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Detection of small-scale landscape elements with remote sensing

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Abstract. Landscape elements located on agricultural fields or on their edges play a crucial role in the biodiversity of agricultural land. The landscape elements' database in Estonia is updated in accordance with the applications of the field owners, and usually it does not represent a real situation of the landscape elements on the field. Hence, the analysis and control over landscape elements are limited. The main aim of this study is to create a methodology to map landscape elements in Estonia with remote sensing data. The first method was created considering the importance of computational efficiency and therefore fast and non-complex map algebra solution was developed. The second, more precise but more computationally expensive way to map landscape elements, was the object-based image analysis method utilizing machine learning classification. Both methods displayed high overall accuracies, but users' and producers' accuracies were lower. Taking into account the computational time and accuracy, it was concluded that the map algebra method is better suitable for fast landscape elements' detection. However, the object-based image analysis method is more suitable for identifying more exact classes of landscape elements.

Keywords. landscape elements, GEOBIA, openness index, machine learning

1 Introduction

The European Union created the Common Agricultural Policy (CAP) in 1962, which aims to provide European farmers with a sustainable environment, enhance agricultural productivity and to supply with numerous other goals beneficial for everyone. There are various measures in CAP to achieve these goals - one of them is greening. The presence of landscape features, such as linear vegetation patches, ditches, or small forest islands on agricultural fields, is an important part of greening. It has a positive effect on landscape diversity, animals' biodiversity and habitats connectivity (Marja *et al.* 2013; Zurqani *et al.* 2020). Mapping such landscape elements in Estonia is conducted by Agricultural Registers and Information Board. Landscape features are added into the database manually in line with the farmers' applications. This is very time-consuming work and not very practical for large scale mapping.

The aim of this study is to develop remote sensing based methodology, which would allow to provide reliable detection of landscape elements in Estonia. In addition, we also estimated the computational time of each model to estimate how feasible would be large scale applicability of the models.

2 Data and methodology

2.1 Study area and data

Six Estonian Topographic Database map sheets 5 × 5 km study areas were chosen from three different landscape regions in Estonia. From each landscape region, one was for training, and one was for validation (Figure 1).

DEM, nDSM with spatial resolution 1 m and orthophotos with pixel size of 0.25 m were used. Orthophotos were then converted into 1 m spatial resolution to reduce the processing time.

2.1 Methodology

First, several derivatives of Digital Elevation Model (slope, longitudinal curvature, minimum and maximum curvature, openness index and valley depth) were tested to enable better detection of ditches. The most efficient derivative was topographic openness index (Yokoyama *et al.* 2002) which accentuates the ditches the most (Figure

2). Second, two models were developed: (1) one was based on map algebra as a non-complex and fast method; (2) second one was an object-based image analysis method utilizing machine learning classification for more detailed and precise detection. Both models were tested in 3 study areas in Estonia: Southern Estonia, Central Estonia and Saaremaa Island (Figure 1).

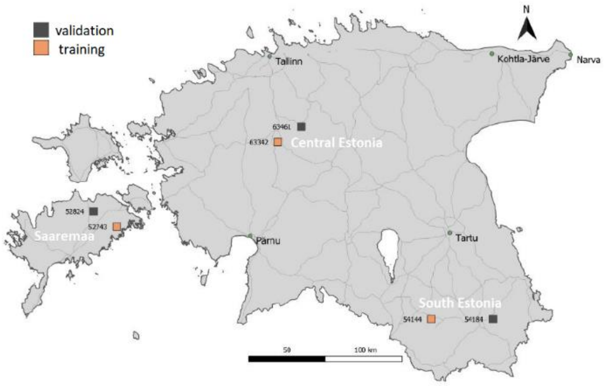

Figure 1 Study areas in Estonia.

The first model (from here on Model 1) used the following layers: 1) binary mask for arable land based on the official registry of agricultural lands. 15m-buffer was created for all arable lands to include potential landscape elements from the edges of the arable lands; 2) binary mask of buildings based on Estonian National Topographic Database (ETAK); 3) binary mask of vegetation based on nDSM model where all vegetation above 2m was assigned value 1 and the rest was assigned value 0; 4) binary mask of ditches based on topographic openness index where based on the histogram was determined that all values below 1.5 were likely to be ditches and were assigned mask value of 1.By using map algebra (multiplication), these four masks were combined to obtain three landscape element types: ditches, ditches with vegetation and vegetation patches. Post-processing was done by using Sieve function to remove patches that consist of only few pixels.

The second model used object-based image analysis (OBIA) where two different sub-models were created based on: 1) topographic openness index + nDSM (from hereon Model 2a) and 2) topographic openness index + nDSM + NDVI (from here on Model 2b). The developed object-based models consisted of segmentation and classification stage. During the first classification stage, segments were classified into vegetation, ditch and ditch covered by vegetation classes based on segment's spectral signatures. During the second stage, segments dissolved by predicted class were classified into linear vegetation patches, vegetation islands on the field and ditches based on spectral properties and shape indices. Segmentation was performed by using open source Orfeo Tooblox (Grizonnet *et al.* 2017).

During the classification stage, initially three machine learning methods were tested: support vector machine, neural network and random forest. However, in the testing phase it was identified that neural network and random forest outperformed the support vector machine, however, neural network was significantly slower than random forest and therefore only random forest were used in the latter stages. Based on spectral properties and shape indices, following landscape elements were identified: linear vegetation patches, vegetation patches (non-linear) on the field and ditches.

For the validation, all landscape elements were manually digitized. Confusion matrices were used to estimate the classification accuracy.

For each model, also computational time was estimated as on large scale implementation, time will be a significant consideration. The used computer specification:

- Processor - AMD Ryzen 5 3500U with Radeon Vega Mobile Gfx, 2,10 GHz
- RAM – 16 GB (of which 13,9 GB are usable)
- System – Windows 10 Pro

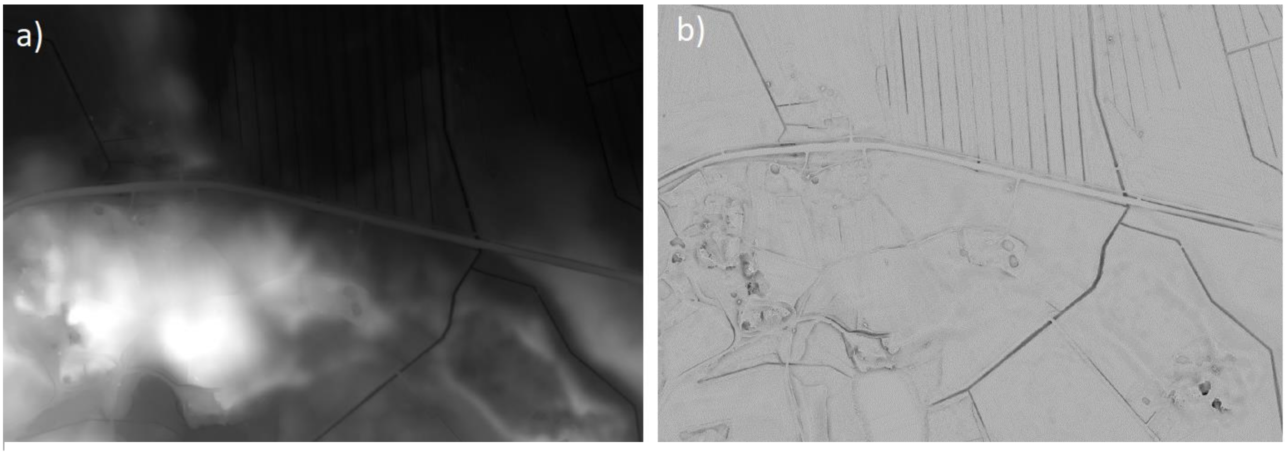

Figure 2 Comparison of the digital elevation model (a) and topographic openness index (b). Topographic openness index enabes to idendify ditches more easily.

3 Results and discussion

The map algebra (Model 1) approach had quite high overall accuracy of 86.78% but lower user's and producer's accuracies (Table 1). The ditches were better detected compared to vegetation islands. As Model 1 approach was pixel based then it was also noisier compared to Model 2a and 2b that were object-based methods (Figure 3). However, cleaning by sieve made the Model 1 result significantly better (Figure 4).

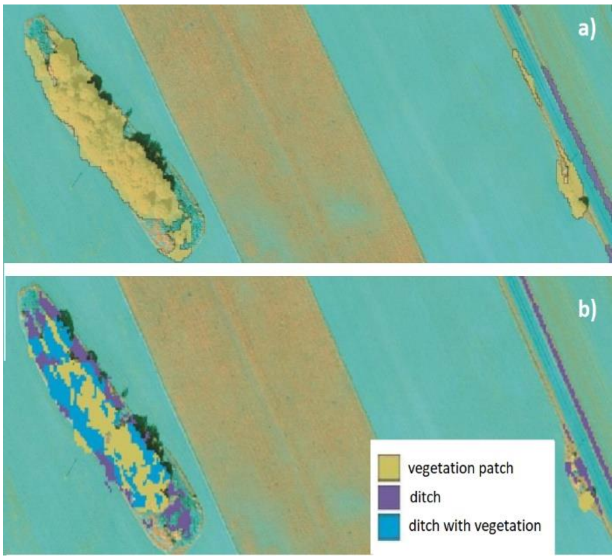

Figure 3 Example of classification by (a) Model 2 (OBIA), and (b) Model 1 (map algebra**).**

The object-based image classification overall accuracies were 86.9% for Model 2a and 86.5% for Model 2b. Adding NDVI did not improve the overall accuracy of the model, moreover, some classification accuracies were even notably higher using only elevation data. This is likely due to lack of sufficient number of training areas within each map sheet and vegetation patches do not have too characteristic spectral signal. The producer's and user's accuracies were the highest for the vegetation islands and lowest for the linear vegetation.

Overall, both methods (map algebra and OBIA) performed reasonably well. The ditches showed the highest accuracies in case of all models, although some parts of the ditches are not detected (Figure 3), especially if they are under higher vegetation. The linear vegetation showed the poorest accuracies for Models 2a and 2b and vegetation islands for Model 1. All models could be improved by adding more training data.

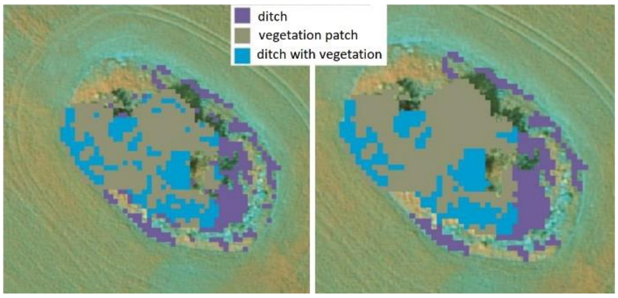

Figure 4 The effect of cleaning by Sieve on Model 1 (map algebra) results: (a) not cleaned and (b) cleaned by sieve.

The fastest model computationally was Model 1 (map algebra, For one 5 × 5 km map sheet, full analysis workflow took less than a minute (53 seconds). If this method would be applied to whole Estonia, then it would take approx. 34 hours. Model 2a and 2b were significantly slower, approx. 8 minutes (504 seconds) and 11 minutes (658 seconds) respectively without training. The most time-consuming part was segmentation taking approx. 70% of the total time. The segmentation parameter selection/optimization is time-consuming and often local approaches outperform global segmentation parameter optimization approaches (Johnson & Ma 2020).

Table 1 Producer's and user's accuracies of the models.

	Producer's accuracy			User's accuracy		
Model	1	2A	2B	1	2A	2B
Ditch	93.5%	85.6%	85.8%	90.2%	99.1%	99.2%
Linear vegetation		77.9%	78.8%		39.1%	38.2%
Vegetation island	63.9%	97.2%	62.1%	68.2%	73.9%	71.5%

For whole Estonia, the computation of these models would take approx. 8 days and 10.5 days respectively.

4 Conclusions

In conclusion, taking into account the computational time and accuracy, the map algebra method is better suitable for quick and robust landscape elements' detection. However, the object-based image analysis method is more suitable for identifying more exact classes of landscape elements.

5 Data and Software Availability

All data used in this study is available on Estonian Land Board (https://geoportaal.maaamet.ee/eng/Spatial-Data-p58.html). No code was developed or used in this work.

Acknowledgements

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