

Landslide Susceptibility Assessment Using Bivariate Method: A Case Study from River Neelum and Jehlum Catchment Area

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Abstract: Landslide is a frequently occurring natural calamity in the northern areas of Pakistan. The current study is aimed to assess the susceptibility of landslide hazard to highlight the vulnerable areas for the purpose of risk reduction along Neelum and Jehlum rivers in district Muzaffarabad. A data-driven predictive approach was adopted to conduct this study by using Weight of Evidence (WOE) model along with eleven conditioning factors. A spatial distribution map of landslides was prepared using orthophoto, previous records, and derivatives (hill shade, topographic openness, slope, aspect, curvature) of Digital Elevation Model (DEM). The results show that the roads, lithology, and rivers are the most important triggering factors for landslides in both valleys. Approximately 30% of the area is under low susceptibility zone in Jhelum valley while only 13% of the area falls under low susceptibility zone in Neelum river valley. In Jhelum river valley the medium susceptibility zone covers 35% of the total area whereas, Neelum river valley has 26% of the total area under medium susceptibility zone. Around 61% of the land in the Neelum river valley and 35% of the land in the Jhelum river valley are under high susceptibility zone. The area under high hazard lies in the north-east of the district due to multiple conducive factors to trigger landslides including weak lithology (mudstone, sandstone, shales, and clays), high altitude along steep slopes and excessive precipitation (1800 mm/ year). Furthermore, the high hazard zone in study area is not suitable for construction purpose but was suitable for plantation. The validation result (89.41%) is justifying the performance of this model.

Keywords: Landslide, spatial distribution, susceptibility, virtual mapping, weight of evidence.

Introduction

Natural disasters are physical phenomena's which occur naturally and triggered by onset of hydrological, geophysical, meteorological and biological events (Garschagen et al., 2016). Moreover, a variety of human induced threats including urbanization, poverty, climate change and increasing threat of pandemics may influence the future humanitarian assistance. According to a 2018 report by CRED and UNISDR, in between 1998 and 2017 (Wallemaq et al., 2018), around 1.3 million individuals died and almost 4.4 billion people have been affected by natural disasters, and costing approximately US\$2 trillion. The frequency and intensity of these disasters is increased many folds in the under developed countries of South Asia in last few decades. According to (Wang, (2020) approximately 409 natural disasters occurred worldwide in 2019. Moreover, the Asian Pacific region is the one which endured the maximum number of natural disasters.

Pakistan is dreadfully exposed to a range of natural disasters such as floods, earthquakes, droughts, and landslides. An earthquake (7.6 magnitude) in 2005, struck the country and caused massive damage. Approximately 1 million individuals died, and approximately \$576 million indirect income losses

were recorded (GFDRR, 2019; Mundial, 2014). Similarly flooding pose a major financial challenge to the country. The likelihood of disastrous incidents are the major attributes of a disaster which can help to calculate the level of risk which is an essential step of decision making process (Zlateva et al., 2011).

Landslides are the regularly occurring events in Pakistan, because of its geophysical and meteorological characteristics and are accountable for serious fatalities and economic losses particularly in northern Pakistan due to young Himalayas and active tectonic movement. In this scenario it is crucial to prepare landslide susceptibility and hazard maps for the region on local as well as regional scales. Though, it is quite challenging in country like Pakistan in the absence of detailed information. However, landslide susceptibility mapping could be carried out for landslide prone areas to minimize the risk.

The purpose of landslide susceptibility assessment (LSA) is to estimate the possibility of landslide occurrence considering multiple predisposing factors and the spatial distribution of past landslides (Vahidnia et al., 2010). The susceptibility has an essential role in risk assessment to attain some quicker decision with minimum human errors (Bibi et al., 2016). The LSA approach has been transformed from knowledge based

to data driven or statistical approaches in last few years. The bivariate statistical analysis for LSA compares each data layer of causative factor to the existing landslide. Distribution weights to the landslide causative factor are assigned base on landslide density and frequency analysis. The weight of evidence model is a log linear form of Bayesian probability model for landslide susceptibility assessment that uses landslide occurrence as training points to derive prediction outputs. The aim of this paper is to assess landslide susceptibility through Weight of evidence model (WOE) for Neelum Jhelum river valleys, district Muzaffarabad, Pakistan. Muzaffarabad (MZD) is situated on 34° - 24' north latitude and 73° 22' east longitude.

Geological and Tectonic Setting

Geological setting in study area ranges from Precambrian to early Miocene from older to younger Hazara formation with dominant lithology green to dark green slates with minor limestone and graphite layer (Table 1). Muzaffarabad Formation with dominant lithology dolomitic limestone, cherty dolomite, and chert bands. Hangu Formation with dominant lithology Laterite, bauxite, and fireclay.

There are two major fault lines in the district known as Muzaffarabad and Jhelum faults. The key tectonic features along this specific zone of deformation were produced in the Cenozoic and Mesozoic eras. According to Baig and Lawrence, (1987) the Jhelum Fault described as left-lateral strike-slip fault (Fig. 2). Highly deformed Abbottabad, Muree and Hazara formations occur along fault in between Muzaffarabad and Balakot. While the Muzaffarabad Fault lies in between Muzaffarabad Formation which is of Cambrian age and Muree Formation belongs to late Miocene age. The Main Central Thrust (MCT) paying a role of boundary between lesser Himalayas and higher Himalayas whereas, the MCT overlies the Lesser Himalayas. Though the higher Himalayas lies on northern part of MCT up to Tibet and Everest.

Materials and Methods

The data base prepared to calculate the susceptibility map consist of variety of secondary and primary datasets. The primary information was obtained via field observations and in later stage field verification. However, the secondary dataset involves different maps (land use/ land cover, geomorphology, lithology, structure), satellite images, digital Terrain Model (DTM) and its derivatives (Fig. 3). The data sets were compiled, modified, and rasterized / reclassified to suit the needs of this study. Different geological, hydro-topographical, anthropogenic and geomorphological factors were used as input data. The various datasets which are used in this study to prepare susceptibility maps are discussed.

Current study elaborates the process of data collection

and analysis utilizing the GIS/RS as a tool. A field verification was done for verification and validation of Landslide inventory (LSI). All the secondary data converted into digital form by digitization. Consequently, the datasets were analyzed by using ARCGIS and SAGA GIS software.

LS mapping techniques are totally statistical approach. The statistical approach has been divided into bivariate statistical analysis and multivariate statistical analysis. In this research method, the distribution weights have been assigned to the landslide causative factor maps based on weights of evidence (WOE) model.

The current study dominantly utilized secondary data including multiple maps acquired from a variety of sources. It includes, Planning and Development department, Land use Planning department, library of Azad Jammu and Kashmir University, Metrological department Azad Kashmir and USGS. These datasets include slope, curvature, aspect, roads, rivers, fault, lithology and land use maps.

Landslide distribution map is used as base to assess the susceptibility of LS in intensity evaluation process of hazard (Bibi et al., 2017). Guzzetti et al. (2012) mentioned that still the LS inventories are prepared or assembled either continuous in time or based on causing event e.g. earthquake, rainfall, and flood. The literature described four probable stages of development of a landslide as: i) pre-failure (strained but intact slope); ii) failure (formation of a continuous surface of rupture); iii) post-failure (after failure until stop the movement); and iv) reactivation, (movement of slope along pre-existing surfaces of rupture) (Eeckhaut et al., 2007; Hungr et al., 2012; Razak and Mohamad, 2015).

Results and Discussion

Different predisposing factors including geomorphic, geological, hydro topographical and anthropogenic factors were considered to evaluate the susceptibility of landslide in the area under study. The slope map shows slope of landslide in study area. The map is divided into six different classes. Each class has its own color and angle range. Aspect is computed and every individual facet of that surface is assigned with a unique code value. The code values represent the ordinal or cardinal direction of its slope and adjacent areas with the same code is merged into one feature. The curvature map is calculated by the second derivative of the surface.

The topographic ruggedness index (TRI) was established by (Riley et al., 1999) to express the amount of elevation difference between adjacent cells of a DEM. It calculates the difference in elevation values from a center cell and the eight cells immediately surrounding it. Then it squares each of the eight altitude difference values to make them all positive and averages the squares. The topographic

ruggedness index is then resultant by taking the square root of this average. The TRI map is further divided in to 11 classes according to elevation differences. Each has its own color and angle range.

The calculation follows description in (Iwahashi and Pike, 2007). *Terrain surface texture* is calculated by smoothing input elevation using a median filter over a neighborhood specified by the filter size parameter (in pixels). Second, pits and peaks are extracted based on the difference between the smoothed DEM and the original terrain surface. By default, algorithm uses a threshold of 1 (> 1 m elevation difference) to identify pits and peaks. The spatial frequency of pits and peaks is then calculated using a Gaussian resampling filter over a neighborhood size specified in the counting filter parameter (default is 21 x 21 pixels, as per (Iwahashi and Pike, 2007). These metrics are combined using the mean of each variable as a dividing measure into a 8, 12 or 16 category classification of the topography. The TST map is divided into twelve different classes. Each class has its own color and angle range.

A buffer layer for *rivers and roads* was created to delineate the impact of roads and rivers on susceptibility zones. The road map is prepared from the satellite image. The area has a dense road network consist of three common classes including main road, link road, tracks, and trails. The key finding of this study is that the availability of bare earth images enhanced the ability of virtual interpretation of different types of landslides (active as well as dormant) in densely vegetated areas many folds. In fact, the mapping and monitoring of old landslides covered by dense vegetation is not possible unless used modern technology.

The comprehensive mapping of vegetated terrain with the help of high-resolution data enhanced the landslides inventory mapping ability, consequently the quality of susceptibility, hazard and risk maps will improve. A geodatabase was created to store the comprehensive landslide inventory including its attributes by observing satellite images and cross verified by field visits. From the results it is detected that the key cause of landslide activation in the study area is change in land use/ land cover. The forest degradation for construction purpose is significantly contributing to the initiation of landslides due to lose morphological characteristics of rock types existing in study area.

Most of the debris flow are found along road channels which is highlighting the impact of slope disturbance activities. In most of the cases the river Neelum and Jhelum itself are adding much in deteriorating the land and triggering landslides by ground cutting on river bends. Furthermore, majority of the houses built in the area were found on bodies of dormant landslides due to which the vulnerability to life and property is increasing many folds. The damage of infrastructure

including buildings and roads expose the significance of spatial distribution of landslide map in land-use planning to prevent future damages to life and property. In fact, the density and intensity of landslides can be seen very clearly which is wider beside the riverbanks.

The spatial distribution of landslide has been mapped with the help of ALOS DEM (12.5m) and its derivatives as well as orthophoto of the study area. The virtual interpretation technique of landslide is done with the help of hill shade image, plan curvature, slope image, topographic openness image and orthophoto. These images were utilized simultaneously to interpret the features of landslides e.g. body and scarp of landslide, the type of landslide and the topographic characteristic of a landslide. Although, all these derivatives and orthophoto individually have some advantages and disadvantages, for example, the shape of the landslide is sharply identifiable in topographic openness map. However, it is concluded that the interpretation of landslide through visualization could only be possible in the presence of very high-resolution dataset.

The landslide susceptibility map is classified into three key zones. Approximately 30% of the area is under low susceptibility zone (Fig. 2) in Jhelum valley, conversely, only 13% of the area falls under low susceptibility zone in Neelum river valley. In Jhelum river valley the medium susceptibility zone covers 35% of the total area while Neelum river valley has 26% of the total area under medium susceptibility zone. Around 61% of the land in Neelum river valley constitutes high susceptibility zone while around 35% of the land in the Jhelum river valley is high susceptibility zone.

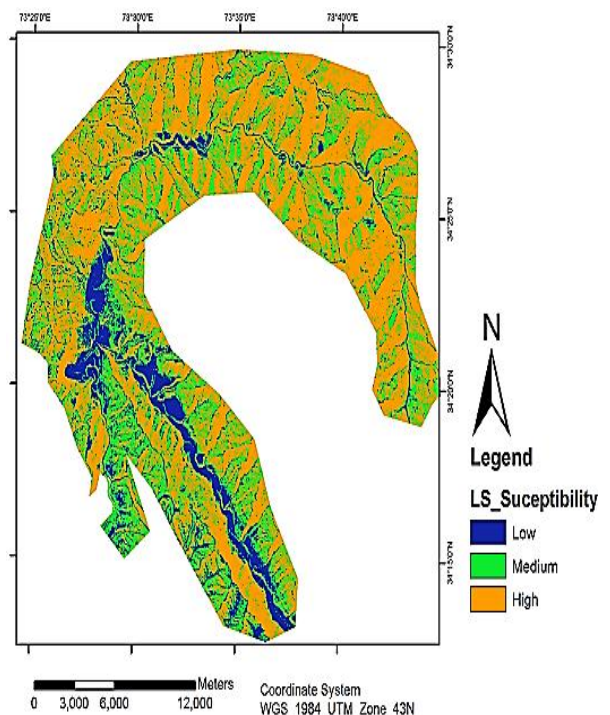


Fig. 1 Landslide susceptibility map

The high hazard zone covers a major portion of north eastern part of the district where many causative factors were favorable to trigger landslide hazards, for example, high elevation and weak lithology (mudstone, sandstone, shales and clays). Moreover, the high precipitation (max 1800 mm) in the area is working as an additional triggering factor to activate the landslides on steep slopes. It is suggested that this land is least suitable for any developmental scheme but is suitable for afforestation. The validation value of susceptibility is 89.41% which is showing the high efficiency of the model (Fig. 1).

Conclusion

It is concluded that mass movement is most frequent occurring hazard in the study area. It is mainly due to weak lithology along with frequent seismic incidences. The steep gradient of the terrain in both river valleys followed by heavy rain is another important triggering factor. The mapping of landslide with the help of remote sensing data is an efficient way in spite of opting geomorphological field mapping method on vegetated terrain. The visual interpretation of landslides using numerous DEM derivatives is quite useful for preparing an accurate and updated inventory in contrast with single dataset interpretation e.g. orthophoto. The efficiency of virtual mapping be more useful because is to visualize the dataset on multi scales and the easy updating of the database.

The landslide susceptibility index is clearly shows that the major landslide concentration areas are situated at river incision areas and fault zones. The presence of active faults (Jhelum and Muzaffarabad) along with weak lithology proved that the landslide activity along Neelum Jhelum valleys is highly under control of geological and structural factors. The roads are the most vulnerable in the area due to anthropogenic slope disturbance activity.

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