AN OBJECT-BASED APPROACH TO QUANTITY AND QUALITY ASSESSMENT OF HEATHLAND HABITATS IN THE FRAMEWORK OF NATURA 2000 USING HYPERSPECTRAL AIRBORNE AHS IMAGES

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ABSTRACT:

Straightforward mapping of detailed heathland habitat patches and their quality using remote sensing is hampered by (1) the intrinsic property of a high heterogeneity in habitat species composition (i.e. high intra-variability), and (2) the occurrence of the same species in multiple habitat types (i.e. low inter-variability). Mapping accuracy of detailed habitat objects can however be improved by using an advanced approach that specifically takes into account and exploits these inherent patch characteristics. To demonstrate the idea, we developed and applied a multi-step mapping framework on a protected semi-natural heathland area in the north of Belgium. The method consecutively consists of (1) a 4-level hierarchical land cover classification of hyperspectral airborne AHS image data, and (2) a kernel-based structural re-classification algorithm in combination with habitat patch object composition definitions. Detailed land cover composition data were collected in 1325 field plots. Multi-variate analysis (Ward's clustering; TWINSPAN) of these data led to the design of meaningful land cover classes in a dedicated classification scheme. Subsequently, the data were used as reference for the classification of hyperspectral AHS image data. Linear Discriminant Analysis in combination with Sequential-Floating-Forward-Selection (SFFS-LDA) was applied to classify the hyperspectral images. Classification accuracies of these maps are in the order of 74-93% (Kappa= 0.81-0.92) depending on the classification detail. To subsequently obtain habitat patch (object) maps, the land cover classifications were used as input for a kernel-based spatial re-classification process, in combination with a rule-set that relates specific Natura 2000 habitats with a composition range of the land cover classes. The resulting habitat patch maps illustrate the methodology's potential for detailed heathland habitat characterization using hyperspectral image data, and hence contribute to the improved mapping and understanding of heathland habitat, essential for the EU member states reporting obligations under the Habitats Directive.

1. INTRODUCTION

Human activities such as urbanization, industrialization and successive agricultural revolutions cause rates of habitat destruction and species loss to continue to rise. As a result, conserving biodiversity has become imperative during the last decades, and conservation action is increasing globally as the scale of the threat to biodiversity is more widely recognized (Pullin *et al.*, 2004).

In Europe, the most important standards for biodiversity protection are the Habitats Directive (92/43/EEC) (HabDir) and the Birds Directive (79/409/EEC), which form the legal basis of the Natura 2000 network. Among the various commitments imposed by these legal initiatives on EU member states, are (1) the design of accurate, simple and repeatable methods for habitat and species monitoring and surveillance; and (2) the reporting on the '*conservation status*' of the habitats present in the member state. In practice, these commitments imply that every 6 years all EU member states are obliged to report on the conservation status of the protected habitats, and the methodology applied for the assessment (Förster *et al.*, 2008). The conservation status of the habitats has to be assessed in terms of the range, the covered area, and the overall quality as expressed by the structure and ecological functioning of the habitat. These assessments require detailed, reliable and up-to-date habitat distribution maps, stretching further than merely attributing a given vegetation patch to a habitat type, but also giving indications on its quality. The first implementations of the directive by member states however revealed a great lack of knowledge on habitat distribution in many member states (Evans, 2006). An easily operated, economically priced and as far as possible automated application is hence desired to meet these high data needs.

As remote sensing products can provide a systematic, synoptic view of the earth cover at regular time intervals, they have been repeatedly indicated as a possibly useful tool to aid in the mapping and monitoring of habitat types and biodiversity (Förster *et al.*, 2008; Nagendra *et al.*, 2008). Most efforts have however been directed at providing data at larger patch- and landscape-scales using multispectral satellite imagery, such as Landsat ETM+ or Quickbird data. Whereas the scale of such analysis may be very valuable for the studies of human drivers of land cover change or coarse habitat mapping at a global or national scale, its application in the field of detailed biodiversity or habitat mapping (scales 0.01-0.1 ha) is rather limited and tends to be less effective due to errors related to terrain shadowing, geo-locational discrepancies, and other factors (Carlson *et al.*, 2007; Díaz Varela *et al.*, 2008; Nagendra *et al.*,

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2008). Hyperspectral data (15-200 bands), with the ability to collect information at a high spectral resolution using contiguous spectral bands, each with a narrow spectral range, are known to be capable of fairly accurate identification of different species (Carlson *et al.*, 2007). Clark *et al.* (2005) for example have shown that variability in hyperspectral information can be used to great effect for discriminating tree species in landscapes including tropical forests, despite the greater complexity of such environments. Notwithstanding the potential of hyperspectral imagery for habitat and diversity studies, its use in this research domain is rather limited (Nagendra *et al.*, 2008).

Our objective is to demonstrate the potential of hyperspectral remote sensing in combination with advanced image analysis techniques to map and discern detailed (even ≤ 0.1 ha) heathland habitat patch objects and valuable quality-indicating characteristics. By doing so, we contribute to making remote sensing more relevant for applied ecology, and provide a remote sensing framework with possible use for the legislative reporting obligations of each EU member state under the Habitats Directive.

2. MATERIALS AND METHODS

2.1 Study area

The study area, the *Kalmthoutse heide* (Figure 1), has been designated by the Flemish authorities as a part of the Natura 2000 network since 1996, and is located in the north of Belgium (Lat.: 51.41°, Long.: 04.37°). Its central heathland area is almost a 1000 ha in size and contains a mixture of wet and dry heath, inland sand dunes and water bodies (De Blust & Slootmaekers, 1997). An overview of the Natura 2000 habitat types that are well-represented in the area is given in Table 1.

Despite its protected status, and due to its location in the vicinity of the city and the harbour of Antwerp, the area is still affected by anthropogenic influences such as eutrophication, intense recreation and desiccation (through drinking water extraction). Nitrogen deposition from the sky accelerates dune fixation by the alien invasive moss species *Campylopus introflexus*, and leads to an increased dominance of *Molinia caerulea* (purple moorgrass) in wet and dry heaths, at the expense of the former species diversity. In recent years, some intensive and uncontrolled fires have destroyed nearly one-third of the area's heaths, which were subsequently rapidly colonized by *Molinia caerulea*. To counteract negative influences, dedicated management has been implemented since the 1970s. Measures include mainly grazing with sheep and cows, sod-cutting, mowing and tree removal, to keep the heathland open and in good condition (De Blust & Slootmaekers, 1997; De Blust, 2007). The resulting large spatial heterogeneity of habitat types (and quality) makes the area specifically suitable to demonstrate the potential of the proposed methodology.

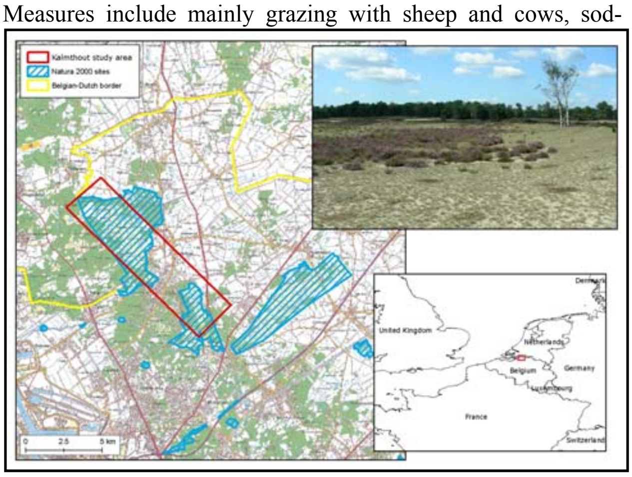

Figure 1. Figure 1. Location and illustration of the study area 'Kalmthoutse Heide' in the north of Belgium.

HabDir code	Habitat type
2310	Dry sand heaths with *Calluna* and *Genista*
2330	Inland dunes with open *Corynephorus* and *Agrostis* grasslands
4010	Northern Atlantic wet heaths with *Erica tetralix*
4030	European dry heaths
6230	Species-rich *Nardus* grassland
7150	Depressions on peat substrates of the *Rhynchosporion*
3160	Natural dystrophic lakes and ponds
9190	Old acidophilous oak woods with *Quercus robur* on sandy plains

Table 1. Natura 2000 habitat types present in the '*Kalmthoutse heide*' study area

2.2 Ground reference data

Two extensive and independent field reference data sets were acquired in June-September 2007 (period of image acquisition), and June-September 2009 respectively.

During the field campaign of 2007, sample plots were selected in the field as circles of 10 m diameter that represented homogeneous examples of one of the predefined land cover classes. Centre points of plot circles were located using GPS. To ensure adequate description of vegetation composition and structure in the sample plot, data collection was based on the BioHab-methodology (Bunce *et al.*, 2008), and included cover of plant life forms and dominant species, as well as environmental and management qualifiers. Cover was always estimated as seen from above, thus adding up to 100%, to resemble a sensor's viewpoint. Some plant species were split up into multiple land covers, and recorded separately to provide data on quality indicators (e.g. *Calluna vulgaris* development phases: young, mature, old, and mixed). In 2007, samples were collected at a total of 694 plots, to which an extra 146 plots were added that were collected in the same area in 2006. Additionally, sample plots of easily recognizable classes were taken from orthophoto-interpretation, supported by expert terrain knowledge. This specifically provided additional samples for bare sand, arable fields, agricultural grasslands, *Juncus effusus*-swards and unvegetated water bodies, raising the total sample size in the ground reference (land cover training) dataset to 1325 plots.

To enable independent validation of the habitat map results, an additional field campaign was performed in 2009. A thematically and geometrically stratified random sampling survey (586 plots) was set out to directly collect habitat information, in contrast to the detailed land cover survey of 2007. Although there is a two-year time gap between both surveys, the habitat patches present are expected to not have changed drastically over this period, and areas that clearly had changed since 2007 were omitted from the sample. Possible additional errors in the validation accuracies are therefore thought to be of minor influence. The field surveys were performed by two different people to enhance the independency of the data sets.

2.3 Hyperspectral image data

In June 2007, Airborne Hyperspectral line-Scanner radiometer (AHS-160) images of the *Kalmthoutse Heide* study area were acquired. The AHS sensor was mounted on a CASA C-212 airplane operated by INTA, equipped with 63 spectral bands in the visual and near-infrared spectral domain (400 to 2500 nm). The images, acquired with a spatial resolution of 2.4 by 2.4m, were radiometrically calibrated and accurately geo-referenced. Geometric and atmospheric correction were performed using VITO's in-house Central Data Processing Center (CDPC) (Biesemans *et al.*, 2007). Subsequently, all 6 image products were mosaicked into a nearly seamless data product. To do so, atmospheric influence on reflectance values caused by off-nadir viewing was minimized by using data from the image with the smallest View Zenith Angle (VZA) in overlapping areas.

2.4 Methodological framework

Based on the inherent properties of (semi-)natural heathland habitats and of hyperspectral image data, we developed a methodological framework that enables (semi-)operational habitat quantity and quality mapping at the patch level. In summary, the method consists of breaking down habitats into a number of (hierarchical) land cover classes that 1) are expected to be spectrally distinct; 2) incorporate parameters that can serve for habitat quality assessment; and 3) enable the subsequent reconstruction to habitats using patch composition. In a two-step process, the hyperspectral data are first classified using field data as training, and subsequently the obtained land cover classification maps are transformed to habitat (quality) patch maps by means of a spatial kernel-based re-classification technique in combination with a habitat reconstruction rule-set. Figure 2 gives a schematic overview of the proposed methodology. In the following sections, each separate step in the methodology is explained in detail.

2.5 Design of a dedicated classification scheme

In most cases, the observed land cover pattern in a habitat patch (presence/absence, relative abundance) is a result of processes acting on the habitat patch, and therefore reveals information that can be used to assess the quality of that patch. While some land cover types indicate a good habitat quality, others indicate processes that negatively affect habitat quality. Several member states have made use of this inherent complexity of habitats to draw up evaluation frameworks for the assessment of quality of habitat patches (e.g. T'jollyn *et al.*, 2009). For habitat type 2310 for example (Table 1), positive quality indicators are the presence of bare sand and patches of mosses and lichens, whereas encroachment by grasses (especially purple moorgrass, *Molinia caerulea*), trees and the invasive *Campylopus* moss are negative quality indicators.

In order to raise the chances of successful habitat mapping and quality information extraction from hyperspectral remote sensing data, the classification scheme should comprise of classes that are delimited based on attributes that strongly influence the spectral signature. Plant architecture, above-ground biomass and dominant species are such attributes. Therefore, the list of habitats present in the study area (Table 1) was translated into a list of land cover classes, which can be interpreted as spatial units of homogeneous vertical structure and plant species dominance. Once the image is classified, these classes can then be translated back into Natura 2000 habitats, by making use of the spatial arrangements of classes in the image to facilitate this back-translation and to incorporate information on habitat quality.

In a first step, a provisional list of expected land cover classes was drawn up from the list of habitats present. Habitat definitions (European Commission, 2007; amongst others) and quality indicators (T'jollyn *et al.*, 2009) served as input for this translation. Focus was put on quality indicators that relate to vegetation patterns and processes in the habitat, and not to species composition, because the latter relies on the presence of typical but usually rare (and often small) plant species that hardly influence the spectral signature. In a second step after the field work, the collected data were analysed using two contrasting techniques of multivariate analysis: (1) TWINSPAN (a divisive method; Hill and Smilauer, 2005) and (2) Ward's clustering with Euclidean distance measure (an agglomerative method; McCune and Mefford, 2006). For each plot, the cover (in %) of the plant life forms as well as of the dominant species (i.e. all species having 10% or more cover in the vegetation) were used as input variables, thus restricting the analysis to those parameters that are hypothesized to show the highest correlation to the spectral signatures. The outcome of both methods was compared and clear outliers were removed from the dataset, to assure that remaining clusters were homogeneous in sample composition. Each of the retained clusters was consequently interpreted and identified with a land cover class from the provisional list. Some of these predefined classes turned out not to be present in the study area in sufficient amount or in sufficiently large patches and were removed from the list (e.g. *Rhynchosporion* vegetations). Others were slightly adapted to better correspond to the field situation. This led to a final list of land cover classes (Figure 3d). In a final step, the land cover classes were manually arranged in a 4-level hierarchical classification system, based on similarity of plant life forms or dominant species present.

2.6 Detailed land cover classification

The land cover classifications were performed using one-against-one majority-voting Linear Discriminant Analysis

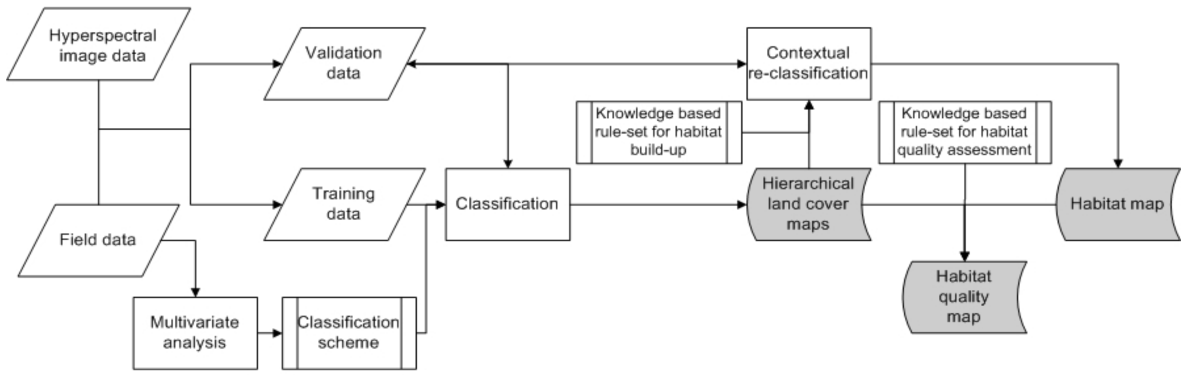

Figure 2. Flowchart of the proposed methodology for habitat patch quantity and quality mapping

(LDA) in combination with Sequential-Floating-Forward-Search (SFFS) band selection algorithm. With this methodology, the complexity of the multi-class assignment problem is circumvented by combining several binary LDA classifiers. The one-against-one approach implies that for each pixel spectrum all possible pairs of output classes are compared, resulting in C(C-1)/2 classifiers. The finally assigned land cover class is then decided through a maximum-voting decision rule. The Sequential-Floating-Forward-Search band selection technique was used to extract the band combination that leads to the highest accuracies. In short, the technique sequentially adds one additional band at each step, but additionally one or more backward steps are taken to remove a previously selected variable to see if the separability measure can be increased at that level (Pudil *et al.*, 1994). One of its main advantages over other feature selection or extraction techniques is that it optimizes the selection to the problem at hand, instead of merely reducing the computational complexity or feature space. This classification approach has proven to be robust for classification of hyperspectral data in previous vegetation studies (Deronde *et al.*, 2008; Kempeneers *et al.*, 2005).
The results of the land cover classifications are discussed in section 3.1, albeit briefly as they are not the focus of this study.

2.7 Rule-set for habitat compositions of land cover classes

The classification scheme was designed in such a way that the list of habitats present in the study area is translated into a list of land cover classes that can be classified using the spectral signatures. These land cover classes can conversely be interpreted as spatial units which can serve to build up a map of Natura 2000 habitat patch objects. Certain land cover classes can however occur in different habitat types, hampering a straightforward re-classification.
To circumvent this issue, we defined a number of rule-sets that characterize each habitat, using percentage ranges of land cover composition. Based on the descriptions of habitats (European Commission (2007); amongst others), we identified which land cover classes can occur in each habitat type, and what the minimal and maximal percentage of occurrence within a habitat patch are. Two different rule-sets were compiled: (1) one that relates the land cover composition only to the type of habitat; and (2) a second in which the composition rules not only relate to the habitat type, but to specific quality indicators as well. Composition overlap between different habitat type definitions was allowed as this possibly might reflect and allow to map the true fuzziness of patches (e.g. at the borders). For each habitat type, a maximum presence of 10% of land cover classes other than those that characterize the habitat was also allowed. This rule was added because habitats are intrinsically heterogeneous and the presence of a non-typical land cover to such a low extent does not influence the overall habitat patch characterization. Moreover, such a rule tolerates up to 10% of misclassification in the land cover classification, making the final habitat map result more robust, i.e. less sensitive, to errors/noise in the prior land cover classification.

2.8 Contextual re-classification to habitat patch objects

To reclassify the land cover classification map to a habitat map, we adopted a modification of the algorithm proposed by Barnsley and Barr (1996). In their kernel-based re-classification technique, a convolution kernel is moved across the land cover classification image. At each pixel, the local spatial patterns in a kernel of fixed size (e.g. 3x3) are explored, and compared to a set of reference kernels. These (reference) template kernels characterize each desired output class type, and are based on training datasets in the initial land cover map. Our re-classification method differs from the above technique in that:

- it does not take into account the spatial arrangement within the kernel, but merely looks at the class composition (in %).
- template kernels are not defined based on training areas in the initial land cover map, but using knowledge-based habitat compositions.

In a first approach a habitat (or overlap) class was only assigned when the window land cover composition specifically fell into the percentage ranges of that habitat. If it did not fit any of the percentage definitions, the pixel was marked as being no habitat (of interest).

3. RESULTS AND DISCUSSION

3.1 Land cover classification results

A true-color image and level-4 (most detailed) classification extract (587 x 455 pixels) of the core study area is shown in Figure 3a and 3b. Overall classification accuracies (and Kappa indices) using leave-one-out validation proved to be rather high at all levels of detail (level 1-3 > 80%; level 4 > 70%; Table 2). Accuracies drop the most from level 3 to 4. At level 3, all classes still consist of specific vegetation species or land cover types. At level 4 however, structural elements within one species are introduced. Confusion specifically occurs within (1) the age classes of *Calluna* heath (young, adult, old, and mixed); and (2) the permanent grassland types (species rich and species poor). Different strategies might be pursued to improve the accuracy of the structural quality classes (level 4), e.g. using spectral unmixing techniques to characterize the age classes, or exploiting spatial dependency information. This is however not the focus of this study, the reader is referred to Delalieux *et al.* (2010) and Thoonen *et al.* (2010), respectively.

Level	Number of classes	Overall Acc.	Kappa
1	6	93	0.92
2	11	88	0.85
3	17	84	0.84
4	24	74	0.81

Table 2. Overall classification accuracies and Kappa indices of the land cover classifications at different levels of detail.

3.2 Habitat patch map results

Figure 3c shows the resulting habitat map for an extract of the study area. The habitat patch map consists of 10 classes relating to 6 Natura 2000 habitat types. The *2310/4030* class is included because of the high similarity between both habitat types in certain circumstances. Pixels belonging to this class can either be *2310* or *4030,* but differentiation in the field was not feasible. In Table 3, the confusion matrix is shown using the habitat data collected in 2009 in the field (ground reference data in the columns). Two accuracy interpretations are given for both the user's (UA) and producer's (PA) accuracy: (1) a strict accuracy number corresponding to the conventional interpretation (strict UA and PA); and (2) an accuracy number for which confusion between *2310* or *4030* on the one hand and *2310/4030* on the other hand is not interpreted as an error (UA and PA). As confusion also often occurs in field interpretation of these habitats, the second accuracy assessment numbers are a better reflection of the true errors.

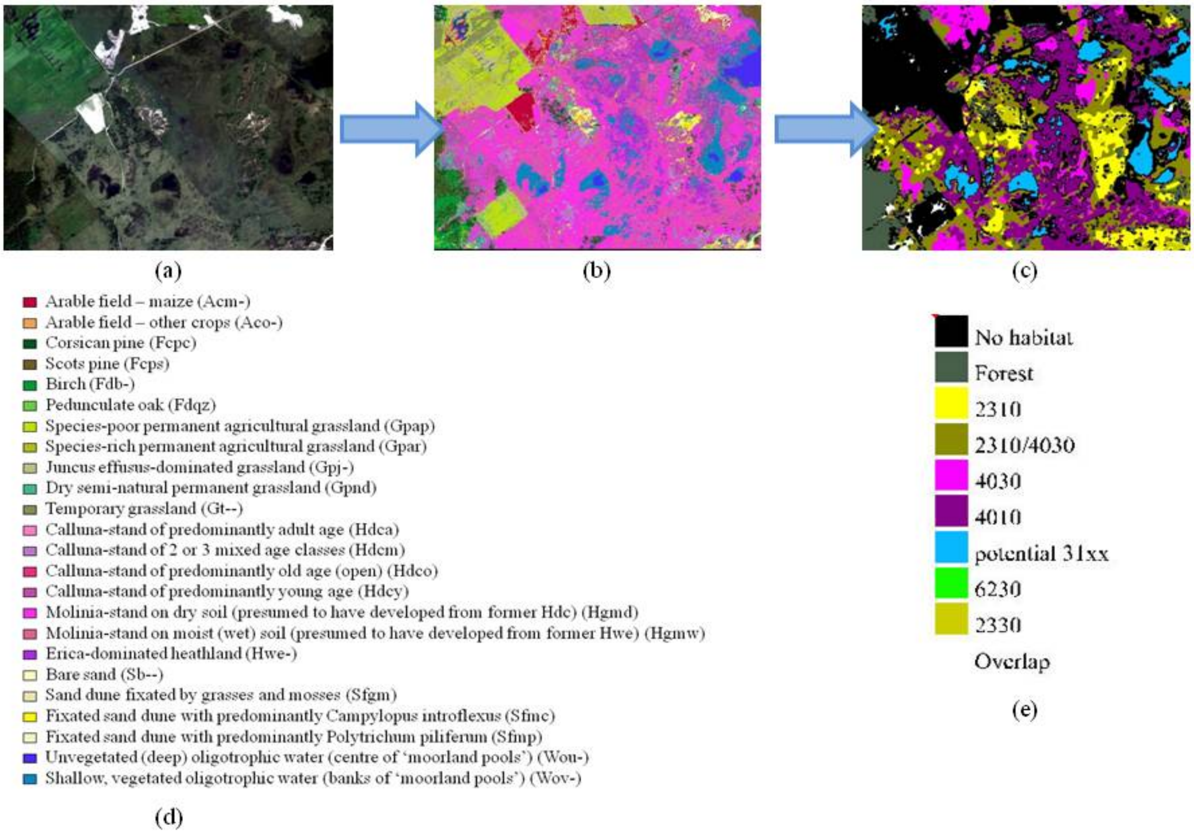

Figure 3. (a) True color extract of the study area; (b) Detailed (highest level) land cover classification; (c) Habitat patch map; (d) Legend of the land cover classification (in b); (e) Legend of the habitat patch map (in c)

	2310	2330	4010	4030	6230	2310-4030	Forest	No habitat	Potential 31xx	TOT	Strict UA	UA
2310	27	3	1	0	0	5	1	4	0	41	65.85	**78.05**
2330	11	49	0	0	0	1	0	3	0	64	76.56	**76.56**
4010	1	0	34	13	0	7	2	12	0	69	49.28	**49.28**
4030	0	0	9	8	0	3	2	10	0	32	25.00	**34.38**
6230	0	0	0	0	0	0	0	1	0	1	0.00	**0.00**
2310/4030	43	8	16	24	1	36	2	56	0	186	19.35	**55.38**
Forest	6	5	6	6	1	5	162	26	0	217	74.65	**74.65**
No habitat	25	21	82	17	3	26	15	158	5	352	44.89	**44.89**
Overlap	0	3	1	1	1	1	1	5	0	13	NA	**NA**
Potential 31xx	0	0	25	0	0	0	0	9	31	65	47.69	**47.69**
Tot	113	89	174	69	6	84	185	284	36	1040		
Strict PA	23.89	55.06	19.54	11.59	0.00	42.86	87.57	55.63	86.11		OA	48.56
PA	**61.95**	**55.06**	**19.54**	**46.38**	**0.00**	**52.38**	**87.57**	**55.63**	**86.11**		POS OA	55.77

Table 3. Confusion matrix of the habitat patch map

Judging on the UA's, the areas mapped as habitat type *2310* and *2330* mainly do belong to these habitat types, although some confusion seems to exist between both, which is most likely due to semi-open areas of sand. An even higher confusion exists between habitat types *4010* and *4030*. This is however mainly in patches which show very high encroachment by *Molinia caerulea,* and hence are also very similar**.** Part of the *4010* habitat patches are classified as *31xx*, which can be explained by the presence of small water surfaces in the wet heath habitat patches. Different approaches will be investigated to tackle these issues. While habitat types 2310 and 4030 both have *Calluna vulgaris* as the dominant species, only little confusion occurs between both, illustrating the potential of our methodology to deal with the low inter-variability between certain habitat types. In general, a significant amount (≈ 18%) of habitat patches still ends up as *No Habitat* while they in fact do belong to one of the habitat types. Future research will reveal if this can be resolved through adaptation of the habitat build-up rules, or by additional analysis of the *No Habitat* class.

4. CONCLUSIONS

It is a well-known problem in the ecology - remote sensing community that detailed habitat patch object mapping is hampered by the high intra-variability of habitat patches, as well as by the low inter-variability between different habitat types. In this study however, we propose a methodology that makes use of high spatial, hyperspectral imagery to exploit these inherent characteristics in order to obtain detailed habitat patch maps. The results illustrate the potential of the methodology to deal with the inter- and intra-variability problems for heathland habitat areas, but certain specific issues remain for which further research is necessary. For example a significant amount of habitat (< 20%) remains unassigned. Our future research will therefore focus on the optimization of the proposed methodology by adaptation of the habitat reconstruction rules or other additional measures.

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