Landslides Risk Prediction Using Cascade Neural Networks Model at Muş In Turkey

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Abstract. Globally, landslides risk represent a challenging issue that negatively affecting the infrastructure and human and neutral life. Among the former studies, the methods of predicting landslides risk maps found to be need further experiments. The aim of this study was to predict the landslide risk map at Muş in Turkey using cascade neural networks model. In this article, Trainlm function used to train 9954 sample points in the dataset using Matlab software. ArcGIS employed to prepare the explanatory variables, inventory landslides map, data sampling and producing the final landslides risk map. The developed model achieved the best performance accuracy by implanting an optimizer for the used number of neurons. After 60 training experiments, 52 neurons found the best number in this model. Chunks computing using Python programing in ArcGIS implemented to solve the intensive computing and data restructuring issues. Although the implementation at regional scale with 14015 km2, the final landslides risk map was successfully produced. The best-achieved performance accuracy was 80% based on receiver operating characteristic curve (ROC) and area under the curve (AUC). To summarize, the cascade neural networks model can reliably be implement in predicting landslides risk maps at regional-scale with the aid of chunks computing.

1. Introduction
Landslides risk issue is one of the devastating threat for life and infrastructure in the mountains areas in the world (Pham et al., 2019). Landslides risk defined as the sloped land movements downward and outwards composing soil, rocks, artificial material and debris (Malamud, Turcotte, Guzzetti, & Reichenbach, 2004). Globally, landslides are responsible of several life losses and infrastructure damage, in some cases, the damage caused by landslides is more than the damage form the earthquakes (Chae, Park, Catani, Simoni, & Berti, 2017; Felicísimo, Cuartero, Remondo, & Quirós, 2013; Pradhan & Lee, 2010; Yıldırım & Güler, 2016). Therefore, varied studies have been applied to analysing the historical landslides in order to generalize models and predict the possible future landslides locations (Chae et al., 2017; Felicísimo et al., 2013; Li, Chen, Tang, Zhou, & Zheng, 2012; Song et al., 2012; Vakhshoori, Pourghasemi, Zare, & Blaschke, 2019). In other words, studies tried to identify the best methodology to predicting the landslides risk-prone areas and avoiding the possible...
harm. In addition, selecting and optimizing the methods support decision making process and reduce the environmental risks (Yıldırım & Güler, 2016).

According to the past research, landslides risk maps could be predicted by relying on three assumptions (Vakhshoori et al., 2019). The first one is that the inventory map of former landslides can be generated from the fieldworks or from the analysis of digital information model. Second, to extract the knowledge or the rules and explain why the former landslides occurred, the explanatory variables of the same analysis area need to be prepared. Third, specific machine learning or spatial data mining algorithms need to be employed to generate the training model based on the explanatory variables and predict the landslides risk map (Vakhshoori et al., 2019).

At regional and national spatial scale, landslides risk mapping research have been implemented using several types of statistical methods for example; support vector machine (SVM) (Vakhshoori et al., 2019), logistic regression (LR) (Choi, Oh, Lee, Lee, & Lee, 2012; Shahabi, Khezri, Ahmad, & Hashim, 2014), and analytical hierarchy process (AHP) (Shahabi et al., 2014). In addition, frequency ratio (FR) (Choi et al., 2012; Pradhan & Lee, 2010; Vakhshoori et al., 2019) and neural networks (NN) (Vakhshoori et al., 2019; Valencia Ortiz & Martínez-Graña, 2018).

Although the usage of several methods for predicting and mapping the future risk of landslides, the modes performance need further experiments in the different geographical condition and at regional-scale. Therefore, the aim of this study is to predict landslides risk map using cascade neural networks (CNN). CNN is an advanced NN algorithm that can be employed in geospatial area to generalize high performance accuracy models in different geographical circumstances. This article consists of four sections, the introduction, methods, results as well as conclusion.

![Figure 1. Muş study area. The map displaying the geological faults and water streams networks.](image-url)
2. Methods

2.1. Study area and information acquisition

The primary step to predict the landslide risk map is to select the study area. In this study, Muş state in the east part of Turkey had been selected as analysis area. The location map of study displayed in Figure 1. The total area is 14015 km². Muş is a mountainous area and consisting three geological fault lines as well as good water streams network. Approximately 689 km² classified as active landslides in the area.

Among the former literature, plenty of parameters has been employed to predict the landslide risk map. The authors collected spatial layers and derived several maps from each other by using ArcGIS software and (Geomorphometry & Gradient Metrics toolbox). These variables are Distance from roads, distance from geological faults, distance from water streams, land use type, geology type, Slope/Aspect Transformation, Site Exposure Index, Heat Load Index, Compound Topographic Index, 2nd Derivative Slope, Surface Relief Ratio, Surface Area Ratio, Roughness, Slope Position, Landform, Dissection, Flow Direction, Hill shade, Aspect, Plan Curvature, Profile Curvature, General Curvature, Slope, and Elevation.

![Flowchart](image)

**Figure 2.** Methodology of model development and predicting landslide risk map.

The collected data divided into two sections as inventory landslide map and explanatory maps. Then, three stages applied to implement the methodology. Figure 2 illustrating the application
methodology of this study. In the first stage, pre-processing functions applied. The spatial data processed based on Muş area and the coordinate systems as well as size of matrices unified. From the spatial layers 10000 points randomly defined in the study area to generate the training dataset. The random points had been generated equally between the landslides and non-landslides zones. Out of the training samples, 46 points removed due to the missing data. In the second stage, the cascade neural networks model was developed. The model consisting 24 input variable as input layer, one hidden layer and one output layer. The employed cascade neural networks model illustrated in Figure 3. The model trained 60 times and the best experiment used to predict the landslide risk map. At the third stage, the developed model used to produce the full risk map based on the 24 variable maps.

![Cascade Forward Neural Network](image)

**Figure 3.** Cascade neural networks model.

### 3. Results

According to the applied methodology, the developed CNN model optimized using 60 experiments. The experiments start by testing 1 to 60 neurons in the hidden layer. The outcomes showed that the optimum performance accuracy of the CNN model based on 52 neurons using Trainlm training function. The experiments outcomes for each number of neurons illustrated in Figure 4. The figure shows that the change in number of neurons is slightly affecting the performance accuracy. The performance accuracies calculated by using receiver operating characteristic curve (ROC). The ROC metric calculating the performance accuracy by measuring the area under the curve (AUC) Figure 4. The best performance accuracy was 80%, while the worst was 71.6%.

![Model optimizer](A)  ![Model performance accuracy](B)

**Figure 4.** (A) Model optimizer based on number of neurons in the hidden layer. (B) Model performance accuracy based on receiver operating characteristic curve (ROC).
The final risk map predicted and illustrated in Figure 5. The main percentage of the study are located in the non-landsides zones, while few zones classified as high landslides risk possibility. In Figure 6, the predicted Landslides risk map illustrated with the former active landslides locations. The two maps shows identical locations between the prediction and the former polygons, which reflects the successful application of cascade neural network model in predicting the landslide risks.
4. Conclusion

From the former studies, the predicting processing of landslides risk map found to be need further experiments for new methods. Cascade neural networks algorithm rarely investigated in landslides risk mapping. In addition to that, the need to the experiments in the different geographical condition. Therefore. CNN is an advanced NN algorithm that can be employed in geospatial area to generalize high performance accuracy models in different geographical circumstances. The objective of this paper is to employ cascade neural networks model to predict landslides risk map at regional scale in Muş state-Turkey. ArcGIS employed to prepare the explanatory variables, inventory landslides map, data sampling and producing the final landslides risk map. Matlab software used to train 9954 sample points in the dataset and generalized the model utilizing cascade neural networks. With the aid of chunks computing ArcGIS python and cascade neural network algorithm structure as well as Trainlm training function, the model achieved 80% performance accuracy based on receiver operating characteristic curve (ROC) and area under the curve (AUC). Additionally, future research could benefit substantially from chunks computing at national scale landslides risk map prediction using varied number of machine learning algorithms.

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