



Object-oriented methods for habitat mapping at multiple scales – Case studies from Northern Germany and Wye Downs, UK

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Summary

This paper presents an application of object-oriented techniques for habitat classification based on remotely sensed images and ancillary data. The study reports the results of habitat mapping at multiple scales using Earth Observation (EO) data at various spatial resolutions and multi temporal acquisition dates. We investigate the role of object texture and context in classification as well as the value of integrating knowledge from ancillary data sources. Habitat maps were produced at regional and local scales in two case studies; Schleswig-Holstein, Germany and Wye Downs, United Kingdom. At the regional scale, the main task was the development of a consistent object-oriented classification scheme that is transferable to satellite images for other years. This is demonstrated for a time series of Landsat TM/ETM+ scenes. At the local scale, investigations focus on the development of appropriate object-oriented rule networks for the detailed mapping of habitats, e.g. dry grasslands and wetlands using very high resolution satellite and airborne scanner images. The results are evaluated using statistical accuracy assessment and visual comparison with traditional field-based habitat maps. Whereas the application of traditional pixel-based classification result in a pixelised (salt and pepper) representation of land cover, the object-based classification technique result in solid habitat objects allowing easy integration into a vector-GIS for further analysis. The level of detail obtained at the local scale is

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comparable to that achieved by visual interpretation of aerial photographs or field-based mapping and also retains spatially explicit, fine scale information such as scrub encroachment or ecotone patterns within habitats.

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Background and objectives

The application of Earth Observation (EO) data for nature conservation monitoring has been limited because until recently there was a mismatch between the spatial and thematic resolution of EO data and the user and legal requirements for detailed maps and habitat monitoring. In the recent past most of the operational land cover or habitat mapping applications relied either on visual interpretation of satellite images (e.g. Corine Land Cover, 2000), aerial photograph interpretation (e.g. the biotope and land use survey in the German states) or field surveys (Natura 2000 Annex II habitat maps). However, these traditional methods of monitoring are not compliant with the increasing demand for spatially explicit data on the ecological quality of, and threats against, designated protected sites. To meet the requirements of European policies such as Natura 2000 Habitats Directive, the Water Framework Directive (WFD), the Alpine Convention and the reform of the Common Agricultural Policy (CAP) the development of more cost and time effective monitoring strategies are mandatory. With the increasing availability of very high resolution (VHR) satellite and airborne scanner imagery, however, a growing interest in EO applications for nature conservation can be observed (e.g. Kerr & Ostrovsky, 2003; Wulder, Hall, Coops, & Franklin, 2004; Turner et al., 2003). But a change in the traditional monitoring practices will only be accepted if it brings a reasonable reduction in cost and the data provide the required level of information and scale and can be easily integrated into the user's GIS and working environment.

The applicability of semi-automated and object oriented approaches for EO-based habitat mapping and monitoring have only recently been the subject of research (Andresen, 2004; Bock, 2003; Ehlers, Gähler, & Janowsky, 2003; Frick, 2004; Gähler & Janowsky, 2003; Leser, 2003). The advantage of the object-oriented approach is that it offers new possibilities for image analysis because image objects can be characterised by features of different origin incorporating spectral values, texture, shape, context relationships and thematic or continuous information supplied by ancillary data. Integration of additional knowledge is a

valuable means to distinguish ecologically meaningful habitat types that do not have necessarily very distinct spectral features. Moreover integration with existing vector-databases can be achieved during all steps of the classification process.

In this paper, the results of the application of the object oriented classification to two different case studies, one in Schleswig-Holstein, Germany and one in the Wye Downs, south-east England are presented. We tested the suitability of object-oriented classification for habitat mapping at different spatial scales, from regional to local, and using different EO data, from Landsat with 30m spatial resolution to Quickbird with 0.7m spatial resolution. We also addressed the transferability of classification schemes between different EO datasets. Finally, we compare the results of object-oriented classification with the results obtained using other methods such as field survey and air photo interpretation.

Methods

Landcover and habitat classification systems

The first harmonised land cover classification system in Europe was the CORINE land cover project (European Environment Agency (EEA), 1999; Heymann et al., 1993) and the complementary CORINE BIOTOPE classification (EEA, 1995). Both systems utilised EO data and techniques but have not yet achieved Europe-wide implementation and coverage. One of the problems with CORINE is that many landscape details are missed in the 25 ha minimum map unit. Several more recent classifications are emerging as important standards for conservation in Europe, e.g. EUNIS system developed by the EEA (Davies & Moss, 2002; European Environment Agency (EEA), 2003). The EUNIS habitat classification is a comprehensive pan-European system to facilitate the harmonised description and collection of data across Europe through the use of criteria for habitat identification; it covers all types of habitats from natural to artificial, from terrestrial to freshwater and marine. EUNIS is also cross-comparable with CORINE and with the Natura 2000 habitat system (European

Commission, 2003). The scope of the EUNIS classification is limited to its level 3 (level 4 for marine habitat types). At level 4 (5 for the marine types) and below, the component units are drawn from other classification systems (e.g. national systems) and combine these in the common framework. The EUNIS habitat classification key was chosen for use in the current study as a commonly used and ecologically sound classification system.

Object-based modelling of habitats with EO data

Environmental objects are parts of the real world for which information can or should become available, e.g. a certain biotope, a forest or a tree. As soon as we reflect the parts of the real world as formal data objects in a spatial dimension, this is subject to some kind of classification – a systematic delineation and order of objects. This systematic order is always characterised by a specific point of view or task (function, land use, land cover, habitat or vegetation type), which is reflected in the structure, the semantics, the spatial definition and the characterisation of the entities – the target objects (Bock & Lessing, 2000). Habitats can be grouped and classified by floristic, physiognomic, hydrological and ecological features. The observer, the method and the scale of investigation mainly determine the registration and the semantic and spatial delineation of objects (field mapping versus aerial photographs and satellite sensors). For EO data the reflection of objects on the earth surface is determined by physical and chemical properties, always depending on the spatial, spectral and radiometric resolution of the observing sensor and the acquisition date. Essential to the reflection of biotopes are the vital, photosynthetically active biomass, the dead biomass, soil-cover and water (Hildebrandt, 1996). Leser (2003) describes the complexity of EO-based mapping of biotope and land-use types as a result of complex spectral overlaps within the features identifiable by remote sensing. The reflection of single plant parts (e.g. leaves) is quite different to the variable reflection of heterogeneous vegetation communities that can be hardly defined mathematically. The characterisation of habitats involves additional features, e.g. grazing pattern, that are easily assessed by visual interpretation but are problematic for automated image interpretation. Therefore, Leser (2003) advises to develop study area specific approaches and knowledge-based formation of super objects as spatially and thematically defined reference units (e.g. borderlines of main habitat types).

With object-based modelling, definition of target objects can be extended by shape, texture, context and information supplied by ancillary data. The integration of ancillary data includes application of existing maps for segmentation or soil maps and digital elevation models for defining a certain habitat type by inheritance and/or neighbourhood. The representation and combination of knowledge gained has to be implemented by modelling task-oriented concepts in semantic networks (Benz, Hofmann, Willhauck, Lingenfelder, & Heynen, 2004; Bock & Lessing, 2000; Gahegan & Flack, 1996; Tonjes, Growe, Buckner, & Liedtke, 1999). A prerequisite for any object-oriented image analysis is the use of computer-assisted segmentation to divide the image into more or less homogenous regions of spatially connected pixels that should refer to meaningful objects in the real world. Various segmentation algorithms have been developed, which rely on edge, region or texture-based methods (Andresen, 2004; Blaschke, 2000; Kettig & Landgrebe, 1976; Meinel & Neubert, 2004).

Recently, multi-scale segmentation (MSS) has been introduced by Baatz and Schäpe (2000) and implemented in the software package eCognition (Definiens, 2004). The MSS technique offers the extraction of image objects at different resolutions to construct a hierarchical network of image objects, in which each object knows its context, its neighbourhood and its sub-objects. In addition eCognition provides an extensive set of object features beyond spectral information such as texture, shape and context, which can be combined within the hierarchical semantic rule network for classification. EO data can be integrated with any other type of spatial data, which provide either known object borders or add ancillary knowledge. Classification in eCognition is based on fuzzy membership functions or a fuzzy realisation of the standardised nearest neighbour (NN) algorithm. Fuzzy classification translates feature values of arbitrary range into standardised fuzzy values between 0 and 1, indicating membership to a specific class. A class can be described by one-dimensional membership functions or by a combination of membership functions to cover a multi-dimensional feature space. As the overlap in the feature space increases with the number of dimensions, a direct definition of the membership function using NN, trained by image samples, is advisable in high-dimensional space (Fig. 1). In contrast, membership functions are more suitable for the definition of classes by a few features (Definiens, 2004).

A main advantage of fuzzy classifiers is to express uncertainty of membership and knowledge. The

Membership Functions

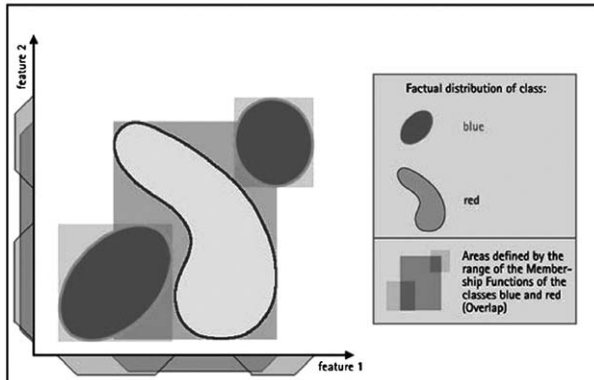


Figure 1. Overlap of class descriptions based on membership functions in a two-dimensional feature space (Definiens, 2004, p. 99).

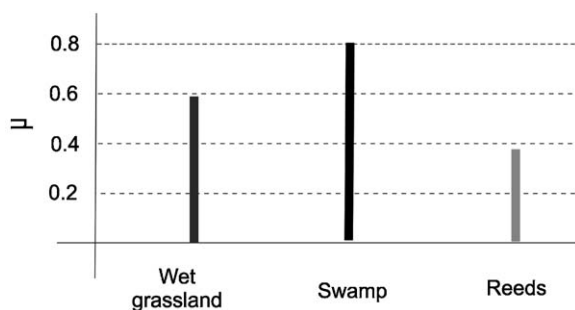


Figure 2. Degree's of fuzzy membership of an image object to the habitat classes reeds, swamp and wet grassland.

membership of an object to more than one class is defined by different degrees of membership. This concept relates very well to the often heterogeneous composition of semi-natural habitats and the soft ecological boundaries between them (Fig. 2). The higher the degree of membership for the most likely class, and the bigger the difference to the second probable class, the more reliable and stable is the definition (Benz et al., 2004).

Because eCognition is currently the most flexible and comprehensive object-oriented system for image classification it was selected as the common software for testing the suitability of object-oriented habitat classification in this study.

Mapping of habitats at regional and local scale, Schleswig-Holstein, Germany

Study area

A hierarchical concept of study areas is defined which is linked to specific operational levels. At the regional scale the study area covers the districts of

Schleswig-Flensburg and Nordfriesland in northern Germany covering an area of approximately 4156 km². The dominant land use is agriculture, mainly cereal cropping on the fertile soils of the young quaternary moraines in the east, lime marshes in the west, grasslands and pastures on the leached, sandy or wet soils in the Geest and marshes in the middle.

At the local scale, the core study area covers 5.5 km² and is part the Eider-Treene-Sorge lowland. Before the lowland was drained and cultivated, it consisted of a mosaic of wetlands, fens, swamps and raised bogs between the three rivers Eider, Treene and Sorge. Today, most (about 80%) of these wetlands have been destroyed and are used as pastures and semi natural wet grasslands. However, the area still constitutes one of the largest coherent wetland areas in northern Germany, is designated as a RAMSAR site and the most valuable areas are designated as Natura 2000 sites.

Data used

An overview of all the spatial data used is given in Table 1. The regional habitat classification is based on multi-date sets of Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper (ETM+) scenes of 1990, 1995 and 2001. Radiometric correction "first order" spectral normalisation was carried out converting the DN-values at sensor reflectance values based on standardised equations described by Markham and Barker (1986). Finally, the scenes were geometrically co-registered and corrected on the basis of topographical maps at a scale of 1:10 000.

Airborne scanner data recorded with the High Resolution Stereo Camera Airborne Extended (HRSC-AX) in August 2001 were used for habitat mapping at a local scale. Data included three visible and one infrared spectral channels at a spatial resolution of 20 cm and a digital surface model (DSM) at a resolution of 1 m. Owing to the high processing demands of the eCognition software, and to provide comparability of assessed methods to applications on VHR satellite images such as Ikonos and Quickbird, the resolution of the HRSC scanner image was resampled from 20 cm to 4 m. A pre-processing of the DSM was done to achieve a relative measure of object heights. The difference between a mean filtered smoothed surface and the original surface of the DSM allows the detection of the steep rise in elevation caused mainly by trees, hedgerows and buildings. In addition, an Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) scene from summer 2001 and the above Landsat ETM+scenes from 2001, were included to assess the spectral

Table 1. Satellite and ancillary geodata used in the case study Schleswig-Holstein

Sensor/data type	Acquisition date(s)/period	Resolution/scale	Scale applied
<i>Satellite data</i>			
Landsat TM 4/5	2.4 & 15.7.1990 24.4 & 27.6 95	30 m	Regional
Landsat ETM+	2.5 & 5.7 2001	30 m	Regional/local
ASTER	26.6. 2001	15 m	Local
<i>Airborne</i>			
HRSC	August 2001	4 m	Local
<i>Ancillary data</i>			
Field data	July 2002 and July 2003	1:5000	Regional/local
BNTK	1988–1990	1:10 000	Local
FFH mapping	2003	1:5000	Local
Soil map	2000	1:200 000	Regional/local
ATKIS	2001	1:50 000	Regional

variability caused by phenology and land use practises to support the classification.

For both local and regional levels, additional information was included in the classification process by integration of a soil map at a scale of 1:200 000. At the regional level, the official German topographical information system ATKIS was used for the integration of constructed areas, roads and lanes, while at the local level the federal survey of biotope and land use types BNTK (BFN, 1995) was used for the pre-delineation of the scene content. Ground truth data were obtained during two field surveys in 2002 and 2003. For the more detailed local classification, ground truth data were supplemented by the states Natura 2000 field survey in 2001 and vegetation maps that were available for parts of the study area.

To assess the different spectral variations of arable land and grasslands in the images, ground truth data were distributed over all natural zoning areas. Nevertheless, not all spectral variations of arable land and grasslands could be covered; therefore, the field database was not applicable for training in the classification process by itself and a method for widening the training sample was developed. An unsupervised classification was applied to the image to get a representation of all major spectral classes that were thought to be arable land or grasslands by their compact spatial appearance on the image. Clusters were then labelled using the field data and additional geodata from ATKIS and the labelled clusters were filtered to keep only compact objects of a minimum size of 40 pixels. This mask was then used to support visual training sample selection across the whole study area. A retrospective training data assessment for the years 1990 and 1995 was developed using a change detection tool (Kleinod et al., 2005) to

identify unchanged training samples between 2001 and the earlier years. These unchanged training samples were then again used for labelling cluster images of the other years. Further processing was then run as described above. More detailed information on the method is given in Rossner and Bock (2004).

Regional classification scheme

The underlying principles for the development of the classification scheme were practicality for applications at a regional scale on the one hand and transferability on the other. Practicality was provided by considering two critical points: a reasonable processing demand and a comprehensive class hierarchy to allow for easy adaptation when transferring to other scenes. A commonly used way to address these points is to develop the classification first on a small subset and to apply it later to the full area (Esch, Roth, Strunz, & Dech, 2003). Most often such transfers do not succeed, because of differences in the spectral distribution. In our case, due to phenological gradients in the study area from north to south as well as from west to east, caused by different mowing or ploughing times, the classification method was directly developed for the full scene. Transferability was then investigated by applying the classification procedure developed for the 2001 data set to the data sets for 1995 and 1990. A hierarchical scheme using four scale levels was implemented using eCognition 2.1. Levels 1 and 4 were both used to provide additional data (Figs. 3 and 4).

At the first level, image objects were classified into different soil types, using soil data that have been integrated in the classification process, to serve as knowledge-based rules. Level 4 was segmented on a coarse scale and then classified

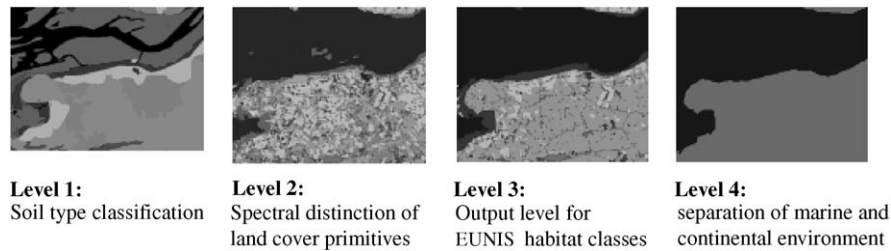


Figure 3. Classification purposes of the four hierarchical levels implemented for the regional classification.

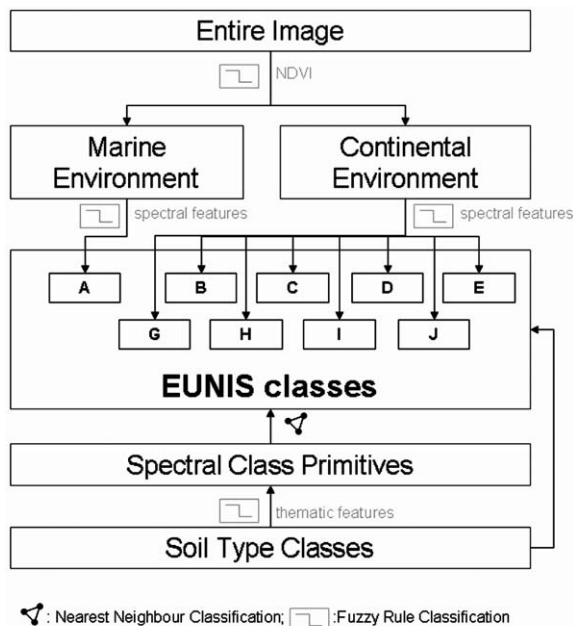


Figure 4. Classification scheme for the regional classification.

with an NDVI threshold for separation of marine and continental environment. An NN classification based on the training samples was performed on level 2. This together with the additional information of levels 1 and 4 were then used for the classification of EUNIS habitats on level 3. To provide higher spatial accuracy for rather small objects of constructed areas and infrastructure the classification outcome of level 3 was resampled to 15m. Infrastructures such as highways, railways, streets, as well as constructed areas, were taken from the ATKIS. A separation of dense inner city building areas, suburban building areas and sparse building areas was achieved by application of thresholds of NDVI. The classification scheme developed for the classification of the 2001 Landsat ETM+ data set was then transferred and applied to the data sets of 1995 and 1990. A detailed description of the regional classification approach is presented in Rossner and Bock (2004).

Table 2. Hierarchical levels in eCognition

Level	Objects and classes extracted
1	Soil types
2	Buildings, bare ground, trees & woods, water, raised bog habitats
3	Arable and grasslands, topogenous bog habitats
4	BNTK Forest & Settlement, BNTK object border
5	Soil types within BNTK object border

Local classification scheme

For the local classification a multi-scale strategy was developed for the detection of the different habitat types that are represented in different object and habitat scales on the image, e.g. recognition of trees and buildings, classification of larger habitats of forests, grasslands and arable fields and classification of small habitats such as bog vegetation and water holes. Five spatially consistent levels were created in eCognition to classify object primitives, target classes or to supply thematic pre-knowledge as shown in Table 2. The object size increased from levels 1 to 5 while the number of objects decreased.

The first level represents the knowledge-based soil map as in the regional classification. To avoid inappropriate object delineation by the soil map, this layer was segmented after all other segmentation runs at the scale level 1. In contrast to this, level 4 was segmented first of all to represent the spatial object structure of the BNTK as a spatial super object level. In addition it served the definition of a settlement, road and forest mask. At the second level, firstly a very basic spectral delineation of the scene into very small-sized objects of vegetation, non-vegetation and water was applied. The DSM was used to separate trees, woodland and buildings (Bock et al., 2003). The further classification of habitats was carried out within spatial soil masks. By this means, spectral

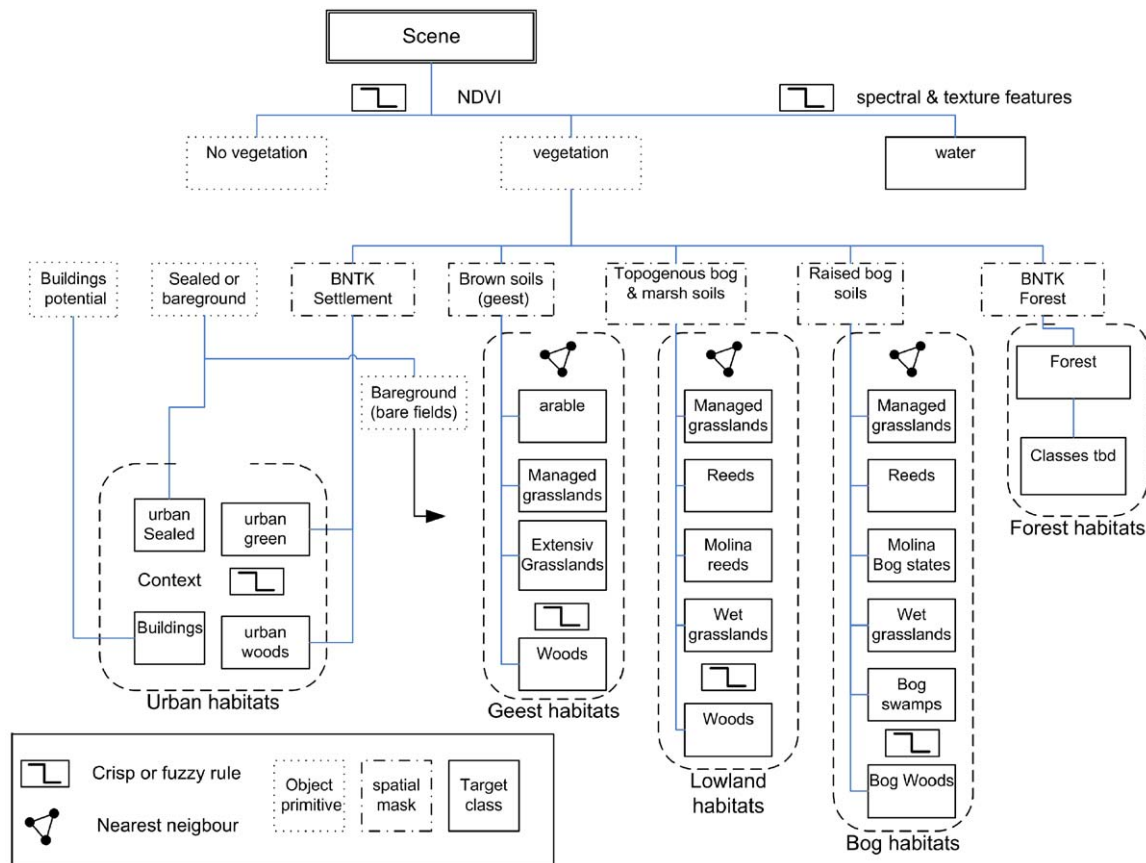


Figure 5. Classification scheme for the habitat classification in local scale.

overlaps could be limited to the classes inside a group. Habitats on raised bog soils were extracted at level 2, while the larger scale habitats on topogeneous bog and the remaining, non-water influenced soil types, were classified at level 3. The spectral separation between arable land, grassland and semi-natural habitats is not always feasible using an EO data set from only one acquisition date. This problem was solved by the integration of Landsat ETM+ and ASTER spring and summer scenes available for the same year. Separation of urban habitats was carried out within the BNTK settlement mask, while buildings were also classified outside the mask to allow detection of urban encroachment. The hierarchical classification scheme and classification rules are given in Fig. 5.

Mapping of habitats at local scale with Quickbird, Wye Downs

Study area

The Wye Downs National Nature Reserve (NNR) is the most easterly NNR in England and comprises part of the complex of steep scarp slopes and dry valleys known as the North Downs (latitude:

51°09'N, longitude: 0°58'E). This characteristic chalk landscape has been formed during a 500-year period around 10 000 years ago through the process of solifluction (freeze-thaw) in the arctic climate conditions prevalent at that time. The reserve was established in 1961 and 1967 with a small addition made in 2003. The primary conservation objective is to maintain one of the best remaining examples of chalk downland (calicolous grassland) in the study area. This is a habitat, which has declined markedly in the last 50 years due to modern farming methods. The reserve covers about 100 ha about half of which is mixed deciduous woodland and the remaining half is grassland. Owing to the close proximity of the continental European mainland the calcicolous grassland is rich in wild flowers including 17 species of orchids. The species-rich sward is the product of traditional hill grazing by sheep and cattle, although in recent decades undergrazing has resulted in increase of coarse grasses and scrub.

Data used

Both multi-spectral and panchromatic Quickbird images of the study area were acquired on 9 December 2002 at 10:31 h for the application of

object-based habitat mapping at the local scale. The panchromatic image covers a spectral length of 450–900 nm at a spatial resolution of 0.7 m while multi-spectral image consists of four bands Blue: 450–520 nm; Green: 520–600 nm; Red: 630–690 nm; Near-IR: 760–900 nm at a spatial resolution of 2.7 m. The two images were fused using a smoothing filter-based modulation approach (SFIM), (Liu, 2000), and a pan-sharpened product with a spatial resolution of 0.7 m was produced where the tested mapping technique was applied. SFIM was found to be the most appropriate technique for fusion of Quickbird images since the four bands of the pan-sharpened product had a correlation with the original multi-spectral one of more than 96% in all cases. The pan-sharpened image was geometrically corrected using Land-Line data (1:2500) to a spatial accuracy of 1 m. Apart from the four multi-spectral bands, the normalised difference vegetation index (NDVI) layer was also calculated and used in the classification process. Only a subset of the original 64 km² image was used which had a total size of 9.5 km².

The acquisition date, and especially the acquisition time, had consequences for the image quality. Firstly, in December there was no foliage on the deciduous broadleaved species making distinction between different broadleaved woodland habitats impossible. Secondly, and most crucially, at 10:31 h the sun was at a low angle and in combination with the sharp relief of the area a large proportion of it was covered by shadows. Consequently, the shadowed areas were separated from the unshadowed areas early in the classification process and dealt in a completely different manner.

A solid and drift geology map in digital format at a scale of 1:50 000 was used to aid the classification process. Furthermore, a DTM at scale of 1:10 000 and a vertical resolution of 2 m was used from which a slope and an aspect layer were produced.

The aim of the classification process was to identify the eight EUNIS classes shown in Table 4. For the classes E1.2, E2.1, I, G1, G3.F2, F3 an appropriate training set had to be selected while for FA and G5 their identification relied on the geometry of the objects. The selection of training areas involved the following steps: firstly, we identified on the image potential training areas using the information that could be derived from Phases 1 and 2 habitat maps (Kent Wildlife Habitat Survey Partnership, 1995) as well as information that could be derived from a visual inspection of the image. Special care was taken to include areas in the training set that illustrated a variety of examples of the target class differing in appearance, etc. The final set of training areas was

selected after field visits in May 2003 to all the areas included in the first set of potential training areas and confirming their landcover type in situ. The percentage of the training set in relation to the total classified area in each class was 13% for E1.2, 15% for E2.1, 2% for I, 7% for G1, 19% for G3.F2, and 21% for F3.

Classification scheme

A hierarchical approach was adopted for the image classification and habitat identification. Under this approach the image was segmented into five levels using MSS (Baatz & Schäpe, 2000). At each level we selected the most suitable scale parameter and homogeneity and colour criteria which gave the smallest possible number of objects whilst at the same time was homogenous in terms of the targeted class. Therefore, at the higher levels (larger objects) we identified broad land-cover types, which at the lower levels, were further divided until the final targeted classes were identified. Figure 6 shows the classification process schematically indicating the functions used for each class description.

The NN algorithm was used to describe and identify the classes, and occasionally single feature fuzzy or crisp rules were also applied. The most appropriate features for the NN function in each class were determined using canonical variate analysis (CVA) (Jongman, Ter Braak, & Van Tongeren, 1995). CVA, otherwise known as linear discriminant analysis, is a non-parametric method which identifies, from a set of explanatory variables, those that best discriminate between classes

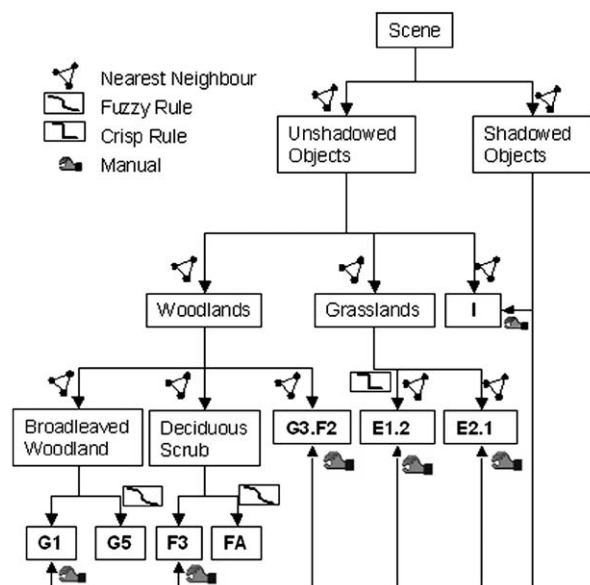


Figure 6. Classification workflow indicating the method used for the class description.

defined as a single nominal response variable. CVA revealed that the various texture measures (homogeneity, dissimilarity, contrast, etc.) calculated using a GLCM (Haralick, Shanmugan, & Dinstein, 1973) proved to be very important throughout the classification process. They appear in the description of all classes when NN was applied and account for a large proportion of the variation in the targeted classes. Finally, in the cases where the spectral information were poor (shadowed areas in this case) manual classification was adopted for the classification of those image objects.

At the highest hierarchical level, the shadowed areas were identified and separated by selecting an appropriate training set of shadowed and non-shadowed objects. Shadowed objects were selected subjectively including the different appearances of shadow on the image. Non-shadowed objects were those of the chosen training set for the target classes. NN was then applied using the most significant differentiating features for the two classes.

At the next lower level the unshadowed areas were classified into the three main landcover types, namely: woodlands, grasslands and arable land using NN. Arable land was not further divided and represents class I of the EUNIS classification. Woodlands were further divided into broadleaved woodland, deciduous scrub and coniferous woodland using NN and a set of appropriate differentiating objects features. Coniferous woodland was not further divided and represents class G3.F2. At the same level, grasslands were divided into classes E1.2 and E2.1 using NN as well as two crisp rules, which define E1.2 as present only in areas with no drift geology and where the geology is calcareous. At the lowest hierarchical level, broadleaved woodland was further divided into class G1, broadleaved woodlands, and class G5, man-made lines of trees identified. G5 was identified using two fuzzy rules; objects representing lines of trees should have a width/length ratio higher than three and should not be surrounded by other woodland objects. At the same level, and following a similar approach, the class deciduous scrub was divided into class F3, which represents temperate scrub habitats and FA, which represents hedgerows. In the case of hedgerows the length/width applied was 3.95 and the objects were also defined as not to be surrounded by other woodland or scrub habitats.

The final step was to classify the shadowed areas. Only a limited amount of information could be extracted from the image in those areas and it was impossible to describe the targeted classes based on the image spectral reflection. Hence, manual

classification was used and information about the habitats in the shadowed areas were collected from the field survey as well as from the two digital maps of Phases 1 and 2 survey from the area and were classified into the classes shown in Fig. 6.

Results and discussion

Mapping of habitats at regional and local scale, Schleswig-Holstein, Germany

In the German case study at the regional scale, three EUNIS level 1 habitat maps and three extended maps with selected EUNIS level 2 classes for the 3 years 1990, 1995 and 2001 were produced. The classification accuracy of the regional land cover map of 2001 was assessed by means of an error matrix. The overall accuracy was 86.19%, the overall Kappa Statistic was 0.80. The assessment was based on ground truth data from the field survey in 2003 that had not been used for training (Table 3). The points selected were visually checked with the image data of 2001 and in cases of uncertainty excluded from the sample. Five hundred and thirty-four sample points remained with a focus on arable land and grasslands which had the highest share of area and a minimum of 10 sample points for EUNIS class B (coastal sands) which appears at very few sites in the area. The producers accuracy of the classes was 36%, 80%, 75%, 76%, 91%, 68% and 91% for EUNIS classes A, B, C, D, E, G, I, J, respectively. The reason for the rather low accuracy for marine habitats was the difficulty of the classification of littoral salt marshes. Their phenology varies much due to the variability in flooding times; furthermore their classification is based on a separation of marine and continental environment at level 4 in the classification process, which is difficult at the coastline, due to the object segmentation algorithm (Table 4).

The classification accuracy of the habitat maps of 1990 and 1995 was assessed using statistical survey data, since no field data from the corresponding years were available. Statistical data provided the area (ha) of crops, maize and grassland for each community as a reference unit. The habitat areas were summarised for each community and correlated with the statistical data. The representativeness of the habitat maps for the most dynamic classes of agricultural land use is demonstrated by correlation coefficients of more than 0.9 ($p = 0.01$). A similar validation for other classes was not possible because of insufficient reference

Table 3. Accuracy assessment for the EUNIS level 1 land cover classification of 2001

EUNIS 1	Class name	Reference totals	Classified totals	Number correct	Prod. accuracy (%)	User's accuracy (%)
	Unclassified	0	19	0		
A	Marine	11	6	4	36.4	66.7
B	Coastal habitats	10	8	8	80.0	100.0
C	Inland surface water	12	9	9	75.0	100.0
D	Mire, bog and fen	25	21	19	76.0	90.5
E	Grassland	211	220	191	90.5	86.8
F	Heathland	—	—	—	—	—
G	Woodland/Forest	57	42	39	68.4	92.9
H	Inland unvegetated	—	—	—	—	—
I	Regularly cultivated	210	208	192	91.4	92.3
J	Constructed	0	3	0		
	Totals	536	536	462	86.2	86.2

Table 4. Class description and accuracy assessment table for Wye Downs study area

Eunis code	Class description	Reference totals	Classified totals	Number correct	Prod. accuracy (%)	Users accuracy %)
E1.2	Perennial calcareous grassland	13	13	10	76.9	76.9
E2.1	Permanent mesotrophic pastures and aftermath-grazed meadows	10	12	10	100	83.3
G1	Broadleaved deciduous woodland	31	26	20	64.5	76.9
G3. F2	Exotic conifer plantations	7	11	7	100	63.6
G5	Lines of trees	7	11	6	85.7	54.5
F3	Temperate and mediterraneo-montane scrub	8	11	6	75.0	54.5
FA	Hedgerows	9	10	7	77.8	70.0
I	Regularly or recently cultivated agricultural, horticultural and domestic habitats	64	56	55	85.9	98.2
	Totals	150	150	121	80.7	80.7

data. In general, however, it can be stated that land cover types with variable object sizes and forms reach lower accuracy values than classes with clearly distinguishable object boundaries, as is the case for agricultural and grassland parcels.

The quality of habitat mapping at scales smaller than 1:10 000 is measured against traditional methods such as aerial photo interpretation or in situ field survey. Moreover, the results have to match the requirements for a minimum mapping unit of 0.3–1 ha defined by the national implementation of European measures such as Natura 2000,

the WFD and the CAP. Comparability of different habitat maps or any field record begins with the semantic definition of classes according to a certain nomenclature. Figure 7 shows three habitat maps of the “Wildes Moor” bog with a harmonised class legend. After a long period of degeneration caused by drainage, the bog is now largely under nature conservation management and measures for regeneration include raising the water level. A visual analysis shows that FFH- and BNTK-maps follow the field parcel boundaries while the HRSC classification represents the ecotone character of the bog

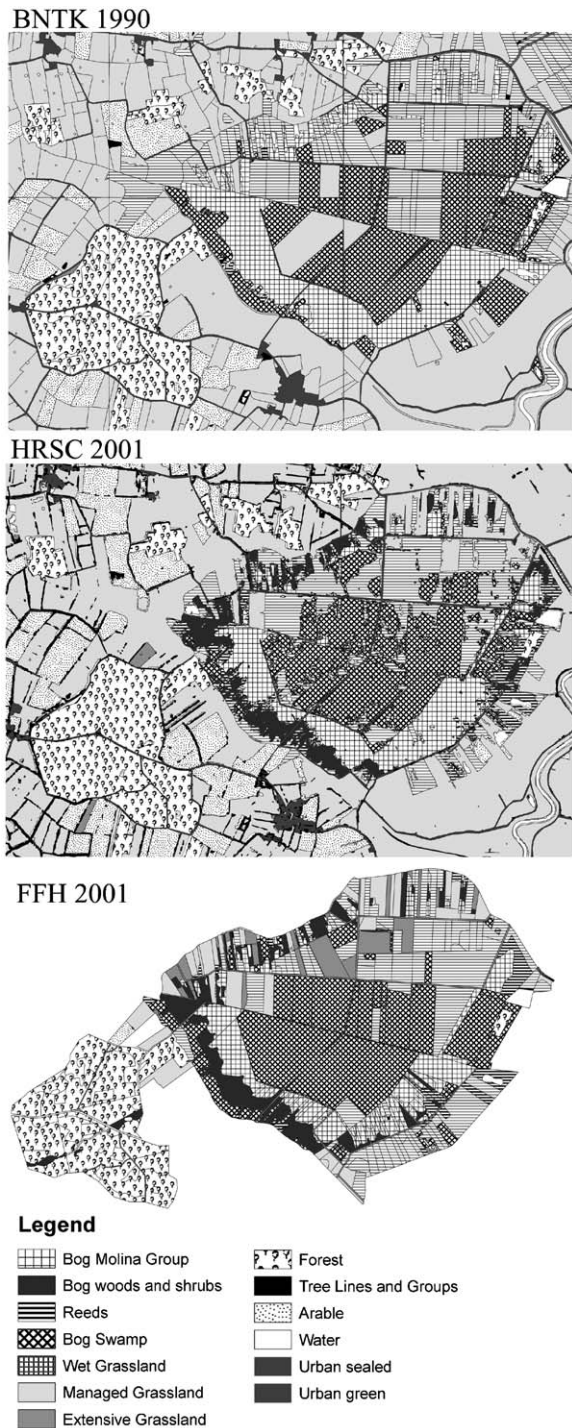


Figure 7. Natura 2000 habitat “Wildes Moor”, Schleswig-Holstein, Comparison of three habitat maps from different origin using a harmonised classification key.

more realistically within the BNTK borders. All maps vary in the definition and delineation of habitats. The object-oriented classification procedures applied on VHR-data give similar results and additionally with higher spatial detail. On the other hand, the high differentiation of objects and within

objects needs to be harmonised to be compatible and comparable with existing maps. Accuracy was not evaluated by statistical methods due to a lack of sufficient ground truth data, but visual inspection shows promising results within all habitats. As stated before, EO-based mapping of habitats with VHR data can be characterised as a complex problem that can only be solved by focusing on specific target objects. This implies the use of a combination of existing knowledge, such as the BNTK maps and soil data, and the spectral and contextual properties of the object. Detection of woodlands and buildings performed well with the use of the DSM and integration of the temporal domain with lower resolution satellite data supporting the classification at all levels.

Mapping of habitats at local scale with Quickbird, Wye Downs

A subset of the final classification map of the Wye downs area is shown in Fig. 8 and the accuracy assessment in Table 4. The application of traditional pixel-based classification on VHR images resulted in a pixelised (salt and pepper) representation of land cover, which does not allow easy demarcation of habitat maps for conservation applications. On the other hand, the object-based classification technique resulted in solid habitat blocks, as well as retaining small scale information such as scrub encroachment into calcareous grassland, which is more amenable to mapping and also allows the integration of the classification result directly into a vector-GIS for further analysis.

The accuracy assessment was done by means of an error matrix based on stratified and randomly selected points across the classified image. One hundred and fifty points were selected in total, stratified according to the size of the area covered by each class and randomly located within each class. A minimum number of 10 points per class was set because the predominance of agricultural land would have resulted in the remaining classes being highly under represented in the accuracy assessment. The ground truthing was carried out by field survey visiting all the selected points and confirming their land-cover in situ. For the assessment of the methods performance we used the overall correct classification rate and the correct classification rate for each of the target classes. The kappa coefficient was also used as suggested by Congalton (1991). The kappa coefficient expresses the proportionate reduction in error generated by a classification process compared with the error of a completely random classification. A kappa

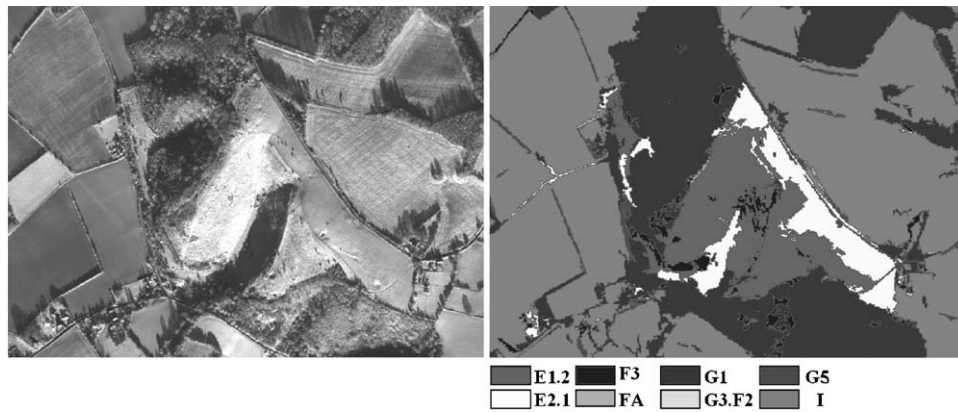


Figure 8. Subset of the Quickbird panchromatic image and subset of the final result of the object-based classification for Wye Downs.

coefficient of 0.75 for example indicates that the classification process is avoiding 75% of the errors that a completely random classification generates (ERDAS, 1999).

The overall accuracy of more than 80% and the kappa coefficient of 0.7513 which is an indication of an “excellent” model (Fielding & Bell, 1997) is considered a good result. This is especially the case bearing in mind the rather extensive problem of shadow and the lack of foliage on the deciduous vegetation. This last point is reflected in the confusion between classes G1 and F3 both consisting of different broadleaved species. The distinction between G1 and F3 would be expected to be much more effective for an image acquired during the growing period where different broadleaved species could have been detected. The relatively low users accuracy for class G5 is due to the spatial mismatch of a few metres between the classified data and the reference data and G5 is confined to narrow strips between arable fields. Furthermore, class G5 is confused with class FA mainly due to the absence of foliage to distinguish between tree and scrub species. The reference data for class G3.F2 are accurately confirmed by the classification; however, in some cases broadleaved woodlands have been classified as coniferous. This is probably due to the low angle of the sun at the image acquisition time, which creates micro-patches of shadow in both coniferous and broadleaved woodlands, which hinders their separation. One of the main targets of the current mapping exercise was to detect the two different grassland types, E1.2 and E2.1 which has proved a hard task when remotely sensed data are used (Fuller, Groom, & Jones, 1994). The method performed very well in this task, almost 77% correct classification for the former and 83% for the latter.

Another possible source of misclassification error is the manual classification performed on a large part of the image. Although an advantage of the method is the ability to intervene manually in the classification and assign classes to objects where no sufficient spectral information is available, this can also generate some errors because the manual classification relies on field data as well as data retrieved from existing thematic maps of the area. Although, the field data are considered thematically and spatially accurate, the remainder of the ground truth data carries the misclassification error of the maps from which they are derived and this accounts for a large proportion of the misclassification error of the classified image. Furthermore, some changes that occurred between the year where that reference data were produced (1992) and the year the image was taken could not be incorporated in the manual classification.

Textural information has been found to be an important tool for the discrimination of classes and it is increasingly being used for the classification of remotely sensed images. This is due to the development of computer systems which have made the calculation of the complex textural properties much easier and also due to the fact that with the new VHR sensors the detection of micro-scale texture properties becomes possible as opposed to the more coarse resolution of sensors in the past (Mather, 1999).

Part of the study area has also been classified using a kernel-based method (see Keramitsoglou, Kontoes, Sifakis, Mitchley, & Xofis, 2005). Kernel-based reclassification is a pixel-based technique, which reclassifies an unsupervised classified image based on its texture in relation to the target classes. Subsequently it combines the spectral information of an image summarised in the initial ISODATA classification as well as texture informa-

tion (for details of the methodology see Keramitsoglou et al., 2005). Although the results of kernel reclassification and object-oriented classification are not entirely comparable, some speculation can be made about the efficiency and some methodological aspects of the two methods. Both methods give quite accurate results, exceeding 80%. The object-oriented method however, unlike the kernel-based method, allows the integration of external knowledge into the classification process which in this study was of great help in the classification of shadowed objects as well as for the distinction between calcareous grassland (E1.2) and mesotrophic pastures (E2.1). On the other hand, the kernel-based method was much quicker and less demanding in terms of computer power.

Conclusions and outlook

The results presented in this paper show that object oriented classification of EO data is a valuable method for habitat mapping at a range of different scales. It performs very well when applied to HSR data (Landsat 30 m) for the production of habitat maps at a regional level with coarse thematic resolution. The method performs extremely well when applied to VHSR data (Quickbird 0.7 m, HRSC 4 m) for the production of local scale maps with fine thematic resolution.

One of the major tasks in conservation monitoring is the production of maps for previous time periods. The results presented here show that object oriented methods provide flexibility in the ability to transfer classification schemes developed using recent images, where a fair set of ground truth data is available, to past images where acquisition of ground truth data is usually impossible.

Compared to traditional habitat mapping techniques (air photo interpretation, field study), object oriented methods provide results of comparable accuracy whilst providing at the same time enhanced spatial detail and the ability to detect within-habitat variation and gradients, such as ecotones, by analysis of fuzzy class memberships. The ability to detect gradients in successional ecosystems such as the bog habitats in the German case study area is an important capability.

The hierarchical classification approaches employed in the current study allow for the accurate classification of habitat types, which occur at different spatial scales. For instance, large-scale

woodland habitats can be detected at higher, coarser segmentation levels, while small-scale habitats such as woodland corridors and hedgerows can be detected at lower, finer segmentation levels.

The ability to extract the image objects at any point throughout the classification process allows the incorporation of sound statistical methods, such as Linear Discriminant Analysis, in the detection of the most significant object features for the differentiation of the targeted classes.

One major advantage of object-oriented methods is the ability to integrate external knowledge or additional EO data into the classification process and to develop knowledge-based rules in the classification. This facility allows the accurate identification and classification of habitats with similar spectral characteristics, such as grasslands. The effective separation of different grassland types using EO data and classification techniques has long been a problem; however in the Wye Downs case study we were able to distinguish between the closely related calcareous and mesotrophic grassland habitats to a high degree of accuracy using geological data. Similarly, the uncertain assignment of arable lands, managed grasslands and semi-natural habitats in the German case study was solved by the integration of multi-temporal EO data.

Object oriented classification methods and knowledge-based sets of rules enable the substantial limitations of purely spectral and pixel-based methods to be overcome and raise the potential for the use of EO data for nature conservation monitoring tasks. The wider use of remote sensing data for habitat mapping depends, however, on a multiplicity of additional factors, including spectral and temporal resolution, semantic and geometrical accuracy and availability of suitable EO and ancillary data. At the European policy level, the main driving force in this decade is the ongoing implementation of Global Monitoring for Environment and Security (GMES) the joint initiative of the European Commission and the European Space Agency (www.gmes.info). Addressing the nature and biodiversity issues, GMES should facilitate the establishment of consistent EU-wide machinery for inventory and mapping of terrestrial and marine habitats by following agreed EUNIS and Habitat Directives typologies (Wyatt, Briggs, & Ryder, 2003). But, most importantly, the general acceptance by the user community and the successful integration of these new information products into existing conservation monitoring procedures depends ultimately upon their cost-effectiveness.

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