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Research Article

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Analysis, Assessment and Early Warning of Mudflow Disasters along the Shigatse Section of the China–Nepal Highway

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Abstract: China–Nepal Highway is an important international passage connecting China and Nepal. Owing to its location in a complex mountainous area in the Qinghai–Tibet Plateau, the Shigatse section of the China–Nepal Highway is often impacted and troubled by mudflow. In order to effectively conduct road construction and maintenance and improve early disaster-warning capability, the relationship between various hazard factors and disaster points was analysed. It is found that four factors such as slope, precipitation, soil type and digital elevation have the strongest correlation with the occurrence of the disasters. From the distribution of disaster points, it is observed that the disaster point is closely related to the slope, its local correlation with precipitation is good and the its local correlation with the soil type and Digital Elevation Model (DEM) data is significant. In order to quantitatively evaluate the susceptibility of mudflow disasters in the Shigatse region, this paper uses the analytic hierarchy process (AHP) as the main analysis method supplemented by the fuzzy clustering method. The results show that the slope, when accompanied by heavy rainfall, is the most important factor among four factors. In this paper, the neural network method is used to establish the identification and early warning model of mudflow susceptibility. When the recognition rate reaches 66% or above, it can be used as an early-warning threshold for mudflow disasters. This study has conducted a useful exploration of the research, assessment and early warning of mudflow disasters along the Shigatse section of the China–Nepal Highway.

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Keywords: Shigatse section of the China–Nepal Highway, mudflow, disaster analysis, risk assessment, early warning model

1 Introduction

1.1 Introduction to the Shigatse section of the China–Nepal Highway

China–Nepal Highway, located in the central part of the Hindu Kush–Himalayan region, begins in the east in Lhasa, which is the capital city of the Tibet Autonomous Region of the People's Republic of China; it ends towards the west in Kathmandu, which is the capital of the Federal Democratic Republic of Nepal. It is 943 km long and the most important land-based connecting passage between China and Nepal. It is the "golden corridor" of tourism in the Tibet Autonomous Region and an important part of China's "One Belt, One Road" initiative, as shown in Figure 1. According to the statistics of the Ministry of Commerce of the People's Republic of China, the bilateral trade volume between China and Nepal reached 993 million USD in 2017, a yearly increase of 11.2% over the last year. China–Nepal Highway has played a very important role as the main connecting road between the two countries. In 2017, bilateral trade between China and Nepal reached US$993 million.

The Shigatse region is the bridgehead from China to Nepal, additionally, it is a region susceptible to mudflow. The frequent mudflow disasters in the Shigatse section have hindered the smooth traffic of the China-Nepal Highway. Therefore, it is urgent and pragmatic to study the identification and early warning of mudflow disasters in the plateau and mountains.

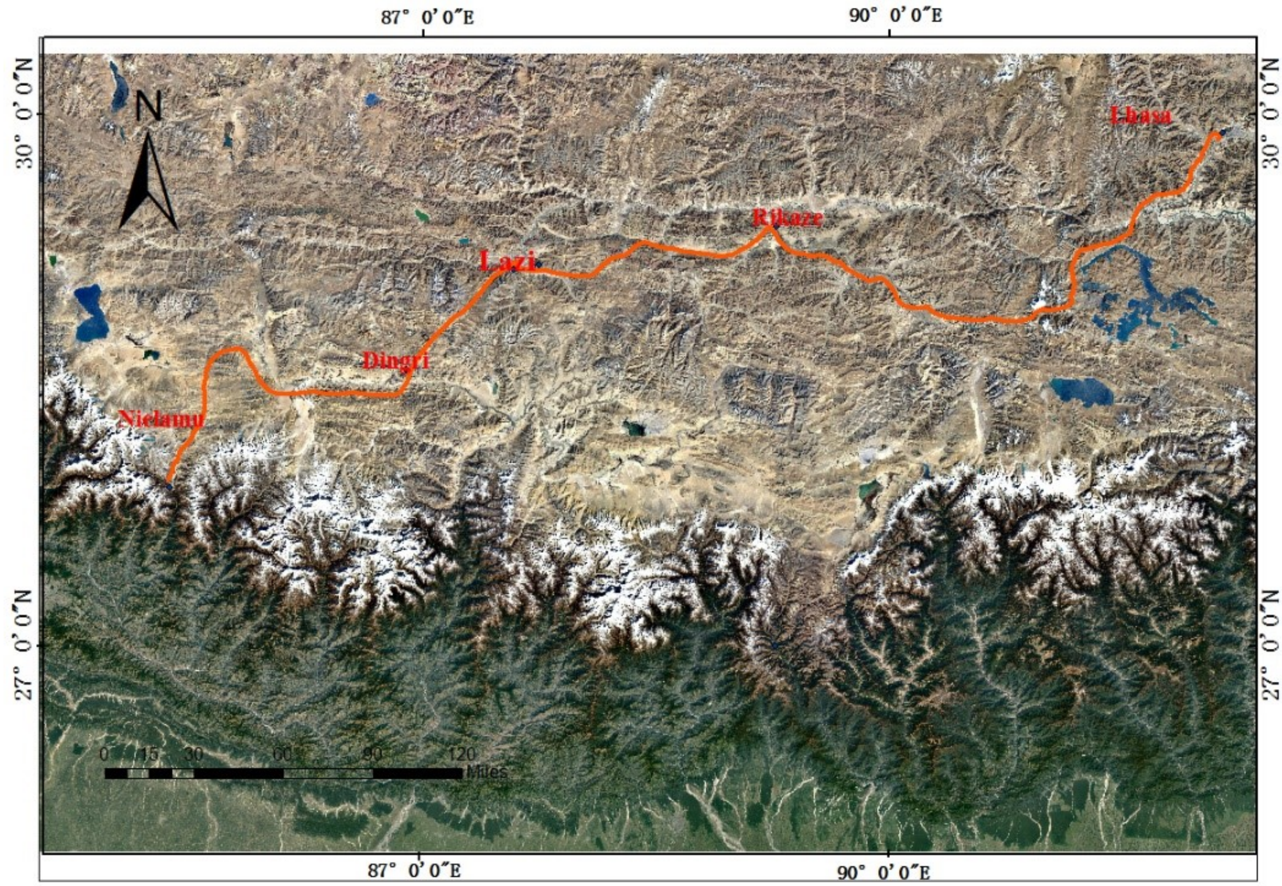

Figure 1: Location map of China–Nepal Highway (the red line in the picture represents the China–Nepal Highway)

1.2 Research progress

Nguyen combined remote sensing and GIS (Geographic Information System) technology with the AHP to determining the weights of various environmental factors in triggering debris flow and to map the ecotone [1]. Xu established an information value model to calculate a total of seven impact factors: elevation, slope, aspect, flow accumulation, vegetation coverage, soil type and land use. The comprehensive information value was analysed using GIS technology to determine the mudflow susceptibility [2]. Zhang selected the following seven major factors: loose material volume per square kilometre, loose material supply length ratio, average gradient of the main channel, average hill slope, drainage density, curvature of the main channel and poor vegetation area ratio and then analysed their impacts on the susceptibility of mudflow. The researchers used the combination weighting method, AHP and entropy weight method to select major factors causing mud-rock flow [3]. Chen modified the method of determining training points by setting the cells covered by the mudflow catchment area as training points instead of using a point to represent the mudflow catchment; then, geomorphology, lithology, faults, earthquakes and river system were selected to serve as evidence for analysis. The optimal buffer cutoff distance of faults and rivers is determined by the maximum study value of contrast ratio; finally, based on the subject of evidence, the mudflow susceptibility map in Kangding County is obtained [4]. Wang used SPOT5 images, DEM, the lithology distribution map and rainfall data to identify the triggering factors for mudflow susceptibility classification. Principal Component Analysis and Self-organising Maps methods were used to analyse the triggering factors such as basin relief ratio, slope gradient in the initiation zone, drainage density, downslope curvature of the main channel, vegetation coverage, main channel aspect, topographic wetness index(TWI), Meltons ruggedness number, lithology, annual rainfall, form factor, and cross-slope curvature of the transportation zone. The 14 triggering factors were analysed to evaluate the mudflow disasters, and the results were further verified [5]. Truong proposed a new machine learning integration method, *i.e.*, a hybrid method of Bagging Ensemble (BE) and Logistic Model Tree (LMtree), called BE-LMtree. The following eight triggering factors were extracted: slope, aspect, elevation, land cover, soil type, lithology, distance to faults and distance to river; 255 landslides were trained and verified. The performance of the new method is better than the support vector machine and LMtree models [6]. Chang numerically simulated the mudflow intensity, velocity and maximum depth using the FLO-2D numerical analysis software and combined the regression cycles of 20, 100 and 200 years to classify the mudflow hazard levels in the study area [7]. Aditian selected the following eight mudflow susceptibility factors in Ambon to verify and compare the accuracy of the mudflow susceptibility models based on bivariate frequency ratio, multivariate logistic regression and artificial neural network: elevation, slope, aspect, distance to river network, lithology, density of geological boundaries, distance to faults and distance to road network. Among these susceptibility factors, Neural network model has advantages in explaining the relationship between debris flow and other factors [8]. Othman extracted 16 geomorphological factors mainly from the Digital Elevation Model (DEM) and evaluated and compared the frequency ratio, weight of evidence, logistic regression and probability regression methods combined with geomorphological factors to determine mudflow susceptibility. The results show that the prediction results of each model are similar, and the focus should be on the careful selection of key factors. The most important factors for mudflow are lithology and slope [9]. Polykretis (2018) compared the performance of the weight of evidence, logistic regression (LR) models and artificial neural network models in mudflow susceptibility. The models selected the following eight factors: elevation, slope angle, aspect, distance to road network, distance to drainage network, distance to tectonic elements, land cover and lithology to evaluate the factors responsible for mudflow formation based on model training. The results show that the training results of the three models are promising, and the LR model is optimal [10]. Mahdadi identified ten mudflow-related factors for assessing the susceptibility of mudflow and establishing models to predict mudflow-prone areas. LR, frequency ratio and weight of evidence were used to evaluate the susceptibility. Through the visual interpretation of satellite images and field survey data, the mudflow inventory map was established, and the study area was divided into the following five levels of susceptibility: very low, low, moderate, high and very high is verified that the LR model is more reliable than the other two methods [11]. Shirani used the Index of Entropy and Dempster–Shafer (DS) models to establish mudflow susceptibility maps in the study area and compiled the following ten mudflow conditioning factors to determine the relationship between mudflow conditioning factors and mudflow inventory map: land use, distance to drainage, slope, elevation, lithology, distance to roads, distance to faults, slope orientation, TWI, and stream power index. Among these mudflow conditioning factors, land use was found to be an important factor affecting mudflow [12] Ba compared the slope unit and grid cell as the mapping unit for mudflow susceptibility assessment. Using the improved information value model, the mudflow susceptibility maps based on slope units and grid cells were obtained. Receiver Operating Characteristic curve was used to evaluate the results, and mudflow susceptibility mapping based on slope units was found to perform better than the grid cell-based method [13]. Tekin selected 78%–83% for the training set and 17%–22% for the validation set and used the LR model to model the mudflow susceptibility, including factors such as geology, landform classification, land use, elevation, slope, plane curvature, profile curvature, slope length factor, solar radiation, stream power index, slope second derivate, TWI, heat load index, mean slope, slope position, roughness, dissection, surface relief ratio, linear aspect and slope/aspect ratio. The results show that the susceptibility map generated using the random selections considering the entire mudflow polygons has better predictive ability [14]. Li mainly analysed the geological background, structure and genesis of the large-scale mudflow in Guanzhong region. Through geological surveys and physical mechanism testing, it is found that the clay layer is the main rupture surface of geological disasters [15].

1.3 Destruction of roads by mudflow disasters

Owing to the instability of the young mountain range in the Hindu Kush–Himalayan region, the geological structure and stratigraphic lithology along the Shigatse section of the China–Nepal Highway are complex. The active neotectonics movement, varying hydrothermal conditions and strong glacial activity all contribute to the frequent occurrence of mudflow disasters. The mountainous disasters have seriously affected the normal operation of the highway and hindered the progress of bilateral trade between China and Nepal. In addition, in recent years, because of the impact of extreme global climate change and the increasing disturbance of the geological environment caused by major engineering activities, the frequency and intensity of mountainous disasters along the China–Nepal Highway have increased, resulting in growing casualties and economic losses. Therefore, in order to reduce the hazards posed by mountainous disasters such as mudflow along the China–Nepal Highway, safeguard people's lives and property along the highway and provide decision support for the road reconstruction and rectification, conducting scientific research, risk assessment and provision of early warning of the mountainous disasters along the China–Nepal Highway has meaningful research significance and application values.

1.4 Significance of research on disaster warning

The natural geographic environment along the Shigatse section of the China–Nepal Highway is extremely harsh. The alpine and anoxic areas have high relief value, the mountains are mostly covered by glaciers, and most areas are inaccessible. The conventional regional surveys on ground are difficult to conduct and the level of research is low. With the rapid development of satellite remote sensing technology, the use of remote sensing images has become an effective and important means to dynamically monitor mountainous disasters such as mudflow. The monitoring and early warning of mudflow and other disasters have attracted the attention of many scientists.

This paper extracts the major mudflow influencing factors through the analysis of disaster-causing factors, disaster-pregnant environment and disaster-bearing bodies of mudflow along the China–Nepal Highway; quantitatively evaluates the susceptibility of mudflow disasters in the Shigatse region and establishes identification and early warning models with threshold values for mudflow disasters. It aims to improve the prevention of mountainous disasters along the Shigatse section of the China–Nepal Highway.

2 Overview of the study area

Shigatse is located between 82°00′ and 90°20′ east longitude and between 27°23′ and 31°49′ north latitude. The world's highest peak, Mount Everest, is located in this region. Shigatse is generally positioned between the middle sections of the Himalayas and the Gangdise- Nyenchen Tanglha Mountains. It has a high north–south terrain, including the southern Tibetan Plateau and the Yarlung Zangbo river basin. The terrain of Shigatse is complex and diverse and comprises mountains, wide valleys and lake basins with an average elevation of over 4,000 m [16].

There are roughly three regional climates in Shigatse: plateau temperate semi-arid monsoon climate between the north of the Himalayas and south of the Gangdise-Nyenchen Tanglha Mountains, plateau sub-frigid monsoon semi-arid and arid climate in a small part of the Gangdise- Nyenchen Tanglha Mountains and plateau temperate monsoon semi-humid climate in the area south of the main ridge of the Himalayas. The dry and rainy seasons in Shigatse are distinct. The spatial distribution of precipitation is uneven; there is more precipitation in the east (200–430 mm) and less in the northwest (<200 mm). Precipitation in the east occurs earlier than in the west, and precipitation fluctuates greatly throughout the year [16, 17].

3 Analysis of hazard factors of mudflow in the Shigatse region

3.1 Selection of environmental factors affecting the occurrence of mudflow

Based on a detailed literature review, nine environmental factors affecting the occurrence of mudflow were selected and divided into four categories, as shown in Table 1:

By analysing a large amount of data on the above environmental factors, it is found that the correlation between mudflow disasters and factors such as digital elevation, slope, average annual precipitation and soil type (clay and sand ratios) is more obvious, and is discussed in the following sections.

3.2 Digital elevation

Located in the Shigatse region of the Qinghai–Tibet Plateau, the Shigatse region has undulating terrain and a varying climate. There are alpine snowy areas as well as grassy valleys in the region, and the altitude difference between them is large. DEM data with a resolution of 30 m was used in this study, DEM was from the Shuttle Radar Topography Mission Digital Elevation Model (SRTM DEM) extract, and data were from the geographical spatial data cloud (https://www.gscloud.cn/search). In general, the elevation is positively correlated with the occurrence of mudflow, and the elevation of the study area is between 1,387 and 8,776 m.

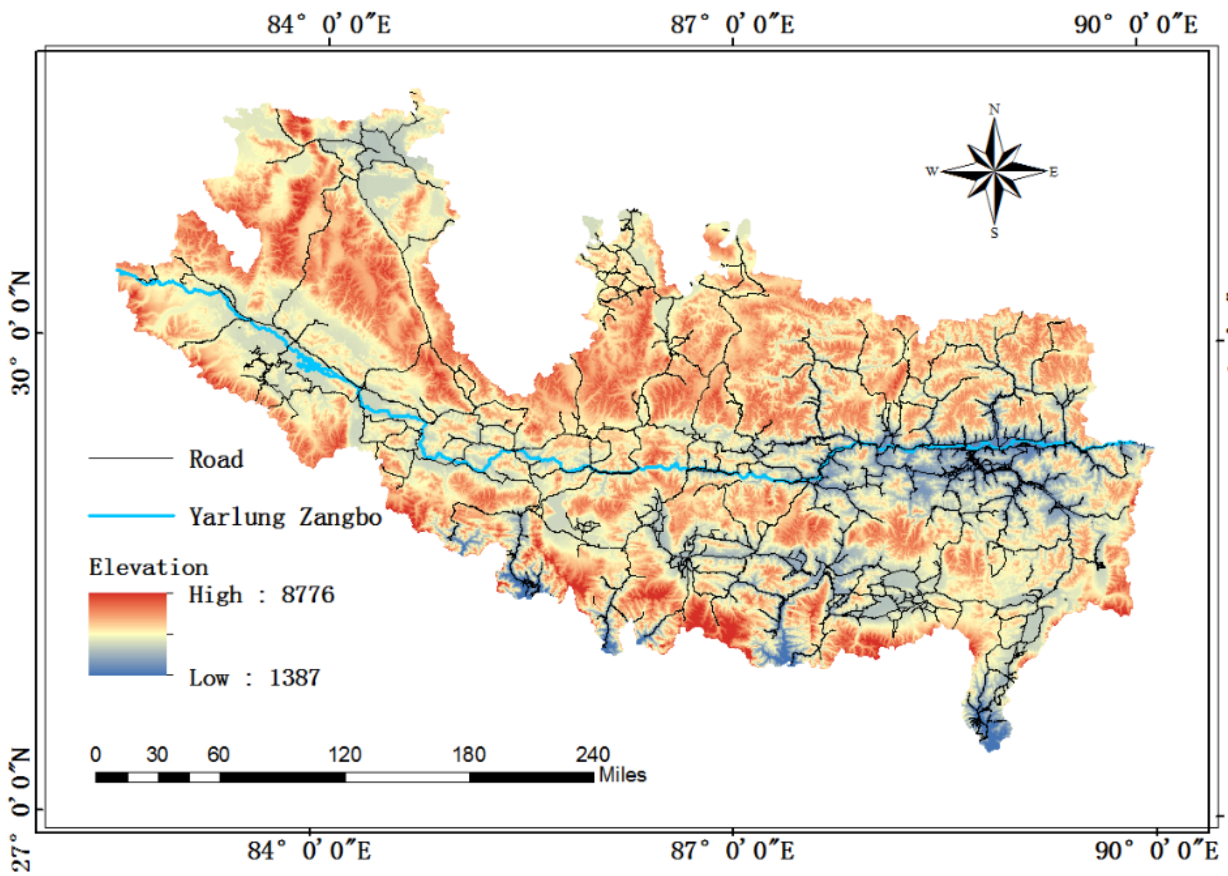

Figure 2: Shigatse area map (including roads and the Yarlung Zangbo River)

Table 1: Classification of environmental factors affecting mudflow

Type	Factor	Data	Scale (resolution)	Source
Terrain	Slope, Aspect, Elevation, Curvature	DEM	30m·30m	Geospatial data cloud
Soil	Sand, Clay, Silt	Soil type map	1:1000000	Institute of Geographic Sciences and Natural Resources Research at Chinese Academy of Sciences
Vegetation	NDVI	Landsat8	30m·30m	Geospatial data cloud
Climate	Average annual precipitation	Tropical Rainfall Measuring Mission (TRMM)	0.25°·0.25°	NASA

It can be seen from Figures 3 and 4 that the Yarlung Zangbo River crosses the Shigatse region from west to east. The China–Nepal Highway runs along the valley, and the river generally runs parallel to the road. In the figure, the brown area is the plateau mountain, green corresponds to the valley and the grassland and different colour blocks represent the difference in elevation. This difference in digital elevation forms a significant slope, which is more susceptible to mudflow.

The mudflow information was provided by Tibet Meteorological Bureau of China. The location of point element is the core area of debris flow event. These events could be

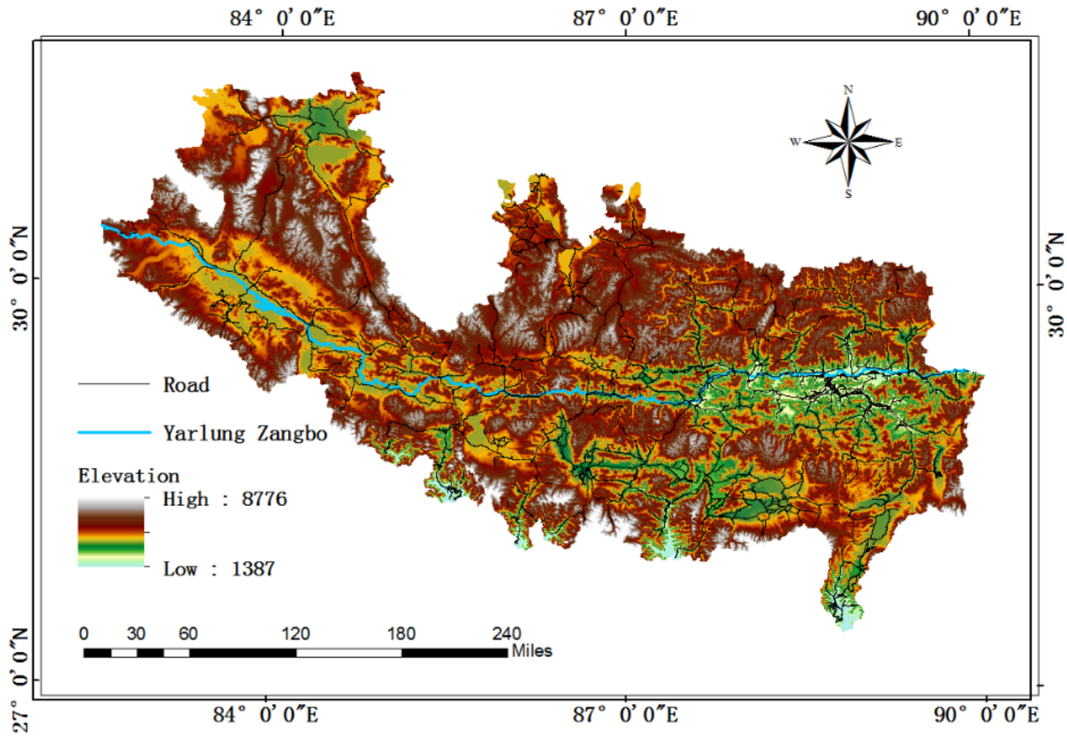

Figure 3: Digital elevation map of the Shigatse region (blue represents the river, black represents the road)

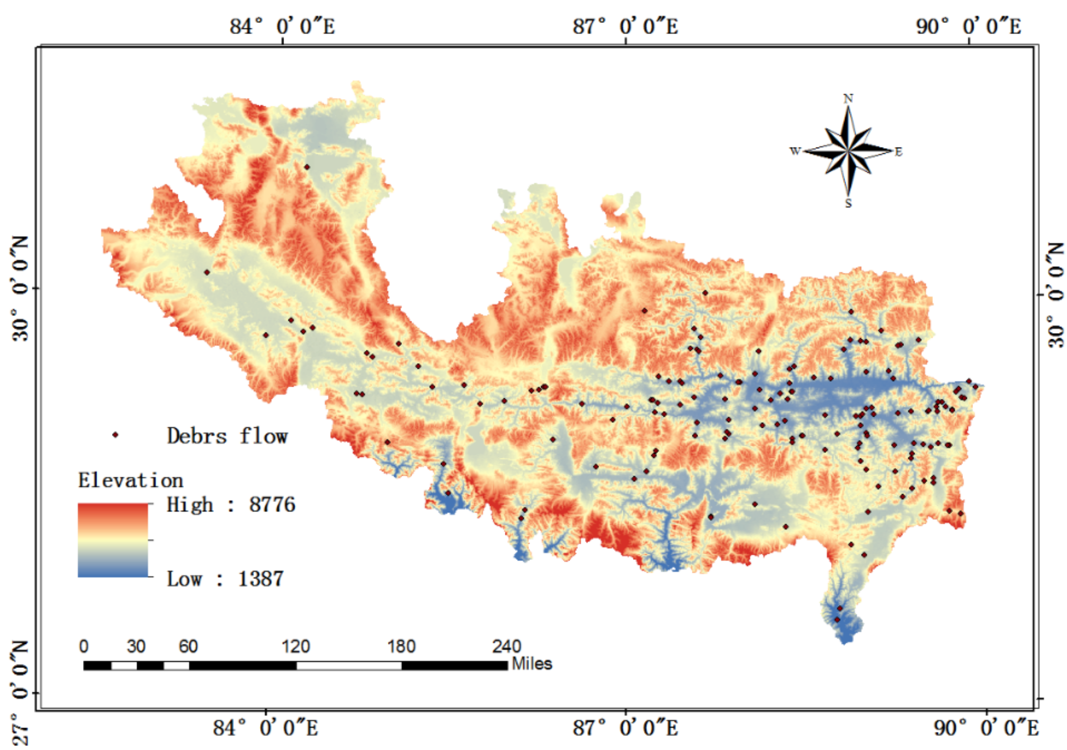

Figure 4: Digital elevation map of the mudflow disasters in the Shigatse region (black dot represents the disaster point)

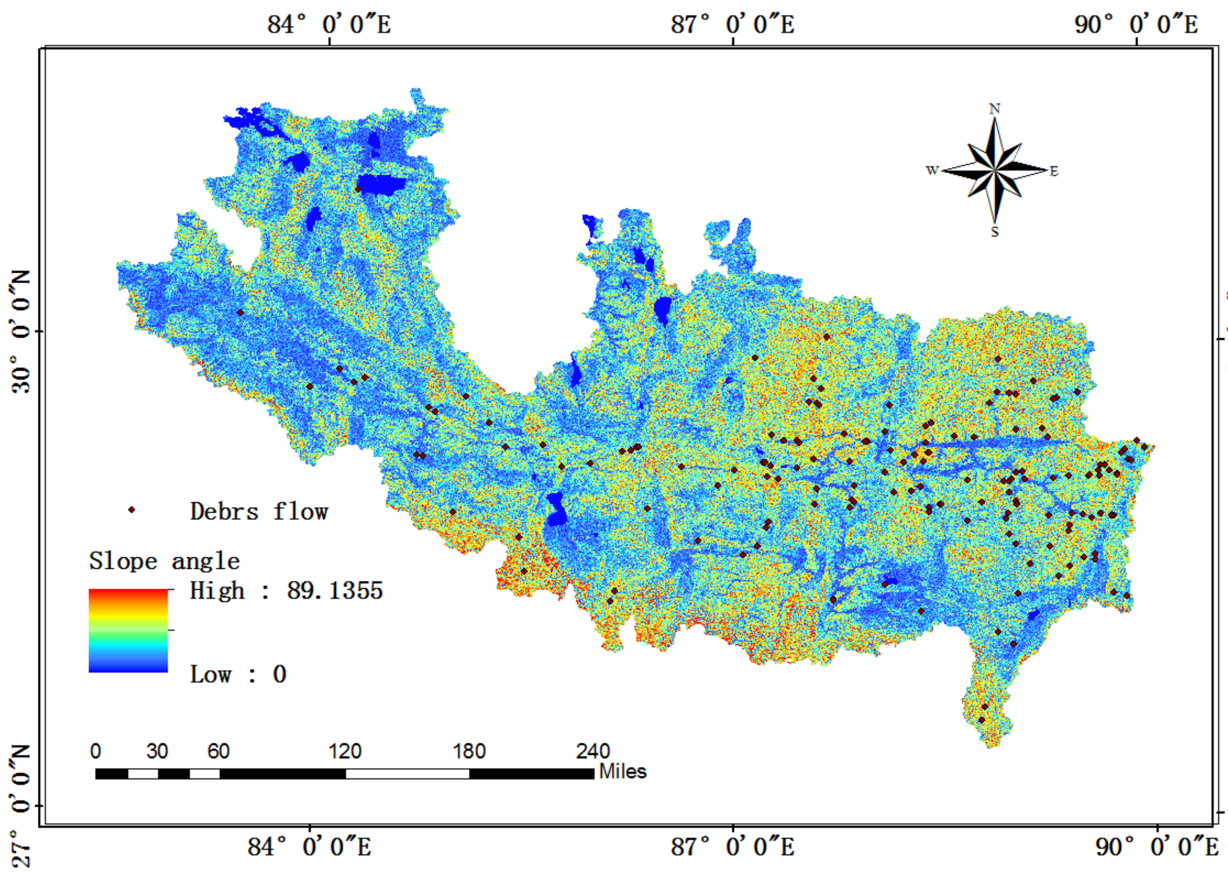

Figure 5: Distribution of mountain slopes and mudflow disaster points in the Shigatse region (black dot represents the disaster point)

found in geological cloud site (http://geocloud.cgs.gov.cn/#/portal/home).

3.3 Slope

The unique plateau mountainous landforms in the Shigatse region makes the area gully and undulating, and the slopes of the mountains are steep. Slope is an essential factor in the assessment of mudflow susceptibility because heavy precipitation in the region causes mudflow with larger slopes. In the test, the slope angle was calculated by ARCGIS based on the DEM data, and the values ranged from 0° to 89.1355°.

It can be seen from Figure 5 that in the vicinity of the valley and the Shigatse section of the China–Nepal Highway, the slope angle is large, wherein the area with larger slope has higher occurrence of mudflow disasters.

3.4 Average annual precipitation

May to September every year is the rainy season of the Shigatse region. The precipitation in this period accounts for more than 90% of the annual precipitation. The precipitation mainly occurs in July and August. During this period, it rains more at night, and thunderstorms and hail are common. The precipitation at night accounts for 70%–80% of the total precipitation. The spatial distribution of precipitation is uneven, with more in the east (200–430 mm) and less in the northwest (<200 mm). Precipitation in the east occurs earlier than in the west, and precipitation fluctuates greatly throughout the year. Precipitation is an important variable in the evaluation of mudflow susceptibility because it represents the climatic conditions of the area. In order to evaluate the rainfall distribution in the Shigatse region, a total of 11 years of precipitation data from 1998 to 2008 were selected from the satellite data of the TRMM, and an average annual precipitation distribution map was generated. Figure 6 shows the average annual precipitation and distribution of mudflow disaster points in the Shigatse region. The analysis shows that the rainfall in the

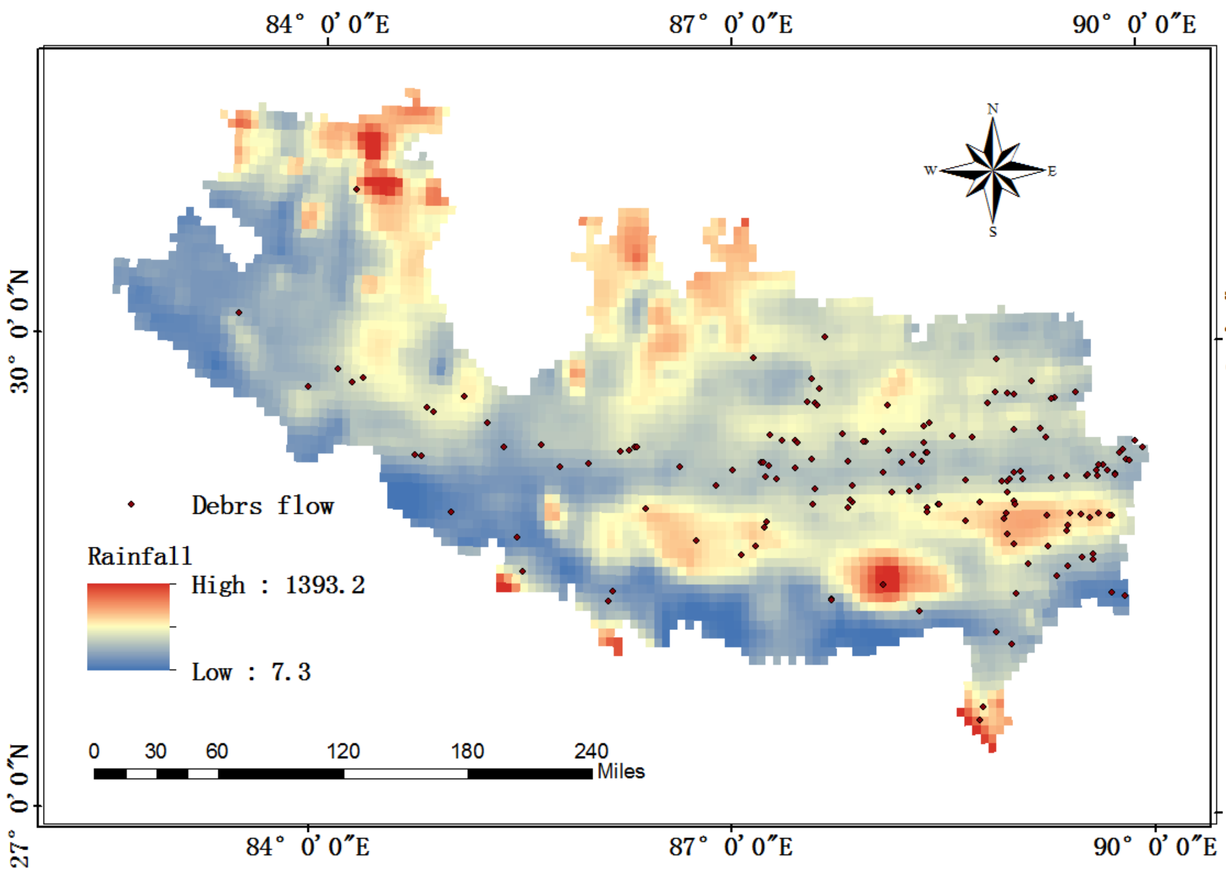

Figure 6: Distribution of average annual precipitation and mudflow disaster points in Shigatse region (black dot represents the disaster point)

valley area is less than the rainfall in the high mountains on both sides of the river. The south side of the China–Nepal Highway is the windward slope of the Himalayas, and the warm and humid air from the Indian Ocean along the Bay of Bengal supplies abundant water vapour to the area. Combined with large elevation drop and slope, all factors lead to the high occurrence of mudflow disasters in the area.

3.5 Soil condition

The Shigatse region has complex geological structures, varied stratigraphic lithology and fragile geological environment. The soil is mostly composed of clay, sand and silt. Under normal circumstances, areas with lower clay and higher sand ratios are more susceptible to mudflow. The area with a low clay ratio in the east, shown in Figure 7, and the area with a high sand ratio in the west, shown in Figure 8, are susceptible to mudflow owing to their soil type.

The topography and geology of Tibet are as follows: mountainous areas account for 20%, high mountains account for 53%, and steep mountains account for 27%. The high slopes along the route are steep, and adverse geological processes are well developed. The soil quality ratio is clay and fine medium sand: gravel and other gravel soil: rock =10:6:84. (https://wenku.baidu.com/view/0e754340f11dc281e53a580216fc700abb6852ec.html?from=search).

It can be seen from Figure 7 that along the China–Nepal Highway, particularly in the 88°–90° degrees eastern region, the ratio of clay to sand is obviously lower, the soil is relatively loose, and it is difficult to lock the roots of plants. During extreme weather such as heavy precipitation, mudflow will likely occur.

As shown in Figure 8, the valley area along the China–Nepal Highway is in the 86°–88° western region. Corresponding to the clay ratio distribution in Figure 7, the sand ratio in this area is obviously higher, the soil is relatively loose and it is difficult to lock the roots of plants. Mudflow

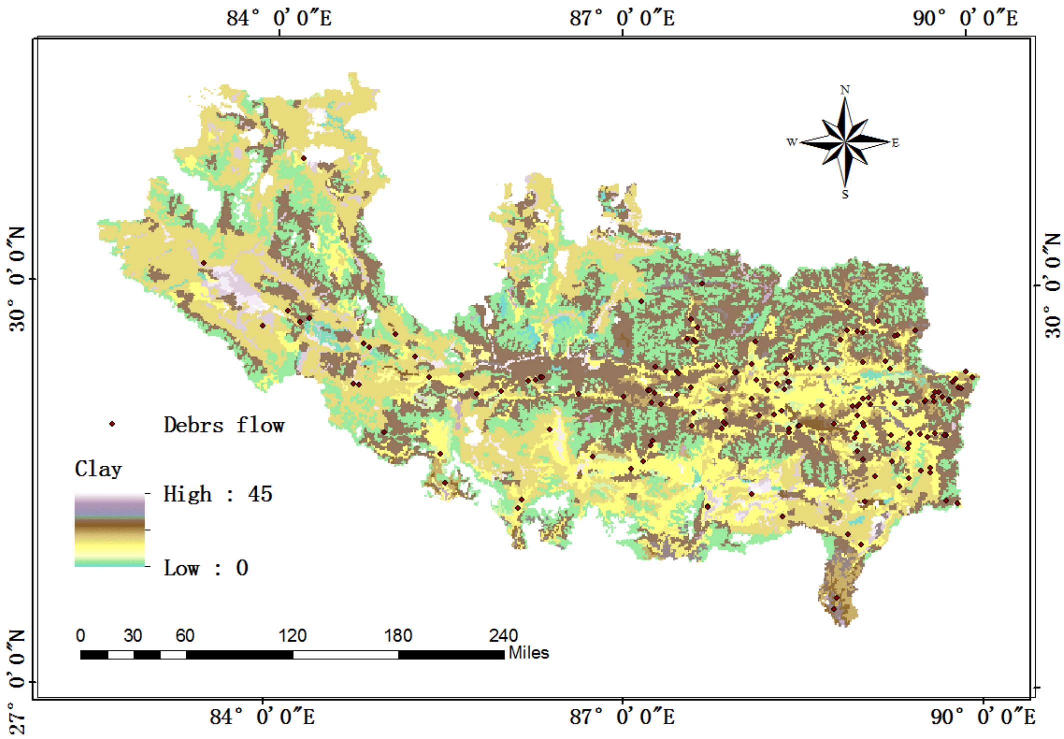

Figure 7: Distribution of clay ratio and mudflow disaster points in Shigatse region (black dot represents the disaster point)

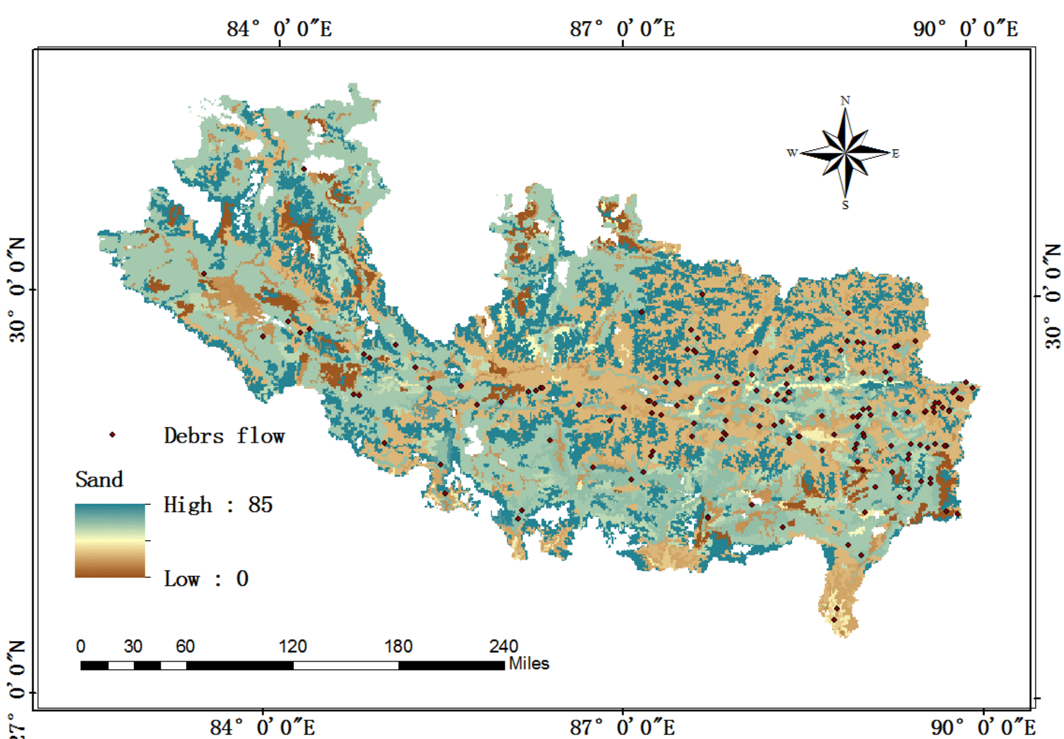

Figure 8: Distribution of sand ratio and mudflow disaster points in the Shigatse region (black dot represents the disaster point)

Table 2: Test data for verifying the susceptibility of mudflow disasters

No	Location 1	Location 2	Location 3	Location 4	Location 5	Location 6
Latitude	30.00	30.00	30.00	29.33	29.33	29.33
Longitude	84.00	87.00	88.50	84.00	87.00	88.50
Digital Elevation	5802	6925	6925	5079	3233	6002
Slope	33	33	45	30	66	44
Precipitation	700	1115	284	423	700	561
Sand Ratio	3	8	32	22	16	32

is likely to occur in extreme weather conditions such as heavy precipitation.

4 Evaluation of mudflow disaster

4.1 Evaluation method

Mudflow refers to the mountains or other deep valleys, steep terrain regions, because of heavy rain, blizzard, or other natural disasters caused by landslides and special with a large number of sediment and rocks in the torrent, is essentially a strong surface change, only when the debris flow of human living environment including buildings, transport facilities, life and property is dangerous, as disasters. Take for example the landslide in Zhangmu section on 18 September 2017, which caused damage to the China-Nepal Highway, so it is called a disaster. Figure 9 is the landslide between Nyalam and Zhangmu on 18 September 2017, covers an area of about 300 square meters. In general, this paper only focuses on the distribution of landslides or debris flows, and do not care about some specific area.

According to the above analysis of the hazard factors, the factors causing the mudflow disasters along the China–Nepal Highway are diverse. The physical mechanism of the interaction between these factors is complex. In order to quantitatively assess the mudflow susceptibility in the Shigatse region, this research uses the analytic hierarchy process (AHP) and fuzzy clustering method for calculation, with AHP [18] as the main analytical method and fuzzy clustering method [19–21] as the verification method. AHP combines qualitative and quantitative decision analysis methods to provide a basis for selecting the best solution by dividing complex problems into several levels and factors. The fuzzy clustering method constructs the fuzzy matrix according to the attributes of the research object itself. Subsequently, the clustering relationship between the samples is determined on the basis of a certain degree of similarity.

Figure 9: The Mudflow occurred between Nyalam and Zhangmu on 18 September 2017. (Photographed by the author)

4.2 The verification of the vusceptibility of mudflow disasters

In order to verify the susceptibility of mudflow disasters by using AHP and fuzzy clustering method, six locations in the Shigatse region were selected for this test. The relevant data are shown in Table 2, and the corresponding location distribution map is shown in Figure 9. These locations were selected based on the following characteris-

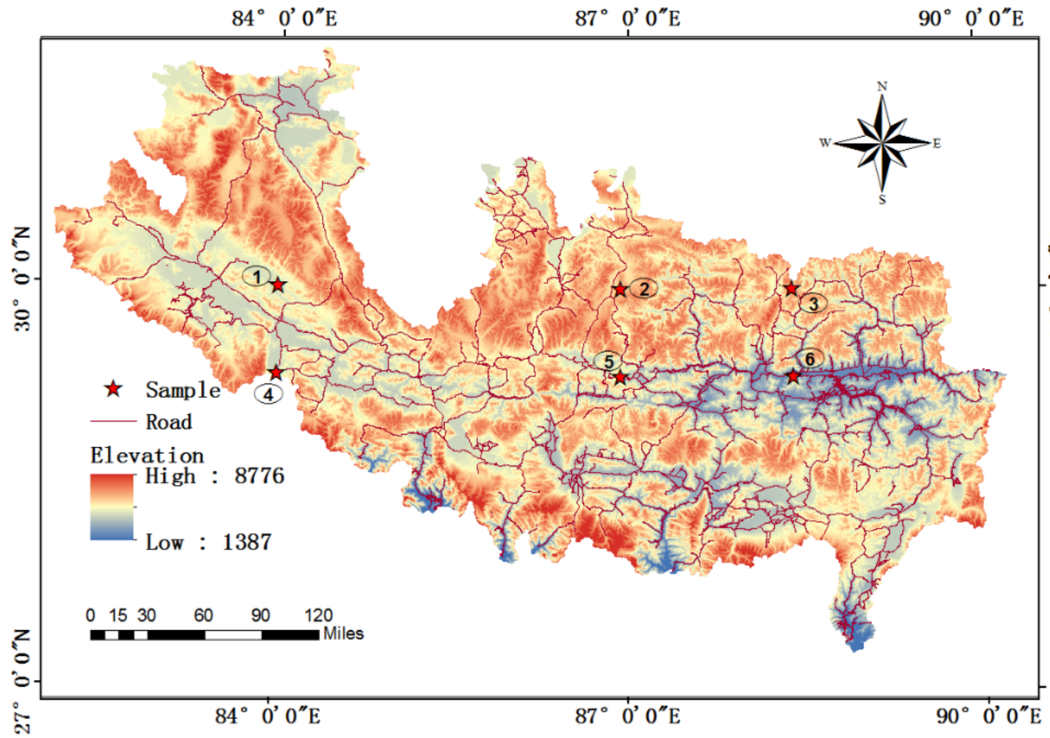

Figure 10: Distribution map of six test locations for mudflow susceptibility analysis (the star represents sample point)

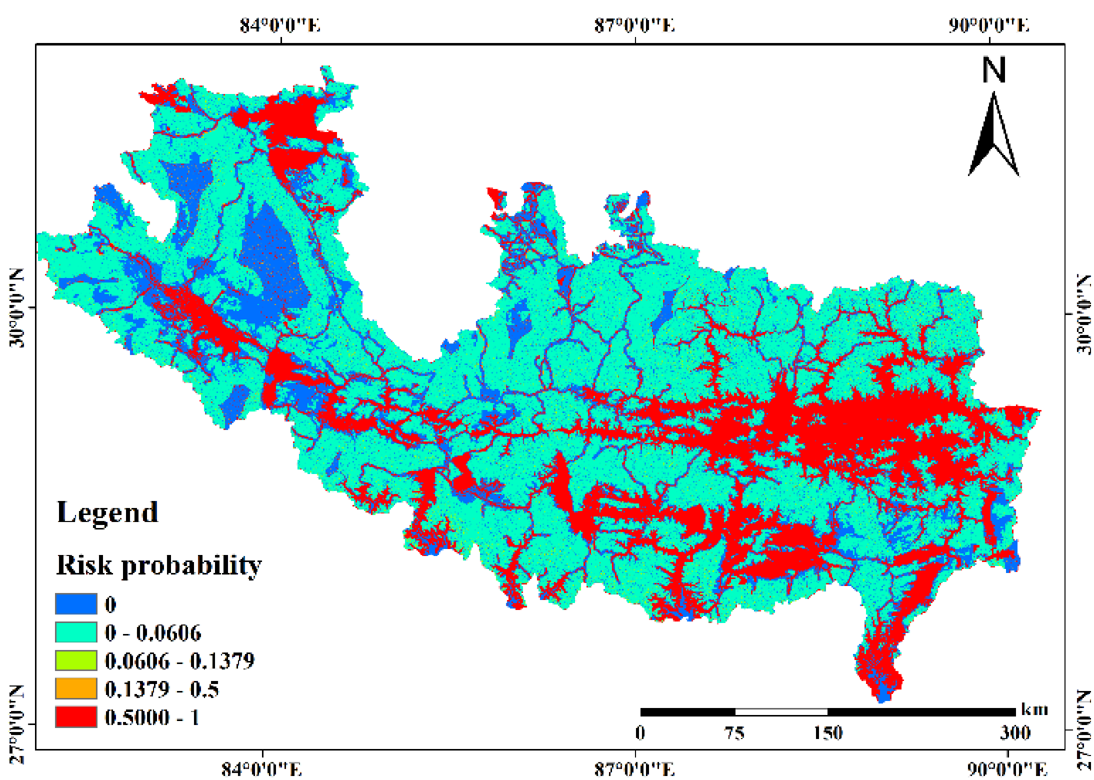

Figure 11: Overall risk map of the Shigatse area along with the China–Nepal Highway

tics: locations 1 and 4 are distributed along the north and south sides of the valley in the western part of the study area, locations 2 and 3 are distributed on the mountains on the north side of the valley in the eastern part of the study area and locations 5 and 6 are distributed near the valley in the eastern part of the study area. These six locations represent various topographies in order to make the mudflow susceptibility verification relatively objective.

In order to know the total risk of debris flow in Shigatse area, it is necessary to get the overall risk map of this place. Based on the above research, the risk value of each grid point in the whole area is used to generate the overall risk map. The overall risk map of debris flow in Shigatse area is shown in Figure 11. As can be seen from Figure 11, the risk of red area is high, so along the valley of the China–Nepal Highway, the risk of debris flow is high.

4.3 AHP test

AHP (analytic hierarchy process) is the decision making method combining qualitative and quantitative analysis [18]. Weight factors of hierarchical decision-making can be selected by experts. After discussion by researchers, initially it is considered that the contribution of digital elevation, slope, precipitation and ratio of sand and soil to debris flow is the same, so the selected analytic hierarchy process weights are the same. Following are steps for analysis.

1. To find the weight vector of the consistency decision matrix, the summation method is used. The specific formula is:

$$w_i = \frac{1}{n}\sum_{j=1}^{n}\frac{a_{ij}}{\sum_{k=1}^{n} a_{kj}}(i = 1, 2, \cdots, n) \qquad (1)$$

   where a_{ij} is the element of the consistency decision matrix.
2. In the test, for objective decision, the weights of the digital elevation, slope, precipitation and sand ratio are assumed to be the same. Using MATLAB programming calculation, the total AHP scores of locations 1–6 were 0.0754, 0.0992, 0.1171, 0.1171, 0.1171 and 0.1409 respectively. Therefore, the disaster susceptibility ranked from low to high is: location 1, location 2, location 3, location 4, location 6 and location 5. According to the analysis, locations 5, 6 and 4 are close to the China–Nepal Highway and the river valley, which are prone to disasters. Hence, the result is in good agreement with the actual situation.
   It can be seen from the data in Table 2 that the level of susceptibility of the mudflow is complex and is determined using different values of multiple factors: although its digital elevation is the smallest, location 5 is where the mudflow is most likely to occur because it has the highest slope. Although location 2 has the largest amount of precipitation, mudflow susceptibility is lower owing to its lower slope. Location 1 has the lowest sand ratio and lower slope, so mudflow is the least likely to occur. Although location 3 has the highest sand ratio and digital elevation, the amount of precipitation is the lowest; therefore, the mudflow susceptibility is low.
   Therefore, in the mudflow disaster along the China–Nepal Highway, the slope is the most important among the four factors, and need to be combined with heavy rainfall. The area with high sand ratio is only susceptible to mudflow when supplemented by a larger amount of precipitation. The digital elevation has the lowest impact among the four factors.

4.4 Fuzzy clustering test

1. When constructing fuzzy matrix R, the maximum and minimum method in the similarity coefficient method is used, *i.e.*

$$r_{ij} = \frac{\sum_{k=1}^{m}\left(x_{ik} \wedge x_{jk}\right)}{\sum_{k=1}^{m}\left(x_{ik} \vee x_{jk}\right)}, \qquad (2)$$

2. The fuzzy equivalent matrix of this paper is:

$$\begin{bmatrix} 1 & 0.7332 & 0.5974 & 0.5974 & 0.5974 & 0.5974 \\ 0.7332 & 1 & 0.5974 & 0.5974 & 0.5974 & 0.5974 \\ 0.5974 & 0.5974 & 1 & 0.7346 & 0.6172 & 0.8719 \\ 0.5974 & 0.5974 & 0.7346 & 1 & 0.6172 & 0.7346 \\ 0.5974 & 0.5974 & 0.6172 & 0.6172 & 1 & 0.6172 \\ 0.5974 & 0.5974 & 0.8719 & 0.7346 & 0.6172 & 1 \end{bmatrix}$$

   The optimal threshold can be determined by actual conditions or by experienced experts. The general approach is to take the elements on the main diagonal of the fuzzy equivalence matrix as the threshold. The selection of 0.5974 as the threshold can exactly divide the six sites into two categories.
3. Through a MATLAB programming calculation, it can be concluded that when the threshold value is 0.5974, the abovementioned six locations can be divided into the following two categories: the first is less susceptible to disasters (locations 1 and 2) and the second is more susceptible to disasters (locations 3, 4, 5 and 6).
   Comparing the test results of the abovementioned methods, both test results are consistent with each other. The ranking results of the AHP method are

Table 3: Disaster data in the Shigatse region [Note: In the columns "less susceptible", "more susceptible" and "highly susceptible", the “0” and “1” stand for "no" and "yes", respectively.]

No	Longitude	Latitude	Digital Elevation	Slope	Precipitation	Sand ratio	Less susceptible	More susceptible	Highly susceptible
1	87.28	29.20	4282	22.85	259.51	68	0	1	0
2	87.23	29.23	4408	21.96	270.48	44	0	1	0
3	89.65	28.77	4144	20.56	536.68	68	0	1	0
4	87.65	29.64	4116	15.47	361.23	68	0	1	0
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153	83.02	30.22	4625	6.89	217.17	66	0	1	0
154	89.83	28.82	4283	12.04	586.80	68	1	0	0
155	89.56	28.41	4395	4.14	244.74	68	1	0	0
156	83.95	29.76	4571	10.03	379.60	66	0	1	0

more accurate and effective; hence, it is suitable for the analysis of mudflow susceptibility in the region. The results of the fuzzy clustering method validate the conclusion of the AHP and can be used as an auxiliary method for the analysis of mudflow susceptibility in the region.

5 Establishment of an early warning model

In order to further study the early warning of mudflow disasters along the Shigatse section of the China–Nepal Highway, the neural network prediction method was used to repeatedly test and calculate the identification and early-warning threshold value.

In this test, a total of 156 datasets were selected from Shigatse region, 40 of which were less susceptible to disasters, 108 were more susceptible to disasters and eight were highly susceptible to disasters. Each group of data consists of six attributes: longitude, latitude, digital elevation, slope, precipitation and sand ratio. Part of the data is shown in Table 3.

5.1 Neural network method

The neural network [22, 23] is a broad and interconnected network of adaptive yet simple units whose organisation can simulate the interaction of biological nervous systems with real-world objects. In this paper, the neural network method is used to establish the identification and early warning model.

5.2 Test plan design

70% of the data was randomly extracted from the 156 datasets as training set, and 30% of the data was used as test set. The attributes of digital elevation, slope, precipitation and sand ratio in each data set are normalized and trained as input nodes. The neural network parameters of this test were set as follows: four neurons in the input layer, three neurons in the output layer and three hidden layers with ten neurons in each layer, as shown in Figure 12.

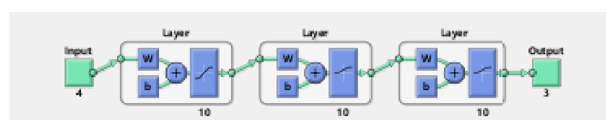
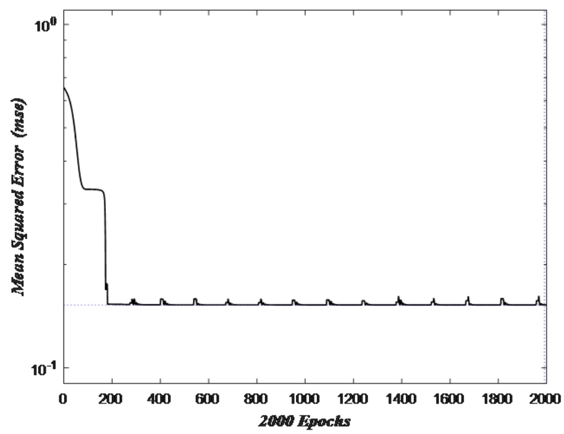


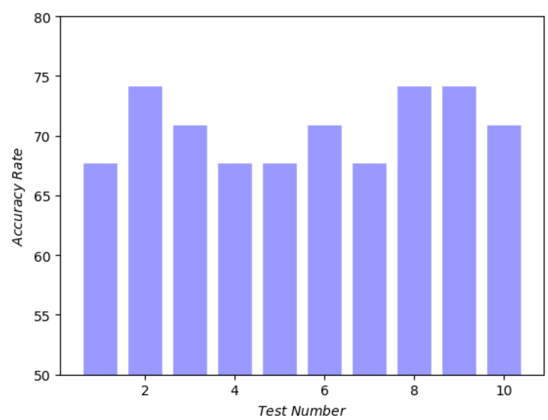
Figure 12: Schematic diagram of the neural network

The learning algorithm selected in this experiment is the error inverse propagation algorithm. The activation function from the input layer to the hidden layer, between the three hidden layers and from the hidden layer to the output layer are all ReLU functions (Rectified Linear Units, ReLU = max(0,x)). The advantages of the ReLU function are as follow: (1) solves the vanishing gradient problem (in the positive region); (2) faster calculation and convergence speeds; (3) ReLU will make part of the neuron output become 0, causing a sparse network and reducing the interdependence of parameters, which alleviates the problem of over-fitting.

The maximum number of iterations in the test was 2000, the learning rate was 0.01 and the error of the training target was 0.01. In order to avoid over-fitting, some interventions were performed during the training process, *i.e.* randomly “killing” some neurons.



(a)



(b)

Figure 13: Results of neural network algorithm: (a) The error decreases with the number of iterations; (b) The accuracy rates of ten independent tests

5.3 Analysis of test results

After running many tests, we found that using the BP neural network prediction algorithm, the identification rate of mudflow disaster susceptibility on the test set stabilised at 66%–74% (as shown in Figures 13(a) and 13(b)). Figure 13(a) is a graph showing the error as a function of the number of iterations, and Figure 13(b) is a graph showing the accuracy rates of ten independent tests. This prediction provides a basis for the early mudflow warning in the Shigatse region. When inputting several major factors extracted from this paper, although there are complex physical relations among these factors, when the identification rate from the neural network prediction algorithm is greater than 66%, an early warning of mudflow disasters in the region can be raised.

It is important to note that the identification rate on the training set is close to 100% and over-fitting is likely to occur. When observing the original datasets, it can be found that there are more datasets for cases susceptible to disasters, which is up to 108 sets, and the data of cases highly susceptible to disaster are too few, with only eight sets. This may be the reason for the occurrence of over-fitting. Therefore, when collecting data, if the ratio of the three datasets can be controlled at approximately 1:1:1, the identification rate on the test set will be further improved.

6 Summary and discussion

This paper studies the mudflow disasters in the Shigatse section of China–Nepal Highway, including the relationship between hazard factors and disaster points, the evaluation of disaster susceptibility and its early warning. The conclusions are as follows.

By analysing the relationship between various hazard factors and disaster points, it is found that the factors such as slope, precipitation, soil type and digital elevation are the most strongly correlated with the occurrence of disasters. From the distribution of disaster points, the disaster points are closely related to the slope and the local correlation with precipitation is well. The local correlation with soil type and DEM data is obvious. Areas where low proportion of clay and a high proportion of sand are susceptible to mudflow.

In order to quantitatively evaluate the susceptibility of mudflow disasters in Shigatse region, six representative locations were selected for reflecting difference between the eastern and western of the region, as well as the topographic difference between valleys and hillsides.

AHP was used as the main analytical method and was supplemented by the fuzzy clustering method as the verification method. The results show that the slope is the most important of the four factors, but it is complex and needs to be accompanied with heavier precipitation; however, the area with high sand ratio is only susceptible to mudflow when supplemented by heavier precipitation. The digital elevation has the lowest impact among the four factors.

The neural network method was used to establish the identification and early warning model of mudflow susceptibility, and the identification rate was stabilised between 66% and 72% It is concluded that when the identification rate reaches 66% or higher, it can be used as an early-warning threshold for mudflow disasters.

Although the influencing factors of mudflow disasters along the Shigatse section of China–Nepal Highway are diverse and the mechanism of the impact is complex, this study explores the research, evaluation and early warning model of mudflow disasters in the region, which is conducive to the rectification and upgrading of China–Nepal Highway. Additionally, it has important theoretical meaning and practical value, and provides a typical demonstration for the prevention and early warning of plateau mountain disasters.

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