Geomorphology 204 (2014) 646–656

Contents lists available at ScienceDirect

Geomorphology

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

Producing a landslide inventory map using pixel-based and object-oriented approaches optimized by Taguchi method

Vahid Moosavi [a], Ali Talebi [a,*], Bagher Shirmohammadi [b]

[a] Department of Watershed Management Engineering, Faculty of Natural Resources, Yazd University, Iran
[b] Department of Environmental Science, Faculty of Natural Resources and Marine Sciences, Tarbiat Modares University, Iran

ARTICLE INFO

Article history:
Received 2 June 2013
Received in revised form 12 September 2013
Accepted 16 September 2013
Available online 26 September 2013

Keywords:
Landslide inventory
Taguchi method
Optimization
Pixel-based classification
Object-oriented classification

ABSTRACT

Landslides are considered one of the most important natural hazards. Mapping landslides and producing landslide inventory maps have received special attention from a wide range of specialists. The main objective of this study was to produce landslide inventory maps using advanced pixel-based (ANN and SVM) and object-oriented approaches. The most important challenge in this case is to determine the optimum structure of classification methods. The Taguchi method was to perform optimization of the structure of ANN and SVM and segmentation process in the object-oriented classification method. Results showed that the Taguchi method can be effectively used to cope with this problem. It significantly reduces the number of classification tests. We also showed that there were no significant differences existed between ANN and SVM approaches (χ^2 value of 3.33). However, we demonstrated that object-oriented approaches significantly outperformed the pixel-based classification methods (Z value of 5.70) in producing a landslide inventory map. The accurate map produced using an object-oriented approach (overall accuracy of 0.90) effectively determines the shape of landslides and also efficiently shows the intensifying effects of land use changes in the occurrence of landslides.

1. Introduction

A landslide is the movement of a mass of rock, debris, or earth down a slope, under the influence of gravity. Different phenomena can cause landslides, consisting of intense or extended rainfall, swift snow melting, earthquakes (Wilson and Keefer, 1985; Inglès et al., 2006), volcanic activity (Ablay and Hürliman, 2000; Moon and Simpson, 2002), and human activities (Skempton and Hutchinson, 1969). Landslides can involve flowing, sliding, toppling, or falling; and many landslides exhibit a combination of two or more types of movements at the same time or during the lifetime of a landslide (Cruden and Varnes, 1996; Philip and Ritz, 1999; Brückl, 2001; Sörensen and Bauer, 2003). Landslides are the most important, costly, and damaging natural hazards in mountainous regions (University of Utah, 1984). Landslide susceptibility analysis and mapping are key steps in better predicting future landslides and improving protection in these areas. Several studies have been performed on landslides such as Schicker and Moon (2012) that compared bivariate and multivariate statistical approaches for landslide susceptibility mapping or Pourghasemi et al. (2012) that produced a landslide susceptibility map using the index of entropy. The use of GIS and remote sensing approaches to study landslides are also intensively reported (Weirich and Blesius, 2007; Akgün et al., 2008; Booth et al., 2009; Martha et al., 2010; Pradhan and Lee, 2010; Oh et al., 2012; Song et al., 2012).

The situations in which landslides are likely to occur are assumed to be the same areas in which historical landslides have already occurred. Therefore, landslide inventory mapping is a vital requirement for trustworthy hazard and risk analysis. Inventory maps are available in only a few countries and mostly for limited areas (Ayenew and Barbieri, 2005; Duman et al., 2005; Harp et al., 2011). These maps can be used in several scientific studies. Blahut et al. (2010) analyzed the landslide inventory maps to accurately predict debris flow source areas. A combination of aerial photograph visual interpretation and field work has conventionally been used to produce landslide inventories and, until now, it remains the most often used approach for the extraction of inventory maps in scientific studies and by managerial organizations (Hervas and Bobrowsky, 2009). Although this approach is time consuming and labor intensive, the results are somewhat unreliable (Galli et al., 2008). Satellite image processing techniques can be suitable to produce more reliable inventory maps. There are several image processing techniques that can be categorized into two groups: i.e., pixel-based and object-oriented approaches. The traditional digital image analysis approaches, which exclusively gain statistical methods, have proved to be constrained for detecting targets of greater complexity.

Pixel-based techniques classify each pixel in the image without regard to neighboring pixels. Several studies have been carried out using a pixel-based approach, and they have examined several pixel-based techniques (Breiman, 2001; Huang et al., 2002; Pal, 2005; Carreiras et al., 2006; Gislason et al., 2006; Brenning, 2009; Otukei and Blaschke, 2010). A number of pixel-based approaches are on hand for image classification, such as maximum likelihood, minimum distance,

* Corresponding author. Tel./fax: +98 351 8210312.
E-mail address: talebisf@yazd.ac.ir (A. Talebi).

0169-555X/$ – see front matter © 2013 Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.geomorph.2013.09.012

parallelepiped, ISODATA, K-mean, etc. (Lillesand et al., 2007). Classification using pixel-based approaches has some deficiencies, especially dealing with the rich information content of high resolution data, e.g., Geoeye multispectral (VNIR) and very high resolution (VHR) satellite imageries. In fact, these conventional pixel-based approaches use only gray values; but the advanced pixel-based techniques such as artificial neural network (ANN) and support vector machine (SVM) consider the texture, tone, and several other characteristics (Pakhale and Gupta, 2010). A neural network is, like supervised classification, a method that is first trained from known data and then used to categorize unknown pixels. Support vector machines (SVMs) demonstrate a set of theoretically superior machine-learning algorithms. The development of SVM was initially triggered by the exploration and formalization of learning machine capacity control and overfitting issues (Vapnik, 1998).

Object-oriented approaches are also one of the most useful image processing techniques. These approaches are based on the assumption that a pixel is very likely to belong to the same class as its neighboring pixels. In the first step, the image is segmented into homogeneous objects consisting of similar pixels. These objects are then categorized into specific classes (Koch et al., 2003). Object-based image analysis have been applied in various fields in environmental sciences and disaster monitoring and assessing (Langanke et al., 2004; Blaschke, 2005; Chandra et al., 2005; Laliberte et al., 2006; Castillejo-González et al., 2009; Blaschke, 2010; Linke and McDermid, 2011; Van Den Eeckhaut et al., 2012).

One of the most important challenges in these cases is the determination of the optimum combination of affecting parameters on the performance of classification approaches. Trial and error approaches are usually time consuming and labor intensive. A fractional factorial design of experiments such as the Taguchi method can be an effective way to cope with this problem. Taguchi (1990) developed a family of FFE matrices that could be utilized in various situations. This method has been generally adopted to optimize the design parameters (based on a signal-to-noise parameter) and significantly minimize the overall testing time and the experimental costs (Wang and Huang, 2007; Chou et al., 2009) following a systematic approach to confine the number of experiments and tests.

To the best of our knowledge, no research uses the Taguchi method to optimize the classification parameters. Several researchers compared the two classification approaches (Yan et al., 2006; Platt and Rapoza, 2008; Castillejo-González et al., 2009; Myint et al., 2011); but a few researchers evaluated the statistical significance of differences between these two classification approaches, especially in producing landslide inventory maps (Pakhale and Gupta, 2010). The main objective of this research is to produce a landslide inventory map using Taguchi-based optimized advanced pixel-based and object-oriented approaches and also to compare these methods using statistical indices.

2. Study area

The study site is located 40 km southeast of Kermanshah city, Kermanshah Province, Iran, between 47°00′ to 47°07′ E. longitude and 33°40′ to 34°00′ N. latitude. The minimum and maximum elevations in this region are 1580 and 1950 m asl, respectively. This area encompasses plains, hilly, and mountainous areas with forest, rangeland, and agricultural areas. The mean annual precipitation and temperature are 481 mm and 17.7 °C, respectively. This area is vulnerable to landslide, which is partly related to its geological origin. This area is almost completely occupied by the Zagros fold and thrust belt (Zagros FTB); the Zagros FTB is due to the oblique convergence with the Arabian plate and the Eurasian plate at 3 cm/y. Deformation within the Zagros FTB began during the Oligocene and continues until the present day. This region is formed by a sequence of Precambrian–Pliocene shelf sediments (Karimibavandpoor et al., 1999) and contains many evaporitic layers (Alavi, 2004) that are a good candidate for landslide shear plane. The other reasons for this high vulnerability can be related to the uncontrolled deforestation, overgrazing, and offensive tillage activities (Heshmati et al., 2011). Fig. 1 shows the location of the study area and the main geological structures of the Zagros FTB.

The Geoeye multispectral VNIR imagery (4 bands with spatial resolution of 1.65 m) for 29 March 2011 was used in this study. The spacecraft is intended for a sun-synchronous orbit at an altitude of 681 km and an inclination of 98°, with a 10:30 a.m. Equator crossing time. Geo images are shipped with the sensor camera model in RPC format and a metadata file (GeoEye, Inc., 2009).

3. Materials and methods

3.1. Image classification

Classification of images involves using a procedure to decide whether different pixels in an image have analogous characteristics. These rules segregate the total data space into subsets divided by so-called decision boundaries. All pixels that fall within a number of pixels delimited by such decision borders are then labeled as belonging to a distinct class (Elachi and van Zyl, 2006). As mentioned before, we use two main classification approaches: namely, pixel-based and object-oriented. Before classification, the image was geometrically corrected with first-degree polynomial using homogenously distributed ground control points (45 points) obtained from field surveys. This algorithm was applied and achieved a root mean square error (RMSE) of 1.8 m. A brief explanation of these two classification approaches is presented below.

3.1.1. Pixel-based approach

In this part, three essential steps were conducted, i.e., selection of training samples that are representative for different information classes; executing classification algorithms; and finally, assessing the accuracy of the classified images through analysis of a confusion matrix (Tso and Mather, 2009). Training samples were selected according to the ground truth data. These homogenous areas were identified in the image to form the training samples for all of the information classes. Two advanced supervised pixel-based classifications, i.e., ANN and SVM, were conducted in this part.

The advantage of neural networks is related to the high computation rate accomplished by their inherent parallelism that is a result of a potent arrangement of interconnections (weights) and simple processors (neurons), which allows processing of very large data sets. This approach is commonly described as nonparametric (Frizzelle and Moody, 2001). The revenue of a neural network depends on how appropriate it has been trained. During the training phase, the neural network *learns* about regularities present in the training data and, based on these regularities, constructs rules that can be extended to the unknown data. This is one particular ability of neural networks (Tso and Mather, 2009).

In the neural network classification, the most accepted algorithm commonly used for updating the neuronal activities and the interconnection in a multilayer perceptron (i.e., back-propagation algorithm) was used for supervised classification of images using the ENVI software package. Back-propagation consists of two main steps, i.e., forward and backward propagation, to achieve its adjustment of the neural state. In this approach, learning takes place by regulating the weights in the node to minimize the difference between the output node activation and the desired output. The error is back propagated through the network, and weight modification is made using a recursive method (Hopfield, 1982; Richards, 1999). In both approaches (ANN and SVM), in addition to the original image, NDVI, a digital elevation model (DEM) and some of its derivatives (i.e., slope and curvature) have been used. Fig. 2 shows the original image and examples of deforestation and landslides.

The SVM also is a classification system resulting from statistical learning theory that provides good classification results from complex data. There are four main kernel types in SVM: namely, linear, polynomial, radial basis function, and sigmoid. All of these are different ways