Geomorphometry and statistics-based approach for recognition of areas of enhanced erosion and their morphotectonic interpretation

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Abstract—**Areas of enhanced erosion may be considered as markers of tectonic processes as far as the signals resulting from non-tectonic controls of landform evolution can be isolated. In this study spatial distribution of strong erosional signal recorded in morphometric attributes of the land surface, longitudinal stream profiles and valley morphology is examined and confronted with lithological diversity of the area.**

I. Introduction

Areas of enhanced erosion may indicate higher tectonic activity (as uplift drives erosion), lower resistance of bedrock to erosional factors and forces, or abundant precipitation. These controls frequently occur in combination and thus, one of the most important and challenging tasks in tectonic geomorphology is to separate the signal resulting from different controlling variables and to avoid overinterpretations.

In this study we first aim at identification of areas whose morphometric properties may reflect the enhancement of erosional processes, whatever reasons stood behind. To do so, a few different approaches were involved, all basing on morphometric and statistical analysis of various datasets. These include maps of spatially continuous morphometric parameters derived from LiDAR-based DEM, as well as discrete measures calculated for specific locations and ascribed to points or lines.

The protocol for identification of erosional 'hotspots' was applied to the Orlickie-Bystrzyckie Mountains Block (Sudetes, Central Europe), which owes its emergence to late Cenozoic uplift resulting from stresses from the Alps and the Carpathians, with the superimposed effects of long-term rock-controlled denudation. As lithological diversity of the area is high, the influence of bedrock properties on geomorphological markers of uplift needs to be considered in more detail. By contrast, spatial distribution of rainfall is relatively uniform over the area.

II. Methods

A. Erosional signal in morphometric attributes of the land surface

To distinguish highly dissected terrains eight morphometric parameters with the potential to record erosional signal were selected in the first step. These include:

(1) relative elevation (rel_elev)

(2) standard deviation of elevation (std_elev)

(3) coefficient of variation of elevation (cv_elev)

(4) Terrain Ruggedness Index (TRI, [1])

(5) standard deviation of curvature (std_curv, [2,3])

(6) slope

(7) Topographic Wetness Index (TWI, [3,4])

(8) Valley Depth (val_dep, [5])

These parameters were derived form LiDAR-based DEM, resampled to 30x30 m spatial resolution. Most of them were calculated for the local neighbourhood, that is within 5x5 moving window. The approach is based on the assumption that the increase in values of the parameters reflects an increase in erosional dissection of the area, although this may be debatable for TWI.

To eliminate variables that do not discriminate observations efficiently, the coefficient of variation for each parameter was calculated. As for all eight variables it exceeds 10%, there was no need to eliminate any of them in this step.

As some of the parameters were suspect to be highly correlated, the correlation analysis was performed in order to eliminate variables which replicate information. The selection of the Spearman's correlation coefficient, as a measure of mutual

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dependency, was determined by both statistical distribution of the variables (far from being normal) and the presence of outlier observations. Prior to correlation analysis median filter was applied to all parameters as a smoothing technique. This was dictated by relatively small neighbourhood for the calculation of some parameters and thus their high differentiation in space.

In the correlation matrix all pairs of variables characterized by the absolute value of Spearman's correlation coefficient equal or exceding 0.8 were identified. From each of these pairs the parameter with the higher average degree of correlation with other variables was eliminated. This approach enabled us to reduce the total number of parameters taken into consideration in this study from eight to four (cv_elev, std_curv, TWI, val_dep).

Nearly 2 million points ascribed to the central parts of the raster cells and characterized by a sequence of four selected parameters were then subject to clustering procedure in order to distinguish objects similar to each other from morphometric perspective and thus possibly recording the erosional signal of similar strength. Such a great number of observations prevents the application of hierarchical clustering algorithms and from the non-hierarchical ones the k-means method was selected. In order to determine the optimal number of clusters to distinguish (Fig. 1), the pseudo *F* statistics, also known as Caliński-Harabasz index [6], was calculated. As only two groups of observations should be created in the light of this measure, the alternative elbow method was also applied, but no clear indication of the optimal number of clusters was obtained in this way.

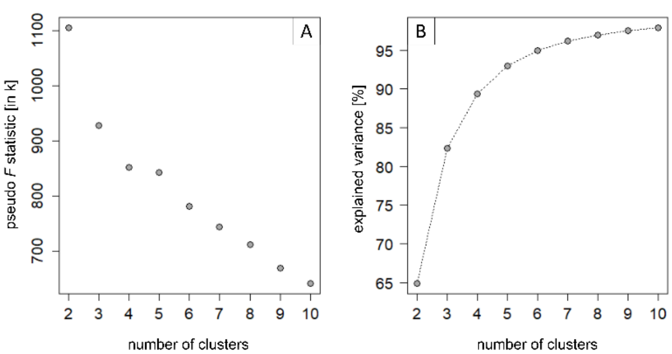

Figure 1. The attempts to establish optimal number of clusters with the use of Caliński-Harabasz pseudo *F* statistic (A) and elbow method (B).

B. Erosional signal in stream longitudinal profiles and valley morphology

To identify 'erosional' sections of the streams, that is channel segments abnormally steep in respect to the adjacent ones, stream length–gradient index (SL index) [7] was applied. It was calculated for 400 m long river segments according to the formula below (1):

$$SL = (\Delta H/\Delta L)L \tag{1}$$

where:

ΔH – change in elevation

ΔL – horizontal length of the segment

L – distance to the highest point in the channel

All river segments with the local slope possibly affected by anthropogenic elements (roads, bridges, reservoirs) were excluded from further analysis. Channel segments of higher steepness, that is those characterized by higher SL-index values, were identified in two different ways. In the quantile-based approach they were distinguished as those exceeding upper tercile, quartile and quintile of SL-index statistical distribution in which all examined river segments in the study area were taken into account. In the alternative, model-based approach erosive segments of river channels were recognized as follows. In the first step the chart presenting the variablity of SL-index along the river course was plotted for each stream separately (Fig. 2A). To this plot a linear model was adjusted and the residuals for each location were computed. For the positive ones the average residual value was calculated. All river segments typified by residuals exceeding this value were considered 'erosive'. This procedure was repeated also in local slope analysis, in which distance between the river segment (its midpoint) and the spring of a river (*L*) was not considered. The only difference was the adjustment of the logarithmic curve to the data, instead of the linear trend (Fig. 2B).

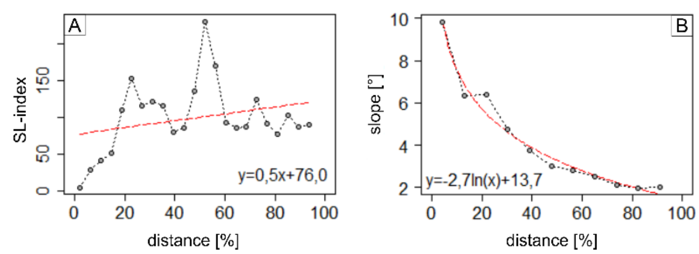

Figure 2. Variability of SL-index (A) and local slope (B) along exemplary streams with adjusted models.

In the final distinction (aggregate approach) erosive segments of river channels were identified as locations of superposition of 20% of observations with the highest SL-index values (quantile-based approach) and those distinguished as erosive in both model-based approaches (Fig. 2).

In the identification of erosive sections of river valleys, that is segments shaped by intensive river downcutting, valley floor width –valley hight ratio (V_f index) given by formula (2) was applied [8].

$$V_f = \frac{2V_{fw}}{(E_{rd} - E_{sc}) + (E_{ld} - E_{sc})} \tag{2}$$

where:

V_{fw} – valley floor width

E_{rd}, E_{ld} – elevation of right and left divides

$(E_{sc}$ – elevation of stream channel

As many minor streams crossing the mountain-piedmont junction in the eastern part of the study area do not have any distinctive valley forms, the delimitation of which is essential for the purpose od V_f index calculation, this analysis was restricted to the western slope of the Orlickie Mountains.

The V_f index was calculated for the same locations for which SL-index was computed in order to allow their comparative analysis, mostly in terms of mutual correlation. Contrary to the latter, lower values of V_f index are indicators of more intensive erosion related to river downcutting. For identification of erosive valley segments the quantile-based approach, similar to the one introduced in the SL-index analysis, was applied.

As V_f index does not take account of slope of valley sides in a direct way, spatial distribution of steep valley sides (that is raster cells with the slope exceeding the upper quartile of statistical distribution) was also examined.

C. Lithological control on indicators of erosional signal

To assess the influence of diversified lithology on erosional dissection the non-parametric chi-square test of independence was performed. The categorical variable was considered in two different levels: general and detailed. While in the former the distinction was made only between crystalline basement and sedimentary cover, lithological diversity in the latter was considered in a more detailed way.

In chi-square test of independence the comparison is made between observed (empirical) values of a numeric variable with the theoretical ones established on the basis of the marginal distribution [9]. The assumption of the null hypothesis is that the numeric variable does not depend on the categorical one. The test statistic is given as below (3):

$$\chi^2 = \sum_{i=1}^{k}\sum_{j=1}^{s}\frac{(n_{ij} - n'_{ij})^2}{n'_{ij}} \tag{3}$$

where:

n_{ij} – observed values

n'_{ij} - expected values

k, s – number of levels in both variables

Given the null hypothesis is true, the test statistic has chi-squared distribution with (k-1)(s-1) degree of freedom. For significant test results mosaic plots were used to illustrate the pattern of deviation from independence [10].

In this study the numeric variable was expressed relatively, that is as percentage of area occupied by 'erosive' cluster within different lithological units or, respectively, as the length of erosive segments of river channels or valleys.

III. Results and interpretation

Given that no clear indication of the optimal number of groups to distinguish in the clustering procedure was obtained in the light of the elbow method, this number was established arbitrarily as five (Fig. 3A). As the cluster-specified average values do not maintain the same order for the parameters taken into consideration (Fig. 3B), it is not possible to rank the clusters in terms of increasing signal of erosional dissection. Nevertheless, basing on both their spatial and statistical characteristics, clusters no. 3 and 4 were considered as carriers of the strongest erosional signal.

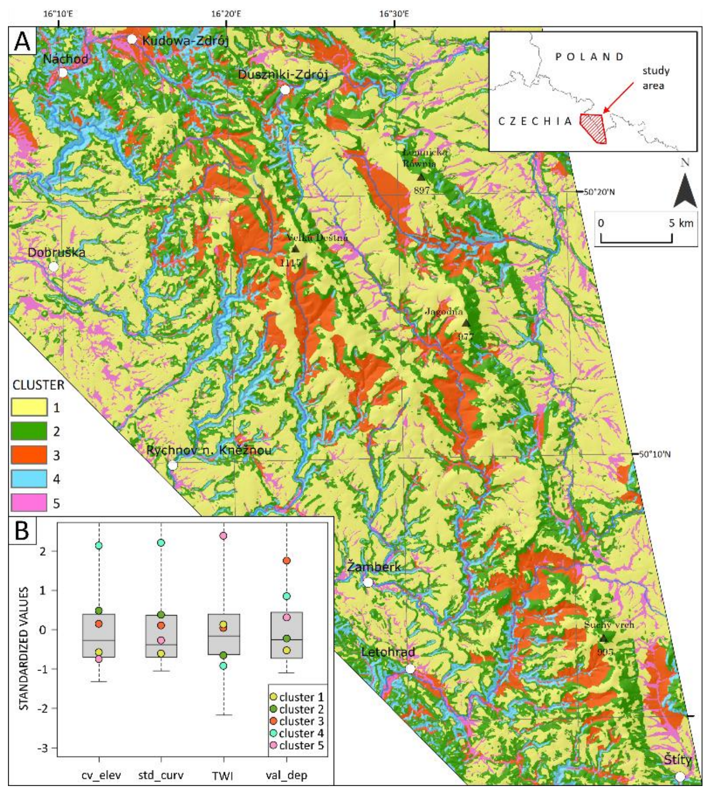

Figure 3. The results of k-means clustering (A) with the average values of all parameters calculated for each cluster separately (B).

Erosive segments of river channels obtained on the basis of the aggregate approach were sparse and short. Therefore, the quantile-based approach to their identification was solely included in further interpretations. Surprisingly, no statistically significant correlation between SL- and V_f index values calculated for the same locations was demonstrated (rho = -0,26).

In the final distinction of areas, whose morphometric properties may reflect the enhancement of erosional processes, the superposition of the most 'erosive' clusters (3 and 4 on Fig. 3) and erosive segments of river channels and river valleys, both identified in the SL and V_f quantile-based approaches, was considered (Fig. 4). The spatial distribution of steep valley sides was also taken into account.

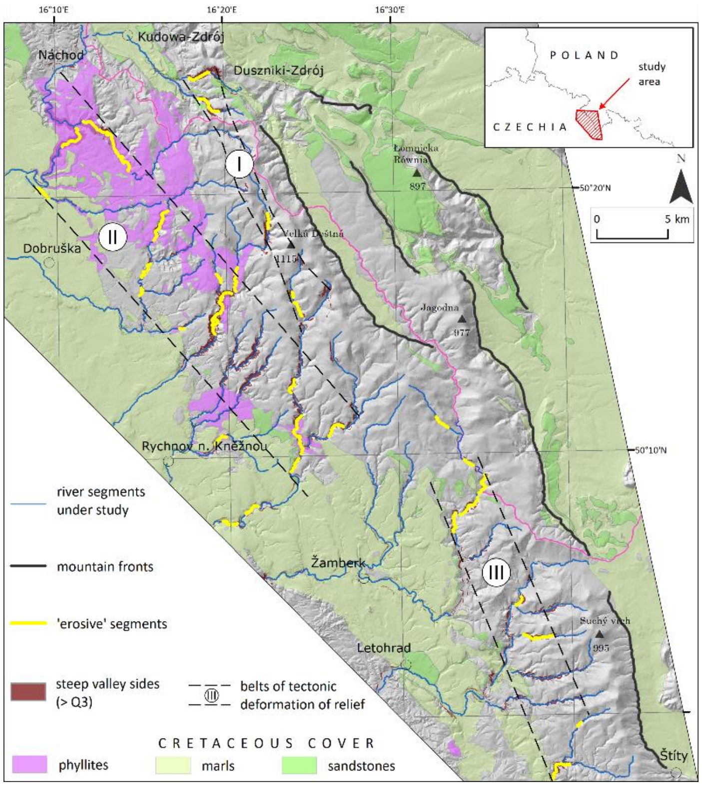

Figure 4. Belts of tectonic deformation of relief distinguished on the basis of spatial distribution of erosive segments of river channels and river valleys identified by SL- and V_f index and their affiliation to the most 'erosive' clusters (no. 3 and 4 on Fig. 3). Basement rocks other than phyllites are indicated in grey.

As the influence of lithological diversity of the area can be considered minor (Fig. 5), the erosive signal recorded in morphometric attributes of the land surface, longitudinal stream profiles and valley morphology is interpreted as the response to geologically recent and ongoing uplift of the area.

Three belts of tectonic deformation of relief, elongated parallel to the morphological NNW–SSE axis of the mountain block, were recognized (Fig. 4). The spatial pattern of variable intensity of endogenic processes is consistent with the geological situation of the region, especially with the distribution of remnants of the Cretaceous sedimentary cover.

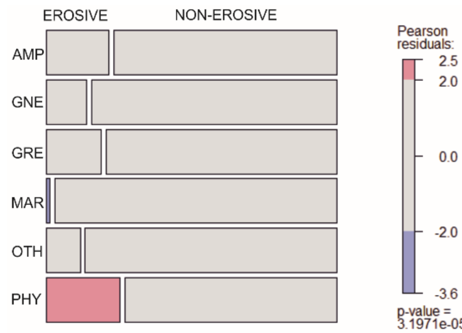

Figure 5. Relationships between relative frequencies of segments identified as erosive (see Fig. 4) in total length of the streams for different lithological units. Note statistically significant overrepresentation of these segments within phyllites (AMP – amphibolites, GNE – gneisses, GRE – greenschists, MAR – marls, OTH – other metamorphic schists, PHY – phyllites).

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REFERENCES

[1] Riley, S., S. DeGloria, R. Elliot, 1999. "A Terrain Ruggedness Index that quantifies topographic heterogeneity". Intermountain Journal of Sciences 5, 23-27.

[2] Zeverbergen, L., C. Thorne, 1987. "Quantitative analysis of land surface topography". Earth Surface Processes and Landforms 12, 47-56.

[3] Moore, I., R. Grayson, A. Landson, 1991. "Digital terrain modelling: A review of hydrological, geomorphological and biological applications". Hydrological Processes 5, 3-30.

[4] Sørensen, R., U. Zinko, J. Seibert, 2006. "On the calculation of the Topographic Wetness Index: Evaluation of different methods based on field observations". Hydrology and Earth System Sciences 10, 101-112.

[5] Conrad, O., B. Bechtel, M. Bock, H. Dietrich, E. Fischer, L. Gerlitz, J. Wehberg, V. Wichmann, J. Böhner, 2015. "System for Automated Geoscientific Analyses (SAGA) v. 2.1.4.".Geoscientific Model Development 8, DOI: 10.5194/gmd-8-1991-2015.

[6] Caliński, T., J. Harabasz, 1974. "A dendrite method for cluster analysis". Communications in Statistics 3, 1-27.

[7] Hack, J., 1973. "Stream-profile analysis and stream-gradient index". U.S. Geological Survey Journal of Research 1, 421-429.

[8] Bull, W., 2007. "Tectonic Geomorphology of Mountains: A New Approach to Paleoseismology". Blackwell Publishing, Oxford, pp. 316.

[9] McHugh, M., 2013. "The chi-square test of independence". Biochemia Medica 23, 143-149.

[10] Meyer, D., A. Zeileis, K. Hornik, 2006. "The strucplot framework: Visualising multi-way contingency tables with vcd". Journal of Statistical Software 17, 1-48.