Developing a neuro–fuzzy system to classify drainage sub-basins according to erosion processes on the Island of Lefkas, Greece

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ABSTRACT

In this paper we attempt to classify drainage sub-basins according to their erosion risk. We have adopted a multi-step procedure to face this problem. The input variables were introduced into a GIS – platform. These variables were the vulnerability of the surface rocks to erosion, topographic variations, vegetation cover, land use and drainage basin characteristics. We constructed a fuzzy inference mechanism to pre-process the input variables. Next we used neural-network technology to process the input variables. The system was trained to 'learn' and classify the input data. The output of this procedure was a classification of the sub-drainage basins related to their risk of erosion. This neuro–fuzzy system was applied to the island of Lefkas (Greece).

KEYWORDS

erosion; fuzzy sets; neural networks; GIS; Ionian Sea

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1. Introduction

Environmental settings such as geological, geomorphological and climatic conditions affect drainage structures. Characteristics of rocks and soils, geographical distribution and intensity of rainfall, along with micro-topography, determine surface and

underground water. Runoff can be either Hortonian or not depending on the infiltration capacity of surface rocks. Emmet (1978) has stated that the flow characteristics of the surface waters may produce rills or sheet flow, and as a result, weathered material can be transferred by water movement. Tem-

poral and spatial aspects also affect erosional processes. Splash erosion, caused by raindrop impact, seems to greatly influence the detachment of material. According to Kirkby (1978), the rate of soil erosion is proportional to the distance from the divide multiplied by the power of slope gradient. The phenomenon of soil erosion has been studied by many researchers (Stocking, Elwell, 1973; Elwell, 1978;

Wischmeier and Smith, 1978; Morgan et al., 1984; Nearing et al., 1989; Briggs and Giordano, 1992; Thornes et al., 1996; Baturst et al., 1996; Koulouri and Giourga, 2007; Cerdan et al., 2010). Some methodologies of artificial intelligence, especially fuzzy set theory, have also been previously applied to erosion issues by Burrough (1989), Burrough et al. (1992), Gournelos et al. (2005).

Figure 1 Location of the study area

In addition to the natural modification of drainage basins, human induced factors also play an important role: activities such as the expansion of agricultural areas, building activity and fires greatly affect erosion rates. Soils are key to ecosystems and human societies, and their critical importance requires a better understanding of how they evolve through time. However, identifying the role of natural climate change versus human activity (e.g. agriculture) on soil evolution is difficult (Rothacker et al., 2018).

The Mediterranean region is particularly vulnerable to erosion. This is primarily owed to major

land-use changes during the last decades and the long dry periods followed by intensive and erosive rainfall, particularly on areas of steep slopes with fragile soils, (Van der Knijff et al., 1999).

In this paper, the combination of fuzzy set theory and neural network technology constitutes an innovative methodology that was used to study erosion processes, by generating classifications of autonomous drainage units. All variables affecting and defining erosion were considered here, and the methodology was applied on the island of Lefkas.

Figure 2 The hipsometry of Lefkas island

2. Study area

Lefkas Island is located in the Ionian Sea, in the western part of Greece (Fig. 1) and covers an area of 294 km². The island is mainly characterized by mountainous and hilly landscapes and a few basins of low altitude (Fig. 2). It is composed of alpine and post-alpine rock formations, some of which are extremely vulnerable to erosion processes. The geological study of Lefkas has been the object of several studies, such as Bornovas (1964), Verginis

(1976), Livaditis and Verikiou-Papaspiridakou (1987) and Underhill (1989). The study area is composed of two geotectonic units, Ionian and Paxoi. The greater part of Lefkas is covered by the Ionian unit (210 km²) while the Paxoi unit is located in the southwest part of the island (covering an area of 63 km²). The main lithologies of the alpine substratum are limestones and flysch. There are also some Neogene and Quaternary formations in the internal and coastal basins of the island (Fig. 3). It becomes clear

from the lithological composition that some of the island's surface rock formations are extremely vulnerable to weathering and erosion processes.

The island's annual precipitation levels are relatively high (mean value: 942.3 mm/year. for the

years 1975–1997; Nastos, 2001). Lefkas belongs to a zone of high seismicity. A recent earthquake with a magnitude of 6.4 (14/08/03) resulted in a number of landslides in its western part, where steep slopes are dominant (Fig. 2).

Figure 3 Lithological formations of Lefkas island

3. Methodology

In order to study a process as complex as erosion, it was deemed necessary to develop a GIS-based procedure. Firstly, data from various thematic maps, aerial-photos and fieldwork were digitized and im-

ported into a GIS (MapInfo 2006). Secondly, the definition of the input and output variables was accomplished. The input variables that were processed are the following: vulnerability of surface rocks to erosion, vegetation cover and land use, drainage characteristics and slope gradient.

The three first variables are closely related to the erodibility of rocks. Rock vulnerability to erosion is the result of several physical and chemical factors, such as rock composition and structure and the presence or absence of protective vegetation. Vegetation and land use firstly control the infiltration mechanism and hence water runoff (sheet flow or rills), and secondly they affect the impact of precip-

itation (Kirkby, 1995). The drainage network is the result of an established surface and subsurface flow system. The drainage system characteristics were studied by using the drainage density variable. The slope gradient determines the surface flow regime. This flow system becomes very erosive when the terrain morphology is dominated by steep slopes.

Figure 4 A neural-fuzzy system to produce erosion risk map

Erosion risk was the output variable. The sub-basins of the drainage system constituted the basic units for the evaluation of the input variables.

The next step was to establish an interference mechanism with which to transform the input parameters into output parameters. This process consisted of two stages: a fuzzy-based transformation and the creation of a neural network system (Fig. 4). In the first stage the input variables used were: a) rock vulnerability to erosion, b) vegetation – land use, and c) drainage density. The output variable was the rock's erodibility to erosion. All the aforementioned variables present problems of imprecision in terms of their quantification and the definition of their spatial boundaries. For this reason, it was necessary to use fuzzy set theory (Zimmermann, 1991; Klir and Yuan, 1995) (Fig. 4). The fuzzy model was produced by assigning an appropriate membership function to all variables involved and by using logical rules as a transformational mechanism

(Mamdani and Assilion, 1975). The formulation of fuzzy logical rules (Table 1) was based on numerous field observations and the authors' experience of erosion processes. The system's output is of a fuzzy nature. Therefore, defuzzification was carried out, using the centroid technique.

In the second stage we developed an artificial neural network model to classify the drainage sub-basins. In this model the input variables were rock erodibility, as derived from the fuzzy model, and slope steepness. In the neural network model, we constructed a three-neuron layer to classify the sub-basins according to the degree of erosion risk (Fig. 5). We used competitive learning architecture, which is based on the distance between data input and the weight. The winning neuron is the one with the minimum distance. This process is repeated until all input data are classified (Kohonen, 1982; Rumelhart and Zipser, 1985).

Table 1 Fuzzy interfaces rules

If VULNERABILITY IS High	&	VEGETATION – LAND USE INDEX IS Low		Then ERODIBILITY of ROCKS Is High
If VULNERABILITY IS High	&	VEGETATION – LAND USE INDEX IS Low	& SLOPE IS High–Medium	Then ERODIBILITY of ROCKS Is Medium
If VULNERABILITY IS High	&	VEGETATION – LAND USE INDEX IS Low–Medium	& SLOPE IS Low	Then ERODIBILITY of ROCKS Is Medium
If VULNERABILITY IS Medium	&	VEGETATION – LAND USE INDEX IS Low	& SLOPE IS High	Then ERODIBILITY of ROCKS Is High
If VULNERABILITY IS Medium	&	VEGETATION – LAND USE INDEX IS Low	& SLOPE IS Medium–Low	Then ERODIBILITY of ROCKS Is Medium
If VULNERABILITY IS Medium	&	VEGETATION – LAND USE INDEX IS Medium	& SLOPE IS High	Then ERODIBILITY of ROCKS Is Medium
If VULNERABILITY IS Medium	&	VEGETATION – LAND USE INDEX IS Medium	& SLOPE IS Medium	& Drainage density IS Medium Low
If VULNERABILITY IS Medium	&	VEGETATION – LAND USE INDEX IS Medium	& SLOPE IS Low	& Drainage density IS Medium–Low
				Then ERODIBILITY of ROCKS Is Low
				Then ERODIBILITY of ROCKS Is Medium

Figure 5 A three–neuron layer was used with biases

The erosion risk was the output variable of this final stage. The implementation of the aforementioned procedures was achieved using a G.I.S. (MapInfo 2006) and the Matlab software platform (Matlab 2005). The fuzzy model and the artificial neural network model were constructed in a Matlab environment loosely coupled with the G.I.S. The values of the input variables were obtained by digitizing topographic and geological maps (1:50.000 Geographic Military Service; Bornovas, 1964), by analyzing aerial photos (1:33.000, 1986) and satellite images (Landsat, 1980) and through field observations.

Figure 6 The drainage basins of the island of Lefkas

In the fuzzy model, triangular functions were adopted in the pre-processing stage. All variables were characterized by fuzzy set values, and were expressed with the appropriate membership function. In the present study, “low”, “medium” and “high” define the different degrees of rock vulnerability. Rock vulnerability values for Lefkas were

based on empirical knowledge, field observations and published material (Kuenen, 1956; Leopold et al., 1964; Sparks, 1965; Bolton, 1979; Selby, 1987). We assigned high vulnerability values to the Quaternary and Neogene formations (marls, conglomerates), medium values to the flysch formations and low values to the limestones. The slope gradient and

the drainage density variables were obtained from the topographic maps, through GIS analysis. The vegetation and land use variable was based on aerial photos, satellite images and field data. The island's vegetation cover consists of trees, bushes and agricultural areas. Land use has largely changed as a result of tourist developments over the last decades.

Figure 7 The input variables used in order to extract the erosion risk variable, a) vulnerability, b) vegetation–land use, c) drainage density and d) slope

Table 2 Input variables

Id	Vulnerability Normalized	Vegetation – Land use Index Normalized	Drainage Density Normalized	Slope gradient Normalized
1	1.00	0.62	0.36	0.26
2	0.92	0.54	0.44	0.42
3	0.98	0.85	0.59	0.39
4	0.74	0.90	0.27	0.49
5	0.73	0.64	0.68	0.43
6	0.79	0.81	0.48	0.63
7	0.61	0.85	0.48	0.68
8	0.67	0.94	0.71	0.51
9	0.52	0.98	0.62	0.66
10	0.75	0.85	0.58	0.52
11	0.77	0.90	0.73	0.83
12	0.56	0.97	0.62	0.80
13	0.53	0.90	0.69	0.59
14	0.39	0.95	0.66	0.72
15	0.53	0.83	0.60	0.72
16	0.38	0.97	0.45	0.94
17	0.47	0.88	0.46	0.85
18	0.42	0.91	0.61	0.49
19	0.37	0.80	0.37	0.62
20	0.49	0.64	0.46	0.34
21	0.52	0.62	0.39	0.41
22	0.79	0.98	0.26	0.55
23	0.85	0.58	0.68	0.60
24	0.58	0.96	0.79	0.65
25	0.70	0.90	0.78	0.72
26	0.82	0.55	1.00	0.43
27	0.81	0.64	0.46	0.37
28	0.64	0.91	0.48	0.49
29	0.36	0.99	0.54	0.81
30	0.37	0.98	0.31	0.65
31	0.39	1.00	0.14	0.74
32	0.36	0.61	0.30	0.55
33	0.38	0.52	0.69	0.60
34	0.38	0.52	0.67	0.55
35	0.36	0.64	0.61	0.57
36	0.37	0.61	0.59	0.44
37	0.36	0.95	0.70	0.87
38	0.36	0.82	0.58	0.72
39	0.36	0.81	0.41	1.00
40	0.50	0.90	0.50	0.60
41	0.55	0.57	0.24	0.61
42	0.44	0.98	0.46	0.61
43	0.39	0.60	0.19	0.63
44	0.39	0.83	0.62	0.80
45	0.42	0.57	0.32	0.75
46	0.48	0.62	0.34	0.58
47	0.38	0.11	0.18	0.44
48	0.36	0.16	0.14	0.40
49	0.81	0.81	0.24	0.27
50	0.79	0.59	0.56	0.37

We used the same fuzzy classes for the drainage density and vegetation – land use variables. Thus, low index values for vegetation and land use indicate drainage basins with sparse or no vegetation, medium values indicate underdeveloped vegetation cover, whereas high values signify relatively dense vegetation cover.

The drainage network is defined by topography and surface rock formations. We have identified 50 drainage sub-basins for the whole island (Fig. 6). In order to combine data layers, all the original data were normalized by dividing them by their maxi-

um value. All normalized values are presented in Table 2.

Using the rules of Table 1, mapping of the three input variables was accomplished, rock vulnerability, vegetation/land use and drainage density (Fig. 7a, b, c), in order to create the output variable, the rock's erodibility. The erodibility variable was then combined with slope steepness (Fig. 7d) within the developed neural network to create the erosion risk variable. The final output variable of this neuro-fuzzy system was the erosion risk for all the drainage sub-basins on Lefkas (Fig. 8).

Figure 8 Erosion Risk index of all the drainage sub-basins on Lefkas

4. Discussion and conclusions

In the case of Lefkas island, we established three classes of erosion risk: high, medium and low. A

sensitivity analysis was carried out in order to test the model's behavior to minimal changes in the input variables. As was expected, small perturba-

tions in the values of the three input variables cause no significant changes in the output variables (i.e. the erosion risk index).

We have established three classes of erosion risk: high, medium and low (Fig. 8). The drainage sub-basins belonging to the upper classes (high erosion risk) are situated in the northeastern and the southern parts of the island. The medium risk drainage sub-basins are situated in the central part, while the low risk basins are located mainly in the eastern part. The spatial distribution of the erosion risk index variable may be primarily related to the spatial distribution of the lithological formations: where highly vulnerable rocks are present (Neogene and Quaternary) high risk drainage sub-basins are also located, whereas low risk drainage sub-basins are situated in locations with rocks that are more resistant to erosion (limestones). The whole classification scheme takes into account all the input variables involved, especially the nature of surface rocks and topography.

This neuro-fuzzy approach for studying erosional processes is an extremely practical tool because of its ability to handle and classify qualitative data. Erosion risk maps, such as the one produced for Lefkas Island, may be used to identify areas of risk and for the implementation of mitigation measures to protect agricultural and urban areas. This relatively simple model may be used in local- and region-level planning, environmental protection and hazard assessments. This methodology may be further improved by using smaller scale grid-based data as elementary input variables.

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