Automated classification of topography from SRTM data using object-based image analysis

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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. Preliminary results of classification at global level are promising. Most objects have boundaries matching natural discontinuities at regional level. The results display a level of detail in between cell-based classifications and manually drawn maps. The method is simple and fully automated. The input data consists 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. Unlike cell-based methods, results are customizable for specific applications; objects can be re-classified according to the research interest by manipulating their attributes. The tool can be applied to any regional area of interest and can also be easily adapted to particular tasks.**

I. INTRODUCTION

Automation of information extraction from DEMs is the essence of geomorphometry [1]. Land-surface objects (LSO) are examples of DEM-derived entities fundamental to modern geomorphometry [2]. Landforms, as particular case of LSOs, 'define boundary conditions for processes operative in the fields of geomorphology, hydrology, ecology, pedology and others' [3]. Therefore, the research interest in designing classification systems of landforms at various scales (for a comprehensive review see [3]) is not surprising. Physiographic classifications at global scale are particularly important as they provide standardized datasets that enable consistent and comparative analyses of the Earth's surface.

Meybeck et al. [4] and Iwahashi and Pike [5] produced probably the most remarkable examples of such classification systems. The former approach is based on relief roughness and elevation, which are classified following *a priori* thresholds, while the later one is data-driven, consisting in an unsupervised nested-means algorithm and a three part geometric signature. Nelson and Reuter have replicated both methods and provided the classification results as free data via an ArcIMS viewer[1].

Object-based image analysis (OBIA) has been credited with the potential of overcoming weaknesses associated to the per-cell methods (see e.g. [6]). Though the number of OBIA applications in geomorphometry 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 at the level of landform types according to [3] from Shuttle Radar Topography Mission (SRTM) data. This method should have the following characteristics: 1) simplicity; 2) versatility (e.g. a general-purpose method easily customizable for specific applications); and 3) multi-scale character.

II. DATA AND METHODOLOGY

We used as input SRTM data V4 resampled at 1 km (more than 600 mil cells for the global dataset)[2]. The OBIA procedure was implemented in the eCognition Developer®, version 8.64.

OBIA performs analysis in two steps: segmentation and classification of primitive objects [7]. The most critical decision in segmentation is objectively finding an appropriate scale parameter (SP) [7]. Drăguț et al. [8] introduced a method based on the concept of local variance (LV) graphs [9] that assist an objective decision on the SP. While in the cited work interpretation of graphs is needed, here we automated the process. The other two main parts of this methodology include decomposing complexity in a multi-scale approach and establishing an appropriate classification scheme.

1 (http://eusoils.jrc.ec.europa.eu/website/SRTMTerrain/viewer.htm).
2 http://srtm.csi.cgiar.org

A. Automated optimization of scale parameter

When applied on DEMs, the method of LV graphs shares the rationales of the *topographic grain* concept (Wood and Snell, cited by [10]). In this work local relief is replaced by standard deviation, as in [10], which is calculated within growing irregular objects that replace regular circles. In brief, the method consists in producing segmentations of the same dataset by constantly increasing SPs, calculating LV for each scale as the average standard deviation (SD) of objects at the scene level, plotting the LV values against SPs, 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; the objects reached the maximum internal homogeneity while maximizing the external heterogeneity [11].

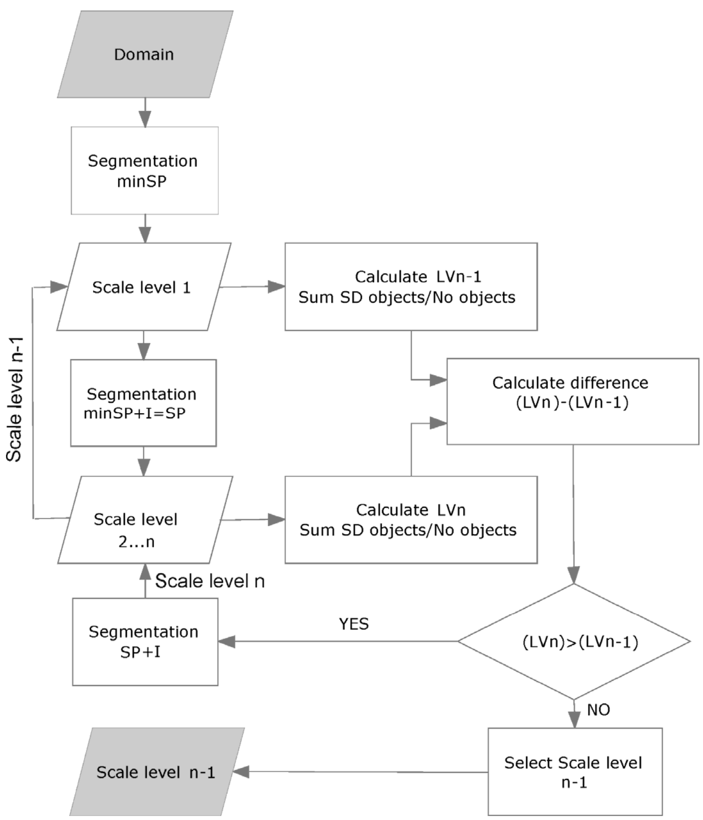

Figure 1. Automated optimization of scale parameter.

Here we replaced interpretation of graphs with an automatic procedure for selecting the SP at range (Fig. 1). For an input domain (the first one being the extent of interest on the SRTM data), segmentation of the elevation layer is performed in a bottom-up approach, starting from the minimum SP (*minSP*). At each upper scale, the SP increases with the increment *I* (similar to *lag*). Difference in LV between each new level and the previous one is calculated, 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.

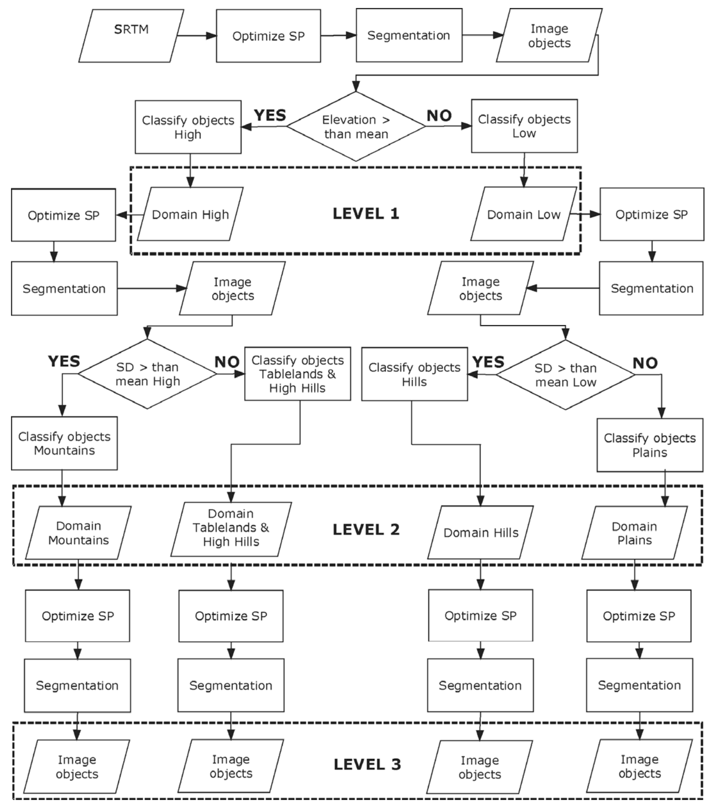

Figure 2. Multi-scale decomposition of complexity.

B. Multi-scale decomposition of complexity

The multi-resolution segmentation (MRS) algorithm minimizes the average heterogeneity of image objects weighted by their size [12]. When applied on DEMs, particularly on large extents and contrasting topography, the same SP tends over-segmenting 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 [5].

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

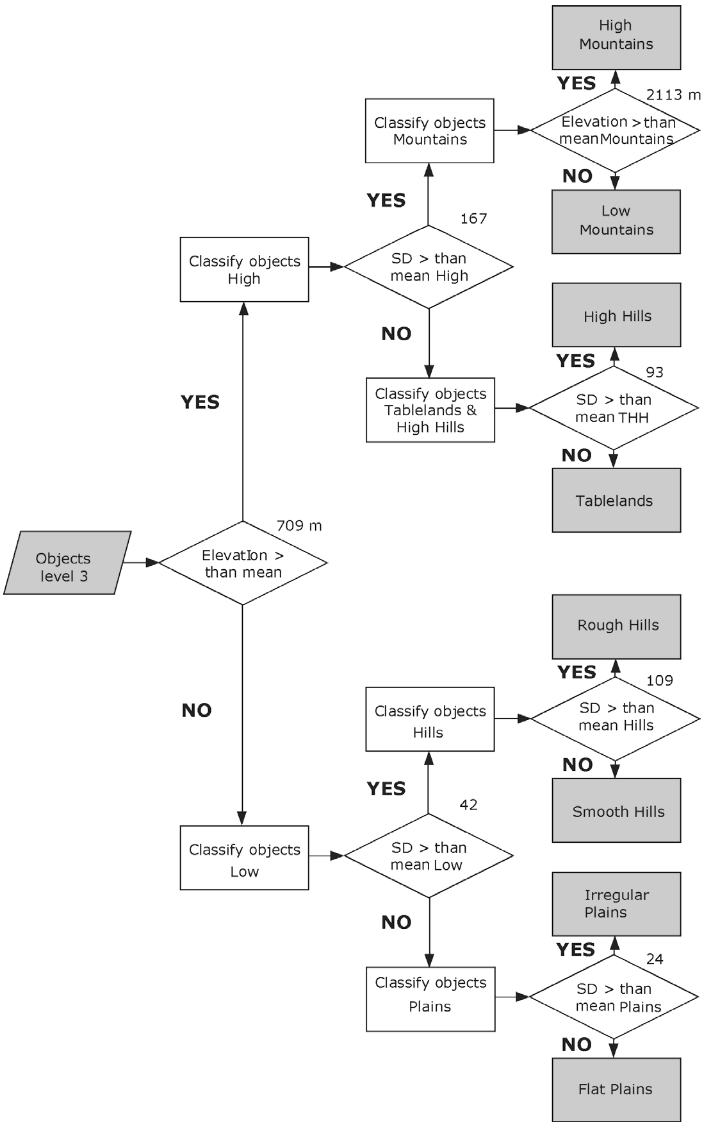

Figure 3. Classification scheme.

C. Classification scheme

The objects of the third level (Fig. 2) are classified into eight classes (Fig. 3), labeled according to a simplified version of Hammond's [13] scheme. Classification is structured on three levels (Fig. 3). At each level, thresholds are automatically set up as object means of elevation and SD elevation (Fig. 3). Classification at the third level is independent of the first two levels to allow e.g. an isolated mountain within a plain being classified.

III. Results and Discussion

Preliminary results of this methodology were embedded in a web application[3]. Islands will be processed separately for technical reasons. For practical reasons, we only discuss the results at Level 3 (Fig. 4).

The global dataset was processed in more than 138 hours on a machine of 2.66 GHz quad-core processor, 8 GB RAM. Segmentation provided 9381 objects of reasonably good quality. Most of boundaries follow major natural discontinuities at regional level. The size of objects, i.e. the level of detail, is controlled by natural variability in elevation specific to each domain, as expected (e.g. smaller objects in Himalaya compared to the Alps). In the domain of 'Plains' at the second level, segmentation was biased by small-sized objects (e.g. isolated mountains). As the overall heterogeneity specific to this domain is low, segmentation was constrained by the size of the smallest objects, thus resulting in objects elongated along contour lines. When neighbor objects have SD elevation values around the threshold, they are classified in a banding appearance (e.g. East Africa). To address this issue, classes 'Irregular Plains' and 'Flat Plains' should probably be segmented and classified again.

Objects were classified following the dynamic thresholds showed in Fig. 3 (upper-right sides of decision boxes). Classification produced general patterns visually comparable to cell-based classifications ([4, 5]), although it appears more generalized. The object-based classification comes much closer to a visual appearance of manually drawn maps. Classification patterns have been compared to [4] by calculating the percentage of cell-based classes falling within object-based categories. Despite differences in parameterization, thresholding, and number of classes, there are clear similarities between the outputs of the two methods. More evaluation is ongoing.

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[3]http://zgis205.plus.sbg.ac.at/PhysiographicClassificationApplication/default.aspx

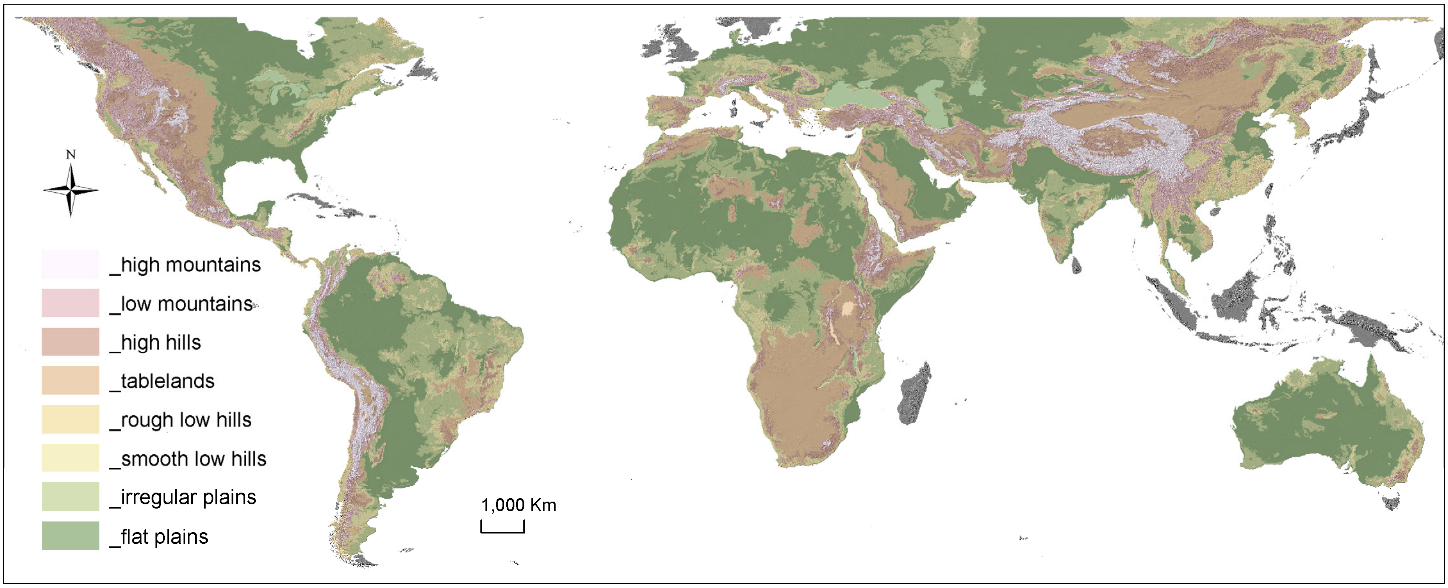

Figure4. Global classification of topography

Both segmentation and class thresholds are relative to the extent and characteristics of the dataset. The methodology has been designed for general purposes. However, the results can be easily tuned to specific applications, by using the object attributes, without a need of running the classification again.

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REFERENCES

[1] Evans, I.S., T. Hengl, P. Gorsevski, 2009. "Chapter 22 Applications in Geomorphology", In Geomorphometry-Concepts, Software, Applications. Developments in Soil Science, vol. 33, Edited by: Hengl, T. and H. I. Reuter, Elsevier, Amsterdam.

[2] Pike, R.J., I.S. Evans, T. Hengl, 2009. "Chapter 1 Geomorphometry: A Brief Guide", In Geomorphometry-Concepts, Software, Applications. Developments in Soil Science, vol. 33, Edited by: Hengl, T. and H. I. Reuter, Elsevier, Amsterdam.

[3] MacMillan, R.A., P.A. Shary, 2009. "Chapter 9 Landforms and Landform Elements in Geomorphometry", In Geomorphometry-Concepts, Software, Applications. Developments in Soil Science, vol. 33, Edited by: Hengl, T. and H. I. Reuter, Elsevier, Amsterdam.

[4] Meybeck, M., P. Green, C. Vorosmarty, 2001. "A new typology for mountains and other relief classes: An application to global continental water resources and population distribution". Mountain Research and Development, 21:34-45.

[5] Iwahashi, J., R.J. Pike, 2007. "Automated classifications of topography from DEMs by an unsupervised nested-means algorithm and a three-part geometric signature". Geomorphology, 86:409-440.

[6] Drăguț, L., C. Eisank, 2011. "Object representations at multiple scales from digital elevation models". Geomorphology, 129:183-189.

[7] Drăguț, L., T. Blaschke, 2006. "Automated classification of landform elements using object-based image analysis". Geomorphology, 81:330-344.

[8] Drăguț, L., D. Tiede, S. Levick, 2010. "ESP: a tool to estimate scale parameters for multiresolution image segmentation of remotely sensed data". Int. Journal of Geographical Information Science, 24:859-871.

[9] Woodcock, C.E., A.H. Strahler, 1987. "The factor of scale in remote-sensing". Remote Sensing of Environment, 21:311-332.

[10] Pike, R.J., W. Acevedo, D.H. Card, "Topographic grain automated from digital elevation models," in Proceedings, Auto-Carto 9, ASPRS/ACSM Baltimore MD, 2–7 April 1989, 1989, pp. 128–137.

[11] Drăguț, L., C. Eisank, T. Strasser, 2011. "Local variance for multi-scale analysis in geomorphometry". Geomorphology, 130:162-172.

[12] Baatz, M., A. Schäpe, 2000. "Multiresolution Segmentation-an optimization approach for high quality multi-scale image segmentation", In Angewandte Geographische Informationsverarbeitung, Edited by: Strobl, J., T. Blaschke and G. Griesebner, Wichmann-Verlag, Heidelberg.

[13] Hammond, E.H., 1954. "Small-Scale Continental Landform Maps". Annals of the Association of American Geographers, 44:33-42.