Morphometric and Landscape Feature Analysis with Artificial Neural Networks and SRTM data
Applications in Humid and Arid Environments

Doctoral Thesis

Amir Houshang Ehsani

Environmental and Natural Resources Information Systems
Department of Civil and Architectural Engineering
Royal Institute of Technology (KTH)
Stockholm, Sweden
June 2008
‘I prefer a short life with width to a narrow one with length’

Avicenna (Ibn Sina), 980-1073 A.D. Iranian Physician, Mathematician, philosopher and father of early modern medicine.
Abstract

This thesis presents a semi-automatic method to analyze morphometric features and landscape elements based on Self Organizing Map (SOM) as an unsupervised Artificial Neural Network algorithm in two completely different environments: 1) the Man and Biosphere Reserve “Eastern Carpathians” (Central Europe) as a complex mountainous humid area and 2) Lut Desert, Iran, a hyper arid region characterized by repetition of wind-eroded features.

In 2003, the National Aeronautics and Space Administration (NASA) released the SRTM/SIR-C band data with 3 arc seconds (approx. 90 m resolution) grid for approximately 80 % of Earth’s land surface. The X-band SRTM data were processed with a 1 arc second (approx. 30 m resolution) grid by the German space agency, DLR and the Italian space agency ASI, but due to the smaller X-SAR ground swath, large areas are not covered. The latest version 3.0 SRTM/C DEM and SRTM/X band DEM were re-projected to 90 and 30 m UTM grid and used to generate morphometric parameters of first order (slope) and second order (cross-sectional curvature, maximum curvatures and minimum curvature) by using a bivariate quadratic surface. The morphometric parameters are then used in a SOM to identify morphometric features (or landform elements) e.g. planar, channel, ridge in mountainous areas or yardangs (ridge) and corridors (valley) in hyper-arid areas.

Geomorphologic phenomena and features are scale-dependent and the characteristics of features vary when measured over different spatial extents or different spatial resolution. Morphometric parameters were derived for nine window sizes of the 90 m DEM ranging from 5 × 5 to 55 × 55. Analysis of the SOM output represents landform entities with ground areas from 450 m to 4950 m that is local to regional scale features. Effect of two SRTM resolutions, C and X bands is studied on morphometric feature identification. The difference change analysis revealed the quantity of resolution dependency of morphometric features. Increasing the DEM spatial resolution from 90 to 30 m (corresponding to X band) by interpolation resulted in a significant improvement of terrain derivatives and morphometric feature identification.

Integration of morphometric parameters with climate data (e.g. Sum of active temperature above 10 ° C) in SOM resulted in delineation of morphologically homogenous discrete geo-ecological units. These units were reclassified to produce a Potential Natural Vegetation map. Finally, we combined morphometric parameters and remotely sensed spectral data from Landsat ETM+ to identify and characterize landscape elements. The single integrated data set of geo-ecosystems shows the spatial distribution of geomorphic, climatic and biotic/cultural properties in the Eastern Carpathians.

The results demonstrate that a SOM is a very efficient tool to analyze geo-morphometric features under diverse environmental conditions and at different scales and resolution. Finer resolution and decreasing window size reveals information that is more detailed while increasing window size and coarser resolution emphasizes more regional patterns. It was also successfully applied to integrate climatic, morphometric parameters and Landsat ETM+ data for landscape analysis. Despite the stochastic nature of SOM, the results are not sensitive to randomization of initial weight vectors if many iterations are used. This procedure is reproducible with consistent results.

KEY WORDS: Self Organizing Map, Neural Network, Morphometric Feature, Landscape, Yardang, Lut Desert, Potential natural vegetation, geocystem, Landform, Landsat ETM+, Morphometric Parameters, SRTM, Resolution, Curvatures, DEM.
Sammanfattning

Avhandlingen presenterar en halvautomatisk metod för att analysera morfometriska kännetycken och landskapselement som bygger på Self Organizing Map (SOM), en öövervakad Artificiell Neural Nätverk algoritm, i två helt skilda miljöer: 1) Man and Biosphere Reserve "Eastern Carpathians" (Centraleuropa) som är ett komplext, bergigt och humid område och 2) Lut öken, Iran, en extrem torr region som kännetecknas av återkommande vinderoderade objekt.

Basen för undersökningen är det C-band SRTM digital höjd modell (DEM) med 3 bågsekunder rutnät som National Aeronautics and Space Administration släppte 2003 för ungefär 80 % av jordens yta. Dessutom används i ett mindre område X-band SRTM DEM med 1 bågsekund rutnät av den tyska rymdagenturen DLR. DEM transformerades till 90 och 30 m UTM nätet och därav genererades morfometriska parametrar av första (lutning) och andra ordning (tvärsnittböjning, största och minsta böjning). De morfometriska parametrar används sedan i en SOM för att identifiera morfometriska objekt (eller landform element) t.ex. plan yta, kanal, kam i bergsområden eller yardangs (kam) och korridorer (dalgångar) i extrem torra områden.

Geomorfiska fenomen och objekt är skalberoende och kännetycken varierar med geografiska områden och upplösning. Morfometrisk parametrar har härlemts från 90 m DEM för nio fönsterstorlekar från 5 × 5 till 55 × 55. Resultaten representerar landform enheter för områden från 450 m till 4950 m på marken dvs. lokal till regional skala. Inflytande av två SRTM upplösningar i C och X-bandet har studerats för identifikation av morfometriska objekt. Förändringsanalyser visade storleken av upplösningsberoende av morfometriska objekt. Ökning av DEM upplösningen från 90 till 30 m (motsvarande X-bandet) genom interpolation resulterade i en betydande förbättring av terräng parametrar och identifiering av morfometriska objekt.

Integration av morfometriska parametrar med klimatdata (t.ex. summan av aktiv temperatur över 10° C) i SOM resulterade i avgränsningen av homogena geokologiska enheter. Dessa enheter ha används för att producera en karta av potentiell naturlig vegetation. Slutligen har vi kombinerat morfometriska parametrar och multispektrala fjärranalysdata från Landsat ETM för att identifiera och karakterisera landskapselement. Dessa integrerade ekosystem data visar den geografiska fördelen av morfometriska, klimatologiska och biotiska/kulturella egenskaper i östra Karpaterna.

Resultaten visar att SOM är ett mycket effektivt verktyg för att analysera geomorfometriska egenskaper under skilda miljöförhållanden, i olika skalar och upplösningar. Finare upplösning och minskad fönsterstorlek visar information som är mer detaljerad. Ökad fönsterstorlek och grövre upplösning betonar mer regionala mönster. Det var också mycket framgångsrikt att integrera klimatiska och morfometriska parametrar med Landsat ETM data för landskapsanalys. Trots den stokastiska natur av SOM, är resultaten inte känsliga för slumpvisa värden i de ursprungliga viktevektorerna när många iterationer används. Detta förfarande är reproducierbart med bestående resultat.
Acknowledgements

I would like to express my sincere gratitude and appreciations to the following persons and organizations:

My supervisor, Professor Friedrich Quiel for his critical guidance, discussions and encouragements. I highly acknowledge his valuable and constructive comments and criticism. I’m very grateful for all your help and kind support from the beginning to the end of my doctoral education. I will never forget this golden time I spend with you at KTH.

The Ministry of Science, Research & Technology (MSRT) and the International Center for Living with Desert, University of Tehran, Iran for granting a scholarship and financial support. Their support is gratefully acknowledged.

My former supervisors Prof. Zehtabian and Dr. Alavi panah for their essential support and opening this great chapter of my life.

The Swedish Institute that funded all travel expenses in the framework of the Visby program.

NASA for conceiving the SRTM project, the German space agency (DLR), CGIAR-CSI GeoPortal database for access to the DEM data and the Global Land Cover Facility (GLCF) server at the University of Maryland for providing Landsat data.

All our colleagues especially Docent Ivan Kruhlov at the Department of Physical Geography, Ivan Franko University in Lvov, Ukraine and Dr. Mieczyslaw Sobik at the Institute of Geography and Regional Development, University Wroclaw, Poland for interesting discussions and for providing data and facilities.

Deepest gratitude goes to my parents, Reza and Zahra and my parents-in-law, Manochehr and Rezvan, for their major support and inspiration in keeping me moving along.

Last but not least, I dedicate this thesis with love to my darling wife, Shohreh, for all continuous encouragement, support and patience in my efforts during these past four years. Without your tolerance and patience, this thesis never would be completed. Thank you for your love and compassion.

Amir Houshang Ehsani
Stockholm, Sweden, June 2008
List of Papers

This doctoral thesis is based on the following papers:


Table of Contents

CHAPTER 1. INTRODUCTION .................................................................................................. 1
  1.1 LITERATURE REVIEW.......................................................................................................................1
    1.1.1 Artificial Neural Networks..............................................................................................................1
    1.1.2 Shuttle Radar Topography Mission (SRTM) ....................................................................................3
    1.1.3 Geomorphometry .........................................................................................................................4
    1.1.4 Potential Natural Vegetation (PNV) and Landscape analysis ....................................................6
    1.1.5 Yardang Characterization...........................................................................................................8
  1.2 OBJECTIVES ...............................................................................................................................9
  1.3 STUDY AREAS ...............................................................................................................................10

CHAPTER 2. DATA AND METHODS ....................................................................................... 13
  2.1 DATA ...........................................................................................................................................13
  2.2 METHODS ....................................................................................................................................14
    2.2.1 Morphometric Feature Analysis ...................................................................................................14
      2.2.1.1 Morphometric feature parameterization (Wood’s method) ......................................................14
      2.2.1.2 Self Organizing Map (SOM)..................................................................................................18
    2.2.2 Potential Natural Vegetation (PNV) .............................................................................................22
    2.2.3 Landscape Analysis ..................................................................................................................22

CHAPTER 3. RESULTS ............................................................................................................... 25
  3.1 MORPHOMETRIC FEATURE ANALYSIS ......................................................................................25
    3.1.1 Morphometric feature parameterization (Wood’s method) ..........................................................25
    3.1.2 Self Organizing Map (SOM) .......................................................................................................27
      3.1.2.1 Self Organizing Map optimization .........................................................................................31
      3.1.2.2 Effect of scales on morphometric features ...........................................................................33
        3.1.2.2.1 Statistics of morphometric parameters at different scales ...............................................33
        3.1.2.2.2 Identification of morphometric features at different scales ............................................34
      3.1.2.3 Effect of resolution on morphometric features .......................................................................37
        3.1.2.3.1 Effect of SRTM-DEM grid size on statistics of morphometric parameters ......................37
        3.1.2.3.2 Effect of SRTM-DEM grid size on identification of morphometric feature .....................38
      3.1.2.4 Desert geomorphometry .......................................................................................................44
  3.2 POTENTIAL NATURAL VEGETATION MAP (PNV) .................................................................48
  3.3 LANDSCAPE ANALYSIS ..........................................................................................................50
    3.3.1 Identification of Landscape elements ..........................................................................................50
    3.3.2 Spectral and morphometric signatures of landscape elements ...............................................52

CHAPTER 4. DISCUSSIONS AND CONCLUSIONS .................................................................. 57

REFERENCES ............................................................................................................................... 61

APPENDIX A-POTENTIAL NATURAL VEGETATION MAPPING.............................................. 71
Chapter 1

Introduction

This thesis presents a robust semi-automatic method for identification of morphometric and landscape features at various scales and resolutions aiming to cover large areas, being relative easy to use and allowing fast assessment and comparison of terrains. The potential of artificial neural network algorithms together with the global availability of SRTM data makes it very attractive to develop methods for rapid monitoring and inventory of landscapes in diverse environments ranging from humid to hyper arid.

1.1 Literature Review

1.1.1 Artificial Neural Networks

In 1943 the first model in artificial neural networks (ANN) was proposed by McCulloch and Pitts (1943) carrying now their names: a binary device with two states and a fixed threshold that receives excitatory connections or synapses, all with the same value and inhibitors of global action. They simplified the structure and functioning of the brain neurons with $m$ inputs, one single output and only two possible states: active or inactive (Rabunal and Dorrado 2006). The human brain consist of $10^{11}$ neurons that communicate through a network of axons and synapses ($10^4$-$10^5$ per neuron). The communication is performed by electrical impulses. The main element in the biological network is called Soma or cell body. The electrical impulses or signals are collected by Dendrites of the cell and transported between neurons by Axons. Neurons receive only signals from neighboring neurons and the neuron itself. If the total incoming signals exceed a certain threshold in the soma then the neuron fires and sends a signal to the next neuron. Therefore, our entire brain is composed of these interconnected electro-chemically transmitting neurons. The brain manages to perform extremely complex tasks with a very large number of extremely simple processing units, each collecting a weighted sum of its inputs, and firing a binary signal if the total input exceeds a certain level.

In 1949 the next major development in neural network technology arrived with the book, "The Organization of Behavior" written by Donald Hebb (1949). The book supported and further reinforced McCulloch-Pitts's theory about neurons and how they work. A major point brought forward described how neural output signals are strengthened each time. In 1958 Frank Rosenblatt, a neuro-biologist at Cornell University began working on the Perceptron (Rosenblatt 1958). The perceptron was the first "practical" artificial neural network with ability of learning. A perceptron is a mathematical model of a biological neuron (figure 1). In actual neurons, the dendrite receives electrical signals from the axons of other neurons; in the perceptron, these electrical signals are represented as numerical values. At the synapses between the dendrite and axons, electrical signals are modulated in various amounts.
1. Introduction

In a perceptron, this is modeled by multiplying each input value by a value called the weight. A neuron fires an output signal only when the total strength of the input signals exceeds a certain threshold. A perceptron calculates the weighted sum of the inputs to represent the total strength of the input signals, and applies a function on this sum to determine its output. As in biological neural networks, this output is fed to other perceptrons.

![Fig. 1. A simple biological (left) and artificial neuron (right).](image)

In 1959 and 1960 Bernard Wildrow and Marcian Hoff of Stanford University, developed the ADALINE (ADAPTIVE LINEAR ELEMENTS) and MADELINE (Multiple ADAPTIVE LINEAR ELEMENTS) models. These were the first neural networks that could be applied to real problems. The ADALINE model was used as a filter to remove echoes from telephone lines. In the period between 1969 and 1981 much attention paid towards neural networks (re-emergence period) when several academic centers published articles and distributed software (Parks et al. 1998; Zurada 1992).

In early 1980 the Self-Organizing Map (SOM), one of the most distinguished unsupervised artificial neural network models is introduced and developed by Teuvo Kohonen (Kohonen 1989, 2001). The algorithm for learning a SOM is a competitive algorithm. This algorithm is similar to the spatial organization of the brain's functions, as observed especially in the cerebral cortex. It was originally meant for a model of brain maps, but it soon turned out to be better suited as a data-mining tool (Kohonen 2006). In this network, there is an input layer fully connected to a two-dimensional output layer. SOM will be discussed in detail later in this thesis. Since that time, neural networks algorithms have been the topic of substantial and computational development. Many researches developed different neural network algorithms. Recent works include Boltzmann machines, Hopfield nets, back propagation networks, and adaptive resonance theory models (Parks et al. 1998). These models share all certain architectural and processing features:

1. they contain many simple processing units operating in parallel;
2. these units communicate along connections of varying strength (weights);
3. the algorithm learn by adjusting their weights as they iterate (Parks et al. 1998; Zurada 1992).

Most published applications of ANN in physical geography are in the field of remote sensing (Atkinson and Tatnall 1997; Skidmore et al. 1997) and slope stability evaluation (Guzzetti et al. 2008; Guzzetti et al. 1997).
1. Introduction

Relatively few examples exist of ANN being used to assess the spatial distribution of geomorphological processes and landforms (Leverington and Duguay 1997; Brown et al. 1998). Lek and Guegan (1999) proposed that ANN models are more powerful than multiple regression when modeling nonlinear relationships. In instances with complex and/or nonlinear influences in geomorphological processes, ANN may well turn out to be advantageous (Lek and Guegan 1999).

SOM, which are used in this thesis, are unsupervised and nonparametric artificial neural network algorithms that cluster high dimensional input vectors into a low dimensional (usually two dimensional) output map in such a way which preserve topology of the input data. Preserving topology means that the SOM preserves the spatial relations between input neighboring points.

This important property among others such as versatile, spatially organized internal representations, potential as a robust substitute for clustering and visualization analysis (Suganthan 2001), learning ability from complex, multi-dimensional data and transformation to visual clusters (Kiang 2001) make a SOM to a very efficient tool for many applications. Some examples are: speech recognition (Leinonen et al. 1993), image data compression (Manikopoulos 1993), image or character recognition (Bimbo et al. 1993; Sabourin and Mitiche 1993), robot control (Ritter et al. 1989; Takahashi et al. 2001; Walter and Schulten 1993), medical diagnosis (Vercauteren et al. 1990), lithological discrimination using Landsat TM data (Mather et al. 1998), urban land use classification (Özkan and Sunar Erbek 2005), ecological modeling (Lek and Guegan 1999), Morphometric features analysis (Ehsani and Quiel 2008b), landscape elements analysis (Ehsani and Quiel 2008d; Ehsani and Quiel 2008c), yardangs identification (Ehsani and Quiel 2008a), visualization of high-dimensional data (Penn 2005), surface geology mapping (Penn and Livo 2001), financial markets (Deboeck 1998; Deboeck and Kohonen 1998), data mining and knowledge discovery (Bigus 1996; Koua et al. 2006; Vesanto and Alhoniemi 2000), hyperspectral image classification and anomaly detection (Penn 2002a, 2002b; Penn and Wolboldt 2003) and classification of remote sensing data (Duda and Canty 2002; Jianwen and Bagan 2005).

1.1.2 Shuttle Radar Topography Mission (SRTM)

Information about landforms and landscape is one of the fundamental requirements for a large variety of modeling problems in environmental science. Information about landforms is necessary, for example for landscape evaluation, soil suitability studies, erosion studies, hazard prediction, geocosystem classification, natural vegetation mapping, hydrological and ecological application, desert geomorphology, landslide hazards and various fields of landscape and regional planning or land system inventories. The classic way to incorporate relief units into a landscape assessment is to delineate them during field survey or using stereo aerial photographs. This approach is time-consuming and the results depend on subjective decisions of the interpreter and are, therefore, neither transparent nor reproducible (Dragut and Blaschke 2006). The emergence of suitable algorithms such as SOM in combination with the increasing availability of high resolution digital elevation models (DEM) from reliable sources like the Shuttle Radar Topography Mission (SRTM) has made development and application of procedures for automated landform identification increasingly feasible and cost effective. On February 11th 2000, the space shuttle Endeavour with the SRTM payload on board was launched to an altitude of 233 Km.
1. Introduction

During 11 days the SRTM collected data to produce a consistent DEM covering all landmasses on earth between 60° N and 57° S at a spatial resolution of 1 arc second (Blumberg 2006; Rabus et al. 2003a; Rabus et al. 2003b; Wright et al. 2006). SRTM utilized dual Space borne Imaging Radar (SIR-C) and dual X-band Synthetic Aperture Radar (X-SAR) configured as a baseline interferometer, acquiring two data sets at the same time. The SRTM "finished" data exceeded the absolute horizontal and vertical accuracies of 20 meters (circular error at 90% confidence) and 16 meters (linear error at 90% confidence), respectively, as specified for the mission.

The vertical accuracy is actually significantly better and close to +/- 10 meters. In 2003, the National Aeronautics and Space Administration (NASA) released the SRTM/ SIR-C band data with 3 arc seconds (~ 90 m) grid for most of the non polar world and with 1 arc second (~ 30 m) for the United States. NASA's Jet Propulsion Laboratory (JPL) performed processing of the raw C-band SRTM data. The X-band SRTM data was processed by the German space agency, DLR (Deutsches Zentrum für Luft und Raumfahrt, Germany) and the Italian space agency ASI (Agenzia Spaziale Italiana). Unfortunately, due to the smaller X-SAR ground swathes, large areas are not covered (Hancock.G.R. et al. 2006; Kaab 2005; Kellndorfer et al. 2004; Miliaresis and Parascou 2005; Rabus et al. 2003b). Since the SRTMDEMs (DEM) became widely available, many studies utilized them for applications such as topography and terrain characteristics (Falorni et al. 2005; Gorokhovich and Voustianiouk 2006; Rabus et al. 2003b), volcano morphology (Wright et al. 2006), vegetation studies (Kellndorfer et al. 2004), analysis of large aeolian bedforms (Blumberg 2006), hydrologic modeling (Ludwig and Schneider 2006), morphotectonic analysis (Grohmann et al. 2007) and topography classification (Iwahashi and Pike 2007).

1.1.3 Geomorphometry

For a semi-automatic classification of morphometric features (or landform elements) it is necessary to identify and implement algorithms that can convert raw elevation data to quantitative and numerical measures of those landform attributes. The terrain derivatives most widely were used in landform classification. Geomorphometry is a quantitative technique to analyze land surface features. In simple terms, geomorphometry aims at extracting (land) surface parameters (morphometric, hydrologic etc.) and objects (watersheds, stream networks, landforms etc.) using a set of numerical measures derived from DEMs such as slope steepness, profile curvature, plan convexity, cross-sectional curvature, minimum and maximum curvatures (Fisher et al. 2004; Pike 2000; Wood 1996a). Numerical characterizations are used to quantify generic landform elements (morphometric features) such as point-based features (peaks, pits and passes), line-based features (channels and ridges) and area-based features (planar) (Evans 1972; Wood 1996c).

Landforms as physical constituents of landscape may be extracted from DEMs using various approaches including combination of morphometric parameters subdivided by thresholds (Dikau 1989), fuzzy logic and unsupervised 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), automated classification using object-based image analysis (Dragut and Blaschke 2006) multivariate descriptive statistics (Dikau 1989;
Evans 1972), double ternary diagram classification (Crevenna et al. 2005), discriminant analysis (Giles 1998) and neural networks (Ehsani and Quiel 2007b).

Geomorphic features and phenomena are scale-dependent (Evans 2003). This scale-specific and scale-dependent behavior of landscape morphology can not be denied. Landform scale-specificity and scale-dependency is recognized by geomorphologists either implicitly or explicitly (Evans 1972; Wilson and Gallant 2000; Wood 1996b). “…I assert that most recognizable landform types are scale-specific, at least regionally or locally” (Evans 2003). Scale dependency in this context means that the characteristics of a point or an area on a surface vary when measured over different spatial extents or different spatial resolution (Tate and Wood 2001; Walsh et al. 1998; Wood 1996b, 2002). Hence, spatial resolution is the size on the ground of one grid cell or raster element and spatial extent is the area on the ground (window size × DEM resolution) used to measure the morphometric parameter. A ridge for instance can be observed at various spatial extents ranging from few tenths of meters through tenths of kilometers. For example, Kienzle (2004) studied the effect of DEM raster size from 100 to 5 m on first order, second order and compound terrain derivatives. He concluded that optimum grid cell size depending on terrain complexity is between 5 and 20 meter.

Most existing methods for numerical characterization of the terrain pass a local window over a DEM. This information however is only relevant to the resolution of the DEM. Since this resolution is not necessarily related to the scale of morphometric features of interest, derived features might not always be appropriate (Wood 1996a). Gallant and Dowling (2003) showed that it is problematic to use a single-size window to estimate terrain parameters and multi-resolution terrain attributes should be considered. Burnett and Blaschke (2003) introduced a five step methodology based on multi-scale segmentation and object relationship modeling for landscape analysis. They adopted hierarchical patch dynamics (HPD) as the theoretical framework to address issues of heterogeneity, scale, connectivity and quasi-equilibriums in the landscapes. They conclude that HDP provides a better tool to characterize multi-scale patterns of landscape.

Dikau (1989) developed an approach to identify plateaus, convex scarps, straight front slopes, concave foot-slopes, scarp forelands, cuesta scarps, valleys and small drainage ways, and crests. Many of these landform features are, however, at the nano- or microscale. Their derivation is appropriate for applications such as avalanche tracking, the exploration of karst phenomena or studying gully erosion (Dragut and Blaschke 2006). These landscape features are too detailed for regional to national landscape classifications. Conversely, in physiographic analysis the segmentation of terrain is performed on a regional scale, thus a moderate resolution DEMs e.g. at 30-arc seconds, is more desirable. This scale takes into account the size of features used in physiographic analysis (Miliaresis and Argialas 1999). Ideally the scale of analysis (spatial extent or resolution) can vary from the original data sampling to coarser one in order to obtain the optimal scale for the given analysis (Luoto and Hjort 2006).

Effects of DEM resolution on landform attributes were studied by many researchers. For example, Deng et al (2007a) proved by correlation and regression analysis that terrain attributes across a landscape are dependant on DEM resolution. They also demonstrate (2007b) that spatial resolution change may not only cause point-specific effects on -
calculation terrain attributes but also shifts in the meaning of the topographic attributes. Schoorl et al (2000) examined the effect of five different DEM resolutions 1, 3, 9, 27 and 81 m on the result of geomorphological models. This study demonstrates that DEM resolution greatly affected the values of computed terrain characteristics. Sorensen and Seibert (2007) studied the effect of three different DEM resolutions (10, 25 and 50 m), derived from the original 5 m LIDAR DEM, on topographic indices. Their results showed interpolating DEMs to higher resolution causes differences between topographic indices and affect more in upslope area. Thompson et al (2001) demonstrated how DEM resolution (10 m from field survey and 30 m acquired from USGS) affects terrain attribute calculation and quantitative soil-landscape modeling. They conclude that decreasing the resolution of the field survey DEM produced lower slope gradients on steeper slopes, steeper slope gradients on flatter slopes and narrower ranges in curvatures. Overall, certain landscape features were less discernible in the 30 m DEM than in the 10 m DEM. A number of more recent studies emphasize the importance of DEM resolution on terrain, landscape and soil analysis. Examples are the effect of DEM resolution on soil landscape (Wu et al. 2008), effect of DEM resolution and neighborhood size on digital soil survey (Smith et al. 2006), effect of contour intervals and grid cell size on the accuracy of DEMs and slope derivatives (Ziadat 2007) and modeling small watersheds with SRTM 90 m and interpolated to 30 m data (Valeriano et al. 2006). Many studies have shown the effect of DEM resolution on the spatial pattern of terrain attributes but to our knowledge, the impact of increasing spatial resolution from SRTM-3arc" to 1 arc" for morphometric feature identification with a neural network procedure has not been investigated previously.

1.1.4 Potential Natural Vegetation (PNV) and Landscape analysis

The availability of SRTM data and other remotely sensed data provides a wealth of information to develop new methods for Potential Natural Vegetation (PNV) mapping and landscape analysis. Landform information is contained in a DEM as regularly spaced elevation matrix, whereas land cover information can be derived from multi-spectral satellite data (Ehsani and Quiel 2007a). PNV is an expression of environmental factors such as topography, soils and climate across a landscape. Most researchers define landscape as an essentially visual phenomenon or as a particular configuration of topography, land use, vegetation cover and settlement pattern (Blankson and Green 1991; Otero Pastor et al. 2007). Landscapes are dynamic systems involving interrelation between physical characteristics (such as landform, soil) and anthropogenic processes (such as land use). So any landscape (Fig. 2) can be defined in terms of its form (morphology) and what lies upon it (land cover) and what it is used for (land use). Relationship between these physical properties and human impact on the land has led to the development of different analysis models.

These models vary from visual analysis and quantitative techniques to rule-based geocosystem techniques (Benefield and Bunce 1982; Bernert et al. 1997; Blankson and Green 1991). However all these models depend on the common task to find the basic elements in a heterogeneous landscape. The basic concept of natural landscape units, called geochores, was developed in the 1950s and 1960s. The term ‘geochore’ means a geographically defined or limited unit and can be regarded as mosaics of basic topic elements (Bastian 2000).
1. Introduction

![Diagram of Landscape Components and PNV map from DEM and remote sensing data.]

Landforms possess at least two important properties. They are (Dehn et al. 2001):

- the result of past geomorphic and geologic processes
- the controlling boundary condition for actual geomorphic processes

For disciplines dealing with landforms, the properties of consideration are different. For geomorphologists both properties of landforms are important. However, a common perspective of all landform studies regardless of discipline is to delimit homogeneous areas from digital elevation data. Combining land surface forms (Morphometric features) with spectral information from remotely sensed data contributes to the explanation of relationships between landscape component processes (physical, biotic and human activities) on one hand and delimiting boundaries of homogenous landscape elements on the other hand. This complex task can be achieved through efficient tools like SOM that are able to learn and are not depend on the statistical distribution of data.

Since the introduction of PNV as a concept in vegetation science by Tüxen (1956), many PNV-maps have been made. Tüxen emphasized the great value of PNV-maps for different purposes in land use, landscape planning and nature conservation, in particular for forestry, agriculture and landscape management. A SOM method is regarded as very convenient and fast procedure for PNV delineation of trans-boundary between different national and regional landscapes. Integration of a GIS with SOM output facilitates to organize a common geographical database for the support of the sustainable and integrated managements of land resources within different administrative and political parts of Eastern Carpathians. The geo data set will to be used as one of the principal inputs in different GIS-based land resources inventory, assessment and planning procedure.
1. Introduction

1.1.5 Yardang Characterization

The other goal of this thesis is to investigate the effectiveness of SOM algorithm and SRTM data to analyze and characterize Yardangs, a distinctive landform in Lut desert of Iran. The Lut desert (Dasht-e Lut, or Dasht-i Lut) in the south east of Iran is described as the “thermal pole of the Earth”. With an area of about 80,000 square km it is regarded as the hottest and the driest desert in the world (Alavi Panah et al. 2007; Gabriel 1938; Mildrexler et al. 2006). The eastern part of Lut desert is characterized by a great massif of dunes and sand sheets, while the western part consist of Yardangs, some of the world’s largest desert forms separated by large wind-swept corridors (Walker 1986). The yellowish-red Pleistocene clay deposits of the former Lut lake are now sculptured into straight bizarre shapes Yardangs (called Kalut, desert cities by the Iranian Baluchis) up to 80 m high and 120 km long running in NNW-SSE direction (Gabriel 1938). Alfons Gabriel, one of the first explorers in this area, describes this area as "In one row of “desert cities” after another Kalut stretch, probably in one uninterrupted formation, for about 100 miles in length and 25 miles in breadth" (1938, p. 199). He notes, “apart from sand dunes of the Lut, the Kalut were the most impressive sight we had ever seen” (p. 198).

Yardangs a Turkmen word used by the Swedish explorer Sven Hedin (1903) meaning ‘steep bank’ occur also on Mars and possibly on Venus (Goudie 2007). They are streamlined forms up to 150 km long and 75 m in height resulting from a number of formative processes, including wind abrasion, deflation, fluvial incision, desiccation cracks, slumping, weathering and mass movement (Goudie 2007; McCauley et al. 1977; Ward and Greeley 1984). A limited number of morphometric investigations have been done on yardangs. Goudie (2007) identified mega-yardangs in hyper-arid environments with total rainfall less than 50 mm including central Asia, the Lut desert in Iran, northern Saudi Arabia, Bahrain, the Libyan desert in Egypt, the central Sahara, the Namib desert, the high Andes and Peruvian desert. According to him, these features develop in a wide range of rock types e.g. sandstones, ignimbrites, limestones and basement rocks with a unimodal wind direction. Yardangs tend to occur in areas of sand transport rather than sand accumulation (e.g. Lut, Saudi Arabia, northern Namibia) and may have been shaped over millions of years (Goudie, 2007). Gutierrez-Elorza et al (2002) studied the existence and generation of yardangs in the semiarid central sector of the Ebro Depression in Spain. They concluded that generation of yardangs in that area is related to the presence of playas, which constitute the source of abrading particles during dry periods. In another study Alavi Panah et al (2007) used Landsat Thematic Mapper (TM) data to characterize land cover and surface conditions of yardangs in Lut desert. They showed that the main land cover types of Lut desert could be differentiated by supervised maximum likelihood classification. However, their study was based on extensive time-consuming field work and Landsat data. The results depended on subjective decisions of the interpreter in selection of training areas. Inbar and Risso (2001) studied different size yardangs of volcano terrains in the southern Andes, Argentina. They showed that micro and meso-yardangs are formed on ignimbrite flows but mega-yardangs are developed in basaltic lava flows as long parallel corridors.
1. Introduction

1.2 Objectives

The overall aim of this thesis is to develop and investigate a method using unsupervised artificial neural network - Self Organizing Map - to analyze morphometric and landscape features. In summary, this study has the following objectives:

1. Provide a semi-automatic method for morphometric feature analysis as an alternative method to manual interpretation or parameterization algorithms such as Wood’s (1996a) method (Papers I and VIII).

2. Investigate the effect of resolution, DEM interpolation and window size on morphometric parameters, quantization error, classification results and type of landscape features. (Papers IV, V, VII and X).

3. Evaluate the effect of main SOM learning parameters (e.g. Initial radius, final radius and number of iterations) and random weight initialization on average quantization error and classification results (Papers II, III and IV).

4. Investigate this method to characterize dominant morphometric features (e.g. Yardangs) in a hyper-arid region (Papers III and VII).

5. Investigate the use of SOM to delineate topo-climate units based on morphometric and climate data as a base for potential natural vegetation mapping.

6. Investigate the combination of morphometric parameters and remotely sensed spectral data e.g. Landsat 7 for landscape analysis via SOM (Papers II, VI and IX).
1. Introduction

1.3 Study areas

We applied the present method in two completely different environments:

1- The Man and Biosphere Reserve “Eastern Carpathians” covers the the Bieszczady national park in Poland, Uzanski national park in Ukraine and Poloniny national park in Slovakia, in a complex mountainous humid environment. This area (Fig. 3) is centered on the common border point of Poland, Slovakia and Ukraine and is located between 48° 52' N and 49° 25' N latitude, 21° 59' E and 23° 1' E longitude with a total area of 4 543 Km². Most of the study area is characterized by mountain ranges stretching from southeast to northwest as part of the Carpathian (Bieszczady) Mountains with altitude ranging from 163 to 1324 meters above sea level and slopes from up to 42 degrees.

![Fig. 3. location of the study area (modified from Grodzinska et al. 2004) and Relief shaded topography from SRTM data of the study area at the border of Poland, Slovakia and Ukraine in “Eastern Carpathians”](image)

Historically, the region had shifting borders. After World War II, fundamental changes in political systems had different effects on the landscape of these countries. For example, population density in Ukraine and Slovakia increased and agricultural land was collectivized. Parts of the Polish side were depopulated and large areas converted to forest (Kuemmerle et al. 2006).

The bedrock is composed mainly of Carpathian flysch consisting of sandstone and shale (Denisiuk and Stoyko 2000; Kuemmerle et al. 2006) and in the southwest volcanic rocks. Climatic conditions, different political and socioeconomic systems as well as ecological conditions resulted in complex landscape units. Land covers include 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 center 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). Grassland is the dominant landscape in the northwest, northeast and east. Arable lands are mainly found in the south west in Slovakia and in the north east in Ukraine.
1. Introduction

Lut Desert (Dasht-e Lut, or Dasht-i Lut) is a low area of about 400 × 800 km\(^2\) consisting of several large basins separated by low ridges (Krinsley 1970; Walker 1986) in southeast Iran. The desert includes low basins that stretch southward from the Khorasan province into the Kerman province between 29° 30' N and 30° 49' N, and 57° 47' E and 59° 53' E. The Lut desert depression contains several hundred meters of upper Pliocene to Pleistocene lacustrine silts over a basement of flat-lying Paleogene andesitic lavas and tuffs. Several Quaternary basalt flows occur near the Nayband fault on the western edge of the Lut. Further to the west the anticlinal ridges of the Shahdad belt are formed of up to 3000 m of stratified marls containing gypsum, sandstone and conglomerates (Aghanabati 1993; Sahandi 1992; Walker and Jackson 2002). The eastern part of Dasht-e Lut is a low plateau covered with salt flats. This area consists of some of the world’s highest dunes reaching a height of 300 meters (Krinsley 1970; Walker 1986). The study area is located in the western part of Lut desert (Fig. 4) with strong diagonal features resulting from wind erosion and episodic floods acting on the Neogene silts (Berberian et al. 2001).

Fig. 4. (a) Location of study area in the south east of Iran, (b) Geological map of the study area and (c) Red-Green-blue (RGB) color composite of bands 7, 5 and 2 of Landsat 7 data (Acquired from http://glcf.umiacs.umd.edu).
1. Introduction

Altitude ranges from 100 m in the north and east to 404 m above sea level, in the center and south east. Slopes range from 0 to 19 degrees. The Lut desert is characterized by a hyper-arid climate with an annual rainfall less than 10 mm (Fig. 5c) mainly falling in winter. The average mean daily temperature ranges from 11° in January to 40° in July. The mean annual wind speed is 6 m/s. Winds are strongest in April with average speed of 9.35 m/s (Fig. 5b). The direction of the prevailing wind known as “wind of 120 days” or Bad-i-sad-o-bist roz Systan running from NNW- SSE corresponds exactly to the direction of the elongated yardangs (Fig. 5a).

Fig. 5. (a) Compass Plot of annual wind direction and magnitude (m/s) during 1970-2003 period, (b) Mean of monthly wind speed during 1970-2003 period and (c) Ombrothermic diagram of Ziyaratgah Deh Seyf station in the north-west of study area with a hyper-arid climate (data are from Iran meteorological organization).
Chapter 2

Data and Methods

2.1 Data

The data sets in this study consist of:

- “Finished” SRTM data are currently distributed by NASA ftp server (ftp://e0srp01u.ecs.nasa.gov/srtm/version2/SRTM3/). The finished SRTM data contain "no-data" holes where water or deep shadow prevented the quantification of elevation. These holes are generally small, but render the data less useful, especially in e.g. hydrologic modeling which requires continuous flow surfaces (Jarvis et al. 2006). The version 3.0 SRTM data are the result of substantial post processing efforts of the original release SRTM data and are provided by the Consortium for Spatial Information (CSI) of the Consultative Group for International Agricultural Research (CGIAR). The data are distributed in a geographic (Lat/Long) projection, with the WGS84 horizontal datum and the EGM96 vertical datum and are currently available from the CGIAR-CSI SRTM database: http://srtm.csi.cgiar.org. The version 3.0 SRTM data represents an improvement from previous versions, due to use of NASA "finished" grade data, further optimization of the hole filling algorithm and the use of auxiliary DEMs for filling in the holes (Jarvis et al. 2006). In this study, the version 3 of SRTM 3 arc second, C band, in geographic projection was acquired from CGIAR-CSI GeoPortal database. It was re-projected to UTM grid with 90 and 30 m resolution with WGS84 Datum, zone 34 using cubic convolution interpolation.

- SRTM 1 arc second, X band, available only for part of study area in geographic projection was acquired from German space agency, DLR. Also this data was re-projected to UTM grid with WGS84 Datum, zone 34.

- Landsat ETM+ data, path 186, row 26 dated 2000-09-30 (Poland) and path 159 row 39 dated 2001-08-03(Iran) were acquired from the Global Land Cover Facility (GLCF) 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://glef.umiacs.umd.edu).

- 60 cm resolution QuickBird satellite image collected on Oct 15, 2005.
2. Data and Methods

- Climate data, such as monthly and yearly average temperature, degree days and annual rainfall. The climate data are obtained via models based on analysis of long weather station time series and DEM.

- Auxiliary data such as a land cover map provided by Kuemmerle (2006), topographic maps (scale 1:100 000) and field observation data.

2.2 Methods

The methods are presented in two sections. In the first section, we describe two different methods for morphometric analysis in the “Eastern Carpathians” study area (papers I and XIII). The first method is based on the morphometric feature parameterization proposed by Wood (1996a) and can be achieved by Geographic Information Systems (GIS) software. The second method is our development for such morphometric analysis using a Self Organizing Map (SOM). We also investigate the scale and resolution dependency of identified features (papers IV, V, VI and X). Then we evaluate the effectiveness of the proposed method in a hyper arid environment (papers III and VI). The second section describes the development of our method for landscape element analysis (papers II and VII) and potential natural vegetation mapping. Open source GRASS software, version 6.0 (GRASS Development Team 2006) was used for morphometric analysis, co-registration and resampling of data. Self Organizing Map algorithm was used in Matlab and SOM Tool box software Version 2.0 which is freely available from the Laboratory of Computer and Information Science (CIS) at Helsinki University of Technology, Finland (Vesanto et al. 1996). Presentation and perspective analysis was carried out in ENVI Ver. 4.1 and ARC VIEW Ver.3.2a software.

2.2.1 Morphometric Feature Analysis

2.2.1.1 Morphometric feature parameterization (Wood’s method)

Parameterization has been defined as “the numerical description of continuous surface form” (Pike 2000). Geomorphologically, it has been described as “a set of measurements that describe topographic form well enough to distinguish topographically disparate landscapes (Pike 2001; Wood 1996b). Numerical geomorphology studies the statistical and spatial characteristics and relationships of point attributes (Evans 1972).

Morphometric feature analysis is a numerical approach to classify terrain in point features like peak, pit and pass; linear features like ridge and channel and areal category like plane from sets of terrain parameters (Fig. 6). For an effective geomorphological parameterization, firstly, terrain parameters should be sensitive to geomorphological processes as well as form. Secondly, a complete surface parameterization must include reference to scale-based characteristics. The effect due to the scale of sampling and the way in which the surface model is stored should be separated from true surface scale-dependencies as far as possible (Wood 1996a).
First (slope) and second order derivatives of a DEM (Table 1) are the basic components for studies of landscapes (Evans 1972). The measurement of second derivatives of elevation as surface curvature is useful in that it is strongly related to geomorphological processes. Evans (1972) separates curvatures into two orthogonal components - profile and plan curvature. These measures can only be calculated if the slope normal is not vertical. For this special case, two alternative measures, minimum and maximum curvatures are used (Evans 1972; Wood 1996b). Wood also proposed cross-sectional curvature as another second order derivative of DEM (Wood 1996a). This parameter is computationally simpler and directly related to geomorphological form when surface concavities (i.e. channel) are detected.

\[ Z = ax^2 + by^2 + cxy + dx + ey + f \]  

Where: x, y, Z are local coordinates and a to f are quadratic coefficients (Evans 1972).

Morphometric features can be identified using rules and definitions. Wood (1996a) defined a set of criteria to classify digital elevations models into morphometric classes (Table2).

![Morphometric Features](image.png)
2. Data and Methods

For locations with zero slope, the cross sectional curvature is undefined (because the aspect is undefined) and maximum and minimum curvature are used as alternative parameters.

Table 1. Morphometric parameters (Evans 1972; Shary et al. 2002; Wood 1996b).

<table>
<thead>
<tr>
<th>Morphometric parameter</th>
<th>Formula</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slope (°)</td>
<td>( \arctan(\sqrt{d^2 + e^2}) )</td>
<td>Magnitude of steepest gradient in both X and Y directions.</td>
</tr>
<tr>
<td>Cross Sectional curvature (1/m)</td>
<td>( n \times g \times \frac{(b \times d^2 + a \times e^2 - c \times d \times e)}{(d^2 + e^2)} )</td>
<td>Measures the curvature perpendicular to the down slope direction. (Intersecting with the plane of slope normal and perpendicular to aspect direction).</td>
</tr>
<tr>
<td>Maximum curvature (1/m)</td>
<td>( n \times g \times (-a-b \times \sqrt{((a-b)^2 + c^2)}) )</td>
<td>In any plane</td>
</tr>
<tr>
<td>Minimum curvature (1/m)</td>
<td>( n \times g \times (-a-b \times \sqrt{((a-b)^2 + c^2)}) )</td>
<td>In any plane</td>
</tr>
<tr>
<td>Profile curvature (1/m)</td>
<td>( n \times g \times \frac{(a \times d^2 + b \times e^2 - c \times d \times e)}{(d^2 + e^2)} \left(1 + \frac{(d^2 + e^2)}{1.5}\right) )</td>
<td>Vertical component in direction of aspect. (Intersecting with the plane of z axis and aspect direction).</td>
</tr>
<tr>
<td>Plan curvature (1/m)</td>
<td>( n \times g \times \frac{(b \times d^2 + a \times e^2 - c \times d \times e)}{(d^2 + e^2)} \left(1 + \frac{(d^2 + e^2)}{1.5}\right) )</td>
<td>Horizontal component in direction of aspect (Intersecting with the X, Y plane).</td>
</tr>
<tr>
<td>Longitudinal curvature (1/m)</td>
<td>( n \times g \times \frac{(a \times d^2 + b \times e^2 - c \times d \times e)}{(d^2 + e^2)} )</td>
<td>Measures the curvature in the down slope direction. (Intersecting with the plane of slope normal and aspect direction).</td>
</tr>
<tr>
<td>Gaussian curvature (1/m²)</td>
<td>Maximum curvature × Minimum curvature</td>
<td>Indicate whether a surface has been wrapped or not.</td>
</tr>
</tbody>
</table>

\( g \): Grid size of DEM, \( n \): Size of window, \( x, y \): Local coordinates, a to f: Quadratic coefficients.

With these criteria, it is assumed that all point features (Peak, pit and pass) occur only where local slope is zero. At locations with positive values for slope, channels have negative cross-sectional curvature, ridges have positive cross-sectional curvature and sloping planes have zero cross-sectional curvature. Peaks have zero local slope but positive value for both maximum and minimum curvatures. Pits have a converse situation, with negative values for both maximum and minimum curvatures. Passes are characterized by zero slope, positive values for maximum and negative values for minimum curvatures.

DEM data were imported into GRASS software. First order derivative (slope) and second order derivatives such as maximum, minimum and cross-sectional curvatures were calculated. In order to avoid artifacts (Grohmann et al. 2007) and effects of noise present in flat areas (Guth 2006; Huisenga 2005) a window size of 5×5 is used. Statistical measurements such as correlation coefficient, minimum, maximum, mean and standard deviation were calculated for each of the morphometric parameters. Due to very low values and to simplify graphical presentations, curvature parameters were multiplied by \(10^4\).
2. Data and Methods

Table 2. Morphometric features classification criteria (modified from Wood (1996a)). For features with positive value for slope (+va) the cross sectional curvature should be considered but for features with zero value for slope (0), cross sectional curvature is undefined (UV) so the maximum and minimum curvatures are the main criteria.

<table>
<thead>
<tr>
<th>Morphometric Feature</th>
<th>Slope (º)</th>
<th>Cross-sectional curvature (1/m)</th>
<th>Maximum curvature(1/m)</th>
<th>Minimum curvature(1/m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peak</td>
<td>0</td>
<td>uv</td>
<td>+va</td>
<td>+va</td>
</tr>
<tr>
<td>Ridge</td>
<td>0</td>
<td>uv</td>
<td>+va</td>
<td>0</td>
</tr>
<tr>
<td>Planar</td>
<td>0</td>
<td>uv</td>
<td>+va</td>
<td>-va</td>
</tr>
<tr>
<td>Channel</td>
<td>0</td>
<td>uv</td>
<td>0</td>
<td>-va</td>
</tr>
<tr>
<td>Pit</td>
<td>0</td>
<td>#</td>
<td>-va</td>
<td>-va</td>
</tr>
</tbody>
</table>

va: derivatives value, uv: undefined value, *: not part of selection criteria.

Applying Wood’s method to a DEM will normally produce a map consisting only of channels, ridges and planes. This is due to the fact that point based features such as peaks, passes and pits usually have a slope when the neighbors in a window are considered. Also DEM rarely produce planar facets with curvature component of zero. To overcome this problem, Wood (1996a) introduced two parameters Slope Tolerance (ST) and Curvature Tolerance (CT). Slope tolerance separates horizontal and sloping surfaces. Curvature tolerance value that defines a planar surface is used to decide if the curvatures are sufficient to classify pixels as ridge or channel (Table 3).

Table 3. The criteria for morphometric feature map classification with Wood’s method. For inclined surfaces, cross sectional curvature is a criterion but in flat areas, maximum and minimum curvatures are the main criteria.

<table>
<thead>
<tr>
<th>Slope &gt; ST (Surface is inclined)</th>
<th>Ridge</th>
<th>Cross &gt; CT</th>
<th>-</th>
</tr>
</thead>
<tbody>
<tr>
<td>Channel</td>
<td>Cross &lt; -CT</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>Planar</td>
<td>CT &gt; Cross &gt; -CT</td>
<td>-</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Slope &lt; ST (Surface is horizontal)</th>
<th>Peak</th>
<th>Maxic &gt; CT</th>
<th>Minic &gt; CT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pass</td>
<td>Maxic &gt; CT</td>
<td>Minic &lt; -CT</td>
<td></td>
</tr>
<tr>
<td>Pit</td>
<td>Maxic &lt; -CT</td>
<td>Minic &lt; -CT</td>
<td></td>
</tr>
<tr>
<td>Channel</td>
<td>Maxic &gt; -CT</td>
<td>Minic &lt; -CT</td>
<td></td>
</tr>
<tr>
<td>Planar</td>
<td>Maxic &lt; CT</td>
<td>Minic &gt; -CT</td>
<td></td>
</tr>
<tr>
<td>Ridge</td>
<td>Maxic &gt; CT</td>
<td>CT &gt; Minic &gt; -CT</td>
<td></td>
</tr>
</tbody>
</table>

Maxic, Minic and Crossc = maximum, minimum and cross sectional curvatures (1/m).
ST= Slope Tolerance (º), CT= Curvature Tolerance (1/m).
2. Data and Methods

The values of these tolerances depend on subjective decisions of the interpreter, the nature of the study area and quality of the DEM. In this study, different slope tolerance values ranging from 1° to 10° and curvature tolerance values from 0.001 to 0.00001 are tested. Perspective views of the classification results draped over the DEM were used to validate the classification results.

2.2.1.2 **Self Organizing Map (SOM)**

In this section, we present an alternative method -SOM- for morphometric feature analysis. The Self Organizing Map (SOM) is a realistic model of the biological brain function (Kohonen 2001). It converts the nonlinear statistical relationships of high dimensional input data to low dimensional (usually two dimensional) output grid preserving the topology of data (Kohonen 2001). The SOM characteristics like learning ability, abstraction with topology preservation and visualization can be utilized in complex tasks such as morphometric analysis and landform classification (Ehsani and Quiel 2008b). An example of a Self-Organizing map network is shown in figure 7.

![Self Organizing Map](image)

**Fig. 7.** Kohonen’s Self Organizing Map structure.

The input layer consists of \( x_k \) units, fully connected to all output map units. The output map units known as *mapping cortex (MC) or Kohonen layer or map units* are made up from \( n \times m \) output units (Schaale and Furrer 1995). Each output map unit \( i \) is assigned randomly a model weight vector \( w_i \) in the high-dimensional data space. It is assumed that adjacent neurons have a Euclidian distance of unity. The primary aim of the model is to let the weight vectors learn what is presented by the input vectors \( (x_k) \). The learning procedures move the randomly initialized weight vectors into the positions, which describe best what is presented to them. The processing unit in the output layer measures the Euclidian distance from the model weight vector \( w_i \) to the input vector \( (x_k) \). During learning, the node \( I_k \) with the shortest Euclidean distance commonly known as Best Matching Unit (BMU) is selected as a winner \( C_k \) (Fig. 8):

\[
C_k = \arg \min_i \| x_k - w_i \| \quad (2)
\]
This winning neuron becomes the centre of an update neighborhood. Update neighborhood is an area, within which nodes and their associated weights will be updated according to:

\[ w_{i(t+1)} = w_{i(t)} + h(t) \alpha(t) (x_k - w_{i(t)}) \] (3)

where: \( w_{i(t+1)} \) is the new weight vector, \( \alpha(t) \) is a learning rate \((0 \leq \alpha(t) \leq 1)\) that decreases in time and converges to 0, and \( h(t) \) is the neighborhood function.

Two control mechanisms, \( \alpha(t) \) and \( h(t) \) are imposed for guarantying that the algorithm operates properly. Since \( \alpha(t) \) is slowly decreasing, the updating will eventually stop and the map converges. The mathematical details are provided by Kohonen (1989). The neighborhood function \( h(t) \) shrinks the update neighborhood area gradually over time. An initial large neighborhood radius will help to achieve a stable convergence of the map. By beginning with a large initial radius and then gradually reducing it to a very small neighborhood, the SOM achieves both ordering and convergence properties.

The final weight vectors set up the topological feature space also known as codebook vector (Schaale and Furrer 1995). As learning proceeds, the size of the update neighborhood is decreased until it reaches the predefined final radius value. This process is repeated for every input sample as they are passed sequentially to the SOM. Each vector, which is presented to the topological feature space, is replaced by the index of corresponding BMU in the mapping cortex (Richardson and Risien 2003; Sueli and Lima 2006). This ends up in a reduction of dimensions and compresses the input data vectors needed to describe the topological feature space. Moreover, those neighboring units in the
2. Data and Methods

mapping cortex, remain neighbors in the topological feature space (topology preserving). This procedure is cycling up to a preset number of iterations for learning.

Neural network learning becomes more efficient with preprocessed input data. Scaling of input variables affects mainly Euclidian distances between vectors. Without normalization, the variable with the largest range will dominate the map organization. Following standard procedure all input morphometric parameter are normalized to the range of 0-1 using a logistic function. The number of classes or map units was set to 10. This is a compromise between the effort to identify and label classes and the expected number of unique morphometric classes according to expert knowledge and complexity of the area. Before learning, weights of the map units were randomly initialized. The learning was performed in two phases, rough learning and fine tuning. During rough learning, initial neighborhood radius and learning rate are large. In this stage, the neighborhood area starts with the radius initialized for the neurons and decreasing to the fine tuning value.

The learning rate decreases also from a large value of 0.5 to fine tuning learning rate of 0.05. During fine tuning, the learning rate and neighborhood distance decrease slowly, while keeping the topological order learned in the previous phase. After learning, the map units are evenly distributed across the input space so that SOM can recognize the best matching units for each input data.

The quality of the results is measured with the average quantization error. Quantization error is the Euclidian distance between an input data vector and the best matching unit (Kohonen 2001). This measure is useful in choosing suitable learning parameters such as initial radius, final radius for neighborhood and number of learning iterations for the optimal map. The optimal map is expected to yield the lowest average quantization error, because it is fitted best to the input data (Kohonen 2001). Once the weights were randomly initialized, forty-two SOMs each with different settings of learning parameters were tested and the optimal map with the lowest average quantization error was selected for morphometric features identification.

One important methodological question is how the random weights selection influences the average quantization error, and to what degree the result depends on this parameter. The answer to this question is crucial to assess the consistency of the method to produces the same result. Thirty SOMs were tested with the same learning configuration of an optimal SOM but different random weight initializations. The frequency histogram and average quantization error of the results are compared. Using feature space analysis, spectral signature analysis, three-dimensional inspection and auxiliary data, dependency of map units to morphometric features were defined. The characteristics of each proposed morphometric feature were defined using Woods adopted criteria in table 2 (Wood 1996a). Mean and standard deviation for each input parameter for morphometric classes were calculated. Morphometric signatures of morphometric features were plotted using mean values of input parameters for output classes. Morphometric signatures were compared in detail to clarify the role of morphometric parameters to separate landform elements.

The mean value of the output classes were plotted in two-dimensional feature spaces (scatter plot) of morphometric parameters. Two feature spaces were used. One with the maximum curvature (x-axis) and minimum curvature (y-axis), the other with cross-
sectional curvature (x-axis) and slope (y-axis). The later feature space shows the spatial
distribution of morphometric features in slope categories as: gentle: slope < 5°, moderate:
5° < slope < 8°, steep: 8° < slope < 12° and very steep: slope > 12°. This yields
morphometric sub classes regarding slope conditions. In these feature spaces, major
morphometric features of ridge, channel, planar, crest line were identified in the humid
area. In the hyper-arid area yardangs (ridge), corridors (valley) and planar features were
characteristic. The quality of produced maps was evaluated by overlaying contour lines
and analyzing oblique views.

Morphometric analysis in different scales was performed using the data set proposed by
Wood (1996a) for the study area. The derivatives were selected based on Wood’s
methodology and their ability to provide quantitative measurements of landform elements.
Nine local windows of 5×5, 9×9, 11×11, 13×13, 17×17, 23×23, 27×27, 33×33 and 55×55
are passed over the SRTM 90m DEM and morphometric parameters are derived by using a
bivariate quadratic approximation surface.

These window sizes cover 450, 810, 990, 1170, 1530, 2070, 2430, 2970 and 4950 meters
on the ground, that is local to regional scales (multi-scale analysis). A window size of 5×5
provides the minimum operational units for this study. Applying the window size 3×3
caused artifacts and noise in the morphometric features (Guth 2006; Huisenga 2005). These
nine data sets were used as inputs to the SOM.

The effect of SRTM resolution on morphometric features characteristics was investigated
using SRTM-1 arc” DEM and SRTM-3 arc” DEM data. In the following sections we use
these terms:
- X30: X-band data, 1 arc", re-projected to 30 m grid.
- C90: C-band data, 3 arc", re-projected to 90 m grid.
- C30: C-band data, 3 arc", re-projected and interpolated to 30 m grid.

To reduce misregistration between two DEMs, spatial co-registration was performed and a
RMSE of 0.48 pixel was achieved. Morphometric parameters were computed for two data
sets:
- C30 and X30 with window size 9×9 (270 m on the ground)
- C90 with window size 5×5 and X30 with window size 15×15(450 m on the ground)

The change analysis showed the resolution dependency of morphometric features. We also
investigated the effect of interpolating C90 to 30 m grid (C30) on morphometric
characterization and topography derivatives. A local window of 9×9 was passed over the
X30 and C30 data. This is a minimum operational window without arising artifacts
problem. Using X30 as benchmark, a change detection technique was used to
quantitatively analyze differences in morphometric features and to assess the downscaling
effect on C90 to 30 m. The quality of the produced maps was evaluated by overlaying
contour lines and analysing oblique views. Details are presented in paper V.

Yardang characterization and analysis of morphometric features in the Lut desert was
performed with the same procedure. Here a local window of 5×5 was used to produce
morphometric parameters (See further details in papers III and VI).
2. Data and Methods

2.2.2 Potential Natural Vegetation (PNV)
Delineation and classification of the PNV is performed in several steps. First, morphometric parameters of slope, cross sectional curvature, maximum and minimum curvatures are derived via a window size of 9×9 over a 28.5 m DEM corresponding to Landsat ETM+ data resolution. In the second step, the climate layer -“Sum of Active Temperature (SAT) above 10 °C”- and morphometric parameters are used as input for an optimal SOM. The output of the SOM according to knowledge and potential of layers to produce suitable classes is set to 30 units. In the third step, the feature space analysis is applied to the delimited SOM units as potential natural vegetation using published ecological information (appendix A) and limited field data. As result the final PNV map as a single integrated geo-data set of geocosystem is provided.

2.2.3 Landscape Analysis
In the previous section, we introduced SOM for morphometric feature analysis with the four morphometric inputs parameters slope, cross sectional curvature, maximum and minimum curvatures at different scales and resolutions. We also used this method to analyze dominant landforms in a hyper arid environment and potential natural vegetation mapping. In this part, we extend this method to landscape analysis combining morphometric parameters with remotely sensed spectral data from Landsat 7 ETM+. To process the DEM derivatives together with remotely sensed spectral data, they have to be registered correctly in one common projection. Therefore the DEM was re-projected to Universal Transverse Mercator grid UTM zone 34 with 28.5 m resolution (corresponding to the Landsat data resolution) using cubic convolution interpolation method. Cubic convolution compared with bilinear interpolation showed better results with fewer artifacts on morphometric parameters (Fig.9).

Fig. 9. Maximum curvature extracted from DEM produced with cubic convolution (left) and bilinear interpolation (right).

In order to avoid artifacts (Grohmann et al. 2007) and effects of noise present in flat areas (Guth 2006; Huisenga 2005) a window size of 9×9 is used for deriving morphometric parameters. Curvature parameters were multiplied by 10^4 to simplify plot presentations. Figure 10 shows the overall scheme of the developed method for landscape analysis. Four morphometric parameters together with all Landsat ETM+ bands are used as input to the Self Organizing Map.
Including all 7 ETM+ bands increased the classification accuracy. (For details, see paper IX). In SOM, no specific classes are defined beforehand; instead, the set of novel landscape elements emerge from the input. However, the interpretation and labeling of results is a manual task.

Fig. 10. Flow chart of landscape analysis method with SOM.

The number of classes or map units was set to 20 based on local knowledge and expert judgment. Using feature space analysis, signature analysis, three-dimensional inspection and auxiliary data, dependency of map units to landscape elements were defined. Two properties of landscape elements - morphometric forms and land cover - were analyzed separately. As in the other examples, morphometric features were analyzed by plotting the mean value of classes in the two-dimensional feature space (scatter plot) of morphometric parameters. Mean of classes are also plotted in the feature spaces of Landsat ETM+ bands. Spatial distribution and relationships among map units were studied in various
2. Data and Methods

combinations of two Landsat bands and each land cover class was labeled based on spectral properties. A post classification step allowed separation of misclassified water bodies from coniferous forest class. A majority filter with kernel size 5×5 is used to clean up the final map and to eliminate spurious pixels. At the end by combining spectral and morphometric information homogeneous landscape elements of the study area were defined.

The values of 20 output map units in each 11 inputs are transformed to Z score using this formula: 

\[ Z_x = \frac{X - \mu_x}{\sigma_x} \]

where \( Z_x \) = Z score of output map units, \( X \) = value of output map units in input bands, \( \mu_x \) = mean value of \( X \) and \( \sigma_x \) = standard deviation of \( x \) value in each input bands. The Z score is used to compare the relative standings of map units from distributions with different means and/or different standard deviations. Spectral and morphometric signatures of landscape elements were plotted using Z scores of map units and studied in detail.
Chapter 3

Results

3.1 Morphometric Feature Analysis

3.1.1 Morphometric feature parameterization (Wood’s method)

The four morphometric parameters slope, cross-sectional curvature, minimum and maximum curvatures derived from the SRTM-90m data with window size 5×5 are shown in Figure 11. 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 for mountainous locations with steep slopes, morphometric parameters vary significantly.

![Fig. 11. Morphometric parameters derived from DEM (a) slope, (b) cross-sectional curvature, (c) minimum curvature and (d) maximum curvature.](image)

In Wood’s algorithm, slope tolerance (ST) and curvature tolerance (CT) values have a crucial effect on classifying derivatives into point (peak, pit and pass), line (ridge and channel) and plain features. In this study, the basic algorithms were tested with different combinations of ST and CT values, arranged in Fig. 12 as follows: horizontally the CT increases from 0.00001 on the left side to 0.001 on the right; vertically ST increases from 1
3. Results

degree at the top to 10 degrees at the bottom. If ST increases from 1 to 10 degrees, the number of cells with slope values lower than ST will increase. This means that more surfaces become horizontal and chances to qualify as point-based features such as peaks, passes and pits increase. Conversely, the numbers of pixels classified as ridge or channel are decreasing. If CT increases from 0.00001 to 0.001, the number of cells with curvature large enough to qualify as ridges or channels decreases and many areas become planar.

With decreasing CT from 0.001 to 0.00001 and increasing ST from 1 to 10 degrees, (from upper right to lower left in fig. 12) the percentage of channels increases from 7.9% to 17 %, and the percentage of ridges increases from 10.2% to 21.8%. Point-based features (peaks, passes and pits) also increase significantly. For example, percentage of peaks increases from 0.004% to 14.3%, whereas the area of plane features decreases from 81.8% to 0.46%.

Fig. 12. Effect of choosing different tolerance values for Wood’s method. The default and selected tolerances for model are represented by red and blue border respectively.

Results were compared considering e.g. the extent of planar areas to select proper CT and percentage and location of elements classified as point features that is peak, pass and pit to determine ST. Comparing different results in oblique views and with topographic maps, slope tolerance of 1° and curvature tolerance of 0.0005 was considered the best compromise.

Running the basic model with these tolerances, a morphometric feature map of the study area was produced (Fig. 13). The result shows a very clear distinction between the disparate morphometric features. Four perspective zoom samples from different parts of the study area are selected for detailed investigation. In all cases the channel pattern appears similar to drainage network. Perspective views of the classification results draped over the DEM were used to validate the classification results.
In the Slovakian and Polish part, a dendritic pattern with frequent change of channels and ridges is typical while in Ukrainian part a discontinuous rectangular pattern is more obvious. In this map about 56% of the area is planar, 19.5% are channels and 24.33% are ridges. As expected point-based features such as peaks, passes and pits cover only 0.17% of the study area. There are a couple of reasons. Firstly, point based features are comparatively rare. Secondly, due to the rugged terrain many peaks with steep slopes exceed the slope tolerance value and are classified as ridge. Furthermore, the 5×5 window of the DEM with 90m grid covers a surface of 450×450 meters, restricting the detection of small point-based features.

![Perspective view of the morphometric feature map based on Wood’s method and four enlarged sections (Vertical exaggeration =5).](image)

**3.1.2 Self Organizing Map (SOM)**

As an alternative procedure for Wood’s method, we proposed the SOM. Learning of the SOM was performed with a subset of the data points with the four morphometric parameters as input and a two-dimensional output of 10 neurons. At the beginning of the learning, neurons in the SOM were distributed randomly. However, after the learning, the map units were evenly distributed across the input space so that neighboring neurons can recognize the best matching input for each trained map units (Fig. 14). The BMUs (final classes) with minimum average quantization error (0.178) were extracted. Analysis and interpretation of the output SOM is a crucial step. It was performed by morphometric
3. Results

signature analysis (Fig. 15) and displaying mean values of the BMUs (classes) in a two-dimensional morphometric feature space (Fig. 16). This representation not only highlights that slopes vary for different classes but also reveal that minimum, maximum and cross sectional curvatures have similar trends.

Fig. 14. Three-dimensional feature spaces of input morphometric parameters with randomly initialized weight vectors (images a and b) and with ordered weight vectors (images c and d) after SOM learning. Lines show connection between map units and circles show position of weight vectors. Morphometric values are normalized between 0 and 1.

Classes 1 and 6 have the lowest values for maximum, minimum and cross sectional curvatures and represent channels. Class 10 with the highest mean value of minimum and maximum curvatures is labeled as crest line. The maximum and minimum slopes are observed for class 5 and 7 with a mean of 15.2 and 3.7 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 views are used to label classes with corresponding morphometric features. From the six possible combinations of feature space plots, just two are shown (Fig. 16). According to these feature spaces, six major morphometric features including ridge, channel, planar, valley bottom, transition zone (between valley bottom and planar), crest line and four subclasses based on slope condition were defined.

Fig. 16. Distribution of the major (box) and subclasses (divided by dashed line) of morphometric features in a two-dimensional feature space. Subclasses are based on slope categories.
3. Results

Fig. 17. Morphometric features map using SOM (Middle). For two sample areas the result of the SOM method (left) and the morphometric features parameterization method (right) are shown. The circle shows the channel differentiation according to slope which can not be seen in Wood’s result.
Classes with a positive cross-sectional curvature and high minimum and maximum curvatures are identified as ridges. In contrast, low minimum and maximum curvatures and a negative cross-sectional curvature characterize channels. Classes with properties between these two categories are planar features but with different slope categories. Fig. 17 shows the final map from the SOM procedure and maps of two sample areas with the results from both the SOM and Wood’s morphometric feature parameterization. As it is obvious from figure 17, SOM has much more potential for identification of non-point morphometric features than Wood’s method. The overall pattern of channels, ridges and planes is similar in both methods, but the SOM results are more informative and include slope information. For example, channels are divided into two classes according to slope condition (class 1 with very steep slope and class 6 with moderate slope). In this method, the slope parameter is 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. Furthermore, the SOM capability of identifying crest lines on mountain ranges is another merit. Last, the SOM method does not rely on curvature and slope tolerance values.

3. Results

3.1.2.1 Self Organizing Map optimization

Very different learning processes can be defined starting with different initial weight values \( w_i(0) \), different sequences of the training vectors \( x_k(t) \) and different learning parameters. It is obvious that optimal SOM for the same input data must exist. The optimized map is expected to yield the smallest average quantization error because it is then fitted best to the same data. The average quantization error is a useful performance index and is identical for each input data set. Therefore there would be no sense in comparing quantization errors for different data set. Here to avoid repetition we provide general results achieved with a window size of 5×5 over SRTM 90 m data. Learning of SOM was performed with randomly initialized weights of the map units. Table 4 shows results of producing 42 SOMs with different main learning control parameters. Learning of the SOM was performed with four morphometric parameters as input and a two-dimensional output of 10 neurons for each window size.

The initial radius for learning was set to 3, 2 and 1 respectively with eight different final radius starting from 3, decreasing to 0.01. The map with an initial and final radius of three produced the highest average quantization error. Results indicate that the final radius should be much smaller than 1. SOM 14 produced the best map with the lowest average quantization error of 0.1780. This means that the map with initial radius of 3, final neighborhood radius of 0.01 and 1000 iterations is an optimum SOM for morphometric analysis and shows the best performance. Though the difference between average quantization errors for maps with the same learning sets and different number of iterations (e.g SOM 11 and SOM 14) is not large, the number of iterations for the final optimal map should be reasonably large. This is due to the stochastic nature of the learning process. Therefore, the number of iterations was set to 1000. The decrease in average quantization error with increasing number of iterations for the best self organizing map (SOM14) is shown in figure 18.
3. Results

Table 4. Set of parameters for SOM learning and average quantization error. The optimal SOM, SOM 14 (darker cell), has the lowest average quantization error.

<table>
<thead>
<tr>
<th>Final Radius</th>
<th>Iterations</th>
<th>Initial Radius=3</th>
<th>Initial Radius=2</th>
<th>Initial Radius=1</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Map Qe</td>
<td>Map Qe</td>
<td>Map Qe</td>
</tr>
<tr>
<td>3</td>
<td>10</td>
<td>SOM 1 0.3271</td>
<td>SOM 15 0.3271</td>
<td>SOM 29 0.3273</td>
</tr>
<tr>
<td>2</td>
<td>10</td>
<td>SOM 2 0.2935</td>
<td>SOM 16 0.2933</td>
<td>SOM 30 0.2933</td>
</tr>
<tr>
<td>1</td>
<td>10</td>
<td>SOM 3 0.2321</td>
<td>SOM 17 0.2316</td>
<td>SOM 31 0.2325</td>
</tr>
<tr>
<td>0.5</td>
<td>10</td>
<td>SOM 4 0.1887</td>
<td>SOM 18 0.1883</td>
<td>SOM 32 0.1905</td>
</tr>
<tr>
<td>0.25</td>
<td>10</td>
<td>SOM 5 0.182</td>
<td>SOM 19 0.1808</td>
<td>SOM 33 0.1813</td>
</tr>
<tr>
<td>0.1</td>
<td>10</td>
<td>SOM 6 0.1817</td>
<td>SOM 20 0.1803</td>
<td>SOM 34 0.1812</td>
</tr>
<tr>
<td>0.05</td>
<td>10</td>
<td>SOM 7 0.1815</td>
<td>SOM 21 0.1802</td>
<td>SOM 35 0.1811</td>
</tr>
<tr>
<td>0.01</td>
<td>10</td>
<td>SOM 8 0.1813</td>
<td>SOM 22 0.1801</td>
<td>SOM 36 0.181</td>
</tr>
<tr>
<td>0.1</td>
<td>50</td>
<td>SOM 9 0.1789</td>
<td>SOM 23 0.1788</td>
<td>SOM 37 0.1788</td>
</tr>
<tr>
<td>0.05</td>
<td>50</td>
<td>SOM 10 0.1789</td>
<td>SOM 24 0.1788</td>
<td>SOM 38 0.1788</td>
</tr>
<tr>
<td>0.01</td>
<td>50</td>
<td>SOM 11 0.1789</td>
<td>SOM 25 0.1788</td>
<td>SOM 39 0.1788</td>
</tr>
<tr>
<td>0.01</td>
<td>100</td>
<td>SOM 12 0.1788</td>
<td>SOM 26 0.1783</td>
<td>SOM 40 0.1785</td>
</tr>
<tr>
<td>0.01</td>
<td>500</td>
<td>SOM 13 0.1783</td>
<td>SOM 27 0.1783</td>
<td>SOM 41 0.1783</td>
</tr>
<tr>
<td>0.01</td>
<td>1000</td>
<td>SOM 14 0.1780</td>
<td>SOM 28 0.1783</td>
<td>SOM 42 0.1783</td>
</tr>
</tbody>
</table>

Qe: Quantization error.

At the early stage of learning (rough tuning), the map tends to order itself over input vectors so the average quantization error decreases drastically. The neighborhood radius starts from a large initialization value, here 3, and decreases to the final fine tuning neighborhood radius of 0.01. The learning rate decreases in this stage until it reaches the fine tuning phase learning rate of 0.05. During the fine tuning, average distance between best matching units and input vectors is slowly decreasing. This phase lasts until iteration 900. At the end of fine tuning phase, (here from iteration 900 to 1000) the average quantization error has a steady trend and almost all map units are ordered as good as possible over input vectors. At this stage, the network is well ordered and map units are spread out across the input vectors.

![Fig. 18. Changes of the average quantization error versus number of iterations for optimal self organizing map.](image-url)
3. Results

As discussed earlier, one important methodological question was how the random weights influence the average quantization error, and to what degree the result is dependant on this parameter. To investigate the effect of random starting weights on the average quantization error, initial weight vectors were selected randomly ten times and the average quantization error was calculated for each map (Fig. 19). Examination of the results in this study revealed an important finding. Low numbers of iteration (for instance 10 iterations) are not sufficient for SOM to learn the characteristics of the input data and the weight values have not sufficient time to reach a configuration with the minimum error. Consequently, average quantization errors of the output map units for each random weight initialization are different and perform poorly. Increasing the learning iterations to 1000 resulted in a consistent network with high accuracy. In this condition, initial weight values are being learned longer and Euclidian distances between input data vectors and best matching units (quantization error) decrease and reach the minimum level. In this condition, the map is optimized and fitted best to the data. The examination of the frequency histogram showed that the output maps are identical. These results indicate that, at least in this particular study, if many iterations (about 1000) are used, the output classes and the global minimum error of the network are not sensitive to random initialization of the input weight vectors. This implies that the output of the network is consistent and independent of the starting weights. This makes the procedure repeatable and applicable for the same data set.

Fig. 19. Effect of random weights initialization on the average quantization error of the optimal SOM.

3.1.2.2 Effect of scales on morphometric features

3.1.2.2.1 Statistics of morphometric parameters at different scales

Figure 20 shows the mean, standard deviation, minimum and maximum value of slope and curvatures for various window sizes. It is obvious that all statistics of morphometric parameters vary with window size. As window size increases, a tendency to regress toward a mean value will increase. The maximum value for slope is 38 degrees for window size 5×5 while this value decreases to 8 degrees for window size 55×55. The decrease in standard deviation from window sizes 5×5 to 55×55 are 3.7 for slope, 7.06 for cross sectional curvature, 6.07 for maximum curvature and 6.27 for minimum curvature. This implies the larger window size, the greater the reduction in range of morphometric parameters. This reduction is more obvious from window size 5×5 to 9×9. This shows the potential of morphometric parameters for identification of landform elements at smaller
3. Results

window sizes (e.g. 5×5) and more general land forms at larger window sizes (e.g. 55×55). Figure 21 shows an example of the variation in cross sectional curvature. The six images show the distribution of ridges and channels at window sizes of approximately to 450m to 5 km. The smaller window (Fig. 21a) tends to be dominated by clear variation of ridge and channel networks as landform elements. At coarser scales, the larger general ridges and channels appear. Certain features appear to dominate at characteristics scales, most notably the crest, which is expressed most strongly at the 55×55 window size. The cross sectional curvature for window 5×5 ranges from -49 to 45 but in window 55×55 this range decreases from -1.10 to 1.18.

Fig. 20. Statistics properties of a) slope, b) Cross section curvature, c) maximum curvature and d) minimum curvatures over window sizes from 5×5 (450m) to 55×55 (4950 m).

3.1.2.2.2 Identification of morphometric features at different scales

The optimum SOM with an average quantization error of 0.1780 is used for morphometric analysis at different window sizes. We used feature space analysis to interpret and label the output of SOM as morphometric features. The result maps for window sizes of 5×5, 13×13, 23×23 and 55×55 (corresponding to 420m, 1170m, 2070m and 4950m) are shown in fig. 22. It is clear that the pattern of the morphometric features varies considerably with scales. At the finest (450m) scale, a good network of ridges and channels with different slope classes is revealed. Smaller, well dissected valley and ridge systems with steep slopes are relatively well defined, while major broad valleys and ridges are not delineated (Fig. 22a). At this scale, much of the surface is represented as minor concavities and convexities that characterize landform elements. At a coarser scale, there is more spatial continuity with major convexities and concavities. Figure 22d for example shows in the upper part a broad connected valley (classes 5 and 10). Thus, a specific feature can be identified as one single morphometric object at a small scale but as series of forming elements at another, larger scale. This indicates scale dependency in morphometric features.
3. Results

Fig. 21. Perspective view of Cross sectional curvature for Trohaniec mountain in Poland calculated with window sizes of a) 5×5; b) 9×9; c) 13×13; d) 23×23; e) 33×33 and f) 55×55. Lighter and darker color indicates increasing surface convexity and concavity respectively. Values have been multiplied by 10000 (Vertical exaggeration = 5).

The ability to analysis morphometric features at different scales makes this an appropriate semi-automatic method. Fig. 23 shows the standard deviation of class averages for all four morphometric parameters versus window size. With increasing window size the standard deviation of morphometric parameters decreases. This decrease is smaller for the first derivative (slope) than for the second derivatives. At all window sizes maximum and minimum curvatures have nearly the same standard deviation. At window size 5×5 (450 m), all morphometric parameter have high standard deviation. At window sizes of 9×9 (810 m), 11×11 (990 m), 13×13 (1170 m) cross sectional curvature shows slightly larger values than maximum and minimum curvatures. At very large window sizes, e.g. 55 × 55 all curvature parameters show very low standard deviation. At large window sizes the detailed information is lost but in contrast, more generalized information emerges.
3. Results

Fig. 22. Morphometric feature map using SOM with DEM-90 and a window size of 5×5 (Middle). Zoom samples are SOM results with window sizes of (a) 5×5, (b) 13×13, (c) 23×23 and (d) 55×55.
3. Results

3.1.2.3 Effect of resolution on morphometric features

3.1.2.3.1 Effect of SRTM-DEM grid size on statistics of morphometric parameters

For all SRTM-DEM derivatives, statistic parameters such as mean, standard deviation, maximum and minimum values were calculated (Fig. 24). In general, the larger the grid sizes the smaller the derived range of values. Differences in slope as first order derivatives - even with different window size - are less obvious than second order derivatives. However, differences in maximum value of slopes for X30 and C90 DEM are about 3.7 degrees. This has a particularly effect on morphometric features of upland areas and is complicated by the inherent scale-dependence of morphometric parameters (Pike 2001). Interpolating C90 to C30 DEM improved especially all second order parameters. However, this effect is less obvious for slope. It is obvious that ranges of morphometric parameters decrease with increasing window size. However, for the same size of the window area on the ground, C90 and X30 DEMs show very small differences in parameter statistics. But even these minor irregularities can be important and influence classification results. Scatter plots of elevation, slope, maximum curvature, minimum curvature and cross sectional curvature (Fig. 25) showed that interpolated SRTM data C30 follow the distribution of X30 data set while for C90 data, due to lower resolution, the distribution of points is limited to a much smaller region near the center of data distribution. This result also confirms the efficiency of interpolation to C30 for such studies.
3. Results

3.1.2.3.2 Effect of SRTM-DEM grid size on identification of morphometric feature

The best SOM performance with the lowest average quantization error of 0.1797, 0.1779 and 0.1798 were achieved for X30, C30 and C90 respectively. The results of feature space analysis for X30 with window size 9×9 are shown in figure 26. The other plots show very similar patterns but with different range of values.

These plots in conjunction with perspective presentation were used to label classes with corresponding morphometric features. Five major morphometric features ridge, channel, planar, transition zone between channels and planar and crest line within three slope categories were defined. Classes with high values for cross-sectional, minimum and maximum curvatures classified as ridges and crest line. In contrary low values for minimum and maximum curvatures and negative value for cross-sectional curvature, characterize channels. Classes with properties between these two categories should be planar features with different slope categories. Sloping surfaces with positive cross-sectional curvature are convex ridges. Crest lines along mountain tops show the same properties but the slope is less. Planar forms are characterized by zero or near zero curvature values. Increased spatial resolution of the DEM extends the range of values of morphometric parameters but overall class categories remain the same. These changes are more obvious for minimum curvatures values of channels (class 5 and 10) and maximum curvatures...
3. Results

curvatures of upland ridges (no. 6) and transition zone (no. 4). The final morphometric maps zoom samples and morphometric signatures for the first data set (C30 and X30 with window size 9×9) are shown in figure 27.

Fig. 27. Morphometric features map using SOM with X30 (left) and C30 (right) window size 9×9. 3D close up views overlaid with contour lines (30 m intervals) and morphometric signatures are shown on top and bottom respectively (Copyright DLR, 2008).
3. Results

Comparing these findings with an oblique view and overlaid contour lines (convex for ridges and concave for channels) confirms this situation. The signature graph in the right-bottom of figure 27 reveals that classes 3, 8 and 9 are identified as planar belonging to different slope classes on the ground. Nearly straight contour lines and long distances between contours confirm this fact for class 3 and decreasing distance between contour lines for classes 8 and 9. Using X30 as a benchmark, a change detection technique was used to analyze quantitatively differences in morphometric features and to assess the effect of interpolation from C90 to C30. Table 5 shows a cross tabulation between the two classifications shown in figure 27. While the statistics report does include a class-for-class image difference, the analysis focuses primarily on the classification changes—that is, for each class on X30, the analysis identifies the classes into which those pixels were classified using C30.

<table>
<thead>
<tr>
<th>Morphometric classes*</th>
<th>X30 DEM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class 1</td>
<td>77.1</td>
</tr>
<tr>
<td>Class 2</td>
<td>69.5</td>
</tr>
<tr>
<td>Class 3</td>
<td>78.1</td>
</tr>
<tr>
<td>Class 4</td>
<td>46.1</td>
</tr>
<tr>
<td>Class 5</td>
<td>71.5</td>
</tr>
<tr>
<td>Class 6</td>
<td>63.8</td>
</tr>
<tr>
<td>Class 7</td>
<td>66.7</td>
</tr>
<tr>
<td>Class 8</td>
<td>66.4</td>
</tr>
<tr>
<td>Class 9</td>
<td>70.7</td>
</tr>
<tr>
<td>Class 10</td>
<td>29.3</td>
</tr>
</tbody>
</table>

Table 5 shows that the smallest changes of morphometric classes occurred for class 3 (planar, slope 5-10°) with 21.9%, class 1 (crest line, slope 5-10°) with 22.9 %, class 6 (ridge, slope >15°) with 25.1 %, class 5 (channel, slope 5-10°) with 28.5 % and class 10 (channel, slope >15°) with 29.3%. However, the change for the planar features including classes 2, 7, 8 and 9 is between 30-40%. The largest change occurred for class 4 (Transition zone between channel and planar with mean slope >10°) with more than 50 %. The overall rate of change for the whole study area is 31.5%. About 17% of this rate correspond to class 4 and 12 % correspond to class 7 (planar with mean slope >15°) which are less frequent in the study area. This means that the refinement of DEM 3 arc" to 30 m has much more effect for these classes than for the other classes.

The other goal of the thesis was to investigate morphometric features for different resolutions. Hence, morphometric parameters for C90 were computed with a moving window size 5×5, corresponding to 450 m on the ground. To cover the same ground area, a moving window size 15×15 was used with the X30 DEM. The results of this analysis are presented in figure 28. Visual 3D analysis of morphometric features, situation of contour lines and morphometric signatures reveal about the same results as the first experiment.
Results

Despite the same ground area, differences in the final maps are obvious in figure 28.

Fig. 28. Morphometric feature map using SOM with X30 data and window size 15×15 (left), C90 and window size 5×5 (right). 3D close up views overlaid with contour lines (30 m intervals) and morphometric signatures are shown on top and bottom respectively (Copyright DLR, 2008).
Results

These differences are due to the fact that the SRTM-DEM resolution influences the morphometric parameters and the classification results. As grid cell size increases, the slope and ranges in curvatures decreases. The visual comparison between morphometric signatures at the bottom of figure 27 and 28 presents the same information. This issue is complicated by the inherent scale-dependency of morphometric features (Iwahashi and Pike 2007; Pike 2001). The X30 compare to C90 capture fine variation in surface and shows the same area to a finer texture features. For instance in figure 28, class 7 (planar, slope 10-15°) are isolated single pixels in C90 (right) but form continuous areas in X30 (left). This effect also is obvious for results of C30.

As before, using X30 as a benchmark, a change detection technique was used to analyze quantitatively differences in morphometric features due to resolution. Table 6 shows a detailed cross tabulation between the two classifications shown in figure 28.

Table 6. Cross tabulation of SOM classification results with X30, window size 15×15 as reference and C90 window size 5×5 (corresponding to 450 m on the ground). Grey cells show the percentage of unchanged elements.

<table>
<thead>
<tr>
<th>C90 DEM - W 5×5</th>
<th>X30 DEM - W15×15</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Morphometric classes</strong></td>
<td><strong>Class 1</strong></td>
</tr>
<tr>
<td>Class 1</td>
<td>74</td>
</tr>
<tr>
<td>Class 2</td>
<td>12</td>
</tr>
<tr>
<td>Class 3</td>
<td>0.4</td>
</tr>
<tr>
<td>Class 4</td>
<td>2.7</td>
</tr>
<tr>
<td>Class 5</td>
<td>0.1</td>
</tr>
<tr>
<td>Class 6</td>
<td>6.1</td>
</tr>
<tr>
<td>Class 7</td>
<td>3.8</td>
</tr>
<tr>
<td>Class 8</td>
<td>0.8</td>
</tr>
<tr>
<td>Class 9</td>
<td>0</td>
</tr>
<tr>
<td>Class 10</td>
<td>0.1</td>
</tr>
<tr>
<td><strong>Class Changes</strong></td>
<td>26</td>
</tr>
</tbody>
</table>

*Classes descriptions are on figure 28.

The total unchanged area is 68.8%. Least changes of morphometric classes like in the first experiment occurred in class 3 (planar, slope 0-5°) with 21.1%, class 5 (channel, slope 5-10°) with 24.7 %, class 1 (crest line, slope 5-10°) with 26 %, class 6 (ridge, slope 10-15°) with 27.5 % and class 10 (channel, slope 10-15°) with 29.4%. The change for the planar features including classes 2, 7, 8 and 9 is between 30 - 40%. This analysis showed a rate of change of 31.2% for the whole study area that is due to resolution. The highest change rates occur in class 4 (Transition zone between channel and planar with mean slope 5-10°) and class 7 (planar with mean slope 10-15°) respectively which are less frequent than the other classes in the study area. This analysis shows that with the same spatial extent, planar with high slopes are more sensitive to DEM resolution than channels or ridges. This can be explained by the fact that for sloping planar features the cross sectional curvature is a major parameter.
Table 7 shows a cross tabulation between the two classifications with X30 DEM window size 9×9 and 15×15. The overall change due to increasing window size is 53.31%. Like the other analysis the largest change occurred for class 4 (Transition zone between channel and planar with mean slope >10°) with 69.8%. The lowest change of morphometric classes occurred for class 3 (planar, slope 5-10°) with 39.7%. This analysis implies that that with the same resolution, increasing the window size has more effect on transition zones, planar with slope more than 5 degrees and channels with slope more than 10 degrees. Actually, these features are more scale dependant.

Table 7. Cross tabulation of SOM classification results with X30, window size 9×9 and 15×15. Grey cells show the percentage of unchanged elements.

<table>
<thead>
<tr>
<th>Morphometric classes</th>
<th>X30 DEM -W 9×9</th>
<th>X30 DEM -W 15×15</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class 1</td>
<td>57.8</td>
<td>10.3</td>
</tr>
<tr>
<td>Class 2</td>
<td>18.7</td>
<td>46.5</td>
</tr>
<tr>
<td>Class 3</td>
<td>2.0</td>
<td>22.1</td>
</tr>
<tr>
<td>Class 4</td>
<td>1.7</td>
<td>30.2</td>
</tr>
<tr>
<td>Class 5</td>
<td>0.3</td>
<td>1.7</td>
</tr>
<tr>
<td>Class 6</td>
<td>10.3</td>
<td>0.6</td>
</tr>
<tr>
<td>Class 7</td>
<td>5.0</td>
<td>3.2</td>
</tr>
<tr>
<td>Class 8</td>
<td>2.4</td>
<td>8.2</td>
</tr>
<tr>
<td>Class 9</td>
<td>0.1</td>
<td>0.2</td>
</tr>
<tr>
<td>Class 10</td>
<td>0.0</td>
<td>0.1</td>
</tr>
<tr>
<td>Class Changes</td>
<td>42.2</td>
<td>53.5</td>
</tr>
</tbody>
</table>

The standard deviation (SD) indicates how widely the values in a data set are distributed. As it is in figure 29 increasing spatial resolution of the DEM, increase SD for all morphometric features significantly. Of four morphometric parameters, the SD of map units in cross sectional curvature derived from C30 is 4.11 units higher than C90. SD of minimum and maximum curvatures of map units are 3.92 and 3.18 unit respectively. This implies that the general potential of cross sectional curvature for identification of features is more than other derivatives.

Fig. 29. Standard deviation of class averages on morphometric parameters for SRTM-DEM.
In this chapter, we evaluate the effectiveness of the SOM to identify dominant morphometric features, e.g. yardangs in the western part of Lut desert, Iran. These features are among the world’s largest desert forms separated by large wind-swept corridors. Morphometric parameters elevation, slope, cross sectional curvature, maximum and minimum curvature are shown in figure 30 along a 13230 m transect with yardangs in the eastern part of the study area. The various parts of the transect reflect significant differences in elevation, slope and curvature parameters.

Point 4 (Figs. 30a-d) shows a typical individual sharp yardang with an elevation of more than 350 m, steep slopes and high values for maximum and cross sectional curvatures. Points 1 and 2 (Figs. 30a-d) show similar conditions but the tops of yardangs are broader and sculptured by medial narrow ravines that do not reach to the depth of the base level of the corridors. Point 3 (Figs. 30a-d) lies on a typical straight corridor between yardangs with elevation around 300 m, steep slopes and large negative values for minimum curvature. Point 7 (Figs. 30a-d) implies the same features as point 3 but with lower elevation just above 200 m, near zero values for slope and curvatures. Therefore, these features characterize a broad, flat corridor at low elevation whereas point 3 corresponds to a small corridor with a concave shape at higher elevation. Point 6 (Figs. 30a-d) shows broad yardangs. These shapes are located at an elevation around 250 m and are divided into small partitions on top with their axes running parallel to the corridors. They look like castles, the top crowned with walls. This information provides an overall visual indication of terrain at a certain selected spacing. The thematic map of distributional pattern of yardangs in the entire area can be obtained by the SOM outlined earlier. The optimum SOM in this study achieved with an average quantization error of 0.1040.

Fig. 30. W_E profiles of (a) RGB 752 false color composite of Landsat 7 data, (b) Morphometric parameters, (c) Elevation and (d) Slope.
The output map units from SOM are interpreted as major morphometric features e.g. yardangs via feature space analysis. Major morphometric features (corridor, planar and yardang) are identified in two-dimensional feature space plots of mean values of maximum curvature (x-axis) and minimum curvature (y-axis) for map units (Fig. 31a). Dissected corridors or valleys between yardangs show negative minimum curvature and zero or near zero maximum curvature. Conversely, yardangs (ridges) revealed positive maximum curvature and zero or near zero minimum curvature. Planar features were located between corridors/yardangs and had small values for minimum and maximum curvatures. The same results could be achieved with cross-sectional curvature by plotting in two-dimensional feature space mean values of slope (y-axis) and cross-sectional curvature (x-axis) (Fig. 31b). Adding a slope axis helps to explain the difference between classes placed within the same category. For example, three classes with negative values for cross-sectional curvature (7, 8 and 9) were interpreted as corridors with differences in mean slope value. Sloping surfaces with positive cross-sectional curvature are yardangs (class 5). Sloping planar areas are characterized by zero or near zero cross-sectional curvature and average slope of more than 5 degrees (class 10). Plateau consisting of relatively flat terrain (class 1) were interpreted as area with zero value for all morphometric parameters.

Figure 32 shows the resultant classification map where yardangs and corridors between them are represented by red and cyan colors to facilitate interpretation. Two zoom images (Figs. 32 b2 and c2) present SOM result, corresponding 30m resolution Landsat ETM+ data (Fig. 32 b1) and 60 cm resolution Quickbird satellite image (Fig. 32 c1). The results and corresponding satellite images show the effectiveness of the SOM to identify the overall pattern of morphometric features in the Lut desert. It is clear that the pattern of yardangs and their corridors running from NNW to SSE direction is parallel to the prevailing winds. Five classes (1, 2, 3, 4 and 6) of planar features with low elevation and slope are found extensively in the north and east of the study area.

The sloping planar features (class 10) are detected mainly in the transition zone between yardangs and corridors where the edge of features are abraded and flatted by wind or other processes. Yardangs (class 5) were very well identified in parallel ranks running northwest to southeast with average slope between 3 to 4 degrees. The base of the convex slope forms a steep angle with the corridor floor and riddle with rills and ravines from periodic floodwaters. The relief of the yardangs probably controls the wind regime among the corridors.
Fig. 32. (a) Morphometric feature map of Lut desert using SOM with 90 m resolution DEM. (b) Eastern part of the study area. (c) Southwestern part of the study area as shown in fig. 32a. (b2) and (c2) are classified map by SOM. (b1) RGB 752 false color image of Landsat ETM+ (3rd Aug. 2001) showing the yardangs. (b2) Classified map by SOM for the area of (b) showing yardangs with average slopes of 3-4° in red and corridors with the same slopes in cyan colors. (c1) Natural color 60-centimeter QuickBird image (acquired on 15th Oct. 2005) showing the mega yardangs and corridors with 300 m width. (c2) Classified map by SOM for the area of (c) showing the corresponding identified mega yardangs and corridors. Dashed lines are examples of classified yardangs and corridors.
Three classes were identified for corridors (valleys) with mean slopes between 0 to 4 degrees. In some places, crescent dunes wander along these corridors. Due to the 90 m resolution of the DEM, yardangs and corridors can clearly be recognized and classified when their width is larger than the DEM resolution but become unrecognizable if their width is less than the grid resolution. This can be seen in fig.32 c1 where two classes 5 (yardang) and 9 (corridors) with a width of about 300 meter are marked by a dashed line in the QuickBird satellite image. Most of the features with width larger than 90 meter could be easily detected. Morphometric signatures for slope, cross sectional curvature, maximum and minimum curvatures of SOM resultant classes for yardangs and corridors are illustrated in figure 33. This representation not only highlights that slopes vary for different classes but demonstrates also that yardangs and corridors can be detected easily by the fact that they show different morphometric signatures. Yardangs are associated with high values for maximum curvature and corridors show high negative values for minimum curvature. The steepest slopes are observed in class 10 (planar) with a mean of 5 degrees.

Results of this study revealed that from the total of 6481 km² of the study area, about 2035 km² (31%) are classified as yardang while corridors, described by 3 classes (7, 8 and 9), in total cover 2732 km² (42%). Class 6 characterizes planar areas with slope 0-1°, which is smallest detected area with only 18 km².

Fig. 33. (a) Morphometric signatures of yardangs and corridors. (b) 60-centimeter QuickBird image. (c) Field photograph from western side of the study area in Lut desert. Yardangs oriented to the prevailing wind direction 330°. Corridors in some places are covered by sand sheets.
3.2 Potential natural vegetation map (PNV)

The optimal SOM for this analysis has an average quantization error of 0.1857. The output map units from SOM are interpreted corresponding to morphometric features and topo-climate classes respectively using two-dimensional feature space plots (Fig. 34). Analyzing the climate and, morphometric parameters information for a geo-ecological map is provided. Together with published ecological information (Appendix A) we could express the results in terms of potential natural vegetation map with 10 PNV units (Fig. 35). This map as a single integrated geo-dataset shows the overall spatial distribution of geomorphic and climatic properties of the landscape. This layer is regarded as one of the principal input of geo-data sets for the comprehensive inventory, assessment and further management of the Eastern Carpathians. Table 8 shows the overall properties of the PNV map corresponding to morphometric features and topo-climate characteristic.

Fig. 34. Analysis of SOM output map units with two-dimensional feature spaces of morphometric features (left) and topo_climate classes (right). The colors are represent the to the heat provisions classes.

Fig. 35. Potential natural vegetation map by SOM.
As it is obvious visually from the map (Fig. 35), large parts in the north east in Ukraine are mostly mapped by forest communities 3c, 1c, 4a and 4b in either planar, channel or ridge position. PNV unit of 3d (brownish) delimited in the central part of the image on the eastern Carpathian mountains and spread out to the south east. This unit mainly appears on the steep slopes with cool climate on the ridge or channels. The unit of 1b (dark greenish) is a major unit for Slovakian part with planar feature and warm weather conditions. Units of 3c, 3d, 4b and 4a includes the dominant PNV units of the study area, which cover 19 %, 18.6 %, 17.4 % and 14 % of the study area respectively.

### Table 8. Potential natural vegetation properties.

<table>
<thead>
<tr>
<th>SOM Unit</th>
<th>Slope class(°)</th>
<th>Morphometric features</th>
<th>Topo_climate</th>
<th>PNV units</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>6</td>
<td>0-4</td>
<td>planar</td>
<td>Warm</td>
<td>1b</td>
<td>Fraxineto-Querceta, Alneta glutinosae et Saliceta</td>
</tr>
<tr>
<td>16</td>
<td>0-4</td>
<td>planar</td>
<td>Moderately warm</td>
<td>1c</td>
<td>Alneta glutinosae, A. incanae et Saliceta</td>
</tr>
<tr>
<td>7</td>
<td>&gt; 10</td>
<td>channel-concave</td>
<td>Warm</td>
<td>3a</td>
<td>Carpineto-Querceto-Fageta</td>
</tr>
<tr>
<td>8</td>
<td>&gt; 10</td>
<td>ridge-convex</td>
<td>Warm</td>
<td>3a</td>
<td>Carpineto-Querceto-Fageta</td>
</tr>
<tr>
<td>2</td>
<td>&gt; 10</td>
<td>channel-concave</td>
<td>Moderately warm</td>
<td>3b</td>
<td>Abieto-Fageta</td>
</tr>
<tr>
<td>10</td>
<td>&gt; 10</td>
<td>ridge-convex</td>
<td>Moderately warm</td>
<td>3b</td>
<td>Abieto-Fageta</td>
</tr>
<tr>
<td>18</td>
<td>&gt; 10</td>
<td>ridge-convex</td>
<td>Moderately warm</td>
<td>3b</td>
<td>Abieto-Fageta</td>
</tr>
<tr>
<td>9</td>
<td>&gt; 10</td>
<td>Transition zone</td>
<td>Moderately cool</td>
<td>3c</td>
<td>Piceeto-Abieto-Fageta</td>
</tr>
<tr>
<td>12</td>
<td>&gt; 10</td>
<td>planar</td>
<td>Moderately cool</td>
<td>3c</td>
<td>Piceeto-Abieto-Fageta</td>
</tr>
<tr>
<td>13</td>
<td>&gt; 10</td>
<td>channel-concave</td>
<td>Moderately cool</td>
<td>3c</td>
<td>Piceeto-Abieto-Fageta</td>
</tr>
<tr>
<td>19</td>
<td>&gt; 10</td>
<td>ridge-convex</td>
<td>Moderately cool</td>
<td>3c</td>
<td>Piceeto-Abieto-Fageta</td>
</tr>
<tr>
<td>23</td>
<td>&gt; 10</td>
<td>planar</td>
<td>Moderately cool</td>
<td>3c</td>
<td>Piceeto-Abieto-Fageta</td>
</tr>
<tr>
<td>27</td>
<td>3-10</td>
<td>channel-concave</td>
<td>Moderately cool</td>
<td>3c</td>
<td>Piceeto-Abieto-Fageta</td>
</tr>
<tr>
<td>1</td>
<td>&gt; 10</td>
<td>channel-concave</td>
<td>Cool</td>
<td>3d</td>
<td>Piceeto-Abieto-Fageta et Aceroeto-Fageta</td>
</tr>
<tr>
<td>11</td>
<td>&gt; 10</td>
<td>channel-concave</td>
<td>Cool</td>
<td>3d</td>
<td>Piceeto-Abieto-Fageta et Aceroeto-Fageta</td>
</tr>
<tr>
<td>20</td>
<td>&gt; 10</td>
<td>ridge-convex</td>
<td>Cool</td>
<td>3d</td>
<td>Piceeto-Abieto-Fageta et Aceroeto-Fageta</td>
</tr>
<tr>
<td>21</td>
<td>&gt; 10</td>
<td>ridge-convex</td>
<td>Cool</td>
<td>3d</td>
<td>Piceeto-Abieto-Fageta et Aceroeto-Fageta</td>
</tr>
<tr>
<td>22</td>
<td>&gt; 10</td>
<td>ridge-convex</td>
<td>Cool</td>
<td>3d</td>
<td>Piceeto-Abieto-Fageta et Aceroeto-Fageta</td>
</tr>
<tr>
<td>24</td>
<td>&gt; 10</td>
<td>planar</td>
<td>Cool</td>
<td>3d</td>
<td>Piceeto-Abieto-Fageta et Aceroeto-Fageta</td>
</tr>
<tr>
<td>4</td>
<td>3-10</td>
<td>channel-concave</td>
<td>Moderately warm</td>
<td>4a</td>
<td>Fageto-Abieta</td>
</tr>
<tr>
<td>5</td>
<td>3-10</td>
<td>channel-concave</td>
<td>Moderately warm</td>
<td>4a</td>
<td>Fageto-Abieta</td>
</tr>
<tr>
<td>15</td>
<td>3-10</td>
<td>channel-concave</td>
<td>Moderately warm</td>
<td>4a</td>
<td>Fageto-Abieta</td>
</tr>
<tr>
<td>29</td>
<td>3-10</td>
<td>ridge-convex</td>
<td>Moderately warm</td>
<td>4a</td>
<td>Fageto-Abieta</td>
</tr>
<tr>
<td>3</td>
<td>3-10</td>
<td>channel-concave</td>
<td>Moderately cool</td>
<td>4b</td>
<td>Picetto-Fageto-Abieta</td>
</tr>
<tr>
<td>14</td>
<td>3-10</td>
<td>channel-concave</td>
<td>Moderately cool</td>
<td>4b</td>
<td>Picetto-Fageto-Abieta</td>
</tr>
<tr>
<td>25</td>
<td>3-10</td>
<td>planar</td>
<td>Moderately cool</td>
<td>4b</td>
<td>Picetto-Fageto-Abieta</td>
</tr>
<tr>
<td>26</td>
<td>3-10</td>
<td>ridge-convex</td>
<td>Moderately cool</td>
<td>4b</td>
<td>Picetto-Fageto-Abieta</td>
</tr>
<tr>
<td>17</td>
<td>3-10</td>
<td>ridge-convex</td>
<td>Warm</td>
<td>2</td>
<td>Fageto-Carpineto-Querceta</td>
</tr>
<tr>
<td>28</td>
<td>3-10</td>
<td>ridge-convex</td>
<td>Warm</td>
<td>2</td>
<td>Fageto-Carpineto-Querceta</td>
</tr>
<tr>
<td>30</td>
<td>3-10</td>
<td>top surface-crest line</td>
<td>Cool</td>
<td>5</td>
<td>Picetto-Fageta, Sorbo-Fageta (incl. shrub form) et Alneta viridi</td>
</tr>
</tbody>
</table>
Results

3.3 Landscape Analysis

3.3.1 Identification of Landscape elements

In the preceding chapters, SOM is used to characterize and analyze morphometric features. Here we present the results of combining remotely sensed data (seven ETM+ bands) and DEM derivatives (slope, cross-sectional curvature, minimum curvature, and maximum curvature) for landscape analysis of Eastern Carpathians area. The results of a separate study showed that inclusion of the thermal band in the data set provides the best band combination for classification and increases the accuracy (Fig. 36). For further details, see paper IX.

![Fig. 36. Kappa accuracies of Landsat ETM+ classification results with Sequential Maximum a Posteriori (SMAP) algorithms.](image)

An optimum SOM with an average quantization error of 0.3394 is achieved for this analysis. The quantization error for the whole study area is shown in figure 37. The highest quantization error (red-brown in Fig. 37) is related to thin high cold clouds and their shadows visible in the Landsat ETM+ data, especially the thermal band 6, in the west of the study area. In contrast, the SRTM data and derived morphometric parameters are independent of cloud effects. Deviations in spectral properties of these map units increase the distance between input data vector and corresponding best matching unit and consequently the quantization error. The SOM is a robust method and can handle this problem.

The output map units from SOM were interpreted corresponding to morphometric features and land cover classes respectively via two-dimensional feature space plots (Fig. 38). By analyzing the spectral and morphometric information for each class, we could integrate the results in terms of landscape elements. In two-dimensional feature space plots of mean values of maximum curvature (x-axis) and minimum curvature (y-axis) for map units, four major morphometric features (channel, planar, ridge, crest line) are identified. Channels showed negative minimum curvature and zero or near zero maximum curvature. Conversely, ridges revealed positive maximum curvature and zero or near zero minimum curvature. Values of both maximum and minimum curvature were positive for crest line Class.
Classes with plane features were located between ridge and channels and had small values for minimum and maximum curvature.

The same result can be achieved by cross-sectional curvature. Concave channels show negative values for cross-sectional curvature. Sloping surfaces with positive cross-sectional curvature are ridges. Sloping planar areas are characterized by zero or near zero cross-sectional curvature. These four major landscape forms are extended to ten classes by adding slope parameter. This is shown by plotting in two-dimensional feature space mean values of slope (y-axis) and cross-sectional curvature (x-axis). For example, map units 4 and 6 have common morphometric features with map units 19, 3 and 7 (ridge) but different slope conditions.

Map units 4 and 6 have very steep slope but map units 19, 3, and 7 have only steep slope. Generally, relationship among adjacent map units is constrained by weight vectors of self organizing map. This means that map units within the same group represent similar trend of weight vectors in input Landsat bands. SOM is a”topology preserving“algorithm thus neighborhoods with similar spectral attributes are preserved throughout the learning process. Grouping and assignment of land cover labels is made subsequently using also ground information and auxiliary maps.

Overall, 6, 5 and 4 map units are devoted to deciduous, coniferous and mixed forest respectively. Two map units were categorized as grasslands but shrub lands, settlements and arable land were only represented by one map unit. Because water bodies were misclassified as coniferous forest, water was separated using a threshold in band ETM+4. After interpretation and analysis of the output map units in relation to morphometric and land cover characteristics, homogeneous landscape elements were defined by combining these attributes. For example, map unit No.19 covers shrub lands on ridges with steep slopes. Figure 39 shows the final landscape elements map for the study area. The legend in
Results

Fig. 39 summarizes our interpretation in terms of morphometric and land cover classes. Colors were selected to reflect land cover by different hues, e.g. green for deciduous forest and morphometric classes by brightness, e.g. flat areas with bright colors and very steep slopes with dark colors.

Fig. 38. Analysis of SOM output map units to landscape elements with two-dimensional feature spaces of morphometric features (up) and land cover (down).

3.3.2 Spectral and morphometric signatures of landscape elements

The map in figure 39 depicts the complex landscape elements in the study area based on both landform and land cover. As it is obvious visually from the map, large parts in the north east in Ukraine are coniferous forests (bluish colors) in either planar, channel or ridge position and arable lands (magenta). Arable and settlement are generally on planar areas. Deciduous forests (greenish) appear in the central part of the image near the common border with Slovakia and Poland and spread out to the south west. This landscape has moderate to very steep slopes and contains channels, planar areas and ridges. Mixed forest (yellowish) is common on planar areas, channels or crest lines. Grasslands (brownish - magenta) are located on moderate slopes in channel or planar positions but conversely shrub lands (orange) are mainly on ridges with steep slopes. In order to present these landscape elements in more detail, we have extracted spectral and morphometric signatures for all classes.
Fig. 39. Landscape elements map of study area.

Figures 40 and 41 show selected signatures and relevant zoom views with superimposed contour lines (interval 28.5 meter). The graph in the upper panel of figure 40 shows the signatures of four groups of landscape elements with the same land cover and slope condition but located on different morphometric features. The lower panels displays the situation of these selected classes in the final map (Fig. 39) overlaid with contour lines. A visual comparison of contour lines with the landscape elements reveals that our classification is, overall, in good agreement with the situation on the ground. For example according to the signature graph, landscape elements in group d (class number 6 and 8) should be on the ridge (class 6) or planar (class 8). Comparing this finding with figure 40.d and the contour lines confirms this situation. Landscape elements of groups a, c and b (class number 16, 12 and 14) are typical example of channels with concave contour lines. The graph in upper part of figure 41 reveals that landscape elements 17 and 20 are planar and belong to the same morphometric feature class. Figure 41 with nearly straight contour lines and long distances between contours in arable land confirms this fact.

All 21 unique landscape elements can be grouped into eight heterogeneous groups (Table 9). Deciduous forest with three slope categories and three morphometric forms (planar, channel and ridge) characterizes six homogenous landscape elements that cover 26.38 % of the study area. Landscape elements including shrub lands are on ridges with steep slopes and cover 4.59%. Landscape elements with grassland cover are on planar areas or channels with moderate slope and cover 11.05 % of the study area.
Fig. 40. Spectral and morphometric signatures and close up views of landscape elements overlaid with contour lines.
Results

Fig. 41. Spectral and morphometric signatures and close up views of landscape elements overlaid with contour lines.

Table 9. Landscape elements properties and percentage of area covered

<table>
<thead>
<tr>
<th>Groups</th>
<th>No of landscape elements</th>
<th>Land cover</th>
<th>Morphometric forms</th>
<th>Slope class</th>
<th>Area (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>group 1</td>
<td>5</td>
<td>Coniferous forest</td>
<td>planar, channel and ridge</td>
<td>moderate, steep and very steep slopes</td>
<td>25.70</td>
</tr>
<tr>
<td>group 2</td>
<td>6</td>
<td>Deciduous forest</td>
<td>planar, channel and ridge</td>
<td>moderate, steep and very steep slopes</td>
<td>26.38</td>
</tr>
<tr>
<td>group 3</td>
<td>4</td>
<td>Mixed forest</td>
<td>planar, channel and crest line</td>
<td>moderate, steep and very steep slopes</td>
<td>20.99</td>
</tr>
<tr>
<td>group 4</td>
<td>2</td>
<td>Grass lands</td>
<td>planar, channel</td>
<td>moderate slope</td>
<td>11.05</td>
</tr>
<tr>
<td>group 5</td>
<td>1</td>
<td>Shrub lands</td>
<td>ridge</td>
<td>steep slope</td>
<td>4.59</td>
</tr>
<tr>
<td>group 6</td>
<td>1</td>
<td>Arable lands</td>
<td>planar</td>
<td>gentle slope</td>
<td>4.24</td>
</tr>
<tr>
<td>group 7</td>
<td>1</td>
<td>Settlements</td>
<td>planar</td>
<td>moderate slope</td>
<td>6.64</td>
</tr>
<tr>
<td>group 8</td>
<td>1</td>
<td>water bodies</td>
<td>planar</td>
<td>gentle slope</td>
<td>0.40</td>
</tr>
</tbody>
</table>
Chapter 4

Discussions and conclusions

In the first section of this thesis, we present a semi-automatic method using Neural Networks - Self Organizing Map – and Shuttle Radar Topography Mission (SRTM) data to identify morphometric features. This method is compared with a different parameterization approach (Wood’s method) which is available in GIS software e.g. GRASS. Each method has its own merits. Results of Wood’s method, are six explicit morphometric features point (pit, peak, pass) line (ridge, channel) and area based (planar). A weakness of this procedure is that the criterion for point-based features is zero slope. Pits, peaks and passes are assumed to occur only where the local slope is zero, but in reality when their neighborhood is considered they have an overall slope. So with normal procedures the result would consist mainly of channels and ridges. The other problem is the criteria for planar features. Ideally, these features should have zero values for maximum, minimum and cross-sectional curvatures. But in reality, most planar facets have small not-zero curvature components. Therefore, results depend strongly on the selected values for slope tolerance and curvature tolerance. Choosing the right thresholds is crucial and small differences can change the nature of detected morphometric features significantly. So in this method, it is necessary to strictly adhere to the constraints imposed by these thresholds. Slope as a first derivative of DEM is used only as threshold to define horizontal terrain. Slope tolerance in connection with true slope values are the major measures for breaking channels and ridges into a series of pits, passes and peaks.

Identification of morphometric features using Self Organizing Map was not explored before. The output of the approach presented in this thesis, using slope and curvature information, is set to 10 morphometric features. Unlike Wood’s method, morphometric classes do not depend on settings for curvature tolerance and slope tolerance. There is no predefined underlying assumption for classes like ridge, channel or planar. Specifically in this method, slope contributes to characterize classes with more informative features, e.g. ridge with steep slope. This is one significant advantages of SOM, which can not be achieved with Wood’s method. Ability to learn from complex, multidimensional data and transform those to other data sets also makes the SOM to a powerful tool. However, a drawback of SOM is that the number and arrangement of output map units must be defined in advance. But on the other side, this makes SOM as a versatile and flexible method for geomorphologic application in a variety of environments.

Since the SOM is a nonparametric clustering algorithm, unlike Wood’s method, identification of individual point-based features (pits, peaks and passes) is very limited. Instead, contiguous crest lines are identified in mountains.
4. Discussions and Conclusions

Direct comparison between the two approaches is difficult as the results are different. Each method has its own merits and makes it possible to extract useful information for further geomorphological analysis.

Characteristics of land properties are not scale free and vary when measured over different spatial extents or different DEM resolution. Landform elements are smallest homogeneous divisions of the land surface, at a given scale or resolution. With a multi-scale approach, each location has multiple morphometric features. DEM resolution and window size have a critical influence on identification of morphometric features depending on terrain characteristics. The scale dependencies in this study are due to spatial extent with window sizes ranging from $5 \times 5$ cells ($450 \times 450$ m) to $55 \times 55$ ($4950 \times 4950$ m) rather than spatial resolution ($90$ m). The statistical properties of morphometric parameters follow the spatial extent. With increasing window sizes, the measurement values decrease and at very large window sizes (i.e. $55 \times 55$) approach zero. Finer resolution and decreased window size reveals information that is more detailed while increasing window size and coarser resolution emphasizes more regional patterns. Thus, map units from smaller window sizes can be characterized as single landform elements but also as part of large terrain features at a larger window size. Higher resolution SRTM 1 arc second data, derived from the German X-band data, are not available for all areas due to the smaller ground swath width. We investigate how the SRTM/C band data with $30$ m interpolated grid, corresponding to SRTM/X band $30$ m, affects terrain derivatives and the morphometric characterization. In general, the larger grid size the smaller the derived range of values. In comparison with the original X30 DEM, the second order derivatives e.g. cross sectional curvature, maximum and minimum curvature were specially improved by interpolating C90 DEM to 30 m. Standard deviation of cross sectional curvature derived from C30 is nearly double than that from C90 for morphometric features while it deviates fairly little from the original X30. Standard deviation of minimum and maximum curvature for C30 also increased significantly with very small differences compared with X30.

To sum up, the interpolation of DEM 90 m to 30 m resulted in a significant improvement of terrain derivatives and morphometric features identification. These results are very similar to results produced from original X30 data. In addition, scale dependency of features when measured over different spatial extents or different spatial resolution should be considered. With the same spatial extent, the characteristics of morphometric features with different resolution show more than 70% similarity. With the same spatial extent, planar areas with steep slopes are more sensitive to DEM resolution than channels or ridges. Increasing the spatial resolution overcomes the main constrains for morphometric analysis with SRTM-90 m, such as artifacts, unrealistic feature presentation and single raster elements in the output map.

The Yardangs are interesting unidirectional features resulting from complex interactions between internal factors (lithology and structure) and external factors e.g. one-directional strong winds, fluvial incision and occasional rainfall. Nevertheless, other non aeolian processes such as cracking, weathering, slumping, piping, etc., are important for their evolution. SOM was very effective and useful for identification and characterization of yardangs in the Lut desert, Iran. A rose diagram of wind direction and strength during the 1970-2003 period showed that identified yardangs and corridors are aligned from NNW to SSE direction, parallel to the prevailing direction of the strong local 120 days wind starting.
4. Discussions and Conclusions

from April-May. The results showed that all yardangs and the corridors between were clearly recognized and classified by this method when their width was larger than the DEM resolution but became unrecognizable if their width is much smaller than the grid resolution. The identified yardangs and corridors cover about 31% and 42% of the study area respectively. The results demonstrate the efficiency of SOM for analyzing geomorphometric features under hyper-arid environmental conditions.

We also developed the presented method for Potential Natural Vegetation (PNV) delineation and landscape analysis. Integration of morphometric parameters with climate data (e.g. Sum of active temperature > 10° C) in SOM resulted in delineation of morphologically homogenous discrete PNV units. According to our analysis, about 19% of the Eastern Carpathian project area has a PNV unit including *Piceeto-Abieto-Fageta* formation with moderately cool topo-climate, very steep slope and channels or ridges as morphometric features. This is the most common PNV unit in this area. 18.6% have a PNV unit including *Piceeto-Abieto-Fageta et Acereto-Fageta* formation with cool topo-climate, very steep slope and morphometric features of channels or ridges.

Combining morphometric parameters from a DEM with remotely sensed spectral data facilitates the analysis of landscape components characterized by landforms and land cover. Landscape elements were classified into eight heterogeneous groups according to form, cover and slopes. The group of landscape elements with deciduous forest and three forms of planar, channel and ridge on moderate, steep and very steep slopes is most common and covers 26.3% of the project area in the Eastern Carpathians. Landscape elements with coniferous forest and three forms of planar, channel and ridge on moderate, steep and very steep slopes cover 25.7%. From the remotely sensed spectral data, the highest contributions are from ETM+5, ETM+4 and ETM+7. All curvature components have a very important role for morphometric analysis but the effect of cross sectional curvature is more obvious.

The average quantization error is a useful SOM performance index. Nevertheless, the result of this index is unique for each data set. So, there would be no sense in comparing quantization errors for different data sets. Therefore, for each data set, different learning parameters such as initial and final radius for neighborhood and large number of learning iterations should be tested and optimal map with lowest average quantization error should be selected.

SOM has its stochastic nature due to the random distribution of the initial weights. Examination of the effect of random weight initialization on optimal SOM revealed that with a high number of iterations (in this study 1000 steps) the network becomes stable and the weight vectors move to the same global minimum error. This important finding implies that the method is reproducible and provides consistent results.

The rapid development of geo-morphometry runs parallel to that of computer technology e.g GIS and image processing. New and enhanced terrain data such as ASTER DEM, SRTM or LIDAR data will increase the need for automatic methods. SOM presented in this thesis is an alternative method for fast assessment and comparison of landscapes over large areas. This makes it possible to develop monitoring and rapid response (near real time) applications for a wide range of environmental studies.
References


References


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


Evans, I.S. (2003). Scale specific landforms and aspects of the land surface. In I.S. Evans, R. Dikau, E. Tokunaga, H. Ohmori & M. Hirano (Eds.), *Conceptsand modeling in geomorphology: International Perspectives* (pp. 61–84)


References
References


Grodzinska, K., Godzik, B., Fraczek, W., Badea, O., Oszlanyi, J., D, P., & Shparyk, Y. (2004). Vegetation of the selected forest stands and land use in the Carpathian Mountains. Environmental Pollution, 130, 17-32


References


References


References


References


References


Appendix A-Potential natural vegetation mapping

Sum of active temperature (>10 °C) are grouped according to the heat provisions into five categories:

- 761-1200: Very cool
- 1200-1600: Cool
- 1600-2000: Moderately cool
- 2000-2400: Moderately warm
- 2400-2959: Warm

<table>
<thead>
<tr>
<th>Map Codes</th>
<th>Topo-climate</th>
<th>Slope (°)</th>
<th>Morphometric feature</th>
<th>Potential natural vegetation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1b</td>
<td>Warm</td>
<td>0-2</td>
<td>Flat (terraced) valley bottoms</td>
<td>Fraxineto-Querceta, Alneta glutinosae et Saliceta</td>
</tr>
<tr>
<td>2</td>
<td></td>
<td>3-10</td>
<td>Concave and convex slopes</td>
<td>Fageto-Carpineto-Querceta</td>
</tr>
<tr>
<td>3a</td>
<td></td>
<td>3-10</td>
<td>Top surfaces</td>
<td>Carpineto-Querceto-Fageta</td>
</tr>
<tr>
<td>3a</td>
<td></td>
<td>Over 10</td>
<td>All (Concave and convex slopes)</td>
<td>Carpineto-Querceto-Fageta</td>
</tr>
<tr>
<td>1c</td>
<td>Moderately warm</td>
<td>0-2</td>
<td>Flat (terraced) valley bottoms</td>
<td>Alneta glutinosae, A. incanae et Saliceta</td>
</tr>
<tr>
<td>4a</td>
<td></td>
<td>3-10</td>
<td>Concave and convex slopes</td>
<td>Fageto-Abieta</td>
</tr>
<tr>
<td>3b</td>
<td></td>
<td>3-10</td>
<td>Top surfaces</td>
<td>Abieto-Fageta</td>
</tr>
<tr>
<td>3b</td>
<td></td>
<td>Over 10</td>
<td>All (Concave and convex slopes)</td>
<td>Abieto-Fageta</td>
</tr>
<tr>
<td>1d</td>
<td>Moderately cool</td>
<td>0-2</td>
<td>Flat (terraced) valley bottoms</td>
<td>Alneta incanae et Saliceta</td>
</tr>
<tr>
<td>4b</td>
<td></td>
<td>3-10</td>
<td>Concave and convex slopes</td>
<td>Piceeto-Fageto-Abieta</td>
</tr>
<tr>
<td>3c</td>
<td></td>
<td>3-10</td>
<td>Top surfaces</td>
<td>Piceeto-Abieto-Fageta</td>
</tr>
<tr>
<td>3c</td>
<td></td>
<td>Over 10</td>
<td>All</td>
<td>Piceeto-Abieto-Fageta</td>
</tr>
<tr>
<td>4b</td>
<td>Cool</td>
<td>3-10</td>
<td>Concave and convex slopes</td>
<td>Piceeto-Fageto-Abieta</td>
</tr>
<tr>
<td>5</td>
<td></td>
<td>3-10</td>
<td>Top</td>
<td>Piceeto-Fageta, Sorbo-Fageta (incl. shrub form) et Alneta viridi</td>
</tr>
<tr>
<td>3d</td>
<td></td>
<td>Over 10</td>
<td>All</td>
<td>Piceeto-Abieto-Fageta et Acereto-Fageta</td>
</tr>
<tr>
<td>4b</td>
<td></td>
<td>3-10</td>
<td>Concave and convex slopes</td>
<td>Piceeto-Fageto-Abieta</td>
</tr>
<tr>
<td>6</td>
<td></td>
<td>3-10</td>
<td>Top surfaces</td>
<td>Piceeto-Fageta (shrub form), Alneta viridi et Prata subalpestris</td>
</tr>
<tr>
<td>3d</td>
<td></td>
<td>Over 10</td>
<td>Concave slopes</td>
<td>Piceeto-Abieto-Fageta et Acereto-Fageta</td>
</tr>
<tr>
<td>5</td>
<td></td>
<td>Over 10</td>
<td>Convex slopes</td>
<td>Piceeto-Fageta, Sorbo-Fageta (incl. shrub form) et Alneta viridi</td>
</tr>
</tbody>
</table>

1- Personal communication of Ivan Kruhlov.