

NATURA 2000 HABITAT IDENTIFICATION AND CONSERVATION STATUS ASSESSMENT WITH SUPERRESOLUTION ENHANCED HYPERSPECTRAL (CHRIS/PROBA) IMAGERY

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ABSTRACT:

Monitoring and reporting on the status of Natura 2000 habitats is an obligation under the 1992 Habitats Directive for each member state of the European Union (EU). Satellite imagery providing up-to-date information for a large areal coverage could be an interesting source to complement conventional, but laborious, field-driven surveying methods. Quality of habitats can be assessed through their structures as represented by combinations of various life forms. If these life forms can be classified by remote sensing, then structural analysis can be applied and readily translated into useful information for conservation status assessment. Previous experiences have shown that hyperspectral imagery is more effective for detailed vegetation classification than multi-spectral images. A limitation of spaceborne hyperspectral imagery, however, is that the resolution is too coarse. In this study, we investigated the use of superresolution (SR) enhanced CHRIS/Proba imagery for the derivation of a habitat map. To obtain the final habitat map, two strategies were compared. The first strategy consists of a direct classification of the habitats (objects) from the imagery. The second strategy is an indirect classification approach, consisting of two steps. First, a detailed classification of twenty-four vegetation types was performed, while in the second step, the obtained vegetation patches were subsequently merged into habitat patches using predefined rules. Kalmthoutse Heide, a nature reserve in the North of Belgium dominated by heathland, was used as a study area. The tree-based ensemble classifier Random Forest was used for the classification, with its internal unbiased Out-Of-Bag estimation as a measure of accuracy assessment. While both strategies achieve around 62% overall accuracy, the area distributions of various habitats show large differences. Visual interpretation confirms that the indirect classification approach, which aggregates detailed vegetation patches into habitat patches, better reflects a field mapping approach. A method to combine the strengths of these two strategies could provide more valuable results for Natura 2000 habitat identification.

1. INTRODUCTION

1.1 Natura 2000 habitat mapping

With the implementation of the Habitats Directive in 1992, EU member states committed themselves to protect a range of highly threatened habitats within their territory. Monitoring and reporting on the status of the Natura 2000 habitats is an essential part of an effective conservation, and an important obligation under the Habitats Directive: every six years, member states have to report on the actual area, the range, the quality and the future prospects for each habitat type.

To date, the gross of the data needed for this reporting are gathered through field mapping and the visual interpretation of aerial pictures. Such an approach does, however, have some major drawbacks. First, these labour-intensive techniques are highly expensive. Second, field mapping is often slow, making it difficult to cover vast areas during the optimal season of inventory. Third, despite the existence of strict rules for field mapping, inter-observer errors are an issue (e.g. Stevens et al., 2004).

Remote sensing techniques are often suggested as a proper alternative for this monitoring. Clearly, the possibility to cover large areas, the lower costs and the repeatable data processing make these methods appealing. Unfortunately, some objects are

difficult to differentiate with conventional satellite images, and the low resolution may also be a problem.

1.2 Hyperspectral data and superresolution enhancement

For detailed ecotope mapping, it has been shown that multi-spectral classification only achieves limited accuracy. Hyperspectral data with richer spectral information, however, are more effective (Chan and Paelinckx, 2008). While airborne imagery can provide higher spatial resolutions, it is much more expensive and harder to obtain than satellite imagery. To date, the only operational hyperspectral satellite is HYPERION. Unfortunately, its spatial resolution of 30m is considered too coarse for many applications. Another option is the demonstrator CHRIS/Proba, which is a transitional hyperspectral-oriented satellite that operates between 0.4-1 μm with 63 bands, at a spatial resolution of 36 m. It can acquire data at a higher spatial resolution, but at the expense of the number of spectral bands. In Mode 3, it acquires 18 bands at 18m. In terms of spatial resolution of hyperspectral (-oriented) imagery, this is the highest that can be obtained to date. Next to that, CHRIS/Proba also allows multi-angular acquisition where several images of the same scene are obtained within a very short period of time. Recent efforts to obtain a superresolution (SR) enhanced image from multi-view CHRIS images produced encouraging results with the SR images showing significantly higher contrast and detail (Chan et al., 2008a; Chan et al.,

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2010). SR enhanced images used in land-cover classification are reportedly superior than the original image sets which are with a lower spatial resolution (Chan et al., 2008b; Li et al., 2009). For applications that require a higher resolution than the current satellites can provide, the SR approach could be an interesting alternative.

1.3 Treating habitats as objects

In order to assess the conservation status of habitats, the habitat patches have to be identified first. Since the original spatial resolution of CHRIS is 18m, habitat patches that are smaller than this resolution will be lost. By applying SR algorithms using multi-view CHRIS images as input, a new image set at 9m resolution can be simulated. Although the SR image cannot be treated as having the real 9m spatial resolution, it incorporates useful information from multiple input images and thus can improve classification, especially at object boundaries where mixed pixels are normally present. It is hoped that with more image detail and contrast, the SR image can improve object (habitat) boundary delineation and hence will be more effective in defining habitat patches.

There are various ways to arrive to the patch level. For example, object-based image analysis can be exploited to recover the boundary of surface objects through multi-scale segmentation (Mathieu et al., 2007), followed by a classification of these objects. This approach has proven to be effective with very high spatial resolution satellite data such as Quickbird and Ikonos data and is particularly useful in complex environments such as urban areas. Natura 2000 habitats constitute an equally or even more complex environment, for a number of reasons. In the first place, they are composed of a limited number of dominant plant species, which occur in vegetation patches of very small scale (Fig. 1). Such vegetation elements can be very different from each other, yet together they constitute a larger patch that can be assigned to a Natura 2000 habitat type. Moreover, the composition of the vegetation elements in the habitat patch is an important source of information for the conservation status assessment status of the habitat. Unfortunately, there is no 1-to-1 relation between the vegetation elements and the habitat type, since the same type of vegetation element can belong to different habitat types, depending on its spatial context. This hampers straightforward habitat identification.

Such a high structural complexity would require high spatial and spectral resolution imagery to be mapped adequately, but to date, this cannot be delivered by satellite imagery. Therefore, we experimented with two alternative approaches to arrive to the object (habitat) level. As a first approach, we applied a direct habitat classification on a satellite image, using eight habitat types as classes in the legend. In this approach, we assumed that the spectral signature of several different vegetation elements would be mixed into the signal of the pixel, leading to a possibly characteristic overall spectral signature for each of the classes. As a drawback, this approach will not deliver any information on the constituting parts of the habitat. Our second approach involved a two-step indirect habitat classification of the same image, starting with a detailed classification of twenty-four types of vegetation elements, followed by a rule-based approach to re-classify these vegetation classes into habitat classes. In this approach, we expected to obtain more information on the composition of vegetation elements, and hence enable conservation status assessment, but possibly at the expense of a reliable habitat patch identification. We used both classification accuracy and

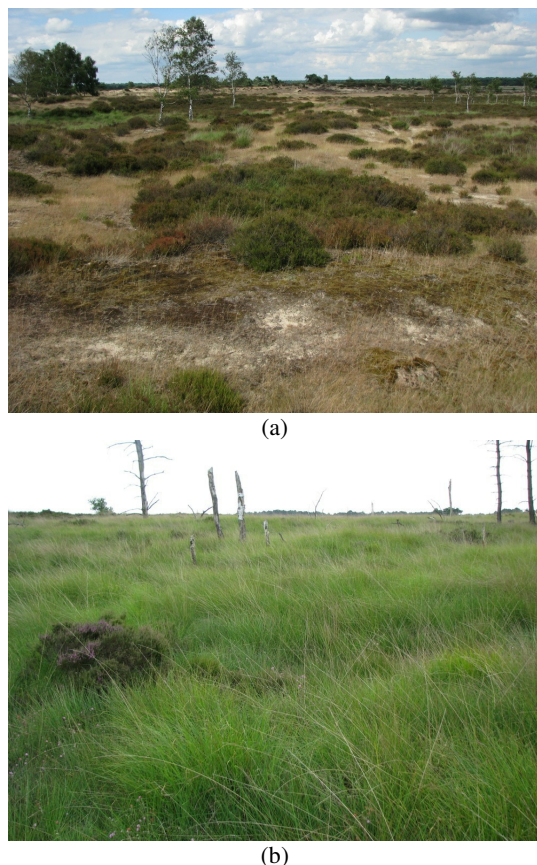


Figure 1. “Dry sand heaths with *Calluna* and *Genista*” (2310) is a Natura 2000 habitat commonly found in the study area. In favourable conditions, it consists of a mixture of dwarf scrub, open sand and patches of pioneer grasses and mosses (a); but as a result of eutrophication, encroachment with purple moor grass (*Molinia caerulea*) leads to a monotonous vegetation (b), with a heavily reduced ecological value.

visual interpretation of the obtained maps to assess and compare the quality of habitat patch identification for both approaches.

2. METHODOLOGY

2.1 Superresolution enhancement of CHRIS/Proba

SR theories can be based on frequency or spatial domain, but those based on spatial domain provide better flexibility in modelling noise and degradation, and are more suitable for our purposes (Park et al., 2003). The idea of SR is to reconstruct a high resolution (HR) image through the use of several low resolution (LR) images. The objective is to achieve the best image quality possible from several LR images. However, the application of SR algorithms is effective only if the LR images are sub-sampled, that means if aliases exist, and if the LR images include sub-pixel shifts. Superresolution methods have been applied to remote sensing images such as Landsat and Quickbird (Merino and Núñez, 2007), as well as hyperspectral data (Akgun et al., 2005). The LR remote sensing images are preferably acquired within a short period of time so that the occurrence of changes is minimized. As the angular images of CHRIS/Proba (+55°, +36°, 0°, -36°, -55°) are acquired within

minutes, they are ideally suited as input images for SR operations.

If we have N LR images and \underline{Y}_k is the matrix form of the k th LR image and \underline{X} is the matrix form of the HR image, then their relationship can be formulated as:

$$\underline{Y}_k = D_k B_k M_k \underline{X} + \underline{V}_k \quad k = 1, \dots, N \quad (1)$$

where M_k is the warp matrix that represents the shift and rotation of the LR images, B_k is the blur matrix that represents the blurring effects during the acquisition and D_k is the subsampling or decimation factor. An ordered noise vector \underline{V}_k is added at the end.

There are many approaches to conduct superresolution image reconstruction (Park et al., 2003). In this paper, we use the intuitive iterative backprojection (IBP) proposed in Irani and Peleg (1991). IBP is based on a similar idea as computer-aided tomography, where a 2-D object is reconstructed from its 1-D projections. The method involves a registration procedure, an iterative refinement for displacement estimation, and a simulation of the imaging process (the blurring effect) using a point spread function (PSF). The process starts by producing an initial guess of the HR image. This initial HR image can be generated from one of the LR images by decimating the pixels. In the case of CHRIS/Proba, the nadir image set was used as the first guess. The HR image is then down-sampled to simulate the observed LR images using the motion estimation and blurring component. The simulated LR images are subtracted from the observed LR images. If the initial HR image is the real observed HR image, then the simulated LR images and the observed LR images would be identical and their difference zero. If they are not identical, the computed differences can be “back-projected” to improve the initial guess. The back-projecting process is repeated iteratively to minimize the differences between the simulated and the observed LR images, and subsequently produce a better HR image.

The iterative procedure can be described by

$$\underline{X}^{n+1} = \underline{X}^n - G^{BP} (H \underline{X} - \underline{Y}),$$

$$\text{where } \underline{Y} = \begin{bmatrix} y_1 \\ \vdots \\ y_k \end{bmatrix} \text{ and } H = \begin{bmatrix} D_1 B_1 M_1 \\ \vdots \\ D_k B_k M_k \end{bmatrix}.$$

G^{BP} represents the back-projection filter, \underline{X}^{n+1} is the improved HR image at the $(n+1)$ th iteration, and \underline{X}^n is the HR image at the n th iteration. IBP is intuitive, hence it is easy to understand. In this study the back-projection filter was represented by a transpose of a PSF approximated by a 7 x 7 Gaussian filter.

2.2 Vegetation classes and habitat types

In order to test both approaches of habitat identification, we identified in the study area eight dominant habitat types and a Level 4 classification scheme with twenty-four vegetation classes (Table 1). The vegetation was classified based on a hierarchical classification scheme, i.e. starting with six broad land-cover categories at the first level (heathland, grassland, forest, inland dune, water body and arable fields), but comprising twenty-four detailed vegetation classes at the fourth

| Level 4 Classcode | Class description | Natura2000 habitat |
|-------------------|--------------------------------|----------------------|
| Hdcy (13) | Young <i>Calluna vulgaris</i> | <i>Calluna</i> heath |
| Hdca (9) | Mature <i>Calluna vulgaris</i> | <i>Calluna</i> heath |
| Hdco (0) | Old <i>Calluna vulgaris</i> | <i>Calluna</i> heath |
| Hdcm (52) | Mixed-age <i>Calluna</i> | <i>Calluna</i> heath |
| Hwe- (52) | <i>Erica tetralix</i> | Wet heath |
| Hgmd (107) | <i>Molinia caerulea</i> (dry) | <i>Molinia</i> heath |
| Hgmw (80) | <i>Molinia caerulea</i> (wet) | <i>Molinia</i> heath |
| Gpap (20) | Species poor grassland | (Agricultural) |
| Gpnd (22) | Dry semi-natural grassland | Inland dunes |
| Gpj- (6) | <i>Juncus effusus</i> | Water bodies |
| Gpar (3) | Species rich grassland | (Agricultural) |
| Gt-- (5) | Temporary grassland | (Agricultural) |
| Fcpc (3) | <i>Pinus nigra</i> | (Conif. forest) |
| Fcps (41) | <i>Pinus sylvestris</i> | (Conif. forest) |
| Fdb- (13) | <i>Betula</i> spp. | Decid. forest |
| Fdqz (16) | <i>Quercus robur</i> | Decid. forest |
| Sb-- (20) | Bare sand | Inland dunes |
| Sfgm (14) | Fixated sand (grass+moss) | Inland dunes |
| Sfmc (4) | <i>Campylopus introflexus</i> | Inland dunes |
| Sfmp (4) | <i>Polytrichum piliferum</i> | Inland dunes |
| Wov- (18) | Water with vegetation | Water bodies |
| Wou- (16) | Water without vegetation | Water bodies |
| Acm- (12) | Maize field | (Agricultural) |
| Aco- (4) | Field with other crops | (Agricultural) |

Table 1. List of twenty-four vegetation classes and the most plausible corresponding Natura 2000 habitats (between brackets are land-cover types that do not constitute a protected Natura 2000 habitat). The figures next to the Classcode represent the number of training samples.

level. The twenty-four vegetation classes were used for the assessment of the conservation status in the habitat patches, but for the habitat identification, eight “habitats” were discerned (Natura2000 code between brackets): *Calluna*-dominated dry heathland (2310 or 4030), wet heathland (4010), open grasslands on inland dunes (2330), *Molinia*-encroached heath (degraded form of the habitats above), oligotrophic water bodies (potentially 3110, 3130 or 3160), deciduous forest (potentially 9190), coniferous forest and other land cover types (no habitats from the Habitats directive, including urban and agricultural land). Although these habitats are inspired by the Habitats Directive, they do not completely correspond: *Molinia*-encroached heath is a degraded form of heathland with low ecological value that can originate from inland dunes as well as from dry and wet heathland. However, the origin is difficult to trace back. Also, ancillary data on soil type and micro-elevation are necessary to separate *Calluna*-dominated heath on inland dunes and on a podzol-like soil.

2.3 Study site

“Kalmthoutse Heide” and “Klein Schietveld” are two Natura 2000 sites in northern Belgium (51°22’N, 4°27’E), consisting mainly of dry and wet heathland habitat, inland dunes, water bodies and forests. Historically, heathlands were used as grazing grounds for livestock, and the organic topsoil was regularly removed to be used as a fertiliser. With the intensification of agriculture, heathlands were abandoned, resulting in high levels of tree-encroachment. Also, atmospheric nitrogen depositions increase the encroachment with purple moor grass (*Molinia caerulea*) as well as the speed of inland

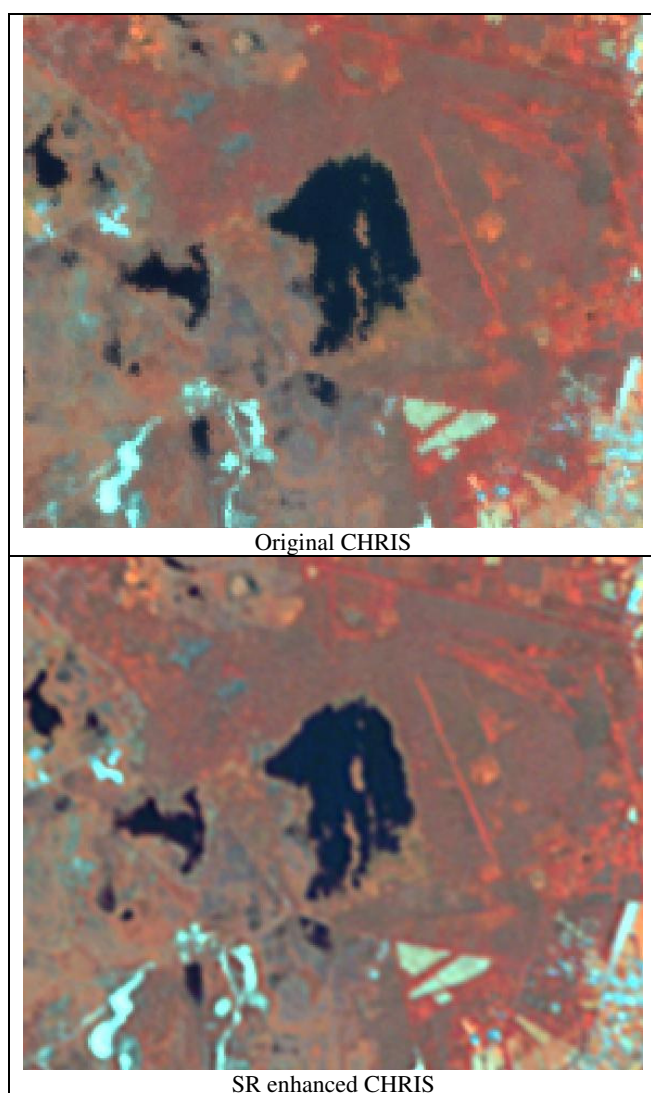


Figure 2. A comparison of the original CHRIS image (top) and the SR CHRIS image (bottom), showing a lake in the middle of the Kalmthoutse Heide and its surroundings. Bands 13, 5 and 2 are used.

dune fixation. Current nature management includes sheep grazing, sod cutting, tree removal and occasional mowing.

A CHRIS image set of the study site of excellent quality was acquired on 1st July 2008. The CHRIS image was atmospherically corrected and de-noised using the BEAM toolbox freely available through the ESA website (<http://www.brockmann-consult.de/cms/web/beam/>).

3. RESULTS AND DISCUSSION

3.1 Superresolution enhancement of CHRIS imagery

As suggested by Chan et al. (2010), only the 0° and ±36° images were used. High off-nadir images do not improve the result of the SR operation due to serious geometric distortion. A registration routine described by Ma et al. (2010) was implemented and the registration accuracy obtained was below 0.2 pixels. Visual inspection confirmed the high quality of the registration process. The IBP SR method was applied band-by-band, and then the 18 bands were stacked. Fig. 2 shows an

extract from the original CHRIS nadir image and the SR enhanced CHRIS image. The original CHRIS has 18m spatial resolution, while the SR CHRIS has 9m resolution. The amount of image detail is substantially higher in the SR image than in the original image, and the boundaries of objects such as lakes, fields and off-road paths are more crisp.

| N2000 habitat | Direct classification | Indirect classification |
|-----------------------|-----------------------|-------------------------|
| <i>Calluna</i> -heath | 133.3 | 128.6 |
| Wet heath | 73.0 | 141.5 |
| <i>Molinia</i> -heath | 756.1 | 687.7 |
| Agriculture | 220.6 | 133.6 |
| Inland dunes | 108.0 | 215.3 |
| Water bodies | 109.9 | 160.8 |
| Conif. forest | 1113.6 | 864.4 |
| Decid. forest | 193.0 | 375.5 |

Table 3. Area estimates of habitat classes, in hectares, obtained with the two approaches.

3.2 Vegetation and habitat classification

We performed a supervised classification on the SR CHRIS image, with training samples acquired by a field expert during the summer of 2009. A total of 534 points were sampled using a stratified random sampling method, which took into account the geographic distribution of each vegetation type. As a classification algorithm, we applied a decision tree based ensemble classifier - Random Forest (Breiman, 2001). Random Forest has proven to be one of the most robust and accurate machine learning classifiers. It is easy to use with only one parameter to be tuned. For more details on the application of Random Forest for vegetation classification, we refer to Chan and Paelinckx (2008). Accuracy assessment was done using the unbiased Out-Of-Bag (OOB) internal estimate of Random Forest.

The first approach, where we classified the eight habitats directly, revealed an OOB accuracy of 61.9%. In the second approach, the classification accuracy of the twenty-four vegetation classes was only 45.3%. Due to the presence of hard-to-distinguish classes at Level 4, even in the field, this low accuracy is not entirely unexpected. The classification at Level 4 was subsequently merged into the eight habitat classes using the correspondence described in Table 1. After merging into eight habitat classes, the overall accuracy was once again assessed, and now reached 62.4%. This is on par with the direct strategy.

Figure 3 shows the final habitat maps obtained with the two approaches, using all 534 samples as input. While there is general conformity between the two classifications, they also differ quite substantially. In general, very small patches consisting of a few pixels are much less present in the indirect approach, which makes this map more like a field-driven map. A comparison of the habitat area obtained with the two approaches is given in Table 3. There are big differences in derived habitat area for all habitats, except *Calluna*-dominated and *Molinia*-encroached heathland. But even in these habitats, minor shifts in the boundaries occur.

The area estimate of wet heathland in the direct classification is almost half of the area calculated using the indirect method. Most of the discrepancies occur in the border zones of wet

heathland and *Molinia*-heathland, and correspond with wet heathlands that are heavily encroached by purple moor grass *Molinia caerulea*. Subtle differences in estimating the *Molinia* cover between fieldworkers and computer algorithms may equally play a role (see also Múcher et al. 2010). Similarly, the large differences in coverage of coniferous and deciduous forest types are mainly related to the presence of mixed forest stands.

Conversely, large differences in the cover of inland dune habitat, water bodies and agricultural land are apparently not related to the difficulty of classifying transition zones. Misclassification of spectrally similar, but ecologically very different vegetation types and habitats are the main cause of errors: some coniferous forests appear very dark on the satellite image, resulting in their classification as water. Also, inland dunes can easily be confused with recently ploughed fields. As agricultural areas and forests were not target habitats in this study, relatively little training points were located in these areas, and the high number of misclassifications are not really surprising.

4. CONCLUSION

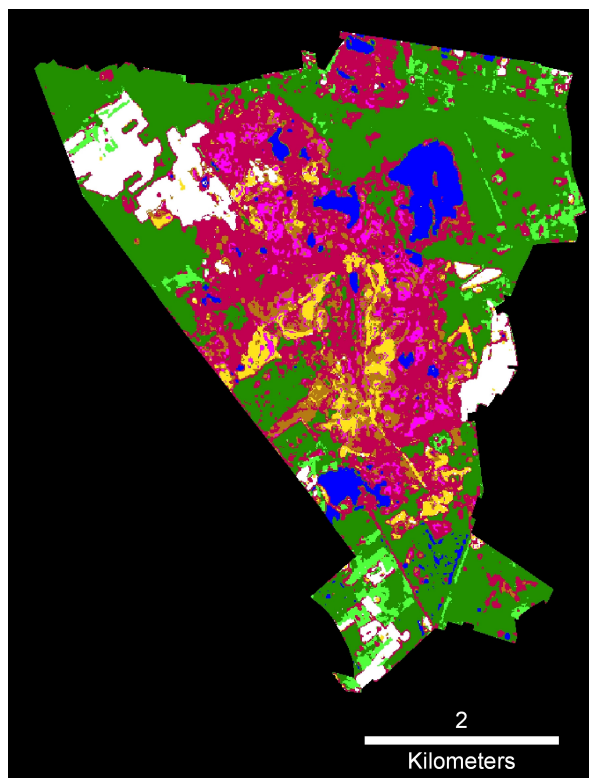
Superresolution enhancement of hyperspectral imagery is a valuable tool for reducing the pixel size and thus increasing the image contrast and spatial detail. For a CHRIS/Proba satellite image of a heathland in Belgium, an SR image resolution of 9m was obtained, compared to 18m for the original image. SR enhanced satellite images appear to be suitable for habitat mapping of heathlands: a direct and indirect classification method both achieve classification accuracies that approach the accuracy of manual field mapping. Also, in general, the maps produced with the two methods are largely comparable, and correspond well with the real distribution of the habitats. However, the exact area estimates for each habitat derived from both maps strongly differ. This has been shown to be related to classification difficulties in transition zones, yet misclassification of spectrally similar vegetation and habitat types also seems to play a role.

In the context of Natura 2000 monitoring, the results of this study are promising. First, for a large proportion of the study area, both methods indicate the presence of the same habitat type, which mostly corresponds with the actual habitat type present. Second, although discrepancies between the two maps may be linked to real classification errors in one of the maps, such differences may also indicate the presence of gradual transition zones that cannot be easily classified. The delineation of such zones is very relevant for field managers and ecologists, as these areas often correspond with rapidly evolving zones that need proper management.

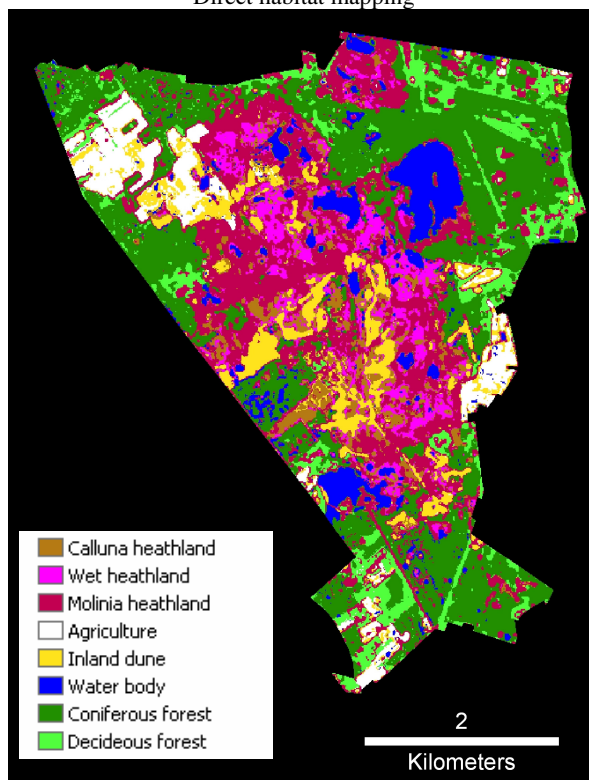
We can conclude that the application of novel superresolution techniques, combined with multiple habitat classification approaches, can help to overcome the shortcomings of satellite imagery and lead to satisfactory habitat map production. This is a promising finding in the light of the development of operational methods for Natura 2000 habitat monitoring and reporting, based on satellite imagery.

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Indirect habitat mapping

Figure 3. Comparison of the direct habitat classification (top) and the indirect habitat classification based on aggregation of a detailed Level 4 vegetation map (bottom).

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