Landslide risk potential mapping by using continuously-weighted spatial criteria and convolution artificial neural network

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Abstract

Landslides are one of the most dangerous natural phenomena. The occurrence of this phenomenon at low speeds and high rates causes financial and human losses without warning signs. Therefore, it is essential to study the geological and anthropogenic factors affecting the occurrence of this phenomenon and determine the potential landslide zones. This study aims to use a supervised convolutional artificial neural network to model landslide potential. For this, evidence maps of seven effective factors in landslide occurrence, including slope, slope direction, geology, precipitation, distance from the fault, height, and density of waterway, were prepared. Then the values in the maps were assigned by continuous fuzzy weights through a logistic function, without data classification to feed convolution artificial neural network algorithm. For training the network and testing the results, 70% and 30% of training sites, in Oshvand basin, Hamedan province, Iran were used to generate landslide potential model. A prediction-area plot was used to evaluate and quantify the effectiveness of the models produced. The results showed that 70% of the landslides occurred in 30% of the area.

Keywords: Convolution neural network, GIS, Logistics function, Prediction-area plot diagram, Zoning.

1- Introduction

Mass movements are the displacement of a large volume of soil masses, rocks, or a combination of them down the slope due to the force of gravity, and this phenomenon occurs when the force of the weight of the material is more than the shear strength of the soil by Moghimi et al, [1]. A large part of Iran is made up of mountainous areas, so landslides are one of the natural disasters that cause human and financial losses to the country annually. In addition, the social and environmental effects of this phenomenon, such as migration and unemployment, should not be ignored, Lin et al, [2]. Landslide potential zoning surveys help designers to select suitable areas for the implementation of development plans, and therefore, this practice has attracted the attention of many earth science engineers and researchers (Zhang et al, [3], Ahmed and Pourghasemi, [4], Aram et al, [5], Ghiasi et al., [6]). Since predicting the time and place of a landslide is beyond the power of our present knowledge, to express the sense of the slopes, landslide potential mapping is a common practice to model the risk of landslides in different areas aiming at classifying the areas into low and high risk parts and some classes between them (Shadfar et al, [7]; Lee et al, [8]). This process is implemented through recognizing natural features controlling landslide sites using available data. There are several methods for landslide risk zoning dividing into two general categories, direct and indirect methods. Direct zoning methods are based on experts' judgments and knowledge obtained from known landslide sites. Indirect methods are based on identifying landslide controlling factors and combining them as indicators of landslide potential (Rakei et al, [9]). One of the methods of landslide risk mapping is the artificial neural network. The artificial neural network method is a computational procedure that can provide a set of new information by analyzing geological and anthropogenic data (Lee et al, [8]). In this network, an attempt is to build a structure similar to the biological structure of the human brain to have the similar power of learning, generalization, and decision making (Gomez and Kavzoglu, [10]) in a multivariate space through the information received (Lee et al, [8]). The artificial neural network method is independent from data distribution and does not require special statistical variances (Lee et al, [8]; Caniani et al, [11]). The artificial neural network faces with the issues and problems that statistical methods cannot, which is due to the limitations in their theory (Caniani et al, [11], Ermini et al, [12]). This model estimates the probability of landslide occurring in the future by examining the history and characteristics of present landslides in the region under study (Gomez and Kavzoglu, [10], Lee et al, [13]).

The convolutional neural network (CNN) has been applied to model landslide potential zones (Wei et al, [14]; Yi et al, [15]). The CNN has shown excellent performance in classifying and identifying data as a powerful deep learning technique. CNN has the ability to automatically extract strong and general properties from convolution and integration layers without defining additional parameters (Zhao et al, [16]). Usually, a prediction-area (P - A) diagram is used to determine what percentage of the final model was able to predict landslides in the study area. Yousefi et al. [17], used a P -A plotand concluded that instead of using the input of experts, the input maps should be weighted using a P -A chart, so it can be used for effective evaluation and ranking of the predictive models (Yousefi et al, [17]).

2-Materials and Methods

2-1- Study area

Oshvand watershed is located in Hamadan province, northeast of Nahavand city, and meager area about 47.96 square kilometers and approximately 42.24 kilometers. It has the geographical coordinates of "51 '22 ° 48 to" 50 '30 ° 48 east longitude and "51 '9 ° 34 to" 23 '15 ° 34 north latitude, as shown in Figure (1). This watershed's maximum and minimum altitudes above sea level are 2578.99 and 1709.65 meters, respectively. The region's climate is semi-humid, using the Domarten method, which is calculated based on the two factors of temperature and annual rainfall. Precipitation is 482 mm in the Oshvand region (Ildermi et al, [18]). Waterway density in the study area is also high, and the average yearly temperature is 8.8 degrees Celsius (Hosseini, [19]).

2-2- Landslide controlling factors

The occurrence of landslides is directly related to the combination of various factors such as topography, geology, and other environmental indicators. The correct combination of influencing factors gains a more reliable model (Chen and Chen, [20]). Due to the complexity of landslides and the variety of stimulus sources, the influencing factors should be selected based on the specific conditions of the region.

In this study, by visiting the study area and examining the characteristics of landslides, seven controlling factors including slope, height, precipitation, waterway density, distance from the fault, slope direction, and geology of the region, were selected. Then maps of the slope, slope direction, stream density, and height were made based on the topographic and DEM models. The geological map on a scale of 1: 100000 was prepared by the Geological Survey of Iran. The distance map from the fault was made using the geological map. Hamedan Regional Water Department also prepared a precipitation map. Figure (2) show maps of the seven factors affecting the occurrence of landslides in the Oshvand region).

2-2-1- Generation of layers of weighted controlling factors by a continuous fuzzy method using a logistic function

Yousefi and Carranza, [21] used a continuous fuzzy logic method to generate weighted controlling layers. The logistic function assigns fuzzy membership values to the criteria. They applied linear and nonlinear transformations (using the logistic function) on the values of evidence events and compared the results, and showed that nonlinear modeling are more suitable for weighting. The logistic function transfers all data to a limited space between zero and one based on the minimum and maximum values of the input data and the slope changes between them (Yousefi, and Carranza, [21]). Values in the resulting generated maps lie between 0.01 and 0.99, i.e., the areas with the highest risk given values close to 0.99 and the low-risk areas assigned by values close to 0.01 (Yousefi et al, [22]). In this regard, the logistic function expressed in Equation (1) has been used to fuzzify the controlling factors (Yousefi, and Nykänen, [23]):

$$F_{EV} = \frac{1}{1+e^{-s(EV-i)}} \quad (1)$$

F_{EV}: fuzzy weight such as EV, I: turning point, S: of function slope, and EV: is the numerical value of each criterion.

Slope, height, precipitation, stream density, and distance from the fault were weighted using the continuous fuzzy method and logistic function.

2-2-2- Generation of layers of weighted controlling factors by discrete fuzzy method (unsupervised)

According to expert's inputs, slope direction and geological map criteria were weighted using the classical fuzzy method, according to which the scores of fuzzy evidence were classified into spatial weighted discrete data.

2-2-3- Prediction-area plot

In the final model, a prediction-area diagram was used to determine what percentage of landslides occurred in the total area of the study area. The P-A diagram consists of two curves: the first curve shows the prediction rate of known landslide position and the other curve shows the area covered in the percentage of each class of the model relative to the entire study area in Figure (3). In this diagram, the intersection point of the two curves is a criterion. the higher the intersection point is, the higher the effectiveness of the model (Yousefi et al, [24]).

Equation (2) is used to calculate the normalized density, and Equation (3) is used to calculate the weight of the controlling layers.

$$N_d = \frac{P_r}{O_a} \tag{2}$$

N_d: normalized density, P_r: prediction rate, and O_a: area covered.

$$W_E = L_n\left(N_d\right) \tag{3}$$

W_E: weight of controlling layer, L_n: normal logarithm, and N_d: normalized density.

The predicted rate defined at the point of intersection of the two curves in the P-A diagram shows the relative importance of the controlling layers as a suitable criterion for evaluating the generated models. However, the weight of the layer at the point cannot be obtained. To obtain the normallized density based on the area, the predicted rate of each class was divided by the corresponding area of each class to calculate the quantitative weight of controlling layers (Ghiasi et al, [26], Mihalasky, and Bonham-Carter, [27]). Yousefi and Caranza [21] modified and expanded the area of this method to calculate the value of each controlling map (not just any class of it) or any landslide potential model using the P-A diagram. The parameters obtained from the intersection point P-A diagram were used in Equation (2). They used the obtained normalized density to calculate the map weight in the P-A diagram (Yousefi, and Carranza, [21], Aram et al, [5], Ghorbani et al, [28], Barani and Bagherzadeh, [29] Ghiasi and Koushki, [30]).

2-2-4- Convolution artificial neural network

The CNN or ConvNet was introduced in 1990, inspired by the experiments performed by Hubble and Wiesel on the cat's visual cortex in 1962. CNN is one of the most important deep learning methods in which several layers are taught powerfully (LeCun et al, [31]). The architectural overview of a convolutional neural network is shown in Figure (4) for grouping images layer by layer.

A CNN consists of several main layers: the input layer, convolution layer, nonlinear layer, polishing layer, fully connected layer, and output layer, each of which performs different functions (Krizhevsky et al, [32]).

The input layer enters the data information into the neural network for processing in the hidden layer. In hidden layers, the processing work is done with the information received from the previous layer, which is sent to them, and the output is transferred to the subsequent layers. The output layer takes the processed information from the hidden layer and displays the final result as the final layer (Ghiasi et al, [33]). The flowchart of the research method is illustrated in Figure (5).

3- Results

3-1- Fuzzification (weighting) of controlling layers

Five criteria influencing the occurrence of landslides including slope, height, precipitation, watercourse density, and distance from the fault were weighted using the logistic function, and two criteria namely slope direction and geology were weighted using expert's opinion. For the weighted map, a score between 0.01 and 0.99 was obtained. Values closer to 0.99 have a greater effect on landslides and values that moves toward 0.01 have less effect on landslides. Figure (6) show the weighted controlling layers.

3- 2- Integration of the maps with CNN

After assigning the weight using the logistic function to all criteria, CNN method combined all weighted maps. The size of the pixels is the same in all generated maps, so in this operator, the whole maps were combined pixel by pixel, and the generated map assigned by weights between 0.01 and 0.99, i.e., the areas with the highest risk get a score close to 0.99 and low-risk areas get values close to 0.01.

3-3- Generation the final model by CNN

To feed the information to the artificial neural network, the study area was rasterized with a square units of 100*100 meters, and the area was divided into 4,799 pixels. Each point received information about that map from each layer of the map and finally received seven characteristics of information about the layers that affected the landslide. Then, output was obtained from 4,799 points with seven weighted layers' characteristics.

3-4-Landslies and non-landslide points

After selecting all the points in the study area for analysis training and testing of the neural network system, it is necessary to determine the information of landslides points and non-landslide points (equal to the number of landslides points) that have the characteristics of seven weighted layers.

The number of landslides that occurred in the study area was known in advance using satellite imagery and areas prone to suspected landslides, and many landslides due to their small size or appearance, similar to the adjacent range in recognizable satellite images. Therefore, to complete the information, all available landslides have been inspected. A total of 81 landslides has been identified in the Oshvand's study area Figure (7).

Non- landslide points are areas where the risk of slipping is less. As a default, landslides will not occur on slopes less than five degrees (Gomez et al, [34]). Therefore, 81 non- landslide points, equal to the number of landslides points, were selected manually within the study area.

3-5- Neural network training

In this study, to prevent any prejudice and interference in the neural network results, non- landslide points equal to slip points were randomly selected for training and testing of the network. A total of 162 landslides and non-landslide pixels were selected for training and testing the network. In a CNN, 70% of the data were selected for training, and 30% were selected for network testing. Network training and testing were performed with 162 landslides and non- landslide information, of which 114 pixels were used for training and 48 pixels for network testing. According to Figure (8), in the experimental stage, the output response of the artificial neural network showed that the created neural network could correctly report 72 cases (in blue) out of 81 landslides pixels, which indicates a detection sensitivity of 88.89%. Also, out of 81 non- landslide pixels, the network detected 75 (green) items from the experimental samples, representing 92.59%. 15 cases (in yellow) that 9 of which are related to landslides points and 6 related to non-landslide points have not been recognized correctly. In total, by averaging the values obtained from all landslides and non- landslide points, the accuracy of the whole network was calculated as 90.74%.

3-6 CNN structure

After determining the neural network algorithm's parameters, the structure of 7-15-1, i.e., seven neurons in the input layer, 15 neurons in the hidden layer, and one neuron in the output layer, was used for the final modeling according to Figure (9). Due to the application of Softmax enabled function, the network output value varies between zero and one. Table (1) shows the layers and calculations performed by the convolutional neural network in the MatlabR2019b program.

3-7 Learning ratio

The learning ratio is the reduced rate of the cost function per repetition that should be chosen very carefully, not so high that it overrides the optimal state and not so small that it takes a long time to learn the network. To determine this parameter, the trial and error method was examined to achieve the minimum amount of error from 0.001 to 0.5. The network had the lowest error with a learning ratio of 0.01 Figure (10).

3-8 Cost foundation

When a network is formed, the network tries to predict the output as accurately as possible. The cost function obtains the value of this accuracy in the network. This function tries to correct the network when it makes a mistake. When a network is set up, the goal is to increase the prediction accuracy and to reduce the errors needed to the cost function. At the best output, there is the lowest cost Figure (11). The number of repetitions, as one of the parameters of the artificial neural network in the training phase, is determined by the trial and error practice to prevent the increase of error and overtraining. According to the figure (11), in this research, by examining 500 repetitions to 10 thousand repetitions, the network reached the lowest error value with 5 thousand repetitions by the trial and error method.

3-9 Preparing the final model

After identifying the basic structure of the neural network and providing the information needed from the landslides and non- landslide points for neural network training and achieving acceptable error, the network is prepared to perform a logical analysis of information not previously encountered to make the necessary predictions and simulations. For this purpose, using the weights of the final training, a dataset of seven values of the 4,799 pixels, corresponding to the related seven landslide controlling factors, was provided to the network. For each pixel, a value between zero and one was determined by the system. With the end of the nervous system, the network reached a stable state, and the weights and ranges for landslide risk classification were extracted from this network. Then the final landslide potential map of the Oshvand watershed was obtained Figure (12). By classifying the values obtained from the neural network, the study area can be divided into different areas in terms of landslide risk.

3-10 Evaluation of the model

In landslide risk modeling, the weight assigned to each of the effective criteria in landslides should indicate the relationship between each criterion and the severity of its effect on the occurrence of landslides. Therefore, known landslide points in the study area were used as test points to evaluate the weighted map. In this study, 81 known landslide points t were used to investigate the predictability of the produced models. In the P-A diagram, the percentage of known points and the area covered by each class of the model are plotted as a percentage (according to the total area of the study area) against the thresholds of the predicted classes of the generated model (Yousefi and Carranza, [21]). In the P-A diagram, there are two curves. The first curve is related to the prediction rate of known points corresponding to the model classes. The other curve is the area covered in terms of the percentage of each class of the model in the whole study area. In this diagram, the intersection point of the two curves is a criterion for evaluating landslide zoning models. To evaluate the final map, it was classified into five classes Figure (13).

A P-A diagram based on the information in Table (2) was drawn using the final map classification of the Oshvand area. As shown in Figure (14), the prediction rate diagram shows the intersection the two curves. The prediction rate is approximately 70%, and the area covered is about 30% meaning that 70% of the landslides occurred within 30% of the study area.

3-11 Obtain the normalized density of the final map

According to the equations (2 and 3), using the normalized density function, the weights of all the criteria were obtained as follows. Nd is normalized density, Pr is the amount of predicted landslide, Qa is the surface of the area where the landslide occurred and W_E is the criteria weight.

$$N_d = \frac{P_r}{O_a} = \frac{70}{30} = 2.333$$

$$W_E = L_n\left(N_d\right) = L_n(2.333) = 0.847$$

3-*12 Comparison with previous works in the Oshvand watershed*

According to the study conducted in the Oshvand watershed area using the data-driven index overlay method, it was found that 55% of landslides occurred in 45% of the area (Mirzaei, [35]). In another study in the Oshvand watershed continuous fuzzy models and the geometric average method, were applied and 60% of landslides occurred in 40% of the area (Ghasemi, [36]). However, the CNN method in this study Figure (14), showed that 70% of landslides occurred in 30% of the area. Therefore, by comparing the convolution method with data-driven index overlay, geometric average, and gamma operators, it was found that the CNN method has better performance compared to other above-mentioned methods.

4 – Discussion

Fuzzification of slope factor, rainfall, watercourse density, height, and the fault with numerical values of Ev_{max} (the value of the large pixel) and Ev_{min} (the value of the smallest pixel) was obtained from the prepared map of the slope, height, precipitation, watercourse density and distance from the fault. Then according to the logistic function (sigmoid) equal to equation, the numerical value of me (turning point) was calculated from equation and the value of S (slope of the function) was calculated from equation. And according to the values obtained in Table 3, a weighted map of the slope, height, precipitation, watercourse density, and distance from the fault of the region was prepared with ArcGIS 10.4.1 software.

$$F_{EV} = \frac{1}{1+e^{-S(E_V - i)}} \tag{4}$$

$$i = \frac{\left(E_{V_{\max}} + E_{V_{\min}}\right)}{2} \tag{5}$$

$$s = \frac{9.2}{\left(E_{V_{\max}} - E_{V_{\min}}\right)} \tag{6}$$

For landslide zoning and how to identify landslide risk areas, a method should be considered that can be used to identify and introduce these areas with the least amount of error. For this purpose, the relative importance of each factor, the ranking of the study area, and the simultaneous study of the effect of factors in landslide risk zoning are noteworthy. The researchers used the Geographic Information System (GIS) capabilities for landslide zoning, so various methods have been developed in the GIS environment to generate zoning models, which are generally divided into supervised and unsupervised methods. In the unsupervised method, to weigh the criteria and effective factors in location, expert opinion and experience are used. Due to the combination of natural and human factors, the Oshvand study area has great potential for landslides. These landslides cause a lot of damage to roads, residential areas, agricultural lands, and other resources in the region every day. This study aims to weight each of the factors using logistic function and convolution artificial neural network method to combine weighted maps and prepare the final map to evaluate areas with slip potential. This study used the continuous weighting method without classification (classification). The unsupervised method is still used for geological criteria and slopes due to the discretization of the soil environment. For this reason, in the continuous fuzzy model, weighting is done with minimal expert judgment, in contrast to the unsupervised model (classical fuzzy). This method is done completely with an expert's opinion, which was also used. The CNN method was used to integrate the generated maps of the models. The maps were obtained in the form of landslide risk zoning models. In landslide risk zoning, a process can be designed to identify landslide risk areas and target areas based on the steps presented in it. According to the conducted study, it can be concluded that before the search operation, the field plan should be designed systematically and in the form of an algorithm in which the zoning process is defined step by step, optimal time management, cost, and project control is done. The risk of location operations is reduced, so by studying landslide zoning, a Descriptive and conceptual model of landslide zoning characteristics was obtained and then used this conceptual model. Known features and the best effective criteria for Zoning in the form of a target model were designed. In the next step, each of the target identification criteria was weighted as a continuous model. All weighted maps were combined using the convolutional artificial neural network method to the points where all appropriate criteria of the target model are confirmed as a landslide risk zoning model. Get it. This research used landslide points in the area to test and evaluate the method. And the continuous fuzzy model with the convolution artificial neural network method was able to predict landslide risk points. By classifying the values obtained from the neural network, the study area can be divided into different areas in terms of landslide risk. According to the maps generated in the continuous fuzzy model and integrated with the artificial neural network method, 70% of the landslide points were predicted at 30% of the study area. And the proposed method has been able to minimize the study area and predict suitable areas for landslide risk zoning in the Oshvand watershed. The slope factor has the most effect on landslide occurrence and the slope direction factor has the least effect on landslide occurrence. And precipitation is the trigger for landslides in the study area. This model has been able to reduce the studied area favorably and identify suitable areas for landslide risk zoning. Therefore, it is suggested that for any implementation measures in the region, the managers should use the prepared model to plan the development policies of the region by identifying the areas with a high risk of landslides to change the use and construction, which causes an increase in the weight load on the unstable slopes.

5- Concluding Remarks

- Convolutional neural network returned about 30% of the study area as high-risk. Out of the total 81 existing landslides, 60 landslides are located within the high-risk area. Therefore, this model has been able to reduce the investigated area and identified potential areas for zoning the risk of landslides in the Oshvand watershed.
- Using the conceptual model defined, the information on each of the criteria was prepared in the form of digitized controlling layers. Then digital controlling maps were prepared for all criteria using the continuous fuzzy method, which is based on a continuous weighting method without simplification of data.
- The landslide potential model was obtained with minimal expert’s judgment in assigning weights, which was evaluated with real landslide maps of the studied area.
- The continuous fuzzy model in conjunction with the convolution artificial neural network method capable to predict the landslide risk points adequately.
- The results showed that the slope factor has the most influence on landslide occurrence and the slope direction factor has the minimum effect on landslide occurrence. Precipitation is the trigger for landslides in the study area as well.

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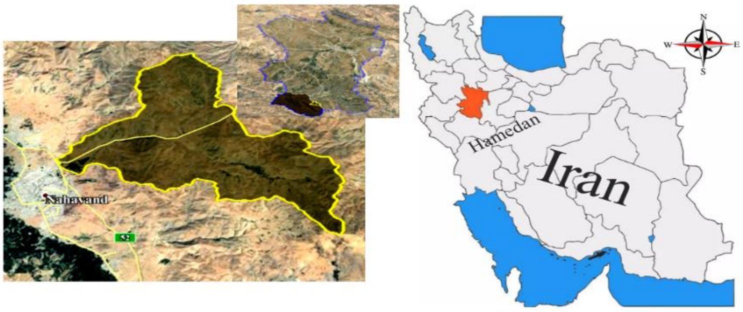

Figure 1. Location of Oshvand watershed in Nahavand, Iran.

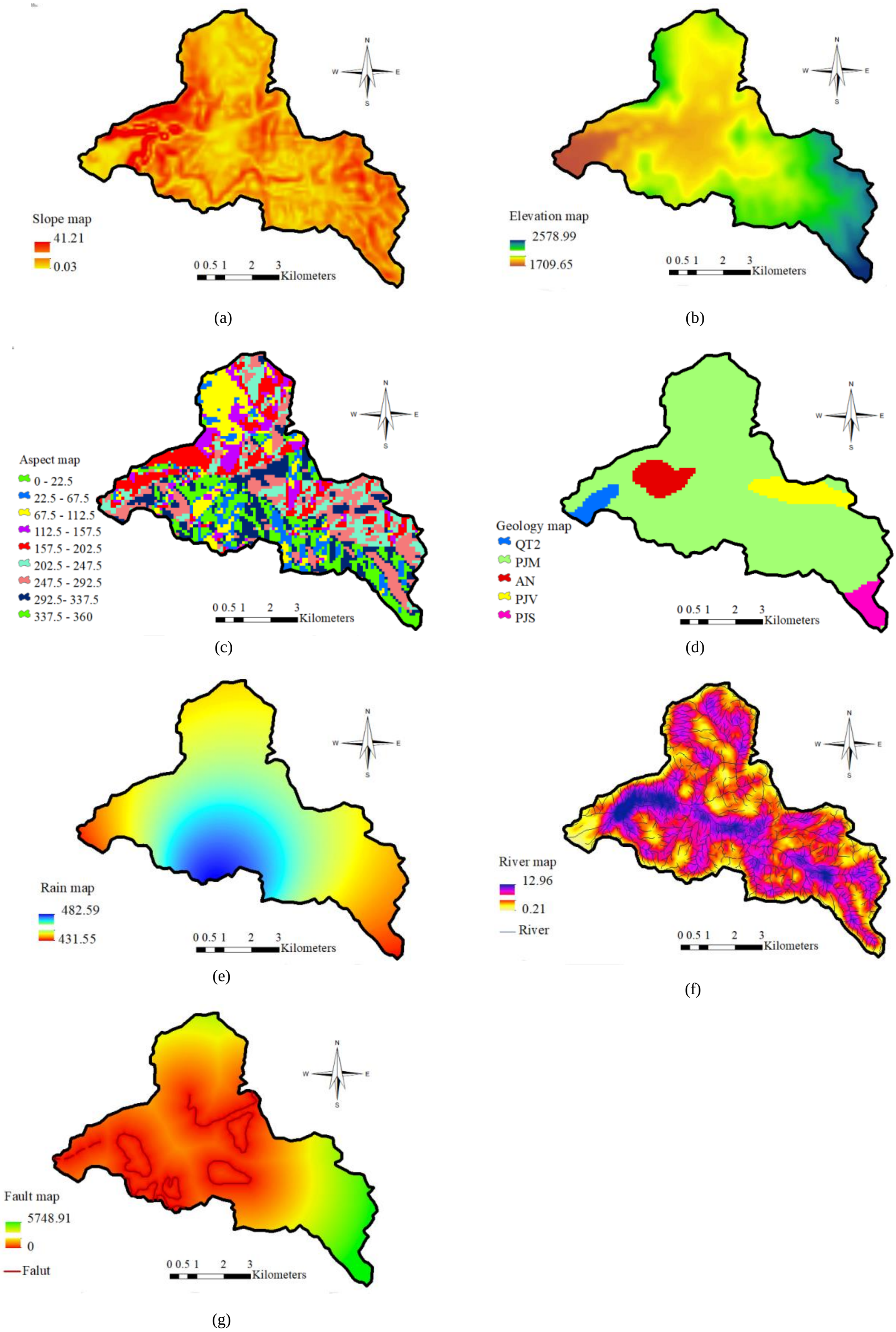

Figure 2. Slope map (a), Elevation map (b), Aspect map (c), Geology map (d), Rain map (e), Stream Density map (f), Fault distance map (g).

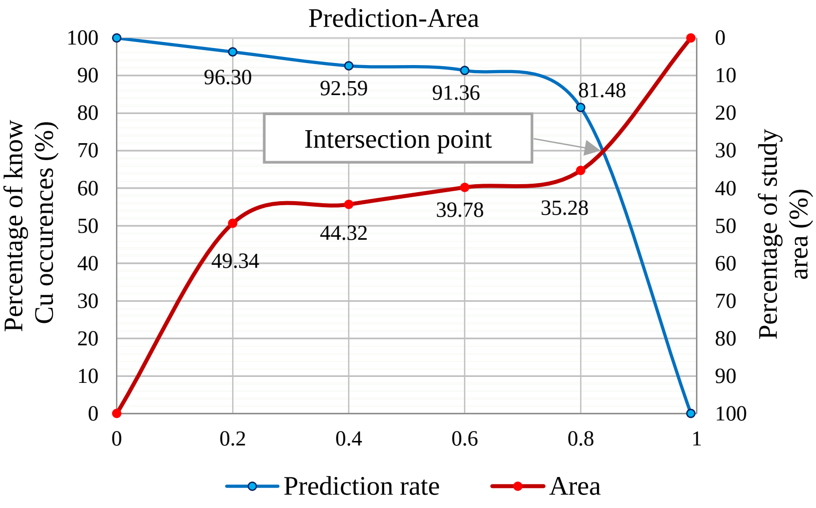

Figure 3. Forecast rate-area diagram (Yousefi, and Carranza, [25]).

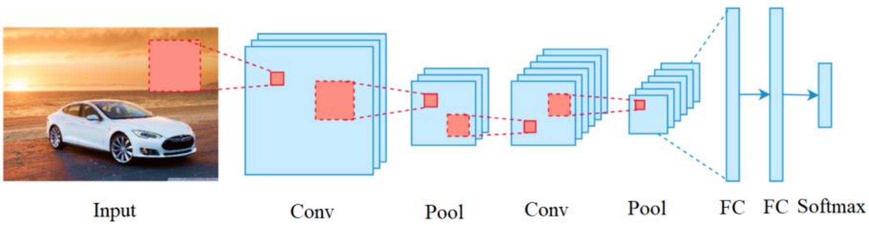

Figure 4. The general architecture of convolution neural networks (Potrimba, [37]).

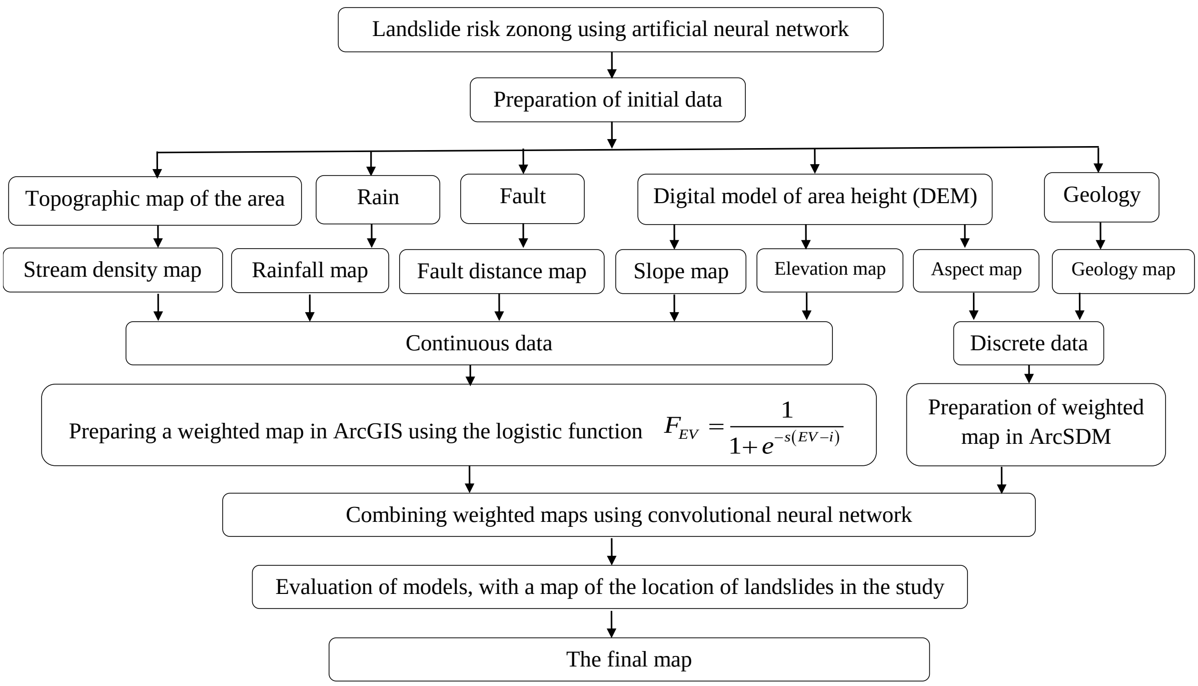

Figure 5. Flowchart of research methods.

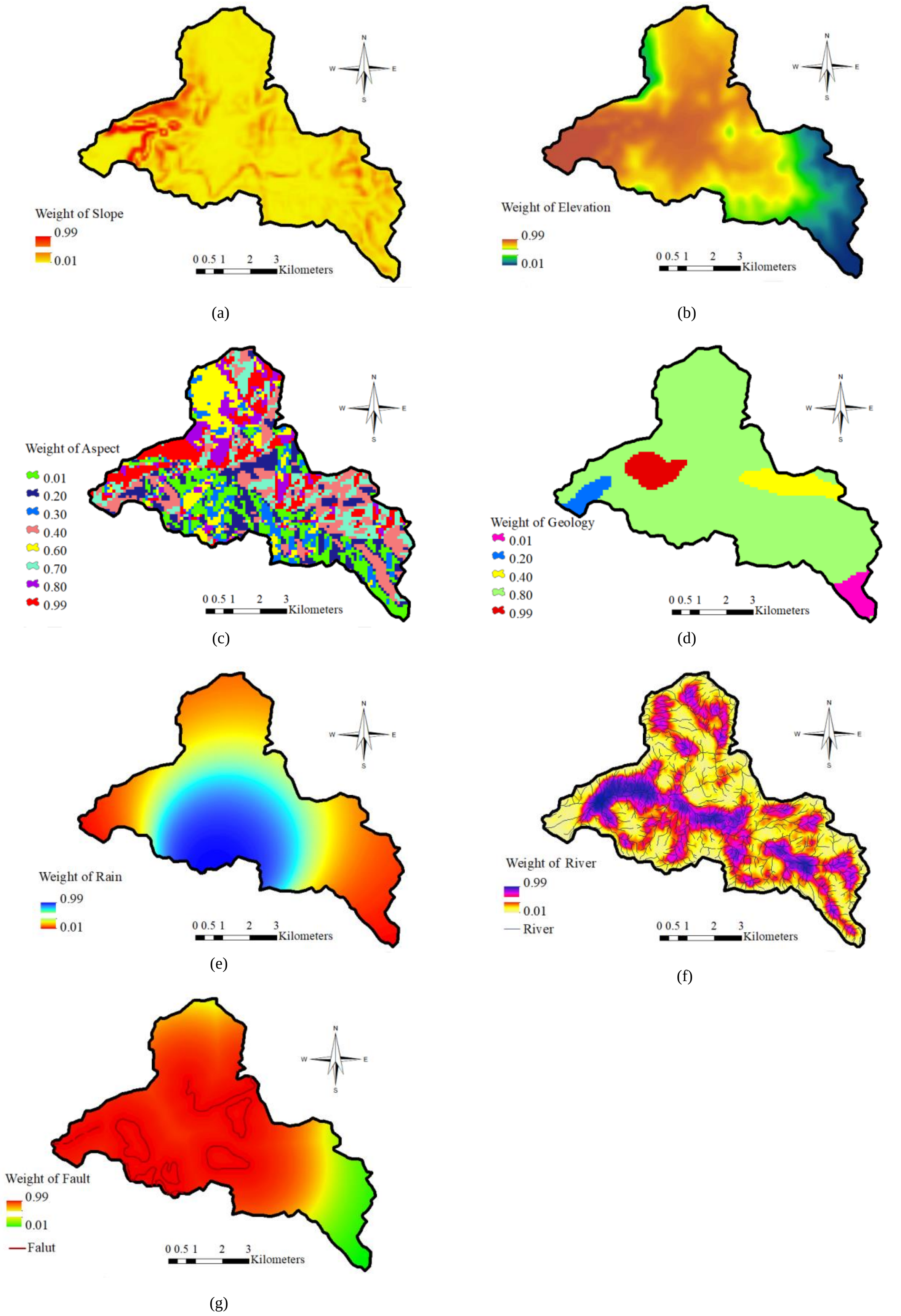

Figure 6. Slope weighted map (a), Elevation weighted map (b), Aspect weighted map (c), Geology weighted map (d), Rain weighted map (e), Stream Density weighted map (f), Fault distance weighted map (g).

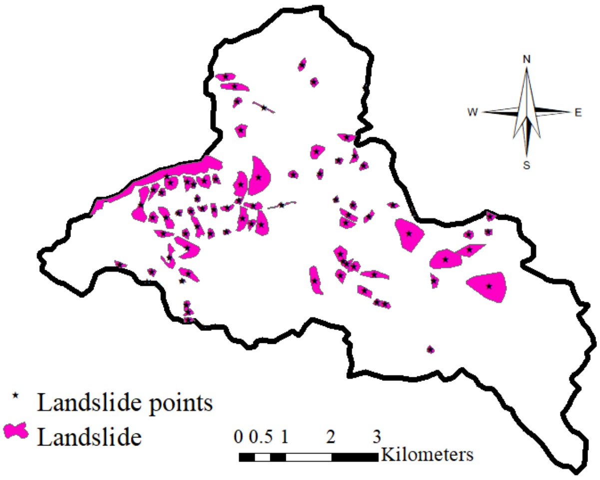

Figure 7. Landslide distribution map in the study area.

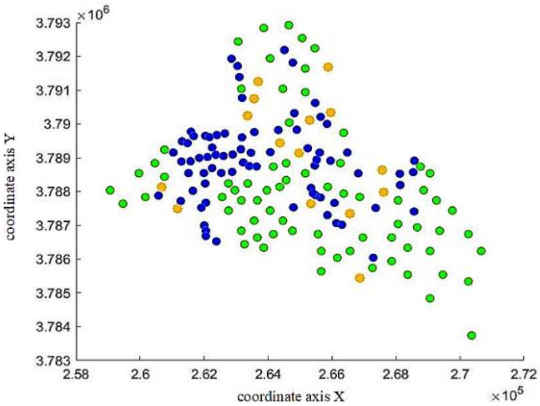

Figure 8. The output of selected slip points and non-slip points of the Oshvand watershed

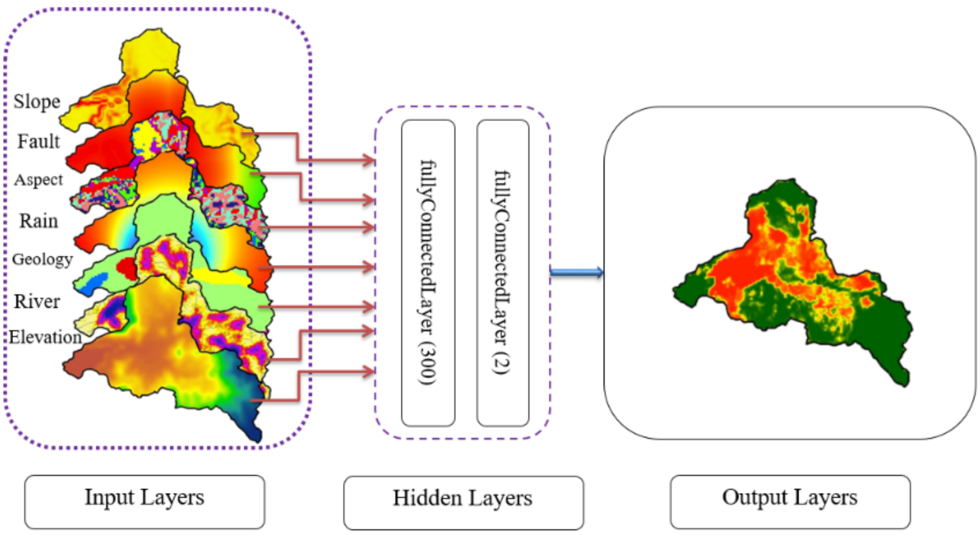

Figure 9. Convolution neural network structure in Oshvand watershed.

Table 1. Layers and calculations performed in MatlabR2019b software.

No	Name	Type	Active Layer	Calculation	Results
1	Input	7*1*1 images with 'zero center' normalization	7*1*1	-	0
2	Convolution	15* 3*3*1 convolutions with a stride [1 1] and padding ‘same’	7*1*15	Weights 3*3*15 Bias 1*1*15	150
3	Function ReLU	ReLU	7*1*15	-	0
4	Fully connected	fc_1 300 fully connected layers	1*1*300	Weights 300*105 Bias 300*1	31800
5	Fully connected	fc_2 2 fully connected layers	1*1*2	Weights 2*300 Bias 2*1	602
6	Function Softmax	Softmax	1*1*2	-	0
7	Output	Classoutput With classes 'false and true	-	-	0

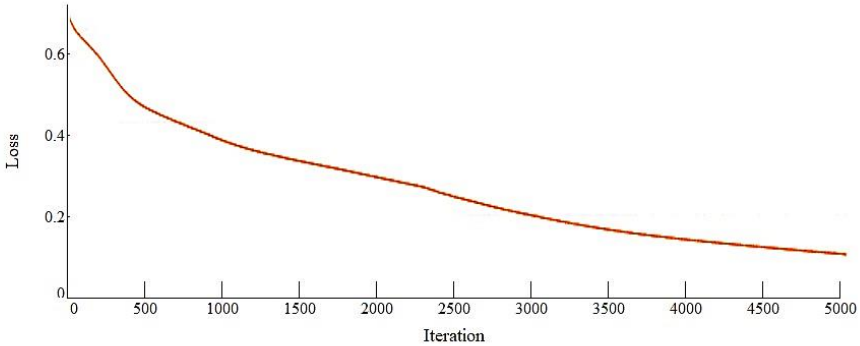

Figure 10. Graph of network error rate.

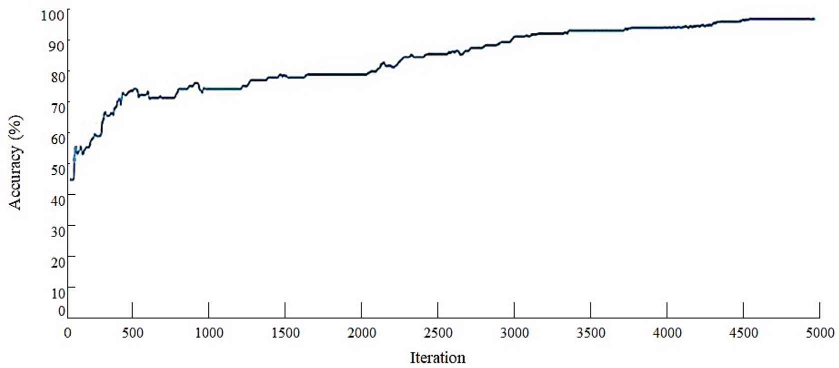

Figure 11. Network training accuracy graph.

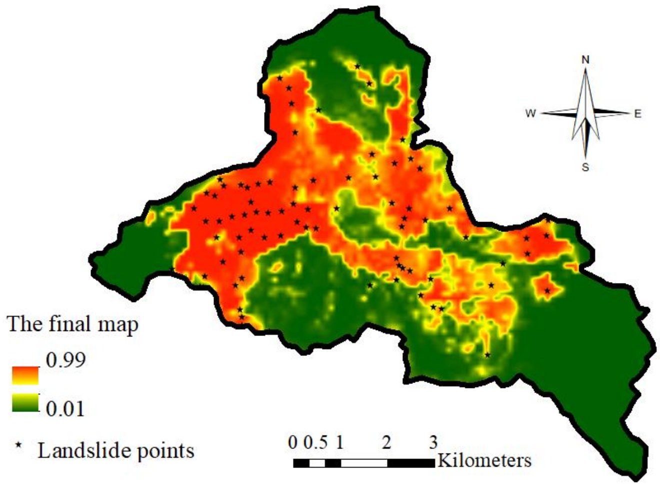

Figure 12. Integration map of criteria by convolution neural network method.

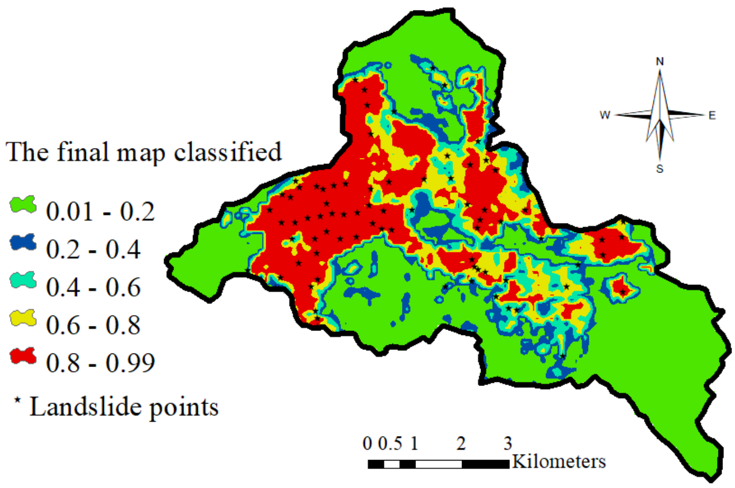

Figure 13. Final map classified in Oshvand watershed.

Table 2. Results for plotting the forecast rate - the area of the final map in the field of Oshvand.

Class	Classification	Percentage of cumulative area	Area (hectares)	Sliding points	Forecast rate
1	0.01-0.2	100	2431	3	100
2	0.2-0.4	49.34	241	3	96.30
3	0.4-0.6	44.32	218	1	92.59
4	0.6-0.8	39.78	216	8	91.36
5	0.8-0.99	35.28	1693	66	81.48

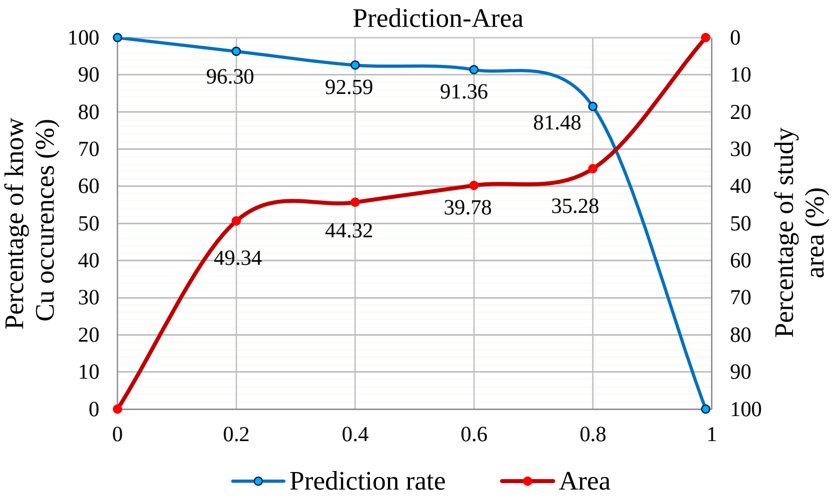

Figure 14. Forecast rate chart - the area of the final map in the Oshvand watershed.

Table 3. Ev_{max}, Ev_{min}, i, and S values of the slope, precipitation, waterway, elevation, and fault map.

Benchmark Map	Ev_{max}	Ev_{min}	i	s
Slope	40.2079	0.028888	20.6183	0.22341
Rain	482.599	557.431	457.078	0.18024
Waterway Density	12.9601	0.2128	6.5865	0.7217
Height	2578.99	1709.65	2144.32	0.01058
Distance From The Fault	5748.91	0	2874.46	0.0016

Biographies

Vahed Ghiasi, is an Assistant Professor at the Department of Civil Engineering, Iran Malayer University. He received his BSc degree in Civil Engineering his MSc in Civil Engineering (Geotechnical Engineering) and his PhD degree in Civil Engineering (Geotechnical Engineering) from the University Putra Malaysia(UPM) in 2012. His major research interests include Geotechnical Engineering. He has published some books and a large number of papers in high-impact international journals and many papers in research-indexed journals and international conferences.

Ahmad Mahmudi, received his BSc degree in Civil Engineering from the University of Malayer, Malayer, Iran, and his MSc degree in Civil Engineering(Geotechnical Engineering), from Malayer University in 2021, Malayer, Iran. His research interests include Convolution neural networks, GIS, and Logistics functions. He has published some journals and international conference papers.

Mahyar Yousefi is an associate professor at the Malayer University. His main field of study is geographical information system-based natural resources and natural hazards potential mapping. During his career, he has developed novel approaches dealing with problem solving and improvements on the topics within and around this field. He contributes as reviewer for many scientific journals as well. Recently, he has proposed a new information system for the future use of geographical information systems for natural resources potential mapping. The system was called exploration information system (EIS), and now is an ongoing project funded by the European Commision. At present Dr. Yousefi's main focus is on EIS-related topics.