# Burial mound detection using geomorphometry and statistical methods: pixels versus objects

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*Abstract*—**Burial mound detection on high resolution data is a practical aspect of geomorphometry that has recently been in the focus of various researchers. Considering two of the best rated approaches in the literature, one based on a pixel approach and the other based on an object approach, a comparison was performed between the results of the two applied for a study area in North-Eastern Romania. The conclusion is that classification is slightly better in the case of the object-based approach in terms of confusion matrix, and much better in terms of false positive results, that need to be checked in order to separate the true positive cases. The object-based approach performs much better due to the reduction of feature space and the ability of the Random Forest algorithm to identify the geomorphometric signature of the burial mounds.**

## I. Introduction

In a previous research [1] burial mounds were detected using a three stages approach: a system of surface specific points, a segmentation approach and Random Forest classification using geomorphometric variables and shape descriptors. The proposed method obtained the second-best results in the literature regarding the confusion matrix [2]. The method that is rated as the first [3] used a multi-scale geomorphometric variable and Random Forest classifier trained on that variable to classify pixels as burial mound or not burial mound. Beside the fact that is pixel based, this methodology was not tested enough to convince that actually is the best: there was no exterior validation and the confusion matrix was computed based on pixels which gives biased measures since the classes are very imbalanced. We believe that actually if applied to a wide area, the number of false positives will be quite high, since any dominant position revealed by this index will be identified.

Classification problems assessed from a statistical point of view were shown to have multiple pitfalls [4], while multiple approaches for dealing with this were proposed [5-7]. While these results are not in the geoscience field, their conclusion is transferable since the machine learning methods are not different. Beside the normalization, multicollinearity and outlier removal, very often variable selection is an important approach. Cross-validation and bootstrapping are good methods for testing the improvement on the model for every variable, but biased results can be obtained if this is performed over the training data, the use of external data being proposed as an alternative approach [5,4]. Very few classifications from geosciences validate both internally and externally, regression or classification predictive models.

If for regression approaches the prediction power is assessed using various approaches (RMSE or AUROC), in classification problems the overall measures of confusion matrix like accuracy or even sensitivity can be inflated, if large number of false positives are present. It was shown that for Random Forest (RF) even importance measures are biased [8], situation that was found also in the object-based burial mound delineation previously [1].

In the present research I have considered the study case presented in [1], with two study areas of the same size and in proximity of each other (the two study areas are available in high-resolution images at https://doi.org/10.6084/m9.figshare.11798517.v2 and https://doi.org/10.6084/m9.figshare.11798613.v2), reflecting similar physiographic condition and archaeologic setting. The results obtained in [1] with geomorphometric objects segmented from local convexity and filtered by peak and seed presence are compared with a pixel-based approach implemented in this study.

While the final objective of the research is to find which method is better at identifying burial mounds from a certain area based on their geomorphometric signature, there are some details that need to be clarified in the case of pixel-based approach. The object-based approach has the advantage that the result is an object that can be easily assessed as burial mound or not based on a validation dataset of existing burial mounds, or if a user will browse the predicted objects. For the pixel-based approach since the number of predicted pixels is large, two approaches can be used: a quadtree search through which pixels clusters of predicted burial mound class are evaluated or the browsing of the spatial clusters of pixels with the burial mound class predicted. The

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quadtree approach is too expensive in terms of time, so the spatial clusters approach chosen as the best way to validate.

## II. Methods

Iterative tuning of the RF parameters and variables was performed in R software [9]. Rather than starting with parameter tuning, which is inexpensive from a computational point of view, training dataset setting selection was performed first. Then, variable selection was performed, and finally RF parameter tuning was realized.

In the literature, the training and validation can be performed both internally (intra-domain) and externally (extra-domain) [10], by using various proportions of class membership and training/validation ratios. In the present study latin hypercube sampling [11,12] was used to select the training dataset with the clhs package [13]. 75% percent of the burial mound (BM) pixels from the northern study area were used for training with a various number of non-burial mound (NBM) pixels: 13302, 43302 and 93302 (Figure 1) to model the class imbalance. Since if the number of burial pixels is decreased under 75% the fitted models performance degrades too much, values under this threshold were not considered. The 28 geomorphometric variables used by [1] (listed in Table S1 from the supplementary files) were used for selection based on the results of the prediction confusion matrix on the southern study area (external validation). The variables were evaluated both as single predictors (to assess the best performing variable), but also by bootstrapping to select the best prediction set of variables.

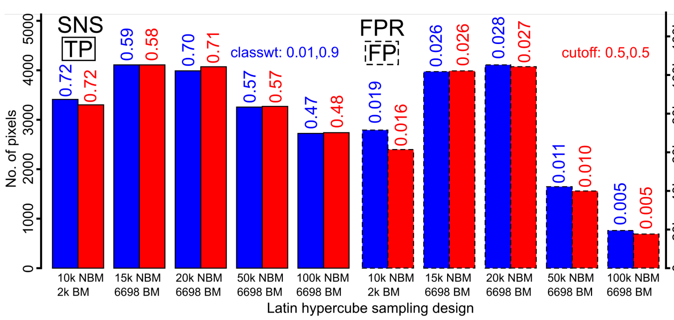


**Figure 1.** True positives and false positives and their confusion matrix measures for various settings of the latin hypercube sampling (SNS is sensitivity, FPR is false positive rate) and RF imbalance (blue is imbalanced, red is not).

For the selection of spatial clusters of predicted burial mounds, first single predicted burial mound pixels were excluded, then the prediction raster was converted to a polygon vector.

## III. Results and Discussions

The pixel-based approach is performing worse than the object-based approach both in terms of true positives (sensitivity) and false positives (false positive rate) for any setting of variables (Figures 1 and 2, Table 1). The main issue in the pixel-based approach scenario is related to the large number of false positives (Figures 3 and 4). Only by increasing this number to approx. 75% of the pixel candidates, the sensitivity (SNS) reach a reasonable value, similar with the object-based approach. But these results might be misleading, since the true validation should be done on how these predicted pixels characterize the burial mound sites.

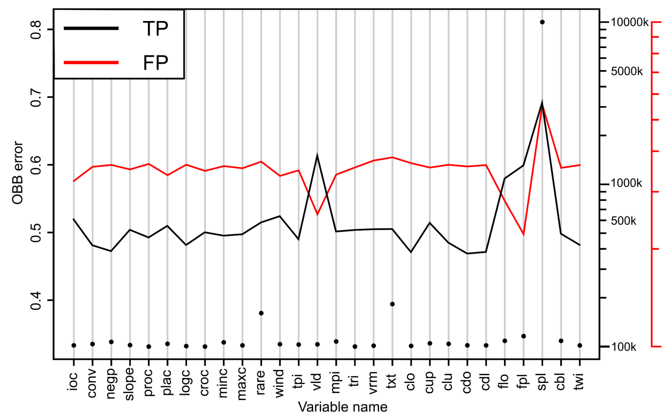


**Figure 2.** The OBB error (black points), true (TP) and false (FP) positive pixels (lines) for single RF models fitted with a single geomorphometric variable (the codes correspond to the Table S1 supplementary files of [1]).

Table I. Confusion matrix and its measures for the object-based approach of [1] for the southern study area (first row) and the pixel-based approach (second row)

| RF parameters | OBB error | TP | FP | SNS | FPR |
|---|---|---|---|---|---|
| 1000 segments from which 75% burial mounds, 100 ntree, 5 mtry, 1 nodesize | 3.1 | 25 | 46 | 0.93 | 0.004 |
| 15000 pixels from which 6698 burial mounds, 100 ntree, 3 mtry, 1 nodesize | 0.08 | 4109 | 101763 | 0.72 | 0.026 |

If the validation is performed in a small area where the burial mound density is high, very high SNS and FPR could be achieved, which is what [3] have done. But the validation needs to be achieved globally, for the training dataset (the northern study area – intra-domain) and for the validation dataset (the southern study area – extra-domain). A first approach could be the evaluation of how many pixels predicted as burial mounds were identified for every delineated burial mound. This analysis show that the majority of the burial mounds, both for the northern and the southern study areas have predicted burial mound pixels for over than 50% of their surface.

The second approach is to check if the predicted burial mound pixels are spatially clustered, so that the high number of false positive pixels can reach a reasonable amount, that allow the manual checking by an expert, in order to find all the burial mound sites.

Unfortunately, this result is not possible to be applied. If the spatial clusters are allowed to have more than 20 pixels, which is the smallest number of pixels that fit a delineated burial mound, five burial mounds for the northern study area will be missed. These results are showing that some burial mounds overlay only a small number of pixels predicted as burial mounds.

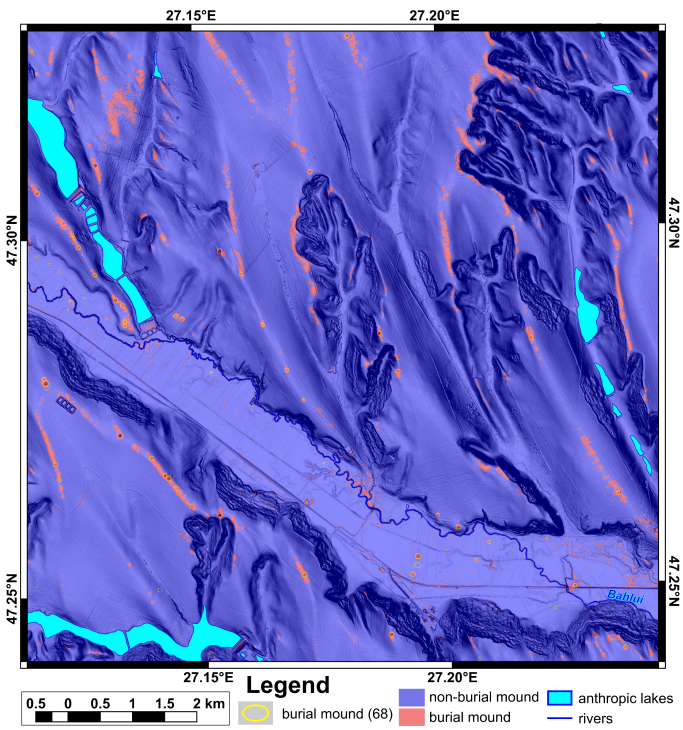


**Figure 3**. The results of the pixel-based approach for the northern study area (a high-resolution version is available at https://doi.org/10.6084/m9.figshare.11853564.v1).

For the southern study area, the results are better, all the 29 burial mounds having more than 20 pixels predicted. But, the number of these spatial clusters is still higher than the false positives obtained through the object-based approach.

For the northern study area 8592 clusters are obtained, while for the southern study area 9838 are obtained. The object-based approach of [1] obtained only 52 and 46 respectively.

Another observation is that sometimes the spatial clusters are very big or too small, situation that can hinder the manual or the semi-automatic verification of the predicted burial mound potential areas (Fig. 5).

## IV. Conclusions

In conclusion, I have shown that the object-based approach performs better than the pixel-based approach, both in terms of confusion matrix measures and in practical validation. The explanation of the superiority of the object-based approach is given by its power of feature space reduction, spatial aggregation and the usability of shape descriptors in the RF model. In this way the RF algorithm is able to find the geomorphometric signature of the burial-mound segments.

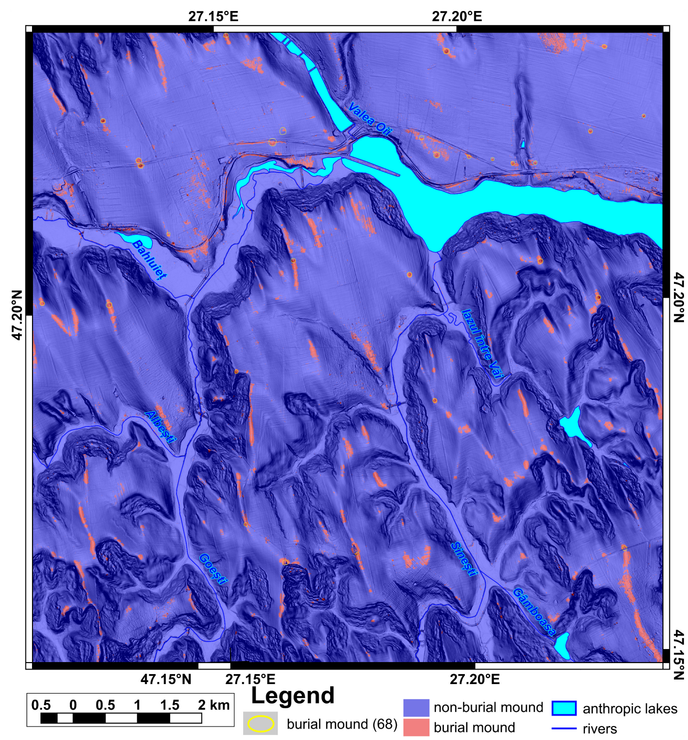


**Figure 4**. The results of the pixel-based approach for the southern study area (a high-resolution version is available at https://doi.org/10.6084/m9.figshare.11853570).

Because the classification problem is an imbalanced one, a certain amount of false positive cases is found, that need to be checked by an operator, in order to identify the burial mound sites. In the case of object-based approach the number of false positive segments is low enough to allow this check, while for the pixel-based approach the number is not reasonable enough.

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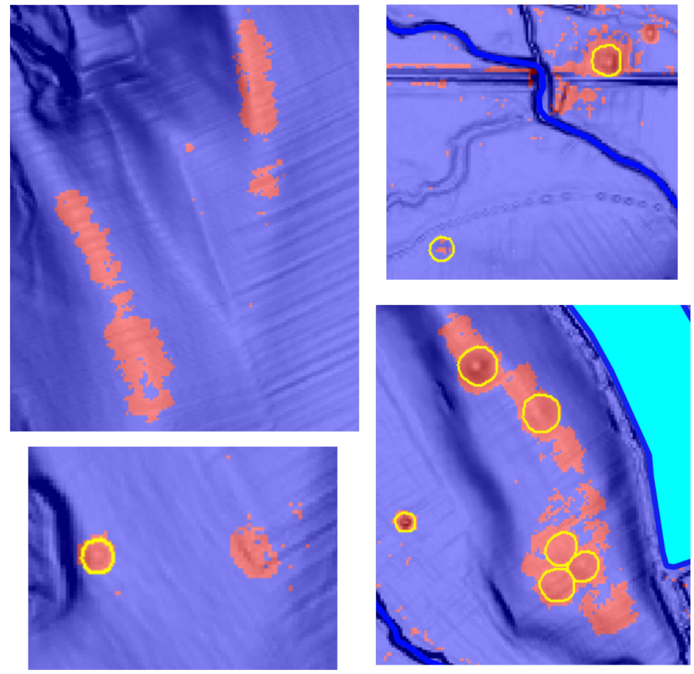

**Figure 5**. The results of the pixel-based approach for several situations: top left – false positive pixels with clear spatial clusters; top right – true positive pixels with spatial clustered and non-clustered false positives; bottom left – spatial cluster of true positive pixels for a well delineated burial mound and a false positive spatial cluster; bottom right – true positive and false positive spatial clusters of pixels in an area with high burial mound density (the legend is similar with Fig. 3).