Computers & Geosciences 45 (2012) 199–211

Contents lists available at SciVerse ScienceDirect

Computers & Geosciences

journal homepage: www.elsevier.com/locate/cageo

Landslide susceptibility mapping at Hoa Binh province (Vietnam) using an adaptive neuro-fuzzy inference system and GIS

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ARTICLE INFO

Article history:
Received 25 July 2011
Received in revised form
6 October 2011
Accepted 7 October 2011
Available online 12 November 2011

Keywords:
Adaptive neuro-fuzzy inference system (ANFIS)
Landslide susceptibility
GIS
Hoa Binh province
Vietnam

ABSTRACT

The objective of this study is to investigate a potential application of the Adaptive Neuro-Fuzzy Inference System (ANFIS) and the Geographic Information System (GIS) as a relatively new approach for landslide susceptibility mapping in the Hoa Binh province of Vietnam. Firstly, a landslide inventory map with a total of 118 landslide locations was constructed from various sources. Then the landslide inventory was randomly split into a testing dataset 70% (82 landslide locations) for training the models and the remaining 30% (36 landslides locations) was used for validation purpose. Ten landslide conditioning factors such as slope, aspect, curvature, lithology, land use, soil type, rainfall, distance to roads, distance to rivers, and distance to faults were considered in the analysis. The hybrid learning algorithm and six different membership functions (Gaussmf, Gauss2mf, Gbellmf, Sigmf, Dsigmf, Psigmf) were applied to generate the landslide susceptibility maps. The validation dataset, which was not considered in the ANFIS modeling process, was used to validate the landslide susceptibility maps using the prediction rate method. The validation results showed that the area under the curve (AUC) for six ANFIS models vary from 0.739 to 0.848. It indicates that the prediction capability depends on the membership functions used in the ANFIS. The models with Sigmf (0.848) and Gaussmf (0.825) have shown the highest prediction capability. The results of this study show that landslide susceptibility mapping in the Hoa Binh province of Vietnam using the ANFIS approach is viable. As far as the performance of the ANFIS approach is concerned, the results appeared to be quite satisfactory, the zones determined on the map being zones of relative susceptibility.

1. Introduction

In recent years, the occurrences of natural disasters in Vietnam have increased significantly mostly due to the effect of the climate change. The northwest mountainous area of Vietnam is one of the regions, which is heavily affected by landslide activities and flooding events. In most of the cases, landslides occurred following heavy rainfalls and especially during tropical rainstorms. However, to date, little effort has been made to assess or forecast these events. Through scientific analysis of landslides, geoscientists and civil engineers can assess and delineate landslide-susceptible areas, offering the potential for a decrease in landslide damage through proper slope management (Pradhan, 2011). So research on landslide susceptibility mapping for the Northwest area, including the Hoa Binh province, is an urgent task in Vietnam. The result of landslide research may provide valuable information that helps to forecast such events as well as to find measures to mitigate subsequent losses to future landslides.

Many techniques and methods have been proposed and developed in the landslide literature. Basically, they can be divided into direct and indirect methods (Guzzetti et al., 1999). Direct methods can be the methods of using total stations, global satellite navigation systems, or other methods for landslide surveying (Van Westen et al., 2003). Through direct methods, using experiences and knowledge of experts, the degree of susceptibility can be directly determined. However, in such cases fieldworks are extensively required, so they are time-consuming and not cost effective. Whereas in the case of the indirect methods, usually a landslide inventory map is used in conjunction with the landslide conditioning factors (Van Westen et al., 2003). Generally, the landslide susceptibility levels are determined based on the correlation between the existing landslide inventory and the conditioning factors as mentioned above. However, the accuracy of landslide susceptibility maps depends on the level of accuracy of mapping of different conditioning factors and landslide inventory.

In recent years, some newer approaches for landslide analysis have been carried out such as artificial neural networks (Ercanoglu, 2005; Ermini et al., 2005; Lee et al., 2003, 2004; Nefeslioglu et al.,

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doi:10.1016/j.cageo.2011.10.031

2008; Pradhan and Lee, 2010a, c; Pradhan et al., 2010a), fuzzy logic (Akgun et al., 2011; Ercanoglu and Gokceoglu, 2002, 2004; Kanungo et al., 2008; Pradhan, 2010a), decision tree (Nefeslioglu et al., 2010), and neuro-fuzzy (Kanungo et al., 2006; Oh and Pradhan, 2011; Pradhan et al., 2010b; Sezer et al., 2011; Vahidnia et al., 2010). Generally, these approaches give rise to qualitative and quantitative maps of the landslide hazard areas, and the spatial results are appealing (Pradhan, 2010b).

In the case of the neuro-fuzzy, which is a combination of fuzzy logic and neural networks, Kanungo et al. (2006) used the weights of the layers obtained from the trained neural network integrated with the ratings obtained from fuzzy logic to obtain a landslide susceptibility index. The membership degrees of each layer class were determined based on the relationship of existing landslides with the classes. Vahidnia et al. (2010) used the output of a fuzzy inference system as target for a neural network. There is no doubt that expert knowledge played an important role to obtain the accuracy of these results. And the subjectivity is not easy to eliminate.

Another combined method, developed by Jang (1993), is the Adaptive Neuro-Fuzzy Inference System (ANFIS). This method, using the Takagi–Sugeno rule format, is the combination of an optimized premise membership function (gradient descent) with an optimized consequent equation (linear least squares estimator). Based on a given input and target, ANFIS can construct a fuzzy inference system where their membership function parameters are to be adjusted using the hybrid learning algorithm. ANFIS has been widely used in modeling complex systems (Soyguder and Alli, 2009). However, its application in landslide studies is still limited to a very few cases. Pradhan et al. (2010b) used eight landslide conditioning factors for the ANFIS model for landslide susceptibility mapping in a study area in Malaysia. Their results indicated a very high prediction accuracy of 97%. Oh and Pradhan (2011) and Sezer et al. (2011) have also used an ANFIS based model for landslide susceptibility mapping in different parts of Malaysia. However, the disadvantage of these approaches is that it is difficult to objectively determine the epoch where the landslide model starts over-fitting in the training phase. Expert opinions are suggested used to determine the number of membership functions of the inputs, the physical meanings of the inputs, and the number of training epochs for preventing over-learning. Oh and Pradhan (2011) also asserted that, in order to check the performance of the neuron-fuzzy model in landslide susceptibility mapping, and for the method to be more generally applied, more case studies should be conducted.

The main difference between this study and the aforementioned literature is that the ANFIS was applied for landslide susceptibility assessment in the Hoa Binh province of Vietnam, using the subtractive clustering method proposed by Chiu (1994). This is the automated data-driven based method for constructing the primary fuzzy models. The main advantages of this method are that it can process a large number of input observations and avoid the explosion of the rule base (Eftekhari and Katebi, 2008). In addition, the method proposed by Jang et al. (1997) was used to control over-fitting of the landslide model by testing the fuzzy inference system (FIS), trained on the training data against the checking data. Using the six different membership functions, six ANFIS models were constructed. Finally, the comparison was carried out to find the most suitable model for the study area.

2. Study area

The Hoa Binh province is situated at the monsoonal region in the North West part of Vietnam. It covers an area of about 4660 km^2 (Fig. 1) between the longitude 104°48′E and 105°50′E, and between the latitude 20°17′N and 21°08′N. The altitude decreases from Northwest to Southeast and varies in the range from 0 to 1510 m. This province is a "transition" area situated between the Northwest Mountains and the Red River delta.

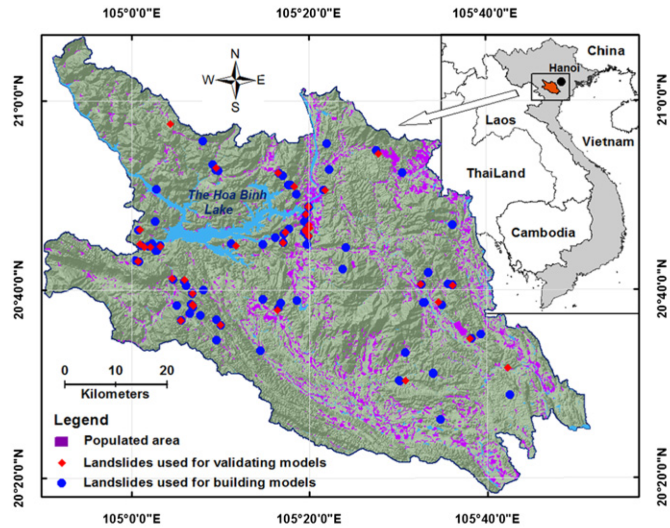

Fig. 1. Landslide inventory of the study area.

The climate of this region is characterized by high temperatures and high humidity, with two distinct rainy and dry seasons. The rainy season is mainly from May to October with the total rainfall accounting to 84–90% of the yearly rainfall. The highest rainfall frequency and intensity occurs during August and September with rainfall peaks that vary between 300 and 400 mm per month.

3. Data used

Since landslide occurrences in the past and present are keys to future spatial prediction (Guzzetti et al., 1999), a landslide inventory map is a pre-requisite for such a study. The landslide inventory map of the study area was compiled by inheriting the landslide locations from three projects: (1) the landslide inventory map in the Northern mountainous province (Hue et al., 2004); (2) the landslide inventory map 2005 (Thinh et al., 2005); and (3) the landslide inventory map 2007 (My, 2007). Four recent landslide locations were identified on SPOT satellite imagery (5 August 2009) with spatial resolution of 2.5 m and other supplementary information. Fieldworks were conducted to verify all the recent landslide locations.

A total of 118 landslides that occurred during the last ten years were identified and registered in the landslide inventory map (Fig. 1). The size of the smallest landslide is about 383 m^2. The largest landslide covers an area of 14,343 m^2. The average landslide size in general is 3443 m^2.

Bui et al. (2011) examined the correlations between landslide occurrence and ten landslide conditioning factors: slope, aspect, curvature, lithology, land use, soil type, rainfall, distance to roads, distance to rivers, and distance to faults for the Hoa Binh province of Vietnam. Based on the findings, we selected the ten aforementioned factors for landslide modeling for this study.

A digital Elevation Model (DEM), with a resolution of 20 m, was generated from the national topographic maps in 1:25,000 scale having a contour interval of 10 m. The slope, aspect, and curvature layers were extracted from the DEM. The slope map was grouped into six different classes e.g., 0°–10°, 10°–20°, 20°–30°, 30°–40°, 40°–50°, > 50° (Fig. 2a). The aspect map was prepared with ten conventional classes (Fig. 2b). The slope curvature map was compiled with three categories: convex, concave, and flat (Fig. 2c).