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Automated classification of landform elements using object-based image analysis

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Abstract

This paper presents an automated classification system of landform elements based on object-oriented image analysis. First, several data layers are produced from Digital Terrain Models (DTM): elevation, profile curvature, plan curvature and slope gradient. Second, relatively homogenous objects are delineated at several levels through image segmentation. These object primatives are classified as landform elements using a relative classification model, built both on the surface shape and on the altitudinal position of objects. So far, slope aspect was not used in classification. The classification has nine classes: peaks and toe slopes (defined by the altitudinal position or the degree of dominance), steep slopes and flat/gentle slopes (defined by slope gradients), shoulders and negative contacts (defined by profile curvatures), head slopes, side slopes and nose slopes (defined by plan curvatures). Classes are defined using flexible fuzzy membership functions. Results are visually analyzed by draping them over DTMs. Specific fuzzy classification options were used to obtain an assessment of output accuracy. Two implementations of the methodology are compared using (1) Romanian datasets and (2) Berchtesgaden National Park, Germany. The methodology has proven to be reproducible; readily adaptable for diverse landscapes and datasets; and useful in respect to providing additional information for geomorphological and landscape studies. A major advantage of this new methodology is its transferability, given that it uses only relative values and relative positions to neighboring objects. The methodology introduced in this paper can be used for almost any application where relationships between topographic features and other components of landscapes are to be assessed.

Keywords: Landform; Geomorphometry; Segmentation; Fuzzy classification; Terrain analysis; DTMs

1. Introduction

Information about landforms is necessary, for example for landscape evaluation, suitability studies, erosion studies, hazard prediction and various fields of landscape and regional planning or land system inventories. The classic ways to incorporate relief units into a landscape assessment is to delineate them during field survey or using stereo aerial photographs. This approach is relatively time-consuming and the results depend on subjective decisions of the interpreter and is, therefore, neither transparent nor reproducible. Terrain analysis is seldom addressed in landscape ecological research even if topography is a key variable in a wide range of environmental processes (Bates et al., 1998; Butler, 2001). Still, this landscape level perspective is important and key to a variety of ecological questions which require the study of large regions and the understanding of spatial pattern. For example, landscape pattern may influence

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the spread of disturbance (e.g. Turner, 1990; Forman, 1995; Butler, 2001), the horizontal flow of materials such as sediment or nutrients (cf. Dalrymple et al., 1968) and other ecologically important processes such as net primary production, water quality (e.g., Hunsaker et al., 1992; Wondzell et al., 1996) and the monitoring and maintenance of environmental quality and biodiversity (Gordon et al., 1994; López-Blanco and Villers-Ruiz, 1995; O'Neill et al., 1997).

Landscape-level phenomena are also receiving increasing attention as questions of global change become more prominent. Therefore, methods to analyze and interpret landform heterogeneity at broad spatial scales are becoming increasingly significant for ecological studies. Landscape metrics or indices are frequently used to assess structural characteristics of landscapes and to monitor change (Turner, 1990; Forman, 1995; Fry, 1998; Griffith et al., 2003). The increasing availability of high resolution satellite imagery leads to a growing number of landscape research applications using remote sensing and GIS (Florinsky, 1998; Walsh et al., 1998; Ehlers et al., 2002). Integrating satellite, aircraft and terrestrial RS systems to achieve a scale-dependent set of observations can be achieved through operational systems and current technologies. Still, most applications do not adequately embrace the 3-dimensionality of landscape features. This paper aims to contribute to a more accurate incorporation of the third dimension of landscapes. We report on a methodology for the automatic classification of morphological landforms using geographic information systems (GIS), object-based image analysis and digital terrain models (DTM).

In the past, manual methods have been used for classifying macro morphological landforms from contour maps. Hammond's (1964) procedure has, to a certain extent, become a de facto standard. Dikau et al. (1991) developed a method which automates Hammond's manual procedures using GIS. In this paper, we build on these ideas and develop them further in two ways. First, we extend the classification category feature set by introducing neighborhood relationships and topological functions. Secondly, we use relative elevation values and fuzzy rules for the classification systems because landform classification is very sensitive to the operational definition used. We will discuss the problems of accuracy assessment of geomorphic elements. The classification system is built on expert knowledge stored as a priori rules in a semantic network and is designed to be used by non-expert users, and which is easily adapted for specific applications. Based on a literature survey we compare our methodology to existing digital geomorphologic classification methodologies and we suggest that the main enhancements are: a) the reduction of human errors by eliminating manual classification steps, b) the facilitation of comparisons of results derived from different datasets, and c) the reduction in processing time (Irvin et al., 1997; MacMillan et al., 2000; Romstad, 2001).

2. Material and methods

2.1. DTMs and digital geomorphologic analysis

The choice between form and processes as a basis of landform classification is a matter of debate amongst geomorphologists. Morphogenetic and morphodynamic criteria are extensively used in geomorphology for mapping and classification. Examples of these types of application are the ITC system of geomorphological survey (Verstappen and van Zuidam, 1968) and Dollinger's (1998) approach to delineate landscape units for planning purposes. Christian and Stewart (1953) proposed a different approach, built on the physiographic aspect of land. In fact, the interaction between form and process is the core of geomorphology (Evans, 1998) and form characteristics are key components of geomorphological systems (Ahnert, 1998). An extensive review on this subject is provided by Lane et al. (1998), who underlined the importance of the form in the relief assessment for a variety of purposes.

Geomorphometric properties have been measured manually for decades (Horton, 1945; Hammond, 1954, 1964; Verstappen and van Zuidam, 1968; Christian and Stewart, 1953) and later methods involved a derivation from topographic maps; a labor-intensive task. Digital terrain analysis evolved about 30 years ago. Evans (1972) first introduced an integrated system of geomorphometry. Since then important progress was achieved in improving DTM accuracies (see Lane et al., 1998), developing new algorithms and new software to calculate terrain derivatives. Among the well known algorithms are those developed by Peucker and Douglas (1975), Heerdegen and Beran (1982), Bauer et al. (1985), Zevenbergen and Thorne (1987), Costa-Cabral and Burges (1994) and Tarboton (1997). Many have been implemented into industry standard GIS software, such as ESRI products, while others were packaged in stand-alone programs, including MICRODEM (Guth, 1995), LandSerf (©Wood, 1996–2002, http://www.soi.city.ac.uk/~jwo/landserf/landserf180/), TOPMODEL (Beven, 1997), TAPES set (Wilson and Gallant, 1998), DiGeM (©Conrad, 2000–2002, http://www.geogr.uni-goettingen.de/ pg/saga/digem/) and TauDEM (©Tarboton, 2002, http://moose.cee.usu.edu/taudem/taudem.html).

During the last two decades the availability of DTM data has been continuously growing, data accuracy has improved, and additional algorithms have been developed to derive new attributes from gridded DTMs (Burrough et al., 2000). Increasingly, GIS allow for 3-D analysis for large areas, however methodological approaches towards comparable geomorphologic classification systems are still rare. More recent developments include cluster analysis methods using generalization algorithms (Friedrich, 1996; Romstad, 2001) or applying fuzzy logic to relief data (Irvin et al., 1997; De Bruin and Stein, 1998; Burrough et al., 2000; MacMillan et al., 2000). Some of the approaches were designed to identifying certain features types, e.g. linear or circular forms (Cross, 1988; Parrot and Taud, 1992), or specific forms, e.g. mountains (Miliaresis and Argialas, 1999; Miliaresis, 2001) hill tops (Tribe, 1990), landslides or strike ridges (Chorowicz et al., 1995) or other features (Tang, 1992; Walsh et al., 1998). Many methods are aiming for the characterization of hillslope forms (Dikau, 1990; McDermid and Franklin, 1995; Irvin et al., 1997; Burrough et al., 2000; MacMillan et al., 2000; Urban et al., 2000). Methodologically, most approaches are based on the analysis of pixels and a two by two or three by three neighborhood analysis.

Expanded feature sets (e.g. spectral channels from scenes of different dates or derived spectral measures such as vegetation indices) are today more or less routinely generated for the classification process. It is relatively common to use topographic derivatives from the DTMs, for example slope, aspect, profile curvature, plan curvature, topoclimatic index and slope length (see Florinsky, 1998). These may be used as inputs to classification processes or in a post-classification layering approach to interpret and label defined spectral clusters. For example, Walsh et al. (1998) use a topoclimatic index, known elevation ranges for plant communities, to classify specific landforms. Shary et al. (2002) developed a conceptual system of types of 12 curvatures which avoids emphasizing grid directions. A successful surface parameterisation is necessary for a flexible terrain taxonomy by providing the information with which to classify landform. Geomorphometric classification of terrain has tended to be either into 'homogeneous regions' (e.g. Dalrymple et al., 1968; Speight, 1976; Dikau, 1989; López-Blanco and Villers-Ruiz, 1995; Schmidt and Dikau, 1999; MacMillan et al., 2000) or the identification of specific geomorphological features as discussed before. In particular, the problem of scale of both spatial extent and resolution make single objective classifications of landscape at least problematic, maybe unfeasible.

2.2. Geomorphometry and GIS-based terrain classification

GIS programs today incorporate techniques for the examination of spatial and non-spatial relationships between spatial objects. These relationships may be analyzed and quantified with respect to a large range of parameters including Euclidean distance, neighborhood relationship, and topology. In the mid-1970s, Collins (1975) was already discussing different algorithms that could be used to identify features such as hill crests, depression minima, watershed or depression boundaries and areas, storage potential of watersheds, slope, and aspect. With the increasing availability of commercial GIS and digital databases in the 1980s, significant advances have been made to identify specific features and/or to classify landforms (Weibel and deLotto, 1988; Dikau, 1989;Weibel and Heller, 1991; Dikau et al., 1991; Chorowicz et al., 1995; Walsh et al., 1998). Many processes for identifying these parameters are now standard functions within a desktop GIS.

Researchers have developed routines for automatic landform extraction and classification for a variety of applications. For example, Barbanente et al. (1992) developed routines for automatically identifying ravines and cliffs. These are not features that can be justifiably included in a general landscape classification methodology because of the need to generalize. Several research groups have developed methodologies to extract terrain features from Digital Terrain Models (e.g. Gardner et al., 1990; Graff and Usery, 1993; Chorowicz et al., 1995). Dikau (1989) developed an approach to identify plateaux, 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. These landscape features are too detailed for regional to national landscape classifications. Other phenomena occur across several scales or along a scale continuum. For instance, debris flows can occur at scales ranging from micro-scale flows a few centimeters in width and several meters in length, through intermediate scale features to massive sturzstroms that leave behind deposits sufficient to impound kilometer-long lakes (Walsh et al., 1998). In addition, many approaches are often very specific and tailored for a single application only.

We identify a need for the classification of landforms at a meso- to microscale aiming to cover large areas and being relatively easily applicable to other data sets. Data availability and GIS advances have made 3-D analysis

operational even for large areas, however methodological approaches formalizing a comprehensive GIS-based geomorphologic classification system are still missing. As briefly discussed, most existing classification systems are very specific. With the advent of worldwide datasets (e.g. Shuttle Radar Topography Mission) and ubiquitous access to GIS the demand for generic and transferable classification systems grows. It is necessary to determine how GIS-based parameters can be used for identifying and classifying landforms. The identification of parameters (parameterization) is an essential first step in identifying landforms.

2.3. Delineating homogeneous landscape objects

The need for tangible landscape objects is increasing as pressure increases on land managers to adopt comprehensive landscape planning, nature conservation and resource management tasks. Pike (2000) calls the landscape-level classification of landscape structure an emerging application compared to other areas in geomorphometry. Basically, most existing approaches rely on remote sensing techniques among which unsupervised methods (e.g. cluster analysis) have gained supremacy in landform elements or land facets classification. Even with enhanced cluster analysis methods, such as the incorporation of generalization algorithms (Friedrich, 1996; Romstad, 2001) or the application of fuzzy logic to relief data (Irvin et al., 1997; De Bruin and Stein, 1998; Burrough et al., 2000; MacMillan et al., 2000), pixel-oriented approaches are limited (Blaschke and Strobl, 2001). A multivariate analysis of pixels does not include topological relationships of neighborhood, embeddedness or shape information of the object that a pixel belongs to. One of the few examples which go beyond pixels is the approach using terrain facets (Rowbotham and Dudycha, 1998) calculated from combinations of DTM-derived slope, aspect and curvature.

Today, per-pixel analyses are often criticized, as Blaschke and Strobl (2001) and Burnett and Blaschke (2003) point out. It is believed that object-based image analysis is needed to extend landscape analysis beyond pixel classifications and taking into account the sizes, shapes and relevant positions of relevant objects (Blaschke and Strobl, 2001). Therefore, we introduce object-based analysis and classification for geomorphologic applications. The maturation of the concept of object-based image analysis and its implementation in commercial software packages are premises for developing enhanced techniques to classify the geomorphologic elements. The shift from per-pixel-based to object-based analysis requires a shift from pixels having meaning to user-defined objects having meaning. Technically, this requires that groups of pixels be aggregated in the raster domain according to user-prescribed rules of homogeneity. This aggregation is most often achieved using image data segmentation techniques. Image segmentation is not new (Haralick and Shapiro, 1985) but only a few of the existing approaches are widely available in commercial software packages. The segmentation routine must produce qualitatively convincing results while being robust and operational. In this paper, an image segmentation algorithm developed by Baatz and Schäpe (2000) is used to derive landform object candidates and subsequently landform objects. The segmentation approach was designed for use with remotely sensed (spectral) data but may also be used for terrain information (Miliaresis and Argialas, 1999; MacMillan et al., 2000; Miliaresis, 2001; Strobl, 2001; Blaschke and Strobl, 2003).

To delineate objects based on geomorphometry we build on the hypothesis that the Earth's surface and its model, a DTM, are decomposable. The decomposing of a landscape's hierarchical structure through multi-scale analysis is an important part of landscape analysis and O'Neill et al. (1986) recommend the use of three hierarchical levels as a minimum in analytical studies. Most approaches adhere to a concept of the pixel as a spatial entity that is assumed to have a de facto relationship to objects in the landscape. Uni-scale, pixel-based monitoring methodologies have difficulty providing useful information about complex multi-scale systems. If we accept that the reality we wish to monitor and understand is a mosaic of process continuums, then our analysis must make use of methods which allow us to deal with multiple yet related scales within the same image and with multiple images of landscape. Burnett and Blaschke (2003) provide a five-step methodology to decompose, model and classify spatial entities based on multi-scale segmentation and object relationship modeling. Hierarchical patch dynamics (HPD) is adopted as the theoretical framework to address issues of heterogeneity, scale, connectivity and quasi-equilibriums in landscapes. In this paper, we apply this methodology to DTM information using the eCognition© object based image analysis software (Baatz and Schäpe, 2000; Flanders et al., 2003). We 'build' topomorphologic objects in the multi-scale segmentation step, delineating areas of relative homogeneity within the spatial layers of topographic variables such as slope and curvature.

2.4. Classification of landform elements

Many approaches in digital geomorphology aim to delineate watershed catchments and sub-catchments

with standard procedures (Gardner et al., 1990) or a specific algorithm from the broad palette available (Wilson and Gallant, 1998). In our approach, the basic geometric entities are relatively homogeneous with respect to their slope gradient and slope curvature characteristics. The resulting objects are input for the classification process in an integrated GIS/image processing software environment. The handling of complex landforms including structural (topological) and hierarchical information is only partly realized in current GIS. Schmidt and Dikau (1999) identified a need for research to develop open, object-oriented and easy-to-use programming tools in GIS. Our methodology uses the following layers of information: profile curvature, plan curvature, slope gradient, altitude, and an additional layer with relative values of altitude. These layers are input to a multiscale image segmentation procedure developed by Baatz and Schäpe (2000). We adopted as a starting point a nine class system from the work of Dikau (1989). He distinguished nine topological/morphological classes based on combinations of convex, straight and concave profiles (Fig. 1). These are all theoretically possible combinations of landform elements relative to plan and profile curvatures. However, four of these classes are less likely to occur in a real landscape (e.g. landforms with concave profile and convex plan curvatures). Thus, we choose to consider five main classes (indicated with numbers 1 to 5 in Fig. 1), assigning the other four as classes with different possible degrees of membership to one or more of the main classes (as indicated by arrows in Fig. 1). We supplement these five Dikau-based classes with another four, irrespective of curvature values, producing a total of nine classes. The four new classes were derived from slope gradient parameterization and on an additional parameter, a local dominance criterion. The dominance criterion is based on the relative altitudes of all neighboring objects. Objects are characterized as dominant forms ('peaks') which are higher than their neighbors, or dominated ones ('toeslopes') which are lower then all of their neighbors. Slope gradients less than 2° are defined as "flat areas", while higher than 45° as "steep slopes". These two values are the only "crisp" values in the classification system. The rest of the classification system is based on fuzzy rules.

Mixed elements are reclassified to different main classes, depending on their curvature values, both in plan and in profile. The fuzzy logic rules like those built into eCognition facilitate this flexible classification. For instance, elements with straight profile, but convex plan are classified as side slope if the convexity value is close to zero, or as nose slopes when this value is far away from this value. Landforms with concave profile and convex curvatures or vice versa are more complex,

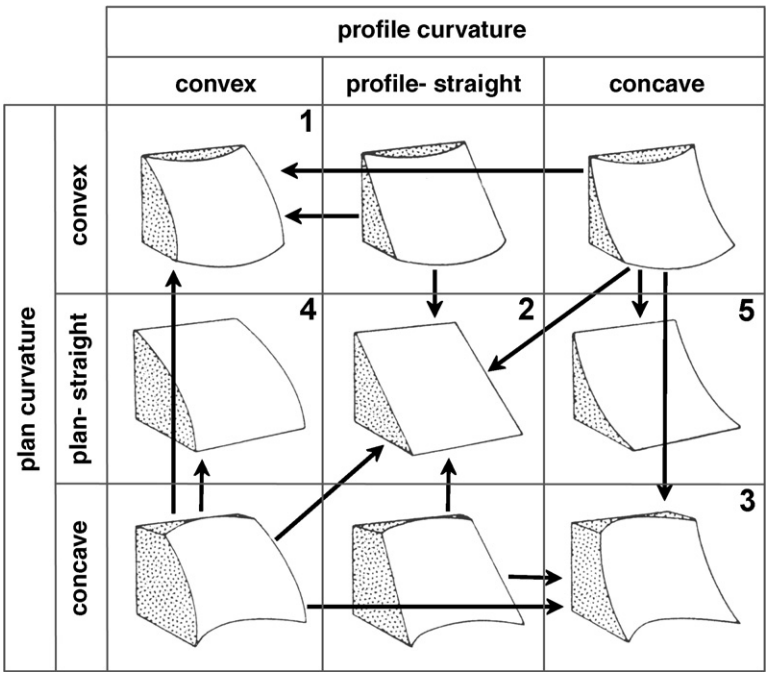

Fig. 1. Classification of landforms on the basis of plane and profile curvature. 1. Nose slope; 2. Side slope; 3. Head slope; 4. Shoulder; 5. Negative contact. Arrows indicate possible combinations in classification. (modified after Dikau, 1989).

Table 1
Parameters directly used in landform classification (ND—not defined)

Landform element		Morphometric feature (directly defined)			
No. Name	Description	Curvature (1/m)		Slope (°)	Altitude
		Profile	Plan		
1 Peak	Dominant surfaces	ND	ND	ND	Higher than neighbors
2 Shoulder	Convex element	+	− or ±0	ND	ND
3 Steep slope		ND	ND	>45	ND
4 Flat or gentle slope		ND	ND	<2	ND
5 Side slope	Rectilinear slope	±0	±0	ND	ND
6 Nose slope	Convex slope	+	+	ND	ND
7 Head slope	Concave slope	–	–	ND	ND
8 Negative contact		–	+ or ±0	ND	ND
9 Toeslope	Flat, bottom position	ND	ND	<2	ND

allowing four different assignments in accordance with specific value combinations.

The nine classes described in Table 1 are structured in a hierarchy (Fig. 2) and grouped into similar object classes. The landform classification consists of three hierarchical levels. At the highest level, uplands, midlands and lowlands were set up using a relative altitude criterion. We used relative altitudes because one of the aims of our research was to develop a classification system applicable to different datasets and being transferable. Technically, this criterion was applied using an additional image layer which contains the altitude values normalized to 8 bit data. The results are relative altitude values between 0 and 255. In this way the classification system becomes independent of specific datasets. It was not used in the segmentation process, but it is used in the classification process as an additional layer for neighborhood relationship definitions. Based on relative altitudes, the membership functions were set up in a simple and flexible manner, as illustrated in Fig. 3. Thus, each object is included in a given class following its membership value and no specific thresholds are needed. Since the classification system is hierarchically built, these classification rules are also inherited by the lower level classes.

The intermediate level of the class hierarchy includes chiefly flat areas and slopes (Fig. 2). Besides these, the parent class Upland comprises one more child class, namely Peaks, and in the Lowland category Toeslope replaces flat areas (Fig. 2). Flat areas were defined by a slope gradient less than 2°. Toeslopes were defined using the same membership function, but spatial superposition between flat areas and Toeslopes is hindered by rules inherited from their parent classes. Finally, Peaks were defined by calculating the degree of dominance over neighboring objects. The rate of lower value area is computed by dividing the sum of shared border length of the object to be classified and its neighbors with

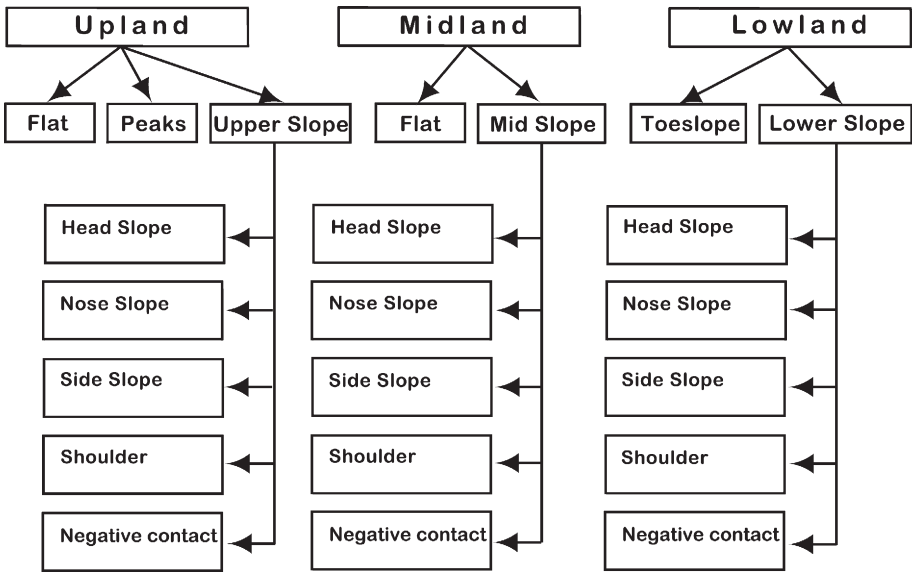

Fig. 2. Class hierarchy.

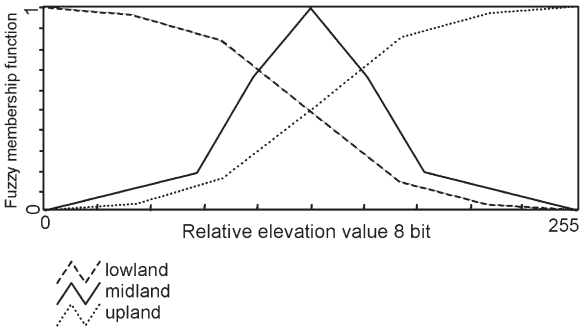

Fig. 3. Membership functions to classify uplands, midlands and lowlands.

lower altitudinal values by the total border length of the same object (Eq. (1)). The output values range between 0 and 1, where 1 expresses a total dominance over the neighbor objects (i.e. the object does not share a border with any objects with a higher altitude).

$$\mathrm{LVA} = \frac{\sum_N a_N, <O}{\sum_N a_N}, \qquad (1)$$

where:

$\sum_N a_N$ sum over all neighbors

a_N relative border length shared by the object to be classified and its neighbors

O altitude value of the object to be classified

At the lowest level, landforms were then defined using a combination of relatively simple and transparent fuzzy membership functions (Table 1). Only the most relevant terrain attributes for a given class were used in class definition to avoid conflicts between fuzzy rules in classification. For instance, curvatures and slope gradient were not included in definition of the class 'peak' (ND in Table 1) since they are core to other classes.

3. Case studies

The methodology was tested in two geomorphologically different areas. Study area 1 comprises two communities from the Transylvanian Plain in central area of Romania (Fig. 4). The second study area is located within the German part of the Eastern Alps. The two Romanian communes are located in a hilly region with altitudes between 270 and 620 m, and slope gradients under 45°. Dominant geologic features are sediments of the Neogene, with large extension of clays and sands. The Unguraş commune covers a surface of 63.6 km^2. The second commune, Ţaga, extends over 100.8 km^2. As input datasets we created DTMs interpolated from digitized 1:50000 contour maps, by applying ArcGIS contour line-based TIN generation (for technical discussion, advantages and limitations see e.g. Wise, 1998). The output spatial resolution is 46 m for the Unguraş and 57 m for Ţaga datasets, respectively.

For the second study area, the Berchtesgaden National Park, Germany (Fig. 5), which covers 210 km^2, a DTM with 5 m spatial resolution and additional data sets

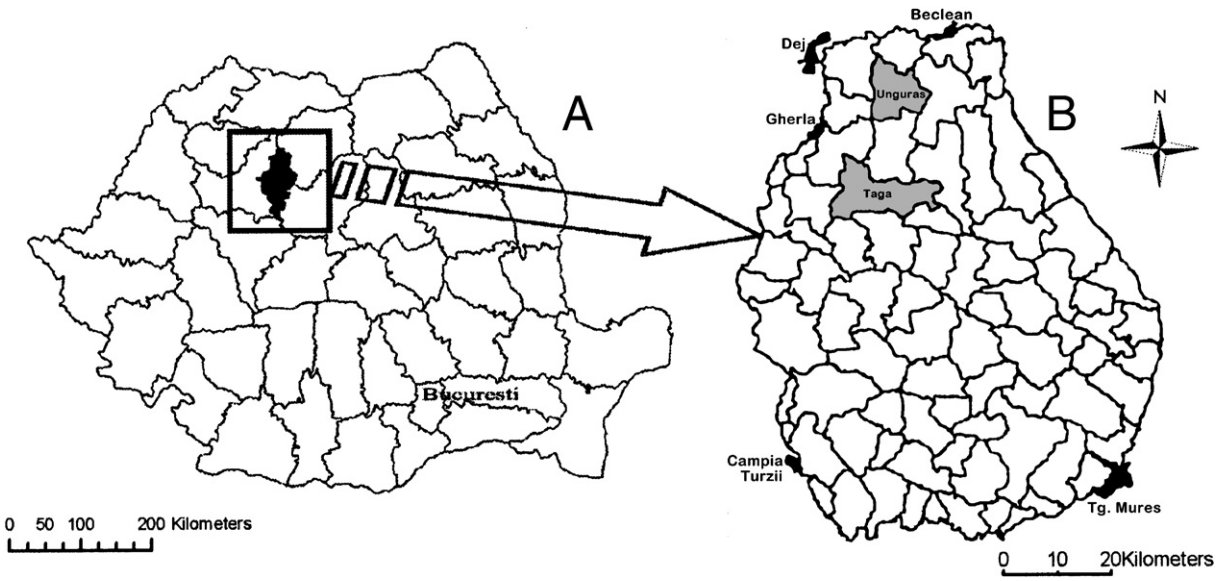

Fig. 4. Location of the Romanian study areas: A. Relative to the national territory; B. Relative to the Transylvanian Plain.

Fig. 5. Location of the German study area.

were made available courtesy of the Berchtesgaden National Park administration. The Berchtesgaden study area stretches from about 620 m above sea level (Lake Königssee) to 2710 m (peak of the Watzmann) within a horizontal distance of just a few kilometers, and exhibits extreme morphological variations, including a wide variety of geomorphological alpine forms.

Several segmentation parameters were tested to create object primitives according to both spatial features and derivatives values. These objects are defined to maximize between-object variability and minimize within object variability for user-chosen inputs. For the resulting segmentation level, the user specifies a unitless 'scale parameter'. Layers containing objects of different sizes can be created as appropriate. For homogeneity, the user chooses the relative weight to be applied to color versus shape criteria; 0.7:0.3 was used here (the sum must total 1.0), emphasizing the importance of within object heterogeneity over the shape of the resulting features. Within the shape parameter settings, smoothness and compactness parameters were weighted equally. These settings assure relatively 'natural' boundaries for resulting segments, avoiding both fractal shapes and artificially compressed objects. Equal weights were assigned to the four input bands (profile curvature, plan curvature, slope gradient and altitude).

In the segmentation algorithm used (Baatz and Schäpe, 2000), the 'scale parameter' is a measure of the maximum change in total heterogeneity that may occur when merging two image objects in a stepwise process. Internally, this value is squared and serves as the threshold which terminates the region-merging segmentation process. When a possible merge of a pair of image objects is examined, a fusion value for the objects is calculated and compared to the squared scale parameter. The color criterion (in our case values for slope gradient, curvature, etc.) is the change in heterogeneity that occurs when merging two image objects, as described by the change of the weighted standard deviation of the derivatives values regarding their weightings. The above-mentioned 'shape parameter' works in a similar fashion: the shape criterion is a value that describes the enhancement of the shape with regard to two different models describing ideal shapes. Adjusting the scale parameter indirectly influences the

Table 2
Statistics of the image object primitives

Study area	No. of objects				Avg. object size (pixel)				Avg. no. of neighbors			
	Scale parameter				Scale parameter				Scale parameter			
	300	200	30	10	300	200	30	10	300	200	30	10
Berchtesgaden	158	280	5711	36858	–	–	728.9	112.9	5.3	5.5	5.89	5.9
Ţaga	27	52	1018	6247	–	–	1826	297.6	5.27	5.4	5.88	5.92
Unguraş	41	55	806	4399	–	–	1322	242.3	4.63	4.9	5.84	5.91

average object size: a larger value leads to bigger objects and vice versa. Additionally, the influence of shape as well as the image's channels on the object homogeneity can be adjusted. During the segmentation process all generated image objects are linked to each other automatically.

For both the Romanian and German data sets, four layers of segmented objects were generated using scale parameters of 300, 200, 30 and 10. The outputs were visually analyzed by draping them over the DTMs of the study areas. Statistics of the resulting image object primitives were also compared (Table 2). The scale parameter of 30 seems to be the best compromise between getting 'meaningful' segments and avoiding an over-segmentation which produces a scattered classification. It is difficult to evaluate the meaningfulness of the segmentation level and this is the most crucial part of using the algorithm of Baatz and Schäpe (2000). In this study it is done by comparing the results at the respective levels with dissecting the terrain manually through interpretation and the level of best agreement is chosen. The corresponding scale parameter results in segments which delineate medium landforms well, although sometimes one object might belong to two or three types of slopes, especially in terms of plane curvature (Fig. 6a, object 1). These shortcomings are drastically reduced when high resolution DTMs are used (Fig. 6, bottom-left). Larger objects would

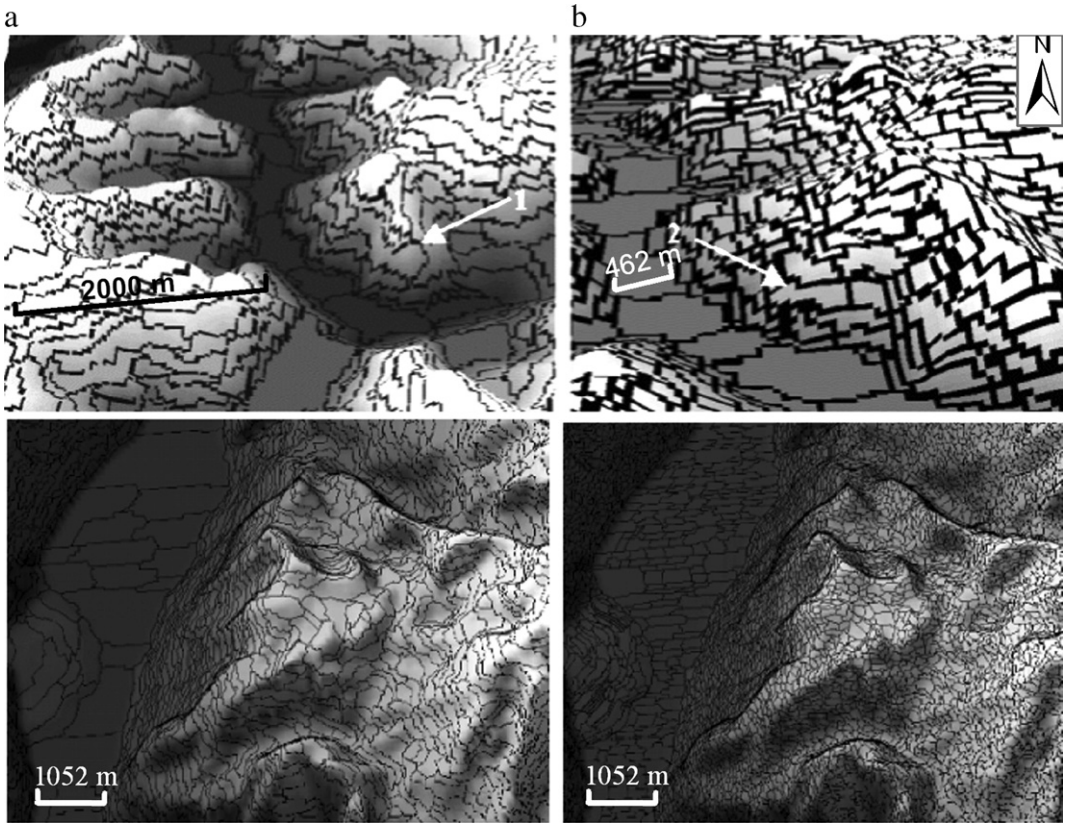

Fig. 6. Image objects primitives draped over the DTM of the Unguraş commune (top), and Berchtesgaden (bottom). a. Scale parameter = 30 (left); b. Scale parameter = 10 (right).

be more suitable to extract toeslopes, but at a greater level of heterogeneity all other segments will lose their meaning as medium-sized landforms. The chosen level of homogeneity is regarded as the best compromise between producing too small objects and objects being so large that they belong to several landforms at once (Fig. 6b, object 2).

4. Results and discussion

The data obtained from the classification were directly integrated in a GIS software. Landform types were visually analyzed by draping them over DTMs of study areas (Figs. 5 and 6). As Blaschke (2002) pointed out, the results of DTM processing are difficult to quantitatively

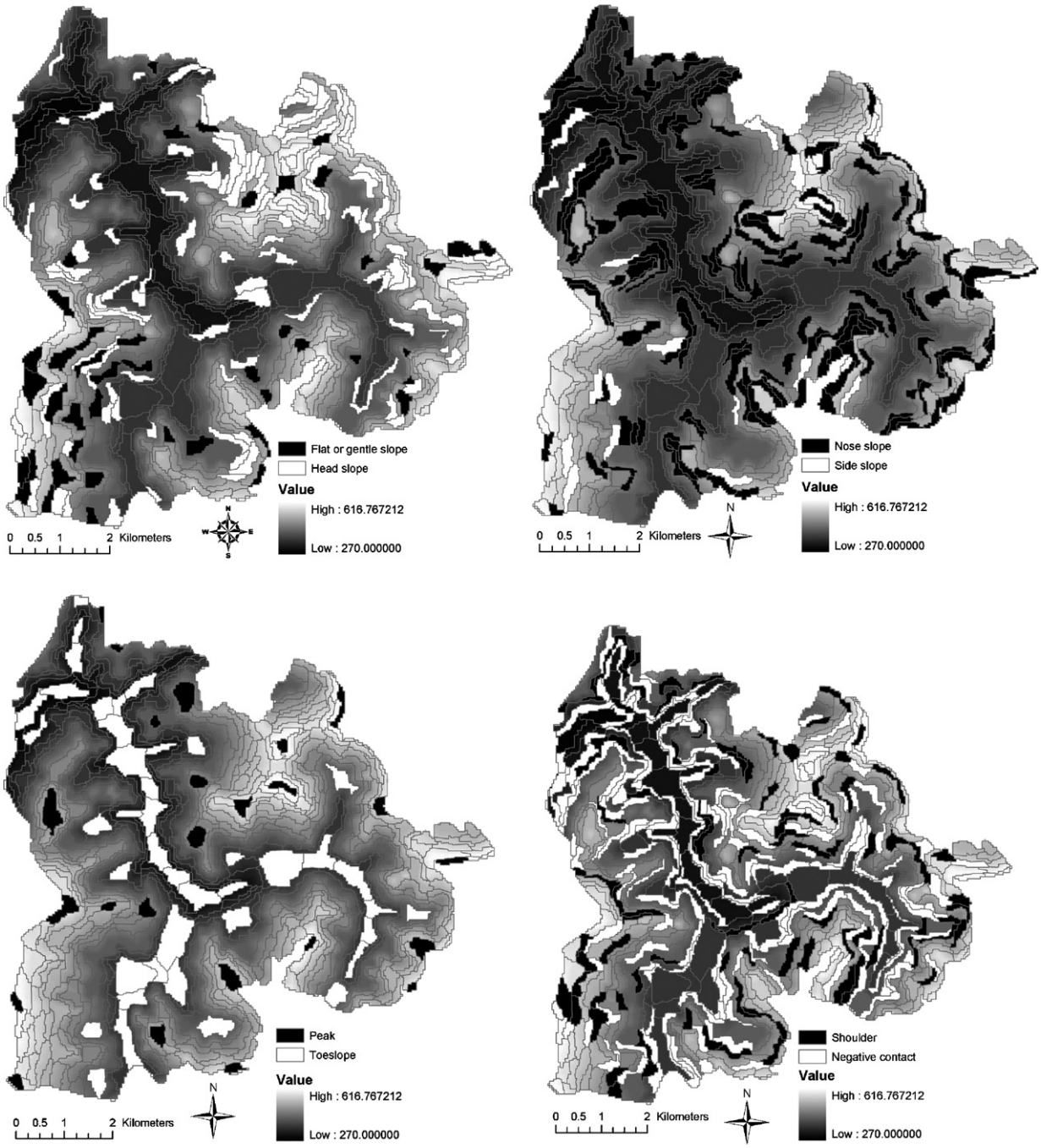

Fig. 7. 3-D visualization of landform classification in the area of the Unguraş commune, Romania.

verify because of the lack of ground truth data for geomorphologic features beyond altitude. Obviously, the geomorphic categories resulting from this type of classification coincide with the topographic surface, and so describe the geomorphology of both study areas well. There are small differences in regard to the object sizes between the datasets from the hilly region (Fig. 7) and the mountainous region (Fig. 8). These differences are caused by the spatial resolution of datasets (46 and 57 m versus 5 m), but more significantly by the difference in topographic complexities. It seems likely that spatial complexity is more important than spatial resolution but this has to be investigated in more detail in further research.

Based on the visual analysis we observed that oversegmentation (characterized by segments with a relatively low mean size) produces a scattered classification, and that further generalization is required. This has been observed in other studies (Friedrich, 1996; MacMillan et al., 2000; Romstad, 2001; Wielemaker et al., 2001). The problem is particularly acute when high resolution datasets are examined; even visual differentiation of objects becomes difficult (Fig. 6, bottom-right). Rather than using filtering techniques, we used the generalization potential of the segmentation process. Unlike a filter, it does not necessarily neglect small forms. Since the homogeneity criterion of the segmentation procedure from Baatz and Schäpe (2000) is based on the minimization of the resulting heterogeneity of the objects, some small objects will remain differentiated as their neighbors coalesce if they are spectrally distinct from their neighbors. By "distinct" we mean that the object's mean values of the used parameters (profile curvature, plan curvature, slope gradient, altitude and relative altitude) are significantly different from neighboring objects. This way, a relatively uniform slope or valley bottom will result in fewer and larger objects than, for example, an upland area characterized by abruptly changing terrain and strong gradients. If both phenomena occur next to each other — large, relatively uniform slopes and small ridges or dikes, both types will be reproduced in the segmentation process. This is especially observable for the study area of Berchtesgaden and the 5 m DTM; while the segmentation procedure works as a generalization process for the relatively uniform slope areas despite their 'within-patch variation', very distinct forms such as avalanche paths or moraines are preserved even if they are very small, sometimes only consisting of a couple of dozen pixels while the larger units consist of a couple of hundred to a few thousand pixels.

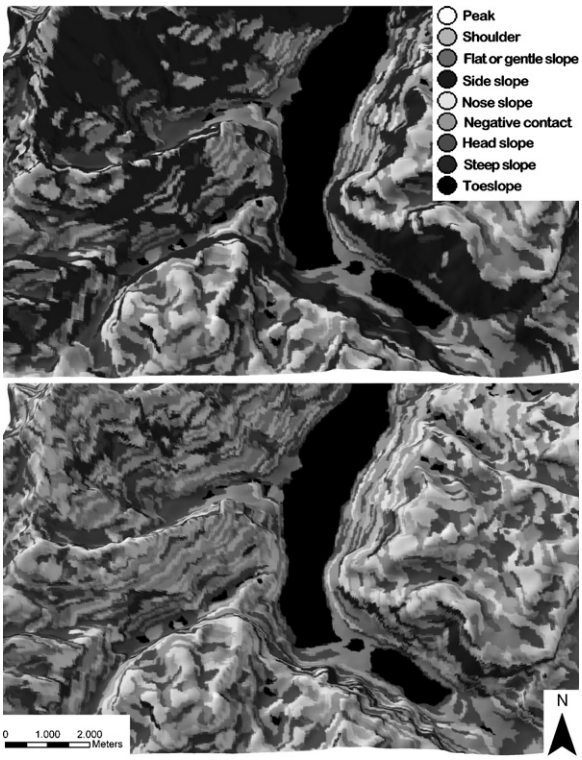

Fig. 8. 3-D visualization of landform classification of the Berchtesgaden area. Steep slopes defined by a slope gradient higher than 45° (top) and higher than 60° (bottom).

It is important to note that using our methodology no object is left unclassified. This is achieved through overlapping fuzzy membership functions which produce for every object one membership value per class rather than one finite classification result per object. Still, the accuracy assessment in an object-based classification is crucial and no standard procedures exist in comparison with per-pixel approaches (Flanders et al., 2003; Blaschke, 2003). At this stage of research the classification accuracy was assessed based on specific fuzzy classification options but we believe that more work needs to be done to improve it. Thus, we analyzed the 'best classification result' and the 'classification stability'. The latter is a measure of the difference of the first and second choice in the classification process, and the corresponding membership functions, respectively. In other words, how much more accurate is the most likely class for a given object compared to the second choice? Both indices resulted in high values for both study areas, expressing a high stability of the classification results. Constant ambiguities in classification have been noticed only between classes defined by the same membership function but belonging to different parent classes in the class hierarchy, or between flat areas and peaks. In the last situation, objects which dominate surrounding areas but having very low slope gradient values will be classified as flat

areas. That is a more suitable option as shape information should reflect the spatial characteristics of geomorphologic processes.

Most automated approaches (e.g. Dikau et al., 1991; Irvin et al., 1997; De Bruin and Stein, 1998) are very dependent on critical thresholds specified for different parameters. For example, an 8% slope threshold is used for flat areas and gentle slopes, and particular boundaries are chosen for the component class intervals. Poor transferability is also generally stated for most pixel-based remote sensing classifications (Townshend et al., 2000). Conversely, robustness is enhanced for object-based classifications, since criteria such as object shape and neighbor-based classification rules and the use of fuzzy rules is less dependent on absolute values of altitude, slope gradient and curvature (Blaschke and Strobl, 2001; Ehlers et al., 2002; Flanders et al., 2003). The ease of modifying protocols enables object-based algorithms to perform more accurately than other techniques when transferred from one geographical area to another. By using relative values, the same classification model is transferable between datasets from various geomorphologic regions.

Moreover, our methodology is applicable to a wide range of possible uses. It is flexible for specific adaptations. Membership functions can be modified for specific purposes such as: assessment of the risk of avalanches (Copland, 1998; Bebi et al., 2001), evaluation of land suitability (Martinez Beltrán, 1993), landscape monitoring and conservation (Gordon et al., 1994; Blaschke, 2002), soil mapping (Wielemaker et al., 2001). There may be also opportunities for research in urban areas using highly detailed DEMs to support flood potential, slope instability, ecology, settlement, and land use issues and decision-making. Such an example of "tweaking" of the rules is provided in ` 6; because of the large share of steep values in the Berchtesgaden area DTM, the classification was additionally run with different values of slope gradients in order to visualize the shapes of slopes with gradients between 45° and 60°. This required only very minor changes in the classification system.

The fuzzy classification approach proposed here allows for soft transitions of the classes and avoids crisp thresholds. This is necessary since the initial calculations of the curvature and slope values use a neighborhood analysis window which is defined by its radius. Consequently, the resulting data layer used in the classification is relatively sensitive to changing the methods or the parameters. As is well known from the literature (Skidmore, 1989; Schmidt and Dikau, 1999), this typically causes differences in slope and aspect values. Fuzzy rules are less sensitive to the absolute values and the underlying method to calculate slope and curvature (Irvin et al., 1997; Burrough et al., 2000; MacMillan et al., 2000).

Slope aspect was not used in the segmentation nor in the classification process but this data layer exists, and within the eCognition software every object has its mean or median exposition and other statistical parameters calculated and stored in an object database. For specific ecological applications this information can easily be utilized. The reason for not employing it in our methodology is that aspect produces an additional zonation, for instance when the aspect of hillslopes changes from south to west or north to east. This zonation makes the outputs too confusing. Moreover, north-facing slopes are artificially split due to the great difference between pixel values (e.g. 1 and 360°). So far, we have not found a solution to these shortcomings. Including slope aspect in the classification is a priority in further work as this representation of the land surface is usually very important for species-specific geo-botanical mapping and for slope stability studies.

We have also tested the behavior of the classification system, running it many times over the same dataset. For every run, the classification results were identical, demonstrating that our fuzzy rule-based classification system assures reproducible outputs. Up to now it was applied only to hilly and mountainous regions, as results from case studies in flat areas have not yet been evaluated. For very flat areas this methodology will certainly find its limits. Automatic classification of landform units allows for a fast assessment and comparison of landscapes over large areas. This makes it possible to develop monitoring and rapid response (near real-time) applications for hazard mitigation and security management.

5. Conclusions

Many existing geomorphometry approaches aim for the identification and/or extraction of discrete landforms, such as drainage basins and barchan dunes, by focusing on specific surface shapes. There are fewer generically applicable methodologies addressing the geometry of continuous surfaces such as agricultural fields, abyssal hill complexes, deformed sea ice and other terrains that require a statistical characterization. We have demonstrated that our methodology is applicable over two very different terrain types, and using different data sets in terms of DTM and ancillary data spatial resolution.

The classification results are reproducible and comparable between various datasets. Geomorphology and computer modeling has become inextricably linked through developments in computer cartography and GIS. Application examples include land erodibility modeling or

modeling the soil erosion potential. Typically, indices, based on the topography, rainfall and soil type, and spatial distributions are represented on various GIS layers. Studying geomorphic processes from graded or cyclic perspectives may be enhanced with future developments in scientific visualization. There has been a lot of work by geomorphologists and hydrologists using GIS to automatically extract terrain information from digital databases. Dikau (1989), Weibel and deLotto (1988), Dikau et al. (1991), Tang (1992), Chorowicz et al. (1995), Brabyn (1996), Wood (1996) and Schmidt and Dikau (1999) have discussed different aspects of this type of research. All these authors conclude that terrain information is important for landscape classifications.

Given the increasing pressure on natural resources and rising landscape monitoring obligations on the one side, and diversity of recent advances in quantitative surface characterization (Pike, 2000) on the other, we argue that an automated landform classification methodology will become central to many ecological applications, including soil resource modeling, landslide hazards, sea-floor and desert geomorphology. The methodology introduced in this paper can be used for almost any application where relationships between topographic features and other components of landscapes are to be assessed (e.g. natural risk assessment). In this way, we hope to redress the lack of land-surface curvatures in earlier approaches (Florinsky, 1998). This is connected with an underestimation of the role of topographic variables indicated in the formation and development of plant cover.

As stated earlier, image segmentation methods were first developed about 20 years ago, but since that time have not been used extensively in remote sensing applications. Early models of object-based image classification faced obstacles in fusing information from multilevel analysis, validating classifications, reconciling conflicting results, attaining reasonable efficiency in processing (time and effort), and automating the analysis (Flanders et al., 2003). They were also limited by hardware, software and interpretation theories. Pixel-based analysis provided reasonably satisfactory results and remained the industry standard for a long time. Advanced pixel-based processes such as texture measurements, linear mixture modeling, fuzzy sets and neural network classifiers were invented to enhance per-pixel image analysis (Blaschke and Strobl, 2001). In this paper, we have demonstrated that a multiscale image segmentation/object relationship modeling methodology (MSS/ORM, cf. Burnett and Blaschke, 2003) can also be efficiently used for geomorphometry and terrain classification. The rapid development of geomorphometry runs parallel to that of computer technology, chiefly GIS, image processing and DTMs. New and enhanced terrain data, such as the high-resolution global DTMs from satellite missions (e.g. ASTER DEM or SRTM), from photogrammetry or LiDAR data will stimulate fresh applications and increase the number of locations where morphometry can be used.

Of course, the limitation of this method should be emphasized too. Although slope aspect is included as a data layer within the eCognition software, this parameter was not used in segmentation or in the classification process so far. Since it is a key variable for a wide range of space-related applications, this issue is a priority in future work.

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