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Automated object-based classification of topography from SRTM data

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ABSTRACT

We introduce an object-based method to automatically classify topography from SRTM data. The new method relies on the concept of decomposing land-surface complexity into more homogeneous domains. An elevation layer is automatically segmented and classified at three scale levels that represent domains of complexity by using self-adaptive, data-driven techniques. For each domain, scales in the data are detected with the help of local variance and segmentation is performed at these appropriate scales. Objects resulting from segmentation are partitioned into sub-domains based on thresholds given by the mean values of elevation and standard deviation of elevation respectively. Results resemble reasonably patterns of existing global and regional classifications, displaying a level of detail close to manually drawn maps. Statistical evaluation indicates that most of classes satisfy the regionalization requirements of maximizing internal homogeneity while minimizing external homogeneity. Most objects have boundaries matching natural discontinuities at regional level. The method is simple and fully automated. The input data consist of only one layer, which does not need any pre-processing. Both segmentation and classification rely on only two parameters: elevation and standard deviation of elevation. The methodology is implemented as a customized process for the eCognition® software, available as online download. The results are embedded in a web application with functionalities of visualization and download.

1. Introduction

Landforms are 'natural objects that partition the Earth's surface into fundamental spatial entities, which define boundary conditions for processes operative in the fields of geomorphology, hydrology, ecology, pedology and others' (MacMillan and Shary, 2009). Therefore, the research interest in designing classification systems of landforms at various scales (MacMillan and Shary, 2009) is not surprising as the demand for subdivisions of the surface into manageable objects even grows (Evans, 2011). While early approaches relied on field surveys, manual processing of topographic maps or drawing boundaries on aerial photographs, digital classifications have greatly benefited from developments in remote sensing in terms of processing techniques and increasing quality of remotely sensed digital elevation models (DEMs). The Shuttle Radar Topography Mission (SRTM) demonstrated the power of synthetic aperture radar (SAR) interferometry to create a global DEM; it marked a milestone in the field of remote sensing (Farr et al., 2007; Shortridge and Messina, 2011) opening new avenues for applications in Earth Sciences.

SRTM DEMs offer new possibilities for landform classifications at regional and global scales, which were previously hindered by the uneven quality of the available data. Physiographic classifications at global scale are particularly important as they provide standardized datasets that enable consistent and comparative analyses of the Earth's surface. Land form information contained within global datasets has the potential of fostering new insights into the land surface analysis (Hammond, 1964), which might be helpful in improving terrain-based environmental modeling through investigations on the areal covariation of properties. However, SRTM data are still rather under-used from this perspective, though it has been released for almost one decade. Iwahashi and Pike (2007) produced the only landform classification at global scale on SRTM data. This is a data-driven approach consisting in an unsupervised nested-means algorithm and a three part geometric signature; slope gradient, local convexity, and surface texture were used as descriptors of the land-surface properties. Individual cells were allocated to classes by using the mean of each variable as the dividing threshold in nested twofold-partitioned maps. The resulting classes resemble existing maps in various regions, including Fenneman's physical divisions (Fenneman and Johnson, 1946) and Hammond's terrain types (Hammond, 1954).

Object-based image analysis (OBIA) has gained prominence in the field of remote sensing during the last decade, being credited with the potential of overcoming weaknesses associated with the per pixel analysis, as for instance neglecting geometric and contextual information (Blaschke, 2010). OBIA has proved effective in landform classification from DEMs (Drăguţ and Blaschke, 2006; van Asselen and Seijmonsbergen, 2006) as it better satisfies the object conceptual model of landforms compared to the traditional per cell methods

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(Drăguţ and Eisank, 2011). As part of OBIA, the multiresolution segmentation (MRS) algorithm has been found the most sensitive to morphological discontinuities in DEMs (van Niekerk, 2010). The ability of capturing morphological discontinuities is an important asset in designing natural spatial entities (landforms or topographic regions) that maximize internal homogeneity while minimizing external homogeneity. Though the number of OBIA applications in analysis of DEMs has increased in the last five years, an object-based methodology applicable at global scale is still missing.

The main objective of our research is developing an object-based method to automatically classify topography from SRTM data at broader scales into landform types (MacMillan and Shary, 2009) or topographic regions (Iwahashi and Pike, 2007). This method should have the following characteristics: 1) simplicity; 2) versatility; and 3) multi-scale character. Simplicity consists in avoiding data preprocessing, derivation of additional input layers (e.g. slope and curvature.), and parameterization, i.e. deciding which combination of input variables are suitable and how to weight their importance in classification. The method was designed to process a single layer of elevation values, which is the support for segmentation and calculation of standard deviation. Elevation and local relief are essential in classification of topography at broad scales (Hammond, 1954; Wood and Snell, 1960). We replaced local relief with standard deviation of elevation, which is a more stable measure of variation (Evans, 1998). Versatility means that this general-purpose method should be easily customizable for specific applications. Results were compared with existing classifications at global (Iwahashi and Pike, 2007) and regional levels (Fenneman and Johnson, 1946).

2. Methods

Building on our previous results (Drăguţ and Blaschke, 2006), we used an MRS algorithm (Baatz and Schäpe, 2000) to partition a digital elevation model (DEM) into homogeneous regions, which were further classified in physiographic regions with the help of the nested-means technique (Iwahashi and Pike, 2007). New algorithms were designed to automate selection of scale parameters for land-surface segmentation (Section 2.1) and to decompose the scene complexity on three levels (Section 2.2). The whole procedure was implemented as a 'push-the-button' solution using the eCognition Network Language (CNL) within the eCognition Developer®, version 8.64.

As input we used the global dataset (more than 600 million cells) of the SRTM DEM V4 (Reuter et al., 2007; Jarvis et al., 2008) resampled to 1 km (http://srtm.csi.cgiar.org). The algorithm was applied to the elevation layer without any prior pre-processing.

2.1. Automated optimization of the scale parameter

MRS provides a region-growing algorithm that merges individual pixels into image objects or regions based on the local homogeneity criteria (Baatz and Schäpe, 2000). The degree of local homogeneity to be used in the merging decision is set by a user-defined parameter called *scale parameter* (*SP*). Drăguţ et al. (2010) introduced a method that assist an objective decision on *SP*, based on the concept of *local variance* (*LV*) graphs (Woodcock and Strahler, 1987). In brief, the method consists in producing multiple segmentations of the same dataset by a constantly increasing *SP*, calculating *LV* for each scale as the average *standard deviation* (*SD*) of objects at the scene level, plotting *LV* against *SP*, and interpreting the resulting variogram-like graph. Similar to the variogram analysis, the *LV* graphs display ranges that approximate sizes of support units (here replacing distance) at which spatial autocorrelation between them tend to cease. Thus, ranges mark the highest spatial independence of objects in the dataset at a given scale (Drăguţ et al., 2011).

Here we replaced the interpretation of graphs with an automatic procedure for selecting *SP* at a range (Fig. 1). For an input domain (the first one being the whole extent of the SRTM data), segmentation of the elevation layer is performed in a bottom–up approach, starting from the minimum value of *SP* (*minSP*). At each upper scale, the *SP* value increases with the increment *I* (similar to *lag*). Difference in *LV* between each new level and the previous one is calculated in an iterative approach, until the value is equal to zero or negative. When reaching this value, the previous level is selected; this is an approximation of the equivalent of *sill* on the *LV* graph.

For processing the global dataset, the value of 10 was set as *minSP*; this was rather a technical constraint, as starting segmentation at an *SP* value of 1 would have prohibitively increased the time of processing. The value of *I* was different for each level as detailed in the next section. The shape criterion was weighted to zero; therefore only elevation values were considered in segmentation, without shape optimization.

2.2. Multi-scale decomposition of complexity

The multiresolution segmentation algorithm minimizes the average heterogeneity of image objects weighted by their size (Baatz and Schäpe, 2000). When applied to DEMs, particularly those with large extents and contrasting topography, the same *SP* value tends to oversegment rough areas, while under-segmenting smooth ones; the weight on objects size would not compensate the high level of heterogeneity. We addressed this issue by decomposing land-surface complexity into increasingly homogeneous domains, structured on three levels (Fig. 2), with the help of segmentation combined with the nested means approach (Iwahashi and Pike, 2007).

The input SRTM was segmented with the optimum *SP* value (Fig. 1) and resulting objects were partitioned into two domains, 'High' and 'Low', based on a threshold given by mean elevation of objects at the level of scene. Each domain was further segmented with optimized *SP* values and partitioned based on a threshold given by the mean *SD* of elevation. The same procedure of segmentation is applied to each domain of the second level to produce the objects at the third level (Fig. 2).

Optimization of *SP* was performed using different values of increment for each of the three levels to replace selection of multi-scale levels through human interpretation of the *LV* graphs by an automated procedure. In previous work (Drăguţ et al., 2010, 2011) we showed that prominent peaks on the *LV* graph indicated the scales where the data are organized in meaningful pattern. Smoothing the *LV* graph by increasing the increment is a solution for automation. To illustrate this procedure, we present the *LV* graphs resulting from segmentation of the DEM at the extent of the Austrian territory (Fig. 3). The *LV* graph obtained by increasing *SP* by an increment of 1 (Fig. 3C) depicts the smallest variations of the *LV* values. The first step in this graph occurred at an *SP* value of 80 (the *LV* value at $SP = 81$ was lower or equal to the *LV* value at $SP = 80$), which coincides with a marked change in the *LV* curve. Performing the same analysis with increments of 10 (Fig. 3B) and 100 (Fig. 3A) leads to the smoothing of details so that two prominent peaks in Fig. 3C are approximated by equivalents of *sill* at *SP* values of 181 (Fig. 3B) and 901 (Fig. 3A), respectively. These equivalents of *sill* can be identified automatically as explained in Section 2.1.

Scale is intimately related to the complexity of scene so that small and large objects can coexist in the same level. Segmentation with a single *SP* value would over-segment larger objects or under-segment the smaller ones. To account for this issue, domains at each level as in Fig. 2 were segmented twice, with consecutively smaller increments. Objects produced with *SP* values detected using larger increments (therefore larger sized) were separated into two groups: those with both mean and maximum elevations lower than the mean elevation of the domain or with both mean and minimum elevations higher than the mean elevation of the domain were retained, while all others were exported to separate maps and further segmented with smaller increments. The former category includes 'pure' objects that do not include any cell lower or higher than the