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Mapping of landscape spatial dynamics patterns by the fuzzy clustering analysis

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Abstract: Spatial dynamics of landscape is largely controlled by lateral abiotic flows. Their studies are possible through the methods of geomorphometry which is rooted in Digital Elevation Models (DEM) automated Geographical Informational Systems (GIS) analysis. The paper presents the method of mapping and classification of landscape spatial dynamics patterns on the basis of lateral flows properties by the fuzzy clustering analysis. The analysis is performed using the k-means method and based on the geomorphometric parameters. Topographic indices underlying the study not only describe morphosculptural, but also explain process-functional component related to the dynamic redistribution of moisture and solid matter in landscape. The comparative analysis of the results for four different in physico-geographical conditions sites has indicated the possibility of meaningful, objective and reproducible classification obtaining.

***Key words*:** lateral abiotic flows, landscape patterns mapping, geomorphometric analysis, fuzzy clustering analysis, the Shuttle Radar Topography Mission (SRTM) DEM

Introduction

One of the research fields of dynamic landscape science are studies of landscape spatial dynamics which is largely controlled by lateral abiotic flows. According to Turner, Cardille 2007 lateral flows define the features of physico-geographical processes related to the relocation of matter and energy that is reflected on the spatial configuration of landscape. In turn, spatial configuration of lateral abiotic flows is sufficiently controlled by relief. Therefore, DEM and its geomorphometric analysis using GIS is an appropriate basis for the automated mapping of abiotic flows spatial pattern configuration.
Additionally, the high potential of DEM application in up-to-date landscape mapping can be explained through a few practical reasons. Firstly, availability – simultaneously with the acquisition of the Open Access DEM the possibility of their independent generation exists. Secondly, usability – DEMs support faster analysis comparing to the analogue cartographic data. Furthermore, as a precise initial material they supply more accurate modeling of different parameters that are of interest to complex landscape studies. Thirdly, functionality – up-to-date landscape researches are based on well-elaborated GIS toolset with the prescribed geospatial models of processes and phenomena. Moreover, the list of meaningful geomorphometric parameters available for the GIS-analysis is constantly improving and opening new possibilities for automated digital mapping.
The procedure of predictive geomorphological (MacMillan et al., 2000), soil (Möller et al., 2008, Gessler et al., 2000), and landscape-ecological (Burrough et al., 2001, Treltz, Howarth 2000) mapping with the application of geomorphometric analysis has a few established stages characterized by the certain methodical features which are as follows:
1) DEM Preparation (or Generation). Open Access DEM (e.g., Jarvis et al., 2008) have a high potential of

application to mid-scale (100 000 – 1 000 000) mapping due to nearly global extent and free of charge distribution. But their use requires preparation that includes grid resolution choice appropriately to research scale (Hengl 2006) and the elimination of data distortions related to acquisition technology (Selige et al., 2006);
2) DEM Geomorphometric Analysis. Being based on the conventional set of variables that mainly describe the shape of surface (rarely – heat and moisture redistribution), it doesn't take into account complex indices that better cover process component;
3) Classification and Results Interpretation. Application of classification algorithms that prescribe number of classes and/or take into account expert knowledge (Dragut, Blaschke 2006) leads to the subjectivity of obtained results. Accordingly, the developed algorithm loses its multipurposeness (and reproducibility) and becomes applicable only for a relatively narrow research field. The content and meaning of delineated territorial units can also significantly vary for researchers with different background (e.g., ecologist and geomorphologist).
The proposed method aims to overcome the above-mentioned problems. Firstly, the procedure of DEM preprocessing is discussed. The procedure is considered to allow fast distortions elimination without significant quality losses (at the research scale given).
Secondly, the procedure of abiotic flows spatial pattern configuration mapping is based on the DEM geomorphometric analysis that takes into account two groups of parameters. The first group includes first- and second-order derivatives that describe the features of surface shape (slope, convexity-concavity etc.). The second group includes complex topographic indices that characterize dynamic moisture and solid matter redistribution under gravity. As a result, we are enabled to delineate morphodynamic territorial units that are uniform in the dynamic parameters of lateral abiotic flows (direction, intensity etc.).
Thirdly, the subjectivity of a researcher is excluded in consequence of initial data and classification statistical parameters objectivity. Also, hard determinacy, not inherent in natural formations in reality, is eliminated due to the application of the fuzzy clustering analysis methods. Additionally, wide opportunities of the results statistical interpretation (number of classes, classification performance, membership measure etc.) are provided. As a result, the obtained classification is more objective and independent of disciplinary field than conventional semantic interpretation.

Materials and Methods

Study Area

There were chosen four training sites with diverse physico-geographical conditions within the territory of Ukraine (tab. 1, fig. 1). Every training site is presented by a square of 10×10=100 km2 area. According to the chosen spatial resolution of 50 m every training site encompasses 40 000 pixels (analytical matrix elements) described by the ten values of geomorphometric variables each. As a result, general data volume assigned with one training site is presented by the set of 400 000 unique values.

Table 1. Some characteristic features of the training sites

№	Abs. height, m	Slope, deg.	Natural zone
1	133.47-166.24	0-3.95	Mixed coniferous-broad-leaved forests
2	209.03-356.33	0-10.49	Forest-steppe
3	69.57-167.75	0-8.11	Steppe (northern subzone)
4	26.60-48.07	0-1.72	Steppe (mid subzone)

Software

Data processing was performed using Free and Open Source Software (FOSS) (Steiniger, Hay 2009). DEM preparation and analysis were performed in the Open desktop GIS SAGA v. 2.0.7 environment (Conrad, 2006) that provides a wide range of raster preprocessing and terrain analysis functions (Olaya, Conrad 2009). The procedures of cluster analysis were carried out using the FuzME v. 3.5b software package that is a multipurpose tool for the performance of fuzzy unsupervised data classification (the k-means method) with the additional results assessment capabilities (e.g., general uncertainty, partition validity) (Minasny, McBratney 2002).

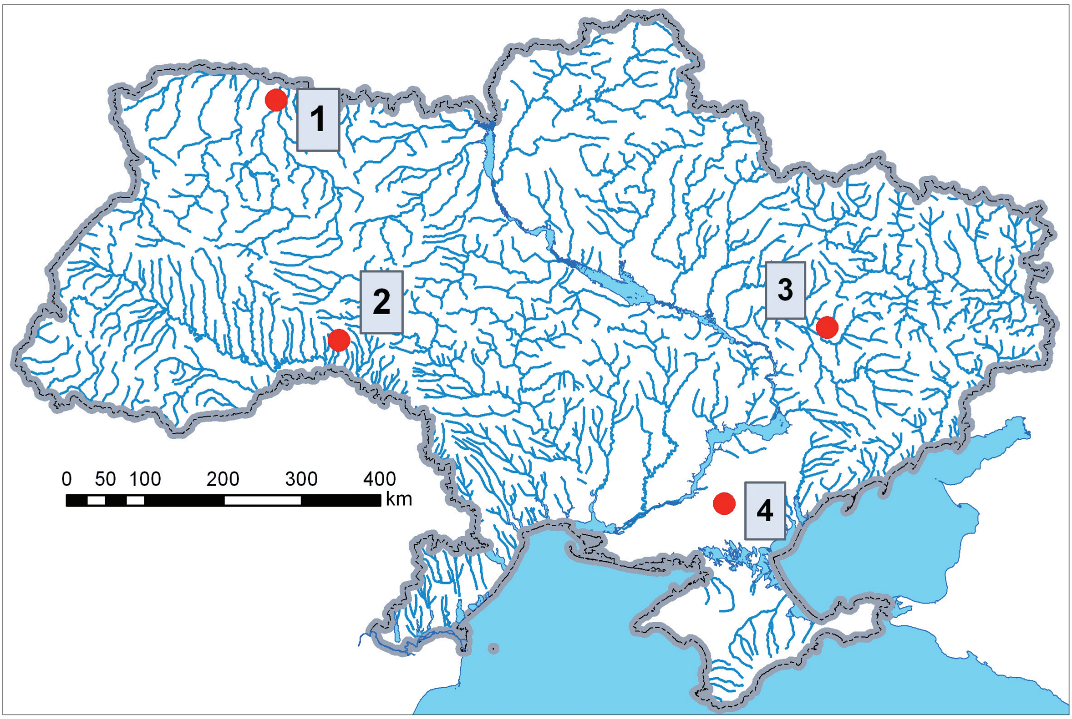

Fig. 1. Location of the training sites

DEM Preprocessing

Since in prospect the research oriented towards the implementation of a mid-scale (1:300 000) mapping procedure, the method elaboration doesn't require an independent high-resolution DEM generation. That has enabled us to use the Open Access global geodata set – the SRTM DEM v. 4 with the spatial resolution of 3 arcseconds (approximately 90 m) (Jarvis et al., 2008, Reuter et al., 2007). According to Karwel, Ewiak 2008 conclusions, the SRTM DEM matrix can be used for DEM and contour lines generation in scales 1:50 000 and smaller that makes it an appropriate input for the study.

Before the analysis started the preparation of the SRTM DEM necessary parts had been performed. The preparatory procedure encompasses reprojecting joined with the choice of an appropriate spatial resolution, filtering, and hydrological correction.

The training sites DEMs were reprojected from geographical to Universal Transverse Mercator (UTM) projection – zones 35, 37 and 36 respectively. In order to provide a higher accuracy comparing to the available materials of thematic mapping, the initial work took into account the DEM quality and was orientated at 1:100 000 scale despite the prospective scale of 1:300 000. While setting the DEM resolution as an initial premise was used the proposition from Hengl, 2006 according to which pixel size should be equal to 0,5 mm of paper-based map that is 50 m at the research scale given.

Filtering is the next critical step to perform. To eliminate data distortions the multidirectional Lee's filter (Selige et al., 2006) has been used. This anisotropic filter was designed to smooth flat areas and simultaneously preserve terrain features like edges and ditches that is sufficient for the following geomorphometric analysis performance.

DEM hydrological correction includes spurious sinks filling and has been based on the method proposed by Planchon, Darboux 2002. Instead of gradually filling the depressions the method first inundates the surface with a thick layer of water and then removes the excess water. Depressions can be also replaced with a slightly sloping surface that is more appropriate for the modelling of flow transformation.

Geomorphometric Analysis

DEM analysis has taken into account two groups of variables that characterize relief features from different sides (table 2).

Table 2. The geomorphometric parameters used for analysis

Parameter [units]	Meaning for lateral abiotic flows analysis	References
Primary topographic attributes		
Abs. height [m]	▪ altitudinal position; ▪ potential energy; ▪ surface runoff velocity	–
Slope [deg.]	▪ overland and subsurface flow velocity; ▪ runoff rate; ▪ quantification of solute transport processes	(Costa-Cabral, Burges 1994)
Plan curvature [m-1]	▪ local factors of the dynamics of surface and intrasoil runoff (ridges and valleys); ▪ relative convergence / divergence of flow-lines (1st accumulation mechanism)	(Moore et al., 1991, Zeverbergen, Thorne 1987)
Profile curvature [m^{-1}]	▪ local factors of the dynamics of surface and intrasoil runoff (relief break-lines); ▪ relative deceleration / acceleration of material flow (2nd accumulation mechanism)	Ibid.
Mean curvature [m^{-1}]	▪ processes of runoff concentration, acceleration and transport; ▪ surface water flow capacity; ▪ determination of erosion, transition, accumulation, and dissipation zones	Ibid.
Secondary topographic attributes (compound indices)		
Topographic Wetness Index (TWI) [$\ln(m \times deg.^{-1})$]	▪ moisture redistribution; ▪ catenary position; ▪ prediction of saturation areas allocation	(Gessler et al., 2000, Moore et al., 1991)
Stream Power Index (SPI) [m×deg.]	▪ takes into account slope profile and altitudinal position; ▪ measure of flowing water erosive power; ▪ stream erosion and accumulation zones allocation	(Moore et al., 1991)
(Sediment) Transport Capacity Index (LS factor) [m×deg.]	▪ relief erosive potential; ▪ measure of surface runoff erosive power; ▪ sheet erosion and accumulation zones allocation	(Desmet, Govers 1996)
Downslope Distance Gradient [deg.]	▪ estimates hydraulic gradients using downslope topography; ▪ controls the deviation of hydraulic gradient from surface slope	(Hjerdt et al., 2004)
Downslope Distance Gradient Difference [m^{-1}]	▪ replacement for local gradient; ▪ better estimate of hydraulic gradients than the local gradient of the surface; ▪ predicts the spatial pattern of recharge and discharge areas in watersheds	Ibid.

Primary topographic attributes that describe the shape of surface and define the rate of height change against spatial coordinates are calculated as the first- and second-order derivatives of topographic surface. Secondary topographic attributes or compound topographic indices are calculated on the basis of the primary ones and intend to assess the intensity of different lateral processes (transport processes capacity, erosion potential etc.).

Fuzzy Clustering Analysis

The fuzzy k-means method (also known as the c-means or simply the FCM) is one of the most popular clustering algorithms. In contradistinction to hard clustering, it uses a fuzzy exponent that controls the rate of overlapping between classes, i.e. one object can simultaneously belong to two or more clusters (Bezdek et al., 2005). Owing to this, fuzzy clustering is more appropriate for continual phenomena analysis since their parameters change gradually. Consequently, the method is actively used for soil (McBratney, Odeh 1997), landscape (Burrough et al., 2001), landform (Burrough et al., 2000) data classification, pattern recognition and remote sensing data processing (Bezdek et al., 2005). The principles of the fuzzy clustering using the FCM are described in detail in Bezdek et al., 2005, Burrough et al., 2001; only the main points of the analysis performance are summarized here.

The clustering procedure was based on the Euclidean distance which is a simple distance in a multidimensional feature space. As the metric use doesn't include the procedure of preliminary data scaling aimed at the elimination of differences in values ranges and standard deviations, the dataset was preprocessed in order to normalize the values using the formula:

$$z = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}}$$

where: z is a normalized value of an attribute; x_i – a non-normalized initial value; x_{min} and x_{max} are the minimal and maximal values of the data range respectively.

As a result, the data was scaled to the set of uniform ranges with the values distribution from 0 (initial minimal) to 1 (initial maximum).

After the metric was chosen and the dataset normalized it is possible to perform iterative clustering procedure using the FCM. Mean initial parameters on this stage are the number of classes and the fuzzy exponent value. Calculations were performed with the fuzziness index 1.3 which is recommended while using the Euclidean distance and the number of clusters from 2 to 10.

The method is sensitive to the randomly chosen initial cluster centers as the following objects redistribution is performed on its basis. To eliminate those effects a random start (initial cluster centers randomly chosen) was selected for calculating clusters. The random start can give rise to different results for each cluster calculation on the same dataset. Once the number of clusters and value for the fuzziness index is determined, the clustering was repeated 10 times on the same dataset. In all tested cases, some of the clustering repetitions were nearly identical, indicating that these results best reflect groups in the original data. The cluster results with the lowest Wilk's Lambda statistic, and a repetition in the 10 calculations were selected for analysis. Wilk's lambda is a general measure for the difference between clusters. Its value ranges between 0 and 1, with values close to 0 indicating the group means are different and values close to 1 indicating the group means are not different.

The output contains cluster allocation of the data points, cluster properties and different statistics describing the clustering performance. To choose the most appropriate number of classes the following clustering performance parameters were analyzed:

– Fuzziness Performance Index (FPI) is a measure of the degree to which different classes share membership (fuzziness). FPI is constrained to values between 0 and 1, whereby 0 means that classes are no longer fuzzy, but are considered crisp;

– Modified Partition Entropy (MPE) estimates the degree of disorganization created by a specified number of classes. MPE values close to 1 indicate high disorganization, 0 means excellent organization;
– Separate Distance (S) based on the objective function by determining the average number of data and the square of the minimum distances of the cluster centers.
Generally, the more separate the clusters, the smaller FPI, MPE, and S values. Thus, the optimal number of classes is where selected measures reach minima.

Results

The Optimum Number of Clusters Determining

The validity of the performed classification was assessed through the performance indices determined for different number of clusters. Minimal values of FPI, MPE, and S indicate a good (clear, non-fuzzy) grouping of data (fig. 2).

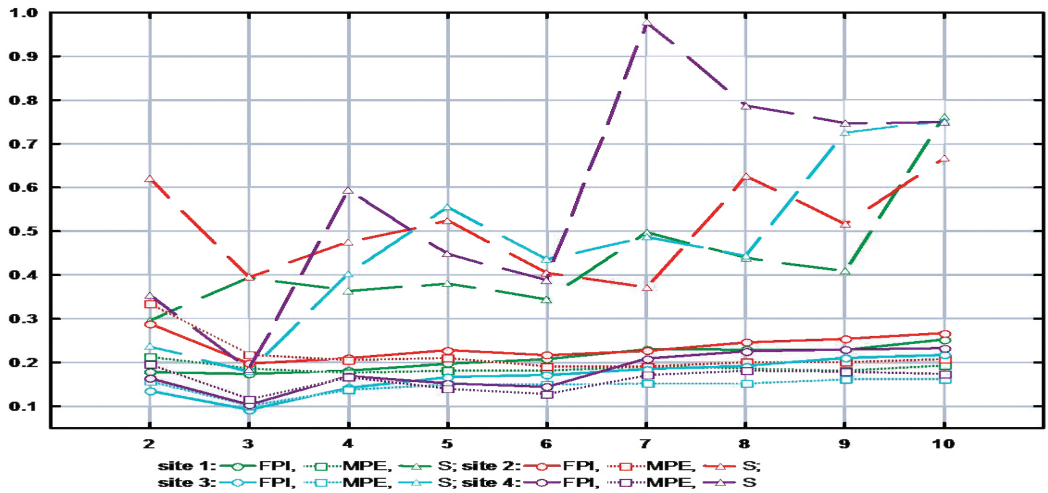

Fig. 2. Determining the optimal number of fuzzy classes

According to the fig. 2 the indices of clustering performance demonstrate variability and partial consistency. The latter could be explained by, firstly, calculation of the indices on the different basis. Secondly, by significant variability of the training sites conditions (table 1). Nevertheless, two alternatives of satisfactory partition can be identified – 3 and 6 classes respectively. This enables to compare the results of classification of different training sites.

Classes Interpretation

In the case of unsupervised classification we can not really provide the legend for the final output. We can only try to assign names to extracted classes a posteriori by carefully analyzing their statistical characteristics. Therefore, the semantic interpretation of obtained classes was done through the statistical analysis of geomorphometric parameters values (fig. 3).
In the case of 3 classes' partition, obtained morphodynamic units considering morphosculptural features and, consequently, direction, intensity, and migration capacity of lateral abiotic flows, can be interpreted as follows:
Class 1 – autonomous eluvial landscapes (A^E) – flat and convex summit sites. It is independent landscapes that gain matter and energy from the atmosphere, the main process here is leaching of matter and descending flow of water and nutrients, the balance of substances is negative. Secondary topographic attributes that

characterize processes of lateral migration approach to minimal values. The exclusion is the training site №1: the class here represented by convex summit sites with the relatively high for the area slope values (0.03–3.95° with the mean value of 1.34°) and with the higher potential for sheet erosion respectively. In this case, the unit can be interpreted as transitionary-eluvial landscapes (T^E);

Class 2 – subordinate transitionary landscapes (T^E) – convex and concave slopes of different height position and steepness. These landscapes obtain matter and energy from autonomous (or simply located upslope) units and responsible for its downslope conduction. Their distinctive feature is parallel to surface (lateral) flow; the balance of substances (in the absence of erosive processes) is close to zero. Mainly characterized by the mean values of secondary topographic attributes that identify the highest (for given area) sheet erosion potential owing to surface flow divergence. For the training sites №1 and 4 this unit can be defined as transitionary-accumulative landscape (T^A) because it is mainly represented by the footslopes and toeslopes with the mid-height superaquatic position, flat or concave profile, and minimal steepness. Respectively, the units are responsible not for matter conveyance, but for its accumulation due to reduction in surface and intrasoil runoff velocity;

Class 3 – subordinate transitionary-superaquatic landscapes (Saq^T) – concave interhill depressions and

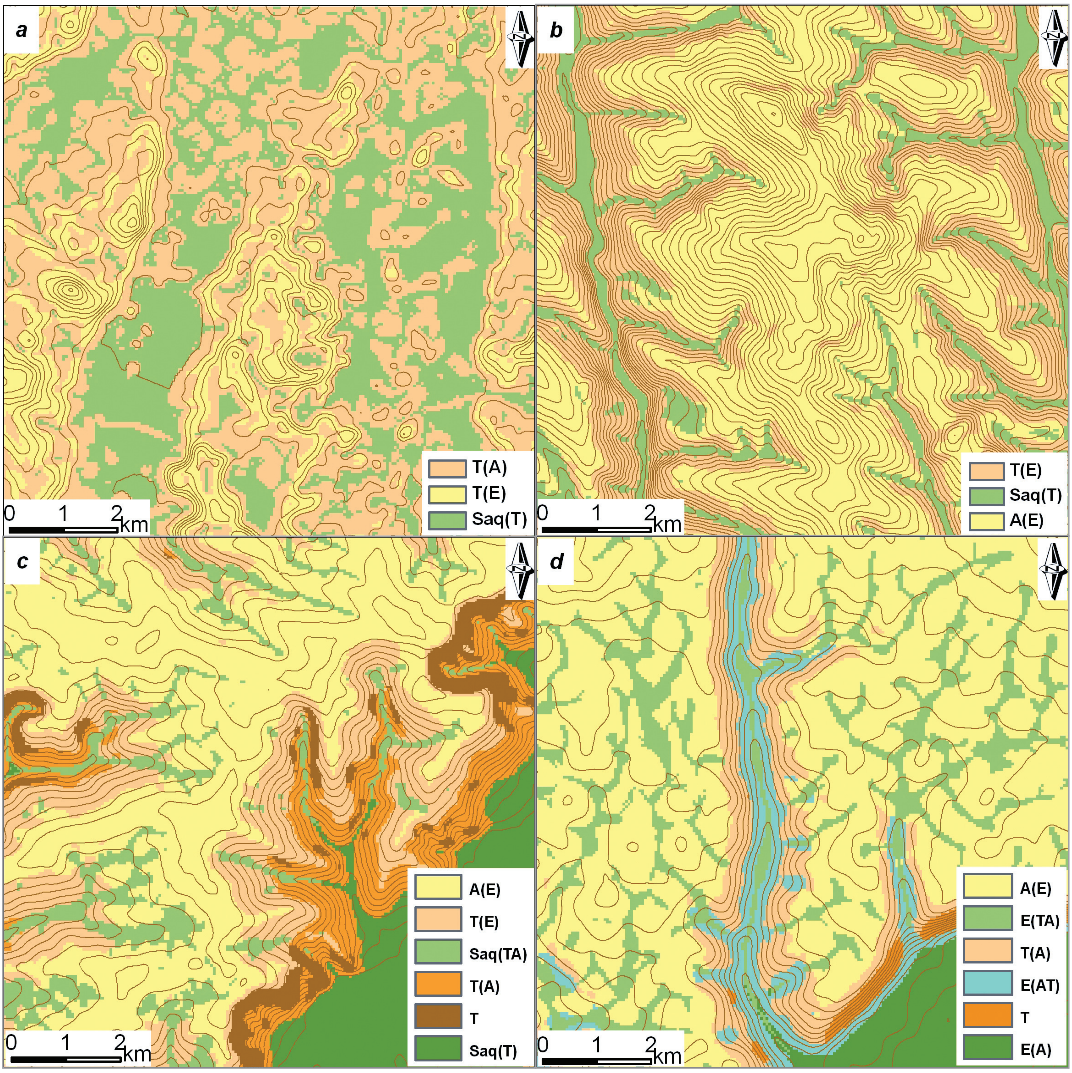

Fig. 3. The examples of the obtained morphodynamic units classes: 3 classes partition for the training sites 1 and 2 – a and b; 6 classes partition for the training sites 3 and 4 – c and d respectively.

channels. Basically represented by erosive network elements, the class is responsible for intense conveyance and accumulation of matter in landscape; balance of substances, as a rule, is positive. The class is defined by the maximum TWI values and the highest potential for linear erosion due to prevailing flow convergence. For the training site №4 this unit can be interpreted as eluvial-accumulative (E^A) because it encompasses mainly closed steppe depressions with deep groundwater bedding.
In the case of 6 classes' partition, the first class of the above-mentioned remains relatively stable, transitionary landscapes additionally subdivided into three classes, and superaquatic transitionary – into two with some differences for the training sites №1 and №4:
Class 1 – autonomous eluvial landscapes (A^E) – flat and convex summit sites;
Class 2 – transitionary-eluvial landscapes (T^E) – shoulder and upper slope (seepage slope and convex creep slope). Gradual rise of sheet erosion potential takes place simultaneously with some increase in steepness. For the training site №4 the class is interpreted as transitionary-accumulative (T^A) landscapes as it represented by footslopes;
Class 3 – transitionary-accumulative landscapes (T^A) – free face and transportation midslopes of the moderate (for given training site) steepness. These territorial units play the key role in providing the processes of matter transportation through sheet surface runoff. For the training site №4 the class is represented by transitionary landscapes (T) without any additional functions;
Class 4 – transitionary landscapes (T) – mainly concave steep slopes. For the training sites №1 and №4 the class is defined as superaquatic accumulative-transitionary (Saq^{AT}) and eluvial accumulative-transitionary (E^{AT}) landscapes respectively represented by well-defined toeslopes with highly concave profile (-0.01 that is maximum mean for all six classes);
Class 5 – transitionary-accumulative superaquatic landscapes (Saq^{TA}) – flat and concave interhill depressions and channels. These forms have a tendency to accumulate moisture and characterized by mid-intense, but mostly convergent flow. The exclusion can be done for the training site №4 where the class is defined as transitionary-accumulative eluvial (E^{TA}) landscapes with prevailing transitionary function;
Class 6 – transitionary superaquatic landscapes (Saq^T) – flat and concave channels' beds associated with the minimal absolute height values, convergent flow and the highest linear erosion potential. For the training sites №1-3 the processes of transport are prevailing, while for the site №4 the class associated with closed depression and accumulation, thus, it defined as accumulative eluvial (E^A) landscapes.

Discussion

The SRTM DEM, provided that data undergo the preparatory procedures of filtering and hydrological correction, is a valid basis for geospatial analysis with the accuracy of 1:100 000 scale as evidenced by the results of its comparison with the topographic and thematic mapping analogue materials.
Since relief is an important factor of hydroclimatic conditions differentiation, geomorphometric parameters obtained by DEM automated GIS-analysis can be effectively applied not only for the morphodynamic territorial units delineation and interpretation but also for more complex (ecological) classifications performance. The potential for further method improvement is connected with the addition of the geomorphometric parameters assessing warmth redistribution (aspect, incoming solar radiation etc.) or multispectral indices assessing primary productivity (e.g., NDVI).
Multidimensional fuzzy clustering analysis using the k-means method is an objective and reliable procedure of data grouping. It enables to define optimal for given number of parameters number of classes and to analyze features of data redistribution within classes. Moreover, maximal values of confusion index potentially can be used for relief break-lines extraction.
The method proposed is reproducible and well-applicable in low-budget projects as it based on FOSS. The software used in its analytical capabilities is not inferior to commercial analogues and owing to interoperability can be easily incorporated with the other professionally-oriented software products.
Thus, a meaningful, objective and reproducible method of mapping and classification of landscape spatial dynamics on the basis of lateral flows properties was developed. Owing to quantitative parameters underlying

the method obtained classes can be easily interpreted that makes the approach flexible and applicable to territories with different types of relief. The primary topographic attributes are of principal importance for the spatial units delineation, while the compound indices complement it with the process-dynamic information. The methodology proposed could be applied for the analysis and prediction of pollutants lateral migration, for fast and accurate predictive landscape-ecological, geomorphological, and soil mapping.

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