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Landslide Susceptibility Mapping Using Shallow Neural Networks Model at Refahiye District in Turkey

Sığ Sinir Ağları Modeli Yardımıyla Türkiye'de Refahiye İlçesinin Heyelan Duyarlılığının Haritalanması

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ORIGINAL PAPER

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Abstract

Landslides represent a continuous hazard for population and infrastructure. Mapping the landslide susceptibility is an essential issue to avoid the landslides risks. The aim of this paper is to produce a high-accuracy model for landslide susceptibility mapping in Refahiye district in Turkey. The model employed shallow neural networks for landslide susceptibility mapping, while bivariate spearman correlation test was utilized to select the related factors to extract the appropriate data and reduce the computation time of training and mapping. 12 out of 21 spatial factors were selected as relevant factors using Spearman correlation test. Relevant factors are geology, distance from roads, distance from geological faults, distance from water streams, flow direction, aspect, hillshade, heat load index, slope/aspect transformation, site exposure index, compound topographic index, and elevation. The generated dataset was divided into training, validation, and testing datasets using 10-folds cross-validation method. The Trainlm was found to be the best training function with an overall accuracy of 86.3%. The developed NN model was tested using IRIS benchmark dataset and showed higher performance against the logistic regression algorithm. As a result, shallow neural networks method was successfully applied in landslide susceptibility mapping in this study and the method is recommended for future studies.

***Keywords**: GIS, Landslide susceptibility mapping, Shallow neural networks*

Özet

Heyelanlar nüfus ve altyapı için sürekli bir tehlike oluşturmaktadır. Heyelan duyarlılığının haritalanması heyelan risklerini önlemek için önemli bir konudur. Bu çalışmanın amacı, Türkiye'nin Refahiye ilçesinde heyelan duyarlılık haritalaması için yüksek doğruluklu model üretmektir. Modelde heyelan duyarlılık haritalaması için sığ sinir ağlarını kullanılırken, uygun veriden gerekli faktörleri çıkarmak ve haritalama ve eğitim hesaplama süresini azaltmak için iki değişkenli Spearman sıra korelasyon testi kullanılmıştır. 21 mekansal faktörden 12'si, Spearman korelasyon testi kullanılarak ilgili faktörler olarak seçilmiştir. İlgili faktörler jeoloji, yollara uzaklık, jeolojik faylara olan uzaklık, su yollarına olan uzaklık, akış yönü, bakı, arazi kabartı, ısı yük endeksi, eğim / bakı dönüşümü, alan maruziyet indeksi, bileşik topografik indeks ve yükseklikdir. Oluşturulan veri kümesi, 10 katlı çapraz geçerlilik yöntemini kullanarak eğitim, doğrulama ve test veri kümelerine bölünmüştür. %86,3'lük genel doğruluk performansı elde edilen en iyi eğitim fonksiyonu (Trainlm)'dir. Geliştirilen NN modeli, IRIS kıyaslama veri seti kullanılarak test edildi ve lojistik regresyon algoritmasına göre daha yüksek performans gösterdi. Sonuç olarak, bu çalışmada heyelan duyarlılık haritalamasında sığ sinir ağları yöntemi başarıyla uygulanmış ve yöntem gelecekteki çalışmalar için önerilmiştir.

***Anahtar kelimeler**: CBS, Heyelan duyarlılık haritalaması, Sığ sinir ağları*

1. Introduction

Refahiye is a Turkish district located in the east Black Sea region, which has been influenced by landslides hazards. In the Black Sea region, infrastructure destruction caused by landslide occurrence is worse than the destruction caused by earthquakes (Dağ and Bulut, 2012). Since the main and active geological fault line in Turkey is crossing through the mountainous area of the Refahiye district, this area is continually at risk of landslides. Landslide risk problem is expected to continue for long years as a consequence of deforestation, global warming, climate change, and urban growth (Yilmaz, 2009). The possibility of landslides occurrence depends on several complex conditions such as topographic structure, soil types, geology structure, land use, land cover LULC activists, precipitation, and several geomorphometrical factors (Nefeslioglu et al. 2012).

During the last two decades, several pieces of research have been conducted to develop methods and frameworks in order to mapping the landslides susceptibility (Chae et al. 2017; Felicísimo et al. 2013; Pradhan and Lee, 2010; Song et al. 2012; Vakhshoori et al. 2019; Yalcin et al. 2011; Yalcin, 2008; Yıldırım and Güler, 2016). An example of the employed methods for landslides susceptibility mapping were random forest (Hamad et al. 2018), neural networks (NN) (Valencia Ortiz and Martínez-Graña, 2018), logistic regression (Nefeslioglu et al. 2008), support vector machine (Wang et al. 2019) and (Tso and Yau, 2007).

The generalization accuracy of NN algorithm is high among the former methods for the landslides susceptibility mapping (Can et al. 2019; Chae et al. 2017; Vakhshoori et al. 2019; Zhang et al. 2018). The NN method exploits the data acquired from the landslide inventories layer to forecast the possibility of landslides that will occur in the future. NN algorithm can generate a weighted model for mapping landslides susceptibility. The fundamental benefits of employing NN in landslide susceptibility mapping are its capability to handle several types of spatial data at different scales as well as ordinal and nominal data. Although the NN model can achieve high generalization in several areas in the world, mapping landslide susceptibility in new geographical areas need further investigation. The change in the area relatively affects the model performance due to several issues. The change in the analysis area is influenced by the quality of the data, data availability of factors, reasons of landslides, and types of landslides. In addition, when the analysis conduct based on regional scale, the model performance highly influenced by the low data quality and low spatial accuracy. Generally, the former studies focused on increasing the prediction accuracy using more data and more computation. The increment in the data and computation lead to several difficulties for conducting LSM analysis. On the other side, several types of research applied deep neural networks to develop prediction models. Although high model generalization is achieved by deep learning, it is not time efficient. Thus, producing a high accuracy model using a simple algorithm with less computation and minimum number of input data becomes a new aspect in the research area of landslide susceptibility mapping (Lee et al. 2020). Using the bivariate spearman correlation test to select the factors and employing time-efficient shallow NN are the original contributions of this study.

The aim of this study is to produce a highly-generalized model for landslide susceptibility mapping in the Refahiye district of Turkey. The model used shallow neural networks for landslide susceptibility mapping, while bivariate spearman correlation test was employed to select the relevant factors that ensured less data collection and less computation time. This paper consists of four sections as the introduction, methodology (containing study location, data collection, and development of the shallow neural networks model), results and discussion, and conclusion.

2. Methodology

2.1 Study area and data collection

Refahiye is a district of Erzincan in the Eastern Anatolia region of Turkey. It is located between 39°04'15"N - 40°04'16"N latitudes and 38°23'33"E - 39°13'18"E longitudes. The administration area of Refahiye covers an area of approximately 1816 km^2, and the elevation is 1589 m. The total population of the Refahiye district is around 10,569, where 3730 live in the town center. The area has usually a high humidity rate in the winter. In Refahiye, the average annual temperature is 9.0 °C. The average precipitation is 537 mm. Winter months are much rainy compared to the summer months. In Refahiye area, several water streams lows in the area. The main active geological fault line is crossing through the study area. Refahiye district is a mountainous area. Figure 1 shows the study area. Considering its geographical location and geological characteristics, Refahiye district can be considered an active area for landslides occurrence.

To develop the NN model and produce the susceptibility map, the data collection stage has to be performed. In this stage, the landslide inventory map and factors map were prepared. Firstly, the landslide inventory map of the study area was generated based on the investigation from the satellite images and published maps. Satellite images were extracted from Google Earth Pro. In spite of the fact that Google Earth offers images since 1984, only images from 2001 to 2019 were used to achieve suitable spatial resolution for landslides.

Moreover, the landslides map published by General Directorate of Mineral Research and Exploration (GDMRE) (http://yerbilimleri.mta.gov.tr) was utilized to enrich the inventory map (Duman et al. 2011). According to the available landslide data, only the active landslides were considered during the mapping stage. Based on the landslide inventory map of Refahiye, there are 237 landslides in the study area (Duman et al. 2011). The total area of landslides is 51.37 km^2, which represents 2.82% of the total area of Refahiye (1816 km^2). The landslide locations are shown in Figure 1. According to the investigation from the satellite images, the landslides in the study area could be classified as shallow translational slides (Pitasi, 2016; Turner and Schuster, 1996). Example photos of landslides from the study area are given in Figure 2. Secondly, the explanatory factors were collected from several sources such as topographic maps and digital elevation model (JAXA, 2019). The list of collected factors was classified and a list of all 21 factors are given in Table 1 in four groups. In addition, the landslide training data set for NN were generated based on random sample points. The samples are randomly generated. The number of samples set equally between the landslides and non-landslides areas. Thus, 5000 points were generated. Then, the dataset was extracted from 21 spatial layers. Afterwards, 45 missing values were removed from the dataset, leading to a total of 4955 samples remaining. Moreover, the bivariate test named 'spearman correlation' was utilized to test the correlation between the factors. Matlab software was utilized to develop the model and test the correlation among the explanatory factors.

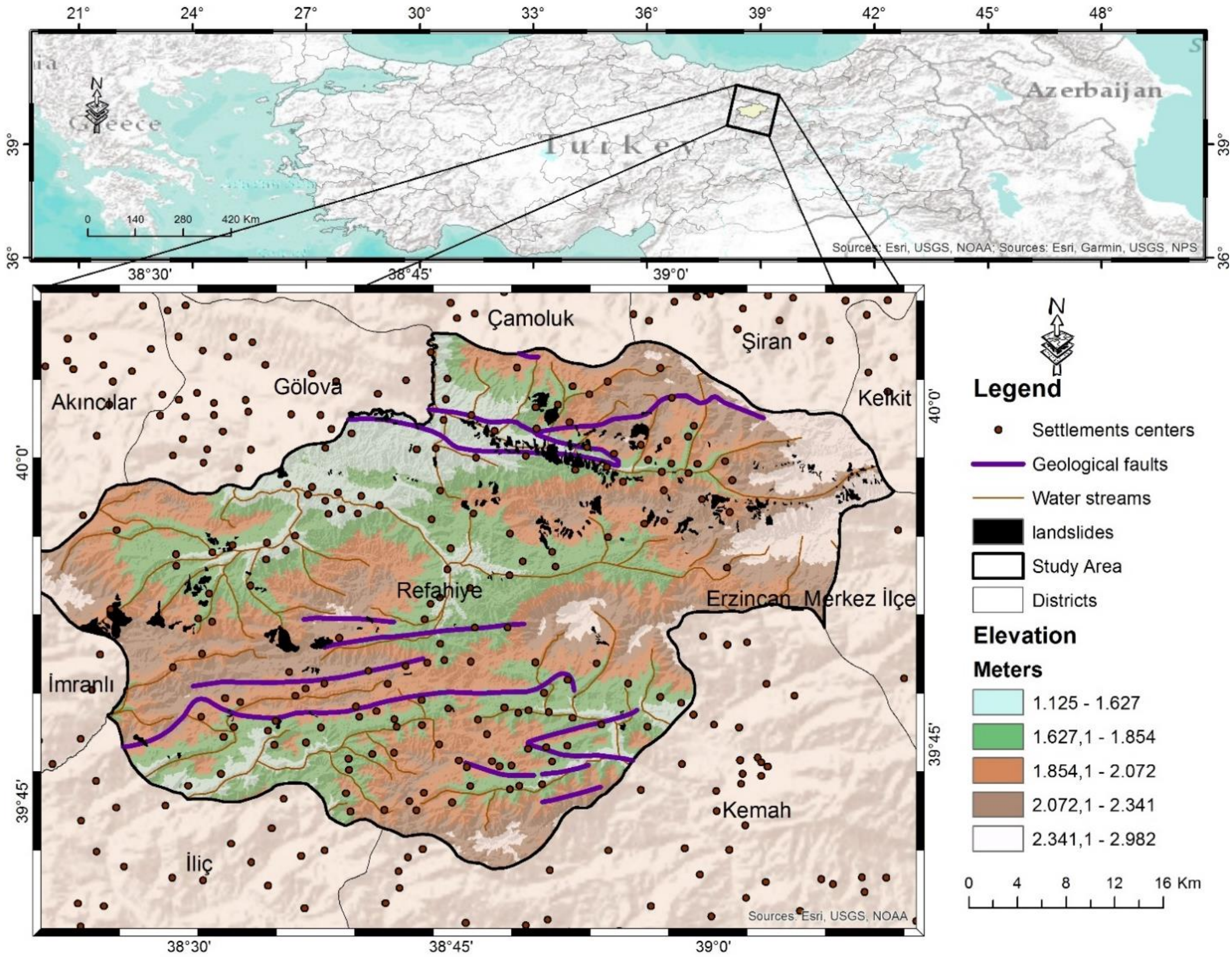


Figure 1. Location map of the study area

Figure 2. Example photos of landslides from the study area

Table 1. Landslides explanatory factors classified in four groups

Group	Factors
Topographic surfaces and Geomorphology texture	1. Elevation 2. General Curvature 3. Dissection 4. Landform 5. Slope Position 6. Surface Area Ratio 7. Surface Relief Ratio 8. Aspect 9. Hillshade 10. Slope 11. Geology 12. Geological Faults
Geomorphometry	13. Flow Direction 14. Water streams
Temperature and moisture	15. Heat Load Index 16. Site Exposure Index 17. Compound Topographic Index 18. Slope/Aspect Transformation 19. 2nd Derivative Slope
Human activities	20. Land use 21. Roads

Spearman correlation test is a non-parametric experiment used to specify the level of association among two factors. The test was employed to select the important factors that enabled less data collection and less computation time. Spearman correlation can be computed as:

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)} \tag{1}$$

Where;
ρ is the Spearman rank correlation
d is the difference between the ranks of corresponding variables
n is number of observations

2.2 Development of the Shallow Neural Networks model

The shallow neural network model is one of two types of neural networks (Kim and Gofman, 2018; X.-D. Zhang, 2020). The second type is the deep neural networks. Shallow NN is only suitable for landslide susceptibility mapping problem. The deep neural networks are suitable for landslide detection problem, allowing for the detection of the location of the landslides after their occurrence, while the problem of this paper is to find the possibility of future landslides. Neural networks imitate the physical structure of the biological cell (dendrites, nucleus and axons). In the artificial neuron, dendrites are represented by the input factors, Nucleus is represented by the artificial neurons and axons are represented by the connection between the neurons and forward or output layers. A group of artificial neurons arranged in input, hidden and output layers construct the shallow NN model. The neural networks method as a machine learning algorithm is able to mapping the landslide susceptibility based on the former landslides. By extracting the geographical and geological parameters of each landslide site, the NN algorithm is able to generate a weighted statistical model that can map the landslide susceptibility for new areas. The chief benefits of employing NN in landslides susceptibility mapping are its capability to handle several types of spatial data at different scales as well as ordinal and nominal data.

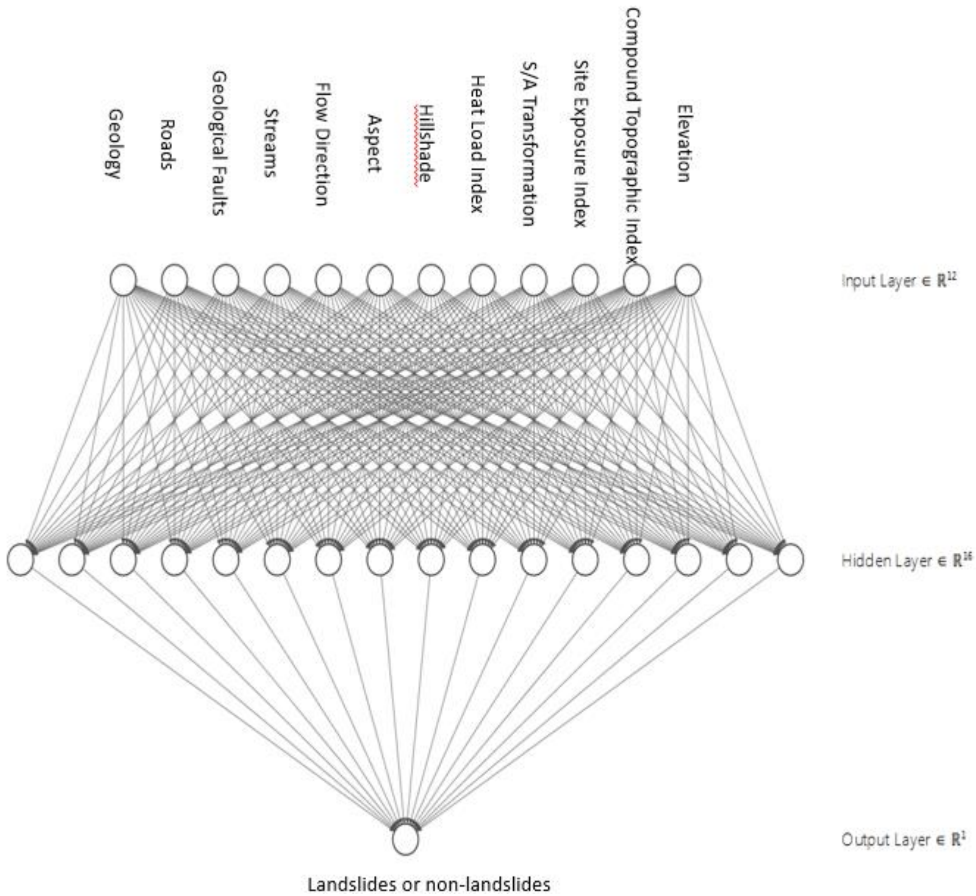


Figure 3. Structure of shallow neural networks

The structure of shallow NN algorithm is displayed in Figure 3. The algorithm structure contains three layers. The first one is the input layer, which represents the input factors. The input factors are the relevant spatial data of the historical landslides. The second layer is the hidden layer, which represents the layer of neurons. This is the most important layer where all operations are performed. The hidden layer contains the artificial neurons that specifying the ability of the model to extract the knowledge from the landslides dataset and build the model. The last layer represents the output layer. The output layer of the current algorithm is scaled between 0 and 1. The values represent the level of susceptibility. The developed model was generated in Matlab software. The Pseudocode of the developed model is given in algorithm 1.

Performance accuracy was calculated for testing dataset by comparing actual state and computed reactions. Performance accuracy of the developed models was measured using Overall Accuracy (confusion matrix), Cohen Kappa Accuracy, and AUC Accuracy (Liang et al. 2015). McCormick (2016) stated that the Cross-validation method effectively assesses the network accuracy through splitting the datasets into training and testing sets (McCormick, 2016). Cross-validation protects the network from overfitting. Wise reported that there are several techniques utilized in former works (Wise, 2011). The 10-fold technique shown in Figure 4 was applied here.

Algorithm 1. Pseudocode of the shallow NN model for landslide susceptibility mapping

```
##Reading the training dataset

## Training step
Separate the dataset into training and testing sets
Normalizing the datasets
Building algorithms for the shallow NN model
Define the NN model (12 inputs, hidden layers, and outputs)

for k=1: number of neurons do
   Training the NN classifier using (k) neuron in the hidden layer
   Calculating the accuracy of the NN model
   If the accuracy is sufficient:
       Stop and store the NN model
   Else:
       Hold on the training process

## Testing step
for i=1: number of chunks do
     read the chunk dataset
     using the trained NN model to test (i) chunk dataset
     Store the output values in TXT format.
```

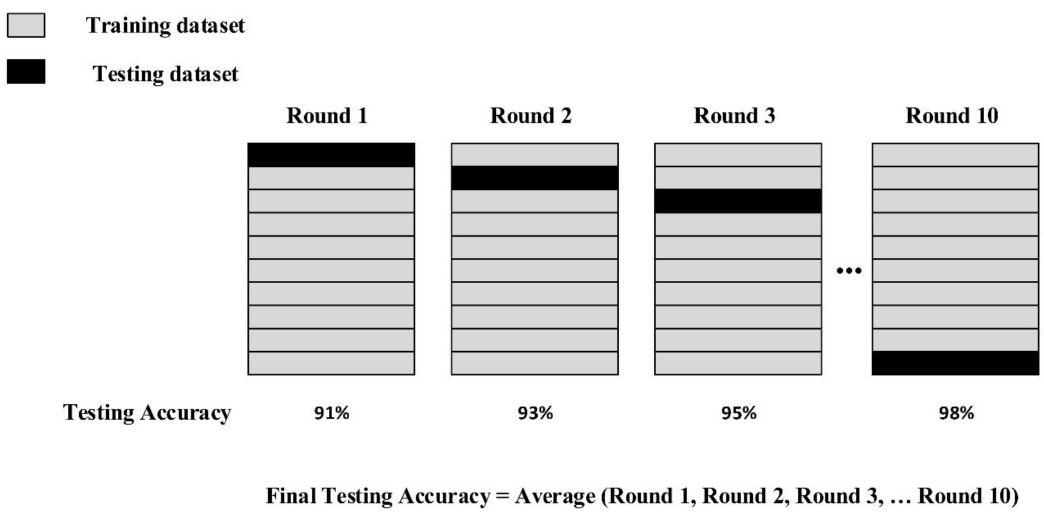


Figure 4. 10-fold scheme for cross-validation

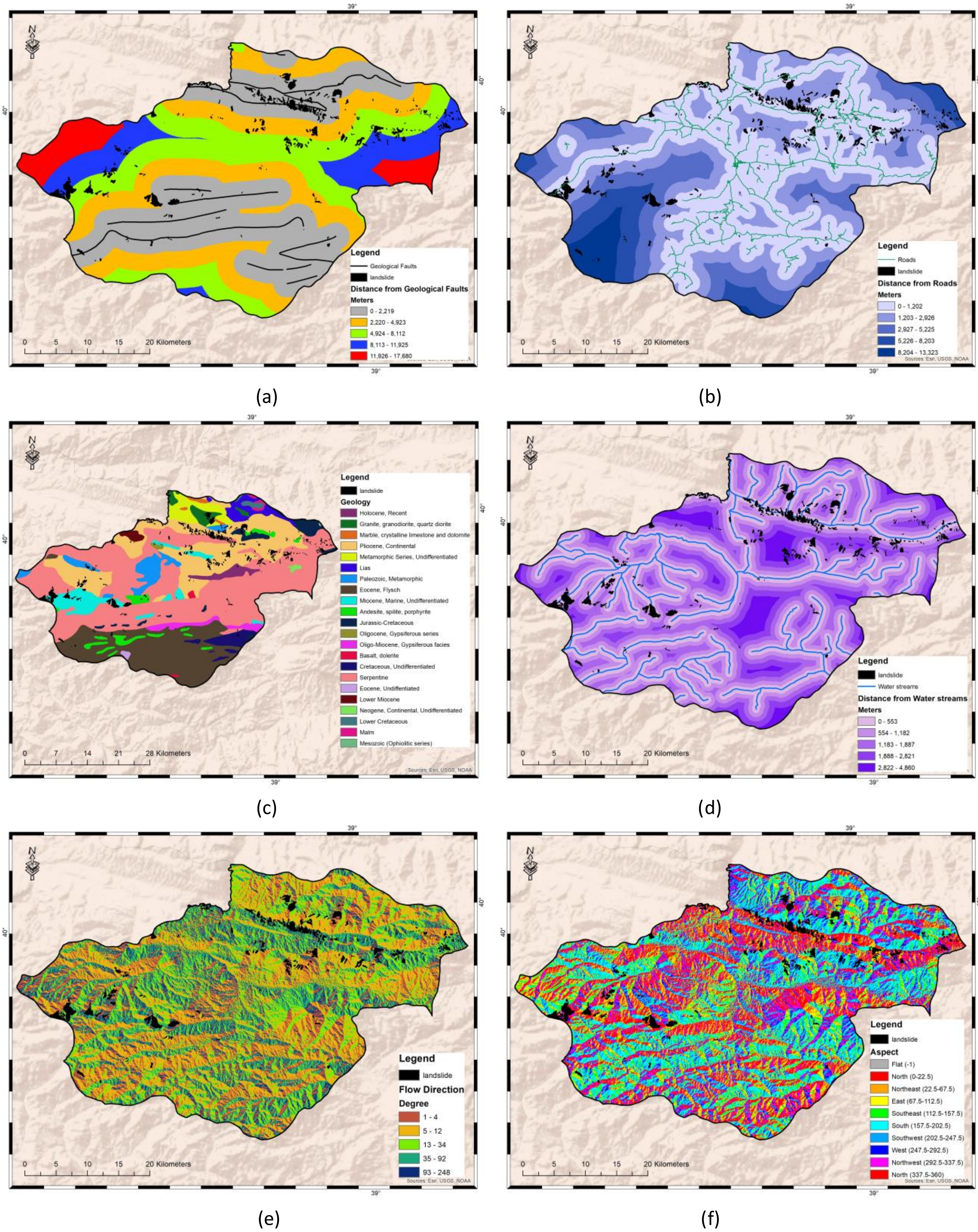


Figure 5. Landslide conditioning factor maps: (a) distance from faults; (b) distance from roads; (c) geology; (d) distance from water streams; (e) flow direction; (f) land aspect

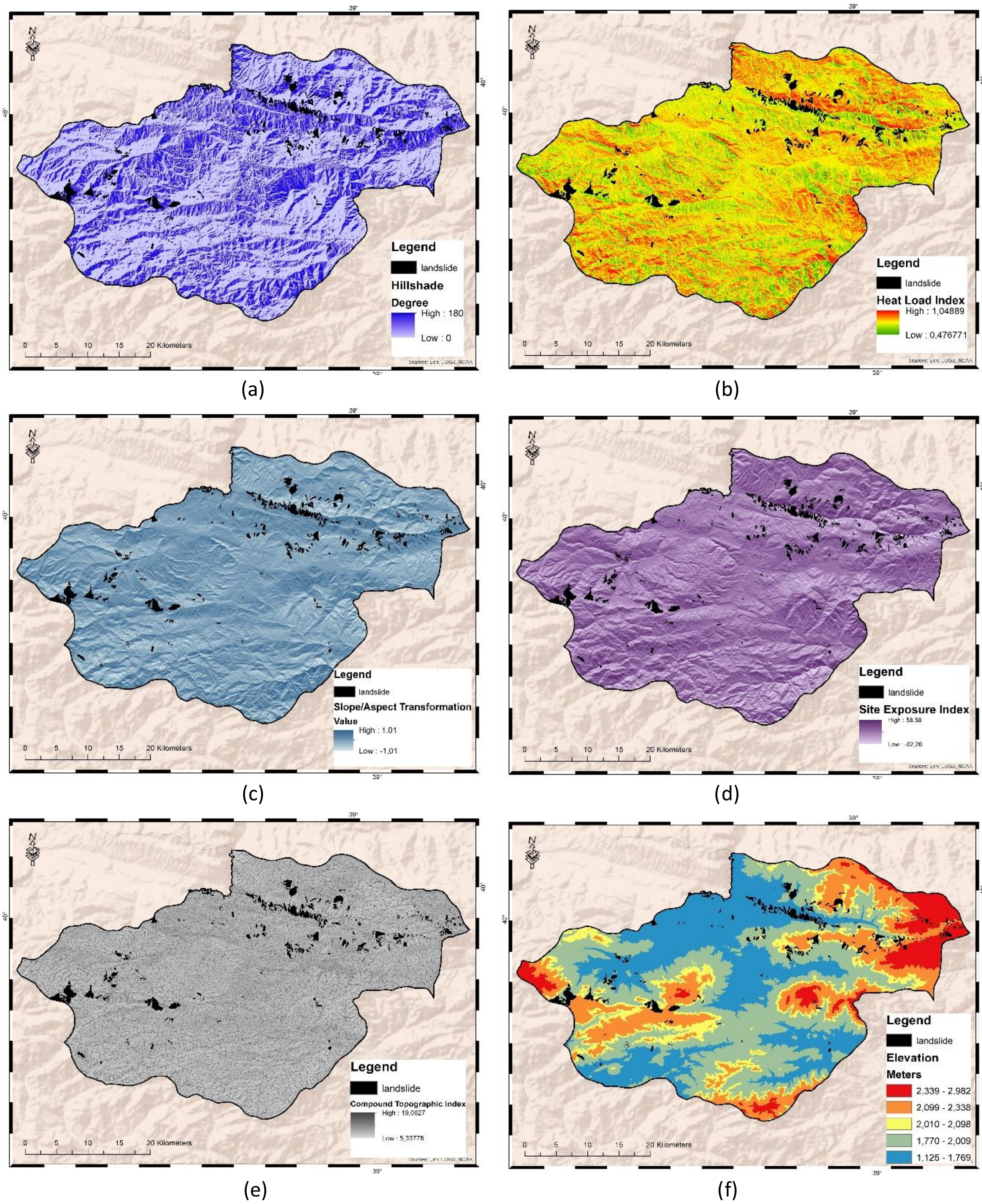


Figure 6. Landslide conditioning factor maps: (a) hillshade; (b) heat load index; (c) slope/aspect transformation; (d) site exposure index; (e) compound topographic index; (f) elevation

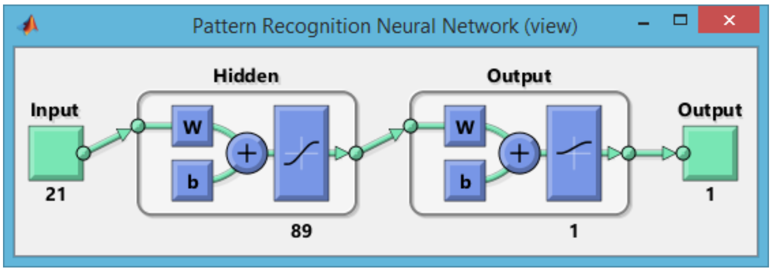
3. Result Analysis and Discussion

In this section, the results of the analysis are given and evaluated. According to the Spearman correlation test, 12 out of 21 factors were selected as relevant factors based on the correlation value of each factor. A factor was selected as relevant if it received a correlation greater than 2%. These 12 factors are geology, distance from roads, distance from geological faults, distance from water streams, flow direction, aspect, hillshade, heat load index, slope/aspect transformation, site exposure index, compound topographic index, and elevation. Some of these factors have a positive correlation and some have negative correlation. For example, if the correlation between the landslides and Compound Topographic Index is positive, that means as long as the Compound Topographic Index increases the landslides are more likely to occur. In addition, if the correlation between the landslides and distance from roads is negative, that means as long as the distance from roads increases the landslides are less likely to occur. The correlation values among the factors are presented in Table 2 and also the maps of selected factors are presented in Figures 5 and 6.

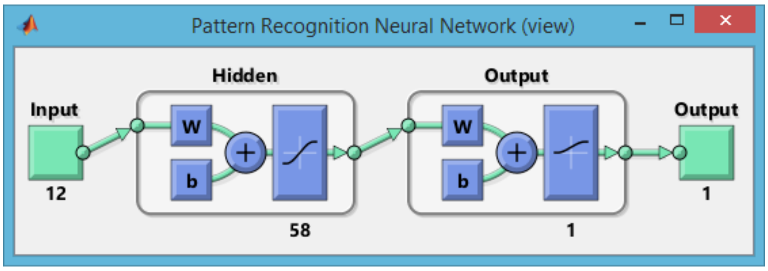
Table 2. The correlation between the occurred landslides and the collected factors

Factors (1-7)	Land use	Geology	Roads	Geological Faults	Water streams	Flow Direction	Slope
Spearman correlation	-0.00376	**-0.2124**	**-0.1764**	**-0.0654**	**-0.2354**	**0.0950**	-0.0062
P_value	0.0081	0.0000	0.0000	0.0000	0.0000	0.0000	0.6621
Factors (8-14)	Aspect	Hillshade	General Curvature	Heat Load Index	Slope/Aspect Transformation	Site Exposure Index	Compound Topographic Index
Spearman correlation	**-0.0432**	**0.0688**	0.0192	**-0.0938**	**0.0926**	**-0.0926**	**0.0519**
P_value	0.0024	0.0000	0.1769	0.0000	0.0000	0.0000	0.0003
Factors (15-21)	2nd Derivative Slope	Surface Relief Ratio	Surface Area Ratio	Slope Position	Landform	Dissection	Elevation
Spearman correlation	-0.0188	0.0290	-0.0062	0.0215	0.0215	0.0332	**-0.0824**
P_value	0.1855	0.0414	0.6620	0.1304	0.1304	0.0195	0.0000

Based on the selected 12 factors and all 21 factors, a new training dataset was generated and used to train the shallow NN model. The developed models are presented in Figure 7. Several training functions were employed to train the NN model and improve their performances. These functions are Levenberg-Marquardt backpropagation (Trainlm), Scaled Conjugate Gradient (Trainscg) and Bayesian regularization backpropagation (Trainbr). The best performance accuracy was obtained by the Trainlm function. In addition, further experiments were conducted to find the effects of the number of neurons on the performance accuracy. Based on the best training function (Trainlm), an optimizer developed to find the accuracy of the developed model using range of number of neurons in the hidden layer. Figure 8 demonstrates the curves of the accuracy over the number of neurons from one to 60 based on the Trainlm training function using the three-evaluation metrics (Overall Accuracy (confusion matrix), Cohen Kappa Accuracy, and ROC-AUC Accuracy). The outcomes illustrate that the best performance accuracies are (Overall Accuracy 88%, ROC-AUC 91.5%, and Cohen Kappa 75.6%) obtained when using 50 neurons in the hidden layer. Thus, the final shallow NN model contained three-layers. The input layer consisted of 12 variables. The hidden layer consisted of 50 neurons and the output layer consisted of one output, which represented the degree of landslide susceptibility.



(a)



(b)

Figure 7. An example of the developed model structure based on all 21 factors (a) and relevant 12 factors (b)

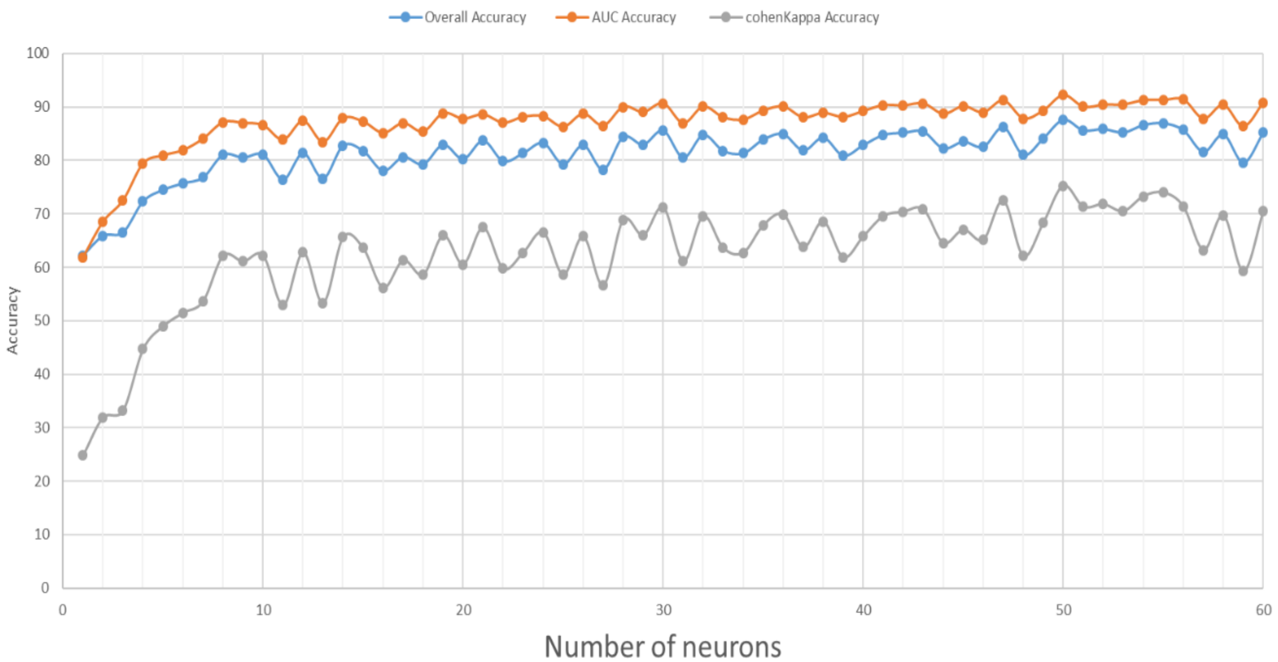


Figure 8. An optimizer to find the accuracy of the developed model across the number of neurons in the hidden layer. Three metrics were used to assess the accuracy: Overall Accuracy (confusion matrix), Cohen Kappa Accuracy, and ROC-AUC Accuracy

Furthermore, for further investigation of the developed NN model, the model was tested again based on the best structure. NN model was tested using the Confusion matrix metric. The experiment was conducted after dividing the dataset into training, validation, and testing datasets using the 10-folds cross-validation method. Thus, the model accuracy using confusion matrix for training, validation, and testing dataset as well as the overall model accuracy illustrated in Figure 9. The performance accuracy based on the training sub dataset was found as 88.6%, while the performance accuracy based on the testing sub dataset was found as 81.0%. The accuracy between training dataset and testing dataset showed that there was no over-fitting problem in the developed NN model since the testing accuracy was less than the training accuracy.

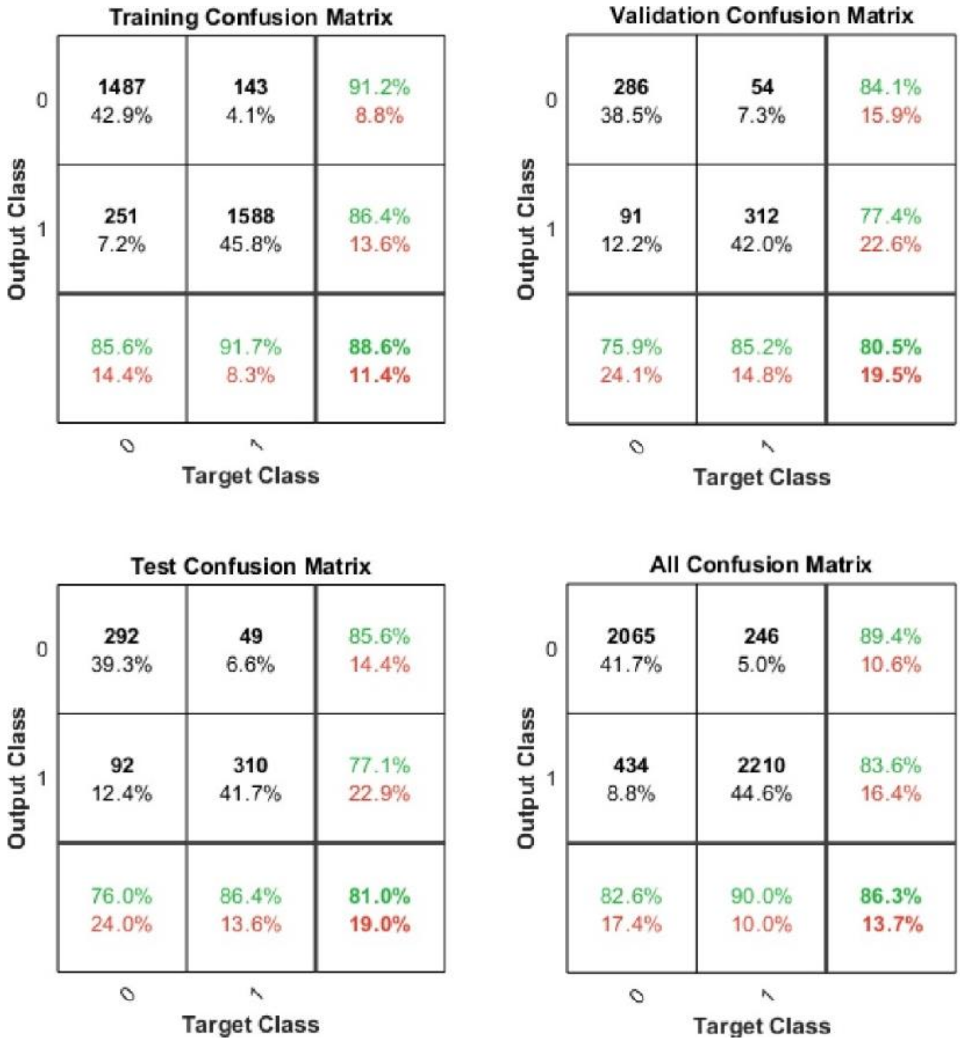


Figure 9. NN model accuracy based on the confusion matrix metric. The overall accuracy is 86.3%

Additionally, the developed NN model was compared to other benchmark data and another convolution method. The NN model was compared with IRIS benchmark data. The IRIS data was tested using the developed NN model and another model was developed using the logistic regression algorithm. Figure 10 illustrates the performance accuracy of each model based on IRIS benchmark dataset. Then, the developed model using logistic regression algorithm applied based on the 21 factors and based on the 12 selected factors. Figure 11 illustrates the performance accuracy of each model with three evaluation metrics. Lastly, the evaluation metrics, which were calculated for the NN model based on the landslide data, are presented in Figure 12.

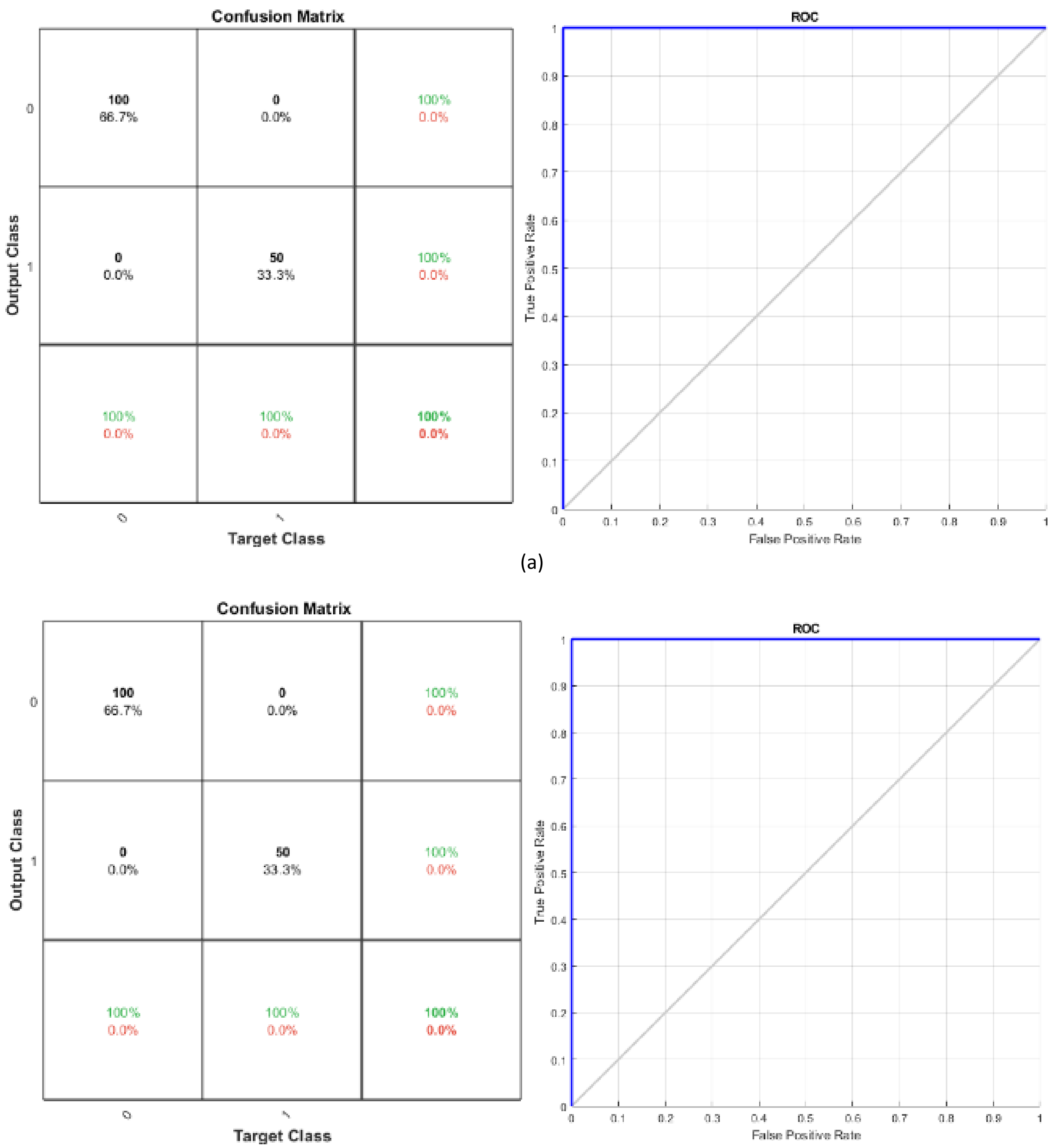
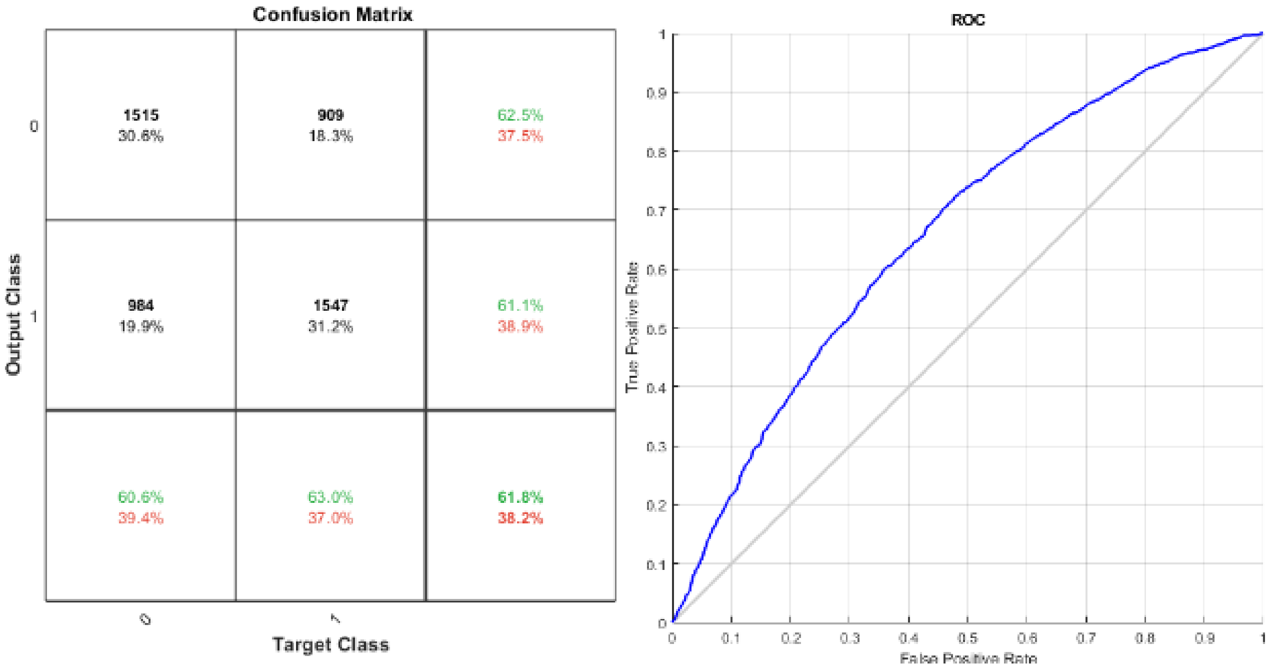
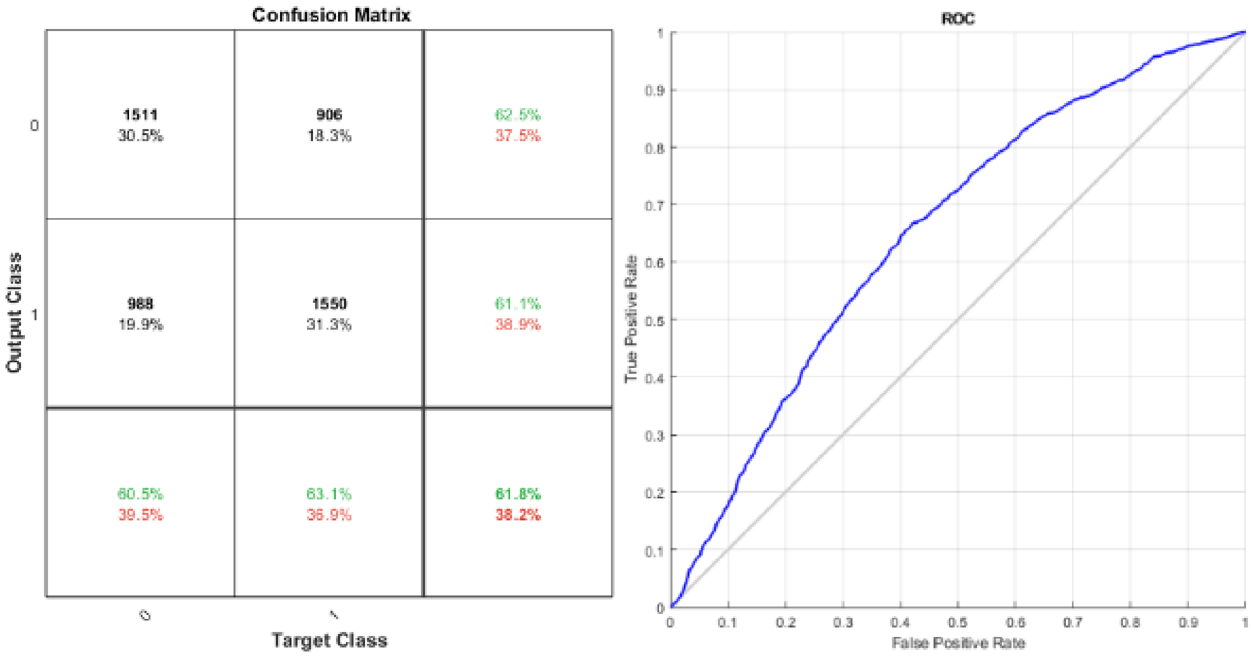


Figure 10. Performance accuracy of developed models based on IRIS data using (a Logistic Regression = Overall Accuracy 100%, Cohen Kappa Accuracy 100%, and ROC-AUC Accuracy is 100%) and (b neural networks = Overall Accuracy 100%, Cohen Kappa Accuracy 100%, and ROC-AUC Accuracy is 100%)).

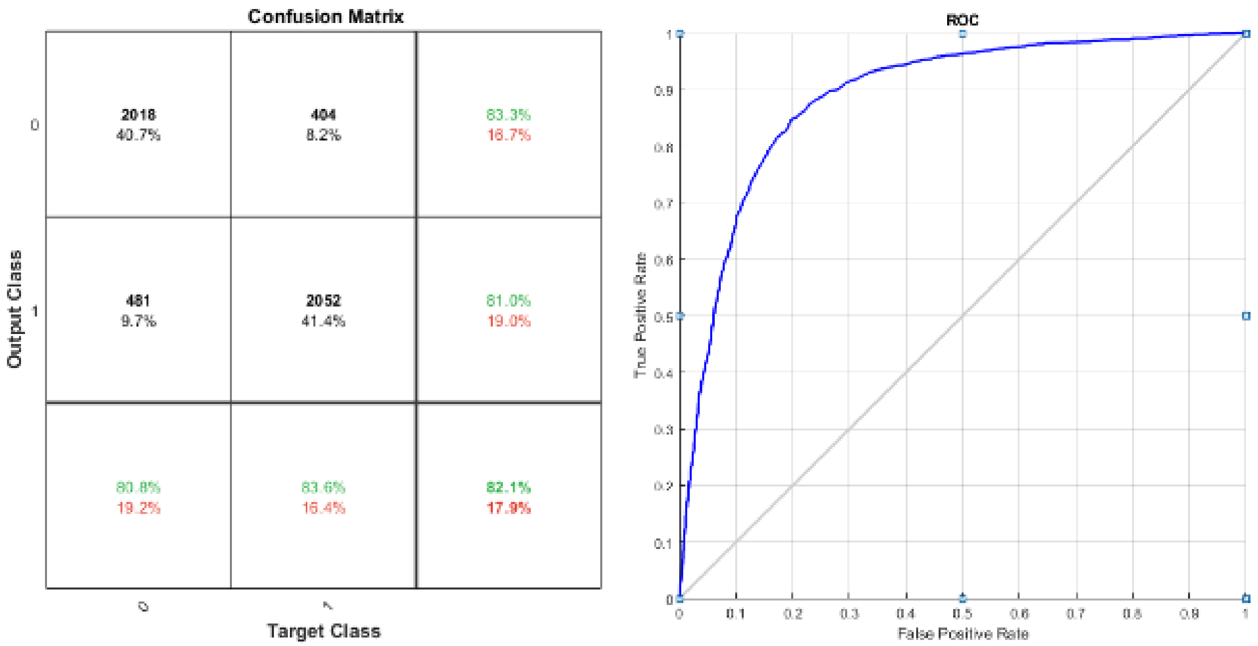


(a)

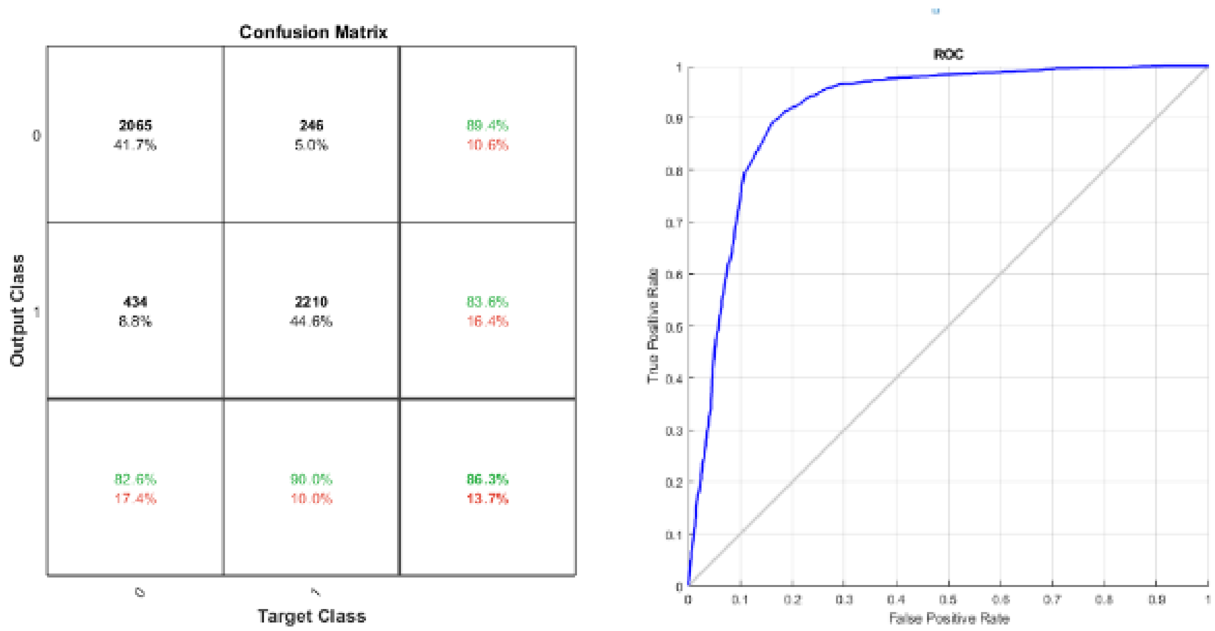


(b)

Figure 11. Performance accuracy of developed models based on landslides data from the study area using Logistic Regression (a 21 factors = Overall Accuracy 61.80%, Cohen Kappa Accuracy 23.60%, and ROC-AUC Accuracy is 66.20%) and (b 12 factors = Overall Accuracy 61.78%, Cohen Kappa Accuracy 23.56%, and ROC-AUC Accuracy is 65.31%))



(a)



(b)

Figure 12. Performance accuracy of developed models based on landslides data from the study area using NN (a 21 factors = Overall Accuracy 82.14%, Cohen Kappa Accuracy 64.28%, and ROC-AUC Accuracy is 88.82%) and (b 12 factors = Overall Accuracy 86.3%, Cohen Kappa Accuracy 72.56%, and ROC-AUC Accuracy is 91.39%))

The final landslide susceptibility map was produced using the developed NN model. The full maps of input factors were processed and extracted from ArcGIS 10.5 software to MATLAB R2019b as text files. The text files were processed using the chunk processing in Python programming language. The study area was divided into 15 chunks. After processing the chunks datasets using the trained NN model, the predicted susceptibility values were extracted to ArcGIS and reshaped to generate the landslide susceptibility map. The landslide susceptibility map is illustrated in Figure 13. The susceptibility levels vary between 0 and 1.

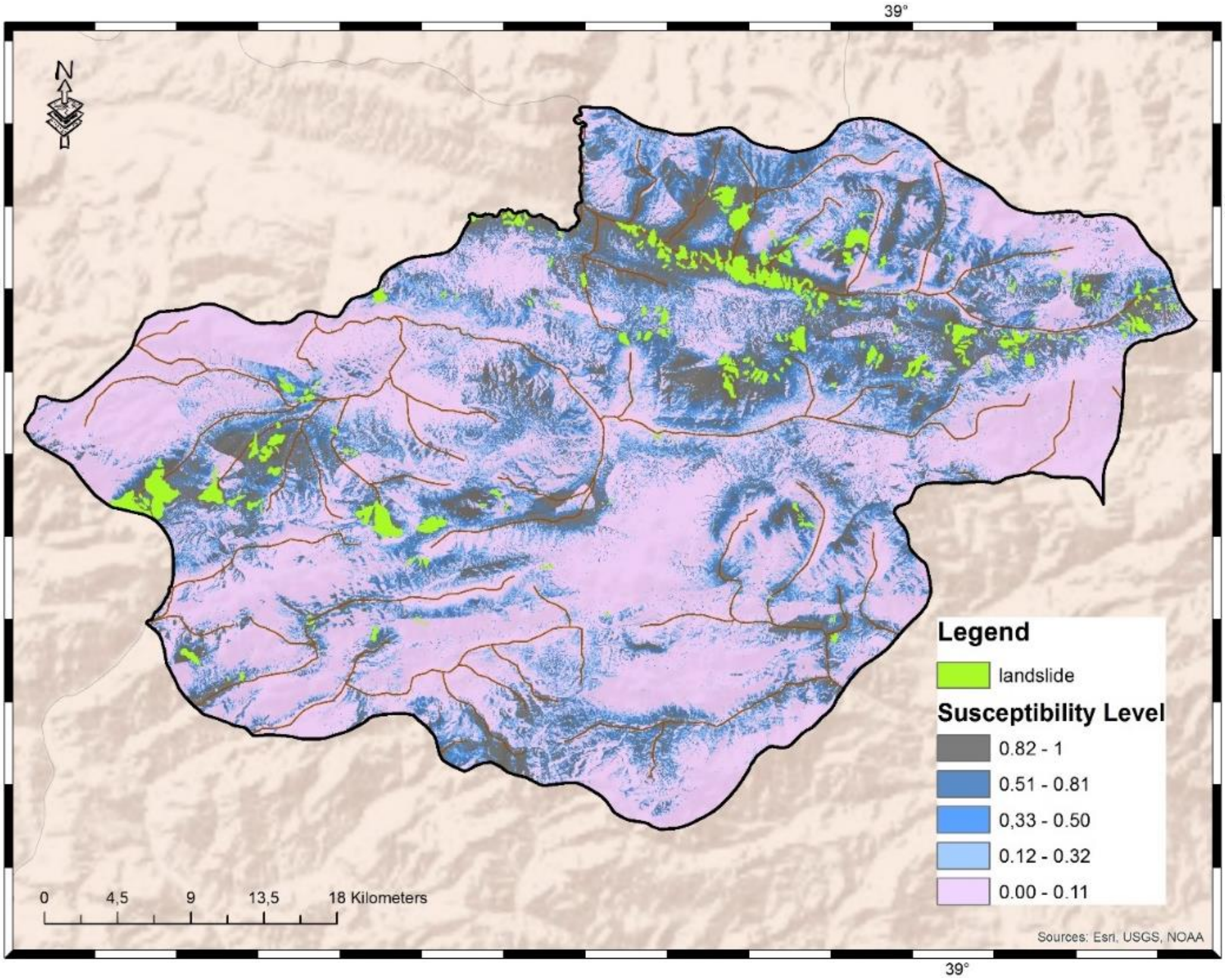


Figure 13. Landslide susceptibility map of Refahiye district in Turkey

4. Conclusion

Landslides are among the most common negative natural phenomena that cause loss of lives and property. In some cases, the damage caused by landslides are greater than that caused by earthquakes. Mapping the landslide susceptibility is an essential issue to avoid or manage the landslides risks. The aim of this study is to produce a highly-generalized model for landslide susceptibility mapping in the Refahiye district of Turkey. The model shallow neural network was used for landslide susceptibility mapping, while bivariate spearman correlation test was employed to select the important factors that enabled less data collection and less computation time. Using the Spearman correlation test, 12 out of 21 factors were selected as relevant factors. Important factors are geology, distance from roads, distance from geological faults, distance from water streams, flow direction, aspect, hillshade, heat load index, slope/aspect transformation, site exposure index, compound topographic index and elevation. The generated dataset was divided using a cross-validation method to test the developed model. The Levenberg-Marquardt backpropagation (Trainlm) was found to be the best training function with a performance accuracy of 86.3% when using 50 neurons in the hidden layer. The generated NN model was tested using the IRIS benchmark dataset and compared against the logistic regression algorithm. The NN model presented a better performance than the logistic regression and shows higher accuracy with the IRIS benchmark dataset. As a result, shallow neural networks method was successfully applied in landslide susceptibility mapping in this study and the method is recommended for future studies.

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