Evaluating the Performance of Logistics and Non-parametric Statistical Algorithms in order to Manage Areas Vulnerable to Mass Movements in Goijabel Catchment

Soghra Andaryani[a1], Mohamad Hosein Rezaei Moghadam[b], Khalil Valizadeh Kamran[c], Vida Barzegar[d]

[a] *Ph.D. Candidate in Geomorphology, University of Tabriz, Tabriz, IRAN.*
[b] *Department of Geography & Planning, University of Tabriz, Tabriz, IRAN.*
[c] *Department of RS & GIS, University of Tabriz, Tabriz, IRAN.*
[d] *M.S. in RS & GIS, University of Tabriz, Tabriz, IRAN.*

Received: 16 October 2015
Accepted: 13 April 2016

1. Introduction

Mass movements are among the most destructive natural disasters in mountainous areas which cause great damages of over millions of dollars to human beings' life and infrastructures across the world. Landslide, **as** a type of mass movement, is a complex process that occurs under the influence of internal and external parameters. The main effective parameters in hillside instability are earthquakes, precipitation and human activities. Landslide risk assessments estimate the probability of their occurrence in a place with a return period. Most of the methods based on educational samples and assignment of a weight to each of the parameters and sub-parameters establish the relationship between effective factors in landslides and spatial analyses. Among these methods are logistic regression, multivariate statistical analysis, artificial neural network, fuzzy model, and neural fuzzy model. In this study, for optimal management in Goijabel basin, we used the logistic regression method, as a statistical method which creates a mutual relationship between the dependent parameter and independent parameters, as well as artificial neural networks with perceptron multilayer algorithm, which allocates a weight to each of the factors in landslide using educational-testing and training data based on non-linear functions.

2. Study area

The study area is located 10 km from the south west of Ahar, in East Azerbaijan Province. The application site lies between the latitudes 38° 21′ 42″ N to 38° 27′ 39″ N, and the longitudes 46° 47′ 21″ E to 46° 56′ 53″ E, and covers an area of 74.62km^2.

[1] Corresponding author: Soghra Andaryani. Tel: +989148137206 E-mail: s.andaryani@gmail.com

3. Material and Methods

To implement the methods used in this study, firstly, the maps of effective factors in landslide occurrence were provided and extracted, including lithology static factors, distance from fault, elevation, slope and aspect and dynamic factors of distance from road, distance from river, land use and land cover.

Fuzzification of effective factors, logistic regression, parameters such as Chi Square, Pseudo R Squared and ROC are used for validation of the logistic regression model. The other method used in this research is perceptron neural network. Accordingly, effective factors in landslide occurrence in the area under study were prepared as the models' input. In the next step, each extracted layer was sectioned with the landslides layers, and based on the histogram and the area of landslides in each of the layers, a reclassification was done in all of the layers.

4. Results and Discussion

Validation of the models used was by ROC method. The results of this model are based on statistical classification analyses. This method indicates higher area under the curve in the neural network model. In other words, the neural network model with the numerical average of 0.91% is introduced as a more efficient model compared to the logistic regression model with the numerical average of 0.89%. Using educational data and hidden nodes and other indexes such as coefficient of acceleration, this model can provide better modeling of the areas sensitive to landslides occurrence.

5. Conclusion

In this study, for an optimized management in the region and avoidance of potential damages caused by mass movements, especially landslides, the zoning of the areas sensitive to these movements was performed using logistic regression models and artificial neural network with perceptron multilayer algorithm. For the modeling, 9 independent parameters were used including precipitation, Lithology, land use and land cover, elevation, slope, aspect, distance from drainage network, distance from fault and distance from road. After standardization of each of the parameters, 9 factors were introduced as the independent variable, the landslides as binary layer for logic model, and standardized factors as input neurons and landslide layer as training of artificial neural network model with perceptron multilayer algorithm. The result of ROC validation shows that the area under the curve in the artificial neural network model has been higher than that of the logistic regression model, indicating a precision of 0.91% compared to logistic regression with a precision of 0.89%. Therefore, an area of over 9% is in high and very high -risk zones and 9/5% of the area is in medium-risk zones. Medium-risk zones can be affected by mismanagement and human constructions such as roads and be changed into high and very high risk zones, considering the fact that in this modeling, the areas close to man-made effects in both models are zoned as areas sensitive to landslide risk.

Keyword: Logistic regression model, Multi-layer perceptron, Landslide, Fuzzy standardization, Goijabel catchment

References (in Persian)

Andaryani, S. (2014). *Remote sensing and GIS techniques application in the study of land use changes and their effects on stream discharge (Case study: Sofichay Basin*) (Unpublished master's thesis), University of Tabriz, Tabriz, Iran.

Bayati Katibi, M. (2010). Landslide hazard evolution and zoning in Garanghoo Chay using statistic bivariate. *Geography and Planning*, *32*, 1-27.

Rafatnia, N., Kaviyanpour, M. K., & Tofig, A. (2011). Investigation of case landslide phenomena in Glandrood forest (Case study: District 3 from catchment area 48). *Sciences and Techniques in Natural Resources, 1*, 53-63.

Rajabi, M., & Feizolahpour, M. (2014). Zoning the landslides of Givichay River Basin by using Multi-Layer Perceptron Model. *Geography and Development*, *36*, 161-180.

Yamani, M., Ahmadabadi, A., & Zare, R. (2012). The zonation of landslide occurrence using support vector machines algorithm (Case study: Darakeh Basin). *Geography and Environmental Hazards*, 3, 125-142.

References (in English)

Anbalagan, R. (1992). Landslide hazard evaluation and zonation mapping in mountainous terrain. *Engineering Geology*, *32*, 269–277.

Atkinson, P. M., & Tatnall, A. R. L. (1997). Introduction of neural networks in remote sensing. *Remote Sensing*, *18*(4), 699-709.

Ayalew, L., & Yamagishi, H. (2004). Slope failures in the Blue Nile basin, as seen from landscape evolution perspective. *Geomorphology*, *57*, 95-116.

Bommer, J. J., & Rodriguez, C. E. (2002). Earthquake-induced landslides in Central America. *Engineering Geology*, *63*, 189–220.

Burrough, P. A. (1989). Fuzzy mathematical methods for soil survey and land evaluation. *Soil Science*, *40*, 477-492.

Clark, W. A., & Hosking, P. L. (1986). *Statistical methods for geographers* (Chap. 13). New York: John Wiley & Sons.

Collison, A., Wade, S., Griffiths, J., & Dehn, M. (2000). Modelling the impact of predicted climate change on landslide frequency and magnitude in SE England. *Engineering Geology*, *55*, 205–218.

Crozier, M. J. and Glade, T. (2005). Landslide Hazard and Risk: Issues, Concepts and Approach. In T. Glade, M. Anderson and M. J. Crozier (eds.), *Landslide Hazard and Risk* (pp. 43-74). England: John Wiley & Sons.

Dahal, R.K., Hasegawa, S., Masuda, T., & Yamanaka, M., 2006a. Roadside slope failures in Nepal during torrential rainfall and their mitigation. In H. Marui., T. Marutani., N. Watanabe., H. Kawabe., Y. Gonda., M. Kimura., H. Ochiai., K. Ogawa., G. Fiebiger., J. Heumader., F. Rudolf-Miklau., H. Kienholz & M. Mikos (Eds.), *Disaster mitigation of debris flow, slope failures and landslides* (P. 503-514). Tokyo: Universal Academy Press.

Dai, F. C., Lee, C. F., Li, J., & Xu, Z. W. (2000). Assessment of landslide hazard on the natural terrain of Lantau Island, Hong Kong. *Environment Geology*, *40*, 381-391.

Garrett, J. (1994). Where and why artificial neural networks are applicable in civil engineering. *Computer Civil Engineering*, *8*, 129-130.

Gong, P. (1996). Integrated analysis of spatial data for multiple sources: using evidential reasoning and artificial neural network techniques for geological mapping. *Phonogram: Engineering Remote Sensing*, *62*, 513-523.

Hong, H., Pradhan, B., Xu, C., & Tien Bui, D. T. (2015). Spatial prediction of landslide hazard at the Yihuang area (China) using two-class kernel logistic regression, alternating decision tree and support vector machines. *Catena*, *133*, 266-281.

Kanungo, D. P., Arora, M. K., Sarkar, S., & Gupta, R. P. (2006). A comparative study of conventional, ANN black box, fuzzy and combined neural and fuzzy weighting procedures for landslide susceptibility zonation in Darjeeling Himalayas. *Engineering Geology*, *85*, 366-347.

Keefer, D. V. (2000). Statistical analysis of an earthquake-induced landslide distribution – the 1989 Loma Prieta, California event. *Engineering Geology, 58*, 231–249.

Lee, C., & Lee, S. (2012). Combining landslide susceptibility maps obtained from frequency ratio, logistic regression, and artificial neural network models using ASTER images and GIS. *Engineering Geology*, *124*, 12-23.

Pachauri, A. K., & Pant, M. (1992). Landslide hazard mapping based on geological attributes. *Engineering Geology*, *32*, 81-100.

Pan, X., Nakamura, H., Nozaki, T., & Huang, X. (2008). A GIS-based landslide hazard assessment by multivariate analysis. *Japan Landslide Society*, *45*(3), 187–195.

Raghuvanshi, T. K., Ibrahim, J., & Ayalew, D. (2014a). Slope stability susceptibility evaluation parameter (SSEP) rating scheme: An approach for landslide hazard zonation. *African Earth Science*, 99, 595–612.

Saha, A. K., Gupta, R. P., Starker, I., Arora, M. K., & Csaplovics, E. (2005). An approach for GIS based statistical landslide susceptibility zonation with a case study in the Himalayas. *Landslides, 2*, 61-69.

Schmucker, K. J. (1982). *Fuzzy sets, natural language computations and risk analysis*. Philadelphia: Computer Science Press.

Shalkoff, R. J. (1997). *Artificial neural networks*. New York, NY: McGraw-Hill.

Van Westen, C. J., Van Asch, T. W. J., & Soeters, R. (2006). Landslide hazard and risk zonation - Why is it still so difficult? *Bulletin of Engineering Geology and the Environment*, *6*5, 167-184.

Wang, L. J., Guo, M., Sawada, M. K., Lin, J., & Zhang, J. (2015). Landslide susceptibility mapping in Mizunami City, Japan: A comparison between logistic regression, bivariate statistical analysis and multivariate adaptive regression spline models. *Catena*, *135*, 271-282.

Wang, X., & Niu, R. (2009). Spatial forecast of landslides in three gorges based on spatial data mining. *Sensors*, *9*, 2035–2061.