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GIS-based landslide susceptibility mapping using analytical hierarchy process: a case study of Astore region, Pakistan

Nouman Afzal[1], Adeel Ahmad[2]*, Safdar Ali Shirazi[2], Isma Younes[2], Le Thi Thu Ha[3]

1 Department of Geography, Forman Christian College (A Chartered University), Lahore, Pakistan
2 Department of Geography, University of the Punjab, Lahore, Pakistan
3 Hanoi University of Mining and Geology, Hanoi, Vietnam

*Corresponding author E.mail: adeel.geog@pu.edu.pk

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Abstract

In this study, landslide susceptibility analysis were undertaken in the Astore region, Pakistan. The Geographical Information System (GIS) and Remote Sensing (RS) techniques were used along with the analytical hierarchy process (AHP) to find out the landslide susceptibility of the region. The Astore, lying in the Himalayan mountains, experiences frequent landslides due to several triggering factors. Factors including slope, lithology, aspect, topographic wetness index (TWI), plan curvature, stream power index (SPI), distance from drainage, land use land cover (LULC) and soil were used. Each factor was processed in the GIS environment and weighted through the AHP technique. AHP weights were derived with a consistency ratio of 0.06. Finally, the five zones, very low, low, moderate, high, and very high are respectively covering 20.5% (28.98 km^2), 33.1% (46.78 km^2), 30.6% (43.26 km^2), 10.8% (15.28 km^2), and 4.9% (6.92 km^2). Slope, lithology and LULC were the most important factors in triggering landslides.

Keywords

landslide susceptibility, GIS, AHP, Astore, lithology

Introduction

Landslides are one of the most destructive natural hazards, particularly in mountainous regions (Landslides. 2005; Yalcin et al., 2011). Like most other developing countries, Pakistan experiences several natural hazards, such as earthquakes, floods, landslides, etc. The mountainous northern area of Pakistan is geomorphologically very active, making landslides a frequent and ever-present hazard for the people living there. The Centre for Research on the Epidemiology of Disasters (CRED) in their Emergency Disaster Database 2007 showed that landslides claimed around 1000 lives and damaged property worth $4 billion annually (Emergency Disasters Data Base, 2007; Sato and Harp, 2009). Our study area, the Astore region, experiences landslides on a regular basis. In 2002, landslides triggered by earthquake killed 23 people in the Astore region and made 1500 people homeless in Astore and Gilgit areas (Iqbal et al., 2017). Landslides damaged buildings and infrastructure, transportation networks, ongoing projects and private property. This enormous loss of property is greater than caused by any other disaster, including floods and earthquakes (García-Rodríguez et al., 2008). Almost 72,496 square kilometers (km^2) of

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Pakistan's land surface comprising high snow-covered peaks with altitudes ranging up to 8000 m above sea level (Kanwal et al., 2016). Three mountain ranges, Karakorum, Himalayas and Hindukush, make up the northern area of Pakistan. Being the youngest of the mountain system, the Himalayas experience 30% of the landslides occurring throughout the world due to intense and prolonged rain showers, active seismicity, erosion and high-topographic relief and most importantly, slope failure (Kanwal et al., 2016). Catastrophic landslide incidents such as the 2005 earthquake and Atta Abad landslides have also been widely reported throughout this region (Kamp et al., 2008; Khan et al. 2010; Cook and David, 2013).

Landslide susceptibility mapping is the first step in landslide assessment, planning and disaster management. Since several factors cause landslide, this leads to decisional imprecision and uncertainty problem. In order to incorporate this, many studies have applied a multicriteria decision-making approach such as Analytical Hierarchy Process (AHP) (Kanwal et al., 2016; Chandio et al., 2013).

Hence, it is critical to carry out landslide susceptibility mapping for better landslide hazard and risk management (Ahmed et al. 2014). Despite this knowledge, the amount of research done on landslides in Pakistan is very limited. The majority of the research has focused on only a few regions such as Murree, Kaghan valley, and Kashmir valley (Akbar and Ha, 2011; Rehman et al., 2011; Khan et al., 2013). In recent years, some studies have shifted their focus to other regions such as Hunza, Gilgit and Ghizer district (Ali et al., 2015, Rahim et al., 2018, Khan et al., 2019). These studies have carried out landslide susceptibility analysis by applying Geographical Information System (GIS) and Remote Sensing (RS) techniques, but overall there is a dearth of reasrat on landslides reas assessment of most reas of Pakistan, including our study rea, the Astore reas (Kanwal et al., 2016), (Kamp et al. 2008; Rahman et al., 2014). Since landslide has a strong social and economic reasra the Astore reas and its people, our study would help identify areas that are more prone to landslides and help guide the decisions of the development authorities. This would ultimately reduce landslide's impact on human life and infrastructure in Astore region.

This study aimis study seeks to integrate GIS and RS to create a landslide susceptibility map of Astore region, identify areas that are more prone to landslides, and find out about the most important factors that trigger landslides. To achieve this outcome, we identified nine factors that can trigger landslides which are categorized into topographic parameters (slope, aspect, plan curvature, soil), hydrological parameters (distance to drainage, topographic wetness index and stream power index), human-induced parameters (land use land cover) and lithology. We used the Analytical Hierarchy Process (AHP) technique, a heuristic approach, to handle uncertainty and decisional imprecision associated with this study (Chandio et al. 2013). A landslide susceptibility map is generated for the Astore region by applying these techniques and is reclassified into five zones: very low, low, moderate, high and very high.

Study Area

The Astore is one of ten districts of Gilgit-Baltistan, which is an administrative territory of Pakistan. It is bounded to the north by the Gilgit district, to the south by Khyber-Pakhtunkhwa and Neelum districts of Azad Kashmir, to the east by Skardu district and the west by Diamer district. The region covers a total area of 5092 km^2. The mean and median elevations of the Astore basin are 4100 and 4564 above sea level, respectively (Tahir et al., 2015). The climate of Astore is moderate during summer and cold during winter, with higher rainfall levels than surrounding areas (Tahir et al., 2016). Figure 1 shows the study area at national, regional and local extent.

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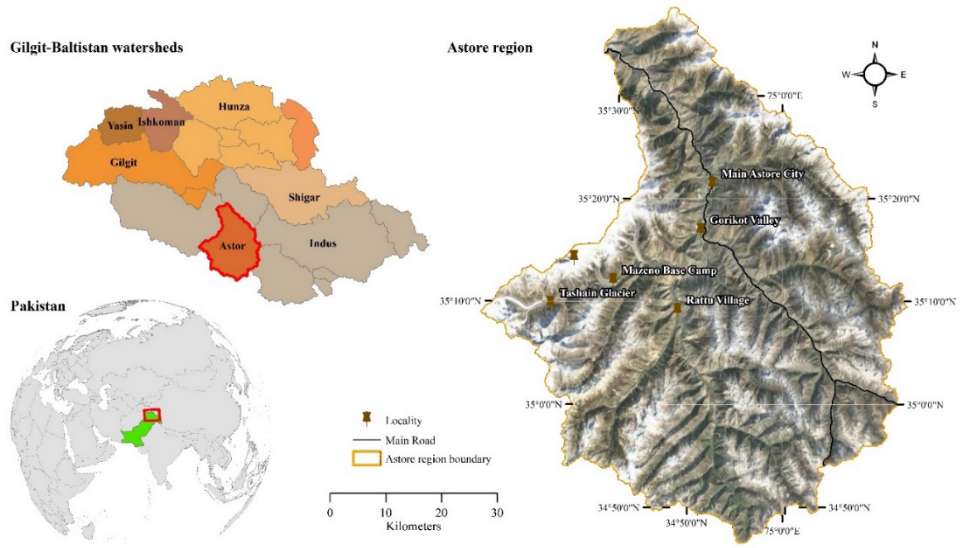

Figure 1. The study area map of the Astore region at the global, regional and local extent.

Materials and Methods

A heuristic approach based on qualitative indexes was applied alongside GIS and RS techniques to perform susceptibility mapping of the Astore region (Solaimani et al., 2013; Sørensen et al., 2006; Hadmoko et al., 2009; Arnous, 2011; Akgun, 2012). The complete research processes undertaken in this study are presented in Figure 2. Landslide is a complex phenomenon influenced or triggered by the interaction of various factors or variables (Saha et al., 2002; Solaimani et al., 2013; Anbalagan et al., 2015). For this study, we selected nine factors for the landslide susceptibility analysis because of their importance and influence in the study area. These nine factors were categorized into four groups. The first group represents topographic parameters: slope, aspect, plan curvature, and soil. The second group comprises hydrological parameters containing topographic wetness index, stream power index, and distance to drainage. The third group includes land use land cover, an anthropogenic factor, while the fourth group consists of lithology.

Topographic factor

It includes parameters that define the topography of an area, such as slope, aspect, plan curvature and soil. A Digital Elevation Model (DEM) was downloaded free from the EarthExplorer website and used to create several thematic layers (Quan and Lee, 2012).

The slope is known to cause landslides and hence, has been repeatedly employed in landslide susceptibility studies (Ercanoglu et al.. 2004). The Slope stability is dependent on the angle of the slope; the steeper the slope, the higher the probability of landslide (Rehman et al., 2011). A slope map was derived, as shown in figure 3, from the DEM with elevation values ranging from 0 to 87.5 and divided into five classes: very gentle slope (0-10°), gentle slope (10-20°), moderately steep slope (20-30°), steep slope (30-50°), and extremely steep slopes or escarpments (>50°). Landslide occurrence is highly unlikely due to lower sheer shear stress in the first class. Each class was assigned weights on the principle that landslide susceptibility increases as slope steepness increases (Kanwal et al., 2016).

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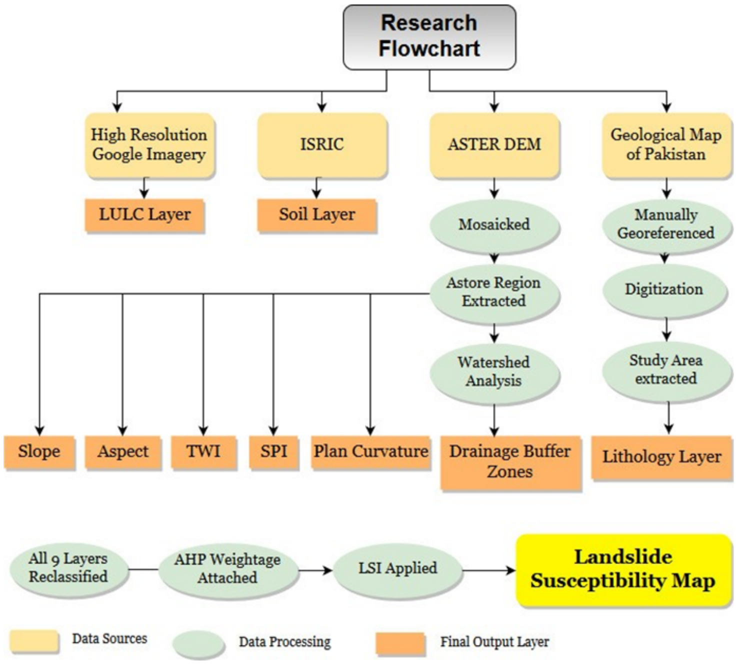

Figure 2. Research flowchart systematically displaying the steps undertaken for this study.

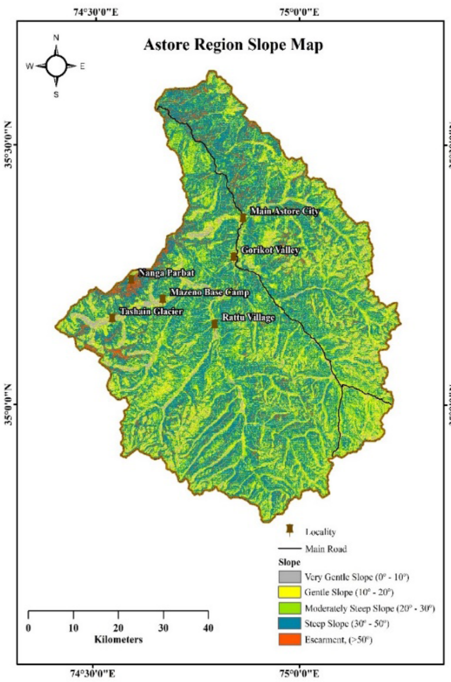

Figure 3. Slope map of Astore region.

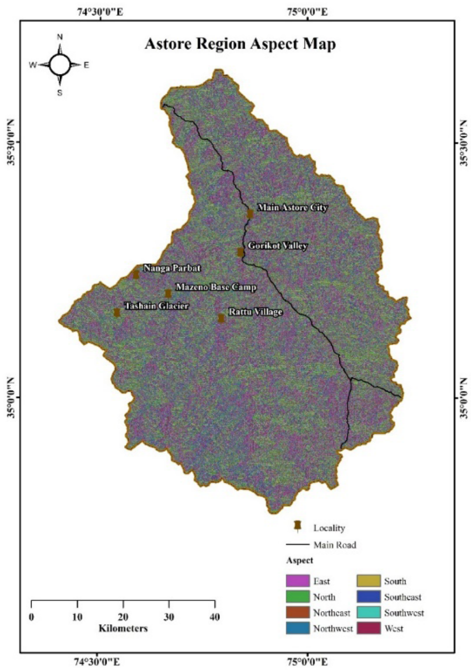

Figure 4. Aspect map of Astore region

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Aspect is another topographic parameter employed in landslide susceptibility analysis. Meteorological events such as the amount of rainfall, exposure to sunlight, and discontinuities can also affect the possibility of landslides (Komac 2006). Aspect deals with these factors and breaks down the slope surfaces unevenly. Aspect was also derived from the DEM of the Astore region. It was observed in the literature that due to south-east to the south-west azimuth of periodic monsoon rainfall, slopes with south to north-west direction experienced the strongest impact (García-Rodríguez et al. 2008; Cook and David 2013). Based on this concept, the west side was given the highest weight, followed by the south-west and north-west. The resultant raster layer, as shown in figure 4, was classified into nine categories: north (0-22.5°, 337.5-360), northeast (22.5-67.5°), east (67.5-112.5°), south-east (112.5-157.5°), south (157.5-202.5°), south-west (202.5-247.5°), west (247.5-292.5°), and north-west (292.5-337.5°).

Curvature is defined as the second derivative of a surface or slope of the surface (Kimerling et al. 2012). Curvature defines the shape and form of the topography. The curvature of a surface could be concave, convex or flat. A concave slope has a higher water retention capability after rainfall and could retain water for a greater period. On the contrary, the convex slope indicates a rocky outcrop of solid bedrock. It means that a concave slope has a higher possibility of landslide occurrence and convex slope a lower chance of landslide occurrence. A plan curvature raster layer was derived from depression-less Aster DEM (Abuckley 2010). A positive curvature value characterizes an ascendingly convex slope, whereas a negative curvature value represents a concave slope.

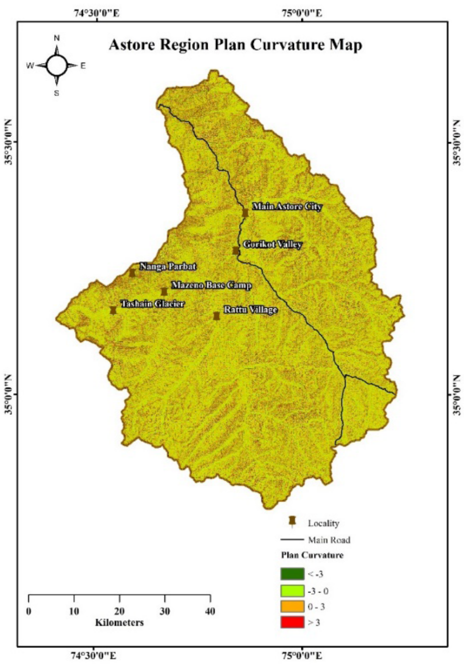

Figure 5. Plan curvature map of Astore region.

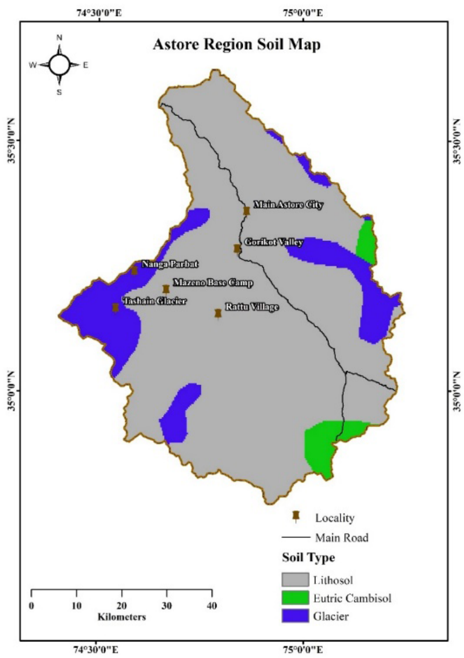

Figure 6. Soil map of Astore region.

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Zero value represents a flat surface (Poudyal et al. 2010). Based on the above relationship, we can say that a negative value poses a higher risk of landslide occurrence and vice versa. The curvature raster file was divided into four classes: <3, -3 – 0, 0 – 3, and >3, as shown in figure 5.
Soil type can also significantly influence the possibility of landslides. Different soil types have different properties such as compactness and water retention quality (Ray et al. 2010). The soil data was obtained from the International Soil Reference and Information Center (ISRIC). It was classified into three categories: Glacier, Eutric Cambisols, and Lithosols. Lithosols are found to have the highest potential for causing landslide. They are a soil type that contains weathered rock fragments and are present mostly on steep slopes. Cambisols are formed of silicate clay but lack adequate soil development (Wageningen). Lithosols were given the highest weight, followed by cambisols and glaciers, as shown in figure 6.

Hydrological factors
Topographic wetness index (TWI), stream power index (SPI), and drainage distance are considered hydrological parameters. TWI is used to measure how local topography controls local hydrological processes and shows the spatial spread of surface saturation and soil moisture (Sørensen et al. 2006). The algorithm for calculating TWI is different for different areas and depends on how the local upslope contributing area is calculated. The algorithm must show the impact of local terrain on drainage (Qin et al. 2011). The equation [1] (Sørensen et al. 2006; Qin et al. 2011) presents calculations for TWI:

$$TWI = ln\left(\frac{As}{tan\beta}\right) \quad [1]$$

Where 'As' is the local upslope contributing area (m^2/m) and β is the local slope gradient in degrees.
The resultant TWI raster layer contained positive values. An increase in TWI values indicates an increase in the catchment area and a decrease in slope angle. The higher the TWI value, the greater is the chance of landslide (Gorsevski et al. 2006; Lee and Min 2001). This TWI layer was reclassified into three categories: <8, 8 – 12, and >12, as shown in figure 7.
SPI calculates stream erosion power and adds instability in an area. It contains both negative and positive values. A higher value of SPI refers to steep and straight gorges, whereas a lower value of SPI represents wide alluvial flats and floodplains (Kamp et al. 2008). Equation [2] (Poudyal et al. 2010) was used to calculate SPI:

$$SPI = As * tan\beta \quad [2]$$

Where 'As' is the local upslope contributing area (m2/m) and β is the local slope gradient in degrees.
Slope values that were originally in degrees were converted into radians. The original raster layer was classified into four categories: - 5.5 – 0, 0 – 3, 3 – 6, and >6, as shown in figure 8.
Distance to drainage is also another parameter that affects the stability of a slope. In mountainous areas such as the Astore region, topographic hill slopes are negatively altered by gorges and streams by erosion. Streams also saturate the slopes until the water level increases. Drainage of the Astore region was extracted from depression-less ASTER GDEM by performing the watershed analysis (Tarboton and Maidment 2015). Four buffer zones were created of the distance to drainage: 0 – 500, 500 – 1000, 1000 – 1500, 1500 – 2000, as shown in figure 9.

Anthropogenic factors
Land use land cover is one of the main anthropogenic factors that can strongly affect slope stability by controlling the mechanical and hydrological mechanisms. The land cover works as a natural shelter and prevents soil erosion and landslides. Vegetation affects soil

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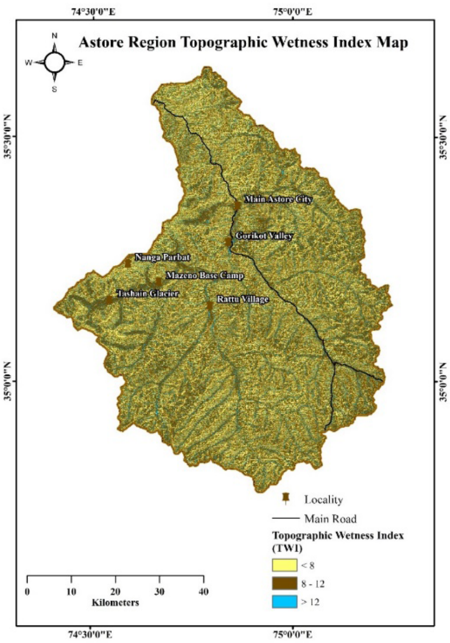

Figure 7. Topographic wetness index map of Astore region.

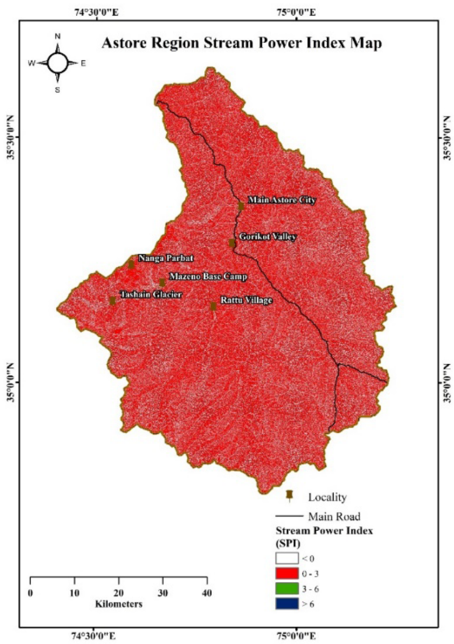

Figure 8. Stream power index map of Astore region.

hydrology in terms of infiltration, interception, and evapotranspiration.

Roots hold the soil and increase soil strength which can significantly decrease the chances of landslide occurrence. On the other hand, Barren land is more susceptible to landslides because it is exposed. Roots also enhance soil permeability and, ultimately, conductivity and infiltration. This allows for better water collection in the soil (Reis et al. 2012). For this study, Land use land cover (LULC) was prepared, as shown in figure 10, by performing Maximum Likelihood Classification on the satellite imagery of the Astore region. LULC was divided into the following classes:

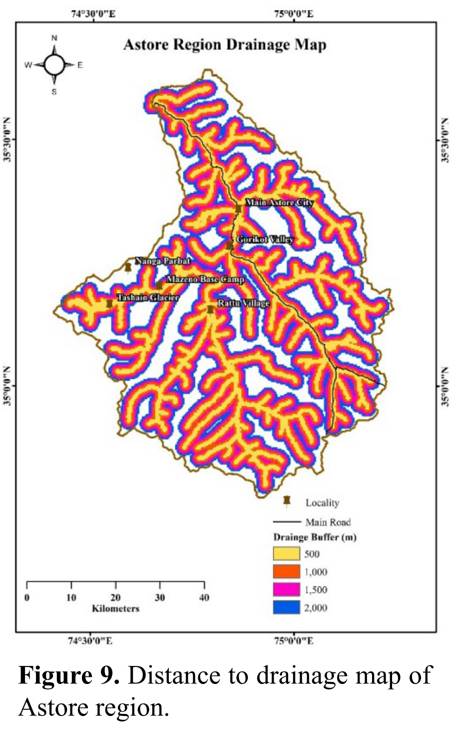

Figure 9. Distance to drainage map of Astore region.

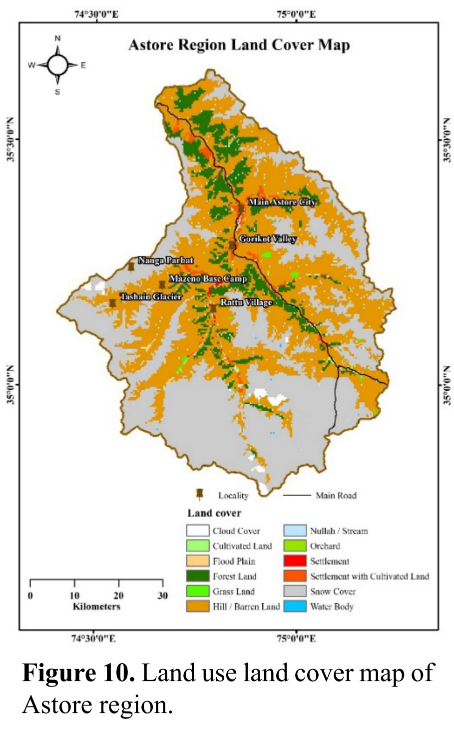

Figure 10. Land use land cover map of Astore region.

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settlements, settlements with cultivated land, waterbody, streams, forest land, cultivated land, cloud cover orchard, floodplain, grassland, and snow-cover and hill/barren land.

Lithology/Geology

A landslide is a geomorphological event that is very much associated with the lithological characteristics of the land. Various lithological units have varying strength and different susceptibility degrees (Yalcin et al. 2011). Lithological data was acquired from the Geological Map of Pakistan prepared by the Survey of Pakistan (SoP). According to the classification defined by SOP, the Astore region contained six different rock classes. For our analysis, these lithological units were classified into three rock types: Hard, medium and soft depending on their power to cause landslide; hard (Gg, Pz, m), medium (Kv), and soft (MPv, pC) (Fig. 11).

Apart from these factors, there are also many other factors that can influence a landslide event, such as rainfall and fault lines (Quan and Lee 2012; Kanwal et al. 2016; Feizizadeh and Blaschke 2011). But these factors were not considered in this research due to the non-availability of data.

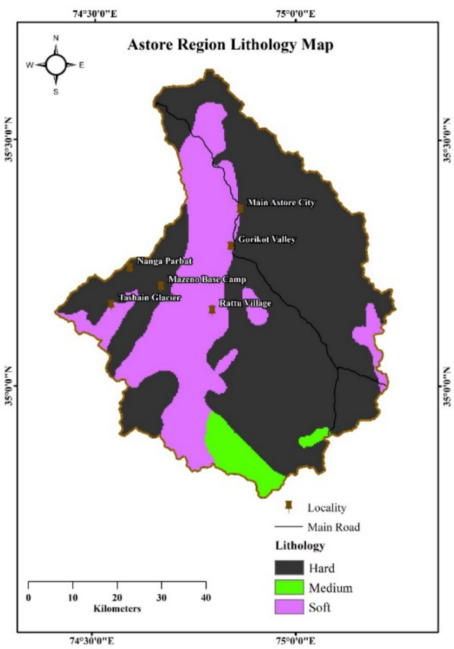

Figure 11. Lithology map of Astore region.

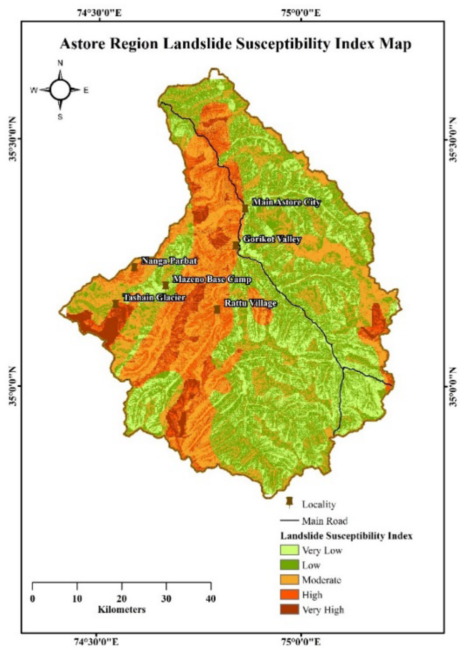

Figure 12. Landslide Susceptibility Index map of Astore region displaying the five susceptibility zones.

1.1.1 AHP Technique

The weights of all the parameters were determined using AHP based on local topographic and atmospheric characteristics, previous literature and expert judgement (Chandio et al. 2013; Feizizadeh and Blaschke 2011; Kanwal et al. 2016; Pourghasemi et al. 2013; Quan and Lee 2012; Reis et al. 2012; Saaty 2001). Before creating the landslide susceptibility map, each factor's weight and rating value was calculated. Each factor was broken down into different classes and systematically assigned a rating value from 1 to 9, based on Saaty's fundamental scale (Table 1).

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Fundamental Scale for Pair-wise Comparisons	
1	Equal importance
3	Moderate importance
5	Essential or strong importance
7	Very strong or demonstrated importance
9	Extremely high importance
2, 4, 6, 8	Intermediate values

Table 1. *Fundamental scale for pair-wise comparisons*

Following the same procedure, weight values were calculated. The weight value provides the relative importance of each factor among other factors. The rating and weight value increased as the degree of susceptibility increased (Saaty, 1980). Pair-wise comparison allowed for the comparison of elements against each other (Thanh and De Smedt, 2012) (for more information on the AHP technique, see Saaty (2001)). We measured the consistency of our expert judgement by calculating the consistency index (CI), which is defined by the following equation [3] (Saaty, 2001; Saaty, 1980).

$$CI = \frac{\lambda max - n}{n - 1} \qquad [3]$$

Where λmax is the principal eigenvalue of the matrix and n is the order of the matrix. We use this index to compare it with the Random Consistency Index (RI). Finally, the consistency ratio was calculated using equation [4]:

$$CR = \frac{CI}{RI} \qquad [4]$$

Ideally, this value should be 0. But if the value is less than 0.1, then the comparison is consistent. Otherwise, values within the matrix based on subjective judgment need to be revised (Gao and Wang 2016). For all our comparisons, this value was less than 0.1.

Random Consistency Index (RI)										
n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

Table 2. *The random consistency index table*

Landslide susceptibility index

Once all the factors are classified and their pair-wise comparison-based matrices are generated, the landslide susceptibility index (LSI) was calculated with the help of the following equation [5] (Kanwal et al. 2016; Gao and Wang 2016):

$$LSI = \sum_{j=I}^{n} W_j W_{ij} \qquad [5]$$

where: Wj = weight value for parameter j; Wij = rating value or weight value of class I in parameter j; n = number of parameters.

LSI values were classified into five categories: very low, low, moderate, high and very high susceptibility.

Results

One of our research objectives was to determine the most important factors that trigger landslides using AHP. The -AHP pair-wise comparison matrix results showed that slope received the highest weightage of 0.304, followed by geology/ lithology (0.243) and LULC (0.140). A complete calculated score of each factor can be found in Table 3. The consistency ratio was found to be 0.062. Slope received the highest weight because it is considered as the prime factor in inducing landslides. In the lithology layer, soft rock type was given the highest weight because soft rocks such as tuff, lava, Dogra slates etc. easily break down and are more prone to landslides due to

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weak composition, spaces in between and more water content, compared to hard rocks such as granite, schist, gneiss etc.

Table 3. AHP weight matrices sheet displaying the weightage value of each factor along with the λmax, consistency index and consistency ratio values

Pair-wise comparison matrix, factors weight, λ max, CI and CR										
Factors	1	2	3	4	5	6	7	8	9	Weightage
(1) Slope	1.00	9.00	6.00	2.00	7.00	8.00	4.00	3.00	5.00	0.304
(2) Aspect	0.11	1.00	0.33	0.13	0.33	0.50	0.17	0.20	0.25	0.020
(3) Plan Curvature	0.17	3.00	1.00	0.20	2.00	3.00	0.25	0.33	0.50	0.052
(4) Geology	0.50	8.00	5.00	1.00	6.00	7.00	3.00	4.00	5.00	0.243
(5) SPI	0.14	3.00	0.50	0.17	1.00	2.00	0.20	0.25	0.33	0.038
(6) TWI	0.13	2.00	0.33	0.14	0.50	1.00	0.20	0.25	0.33	0.028
(7) Soil	0.25	6.00	4.00	0.33	5.00	5.00	1.00	2.00	3.00	0.140
(8) LULC	0.33	5.00	3.00	0.25	4.00	4.00	0.50	1.00	2.00	0.105
(9) Distance from Streams	0.20	4.00	2.00	0.20	3.00	3.00	0.33	0.50	1.00	0.070
λ max						9.713				
CI						0.089				
CR						0.061				

Figure 12 shows the final landslide susceptibility map, the composite map of all nine layers. The map was divided into five susceptibility zones: very low, low, moderate, high and very high. The Astore region is spread over 141.1 km^2 with 4.9% (6.92 km^2) of the area under the very high susceptibility zone. Similarly, 10.8% (15.28 km^2) of the area was labelled high susceptibility zone. As seen in Table 4, the low susceptibility zone occupied the largest area which is 33.1%, followed by 30.6% occupied by the moderate susceptibility zone.

Value	Count	LS Zone	Area (Km^2)	Percentage Area
1	1034777	Very low	28.98	20.5%
2	1670192	Low	46.78	33.1%
3	1544547	Moderate	43.26	30.6%
4	545627	High	15.28	10.8%
5	247037	Very high	6.92	4.9%

Table 4. *Landslide susceptibility zone area distribution showing the pixel count, actual area in km^2 and percentage area*

Discussion

The results show the majority of the high and very high landslide susceptibility is present in the area with a steep slope of 30 – 50°, soft rocks, hill/barren land, and a distance of 0-500 meters to the drainage. In most cases, precipitation is the triggering factor that causes landslides. But since the precipitation is evenly distributed over the whole area and is mainly influenced by the lithology and landscape, it was not included as a factor (Yalcin et al. 2011). A number of studies have found slope, lithology, LULC and distance to drainage as the most critical factors in causing landslides (Sarkar et al. 2014). Rainstorms or earthquakes are more likely to cause slope failure on steep slopes than on moderate or gentle slopes. Hence, 30-50° class received the highest weight within the pair-wise based comparison matrix of slope parameters. Mountains inherently

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have slopes that vary in degree, and this is the most important reason along with the lithology as to why landslides are a more frequent phenomenonphenomenon in mountainous regions. The vertical distance rocks travel due to landslides increases their acceleration and causes more destruction.

Other than slope, LULC also influenced the occurrence of landslides in an area. anthropogenic activities in the region are causing land changes for various purposes such as building roads, houses and hotels, agricultural purposes, or simply cutting trees for personal or commercial use. These activities have caused a change in the area's topography, which puts the area under stress (Kanwal et al. 2016). As seen in our results, barren land is most vulnerable to floods and landslides as it provides exposed surfaces for the free and rapid movement of water (Chandio et al. 2013). Trees are considered important buffers to floods as they reduce the speed of running water and prevent soil erosion.

Following this, the results showed that 96% of the high and very high landslide is present in soft rock type. In contrast to hard rocks, soft rocks are more likely to be a victim of weathering and erosion as a result of it. A number of studies have found the geology of an area as one of the most important landslide triggering factors. In the Astore region, soft rock groups contained Precambrian sedimentary rocks such as Dogra slate and Late Palaeozoic rocks such as lava, turf and agglomerate. These rock types are more likely to be weathered by microorganisms, water and ice, which makes them easy to slide and erode under the influence of gravity (Owen et al. 2008). Other factors such as distance to drainage, SPI, TWI, plan curvature, aspect and soil were also important. For instance, the closer the area was to the drainage, more likely it was to be affected by landslide. This is because streams and gorges shape the earth's surface by eroding the material with them. All of these factors define the characteristics of an area and their influence on triggering landslide, but slope, lithology, LULC and distance to drainage were recognized as the prime factors in landslide susceptibility analysis. It is important to acknowledge some of the limitations of our study. The non-availability of landslide inventory data by far is the most important limitation of this study. It posed a big challenge and limited our choice of methodology (Guzzetti et al. 2012). Therefore, the AHP technique was adopted since it compensates for the lack of landslide inventory data and identifies areas based on their inherent susceptibility to landslide. The DEM downloaded from earth explorer had a spatial resolution of 30 m x 30 m. The spatial resolution of DEM higher than 30 meters would have yielded more accurate results and improved the accuracy of different layers derived from DEM. Although rainfall, road and fault lines are important landslide inducing factors, they were not included in this study due to the non-availability of data. Adding these data sets into the study would have improved the study's accuracy. The AHP used in this research is a rating-based system using expert judgement. Expert input could be very beneficial, but it also raises the issue of subjectivity. Expert opinions may differ depending on their level of knowledge and perspective. The results may be subjected to subjectivity and uncertainty.

Conclusions

This study carried out landslide assessment to highlight high and low vulnerable areas. We identified nine topographical, hydrological, anthropogenic and geological factors that are likely to cause landslides in the Astore region. Given that a combination of these factors causes landslides and the relative importance of each of these factors varies from one area to another, we adopted a qualitative index-based heuristic approach. We carried out multicriteria decision analysis with the help of the analytical hierarchy process. It allowed us to deal with multiple variables using a systematic approach by breaking it down into classes and carrying

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out pair-wise comparisons. We also incorporated GIS and RS into our overall data analysis. With the help of GIS, we created spatial layers of each of our factors and categorized them into various classes. The final landslide susceptibility map of the Astore region was generated by applying a landslide susceptibility index formula within a GIS environment. This map was divided into five zones, from low to high susceptibility zones. The results showed that slope, lithology, LULC and soil were the most important landslide causing factors. In doing all this, we achieved all three of our research aims and objectives. Studies like this one would help highlight the threat posed by a landslide to life and property and show the importance of carrying out landslide susceptibility mapping of landslide-prone regions.

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