-resolution imagery from Google Earth. Ward-level socio-economic data were obtained from Central Bureau of Statistics Nepal and spatially joined to ward boundaries (<https://censusnepal.cbs.gov.np/results/downloads/local-level-report?type=report>) (NSO, 2021). Historical loss and damage records were retrieved from the Disaster Risk Reduction Portal Nepal and attributed to corresponding wards.

2.2.3.2 *Principal component analysis*

PCA was performed on ward-level vulnerability indicators using the FactoMineR package in R, with total observation of 986, and variables of 16 (Detail in Fig. 6). Prior to analysis, variables were standardized using z-score transformation (mean = 0, SD = 1) to ensure equal contribution across different measurement scales. Data suitability for PCA was confirmed using the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity (53). The overall KMO was 0.83, and Bartlett's test was significant ($\chi^2 = 10461.1$, df-120, $p < .001$), jointly confirm that PCA is an appropriate and statistically defensible technique for extracting the underlying structure of the data and deriving objective weights.

Components were retained based on the Kaiser criterion (eigenvalue ≥ 1) (54,55), subjected to Varimax orthogonal rotation, based correlation matrix decomposition to enhance interpretability. Variables were considered to load significantly on a component if their absolute loading was ≥ 0.40 . Component weights were derived by multiplying absolute rotated loadings by the proportion of variance explained by each component, then normalizing the resulting weights to sum to 100 (19).

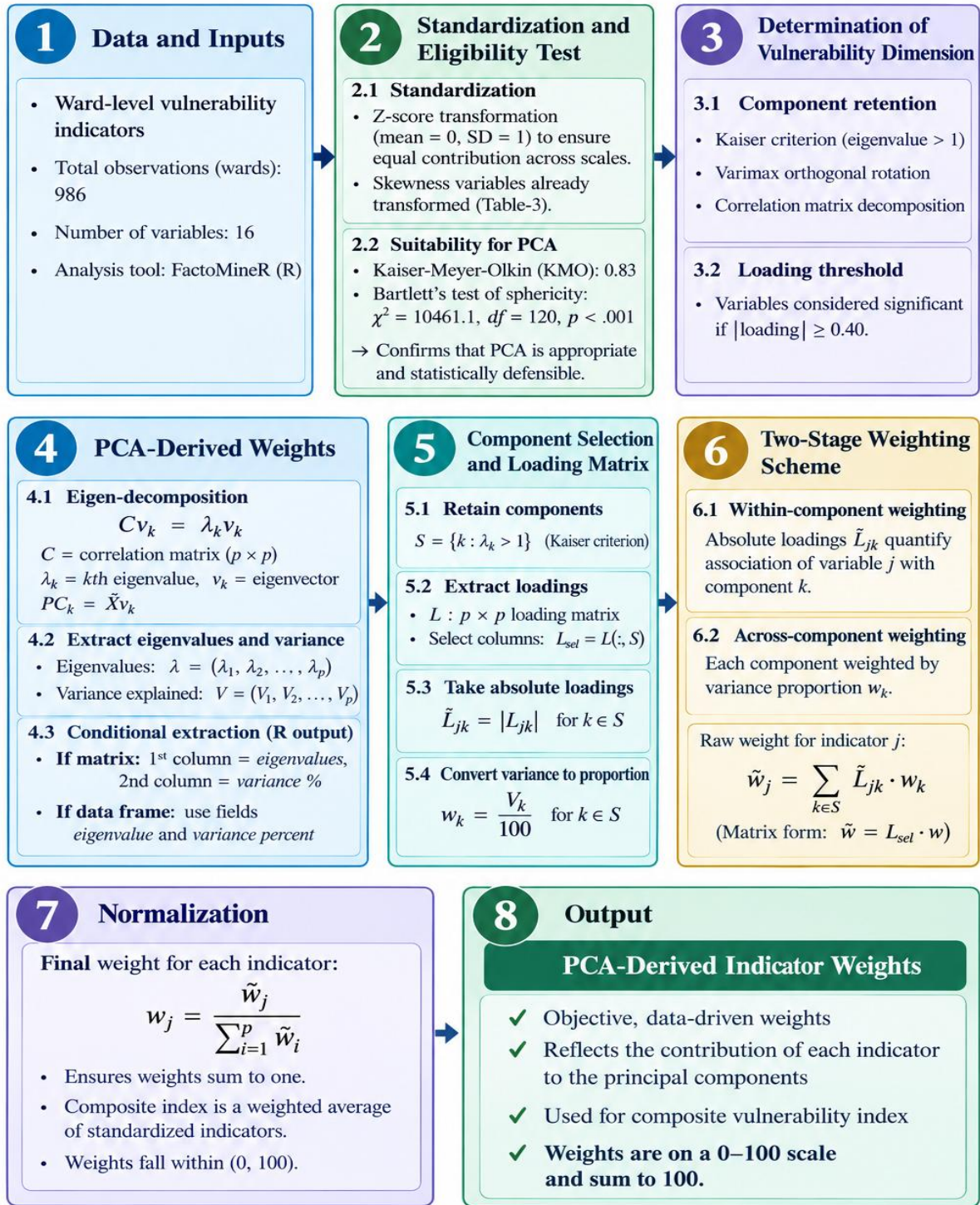


Fig. 6: Steps of PCA and derivation of variables weight

2.2.3.3 Vulnerability Mapping and effect analysis

Vulnerability mapping and effect analysis proceeded sequentially from indicator aggregation to component-level contribution analysis. The standardized indicator variables (Table 3) were multiplied by their PCA-derived weights and aggregated within four dimensions; Socio-economic Vulnerability, Environmental and

Livelihood Exposure, Institutional and Infrastructure Access, and Structural and Economic Stability, to generate the respective component vulnerability indices. These four indices were then combined to derive the composite Total Vulnerability index, representing the multidimensional vulnerability of each study unit. Relationships among the component indices were subsequently examined using correlation analysis to assess the strength and direction of their associations.

Before interpreting their relative importance, multi-collinearity was assessed using the Variance Inflation Factor (VIF), which quantifies the extent to which the variance of a regression coefficient is inflated by correlations among predictors. VIF values were interpreted using conventional thresholds of multi-collinearity: $VIF < 5$ indicates no problematic, $5 < VIF < 10$ indicates moderate, and $VIF \geq 10$ indicates serious multi-collinearity (56). Following this diagnostic assessment, the relative statistical contribution of each dimension to Total Vulnerability was evaluated using the Lindeman–Merenda–Gold (LMG) relative-importance metric, which partitions explained variance among correlated predictors by averaging their incremental contributions across all possible model orderings (57). LMG values were expressed as percentages of explained variance to compare the relative contributions of the four dimensions. Because Total Vulnerability was constructed directly from these component indices, the LMG analysis was interpreted as variance partitioning of the composite index rather than evidence of independent causal effects.

2.2.4 Risk assessment

The ward-level relative landslide risk index was calculated by multiplicatively integrating the normalized LSI, Composite Exposure, and Total Vulnerability. The multiplicative formulation emphasizes the spatial convergence of the three risk dimensions, such that high risk occurs where high susceptibility coincides with substantial exposure and vulnerability. The resulting index represents relative spatial risk for ward-level comparison and prioritization, rather than an absolute probability of landslide occurrence or expected loss.

Spatial variation in the integrated risk index and its constituent dimensions was subsequently evaluated using two-way Analysis of Variance (ANOVA) (58). Separate models were fitted for landslide susceptibility, vulnerability, exposure, and risk to examine their variation across 12 districts, four physiographic zones (Chure-Siwalik, High Mountain, Middle Mountain, and Tarai), and the District $\times$ Physiography interaction (59). Type II tests were applied, with sums of squares obtained through model comparison because the partially nested spatial structure, where not all districts occur within all physiographic zones, resulted in aliased coefficients. All four models were fitted to the same 986 ward-level observations (963 residual degrees of freedom), allowing consistent comparison of the relative contributions of district, physiography, and their interaction across the four outcomes. The analysis was used to evaluate how spatial controls shift from the predominantly physical pattern of landslide susceptibility toward the integrated patterns of exposure, vulnerability, and overall risk.

3 Results

3.1 Landslide susceptibility assessment

The landslide susceptibility assessment resulted that more than 19.6 % hillslope area of Lumbini province fall under high or very landslide susceptible zone (Table 4, and Fig. 7).

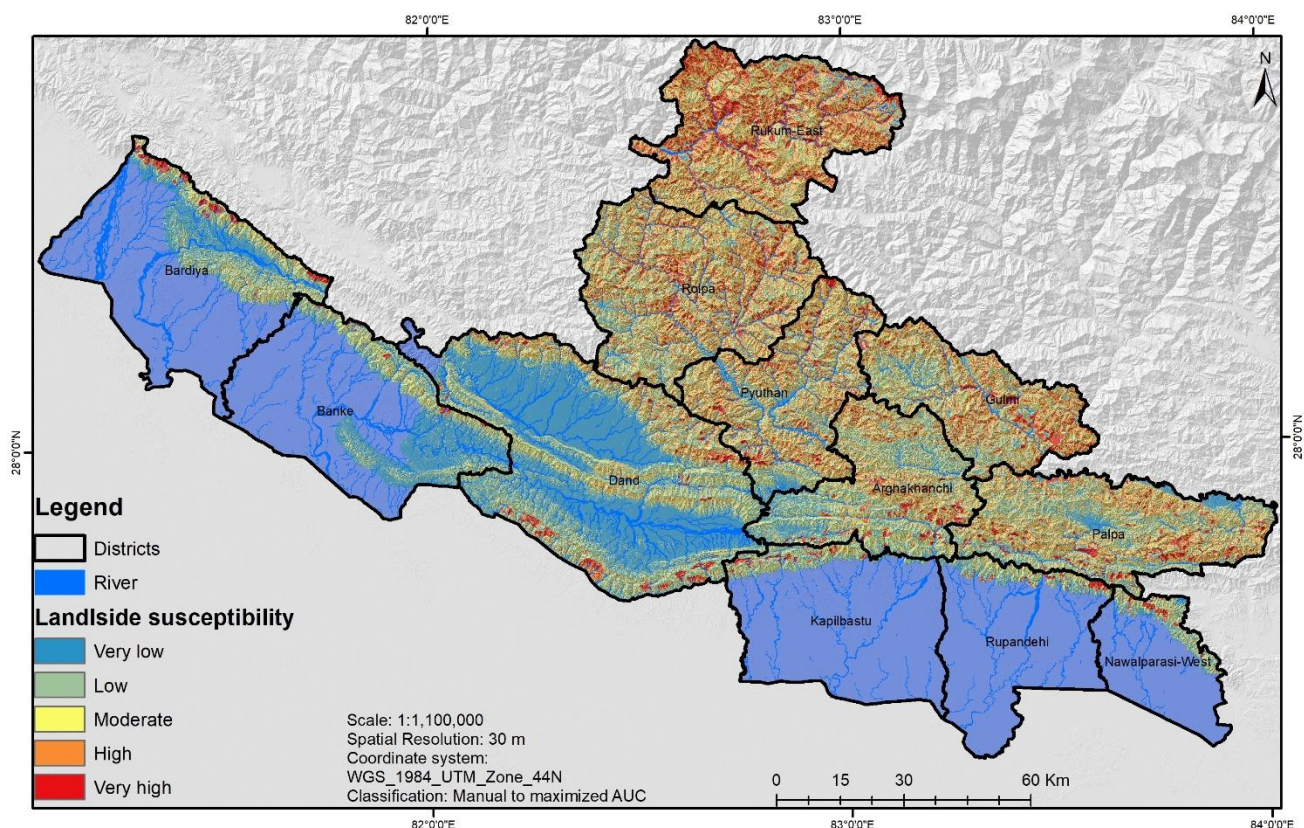


Fig. 7: Landslide susceptibility map

This indicate that Rukum East, the higher mountain zone of the province is more landslide prone, followed by the mid hill of Gulmi, Rolpa, and Pyuthan. Likewise, the Chure of Palpa and Agrakhanchi are equally susceptible to landslide.

Table 4: Landslide susceptibility of Lumbini Province

Landslide susceptibility	Area (Sq Km)	Percentage (%)
Very low	9576.0	49.4
Low	2308.6	11.9
Moderate	3711.2	19.1
High	2483.2	12.8
Very High	1312.2	6.8

Interpreting pixel-based maps can sometimes pose challenges for relevant agencies. To address this, the susceptibility index was created through a zonal analysis of susceptibility and local government ward units, as shown in the Fig. 8.

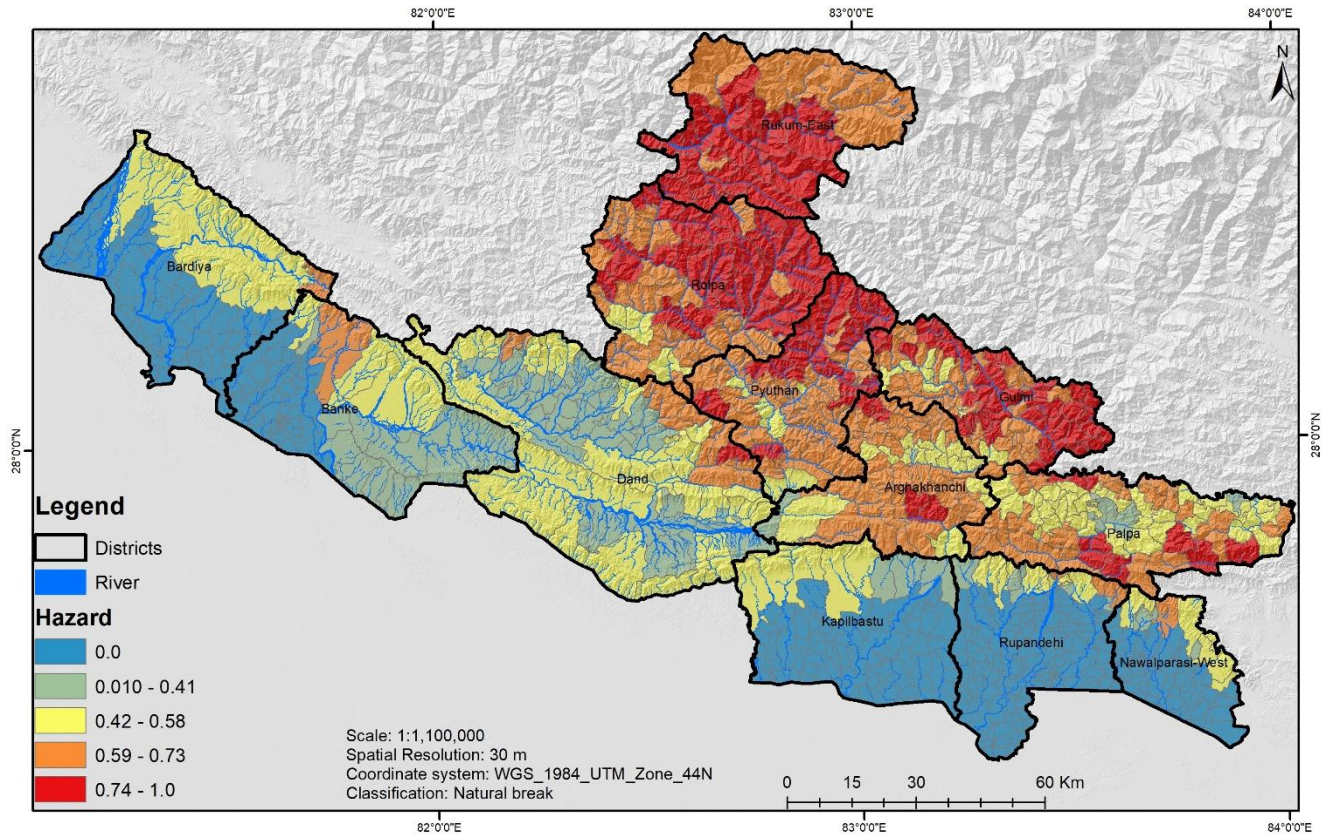


Fig. 8: Landslide susceptibility with respect to wards

3.2 Exposure to the landslide susceptibility

The spatial pattern indicates that landslide exposure is concentrated mainly in the hill and mountain districts, where settlements, infrastructure, and livelihoods are located in environmentally fragile terrain (Fig. 9).

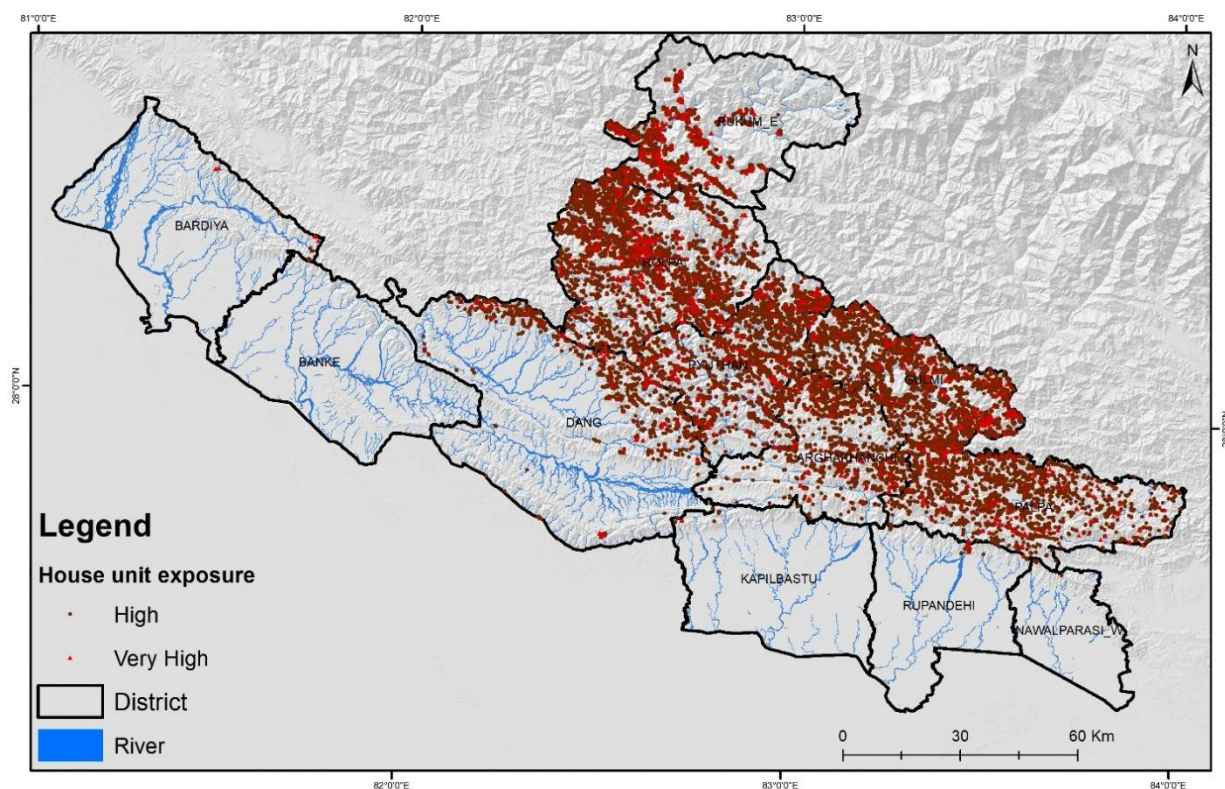


Fig. 9: Landslide susceptible house unit

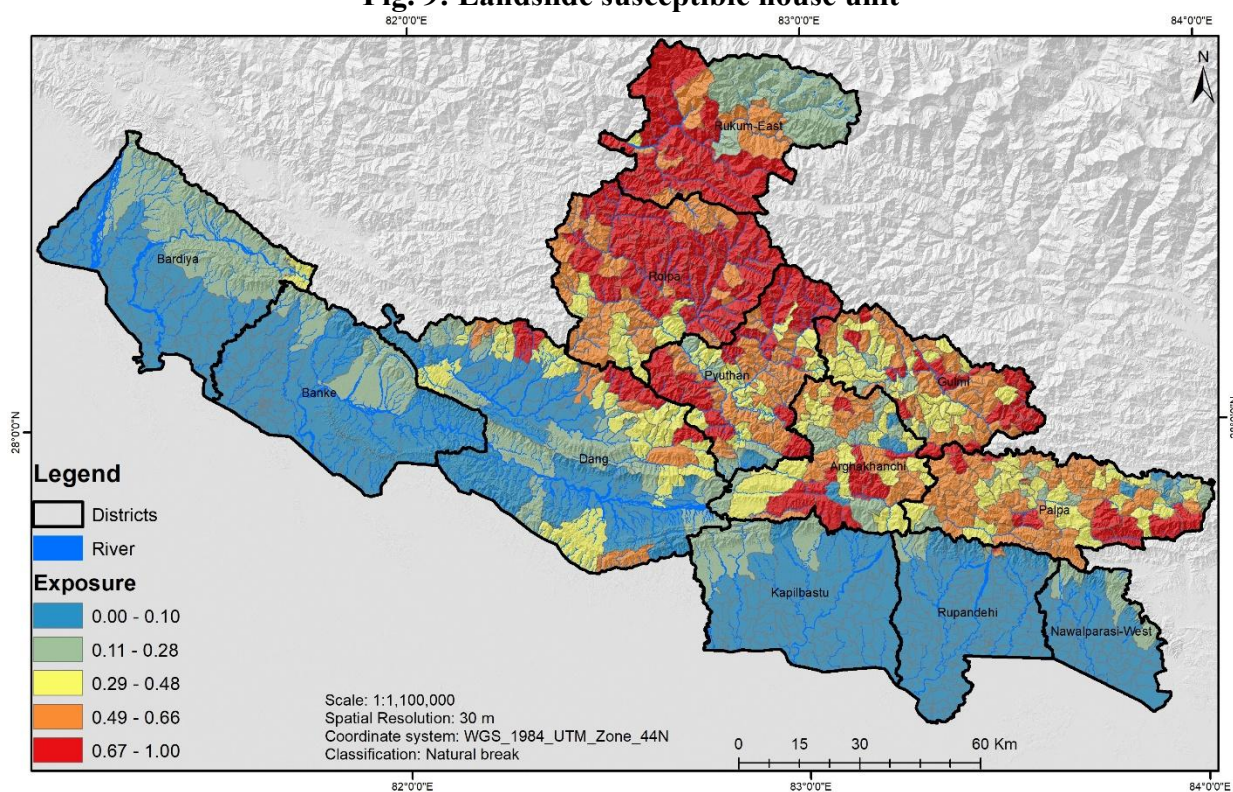


Fig. 10: Landslide exposure with respect wards of local government

The Mid and High Mountain districts, particularly Rolpa, Rukum East, Pyuthan, Gulmi, and Palpa, where many wards fall within high or very high susceptibility categories (Fig. 10). Arghakhanchi and Dang also exhibit localized exposure, though less extensive (Fig. 11). In contrast, the plains districts such as Banke, Bardiya, Kapilbastu, Nawalparasi West, and Rupandehi display minimal landslide exposure due to relatively stable terrain conditions. These findings highlight the need for targeted slope management, bioengineering measures, and risk-sensitive land-use planning in the most exposed hill districts, while maintaining preventive watershed management and monitoring systems in moderately exposed areas.

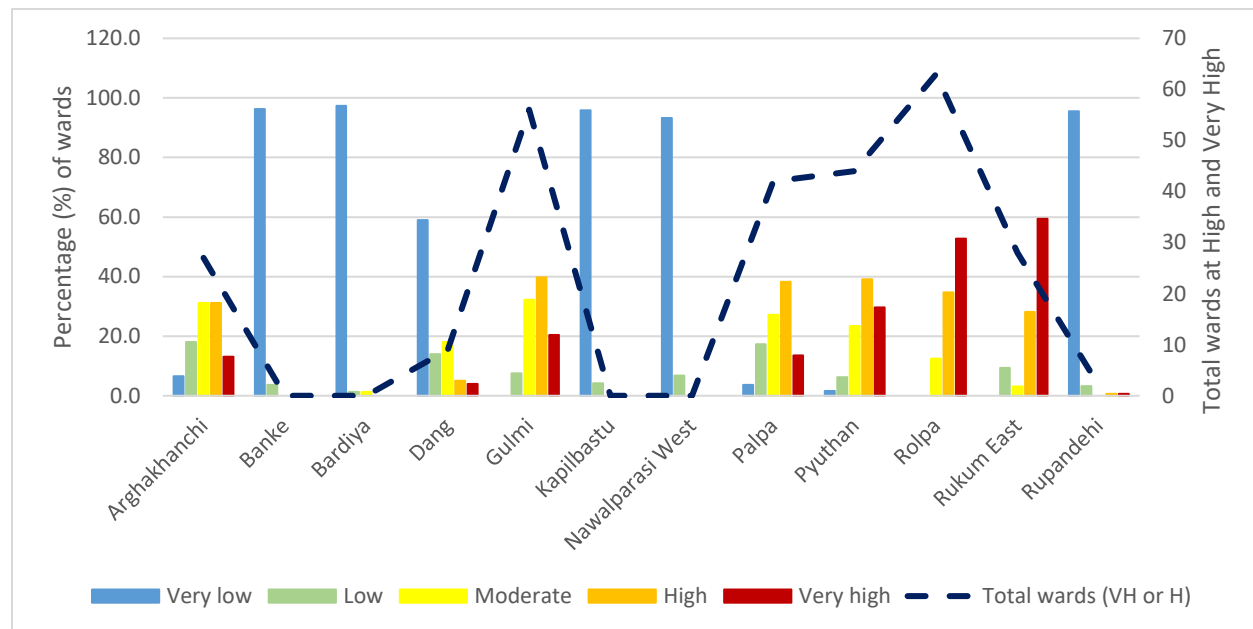


Fig. 11: Distribution of ward-level landslide susceptibility exposure

3.3 Vulnerability to landslide

Vulnerability to landslides is a multifaceted, and the PCA resulted in mainly four cluster; i) Socio-economic, ii) Environmental & Livelihood Exposure, iii) Institutional & Infrastructure Access, and iv) Economic Dependency & Asset Poverty (Table 5).

Table 5: Vulnerability group based on PCAs: Component Loadings

Component Loadings	PC1	PC2	PC3	PC4	Uniqueness
Literacy	0.889				0.153
Female Educational Disadvantage	0.847				0.201
Communication Access	0.79				0.335
Household amenities	0.739				0.303
House facilities	0.71				0.464
Household ownership	-0.601			-0.469	0.299
Forest exposure		0.901			0.149
Water resources exposure		0.833			0.269

Component Loadings	PC1	PC2	PC3	PC4	Uniqueness
Cultivation exposure		0.828			0.218
Previous loss and damaged		0.794			0.362
Ethic composition		0.648		0.481	0.313
House structure		0.572		0.563	0.194
Administration and services			0.868		0.245
Market and services			0.646		0.278
Transportation			0.542		0.602
Economically active				-0.83	0.251
Vulnerability Groups	Socio-economic vulnerability	Environmental & Livelihood Exposure	Institutional & Infrastructure Access	Structural and Economic Stability	
Note. Applied rotation method is varimax.					

369

370 **Socio-economic Vulnerability:** Overall, areas with low literacy, high poverty, gender disparities,
371 inadequate amenities, and limited housing security are more socio-economically vulnerable. PC1 can
372 therefore be interpreted as a Socio-Economic Disadvantage Component, where ownership acts as a
373 protective factor.

374 **Environmental & Livelihood Exposure Vulnerability:** This component (PC2) captures physical exposure
375 combined with livelihood dependence and social sensitivity. Higher scores indicate communities located in
376 susceptibility-prone environments, with repeated losses and socially vulnerable populations, leading to
377 elevated landslide risk.

378 **Institutional & Infrastructure Access Vulnerability:** This component (PC3) captures access to
379 institutions, infrastructure, and essential services. Areas with limited administrative reach, weak market
380 access, and poor transportation are more vulnerable due to delayed response, restricted resources, and
381 slower recovery.

382 **Structural and Economic Vulnerability:** Generally, areas with weak housing structures, socially
383 marginalized populations, lower economic activity, and limited ownership security are more vulnerable.
384 PC4 therefore represents a Structural and Economic Stability Component, where employment and
385 ownership act as protective factors.

386 The four rotated components represent distinct but complementary dimensions of vulnerability (e.g., socio-
387 economic status, exposure–sensitivity, institutional accessibility, and structural-economic stability). The
388 71% cumulative variance suggests the model reliably captures the major drivers of landslide vulnerability
389 while reducing complexity (Table 6, and Fig. 12).

390 **Table 6: Interpretation of PCA Results (Unrotated and Rotated Solution)**

Component Characteristics	Unrotated solution			Rotated solution		
	Eigenvalue	Proportion var.	Cumulative	SumSq. Loadings	Proportion var.	Cumulative
Component 1	5.64	0.35	0.35	3.97	0.25	0.25

Component 2	3.38	0.21	0.56	3.93	0.25	0.49
Component 3	1.34	0.08	0.65	1.75	0.11	0.60
Component 4	1.00	0.06	0.71	1.72	0.11	0.71

Fig. 12: Eigenvalues explained by the resulting components

Considering the all these fact, final weight was determined as in Fig. 13.

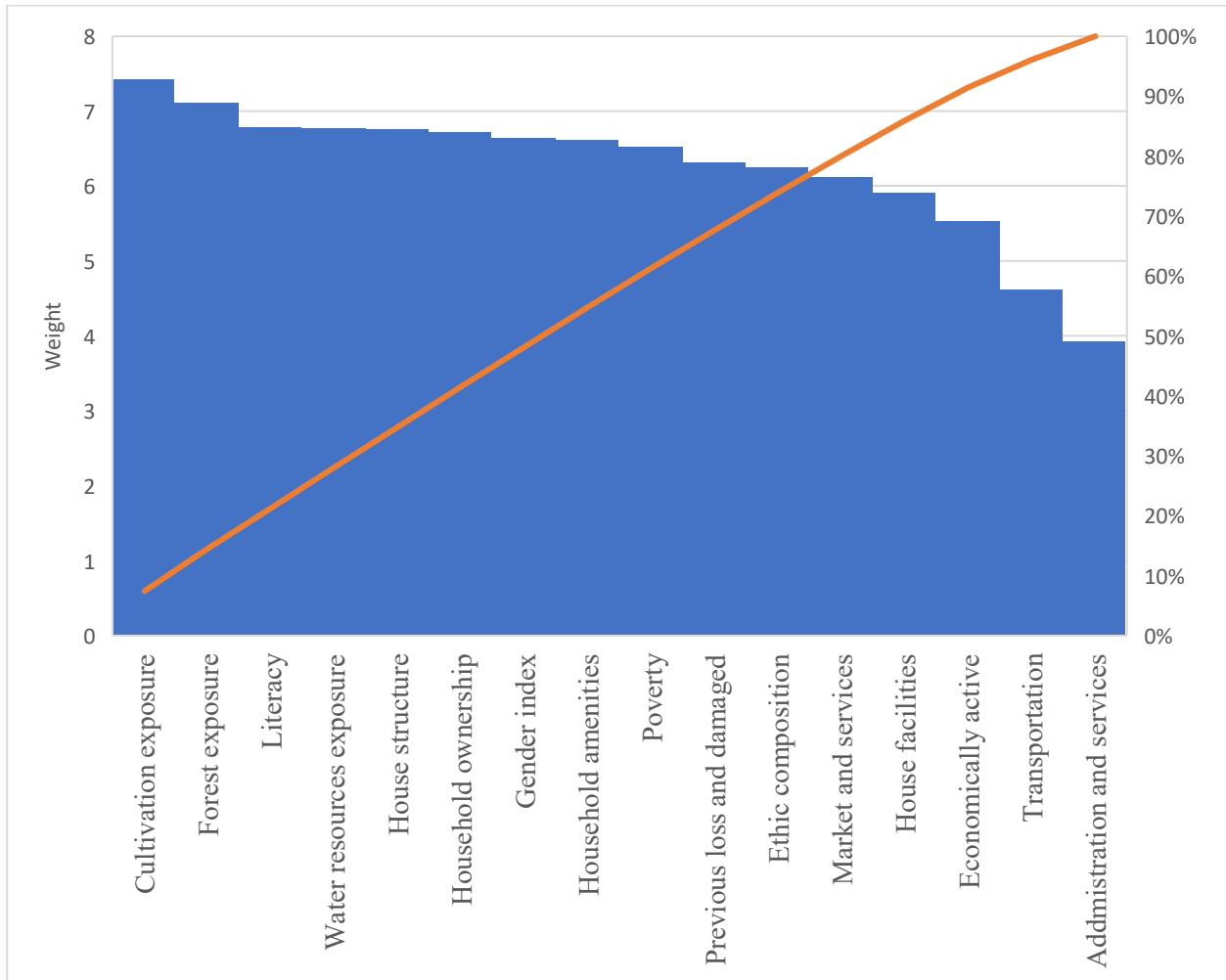


Fig. 13: Weight calculation based on PCAs

Overall vulnerability is obtained through combining the all three; environmental, socio-economic and system vulnerabilities (Fig. 14).

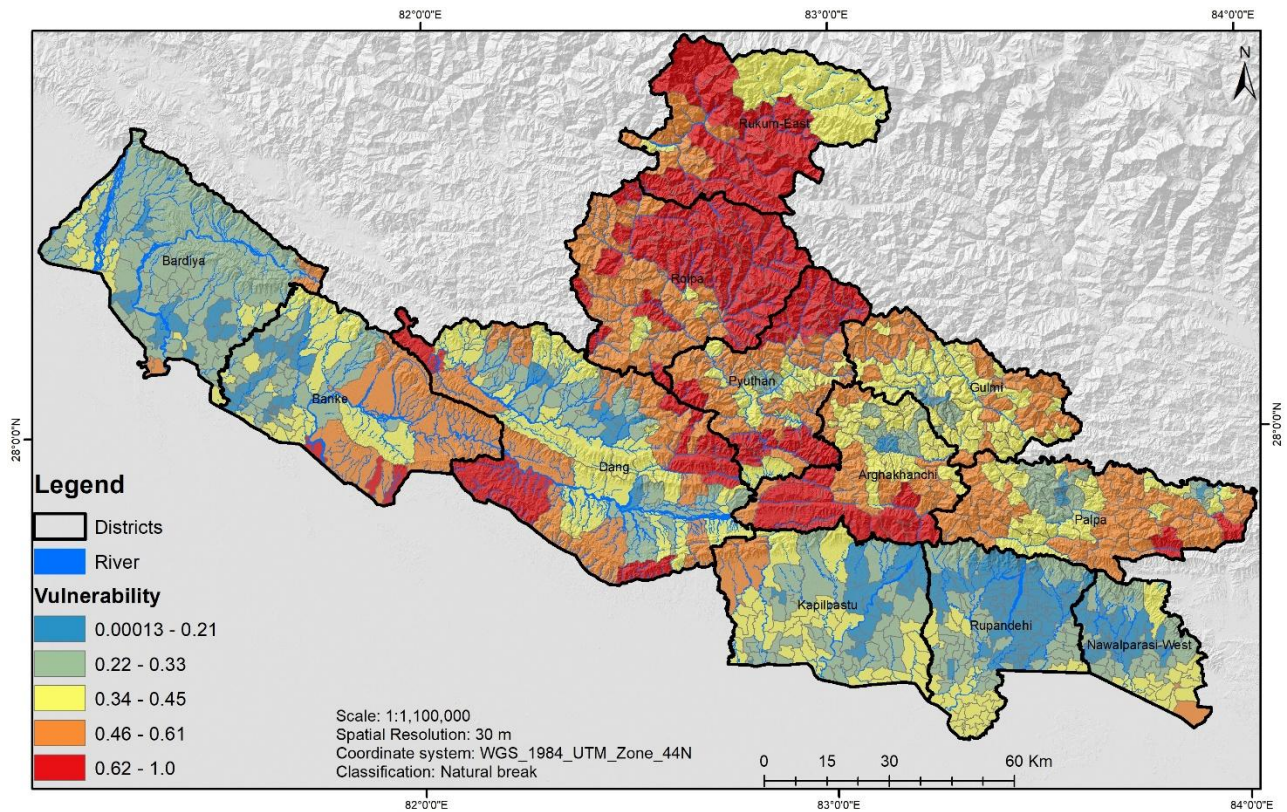


Fig. 14: Overall landslide vulnerabilities

The vulnerability pattern closely follows the spatial distribution of landslide exposure across the districts. Likewise, Rolpa, Rukum East, Pyuthan, Gulmi, and Palpa, show a pronounced concentration of highly vulnerable wards, reflecting the combined influence of fragile terrain, scattered settlements, limited infrastructure access, and socio-economic constraints (Fig. 14). Arghakhanchi and Dang exhibit mixed vulnerability conditions, indicating transitional landscapes where both relatively secure and vulnerable communities coexist. In contrast, the Terai districts, including Banke, Bardiya, Kapilbastu, Nawalparasi West, and Rupandehi, are predominantly characterized by low vulnerability, likely associated with flatter terrain, better accessibility, and relatively stronger service and infrastructure networks. Overall, the results highlight a strong topographic and development gradient in vulnerability across the province.

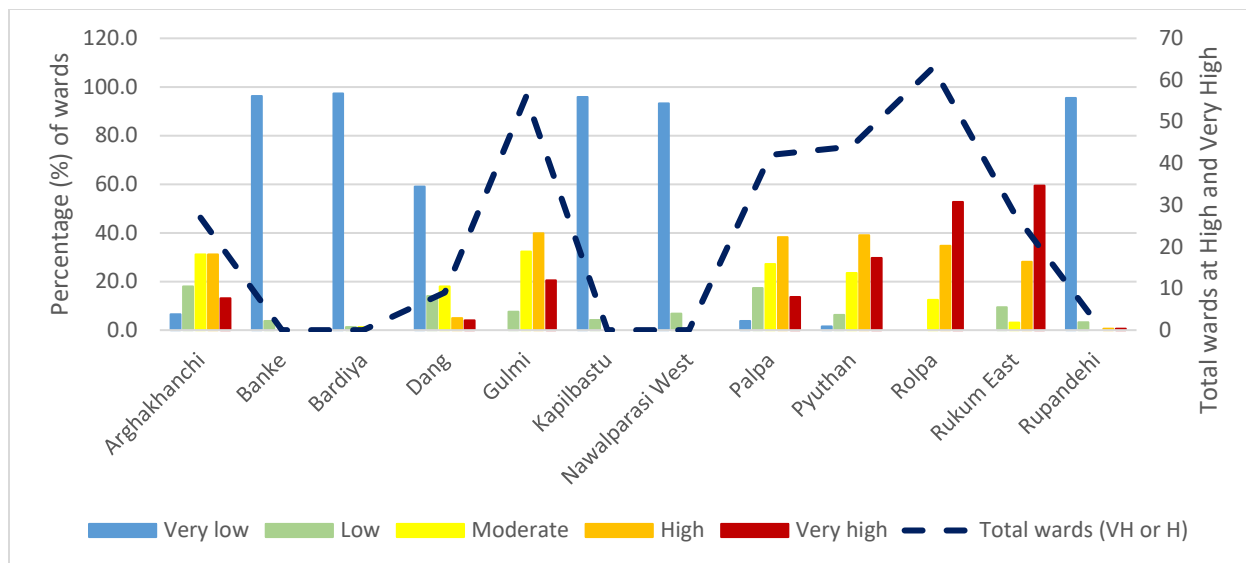


Fig. 15: Distribution of ward-level landslide vulnerability

3.4 Landslide risk

The overall landslide risk pattern across Lumbini Province shows that smaller proportion of wards fall under low (12.6%) and moderate (10.6%) risk, reflecting transitional landscapes where susceptibility and exposure moderately interact. However, a considerable share of wards lies in high (11.1%) and very high risk (5.1%) categories, mainly concentrated in the Middle and High Mountain districts (Fig. 15).

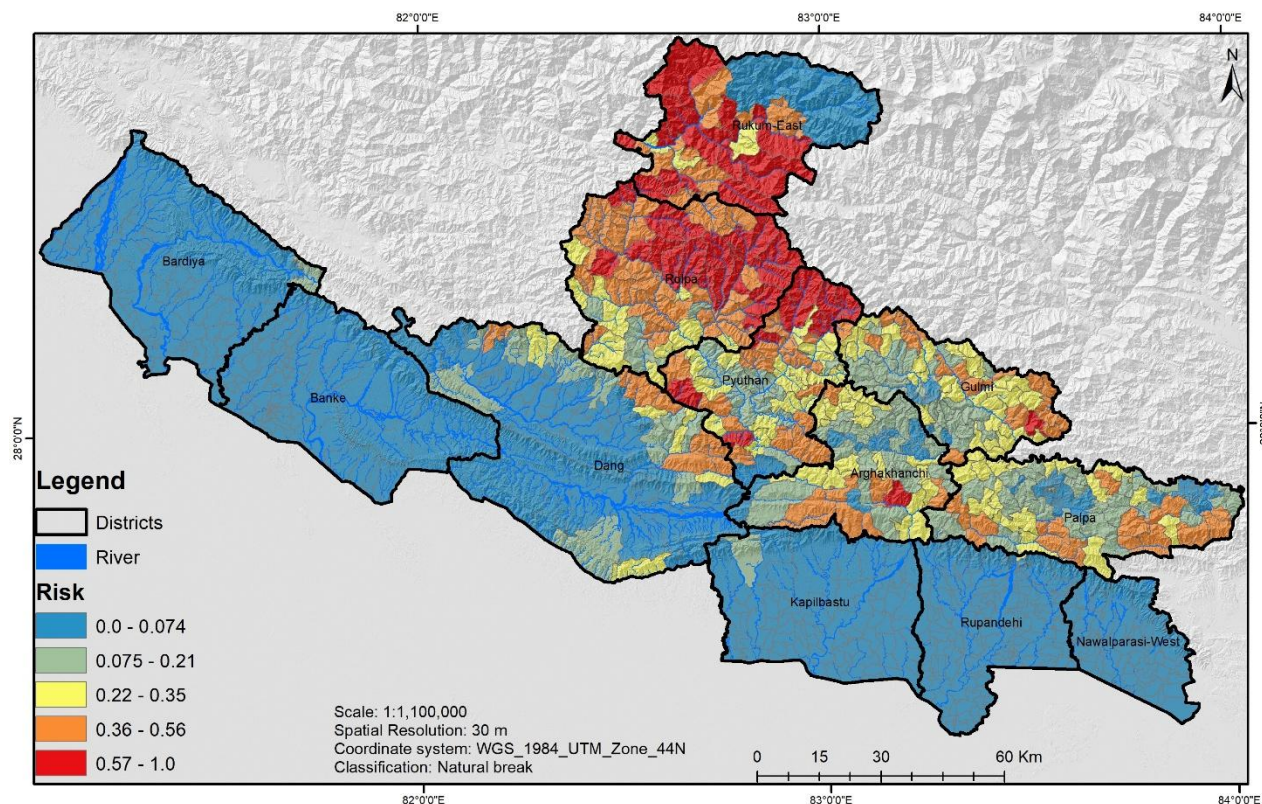


Fig. 16: Landslide risk of Lumbini province

District-level patterns reveal that Rolpa and Rukum East contain the largest concentration of high and very high risk wards, followed by Pyuthan, Gulmi, and Palpa, indicating strong interaction between landslide-prone terrain, exposed settlements, and socio-economic vulnerability (Fig. 17). Arghakhanchi and Dang show localized pockets of elevated risk, while the Tarai districts, remain predominantly under very low risk due to comparatively stable geomorphology and lower landslide exposure.

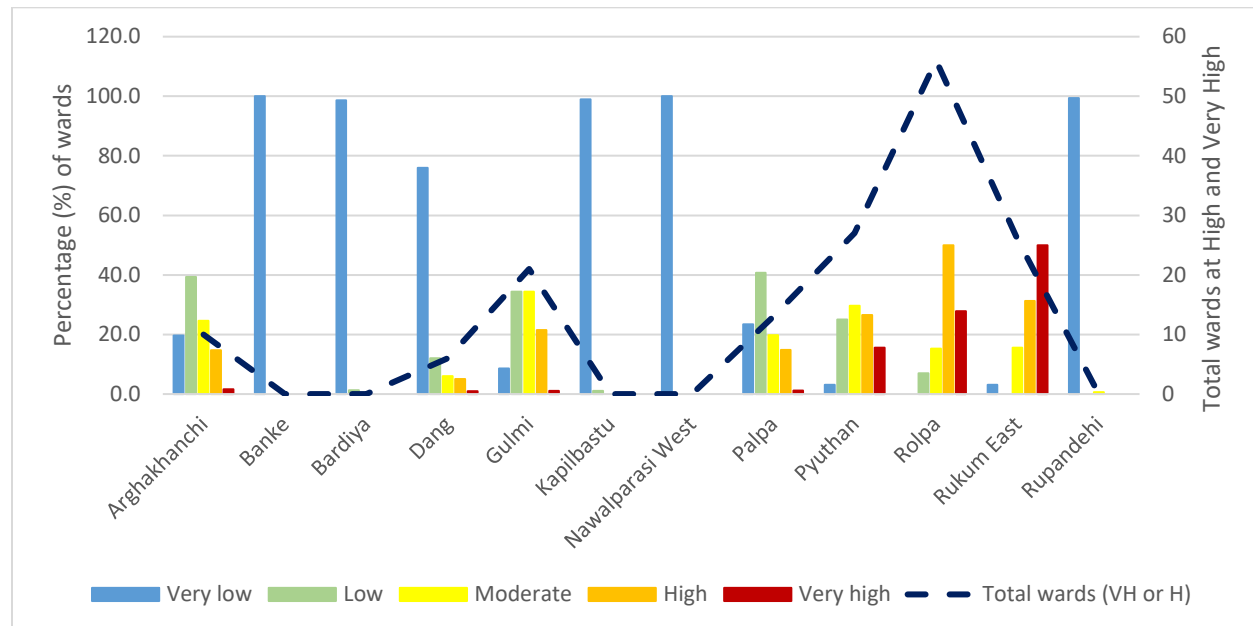


Fig. 17: Distribution of ward-level landslide risk

Overall, the findings highlight that landslide risk in the province is spatially concentrated in the Mid and High Mountain belts, where fragile geology, steep slopes, and settlement exposure combine to elevate disaster risk. The top 20 high-risk wards are listed in Table 7.

Table 7: Highest landslide risk wards of Lumbini Province

Rank	Local Government	Ward Number	Hazard	Exposure	Vulnerability	Risk
1	Sunchhahari Rural Municipality (RM)	1	0.89	0.82	0.92	1.01
2	Thawang RM	5	0.90	0.87	0.85	1.01
3	Putha Uttarganga RM	12	0.85	0.87	0.81	0.90
4	Putha Uttarganga RM	14	0.87	0.86	0.78	0.89
5	Sunchhahari RM	3	0.77	0.75	1.00	0.87
6	Naubahini RM	2	0.81	0.81	0.85	0.85
7	Sunchhahari RM	2	0.81	0.76	0.89	0.83
8	Sunchhahari RM	6	0.83	0.78	0.84	0.82
9	Putha Uttarganga RM	10	0.89	0.80	0.76	0.82
10	Rolpa Municipality (M)	8	0.87	0.86	0.70	0.79
11	Lungri RM	1	0.79	0.75	0.85	0.76
12	Satyawati RM	3	0.92	1.00	0.53	0.74
13	Gaumukhi RM	2	0.79	0.83	0.75	0.74

14	Putha Uttarganga RM	3	1.00	0.63	0.77	0.73
15	Bhume RM	1	0.78	0.86	0.72	0.73
16	Putha Uttarganga RM	5	0.84	0.61	0.93	0.72
17	Sunchhahari RM	5	0.87	0.73	0.74	0.71
18	Sisne RM	1	0.65	0.85	0.85	0.71
19	Lungri RM	7	0.82	0.71	0.80	0.71
20	Gaumukhi RM	3	0.79	0.87	0.67	0.70

Understanding these, planners and decision-makers can develop a comprehensive understanding of the risks and implement targeted strategies to reduce the overall vulnerability of an area to landslides.

4 Discussion

4.1 Understanding the spatial relationship and distribution of vulnerability components

4.1.1 Socio-Economic vulnerability

The strong and statistically significant inter-correlations among literacy, gender index, poverty, and housing conditions indicate that these variables collectively capture a shared dimension of socio-economic deprivation (Fig. 18). Their spatial clustering justifies their aggregation under the composite construct “Socio-Economic Disadvantage and Dependency,” which defines socio-economic vulnerability, as it reflects socially marginalized and economically constrained populations with limited structural security (Table 5). This is a pattern evident not only in Nepal but across many developing countries worldwide (19,60,61).

In contrast, household ownership exhibits a negative relationship with the other variables, suggesting that secure tenure functions as a protective factor. Communities lacking ownership, often characterized by landlessness, tenancy, or informal urban settlements, may experience heightened vulnerability even when other service indicators are relatively adequate (62). Moreover, lower literacy constrains the ability to interpret early warnings, risk information, and official guidance, thereby reducing preparedness and adaptive capacity. Gender inequality further intensifies vulnerability, as limited land rights, property ownership, and participation in decision-making restrict women’s access to resources and recovery mechanisms (49). Poverty compounds these risks by forcing households into unsafe settlements and limiting their capacity to strengthen housing, relocate, or access resources, often resulting in prolonged recovery cycles. In addition, inadequate household facilities, such as safe drinking water and electricity, heighten disruption during disasters, while household amenities reflect both current economic status and the availability of resources necessary to support emergency response and recovery.

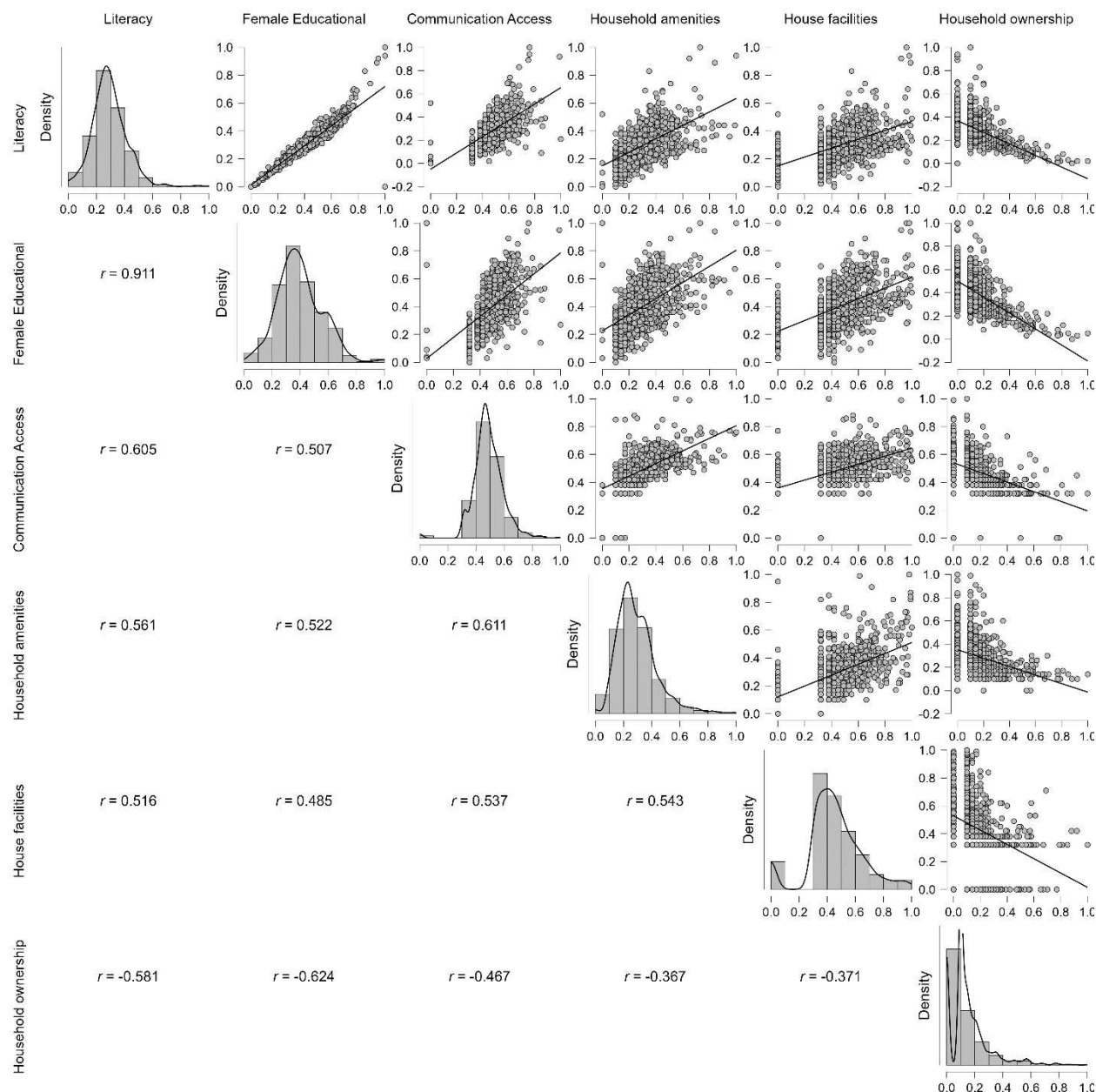


Fig. 18: Correlation/pair plot of Socio-economic vulnerability

From a spatial perspective, most wards in East Rukum, the north-eastern part of Rolpa, and the southern wards of Banke and Kapilvastu exhibit high levels of socio-economic vulnerability (Fig. 19).

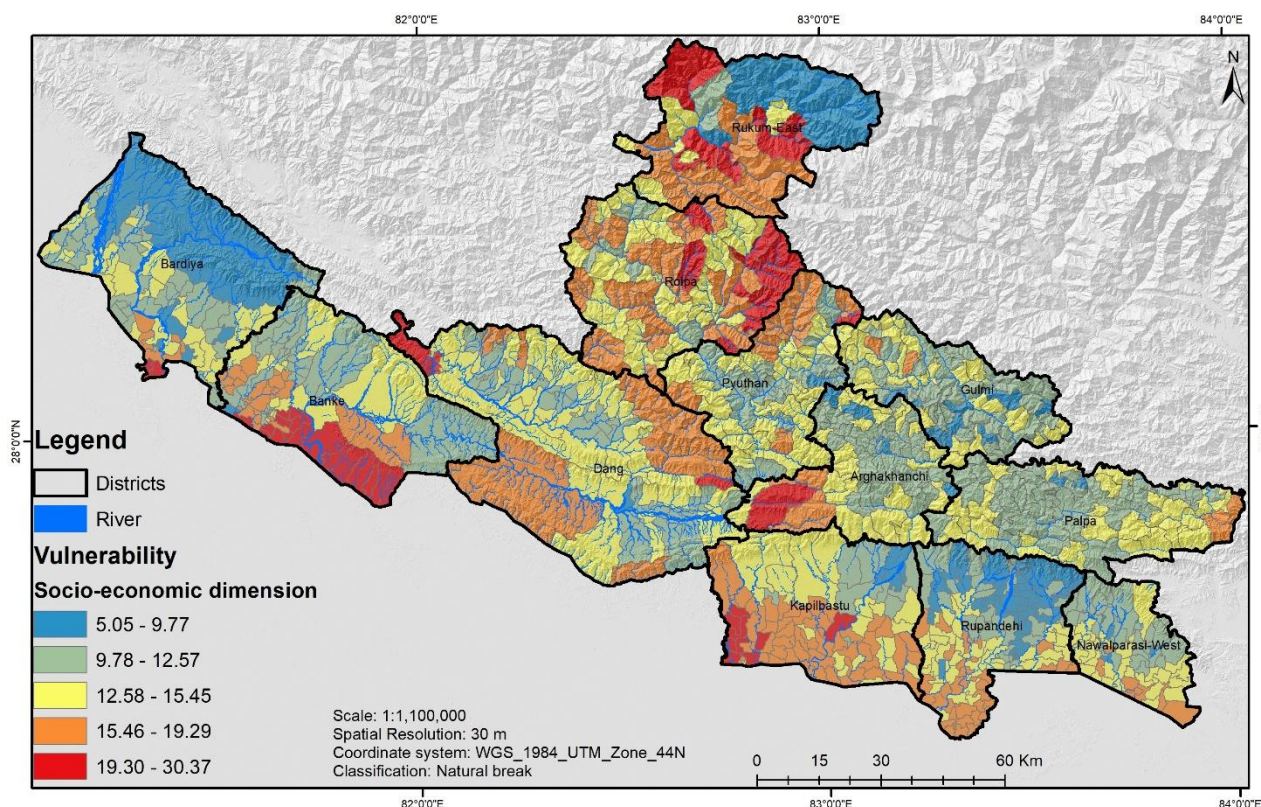


Fig. 19: Socio-economic Vulnerability of Lumbini Province

4.1.2 Environmental & Livelihood vulnerability

Communities whose livelihoods are closely tied to agriculture, forests, and water resources exhibit heightened environmental sensitivity (Fig. 20). The strong association with previous loss and damage further confirms this exposure–impact linkage. The inclusion of ethnic composition and house structure suggests that many of these populations are traditional or indigenous communities residing in settlement types and housing forms that may be structurally vulnerable (Table 5).

In Nepal, rural societies remain heavily reliant on agriculture, forests, and water resources for income, food security, and ecosystem services (63,64). Landslides directly threaten these resources, intensifying livelihood insecurity and overall vulnerability. Moreover, the potential for damage is closely linked to structural characteristics of houses, including foundations, wall materials, and construction quality, which significantly influence the degree of loss during hazard events (65).

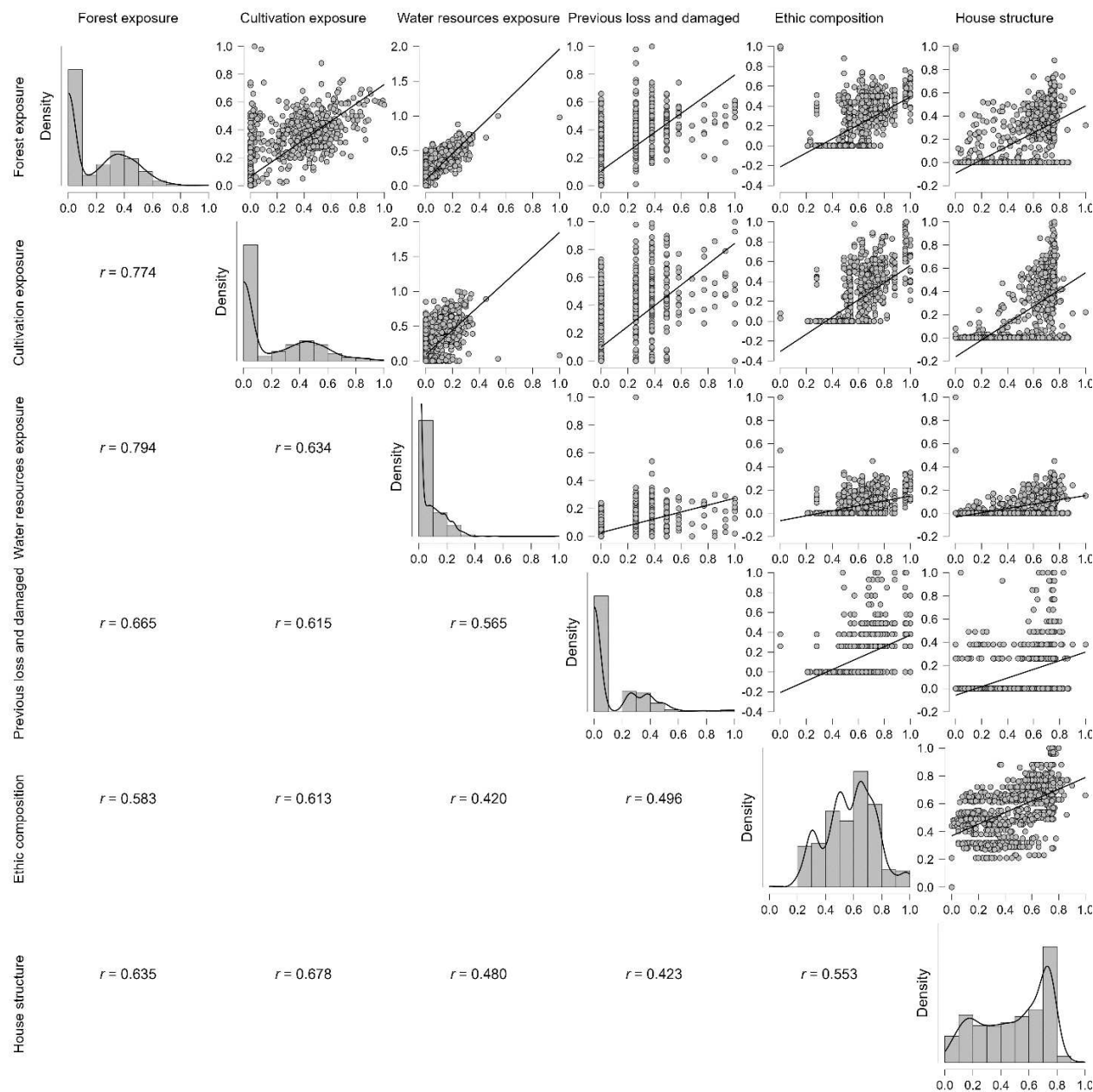


Fig. 20: Correlation/pair plot of Environment and Livelihood Exposure

The environmental vulnerability is higher in the Rukum east district and adjacent area, northern region of Rolpa and Pyuthan (Fig. 21). Likewise, the Chure/Siwalik hill of Palpa, Argakhanchi, and Dang districts is also environmentally sensitive to landslide susceptibility.

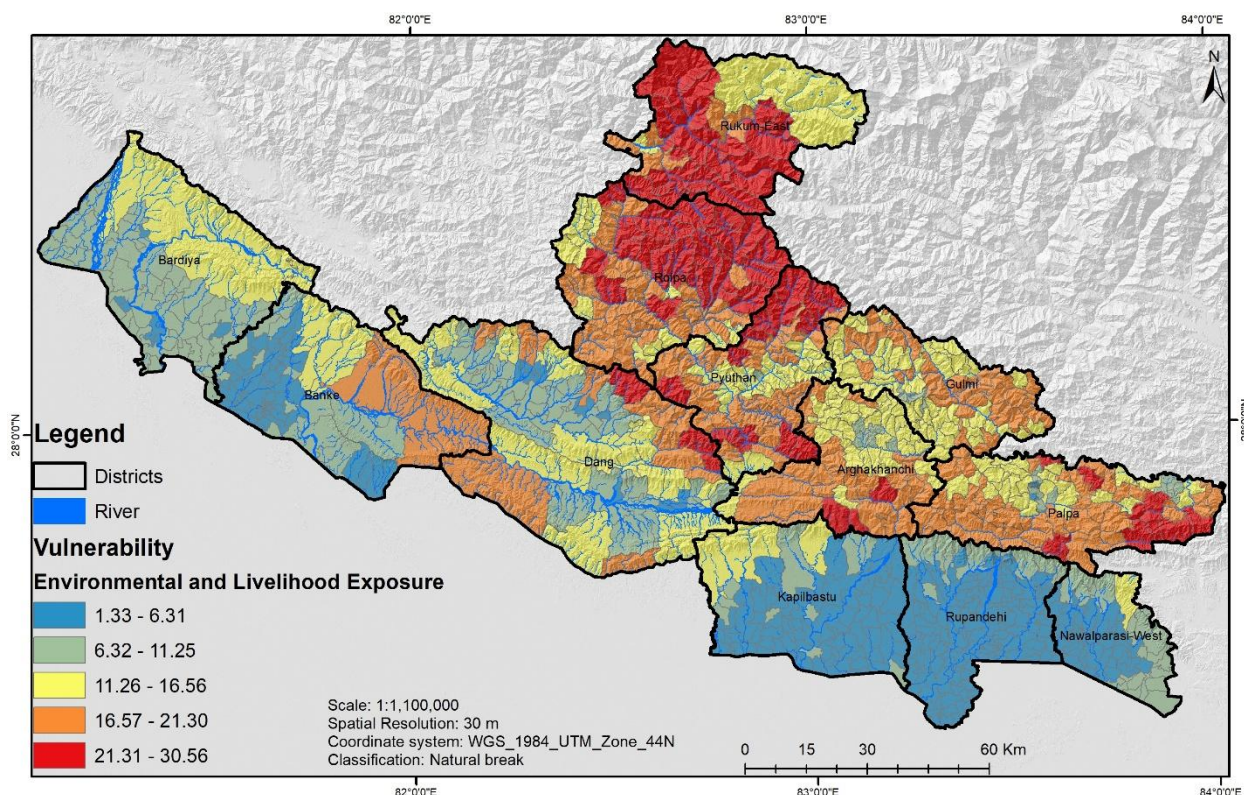


Fig. 21: Environmental and Livelihood Exposure Vulnerability

4.1.3 Institutional & Infrastructure Access vulnerability

This is the most straightforward component captures a community's ability to prepare for, respond to, and recover from landslide events through its connectivity to essential services and networks. The Table 5., represents a gradient of access to administrative centers, markets, and transportation systems, which collectively shape disaster resilience. Lower spatial scores indicate remoteness and institutional isolation, conditions that significantly heighten vulnerability (Fig. 22).

Obviously, access to administrative centers enhances governance effectiveness, early warning dissemination, and coordination of emergency response and relief distribution. Communities located far from these centers frequently experience delayed assistance, weak institutional presence, and slower recovery processes (49). Likewise, market access strengthens economic resilience by enabling livelihood diversification, income stability, and access to health, education, and other services. In contrast, communities' dependent on subsistence agriculture or limited local markets are more susceptible to economic disruption following landslides, constraining their recovery capacity. Similarly, transportation networks are critical for evacuation, aid delivery, medical access, and post-disaster mobility. Damage to key roads or transport corridors can isolate settlements, interrupt supply chains, and prolong social and economic hardship (66). Overall, this component demonstrates that vulnerability is not solely determined by physical susceptibility exposure but also by the degree of institutional reach and infrastructural connectivity. Communities with limited administrative access, weak market integration, and poor transportation infrastructure face compounded risks due to delayed response, restricted resources, and prolonged recovery.

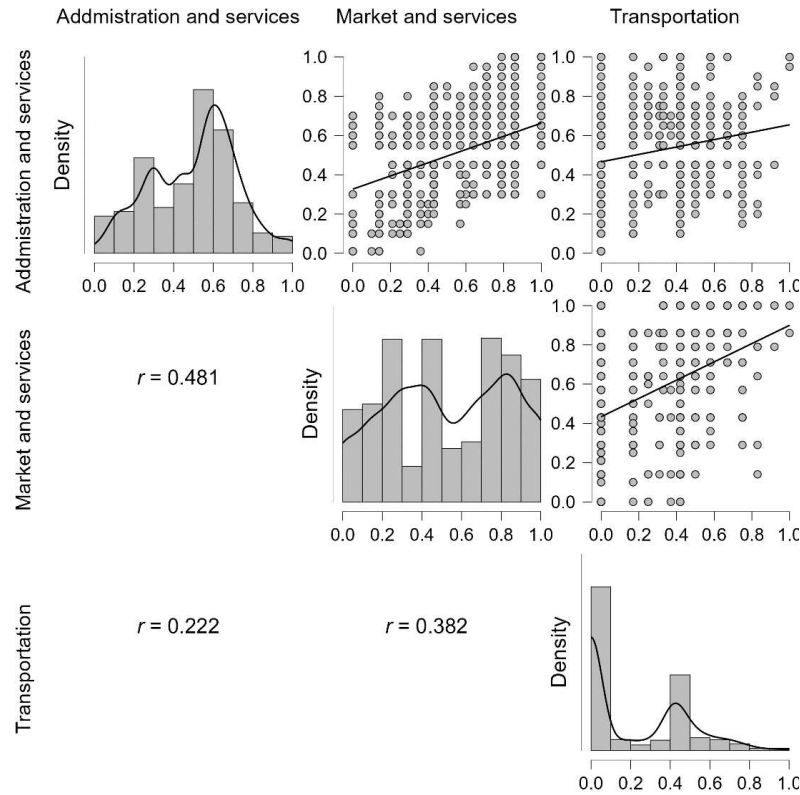


Fig. 22: Correlation/pair plot of Access to Institution and Infrastructures

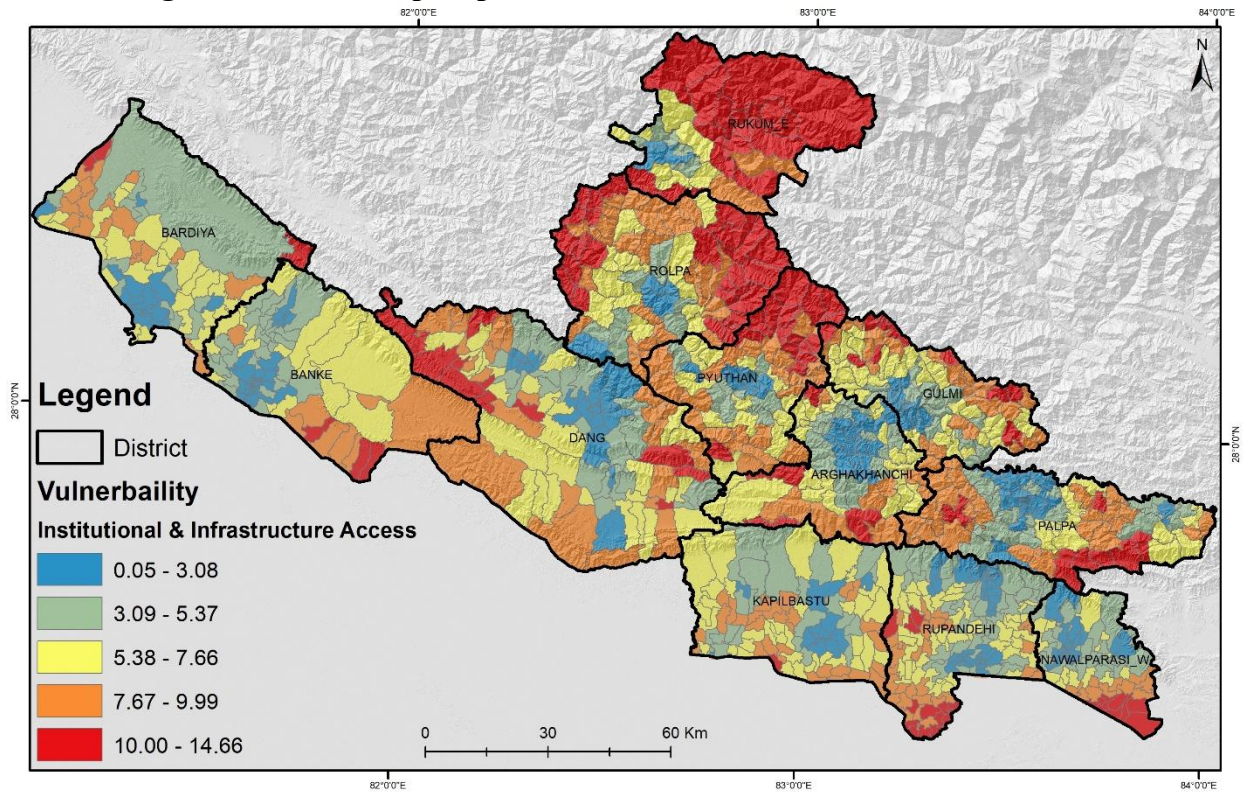


Fig. 23: Institutional and Infrastructure Access Vulnerability

Access-related vulnerabilities are present in all districts in a localized manner; however, the northern wards of Gulmi, Pyuthan, Rolpa, and East Rukum exhibit comparatively higher levels of vulnerability (Fig. 23).

4.1.4 Structural and Economic Vulnerability

The findings indicate communities with a low proportion of economically active individuals, reflecting a high dependency burden from children, the elderly, or the unemployed. This condition is further compounded by limited household ownership, signaling asset poverty and insecure tenure. The positive association with ethnic composition suggests that economic dependency and structural disadvantages may be concentrated among specific ethnic groups, pointing toward patterns of systemic marginalization (Fig. 24).

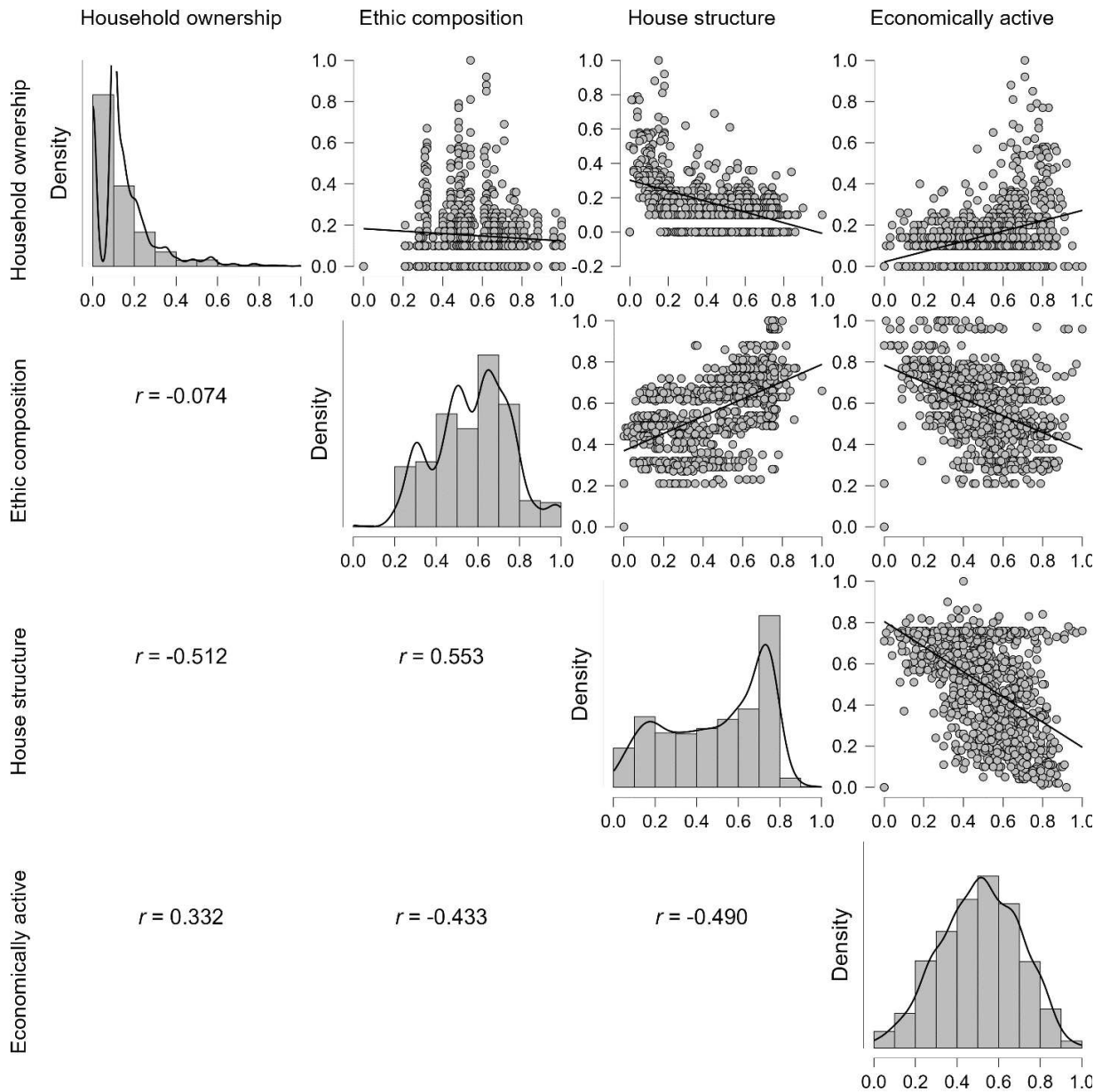


Fig. 24: Correlation/pair plot of Structural and Economic stability

Overall, structural vulnerability appears closely linked to tenure insecurity, ethnic marginalization, and limited economic participation (67,68). Economic engagement and secure ownership strengthen resilience, whereas weak housing conditions and social disadvantage amplify vulnerability.

Most wards in Arghakhanchi, Pyuthan, Rolpa, and East Rukum exhibit higher levels of vulnerability in this dimension, along with parts of the Siwalik region in Dang and Banke (Fig. 25).

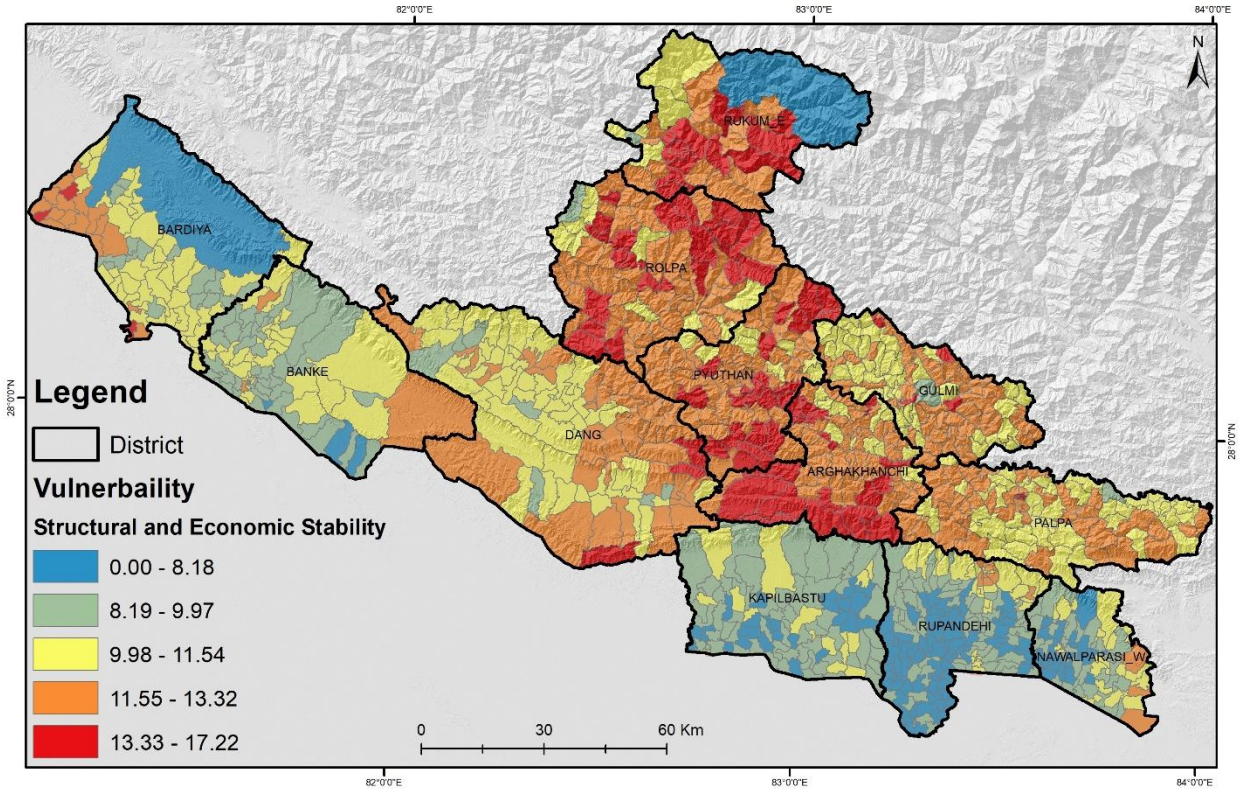


Fig. 25: Structural and Economic Vulnerability

4.2 Effect of Component Vulnerabilities on Overall Vulnerability

The LMG results reveal a clear difference in the contribution of the four dimensions (Table 8):

Table 8: Relative Importance of Component Vulnerabilities

Rank	Component Vulnerability	LMG	Relative Importance (%)
1	Environmental and Livelihood Exposure	0.45	44.89%
2	Institutional and Infrastructure Access	0.21	20.54%
3	Structural and Economic Stability	0.19	19.58%
4	Socio-economic vulnerability	0.15	14.98%
	Total	1	100.00%

The predominance of **environmental and livelihood conditions** indicates that spatial differences in overall vulnerability across the Lumbini province are particularly associated with variations in dependence on and potential disruption of agriculture, forests, and water resources. This pattern is plausible in the Nepalese context, where landslides can affect not only physical assets but also the natural-resource base supporting food, employment, and household livelihoods. Evidence from landslide-affected communities in Nepal

similarly demonstrates that landslide impacts extend beyond direct physical damage to food, shelter, employment, and broader livelihood security (69). This result also supports the multidimensional perspective of the MOVE framework, which emphasizes that vulnerability emerges through interacting environmental, social, economic, physical, and institutional conditions rather than through a single dimension.

Institutional and Infrastructure Access and Structural and Economic Stability contributed almost equally, together explaining approximately 40% of the variation in Total Vulnerability. This highlights the parallel importance of access to transportation, markets, administrative and other services, and the material and economic conditions that determine households' capacity to cope with and recover from disruption (70). Recent evidence from Nepal likewise identifies economic, infrastructural, and governance limitations as interconnected constraints on community resilience, particularly where access to services and disaster-resilient infrastructure remains uneven (71). Consequently, the near-equivalent contributions observed here indicate that vulnerability reduction cannot rely solely on livelihood protection; improvements in accessibility, services, infrastructure, housing and economic stability are also relevant components of risk reduction.

Socio-economic Vulnerability contributed the smallest share (14.98%), but this should not be interpreted as indicating that socio-economic conditions are unimportant. Rather, LMG measures the relative contribution to variation in the composite index within this dataset. Socio-economic Vulnerability showed comparatively weak relationships with the other dimensions ($r = 0.156$ with Environmental and Livelihood Exposure, $r = 0.362$ with Institutional and Infrastructure Access, and only $r = 0.014$ with Structural and Economic Stability), indicating that it captures a relatively distinct dimension of vulnerability. Its smaller LMG share therefore reflects the statistical structure and variability of the component indices rather than diminished conceptual relevance. This distinction is important because multidimensional vulnerability frameworks explicitly recognize social and economic susceptibility alongside environmental, physical and institutional dimensions (71).

The VIF diagnostics further support the statistical separability of the four components. VIF values ranged from 1.15 for Socio-economic Vulnerability to 2.43 for Environmental and Livelihood Exposure, with Institutional and Infrastructure Access (1.42) and Structural and Economic Stability (2.08) also remaining well below the commonly applied threshold of 5. The relatively higher VIF for Environmental and Livelihood Exposure is consistent with its correlation with Structural and Economic Stability ($r = 0.69$), suggesting some shared underlying conditions, but not at a level that would indicate problematic multicollinearity. Thus, although the vulnerability dimensions are interconnected, as expected conceptually, the results indicate that each retains sufficient statistical distinctiveness to represent a meaningful component of the composite vulnerability framework.

Overall, the findings demonstrate that ward-level vulnerability is multidimensional but unevenly structured, with environmental and livelihood conditions explaining the largest proportion of spatial variation, while institutional/infrastructure and structural/economic conditions provide substantial and nearly equivalent contributions. The comparatively smaller contribution of socio-economic vulnerability represents its relative statistical contribution within the present dataset rather than its absolute importance. This reinforces the need to interpret the Total Vulnerability index through its constituent dimensions and supports integrated vulnerability reduction addressing livelihood-resource sensitivity, service and infrastructure accessibility, structural-economic conditions, and socio-economic capacity rather than focusing on any single component.

4.3 Spatial variation in landslide susceptibility, exposure, vulnerability and risk

The relative importance of administrative geography (district) versus physical geography (physiography) in shaping each outcome, to examine the interaction between the two, and to draw out the policy implications of the findings. A summary of the ANOVA results is presented in the table below, followed by a detailed discussion of each effect (Table 9).

Table 9: Two-Way ANOVA Results (Type II Tests) for Susceptibility, Exposure, Vulnerability, and Risk

Response	Effect	Sum Sq	F value	Relative magnitude (%)	p-value	Significance
Susceptibility	District	2.60	28.9	13.7	< 2.2e-16	***
	Physiography	7.76	316.4	41.0	< 2.2e-16	***
	District × Physiography	0.70	10.8	3.7	1.33E-14	***
	Residuals	7.87		41.6		
Vulnerability	District	3.33	25.2	19.7	< 2.2e-16	***
	Physiography	0.67	18.7	4.0	8.55E-12	***
	District × Physiography	1.40	14.6	8.3	< 2.2e-16	***
	Residuals	11.53		68.2		
Exposure	District	2.92	18.1	14.8	< 2.2e-16	***
	Physiography	1.65	37.5	8.4	< 2.2e-16	***
	District × Physiography	0.94	8.0	4.8	1.96E-10	***
	Residuals	14.17		71.9		
Risk	District	3.35	29.1	22.0	< 2.2e-16	***
	Physiography	1.27	40.4	8.3	< 2.2e-16	***
	District × Physiography	0.57	6.8	3.7	1.08E-08	***
	Residuals	10.06		66.0		

Susceptibility was predominantly controlled by physiography, which explained approximately 41.0% of its total variation and produced the largest observed F-statistic ($F = 316.4$), compared with 13.7% explained by district. This strong physiographic signal is consistent with the physical nature of landslide occurrence, whereby terrain, geology, relief, drainage, and associated environmental conditions vary systematically across physiographic regions (72). Nevertheless, the significant district × physiography interaction ($F = 10.8$, $p < 0.001$) indicates that susceptibility differences among physiographic zones are not entirely uniform across districts.

A contrasting pattern emerged for vulnerability, for which district explained 19.7% of variation compared with only 4.0% for physiography. This indicates that vulnerability is less directly structured by terrain and more spatially differentiated by the socio-economic, livelihood, structural, infrastructural, and institutional conditions represented within administrative areas (73). Vulnerability also showed the largest interaction contribution (8.3%), suggesting that these conditions vary considerably among district–physiography combinations rather than following a simple physiographic gradient.

Exposure occupied an intermediate position, with district explaining 14.8% and physiography 8.4% of total variation. This reflects the dual nature of exposure: the distribution of houses and roads is shaped by settlement and development patterns, while their intersection with landslide-prone areas remains

conditioned by terrain. The significant interaction (4.8%) further demonstrates that similar physiographic settings do not necessarily have comparable levels of physical exposure across districts.

Importantly, the transition from susceptibility to overall risk substantially altered the relative importance of these spatial controls. While physiography explained 41.0% of susceptibility variation, its contribution declined to 8.3% for risk. Conversely, the district contribution increased from 13.7% for susceptibility to 22.0% for risk, the largest district contribution among the four responses. This demonstrates that high susceptibility alone does not determine high risk; rather, risk emerges where landslide-prone terrain coincides with exposed assets and vulnerable populations and livelihood systems. Consequently, wards with comparable susceptibility may have substantially different risk levels depending on their exposure and vulnerability conditions.

The significant district $\times$ physiography interaction for risk ($F = 6.8, p < 0.001$) further indicates that these relationships are spatially context-dependent. Main effects should therefore be interpreted cautiously, as physiographic differences vary among districts and district differences vary across physiographic settings. This supports assessment and prioritization at the ward level, rather than assuming homogeneous risk within either districts or physiographic regions.

Finally, residual variation remained substantial, particularly for vulnerability (68.1%), exposure (72.0%), and risk (66.0%). Thus, district and physiography explain important spatial patterns but do not fully capture the local heterogeneity represented by the ward-level indicators. Overall, the results demonstrate a clear transition from strong physiographic control of landslide susceptibility to increasingly socio-spatial differentiation of vulnerability, exposure, and ultimately risk, reinforcing the need to integrate physical susceptibility conditions with local exposure and vulnerability in landslide risk planning.

5 Conclusion

This study presents an integrated, ward-level assessment of landslide susceptibility, physical exposure, and multidimensional vulnerability across Lumbini Province, Nepal. Using the WoE approach, the susceptibility analysis identified more than 19.6 % of the province's area as highly or very highly susceptible to landslides. Rukum East, particularly its higher mountain region, exhibited pronounced susceptibility, followed by the mid-hill districts of Gulmi, Rolpa, and Pyuthan, and the Chure regions of Palpa and Arghakhanchi. The model demonstrated good discriminative performance, with AUC values of 0.89 for the training inventory (2000–2021) and 0.805 for the independent validation inventory (2022–2025).

The PCA identified four vulnerability dimensions: Socio-economic Vulnerability, Environmental and Livelihood Exposure, Institutional and Infrastructure Access, and Structural and Economic Stability. The relative-importance analysis revealed that Environmental and Livelihood Exposure accounted for the largest share (44.89%) of variation in the composite vulnerability index, followed by Institutional and Infrastructure Access (20.54%), Structural and Economic Stability (19.58%), and Socio-economic Vulnerability (14.98%). These findings highlight the importance of natural-resource dependence, institutional accessibility, housing conditions, and socio-economic capacity in differentiating vulnerability among wards. Although environmental and livelihood conditions contributed most strongly to the composite index, all four dimensions represent distinct and complementary aspects of vulnerability.

The integrated risk assessment identified substantial spatial disparities, with 11.1% and 5.1% of wards classified as high and very high risk, respectively. Risk was concentrated predominantly in the middle and higher mountain districts, particularly Rolpa, Rukum East, Pyuthan, Gulmi, and Palpa. Rolpa and Rukum East contained 56 and 26 high-risk (both high and very high) wards, respectively. In contrast, the Tarai districts exhibited predominantly very low landslide risk, reflecting their comparatively limited landslide susceptibility and associated physical exposure. The two-way ANOVA further demonstrated that the spatial controls on susceptibility and risk differ substantially. Physiography explained approximately 41.0% of susceptibility variation, but only 8.3% of risk variation, whereas the district contribution increased from 13.7% for susceptibility to 22.0% for risk. Significant district–physiography interactions further indicated that risk patterns vary across administrative and physiographic contexts. These findings demonstrate that landslide susceptibility alone is insufficient to characterize risk, which also depends on the spatial distribution of exposed assets and the vulnerability of affected communities.

Overall, the study demonstrates the importance of integrating geomorphological susceptibility with physical exposure and multidimensional vulnerability for spatially differentiated landslide risk assessment. The resulting relative risk index provides a practical basis for ward-level risk screening and prioritization, although it should not be interpreted as an absolute probability or expected loss estimate. Effective risk reduction requires context-specific strategies combining risk-sensitive land-use planning, settlement and infrastructure protection, livelihood diversification, improved institutional accessibility, and targeted support for socially and economically vulnerable communities. These findings provide a spatially explicit evidence base for integrating landslide risk reduction into local development planning and disaster risk management in Lumbini Province

Acknowledgements: The authors acknowledge the Ministry of Forests and Environment, Lumbini Province, Rapti Valley (Deukhuri), Nepal, for supporting the project Climate-Induced Susceptibility Mapping in Lumbini Province. The landslide susceptibility result used in this study was derived from that project funded by the ministry, in which several of the authors were directly involved.

Conflict of Interest Statement: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. All authors have read and approved the final manuscript and agree to its submission to the journal.

Clinical Trial Number: Not applicable.

Ethics, Consent to Participate, and Consent to Publish declarations: Not applicable.

Funding: No specific funding was received for the preparation of this manuscript; however, the landslide inventory and validation of the landslide susceptibility results were undertaken under a Ministry-funded project.

Data Availability: The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

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