Which is the best scale? Finding fundamental features and scales in DEMs

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Abstract—**A method is presented to explicitly incorporate scale in geomorphometric analyses. It is based on Wood's 1996 method for morphometric feature extraction, but enhances it by fuzzifying its extraction function, automatically parameterizing it and locally limiting the maximum scale of analysis. As a result, maps of *fundamental features and scales* are produced, which describe well the overall topography of DEMs, as well as its multi-scale nature. The method was applied to diverse DEMs and compared to fixed-scale and modal feature approaches. Multi-scale geomorphometric variables were also produced and evaluated. The results suggest that the method allows thorough unsupervised geomorphometric characterizations of DEMs, stimulating further research.**

I. Introduction

It is widely accepted that a single scale of analysis is insufficient for accurate description or characterization of a landscape [1]. In terms of geomorphometry, this multi-scale character is even more emphasized by the fact that all measures vary with the scale of analysis [2], thus, exhibiting a scale tendency. If parameters and objects vary with scale, it is acceptable to regard landforms as vague objects [3][4]. Moreover, this scale vagueness sums itself up with spatial vagueness because of the continuous distributions of features and values over space. However, this "double vagueness" in geomorphometry is rarely investigated [5].

The existing approaches to deal with scale in geomorphometric analysis may be considered on a continuum, where the level of incorporation of scale increases as the number of approaches decreases. The *de facto* standard is the sole use of the inherent scale of the data. Next in the continuum, some kind of *a priori* knowledge or statistical analysis defines a single better fixed scale to use. Improved approaches derive parameters and/or features in a number of predefined scales and use some kind of statistical summary to produce usable morphometric maps [6][7]. In this kind of analysis, scale fuzziness is an inherent concept. A few other approaches analyze scale signatures globally in search for characteristic scales or thresholds [8][9]. On the rarest end of the continuum, scale breaks are used to derive spatially-varying scale maps [10][11]. The spatial vagueness of geographic objects; however, is not incorporated in these works.

Our conclusion is twofold: (i) scale effects are poorly recognized in digital terrain analysis and; (ii) the double vagueness of landforms is even less investigated. Therefore, our main objective is also twofold: (i) to present an improved method to incorporate scale in geomorphometry and; (ii) to use the inherent double vagueness of objects as its working core.

We hypothesize that the analysis of the scale tendency of fuzzy feature memberships enables the identification of the fundamental features and scales of DEMs. In order to accomplish that, we build upon Wood's 1996 method of morphometric feature extraction [6], further developing it in three ways: by fuzzifying its extraction function, automatically parameterizing it and locally limiting the maximum scale of analysis.

II. Method

A. Fuzzifying Wood's Method

A fuzzy classification system is created based on Wood's original nine rules, each of which now result in a different class and is assigned an approximate geomorphographic term, namely, *pit*, *channel*, *hollow* (sloping channel), *pass*, *ridge*, *spur* (sloping ridge), *peak*, *plane* or *slope* (sloping plane). Crisp thresholds are replaced by fuzzy concepts modeled by fuzzy sets (Fig. 1), as in [12]. The antecedents of each rule are then combined by the fuzzy operator AND to establish a membership map for each feature. The highest membership can then be used to determine the extracted morphometric feature at each location.

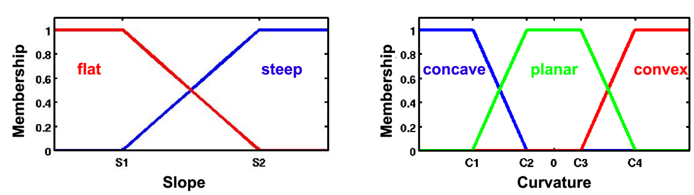

Figure 1. Fuzzy sets for slope and curvature.

B. Automatic Parameterization of Fuzzy Sets

For a successful classification, fuzzy sets must be properly parameterized, so that they can reflect the inherent relationships between concepts and the resultant features. Also, since geomorphometric properties vary with scale, so should fuzzy sets. Therefore, we calculate the mean slope, mean negative cross-sectional curvature and mean positive cross-sectional curvature of a given DEM and use these values as starting points to obtain an adaptive parameterization of fuzzy sets.

However, proper parameterization is hampered by the fact that flat areas shift the mean slope and mean curvature towards lower values. As a solution, the mean slope is used as input to functions of the form $y=ae^{(-x/b)}+c$ that were designed by trial-and-error to provide percentages to be applied to the means, so that increasingly higher parameters are applied to flatter DEMs (Fig. 2). The result is an automatic procedure that adapts the feature extraction function for any DEM in any scale.

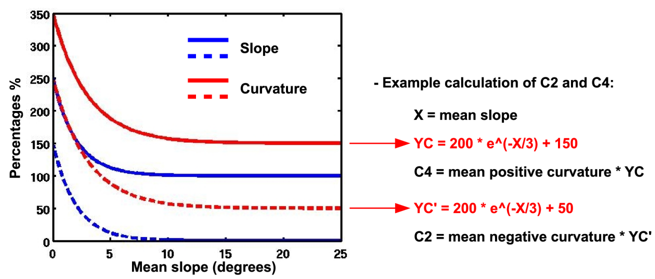

Figure 2. Parameterization functions and example calculation of parameters C2 and C4. See Fig. 1 for reference.

C. Establishing the Maximum Scale of Analysis

This nine-class fuzzy system is then run over multiple scales by increasing the local window of calculation until either (i) a plane feature is extracted after a non-plane feature or (ii) the classification stability is lost (Fig. 3).

The reason for the first scale constraint is to avoid loosing meaningful information. When plane features are extracted after non-plane features, they are considered as an obliteration of smaller-scale features and, therefore, disregarded in the analysis.

We also further restrict scales by analyzing the classification stability. As scale increases, an undulating pattern of intercalating moments of classification stability and confusion is formed (Fig. 3). These "waves" represent dominant scale ranges, whereas their boundaries identify specific scales where fundamental morphometric changes take place. In order to automatically identify these boundaries, we find the scales where classification stability is lost. A classification is considered stable when it produces features exhibiting a small confusion index [13] over a significant number of consecutive scales. By trial-and-error we defined a confusion index of 0.6 and 4 consecutive scales as adequate thresholds. Fig. 3 demonstrates the complete analysis.

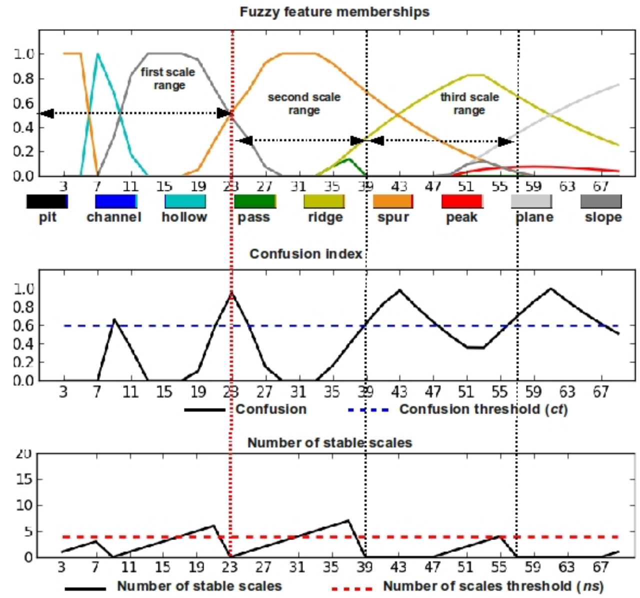

Figure 3. Identification of the maximum scale of analysis (red vertical line).

In the example displayed, the classification becomes stable and then loses stability three times, identifying a total of three scale ranges until a plane feature is extracted. For the purpose of an unsupervised assessment, we consider the use of only the first range of scales as the best compromising approach.

D. Finding Fundamental Features and Scales

After having defined the local range of scales to analyze, we can derive the multi-scale fuzzy feature memberships h_i, given by

$$h_i = \sum_{\forall s \leq smax} g_i(s) \times w(s) / \sum_{\forall s \leq smax} w(s) \quad , \qquad (1)$$

where $g_i(s)$ is the fuzzy feature membership for each i of the set C of nine features in every scale s, $smax$ is the local maximum scale of analysis and $w(s)$ is a weight applied to each scale (kept constant in the analysis).

The highest multi-scale fuzzy membership determines the *fundamental feature*, whereas the *fundamental scale* is simply the one that best represents the entire distribution of fundamental feature fuzzy memberships, i.e., its centroid.

III. The Experiment

In order to test its general applicability, the method was applied to five DEMs of varying resolutions, data sources and spatial extents (Tab.1). No preprocessing was applied to any of the DEMs, which are all freely available on the Internet[1]. The entire method was implemented through a GRASS-Shell script

1 http://www.gebco.net; http://pds.jpl.nasa.gov/; http://www.geomorphometry.org

that needs nothing but a DEM as input. Due to inherent limitations of the underlying GRASS modules, the local window of calculation was set to a maximum of 69x69 cells.

TABLE I. MAIN PROPERTIES OF DEMS USED IN THE ANALYSIS.

	MOLA DEM	*GEBCO_08*	*Baranja Hill*	*Ebergotzen*	*Fishcamp*
Data source	Satellite altimetry	Satellite altimetry / soundings	Topographic maps	Topographic maps	LIDAR
Nº of cells	393,848	750,836	21,903	160,000	320,000
Cell size (m)	7,000	1,000	25	25	5

IV. RESULTS AND DISCUSSION

A. Fundamental Features and Scales

Instead of providing extensive geomorphological descriptions, our main focus here is to evaluate the proposed method in contrast to more common approaches, namely, the choice of one single fixed-scale to analyze; and the use of modal morphometric maps. As such, we derived confusion matrices between the fundamental maps and all fixed-scale and modal maps generated by scales ranging from 3x3 up to 69x69.

The resultant kappa index trends in the fixed-scale analysis show peaks that tend to cluster around scale 13x13 (Fig. 4 left). This indicates that the fundamental maps are biased toward smaller scales, thus, capturing most of the significant features without, however, keeping much noise. As scale increases, the discrepancies also escalate, being more pronounced in rougher DEMs due to excessive obliteration of non-plane features, which is contained in our approach by the adaptive parameterization.

The modal analysis, in turn, shows the majority of maximum kappas around scale 23x23 (Fig. 4 right). However, high kappa values were spread out among a larger number of scales, being less sensible to them. This suggests that there are many choices of maximum scales able to generate comparable results between the modal and fundamental approaches. Note, however, that all experiments were carried out with automatically generated parameters, contrasting with the original modal approach.

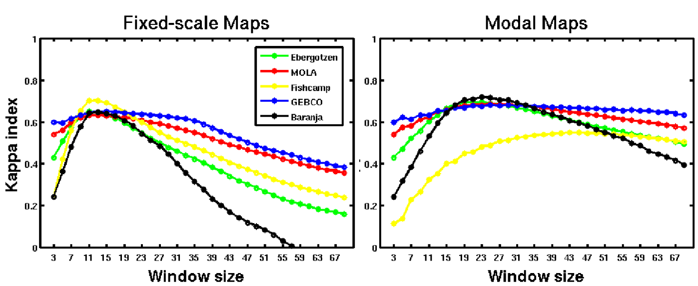

Figure 4. Kappa index trends with scale.

The oblique views of the Baranja Hill DEM depicted in Fig. 5 allow further evaluation of the results. The proposed approach, as well as the detected global scales (maximum kappas), produce morphometric maps that tend to be in good agreement with subjective visual assessments of the overall topography, attesting for the unsupervised character of the method.

Fig. 5 also brings the corresponding fundamental scale map, showing that larger features were coherently assigned to larger scales (darker shades of gray). Examples are seen in the continuous drainage divides, drainage channels and some point features, such as hill passes. In addition to the considered scales, a total of four scale ranges was identified in all studied DEMs; however, an average of 83% of each DEM presented only one range, justifying the choice of the first stability loss as the local maximum scale of analysis.

Also, although capturing detail, the analysis was able to identify fundamental scales up to 61x61 and local maximum scales as high as 69x69. While modal maps generated by considering these scales denote progressive loss of information, the spatially-varying detected scales allow one single map to gather as much information as possible from diverse scales simultaneously. The lack of need to choose a limited range of scales to analyze further emphasize the objective and unsupervised character of the method.

Also obtained in the proposed analysis is a complete set of fuzzy maps that comprise nine feature membership maps for every scale, nine multi-scale feature membership maps and a multi-scale confusion index map. All of them together capture the inherent double vagueness of landforms, enabling a thorough assessment of the multi-scale nature of DEMs that is unlikely to be achieved by crisp or fixed-scale approaches.

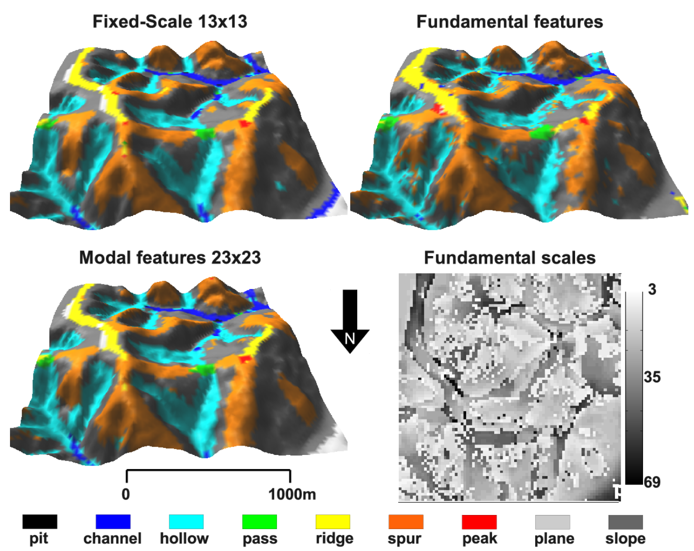

Figure 5. Comparison of morphometric feature maps of the Baranja Hill DEM.

B. *Multi-scale Geomorphometric Variables*

As stated in [10], the detection and delineation of spatially adaptive scales can not only improve the classification of landforms, but also lead to improved approaches in calculating surface derivatives. With this motivation, new geomorphometric variables were derived by a simple map algebra algorithm. It uses the fundamental scale map as a guide to locally select values that correspond to the appropriate scales. Following this approach, Fig. 6 shows a multi-scale slope map as compared to fixed-scale maps of local 3x3 and regional 35x35 scales.

The highlighted areas (black squares) show that the multi-scale map combines information from different scales. When the fundamental scale map indicates local scales (lighter shades) and detail is necessary, it resembles the 3x3 map; when coarser scales dominate, the resultant map is smoother, locally adapting to the detected scales and, hopefully, to the actual geomorphology. We consider these results as truly multi-scale versions of the original variables. Although more in-depth studies are required, we believe these maps should be preferable to any single fixed-scale map or even to statistical summaries based on multiple scales, as far as an unsupervised characterization of topography is desired.

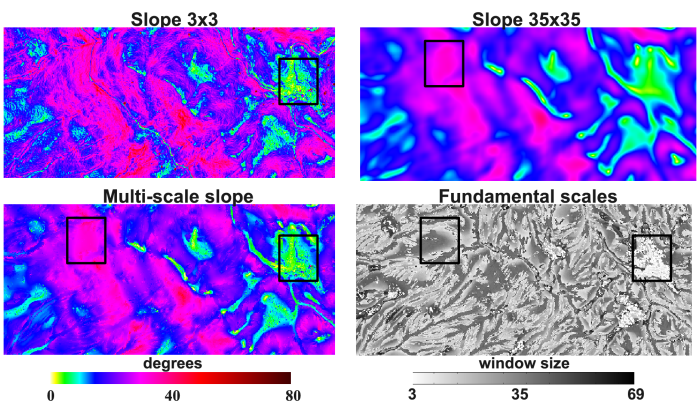

Figure 6. Multi-scale slope map of the Fishcamp DEM.

V. Conclusion

When a general geomorphometric assessment of a surface is needed, parameters and objects are usually extracted using the sole inherent scale of the data. However, the amount of scale-based relationships seen in the results of this paper and in the many others that influenced it show that this approach is insufficient, if not bound to erroneous conclusions. If nothing or little is known beforehand about a surface, how come we so carelessly use a fixed-scale approach? Geomorphology and specially geomorphometry are, in its essence, multi-scale.

With this motivation, our work has presented an unsupervised method to identify the fundamental features and scales of DEMs. We have considered the inherent double vagueness of landforms by applying fuzzy reasoning in every scale *per se* and also in a multi-scale sense. Fuzzy sets were parameterized automatically and the maximum scale of analysis was determined in a cell-by-cell basis, locally adapting to the actual topography. The result was a general and transferable method able to characterize the multi-scale geomorphometry of very discrepant DEMs.

Despite a number of associated shortcomings, such as the artificial limit of 69x69 cells imposed, we believe this effort is in the right direction towards a more thorough approach to geomorphometry, one that not only takes into consideration scale effects, but one that treats scale as an inherent dimension of any data. As such, the most important aspect in efforts like this one is not as much to reach an answer to the research question, as it is to simply keep it in mind:

Which is the best scale?

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