Susceptibility assessment of landslide using Analytical Hierarchy Process and Weighted Overlay Analysis, along N-75 highway, Pakistan

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Abstract: The N-75 highway has a strategic and socio-economic importance in North Pakistan and is prone to frequent disruption by landslides. For landslide mitigation strategies of this highway, comprehensive landslide inventory and susceptibility assessment are rarely available. This study presents the application of Analytical Hierarchy Process (AHP) and Weighted Overlay Analysis (WOA) models for the assessment of landslide susceptibility zonation map of the area. To perform these models, nine usual causative factors of landslides (slope, aspect, curvature, lithology, normalised differentiation vegetation index, rainfall, and distance from faults, roads, and streams) were taken into account. For the preparation of thematic maps and other data layers, Digital Elevation Models (DEM), existing geological maps, and authorized data were being processed in GIS environment (ArcMap 10.3). The output landslide susceptibility maps of the study area were classified into five (i.e. very low, low, moderate, high, and very high) landslide susceptibility classes. The competencies of the landslide susceptibility zonation maps derived from AHP and WOA models were validated using Area under Curve method. The developed susceptibility maps can be adopted for land use planning and landslide mitigation strategies.

Key words: Geohazards, landslide susceptibility assessment, GIS and Remote Sensing, Analytical Hierarchy Process, Weighted Overlay Analysis, Pakistan

1. INTRODUCTION

Landslides are considered as one of the major destructive geological hazards. About 16,000 people were killed in Europe in the last century (Nadim et al., 2006), with major fatalities around the world (20,000 to 50,000 in 1999 in Venezuela, 29,000 in 2008 in China) (Kjekstad & Highland, 2009; Petley, 2012). Economic losses from landslides have apparently increased as urban development spreads to hilly areas. Despite progress in landslide research, the social and economic impacts of landslides remain high because of the lack of proper mitigation strategies and early prediction measures (Westen et al., 2006).

In developing countries like Pakistan, landslides pose a significant threat to the mountain areas of northern Pakistan. Particularly, the threat is well recognized in the young Himalayan Mountains in north Pakistan due to inherently unstable nature of rocks, highly steep slopes, active seismicity, and monsoon rainfall in the area. The landslides caused by the 2005 Kashmir earthquake affected an aerial extent of >7500 km^2 (Kamp et al., 2008). Due to the Kashmir earthquake, about 2500 landslides were caused (Sato et al., 2007), which determined around 26,000 fatalities directly or indirectly (Mahmood et al., 2015). The Hattian Bala rock avalanche was the main landslide connected with the earthquake that entirely destroyed a village and congested the Jhelum River tributaries, forming a dam. The reported deaths were around 1000, due to this huge landslide and with overall volume of around 85×106 m^3; whereas, the affected region was around 1.8 km^2 (Dunning et al., 2007). Besides, massive infrastructure and human loss were caused by numerous landslides in Balakot and its surrounding (Jadoon et al., 2015).

Landslide susceptibility and risk assessment, and hazard analysis are very important to minimize the impact of landslides. Landslide susceptibility maps highlight the prone areas where landslides may occur in the future. Therefore, susceptibility maps are very important for effective landslide mitigation strategies and future planning in an area. The production of landslide susceptibility maps includes several external ecological and internal geological factors affecting the landslide distribution, such as lithology, slope configuration, drainage patterns, land use, rainfall, seismicity, dynamic loads, and climate change (Mehmood et al., 2021). With the advancement of technology, sophisticated and modern techniques such as logistic regression analysis, artificial neural network, analytic hierarchy process, and weighted overlay analysis have gained substantial importance for development of thematic data layers used to generate effective susceptibility mapping (Ahmed et al., 2014; Awawdeh et al., 2018; Basharat et al., 2016; Feizizadeh & Blaschke, 2013).

Despite of high threat to the socio-economic environment of northern Pakistan, especially in the Himalayas region, no recorded data in most areas on landslide susceptibility are available to assess and mitigate the impact of landslides. One such example is of N-75 highway in the Himalayan Mountains of Pakistan, which has national economic and strategic importance because is the only transportation route between Pakistan and

Manuscript received 2022-01-12
Revised version accepted 2023-05-26

Azad Jammu and Kashmir. This article provides landslide susceptibility analysis for the Lower Topa to Kohala bridge portion of the N-75 highway in order to decrease potential landslide damages (Fig. 1). This part of the highway is chosen since it was one of the worst-affected sections by landslides during and after the 2005 Kashmir earthquake. The key objective of this study is to generate landslide susceptibility maps of the N-75 highway using incorporated statistical technique Analytical Hierarchy Process (AHP) and Weighted Overlay Analysis (WOA). This approach uses information from the inventory map to forecast where landslides may occur in the future. The second objective of this study is to compare the results and precision of the two models AHP command tool and AHP combined with WOA and to indicate the future improvements of the technique. The applied approaches are simple and deliver comparatively quick results that can easily be rationalised on demand. This study is an effort to generate landslide susceptibility maps and indicate landslide susceptible zones to reduce destruction by landslides in future.

2. STUDY AREA

The study area encompasses a distance of 34 km along the N-75 highway in the northeast of the capital territory of Islamabad, Pakistan (Fig. 1). Geographically, the study area is located in the close vicinity of Murree, a mountainous tourist city in the NW Himalayan fold and thrust belt in Pakistan. The altitude of the study area ranges from 520 m to 2216 m above sea level and is often affected by landslides, particularly due to active tectonics, steep topography, high seismicity, and heavy rainfall.

Geologically, the study area is located in the southwestern part of the Hazara-Kashmir Syntaxis (HKS) in Pakistan (Fig. 2). The HKS is a regional antiformal syncline that folds the Lesser and Sub-Himalayas. The structural architecture of the study area is controlled by major thrust faults, as the Panjal Thrust (PT), Main Central Thrust (MCT), and Main Boundary Thrust (MBT), which are responsible for historical destructive earthquakes in the region (Baig & Lawrence, 1987; Chambers, 1992; Iqbal & Bannert, 1998). The north-south left-lateral Jhelum Fault (JF) links these major thrusts in the study area (Fig. 2). Stratigraphy of the area shows rock units having an important geological control on the mass movement activities. Along HKS, the Panjal Formation is sandwiched between the MBT and PT. The Cambrian Panjal Formation has been thrusted over the Miocene Murree Formation along the MBT. At the eastern limb of HKS, the PT marks tectonic boundary between Precambrian Tanol Formation and the Carboniferous-Triassic Panjal Formation (Khan & Ali, 1994). On the other side along the western limb of the HKS, the PT separates the Precambrian Tanol Formation from the Precambrian Hazara Formation. While the MBT separates Jurassic-Cretaceous and Palaeocene-Eocene sequences in the north from the Miocene Murree Formation in the south. The Hazara Formation is comprised of slate, phyllite and shale, while the Tanol Formation is

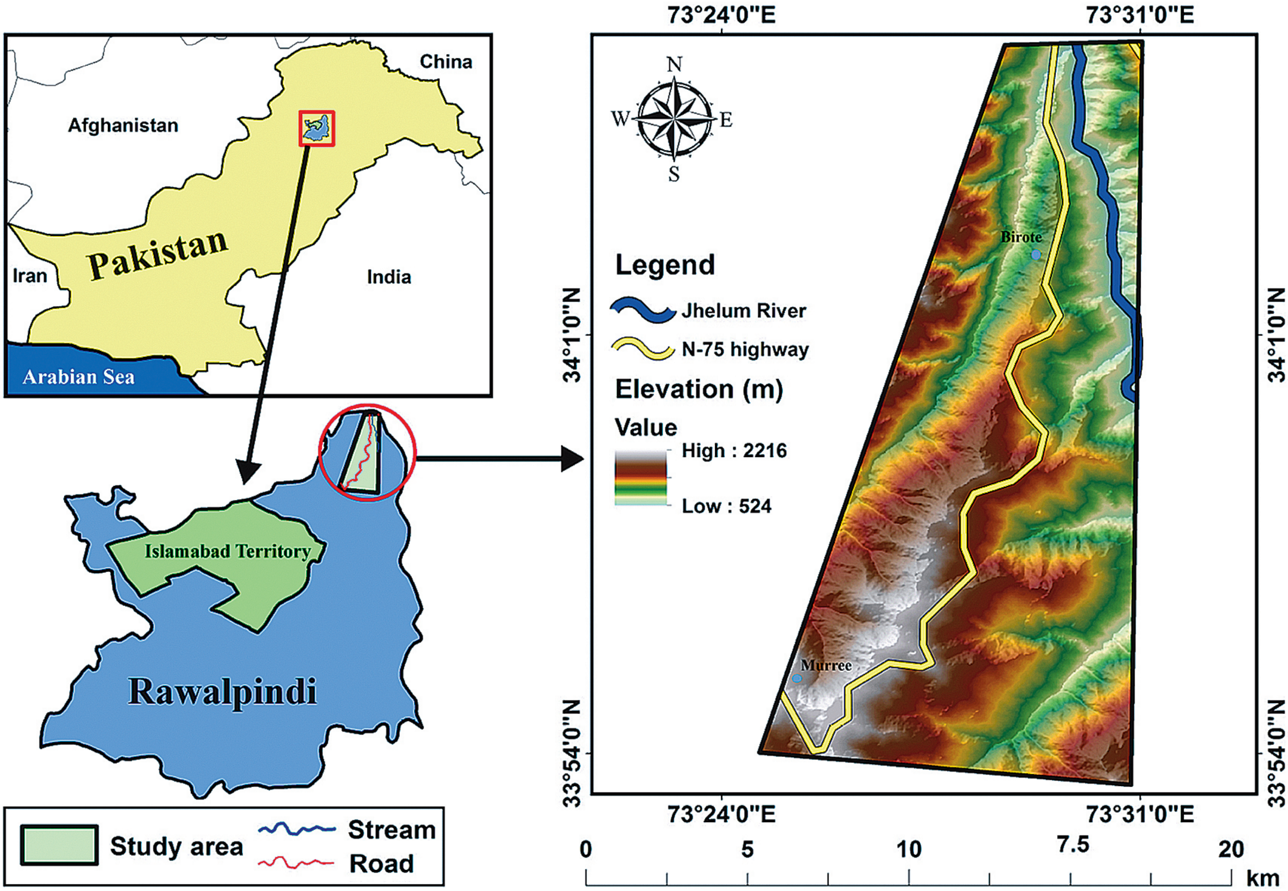

Figure 1. The geographical location of study area and Digital Elevation Model (DEM) of the study area

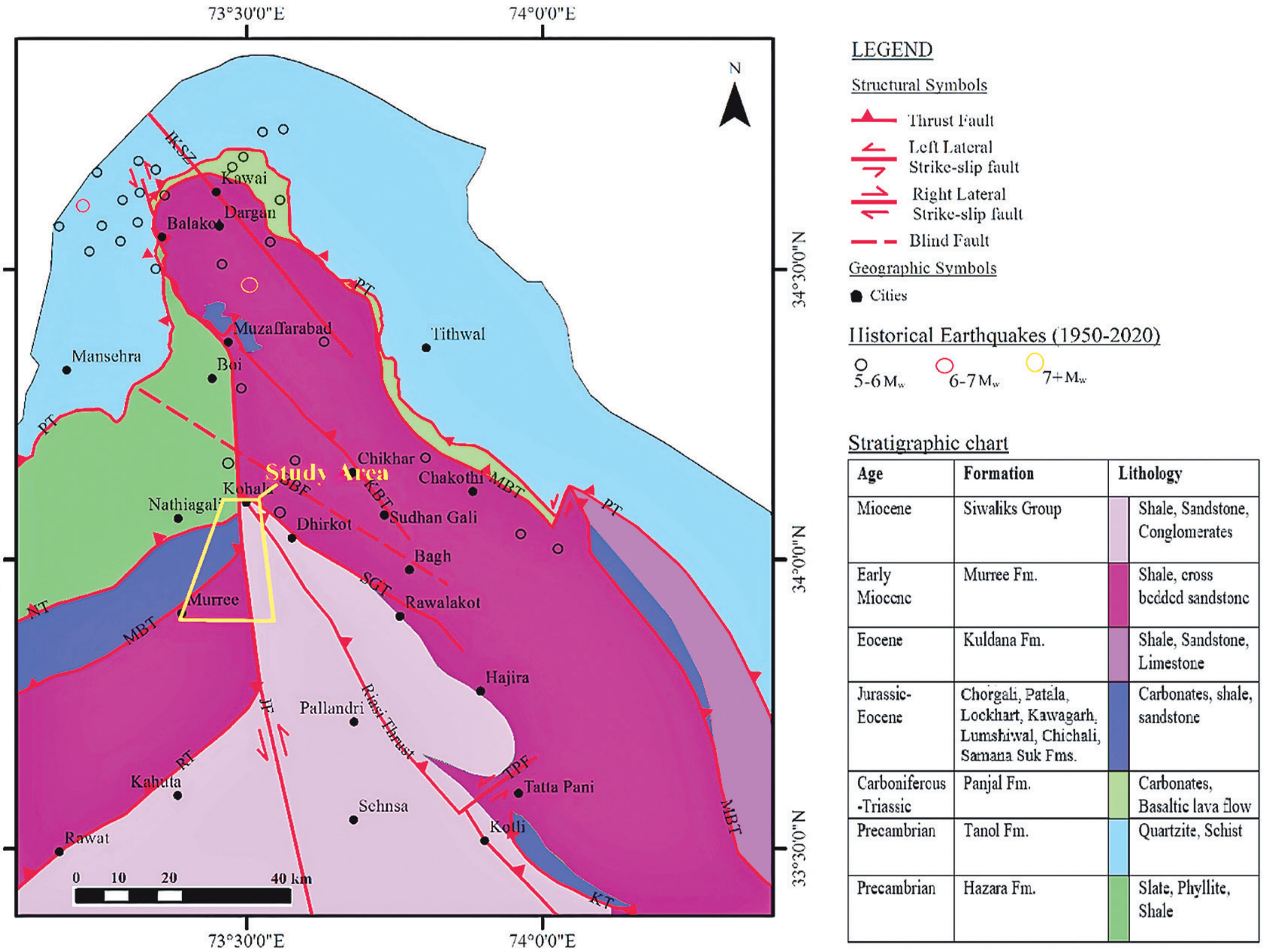

Figure 2. Geological map of the study area and historical earthquakes locations (Khan and Ali, 1994; Wadia, 1928). (Abreviations; MBT:Main Boundary Thrust, NT: Nathiagali Thrust, RT: Rawat Thrust, KT: Kotli Thrust, PT: Panjal Thrust, IKSZ: Indus Kohistan Seismic Zone, TPF: Tatta Pani Fault, JF: Jhelum Fault).

composed of quartzite and schist. The Jurassic to Cretaceous sequence is comprised of carbonates, shales, and sandstones of Samana Suk, Chichali, Lumshiwal and Kawagarh formations. Moreover, the Palaeocene to Eocene sequence is made up of carbonates and shales of Lockhart, Patala, Margalla Hill and Chorgali formations. Shales and sandstones of the Eocene Kuldana and Miocene Murree formations crop out in the core of the HKS (Rehman et al., 2020). However, the Miocene Siwalik Group rocks, which are dominantly sandstone, shale and conglomerate, are exposed at south of the HKS.

The fine-grained lithology (find-grained sandstone and shale) of Kuldana and Murree formations provide weak zone for fault localization (Mughal et al., 2018). In addition, a southwest plunging syncline exist in the study area, wherein the Murree Formation lies in the core of the syncline (Ahmed et al., 2020). This structural setting is responsible for the formation of a large water reservoir, feeding several springs and seepages at the toes of major sandstone layers (Niederer et al., 1989). This seepage also influences slope failure of rock and soil structures, leading to mass movement. Landslides has increased in the region due to poor mechanical properties of the rocks and get worse in recent times by environmental and human activities such as deforestation, engineering developments, and population growth (Neiderer & Schaffner, 1989).

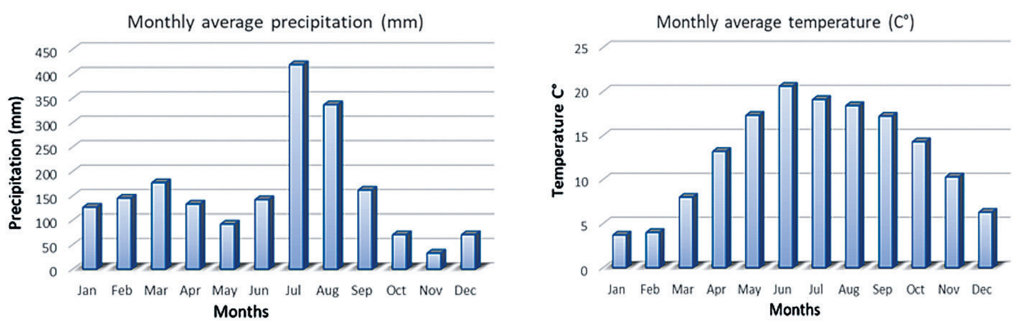

Figure 3. Climate Normal of the study area 1990-2017 (Source NASA)

Generally, the area has variable climatic conditions, mainly due to variations in altitude, quantity of winter snowfall, and extent of snow cover. The average temperature is 20.09 °C (Fig. 3) and can exceed 30 °C in June while it drops below 0 °C in January. The area receives

1320 mm of average annual precipitation in the shape of rain and snow; however different zones of the region receive different precipitation. The highest rainfall occurs in July, August, and September (Fig. 3). In winter, snow falls above 1200 m and retains above 1800 m of altitude during January and February.

Landslides have become more common in the last few years and have severely caused damage to infrastructures along the roads. A total of 38 landslides were considered during the field investigation characterized by a variety of mass movements, including rock fall, debris fall, debris flow, debris slide, and rockslide. However, majority of the mass movements are complex landslides. Monsoon rain and snowmelt at high altitudes mainly trigger debris flow in the area. Debris and rockslides were not only observed uphill along the road but also on the opposite side of the road downhill towards river Jhelum. Most of the landslides in the study area were mainly associated with the toe erosion and undercutting of the recent terraces. The landslides inventory based on the field survey and damages caused by landslides are shown in Fig. 4.

3. MATERIAL AND METHODS

3.1. Data Used

The current study includes four main stages: (1) data acquisition of the study area, including geological, geotechnical, topographical, environmental, and rainfall information, (2) selection of causative factors based on field investigation and earlier research practices, (3) calculation of the weight and the influencing power of factors in landslide occurrence and (4) finally, the generation of susceptibility assessment map of the study area using the AHP and WOA. The flowchart of the steps involved in the susceptibility assessment is given in Fig. 5.

3.2. Model Selection

Landslide susceptibility assessment contains descriptions of the degree of slope movements that can affect terrain and also the occurrence of the landslide in a region under local ground environments (Brabb, 1985). The adoption of GIS and Remote Sensing in research studies made it much easier to map the susceptibility to landslides (Jia et al., 2010; Nasab et al., 2010; Pradhan, 2011; Zhang et al., 2013). To date, many researchers have undertaken to identify potential landslide susceptible areas over the assessment of accountable factors (Khan et al., 2019; Komac, 2006; Lee et al., 2002; Shahabi & Hashim, 2015; Süzen & Doyuran, 2004). The landslide susceptibility maps can be generated based on quantitative and qualitative methods. Statistical approaches are preferred in more recent research, seeking to create associations between the spatial distribution and control factors of a landslide. Because of the effectiveness of the AHP method, it has been used to create the pair-wise comparison of the affecting variables in this study. To generate landslide susceptibility maps of the study area, an incorporated statistical technique (AHP-WOA) and AHP command tool have been evaluated in ArcGIS.

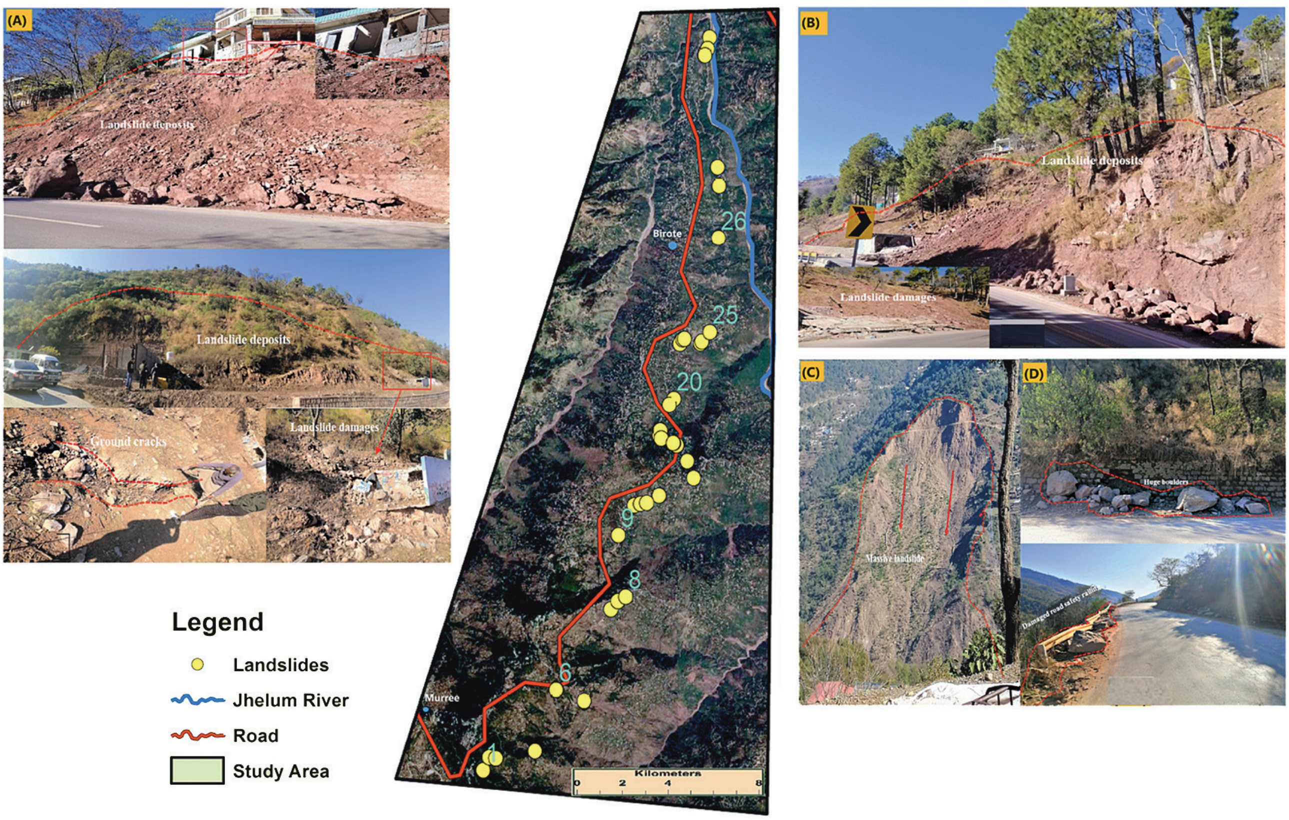

Figure 4. Landslide inventory of the study area, (A) Residential area damages caused by debris and rock slide (landslide point 6 and 9); (B) Complex landslide, (C) Massive landslide on the left bank of Jhelum River (D) Retaining wall and safety railing damaged by rockfalls. (Point 8,26,25)

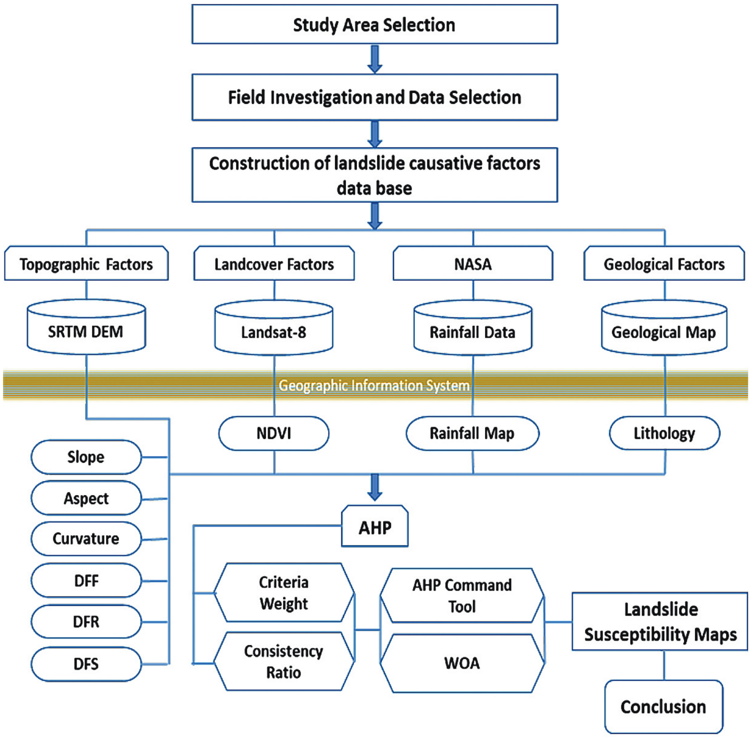

Figure 5. Flowchart of the methodology applied in the study.

3.2.1. Analytical Hierarchy Process

The AHP is the most accepted method for scaling the weight of factors. It is a method based on decision theory requiring to compare each criterion from a set of choices or alternatives. It indicates the most accurate methodology for calculating the weight of a criteria and estimation of relative magnitude of factors through pair-wise comparison with the help of individual experts and experience (Mehmood et al., 2021). Moreover, it indicates the relevance of a certain factor in landslide assessment through a statistical comparison. The scores given are based on reasonable prioritisation of the factor for inducing susceptibility of landslide and depending on the estimation of experts following the evaluation scale given by Saaty (Thomas & Doherty, 1980). The grading of comparative factors is done by allotting weight from 1 to 9, where 1 has equivalent significance and 9 has a drastic importance of a particular factor over others (table 2). Although the comparisons in AHP are assigned by expert judgement, but still there could be any inconsistency found in calculations. The consistency is derived in AHP by coherence ratio (table 3), which is given by random consistency index (RI) (Thomas & Doherty, 1980)

Table 1. Assessment variables frequently used by researchers in landslide susceptibility assessment (Ali et al. 2019)

Authors	Causative factors	Study area
Kamp et al. (2008)	Aspect, Elevation, Lithology, Land cover, Distance from faults, rivers, and roads, Slope, Tributaries, Aspect	Muzaffarabad District. https://goo.gl/maps/eMYgDfVRMHfXS9Yx
Ahmed et al. (2014)	Relief slope, Curvature, Aspect, Rain, Seismic hazard faults, Drainage, Normalised Difference Vegetation Index, Geology	Upper Indus watershed. https://goo.gl/maps/H79kmdmHrs1UCt1e6
Basharat et al. (2016)	Aspect, Elevation, Lithology, Land cover, Hydrology, Distance from Faults and Roads, Slope, Curvature	Balakot Tehsil. https://goo.gl/maps/6nYQhcwPWMRuUeD
Kanwal et al. (2016)	Slope, Aspect, Lithology, Land cover, Distance from faults, road and streams	Shigar and Shyok Basin in Karakoram range. https://goo.gl/maps/No47FAd4s5SHxeG26
Khan et al. (2018)	Slope, Aspect, Curvature, Lithology, Land cover, Distance from stream, faults and road network, SPI, TWI	Haramosh valley, Bagrote valley and Nagar valley https://goo.gl/maps/aFoJaUjUZUYRBH4x6
Khan et al. (2018)	Aspect, Geology, Land cover, Slope, Distance from fault, road, and stream	Hunza–Nagar valley. https://goo.gl/maps/tZaYyHubWSaNVMhY
S. Ali et al. (2018)	Elevation, Slope angle, Aspect, Curvature, Lithology, Seismicity, Faults, Land cover, Rainfall intensity and Distance from streams	Karakoram Highway (China-Pakistan Economic Corridor). https://goo.gl/maps/TWRfyzPN3F878UNo6
This study	Slope, Aspect, Curvature, Lithology, Distance from faults, Distance from roads, and distance from streams, NDVI, Rainfall	N-75 highway (Lower Topa to Kohala bridge)

Table 2. Pairwise comparison 9-point rating scale in AHP, after Saaty (Saaty, 2008).

Dominant values	Description	Explanation
1	Equal importance	Two factors contribute equally
3	Moderate importance	Activity slightly favours one factor over another
5	High prevalence	Activity highly favours one factor over another
7	Very high prevalence	Activity is very highly favoured over another
9	Extremely high prevalence	Activity is of highest possible degree favoured over another
2, 4, 6, 8	Intermediate values	Used when compromise is needed

$$CR = \frac{CI}{RI} \quad (1)$$

Where

$$CI = \frac{\lambda_{max} - n}{n} \quad (2)$$

The consistency ratio is calculated in order to find the continuity of the pair-wise compared weights (Kolat et al., 2012). The uniqueness of the AHP method is that it provides CR as a relationship between the degree of consistency and inconsistency (Chen & Lee, 2010). The suitable value of CR is 0.1 for all large matrices, i.e., n>5. Therefore, a CR of 0.1 or lower is of reliable importance (Malczewski, 1999; Mehmood et al., 2021), however, a CR above 0.1 requires additional evaluation on this statistical parameter.

3.2.2. Weighted Overlay Analysis

The current study also applied the weighted overlay analysis to obtain the landslide susceptibility assessment maps. This method usually uses individual factor thematic raster layers that are overlaid to create a composite map based on their weights. The weights are provided based on the individual factor's comparative importance (Saaty, 1988). The thematic layers of all causing variables were added using the ArcGIS weighted overlay tool for landslide susceptibility assessment mapping.

4. LANDSLIDE SUSCEPTIBILITY MAPPING

The preliminary and most significant principle for carrying out the research objective is the collection and development of attributes which have been identified as conditional factors, which area is considered responsible for making the study area susceptible to landslides.

4.1. Assessment Factors

Recent developments in GIS programmes and improved computational capability make it feasible to use a considerably large amount of independent parameters in data-driven landslide susceptibility assessment. Landslides are triggered by various external and internal factors (Mehmood et al., 2021). Table 1 reports the most frequently used causative factors by various researchers for landslide susceptibility assessment.

For the current study, a combination of significant morphological factors of slope instability together with geographical features and natural vegetation were selected. Geomorphic factors (slope, aspect, curvature) and rainfall have a direct relation with landslide occurrence. Increasing urbanisation in the study area negatively affects the natural vegetation cover. The destruction of root system enhances weathering and degradation of the mechanical properties of the bedrock and soil deposits. Hence normalised difference vegetation index has been chosen one of the causative factors in the study. The parameters distance from faults, roads, and streams has a significant influence in this area. Excavation of slopes, particularly the toe of slope for building and widening of the existing roads, construction work along the road, and the vibration of heavy transport is a common phenomenon in this area. This weakens the existing state of stability, stresses, and encourages landslides. The water level of Jhelum River, located on the right side of the highway, rises in summer due to the heavy rainfall, snow, and glaciers melting at the higher altitudes of the Himalaya Mountains, which increase the flow and under-cutting of rocks and sediments by river water. Several main and minor faults (Fig. 2) are located in the study area. Most of the study area is made of weak (low strength) lithologies such as shale, conglomerate and slate, which may facilitate landslide occurrence during fault activation. Therefore, lithology, distance to fault, roads, and streams have been considered as causative factors that have significant role in the occurrence of landslides.

As previously stated, causative factors can be used as driving factors in forecasting potential outbreaks of landslides (Conforti et al., 2013); however, there is no specific principle for choosing these factors (Ayalew & Yamagishi, 2005). In the present study, the causative factors were chosen amongst those widely reported in the literature for landslide susceptibility assessment. Field investigation and spatial analysis were carried out to determine the influence of these parameters on the landslide distribution in the study area. The nine most relevant factors influencing stability selected in this study include (Fig. 6):

(i) Slope (°): Slope is the indicator of steepness or the grade of inclination of a characteristic compared to the horizontal plane. Slope map was created from DEM of the area using GIS spatial tool since slope is linked directly to the landslide occurrence and is often used to generate landslide susceptibility maps (Khan et al., 2019; Rahman et al., 2019; A Yalcin et al., 2011);

(ii) Aspect: An aspect map indicates the direction of the slope face (Li et al., 2021). An aspect value of 0 implies the north facing of a slope. The aspect map was generated from the study area DEM using the ArcGIS spatial analysis tool;

(iii) Curvature (m-1): A map of curvature was also generated through DEM. A curvature positive value indicates convex, negative value indicates concave and value of zero indicates flat

Table 3. Random index values

n	1	2	3	4	5	6	7	8	9	10
RI	0.0	0.0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

Table 4. Pair-wise comparison 9-point rating scale in AHP, after Saaty (Saaty, 1988).

Factors	Slope	Aspect	Curvature	Lithology	NDVI	DFF	DFR	Rainfall	DFS
Slope	1.0	7.0	4.0	5.0	4.0	3.0	4.0	5.0	6.0
Aspect	0.14	1.0	2.0	3.0	4.0	5.0	6.0	6.0	7.0
Curvature	0.25	0.5	1.0	2.0	3.0	4.0	4.0	5.0	6.0
Lithology	0.2	0.33	0.5	1.0	2.0	3.0	3.0	5.0	4.0
NDVI	0.25	0.25	0.3	0.5	1.0	2.0	3.0	4.0	5.0
DFF	0.33	0.2	0.25	0.33	0.5	1.0	2.0	2.0	3.0
DFR	0.25	0.17	0.25	0.33	0.33	0.5	1.0	2.0	3.0
Rainfall	0.2	0.17	0.2	0.2	0.25	0.5	0.5	1.0	2.0
DFS	0.17	0.14	0.17	0.25	0.2	0.33	0.33	0.5	1.0

Normalized Difference Vegetation Index (NDVI), Distance from Faults (DFF), Distance from Roads (DFR), Distance from Streams (DFS)

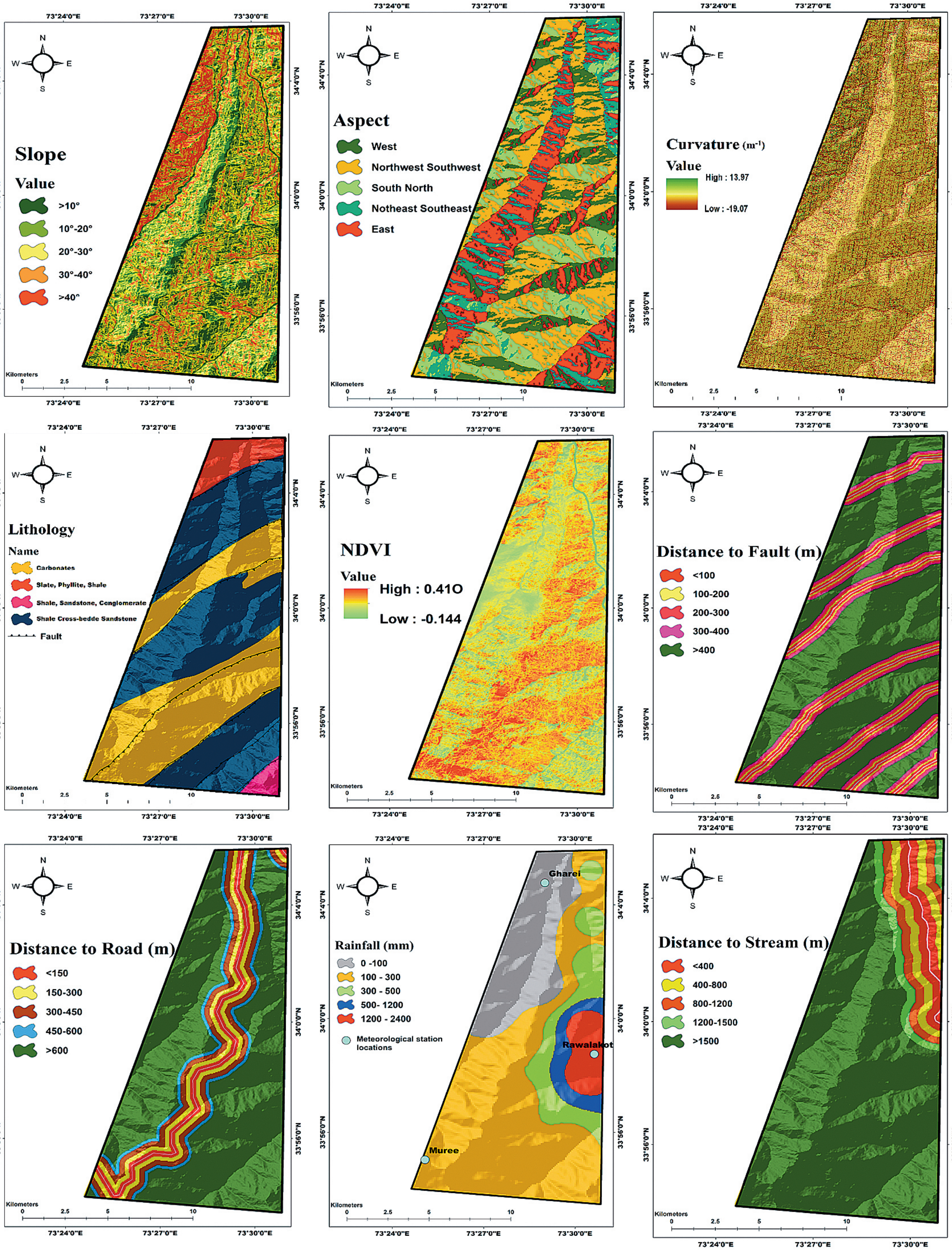

Figure 6. Thematic maps of the nine selected landslide causative factors.

surface (Ahmed et al., 2014). During heavy rainfalls, the water retains at concave and convex slopes for a long time and facilitates landslide activities. High negative or positive values direct the higher probability of landslide activity whilst the landslide probability in flat area is very low (Lee & Talib, 2005; Mersha & Meten, 2020);

(iv) Distance from Fault (DFF): Areas close to active faults are more susceptible to landslides (Li et al., 2021; Rahman et al., 2019). The DFF is extracted from the 1:50,000 geological map of the area and fault lines are buffered at the interval of 100m in ArcGIS 10.3. The DFF is divided into five classes, including; <100, 100–200, 200–300, 300–400 and >400;

(v) Lithology: Lithology exerts a crucial role in slope stability (Khan et al., 2019; Yalcin & Bulut, 2007). Lithological map of the study area was prepared from the 1:50,000 geological map and field investigation of the area. The lithological details of the area are described in the section "Study area".

(vi) Normalised Difference Vegetation Index (NDVI): NDVI is a significant variable in landslide susceptibility assessment studies (Elkadiri et al., 2014; Li et al., 2020). In general, the NDVI value varies from –1 to 1; the heavier the vegetation cover, the greater the NDVI value. The following formula can determine the value of the NDVI:

$$NDVI = \frac{NIR - Red}{NIR + Red} \tag{3}$$

where NIR and Red stand for the spectral reflectance measurements achieved in the Red (visible) and near-infrared regions, respectively. The NDVI map was generated from Landsat-8 Imagery downloaded from Earth explorer by USGS (https://www.usgs.gov/landsat-missions);

(vii) Distance from Road (DFR): Road network in the mountainous regions impacts on slope stability. Road cuttings and other anthropogenic activities destabilise the rock masses, which ultimately results in landslides (Kanwal et al., 2017; Promper et al., 2014). The road network of the region is acquired from the Map Cruzin website (https://mapcruzin.com). The DFR is buffered at an interval of 150 meters and classified into five classes in ArcGIS 10.3 software. The classes are <150, 150–300, 300–450, 450–600, and >600;

(viii) Distance from Streams (DFS): The influence of the stream also has key role in destabilising the slope geometry (Akgün & Türk, 2011; Mersha & Meten, 2020). It includes the erosion of material from the toe of the slope and the saturation of sliding material. The DFS is generated on ASTER DEM by using Arc-Hydro tools. Buffering at the 400-meter interval was prepared to know the effectiveness of streams on landslide activities;

(ix) Rainfall: Rainfall is a crucial triggering factor for all kinds of landslide occurrence (Mersha & Meten, 2020). Data picked up from Pakistan Metrological Department (PMD, 2019) for the year 2019 were interpolated by means of Inverse Distance Weighted (IDW) to calculate the area's rainfall rate.

The maps of the causative factors were developed using ArcGIS 10.3 software and are shown in Fig. 6.

4.2. Modelling Approach

Selection of the causative factors has revealed a number of important parameters that are possibly essential in the development of landslide susceptibility assessment. It is fundamental to integrate them to drive a single numerical value for susceptibility assessment; otherwise, they are individual parameters that provide distinct indications.

4.3. Assigning Weights

In the multi-parameter analysis like landslide susceptibility assessment, one of the fundamental challenges is evaluating each factor's relative value or weight and its influence compared to other factors. This is an issue requiring human judgement augmented by mathematical instruments. As all causative factors discussed till now cannot be weighted correspondingly for the susceptibility assessment, a weighted method must be used where the comparative significance of the factors determines the weightage. For this purpose, AHP was adopted in this study.

One of the key advantages of adopting AHP is that it reorganises the complexity of data set by the hierarchy with a pair-by-pair correlation between different variables, hence reducing weighing error while maintaining consistency in different data processing. Other benefit of AHP is the validation of pair consistency. However, this method is based on expert judgement, and ranking of the causative factors is therefore a minor disadvantage of the process. However, many researchers have used the AHP method in their studies to assess landslide susceptibility mapping (Basharat et al., 2016; Kamp et al., 2008; Pourghasemi & Rossi, 2017; Rahim et al., 2018; Shahabi & Hashim, 2015). Researchers have mainly used AHP to allocate the weighting variables for landslide causative factors, conversely in this study AHP has been adopted for both weighting factors and landslide susceptibility assessment based on causal parameters. Each causative factor was assigned weight over the other variable by the pair-wise judgement of the AHP (table 4). The obtained weight was then measured using the methodology proposed by Saaty (Saaty, 2008).

The AHP calculations were carried out in Microsoft Excel using the following steps of (Bunruamkaew, 2012):

Add the quantities in the pair-wise matrix's columns.

$$Cij = \sum_{i=1}^{n} Cij \tag{4}$$

To obtain a normalised pair-wise matrix, the matrix parameter was divided by the column's sum, respectively.

$$Aij = \frac{Cij}{\sum_{i=1}^{n} Cij} \tag{5}$$

To obtain each criteria weight, the summation of the matrix's normalised columns was divided by the amount of parameters applied.

$$Wij = \frac{\sum_{i=1}^{n} Cij}{n} \tag{6}$$

Where n is the number of parameters and Cij is the pair-wise matrix, Aij is the normalised value and Wij is the criteria weight.

The criteria weights of the causative factors are the following: slope 0.360, aspect 0.192, curvature 0.137, lithology 0.095, NDVI 0.075, DFF 0.051, DFR 0.04, rainfall 0.029, and DFS 0.022 % respectively.

The consistency ratio is the measurement of judgement consistency. In this study, the calculated CR is 0.088, which is below 0.1. The pair-wise comparison ratio specifies a good consistency level, standing sufficient to distinguish the factors weight. The revision of the preferences matrix is needed only when the CR value is higher than 0.1.

4.4. Landslide Susceptibility map using AHP Command Tool

After the calculations of the assigned rank to the causative factors, the landslide susceptibility assessment map was prepared using the AHP command tool in ArcGIS. For the generation of landslide susceptibility assessment map, all the causative variables were added according to criteria weightage level in the AHP tool. The final map of landslide susceptibility was classified into five classes, including very low (10 %), low (14 %), moderate (19 %), high (39 %), and very high (18 %) of the overall research area (Fig. 7B).

4.5. Landslide Susceptibility map using Weighted Overlay Analysis

The weight calculated by AHP were classified according to their importance in landslide susceptibility, in which slope is given the highest weight of 36 % and DTS is assigned the lowest weight with 2 %. After applying the AHP process to the data maps of all the causative factors, the resulting map was created with the help of the spatial analysis tool of ArcGIS 10.3 using the weighted overlay analysis. The generated map was then classified into five classes very low (14 %), low (07 %), moderate (49 %), high (17 %), and very high (13 %) as shown in Fig. 7A.

4.6. Area under Curve

The Area under Curve (AUC) technique is being used to predict the validity of the landslide susceptibility assessment map. The area under the curve is a graphical representation of binary operating classes determining project accuracy. AUC was generated by comparing the generated map using ArcGIS software and the GPS landslide points taken in the field investigation of the study area. A total of 38 sites were selected for validation purposes, showing different types of landslides. These points are taken as the true-positive rate compared with the maps developed by the AHP command tool and the WOA in ArcGIS as the false-positive rate. Graphical representation of AUC explains the accuracy of mapping. The area under curve shows that the map obtained with AHP command tools gives a higher accuracy value of 0.87 compared to WOA 0.81 (Fig. 8), which is above the minimum value of 0.6 consequently and is considered accurate for landslide susceptibility mapping.

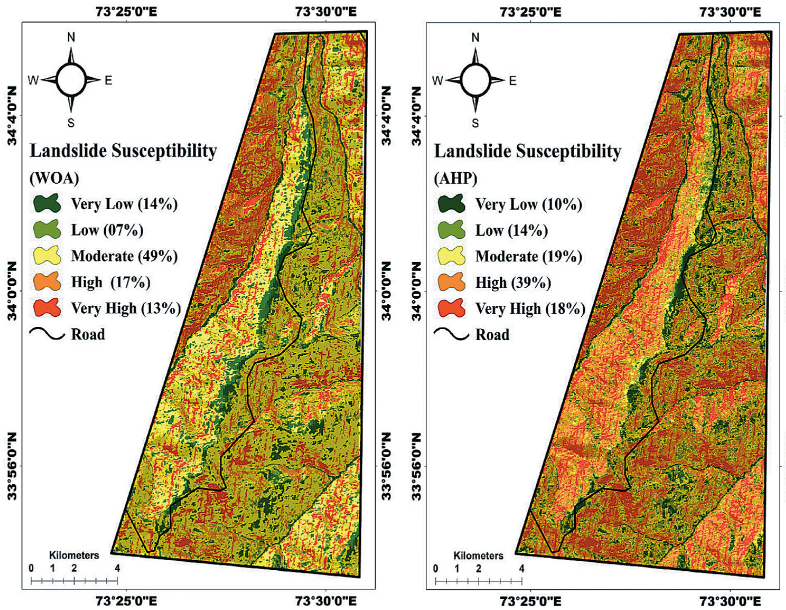

Figure 7. Landslide susceptibility map using (A) Weighted Overlay Analysis (WOA) and (B) Analytic Hierarchy Process (AHP) command tool.

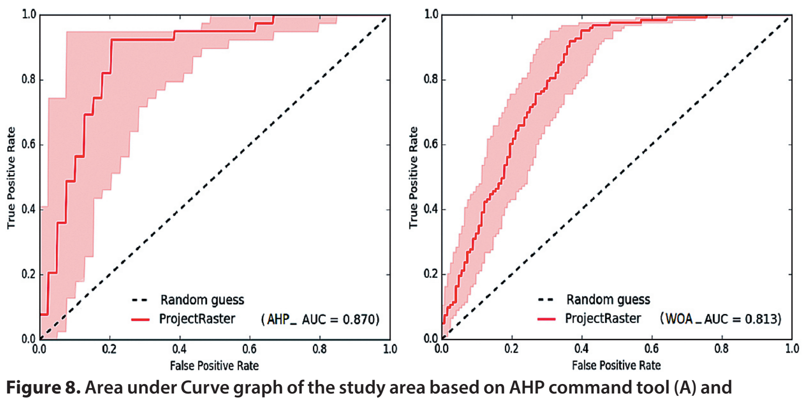

Figure 8. Area under Curve graph of the study area based on AHP command tool (A) and Weighted Overlay Analysis (B).

5. DISCUSSION

Landslide is a complex process prompted by several external triggering and internal geological parameters (Mehmood et al., 2021; Raghuvanshi et al., 2014). So far, researchers have undertaken to identify potential landslide susceptible areas over the assessment of these factors (Basharat et al., 2016; Khan et al., 2019; Komac, 2006). Statistical approaches are preferred in more recent research, seeking to create associations between the spatial distribution and control factors of a landslide (Ali et al., 2019). Many researchers used an AHP-based model to prepare landslide susceptibility maps (Ahmed, 2015; Arizapa et al., 2015; Basharat et al., 2016; Kamp et al., 2008; Park et al., 2013; Pourghasemi & Rossi, 2017; Rahim et al., 2018; Shahabi & Hashim, 2015; Yalcin, 2008). In some studies, the comparison of AHP based model with other methods (Pourghasemi & Rossi, 2017; Shahabi & Hashim, 2015; Yalcin, 2008) proved to be more accurate and precise. The AHP-based model has been disparaged due to its expert-judgment-based subjective method. In fact, expert judgement is necessary in tracking landslides hazard evaluation, and the application of this method can vary from one expert to another, representing a disadvantage with respect to obtained information. Conversely, data driven methods are also powerful in landslide susceptibility mapping and contain less subjectivity. Therefore, it is important to analyse the spatial relationship between the landslide conditioning factors and landslide locations. We employed spatial analysis to weight all key parameters in order to reduce the possibility of errors due to the expert's intellectual limitations. In this study, the two methods AHP command tool and WOA in ArcGIS have given reasonable results. However, the AUC graph shows that the map obtained with AHP command tools has a higher accuracy value of 0.87 compared for WOA 0.81. The results obtained by the two models given 6 percent of accuracy difference, which demonstrates AHP was more accurate in this example.

Regardless of the optimistic results and the model's adaptability, there will always be an inconsistency in any landslide susceptibility mapping due to the uncertain inherency in landslide susceptibility mapping parameters. Expert opinion and judgments are employed to provide weight to the causative parameters, which may differ from the absolute values. The assessment of specific weights also necessitates unyielding efforts. The absence of high-resolution images, DEMs, and research tools, as well as large-scale geology and soil maps, and particularly the lack of publicly accessible landslide data, were key limits in selecting the landslide parameter data. Therefore, the models used to generate the landslide susceptibility maps in this study are of reference importance for comparable studies. In order to discover the most suitable model to generate landslide susceptibility maps, novel hybrid models and new approaches should be considered for future modelling.

6. CONCLUSIONS

Landslides are the high threat to the socio-economic environment of Northern Pakistan, especially the Himalaya region. Despite of high threat, no recorded data in most areas on landslide susceptibility are available to assess and mitigate landslide hazards. This study presents landslide susceptibility maps for part of the N-75 highway in the northeast of the capital territory of Islamabad, Pakistan.

Landslide susceptibility maps were prepared using ArcGIS involving multiple techniques: literature review, remote sensing, and field investigations. Nine causative factors were selected, and weights were assigned using AHP method. Thematic layers of these variables were merged into a single assessment index using AHP command tool and WOA in ArcGIS.

The results based on AHP command tool indicate that 57 % (and 30 % for WOA) of the study area is under high to very high landslide susceptibility. The most influential parameters controlling the spatial distribution of landslides are the geomorphic factors, the fractured and weathered lithology, active faults and extreme weather conditions.

The AUC technique was used to evaluate the accuracy of the susceptibility maps, which shows that the map obtained with AHP command tools gives a higher accuracy value of 0.87 compared to WOA (i.e. 0.81). Based on the obtained results, it is recommended that all types of future development along the highway should be completely prohibited or done with all precautionary measures in the high to very high susceptibility zones.

Acknowledgements: The authors would like to thank the editor and anonymous reviewers for their comments and suggestions, which helped a lot in making this paper better.

Funding – This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Conflicts of Interest – The authors declare no conflict of interest.

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