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Using Self Organising Maps in Applied Geomorphology

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1. Introduction

Geomorphology is the science that studies landscape evolution, thus stands in the centre of the Earth's surface sciences, where, geology, seismology, hydrology, geochemistry, geomorphology, atmospheric dynamics, biology, human dynamics, interact and develop a dynamic system (Murray, 2009). Usually the relationships between the various factors portraying geo-systems are non linear. Neural networks which make use of non–linear transformation functions can be employed to interpret such systems. Applied geomorphology, for example, adaptive environmental management and natural hazard assessment on a changing globe requires, expanding our understanding of earth surface complex system dynamics. The inherent power of self organizing maps to conserve the complexity of the systems they model and self–organize their internal structure was employed, in order to improve knowledge in the field of landscape development, through characterization of drainage basins landforms and classification of recent depositional landforms such as alluvial fans. The quantitative description and analysis of the geometric characteristics of the landscape is defined as geomorphometry. This field deals also, with the recognition and classification of landforms.

Landforms, according to Bishop & Shroder, (2004) carry two geomorphic meanings. In relation to the present formative processes, a landform acts as a boundary condition that can be dynamically changed by evolving processes. On the other hand formative events of the past are inferred from the recent appearance of the landform and the material it consists of. Therefore the task of geomorphometry is twofold: (1) Quantification of landforms to derive information about past forming processes, and (2) determination of parameters expressing recent evolutionary processes. Basically, geomorphometry aims at extracting surface parameters, and characteristics (drainage network channels, watersheds, planation surfaces, valleys side slopes e.t.c), using a set of numerical measures derived usually from digital elevation models (DEMs), as global digital elevation data, now permit the analysis of even more extensive areas and regions. These measures include slope steepness, profile and plan curvature, cross- sectional curvature as well as minimum and maximum curvature, (Wood, 1996a; Pike, 2000; Fischer et al., 2004). Numerical characterizations are used to quantify generic landform elements (also called morphometric features), such as point–based features (peaks, pits and passes), line-based features (stream channels, ridges, and crests), and area based features (planar) according to Evans (1972) and Wood, (1996b).

In the past, manual methods have been widely used to classify landforms from DEM, (Hammond, 1964). Hammond's (1964) typology, first automated by Dikau et al., (1991), was modified by Brabyn, (1997) and reprogrammed by Morgan & Lesh, (2005). Bishop & Shroder, (2004) presented a landform classification of Switzerland using Hammond's method. Most recently, Prima et al., (2006) mapped seven terrain types in northeast Honshu, Japan, taking into account four morphometric parameters. Automated terrain analyses based on DEMs are used in geomorphological research and mainly focus on morphometric parameters (Giles & Franklin, 1998; Miliaresis, 2001; Bue & Stepinski, 2006). Landforms as physical constituents of landscape may be extracted from DEMs using various approaches including combination of morphometric parameters subdivided by thresholds (Dikau, 1989; Iwahashi & Pike, 2007), fuzzy logic and unsupervised classification (Irvin et al., 1997; Burrough et al., 2000; Adediran et al., 2004), supervised classification (Brown et al., 1998; Prima et al., 2006), probabilistic clustering algorithms (Stepinski & Collier, 2004), multivariate descriptive statistics (Evans, 1972; Dikau, 1989; Dehn et al.,2001) discriminant analysis (Giles, 1998), and neural networks (Ehsani & Quiel, 2007).

The Kohonen self organizing maps (SOM) (Kohonen, 1995) has been applied as a clustering and projection algorithm of high dimensional data, as well as an alternative tool to classical multivariate statistical techniques. Chang et al., (1998, 2000, 2002) associated well log data with lithofacies, using Kohonen self organizing maps, in order to easily understand the relationships between clusters. The SOM was employed to evaluate water quality (Lee & Scholtz, 2006), to cluster volcanic ash arising from different fragmentation mechanisms (Ersoya et al., 2007), to categorize different sites according to similar sediment quality (Alvarez–Guerra et al., 2008), to assess sediment quality and finally define mortality index on different sampling sites (Tsakovski et al., 2009). SOM was also used for supervised assessment of erosion risk (Barthkowiak & Evelpidou, 2006). Tselentis et al., (2007) used P-wave velocity and Poisson ratio as an input to Kohonen SOM and identified the prominent subsurface lithologies in the region of Rion–Antirion in Greece. Esposito et al., (2008) applied SOM in order to classify the waveforms of the very long period seismic events associated with the explosive activity at the Stromboli volcano. Achurra et al., (2009) applied SOM in order to reveal different geochemical features of Mn-nodules, that could serve as indicators of different paleoceanographic environments. Carniel et al., (2009) describe SOM capability on the identification of the fundamental horizontal vertical spectral ratio frequency of a given site, in order to characterize a mineral deposit. Ferentinou & Sakellariou (2005, 2007) applied SOM in order to rate slope stability controlling variables in natural slopes. Ferentinou et al., (2010) applied SOM to classify marine sediments.

As evidenced by the above list of references, modeling utilizing SOM has recently been applied to a wide variety of geoenvironmental fields, though in the 90s, this approach was mostly used for engineering problems but also for data analysis in system recognition, image analysis, process monitoring, and fault diagnosis. It is also evident that this method has a significant potential.

Alluvial fans are prominent depositional landforms created where steep high power channels enter a zone of reduced stream power and serve as a transitional environment between a degrading upland area and adjacent lowland (Harvey, 1997). Their morphology resembles a cone segment with concave slopes that typically range from less than 25 degrees at the apex to less than 1 degree at the toe (Figure 1a).

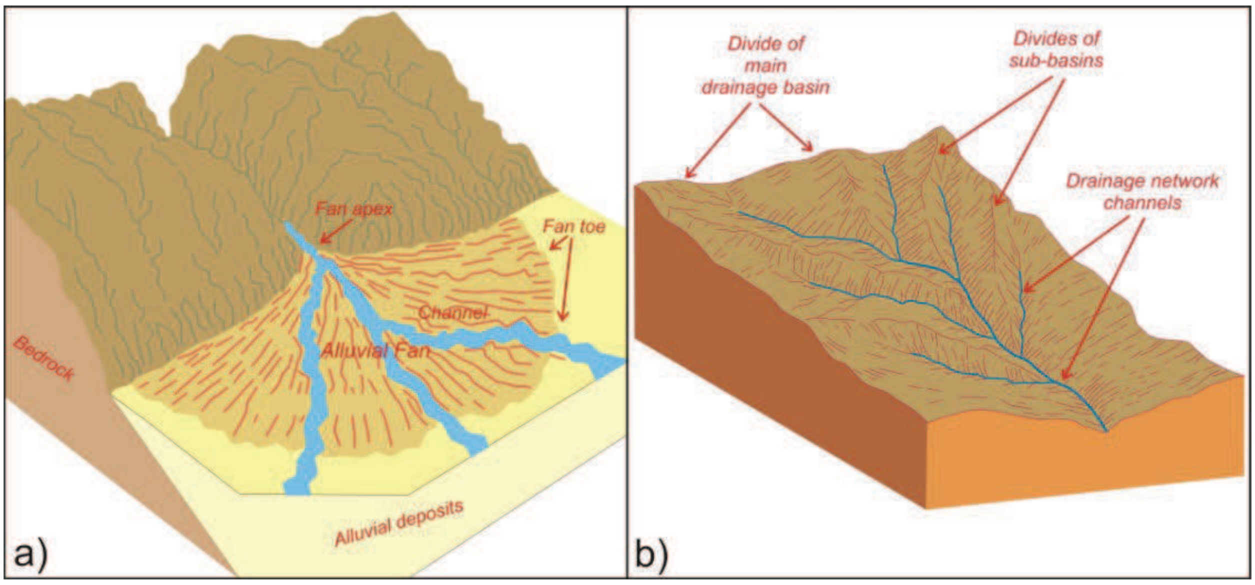


Fig. 1. (a) Schematic representation of a typical alluvial fan, and (b) representation of a typical drainage basin

Alluvial fan characterization is concerned with the determination of the role of the fluvial sediment supply for the evolution of fan deltas. The analysis of the main controlling factors on past and present fan processes is also of major concern in order to distinguish between the two dominant sedimentary processes on alluvial fan formation and evolution: debris flows and stream flows. Crosta & Frattini, (2004), among others, have worked in two dimensional planimetric area used discriminant analysis methods, while Giles, (2010), has applied morphometric parameters in order to characterize fan deltas as a three dimensional sedimentary body. There are studies which have explored on a probabilistic basis the relationships, between fan morphology, and drainage basin geology (Melton, 1965; Kostaschuck et al., 1986; Sorisso-Valvo & Sylvester, 1993; Sorisso-Valvo, 1998). Chang & Chao (2006), used back propagation neural networks for occurrence prediction of debris flows.

In this paper the investigation focuses on two different physiographic features, which are recent depositional landforms (alluvial fans) in a microrelief scale, and older landforms of drainage basin areas in a mesorelief scale (Figure 1b). In both cases landform characterization, is manipulated through the technology of self organising maps (SOMs). Unsupervised and supervised learning artificial neural networks were developed, to map spatial continuum among linebased and surface terrain elements. SOM was also applied as a clustering tool for alluvial fan classification according to dominant formation processes.

2. Method used

2.1 Self organising maps

Kohonen's self-organizing maps (SOM) (Kohonen, 1995), is one of the most popular unsupervised neural networks for clustering and vector quantization. It is also a powerful visualization tool that can project complex relationships in a high dimensional input space onto a low dimensional (usually 2D grid). It is based on neurobiological establishments that the brain uses for spatial mapping to model complex data structures internally: different sensory inputs (motor, visual, auditory, etc.) are mapped onto corresponding areas of the cerebral cortex in an ordered form, known as topographic map. The principal goal of a SOM is to transform an incoming signal pattern of arbitrary dimension n into a low dimensional discrete map. The SOM network architecture consists of nodes or neurons arranged on 1-D or usually 2-D lattices (Fig. 2). Higher dimensional maps are also possible, but not so common.

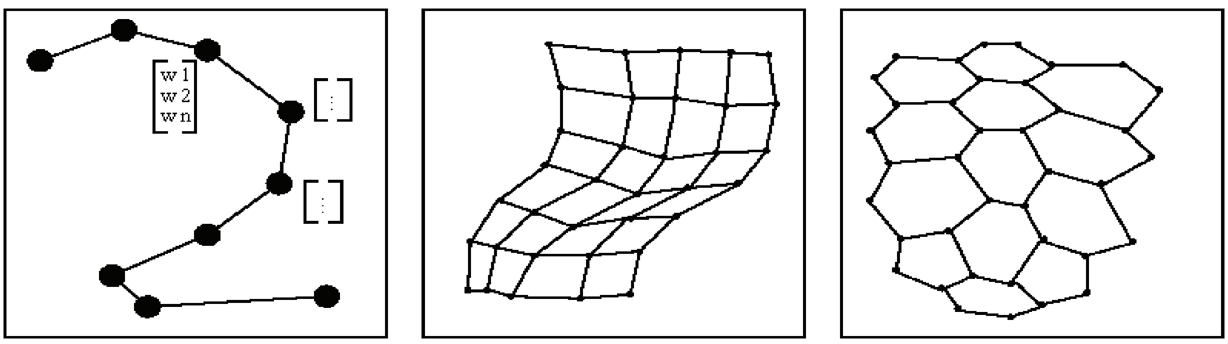


Fig. 2. Examples of 1-D, 2-D Orthogonal and 2-D Hexagonal Lattices

Each neuron has a d dimensional weight vector (prototype or codebook vector) where d is equal to the dimension of the input vectors. The neurons are connected to adjacent neurons by a neighborhood relation, which dictates the topology, or structure, of the map.
The SOM is trained iteratively. In each training step a sample vector x from the input data set is chosen randomly and the distance between x and all the weight vectors of the SOM, is calculated by using an Euclidean distance measure. The neuron with the weight vector which is closest to the input vector x is called the Best Matching Unit (BMU). The distance between x and weight vectors is computed using the equation below:

$$\|x - m_c\| = \min\{\|x_i - m_i\|\} \tag{1}$$

where ||.|| is the distance measure, typically Euclidean distance. After finding the BMU, the weight vectors of the SOM are updated so that the BMU is moved closer to the input vector in the input space. The topological neighbors of the BMU are treated similarly. The update rule for the weight vector of i is

$$x_i(t+1) = m_i(t) + a(t)h_{ci}(t)\left[x(t) - m_i(t)\right] \tag{2}$$

where x(t) is an input vector which is randomly drawn from the input data set, a(t) function is the learning rate and t denotes time. A Gaussian function $h_{ci}(t)$ is the neighborhood kernel around the winner unit m_c, and a decreasing function of the distance between the i_{th} and c_{th} nodes on the map grid. This regression is usually reiterated over the available samples.
All the connection weights are initialized with small random values. A sequence of input patterns (vectors) is randomly presented to the network (neuronal map) and is compared to weights (vectors) “stored” at its node. Where inputs match closest to the node weights, that

area of the map is selectively optimized, and its weights are updated so as to reproduce the input probability distribution as closely as possible. The weights self-organize in the sense that neighboring neurons respond to neighboring inputs (topology which preserves mapping of the input space to the neurons of the map) and tend toward asymptotic values that quantize the input space in an optimal way. Using the Euclidean distance metric, the SOM algorithm performs a Voronoi tessellation of the input space (Kohonen, 1995) and the asymptotic weight vectors can then be considered as a catalogue of prototypes, with each such prototype representing all data from its corresponding Voronoi cell.

2.2 SOM visualization and analysis

The goal of visualization is to present large amounts of information in order to give a qualitative idea of the properties of the data. One of the problems of visualization of multidimensional information is that the number of properties that need to be visualized is higher than the number of usable visual dimensions.

SOM Toolbox (Vesanto, 1999; Vesanto & Alboniemi, 2000), a free function library package for MATLAB, offers a solution to use a number of visualizations linked together so that one can immediately identify the same object from the different visualizations (Buza et al., 1991). When several visualizations are linked in the same manner, scanning through them is very efficient because they are interpreted in a similar way. There is a variety of methods to visualize the SOM. An initial idea of the number of clusters in the SOM as well as their spatial relationships is usually acquired through visual inspection of the map. The most widely used methods for visualizing the cluster structure of the SOM are distance matrix techniques, especially the unified distance matrix (U-matrix). The U-matrix visualizes distances between prototype vectors and neighboring map units and thus shows the cluster structure of the map. Samples within the same unit will be the most similar according to the variables considered, while samples very different from each other are expected to be distant in the map. The visualization of the component planes help to explain the results of the training. Each component plane shows the values of one variable in each map unit. Simple inspection of the component layers provides an insight to the distribution of the values of the variables. Comparing component planes one can reveal correlations between variables.

Another visualization method offered by SOM is displaying the number of hits in each map unit. Training of the SOM, positions interpolating map units between clusters and thus obscures cluster borders. The Voronoi sets of such map units have very few samples ("hits") or may even be empty. This information is utilized in clustering the SOM by using zero-hit units to indicate cluster borders.

The most informative visualizations of all offered by SOM are simple scatter plots and histograms of all variables. Original data points (dots) are plot in the upper triangle, though map prototype values (net) are plot on the lower triangle. Histograms of main parameters are plot on the diagonal. These visualizations reveal quite a lot of information, distributions of single and pairs of variables both in the data (upper triangle) and in the trained map (lower triangle). They visualize the parameters in pairs in order to enhance their correlations. A scatter diagram can extend this notion to the multiple pairs of variables.

3. Study area

The case study area is located on the northwestern part of the tectonically active Gulf of Corinth which is an asymmetric graben in central Greece trending NW-SE across the Hellenic mountain range, approximately perpendicular to the structure of Hellenides (Brooks & Ferentinos, 1984; Armijo et al., 1996). The western part of the gulf, where the study area is located, is presently the most active with geodetic extension rates reaching up to 14-16 mm/yr (Briole et al., 2000). The main depositional landforms along this part of the gulf's coastline are coastal alluvial fans (also named fan deltas) which have developed in front of the mouths of fourteen mountainous streams and torrents. Alluvial fan development within the study area is the result of the combination of suitable conditions for fan delta formation during the Late Holocene. Their evolution and geomorphological configuration is affected by the tectonic regime of the area (expressed mainly by submergence during the Quaternary), weathering and erosional surface processes throughout the corresponding drainage basins, mass movement (especially debris flows), and the stabilization of the eustatic sea-level rise about 6,000 years ago (Lambeck, 1996).

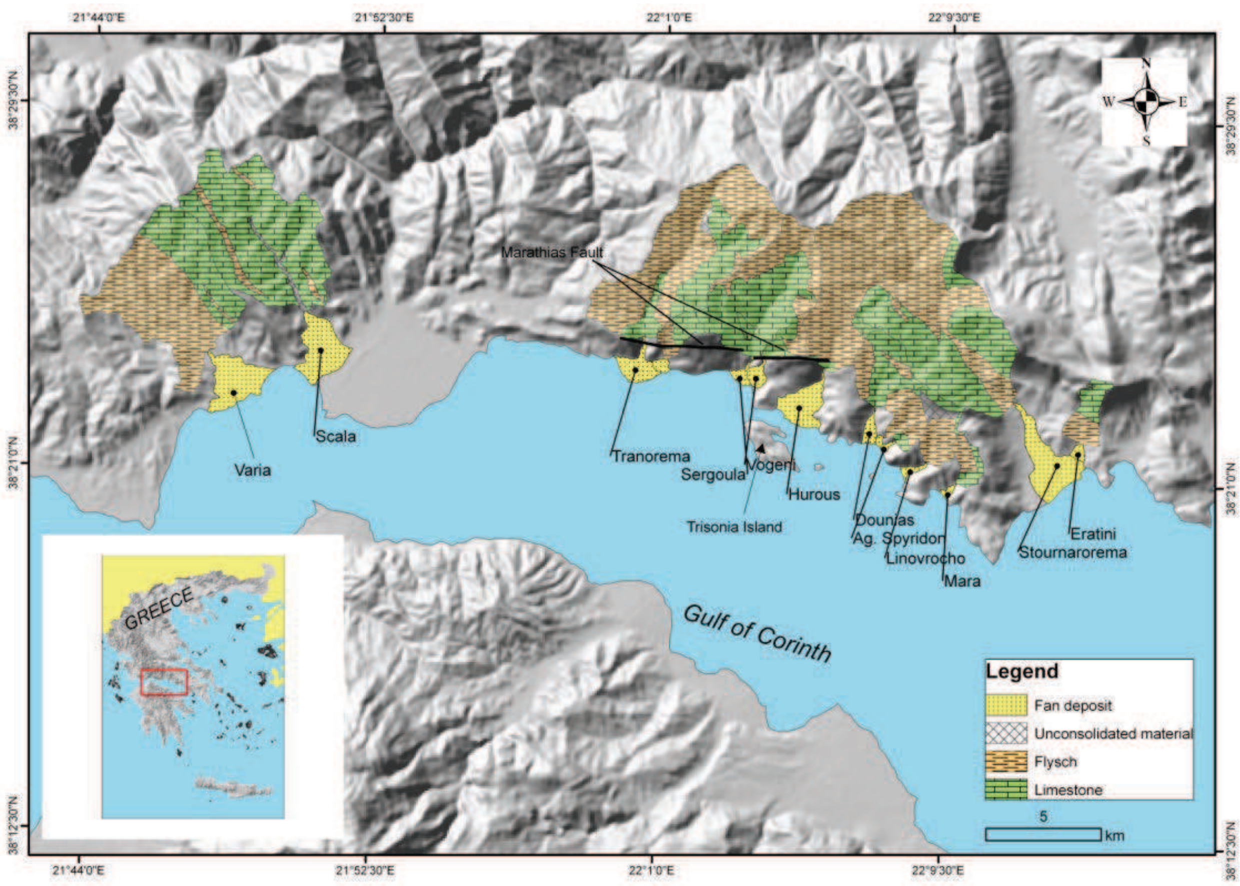


Fig. 3. Simplified lithological map of the study area

Apart from the classification of microscale landforms, such as the above mentioned coastal alluvial fans, this study also focuses on mesoscale landforms characterization. This attempt concerns the hydrological basin areas of the streams of (from west to east) Varia, Skala, Tranorema, Marathias, Sergoula, Vogeri, Hurous, Douvias, Gorgorema, Ag. Spiridon, Linovrocho, Mara, Stournarorema and Eratini, focusing on the catchments of Varia and

Skala streams. Landforms distribution within the studied drainage basins are mainly controlled by the bedrock lithology. Therefore, it is important to outline the geology of the area. The basic structural pattern of the broader area of the drainage basins was established during the Alpine folding. The drainage basins are dominated by geological formations of the geotectonic zones of Parnassos–Ghiona, Olonos-Pindos and Ionian and the Transitional zone between those of Parnassos–Ghiona and Olonos-Pindos. The easternmost basins (Eratini and part of Stournarorema) are made up of Tithonian to Senonian limestones of the Parnassos–Ghiona zone and the Transitional Sedimentary Series (limestones of Upper Triassic to Paleocene age and sandstones and shales of the Paleocene–Eocene flysch). The majority of the catchments consist of the Olonos–Pindos zone formations which are represented by platy limestones of Jurassic-Senonian age and Upper Cretaceous - Eocene flysch lithological sequences (mainly sandstones and shales). Part of the westernmost Varia drainage system drains flysch formations (mainly marls, sandstones and conglomerates) of the Ionian zone. A simplified lithological map of the catchments is presented in Fig3. Tectonically the area is affected by an older NW-SE trending fault system, contemporaneous to the Alpine folding and a younger one having an almost E-W direction with the active normal fault of Marathias (Gallousi & Koukouvelas, 2007) and normal faults located in the broader area of Trizonia Island being the most significant.

4. Application of SOM in landform characterization - Input variables and data preparation

This research is based on quantitative and qualitative data depicting the morphology and morphometry of fans and their drainage basins. These data derived from field-work, SRTM DEM data and topographic and geological maps at various scales. The correlation between geomorphological features (expressed by morphometric parameters) of the drainage basins and features of their fan deltas was detected, in order to determine the role of the fluvial sediment supply for the evolution of the fan deltas.

A simplified lithological map of the area was constructed from the geological maps of Greece at the scale of 1:50,000 obtained from the Institute of Geology and Mineral Exploration of Greece (I.G.M.E.). The lithological units cropping out in the basins area were grouped in three categories including limestones, flysch formations (sandstones, shales and conglomerates) and unconsolidated sediments. The area cover occupied from each one of the three main lithological types in the area of each basin was also estimated.

The identification and delineation of the fans was based upon field observations, aerial photo interpretation and geological maps of the surficial geology of the area at the scale of 1:50,000 (Paraschoudis, 1977; Loftus & Tsoflias, 1971). Detailed topographic diagrams at the scale of 1:5.000, were used for the calculation of the morphometric parameters of the fan deltas. All topographic maps were obtained from the Hellenic Military Geographical Service (H.M.G.S). The elevation of the fan apex was measured by altimeter or GPS for most of the studied fans. All measurements and calculations of the morphometric parameters were performed using Geographical Information System (GIS) functions. The morphometric variables obtained for each fan and its corresponding drainage basin are described in Table 1.

Table 2 presents the values of the (fifteen) morhometric parameters measured and estimated for the coastal alluvial fans and their drainage basins.

Drainage basin morphometric parameters			
	Morphometric Parameter	Symbol	Explanation
1	Drainage basin area	(A_b)	The total planimetric area of the basin above the fan apex, measured in km^2.
2	Basin crest	(C_b)	The maximum elevation of the drainage basin given in m.
3	Perimeter of the drainage basin	(P_b)	The length of the basin border measured in km.
4	Total length of the channels within the drainage basin	(L_c)	Measured in km.
5	Total length of 20 m contour lines within the drainage basin	(ΣL_c)	Measured in km.
6	Basin relief	(R_b)	Corresponds to the vertical difference between the basin crest and the elevation of fan apex, given in m.
7	Melton' s ruggedness number	(M)	An index of basin ruggedness (Melton, 1965, Church and Mark, 1980) calculated by the following formula: $M=R_b A_b^{-0.5}$
8	Drainage basin slope	(S_b)	Obtained using the following equation : $S_b=e\Sigma L_c/A_b$ e is the equidistance (20m for the maps that were used in this study).
9	Drainage basin circularity	(Cir_b)	It is given by the equation: $Cir_b=4\pi A_b/P_b^2$ and expresses the shape of the basin.
10	Drainage basin density	(D_b)	The ratio of the total length of the channels to the total area of the basin.
Fan delta morphometric parameters			
11	Fan area	(A_f)	The total planimetric area of each fan, measured in km^2.
12	Fan length	(L_f)	The distance between the toe (coastline for most of the fans) and apex of the fan, measured in m.
13	Fan apex	(Ap_f)	The elevation of the apex of the fan in m.
14	Fan slope	(S_f)	The mean gradient measured along the axial part of the fan.
15	Fan concavity	(C_f)	An index of concavity along the fan axis defined as the ratio of a to b, where a is the elevation difference between the fan axis profile and the midpoint of the straight line joining the fan apex and toe, and b is the elevation difference between the fan toe and midpoint.

Table 1. Definition of drainage and fan delta morphometric parameters

	Stream/fan name	A_b	C_b	P_b	L_c	ΣL_c	R_b	M	S_b	Cir_b	D_b	A_f	L_f	Ap_f	S_f	C_f
1	Varia	27.5	1420	26.5	85.9	592.2	1376	0.26	0.43	0.49	3.13	4.2	2.6	44	0.017	1.10
2	Skala	28.2	1469	25.6	80.6	785.1	1375	0.26	0.56	0.54	2.86	4.2	2.9	94	0.033	1.29
3	Tranorema	30.3	1540	26.4	112.4	798.7	1452	0.26	0.53	0.55	3.70	1.6	2.1	88	0.042	1.05
4	Marathias	2.3	880	6.8	6.6	52.8	788	0.52	0.46	0.63	2.87	0.4	0.6	92	0.157	1.28
5	Sergoula	18.4	1510	19.7	59.7	569.8	1456	0.34	0.62	0.60	3.24	0.5	1.2	54	0.046	1.16
6	Vogeni	2.4	1035	7.9	5.6	63.7	817	0.53	0.53	0.49	2.34	0.7	1.3	218	0.167	1.38
7	Hurous	6.8	1270	11.6	23.2	158.6	1054	0.41	0.47	0.63	3.43	2.7	2.8	216	0.077	1.63
8	Douvias	6.8	1361	10.6	23.6	190.3	1269	0.49	0.56	0.77	3.46	0.6	1.6	92	0.059	1.42
9	Gorgorema	2.5	1060	7.3	6.2	67.7	1012	0.64	0.55	0.59	2.52	0.1	0.6	48	0.082	1.18
10	Ag. Spiridon	1.0	585	4.4	3.5	32.2	515	0.50	0.62	0.69	3.39	0.1	0.7	70	0.095	1.33
11	Linovrocho	3.6	1020	8.6	11.3	86.4	926	0.49	0.47	0.62	3.09	0.3	1.2	94	0.080	1.04
12	Mara	2.1	711	6.8	7.8	51.4	651	0.45	0.50	0.57	3.76	0.2	0.8	60	0.076	1.14
13	Stournaro-rema	47.1	1360	31.5	142.1	1236.0	1268	0.18	0.53	0.60	3.02	4.7	4.5	92	0.021	1.56
14	Eratini	3.4	1004	8.8	8.6	77.7	974	0.53	0.46	0.55	2.55	0.3	0.7	30	0.044	1.30

Table 2. Values of the measured morphometric parameters for the 14 alluvial fans and their drainage basins

Two more qualitative parameters were studied, the existence or not of a well developed channel in fan area (R), and the geological formation that prevails in the basin area (GEO). Channel occurrence or absence was coded in a binary condition, whereas geological formation prevalence was coded according to relative erodibility.

Nr	Stream/fan name	GEO	R	Nr	Stream/fan name	GEO	R
1	Varia	flysch	1	8	Douvias	limestone	1
2	Skala	limestone	1	9	Gorgorema	flysch	1
3	Tranorema	flysch	0	10	Ag. Spiridon	flysch	0
4	Marathias	limestone	1	11	Linovrocho	flysch	1
5	Sergoula	limestone	0	12	Mara	flysch	1
6	Vogeni	limestone	0	13	Stournarorema	flysch	1
7	Hurous	flysch	1	14	Eratini	limestone	0

Table 3. Values of the studied categorical parameters for the 14 alluvial fans and their drainage basins

Satellite derived DEMs were also used for digital representation of the surface elevation. The source were global elevation data sets from the Shuttle Radar Topography Mission (SRTM)/SIR-C band data, (with 1 arc second and 3 arc seconds) released from (NASA). In this study, two DEMs were re-projected to Universal Transverse Mercator (UTM) grid, Datum WGS84, with 250m and 90m spacing. In the proposed semi-automatic method, it is necessary to implement algorithms, which identify landforms from quantitative, numerical attributes of topography. Morphometric analysis of the study area was performed using the DEM and the first and second derivatives (slope, aspect, curvature, plan and profile curvature), applying Zevenbergen & Thorne (1987) method. Morphometric feature analysis and extraction of morphometric parameters are implemented in the open source SAGA GIS software, version 2.0 (SAGA development team 2004). Routines were applied in order to perform terrain analysis and produce terrain forms using Peuker & Douglas (1975), method. This method considers the slope gradients to all lower and higher neighbors for the cell being processed. For example, if all the surrounding neighbor cells have higher elevations than the cell being processed, the cell is a pit and vice versa is a peak. If half of the surrounding cells are lower in elevation and half are higher in elevation, then the cell being processed is on a hill-slope. The cell being processed is identified as a ridge cell if only one of the neighboring cells is higher, and, conversely, a channel when only one neighbor cell is lower. When slope gradients are considered, a hill-slope cell can be further characterized between a convex or concave hill-slope position. At locations with positive values for slope, channels have negative cross sectional curvature whereas ridges have positive cross sectional curvatures. The differentiation to plan hill-slopes is performed by using a threshold.

Symbol	Description	Nr of data samples in 250m DEM spacing of the whole data set	Nr of data samples in 90m DEM spacing of the subset of Varia and Scala basin
-9	Pit	26	113
-7	Channel	825	6,322
-2	Concave break form valleys	683	5,284
0	Flat	99	1,060
1	Pass	4	371
2	Convex break form ridges	713	5,441
7	Ridge	805	6,289
9	Peak	17	138

Table 4. Terrain form classification according to Peuker & Douglas method

Sampling procedure for the data set describing the drainage basins and alluvial fan regions, was performed. A sampling function was applied to the derivatives grids in order to prepare a matrix of sample vectors. The produced ASCII file was exported to MATLAB in order to use SOM artificial neural networks. The main geomorphological elements according to Peuker and Douglas (1975) method, are channels, ridges, convex breaks and concave breaks and are presented in Table 4. Pits, peaks and passes are not so often in the study area. The morphometric parameters derived were used as input to SOM. Data preparation in general is a diverse and difficult issue. It aims to, select variables and data sets to be used for building the model, clean erroneous or uninteresting values from the data. It also aims to transform the data into a format which the modelling tool can best utilize and finally normalize the values in order to accomplish a unique scale and avoid problems of parameter prevalence according to their high values.

The quality of the SOM obtained with each normalization method is evaluated using two measures as criteria: the quantization error (QE) and the topographic error (TE). QE is the average distance between each data set data vector and its best mapping unit, and thus, measures map resolution (Kohonen, 1995). TE is used as a measure of topology preservation. The map size is also important in the SOM model. If the map is too small, it might not explain some important differences, but if the map is too large (i.e. the number of map units is larger than the number of samples), the SOM can be over fitted (Lee & Scholz, 2006). Under the condition that the number of neurons could be close to the number of the samples, the map size was selected, for each application.

5. Results

5.1 Microscale landform characterization (coastal alluvial fan classification)

The application of the SOM algorithm in the current data set, and the result of the clustering are presented through the multiple visualization in Fig.4. The examined variables are the morphometric parameters of the alluvial fans and their corresponding drainage basins, analytically presented in Tables 1 and 2. The lowest values of QE and TE were obtained using logistic function which scales all possible values between [0,1]. Batch training took place in two phases. The initial phase is a robust one and then a second one is fine-tuning with a smaller neighborhood radius and smaller (learning rate). During rough initial neighborhood radius and learning rate were large. Gradually the learning rate decreased and was set to 0.1, and radius was set to 0.5.

Visualization in Fig. 4 consists of 19 hexagonal grids (the U-matrix upper left, along with the 17 component layers and a label map on the lower right). The first map on the upper left gives a general picture of the cluster tendency of the data set. Warm colors represent the boundaries of the clusters, though cold colors represent clusters themselves. In this matrix four clusters are recognized. In Fig.5a and Fig.5c the same vislualization is presented through hit numbers in Fig. 5a and the post–it labels in Fig. 5c. The hit numbers in the polygons represent the record number, of the data set that belong to the same neighborhood (cluster). Through the visual inspection of both Fig.5a and Fig.5c, one corresponds the hit numbers to the particular record, which is the alluvial fan name. Four clusters were generated. The records that belong to the same cluster are mapped closer and have the same color. For example, Marathias and Vogeni belong to the same cluster represented with blue. The common characteristics of these two fans are visualized through Fig. 4. Using similarity coloring and position, one can scan through all the parameters and reveal that these two records mapped in the upper corner of each parameter map have always the same values represented by similar color.

Except from general clustering tendency, scanning through parameter layers one can reveal correlation schemes, always following similarity colouring and position. Each parameter map is accompanied with a legend bar that represents the range values of the particular parameter. Drainage basin area (A_b) is correlated with fan area (A_{pf}) and fan length (L_f).

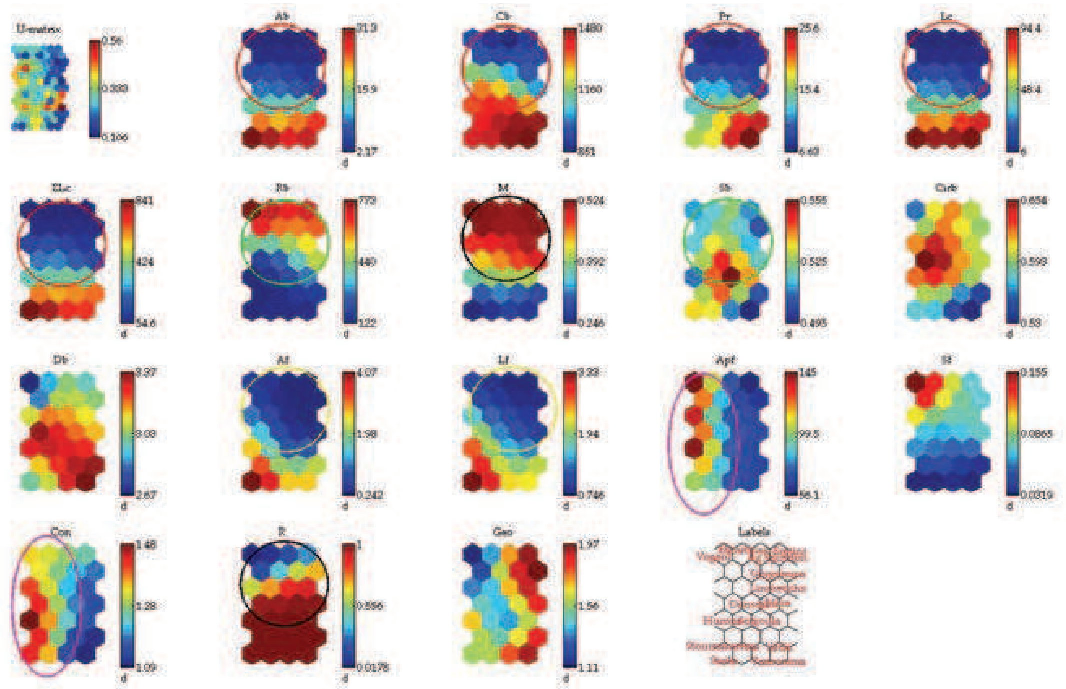


Fig. 4. SOM visualization through U-matrix (top left), and 17 component planes, one for each parameter examined. The figures are linked by position: in each figure, the hexagon in a certain position corresponds to the same map unit

Total length of channels (L_c) within basin area (A_b), and total length of contours (ΣL_c) within the drainage basin are also correlated (see red and yellow circles in Fig. 4). Basin crest (C_b), and basin relief (R_b) are inversely correlated (see green circle in Fig. 4). Melton's' ruggedness number is inversely correlated to fan slope (S_f), but correlated to channel development in fan area (see black circles in Fig. 4). The geological formation prevailing to basin area seems to be inversely correlated to concavity, (i.e. limestone basins have produced less concave fans compared to the flysch ones). Concavity (C_f) is also correlated to fan area (A_{pf}).

Analysis of each cluster is then carried out to extract rules that best describe each cluster by comparing with component layers. The rules to model and predict the generation of alluvial fans, are extracted by mapping the four clusters presented in Fig.5 with the input morphometric parameters (component planes) in Fig.4. Prior to rules extraction each input variable is divided in three categories, that is low and high and medium. The threshold value, which separates each category, is determined from the component planes legend bar in Fig.4.

In the following description, the response of the given data to the map (adding hits number) for each cluster was calculated as a cluster index value (CIV). The higher the cluster index value the stronger the cluster and therefore the most important in the data set and the most representative for the study area.

Cluster 1: Varia, Skala, Sergoula, Stournarorema, Tranorema. The cluster index was calculated (5). Varia and Tranorema form a subgroup. Stournarorema and Scala form a second subgroup. This group includes fans formed by streams with well developed drainage networks and large basins with high values of basin relief. The produced fans are extensively and relatively gently sloping (with a mean slope of 0.03). Varia, Skala, Sergoula and Stournarorema fans have a triangular shape and resemble small deltas while Tranorema has a more semicircular morphology. These fans are intersected by well developed and clearly defined distributary channels consisting of coarse grained material (pebbles, cobles and few boulders). These are generally aggrading fans with an active prograding area near the river mouth. The fans of this group are characterized as fluvial dominated.

Cluster 2: Marathias, Vogeni. The cluster index is (2). This second group involves fans formed by torrents with small drainage basins. They have developed laterally overlaying or confining fans of the cluster 1. Their shape is conical, they do not present well developed channels and are also characterized from high fan gradients (mean fan slope reaches 0.4). Flysch formations prevail in their basin area. According to these features, they seem to be debris flow dominated. Their formation and evolution is inferred to be highly governed from the two serious landslides of Marathias and Sergoula, occurred in the study area.

Cluster 3: Gorgorema, Mara, Linovrocho, Ag. Spyridon, Eratini. The cluster index is (5). This group includes alluvial fans formed by streams of well developed drainage networks with large basins dominated by the presence of flysch formations. The fans are elongated and have well developed and clearly defined distributary channels, relatively incised in the most proximal part of the fan, near the apex, which become indefinite at the lower part near the coastline. The slope of their surface (mean gradient of 0.08) is higher than the slope of the cluster 1 fans and lower than those of cluster 2. According to these findings they are characterized as fluvial dominated with debris flow influences.

Cluster 4: Hurus and Douvias. The cluster index value is (2). The drainage basins of these two streams have similar features. These two fans are elongated and have well developed distributary channels, low slope values and high concavity. Their main characteristic is the large fan area if compared with the catchment area. The anomalously large Hurus torrent alluvial fan in relation to its drainage basin area is interpreted to be the result of abnormally high sediment accumulation at the mouth of this torrent. This exceptional accumulation rate is attributed to reduce of marine processes effectiveness due to the presence of Trisonia Island in front of the torrent mouth. This island protects the area of the fan resulting in deposition of the fluvio-torrential material. They are characterised as fluvial dominated fans.

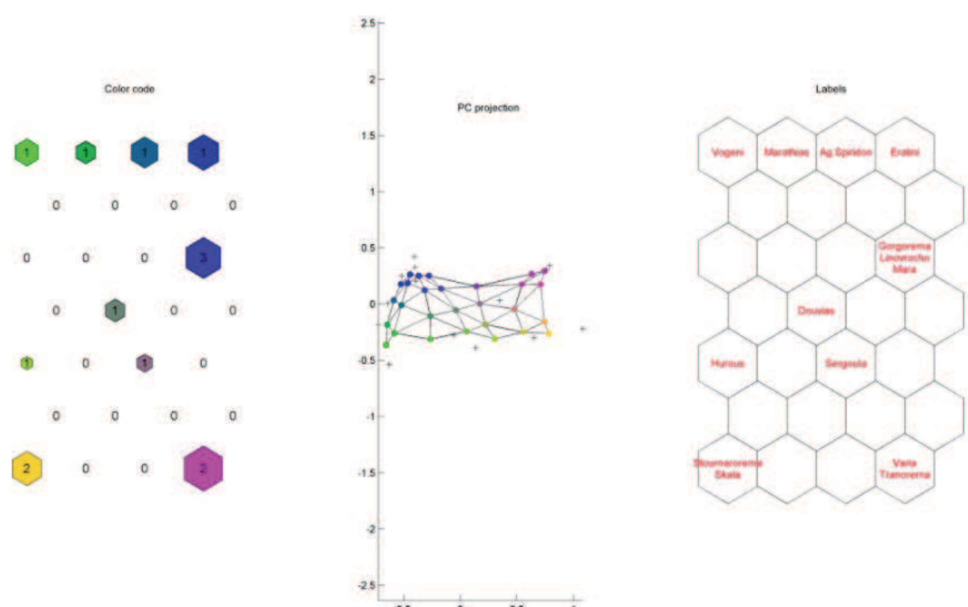


Fig. 5. Different visualizations of the clusters obtained from the classification of the morphological variables through SOM. (a) Colour code using k-means; (b) Principal component projection; (c) Label map with the names of the alluvial fans, using k-means. . The four clusters are indicated through the coloured circles

In Table 5 the rules governing each class are described.

Explanation	Symbol	Group1	Group2	Group3	Group4
Cluster Index Value	CIV	5	2	5	2
		fluvial dominated	debris flow	fluvial dominated with debris flow influences	fluvial dominated
		Varia, Skala, Sergoula, Stournarorema, Tranorema	Marathias, Vogeni	Ag. Spyridon, Mara, Gorgorema, Linovrocho, Eratini	Dounias, Hurous
Drainage basin area	(A_b)	> 15.8 High	< 15.8 Low	< 15.8 Low	Medium
Basin crest	(C_b)	> 1160 High	< 1160 Low	< 1160 Low	> 1160 High
Perimeter of the drainage basin	(P_b)	>15.4 High	< 15.4 Low	< 15.4 Low	< 15.4 Low
Total length of the channels within the drainage basin	(L_c)	> 48.6 High	< 48.6 Low	< 48.6 Low	< 48.6 Low
Total length of 20 m contour lines within the drainage basin	(ΣL_c)	> 421 High	< 421 Low	< 421 Low	< 421 Low
Basin relief	(R_b)	< 437 Low	> 437 High	> 437 High	< 437 Low
Melton' s ruggedness number	(M)	< 0.4 Low	> 0.4 High	> 0.4 High	Medium
Drainage basin slope	(S_b)	Medium to high	<0.08 Low	<0.08 Low	>0.08 High
Drainage basin circularity	(Cirb)	<0.60 Low	<0.60 Low	Medium	>0.60 High
Drainage basin density	(D_b)	> 3.05 High	< 3.05 Low	Medium	> 3.05 High
Fan area	(A_f)	>1.97 High	<1.97 Low	<1.97 Low	Medium
Fan length	(L_f)	<1.93 High	>1.93 Low	>1.93 Low	>1.93 Medium
Fan apex	(Ap_f)	not clear	> 100 High	< 100 Low	> 100 High
Fan slope	(S_f)	< 0.03 Low	> 0.03 High	Medium	< 0.03 Low
Fan concavity	(C_f)	not clear	>1.28 High	Medium	>1.28 High

Well developped channels	R	Yes	No	Yes	Yes
Prevailing geological formation in basin area	Geo	Limestone	Flysch	Flysch	Limestone

Table 5. Clusters originating from SOM classification

5.2 Mesoscale landform characterization using unsupervised SOM

The systematic classification of landforms, their components, and associations, as well as their regional structure is one prerequisite for understanding geomorphic systems on different spatial and temporal scales (Dikau & Schmidt, 1999). The aim is to locate any correlation schemes between first and second derivatives describing the basin areas and alluvial fan regions, and examine clustering tendency of the data to certain line or surface morphometric features, (i.e. channels, ridges, planar surfaces). The data set comprised 3222 records, from a 250m spacing DEM, covering the whole study area (i.e. fourteen drainage basins and corresponding alluvial fans).

In order to assess the optimum SOM, 11 SOMs were developed. Learning of SOM was performed with random initial weighs of the map units. The initial radius was set to 3 and the final radius to 1. The initial learning rate was set to 0.5 and the final to 0.05. Experimenting towards SOM optimization the size of the map progressively augmented from 70 to 300, with a decreasing (QE) from 0.37 to 0.25. The optimum architecture was built through trial and error procedure. The SOM which gave the best map had QE 0.111 after 1000 epochs (Fig. 6). The optimum architecture was used in 10 more trials with random initial weights, so as to test the influence, on (QE). According to the findings of this study, there was no influence, which is probably attributed to the long time of training. That is, initial random weight values are being trained and Euclidian distances between input data vectors and best matching units decrease and reach the minimum value and become stable.

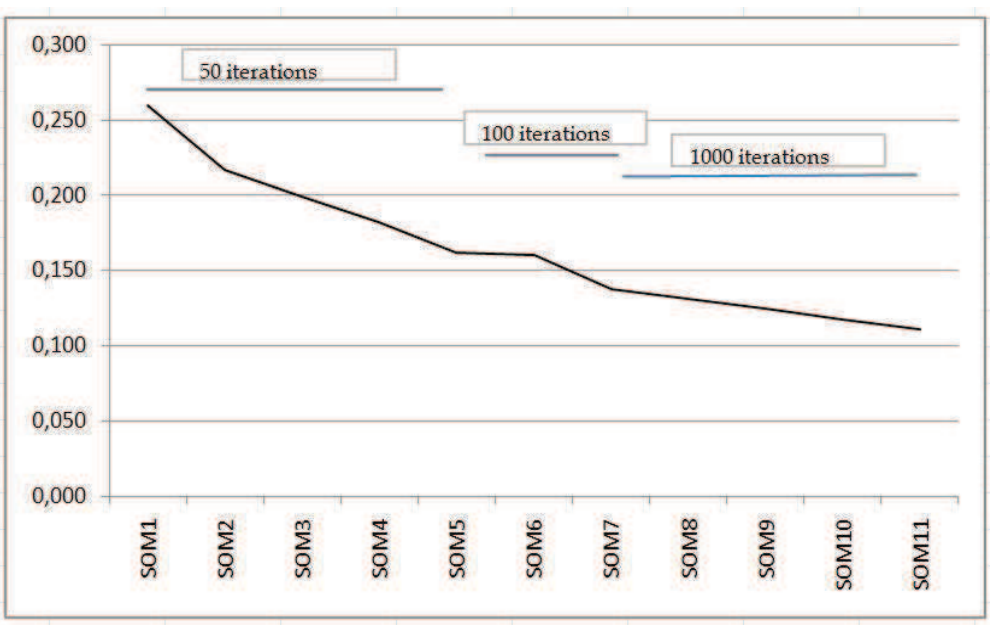
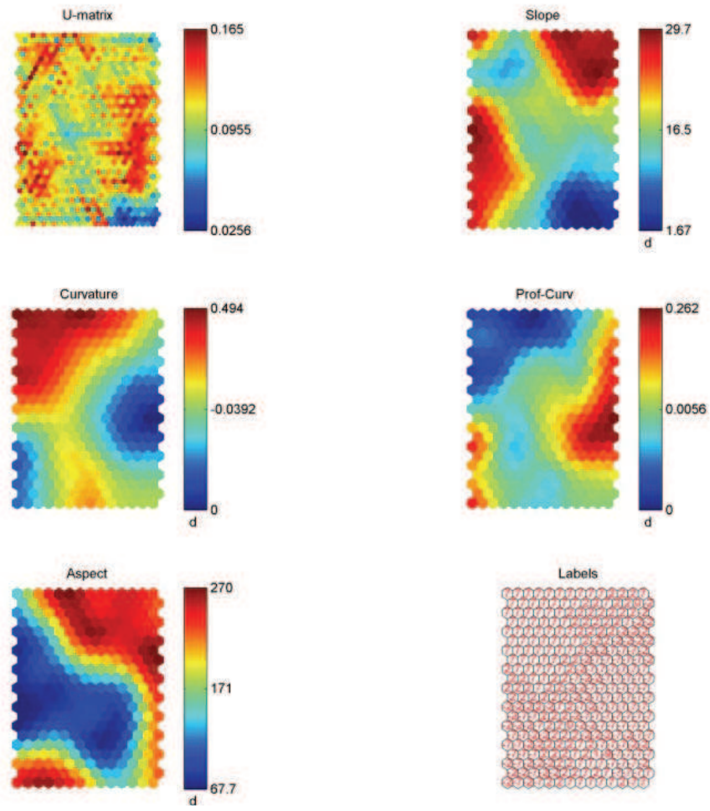
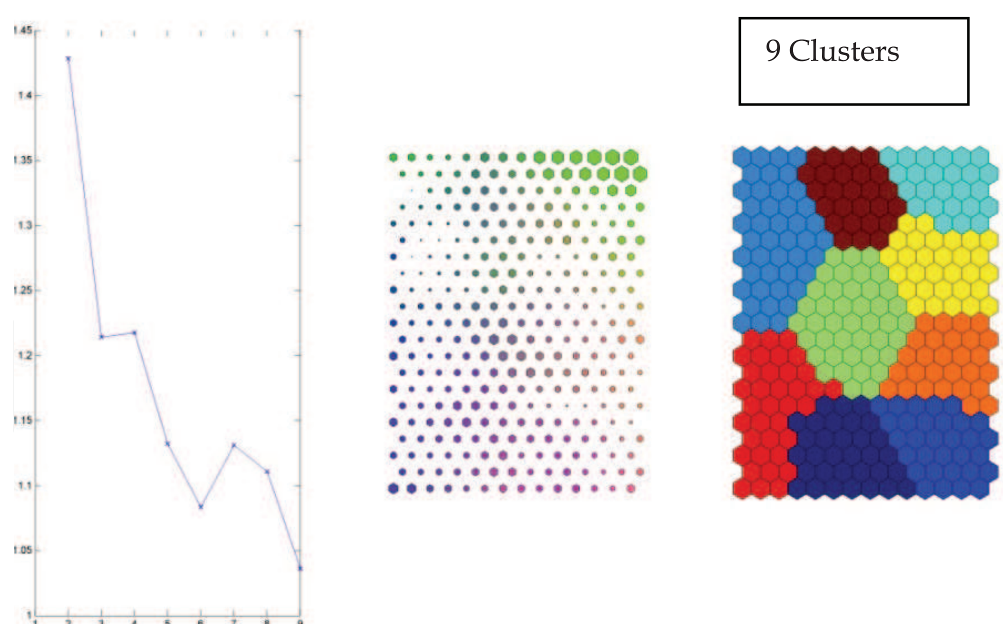


Fig. 6. Effect of number of epochs on average quantization error



a



b

Fig. 7. (a) SOM visualization through U-matrix (top left), and 6 component planes, one for each parameter examined (b) from left to right, through, Davis - Bouldin validity index versus cluster number, colour coding, and clustering using k-means (upper left (1) counting clockwise, (9) in the centre

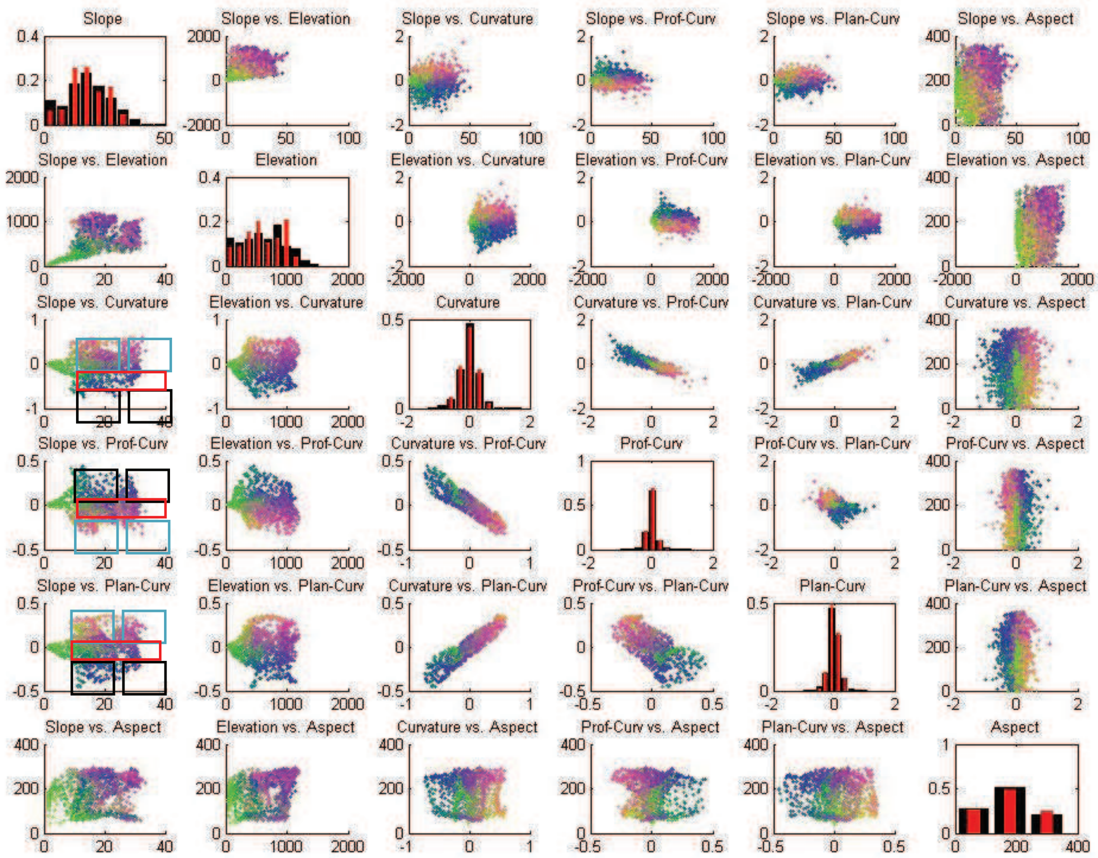


Fig. 8. SOM visualization through scatter diagrams of studied morphometric parameters

The next step is the analysis, interpretation and labeling of the map units as morphometric features. Correlation between slope and elevation, curvature and plan curvature is displayed through U-matrix (Fig. 7) and scatter diagrams (Fig. 8). Profile curvature is inversely correlated to plan curvature. No clear correlation on aspect and the other derivatives is portrayed.

U-matrix shows no clear separation between clusters, but using k-means algorithm and Davis – Bouldin (1979) index (Fig. 7b), it seems that 9 existing clusters correspond to different terrain forms. From the component planes, it can be seen that the features differentiating the clusters are the following presented in Table 7. In this table, the categorized map units and the corresponding morphometric features are summarized. For example ridges in the study area are represented with clusters 1,2,7 but with different slope and elevation conditions. This feature corresponds to both steeper and slopes representing an approximately flat area. Cluster 9 corresponds to flat area, possibly planation areas, in higher elevation almost flat terrain. Cluster 3 and 8 correspond to channels, with different slope conditions.

The black boxes plotted in Fig.8 refer to convex ridges, and the cyan boxes to concave channels. In order to hunt correlations between parameters, one should scan through the scatter diagrams in the lower triangle (resulting after training) where both data and map units are plot. According to SOM training, channels (negative concavities) are recognized and constitute two subgroups from low to steep slopes. Convex ridges are also recognized separated in classes from moderate to steep slopes. Planar surfaces are also recognized and differentiated according to slope angle. It is evident in Fig.8, that planar surfaces of gentle to steep slopes exist, in the study area.

Class	Morphometric element	Slope (^{0})	Elevation (m)	Curvature	Profile curvature	Plan curvature	Aspect
Cluster 1	Ridge	Medium (16)	Medium to High 580 to 1070	+	0	+	E to SE
Cluster 2	Ridge	Medium to High > (16)	High > 750	+	0	+	W
Cluster 3	Channel	High > (23)	Medium - High > 560	-	+	-	W
Cluster 4	Planar	Medium to high	High > 750	0	+	0	E to N
Cluster 5	Planar	Low to Medium	Low < 560	0	+	0	E to NE
Cluster 6	Chanel	Very Low	Low	-	+	-	E
Cluster 7	Ridge	Low	Low	+	-	+	S to SW
Cluster 8	Chanel	High	Low	-	+	-	W
Cluster 9	Planar	Low	High	0	0	0	NE to E

Table 7. Clusters originating from SOM

5.3 Mesoscale landform characterization using supervised SOM

SOM algorithm was proposed, as an alternative procedure for terrain analysis to Peuker and Douglass method. SOM training was performed with a subset of the DEM, referring to Varia and Scala drainage basins (see Fig.3). Six morphometric parameters were used, as input and a two-dimensional output of 3,000 neurons. Sampling procedure for the data set describing the drainage basins was performed. A sampling function was applied to the derivatives grids in order to prepare a matrix of sample vectors. The sampling was performed to the DEM and DEM derivatives, at 90m spacing. Problems handling memory had to be faced, this is why a small subset of the training DEM was used. The produced ASCII file was exported to MATLAB in order to use SOM unsupervised neural networks. The data set is presented in Table 4. The data dimensions was 25,024 x 6.

At the beginning of the learning procedure, neurons in the SOM were distributed randomly. The BMUs (final classes) with minimum average (QE) 0.135 were extracted. The number of map units was finally set to 3,000. Turning the SOM into a supervised classifier the final error was 30%. In table 8 the results of the applied normalizations are displayed. The error of supervised clustering is also presented. “HistD” normalization gave the best results, after 1,000 iterations.

Normalization method	QE	TE	error
histC	0.182	0.040	36.8
Var	0.40	0.045	35.4
Log	0.198	0.036	28.4
Logistic	0.34	0.054	33.61
Range	0.180	0.050	41.52
histD	0.210	0.033	27.92

Table 8. Normalization methods, and calculated QE and TE, for supervised clustering

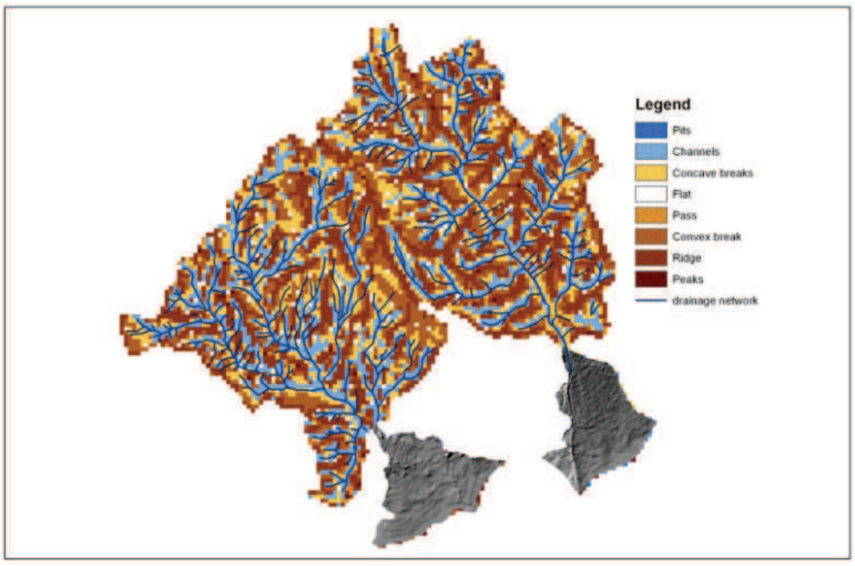


Fig. 9. Outcome of Peuker and Douglas classification

The results of the supervised clustering are presented in Fig. 10. The results illustrate a very clear distinction between the disparate morphometric features. Line-based and planar features were mainly recognized. A rather good network of ridges and channels with different slope classes is revealed. Compared to the outcome of classic morphometric analysis in Fig. 9 the outcome we get through SOM seems more compact, with a very good representation of crest lines. According to Peuker and Douglas method about 41% of the area are concave and convex breaks, 27 % are channels and 28% are ridges. As expected point- based features such as peaks, passes and pits cover only 4% of the study area. This is probably attributed to the fact that point based features are comparatively rare.

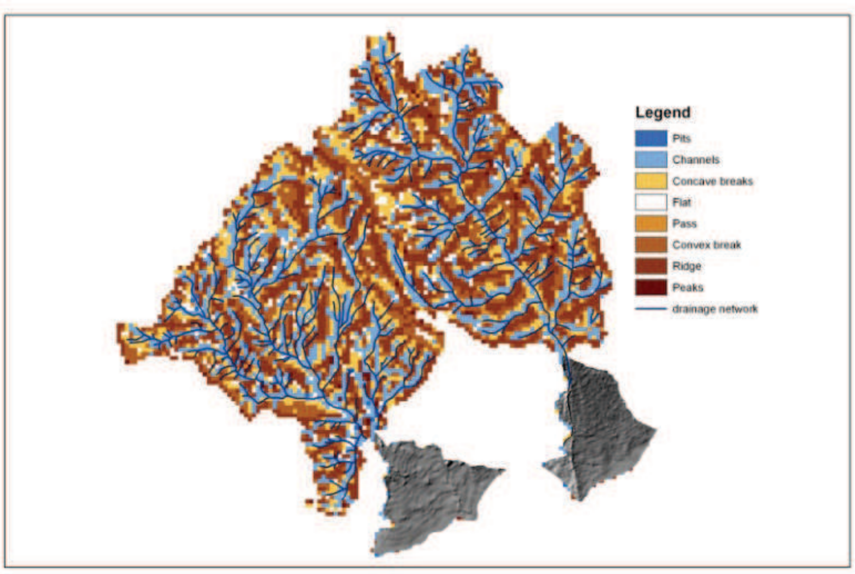


Fig. 10. Outcome of SOM clustering

6. Discussion

Given that geomorphological mapping is the basis for terrain assessment, a geomorphological map was constructed, to validate the results of the SOM drainage basin landscape mesoscale classification, for the catchments of Varia and Skala streams which are the two westernmost among the studied basins (Fig.11). Geomorphological mapping was performed using a 1:50,000 base topographic map through fieldwork, and aerial photo interpretation taking also into account previous geological maps.

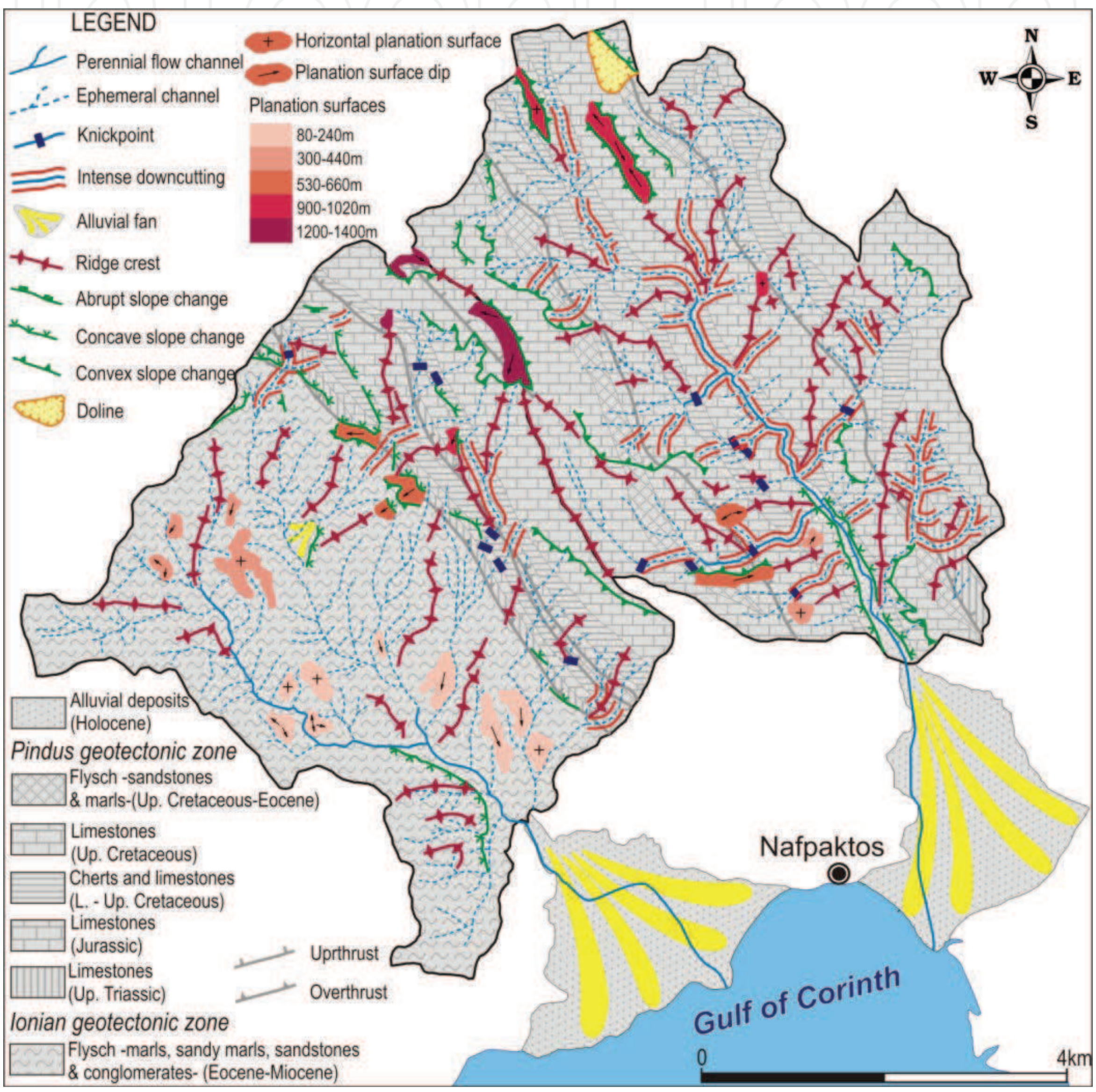


Fig. 11. Geomorphological map of the Varia and Skala streams and drainage basin areas, bedrock lithology is derived by the geological maps of (IGME) and field observations

The purpose of the mapping, which was its comparison with the SOM derived classification map, was the main criterion for the selection of the scale of the map. The scale is critical for effective information delivery. The final map provides information on the distribution of geological formations while landforms identifying landscape features created by surface processes were recorded combining field inspection with maps and aerial photo interpretation. These landforms which include erosional planation surfaces ranging in elevation from 500 m to 1,000m, stream channels and valleys of various shape, knickpoints, abrupt slope breaks, gentler slope changes, ridges and crests, alluvial fans and cones, intense channel downcutting, provide information on earth surface form processes.

Comparative observation of the geomorphological map, Peuker and Douglas classification, and the SOM clustering reveals information on the accuracy of the landscape characterization approach through SOM. Both methods identified stream channels of the drainage networks with very accurately. The more well developed high order channels like those of the main streams of the networks were better detected and recognized using SOM. Additionally, SOM identified correctly ridges and drainage divides providing an ideal method for drawing drainage basins borders. On the other hand landforms like erosional planation surfaces or knickpoints (discrete negative steps in the longitudinal profile of a river), are not identifiable on the SOM clustering.

In terms of evaluation results, Peuker and Douglas method and SOM, were compared, with an oblique view, overlaying contour lines (Figure 12). SOM is much closer to the geomorphological mapping, approach, and has much more potential for identification of non-point morphometric features than Peuker and Douglas method. The overall pattern of channels, ridges and planes is similar in both methods, but the SOM results are more concrete and seem to resemble to the classification of the geomorphological mapping, which recognizes unique landforms. Furthermore, the SOM capability of identifying crest lines on mountain ranges is also important. Last, the SOM method does not rely on curvature and slope tolerance values. In this method, the slope parameter, elevation and aspect, are important in characterizing classes, rather than just being a threshold to separate horizontal surfaces from sloping surfaces. Using the whole potential of the slope parameter in extracting features that are more informative is one of the advantages of the SOM.

Concerning the accuracy of the alluvial fan classification utilizing SOM it is obvious that this approach provides one of the best methods to characterize alluvial fans considering the correlation between alluvial fans and geomorphometric characteristics and quantitative morphometric indices of their corresponding drainage basins.

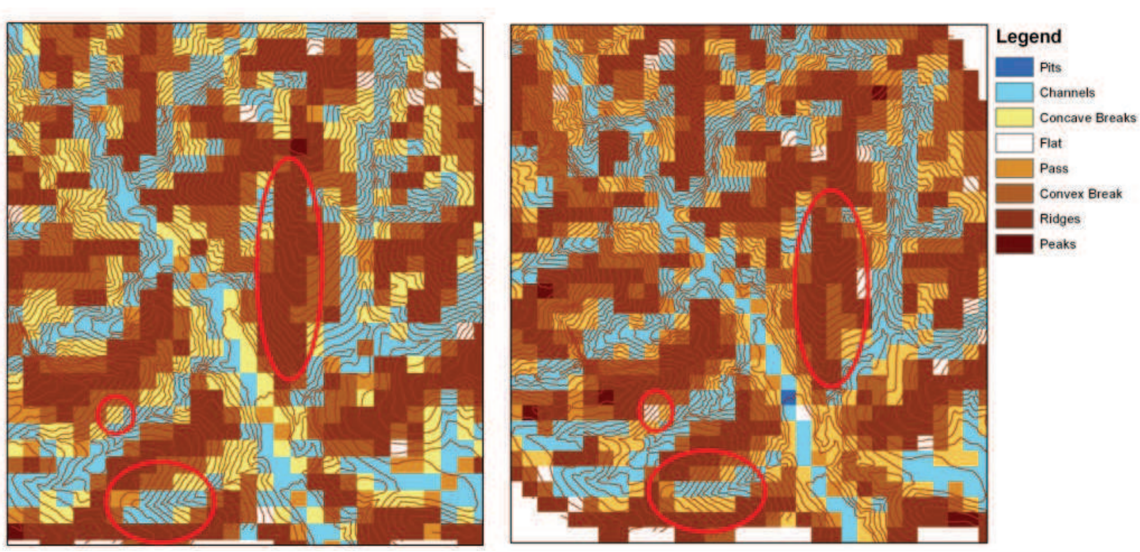


Fig. 12. Classification results (a) Terrain analysis according to SOM clustering, (b) Terrain analysis according to Peuker and Douglas

The results of the SOM characterization of the studied coastal alluvial fans according to the primary processes which are responsible for their formation and evolution, in four classes are in good agreement with a classification of the same fans performed in previous study based on entirely qualitative geomorphological observations and investigation of the relationship between pairs of selected fan – basin morphometric variables (Karymbalis, 2007). Especially the grouping of Marathias and Vogeri fans (cluster 2) and their characterization as debris flow dominated is validated by the existence of two landslides triggered by earthquakes activity along the Marathias normal fault scarp (Gallousi & Koukouvelas, 2007). Field observation showed that these two fans have formed by coarse grained material supplied by landslides. One of the advantages of the method is that provides the opportunity to correlate quantitative variables with qualitative information in order to achieve better results in alluvial fan classification.

7. Conclusion

The purpose of this study is to investigate the effectiveness of Self Organising Map (SOM), as a clustering tool in the field of applied geomorphology for mapping meso and microrelief scale morphometric elements. Unsupervised artificial neural networks, which use knowledge discovery methods, were developed in order to detect the trend of the data to clustering in microrelief scale according to alluvial fan formation and evolution process and in mesorelief scale according to linebased and planar morphometric features. SOM was also used as a semiautomatic tool in terrain analysis, with an accuracy result of 70%. Comparison of the geomorphological map and the SOM mesoscale landform classification results for two drainage basins in central Greece showed that the applied methodology is a promissing method for the mapping of drainage network channels. Furthermore, this approach resulted in successful identification of ridges and crests providing a good way to draw drainage divides and border hydrological basins. Compared to classic terrain analysis method, SOM presented a more concrete and accurate result in line base and planar elements.

The systematic and objective method which was applied in the field of alluvial fan classification, compared to statistical methods (Karymbalis et al., 2010) and geomorphological observations, was reasonable and accurate. This method could be applied as a generic tool of alluvial fan classifier to larger data sets, in order to assess and interpret dominant formation processes, through the study of many morphometric features describing alluvial fans and corresponding drainage basins.

In both mesoscale and microscale the SOM proved an efficient scalable tool for the analysis of geomorphometric features as meaningful landform elements, and uses the full potential of morphometric characteristics, leading to better understanding complex geomorphological systems.

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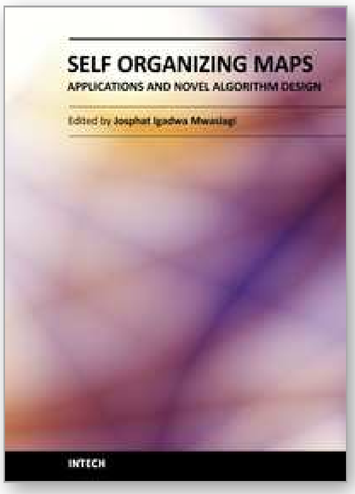

Self Organizing Maps - Applications and Novel Algorithm Design
Edited by Dr Josphat Igadwa Mwasiagi

ISBN 978-953-307-546-4
Hard cover, 702 pages
Publisher InTech
Published online 21, January, 2011
Published in print edition January, 2011

Kohonen Self Organizing Maps (SOM) has found application in practical all fields, especially those which tend to handle high dimensional data. SOM can be used for the clustering of genes in the medical field, the study of multi-media and web based contents and in the transportation industry, just to name a few. Apart from the aforementioned areas this book also covers the study of complex data found in meteorological and remotely sensed images acquired using satellite sensing. Data management and envelopment analysis has also been covered. The application of SOM in mechanical and manufacturing engineering forms another important area of this book. The final section of this book, addresses the design and application of novel variants of SOM algorithms.

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