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Occurrence and Distribution of Landslide in the Pir Panjal Range Due to Hydrological Factors: A GIS and AHP- Based Approach

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ABSTRACT:

Landslides are a major environmental hazard in mountainous regions, and their occurrence is often influenced by hydrological factors. This study focuses on assessing the hydrological impact on landslides and their spatial distribution in the Pir Panjal Range of the Himalayas using a GIS and Analytical Hierarchy Process (AHP) approach. Key hydrological parameters such as rainfall intensity, drainage density, and tropical wetness index are integrated to determine landslide susceptibility and distribution. The AHP method is employed to prioritize these factors based on their contribution to landslide initiation, allowing for a more accurate landslide susceptibility map. GIS tools are used to spatially analyze and visualize the distribution of landslides, providing a comprehensive understanding of the areas most prone to this hazard. This study highlights the significant role of hydrology in triggering landslides and provides valuable insights for land-use planning and disaster mitigation in the region.

Keywords: Landslides, Hydrological impact, Pir Panjal Range, GIS, Analytical Hierarchy Process (AHP), Landslide susceptibility, Drainage density, Groundwater flow, Spatial distribution..

Introduction

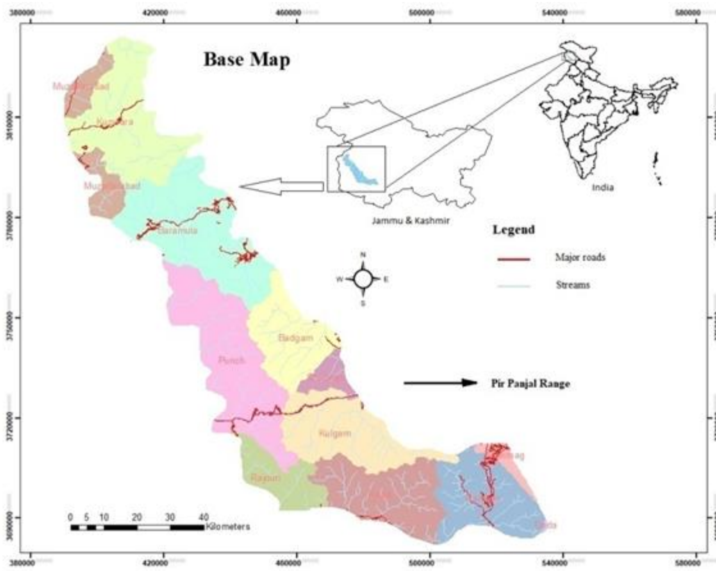
Landslides are debris flow resulting from the outward and downward movement of soil and rock masses along slopes (Varnes, 1984; Cruden, 1991). In the country's mountainous regions, landslides occur frequently, varying in magnitude from minor to severe (Gao & Maro, 2010). This complex geological phenomenon poses significant risks to human lives and infrastructure, especially in hilly areas (Svalova et al., 2019). Landslides are caused by a combination of geological, geomorphological, and climatic factors, making their study crucial for better hazard management (Rai et al., 2014). Recent years have seen an increase in landslide occurrences, largely due to factors such as the overexploitation of natural resources, land-use changes, unsustainable mining practices, deforestation, climate change, traffic congestion, rapid urbanization, and road expansion (Nadim et al., 2006; Hoyois et al., 2007; Schuster, 1996). The growth of tourism, improved water and electricity supplies, and favorable climatic conditions has encouraged more people to settle in mountainous areas, contributing to urbanization. This, in turn, has led to infrastructure development, often without proper slope management practices, exacerbating the risk of landslides (Jaiswal et al., 2011).

When extreme rainfall or earthquakes occur, they can destabilize slopes by increasing shear stress or reducing shear strength, leading to landslides (Dai & Lee, 2002; Guzzetti et al., 2005). Additionally, regional seismic activity may gradually weaken slopes, making them more susceptible to failure (Moore et al., 2011).

This study focuses on analyzing hydrological influences on landslide distribution in the Pir Panjal Range using GIS and the AHP method. The resulting maps provide valuable insights into areas vulnerable to landslides, supporting better risk assessment, land-use planning, and decision-making.

Materials And Methods

In this research, an extensive study of landslides was conducted across the Pir Panjal Range.



The geographical coordinates of this study domain span from Latitude: 33.8893 Longitude: 74.4865.The PirPanjal Range a bunch of mountains in the Lesser Himalayan area. They stretch from the southeast to the northwest, covering places like Himachal Pradesh, Jammu and Kashmir in India, and even some parts controlled by Pakistan in Kashmir

The main objective was to assess the impact of hydrology on landslide distribution. To accomplish this, a robust integration of the Analytic Hierarchy Process (AHP) and Geographical Information System (GIS) was utilized. The AHP method systematically evaluated and prioritized key hydrological factors such as rainfall, proximity to streams, and the Topographic Wetness Index. These critical parameters were then effectively combined within a GIS framework to produce comprehensive and accurate maps, followed by an analysis of landslide distribution. The resulting map is an invaluable tool, offering deep insights into vulnerable areas within the Pir Panjal Range, thereby aiding informed decision-making and enhancing risk management strategies.

The data utilized in this research stems from various different sources. Notably, Survey of India (SOI) Toposheets with designations. 43H/15, 43H/14, 43I/3143H/16, 43I/4, 43I/843O/5,43O/6,43O/9,43O/1043O/11,43O/15,43P/3 were carefully employed to create the basic map at a scale of 1:50,000. Geological information was sourced from the Geological Survey of India (GSI),. These original maps were meticulously traced, aligned, and digitized to construct an accurate spatial representation of distinct litho- units within the geographical domain.

Meteorological data pertaining to rainfall was meticulously gathered from the Indian Meteorological Department (IMD) and subsequently subjected to spatial analysis within a GIS framework.

the Shuttle Radar Topographic Mission (SRTM) Digital Elevation Model (DEM) dataset with a 30-meter resolution was harnessed to create detailed maps of drainage patterns, and drainage density within the research area.

The creation and analysis of models and progressions relevant to this study were accomplished using ArcGIS version 10.6. Field data collection was facilitated by the utilization of Global Positioning System (GPS) technology.

The additional data used in the study include rainfall. These data was collected from Indian Meteorological.

Analytic Hierarchy Process (AHP method)

The Analytical Hierarchy Process (AHP) method, introduced by Saaty (1980), has become a popular tool for Multi-Criteria Decision-Making (MCDM) in analyzing Landslide Hazard Zones (LHZ) (Sangchini et al., 2016; Gupta ., 2016.; Althuwaynee and Pradhan, 2016)**.**AHP involves a structured approach, breaking down complex decisions into a hierarchical model with clear levels of criteria and alternatives (Senouci et al., 2021). In the context of this study, AHP is utilized to prioritize landslide-influencing hydrological parameters and create a landslide susceptibility map for the Pirpanjal range.

- Construction of the Hierarchy

The initial step in the AHP method is to construct a hierarchical structure that organizes the decision problem into manageable components (Saaty, 1980). The hierarchy consists of three main levels: Goal, Criteria, and Alternatives. At the top level, the ultimate goal is defined, which is to develop a landslide susceptibility map for the Pirpanjal Range. The second level comprises criteria that significantly influence landslide occurrence, such as, precipitation , distances from streams , TWI..

- Pair wise Comparisons

Pair wise comparisons play a crucial role in the AHP method, allowing experts and stakeholders to express their preferences between criteria and alternatives (Saaty, 1980). A scale ranging from 1 to 9 is used to represent the relative importance of elements, where 1 indicates equal importance and 9 indicates extreme importance. These pair wise comparisons result in a matrix, known as the pair wise comparison matrix, which quantifies the relationships between elements.

Table 3.4 Comparison Scale (saaty, 1980)

Ordinal Scales	Degree of Preference	Explanation / Remarks
1	Equally important	Two factors influence equally
3	Moderately important	The level of experience and judgment leans towards a moderate preference for one activity over another.
5	Strongly important	Experience and assessment substantially or essentially incline towards giving preference to one activity over another.
7	Very strongly important	One activity is strongly favored over another, and its dominance is shown in practice
9	Extremely important	The indication of favoring one activity over another is of the utmost degree for an affirmation.
2,4,6,8	Intermediate values	Utilized to signify a middle ground between the preferences assigned to weights 1, 3, 5, 7, and 9.

- Calculation of Priority Weights

The data obtained from the pair wise comparisons is used to calculate the priority weights of criteria and alternatives (Saaty, 1980). The Eigen value method or Eigenvector method, based on the largest Eigen value principle, is commonly employed for this purpose. The priority weights represent the relative significance of each criterion and alternative in contributing to the overall goal of landslide susceptibility mapping.

- Consistency Analysis

To ensure the reliability of the decision-making process, it is essential to assess the consistency of judgments made during pair wise comparisons (Saaty, 1980). Saaty (1980) introduced the Consistency Ratio (CR) as a measure of consistency. A CR value greater than 0.1 indicates some level of inconsistency in the judgments, raising the need for reevaluation and adjustment.

$$CI = \frac{\lambda - n}{n - 1}$$

Where λ is the max value of eigenvector and n is the number of criteria.

Saaty (2000) generated a reciprocal matrix randomly by using scales ranging from 1/9 to 9. The purpose was to obtain a random consistency index (RI) and assess if it falls within the range of approximately 10% (0.1) or below. Additionally, Saaty (1977) introduced the consistency ratio (CR), depicted in equation 2, which involves comparing the consistency index with the random consistency index to evaluate their similarities.

$CR = \frac{CI}{RI}$

Where RI is the Random Index, and CI stands for Consistency Index.

- Synthesis of Results

After calculating the priority weights and confirming consistency, the final step involves synthesizing the results to rank the criteria and alternatives based on their importance (Saaty, 1980). High-ranking criteria and alternatives have a more significant influence on landslide susceptibility, while low-ranking ones are relatively less impactful.

A pair wise comparison matrix of each landslide influencing parameters was done and resulted Weight Eigen Vector (WEV) values were calculated.

The consistency index (CI) for the favorable factors is 0.00, which is less than 10%. This indicates that the assigned weights are appropriate for generating the landslide susceptibility map of the study area using the weighted overlay method (WOM) (Shit et al., 2016)

Consequently, a weighted overlay method (WOM) was employed to parameter layers generated to delineate the final landslide susceptibility map (LSM) using the equation specified in the methodology.

$$LSM = \sum_{h}^{m} (Rank_{ih} \times W_h) / \sum_{h}^{m} W_h$$

Where LSM = landslide susceptibility map

$Rank_{ih}$ = rating classes

W_h = weight of each landslide-inducing factors

Drainage Density and Distance from streams

Drainage density, an essential geomorphic parameter, represents the ratio of the total length of streams and rivers to the area of a drainage basin. It plays a vital role in natural processes such as slope stability and landslide occurrence. This article delves into the concept of drainage density, the factors influencing it, and its impact on slope stability and landslides.

The link between drainage density and landslide occurrence is well-documented (Ajin et al., 2016). Areas with moderate to high drainage density are more susceptible to landslides. The concentration of watercourses in these areas enhances erosion and slope destabilization.

Measuring drainage density through proximity to streams provides valuable insights into a landscape's vulnerability to slope instability and landslides. Higher drainage density, marked by closer watercourse proximity, increases landslide risk due to intensified erosional forces.

The study examined existing landslide locations concerning their distance from streams, revealing that landslide events were most frequent within buffer zones of 0-100 meters, 100-500 meters, and 500-1000 meters from streams. This underscores the importance of stream proximity in affecting slope stability and landslide susceptibility.

Using SRTM-DEM, a distance-from-stream map was generated in a GIS environment. The distances were categorized into 0-100m, 100-500m, 500-1000m, 1000-1500m, and >1500m, with the area and number of landslides for each class calculated (Table 1). The distance-from-stream map is shown in Fig. 4.3, and the drainage density map in (Fig.1a).

Tab 1 - Distance from stream and number of landslides in each class.

S No	**Distance from stream**	**Area (Sq.km)**	**Area %**	**Number of landslides**
1	0 – 100m	328	5.35 %	22
2	100 – 500m	1182	19.28 %	95
3	500 – 1000m	1365	22.26 %	46
4	1000 – 1500m	1175	19.16 %	7
5	> 1500m	2080	33.93 %	10

Tropical wetness Index (TWI)

The Topographic Wetness Index (TWI) is a key hydrological metric that helps in understanding how topography influences the formation and extent of saturated source areas for runoff generation. It is a vital element in runoff modeling and has been extensively analyzed by (Pourghasemi et al. (2012) and Pradhan and Kim (2014).

TWI is calculated using the formula: Ln[AS/tan(β)], where AS represents the specific catchment area of each cell, and β is the slope gradient in degrees. This method was first introduced by (Moore et al. (1988) and later employed by (Saadatkhah et al. (2014). In saturated soil conditions, surface moisture follows predictable downhill flow patterns, governed by gravity and flow dynamics.

In this study, TWI was divided into five classes—very low, low, medium, high, and very high—as shown in Table 2. This classification provides valuable insights into the runoff generation potential across different regions and the map in (Fig.1b).

Table 2- Tropical wetness index and Number of Landslides in each Class.

S No	Tropical wetness Index (TWI)	Area (Sq.km)	Area %	Number of landslides
1	Very Low	2762	42.49 %	85
2	Low	2181	35.55 %	56
3	Medium	1044	16.06 %	19
4	High	401	6.16 %	11
5	Very High	112	1.72 %	8

Rainfall

Rainfall plays a crucial role in triggering landslides worldwide, making it the most significant factor in landslide occurrences (Marc et al., 2018; Jia et al., 2020). Rainfall-induced landslides are one of the most common geological hazards, posing severe threats to mountainous regions across various spatial and temporal scales (Lai et al., 2018).

In mountainous areas, shallow landslides are typically triggered by either high-intensity, short-duration rainstorms or prolonged, low to medium-intensity rainfall events (Cheila et al., 2016; Anna et al., 2020). Landslides often cluster during periods of intense rainfall, with the potential to evolve into debris flows or be associated with flash floods, leading to casualties and significant economic losses (Tohari, 2018; Yang et al., 2020).

For this study, an annual average rainfall map was generated in a GIS environment using the interpolation technique IDW (Fig.1c). The station data, collected from IMD, when interpolated, highlighted the rainfall distribution across various locations. The southern part of the study area experienced higher rainfall, whereas the northern regions received comparatively less. About 30.15% (1,850 km²) of the area received very high annual rainfall (>2000 mm) and the majority of landslides occurred in these high rainfall zones, followed by areas with slightly lower rainfall, indicating a clear link between rainfall and slope instability as shown in (Tab. 3).

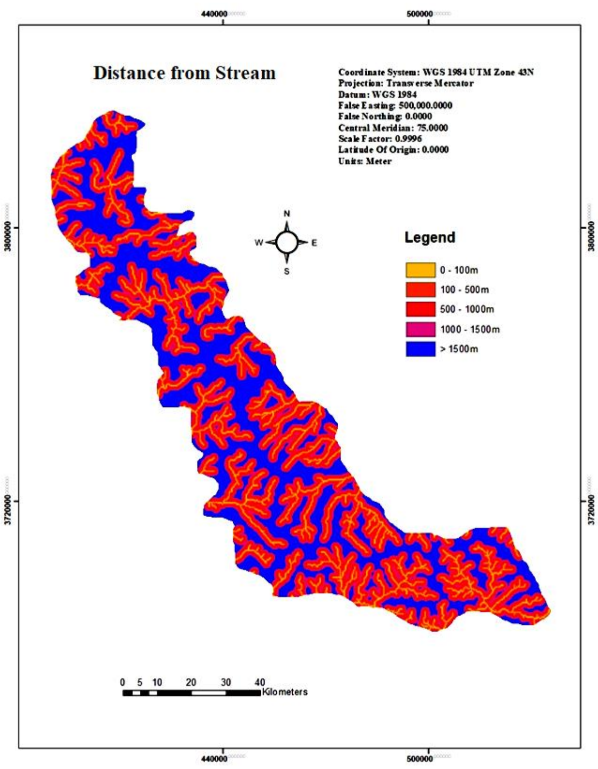
Table 3- Annual Rainfall and Number of Landslides in each Class.

S No	Annual Rainfall	Area (Sq.km)	Area %	Number of landslides
1	< 1250 mm/yr	834	13.60 %	3
2	1250 – 1500 mm/yr	1034	16.86 %	13
3	1500 – 1750 mm/yr	1101	17.95 %	5
4	1750 – 2000 mm/yr	1314	21.42 %	15
5	> 2000 mm/yr	1849	30.15 %	144

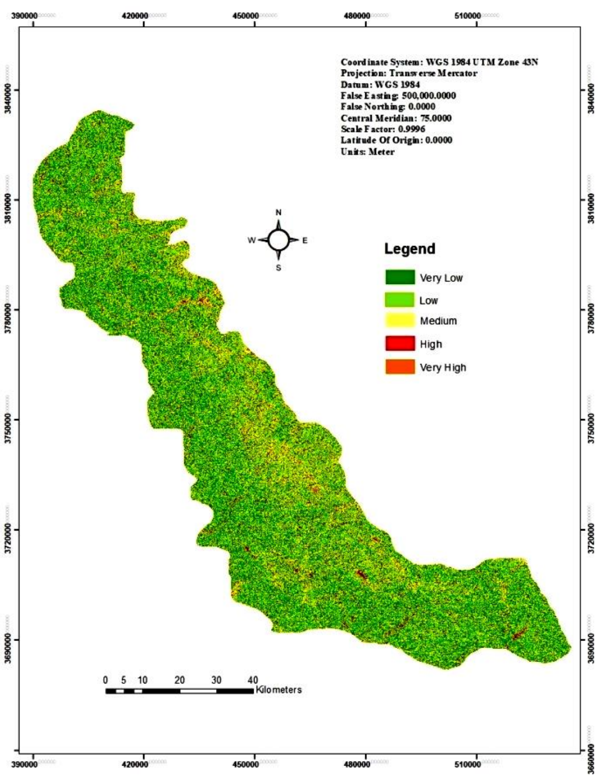
Landslide Inventory Mapping

The first and essential step in understanding landslides is conducting an inventory study (Strom and Abdrakhmatov, 2017). A landslide inventory database helps identify locations affected by landslides within the study area (Gerzsenyi and Albert, 2021), forming a foundation for hazard, risk, and prevention studies (Fan et al., 2019).

In this study, the landslide inventory dataset includes 180 landslides, mapped through visual interpretation of optical satellite images, Google Earth image analysis, news reports from multiple sources (timesofindia.indiatimes.com, indianexpress.com, onmanorama.com, mathrubhumi.com, etc.), GSI field reports (gsi.gov.in), and field surveys (Fig. 1d). The types of landslides identified include debris flow, earth flow, subsidence, rockfall, creep, and rock-cum-debris slide. The landslide footprints were vectorized using high-resolution Google Earth imagery.



(a)



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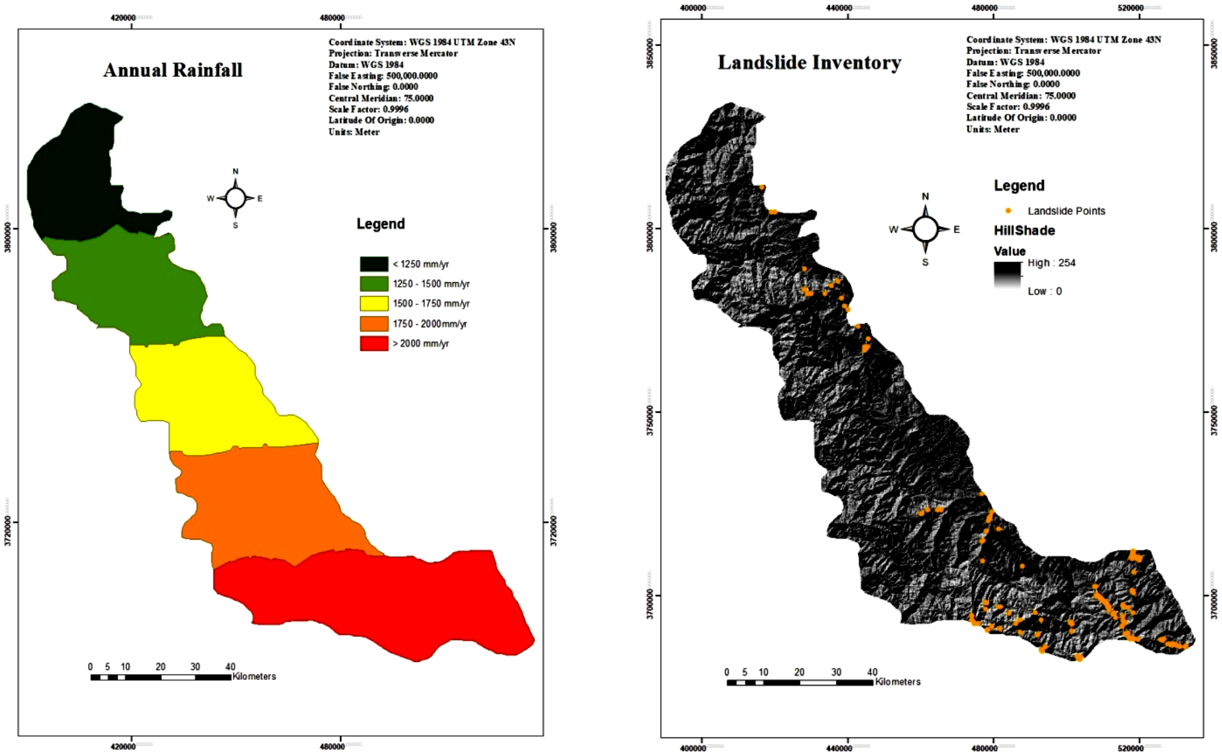

Fig – (a) Streams , (b) Tropical wetness index, (c) Annual Rainfall, (d) Landslides

AHP Ranking

Numerous researchers across the globe have employed the Analytical Hierarchy Process (AHP) method to construct landslide susceptibility maps (Ashok and Reghunath, 2017; Noorollahi et al., 2018; Stanley and Kirschbaum, 2017; Handong et al., 2019; Milevski et al., 2019; Kumar and Anbalagan, 2016). In this particular study, the landslide susceptibility map was prepared using the GIS-based AHP method.The analysis involved three hydrological landslide-influencing parameters, namely rainfall, tropical wetness index, distance from stream. To ensure the accuracy of the weights assigned to each parameter, the AHP method was utilized. The AHP method facilitated obtaining proportion scales from paired comparisons (Saaty, 1977 & 2000), while ranks and weights were assigned based on existing literature (Saaty, 1977).Each parameter's influence on landslides was assessed through expert opinions and ranked on a scale ranging from 1 to 9

The hydrological parameters contributed essential in delineating the landslide susceptibility zones . The ranks and weights assigned for each parameter as per AHP can be found in (Table 4),following the methodology laid out by Satty 1977.

Tab 4- Parameters and weights

Factors	Annual Rainfall	Distance from stream	TWI	Normalized Weights
Annual Rainfall	1	2/3	2/3	0.2501
Distance from stream	1 1/2	1	1	0.3750
TWI	1 1/2	1	1	0.3750
Maximum Eigen Value =3.00 C.R.=0.000				

The overall consistency index, calculated as 0.000, suggests that the assigned weights are suitable and consistent.

GIS Overlay Analysis and results

The identification of landslide susceptibility zones within the study area draws upon a multifaceted set of hydrological factors including rainfall, topographic wetness index, distance from streams. The integration of these diverse inputs, in conjunction with relevant parameters, forms a pivotal step in this process Employing the Analytic Hierarchy Process (AHP) method, suitable weightage is assigned to each factor, ensuring a balanced and informed approach.The amalgamation of this quantitative data takes place within the GIS framework. Through numerical integration, the influencing parameters are subjected to reclassification (refer to Table 5), subsequently undergoing processing within the "Raster Calculator" function of the spatial analysis tool.

Table- 5 Rank and Weights of Influencing Parameters for Landslides

Parameters	Class	Area(km2)	Rank (% influence)	Weight
Annual Rainfall	< 1250 mm/yr	834	40%	3
	1250–1500 mm/yr	1034		5
	1500–1750 mm/yr	1101		5
	1750–2000 mm/yr	1314		7
	> 2000 mm/yr	1849		9
Dist from stream	0 – 100m	328	40%	9
	100 – 500m	1182		9
	500 – 1000m	1365		7
	1000 – 1500m	1175		5
	> 1500m	2080		3
Tropical wetness index (TWI)	Very low	2762	20%	7
	Low	2181		7
	Moderate	1044		7
	High	401		9
	Very high	112		9

Employing a straightforward arithmetic calculation, these parameters are seamlessly combined. The resultant Landslide Susceptibility Zonation map (depicted in Figure 2) is stratified into three distinct zones:, 'High Susceptibility Zone', 'Moderate Susceptibility Zone', and 'Low Susceptibility Zone' and the distribution of landslides in each zone is calculated.

The study found out that the areas under high influence of hydrological factors have the most number of landslides. This signifies that hydrological processes in the region are one of the most important factor that causes landslides as shown in (Tab 6)

Table 6- Spatial Distribution and number of Landslides Presented in each Landslide Susceptibility Classes

Susceptibility Classes	Area in Km^2	Area in %	Landslide in each class
Low	299	4.88 %	1
Moderate	2420	39.55 %	12
High	2734	44.68 %	40

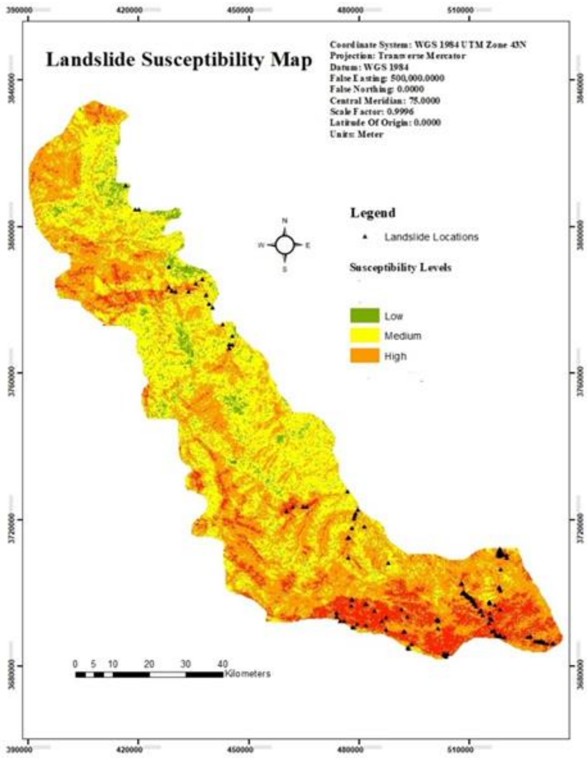

Fig 2- Landslides Susceptibility Map of the Study Area

Conclusion

Regions with high precipitation and elevated wetness indices have been identified as particularly prone to erosion, especially in barren land areas. The methodology employed in this study has proven to be an effective and efficient way to assess erosion susceptibility over vast areas qualitatively. This approach holds significant value for planners and policymakers as they devise conservation strategies. By providing reliable predictions, this study assists decision-makers in reducing potential soil erosion damage in the Sind and Dachigam catchments.To mitigate soil loss, it is crucial to review and refine current scientific management practices and implement appropriate conservation measures at the catchment level. Key recommendations include afforestation, urban tree planting, controlling overgrazing, contour farming, water conservation systems, and the establishment of flood and erosion control structures, as well as runoff water catchment systems. The influence of the aspect factor, which affects the overall erosion dynamics, also demands attention in such evaluations.Moreover, the adoption of conservation techniques like no-till (NT) farming, where seeds are planted directly into unploughed stubble, can greatly reduce soil disruption. This method offers environmental advantages, including diminished erosion risks by improving soil structure and maintaining plant cover. These strategies not only help in reducing soil erosion but also enhance soil health, crop yield, and ultimately, the livelihoods of local communities.It is important to recognize, however, that uncertainties exist in the conditioning factors, and expert judgments may introduce a degree of subjectivity. Future assessments of erosion susceptibility should consider incorporating fuzzy logic or machine learning algorithms, while also accounting for significant variables like changes in rainfall patterns and intensity under evolving climate change conditions.

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