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RESEARCH ARTICLE



Mapping landslide susceptibility and risk assessment on fragile ecosystem of Himalayan River basins

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ABSTRACT

Landslides pose a significant threat in the Himalayan region due to complex geology, steep terrain, and diverse climatic conditions. This study addresses the need for a multi-dimensional approach by integrating Machine Learning with GIS to map landslide susceptibility across Himalayan River basins. Conditioning variables including topographical, climatological, hydrological, and phenological factors, and surface conditions were analysed using SVM to predict landslide susceptibility. For validation, SHAP, ROC curves, and AUC were used. The model attained 87% accuracy. Risk assessment was performed by intersecting land use/land cover (LULC) data with susceptibility zones to quantify agricultural and Urban and Built-up land exposed to landslides, alongside zonal statistics to estimate population risks. The results indicate that 371.5 thousand hectares are at very high risk of landslides, and 209.2 thousand hectares are at high risk, with the Jhelum River Basin emerging as the most vulnerable in terms of population, agricultural land, and built-up areas. This study demonstrates the dominance of hydrological and vegetation-related variables, such as runoff and forest fires, in driving landslide susceptibility, as revealed by SHAP analysis. Integrating susceptibility models with risk assessment, the study provides insights for regional planning, disaster management, and policy-making, stressing targeted mitigation for vulnerable basins.

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Prediction; hazard zonation; geo hazards; Himalayas; machine learning

1. Introduction

Mountains are high-energy environments characterised by instability and variability. Much of this instability is the result of a variety of landsliding processes; mudflows, rockfalls and debris slides/avalanches being especially important. The aforesaid landsliding process constitutes a major hazard in the mountains (Pathak, 2016) affecting millions of people around the world threatening life and livelihood of people across the globe. The climatic extremes also have a significant role to play in the occurrence of landslides all over the world (Bathrellos et al., 2021; Komori et al., 2018). In many of the region of low latitudes that have gentle weather, myriad anthropogenic activities have increased in recent times, causing more and more urban encroachment, construction of new road, expansion of residential areas. The Himalayas, the highest mountain range of the world, offer perfect ground for such events as on one hand the Himalayas contain complex geology and geography, and on the other hand, the ranges experience climatic disturbances such as cloud burst, temporally

concentrated precipitation (Bathrellos et al., 2024; Khan, Mohsin, et al., 2024; Khan et al., 2025). These phenomena render the region highly susceptible to landslides and are at consistent risk of landslides. Consequently, various studies have already been conducted on the Himalayan region mapping the susceptible areas to landslides and tried to exploratory factors.

For instance, Gerrard (1994) examined the association of landslides with geological controls and human actions, and Vashishtha et al. (2022) took geophysical as well as anthropological factor in landslide susceptibility mapping, while scholars like Kamp et al. (2008) adopted a sophisticated spatial and multi criteria decision-making (MCDM) and GIS-based approach. Whereas Saha et al., (2005) applied advanced geospatial techniques for the landslide susceptibility zonation mapping. Kamp et al. (2008), stuck to MCDM and GIS. Sati et al. (2011); Pham et al. (2015); and Gupta et al. (2022) also conducted a detailed assessment of landslide susceptibility in the Himalayan region and its parts. For instance, Kanungo and Sharma (2014),

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modelled landslide susceptibility in Chamoli district of Uttarakhand. And Ambrosi et al. (2018), utilised earth observation data to examine the landslide risk in Nepal. The application of machine learning algorithms (MLA) has also been limited in these studies, which are one of the finest methods for modelling landslide susceptibility and has proved its accuracy in myriad terrains (Dou et al., 2023; Khan, Mohsin, et al., 2024; Korup & Stolle, 2014; Pourghasemi & Rahmati, 2018; Wang et al., 2021; Youssef et al., 2024), where DNN algorithms were proved to be the most accurate one as per the study conducted by Dou, Yunus, Merghadi, et al. (2020b). Apart from that, no study covers the vast Himalayas. For instance, Saha et al. (2021), merely focused on landslides in Bhutan, though, they applied robust machine learning algorithms (MLAs). Rane and Vincent (2021) also applied MLAs for predictive mapping of landslides but study covers only one district of Uttarakhand, i.e. Nainital. As a result, while landslide risks in the Himalayas have been studied in spatial segments, no comprehensive and extensive study has been conducted for the entire region. Furthermore, assessment of risk exposure of agricultural, or Urban and Built-up land or residing populations has rarely been conducted in the Himalayas or elsewhere. Putra et al. (2021) attempted to assess landslide risk on agricultural land using assessed impact of landslides on different agricultural lands. However, no such comprehensive attempts have been made specifically for the Himalayan region (see Table 1).

The present study seeks to utilise widely recognised MLA, leveraging natural condition variables, to accurately predict landslide susceptibility across the expansive Himalayan region. The primary aim of this paper is to develop a comprehensive and reliable landslide susceptibility assessment model that integrates both conventional and unconventional conditioning factors, ensuring a more holistic understanding of landslide risks. Additionally, this study experiments with the adoption of unconventional conditioning variables like forest fires, enhanced vegetation index (EVI) and

leaf area index (LAI) to enhance the precision and robustness of the susceptibility models, addressing gaps identified in previous research. The study further aims to assess the risks faced by human settlements, particularly Urban and Built-up land, and agricultural areas, at the basin level. It endeavours to quantify the vulnerability of populations exposed to different susceptibility categories within each basin. Given the increasing frequency and intensity of landslide events in the Himalayas, this research is critical for informing policy-making and disaster management. The insights derived from this study provide essential data for sustainable land-use planning, prioritising mitigation efforts specific to a river basin.

2. Study area

The delineation of the study area relies on the Digital Elevation Model (DEM). To the south, the study area is defined by the 375-metre contour line, while the northern extent is determined by prominent geographical features such as the Main Boundary Thrust (MBT) in the Trans-Himalayas, the Tsang Po River, and the Indus River. The eastern boundary is characterised by the Brahmaputra River Valley, while the western boundary is demarcated by the Indus River Valley. Spanning elevations from 375 metres to 8847 metres, the study area encompasses a diverse range of altitudes within this geographical expanse (Figure 1a).

The geological composition of the region is diverse, characterised by a series of rock formations and structures (Karpouza et al., 2024; Upreti, 1999). The northern parts, particularly the Higher Himalayas or Great Himalayas, consist predominantly of metamorphic rocks such as gneiss, schist, and marble. The Central Himalayas, known as the Lesser Himalayas or Middle Himalayas, comprise a mix of sedimentary rocks including limestone, sandstone, and shale, along with metamorphic rocks. Outer Himalayas, are primarily made up of unconsolidated sediments, including gravel, sand,

Table 1. Comparative analysis of landslide susceptibility studies in Himalayan and global contexts.

Study	Region Covered	Resolution	Methodology	Model Accuracy	Key Findings
Present Study	River basins falling the Himalayas	30 m	Machine Learning (SVM)	87%	Jhelum River Basins in most susceptible in terms of population, agricultural land, and built-up land
Vashishtha et al. (2022)	Rudraprayag	30m	Overlay Analysis	78.10%	Steep slopes, high altitude and along the roads and fault lines are most susceptible
Saha et al. (2021)	Chukha Dzongkhags district of Bhutan	30m	Machine Learning Algorithms	92.40%	Integrated of both social and physical factors enhanced the precision of vulnerability mapping
Dou, Yunus, Merghadi, et al. (2020b)	Areas affected by the 2018 Hokkaido Earthquake	0.2m	Machine Learning Algorithms	90.40%	DNN demonstrated highest accuracy in landslide modelling
V. Gupta et al. (2022)	Uttarakhand (Kumaun and Garhwal Himalayas)	30m	Weight of Evidence (WoE) and Information Value (IV) methods	79.20%	Slopes ranging between 40° and 60°, located at elevations of 2000–4000 m, and predominantly south-facing slopes are highly prone to landslides.

Source: Reviewed by authors.

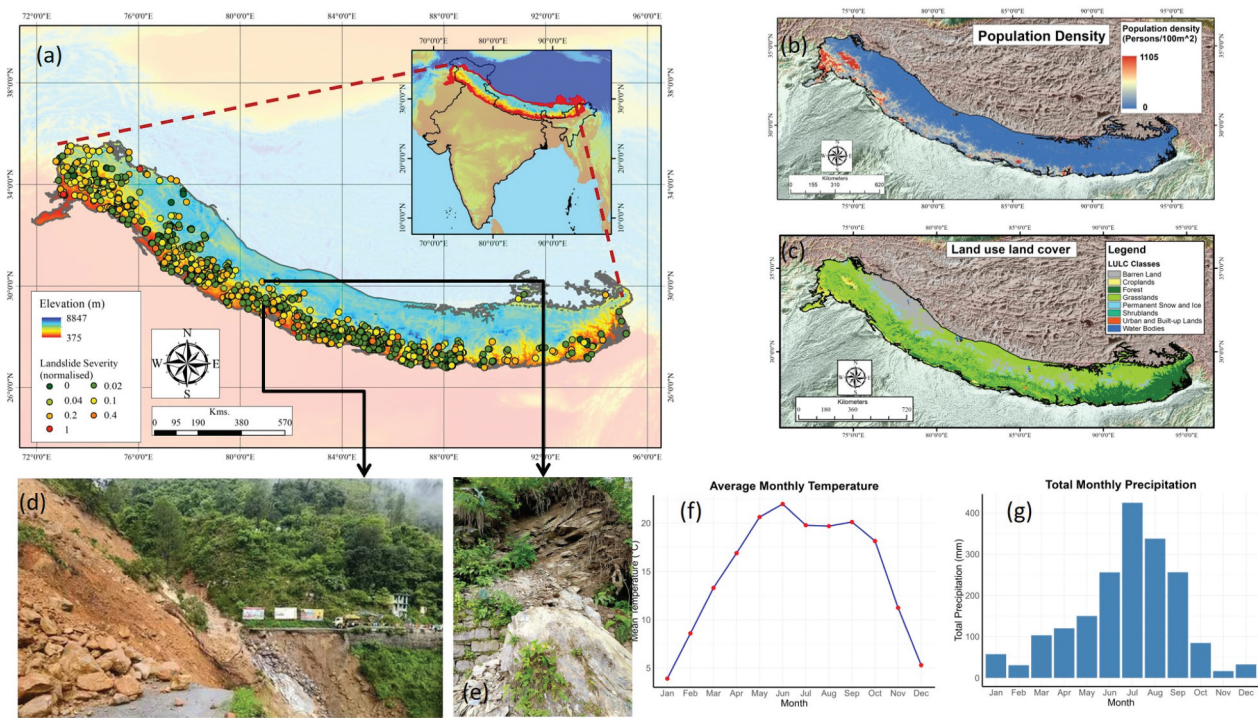


Figure 1. (a) Study area and normalised landslide events, (b) Population density, (c) Land use land cover, (d–e) Field pictures from field, (f) Mean temperature, (g) Total precipitation. Source: Worldclim, ERA5.

and clay, brought down by rivers and glaciers from the higher elevations (Gansser, 1974).

The climate across the vast Himalayan region varies significantly (Figure 1f–g) due to the diverse topography and altitude gradients (Dimri & Dash, 2012; Khan, Khalid, et al., 2024; Khan et al., 2025). Generally, the Himalayas experience a range of climatic zones, from subtropical to alpine, influenced by the Indian monsoon and other regional weather patterns (Negi et al., 2012). The Himalayas boast incredible biodiversity, featuring a rich tapestry of vegetation across its various altitudinal zones (Pandit, 2017). The diverse range of climates and terrains has led to the development of distinct vegetation belts, each characterised by unique flora. In the lower foothills and valleys, subtropical forests thrive, comprising a mix of broadleaf evergreen trees, including sal, teak, and oak (Singh et al., 2019). These forests also host a variety of flowering plants, ferns, and grasses, creating lush and dense ecosystems.

The Himalayan region is highly susceptible to landslides (Figure 1d–e) due to its complex geology, rugged terrain, and diverse climatic conditions (Dikshit et al., 2020). The collision of tectonic plates has led to the creation of steep slopes, making the area prone to slope failures. Factors such as intense monsoon rains, seismic activity, and human interventions further exacerbate the landslide risks (Kumahara et al., 2022; Sarker & Rashid, 2013). Deforestation, construction activities, and improper land use practices weaken soil stability (Lemenih, 2004), increasing the vulnerability to landslides (Karsli et al., 2009). The consequences of landslides in this region can be severe, causing loss

of life, damaging infrastructure, disrupting transportation routes, and impacting the livelihoods of communities. Mitigation strategies, including early warning systems, slope stabilisation measures, and sustainable land management practices, are crucial to minimise the risks posed by landslides in the Himalayan region (Thapa et al., 2022).

In the Himalayan region, land use and land cover (LULC) are undergoing significant transformations, with vast areas devoted to agriculture land and built-up infrastructure. In the present study, extensive agricultural land, amounting to over 145,650 ha, along with urban and built-up areas across various river basins, face varying degrees of landslide susceptibility. Population density distribution closely mirrors these LULC features, with most settlements concentrated in the valleys and foothills where conditions support agriculture and habitation (Gupta et al., 2020). The population in these vulnerable areas ranges from small communities in high-risk zones to larger settlements in medium- to low-risk zones, as identified in this study.

Landslides pose a significant threat to both agricultural and built-up areas in the Himalayas. The removal of vegetation from landslide-prone areas exposes bare slopes, accelerating soil erosion and destabilising the terrain (Mwaniki et al., 2015; Phakdimek et al., 2023). Agricultural lands are particularly at risk, as landslides can destroy crops and render fields unusable, posing a serious threat to the livelihoods of local communities reliant on limited arable land for food production (Garcia-Chevesich et al., 2020). Furthermore, landslides can disrupt vital infrastructure, damaging roads, bridges,

and buildings, and limiting access to essential services. This is especially critical for densely populated valleys, where human settlements and infrastructure are concentrated, putting residents and their homes at considerable risk (Anees et al., 2022; Geertsema et al., 2009). Additionally, landslides can obstruct rivers and streams, creating natural dams that lead to flooding upstream and alter water flow downstream, with far-reaching consequences for ecosystems and water resources. The impact of such events on both agricultural and urban areas could be catastrophic, further compounding the vulnerability of the region's population (Kahlon et al., 2014; Khan et al., 2011). To address these challenges, coordinated disaster response and mitigation strategies are essential for minimising risks to populations and ensuring the resilience of both agricultural lands and human settlements in this region.

3. Database

The database for the present study is taken from various online portals such as CHELSA, NASA Earth data,

Giovanni HydroBasin ESRI atlas, and NASA SEDAC. These variables have been discussed in detail in Tables 2 and 3.

4. Rationale of selection of causative variables

4.1. Topographical variables

Topographical variables, encompassing elevation, slope, aspect, and curvature, geology and faults intricately modulate the predisposition of terrains to landslide occurrences (Figure 2). Elevation contributes significantly to gravitational forces and terrain steepness, rendering higher altitudes more susceptible to slope instability (Nath et al., 2021). Steep gradients amplify gravitational pull, augmenting the likelihood of slope failure and subsequent landslides. Aspect, delineating slope orientation, governs the differential exposure to solar radiation and moisture, thereby exerting a pronounced influence on slope stability dynamics (Gibos, 2010). Furthermore, curvature variations impart distinct characteristics to slopes; convex

Table 2. List of conditioning variables.

Variable category	Variable Name	Resolution	Accessed/Processed database	Source
Inventory	Landslide	NA	Point data	NASA
Topographical	Elevation	30m	DEM	Copernicus DEM, Open Topography
	Slope	30m	DEM	Copernicus DEM, Open Topography
	Aspect	30m	DEM	Copernicus DEM, Open Topography
	Curvature	30m	DEM	Copernicus DEM, Open Topography
	Geology	NA	Vector polygons	USGS
	Proximity to faults	30m	Vector polygons	GEM
Climatological	Skin Temperature	30m (resampled)	Merra-2	Giovanni
	Precipitation	30m (resampled)	Merra-2	Giovanni
Phenological	LAI	30m (resampled)	MODIS	NASA Earth Data
	EVI	30m (resampled)	MODIS	NASA Earth Data
Hydrological	Porosity of Soil	30m (resampled)	Merra-2	Giovanni
	Percolation rate	30m (resampled)	Merra-2	Giovanni
	Runoff	30m (resampled)	Merra-2	Giovanni
	Flow Accumulation	30m	DEM	Copernicus DEM, Open Topography
	Drainage Density	30m (resampled)	HydroRiver	HydroSHED
	Proximity to rivers	30m (resampled)	HydroRiver	HydroSHED
	SPI	30m	DEM	Copernicus DEM, Open Topography
	TWI	30m	DEM	Copernicus DEM, Open Topography
Surface condition	Forest Fires	30m (resampled)	Prepared	Prepared

Source: prepared by authors.

Table 3. Database for risk assessment.

Targeted Feature	Dataset	Source	Data Utilization and Relevance
Major Basins	Basin Area	HydroBasin	HydroBasin is a high-resolution dataset tailored for hydrological studies. Using these basin boundaries for landslide analysis is logical, as landslides are closely linked to local river hydrology and basin-specific ecological conditions.
Built-up Land	LULC	ESRI Atlas	High-quality and globally consistent data on built-up areas is provided by the ESRI LULC dataset. This high-resolution data was utilized to assess the risk to built-up regions, given their significant economic value. Key infrastructure, including residential, commercial, industrial, and institutional sectors, is encompassed by these areas, making accurate risk assessment essential.
Agriculture Land	LULC	ESRI Atlas	Similarly, the ESRI LULC dataset was employed for agricultural analysis due to its critical role in supporting local populations and functioning as a key source of food production and raw materials. The substantial economic importance of agriculture further underscores the necessity of its inclusion in risk assessments.
Population	Population	SEDAC, NASA	The SEDAC dataset, operated by NASA, provides crucial population density data, essential for demographic analysis, urban planning, disaster risk management, and policy development. It was selected to accurately quantify the population exposed to landslide risk, addressing potential gaps in vulnerability assessments that agricultural and built-up area data may overlook by only offering rough estimates of population presence.

Source: prepared by authors.

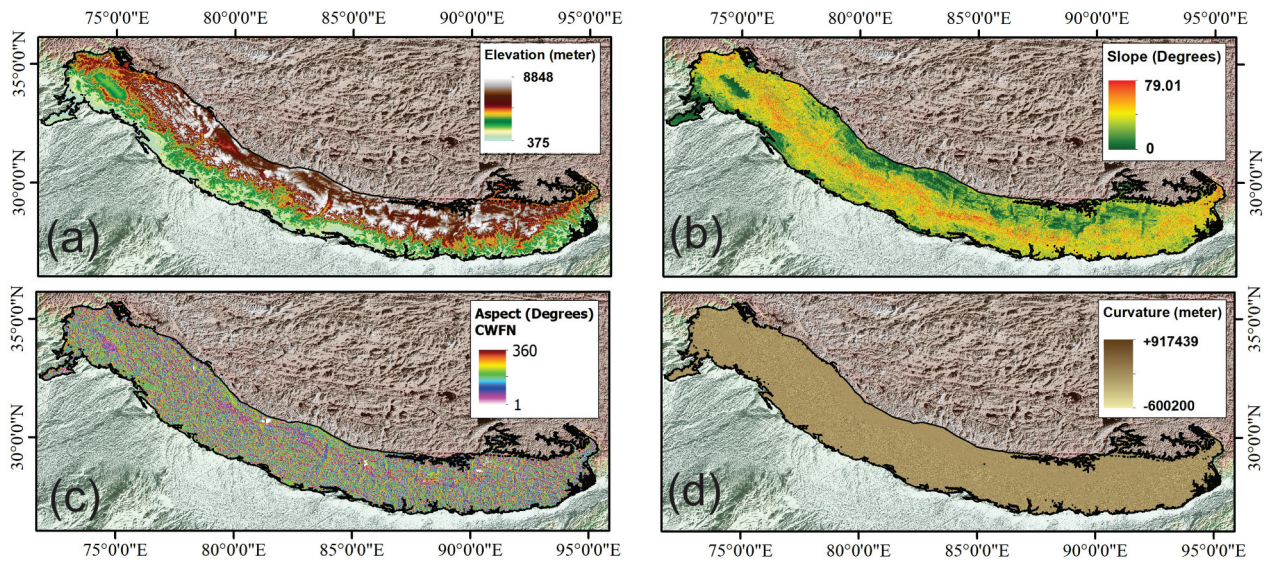


Figure 2. Topographic variables (a) Elevation, (b) Slope, (c) Aspect, and (d) Curvature. Source: Copernicus, Open Topography.

configurations often accumulate material, heightening instability, while concave morphologies may incur tensional stresses predisposing them to failure (Froude, 2011). The combined interplay of these topographical attributes serves as a foundational framework for comprehending landslide triggers and improves the efficacy of predictive models of landslides (Riaz et al., 2023).

4.2. Climatological variables

Climatological variables, notably skin temperature of Earth and precipitation, intricately influence the propensity for landslides, particularly concerning undulating terrains (Dhungana et al., 2023) (Figure 3). Skin temperature, reflective of surface heat, plays a pivotal role in modifying soil properties, inducing thermal expansion and contraction cycles that can weaken the structural integrity of underlying materials (Siegesmund et al., 2000). On undulating surfaces, differential heating and cooling across slopes engender uneven stress distribution, exacerbating the susceptibility to landslides as thermal stresses interact with the topographical contours. Moreover, precipitation events, when coupled with undulating landscapes,

engender varied water infiltration and runoff patterns (Y. Zhang et al., 2016). Higher elevations often experience increased precipitation (Munson et al., 2019), leading to enhanced water infiltration and saturation of soils, amplifying pore pressure, and reducing soil cohesion, thus escalating the predisposition to landslides in these undulating terrains. Understanding the interplay between skin temperature variations and precipitation dynamics on undulating surfaces is critical for discerning the multifaceted triggers governing landslide occurrences in such complex landscapes (Ren & Ren, 2015).

4.3. Hydrological variables

Hydrological variables (Figure 4) wield substantial influence on landslide dynamics, mirroring patterns akin to topographical undulations (Kornejady et al., 2018). Porosity, governing the void space within soil or rock, directly impacts water retention and infiltration (Sekucia et al., 2020). In undulating terrains, varying porosity across slopes engenders disparate water-holding capacities, accentuating the differential saturation levels that intensify landslide susceptibility (Velde et al., 2010). Percolation rates, delineating the

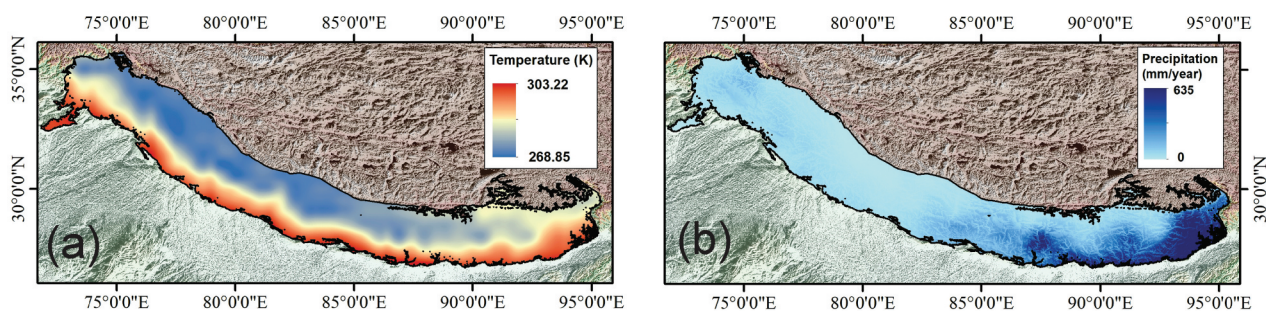


Figure 3. Climatic variable: (a) Temperature, (b) Precipitation. Source: Giovanni.

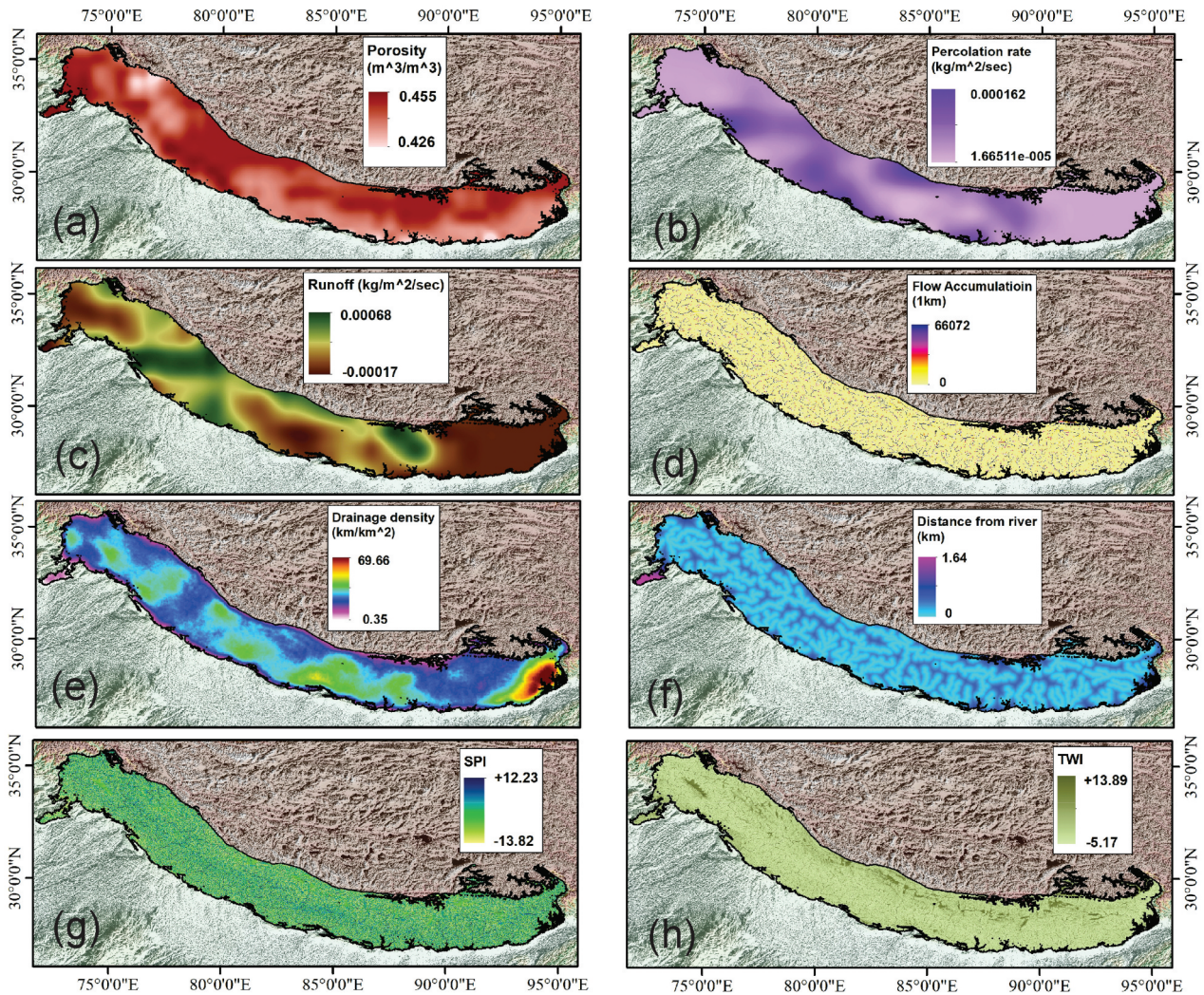


Figure 4. Hydrological variable: (a) Porosity, (b) Percolation rate, (c) Run off, (d) flow accumulation, (e) Drainage density, (f) Distance from river, (g) SPI, (h)TWI. Source: Copernicus, Open Topography, Giovanni, HydroSHED.

speed of water movement through soil (Dahan et al., 2009), vary across undulating surfaces, affecting the rate of soil saturation and subsequent instability (Van Beek & Van Asch, 2005). Runoff patterns on undulating landscapes amplify the risk of landslides, with steeper slopes fostering rapid surface water flow and increased erosion potential (Turlkelboom et al., 2008). Flow accumulation and drainage density, reflective of how water accumulates and disperses, respectively (Murphy et al., 2009), interact intricately with undulating topographies, modulating water distribution and soil moisture content, thereby influencing landslide occurrences (Tucker & Bras, 1998). Proximity to rivers significantly contributes to landslide initiation on undulating surfaces, with the erosive power of river systems affecting slope stability (Guthrie & Evans, 2004). Standardised Precipitation Index (SPI) and Topographic Wetness Index (TWI) further elucidate landslide vulnerability by quantifying precipitation anomalies and terrain wetness, respectively, offering critical insights into the potential triggers of landslides in these complexes, undulating landscapes (Pourghasemi et al., 2012).

Understanding these hydrological variables is imperative for robust landslide hazard assessment and mitigation strategies in such intricate topographic settings.

4.4. Phenological variables

Phenological variables (Figure 5) encompass essential ecological indicators like Leaf Area Index (LAI) and Enhanced Vegetation Index (EVI) (Karkauskaite et al., 2017). While LAI predominantly measures vegetation density (Lin & West, 2016) and aids in rainfall impact reduction and soil stability enhancement, EVI delves deeper into vegetation health and vigour. EVI, derived from spectral reflectance data, offers insights into the overall health, density, and canopy structure of vegetation (Lian et al., 2022; Zhang et al., 2004).

In undulating landscapes, variations in EVI across slopes denote differences in vegetation vigour, influencing root strength, canopy density, and soil binding capacities. Areas with higher EVI values typically exhibit stronger root systems, contributing to enhanced soil stability by reinforcing soil structure and cohesion.

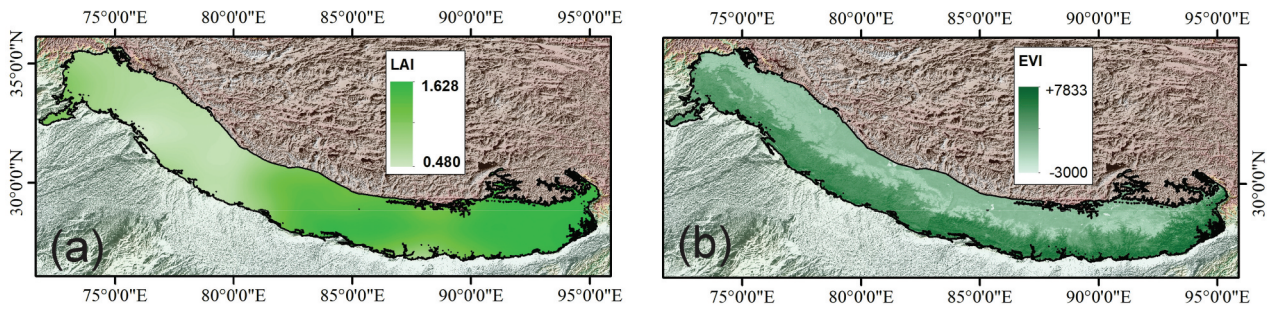


Figure 5. Phenological variable: (a) LAI, (b)EVI. Source: NASA Earth data.

This reinforced stability acts as a pivotal factor in mitigating erosion and landslide triggers in regions characterised by varied topographies. Together, the comprehensive understanding derived from both LAI and EVI assessments significantly enriches the analysis of landslide susceptibility in complex terrains. The rationale of adopting LAI and EVI in landslide modelling lies in their ability to quantify vegetation's density and health, which have a significant role in stabilising soil and slopes. Vegetation holds soil together through its root systems (Reubens et al., 2007), which increase soil cohesion and anchoring capacity, supporting rocks, and reducing slope instability. Additionally, dense vegetation controls erosion by forming a protective layer over the soil and reduces the impact of raindrops through canopy interception (Feddes & Raats, 2004), which diminishes surface runoff and prevents the initiation of landslide triggers.

4.5. Surface condition

Surface conditions play a pivotal role in landslide susceptibility, encompassing a multitude of variables that influence terrain stability. Among the various variables, forest fires represent a significant contributor to altered surface conditions, exerting a profound impact on slope stability (Jakob, 2022; Santoro et al., 2021). Studies by Marzini et al. (2019); Shu et al. (2019) reveal that areas with bare slopes, devoid of tree cover, are particularly more vulnerable to landslides, as the absence of vegetation reduces soil cohesion, increases surface runoff, and exposes the soil to erosive forces, further destabilising the terrain. Therefore, adopting the probability of forest fires as one of the conditioning variables, that profoundly affecting the vegetation cover, is crucial. The combustion of vegetation during wildfires not only removes the protective canopy cover but also weakens the root systems that anchor soil particles, leading to decreased soil cohesion (Scott et al., 2009). The intense heat from fires alters soil properties, creating a hydrophobic layer that impedes water infiltration, promoting rapid surface runoff and increased soil erosion (Mataix-Solera et al., 2011). Additionally, the loss of vegetation cover leaves slopes vulnerable to

direct rainfall impact, enhancing the erosive force of precipitation on exposed soil surfaces, while the absence of roots to anchor loose rocks and soil, along with the loss of canopy to shield and stabilise the terrain, further exacerbates slope instability and increases the risk of landslides (Zhou et al., 2016). In undulating terrains, where surface conditions play a critical role in landslide initiation, the aftermath of forest fires significantly amplifies the susceptibility to landslides, underscoring the intricate relationship between surface alterations and heightened landslide risks in these landscapes (Pradhan & Siddique, 2020). Very large area of Himalayas (Figure 6) experience forest fires each year and hence it is rationale to include the forest fire vulnerability raster as a variable in present research.

5. Methods

5.1. Resampling of data

Bilinear resampling is a widely used interpolation method in geospatial analysis for resizing or transforming raster data. This technique calculates the value of a target cell (V_T) based on a weighted average of the values of the four nearest neighbouring cells (Qianxiang et al., 2003). The formula for bilinear resampling is expressed as:

$$V_T = \frac{(x_1 - x_2)(y_1 - y_2)V_{11} + (x_1 - x_2)(y_1 - y_2)V_{21} + (x_1 - x_2)(y_1 - y_2)V_{12}}{x(x_1 - x_2)(y_1 - y_2)} \quad (1)$$

Where, V_{11} , V_{21} , and V_{12} are the values of the four nearest neighbouring cells. x_1 , x_2 , y_1 and y_2 are the coordinates of the corners of the grid cell containing the target point. x and y are the coordinates of the target point. The weights in the numerator are determined by the proximity of the target point to each of the neighbouring cells, ensuring a smooth transition between values. Unlike nearest-neighbour interpolation, which may introduce abrupt changes, bilinear resampling is particularly suitable for continuous data such as elevation, temperature, or precipitation, where gradual value transitions are critical (Mendez et al., 2019; Merghadi et al., 2020).

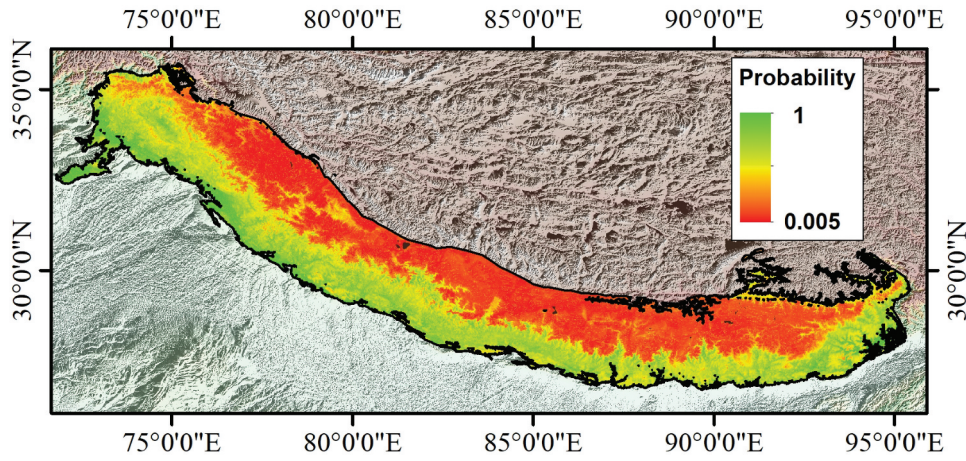


Figure 6. Surface condition: forest fire. Source: prepared by authors.

5.2. Modelling landslide susceptibility

SVMs operate on the principle of finding the optimal hyperplane that best separates classes within a dataset (Awad et al., 2015). With its ability to handle both linearly and non-linearly separable data, SVMs offer a versatile solution for predictive mapping tasks (Ghosh et al., 2019). This is facilitated by the kernel trick, where data is implicitly mapped into higher-dimensional spaces for improved separation (Schölkopf, 2000). SVMs, renowned for their ability to handle complex datasets and nonlinear relationships, are adept at capturing intricate patterns inherent in disaster-related data. By leveraging historical disaster records, environmental parameters, socio-economic factors, and geographical features, SVMs can predict the likelihood and severity of disasters with high accuracy (Linardos et al., 2022). In wildfire-prone landscapes, in flood prediction modelling, SVMs analyse vegetation indices, weather conditions, topographical characteristics, and human encroachment patterns to assess wildfire susceptibility and spread dynamics and help prediction of floods by incorporating the as-precipitation patterns, terrain elevation, land use, and soil permeability (Gizaw & Gan, 2016; Kalantar et al., 2020; Qiu et al., 2021). The applications of SVMs in landslide susceptibility mapping include analysing terrain characteristics, land cover, soil properties, and rainfall patterns to predict areas prone to landslides based on inventory (Dou, Yunus, Bui, et al., 2020a). Additionally, SVM contributes to landslide hazard assessment by classifying regions into different risk levels, considering factors like slope steepness, soil type, land use, and proximity to waterbodies (Chen et al., 2017).

In binary classification adopted in the present study, the basic formula for an SVM with a linear kernel can be expressed as follows:

$$\text{Decision Function } f(x) = w^T \cdot x + b \quad (2)$$

Where, $f(x)$ is the decision function that predicts the class label for input x . x represents the input features. w is the weight vector that determines the orientation

of the decision boundary. b is the bias term. 1000 random landslide inventory points are processed.

5.3. Accuracy assessment

The evaluation of model accuracy holds significant importance in the present study. The study adopts a 70–30 data of split of 1000 points for training and testing based on studies conducted by Pham et al. (2019); Abraham et al. (2021); Zhao and Zhao (2021), Ali et al. (2022), respectively. A graphical representation depicting the performance of a classification model across different classification thresholds is referred to as an ROC curve (Receiver Operating Characteristic). This curve plots two key factors, True Positive Rate (TPR) and False Positive Rate (FPR). TPR, also known as recall, is defined by Equation 15:

$$TPR = \frac{TP}{TP + FN} \quad (3)$$

Where TP represents true positives and FN represents false negatives.

Similarly, FPR is defined by Equation 16:

$$FPR = \frac{FP}{FP + TN} \quad (4)$$

Where FP represents false positives and TN represents true negatives.

The ROC curve illustrates the TPR vs. FPR relationship at various classification thresholds. As the classification criterion is lowered, more items are classified as positive, leading to an increase in both False Positives and True Positives. Threshold for ROC was set to 0.2 for both training and testing data.

5.3.1. 3.2.5 SHAP analysis

In this study, a total of 1000 inventory points were used to train the SVM model for landslide susceptibility prediction. However, to ensure clarity and avoid visual clutter in the Shapley Additive Explanations (SHAP) bee-swarm plot, a subset of 500 points was selected

for the SHAP analysis. This approach was employed to maintain a balance between interpretability and precision, allowing for a clear representation of variable contributions without compromising the integrity of the overall model. SHAP values are grounded in cooperative game theory, ensuring an equitable distribution of each feature's influence on a model's predictions. The formula evaluates the marginal contribution of each feature by comparing predictions with and without it, across all possible feature subsets, providing valuable insights into the model's decision-making process. While SHAP is applied across a range of models, including Random Forest (RF), Generalised Linear Models (GLM), and Boosted Regression Trees (BRT), it is particularly useful for evaluating complex models like Support Vector Machines (SVM). The formula for SHAP is as follows:

$$\phi = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N| - |S| - 1)!}{|N|!} [f(S \cup \{i\}) - f(S)] \quad (5)$$

N is the set of all features.

S is a subset of N that does not include feature i .

$|S|$ is the number of features in the subset S .

$f(S)$ is the model's prediction using only the features in subset S .

$f(S \cup \{i\})$ is the prediction when adding feature i to subset S .

$\frac{|S|!(|N| - |S| - 1)!}{|N|!}$ is a weighting factor based on the size of subset S .

Several studies have employed SHAP values to evaluate model accuracy and performance in the context of landslide predictions. SHAP has been used to interpret complex machine learning models in landslide risk prediction by identifying the most influential factors, such as precipitation, slope, soil type, and vegetation cover. SHAP analysis is used to model the contributions of various environmental factors in predicting landslide occurrence rates. Similarly, SHAP integrates summary plots to understand how slope gradient and rainfall impact landslide risk predictions in the Western Himalaya region. It is used to enhance landslide mapping accuracy by employing SHAP values to analyse the impact of satellite data on predictions. Additionally, it was applied to assess landslide susceptibility on Hawai'i Island, identifying key environmental influences.

5.4. Risk assessment

The assessment of LULC data, along with population risk, was conducted through a systematic process. Initially, the LULC data were extracted from available datasets, following which the Built-up and Agriculture land categories were specifically filtered for analysis. The quantified areas for these land categories were determined by intersecting the vector layers of the selected river basins with the respective LULC data

which were vectorised beforehand. This approach allowed for precise identification and measurement of agricultural and urban areas exposed to landslide susceptibility within each basin. For the population risk assessment, raster data representing population were utilised. Zonal statistics were employed in a GIS-platform to calculate the total population residing within the very high, high, moderate, low, and very low susceptibility zones for each river basin after Dou, Yunus, Merghadi, et al. (2020b). These zones had been previously delineated based on landslide vulnerability using a machine learning model. By overlaying the population raster with the susceptibility vectors, the number of people living in each risk category was summed using the following Eq. 10:

$$\text{Total Risked Population} = \sum_{i=1}^n \text{value}_i \quad (6)$$

Where value_i is the value of the population raster cell in a given risk zone i or in a given susceptibility class. This enabled an accurate estimation of population exposure to landslide risks in each basin, facilitating a comprehensive understanding of both LULC and population vulnerabilities in the study area.

5.5. Results of the model

The classified data on landslide susceptibility indicate that 371.5 thousand hectares are at very high risk, 209.2 thousand hectares are at high risk, 152.1 thousand hectares are at moderate risk, 97.1 thousand hectares are at low risk, and 85.2 thousand hectares are at very low risk (Figure 7). Very high-risk areas, which constitute the most vulnerable parts of the Himalayan region, are characterised by steep terrain, unstable geological formations, and intensified monsoonal precipitation. These factors contribute to the frequent occurrence of slope failures, necessitating urgent mitigation measures. Such actions include immediate slope stabilisation, afforestation projects, and the implementation of controlled drainage systems to mitigate water accumulation and soil saturation-key drivers of landslides in these zones. In high-risk zones, while the susceptibility to landslides is slightly lower than in very high-risk areas, they still exhibit significant vulnerabilities. This is due to the presence of steep slopes, heavy monsoon precipitation, and human activities, such as agriculture, road construction, and urban development. These areas require focused risk management strategies, including sustainable agricultural practices, the regulation of development activities, and the strengthening of community-based disaster preparedness. However, Moderate-risk zones, though relatively less vulnerable, are characterised by moderate-to-steep slopes, significant precipitation levels, and ongoing human activities. These areas require intermediate measures, such

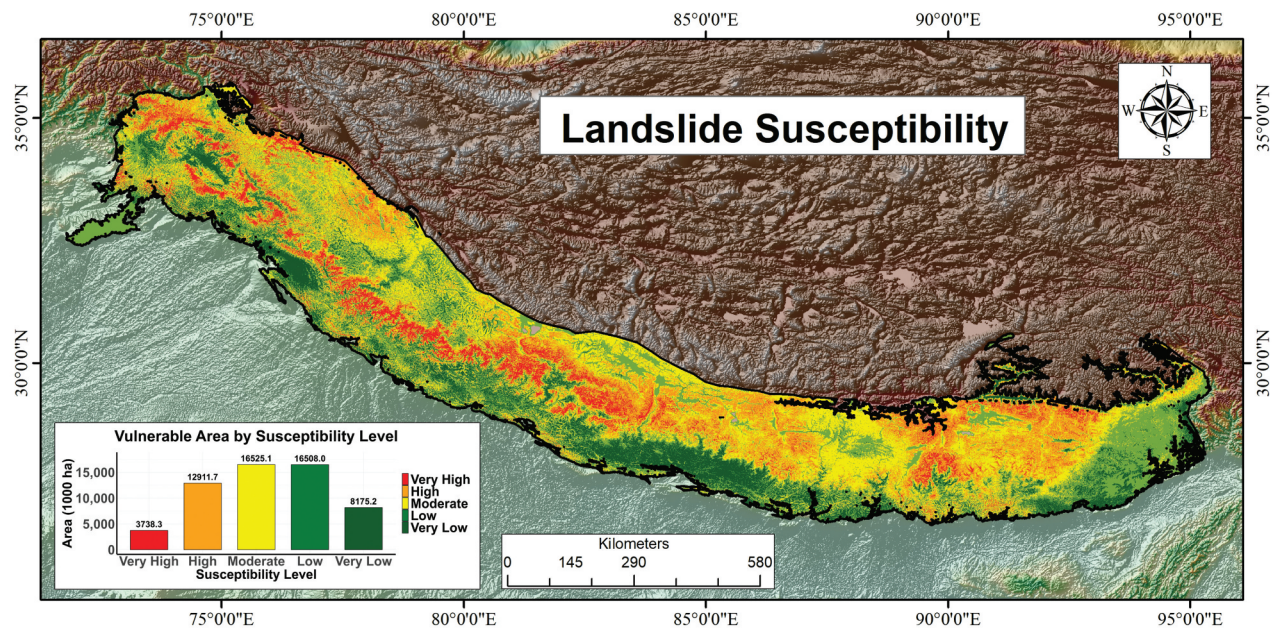


Figure 7. Landslide susceptibility. Source: prepared by authors.

as controlled land-use practices and limited infrastructural developments, to reduce risks. Low-risk zones are relatively stable, often situated at gentler slopes and lower elevations. However, they still require continuous monitoring as they could face increased susceptibility due to natural disasters like cloudbursts, earthquakes, or the evolving impacts of climate change. To maintain their stability, land-use policies must integrate preventive measures such as strict regulation on land clearance, mining, and infrastructure development to avoid introducing new risk factors. Very low-risk zones, constituting the most stable areas, require minimal intervention but must still adhere to sustainable land-use practices to ensure long-term stability.

5.6. Accuracy of the model

The SVM model's ROC curve reflects its landslide susceptibility classification efficacy. Training AUC at 0.990 implies excellent predictive distinction, highly above random chance. Conversely, a testing AUC of 0.870 denotes little lesser AUC still good enough indicating 87% probability of accurate susceptibility classification. Variances in training and testing performance suggest potential test data peculiarity. The threshold for binary classification of probability is set to 0.2 (Figure 8).

In the SHAP analysis (Figure 9), the variables influencing landslide susceptibility in the Himalayan region are categorised into three groups based on their importance: most important, moderately important, and least important variables. The most important factors include Runoff, Forest Fires, Drainage Density, and Stream Power Index (SPI), followed by Slope,

Topographic Wetness Index (TWI), Enhanced Vegetation Index (EVI), Leaf Area Index (LAI), Soil Porosity, Flow Accumulation, Percolation Rate, Skin Temperature, and Proximity to Faults. These variables strongly correlate with landslide occurrences, particularly through their influence on hydrological processes and slope stability. Regions near rivers or with dense vegetation are more prone to landslides due to higher soil saturation and erosion. Moderately important variables, such as Aspect, Precipitation, and Proximity to Rivers, influence moisture dynamics and slope stability. While not as influential as the top factors, they play a crucial role in landslide risk under varying environmental conditions. The least important variables, including Elevation, Geology, and Curvature, contribute minimally to the model but still provide insight into terrain stability. Although these factors have a weaker impact, they help capture subtle variations in landslide susceptibility. Overall, Runoff, vegetation indices, and hydrological factors dominate landslide prediction, while geological factors have a lesser role.

5.7. Risk assessment

Two principal anthropogenic factors associated with landslide risks are land utilisation and population exposure. Consequently, Land Use and Land Cover (LULC) data, alongside the assessment of populations vulnerable to risk, constitute a logical and critical approach for comprehensive analysis and risk assessment. This study delves into the susceptibility of urban and agricultural land across major Himalayan River basins, i.e. larger than 500,000 ha, encompassing the Beas, Brahmaputra, Ganga, Giri, Indus, Jhelum, Kali, Kameng, Mangda Chhu, Rangit, Sama, Sutluj, Spiti, Subansiri, Sutlej River

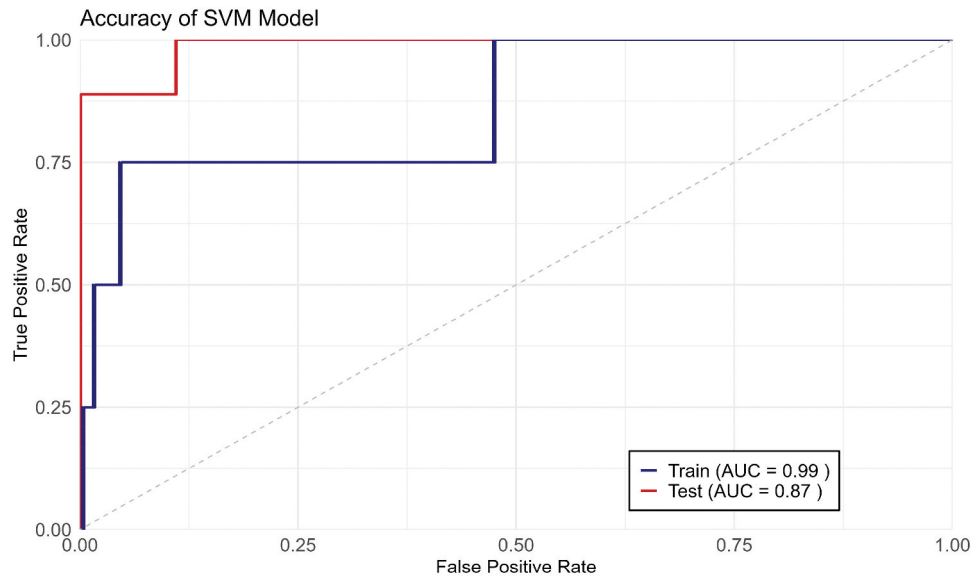


Figure 8. ROC curve. Source: prepared by authors.

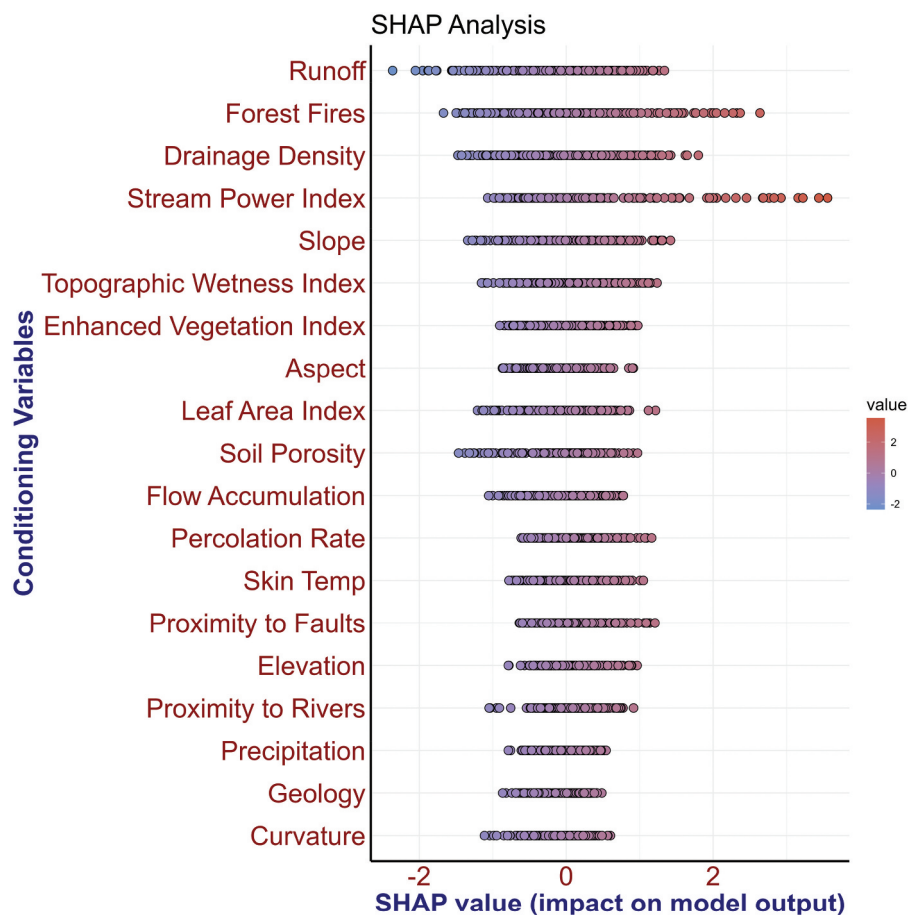


Figure 9. SHAP plot. Source: prepared by authors.

North, Tsari Chu-Zaskar Rivers, Yamuna, Yarlung Zangbo, and Zaskar Rivers (Table 3, Figure 10).

5.7.1. LULC

Land Use and Land Cover (LULC) classifications reveal a diverse array of categories, with human settlements and infrastructural edifices, as well as vast agricultural areas, being particularly critical. The study's focus is to

evaluate the extent of Urban and Built-up land and Agricultural land within selected river basins that are subject to varying levels of landslide susceptibility, noting that LULC characteristics exhibit significant variations across these basins (Figure 10).

For agricultural land, notable vulnerabilities are observed in several basins (Table 4, Figure 11). For instance, the Jhelum River Basin emerges as the most

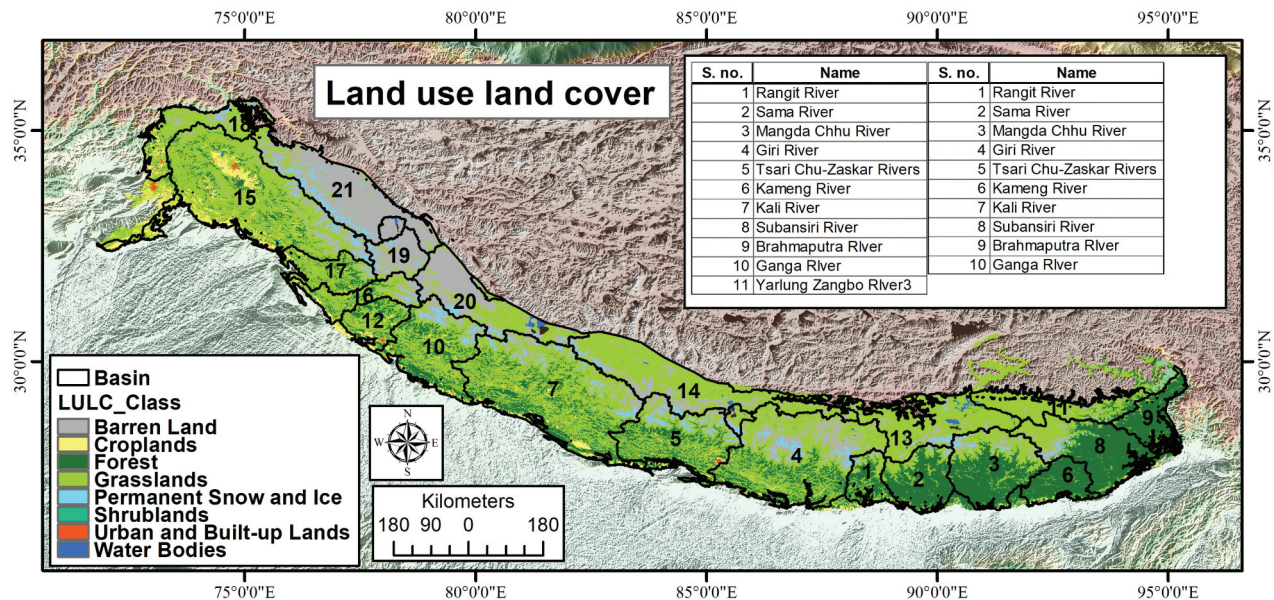


Figure 10. LULC falling in different basins. Source: prepared by authors.

vulnerable in terms of agricultural land, with 47,933.27 ha in very high-risk zones 95,865.02 ha in high-risk categories, and 142,715.93 ha in moderate-risk zones, totalling 898,858.76 ha of vulnerable agricultural land. The Kali River Basin follows, with 9,139.60 ha in very high-risk areas 24,632.41 ha in high-risk categories, and 58,807.08 ha in moderate-risk categories, amounting to 287,807.91 ha of vulnerable agricultural land. Similarly, the Ganga River Basin records 11,906.90 ha in very high-risk areas 11,382.40 ha in high-risk categories, and 22,942.81 ha in moderate-risk category, summing up to 140,499.21 ha of agricultural land at risk. Likewise, in the Indus River Basin, 2,896.58 ha of agricultural land is in very high-risk category 25,060.95 ha in high-risk zones, and 47,533.27 ha in moderate-risk category, highlighting 162,595.33 ha as vulnerable. The Tsari Chu-Zaskar Rivers Basin presents 85.26 ha of agricultural land in very high-risk zones, 1,265.90 ha in high-risk category, and 16,627.06 ha in moderate-risk category, summing up to 125,831.17 ha of agricultural land under threat. The Giri River Basin reports 21.44 ha of agricultural land in very high-risk zones, 194.66 ha in high-risk category, and 8,730.26 ha in moderate-risk zones, reflecting 112,895.22 ha of vulnerable agricultural land. The Satluj River Basin exhibits 11,022.70 ha in very high-risk areas 13,699.58 ha in high-risk category, and 18,511.01 ha in moderate-risk zones, amounting to 101,792.98 ha of agricultural land at risk. Lastly, the Yamuna River Basin records 6,979.81 ha in very high-risk category 15,566.83 ha in high-risk category, and 23,388.45 ha in moderate-risk category, with 102,694.26 ha of vulnerable agricultural land.

When it comes to risked built-up land, the Jhelum River Basin leads with 611.20 ha area in very high-risk category, 1,922.69 ha area in high-

risk zones, and 4,253.78 ha area in moderate-risk zones, summing up to 37,039.07 ha of built-up land exposed to landslide risks. The Ganga River Basin follows closely, with 95.65 ha in very high-risk areas, 165.25 ha in high-risk category, and 529.87 ha in moderate-risk zones, totalling 9,051.66 ha of vulnerable built-up land. The Kali River Basin shows no area in very high-risk category, 119.22 ha in high-risk category, and 179.94 ha in moderate-risk category, highlighting 1,731.62 ha of built-up land at risk. In the Indus River Basin, 43.42 ha of built-up land is in very high-risk category, 786.74 ha in high-risk zones, and 872.65 ha in moderate-risk zones, with a total of 6,873.84 ha under threat. The Tsari Chu-Zaskar Rivers Basin reports 0 ha of built-up land in very high-risk areas, 0 ha in high-risk zones, and 128.26 ha in moderate-risk zones, reflecting 16,611.38 ha of vulnerable built-up land. Likewise, the Yamuna River Basin includes 67.91 ha of urban and built-up land in very high-risk category, 858.07 ha in high-risk zones, and 2,207.59 ha in moderate-risk category, with a total of 10,220.60 ha of built-up land at risk. Similarly, the Satluj River Basin presents 13.60 ha in very high-risk zones, 292.06 ha in high-risk zones, and 472.04 ha in moderate-risk category, amounting to 2,408.09 ha of vulnerable built-up land. Lastly, the Giri River Basin records 0 ha in very high-risk zones, 0 ha in high-risk zones, and 173.71 ha area in moderate-risk zones, totalling 5,086.31 ha of urban and built-up land at risk.

5.7.2. Risked population

The heterogeneity in population distribution throughout the principal river basins underlines the imperative for a meticulous evaluation of the susceptible

Table 4. Vulnerable agricultural and urban and built-up land in different basins.

Vulnerable agricultural and Urban and Built-up land area in (ha) in different basins						
River Name	Very Low	Low	Moderate	High	Very High	Grand Total
Beas River	535761.75	305992.75	173001.85	159374.33	115509.91	1289640.58
Agriculture land	21492.24	13631.05	5146.33	3607.16	2703.64	46580.41
Urban and Built-up land	227.94	77.60	1.48	69.57	55.80	432.40
Brahmaputra River	212392.11	928039.15	103439.27	11870.01	31.91	1255772.45
Agriculture land	0.62	4626.82	0.49	00.00	00.00	4627.93
Urban and Built-up land	0.68	466.02	55.01	00.00	00.00	521.70
Ganga River	589188.80	1021103.07	649041.56	391929.66	345001.07	2996264.16
Agriculture land	44437.79	49829.30	22942.81	11382.40	11906.90	140499.21
Urban and Built-up land	5230.54	3030.36	529.87	165.25	95.65	9051.66
Giri River	1004171.52	1536547.09	2068068.35	1107364.54	69380.36	5785531.86
Agriculture land	62170.69	41778.17	8730.26	194.66	21.44	112895.22
Urban and Built-up land	4317.14	595.46	173.71	00.00	00.00	5086.31
Indus River	86636.35	400333.40	518748.04	431060.94	133116.82	1569895.54
Agriculture land	16472.30	70632.23	47533.27	25060.95	2896.58	162595.33
Urban and Built-up land	1245.58	3925.44	872.65	786.74	43.42	6873.84
Jhelum River	1185590.09	2208173.79	1602548.35	1246899.89	722540.42	6965752.54
Agriculture land	262500.97	349843.56	142715.93	95865.02	47933.27	898858.76
Urban and Built-up land	19431.44	10819.96	4253.78	1922.69	611.20	37039.07
Kali River	1352293.86	1766199.00	1222662.94	1557987.58	991690.16	6890833.54
Agriculture land	85819.99	109408.83	58807.08	24632.41	9139.60	287807.91
Urban and Built-up land	631.05	801.40	179.94	119.22	00.00	1731.62
Kameng River	444091.55	550120.20	151212.28	6797.40	00.00	1152221.44
Agriculture land	23203.53	3549.19	71.98	00.00	00.00	26824.70
Urban and Built-up land	8.26	20.33	00.00	00.00	00.00	28.59
Mangda Chhu River	117605.27	474131.50	1109283.14	1098164.82	74322.63	2873507.36
Agriculture land	2998.80	7396.96	3413.78	1094.95	36.61	14941.10
Urban and Built-up land	32.67	25.75	47.45	35.81	00.00	141.68
Rangit River	190808.09	252348.75	378827.89	101802.14	1239.21	925026.08
Agriculture land	8245.21	3665.65	1858.79	142.24	00.00	13911.89
Urban and Built-up land	300.34	317.56	147.85	5.09	00.00	770.85
Sama River	139240.57	393763.52	536698.87	541821.69	182421.36	1793946.00
Agriculture land	2039.38	2946.62	3072.88	1463.95	256.56	9779.38
Urban and Built-up land	31.65	243.49	670.29	434.21	119.68	1499.32
Satluj River	230428.11	415138.70	365000.56	166915.13	98964.81	1276447.31
Agriculture land	28102.76	30456.93	18511.01	13699.58	11022.70	101792.98
Urban and Built-up land	977.55	652.85	472.04	292.06	13.60	2408.09
Spiti River	87306.32	361717.04	415444.48	147878.57	1008.71	1013355.11
Agriculture land	58.10	75.02	68.20	00.00	00.00	201.32
Subansiri River	352035.86	1450585.05	462215.25	586956.20	33030.39	2884822.75
Agriculture land	5006.57	29070.01	104.27	156.69	9.25	34346.80
Urban and Built-up land	545.28	256.66	0.56	37.27	3.75	843.52
Sutlej River North	148477.06	1060861.80	1133489.18	302986.39	6251.56	2652065.99
Agriculture land	00.00	00.00	00.00	00.00	00.00	00.00
Urban and Built-up land	00.00	00.00	00.00	00.00	00.00	00.00
Tsari Chu-Zaskar Rivers	1228150.93	656148.44	579123.64	699973.86	147442.24	3310839.11
Agriculture land	71089.76	36763.19	16627.06	1265.90	85.26	125831.17
Urban and Built-up land	15173.35	1309.77	128.26	00.00	00.00	16611.38
Yamuna River	125011.29	325995.10	251822.42	204475.11	205737.12	1113041.04
Agriculture land	22223.75	34535.41	23388.45	15566.83	6979.81	102694.26
Urban and Built-up land	2499.04	4587.99	2207.59	858.07	67.91	10220.60
Yarlung Zangbo River (Basin 1)	11698.23	896856.59	1910657.47	1181830.26	42548.63	4043591.18
Urban and Built-up land	00.00	7.62	13.03	00.00	00.00	20.66
Yarlung Zangbo River (Basin 2)	5782.69	388872.61	1017525.92	1229492.16	154483.79	2796157.18
Agriculture land	00.00	2016.01	2844.75	206.52	50.74	5118.02
Yarlung Zangbo River (Basin 3)	72023.46	324569.07	439652.85	715516.29	204948.19	1756709.86
Agriculture land	87.42	261.44	274.54	679.30	529.30	1832.00
Urban and Built-up land	00.00	00.00	00.00	2.22	24.46	26.67
Zaskar River	56488.32	790490.44	1436585.92	1020593.03	208581.52	3512739.22
Agriculture land	00.00	8.78	46.91	124.34	36.46	216.49
Urban and Built-up land	00.00	7.37	204.34	1097.37	595.40	1904.48
Grand Total	8175182.22	16507987.07	16525050.21	12911690.00	3738250.80	57858160.30

Source: calculated by authors.

populace within each basin and across various susceptibility categories. This assessment is critical for understanding the scope and scale of potential risk exposure (Figure 12).

Assessing the population risk across the Himalayan River basins has revealed a pattern of vulnerability that necessitates immediate attention in certain regions for the year 2020 (Table 5, Figure 13). The analysis zeroes in the top 10 key basins which include the Jhelum,

Indus, Ganga, Kali, Yamuna, Sutlej, Beas, Giri, Rangit, and Tsari Chu-Zaskar. These basins are home to populations exposed to varying degrees of vulnerability, with a significant portion residing in very high, high, and moderate-risk zones, reflecting the complexity of risk distribution.

The Jhelum River basin stands out as the most vulnerable, with 512,052 individuals in very high-risk zones, 1,789,198 in high-risk zones, and 2,954,011 in

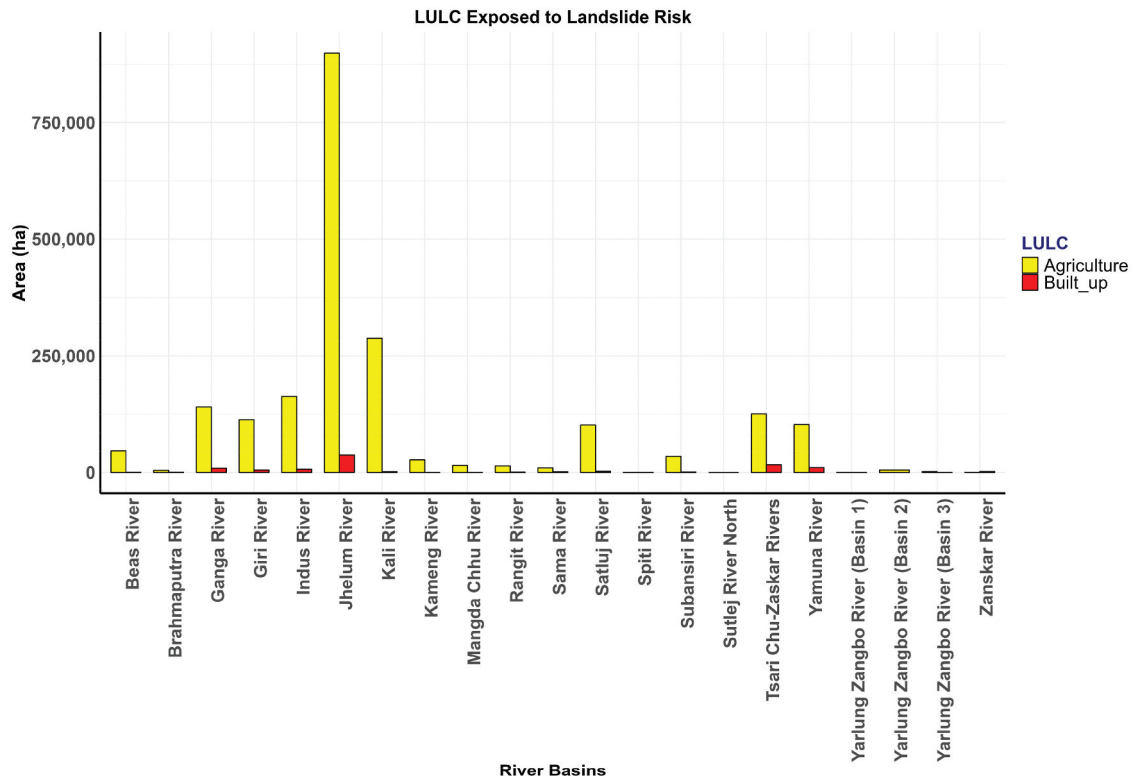


Figure 11. Susceptible LULC to landslide. Source: Estimated by authors.

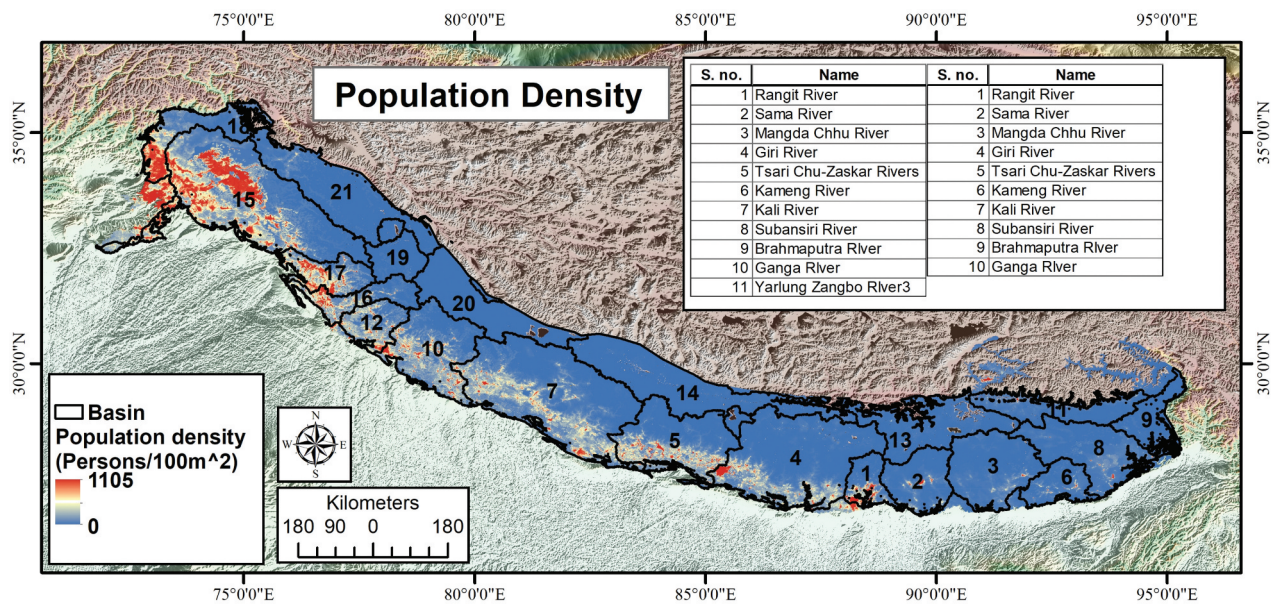


Figure 12. Population falling in different basins. Source: prepared by authors.

moderate-risk areas. These figures underscore the wide-reaching environmental threats faced by its population. Similarly, the Indus River basin shows a significant 104,647 individuals in very high-risk areas, 445,650 in high-risk zones, and 936,957 in moderate-risk zones, highlighting the need for urgent risk management to safeguard its population. In the Kali River basin 40,183 people reside in very high-risk zones, 254,668 in high-risk zones, and 685,866 in moderate-risk areas, emphasising the necessity for targeted intervention strategies. Meanwhile, the Ganga River

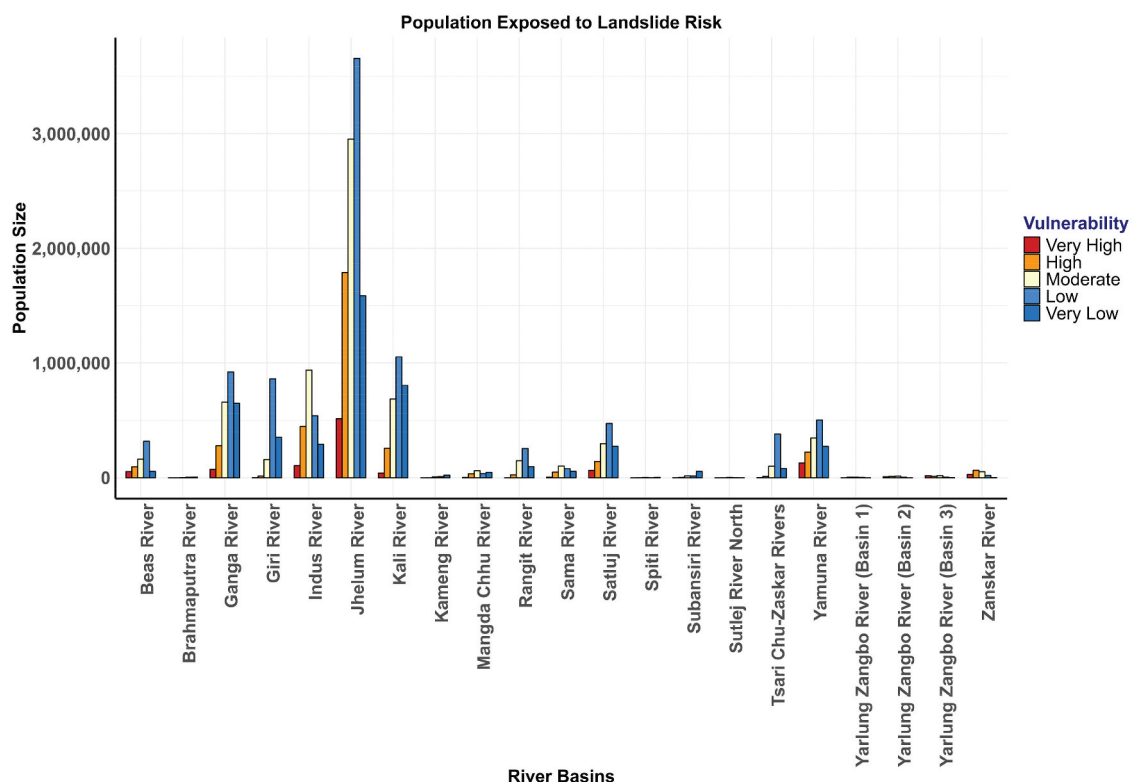
basin sees 71,889 individuals in very high-risk areas, 277,907 in high-risk zones, and 659,403 in moderate-risk zones, reflecting a substantial population exposed to environmental hazards. The Yamuna River basin similarly includes 127,961 individuals in very high-risk zones, 221,664 in high-risk zones, and 344,840 in moderate-risk areas, marking it as an area of significant concern and priority for intervention.

The Sutlej River basin features 63,353 people in very high-risk zones, 140,698 in high-risk zones, and 295,467 in moderate-risk areas, emphasising the

Table 5. Vulnerable population in different basins.

River Name	Very Low	Low	Moderate	High	Very High	Grand Total
Beas River	54604	316581	160733	94689	52439	679046
Brahmaputra River	5436	4326	1846	58	0	11667
Ganga River	650016	922131	659403	277907	71889	2581347
Giri River	351383	861034	157782	14978	1452	1386630
Indus River	290142	539265	936957	445650	104647	2316660
Jhelum River	1585799	3656637	2954011	1789198	512052	10497698
Kali River	805560	1053762	685866	254668	40183	2840040
Kameng River	22049	9666	7871	422		40009
Mangda Chhu River	46474	35597	60555	34406	3118	180151
Rangit River	95904	253562	147194	24947	252	521859
Sama River	55077	77859	101307	48374	4897	287514
Satluj River	272539	471247	295467	140698	63353	1243303
Spiti River	3427	1063	2921	1010	7	8428
Subansiri River	54533	15499	16078	3298	824	90233
Sutlej River North	753	1446	3240	652	22	6112
Tsari Chu-Zaskar Rivers	79449	379365	99386	11755	1950	571904
Yamuna River	271321	500487	344840	221664	127961	1466273
Yarlung Zangbo River (Basin 1)	83	3411	4698	4704	580	13476
Yarlung Zangbo River (Basin 2)	106	4252	14397	12213	8575	39542
Yarlung Zangbo River (Basin 3)	1914	5334	18610	13003	18245	57107
Zaskar River	2151	19768	52009	64259	29250	167437
Grand Total	4648720	9132294	6725171	3458553	1041696	25006434

Source: calculated by authors.

**Figure 13.** Population exposed to landslides. Source: prepared by authors.

widespread exposure within this basin. In the Giri River basin, 1,452 individuals fall in very high-risk zones 14,978 in high-risk zones, and 157,782 in moderate-risk areas, highlighting its localised vulnerabilities. Similarly, the Beas River basin records 52,439 individuals in very high-risk areas 94,689 in high-risk zones, and 160,733 in moderate-risk zones, underscoring its vulnerability to environmental risks. On the other hand, The Rangit River basin portrays 252 individuals in very high-risk areas 24,947 in high-risk

zones, and 147,194 in moderate-risk areas, necessitating focused risk mitigation strategies. Lastly, the Tsari Chu-Zaskar Rivers basin highlights 1,950 individuals in very high-risk zones 11,755 in high-risk zones, and 99,386 in moderate-risk areas, signalling the need for proactive interventions to mitigate potential adverse impacts. Together, these top 10 basins reveal the diverse and widespread nature of vulnerability, necessitating basin-specific strategies to address the risks effectively.

6. Discussion

The present study is a landmark contribution to the understanding of landslide susceptibility within the Himalayan region, covering a broader and more diverse geographical area than previous studies like conducted by Gupta et al. (2020); Vashishtha et al. (2022), and employing a novel integration of ML algorithms and GIS (Korup & Stolle, 2014; Phakdimek et al., 2023). The approach transcends conventional methods by utilising a comprehensive suite of natural variables to predict landslide susceptibility with enhanced accuracy (Chaithong & Komori, 2020). This multidimensional study provides an unprecedented insight into the implications of landslides on human settlements, agricultural lands, and exposed populations. The adoption of ML algorithms, particularly SVM, harnesses the power of advanced computational techniques to interpret complex (Dang et al., 2024; Khan, Ali, et al., 2023; Khan, Khan, et al., 2023; Khan, Mohsin, et al., 2024; Oyedele et al., 2021), nonlinear relationships within the data. This allows for a deep understanding of the interplay between various factors contributing to landslide susceptibility. By incorporating an array of topographical, climatological, hydrological, phenological, and surface condition variables, the study offers a holistic view of the landslide dynamics in the Himalayan region unlike previous studies like Aslam et al. (2024). By incorporating some least explored variables such as forest fires, EVI, and LAI, the study has highlighted the importance of vegetation in understanding of dynamics and has improved the precision of susceptibility models. The SHAP analysis identifies Runoff and Forest Fires two major contributor of landslides followed by Drainage Density, and SPI as the other most influential factors. Then come Slope, TWI, EVI, and LAI, highlighting the dominance of hydrological and vegetation-related variables in landslide prediction.

In the context of disaster risk assessment, the study highlights the importance of safeguarding built-up and agricultural lands that are vital for the survival and livelihoods of local communities. It brings forth the necessity for protecting the agricultural land that can reduce the vulnerability of these lands to landslides. Similarly, protecting built-up areas, including urban infrastructure, residential zones, and critical facilities, is crucial to minimising disruptions to livelihoods and economic activities. The consideration of risk exposure to human populations emphasises the need for enhanced early warning systems and evacuation plans to protect communities from potential landslide events. This necessitates stringent zoning regulations, the adoption of resilient construction practices, and retrofitting of existing structures to withstand potential landslide impacts in most vulnerable basins. It is noteworthy that the Jhelum River Basin is found to be the most vulnerable in terms of population, agricultural land, and built-up areas, followed by the Kali, Ganga, and

Indus River Basins. Vulnerable agricultural areas in these basins include 898,858.76 ha in the Jhelum Basin, 287,807.91 ha in the Kali Basin, and 140,499.21 ha in the Ganga Basin. Vulnerable built-up areas include 37,039.07 ha in the Jhelum Basin and 10,220.60 ha in the Yamuna Basin. The population at risk is equally concerning, with 512,052 individuals in very high-risk zones and 1,789,198 individuals in high-risk zones in the Jhelum Basin alone. Similar patterns are observed in the Indus, Kali, and Ganga River Basins, which emphasises the urgent need for disaster risk reduction strategies.

The implications of this study extend beyond the academic realm into the operational aspects of disaster risk reduction and management. It bears significant implications for regional planning and disaster management. The susceptibility mapping serves as a crucial tool for policymakers and planners, allowing them to prioritise areas for intervention and to allocate resources more effectively. Very high and High-risk basins identified within the study require immediate attention to implement mitigation measures, including reforestation, slope stabilisation, and infrastructure reinforcement. Additionally, these areas necessitate the development of controlled drainage systems to manage water accumulation and prevent soil saturation, which are key triggers of landslides. Furthermore, implementing restricted land-use policies and regulating construction activities in these zones can significantly reduce the risk of triggering landslides. Collaborative efforts between local communities, policymakers, and disaster management authorities are essential to design and execute tailored mitigation strategies for these vulnerable regions. The basin-level susceptibility mapping and risk assessments presented in this study offer actionable insights for implementing targeted disaster management schemes and policies. By identifying high-risk zones within each basin, policymakers can allocate resources strategically to prioritise critical areas, ensuring efficient disaster preparedness and response.

The insights gained from this research have the potential to inform the development of more resilient communities within the Himalayan region, ensuring that they are better equipped to face the challenges posed by natural hazards such as landslides. The current research also paves the way for future studies to incorporate more refined data, such as real-time monitoring of climatic conditions and anthropogenic changes, to improve the predictive capabilities of landslide susceptibility models.

7. Conclusion

The conclusion of this study provides a synthesis of its findings and their broader implications. The integration of ML and GIS for landslide susceptibility mapping in the Himalayan River basins represents a significant

advancement in natural hazard analysis and management. The comprehensive approach undertaken in this study underscores the multifaceted nature of landslide risks and the necessity of adopting interdisciplinary methods to understand risks effectively. The basin-level susceptibility mapping offers actionable insights for targeted disaster management policies. By identifying very high and high-risk zones, policymakers can prioritise critical areas, allocate resources efficiently, and implement localised land-use planning and early warning systems to reduce landslide risks effectively.

The utilisation of SVM in the modelling process underscores the potential of ML algorithms to handle and interpret complex and large datasets. The study also leads to a comprehensive understanding of risk factors and allows for the identification of areas where populations and infrastructures are most vulnerable. The study demonstrates that the greatest susceptibility to landslides often coincides with regions where human activities intersect with sensitive environmental conditions.

Crucially, the study's findings facilitate informed decision-making for disaster preparedness and response. By delineating high-risk areas, authorities can prioritise and tailor mitigation strategies to protect the most vulnerable communities and safeguard essential resources. This targeted approach is vital for enhancing the resilience of human settlements and agricultural lands that sustain local populations.

The implications of this research extend into the planning and developmental policies in the Himalayas. It calls for the integration of susceptibility maps into land-use planning and emphasises the importance of ecological conservation and sustainable development practices. Furthermore, the study highlights the need for ongoing monitoring and updating of landslide risk assessments to adapt to changing environmental conditions and human dynamics.

In conclusion, the study contributes a critical piece to the puzzle of understanding landslide susceptibility in one of the world's most complex mountainous regions. It lays a foundation for future research to build upon, particularly in the realms of risk analysis and real-time data analysis along with the integration of additional ML algorithms. The ultimate aim of this and subsequent studies should be to support the development of robust early warning systems, data-driven land-use policies, and effective disaster risk reduction programs, with careful consideration of population distribution and land use dynamics. These efforts are not only essential for the Himalayan region but also resonate with global needs in the face of escalating environmental and climatic challenges.

8. Limitations

While this study provides valuable insights into landslide susceptibility and risk assessment in the

Himalayan region using ML and GIS, certain limitations should be acknowledged. The spatial resolution of input datasets varied, requiring resampling for consistency. Although bilinear interpolation was used to resample variables such as LAI, EVI, skin temperature, precipitation, forest fire data, runoff, drainage density, proximity to rivers, soil porosity, and percolation rate, resampling can lead to a loss of fine-scale details, potentially affecting model accuracy. Climatological variables, for instance, were resampled to align with the 30 m resolution of the topographic data. However, this resampling might oversimplify localised climatic variations, which are crucial in a region as complex as the Himalayas. Moreover, while the use of a uniform resolution simplifies modelling, it may not fully capture the heterogeneity of the landscape, especially in areas with highly variable terrain and land use patterns. These limitations highlight areas for further refinement and improvement in future studies.

9. Recommendations

- (1) **Mitigation Measures for High-Risk Zones:** Immediate and targeted actions are necessary for very high and high-risk zones and basins which are highly vulnerable. Key measures include reforestation to stabilise soil, slope stabilisation to prevent erosion, controlled drainage systems to manage water accumulation, and infrastructure reinforcement to withstand potential landslide impacts. These measures are essential to minimise risks effectively and protect vulnerable areas.
- (2) **Policy Integration:** Landslide susceptibility maps should be integrated into regional and basin-level land-use planning frameworks. This integration would regulate construction activities, enforce restricted land-use policies in vulnerable zones, and ensure sustainable urban and rural development, preventing further anthropogenic stress on high-risk areas.
- (3) **Built-Up and Agricultural Land Safeguarding:** Built-up areas, including urban infrastructure, residential zones, and critical facilities like hospitals, fire stations, and schools, require resilient construction practices and retrofitting measures to reduce vulnerability. Simultaneously, promoting sustainable agricultural practices can protect critical farmlands from degradation, ensuring the survival and livelihoods of local communities.
- (4) **Community Engagement and Capacity Building:** Collaborative efforts among local communities, policymakers, and disaster management authorities are essential to design tailored mitigation strategies. Training programs, awareness campaigns, and community-based

disaster risk reduction initiatives can empower residents to actively contribute to disaster preparedness and resilience.

- (5) **Enhanced Early Warning Systems:** The development and deployment of robust early warning systems, coupled with evacuation plans, are critical to safeguarding human lives. Regular geotechnical monitoring, soil testing, and integration of real-time data from remote sensing can detect early signs of instability, enabling proactive interventions.
- (6) **Addressing Climate Change Scenarios:** Landslide susceptibility models must incorporate climate change projections to account for evolving precipitation patterns, temperature extremes, and other environmental changes. Scenario-based modelling can help policymakers anticipate future risks and adapt mitigation strategies accordingly.
- (7) **Future Research Directions:** Further research should focus on refining data resolution, integrating real-time monitoring of climatic and anthropogenic activities, and employing additional machine learning (ML) algorithms to enhance predictive accuracy. Moreover, future studies should explore the use of advanced climate models to understand the long-term impacts of climate change on landslide dynamics.
- (8) **Tailored Recommendations for Stakeholders:** Policymakers should leverage the findings of this study to prioritise high-risk zones, allocate resources efficiently, and design localised mitigation strategies. Urban planners can incorporate susceptibility insights into zoning regulations, while environmentalists can focus on conservation practices to maintain ecological balance. Disaster management authorities can use these recommendations to enhance preparedness and response mechanisms tailored to specific basin-level vulnerabilities.

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Data availability statement

The data that support the findings of this study are available at 10.5281/zenodo.13997543 and can be obtained from the corresponding author at khazainub@gmail.com or zkhan@myamu.ac.in.

Statement of AI's assistance

The authors declare the limited and responsible use of OpenAI's ChatGPT, Version 3.5 to only enhance the language of the manuscript. The conceptualisation, content, analysis, figures, intellectual and scientific integrity of the present study remains the sole responsibility of the authors.

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