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MLP learning-based landslide susceptibility assessment for Kurdistan province, Iran

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ABSTRACT

Landslide susceptibility analysis is considered the spatiotemporal pattern of the prone area for landsides occurrences which is mostly used in urban planning, hazard management, and sustainable developments. The presented study tried to analyze the landslide susceptibility condition for Kurdistan province in Iran by using geographic information system (GIS) and multilayer perceptron (MLP). The assessment parameters are categorized in geomorphological, geological, and human-work classes concluded slope aspect, slope angle, elevation, hydraulic condition, distances from faults, weathering, distances from rivers, distances from roads and cities. According to the results of the susceptibility assessment for the studied area, it has appeared the MLP-based model is provided the susceptibility modeling with 85.25% accuracy and 83.79% precision. Also, the middle part and some of the west part of the studied area are located in the high-risk area for landslides failures.

1. Introduction

Landslides cause numerous financial and human losses. Research shows that this phenomenon accounts for about 17% of natural disasters in the world (Lacasse and Nadim, 2009). The damage caused by landslide events is too costly even for countries that are paid for lives or property damage (Azarafza et al., 2018). Iran has also known as one of the most risk-able areas for landslide occurrence which more than 160 deaths and the demolition of 176 houses and 170 roads in 2000 confirm by Akbarimehr et al. (2013). Causes of landslides can be natural factors such as earthquakes, rainfall, and climate change or human factors such as city developments, road/railway construction, power plant construction and mining, etc (De Vita et al., 1998; Gariano and Guzzetti, 2016; Nanehkaran et al., 2021). By conducting the predictive studies on landslide effective parameters, can estimate the landslides occurrence rate which highly impacted on risk management and assessment of landslide-prone areas for reducing the hazardous effects (Lacasse and Nadim, 2009). The landslide susceptibility is the best way to reach that goal which means the possibility of landslides occurrence in an area based on historical background and suitability in the area for failure events (Roslee et al., 2017). In fact, the landslide susceptibility mapping is considered as part of geo-hazard management to minimize human casualties and reduce damage to infrastructure, especially in mountain roads, as well as land-use planning and crisis management (Huang and Zhao, 2018; Roy et al., 2019; Ozer et al., 2020). Marjanović et al. (2011) stated that there are several factors that affect the preparation of this mapping, which are the amount of access to samples in the study area,

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important factors according to environmental conditions, and the model used to prepare the map. However, professionals used different classification systems for landslide susceptibility assessments (Neuhäuser et al., 2012). Conventional models are divided into three general categories which are quantitative, qualitative, and semi-quantitative approaches (Tsangaratos et al., 2017). Another detailed classification system has classified the methods into deterministic, probabilistic, geostatistical, heuristical, inventory-based, and knowledge-based procedures. On the other hand capability of using various predictive models with geographic information systems (GIS) to demonstrate regional conditioning factors are directly used to manage the geo-hazard and urban planning (Azarafza and Ghazifard, 2016). In the meantime, knowledge-based approaches (such as fuzzy logic, logistic regression, neural network, neural fuzzy network, support vector machine, decision tree, random forest, etc.) are respected by scholars that modified techniques and improve traditional methods (Vahidnia et al., 2010).

The multilayer perceptron (MLP) method is one of these quantitative knowledge-based models that have been used in recent-published researches by several scholars due to its high efficiency and good predictive power (Dahoua et al., 2017). An MLP model is a feed-forward artificial neural network (ANN) model that refers to networks composed of multiple layers of perceptrons with threshold activation. MLP consists of at least three groups of layers concluded input layer, hidden layer, and output layer. Except for the inputs, each layer is a neuron that uses a nonlinear activation function. As an ANN-base model, the MLP used a supervised learning method named the back-propagation technique for the training of data-set (Aggarwal, 2018). There are many studies on landslide susceptibility that used the MLP model. Some of the examples include research in the Junguk region of Korea (Lee et al., 2006), Patenza Italy (Caniani et al., 2008), Turkey (Yilmaz, 2009), Malaysia (Pradhan and Lee 2010), Mazandaran (Zare et al., 2013), Rudbar, Sefidargaleh Semnan, Talesh, and Haraz watershed. Paying attention to these assessments can indicate that the use of the MLP model has been well applied in landslide susceptibility analyzes which the results of these studies emphasize on this issue.

The presented study used MLP predictive model to analyze the landside susceptibility for Kurdistan province in Iran. The model used a primary database concluded the information layers such as elevations, slope aspect, slope angle, distance from faults and distance from rivers, etc. that are collected and considered as input parameters of the MLP neural network.

2. Studied Location

Kurdistan province is one of the 31 provinces of Iran that is covered 28,817 km² in the area at the west of Iran. Geopolitically, the province is limited by the Kurdistan region of Iraq on the west, the West Azerbaijan province in the north, Zanjan in the northeast, Hamedan in the east and, Kermanshah to the south (Aghanabati, 2007). Kurdistan Province is a mountainous region that can be topographically divided into a western and an eastern section at Sanandaj (capital of the state) and had several major rivers and hills, so, it is provided a suitable region for landslide occurrences (Aghanabati, 2007). Various recorded historical landslides in different scales in the province indicated that the region is very active related to the landslides and ground movements. Fig. 1 is illustrated the elevation changes of the studied area in Iran and the location of the studied area. Geologically, there are various faults in the region that have caused folded structures and deep valleys. High seismic activity, as well as the cold and humid climate of the region, caused favorable landsliding conditions provided in the area. Thus, the landside susceptibility for Kurdistan province is one of the important necessities for hazard risk management at the regional and state levels.

3. Material and Methods

The artificial neural network techniques have been developed by inspiring the function of the human brain and nervous system (Aggarwal, 2018). These methods find the relationship between their corresponding inputs and outputs and in complex problems where the relationship between variables is unknown; it is a powerful predictive method for prediction of risk or susceptibilities (Fatemiaghda et al., 1994). The general application of ANN is that the input information enters the network through the nodes of the input layers. These nodes are associated with weighty relationships. Hence, each interface has its own weight and the input information is transmitted through these interfaces from the input layer to the middle layer (hidden layer). In this layer, the nodes act as a processor, that is, they perform operations on that input through connections by receiving information from the input layers, and sending it from one node to the next layer node, and the result is the output layer is removed from the network (Guo et al., 2015; Aggarwal, 2018).

MLP will be able to perform more complex analyzes by adding intermediate layers. Activation functions in the output layer are mainly selected according to the user's needs, and each neuron in each layer of the network is connected to each of the neurons of the next layer by weight. Such a structure is called a fully connected network. Now, if some of these connections do not exist, it is called semi-connected (Pham et al., 2017). Fig. 2 is a schematic representation of the MLP network. Normalization of input data is done for reasons such as increasing the speed and accuracy of the network, equalizing the value of input data for the network, not reducing the weights too much, and early saturation of neurons. There are many ways to normalize raw data, but the following method, also called the global approximation coefficient, is usually widely used (Li et al., 2019).

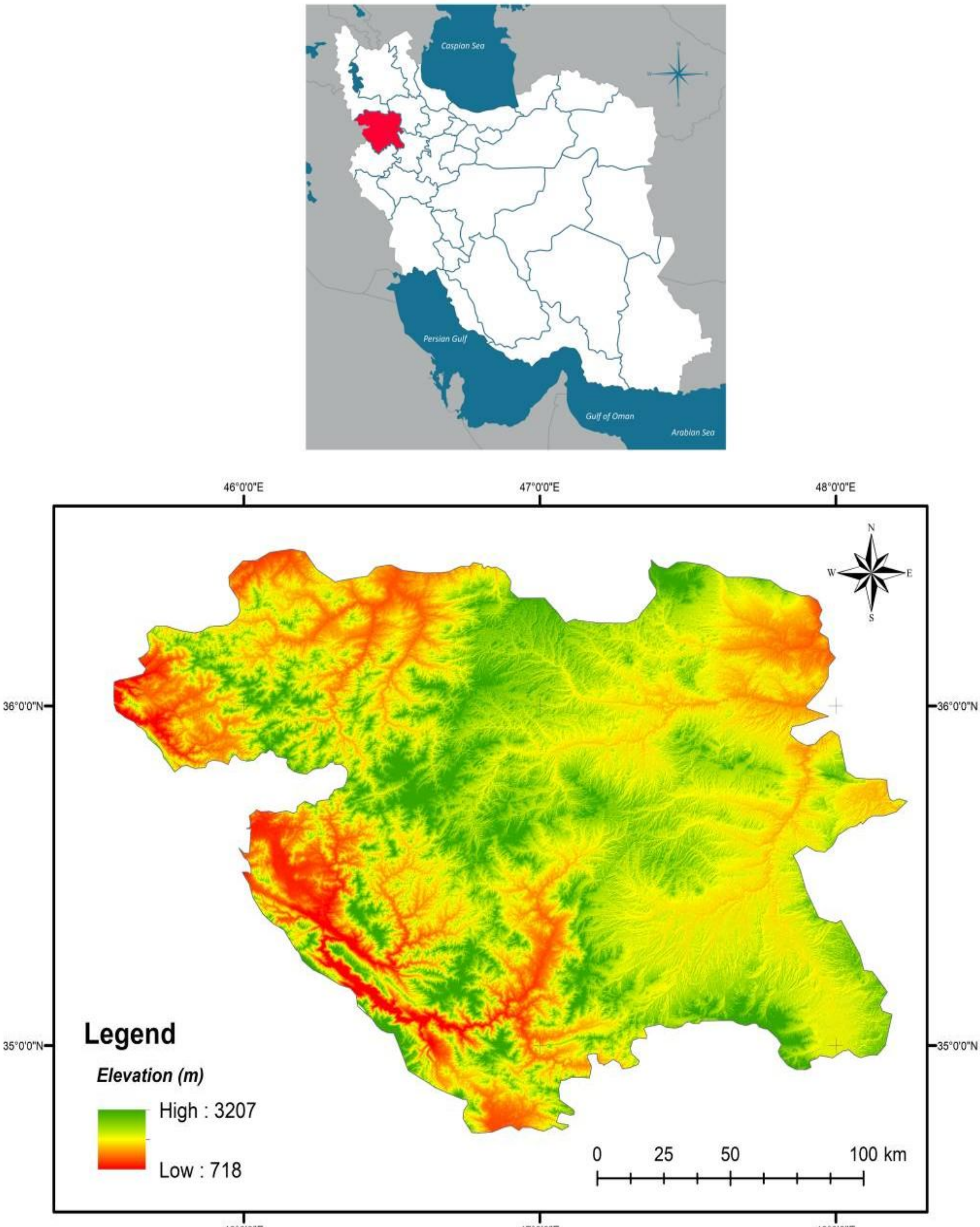

Figure 1. Location of the studied area in Iran

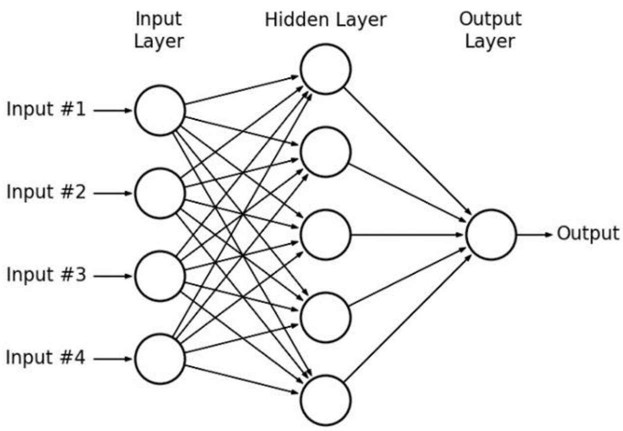

Figure 2. Representation of MLP model (Aggarwal, 2018)

The MLP algorithm used the back-propagation algorithm. Proper neural network architecture is achieved using the trial and error method, which is accompanied by a change in the number of median neurons and the stability of other parameters, and continues until the best state that the least amount of error is achieved in the testing and training phase. For this purpose, at each stage of training, the average square root of the roots is determined so that where the amount increases, the network training is stopped and the optimal repetition rate and the appropriate training error for the network are determined (Huang et al., 2018). However, the main landslide susceptibility studies use data sources mainly include the following (Meng et al., 2019):

- Recorded landslides and related data obtained through field research,
- Digital Elevation Model (DEM) data used to extract environmental topographic factors,
- Geological maps with different scales,
- Remote sensing images that are used to extract ground cover factors,
- High resolution aerial images for landslide interpretation.

One of the key problems in preparing a landslide susceptibility map using the digital elevation model is selecting a suitable mapping unit. The most common mapping units mainly include network unit, slope unit, and sub-basin unit, among which, network unit has the advantages of simple geomorphological expression and high model computational efficiency and is the most common mapping unit (Huang et al., 2017). Determining the resolution of the network is also very important. This is because grid units can more accurately describe the topography and shape of the earth in hilly areas than with lower resolution. The use of low-resolution networks greatly increases the complexity of the model calculations, and the use of low-resolution networks cannot guarantee the rationality of the obtained sensitivity map (Arnone et al., 2016). With the help of the obtained data, scatter maps are prepared for factors such as slope, distance from faults, distance from waterways, and weather conditions. Considering the importance and weight of each of the factors of landslide sensitivity map is provided and the total weight available for each unit of the area actually indicates the probability of landslides in that unit (Shirzadi et al., 2019). The samples used are randomly selected from areas with history or no history in the study area and these samples are used to prepare and test the model. The obtained indices for each unit of the region are estimated between 0 and 1, with index 1 indicating the maximum probability and index 0 indicating the minimum probability of landslide occurrence (Li et al., 2019).

The presented study uses the MLP method to provide the predictive model for susceptibility analysis of landslide occurrence in Kurdistan province. The MLP is a well-known machine learning classifier to provide supervised classifications. The model required training and testing sets which are randomly selected from the primary database. The training set concluded the 70% and the testing set is containing 30% of the main database. The main database is gathered by recording detailed landslide information and triggering factors in the studied area by using full-length field surveys and remote sensing observations of all types of landslides with different scales. The presented study used the regional scale to cover the entire province to estimate the risk of landslides occurrence. According to the investigations, there are several triggering factors such as geomorphological, geologic, and human work is played an important role to trigger the land movements in the studied area. Each of these triggering factors is divided into the sub-factors which are contained slope aspect, slope angle, elevation, hydraulic condition, distances from faults, weathering, distances from rivers, distances from roads and cities. These factors provide a landslide inventory database which represent triggering/effective variables to active the landslide occurrence. Figs. 3 to 5 are provided the thematic maps of effective triggering factors for the study area.

In order to validate the analysis of the predictive model based on MLP, the evaluation criteria and confusion matrix were used. The confusion matrix (known as an error matrix) is a specific table layout that allows visualization of the performance of an algorithm. Each row of the matrix represents the instances in an actual class while each column represents the instances in a predicted class. The confusion matrix provides the indexes to evaluate the performance of machine learning methods named accuracy; precision; recall, and F1 score (Aggarwal, 2018). The confusion table provides the overall accuracy of the algorithm to demonstrate the capability and degree of the learning which presents the performance. So, by increasing the predictive performance of the model, the accuracy and precision will be raised. The presented study uses the confusion matrix to estimate the model accuracy for susceptibility assessment.

4. Results and Discussions

Using the training dataset, the landslide susceptibility map for the studied area was developed for spatial landslide prediction and evaluated the risk-ability rate for landslides. The model is classified in a landslide and non-landslide locations with respect to the triggering factors. Landslide susceptibility maps are deemed as a final product that can assist authorities in land-use planning. Fig. 6 shows the landslide susceptibility map provided for the studied area. The map is indicated the high-susceptible, moderate-susceptible, and low- susceptible, which is represent the degree of the risk-ability for landslide occurrence. Also, Fig. 7 is provided the results of the obtained confusion matrix for the MLP model regarding the landslide susceptibility assessment. According to the results, the model is providing susceptibility modeling with 85.25% accuracy and 83.79% precision. Also, referring to Fig. 6, it can be mentioned that the middle part and some of the west part of the province is obtained as high-risk area regarding the landslide occurrence.

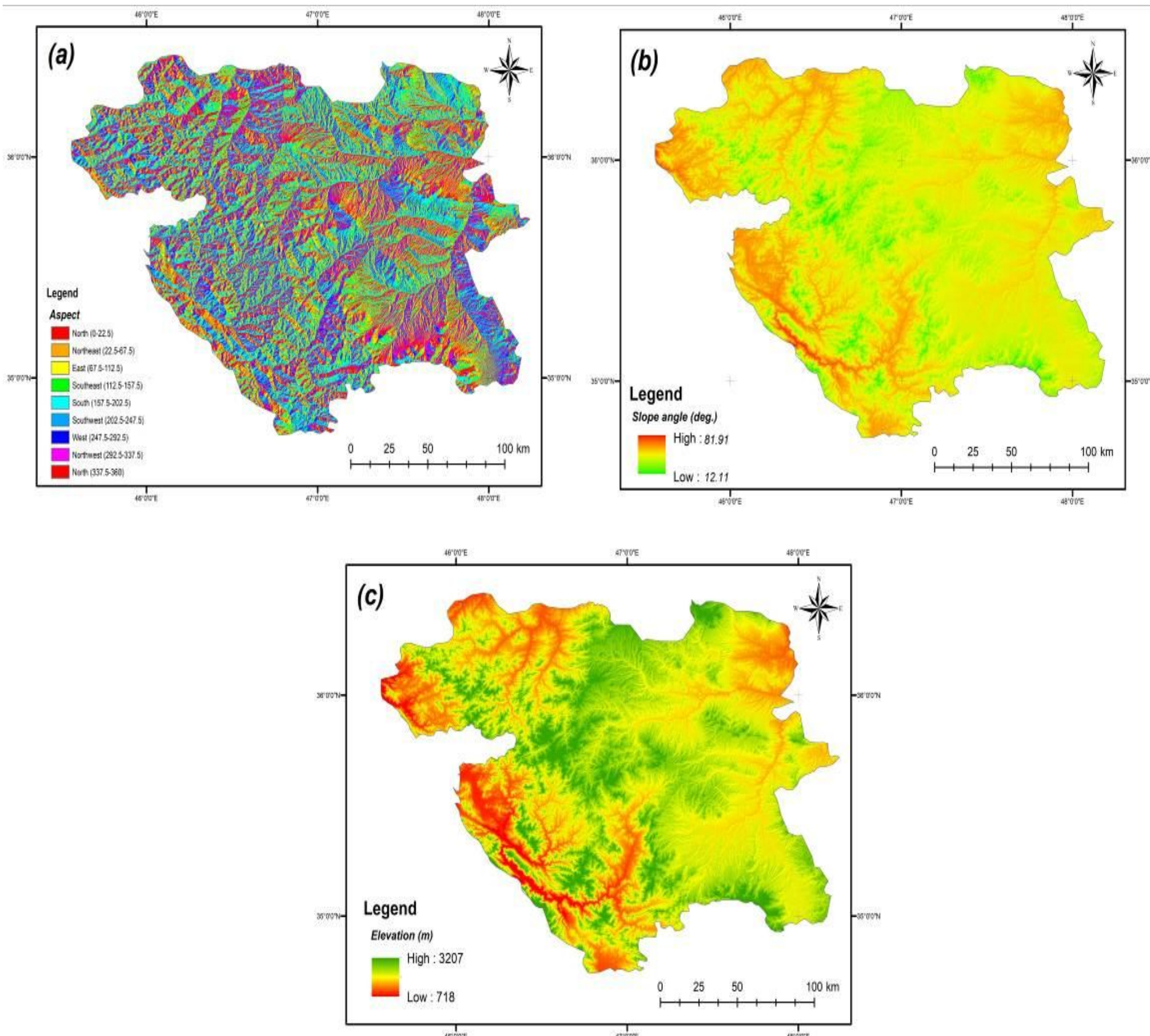

Figure 3. The triggering geomorphological factors maps: (a) slope aspect, (b) slope angle, (c) elevation

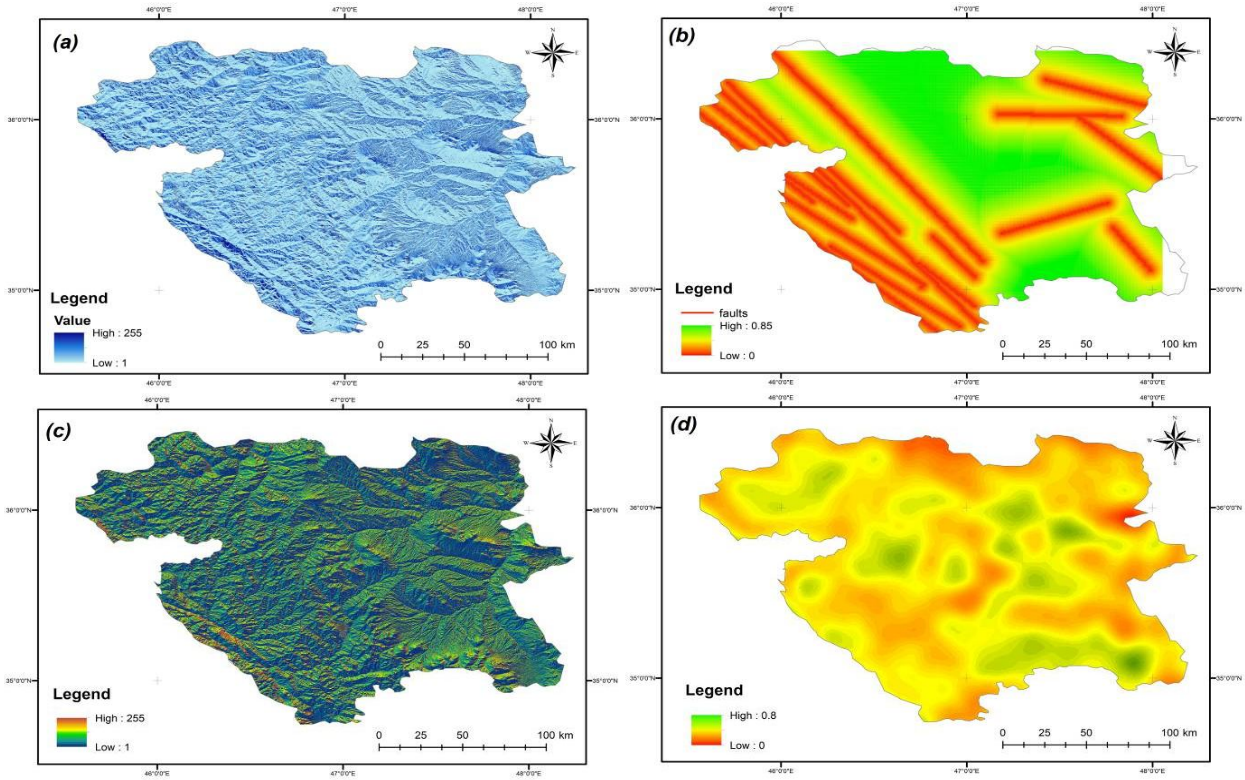

Figure 4. The triggering geologic factors maps: (a) hydraulic condition, (b) distances from faults, (c) weathering, (d) distances from rivers

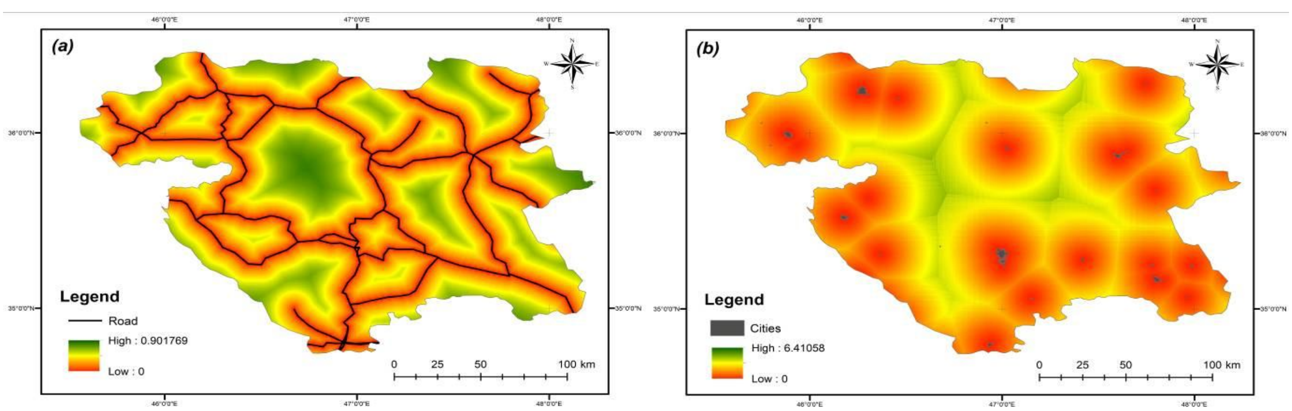

Figure 5. The triggering human-work factors maps: (a) distances from roads, (b) distances from cities

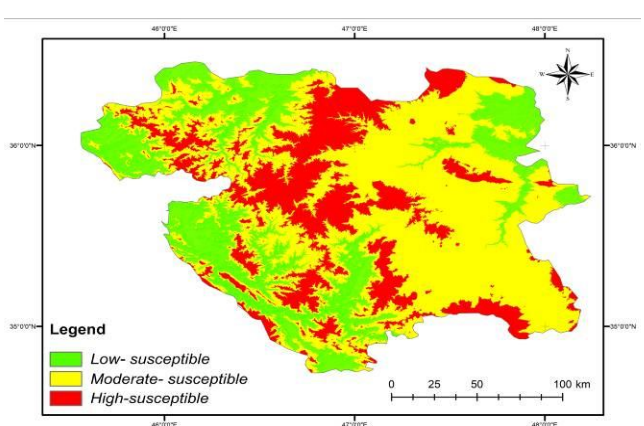

Figure 6. The landslide susceptibility map for studied area

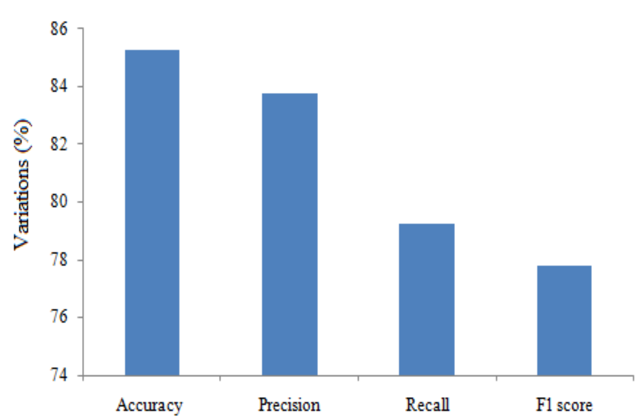

Figure 7. The estimated confusion matrix for studied model

5. Conclusion

The susceptibility assessment is one of the most important stages to provide the risk-ability of geo-hazards. The susceptibility maps demonstrate the degree of probability for the occurrence of the geo-hazards like landslides. There are various methods to assessment of landslides susceptibility which can categorize in quantitative, qualitative, and semi-quantitative procedures. The scholars used different approaches regarding these classifications to precede the susceptibility for landslides occurrence. In the meantime, computer-based methods have received more attention from researchers due to the accuracy of the procedures. The knowledge-based methods are one of the most important impacts on landslides susceptibility mapping. An artificial neural network like MLP was used for the prediction of the probability of landslide occurrences which was successfully implemented with high accuracy. The presented study uses MLP predictive modeling as the methodology for susceptibility evaluation of Kurdistan province. The model was verified by using the confusion matrix and estimation of overall accuracy. Also, the GIS environment used provides the susceptibility map. As result, the model provides 85.25% accuracy and 83.79% precision.

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