Landforms identification using neural network-self organizing map and SRTM data

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Abstract

During an 11 days mission in February 2000 the Shuttle Radar Topography Mission (SRTM) collected data over 80% of the Earth's land surface, for all areas between 60 degrees N and 56 degrees S latitude. Since SRTM data became available, many studies utilized them for application in topography and morphometric landscape analysis. Exploiting SRTM data for recognition and extraction of topographic features is a challenging task and could provide useful information for landscape studies at different scales. In this study the 3 arc second SRTM digital elevation model was projected on a UTM grid with 90 meter spacing for a mountainous terrain at the Polish - Ukrainian border. Terrain parameters (morphometric parameters) such as slope, maximum curvature, minimum curvature and cross-sectional curvature are derived by fitting a bivariate quadratic surface with a window size of 5×5 corresponding to 450 meters on the ground. These morphometric parameters are strongly related to topographic features and geomorphological processes. Such data allow us to enumerate topographic features in a way meaningful for landscape analysis. Kohonen Self Organizing Map (SOM) as an unsupervised neural network algorithm is used for classification of these morphometric parameters into 10 classes representing landforms elements such as ridge, channel, crest line, planar and valley bottom. These classes were analyzed and interpreted based on spectral signature, feature space, and 3D presentations of the area. Texture contents were enhanced by separating the 10 classes into individual maps and applying occurrence filters with 9×9 window to each map. This procedure resulted in 10 new inputs to the SOM. Again SOM was trained and a map with four dominant landforms, mountains with steep slopes, plane areas with gentle slopes, dissected ridges and lower valleys with moderate to very steep slopes and main valleys with gentle to moderate slopes was produced. Both landform maps were evaluated by superimposing contour lines. Results showed that Self Organizing Map is a very promising and efficient tool for land form identification. There is a very good agreement between identified landforms and contour lines. This new procedure is encouraging and offers new possibilities in the study of both type of terrain features, general landforms and landform elements.

Keywords: Self Organizing Map; SRTM; Landforms; Morphometric features; Neural Network

1. Introduction

A Digital Elevation Model (DEM) is a regular grid of elevation values, which characterizes the form of the land surface (Giles and Franklin, 1998). Various numerical geomorphometric and GIS techniques are being developed to automate quantification of terrain related features. Information extracted from a DEM can be used in automated terrain classification and geomorphological studies. Characterizing landforms should reveal much about topographic expression and geomorphic processes. Landform as physical constituent of terrain may be extracted from digital elevation data using various approaches including classification of morphometric parameters (Dikau, 1989), fuzzy logic methods and unsupervised (ISODATA)

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classification (Adediran et al., 2004; Burrough et al., 2000; Irvin et al., 1997), supervised classification (Brown et al., 1998; Hengl and Rossiter, 2003; Prima et al., 2006), probabilistic clustering algorithm (Stepinski and Collier, 2004; Stepinski and Vilalta, 2005), multivariate descriptive statistics (Dikau, 1989; Evans, 1972) ,double ternary diagram classification (Crevenna et al., 2005) Morphometric features analysis (Ehsani and Quiel, 2008a, 2009b), landscape elements analysis (Ehsani and Quiel, 2007; Ehsani and Quiel, 2009a) and yardang analysis(Ehsani and Quiel, 2008b). Landforms possess at least two important properties. First, they are the result of past geomorphic and geologic processes and second, provide a controlling boundary condition for actual geomorphic processes (Dehn et al., 2001). For disciplines dealing with landforms, the properties of consideration are different. For geomorphologists both properties of landforms are important. But a common perspective of all landform studies regardless of discipline is to delimit homogeneous areas from digital elevation data. Digital elevation models (DEM) can be compiled from contour lines or other sources like the Shuttle Radar Topography Mission (SRTM). The SRTM data is a product from a collaborative mission by the National Aeronautics and Space Administration (NASA), the National Geospatial-Intelligence Agency (NGA- previously known as National Imagery and Mapping Agency, or NIMA), the German space agency (DLR), and Italian space agency (ASI). On February 11th 2000, the space shuttle Endeavour with the SRTM payload on board was launched to an altitude of 233 Km. During 11 days the SRTM data were collected to produce a consistent DEM covering all landmasses on earth between 60° N and 57° S at a spatial resolution of 1 arc sec (Blumberg, 2006; Rabus et al., 2003a; Rabus et al., 2003b; Wright et al., 2006). In 2003 the National Aeronautics and Space Administration (NASA) released the SRTM data with 3 arc second (~ 90 m) for all areas and 1 arc second (~ 30 m) for the United States (Hancock.G.R. et al., 2006; Kaab, 2005; Kellndorfer et al., 2004; Miliaresis and Paraschou, 2005; Rabus et al., 2003b).

Automatic classification of geomorphological land units mainly focuses on morphometric parameters (Bue and Stepinski, 2006; Giles and Franklin, 1998; Miliaresis, 2001). First order derivatives (slope and aspect) and second order derivatives (cross-sectional curvature, minimum and maximum curvature) of a DEM, as discussed by Evans (Evans, 1972), provide numerical and quantifiable parameters for landforms and geomorphological processes. The attempt to classify the shape of terrain using a set of numerical parameters (derivatives) is known as morphometry. The generic landform elements are: pits, peaks, channels, ridges, passes and planes known as morphometric features and can be extracted from DEM derivatives by an unsupervised neural network algorithms (e.g. self organizing maps) (Ehsani and Quiel, 2007). These morphometric features are smallest homogeneous divisions of the land surface, at the given scale/resolution. These are areas with relatively homogeneous morphometric properties, bounded by lines. A ridge for instance can be observed at various scales ranging from few hundred meters to hundreds of kilometers. The spatial distribution of landforms is often scale-dependent. In this study, we developed a semi-automatic procedure using Self Organizing Map (SOM) as an unsupervised artificial neural network for both landform elements and larger landform features mapping. A Self Organizing Map clusters or visualizes high dimensional input vectors into two dimensional output based on regularities and correlations between them (Jianwen and Bagan, 2005; Kohonen, 2001; Li and Eastman, 2006).

2. Study area

The study area is located between 48° 52' 21" and 49° 25' 14" N latitude and 21° 59' 34" and 23° 1' 46" E longitude (Fig. 1) centered around the common border point of Poland, Slovakia and Ukraine with a total area of 4 543 km^2. It covers the biosphere reserve "Eastern Carpathians" with the Bieszczady national park in Poland, Uzanski national park in Ukraine and Poloniny national park in Slovakia. The study area is characterized by mountain ranges stretching from southeast to northwest. This part of the Carpathian Mountains (Bieszczady) with highest elevation of 1324 m covers the center of the study area. The bedrock is composed mainly of Carpathian flysch consisting of sandstone and shale (Denisiuk and Stoyko, 2000; Tobias Kuemmerle et al., 2006) and in the southwest volcanic rocks.
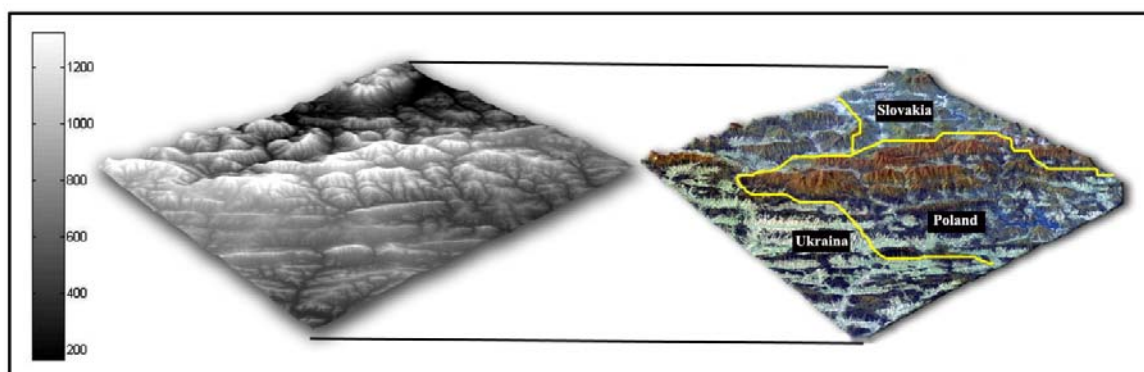
Fig. 1. DEM derived from Shuttle Radar Topography Mission, 3 arc second (left) and RGB color composite of
Landsat 7, ETM+ bands 3, 2 and 1 of the study area at the border of Poland, Slovakia and Ukraine (right)

3. Material and Methods

3.1. Material

The data set in this study consists of:

● Landsat ETM+ data path 186, row 26 dated 2000-09-30 were acquired from the Global Land Cover Facility (GCLF) server at the University of Maryland, Institute for Advanced Computer Studies (UMIACS). GLCF provides free access to an integrated collection of critical land cover and earth science data (http://glcf.umiacs.umd.edu).
● The 3 arc sec. digital elevation model derived from SRTM data (~90 m) in geographic projection was acquired free from the USGS server (http://seamless.usgs.gov).

Morphometric feature analysis and extraction of morphometric parameters are implemented in the open source GRASS software, version 6.0 (GRASS development Team, 2005, (GRASS Development Team, 2006)). SOM_PAK software Version 2.0 which is freely available from the Laboratory of Computer and Information Science (CIS) at the Helsinki University of Technology, Finland (Vesanto et al., 1996) is used for neural network analysis. ENVI Ver. 4.1 and Arc View Ver.3.2a are used for presentation.

3.2. Methods

Figure 2 shows the methodology used in this study. Starting with DEM data, four morphometric parameters are derived by fitting a bivariate quadratic surface with a window size of 5×5 (Wood, 1996a). In geomorphic studies of landscapes the first and second order derivatives of DEM (Table 1) are the basic components for morphometric analysis (Evans, 1972). The second derivatives of DEM are affected by geomorphological processes.

Table 1. Different morphometric parameters (Evans, 1972; Wood, 1996a)

Morphometric parameter	Formula	Description
Slope	arctan (sqrt ($d^2 + e^2$))	Magnitude of steepest gradient in both X and Y directions.
Cross Sectional curvature	$n \times g \times (b \times d^2 + a \times e^2 - c \times d \times e)/(d^2 + e^2)$	Measures the curvature perpendicular to the down slope direction. (Intersecting with the plan of slope normal and perpendicular to aspect direction).
Maximum curvature	$n \times g \times (-a-b + \mathrm{sqrt}((a-b) \times (a-b) + c^2))$	In any plan
Minimum curvature	$n \times g \times (-a-b - \mathrm{sqrt}((a-b) \times (a-b) + c^2))$	In any plan
Profile curvature	$n \times g \times (a \times d^2 + b \times e^2 + c \times d \times e)/(d^2 + e^2)(1+(d^2 + e^2)^{1.5}$	Vertical component in direction of aspect. (Intersecting with the plan of z axis and aspect direction).
Plan curvature	$n \times g \times (b \times d^2 + a \times e^2 - c \times d \times e)/(d^2 + e^2)^{1.5}$	Horizontal component in direction of aspect (Intersecting with the X, Y plan).
Longitudinal curvature	$n \times g \times (a \times d^2 + b \times e^2 + c \times d \times e)/(d^2 + e^2)$	Measures the curvature in the down slope direction. (Intersecting with the plan of slope normal and aspect direction).

g: Grid resolution of DEM, n: Size of window, x, y : Local coordinates, a to f: Quadratic coefficients.
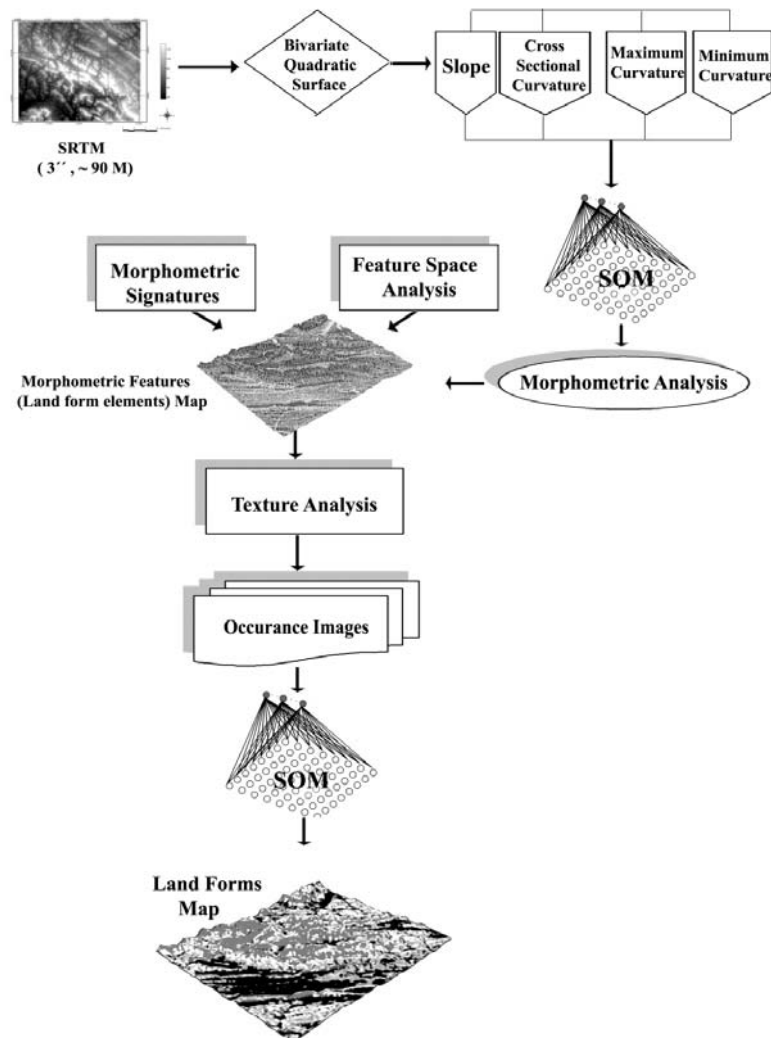
Fig. 2. Flowchart of the methodology

Cross-sectional curvature measures the curvature perpendicular to the down slope direction. This parameter is useful for detecting concave features such as channels and can be directly related to geomorphological form (Wood, 1996a; Wood, 1996b). In regions with zero slopes (flat), the aspect is undefined and maximum and minimum curvatures are used as alternative parameters. These parameters measure minimum and maximum overall surface curvatures. Wood (Wood, 1996a) proposed an algorithm using these parameters to identify morphometric features such as ridge, channel, peak, pit, pass or planar. Rules for this parameterization are shown in table 2. For example, a sloping surface that is concave in the cross-sectional direction is a channel. A sloping surface that is convex in the cross-sectional parameter is a ridge. Sloping surfaces with zero cross-sectional curvature are planar. These four morphometric parameters together are used as input for the Self Organizing Map. This is a semi-automatic method in which no specific classes are defined beforehand. Instead a set of novel landform elements emerge from the input. However the interpretation and labeling of the results is a manual task. The Self Organizing Map (SOM) is a realistic model of the biological brain function (Kohonen, 2001). Formally SOM consists of a regular two-dimensional grid of output map units (or cortex) connected via weights with n input vectors, e.g. four morphometric parameters.

Table 2. Morphometric feature classification criteria (modified from Wood (Wood, 1996a))

Morphometric Feature	Slope	Cross-sectional curvature	Maximum curvature	Minimum curvature
Peak	0	#	+va	+va
Ridge	+va	+va	×	×
Plane	+va	0	×	×
Channel	+va	-va	×	×

Va : derivatives value, # : undefined values, ×: not part of selection criteria.

SOM is a competitive network with topology preserving characteristics (Bação et al., 2005; Kohonen, 1989; Vesanto and Alhoniemi, 2000). Vectors that are close in input feature space will be mapped to units that are close in the output map. Learning of SOM is iteratively and can be conducted with a subset or all data vectors. Prior to learning, the weights of map units are initialized with random values. The initial weight values are the starting point of learning. Every random initialization of the input weights defines a new location for searching the global minimum error. During the learning process, these values are moving toward the global minimum error. In the learning phase each input vector is presented to the network and Euclidean distances between that and all nodes in the network are computed. The node with the shortest Euclidean distance commonly known as Best Matching Unit (BMU) is selected as a winner. This winner neuron becomes the centre of an *update neighborhood area* within which nodes and their neighborhood weights according to Kohonen rule will be updated simultaneously. As a result, weights of the output map (known as code book) are adjusted (or learned) so that they can describe the nature of the input data. The patterns in the input space are therefore clustered.

Neural network learning becomes more efficient with preprocessing of input data. Therefore all data were normalized with logistic transformation to the range of 0 to1. After some trial the number of classes or map units was set to 10. Before learning, weights of the map units were randomly initialized. The learning was performed in two phases, rough learning and fine tuning with different learning parameters and iterations. The quality of the results is measured as average quantization error. Average quantization error is the Euclidian distance between data vectors and best matching unit (BMU) in the map. The optimal SOM with low average quantization error is selected and used for learning and clustering of input data.

Landform elements in the output map were identified by plotting the mean of classes in two-dimensional feature spaces (scatter plot) of morphometric parameters. Two feature spaces with maximum curvature (x-axis) and minimum curvature (y-axis) respectively cross sectional curvature (x-axis) and slope (y-axis) were used. In these feature spaces, major morphometric classes related to ridge, channel, planar and crest line were identified. The second plot shows the distribution of morphometric features in slope categories. Using feature space analysis, morphometric signatures, three-dimensional inspection and auxiliary data, dependency of optimal map units to morphometric features (landforms elements) were defined. All 10 landform elements are masked and separated as 10 new images. An occurrence filter with 9×9 window was applied to these 10 new images and used for texture analysis. Occurrence-based texture filter uses the number of occurrences of each gray level within the processing window for the texture calculations. Texture refers to the spatial variation of image tone as a function of scale. To be defined as a distinct textural area, the gray levels within the area must be more homogeneous as a unit than areas having a different texture. These new ten images were used in SOM as inputs. Applying the SOM in this step, produced a general landform map where each uniform textured region is identified with texture class it belongs to.

4. Results

The four morphometric parameters slope, cross-sectional curvature, minimum and maximum curvature derived from the DEM are shown in Figure 3. Plain areas with low slope values like arable lands in Slovakia (southwest) or Solinskie reservoir in Poland (north) have zero value for minimum, maximum and cross-sectional curvatures. But in mountainous locations with steep slopes morphometric parameters differ, depending on morphometric features.
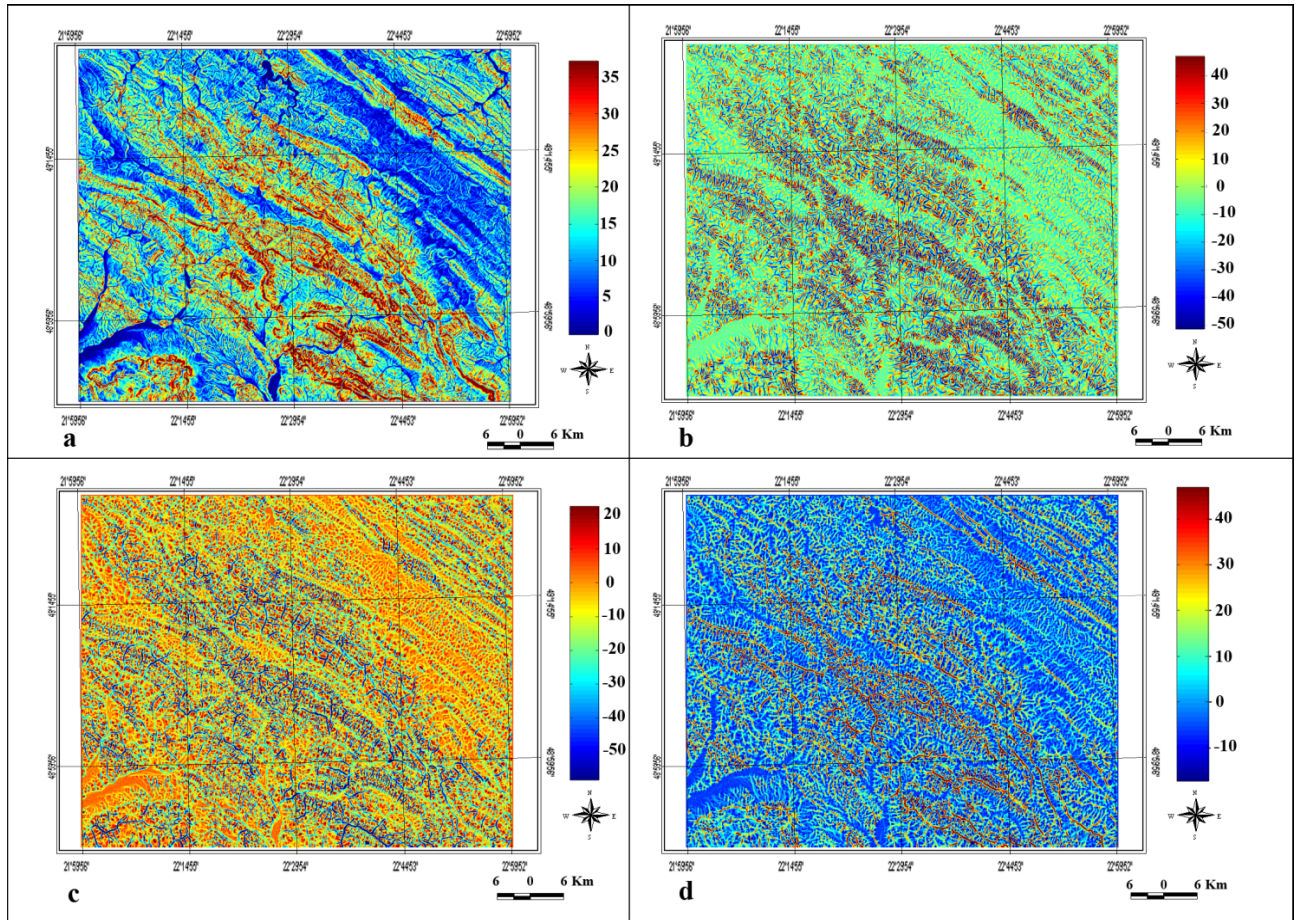
Fig. 3. Morphometric parameters derived from DEM, a slope, b cross- sectional curvature, c minimum curvature,
d maximum curvature

Correlation coefficient as statistical measure indicates the strength and direction of a linear relationship between different morphometric parameters (Fig. 4). As it clearly can be observed from Fig.4, slope as first derivative of the DEM has a very low linear correlation with all second derivatives. The highest positive correlation is between longitudinal and profile curvature (0.998). Cross sectional curvature shows similar positive correlation with both maximum and minimum curvature. Longitudinal, profile and cross sectional curvature have all the same linear correlation with minimum curvature (0.68). Moreover, the same situation can be seen for maximum curvature (0.63). However the correlation between maximum and cross sectional curvature is a bit higher (0.71). Between the second derivatives of DEM, the lowest correlation is between cross sectional curvature and longitudinal and profile curvature (0.25).

Learning of the SOM was performed with a subset of the data points with four morphometric parameters as input and a two-dimensional output of ten neurons. At the beginning of the learning, neurons in the self organizing map are distributed randomly. But after learning the map units are distributed across the input space so that neighboring neurons can recognize the best matching input for each learned map unit. After learning, the minimum average quantization error was 0.423.

The next crucial step is analysis, interpretation and labeling of these map units as morphometric features. It was performed by morphometric signature analysis and displaying mean values of best matching units (clusters) in two-dimensional morphometric feature space. Morphometric signatures for the morphometric parameters of SOM clusters resulting from the DEM are illustrated in figure 5.
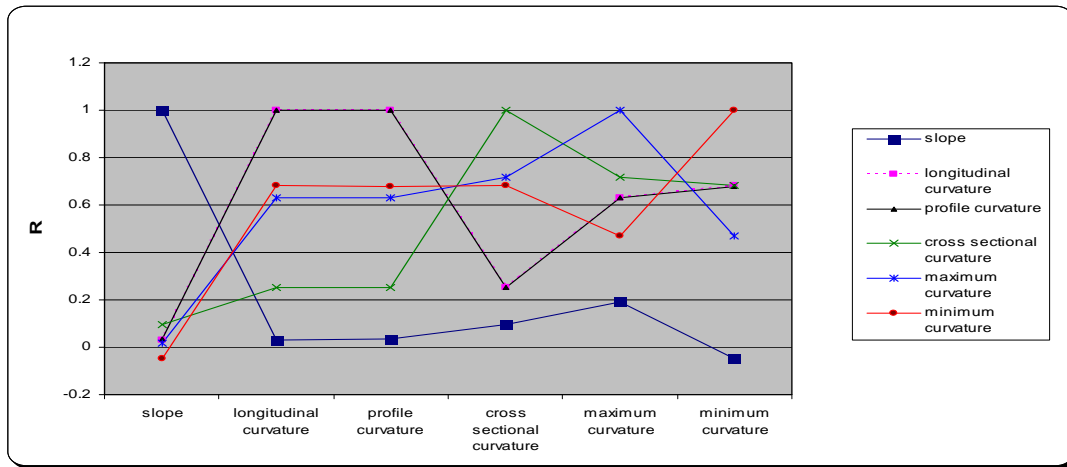
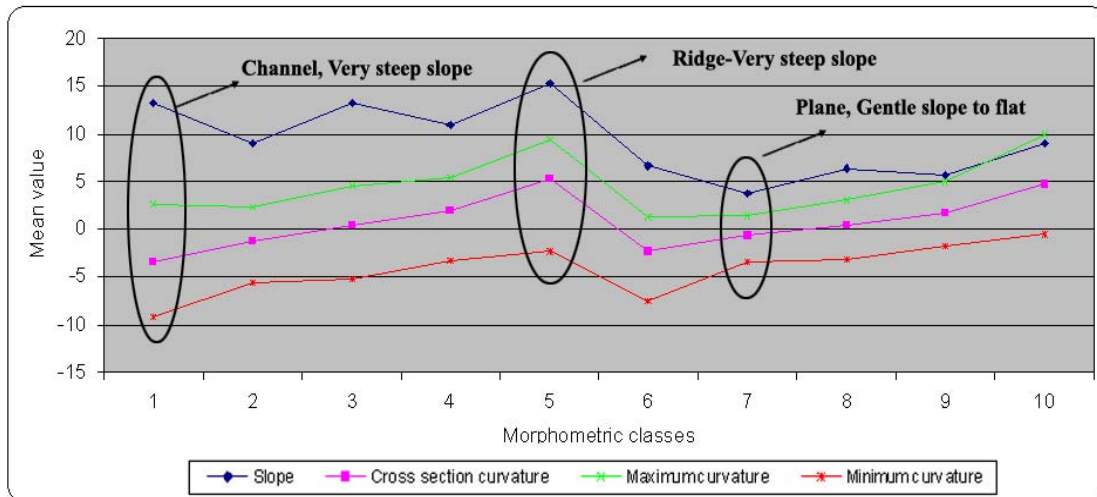Fig. 4. Correlation coefficient between Morphometric parameters derived from DEM

Fig. 5. Morphometric signatures of SOM output classes from DEM. Ellipsoids are examples of dominant morphometric features

This representation not only highlights that slopes vary for different classes but also reveal that minimum, maximum and cross sectional curvatures have similar trends. Cluster 10 with highest mean value of minimum and maximum curvature is labeled as crest line. The steepest and most gentle slopes are observed for class 5 and 7 with means of 15.25 and 3.77 degrees respectively.

Feature space analysis was used to understand the relation between classes in two-dimensional space of morphometric parameters. This method in conjunction with perspective presentation of the cluster map was used to label classes with corresponding morphometric features. From the six possible combinations of feature space plots, one with slope (y-axis) and cross sectional curvature (x-axis) is shown in figure 6. Six major morphometric features ridge, channel, planar, valley bottom, transition zone (between valley bottom and planar) and crest line and four subclasses, based on slope condition, were defined.
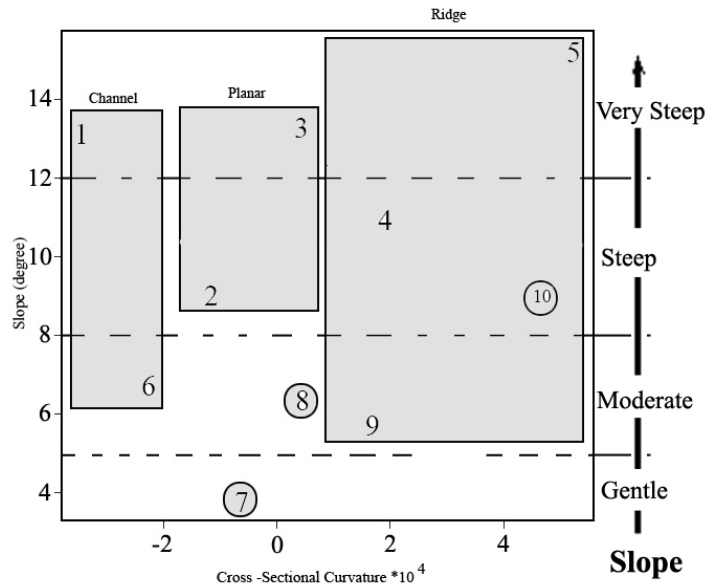
Fig. 6. Distribution of the major (grey box) and sub classes (dashed lines) of morphometric features from DEM in
two dimensional feature spaces. Sub classes are based on slope categories

Classes with positive cross-sectional curvature and high values for minimum and maximum curvature are identified as ridges. In contrary low values for minimum and maximum curvature and negative value for cross-sectional curvature characterize channels. Classes with properties between these two categories are planar features with different slope categories. Sloping surfaces with positive cross-sectional curvature are convex ridges. Plan forms are characterized by zero or near zero curvature values. Crest lines have positive values for both maximum and minimum curvatures. Table 3 summarizes the categorized map units and corresponding morphometric features as landform elements. These results are in good agreement with Wood's studies (Wood, 1996a).

Table3. Map units in relation to morphometric features (landform elements)

Morphometric features (landform elements)		Map units (Class No)
Class	Slope Class	
Channel	Moderate slope	6
	Very steep slope	1
Planar	Steep slope	2
	Very steep slope	3
	Gentle slope to flat	7
Ridge	Very steep slope	5
	Steep slope	4
	Moderate slope	9
Crest Line	Steep slope	10
Transition zone	Moderate slope	8

Texture contents are enhanced by separating the morphometric map into 10 individual feature maps, one for each class.. Applying an occurrence filter with a 9×9 window over these maps resulted in 10 new inputs for the SOM. The same SOM parameters are used for learning. Applying this method produced the general landform map of the study area (Fig. 7).
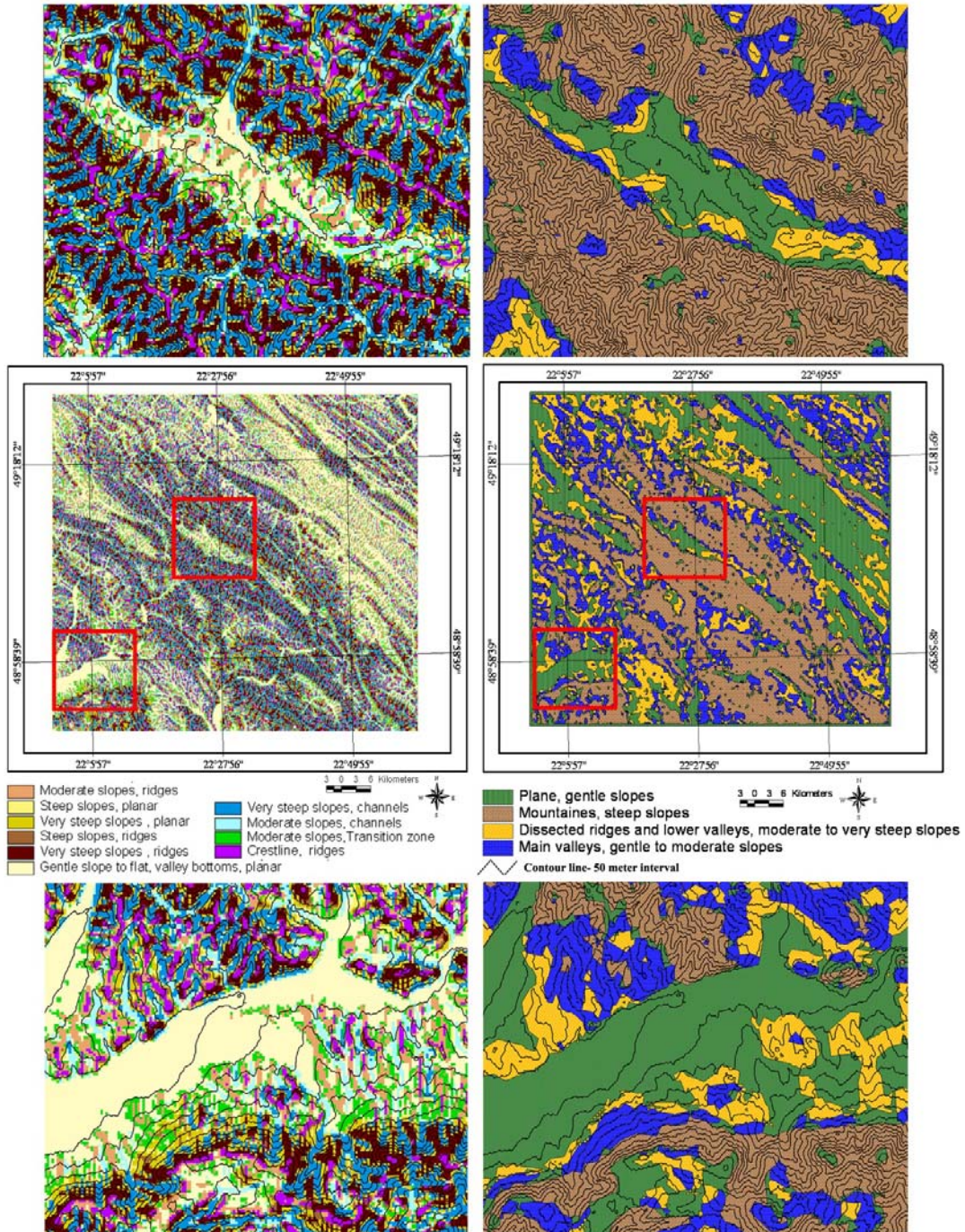
Fig. 7. Morphometric features (left) and general landform maps (right) produced by SOM. Zoom samples are overlaid with contour line -50 meter interval

Comparison of zoom samples in figure 7 shows that the SOM is able to identify detailed landform elements as well as general landforms. In the detailed landform elements map, morphometric classes are categorized based on slope classes while occurrence-based texture filters resulted in a general landforms map. Dominant landforms in the study area are part of

Carpathians mountains stretching from south east to north west and flat landforms in the north east in Ukraine and south west in Slovakia. Elements of mountain landform mainly consist of ridge, channel and crest line with moderate to very step slope. A visual comparison of contour lines (zoom samples in fig. 7) with the landform elements reveals that our results are in good agreement with the situation on the ground. For example class channel with very step slopes should have concave, dense contour lines. The zoom sample in upper left part of the figure 7 confirms this fact. The same situation can be seen for ridge elements with short distances between convex contour lines. Zoom samples in the lower part of figure 7 show planar landforms with gentle to flat slope, nearly straight contour lines and long distances between contours. This situation corresponds to the real condition on the ground and confirms the obtained results.

5. Conclusion

Studying the shape and form of the land is a major consideration for geomorphologists. Landforms are the result of geologic and geomorphologic processes on the land surface. The availability of SRTM data with nearly global coverage provide a good foundation for developing non-parametric, semi automatic methods for landform identification

In this study, we developed a semi-automatic procedure using Self Organizing Map (SOM) as an unsupervised artificial neural network for mapping of both landform elements and general landform features. The advantage is that it provides an objective and automated technique for landform mapping. Since the procedure was unsupervised, interpreting and labeling of classes is an important subsequent step. Morphometric signatures and feature space analyses were used to assign map units into meaningful landform classes.

Morphometric analysis of first and second order derivatives of DEM data such as slope, cross-sectional curvature, maximum curvature and minimum curvature led to the description of continuous features as ridges, channels , plane, crest lines and transition zone (between valley bottom and plane). These morphometric terms coincide with actual geomorphologic entities. Maximum and minimum curvatures are critical to recognize crest lines in mountains, ridges and

channels. Slope allows distinguishing among landform elements in sub levels.

Applying occurrence filter with 9×9 window to 10 individual landform element maps and using the resulting texture maps as input to a SOM allowed the mapping of 4 major landforms including mountains with steep slopes, plane areas with gentle slopes, dissected ridges and lower valleys with moderate to very steep slopes and main valleys with gentle to moderate slopes.

The results show that Self Organizing Map is a very promising and efficient tool for geomorphological studies. There was a very good agreement between identified landforms and contour lines. This new procedure is encouraging and offers new possibilities to study both types of terrain features, general landforms and landform elements.

References

Adediran, A.O., I. Parcharidis, M. Poscolieri, and K. Pavlopoulos. 2004. Computer-assisted discrimination of morphological units on north-central Crete (Greece) by applying multivariate statistics to local relief gradients. Geomorphology 58:357–370.

Bação, F., V. Lobo, and M. Painho. 2005. The self organizing map, the Geo-SOM, and relevant variants for geosciences. Computers & Geosciences 31:155-163.

Blumberg, D.G. 2006. Analysis of large aeolian (wind-blown) bedforms using the Shuttle Radar Topography Mission (SRTM) digital elevation data. Remote Sensing of Environment 100:179-189.

Brown, D.G., D.P. Lusch, and K.A. Duda. 1998. Supervised classification of types of glaciated landscapes using digital elevation data. Geomorphology 21:233-250.

Bue, B.D., and T.F. Stepinski. 2006. Automated classification of landforms on Mars. Computers & Geosciences 32:604-61.

Burrough, P.A., P.F.M. Van Gaans, and R.A. MacMillan. 2000. High-resolution landform classification using fuzzy k-means. Fuzzy Sets and Systems 113:37–52.

Crevenna, A.B., R. Vicente Torres, S. Valentino, D. Frame, and M.A. Ortiz. 2005. Geomorphometric analysis for characterizing landforms in Morelos State, Mexico. Geomorphology 67:407-422.

Dehn, M., H. Gärtner, and R. Dikau. 2001. Principles of semantic modeling of landform structures. Computers & Geosciences 27:1005-1010.

Denisiuk, Z., and S.M. Stoyko. 2000. The East Carpathian biosphere reserve (Poland, Slovakia, Ukraine), *In* A. Breymeyer and P. Dabrowski, eds. Biosphere reserves on borders. UNESCO, Warsaw.

Dikau, R. 1989. The application of a digital relief model to landform analysis in geomorphology. In: Raper, J., Editor,Three Dimensional Applications in Geographical Information Systems, Taylor & Francis, London:51–77.

Ehsani, A.H. and F., Quiel, 2009a. A semi-automatic method for analysis of landscape elements using shuttle radar topography mission and landsat ETM+ data. Computers & Geosciences, 35:373-389.

Ehsani, A.H. and F., Quiel,, 2009b, DEM-based analysis of morphometric features in humid and hyper arid environments using artificial neural network, Journal of Desert, 14: 71-82.

Ehsani, A.H. and F., Quiel, 2008a. Geomorphometric feature analysis using morphometric parameterization and artificial neural networks. Geomorphology, 99(1-4): 1-12.

Ehsani, A. H., & Quiel, F. 2008b, Application of self organizing map and SRTM data to characterize yardangs in the Lut desert, Iran, Remote Sensing of Environment, 112, 3284−3294.

Ehsani, A.H. and F., Quiel, 2007. Artificial Neural Networks for Landscape Analysis of the Biosphere Reserve "Eastern Carpathians" with Landsat ETM+ and SRTM data, The Problems of Landscape Ecology., XX, Warsaw, Poland

Evans, I.S. 1972. General geomorphology, derivatives of altitude and descriptive statistics., p. 17-90, *In* R. J. Chorley, ed. Spatial Analysis in Geomorphology. Methuen & Co. Ltd, London.

Giles, P.T., and S.E. Franklin. 1998. An automated approach to the classification of the slope units using digital data. Geomorphology 21:251–264.

GRASS Development Team. 2006. Geographic Resources Analysis Support System (GRASS), GNU General Public License. Eletronic document. http://grass.itc.it.

Hancock.G.R., Martinez.C., Evans.K. G., and Moliere.D. R. 2006. A comparison of SRTM and high-resolution digital elevation models and their use in catchment geomorphology and hydrology: Australian examples. Earth Surface Processes and Landforms 31:1394-1412.

Hengl, T., and D.G. Rossiter. 2003. Supervised landform classification to enhance and replace photo-interpretation in semi-detailed soil survey. Soil Science Society of America Journal 67:1810-1822.

Irvin, B.J., S.J. Ventura, and B.K. Slater. 1997. Fuzzy and isodata classification of landform elements from digital terrain data in Pleasant Valley, Wisconsin Geoderma 77:!37-154.

Jianwen, M., and H. Bagan. 2005. Land-use classification using ASTER data and self-organized neural networks. International Journal of Applied Earth Observation and Geoinformation 7:183-188.

Kaab, A. 2005. Combination of SRTM3 and repeat ASTER data for deriving alpine glacier flow velocities in the Bhutan Himalaya. Remote Sensing of Environment 94:463-474.

Kellndorfer, J., W. Walker, C. Pierce, D. Dobson, J.A. Fites, C. Hunsaker, j. Ann fites, J. Vona, and M. Clutter. 2004. Vegetation height estimation from shuttle radar topography mission and national elevation datasets. Remote Sensing of Environment 93:339–358.

Kohonen, T., (ed.) 1989. Self Organizing Map and associative Memory, pp. 1-312. Springer_Verlag, New York.

Kohonen, T. 2001. Self Organizing Maps, p. 501. Springer, New York.

Li, Z., and J.R. Eastman. 2006. The Nature and Classification of Unlabelled Neurons in the Use of Kohonen's Self-Organizing Map for Supervised Classification Transactions in GIS 10:599-613.

Miliaresis, G.C. 2001. Geomorphometric mapping of Zagros Ranges at regional scale. Computers & Geosciences 27:775-786.

Miliaresis, G.C., and C.V.E. Paraschou. 2005. Vertical accuracy of the SRTM DTED level 1 of Crete. International Journal of Applied Earth Observation and Geoinformation 7:49-59.

Prima, O.D.A., A. Echigo, R. Yokoyama, and T. Yoshida. 2006. Supervised landform classification of Northeast Honshu from DEM-derived thematic maps. Geomorphology 78: 373-386.

Rabus, B., M. Eineder, A. Roth, and R. Bamler. 2003a. The shuttle radar topography mission--a new class of digital elevation models acquired by spaceborne radar. ISPRS Journal of Photogrammetry and Remote Sensing 57:241-262.

Rabus, B., M. Eineder, A. Roth, and R. Bamler. 2003b. The shuttle radar topography mission--a new class of digital elevation models acquired by spaceborne radar. ISPRS Journal of Photogrammetry and Remote Sensing 57:241-262.

Stepinski, T.F., and M.L. Collier. 2004. Extraction of Martian valley networks from digital topography. Journal of Geophysical Research 109.

Stepinski, T.F., and R. Vilalta. 2005. Digital topography models for Martian surfaces. IEEE Geoscience and Remote Sensing Letters 2:260–264.

Tobias Kuemmerle, Volker C. Radeloff, K. Perzanowski, and P. Hostert. 2006. Cross-border comparison of land cover and landscape pattern in Eastern Europe using a hybrid classification technique Remote Sensing of Environment 103:449-464.

Vesanto, J., and E. Alhoniemi. 2000. Clustering of the Self-Organizing Map IEEE Transactions on Neural Networks 11:14.

Vesanto, J., J. Himberg, E. Alhoniemi, and J. Parhankangas. 1996. Som toolbox. Helsinki University of Technology, Laboratory of Computer and Information Science, http://www.cis.hut.fi/projects/somtoolbox., Finland.

Wood, J. 1996a. The Geomorphological Characterization of Digital Elevation Models, University of Leicester,UK, Leicester.

Wood, J. 1996b. Scale-based charecterisation of digital elevation models. In: Parker, D.Innovations in GIS 3.Tayler and Francis, London:pp.163-175.

Wright, R., H. Garbeil, S.M. Baloga, and P. Mouginis-Mark. 2006. An assessment of shuttle radar topography mission digital elevation data for studies of volcano morphology. Remote Sensing of Environment 105:41-53.