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Production of Landslide Susceptibility Map Using Self Organizing Map (Som) (Case Study: Northwest Iran)

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ABSTRACT: This study is aimed at performing landslide classification using Kohonen Self Organizing Map (SOM) which is implemented on Shuttle Radar Topography Mission (SRTM) digital elevation models (DEMs) with spatial resolution of 30 m in the parts of northwest Iran. Effective parameters for identification of areas susceptible to landslides consist of elevation, profile, plan, curvature, slope angle and slope aspect. After preparing maps for each of parameters in ArcGIS software, standardization was performed on each of the six layers. Then using SOM susceptible zones to landslide was determined. The results of SOM show that there are seven classes for landslide classification in the study area. Also the results showed that the data had high density and had correlation with each other so that it should be seen that the plan, slope and curvature are closely related to each other.

Key words: Landslides, geographical information systems (GIS); landslide classification, Kohonen Self Organizing Map (SOM); Northwest Iran.

I. INTRODUCTION

Using information about landslide occurrence can get accurate information about landslide hazard assessment and risk reduction (Dai *et al*., 2002). Thus, an accurate susceptibility mapping with different risk levels can be key information for a large variety of users (Fell *et al*., 2008). There are different methods for landslide susceptibility mapping such as probability and bivariate statistical modeling (Yalcin and Bulut 2008, Althuwaynee *et al*. 2012; Lee and Pradhan 2006; Youssef *et al*. 2009), multivariate statistics (Yilmaz, 2009; Yilmaz, 2010a and b).

One of the method for preparing landslide mapping with different risk levels is self-organizing map (SOM). A type of artificial neural network (ANN) is SOM that is trained using unsupervised learning to produce a low-dimensional (typically two-dimensional), discretized representation of the input space of the training samples, called a map, and is so a method to do dimensionality reduction. Self-organizing maps differ from other artificial neural networks as they apply competitive learning as opposed to error-correction learning (such as backpropagation with gradient descent), and in the sense that they use a neighborhood function to preserve the topological properties of the input space (Ehsani and Quiel, 2008). Hosokawat and Hoshit (2001) used SOM to generate a damage distribution map in Kobe city in Japan that corresponds with the actual damage recorded following the 1995 earthquake. Ehsani and Quiel (2008) employed SOM and Shuttle Radar Topography Mission (SRTM) data to characterize yardangs in the Lut desert, Iran. The results demonstrate that SOM is a very efficient tool for analyzing aeolian landslides in hyper-arid environments that provides very useful information for terrain feature analysis in remote regions. Ferentinou and Sakellariou (2010) applied SOM in order to rate slope stability controlling variables in natural slopes, while Ferentinou *et al*. (2010) used SOM to classify marine sediments. Mokarram *et al*. (2014) used SOM to study the relationships between geomorphological features of alluvial fans and their drainage basins. The results of the analysis showed that several morphologically different fan types were recognized based on their geomorphological characteristics in the study area. Mokarram and Sathyamoorthy (2015) and Mokarram and Seif (2014) used SOM for classification of landslide. The results of SOM showed that there were five classes for landslide classification in the study area. Cluster 5 corresponds to high slope, high elevation but with different of concavity and convexity that consist of ridge landslides.

In the aim of the study area is to cluster the landslide using SOM based on morphometric characteristics. Flowchart for methodology for classification of landslide hazard show that in the Fig.1.

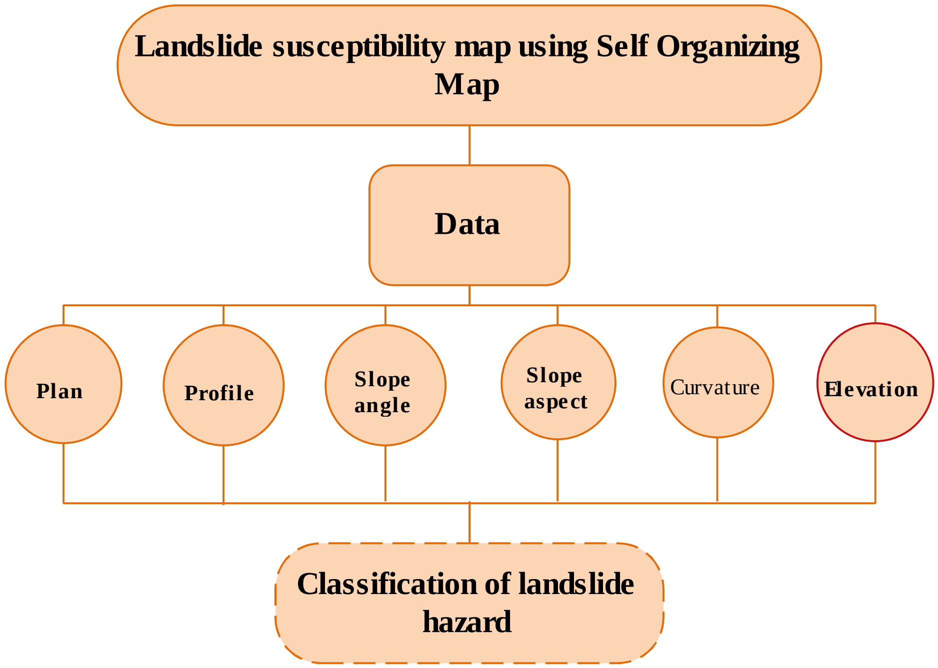


Fig. 1. Flowcharts for the methodology used in the study to classification of landslide hazard

MATERIAL AND METHODS

A. Study area

The study area is located in northwest of Iran, which is shown in Fig. 1. It located between 29° 45' to 35° 42' northern latitude and 45° 24' to 52° 00' eastern longitude (Fig. 2.). Six morphometric parameters were analyzed; elevation, profile, plan, curvature, slope angle and slope aspect (Fig. 3).

To classification of the landslide used 480 sample point for the study area that show in Fig. 4 and Table 1.

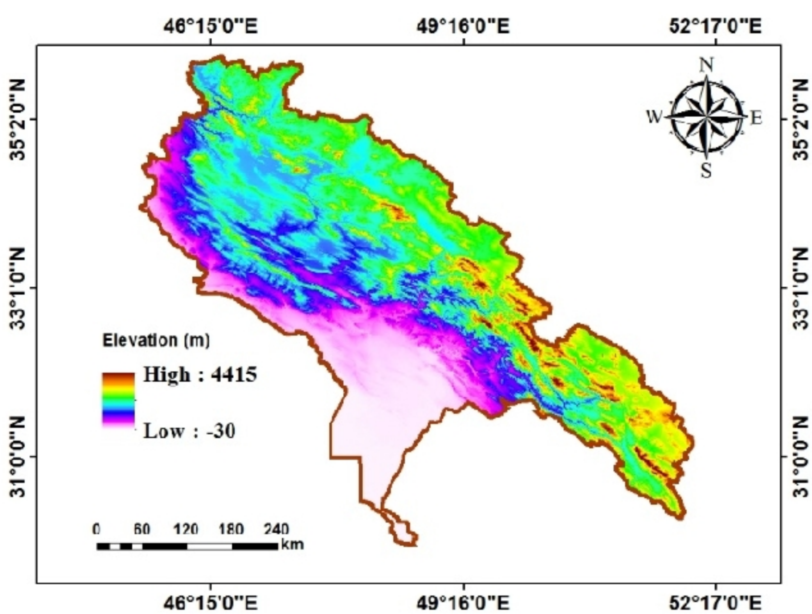
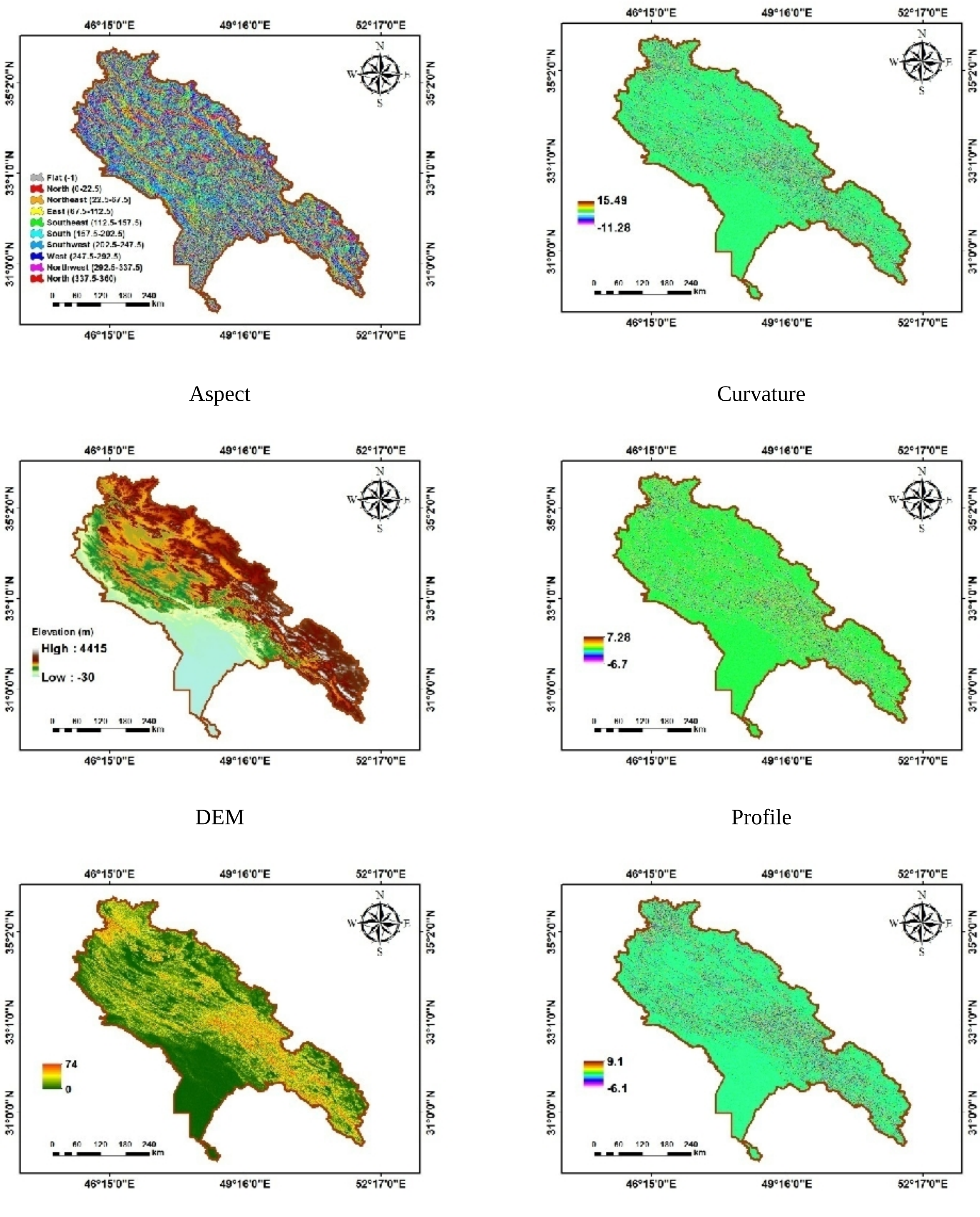


Fig. 2. Location of the study area.



Aspect Curvature

DEM Profile

Slope Plan

Fig. 3. Morphometric parameters as inputs data of the study area.

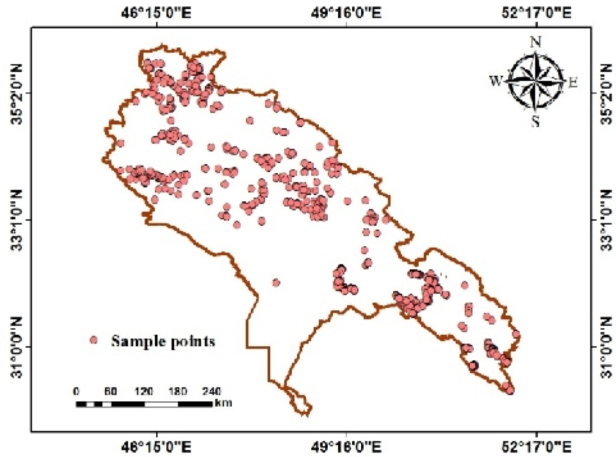


Fig. 4. Sample points for classification of landslide.

Table 1: Morphometric parameters measured for the determination of landslide hazard classification.

Parameter	Max	Min	Average	STDEV
Slope	48.773	0.156	13.817	9.368
Profile	1.174	-1.031	0.008	0.236
Plan	0.818	-1.044	0.004	0.234
DEM	3105	324	1486.867	425.26
Curvature	1.454	-1.974	-0.004	0.416
Aspect	0	165.283	106.101	106.101

B. Self-organizing map (SOM)

SOM has been mainly used for patterning and visualization of complex datasets (Li, *et al*., 2016). SOMs are a form of neural networks and consist of an input layer, an output layer, and connected weights between each input and output neuron. Neurons in the output layer are associated by topological relationships and are represented on a two-dimensional lattice (Barge, *et al*., 2016). SOM is based on unsupervised learning, which means that no human intervention is needed during the learning and little needs to be known about the characteristics of the input data (Figure 5). SOM offers a solution to apply a number of visualizations linked together (Buza, *et al*., 1991). The SOM algorithm consists of two individual stages: the competitive and cooperative stages. In the competitive stage, the best matching neuron is selected, while in the cooperative stage, the weights of the winner are adapted as well as those of its immediate lattice neighbors (Kohonen, 1995). Further explanation for each of the steps is as follows:

Competitive stage:

Let A be a lattice of N neurons with weight vectors $wi = [w\,ij] \in Rd\,, W = (w1, \ldots . wN)$. All the neurons receive the same input vector $v = [U1 \ldots\ Ud] \in V \subset Rd$. For each input v, we select the neuron with the smallest Euclidean distance (‘‘winner-takes-all’’, WTA) [(Hulle, 2012):

$$i^* = \arg\min i\ \|w_i - v\| \qquad \ldots(1)$$

where w_i is neuron weights and v is input vector.

1. **Cooperative stage**

The weight update rule in incremental mode is as follows (Hulle, 2012):

$$\Delta w_i = \eta\Lambda(I, i*, \sigma\Lambda(t))(v - w_i), \forall_i \in A \quad \ldots(2)$$

where Λ is the neighborhood function, which is a scalar-valued function of the lattice coordinates of neurons i and i*, ri and ri *, mostly a Gaussian:

$$\Lambda(i, i^*) = \exp(-\| r_i - r_{i*} \| 2 / 2\sigma\Lambda 2) \qquad \ldots(3)$$

with range $\sigma\Lambda$ (i.e., the standard deviation). The positions ri are usually taken to be the nodes of a discrete lattice with a regular topology (Hulle, 2012).

RESULTS AND DISCUSSION

SOM was applied for the study area to describe the landslide classification. The visualizations in Fig. 5 consist of hexagonal grids, with the U-matrix in the upper left, along with the six component layers (elevation, profile, plan, curvature, slope angle and slope aspect). As previously mentioned, the clustering of landslide classification used the morphometric parameters of elevation, profile, plan, curvature, slope angle and slope aspect (Fig. 6).

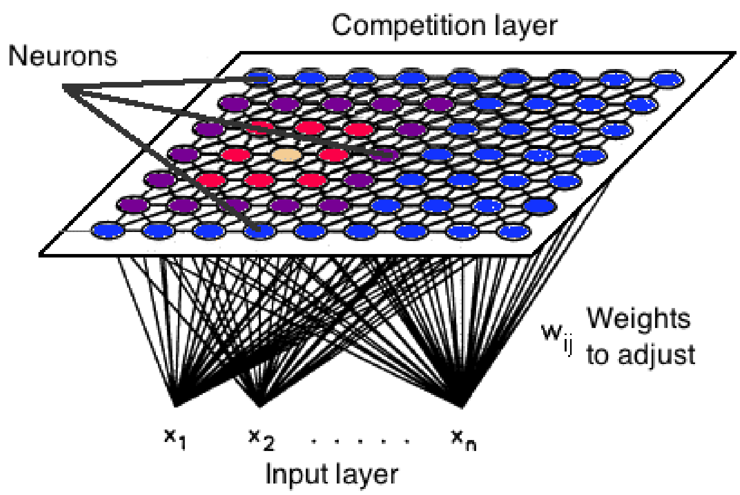


Fig. 5. The structure of a SOM network.

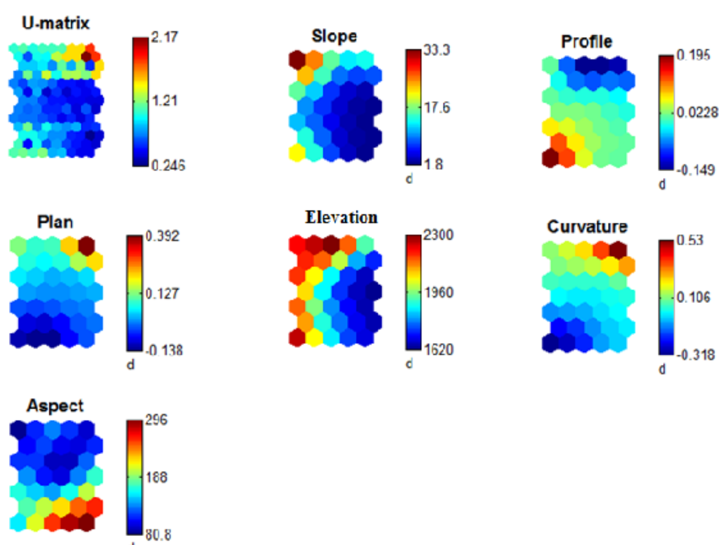
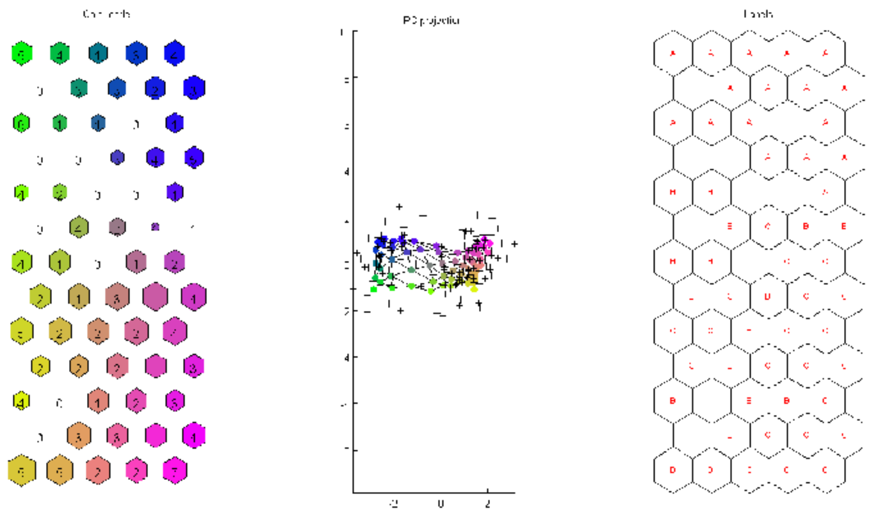


Fig. 6. SOM visualization through U-matrix (top left) and the six component layers for landslide classification.

According to Fig. 6, the six figures are linked by position: in each figure, the hexagon in a certain position corresponds to the same map unit. The legend for each of the hexagons shows the degree of color compared to each other. In the SOM method, similar colors show the direct relationship between the parameters. It can be seen that the plan, slope and curvature are closely related to each other.

As was shown in Fig. 7, the numbers written in the hexagons are data that are absorbed by each of the nodes in the neural network (Venna and Kaski, 2001). According to Fig. 7, the maximum number of hexagons was 7, indicating that the maximum data in these places is 7.



(a) (b) (c)

Fig. 7. Different visualizations of the clusters obtained from the classification of the morphological variation through SOM: (a) Color code. (b) Principal component projection. (c) Label map with the names of the landslide classification.

In addition, the minimum number of hexagons is 0, indicating that in these places, there is no data. According to Fig. 7, the principal component (PC) projection showed that the study data had high density with good distribution. Finally, using the label map (Fig. 7c), the study data was classified into seven classes for landslides. The characteristics of each group determined by the label map are provided in Table 2. It seems that the six clusters correspond to different terrain forms. In this table, the categorized map units and the corresponding morphometric features are summarized.

Table 2: Characteristics of the clusters from the SOM for the landslide classification.

Group	Parameters	slope	Profile (1/m)	Plan (1/m)	DEM	Curvature (1/m)	Aspect (degree)
Cluster 1	Min	0.156	-0.863	-0.749	916.000	-0.887	0.000
	Max	39.063	0.661	0.801	2247.000	1.454	358.877
Cluster 2	Min	0.802	-0.677	-1.044	862.000	-1.549	5.412
	Max	44.837	1.051	0.724	2640.000	1.253	355.646
Cluster 3	Min	0.397	-1.031	-1.029	515.000	-1.974	9.211
	Max	31.453	0.945	0.660	3105.000	1.241	354.668
Cluster 4	Min	0.246	-0.557	-0.815	385.000	-1.348	0.000
	Max	48.773	0.532	0.818	2468.000	1.028	353.660
Cluster 5	Min	1.186	-0.633	-0.450	324.000	-1.560	2.400
	Max	34.683	1.174	0.573	2026.000	1.206	358.727
Cluster 6	Min	0.397	-1.031	-1.044	324.000	-1.974	2.400
	Max	44.837	1.174	0.724	3105.000	1.253	358.727
Cluster 7	Min	0.802	-0.677	-1.044	324.000	-1.549	6.072
	Max	44.837	1.051	0.724	2640.000	1.253	355.646

CONCLUSION

The aim of the study was to determine the effectiveness of SOM as a clustering tool for landslide classification. In SOM, according to qualitative data, the clustering tendencies of the landslides were investigated using six morphometric parameters (elevation, profile, plan, curvature, slope angle and slope aspect). The U- matrix showed that some of the data are closely related to each other, such as elevation and slope. In addition, considering that PC projection represents the amount of data relationship with each other, PC projection was used to determine the study's data had high density. The results showed that the data had high density and had correlation with each other so that it should be seen that the plan, slope and curvature are closely related to each other. Finally, using the labels in the SOM method, seven classes for the landslides were detected.

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