Klasyfikacja krajobrazu. Teoria i praktyka. Problemy Ekologii Krajobrazu. 2008, t. XX. 171-183.

Artificial neural networks for landscape analysis of the Biosphere Reserve "Eastern Carpathians" with Landsat ETM+ and SRTM data

Amir Houshang Ehsani, Friedrich Quiel

Division of Environmental and Natural Resources Information Systems
Department of Civil and Architectural Engineering, Royal Institute of Technology (KTH)
SE-100 44 Stockholm, Sweden
e-mail: Amir.Ehsani@byv.kth.se, Friedrich.Quiel@byv.kth.se

Abstract. In this paper we propose a semi-automatic method for landscape analysis with both spectral and morphometric constituents. SRTM data are used to calculate first derivatives (slope) and second derivatives of elevation such as minimum curvature, maximum curvatures and cross-sectional curvature by fitting a bivariate quadratic surface with a window size 9 by 9. Together with multi-spectral remote sensing data like Landsat 7 ETM+ with 28.5 meter raster elements, these data provide comprehensive information for the analysis of the landscape in the study area. Unsupervised neural network algorithm -Self Organizing Map- divided all input vectors into inclusive and exhaustive classes on the basis of similarity between attribute vectors. Morphometric analysis, spectral signature analysis, feature space analysis are used to assign semantic meaning to the classes as landscape elements according to form, cover and slope e.g. deciduous forest on ridge (convex landform) with steep slopes.

Key words: SRTM, Self Organizing Map, landform, morphometric parameter, ETM+

Introduction

Landscapes are dynamic systems that involve interrelation between physical characteristics, such as landform, soil, and anthropogenic processes, such as land use. Characterization of landscape properties through morphometric parameters and thematic maps is a crucial part in different analysis models. Indeed landscape can be described by its constituents landform and land cover. Landforms are contained in a regularly spaced elevation matrix, DEM (Digital Elevation Model) whereas landscape cover information can be extracted from multi-spectral satellite data e.g. Landsat ETM+. The public release of the Shuttle Radar Topography Mission (SRTM) data and remotely sensed spectral data created a low cost quantitative data source, which brought new possibilities for researchers to develop improved methods for landscape analysis.
Landform as physical constituent of landscape may be extracted from digital elevation models using various approaches e.g. classification of morphometric parameters (Dehn et al. 2001, Dikau 1989), fuzzy set methods and unsupervised (ISODATA) classification (Adediran et al. 2004; Burrough et al. 2000; Irvin et al. 1997), probabilistic clustering algorithm (Stepinski, Collier 2004, Stepinski, Vilalta 2005), multivariate descriptive statistics (Dikau 1989, Evans 1972) and double ternary diagram (DTD) classification (Crevenna et al. 2005).
First order derivatives (slope and aspect) and second order derivatives in a DEM, as discussed by 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) such as slope,

profile curvature, plan convexity, cross-sectional curvature, minimum and maximum curvature is known as morphometry. In morphometry simple forms or morphometric features such as saddle, channel, ridge and plane are identified based on the value of these measures (Fisher et al. 2004, Pike 2000, Wood 1996a). The idea of this paper is that combining morphometric parameters derived from DEM with spectral information from multi-spectral remotely sensed data e.g. Landsat 7 characterizes landscape elements. Therefore the final map shows homogenous landscape elements with same landforms, land cover and similar slope conditions. These landscape elements are considered to be complete and informative. In order to bring this idea into practical application, we developed a semi-automatic procedure using Self Organizing Map (SOM) as an unsupervised artificial neural network. The output thematic map shows land cover of landscape elements on one hand and morphometric features on the other hand. This approach allows a quick assessment of the spatial distribution of different landforms and land covers in the study area. The main objective of this paper is the characterization of landscape elements through combination of morphometric parameters and remotely sensed multi-spectral data.

Study area

The study area (Fig. 1) is centered on the common border point of Poland, Slovakia and Ukraine. It is located between 48° 52’ 21” N and 49° 25’ 14” N latitudes, 21° 59’ 34” E and 23° 1’ 46” E longitude. 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 with a total area of about 4543 km^2 (fig. 1).

The study area is characterized by the Bieszczady Mountains, a part of the Carpathian Mountains, with highest elevation of 1324 m stretching from southeast to northwest. The uniform bedrock is composed of Carpathian flysch consisting of sandstone and shale (Denisiuk, Stoyko 2000, Kuemmerle et al. 2006) and in the south west volcanic rocks.

Climatic conditions, different political and socioeconomic systems as well as ecological conditions resulted in complex landscape units. Land cover are mainly deciduous forest dominated by beech (*Fagus sylvatica*) and sycamore (*Acer Pseudoplatanus*) in the central part, mixed forest dominated by beech and fir (*Abies Alba*) in the central and north eastern part, coniferous forest composed of fir, Norway spruce (*Picea abies*) and Scots pin (*pinus Sylvestris*) in Southern and Northeastern part (Kuemmerle et al. 2006). Grasslands are the dominant landscape in the Northeast, Northwest and East of the area. Arable lands are mostly found in the south west.

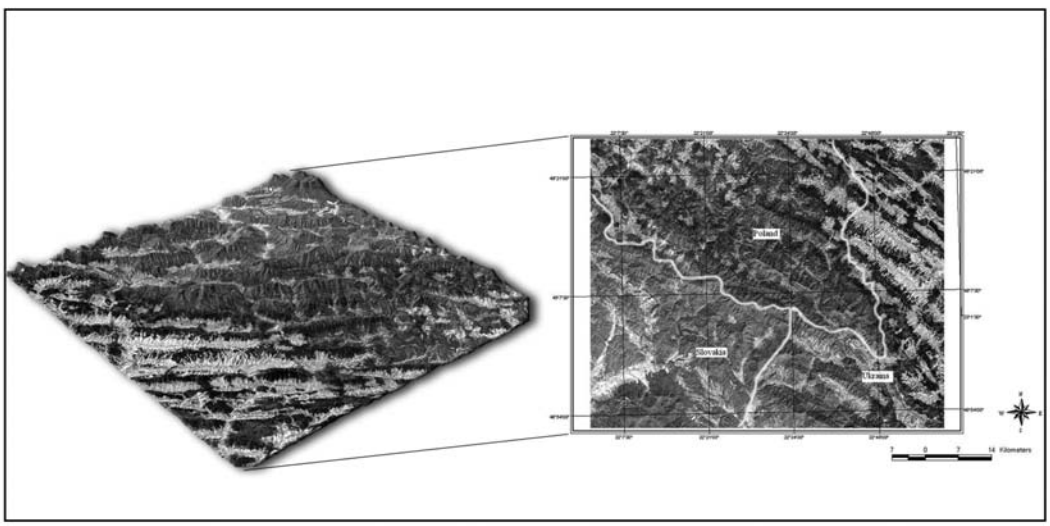

Fig.1. The study area at the border of Poland, Slovakia and Ukraine (Landsat 7, ETM+ composite of bands 3, 2 and 1 - *from editorial reasons changed to B&W by editors of Journal*)

Material and methods

Material

Landsat ETM+ data path 186, row 26 dated 2000-09-30 were acquired from the Global Land Cover Facility (GCLF) server (http://glcf.umiacs.umd.edu/index.shtml) of the University of Maryland. The 3 arc second (~ 90 m) SRTM data are publicly available at http://seamless.usgs.gov. Due to differences in projection and spatial resolution of SRTM with Landsat ETM+ data, the DEM was re-projected and re-sampled to Universal Transverse Mercator UTM zone 34 with 28.5 m pixel size. For interpretation of results we used a land cover map provided by Tobias Kuemmerle (Kuemmerle et al. 2006), topographic map (scale of 1:100 000) and field observation with GPS coordinates.

Methods

The Self Organizing Map is an unsupervised artificial neural network for clustering and visualization of information, preserving the topological relationship in the input. It converts the nonlinear statistical relationships of high- dimensional input data to an usually two-dimensional grid of output (Kohonen 2001). These two aspects, abstraction and visualization, can be utilized in complex tasks such as landscape analysis for both landforms and land cover. Figure 2 shows the overall scheme of the method. Starting with DEM data, four morphometric parameters are derived by fitting a bivariate quadratic surface with a window size of 9*9 (Wood 1996a). 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). 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 (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 1. 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 with all seven Landsat ETM+ bands are used as input for the Self Organizing Map (Fig. 3). This is a semi-automatic method in which no specific classes are defined beforehand. Instead a set of novel landscape elements emerge from the input. However the interpretation and labeling of the results is a manual task. Neural network learning becomes more efficient with preprocessing of input data. Therefore all data are normalized with logistic transformation to the range of 0 to 1. After some trial the number of classes or map units was set to 20. 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 iteration. The quality of the results is measured as average quantization error and topographic error. Average quantization error is the Euclidian distance between data vectors and best matching unit (BMU) in the map. Topographic error shows the proportion of all data vectors for which first and second BMUs are not adjacent units and is an index for preserving topology in the map (Kohonen 2001).
These measures are useful in choosing suitable learning parameters such as radius at initialization, radius of final neighborhood and number of learning iterations. Selecting the optimal map ought to be done for the same input but with different learning setting. The optimal map should yield the smallest average quantization error, because it is then fitted best to the data (Kohonen 2001). The optimal SOM is selected and used for learning and clustering of input data. Landforms in the output map were identified by plotting the mean of classes in the two-dimensional feature space (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. The slope categories are shown in table 2 yielding morphometric sub classes related to slope conditions.

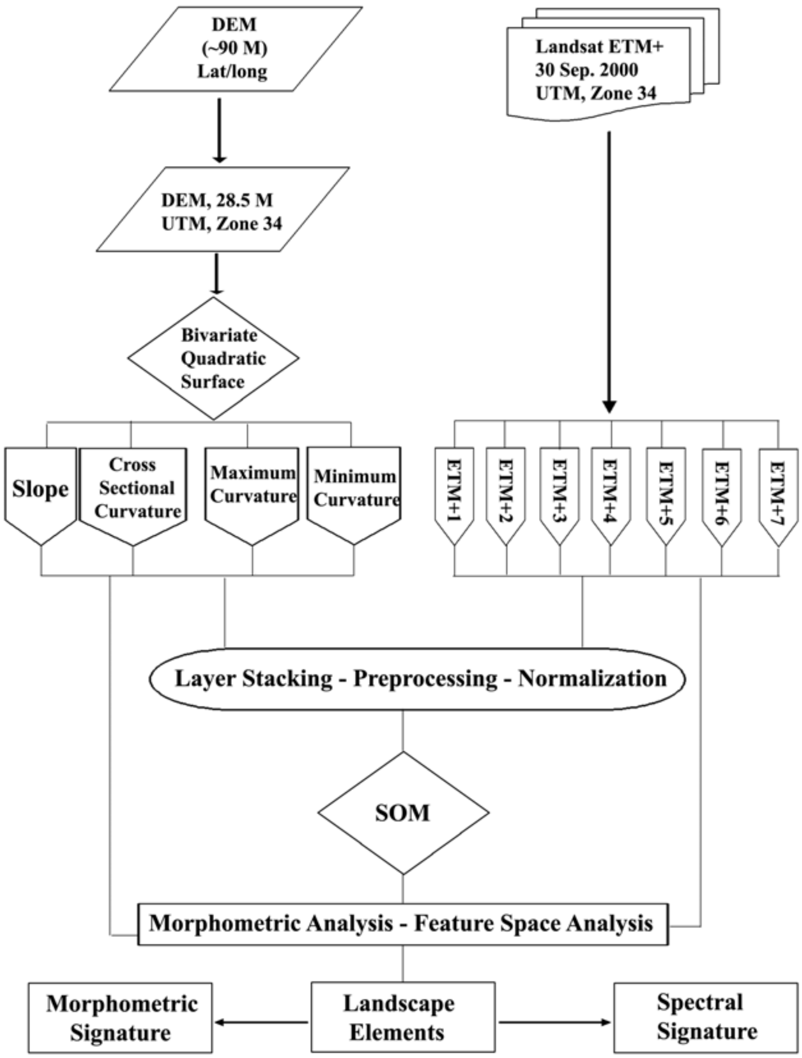

Fig.2. Flow chart of landscape analysis method

Table 1. Morphometric feature classification criteria (modified from 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.

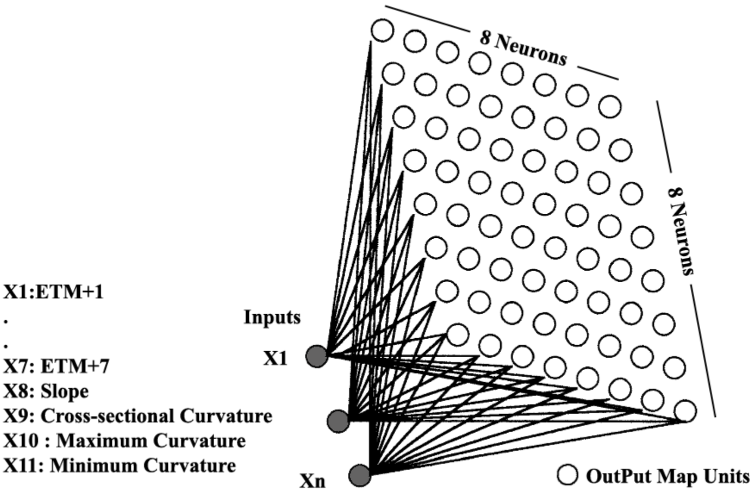

Fig.3. Structure of Self Organizing Map with in this schematic image 11 input bands and 8×8 output map units.

Table 2. Qualitative slope categories

Category	Slope(degree)
Gentle	slope < 5
Moderate	5 <slope < 8
Steep	8< slope < 12
Very Steep	slope > 12

Class means are also plotted in the feature spaces of Landsat ETM+ bands. Spatial distribution and relationships among map units were studied in combinations of two bands.

Each land cover class was labeled based on the spectral properties in different bands. A post classification step, defining a threshold in ETM+ band 4, allowed the separation of a water class from coniferous forest classes. Combining spectral and morphometric information homogeneous landscape elements were defined. A majority filter with kernel size 5×5 is used to clean up the final map and to eliminate spurious pixels. Signatures of landscape elements in eleven input bands were plotted as standardized values for all output classes. These signatures are used to evaluate the results and investigate landscape elements in detail.

In this study an open source software GRASS version 6.0 (GRASS Development Team, 2006) was used for morphometric analysis, co-registration and re-sampling of data. We applied the Self Organizing Map algorithm implemented in the 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).

Results

Optimal Self Organizing Map

Among sixteen self organizing maps with different learning settings, the best was achieved with an initial radius of 3, a final radius of 0.05 and 1000 iterations. The average quantization error for this map was 0.3394. This map fits best to the spectral and morphometric input data. The quantization error for the whole study area is shown in figure 4. The highest quantization error is due to thin clouds in the western study area. The cloud cover affects the radiation from that part with a mixture of radiance from the ground and the clouds. In contrast, the SRTM data and derived morphometric parameters are independent of cloud effects. Deviations in spectral and morphometric properties of these data points increase the distance between input data vector and corresponding best matching unit and consequently the quantization error. The SOM is a fairly robust method and can handle this problem.

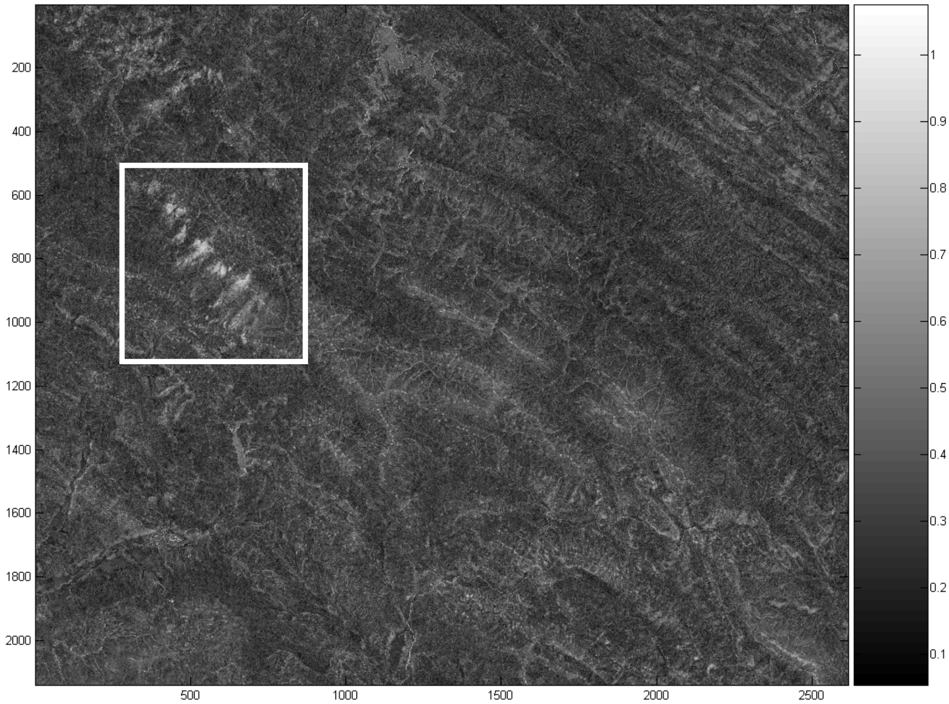

Fig.4. Quantization error of self organizing map for study area. The highest quantization error due to clouds is visible in the dashed box

Landscape Analysis

The initial output map units from SOM require manual interpretation. Labeling the output map units of SOM based on both morphometric and spectral properties is achieved through feature space analysis. Combining spectral and morphometric information for each class allows us to interpret the result as landscape elements. Based on the position of mean values of map units in two-dimensional feature spaces four major morphometric features or landforms channel, planar, ridge, and crest line are identified (fig. 5).

Map units with negative values of cross-sectional curvature are concave channels. 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. These results are in good agreement with Wood's (1996)

Overall eight land covers are characteristic for the study area (fig. 6). After interpretation and labeling the output map units of the self organizing map in relation to the landscape characteristics of landform and land cover, homogeneous landscape elements were defined by combining this information (fig. 7). This map shows the distribution of major components of landscape (land covers and landforms). Properties of these landscape elements are shown in table 3.

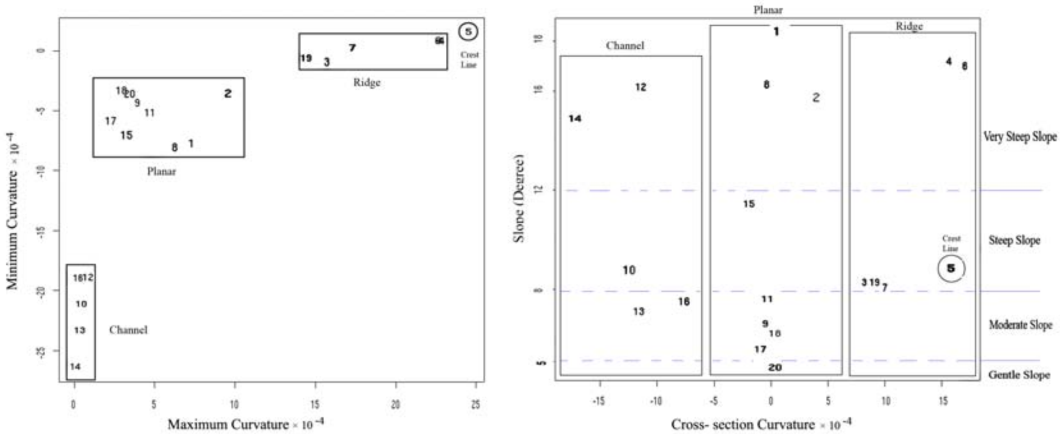

Fig. 5. Morphometric analysis of landscape using two-dimensional feature spaces.

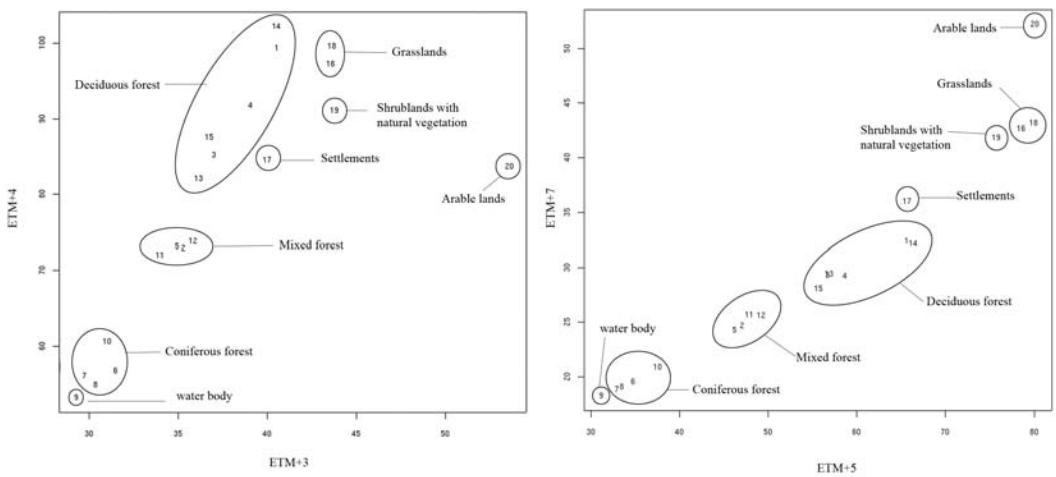

Fig. 6. Spatial distribution of land covers in two-dimensional feature spaces of Landsat bands.

Analysis and signatures of landscape elements

21 unique landscape elements in 8 groups are identified in the study area. Values are standardized for a distribution characterized by mean and standard deviation. Signatures and properties of these landscape elements are as follows:

Landscape elements group 1: This group (fig. 8) includes 5 landscape element classes (6, 7, 8, 9 and 10) with coniferous forest cover and 3 morphometric forms (planar, channel and ridge) in 3 slope conditions (moderate, steep and very steep slopes).This group covers 25.7% of the study area and compared with other groups, has the lowest spectral values in all Landsat bands.

Landscape elements group 2: This group (fig. 9) includes 6 landscape element classes (1, 3, 4, 13, 14 and 15) with deciduous forest cover and 3 morphometric forms (planar, channel and ridge) in 3 slope conditions (moderate, steep and very steep slopes). This group covers 26.3% of the study area and spectral values are higher than for mixed forests. Average of spectral values in ETM+ 4 is higher than for other bands.

Landscape elements group 3: This group (fig. 10) includes 4 landscape element classes (2, 5, 11 and 12) with mixed forest cover and 3 morphometric forms (planar, channel and crest line) in 3 slope conditions (moderate,

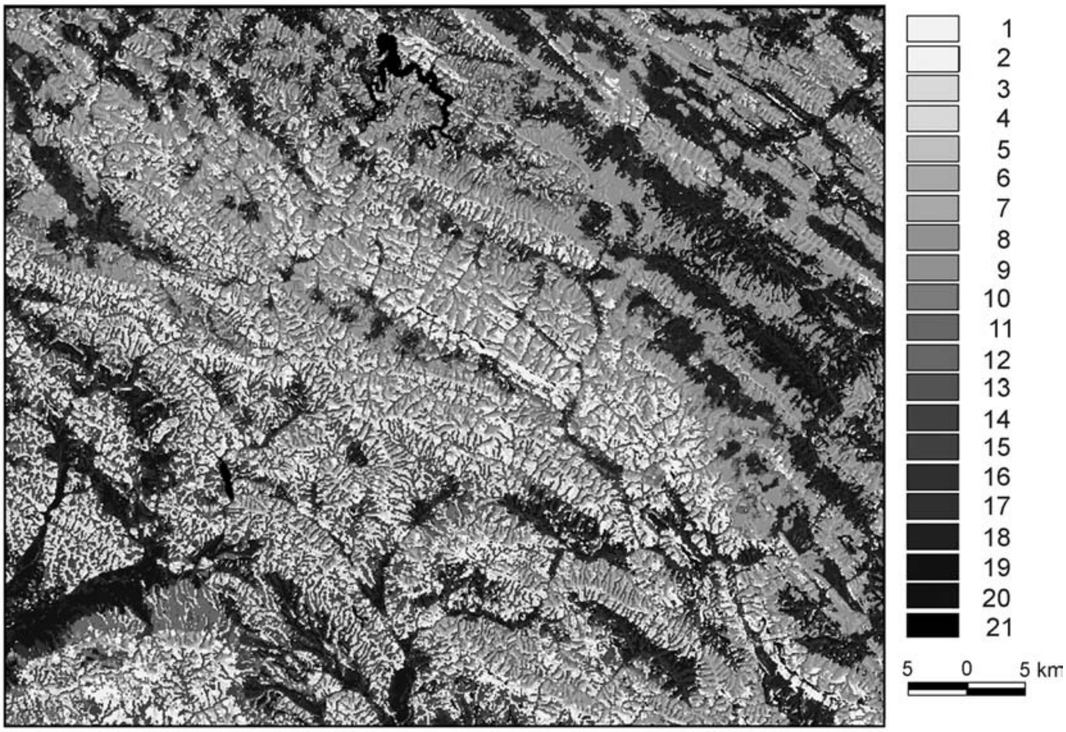

Fig. 7. Landscape elements map of study area. Legend is from table 3.

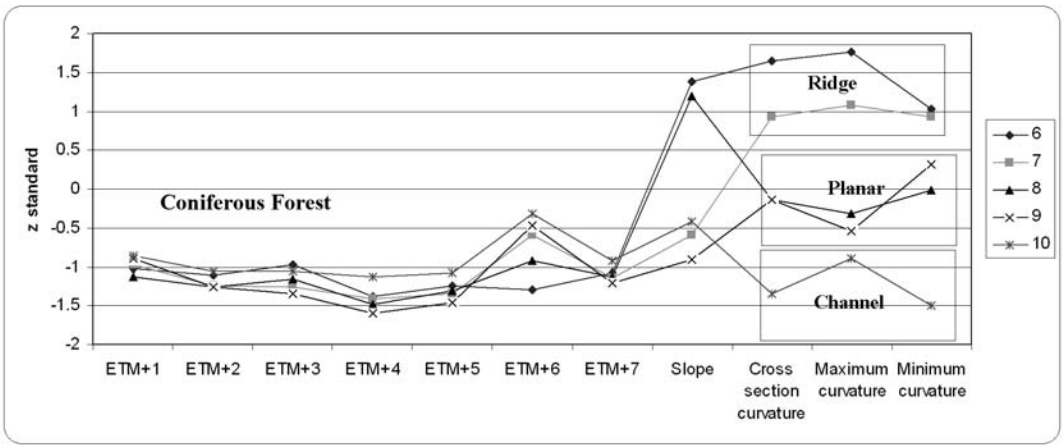

Fig. 8. Signatures of landscape elements in group 1. Legend is from table 3.

Table 3. Properties of landscape elements

Map unit	Average of Slope	Cross sectional curvature	Maximum curvature	Minimum curva-ture	Slope class	Morphome-tric features	Land cover class	Landscape elements
1	18	1	7	-8	very steep	planar	decidious forest	deciduous forest - very steep slope-planar
2	16	4	10	-4	very steep	planar	mixed forest	mixed forest - very steep slope-planar
3	8	8	16	-1	steep	ridge	decidious forest	deciduous forest - steep slope-ridge
4	17	16	23	1	very steep	ridge	decidious forest	deciduous forest - very steep slope-ridge
5	9	16	25	2	steep	crest line	mixed forest	mixed forest - steep slope-crest line
6	17	17	23	1	very steep	ridge	coniferous forest	coniferous forest - very steep slope-ridge
7	8	10	17	0	steep	ridge	coniferous forest	coniferous forest - steep slope-ridge
8	16	0	5	-8	very steep	planar	coniferous forest	coniferous forest - very steep slope-planar
9	7	0	4	-5	mode-rate	planar	coniferous forest	coniferous forest - moderate slope-planar
10	9	-12	1	-21	steep	channel	coniferous forest	coniferous forest - steep slope-channel
11	7	0	4	-6	mode-rate	planar	mixed forest	mixed forest - moderate slope-planar
12	16	-12	1	-19	very steep	channel	mixed forest	mixed forest - very steep slope-channel
13	7	-12	0	-23	mode-rate	channel	decidious forest	deciduous forest - moderate slope-channel
14	15	-18	0	-26	very steep	channel	decidious forest	deciduous forest - very steep slope-channel
15	12	-2	3	-7	steep	planar	decidious forest	deciduous forest - steep slope - planar
16	8	-8	0	-19	mode-rate	channel	grass land	grass lands - moderate slope-channel
17	6	-1	2	-6	mode-rate	planar	settlement	settlement - moderate slope-planar
18	6	0	3	-4	mode-rate	planar	grass land	grass lands - moderate slope-planar
19	8	9	14	-1	steep	ridge	shrub land	shrubland - steep slope-ridge
20	5	0	3	-5	gentle	planar	arable land	arable lands - gentle slope-planar
21	7	0	4	-5	gentle	planar	water	water - gentle slope-planar

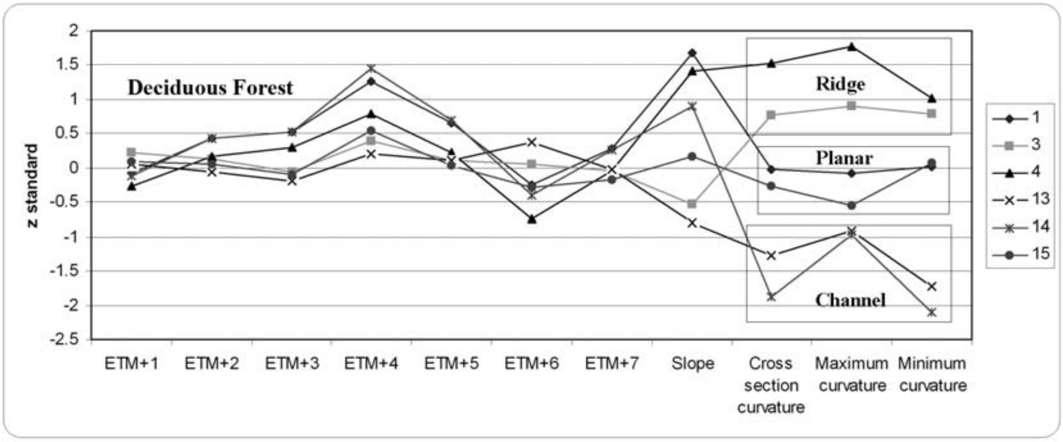

Fig. 9. Signatures of landscape elements in group 2. Legend is from table 3.

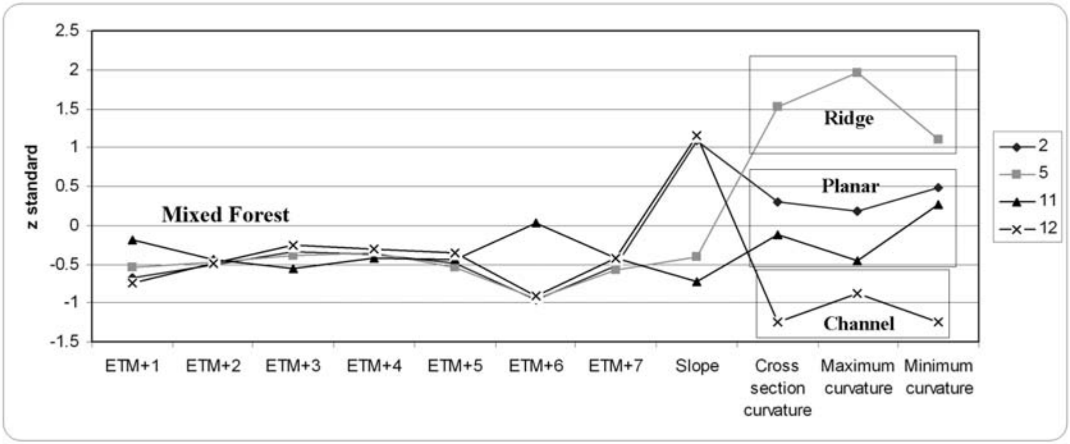

Fig. 10. Signatures of landscape elements in group 3. Legend is from table 3.

steep and very steep slopes). This group covers 20.99 % of the study area. Spectral signature of this group is higher than for coniferous forests but lower than deciduous forest.

Landscape elements group 4: This group (fig. 11) includes 2 landscape elements (16 and 18) with mostly grassland cover and 2 morphometric forms (planar, channel) on moderate slope. This group covers 11.05 % of the study area and has highest spectral signature in all Landsat bands Spectral signature of grasslands is similar to shrub lands (class 19) and settlements (class 17) but values are higher.

Landscape elements group 5: This group (fig. 11) consists of 1 landscape element (No. 19) with mostly shrub land cover and ridge as morphometric form with steep slopes. This class covers 4.59 % of the study area. The trend of spectral signature is the same as for settlements and grasslands, but values are higher than for settlements and lower than for grasslands.

Landscape elements group 6: This group (fig. 12) consists of 1 landscape element with arable lands and planar morphometric form on gentle slopes. This group covers 4.24 % of the study area. Averages of spectral values in the visible bands are higher than in infrared bands. The lowest value is in ETM+ band 4.

Landscape elements group 7: This group (fig. 12).consists of 1 landscape element with settlements and planar morphometric form on moderate slopes. This group covers 6.63 % of the study area. The trend of spectral signature is the same as for shrub lands and grasslands but values are lower (fig. 12).

Landscape elements group 8: This group consists of 1 landscape elements of water bodies and planar

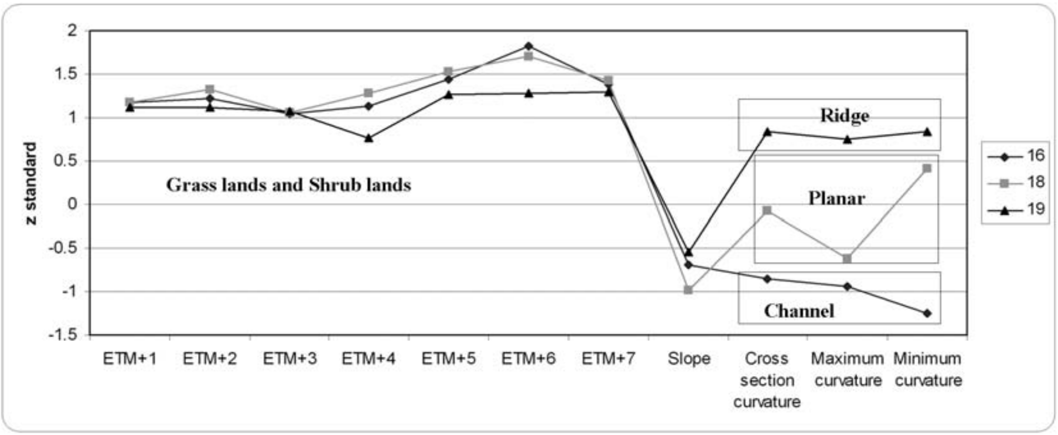

Fig. 11. Signatures of landscape elements in group 4 and 5. Legend is from table 3

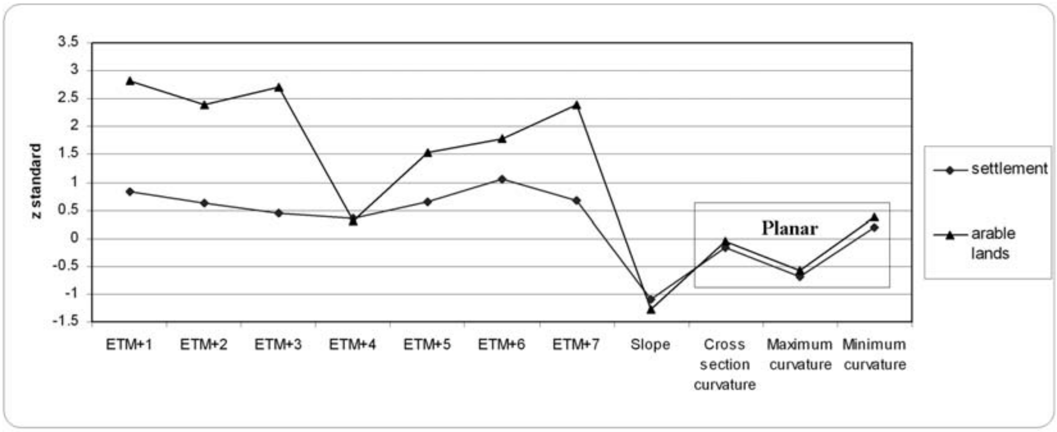

Fig. 12. Signatures of landscape elements in group 5, 6 and 7.

morphometric forms on gentle slope. This group covers 0.40% of study area.

Conclusions

A method to identify landscape elements integrating remotely sensed spectral data and DEM derivatives is presented. The four morphometric parameters of slope, cross-sectional curvature, maximum and minimum curvature led to the description of landforms as ridge, channel, planar or crest line. These morphometric terms coincide with actual geomorphologic entities.

Remotely sensed multi-spectral data provided valuable information on land cover in the study area, but water bodies can not be separated as a separate cluster. The self organizing map is a very efficient and robust algorithm for such unsupervised analysis. Our study also highlighted that combining morphometric parameters from a DEM with multi-spectral data facilitates the analysis of the landscape components landform and land cover. But for classes with low frequency and similar spectral signatures like settlements, shrub lands and grasslands misclassification may occur. Morphometric analysis with feature space analysis is a very efficient tool for interpreting and labeling a landscape elements map. Landscape elements were classified into eight heterogeneous groups according to landform, cover and slope. The group of landscape elements with deciduous forest and three landforms of planar, channel and ridge on moderate, steep and very steep slopes has with

26.3% the highest frequency in the study area.
This study presented a valuable method for extracting land information that can be used in geomorphological applications and geoecosystem models. The method allows important saving in field work and can be used as alternative for manual methods like rule-based geoecosystem classification.

Acknowledgment. The authors would like to acknowledge the support of the Ministry of Science, Research and Technology and the University of Tehran, Iran for granting a scholarship for the main author. The Swedish Institute funded all travel expenses in the framework of the Visby program. We want to thank our colleagues especially Docent Dr. Ivan Kruhlov, Department of Physical Geography, Ivan Franko University in Lvov, Ukraine and Dr. Mieczyslaw Sobik, Institute of Geography and Regional Development, University Wroclaw, Poland for interesting discussions and for providing facilities and support. We thank Dr. Kuemmerle for providing his land use map of the project area.

References

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

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

Crevenna, A. B., Vicente Torres-Rodríguez, Valentino Sorani, Dawn Frame and Mario Arturo Ortiz, 2005. Geomorphometric analysis for characterizing landforms in Morelos State, Mexico. Geomorphology, 67(3-4). 407-422.

Dehn, M., Gärtner, H. and Dikau, R., 2001. Principles of semantic modeling of landform structures. Computers & Geosciences, 27(8): 1005-1010.

Denisiuk, Z., Stoyko, S. M., 2000. The East Carpathian biosphere reserve (Poland, Slovakia, Ukraine). In: A. Breymeyer and P. Dabrowski, Editors, 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.

Evans, I. S., 1972. General geomorphometry, derivatives of altitude and descriptive statistics. Spatial Analysis in Geomorphology. In: Chorley, R.J., Editor, Methuen, London. 17–90.

Fisher, P., Wood, J. and Cheng, T., 2004. Where is Helvellyn? Fuzziness of Multiscale Landscape Morphometry. Transactions of the Institute of British Geographers, 29(1). 106-128.

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

Irvin, B. J., Ventura, S. J. and Slater, B. K., 1997. Fuzzy and isodata classification of landform elements from digital terrain data in Pleasant Valley, Wisconsin. Geoderma, 77(2-4). 137-154.

Kohonen, T., 2001. Self_ Organizing Maps. Springer, New York, 501.

Pike, R.J., 2000. Geomorphology - Diversity in quantitative surface analysis. Progress in Physical Geography, 24. 1-20.

Stepinski, T. F. and Collier, M. L., 2004. Extraction of Martian valley networks from digital topography, Journal of Geophysical Research 109 (E11005).

Stepinski, T. F. and Vilalta, R., 2005. Digital topography models for Martian surfaces. IEEE Geoscience and Remote Sensing Letters, 2(3). 260–264.

Kuemmerle, T., Radeloff, V. C., Perzanowski, K. and Hostert, P., 2006. Cross-border comparison of land cover and landscape pattern in Eastern Europe using a hybrid classification technique. Remote Sensing of Environment, 103(4). 449-464.

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

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

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