# ASSESSING THE QUALITY OF HEATHLAND VEGETATION BY CLASSIFICATION OF HYPERSPECTRAL DATA USING SPATIAL INFORMATION

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Due to urbanization, conversion to forest or agricultural land, but also atmospheric changes, heathland areas in Western Europe started to decline from the beginning of the 20th century [1]. As a result, many heathland sites, among which Kalmthoutse Heide in Belgium, were included in the European Natura 2000 program, a network of protected areas all across the European Union [2]. The EU-member states, that are responsible for the management of the sites on their territory, are required to monitor the conservation status and report to the European authorities on a regular basis . Consequently, accurate and up-to-date vegetation maps, that also include information on the status of the vegetation, are of great importance. This article deals with a method for acquiring such vegetation maps, suitable for monitoring and evaluating the conservation status of heathland vegetation.

As the heathland area harbors a multitude of habitat types, the additional requirement of providing information on the status of these habitats, narrows down the way of acquiring the data to hyperspectral airborne sensors. Only this way, enough spectral and spatial detail is present to provide a good vegetation map. For Kalmthoutse Heide, the airborne hyperspectral data were obtained in June 2007 with an AHS sensor with a ground resolution of approximately 2.5m. The range of 450nm-2550nm is covered by 63 spectral bands.

During summer 2007, ground reference data were collected in homogeneous plots of 10 meters diameter. The vegetation data of the sampled plots, approximately 1200 in total, were analyzed and plots were grouped in a hierarchical classification scheme with 4 levels of detail. The first level(lowest detail) comprises only 6 classes: heathland, grassland, forest, sand dunes, water bodies and arable fields. Level 2 and 3 mostly determine specific habitat types of the Natura 2000 program, containing 11 and 17 classes respectively. Level 4 (highest detail) comprises 24 classes, focusing on vegetation structural elements that determine the conservation status of the habitat types. For example, a distinction is made between Calluna-stands of predominantly young, adult or old age.

The unique way in which the data have been collected and subdivided offers the freedom of classifying on a per-level basis, but also allows the creation of a hierarchical tree, through which we can classify one level after another. In addition, in search for obtaining more readily interpretable vegetation maps, including textural/contextual features in the classification process is an important consideration. A popular way of taking into account the spatial features is to incorporate dependencies between neighboring pixels as prior knowledge in a Bayesian classification framework and model them by Markov Random Fields [3, 4]. [5] proposes a recursive supervised segmentation algorithm based on a tree-structured Markov Random Field (TS-MRF). The hierarchical structure of the heathland data makes this technique especially interesting.

In [5, 6], a binary tree is constructed, exploiting the hierarchical structure exhibited in the image. The leaves of this tree correspond to the end classes. The TS-MRF model describes a K-ary label field by means of a sequence of binary MRFs, each one corresponding to a node in the tree. Each field is configurable separately and therefore allows for many more degrees of freedom than conventional models. The tree structure is by no means restricted to the binary case, but is selected because of its relative simplicity, as it reduces the computational burden.

In our work, the applied tree is not binary and is no longer determined during classification. Rather, it is built from the structural dependencies which follow naturally from the hierarchy, that is already present in the ground reference data. This way, a trade-off is made between the computational feasibility and a tree that reflects the biological situation in a more suitable way.

The obtained classification results are compared to tree-based spectral classification results, and the former with post-processing (spatial smoothing in the form of majority analysis) applied. In general, the classification accuracies of the various techniques, obtained through cross validation, are very comparable. With respect to spectral classification, both the simple post-processing method as TS-MRF provide more easily interpretable results. Unlike the post-processing technique, however, TS-MRF is capable of better preserving important structural elements and vegetation transitions.

(a) 200 × 200 area in Kalmthoutse Heide
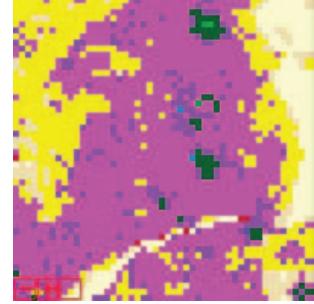


(b) Spectral tree-based classification result
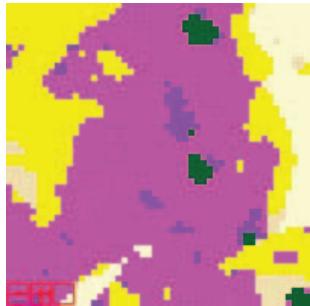


(c) Tree-based classification with MA
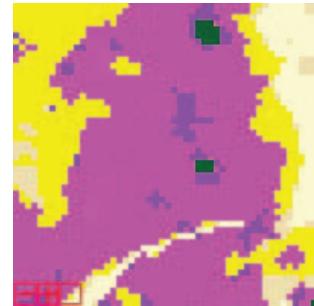


(d) TS-MRF Classification

**Fig. 1**. Example area classification results

In Fig. 1 these findings are illustrated on a small patch of the Kalmthoutse Heide dataset. Fig. 1(a) shows several types of heathland in the center, classified in purple, with a few trees, classified in dark green. Sand dunes (bare and fixated) are shown at the edges and in the form of a narrow sandy road and are classified in yellow. Spectral classification based on the hierarchical tree, excluding contextual information, is shown in Fig. 1(b). Application of post-processing in the form of majority analysis (MA) on this result is depicted in Fig. 1(c). Clearly, the classified image becomes more easy to interpret, with more homogeneous regions. Unfortunately, important details, like the narrow sandy road, disappear. Classification using the TS-MRF technique is shown in Fig. 1(d). The image becomes more easily interpretable as well. But at the same time, structural elements, such as the small road, are better preserved.

## 1. REFERENCES

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