



# Semi-quantitative landslide risk assessment of district Muzaffarabad, northwestern Himalayas, Pakistan

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## Abstract

The southwestern foothills of the Himalayan Mountain range have been experiencing a surge of catastrophic landslides in the last two decades, as a tragic result of the adverse effects of climate change. This research is about the landslide risk assessment (LRA) which has not been explored yet in the landslide-prone district Muzaffarabad, Pakistan. Landslide susceptibility (spatial probability) was analyzed using random forest model while landslide hazard (temporal probability) was analyzed using Poisson probability model. A random forest-based landslide susceptibility map depicts an accuracy of 0.90. A landslide hazard map was generated by multiplying the temporal probability with the spatial probability and classified as well. Semi-quantitative danger pixels and a fuzzy set theory approach for LRA have been adopted to estimate future landslide risks in the region. The pixel-based LRA approach indicates that 14, 18 and 20 km<sup>2</sup> area of settlement while, the fuzzy set theory-based approach depicts that 15, 19 and 21 km<sup>2</sup> area of the settlement are under very high landslide risk for 1-, 3-, and 5- year return period respectively. Both approaches produced risk maps that designated various risk zones with almost the same area coverage and results. The LRA maps were classified into five classes including very high (1.99%, 2.33%, 2.80%), high (2.16%, 2.53%, 3.04%), moderate (8.02%, 9.79%, 11.22%), low (17.76%, 22.94%, 23.20%), and very low (70.08%, 62.40%, 59.74%) risk zones for 1, 3 and 5 years return period respectively. This research will assist planners and scientists in developing high-precision management strategies for landslide-affected natural resources, especially in the context of the increasing impact of geomorphic hazards on climate change.

**Keywords** Climate change · Landslide risk · Fuzzy set theory · Random forest · Danger pixel · Himalayan Foothills-Pakistan

## 1 Introduction

Landslides are a significant threat to human settlements and infrastructure worldwide, and their impact is expected to increase due to the adverse effects of climate change on geomorphic processes (Gao et al. 2022). Landslides are complex phenomena that are difficult to predict and manage, but recent advances in geospatial technologies and modeling approaches have provided new tools for landslide risk assessment (LRA). Implementing adequate

management strategies, such as risk assessment and landslide susceptibility mapping, can help reduce the damages caused by landslides. The LRA techniques may be used at many phases of the decision-making process, from regional development planning to local site appraisal. According to earlier studies (e.g., Abdulwahid and Pradhan 2017; Kappes et al. 2012; Zezere et al. 2008), landslide vulnerability is largely influenced by several factors, including the run-out distance, magnitude and speed of sliding, type and proximity of at-risk resources, and the nature of buildings and roads. LRA still faces difficulties with quantitative vulnerability assessments (Chen et al. 2011; Peduto et al. 2017). However, a large- or local-scale physical vulnerability assessment can be carried out (Li et al. 2010; Quan Luna et al. 2011).

LRA has been conducted using various approaches including quantitative, qualitative and semi-quantitative

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(Li and Wang 2020; Guo et al. 2020; Shano et al. 2022; Gao et al. 2022; Fu et al. 2020; Chang et al. 2021). Corominas et al. (2014) proposed numerous ways for constructing a landslide risk map, including heuristic, empirical, and rational methods, magnitude-frequency relations, and indirect approaches. The magnitude-frequency technique, which is the most prevalent technique, combines landslide spatial probability with temporal landslide-triggering events like earthquakes or rainfall (Abdulwahid and Pradhan 2017). The resulting landslide hazard model is then coupled with the demographic parameters to create the probable risk of various resources, including forests, structures, and buildings (Mallick et al. 2021). However, in most situations, data on previous landslides is sparse, which makes it difficult to accurately estimate temporal landslide probability and, as a result, hampers future quantitative LRA. As a result, LRA is exceedingly difficult, if not impossible, in areas where historic knowledge of previous landslides is lacking or insufficient (Van Westen et al. 2006). Particularly in developing countries like Pakistan, this issue is frequent, prompting many landslide experts to depend increasingly on spatial probability models to conduct qualitative or semiquantitative LRA. Two unique semi-quantitative LRA methodologies have been suggested here, one established on danger pixels and the other on the concept of fuzzy linguistic set theory (Shano et al. 2022; Mallick et al. 2021; Kanungo et al. 2008). Both methodologies express various aspects of spatial landslide risk evaluation. The fuzzy linguistic approach and the danger pixel approach are useful for LRA in large areas where the mapping scale is small, and access to historical landslide records is limited (Kanungo et al. 2008; Shano et al. 2022). The methodology used demonstrates the categorical classification of elements at risk, which is especially useful when historical landslide data is lacking.

Recently, several statistical and machine learning methods have been employed to develop landslide susceptibility maps around the globe (e.g., Youssef and Pourghasemi 2021; Pham et al. (2021); Sun et al. (2021); Khaliq et al. (2022); Riaz et al. (2022a, b); Khalil et al. (2022); Islam et al. (2022)). These studies have primarily focused on the spatial component of landslides which can be helpful in decision-making for land-use planning. However, main limitation is that these methods may not take into account the temporal variability of landslide occurrences, it does not provide a comprehensive assessment of the risk posed by landslides. Therefore, there is a need for further research in the development of semi-quantitative risk assessment methods for landslides. A few research on spatial probability (i.e., susceptibility) has been conducted in northern Pakistan using various statistical, machine learning and deep learning techniques. For

example, Khalil et al. (2022) performed a comparative analysis of landslide susceptibility mapping using five different techniques (i.e., multicriteria decision-making and machine learning) in the district Muzaffarabad. However, without considering the temporal variability of landslide occurrences, their study only provides a partial understanding of the landslide hazard and does not fully address the needs of decision-makers and stakeholders in the region. While the study by Aslam et al. (2021) used advanced machine learning and deep learning techniques for landslide susceptibility assessment. The study primarily focused on spatial probability and feature extraction using deep learning but did not estimate the temporal probability of landslide occurrence. Aslam et al. (2022a, b) conducted comprehensive studies on landslide susceptibility mapping using various conventional and unconventional machine learning techniques, as well as deep learning techniques. They employed a broad range of landslide conditioning factors and feature selection techniques to assess landslide susceptibility and evaluated the most superior landslide susceptibility model using multiple convolutional neural networks frameworks and residual networks (ResNet). While their studies provide important insights into landslide susceptibility mapping and modeling, a gap still exists in terms of considering the temporal variability of landslide occurrences and the development of quantitative risk assessment. Therefore, future research should focus on incorporating temporal variability and risk assessment into the landslide susceptibility mapping framework to provide a more comprehensive understanding of landslide risk. Sarfraz et al. (2022) conducted an important study on landslide susceptibility mapping along three main road corridors of Muzaffarabad in northern Pakistan. They employed statistical and machine learning techniques to identify the main contributing factors for landslide occurrences along the study road corridors. While the study provided valuable insights into the spatial distribution of landslide susceptibility, it did not consider the temporal variability of landslide occurrences. Thus, future research could focus on integrating temporal probability estimates into landslide risk assessment frameworks to provide a more comprehensive understanding of landslide risk along these road corridors.

One key limitation of the existing studies on landslide risk assessment in northern Pakistan is the lack of consideration for temporal probabilities and LRA, which are crucial for minimizing landslide-related deaths and economic losses in the region. While various knowledge-driven, data-driven, machine-learning, and deep-learning techniques have been used to evaluate the spatial component of landslide susceptibility, no studies have focused on the temporal component of landslide hazard mapping. The current study seeks to fill this research gap by investigating

and integrating the landslide hazard and factors at risk in the area, focusing specifically on the calculation of temporal probability using rainfall thresholds, a novel approach that has not yet been considered in Pakistan. The current research investigates a large area (about 1300 km<sup>2</sup>) including population, agricultural land, road network and infrastructure, and other land use classes, all of which are at risk. Even though some theories and methods are used all over the world (Van Westen et al. 2006; Jiménez-Perálvarez et al. 2017; Van Westen and Greiving 2017), they have not still been implemented in the southwestern foothills of the Himalayan Mountain range Pakistan.

In the current research, we have analyzed the landslide susceptibility mapping (spatial component) by applying a machine learning-based random forest model, while landslide hazard (temporal probability) was obtained by the estimation of empirical rainfall thresholds. Resource damage potential has been determined to be the vulnerability of the resources at risk. The semi-quantitative approach used in this study may make it easier to assess risk over a broad region in less time with fewer resources and budgets, providing critical information for transportation infrastructure construction, ecological restoration, and mitigation measures in Muzaffarabad. Furthermore, the risk assessment can help estimate the level of risk to the current infrastructure and residents in the study region, facilitating preventative actions to protect lives and assets. Overall, this research has the potential to make a significant impact on the region's preparedness for landslides and ultimately contribute to saving lives and reducing economic losses.

## 2 Study area

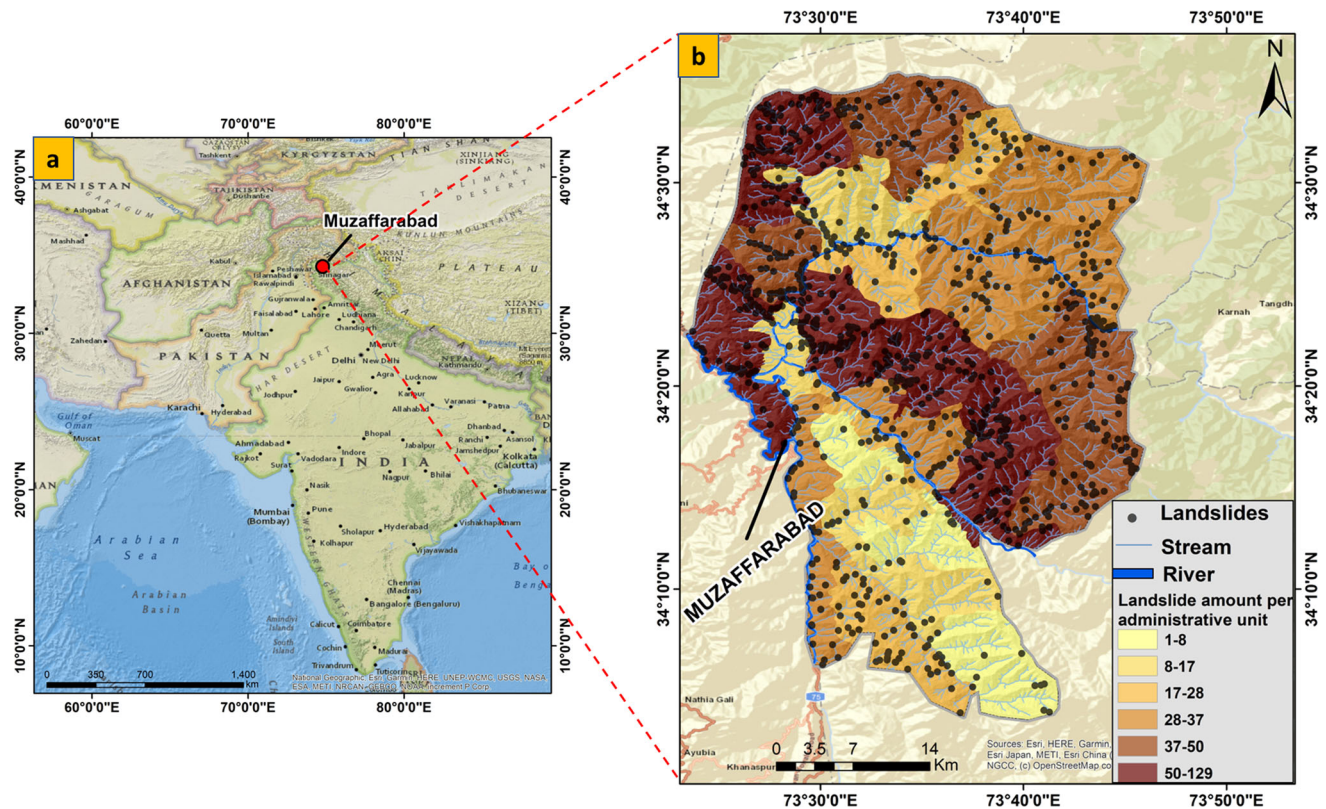
The Muzaffarabad district (Fig. 1), characterized by mountain plateaus, slopes, and inter-mountainous valleys, is mainly underlain by sedimentary, metasedimentary, metavolcanic, and minor granitic rocks, with the majority of the area being exposed as the Miocene Murree Formation consisting of sandstone, siltstone, and shales (Riaz et al. 2018). The Muzaffarabad region is no stranger to the devastating effects of landslides, with steep slopes, cut slopes, and road embankments putting lives at risk and wreaking havoc on vital infrastructure such as highways and communication systems (Fig. 2). These incidents have become increasingly frequent since the 2005 earthquake in Kashmir, particularly during the monsoon season (Kamp et al. 2008; Owen et al. 2008; Khattak et al. 2010). Despite being marked by a substantial amount of geodynamic activity, including intense monsoon rains, river undercutting, and earthquakes, the region's rugged geography continues to put local people in grave danger (Ahmed et al.

2021; Sarfraz et al. 2022). From the massive landslide in Danna village (Fig. 2b) to the disastrous slope failure in the Murree Formation, the impact of landslides on the people of Muzaffarabad cannot be understated (Basharat et al. 2021). Several deadly landslides have occurred in Muzaffarabad, Pakistan in recent years. In February 2013, a landslide caused 17 deaths and road closures. In March 2014, another landslide killed two people. In February 2016, massive landslides destroyed 113 houses and in March of that same year, a rock fall killed six people. In July 2018, one person died due to a landslide along the Muzaffarabad-Srinagar road. Most recently, in July 2022, a landslide triggered by rainfall destroyed a house and killed a child while injuring the rest of the family in the village of Sarli Sacha. Therefore, the current research aims to analyze the LRA of the Muzaffarabad district, highlighting the pressing need for proactive measures to prevent further loss of life and infrastructure damage.

Available source material (e.g., archives, articles, previous landslide inventory maps, satellite data) and field surveys were carried out to collect and create landslide inventory maps for the research region for the last 22 years (2000–2022). Field surveys were conducted to collect data on the distribution of landslides throughout the years 2019–2022. These surveys helped with the generation of training and validating datasets, the identification of fuzzy membership values, and the verification of landslide inventory maps. Utilizing field and remote sensing data, a total of 961 landslides with varied sizes (63 to 703,005 m<sup>2</sup>) were mapped (Riaz et al. 2022b). Aside from the landslide inventory dataset, the ALOS-PALSAR digital elevation model (DEM) with a resolution of 12.5 m × 12.5 m was employed. A database was built with seventeen thematic layers related to landslides, including topographic, geologic, environmental and anthropogenic factors. One layer includes the landcover map, which was prepared from Landsat imagery using supervised and field-verified classification. Settlements/Urban land, grassland/agricultural land, forest, water bodies, barren land, snow cover and road networks are the main resource classes of the area.

## 3 Methodology

The methodology for semi-quantitative landslide risk analysis at the community level involves five major categories of activities, as outlined below and shown in Fig. 3. Database development: In this activity, data is gathered from various sources such as government organizations, data advisory services, statistics, satellite and field-based data, and open-source information sites to carry out LRA. Susceptibility assessment: The development of landslide probability models of the area is required for the LRA. We



**Fig. 1** a Geographical location map of the study area; b) landslide densities per administrative unit

utilized five different machine learning models to create susceptibility maps, including Random Forest, Extreme Gradient Boost, Naïve Bayes, K-nearest neighbors, and Logistic Regression. A detailed overview of these susceptibility mapping methodologies and their comparative analysis is provided in Riaz et al. (2022a, b). The best model, Random Forest, was used as input for the LRA. Hazard assessment: Using the susceptibility maps and temporal and spatial probability, a landslide hazard map was created for semi-quantitative risk assessments. Resource elements vulnerability: On the GIS platform, each data type (resource map) was allocated a weight, which was then overlaid by the raster computation to generate the vulnerability rating. Risk assessment: Finally, landslide risk maps were created by integrating hazard and vulnerability. Overall, the semi-quantitative LRA methodology involves combining spatial and temporal probabilities to produce a grid-unit-based hazard probability, creating hazard maps with different return periods, integrating hazard and vulnerability maps to calculate risk value, and ultimately producing risk maps for visualization.

### 3.1 Landslide hazard mapping

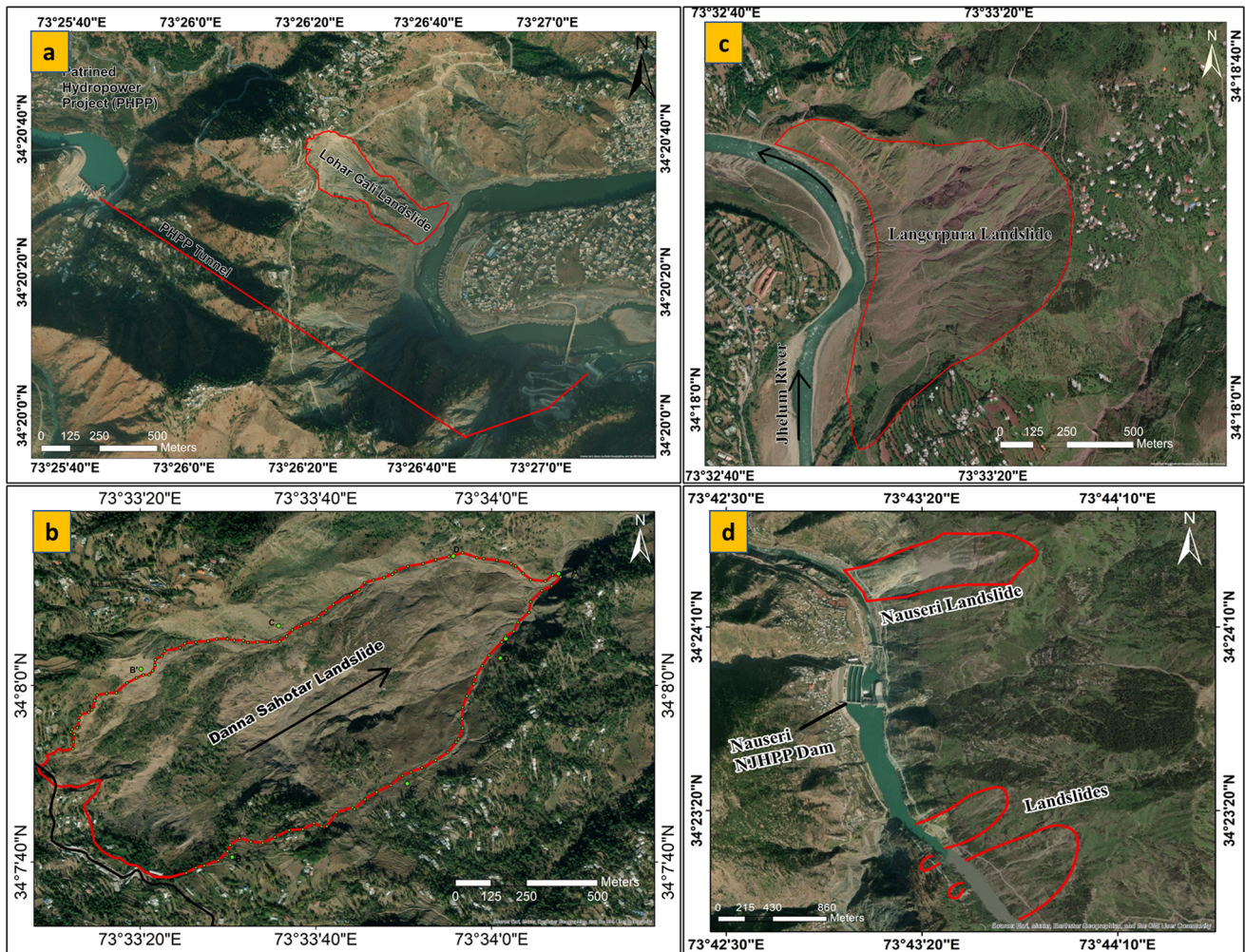
LRA may be accomplished at the community level using the deterministic model (Qiao et al. 2019; Gökçeoglu and

Aksoy 1996). The deterministic technique could not be used in the study area because rock and soil strength characteristics were inaccessible. We utilized the following equation to address issues about where and how probable landslides may occur in a given period (Guzzetti et al. 2005) utilizing two probabilities (spatial and temporal).

$$\text{Hazard } (H) = P_s \times P_t \quad (1)$$

where spatial probability (landslide susceptibility) is denoted by  $P_s$  while temporal probability (landslide hazard) is denoted by  $P_t$ .

Topographic, morphometric, geological, and anthropogenic parameters were considered landslide-predisposing factors in this study. These causative parameters are lithology, slope, aspect, faults, land use, road, drainage, normalized difference vegetation index (NDVI), curvature, topographic wetness index (TWI), elevation, stream power index (SPI), Terrain Ruggedness Index (TRI), peak ground acceleration (PGA), rainfall and solar radiations. For temporal probability five antecedent periods (3, 5, 10, 15, and 30 days) and the daily rainfall of the reported landslide were used to compute the relative rainfall thresholds. The analysis was also useful to identify the maximum rainfall with no landslide (Tien Bui et al. 2013). To determine the landslide recurring time, historical landslide episodes were investigated and evaluated. Empirical rainfall thresholds



**Fig. 2** Examples of high-risk landslides from Google Earth images that have occurred in Muzaffarabad. **a** Lohar Gali landslide affecting about 150 houses, road, agricultural land and infrastructure; **b** Danna-Sahotar landslide occurred in the south of the district Muzaffarabad triggered in 2016, affected about 113 houses, cultivated land, road and

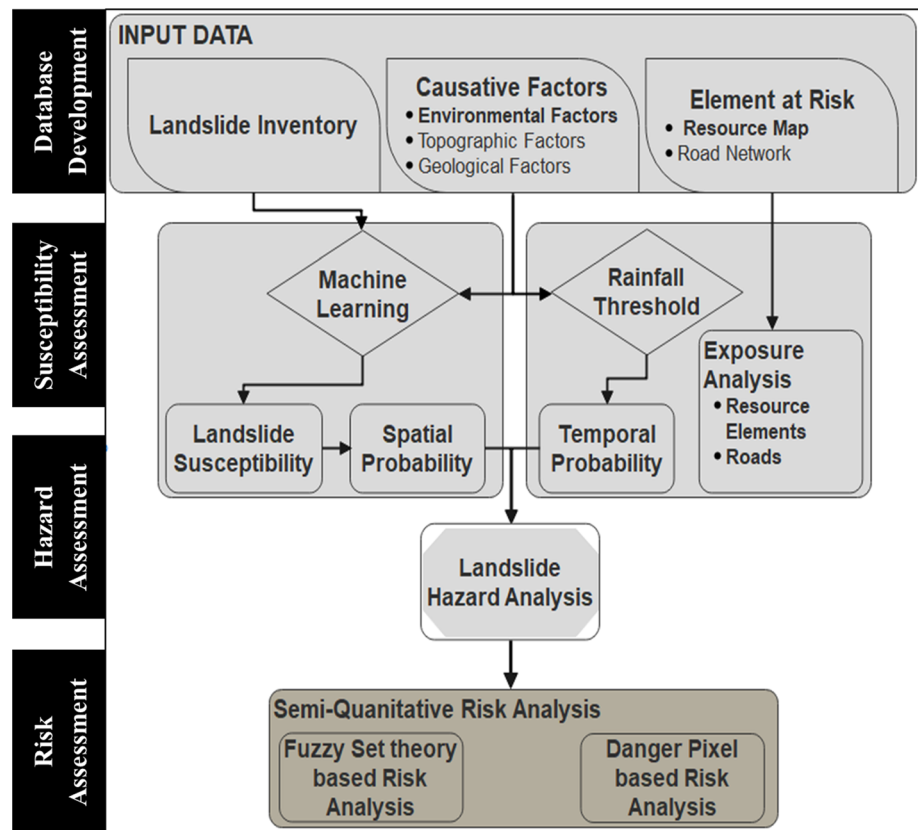
infrastructure; **c** Vulnerable Langerpura landslide along the Jhelum river posing a risk to the associated population; **d** Nauseri landslide along with other landslides occurred in northeast of the district Muzaffarabad, a great threat to the reservoir of Neelum Jhelum Hydropower Project (NJHPP)

(*ED* and *ID*) were developed using rainfall data from a weather station and historical landslide events. After determining the temporal likelihood, the rate of excess day-to-day precipitation during the ensuing 1, 3, and 5 years was calculated using landslide records from 2006 to 2020. The comparative rate of landslides, when the threshold was surpassed was estimated using an empirical Poisson distribution (a continuous-time model) (Jaiswal et al. 2010; Tien Bui et al. 2013). The findings of the threshold analysis are fed into a Poisson probability model to predict landslide temporal probability. Landslide hazard maps are obtained by integrating spatial and temporal probabilities. These thematic layers were processed in ArcGIS and desired computations were made using the Map algebra tool. Finally, validation of resultant landslide hazard maps is done using a previously unused landslide inventory (landslide incidents that happened in 2021).

### 3.2 Resource elements vulnerability

The present study employed resource vulnerability at risk and landslide hazard, to analyse and map the landslide risk. Due to the large area, assessing vulnerability in terms of individual items at risk and assessing precise landslide consequences is not possible in this study. As a result, rather than using assessments of elements at risk, the resources (land use, roads etc.) were employed. Using ENVI 5.3 software, the resource map is generated by considering several resource elements. To evaluate the accuracy of the land cover classifications, a total of 120 points were randomly selected on the classed land cover map, with at least 20 points for each class. Field surveys were conducted using GPS to collect the ground truth locations, which were then compared and validated with

**Fig. 3** Procedure for the application of pixel-based and fuzzy set theory-based semi-quantitative risk assessment



the random points. The present study was performed on a medium scale relying on the vulnerability (i.e., resource damage potential); hence the run-out distance of landslides is not considered, as with a thorough or site-specific examination of landslides (Kanungo et al. 2008).

### 3.3 Landslide risk assessment method

In this work, the relationship between (a) landslide hazard potential (LHP) and (b) resource damage potential (RDP) is used to determine the risk of landslides. To compute and analyze landslide risk in the area, two different approaches for LRA were developed and implemented (i.e., the danger pixels approach and fuzzy set theory). To assess the risk of landslides in the region, these layers are combined using Eq. 2:

$$LR = LHP \times RDP \quad (2)$$

where LR is landslide risk, LHP is landslide hazard potential and RDP is resource damage potential.

#### 3.3.1 Danger pixel

To compute spatiotemporal LRA maps with limited datasets, the danger pixel and land use information (resource map) has been applied in a semi-quantitative manner.

Danger pixels (very high and high hazard pixels) have been merged to create a danger pixel map while the remaining pixels in the moderate zone, low zone and very low zone were clipped out. The final danger pixel-based risk map is an integration of all the pixels in the landslide hazard map with very high and high attributes. It's a binary map, with 1 denoting a danger pixel and 0 denoting a clipped pixel. Finally, by multiplying the pixel values in both maps, the resource map (land use and road network) and the risk pixel map were merged to create the LRA map of the research region. The geographic distribution of many resource classes that emerge to be in danger from landslides is shown on the landslide risk map.

#### 3.3.2 Concept of fuzzy set theory

Anbalagan and Singh (1996) developed a risk ranking matrices technique for LRA, which might be regarded as an extension of the proposed approach. The LHP and RDP categories were computed by fuzzy membership functions based on their respective significance to risk by combining risk matrix and risk scoring techniques. The membership values of resources in the fuzzy set theory are computed in the (0, 1) range depending on the degree of confidence about the event. The fuzzy membership values to various categories of these maps (such as landslide hazard zones

and resource components) were produced based on a linguistic scale constructed from expert knowledge. As a result, distinct categories of elements used as input for LRA might have different membership values assigned to them. In this work, an accurate landslide susceptibility map of the area was employed as LHP to assess landslide potential, which was created using the machine learning-based RF method. In addition, the area’s road network map and maps of the land use and land cover were considered resource maps utilized to enumerate the RDP. To build an LRA map displaying various risk classes (very low, low, moderate, high and very high), these two layers of data, which reflect fuzzy membership values, were multiplied together in a raster GIS environment.

### 4 Results

The study generated spatio-temporal landslide hazard zonation maps (Fig. 4) by integrating spatial probability (RF model; Fig. 5) and temporal probability derived from rainfall threshold analysis. A resource map comprised of several resource elements such as settlement/urban land, grass/agricultural land, forest, barren land, water bodies, snow land and road network (Fig. 6). The land cover map has an accuracy of about 86%.

#### 4.1 Spatiotemporal LRA using the concept of danger pixel

The pixel-based technique identified the total pixels across various resource classes that are impacted by the

landslides. These two maps were superimposed to determine the hazard or danger pixels (Fig. 7). At various return periods, the resource map (Fig. 8) was integrated with the danger pixels. Table 1 lists the total pixels and the landslide-affected pixels for each resource type, along with the percentage of pixels involved for each resource type out of the total number of affected pixels. It shows risk coverage as a percentage of the total impacted area in the research region.

The percentage of affected pixels under forest at risk was 49%, 45% and 43% at 1-, 3-, and 5-year return periods respectively (Table 1). Instead, the percentages of affected pixels under settlements at risk were 21%, 22% and 22% for 1,3, and 5-year return periods respectively. Percentages of main roads affected pixels are 1.8%, 2% and 1.8% whereas affected pixels for link roads are 4%, 6% and 6% for 1,3 and 5 years return period (Table 1). Overall total pixels of landslide resource categories are 1,552,278. Among these 74,940 (5%), 93,682 (6%) and 102,776 (7%) pixels of resource categories are affected by landslides for 1, 3 and 5 years return periods respectively, indicating that damaged pixels are increasing with time (Table 1).

#### 4.2 Utilizing fuzzy set theory for spatiotemporal LRA

Table 2 provides linguistic criteria for hazard rating as well as fuzzy membership functions for different landslide hazard classes. The maximum membership value of 1 was given to a very high hazard zone because this area will likely experience the most landslides, whilst the lowest membership value of 0.1 was given to a very low hazard

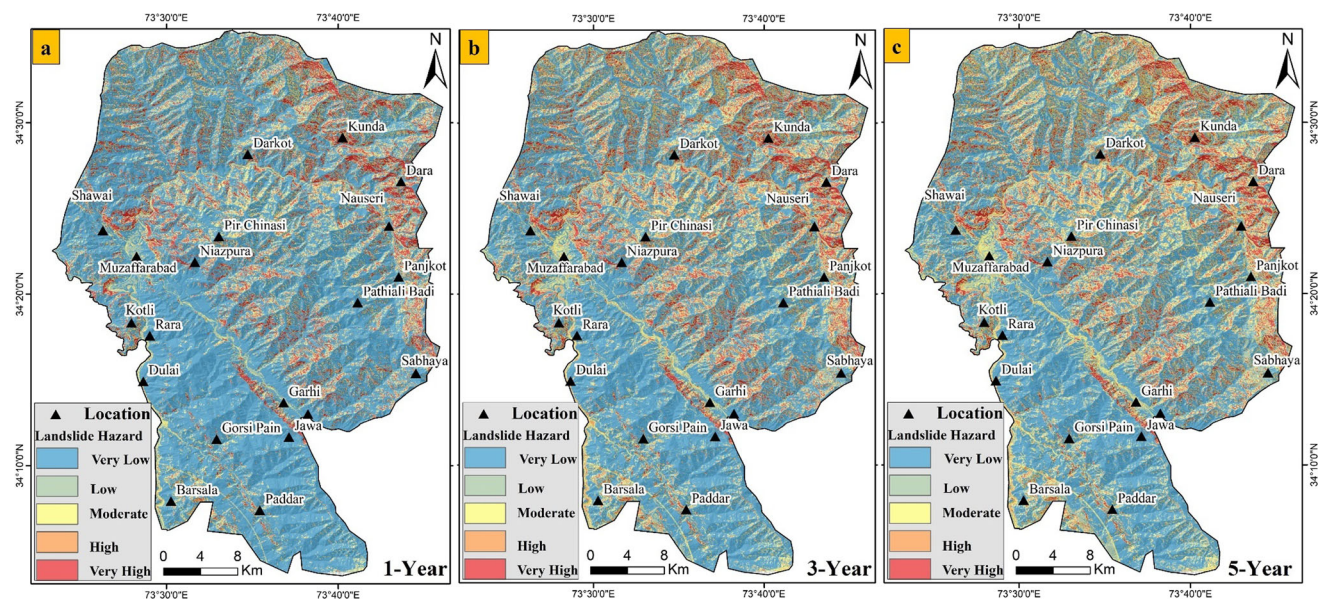
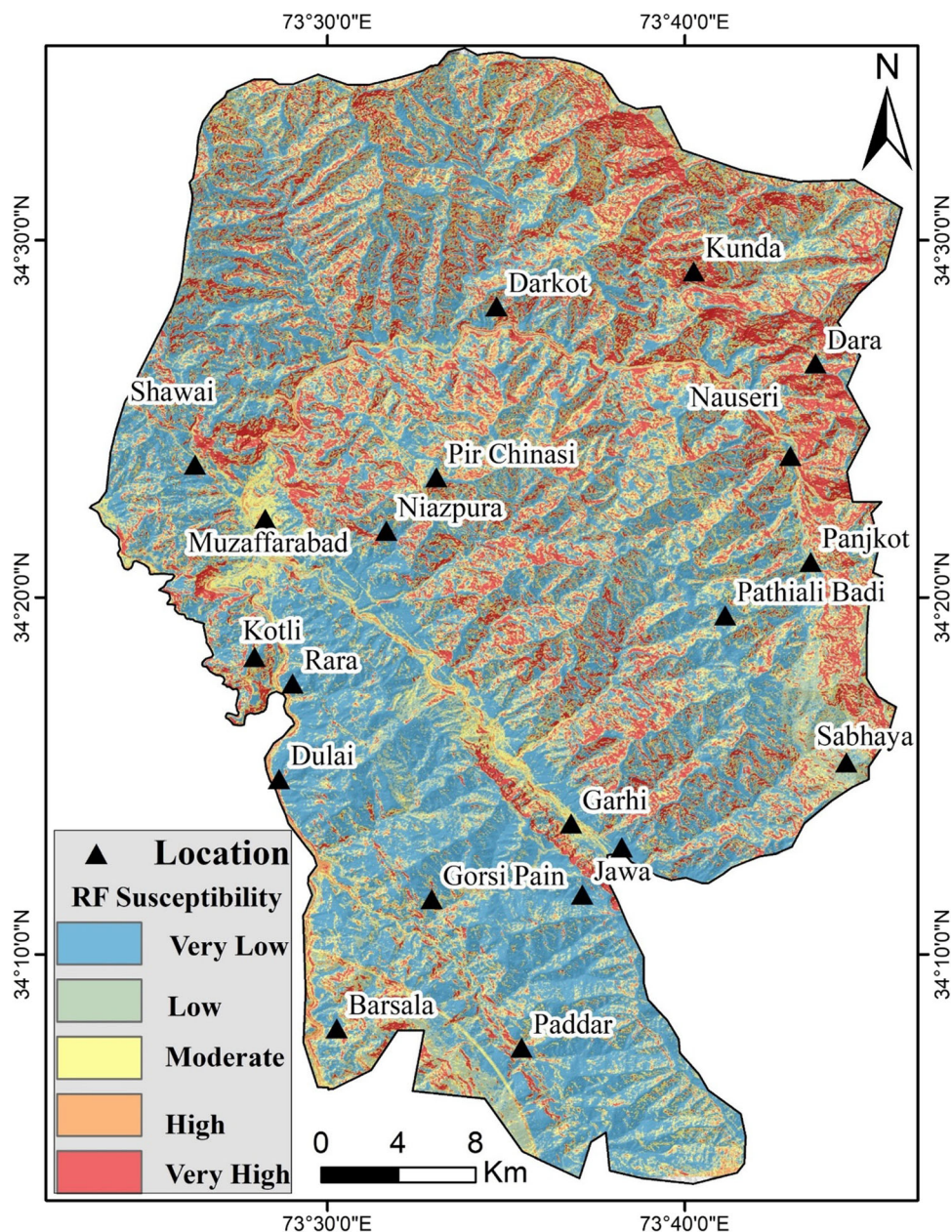


Fig. 4 Landslide hazard map the scenario a 1 year; b 3 years; c 5 years

**Fig. 5** Landslide susceptibility map computed by the application of machine learning-based Random Forest algorithm having prediction accuracy of 90%



zone because this area will likely experience the fewest landslides (Table 2). Similarly, a hazard proportional membership value of 0.80 was assigned to high, 0.55 was assigned to moderate, and 0.30 was assigned to a low-risk class (Table 2). Fuzzy membership values assigned to several resource categories, primarily land use classes, are closely tied to the socio-economic interests of the local community (Table 3). The settlement resource category was given a maximum fuzzy membership value of 1.0 since any likely landslide activity will directly affect the residents and their assets, such as homes and in-house properties. Considering this, the inhabited area (communities and property, for example) has been given the

highest LHP. Landslide damage is thought to be limited in areas such as barren land and water bodies. The membership values for the other resource categories were likewise allocated according to their relevance to the associated population. Table 4 shows the developed linguistic rules for risk assessment as well as the associated fuzzy membership values for the various resource categories. The landslide risk in the region was determined by converting the landslide risk into a matrix using this fuzzy linguistic method (Table 5). Using ArcGIS, the LHP and RDP raster data sets were multiplied to create an LRA map (Fig. 9).



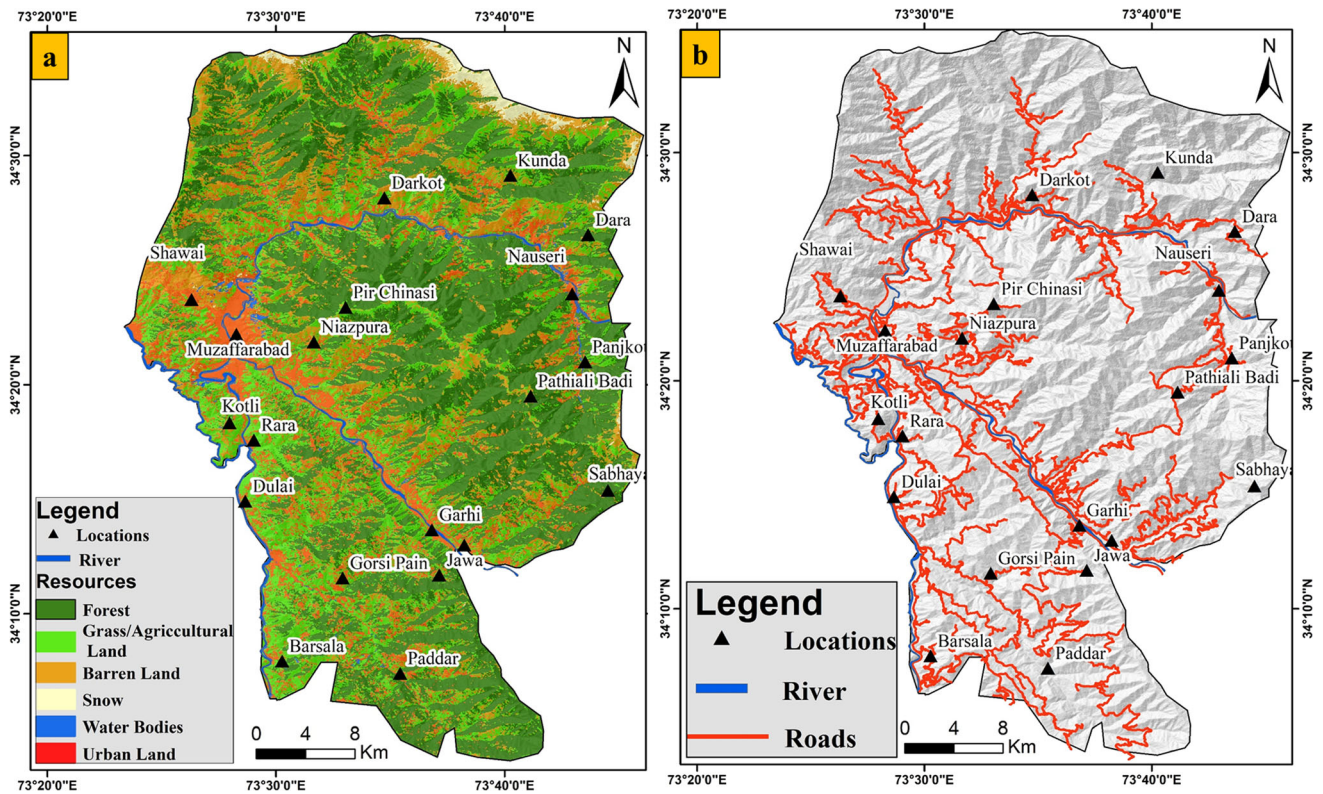


Fig. 6 Thematic maps: a resource map; b road network of the area

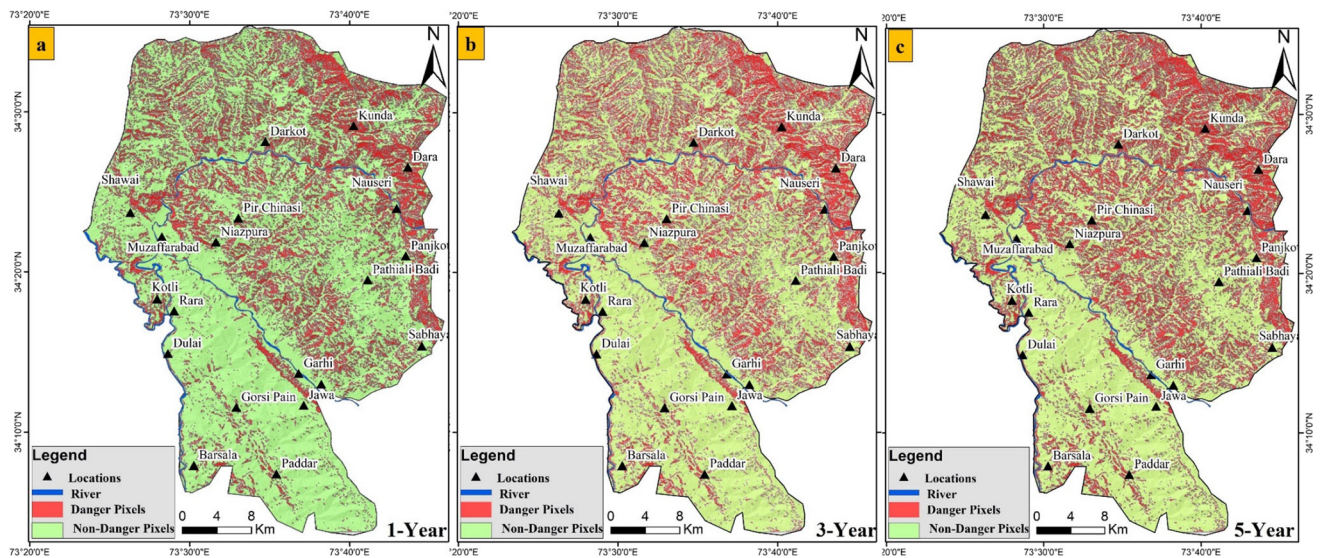


Fig. 7 Landslide danger and non-danger pixels based on hazard: a 1; b 3; c 5 years return period

### 4.3 LRA mapping

The resource map depicts the area’s road network as well as all the current land use and land cover categories. Settlements, expressways, national highways, main roads, link roads, grassland, forest, water bodies, barren land, and snow land are the ten categories represented. Fuzzy

membership values have been used to quantify LHP and RDP as raster data layers. Table 4 demonstrates how an LRA matrix may be used to describe and estimate landslide risk for landuse resources and hazard classes. According to the LRA matrix, each pixel’s LRA value falls within the ranges of 0.01 and 1.00. In resource classes e.g., barren land, water bodies, and snow land, a score of 0.01

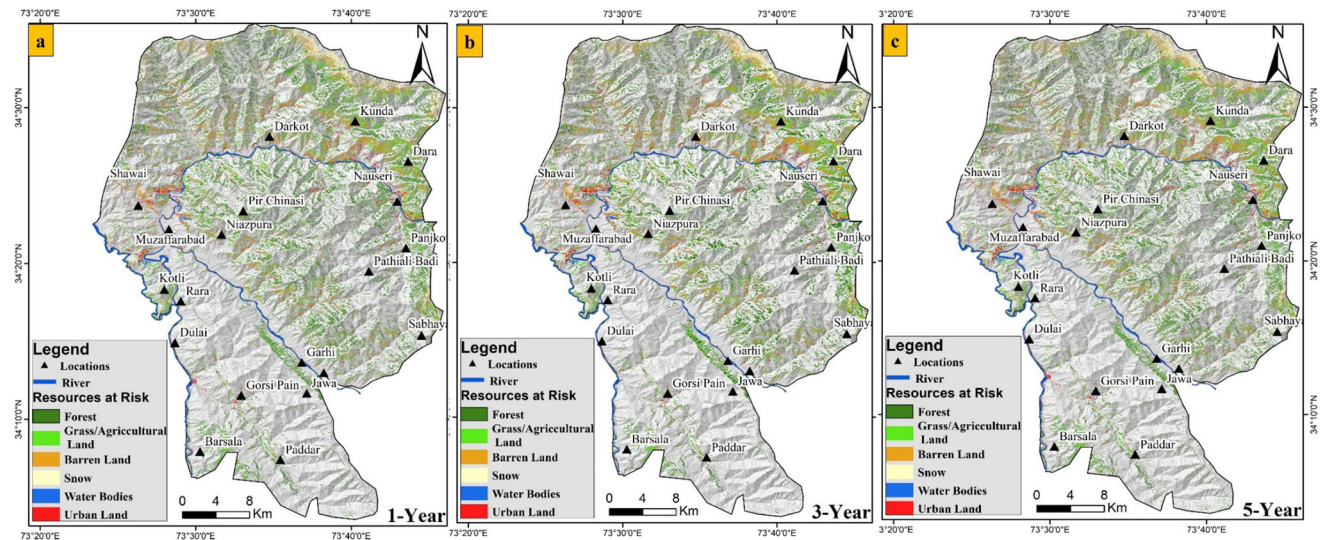


Fig. 8 Danger pixel-based landslide risk maps: a 1; b 3; c 5 years return period

Table 1 Total and impacted pixels across many resource categories

Resource class	Total pixels	Affected pixels 1-year scenario		Affected pixels 3-year scenario		Affected pixels 5-year scenario	
		Affected pixels	% of affected pixels in the resource class out of the total affected pixel	Affected pixels	% of affected pixels in the resource class out of the total affected pixel	Affected pixels	% of affected pixels in the resource class out of the total affected pixel
Settlements	205,288	16,159	21.56	20,689	22.08	22,989	22.37
Expressway	1420	538	0.72	628	0.67	751	0.73
National highway	1248	306	0.41	458	0.49	698	0.68
Main road	7275	1312	1.75	1801	1.92	1834	1.78
Link road	48,451	2950	3.94	5884	6.28	6456	6.28
Grass land	378,039	3465	4.62	4896	5.23	6958	6.77
Forest	677,585	36,486	48.69	42,486	45.35	44,265	43.07
Water bodies	17,576	546	0.73	688	0.73	963	0.94
Barren land	198,513	9489	12.66	11,256	12.02	12,652	12.31
Snow land	16,883	3689	4.92	4896	5.23	5210	5.07
Total	1,552,278	74,940 (4.83%)	100%	93,682 (6.04%)	100%	102,776 (6.62%)	100%

designates extremely low landslide potential, whereas a value of 1.00 designates very high landslide risk in settlement areas and expressways. The method described in Table 5 was used to divide the landslide risk values from 0.01 to 1.00 into five risk zones, which were then used to construct the LRA map (Fig. 9) of the area. To estimate the geographic distribution of various hazard zones in various resource categories, the LRA map was overlaid on the resource map (Table 6). This table shows that 10,158 pixels (0.7% of total area); 12,689 pixels (0.82%) and 13,698 (0.88%) pixels are lie in the very high-risk zone in 1,3 and

5 years return periods. This may be because settlements were given very high fuzzy membership values. Further, 14,400 pixels (0.93% of total area); 15,593 pixels (1.0%) and 18,621 pixels (1.20%) lie in very high-risk zone, for 1, 3 and 5 years return period for forest respectively. Landslides provide a very significant risk to habitation in and around Muzaffarabad city as well as along major traffic corridors in the Neelum and Jhelum valley, according to a deeper examination of the LRA map (Fig. 9).

LRA research conducted in this work may be used to analyze the risks associated with landslides or any other

**Table 2** Linguistic rules for hazard scoring of various landslide hazard classes

Landslide hazard class	Linguistic rule for hazard scoring	Fuzzy membership value for landslide potential
Very high	Landslides frequently occurred; On-going severe landslides were widespread. Landslide almost certain to occur	1.0
High	Landslide activities are evident at many locations. Landslides repeatedly occur in severe conditions	0.80
Moderate	In the past landslides have occurred locally. Adverse environmental conditions are responsible for the possible occurrence of landslides	0.55
Low	Landslides are unlikely to occur. Slopes are generally stable	0.30
Very low	Very rare or no occurrence of landslides. Inherently stable slopes naturally	0.10

**Table 3** Linguistic rules for risk scoring of different resource and road classes for damage potential

Resource classes	Linguistic rules for risk scoring	Fuzzy membership value for damage potential
Settlements	Impact on the people as well as assets such as buildings and property. Deaths, injuries, and property loss are all examples of damages	1.0
Road		
Expressway	Damage caused by a lack of connection in the region, might impede rescue and rehabilitation efforts during the post-disaster recovery period	1.0
National highway	Effect on critical infrastructure and services (i.e., road network)	0.8
Main road	Disturbance in communication between other districts and administrative offices	0.6
Link road	Road damages along hilly terrain due to slope instabilities	0.35
Grass land/ agriculture	Direct influence on the economy (revenue) and survival food items	0.35
Forest	Although there is no direct influence on individual economies, the nation’s forest supply is being depleted	0.15
Water bodies	Little damage	0.1
Barren land	Little damage	0.05
Snow land	Little damage	0.05

catastrophe in a given location. Table 6 and Figs. 9, 10, and 11 show that the risk was divided into five categories; very high risk (2% for 1- and 3- years, 3% for 5-years), high risk (2%, for 1-year, 3% for 3- and 5-years), moderate (8% for 1-year, 10% for 3-years, 11% for 5- years), low (18% for 1-year, 23% for 3- and 5-years), and very low risk (70% for 1-years, 62% for 3-years, 60% for 5-years). High and extremely high-risk zones include the northern, central, and northeastern sectors of the district, as well as parts of the south.

**4.4 Comparison of LRA maps**

The risk matrix table was created by analyzing the landslide potential values with the fuzzy membership values of land use classes, and the landslide risk map was then fashioned using fuzzy linguistic analysis. Heuristic

weighting was used for both the resource categories and the landslide danger zones. The two methodologies were used to create landslide risk maps, which were compared (Table 7; Fig. 12). The danger pixels extraction concept only considered the landslide-affected pixels for different land-use classes under the very high and high landslide hazard zone classes, hence the risk map created using the fuzzy set linguistic technique was only equated for those zones. In Table 7, the comparative findings of the research area’s LRA are shown. It’s worth noting that the outcomes of the applied approaches are almost identical. According to a risk perspective, the most significant resource classes are forests, settlements, link roads and main roads. The danger pixel extraction approach shows 49%, 45% and 43% affected pixels of forest, 21.56%, 22.08% 22.37% affected pixels for settlements, 3.94%, 6.28% and 6.38% affected pixels for link road and 1.75%, 1.92% and 1.78%

**Table 4** LRA matrix for different combinations of RDP and LHP

		Landslide Hazard Potential (LHP)				
		Very High (1.0)	High (0.8)	Moderate (0.55)	Low (0.3)	Very Low (0.1)
Resource Damage Potential (RDP)	Settlements (1.0)	1.0	0.8	0.55	0.3	0.1
	Expressway (1.0)	1.0	0.8	0.55	0.3	0.1
	National Highway (0.8)	0.8	0.64	0.44	0.24	0.08
	Main Road (0.6)	0.6	0.48	0.33	0.18	0.06
	Link Road (0.3)	0.35	0.28	0.19	0.11	0.04
	Grass Land (0.35)	0.35	0.28	0.19	0.11	0.04
	Forest (0.15)	0.15	0.12	0.08	0.05	0.02
	Water Bodies (0.1)	0.1	0.08	0.06	0.03	0.01
	Barren Land (0.05)	0.05	0.04	0.03	0.02	0.01
	Snow Land (0.05)	0.05	0.04	0.03	0.02	0.01

Dark green—very low risk, light green—low risk, yellow—moderate risk, light brown—high risk, red—very high risk

**Table 5** Landslide risk values are segmented into distinct landslide risk zones

Landslide risk values	Landslide risk zones
< 0.1	Very low
< 0.2	Low
< 0.4	Moderate
< 0.6	High
> 0.6	Very high

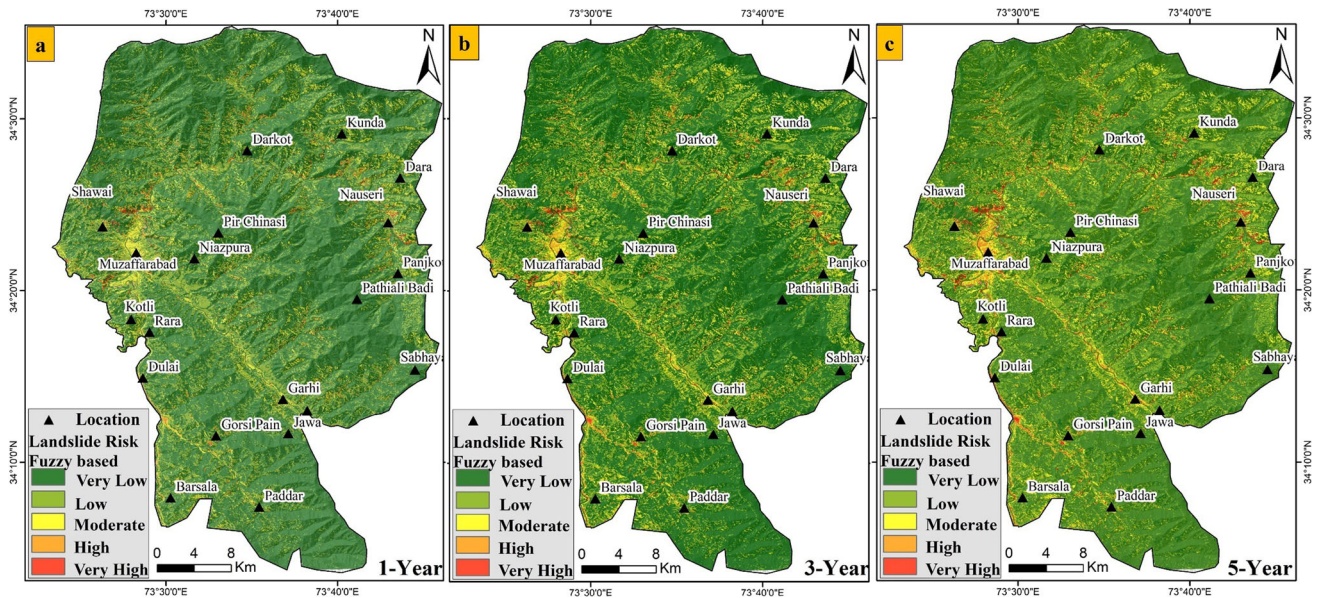
affected pixels for main roads for 1, 3 and 5 years respectively. Also, the Fuzzy set linguistic method depicts 50.35%, 48% and 46.64% of affected pixels for the forest, 25.27%, 28.33% and 25.97% affected pixels for settlements, 3.13%, 4.82% and 4.66% affected pixels for the link road and 1.71%, 1.65% and 2.57% affected pixels for main roads for 1, 3 and 5 years return period respectively. Forests and settlements, which are located in a zone of extreme risk, are the main resource elements of concern. Furthermore, a notable large percentage of the area 8.02%, 9.79% and 11.22% of the total area lies in the moderate risk zone. However, a large portion of the area 87.84%, 85.34% and 82.94% of the total area collectively lies in a very low and low-risk zone for 1, 3 and 5 years return period. Out of the

total area 4%, 5% and 6% area of resource categories lies in the very high- and high-risk zone for 1, 3 and 5 years return periods, respectively.

**4.5 Expected impact on the population in the Muzaffarabad district**

The 13,297 km<sup>2</sup> Pakistan Administrated Kashmir (PAK) region is split into 10 districts and 1,771 villages. About 12% of the population resides in urban regions, while 88% lives in rural areas. According to estimates from the 2017 census, the PAK would have a total population of 4.1 million by 2018. A significant portion of the population relies on the agriculture and forestry sectors for their livelihood, with farm income making up 30–40% and the remaining 60–70% coming from sources other than farms. Given the abundance of natural beauty, the area is currently receiving more attention and has a great deal of potential to become a tourism hotspot.

A total of two tehsils makes up Muzaffarabad. a) Tehsil Pattika Naseerabad, which has 12 Union Councils, one Municipal Committee (Pattika) and one Town Committee (Khori); b) Tehsil Muzaffarabad, which has a total of 29 Union Councils and includes the Municipal Corporation of Muzaffarabad and the Town Committee Ghari Dupatta. Muzaffarabad district has about 415 villages in total. In the



**Fig. 9** Fuzzy linguistic approach-based landslide risk map of district Muzaffarabad: **a** 1; **b** 3; **c** 5 years return period

district, there are about 6 people per home. LRA map (Fig. 9) depicts that Muzaffarabad municipal corporation (most populated i.e., 149,005 persons) comprises 8.48 km<sup>2</sup> area (31%) in very low-risk zone, 7.05% area (26%) in low-risk zone, 6.84 km<sup>2</sup> area (25%) in moderate risk, 3.72 km<sup>2</sup> area (14%) in high risk while 0.981 km<sup>2</sup> area (4%) in a very high-risk zone. While town committee Garhi (having a population of 7931 persons) comprises 2.18 km<sup>2</sup> (38%) area in a very low-risk zone, 2.16 km<sup>2</sup> (37%) area in low risk, 0.1 km<sup>2</sup> area (17%) in moderate risk, 0.3 km<sup>2</sup> area (5%) in high risk and 0.14 km<sup>2</sup> area (2%) in a very high-risk zone. Municipal committee Pattika (having a population of 14,098 persons) comprises 31%, 28%, 21% 12% and 8% areas in very low, low, moderate, high and very high-risk zones. While Town committee Ghorī (population of 5278 persons) comprises 29% area in a very low-risk zone, 27% area in low-risk zone, 22% area in moderate risk zone, 13% area in high and 9% area in a very high-risk zone. Most of the people live in Muzaffarabad, which is mostly comprised of valley bottoms, river terraces, and flat terrain. The ecosystems of the mountain are severely under threat because of the high population density (Fig. 13).

## 5 Discussion

The study evaluated the spatiotemporal landslide risk in the district of Muzaffarabad, Pakistan, by integrating a random forest model and a semi-quantitative technique to estimate landslide hazard and risk for different return periods. The study highlights the importance of considering both natural and anthropogenic predisposing factors in assessing

landslide risk in hilly regions, especially as settlement areas at risk are expected to increase with population growth and land cover changes. This study provides important insights into the complex interplay between geomorphology, natural hazards, and climate change, and underscores the need for long-term landslide management plans to reduce economic damage, preserve natural resources, and protect human lives.

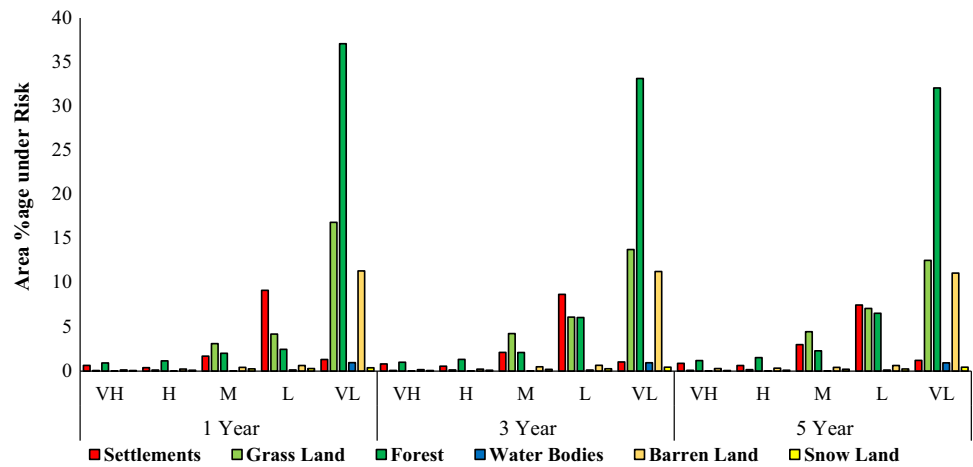
Random forest model depicts higher prediction accuracies which are comparable with other studies (e.g., Pham et al. 2021; Park and Kim 2019). To lessen the effects of landslides in hilly places, it is crucial to evaluate both the natural and anthropogenic predisposing variables (Tariq et al. 2021a, b; Islam et al. 2022). Various research on LRA has been conducted in the world (e.g., Shano et al. 2022; Mallick et al. 2021; Banshtu et al. 2020; Fu et al. 2020; Althwaynee and Pradhan 2017; Pereira et al. 2020). For the assessment of landslide risk, socio-economic data have been used by many researchers (Remondo et al. 2008; Leonardi et al. 2020; Mineo 2020; Winter and Wong 2020), but in areas with a dearth of data, such as Pakistan, socio-economic and damage data are unavailable and extremely challenging to gather. Therefore, the present work used the theory of danger pixels and fuzzy sets to describe risk assessment. Althwaynee and Pradhan (2017) used the semi-quantitative approach for the assessment of landslide risk in Kuala Lumpur. The notion of danger pixels and the fuzzy set was used by Kanungo et al. (2008) to evaluate the landslide risk assessment. Furthermore, very limited research on landslide risk assessment at a temporal scale has been carried out (Dikshit et al. 2020; Mallick et al. 2021).

**Table 6** Spatial distribution of risk zones and resource classes

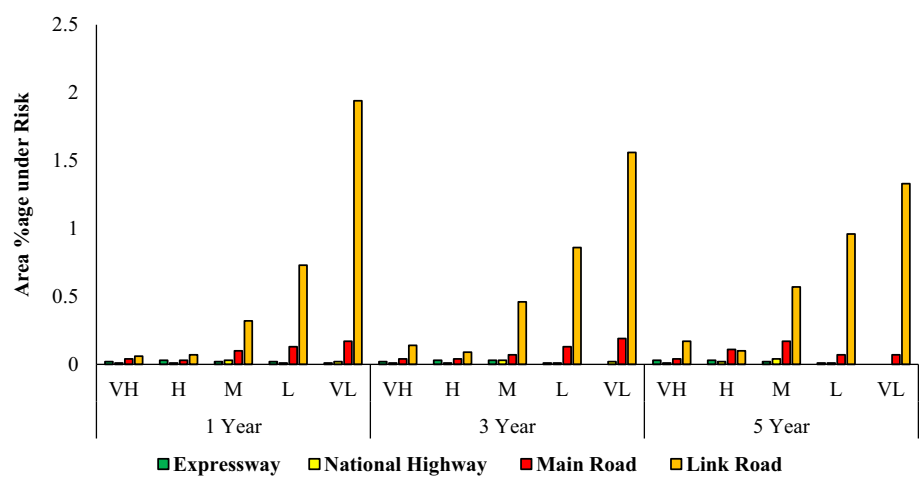
Resource class	Risk Level 1 year										Risk Level 3 year										Risk Level 5 year									
	Number of Pixels/% of total area		Risk Level 1 year		Risk Level 3 year		Risk Level 5 year		Risk Level 1 year		Risk Level 3 year		Risk Level 5 year		Risk Level 1 year		Risk Level 3 year		Risk Level 5 year		Risk Level 1 year		Risk Level 3 year		Risk Level 5 year					
	VH	H	M	L	VL	VH	H	M	L	VL	VH	H	M	L	VL	VH	H	M	L	VL	VH	H	M	L	VL					
Settlements	10,158	6109	26,421	142,107	20,493	12,689	8698	32,857	134,929	16,115	13,698	9863	46,524	116,267	18,936															
	0.65	0.39	1.70	9.15	1.32	0.82	0.56	2.12	8.69	1.04	0.88	0.64	3.0	7.49	1.22															
Expressway	350	389	366	234	81	388	410	460	137	25	526	427	290	157	20															
	0.02	0.03	0.02	0.02	0.01	0.02	0.03	0.03	0.01	0.00	0.03	0.03	0.02	0.01	0.00															
National highway	113	207	419	204	305	117	230	428	194	279	179	239	576	215	39															
	0.01	0.01	0.03	0.01	0.02	0.01	0.01	0.03	0.01	0.02	0.01	0.02	0.04	0.01	0.00															
Main road	557	542	1500	1996	2680	588	661	1087	1981	2958	657	1675	2690	1130	1123															
	0.04	0.03	0.10	0.13	0.17	0.04	0.04	0.07	0.13	0.19	0.04	0.11	0.17	0.07	0.07															
Link road	986	1029	4989	11,263	30,184	2214	1428	7175	13,345	24,289	2636	1596	8821	14,826	20,572															
	0.06	0.07	0.32	0.73	1.94	0.14	0.09	0.46	0.86	1.56	0.17	0.10	0.57	0.96	1.33															
Grass land	1018	1877	48,400	65,146	261,598	1284	2057	65,957	94,993	213,748	1356	2565	69,286	110,183	194,649															
	0.07	0.12	3.12	4.20	16.85	0.08	0.13	4.25	6.12	13.77	0.09	0.17	4.46	7.10	12.54															
Forest	14,400	18,005	31,353	38,292	575,535	15,593	20,651	32,710	94,271	514,360	18,621	23,696	35,699	101,676	497,893															
	0.93	1.16	2.02	2.47	37.08	1.00	1.33	2.11	6.07	33.14	1.20	1.53	2.30	6.55	32.07															
Water bodies	102	210	412	2004	14,848	118	286	499	1905	14,768	269	321	649	1802	14,535															
	0.01	0.01	0.03	0.13	0.96	0.01	0.02	0.03	0.12	0.95	0.02	0.02	0.04	0.12	0.94															
Barren land	2123	3662	6633	9888	176,207	2150	3378	7677	10,196	175,112	4425	5236	6447	9894	172,511															
	0.14	0.24	0.43	0.64	11.35	0.17	0.22	0.49	0.66	11.28	0.29	0.34	0.42	0.64	11.11															
Snow land	1021	1504	3989	4477	5892	1023	1541	3123	4194	7002	1120	1618	3243	3918	6984															
	0.07	0.10	0.26	0.29	0.38	0.07	0.10	0.20	0.27	0.45	0.07	0.10	0.21	0.25	0.45															
Total	30,828	33,534	124,482	275,611	1,087,823	36,164	39,340	151,973	356,145	968,656	43,487	47,236	174,225	360,068	927,262															
	1.99	2.16	8.02	17.76	70.08	2.33	2.53	9.79	22.94	62.40	2.80	3.04	11.22	23.20	59.74															

VL very low risk, L low risk, M moderate risk, H high risk, VH very high risk

**Fig. 10** Percentages of each resource category’s area that is in a risk zone

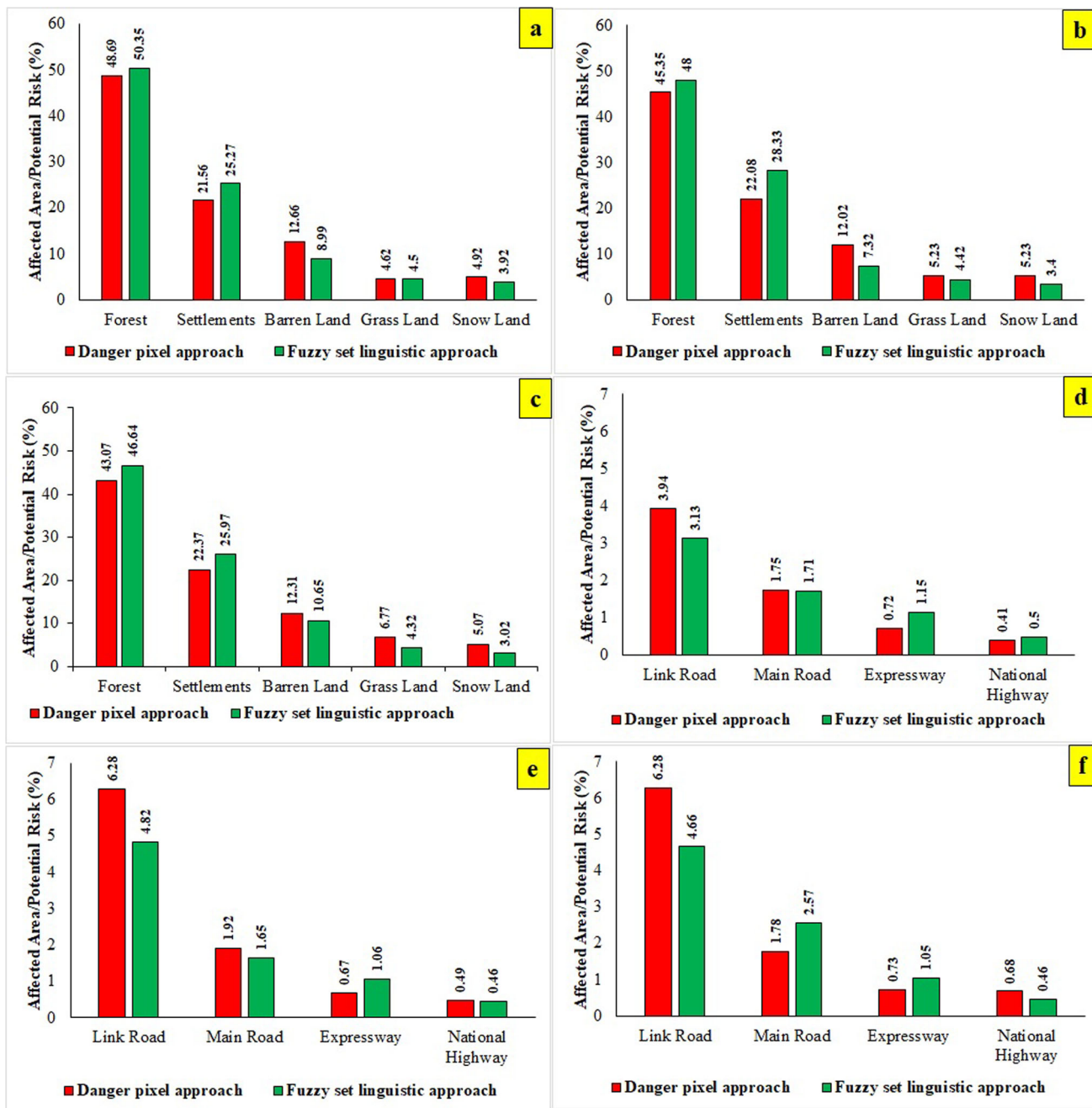


**Fig. 11** Distribution of the percentage of each road type’s area that is in a risk zone



**Table 7** Comparison of results from Fuzzy set linguistic approach and Danger pixel approach

Resource class	Danger pixel approach 1 year		Fuzzy set linguistic approach 1 year		Danger pixel approach 3 years		Fuzzy set linguistic approach 3 years		Danger pixel approach 5 years		Fuzzy set linguistic approach 5 years	
	Affected pixel	(%)	Affected pixel	(%)	Affected pixel	(%)	Affected pixel	(%)	Affected pixel	(%)	Affected pixel	(%)
Settlements	16,159	21	16,267	25	20,689	22	21,387	28	22,989	22	23,561	26
Expressway	538	0.8	739	1	628	0.7	798	1	751	1	953	1
National highway	306	0.4	320	0.5	458	0.4	347	0.4	698	0.7	418	0.4
Main road	1312	1.8	1099	1.8	1801	2	1249	2	1834	1.8	2332	2.6
Link road	2950	4	2015	3	5884	6	3642	5	6456	6	4232	4.7
Grass land	3465	5	2895	5	4896	5	3341	4	6958	6.8	3921	4
Forest	36,486	49	32,405	50	42,486	45	36,244	48	44,265	43	42,317	46.7
Water bodies	546	0.8	312	0.4	688	1	404	1	963	1	590	0.7
Barren land	9489	12	5785	9	11,256	12	5528	7	12,652	12	9661	10.7
Snow land	3689	5	2525	4	4896	5	2564	3	5210	5	2738	3
Total	74,940	100	64,362	100	93,682	100	75,504	100	102,776	100	90,723	100



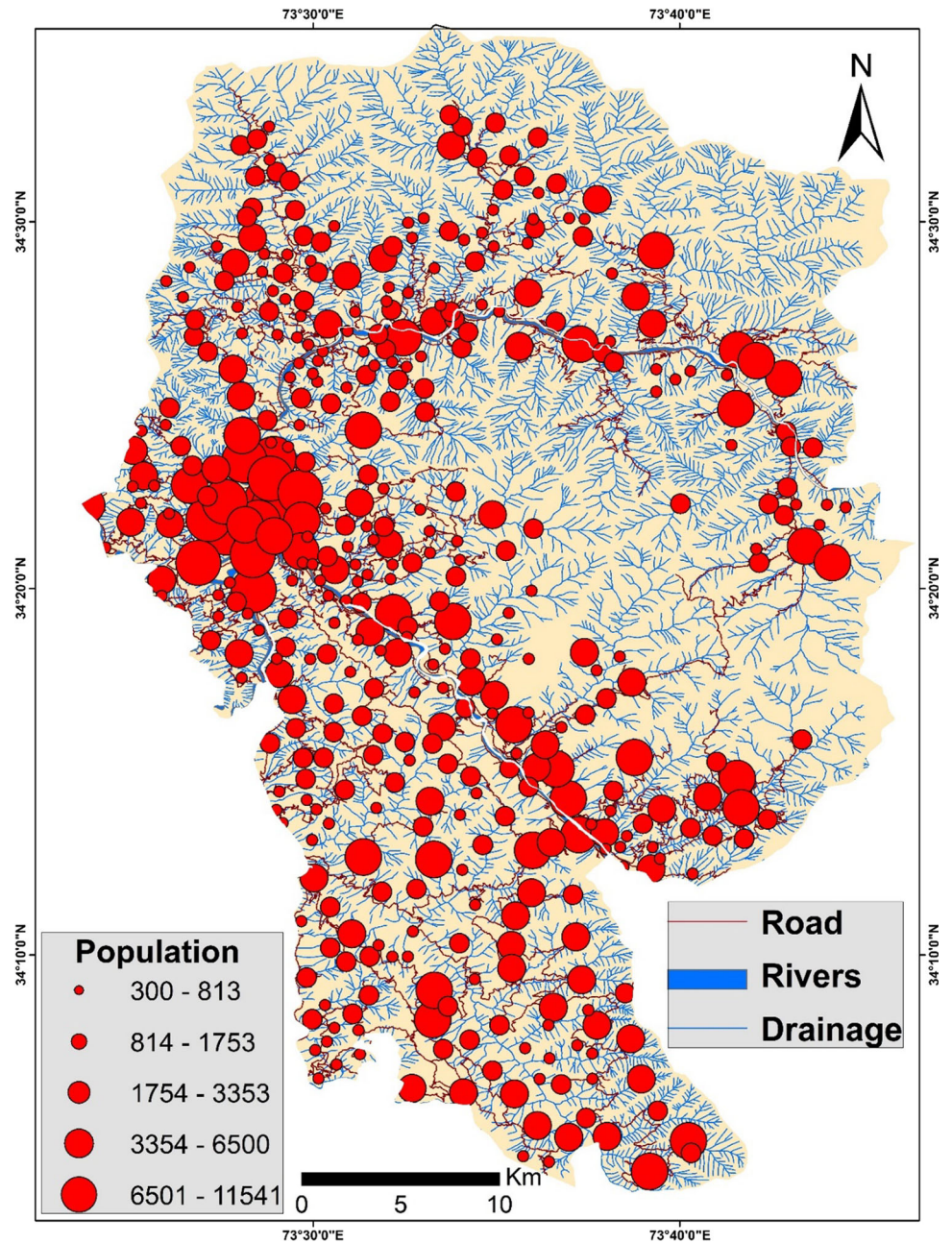
**Fig. 12** Analysis of the differences between the fuzzy set linguistic approach and the danger pixel approach’s findings: resource classes at risk for **a** 1; **b** 3; **c** 5 years return period; road classes at risk for **d** 1; **e** 3; **f** 5 years return period

The LRA maps produced using both techniques indicated distinct risk zones with virtually identical area exposure for high and extremely high landslide zones. Forest land is the most impacted resource, according to the final risk map at various return periods followed by urban land/settlements. Landslides mostly happen in hilly regions since various steep slope areas lie in sparse to modest amounts of vegetation. Due to the mapping scale’s limitations, the pixel-based study did not include isolated small

resource components, such as individual homes and small plots of agricultural land, that are found inside sparse and intermediate forest land. Nevertheless, landslide risk will also exist for this isolated resource inside a somewhat sparse forest area. Over time, the number of settlements at risk has grown, raising concerns for the security of human life. Additionally, it is anticipated that more settlement areas will be at risk for landslides because of the continued growth and extension of population areas with noticeable



**Fig. 13** Population dot density map of 415 villages of district Muzaffarabad



variations in land cover. The settlement class, as indicated in Table 1, shows the concentration of inhabited areas; nevertheless, remote dwellings are also found in risk zones. These communities are small and weren't included in the pixel-based study. In the current study region, congested settlements are present in Muzaffarabad city and along the river Neelum and Jhelum. Affected pixels are also increasing due to road construction along steep slopes and unplanned population expansion. For national highways and water bodies, as time passed (1–5-year return intervals), the area at risk also increased. According to Kanungo et al. (2008) high or extremely high landslide hazard zones

can be used to categorize danger pixels for different land-use classes. The current research, therefore, examined landslide-impacted pixels for several land use classes in high and very high-risk zones. It indicates the overall risk hotspots in the area. Consequently, a different strategy (fuzzy membership) was also used in the current investigation. To determine how to reduce the danger from landslides, proper systematic slope stability assessments are required for any future building of homes and other infrastructure that is located in high- or extremely high-risk zones. The experimental procedure and study design presented in this manuscript were developed to answer the

research questions related to semi-quantitative landslide risk assessment using danger pixel and fuzzy linguistic method in a data-scarce environment of District Muzaffarabad. The proposed method combines expert knowledge and remote sensing data to identify landslide risk zones and assess the degree of risk in the study area. The results showed that the proposed method was effective in identifying landslide risk zones and the degree of risk, which were consistent with the existing landslide inventory map. Therefore, the evidence presented in this manuscript supports the conclusions drawn from the experimental procedure and study design. The results demonstrated that the proposed methodology is effective in identifying areas with high, moderate, and low levels of landslide risk, which can aid in the development of appropriate risk management strategies. The proposed method can provide decision-makers with a better understanding of the landslide risk and can be applied in other data-scarce regions with similar conditions. The fuzzy set linguistic technique was revealed to be useful for future land use planning and to develop potential corrective actions to lessen the problem of landslides and the risk. The future harm to natural and man-made resources, depending on the severity of the landslide, may be predicted with detail by predicting the long-term risk of landslides. Economic damage, the devastation of natural resources, and loss of human lives might all be reduced if authorities take decisive action while taking into account long-term risk assessment. As a result, it may be feasible for the landslide-affected areas to experience sustainable growth. This study offers a wealth of data that are essential for long-term landslide management plan proposals.

## 6 Conclusion

Despite the lack of data on historical landslide inventory and building evaluation, the current study attempts to create a semi-quantitative LRA for district Muzaffarabad. The semi-quantitative LRA methods used in this work could forecast potential losses of resource elements in this data-scarce environment. Using the machine learning RF approach, a spatial probability (susceptibility map) was first created. The exceedance likelihood of short mean recurrence intervals and time were then both tested using Poisson probability. The vulnerability rating for each land-use component in the area was simplified using fuzzy membership values. Two essential thematic maps were employed for the risk assessment in the current study: a) the landslide hazard map and b) the land use (resource) map. The vulnerability of different land use classes in the region was assessed using the danger pixel approach and fuzzy set theory. The risk was divided into five categories

on the LRA map: very high risk, high risk, moderate, low, and very low risk. Results of the Fuzzy set theory depict that area of low and very low-risk zone resource categories is decreasing while the area of very high- and high-risk zone for resource categories is increasing from 1 to 5 years return period. Although this number is relatively little, it is nonetheless significant since it relates to the security of human life. To plan for future land use and to determine potential remedies to lessen the risk and manage the landslide problem the hazard pixel extraction technique and fuzzy set linguistic approach are useful. As a result, such maps may be of great use to engineers and planners working on several engineering projects of national significance, such as choosing a highway's route, general planning, expanding the area where people may live, and putting hydropower projects into action, etc. This research contributes to the broader understanding of the geomorphic impact of rapid climate change on natural hazards, specifically landslides, and highlights the importance of adopting advanced methodologies to manage the risks associated with these hazards.

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**Author contributions** Muhammad Tayyib Riaz contributed to the initial conception and design of the study, developed the methodology used in the research, and wrote the original draft of the paper; Muhammad Basharat oversaw the project as a whole, and played a key role in reviewing and editing the manuscript; Maria Teresa Brunetti contributed in writing, editing and reviewing the manuscript; Malik Talha Malik performed data curation and formal Analysis. All authors have reviewed the manuscript.

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## Declarations

**Conflict of interest** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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