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Applying population-based evolutionary algorithms and a neuro-fuzzy system for modeling landslide susceptibility

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ABSTRACT

The main objective of the present study was to produce a novel ensemble data mining technique that involves an adaptive neuro-fuzzy inference system (ANFIS) optimized by Shuffled Frog Leaping Algorithm (SFLA) and Particle Swarm Optimization (PSO) for spatial modeling of landslide susceptibility. Step-wise Assessment Ratio Analysis (SWARA) was utilized for the evaluation of the relation between landslides and landslide-related factors providing ANFIS with the necessary weighting values. The developed methods were applied in Langao County, Shaanxi Province, China. Eighteen factors were selected based on the experience gained from studying landslide phenomena, the local geo-environmental conditions as well as the availability of data, namely; elevation, slope aspect, slope angle, profile curvature, plan curvature, sediment transport index, stream power index, topographic wetness index, land use, normalized difference vegetation index, rainfall, lithology, distance to faults, fault density, distance to roads, road density, distance to rivers and river density. A total of 288 landslides were identified after analyzing previous technical surveys, airborne imagery and conducting field surveys. Also, 288 non-landslide areas were identified with the usage of Google Earth imagery and the analysis of a digital elevation model. The two datasets were merged and later divided into two subsets, training and testing, based on a random selection scheme. The produced landslide susceptibility maps were evaluated by the receiving operating characteristic and the area under the success and predictive rate curves (AUC). The results showed that AUC based on the training and testing dataset was similar and equal to 0.89. However, the processing time during the training and implementation phase was considerable different. SWARA-ANFIS-PSO appeared six times faster in respect to the processing time achieved by SWARA-ANFIS-SFLA. The proposed novel approach, which combines expert knowledge, neuro-fuzzy inference systems and evolutionary algorithms, can be applied for land use planning and spatial modeling of landslide susceptibility.

1. Introduction

Natural hazards, such as landslides, earthquakes, hurricanes, erosion and tsunamis, are responsible for great loss of human lives and severe damages to properties and the environment, with landslides being one of the most devastating natural hazards worldwide (Yilmaz, 2010). It is reported that landslides are responsible for at least 17% of all natural hazards fatalities worldwide (Pourghasemi et al., 2012). In the developing countries around 0.5% of the Gross National Products (GNP) per year has been lost due to landslide phenomena, while the majority of the recorded landslides worldwide (near 95%) are located in the developing countries (Chung and Fabbri, 2003). China is considered to be one of the most strongly affected countries with 695 annual deaths and a cost of about 500 million US dollars (Petley, 2010). The central region of China, due to complex geo-environmental settings and also the intensive human intervention, are considered as one of the

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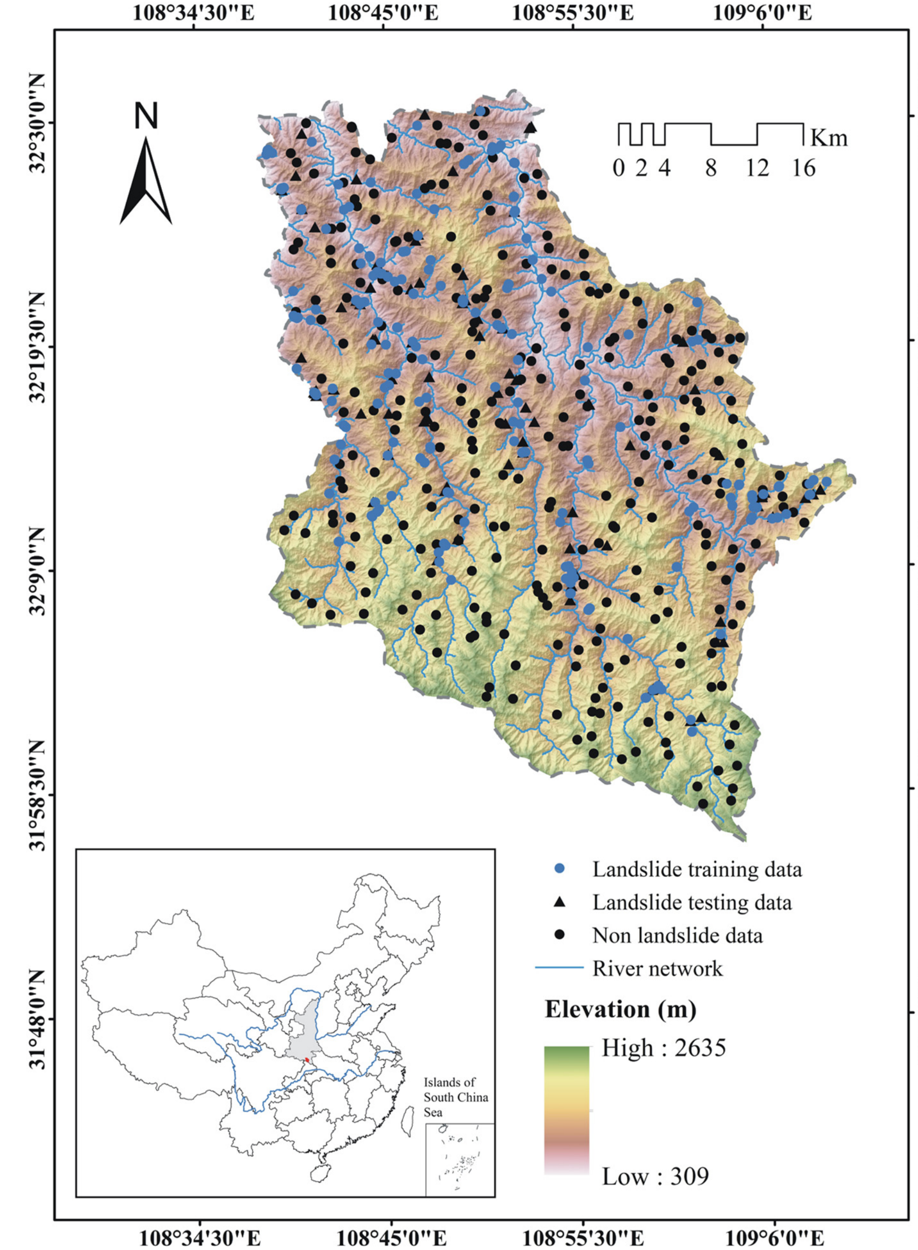

Fig. 1. Location of the study area and distribution of landslides.

most landslide prone areas. Reports show that landslides have caused huge economic losses and casualties every year in the wider area of Langao County, a landslide prone area located in Central China (Dong et al., 2014).

Essential important for understanding and predicting future landslides and also mitigating their consequences in the study area is the construction of a landslide susceptibility map. During the past three decades, the progress achieved in GIS and remote sensing technologies and also the development and application of methods and techniques to assess landslide susceptibility, hazard and risk has been proved feasible and effective (Broeckx et al., 2018; Ciabatta et al., 2015; Kornejady et al., 2017; Oliveira et al., 2015; Reichenbach et al., 2018; Shahabi and Hashim, 2015; Tan et al., 2015). However, there is not yet a standardized procedure for producing landslide susceptibility maps despite the plethora of techniques and methods that have been investigated and suggested (Ercanoglu and Gokceoglu, 2004). In general, the applied techniques and methods could be classified into qualitative and quantitative; qualitative methods are characterized by their subjective nature and the heuristic way they ascertain susceptibility while quantitative methods are based on numerical estimates and involve statistical and probabilistic methods (Tsangaratos et al., 2017).

The most commonly used techniques and methods are quantitative methods such as logistic regression (Hong et al., 2015; Shahabi et al., 2015; Tsangaratos and Ilia, 2016), bivariate statistics analysis (Wang et al., 2015; Youssef et al., 2015), multivariate logistic regression (Conoscenti et al., 2015; Pourghasemi et al., 2018; Pradhan, 2010), multivariate adaptive regression spline (Chen et al., 2018d; Felicísimo et al., 2013; Pourghasemi and Rossi, 2016), discriminant analysis (Dong et al., 2009; He et al., 2012), frequency ratio (Chen et al., 2017f; Romer and Ferentinou, 2016; Shahabi et al., 2014), weight of evidence (Kavzoglu et al., 2015; Tsangaratos et al., 2017), and evidential belief function (Jebur et al., 2015; Pourghasemi and Kerle, 2016). In recent years, in addition to the above mentioned methods, various machine learning algorithms (MLAs), which are known as an advanced automatic inductive approach have been developed in solving a lot of real world problems including landslide and groundwater prediction