Terrain misclassification problem – analysis using pattern simulation approach

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Abstract– **We present the results of a numerical experiment aiming at explaining reasons for classification errors when using an automatic pattern-based terrain classifications algorithm proposed by Jasiewicz et. al. [3]. We use composition of landform elements from incorrectly classified areas, and we use texture pattern from example areas to synthesize a new "terrain" which inherits properties from both sources. Using a new Pattern Analysis Toolbox (GeoPAT, [4,5]) we found that classification errors come from convergence of landscape properties: after replacing texture in misclassified areas with texture as indicated by an example area a new synthetic area shows higher degree of similarity to the landscape class from which it inherits texture. It allow to draw conclusion that short-range textural properties is that feature which at that moment best describes diversity of landscapes for automatic classifications.**

I. Introduction

One of the goals of geomorphometry is an automatic classification of terrain. Automatic classification is much faster than manual mapping (a significant advantage when working with big data sets) and the results are based on clearly defined rules. On the other hand automatic algorithm does not possess human "knowledge" about numerous hidden relations between entities in the data which leads to classification errors. Algorithm performance is based on assessment of classification error and is usually based on confusion matrix which compares amount of correctly classified examples with those which were classified incorrectly. Performance describes the quality of classifier and its real usefulness for automatic mapping. In classical machine learning performance is calculated using a test set – a set of objects for which a class is assigned by an analyst.

With classification of landscapes [1] the problem of performance assessment is more complex. The assignment of a landscape to a particular landscape class is based not only on the information available in the data but also on a knowledge not described by a mathematical description of a landscape, such as location, relation to neighborhood, distance, direction and shapes of objects on several spatial scales. In addition, in geomorphometry, like in other natural sciences, we face the problem of the convergence. Surfaces created by different processes may have similar properties at the level of the data, thus cannot be correctly classified without additional information which is not a part of topographic data.

In terrain classification errors appear for three reasons: (a) selection of inappropriate classifier, (b) lack of clear distinction between classes, and (c) gap between the information available in the data and the knowledge needed to make a correct classification. The third reason is rarely considered when performing automatic terrain classification.

Jasiewicz and Stepinski [2] published a method for classification of landform elements from DEM data; their method, called geomorphons, uses computer vision approach rather than land-surface parameters to classify landform elements into ten types. A local landscape can be considered of a mosaic of landform element types.

Recently, Jasiewicz et al. [3] demonstrated how to classify entire local landscape into landscape types (Fig. 1) using supervised learning methodology. In [3] a 30 m resolution DEM of the entire country of Poland was first transformed into a categorical map of landform elements using the geomorphons algorithm. This categorical map was then divided into a grid of overlapping square areas (300*300 cells each) and for every node in the grid a signature of a local landscape (pattern of landform element types) was calculated as a histogram of features where each feature is one of 55 possible connections between 10 existing landform element types (see [3], [4] and [5] for details). Thus signature contains information on both, the composition of landform elements in the landscape, and their relative configuration (short-distance texture of the terrain). Based on the

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expert knowledge 9 landscape types were selected to best describe variability of geomoprhological landscapes in Poland and example areas for these types were given. As similarity measure between local landscapes a modified Wave-Hedges measure was used which calculated weighted intersection between two signatures representing two landscapes. By default every local landscape can be similar to more than one landscape type because of aforementioned landscape convergence problem. The final single label for each local landscape was assigned using the most similar landscape type. Performance of the method proposed by Jasiewicz et. al. [3] gained 70% against the classification of landscapes in Poland made manually by Kondracki [6].

Our goal here is to investigate the reasons for misclassifications at the level of data description. Using a complex texture-composition signature (see [3]) we want to check what information affects the misclassification: general long-range (of the order of kilometers) composition of the whole area or short-range (order of tens of meters) textural properties. To solve the problem we run 2304 conditional simulations where as the source of information about the long-range composition we used misclassified areas and as a source of short-term texture we used examples of areas which were classified correctly. Simulation will change the texture of the area but will keep its general composition. The similarity between new simulated “landscape” and landscape types used as a source for composition component and texture component will answer which of those two elements plays more important role during classification process.

II. DATA AND METHOD

A. Study area

To analyze the problem we use post-glacial developed areas across the central-European lowlands. One of them is a young, immature surface which preserves the original features remained after regression of the last glaciation. Those features are very slightly or even not changed by further denudation. The second is an older surface and include area which was not covered by ice during the last glaciations; its original postglacial features were transformed into a new assemblage under periglacial conditions [7]. The extension of last glaciation is well defined (Fig. 1), and we used only landscapes which represents class “moranic plateau” so an identification and selection of misclassified areas do not rise doubts.

Areas within the reach of last glaciation (we will use the term "young glacial" in the rest of the paper) stands out by inclined slopes along narrow valleys, domination of undulated plains and numerous closed depressions alternated with small isolated hills; all together forms a very irregular pattern (See fig. 2, TP_04). On the other hand postglacial lowlands outside the extend of the last glaciation ("old glacial" in the rest of the paper) are due to substantial denudation under periglacial conditions characterized by smooth, wide and gently inclined slopes; channels with dendrite pattern, vast plains and lack of closed depressions. (see fig. 2, TN_10). The differences between those areas are expressed both in short-range textural properties represented by connection between individual cells and more general long range composition which is represented by amount and size of given terrain forms in the entire sample area.

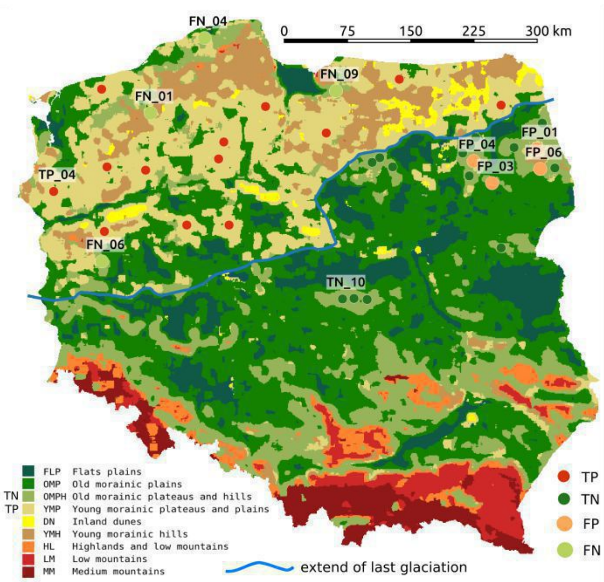

Figure 1. Location of learning and testing areas. True Positives (TP): areas classified as young glacial plateaus and located inside the extent of last glaciation; True Negatives (TN): areas classified as old glacial plateaus and located outside the extend of last glaciation; False Positives (FP): areas classified as young glacial but located outside the extend of last glaciation; False Negatives (FN): areas classified as old glacial but located inside the extend of last glaciation. Labels on misclassified areas and these two correctly classified areas used as examples on fig. 2.

B. Data

To address our problem we selected 3 areas which were used as training examples in [3] both for young and old moraine plateaus. We defined them as True Positive (TP) and True Negative (TN) respectively (fig. 1). Also we choose 8 areas which undoubtedly are located on young and old areas but were classified inversely. We defined them as False Positive (FP) and False Negative (FN) respectively (fig. 1).

C. Processing steps and implementation

To simulate landscape patterns we used FILTERSIM algorithm [8], [9] implemented in the SGeMS software [10]. This is an intermediate solution between the pixel and object-oriented simulations. Its essence is to use a reference image that is divided into small pieces. The algorithm classifies these pieces, and then assembles the image to fit the measurement data and previously arranged parts. The best analogy is perhaps that of building a puzzle. Resulting image should be as similar as possible to the reference (training) image, while keeping the data coming from the sample. The algorithm can be used to generate a desired set of simulations, whose variability is the result of different, random paths defining the stacking order of the pieces of which creates a whole.

In our experiments we sampled composition from incorrectly classified surfaces (FN and FP), and used the patterns from surfaces of TP and TN previously used to train classifier (fig. 2). Each of the 8 selected misclassified surfaces (4 FP and 4 FN) of 300*300 cells size has been subjected to 4 levels random stratified sampling (0.1, 0.2, 0.5, and 1% of whole data). These data was used as the source of texture during the simulations. For the evaluation of the simulations variability arising from the use of different random paths each one was repeated 3 times. One of the most important parameters that affect the quality of the result, is the size of the pieces (template size) which a master image is divided into. To assess its importance calculation was performed for the four sizes: 11, 15, 19 and 23 cells. Other parameters of the algorithm were left to the default settings [10]. In summary, for each tested FP and FN surface 288 simulations was performed (6 training images × 4 sampling levels × 4 template size × 3 repetitions), which gives a total of 2304 simulated surfaces (fig. 2).

All 2304 simulated areas were imported to GRASS GIS and used to calculate the similarity/distance matrix using GeoPAT software [4,5] using identical parameters for signature and similarity measure as described by Jasiewicz et. al. [3]. Similarity matrix was used to present results in a form of Sammon's map (fig. 3) which is a form multidimentional scaling which tries to map distance between objects in multidimentional space into the two dimentional plane.

III. Results

On Fig. 3A we see two distinct groups of samples, one representing correctly classified young glacial samples (red, True Positive), the second correctly classified "old glacial" (green, True Negative). Misclassified old glacial and young glacial areas are marked as FP and FN respectively and show higher similarity to the different group than the area where they are really located. Samples which results form series of conditional simulations (Fig 3B) show a much higher similarity to those areas from which sort-term pattern was taken, rather those which were provided as a source of long-range composition.

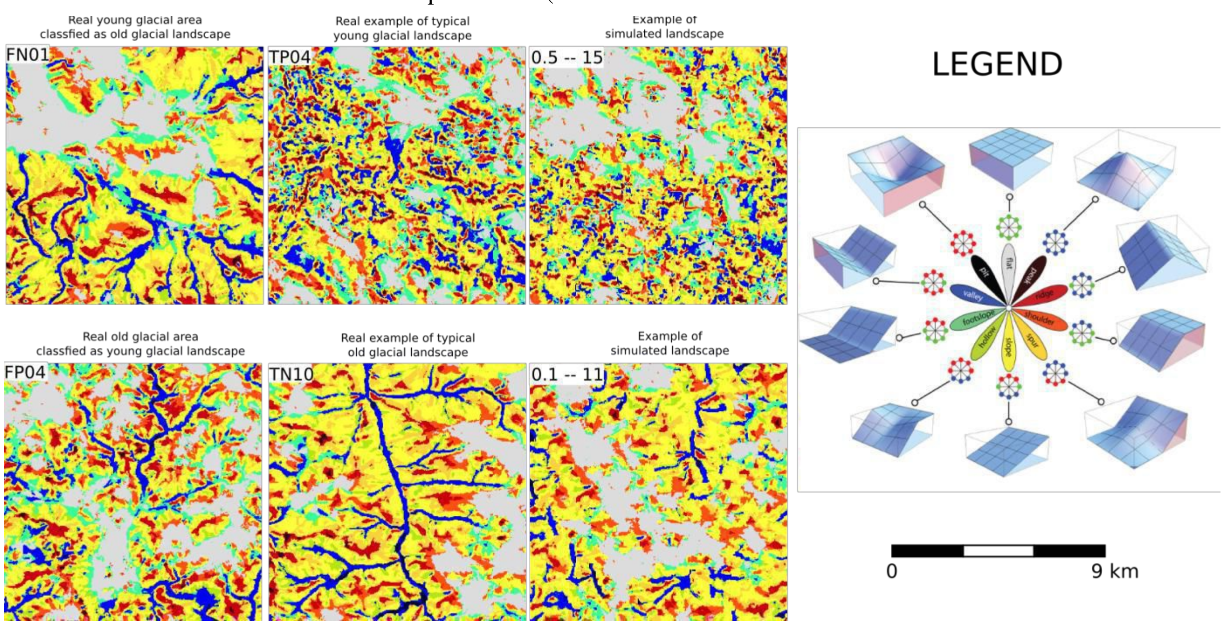

Figure 2. Example of simulations: misclassified young glacial area (upper row) old glacial area (lower row) with appropriate example of patterns used to simulate expected results. See text for details.

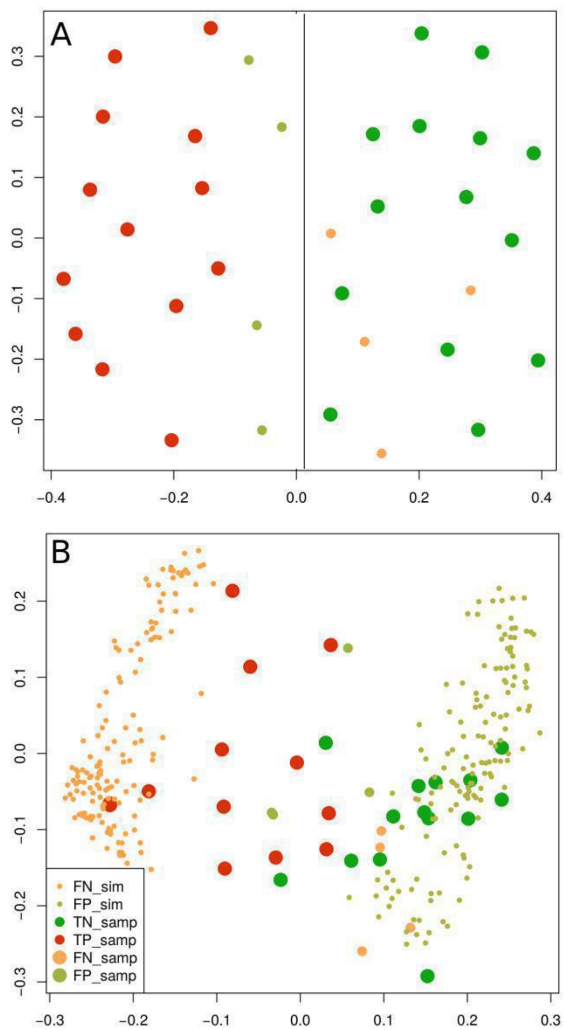

Figure 3. Classification of simulated areas on Sammon's map. Top panel (A) shows similarity between correctly and incorrectly classified samples (real). Bottom panel (B) show similarity between real samples and simulated examples. Both group of simulated areas are more similar to the group of samples from which short-range pattern is taken rather than to the group used as a source for long-range composition. Differences between location of real samples on left and right panels are results of the properties of multidimensional scaling. The values on the axes represent the dimensionless distance (objects similarity).

IV. CONCLUSIONS AND OUTLOOK

We found that misclassification error comes from convergence of landscape properties: after replacing texture in misclassified area with texture taken from correctly classified example new simulated area showed higher similarity to that landscape class from which it inherits texture than general composition. It allow to draw conclusion that short-range textural properties is that feature which best describes diversity of landscapes for automatic classifications.

V. ACKNOWLEDGMENTS

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