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Local variance for multi-scale analysis in geomorphometry

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ABSTRACT

Increasing availability of high resolution Digital Elevation Models (DEMs) is leading to a paradigm shift regarding scale issues in geomorphometry, prompting new solutions to cope with multi-scale analysis and detection of characteristic scales. We tested the suitability of the local variance (*LV*) method, originally developed for image analysis, for multi-scale analysis in geomorphometry. The method consists of: 1) up-scaling land-surface parameters derived from a DEM; 2) calculating *LV* as the average standard deviation (*SD*) within a 3×3 moving window for each scale level; 3) calculating the rate of change of *LV* (*ROC-LV*) from one level to another, and 4) plotting values so obtained against scale levels. We interpreted peaks in the *ROC-LV* graphs as markers of scale levels where cells or segments match types of pattern elements characterized by (relatively) equal degrees of homogeneity. The proposed method has been applied to LiDAR DEMs in two test areas different in terms of roughness: low relief and mountainous, respectively. For each test area, scale levels for slope gradient, plan, and profile curvatures were produced at constant increments with either resampling (cell-based) or image segmentation (object-based). Visual assessment revealed homogeneous areas that convincingly associate into patterns of land-surface parameters well differentiated across scales. We found that the *LV* method performed better on scale levels generated through segmentation as compared to up-scaling through resampling. The results indicate that coupling multi-scale pattern analysis with delineation of morphometric primitives is possible. This approach could be further used for developing hierarchical classifications of landform elements.

1. Introduction

Although debated, it remains unsettled whether scales in digital representations of the land surface are explicitly detectable, or scale is simply a ‘window of perception’ (Marceau, 1999). In both landscape ecology and remote sensing, scale has traditionally been regarded as a function of grain (resolution) and spatial extent. In geomorphometry, scale is predominantly considered a function of the resolution of Digital Elevation Models (DEMs) (Hengl and Evans, 2009; MacMillan and Shary, 2009).

Increasing availability of high resolution DEMs is leading to a paradigm shift regarding scale issues in geomorphometry. Originally, terrain-related analyses were limited by the coarse spatial resolution of available DEMs, leaving questions of scaling aside. Meanwhile, rapid progress in technical and computational domains encourages acquisition and processing of DEMs at ever finer resolutions, e.g. for Austria whole provinces have already been covered by LiDAR DEMs interpolated at 1 m resolution. Along with these developments it has been recognized that analysis should not essentially be driven by the finest available grain size, but that it might be appropriate to upscale the initial grid to a coarser resolution more relevant to particular research objectives. Consequently, the importance of scaling methods has grown significantly. In particular, techniques such as filtering and resampling are frequently applied to high resolution grids to smooth out noise that may lead to erroneous results (MacMillan and Pettapiece, 2000; MacMillan et al., 2003).

The scale dependency of land-surface parameters was noted by Evans (1972) as ‘a basic problem in geomorphometry’ (Shary et al., 2002). Meanwhile, the scale dependency of land-surface parameters and land-surface objects has been confirmed by a number of studies (Chang and Tsai, 1991; Wood, 1996; Florinsky and Kuryakova, 2000; Evans, 2003; MacMillan et al., 2003; Fisher et al., 2004; Schmidt and Andrew, 2005; Hengl, 2006; Arrell et al., 2007; Deng et al., 2007; Fan et al., 2007; Drăguţ et al., 2009a; Wood, 2009) and different methods to account for scale have been proposed. In his thesis Wood (1996) clearly showed the scale dependency of land-surface parameters by computing and analyzing them over a range of spatial scales. As a major outcome he introduced the open-source software package LandSerf that is currently one of two products capable of performing ‘multi-scale surface characterization’. Arrell et al. (2007) particularly examined the scale dependency of morphometric classes. They found that the relative importance of landform classes varies with DEM resolution. Decisions on an appropriate resolution involve

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compromise between noise reduction and generalization. A similar conclusion was drawn by Hengl (2006), who suggested a number intermediate between the finest available and coarsest legible resolutions to be an appropriate pixel size for a specific problem. Schmidt and Andrew (2005) introduced a spatially adaptive scale detection technique, exemplified for curvatures, in order to recognize dominant scale ranges of landforms and to study local landform variability across scales.

Still, additional techniques that allow data-driven detection of scale levels are required. Since statistical properties of land-surface models are also scale dependent, studying their variation across scales may be effective in identifying 'characteristic scales' in both the cell (Wood, 1996, 2009) and the object realms.

As Olaya (2009, p. 146) pointed out 'combining ideas from image analysis and geomorphometry can be a fruitful way of…gaining a better understanding of the information contained in the DEM'. The method of local variance (*LV*) graphs (Woodcock and Strahler, 1987) is such a method, originally developed in image analysis, with potential for dealing with scale in DEM analysis (Li, 2008).

In this research we aim to test whether the *LV* method could help in detecting characteristic scales in geomorphometric analysis, as it has proven to be effective in detecting scale levels in remote sensing applications. Similar to concepts in landscape ecology and remote sensing, breaks in the trend of *LV* values across scales might reveal levels of organization in the structure of data due to similar sized spatial objects. Here 'objects' are not defined as classical geomorphologic objects (e.g. landforms), but rather as 'morphometric primitives' (Gessler et al., 2009) or pattern elements, carriers of information on land-surface parameters. Morphometric primitives can be further classified into landform elements and integrated in nested hierarchies (Giles, 1998; Minar and Evans, 2008; Evans et al., 2009).

2. Data and methods

2.1. Data and test areas

Our experimental research was carried out in two test areas located in the province of Salzburg, Austria (Fig. 1). Both sites have an extent of 3×3 km: they represent two types of land surface in terms of roughness: relatively flat or low relief (Eugendorf) and mountain (Schlossalm). For both areas the federal government of Salzburg provided very high resolution (VHR) DEMs, specifically LiDAR (Light Detection and Ranging) DEMs, acquired during flight campaigns in 2001 and 2006 and interpolated at 1 m spatial resolution.

Schlossalm is located within the Hohe Tauern mountain range in the south of the province of Salzburg. The area is part of a smaller subrange that borders the valley of Gastein to the west. The test site comprises an area at elevation between 1635 and 2578 m around the highest peak of this part of the divide, the Türchlwand (2578 m) representing a typical high alpine, glacially modified topography characterized by glacial cirques, ridges, gullies and steep slopes. According to a recent study at the regional level with additional insights from the application of dating techniques (Ivy-Ochs et al., 2008) it can be estimated that Schlossalm was glaciated until the end of the Younger Dryas about 11.6 ka ago. The Türchlwand peak is a classic, triangular peak in the center of three adjacent glacial cirques. The cirque slopes towards the ridge are very steep, especially to the northern side, where deposits of blocky material evidence ongoing rock fall activity. Lithology of the Schlossalm area is mainly Bündner schists (Exner, 1956), a rock formation prone to slope failures. Recent geomorphic processes include gravitational mass movements such as rock falls and avalanches as well as fluvial erosion. The eastern part of Schlossalm is being used as skiing resort and thus, man-made features such as ski tracks, braking mounds for avalanche protection, and reservoirs are apparent in the data.

The second test area, Eugendorf, is located about 10 km northeast from the city of Salzburg, in the foreland of the Austrian Alps. Geologically, Eugendorf is situated in the Flysch zone that follows north of the calcareous Alps (Herbst and Riepler, 2006). The morphology of the region is dominated by till and drumlins both resulting from the advance of the Salzach glacier during the last glacial maximum in Late Würmian (van Husen, 2000), which occurred between 30 and 18 ka ago (Ivy-Ochs et al., 2008). Glaciation in combination with glaciofluvial processes in the Lateglacial period contributed to the gentle terrain character of the area with elevation ranging from 503 to 639 m.a.s.l. The overall smooth topography is disturbed by sharply incised fluvial channels. Most parts of the area are currently used for settlements, agriculture, and recreation facilities such as a golf course.

2.2. Local variance and multi-scale representation

Based on the previous work of Strahler et al. (1986), Woodcock and Strahler (1987) introduced *LV* graphs to reveal the spatial structure of images using standard deviation (*SD*) as function of scale. The authors proposed measuring *LV* as the value of *SD* in a small neighborhood (3×3 moving window), then computing the mean of these values over the entire image. The value so obtained indices the local variability in the image. The procedure is applied on successively coarser scales, which are obtained through resampling. Graphs of values across scales are used to measure spatial structure in images; the peaks in the *LV* graph would indicate the cell size that approximates the spatial dimension of the most characteristic objects in the scene (Fig. 2). Woodcock and Strahler (1987, p. 313) explain the mechanism as follows: 'If the spatial resolution is considerably finer than the objects in the scene, most of the measurements in the image will be highly correlated with their neighbors and a measure of local variance will be low. If the objects approximate the size of the resolution cells, then the likelihood of neighbors being similar decreases and the local variance rises.' Basically, application of the *LV* concept exploits spatial autocorrelation, which is a fundamental image characteristic (Lees, 2006).

Despite its simplicity and usefulness this method was not widely adopted in remote sensing and GIS (Cao and Lam, 1997). Only a few papers (Hay et al., 1997, 2005) developed the approach further. Bøcher and McCloy (2006a,b) explored the characteristics of various forms of the *LV* function using synthetically generated image data; they demonstrated that the *LV* function peaks at scales related to the geometric size of pattern structures in the scene. The *LV* method was later introduced in the context of object-based image analysis (OBIA) by Kim et al. (2008) and made operational through the Estimation of Scale Parameter (ESP) tool (Drăguţ et al., 2010). Both studies found that the *LV* method applied in the OBIA context does not provide peaked, but relatively smooth variogram-shaped graphs. Drăguţ et al. (2010) introduced rate of change of *LV* (*ROC-LV*) to assess the *LV* dynamics from one scale level to another. By interpreting thresholds and prominent peaks in the *ROC-LV* graph, characteristic scales relative to data properties at the scene level can be found. Thus they expanded the concept and application of *LV* (originally designed for detecting the 'optimal' scale) into multi-scale analysis and representation.

2.3. Application of the LV method on land-surface parameters

According to Schmidt and Andrew (2005), the land surface is hierarchically structured and it can be represented differently across scales (e.g. a convex hillslope embedded into a concave hillslope, which in its turn is embedded into a valley; see Fig. 3 in the cited work). We hypothesize that these kinds of objects are homogeneous areas relative to scale levels. If repeated, they would produce peaks in the *ROC-LV* graphs, where cells or segments are assumed to match types of objects characterized by (relatively) equal degrees of homogeneity, providing

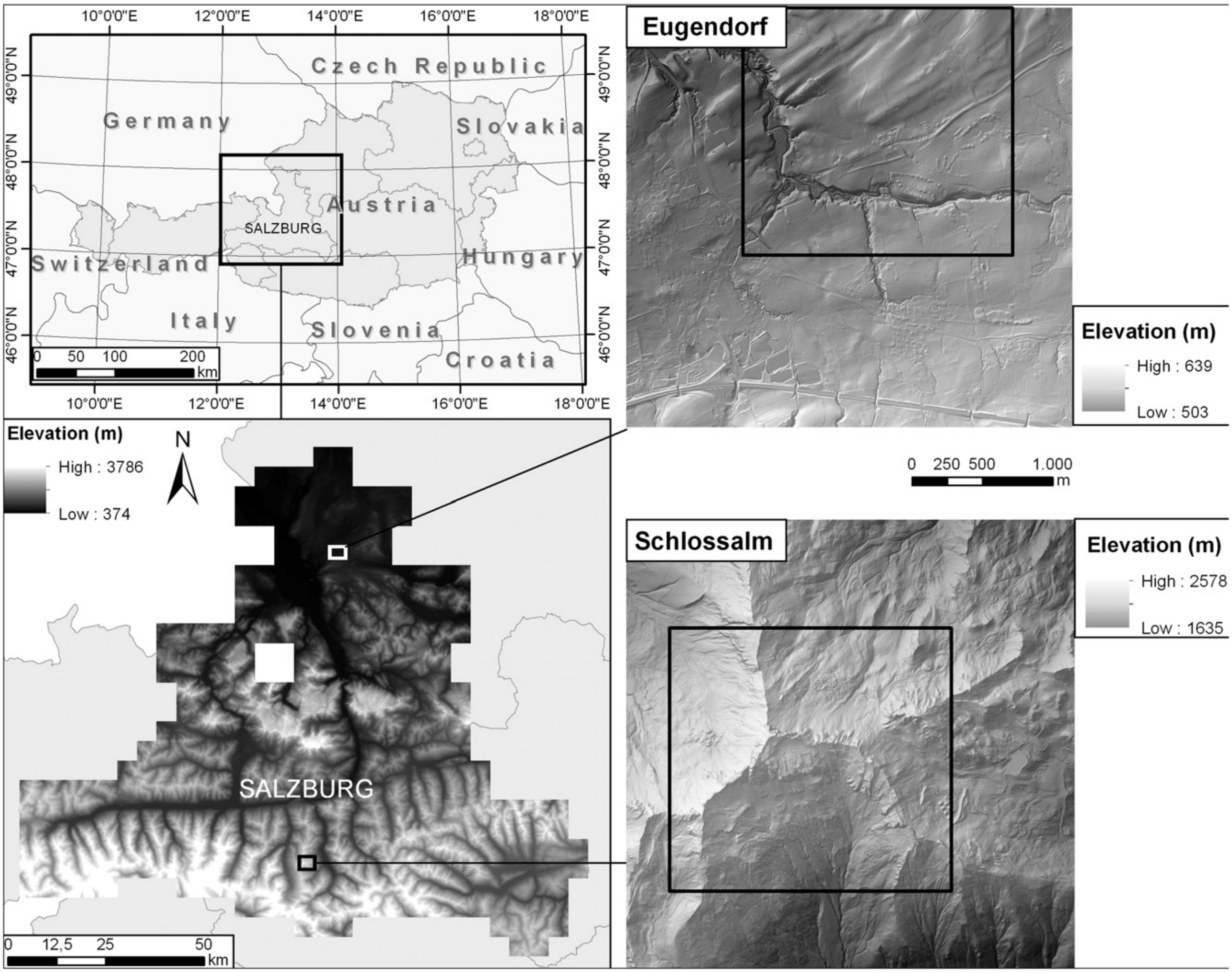

Fig. 1. Locations of test areas. Black frames on the right show the extents of visualization in Figs. 7 and 8.

these objects are representative enough to impact on the scene level *ROC-LV*. In this research, scale levels were produced at constant increments by resampling (cell-based) and image segmentation (object-based), for slope gradient, plan, and profile curvatures.

2.3.1. Resampling

The input LiDAR DEMs were resampled up to a cell size of 49 m using bilinear interpolation and an increment of 2 m. Given the extent of test areas (3000 m broad) and the spatial resolution of input data (1 m), the upper limit of 49 m was selected, based on the rule of thumb that a minimum of 60 pixels on each side is required to calculate *LV* (Woodcock and Strahler, 1987). Thus, a total of 50 layers were obtained (25 per test area). For each dataset slope, plan- and profile curvatures were derived, giving a total of 150 layers. *LV* was then calculated for each of these layers in a 3×3 moving window, as in the original application of Woodcock and Strahler (1987).

2.3.2. Object-based image analysis (OBIA)

The basic processing units in object-based image analysis are segments, so called 'image objects' (Benz et al., 2004). The cells of a raster are grouped into objects through image segmentation in such a way that the incorporated heterogeneity is minimized and the homogeneity is maximized. Heterogeneity refers to value and shape, the primary object features. Weights have to be set that indicate the relative importance of both properties in the segmentation process. Conceptualized as a bottom-up approach, the procedure starts at the cell level and iteratively performs pair-wise merging of objects until the maximum allowed growth in heterogeneity, defined by the user through a scale parameter, is exceeded. The value of the scale parameter

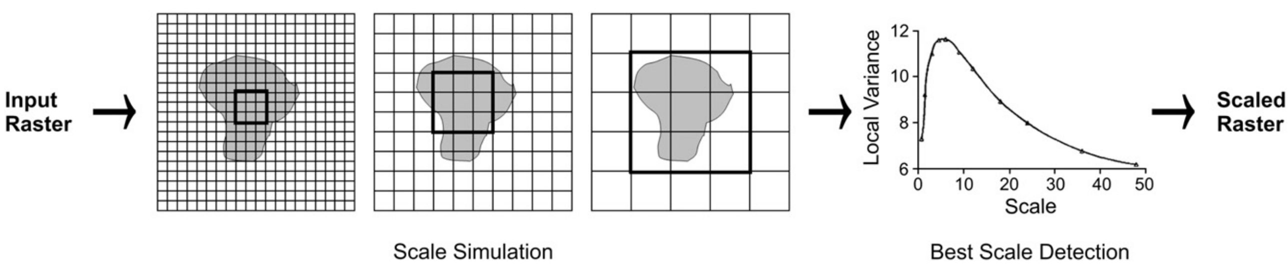

Fig. 2. The method of local variance.

directly influences the average size of objects in the final segmentation result (Baatz and Schäpe, 2000).

Land-surface parameters (slope gradient, plan and profile curvatures), as derived from the initial 1 m LiDAR DEM in a standard 3×3 window, served as input for multi-resolution segmentation. The value assigned to a 'land-surface object' is the mean of the aggregated cells that make up that object (object values). For each land-surface parameter multiple scale levels were produced by increasing the scale parameter from 1 up to 200 resulting in ever larger 'land-surface objects'. The step size from one level to the other was set to 1. Thus, 200 scale levels were simulated for each surface raster. We selected 200 as the upper threshold, because at this level the mean object size is comparable to the size of the maximum moving window in cell-based scaling. Based on previous experiences in land-surface segmentation, the weights for value and shape homogeneity were set to 0.9 and 0.1 respectively. Hence, the relative importance of terrain property values was emphasized and the influence of shape, i.e. compactness or smoothness, was minimized. Segmentation was conducted using the 'hierarchy' option, thus objects at higher scale levels are built from objects at the next lower level (in contrast to the 'non-hierarchy' option, where objects at each scale level are built from cells). At each level *LV* was calculated as the mean value of *SD* of objects. The whole procedure has recently been implemented as an algorithm called ESP (Estimation of Scale Parameter; Drăguţ et al., 2010) for application in the eCognition Developer® software (http://www.ecognition.com).

3. Results

For each scaling method, specific scale signatures (cf. Wood, 2009, but applied globally) have been obtained (Figs. 3–5) in scale ranges between 1 and 49 for cell-based methods, and between 1 and 200 for OBIA. *LV* graphs are provided in two versions to reveal thresholds at higher scale (otherwise obscured due to huge values of *ROC-LV* at lowest levels). Thresholds and peaks in trends of curves have been comparatively analyzed. A comparative view of scale levels interpreted through the analysis of *LV* graphs is provided in Table 1.

3.1. Resampling

For the resampling method, *LV* graphs follow ascendant trends for slope (Fig. 3), while for both curvatures the trends are descendant

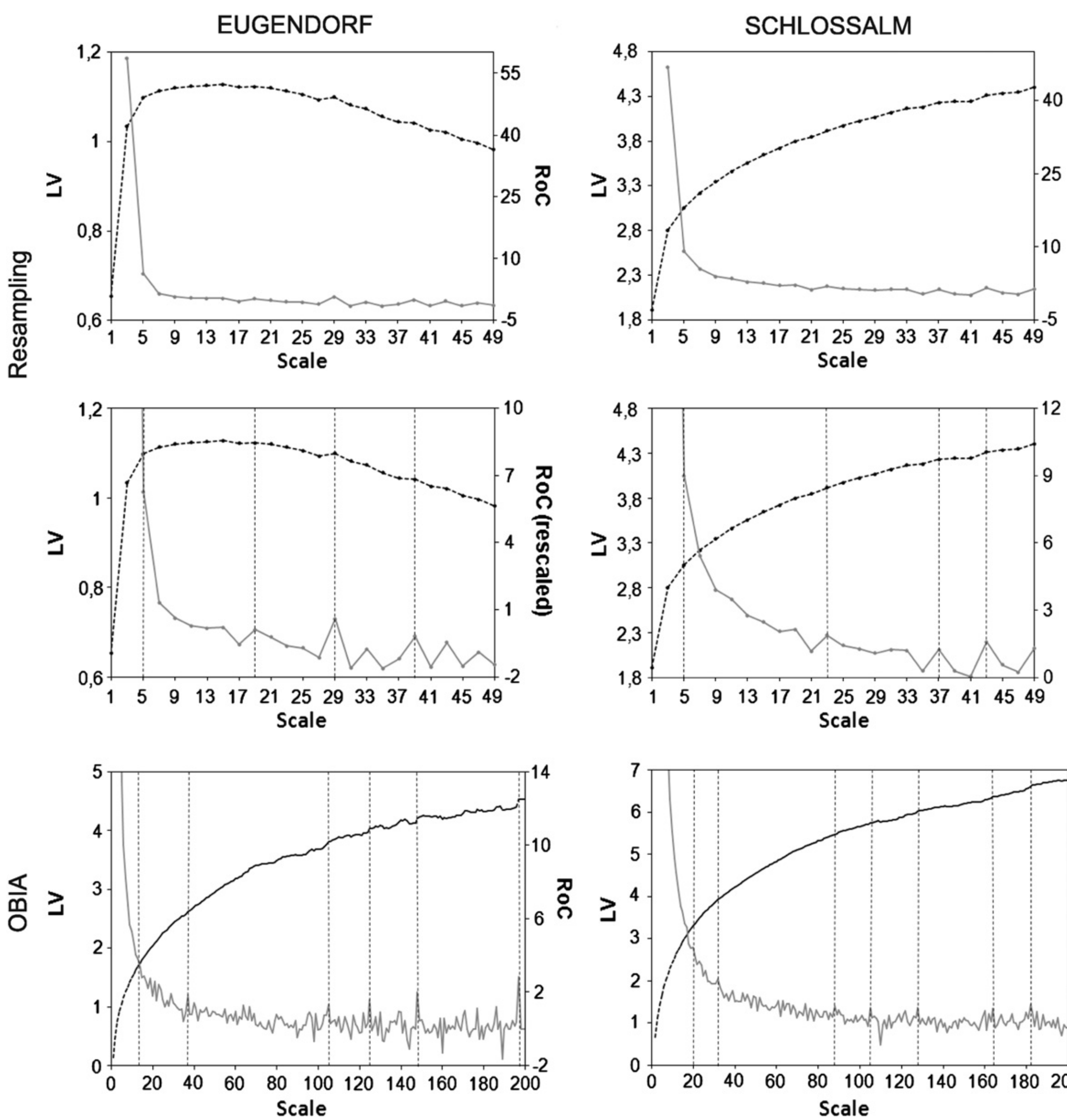

Fig. 3. Comparative view of scale signatures for slope gradient. Where applicable, vertical lines in graphs represent scale thresholds. Black lines represent *LV*; gray lines represent *ROC-LV* (this also applies to Figs. 4 and 5).

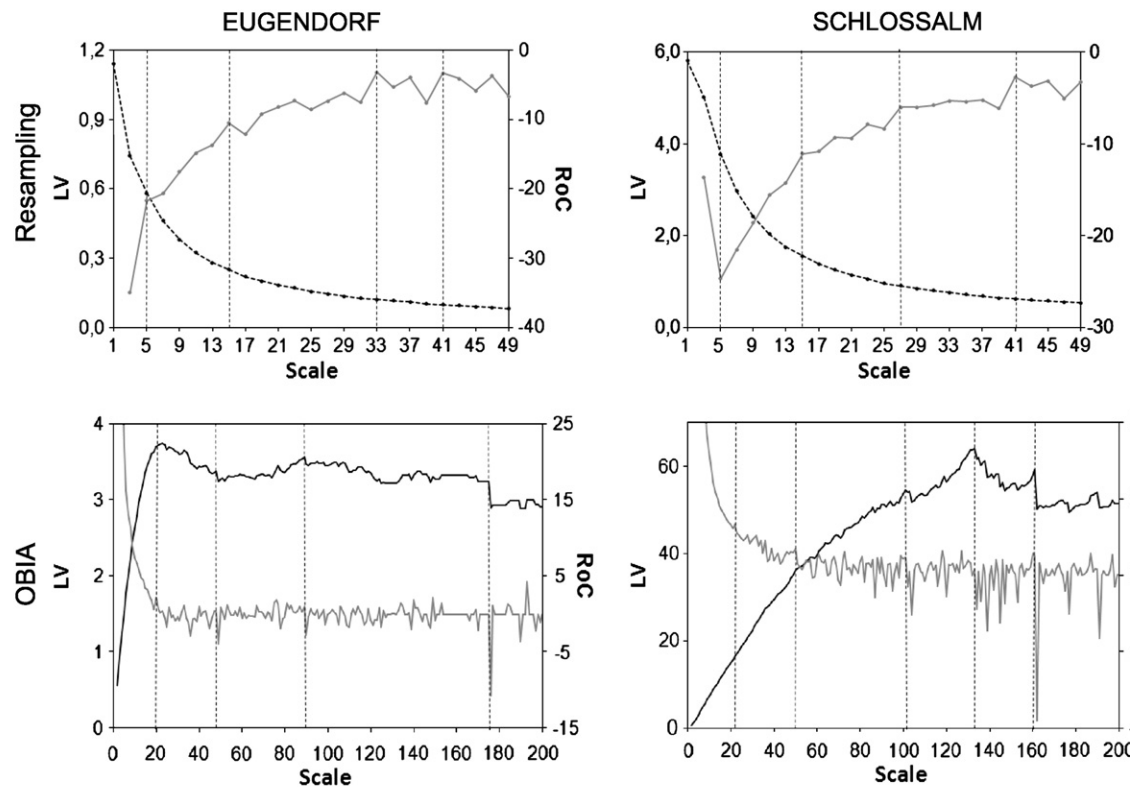

Fig. 4. Comparative view of scale signatures for plan curvature. Legend as in Fig. 3.

(Figs. 4 and 5). *LV* of curvatures declines with the increase of cell size as an effect of averaging *SD* values towards 0 through aggregation. This behavior is inconsistent with the rationale of the *LV* method. For Eugendorf, *LV* of slope starts decreasing after a peak around the scale level of 15 (Fig. 3), while in all other cases *LV* maintains a trend throughout, either ascending or descending (Figs. 3–5). In the relatively flat landscape characterizing the Eugendorf area, the slope variation is induced mostly by small features like stream banks or

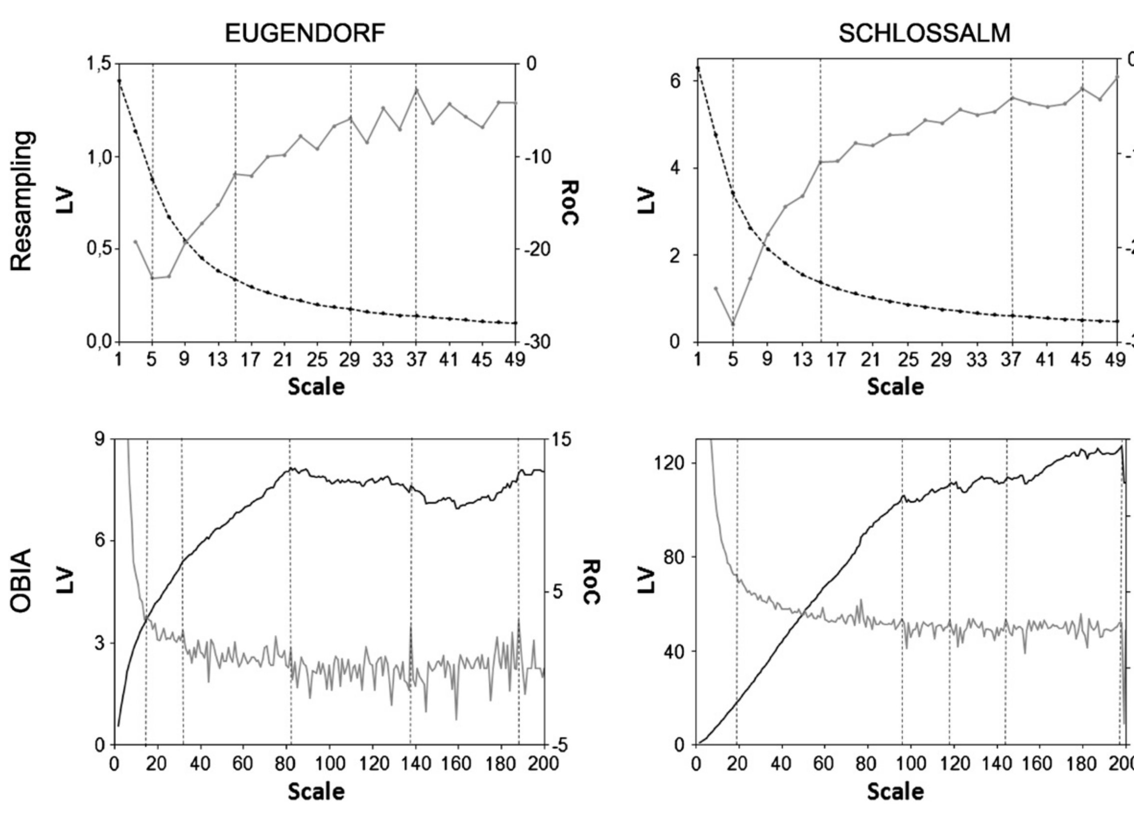

Fig. 5. Comparative view of scale signatures for profile curvature. Legend as in Fig. 3.

Table 1
Comparative view of scale levels detected with *LV*. For resampling, values represent the cell size; for OBIA, values represent the scale parameter used in segmentation.

Scaling method	Resampling		OBIA	
Test area	Eugendorf	Schlossalm	Eugendorf	Schlossalm
Slope	5, 19, 29, 39	5, 23, 37, 43	13, 37, 105, 125, 148, 197	20, 32, 88, 105, 128, 164, 182
Plan curvature	5, 15, 33, 41	5, 15, 27, 41	20, 48, 89, 175	22, 50, 101, 133, 161
Profile curvature	5, 15, 29, 37	5, 15, 37, 45	15, 32, 82, 138, 188	19, 96, 118, 144, 198

ground objects incompletely eliminated in the DEM production. The *LV* curve indicates a size range of these features below 15–20 m. Resampling to cell sizes above these values smoothes out most of the important variation in slope values. Larger structures (e.g. drumlins) only induced local peaks on a declining trend, e.g. at 29 and 39 m. In terms of absolute values, the mountain area (Schlossalm) shows *LV* at least four times higher than the Eugendorf test area (Figs. 3–5), which is explained by differences in land-surface roughness. Four major thresholds have been identified for each of the two test areas, and for all land-surface parameters considered (Table 1 and Figs. 3–5). In all cases, the most significant scale level was identified at the same value, corresponding to a cell size of 5 m (Table 1). The other scale levels differ for slope, but are strikingly similar for curvatures. Since the *LV* method on scales generated through resampling does not apply to curvatures, these levels should not be considered as detected scales.

3.2. OBIA

Unlike resampling, the OBIA methods provided ascending graphs of *LV* for all land-surface parameters (Figs. 3–5). The *LV* curves are much smoother and more similar between the two study areas for slope than for curvatures. Thresholds are visible in the *LV* curves for both plan and profile curvature graphs. The most prominent peaks in *LV* correspond to pairs of peaks and plunges in *ROC-LV*. Except for profile curvature in the Schlossalm test area (Fig. 5), all other curvatures in the two test areas (Figs. 4 and 5) display negative trends of *LV* after reaching prominent peaks at various scale levels (scale parameters of 20 and 133 for plan curvatures in Eugendorf and Schlossalm, respectively; 82 for profile curvature in Eugendorf). This is due to the general trend of averaging curvature values to zero, as a result of aggregating cells into objects after exceeding the size of the most representative pattern elements within the scene. While for slope the absolute values of *LV* are relatively similar, for both curvatures they are about 15 times higher in the mountain test area (Schlossalm) than in the relatively flat one (Eugendorf). Also, the number of significant scales detected is always higher for the mountain test area (Table 1). Contrary to resampling, the thresholds are quite different. As expected, the lowest thresholds, which mark the transition from cells to the smallest objects identifiable in the scenes, are always higher in the mountain test area compared to the relatively flat one (Table 1).

3.3. Visual assessment

As acknowledged (Reuter et al., 2009), accuracy assessment of geomorphometric analysis is not easy to perform. Firstly, there are no consistent guidelines for checking the accuracy of land-surface parameters in the field, and secondly, reference maps of land-surface parameters and objects are missing. Consequently, most evaluations of DEMs and their land-surface parameters are still made visually (Reuter et al., 2009). As regarding OBIA, there is no established standard evaluation method to assess the quality of image segmentation (Neubert et al., 2008). Thus, at the current state of developments, human interpretability is acknowledged as the best test for the segmentation results (Jellema et al., 2009). Quantitative assessment is even more challenging in a multi-scale approach.

In this paper we conducted visual assessment of the delineated objects to check whether the land-surface parameters at detected scales produced reasonably differentiated patterns. While the visualization is straightforward for the object-based approach, for the cell-based approach it was implemented by using profile lines.

3.3.1. Resampling

Fig. 6 displays profiles of slope gradient at scales noted in Fig. 3 (resampling). Variations between the profiles correspond to levels of generalization of the land-surface. This agrees with the concept of decomposing the original signal into multi-resolution components across scale (McBratney, 1998). Compared to profiles on the original slope map derived from 1 m raster (bottom), the first two levels in both test areas show distinct levels of generalization of slope patterns through removing the fine-scale components (Fig. 6). The two upper scale levels in both study areas do not display further generalization on these short profiles, except for the upper most level in the Schlossalm area, which distinguishes the steep slopes of the cirque from the less inclined slopes outside it (on the left side). Slope maps at these scales reveal progressively larger structures such as drumlins and the main valley in the Eugendorf area, and ridges, upper slopes, and cirques in the Schlossalm area. However, cell-based methods lead to a crude representation of land-surface parameters at broader scales due to the isotropic smoothing effect induced by the regular resampling. In the case of curvatures, this smoothing effect is so intense that it makes the *LV* method inapplicable. Calculating surface approximations at different window sizes and different window shapes would allow for spatial anisotropy (Schmidt and Andrew, 2005), thus improving the representation of land-surface parameters across scales. But such methods do not enable scale detection using *LV* (Drăguţ et al., 2009b).

3.3.2. OBIA

In Figs. 7 and 8, areas of similar homogeneity were delineated with OBIA for Eugendorf and Schlossalm, respectively, with the scale parameters as marked in Fig. 3. Good agreements between slope values and their aggregation in objects at these scale levels are depicted. In the Eugendorf area, segmentation of the slope layer using a scale parameter of 197 (the broadest scale level identified on the *LV* graph) reveals the pattern of drumlins in the northern half of the image, and the elements of the valleys, but also artificial features, such as the road crossing the area at the southern border of the drumlins. At lower levels, segmented with scale parameters of 125 and 13 respectively (insets in Fig. 7), increasingly homogeneous objects are delineated as components of larger structures in a perfectly nested hierarchy where borders at coarser scales are maintained at finer scales. The results are equally good for the Schlossalm area (Fig. 8). Again, slope segments of different degrees of homogeneity reveal land-surface patterns with levels of detail that visually fulfill the requirements of representation at various scales.

In OBIA, anisotropy is readily incorporated in analysis, contrary to cell-based methods (see Schmidt and Andrew, 2005, p. 347, for details). Thus, various features in terms of size and shape (from extremely elongated to circular) occur at the same scale level, according to land-surface patterns (Figs. 7 and 8). Regionalization based on homogeneity enables the information derived in a small

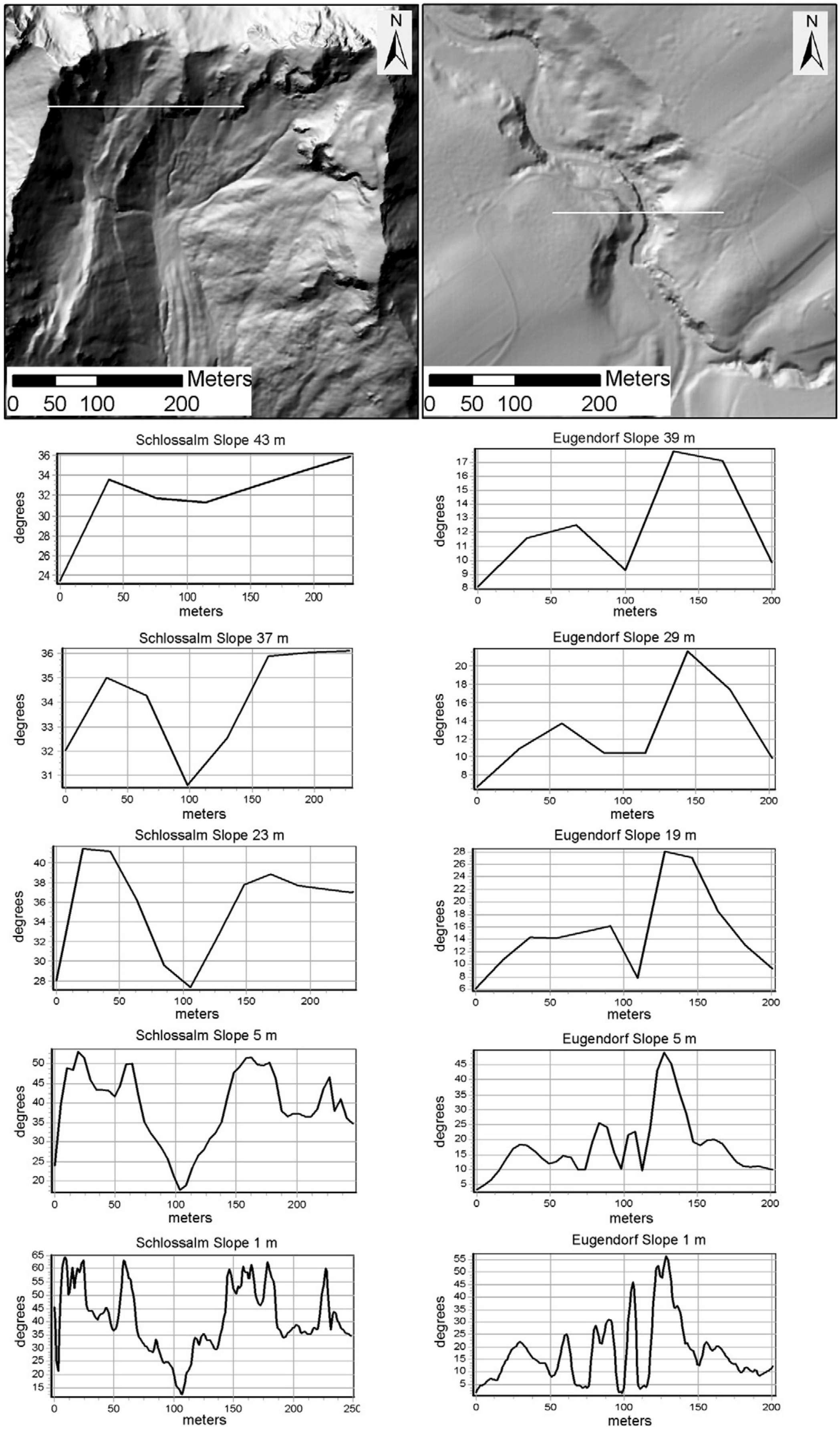

Fig. 6. Slope profiles at original and detected scales for Schlossalm (left) and Eugendorf (right). White lines on shaded maps show profile locations.

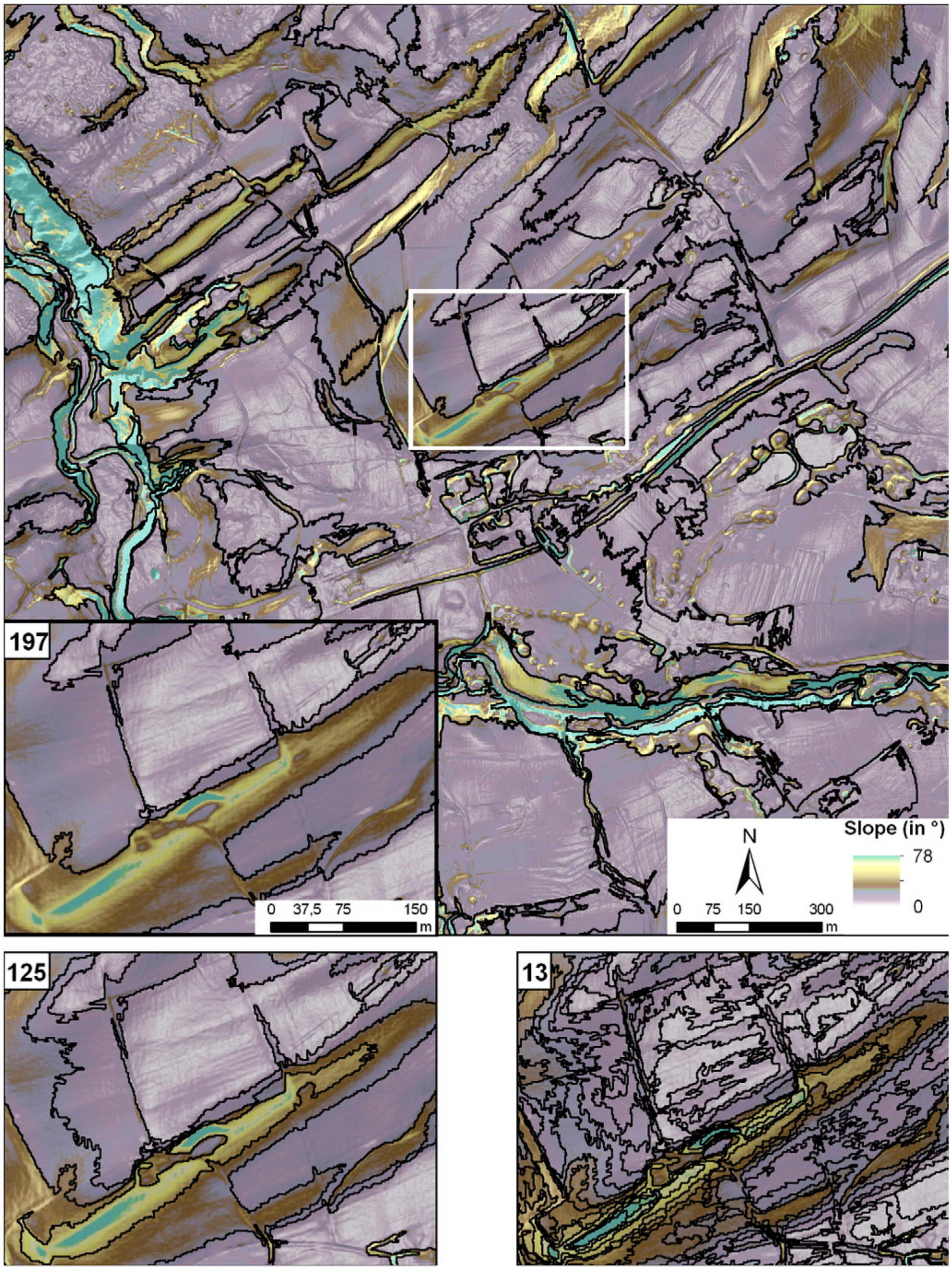

Fig. 7. Multi-scale object representation in OBIA environment for Eugendorf. Results of segmentations with detected scale parameters (*SP*) are visible. The whole Eugendorf test area (top) with slope segments delineated at an *SP* value of 197. For the objects within the white rectangle, detailed views are provided at *SP* values of 125 and 13.

neighborhood to be transferred to broader scales, while adding topology and shape information.

4. Discussion

The method presented in this paper is rooted within the theory of *regionalized variables*, which proposes that values of variables *z* distributed over geographic space are not sampled independently, but instead show strong spatial autocorrelation (Goodchild, 2011). Similar to geostatistics, the *LV* method assumes that the mathematical form of the decline of spatial autocorrelation (or the increase in variance) with distance is a general and measurable property of each field (Goodchild, 2011). Unlike variogram analysis, the *LV* method measures the decline of spatial autocorrelation within a local neighborhood across scales, thus emphasizing variation in spatial patterns of heterogeneity as a scale descriptor. Therefore, the distance is replaced by the size of the support unit (e.g. cells and objects). Still, the interpretation of graphs is relatively similar. As in the variogram analysis, the *LV* graphs (Fig. 3) display ranges that approximate sizes of support units at which spatial autocorrelation between them tends to cease. Thus, ranges mark the highest spatial independence of cells and objects in the dataset; these units reached the maximum internal homogeneity while maximizing the external heterogeneity. These are the scale levels containing the most representative patterns in the dataset. Other scales of spatial variation are detectable following the same principle. However, they are less prominent as part of the spatial autocorrelation has already been 'consumed'. These scale levels can be enhanced with the aid of the *ROC-LV*, which indicates the amount of variation gained at different scales, i.e. decline of spatial autocorrelation.

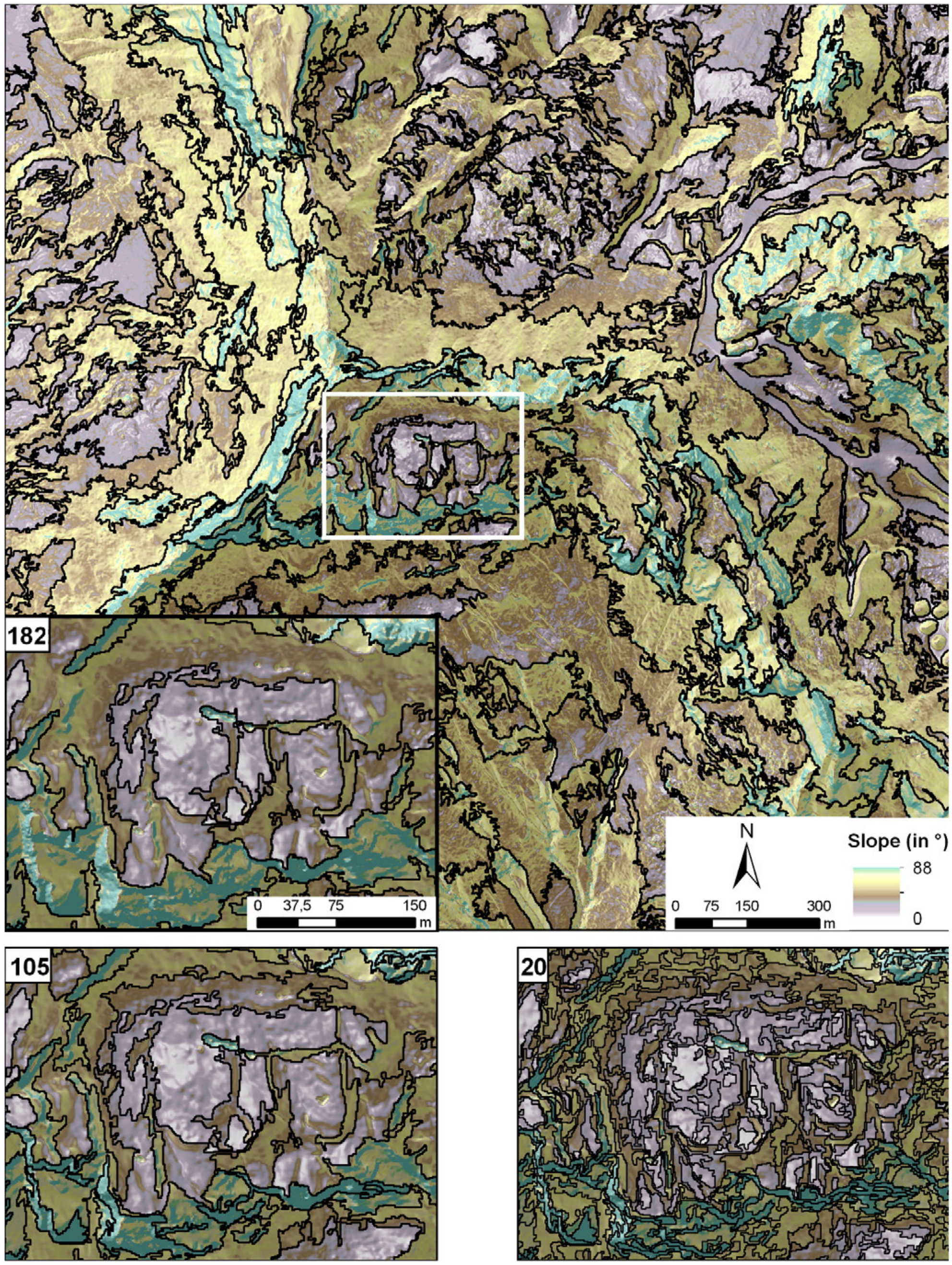

Fig. 8. Multi-scale object representation in OBIA environment for Schlossalm. Results of segmentations with detected scale parameters (*SP*) are visible. The whole Schlossalm test area (top) with slope segments delineated at an *SP* value of 182. For the objects within the white rectangle, detailed views are provided at *SP* values of 105 and 20.

When applied in a cell-based approach, the *LV* method revealed problems related to the smoothing induced by aggregating cells through resampling, as acknowledged also in image analysis (Bøcher and McCloy, 2006a,b). In the case of curvatures, this smoothing effect was so severe that it made the *LV* method inapplicable. For slopes, however, variations in profiles correspond to levels of generalization of the land-surface. In the cell-based approach other methods of multi-scale analysis (Schmidt and Andrew, 2005; Wood, 2009) might be more suitable, particularly for curvatures.

Compared to the results of the *LV* applications to satellite imagery (Drăguţ et al., 2010), the number of scale levels identified is higher in the DEM-based applications. Deng et al. (2007) found that land-surface parameters are sensitive to resolution change particularly in the range of 5–50 m, which coincides with the range of scales used here. The magnitude of the *LV* and *ROC-LV* values is always higher in the mountain area as compared to the relatively flat one (Figs. 3–5), which confirms the findings of Arrell and Carver (2009) that scaling trends of *SD* measures (surface roughness in the cited work) are effective in differentiating landscape types.

When looking closer at the borders of delineated objects, we can distinguish different types of shapes such as smooth or indented. Obviously, there is a relationship between the quality of objects, in terms of homogeneity and contrast to neighboring objects, and the shape of borders. In the case of relatively high contrast to neighbors, boundaries are more likely to be smooth. Conversely, if transitions between adjacent objects are soft, boundaries are curvy due to the vague shape of real-world features (e.g. straight field borders vs. curvy slope breaks; compare levels 13 and 125 in Fig. 7). Moreover, some well individualized objects preserve boundaries across several scale levels (e.g. the cirque floor in levels 105 and 182 in Fig. 8). These unexpected findings open interesting ways for object extraction using multi-scale edge analysis or metrics developed in landscape ecology (Pike, 2000; Benito-Calvo et al., 2009; Zhou et al., 2010) possibly combined with fuzzy logic (Qin et al., 2009). This is what we would like to explore in the future.

We showed in this paper that coupling multi-scale pattern analysis with delineation of morphometric primitives is possible. From a geomorphometry perspective, this opens important avenues for what Olaya (2009, p. 162) called 'discrete analysis of the land surface'. That author emphasized the difficulty of finding suitable criteria for object delineation and proposed elevation zones as a possible solution. The objects we delineate as homogeneous areas relative to a specific scale could serve as suitable candidate units for discrete analysis. As in Jellema et al. (2009), our methodology follows a reverse approach: instead of predefining spatial units, we use patterns of features, i.e. homogeneous areas as delineated with the method of *LV*, to characterize spatial entities for analysis.

Moreover, the approach we presented here is relevant to the multi-scale classification of landforms with the aid of pattern analysis and pattern recognition. Pattern is described as 'the aspect of the complex systems approach that remains particularly problematic' (Baas, 2007, p. 327). Since pattern is intimately related to scale (Ehsani and Quiel, 2009), pattern exploration has the potential to improve modeling of complex systems (Baas, 2007). The proposed *LV* method gives a good indication of the significance of patterns across a range of scales, and thus also of appropriate scales, by quantifying the spatial heterogeneity of the scene at each level. There are few approaches to recognize and classify repeating patterns of landform types by analyzing DEMs (MacMillan et al., 2004). As Pike (1988) emphasized, topographic form is aggregative and synthetic, which means the characterization of topography should be a statistical problem that requires a statistical approach and methodology. The statistical method we proposed has been shown to be valid for multi-scale pattern analysis in OBIA, as it reveals the structural characteristics of the land-surface based on the spatial heterogeneity of land-surface parameters. We therefore consider the LV method straightforward and simple for multi-scale pattern analysis in OBIA.

OBIA provides a powerful framework to overcome some of the cell-based limitations (i.e. non-consideration of anisotropy and context) in multi-scale analysis of complex systems such as the land surface (Drăguţ and Blaschke, 2006; Miliaresis, 2006; Stepinski et al., 2007; Strobl, 2008; Stepinski and Bagaria, 2009; Drăguţ et al., 2010; Ghosh et al., 2010; Martha et al., 2010). It has been widely recognized that objects are closer to human perception (Couclelis, 1996; Goodchild et al., 2007) and patterns better represent real landscapes, if scale is appropriate. Objects are based on natural breaks as a function of homogeneity. This is an asset in further classification steps since it avoids pre-defined categorizations of land-surface parameters (Giles, 1998; Saadat et al., 2008; Gorini, 2009), which might create artificial boundaries. A general problem in image segmentation is finding an appropriate scale parameter; usually this is performed subjectively in a trial-and-error manner (Schneevoigt et al., 2008; Anders et al., 2009; Blanco et al., 2009; Kringer et al., 2009; Romstad and Etzelmüller, 2009; van Niekerk, 2010). We hope that the method of *LV* we introduced here will make a contribution to this issue.

One of the strongest points in this research is that the *LV* method applied to the OBIA environment produces homogeneous spatial entities with boundaries such that coarser-scale entities have precise boundaries within which finer-scale entities nest perfectly. This is a condition for developing hierarchical classifications of landform elements (MacMillan and Pettapiece, 2000), which is the subject of our ongoing research (Eisank, 2010).

5. Conclusions

The objective of this paper was to test whether the *LV* method could help in detecting characteristic scales in geomorphometric analysis of DEMs, as suggested by Li (2008). The *LV* method was applied to both cell-based and object-based approaches. It is difficult to objectively prove whether the scales detected are characteristic; this could only be demonstrated through classification and depends largely on the domain of application and study purposes. However, visual assessment revealed homogeneous areas that convincingly associate into patterns of land-surface parameters well differentiated across scales. We found that the *LV* method performed better on the OBIA-generated scale levels as compared to up-scaling through resampling.

Based on visual assessment, the *LV* method is effective in delineating multi-scale pattern elements with OBIA. Although land-surface 'objects' are characterized by smoother transitions in comparison with land cover objects, application of the *LV* method to segments looks promising for multi-scale analysis in geomorphometry as well.

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