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Landslide Assessments through Soft Computing Techniques within a GIS-based Framework

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Landslides are natural, geological phenomena that include a wide range of soil, debris or rock mass movements that occur in offshore, coastal and inland areas, driven mainly by the force of gravity and the aid of water [1]. They appear as a result of the progressive or extreme evolution of natural events caused by the action of geological, tectonic, geomorphological and climatic processes and also the negative impact of human intervention upon the environment [2, 3].

The assessment of landslides has been recognized from the scientific community as one of the most significant tools in the management of landslide phenomena, especially concerning the development of specific land regulations by local and national authorities that aim at minimizing the loss of lives and the damages to infrastructure and properties. The risk against landslides refers to the probability of occurrence of a potentially injurious event in a specified time period and in a given area. This definition contains two elements; space and time [4]. The spatial element of risk specifies those areas that are susceptible to the development of failure at a given time, while the temporal element specifies the time the event will occur in a given area. According to [5] the prediction through the use of various methods and techniques of the spatial distribution of landslides is by far the most investigated topic that aids land – use planning, decision making and overall landslide risk reduction strategies. A region is considered to be prone to landslide phenomena when the geo – environmental conditions of the region share common features with a region where a failure has been manifested in the past [6]. Thus, the susceptibility of the area could be defined by a set of geological, tectonic and hydrologic conditions, morphological characteristics, soil and vegetation features, land use and human practices. In landslide susceptibility assessments, rainfall and seismic activity that are considered as external variables and are responsible for triggering landslides, are not taken into account since the term susceptibility refers to the probability of the presence of a landslide event considering only the spatial dimension of the problem.

A great number of different approaches have been utilized during the past three decades in the assessment of landslides that can be classified into qualitative, expert – driven methods, and quantitative, data - driven techniques [7, 8, 9, 10]. In general, qualitative methods are mainly based on the experience and knowledge provided by experts, while quantitative methods rely on statistical or probabilistic theories or the use of deterministic models.

Qualitative methods, expert – driven models, include mainly two types of processes: direct and indirect, with expert's judgment playing a significant role. In the direct approach, an expert estimates the boundaries of landslide-prone areas directly in the field, based on the observed phenomena and the geomorphological / geological setting of the area, while in the indirect approach an expert assigns to causative variables weights that represent the influence they have on landslide phenomena. Several methods have been developed and utilized such as boolean overlay, analytic hierarchy process [11, 12], fuzzy logic approach, fuzzy membership values assigned by expert and field knowledge [13], multi-class weighting methods [14, 15] and spatial multi-criteria analysis [9].

Quantitative methods, data – driven models, use data from past landslides, in order to obtain information on the relative importance of each factor on a statistical or probabilistic base. There are two main approaches: Bivariate statistical analysis that includes likelihood ratio model [16-18], information value method [19, 20] and weight of evidence modeling [15, 21, 22] and multivariate methods that include logistic regression and discriminant analysis [23-27].

Recently, Soft Computing techniques and methods are utilized as promising tools to evaluate the susceptibility and risk against landslides. These new applications are characterized by the ability of learning and discovering hidden and unknown patterns from large multi-thematic databases. Along with the advantage of processing and analyzing data, a similar evolution has been achieved with the usage of Geographic Information Systems (GIS). GIS has proven to be a significant scientific tool that provides new possibilities for better data manipulation and more advanced modeling opportunities. Soft Computing techniques include methods and techniques based on the concept of fuzzy logic [28-31], decision tree models [32-39], artificial neural networks [38, 40-42], support vector machine [43-47], and neuro-fuzzy [48-50].

Trying to evaluate the applicability and performance of each approach, expert – based models appear subjective and often ignore the fuzziness of expert judgment. The accuracy of the results depends significantly on the experience and time involvement of the expert. However, expert – based models may provide highly accurate results as they appear to be an efficient approach for landslide phenomena that are caused by different mechanisms [51] (Ruff and Czurda 2008). On the other hand, data – driven models including soft computing techniques, are influenced by the availability and the quality of data, with data of poor quality producing less accurate predictive models. It is also known, that bivariate statistical analysis and multivariate methods work well only if certain statistical criteria are satisfied, while data mining methods produce complex and hard to interpret models. Despite their different approach most of these techniques share a common process. They involve the analytical examination of the settings of known landslide prone areas, in order to provide information and knowledge regarding possible future landslides [10]. The landslide assessments are based on the assumption that past and present are keys to the future and also that areas with similar geo-environmental settings as the areas which have experienced landslides in the past, are also likely to experience landslides in the future [4, 8].

In this context, a special issue on "Landslide assessments through Soft Computing techniques within a GIS-based framework" was proposed in order to provide a forum for advancing the appropriate usage of Soft Computing techniques and GIS, for the assessments of landslide events. Specifically, the main objective of the special issue was to provide a review of the state-of-the-art in using integrated systems for effective landslide assessment and zonation incorporating expert knowledge, artificial intelligence and data mining technology in a GIS-based framework. The intention of the present special issue was to provide a stand for researchers to share ideas and information regarding landslide phenomena and advanced analytic tools. Three studies are presented, a brief description of which appear in the following paragraphs.

The goal of the first paper was to apply a Support Vector Machine for the construction of a landslide susceptibility map in the Nancheng area, China. The analysis was based on a database of 224 sites that was classified into non-landslide and landslide areas. Eight geo – environmental variables were analyzed, namely: lithology, soil, slope, aspect, elevation, topographic wetness index, distance to rivers and distance to faults. The database, 224 sites were separated into a training dataset (70%) and a validation dataset (30%). The validation of the outcomes was achieved using statistical evaluation measures, the receiving operating characteristic and the area under the prediction rate curves. In order to question the predictive performance of the Support Vector Machine, a Naïve Bayes classifier was also utilized, and the predictive accuracy of which was estimated. The analysis showed that the Support Vector Machine identified correctly 89.70% of the instances during the validation, followed by the Naïve Bayes model (86.78%).

The main objective of the second paper was to produce a landslide susceptibility map for the Finikas watershed that is located in the Achaia County, North Peloponnese, Greece, following the principles of Analytic Hierarchical Process. Six parameters were analyzed, namely: lithological units, elevation, slope angle, slope aspect, distance from faults and distance from river network. Each parameter was classified into different classes and weighted according to their susceptibility to slide by implementing the Analytical Hierarchical Process. The landslide susceptibility map was reclassified into five classes of varying landslide susceptibility. The high and very high susceptibility class was estimated to cover the 8.18% and 19.55% of the research area, respectively. The relative landslide density for the high and very high landslide susceptibility class was estimated to be 69.45%. The developed model could be considered as a useful tool for the national and local authorities as it could assist in managing landslide related variables in a much easier and automated manner, maximizing the functionality of GIS environment and producing quite accurate landslide susceptibility maps.

The third paper presents an application of Logistic regression model in the watershed of Krathis River that is located in the Achaia County, North Peloponnese, Greece. Five parameters were analyzed, namely: engineering geological units, slope angle, slope aspect, distance from faults and distance from river network. Each parameter was classified into different classes and weighted according to their susceptibility to slide. It was evaluated that the developed model classified correctly over 80% of the validation data. As reported by the authors, the developed model could be considered as a useful tool for the national and local authorities in order to evaluate strategies to prevent and mitigate the impact of landslides.

We hope the above contributions will assist in realizing the usefulness and effectiveness of Soft Computing techniques and GIS for coping landslide phenomena, in understanding their advantages and limitations and in inspiring researchers for developing new methods and techniques that couple expert and data driven methods.

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