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Object-based mapping and object-relationship modeling for land use classes and habitats

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Abstract: As a contribution to the discussion on classification approaches for very high spatial resolution (VHSR) remote sensing data, we explore the potential of object-based mapping and the usage of additional data layers and contextual information for class description. This paper presents two studies on land-use and habitat mapping in Natura-2000 sites in Austria. Both studies have been performed using VHSR data, namely a pan-sharpened QuickBird scene and digitalized aerial photographs. Image segmentation is demonstrated as an approach to aggregate image information to provide manageable landscape objects. These objects can potentially be of ecological significance as opposed to the pixels of the original image. It is shown that scenes of high spatial and spectral variability (as depicted on VHSR data) can be segmented with the aim of either one-level representation (OLR), or multiscale segmentation (MSS). The first, applicable in landscapes with rather distinct features and clear boundaries, represents landscape elements, which can be directly classified by an advanced set of features, such as colour, form or texture. The latter, resulting in a hierarchical set of landscape objects, provides constituting elements for object relationship modeling (ORM) of complex target classes. Both approaches are discussed in terms of their appropriateness for specific landscape settings concerning complexity and spatial ambiguity of elements at a specific target scale. We also demonstrate how object-based habitat mapping can help to detect fine-scaled changes in the habitat types under consideration and how the approach can be used to support Natura-2000 monitoring.

Zusammenfassung: *Automatisierte objektbasierte Habitat- und Landnutzungskartierung über Zusatzinformation und Objektbeziehungsmodelle*. Als ein Beitrag zur Diskussion der Automatisierungsansätze zur Klassifikation höchstauflösender (VHSR) Fernerkundungsdaten im Bereich Naturschutz untersucht der vorliegende Artikel das spezifische Potenzial objektbasierter Klassifikation und der Einbeziehung zusätzlicher Datensätze bei der Klassenbeschreibung. Bedeutung und Einsatzmöglichkeiten werden anhand von zwei Fallstudien zur Habitat- und Landnutzungskartierung in Natura-2000 Gebieten in Österreich verdeutlicht. Bildsegmentierung wird als ein geeigneter Ansatz vorgeführt, wie detaillierte Bildinformation aggregiert werden kann, um handhabbare Landschaftsobjekte von ökologischer Relevanz zu erhalten. Es wird gezeigt, dass Szenen hoher räumlicher und spektraler Variablität entweder durch einen einzigen geeigneten Objektlevel (OLR) oder multiskalare Bildsegmentierung (MSS) repräsentiert werden können. OLR, anwendbar in Landschaften mit homogen strukturierten Einheiten und klaren Grenzen, stellt Einheiten bereit, die durch Charakterisierung von Farbe, Form und Textur unmittelbar klassifiziert werden können. MSS hingegen generiert eine hierarchische Repräsentation von Landschaftsobjekten und bietet Objekte für die Modellierung komplexerer Klassen (ORM). Beide Ansätze werden für spezifische Landschaftsstrukturen besprochen, die unterschiedliche Komplexität bzw. räumliche Unschärfe aufweisen. Schließlich wird noch anhand des Beispiels zunehmender Verbuschung aufgezeigt, inwieweit objektbasierte Klassifikation genutzt werden kann, um feinmaßstäbige Veränderungen in Habitattypen quantitativ zu erfassen und somit das Monitoring von Natura-2000 Gebieten zu unterstützen.

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Introduction

User acceptance for satellite remote sensing data in local level nature conservation applications has been limited due to a spatial resolution that tends to mismatch the requirements of detailed assessment and monitoring tasks at hand. With recent increase in spatial resolution of satellite imagery (Ikonos, QuickBird), a growing interest from the nature conservation side can be observed (see e. g. Kerr & Ostrovsky 2003, Wulder et al. 2004, Turner et al. 2003). However, with the advent of very high spatial resolution (VHSR) data not only chances, but also challenges of automated information extraction have significantly risen (Lang & Blaschke 2003). Some of the emerging advanced mapping and assessment methods are based on image segmentation approaches in combination with knowledge-based and rule-based classification of the delineated units. Current studies and projects concerning the Natura-2000 EU policy (e. g. SPIN, see Weiers et al. 2004) seek to perform the task of status and change assessment on the basis of remote sensing data in a semi-automated manner. Reproducibility, transparency, transferability and the increased possibility for quantification have been reported by Langanke et al. 2004 as the central advantages of mapping approaches based on Earth observation (EO) within the framework of site assessment. Semi-automated classification methodologies for EO data provide a more objective outcome in the sense of the above mentioned requirements as compared to visual interpretation (ibid.). Due to its subjective character (Albertz 1999, Campbell 2001) reproducibility and transparency of visual interpretation is limited as even the same interpreter is not able to completely reproduce a visual interpretation a second time. Erroneous or biased results of the classification will propagate through any subsequent analysis like quantitative structural assessment or post-classification change detection.

The object-based approach discussed in this paper can facilitate mapping of complex habitat structures (Lang & Blaschke 2003). Experienced field ecologists and remote sensing/visual interpretation specialists are challenged to collaborate on setting up a functioning rule set. The approach therefore bridges the gap between modeling and direct mapping, integrating methods of rule-based classifications of segmented remotely sensed imagery and GIS methods of spatial analysis. Within object-based mapping a cognition network (Binnig et al. 2001) is established which serves as a conceptual framework for the number and parameterization of segmentation layers and the definition of classes. Especially when multiscale segmentation and object-relationship modeling (MSS/ORM, see Burnett & Blaschke 2003) is being applied, such a conceptual outline seems to be indispensable. Any step and setting during the entire classification process is documented, and can be assessed and adopted if needed. Although the result is not necessarily more accurate, it can be reproduced and the process is to a high degree comprehensible. The formalized approach of analysis (i. e. the class definitions and composition and the documentation of the workflow and settings in the semi-automated process) technically allows for a transfer of the classification to other scenes (Lang & Langanke 2004, Benz et al. 2004).

This paper aims to demonstrate the potential of object-based classification methods on two Natura-2000 sites in the Austrian provinces of Salzburg and Styria. Classification has been performed on high-resolution remotely sensed images utilizing expert knowledge. The authors will discuss the strengths of the approach but also demonstrate potential limits and problems which arise partly from the vagueness in class definition, partly from the segmentation algorithm itself.

Study sites and data sets used

Study sites

The first test area comprises a four square kilometre subset of the Styrian Joglland

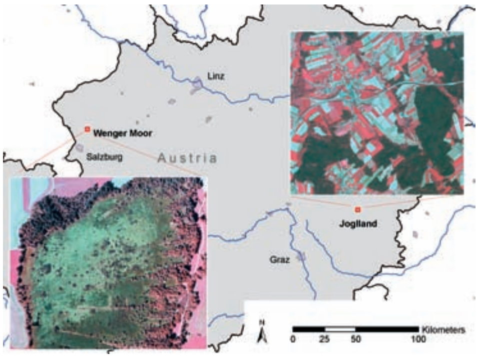

Fig. 1: Locations of the two test sites: Joglland (Styria) and Wenger Moor (north-east of the city of Salzburg). The insets show samples of the data used: a QuickBird scene from 2004 (*right*) and a false-colour air-photo from 1976 (Amt der Salzburger Landesregierung, *left*)

around the town of Dechantskirchen (Fig. 1). The entire Joglland area is considered to form the habitat of various bird species listed in the Bird Directive 79/409/EEC (such as *Lanius collurio*, *Crex crex*, *Tetrao tetrix*, *Pernis apivorus*). The subset used in this study is dominated by a mosaic of agricultural fields (intensively used grassland, various types of crops), hedgerows (as of particular importance for *Lanius collurio*) and forest. A feasibility study for semi-automated classification of QuickBird data was carried out, focusing on object-based mapping using monotemporal VHSR data. This included the distinction between crop types and grasslands, the differentiation between forest types and the delineation of linear structural components (e. g. hedgerows) and land-use classes with 'conceptual' boundaries (e. g. orchards).

The second case-study captures and evaluates fine-scaled change dynamics in a threatened raised bog in the foothill area of the Alps within the province of Salzburg. With an overall size of 298 hectare the Wenger Moor (Fig. 1) is a small remnant of a raised bog, situated at an altitude of 510 m. Dynamics in the bog mainly reflect human-induced changes due to activities within the bog itself (such as drainage, peat extraction, afforestation logging) and in its immediate surrounding (intensive agriculture). Today the former active raised bog is characterised by a complex and intermingled mosaic of remaining raised bog and several stages of degradation such as *Calluna vulgaris* encroached areas (heath bog) *Pinus mugo* (bush bog), and trees (tree bog). Aerial photographs document these changes between 1976 and 1999. Object-relationship modeling has been used to identify the four degradation stages. This included three steps: 1) image segmentation on two distinct levels, 2) classification of high resolution images of two different dates and 3) quantifying and highlighting changes in the habitat types under consideration.

Data

QuickBird data have been acquired for the Joglland study. The data were resolution-merged leading to a ground-resolution of 0.6 m. Spatial enhancement of the QuickBird data was achieved by using a pan-sharpening approach after Liu (2000), a procedure that is optimized to maintain the original spectral values to a large extent (> 90 %), as being compared to methods based on principal component analysis.

For the Wenger Moor study we used two scanned aerial photographs of the bog area, a colour-infrared air-photo from 1976 and a colour air-photo from 1999. Both aerial photographs have been co-registered and re-sampled to a spatial resolution of 0.37 m. A subset (28.8 ha) was used with the core area of the eastern part of the bog (see Fig. 1).

Methods

Segmentation strategy: one-level representation (OLR) vs. multi-scale segmentation (MSS)

Image segmentation (Haralick & Shapiro 1985) aims at partitioning an image exhaustively into homogeneous regions. Detailed image information is aggregated in segments that can be labelled and classified according to their spectral and spatial properties as well as their interrelationships. Image segmentation is considered to be a crucial step in image analysis (PAL & PAL 1993), and by forming the conceptual link to human perception it may be a essential prerequisite for image understanding (GORTE 1998). While an enormous range of different segmentation approaches does exist (ZHANG 2001), the operational use of them within remote sensing applications is still limited (BLASCHKE & STROBL 2001, CHEN 2003). On the other hand the flexibility in performing scale-specific segmentation has led to a growing interest from landscape ecological applications of this approach. Within landscape ecology the hierarchical representation of process-relevant spatial units in various scale domains is one of the fundamental pillars (WU 1999). Segmentation can be used to provide a consistent set of image primitives to be used as landscape objects (LANG & LANGANKE 2004, BURNETT & BLASCHKE 2003).

Image segmentation in both studies has been performed using the software eCognition (BENZ et al. 2004). The algorithm being implemented follows a region-based, local mutual best fitting approach (BAATZ & SCHÄPE 2000), which performs merges in a local vicinity of the image segments according to a fitting gradient ("gradient of degree of fitting"). In a scene being dominated by homogenous geographic features with distinct boundaries (e. g. agricultural fields, or forest types that are more characterized by texture than by spatial arrangement) one single level reflecting the appropriate scale domain is likely to be found. This level may be generated by iterative segmentation, but it will be used as the only level for classification (one-level representation, OLR, see Fig. 2, left). In more complex images with less distinct boundaries, the hierarchical structure of the represented landscape may be better reflected by multi-scale segmentation (MSS, see Fig. 2, right). MSS (BURNETT & BLASCHKE 2003) produces a nested hierarchy revealing homogenous units on different levels of aggregation. These units are subsequently used for defining classes by object-relationship modeling (ORM, ibid., see next chapter). Within MSS/ORM a cognition network guides the number of segmentation layers required for the class modeling (LANG & LANGANKE 2004).

In the Joglland study we used OLR, since a single scale domain has been visually

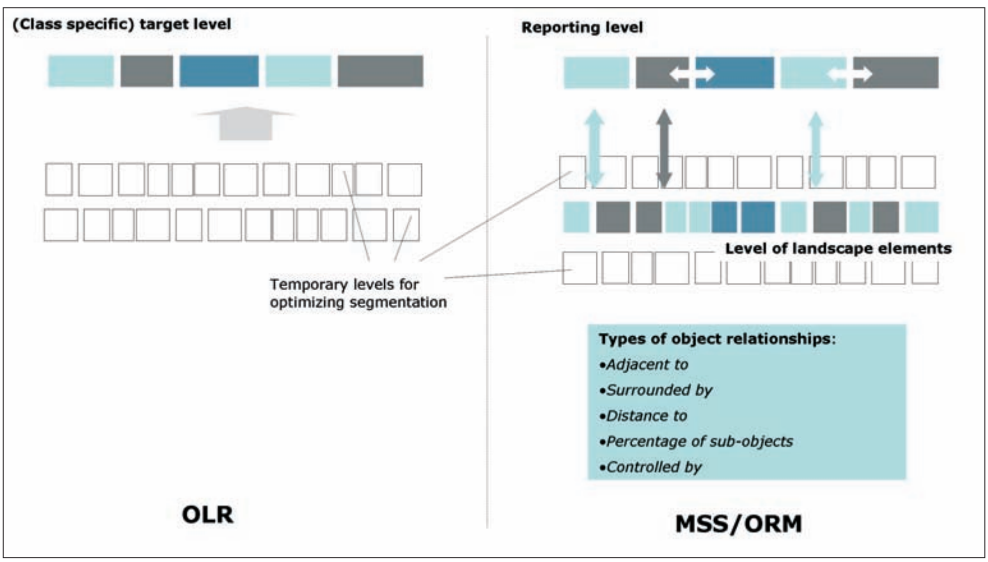

Fig. 2: Two segmentation strategies: one-level representation (OLR, *left*) vs. multi-scale segmentation (MSS, *right*). OLR utilizes one single optimized level. In MSS/ORM two or more levels are used for class modeling.

Tab. 1: Segmentation levels, methods and parameterization for the two test sites. SP = scale parameter (final levels in bold); STD = standard (SP controls average size of segments); SD = spectral difference (SP controls average spectral distance between segments); ColW = colour weighting (against form); CompW = compactness weighting (against curvilinearity).

		SP	*Method*	*ColW*	*CompW*
Joglland	**OLR**				
	Crop types	50/80/120/140/**170**	STD	0.5	0.5
	Forest types	**200**	STD	0.5	0.5
	Linear elements	50/80/120/**140**	STD	0.5	0.5
	Orchard	10/**20**	STD	0.5	0.1
Wenger Moor	**MSS**				
	Level 0	**15**	SD	n.a.	n.a.
	Level -1	**150**	STD	0.8	0.1

identified for the required level of detail. The parameters being used for the segmentation are shown in Tab. 1. In the Wenger Moor case study two such levels were created, namely the level of elementary landscape objects and the reporting or mapping level. The first level of segmentation represents basic landscape elements. Segmentation has to be fine enough to generate objects to be included in later classifications. This level is classified by collecting representative samples for each basic class throughout the image. A second, more aggregated segmentation level is created containing the target objects of the mapping level.

Labeling and classification

Several sub-studies have been performed to investigate different strategies, each of them considered appropriate for the respective category of land use types. A complementary ground survey based on 159 control points has been conducted in the Joglland area. Points were collected under the premise to cover all spectrally distinguishable units and in particular to document the differentiation of different grassland and crop types, as well as different forest types. Ground survey and acquisition time of the satellite data were three months apart, therefore in some cases we additionally had to examine the actual stage three months before.

Crop types have been classified on a subset of 35.9 ha using a sample-based nearest neighbour classifier in spectral feature space. To differentiate between different forest types the third principal component (PC-3) has been used as an extra layer in a subset of 40.8 ha. The standard deviation of PC-3 was used as an additional feature in the classification process. The sub-scene has been classified in sequences: first we distinguished classes of different texture behaviour and secondly we combined it with the spectral information of the NIR band. Linear elements such as hedgerows and denser tree rows usually exhibit similar spectral signatures as deciduous trees. Hedgerows have been addressed by modeling the horizontal spatial relationships of their components, i. e. the continuous tree or shrub line next to an elongated shadow object, all being adjacent to agricultural fields. Orchards, though being easily recognized by a human interpreter due to their specific spatial arrangement of single trees in an otherwise homogeneous matrix (mostly grass vegetation), are hardly captured by segmentation, since outer boundaries are missing. In this case we successfully applied LIST, a tool for

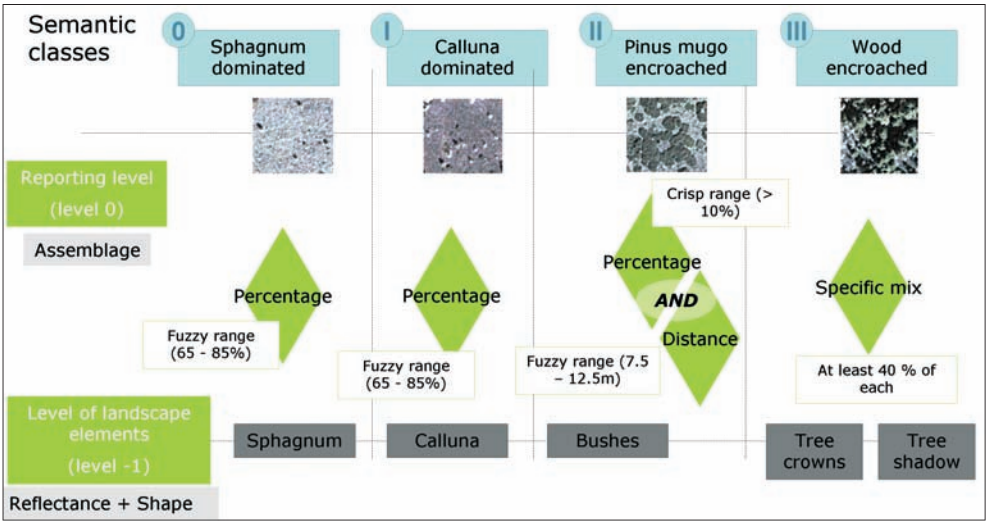

Fig. 3: Cognition network Wenger Moor. The graphic shows how the four degradation stages (semantic classes) can be modeled using both spectral and structural characteristics.

quantifying manually delineated features in terms of the spatial distribution of machine-derived sub-units (Langanke et al. 2004).

In the second case study we used ORM. The cognition network being established (Fig. 3) foresees two levels of segmentation, the first being referred to as the level of elementary landscape objects (level -1), the second being considered the reporting or mapping level (level 0). Level -1 reflects the constitutional homogenous elements in the landscape of interest. It has been classified by collecting representative samples for each class throughout the image. Spectral information was not sufficient to separate all classes, as some of them showed high spectral correlation. While a variety of object features could be used for separating samples, many of them are statistically intercorrelated. A statistical de-correlation analysis (feature space optimization, FSO) could be performed to identify *n* features which manage to separate the classes at best. However, this would not determine, if these features are really distinctive for the specific classes. For example, if the feature length/width ratio is selected by FSO, only coincidentally the samples may show this characteristic. Additional heuristics leveraging spatial properties were encoded using fuzzy rules: the spatial feature 'distance of sphagnum to intensively used grassland' prevents objects adjacent to grassland from being classified as sphagnum. On the mapping level (level 0) classes were established according to the specific stages of degradation in the bog such as (remaining) open raised bog areas, *Calluna vulgaris* encroached areas, *Pinus mugo* bushes and tree dominated areas. The cognition network defines class composition on level 0 by modeling the spatial arrangements of the constituting sub-objects on level -1. Representative image sections were selected and their 'body plans' were documented as structural signatures (Lang & Langanke 2004) according to their typical structural characteristics. Expert knowledge has been incorporated to consider the relevant heuristics of a semantic class. An example for the heuristics being used for defining the class *Pinus mugo* encroached bog is given in Fig. 4.

Change analysis

Post-classification change detection (Singh 1979) has been applied on the 1976 and 1999 classification results. Changes were charac-

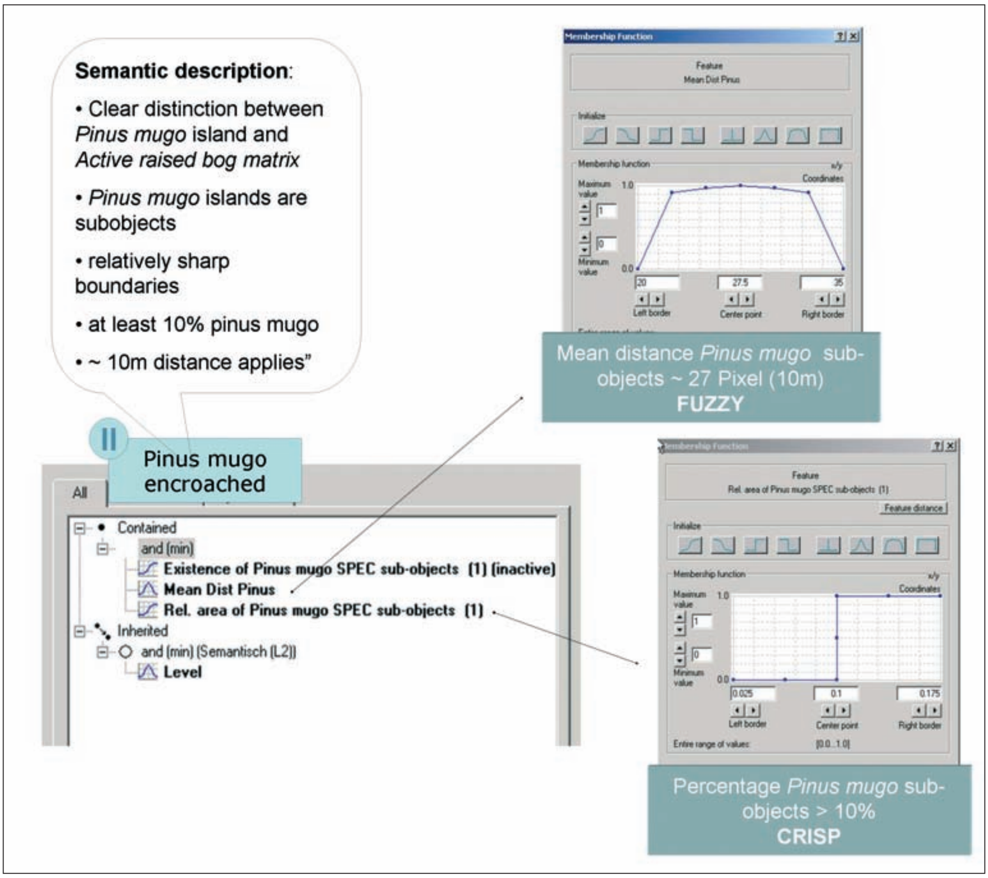

Fig. 4: For the definition of the semantic class *Pinus mugo encroached bog* the relative area of sub-objects (fuzzy rule) and an average distance (crisp rule) are used.

terized according to the increase of advanced degradation stages, mainly the spread of *Pinus mugo* bushes. A map overlay was performed and a set of sixteen change classes was produced. Additionally a transition matrix was computed which shows the transition from the original *Sphagnum* layer to each of the other degradation stages.

Results

Classification on OLR data layers

Sample-based overall classification

A sample-based overview classification, only using the original four bands of QuickBird would generate high confusion between forest type classes and agricultural fields. In a test run we only obtained poor results (percent correct: 54.1 %). Spectral profiles collected for the investigation of ambiguous classes showed broad overlaps.

Crop fields vs. grassland

Since grassland in the study area is mainly intensively used, most parcels have already been mowed at the time of image acquisition in early May. These fields are characterized by a high portion of bare soil. Furthermore hay bundles lying on the ground are detectable and help differentiate grassland from corn (*Zea mays* L.) fields. Crop fields (other than corn) at the time of capturing are characterized by higher biomass content, showing uneven textures in shades of red. Classification problems arose with grassland not yet being mowed, which exhibits a fuller red colour with an even texture. As a special case freshly mowed parcels were captured. Shortly after being mowed these fields show a light red to orange signature. Parcels, which at this phenological stage show limited photosynthetic activity, are mostly corn fields (with the exception of disturbed surfaces or freshly made up fallow ones).

Crop types

On false-colour representations of the QuickBird data, the early growth stage corn fields appear in bluish tones in the original data. All other grain types were already in the growth stage with a certain portion of biomass at this time. In the study area this applies for crop types with ears (barley, wheat, rye, triticale) more clearly than to crops with panicles (here only oats). The result of the crop type classification is depicted in Fig. 5. For evaluating the classification stability we used membership assessment, assigning each segment a value reflecting the degree of best class membership. Additionally we examined every single polygon, and verified its label. Of these 104 segments, 98 (i. e. 94.2 %) were classified correctly. Main confusion appeared at the edges of single parcels, where agricultural roads, tracks and field edges have been merged with the actual parcels in the segmentation process.

Forest types

The distinction of different forest types has been successfully performed using additional data layers. Based on the third principal component a texture image has been calculated (see Fig. 6). Using the specific roughness, young spruce stocks could be identified, which otherwise due to their high spectral reflectance in near infrared were mistaken as deciduous trees. Pure pine forest could be separated from mixed woodland. 93 generated random points were used for evaluation, of which 90 points (96.8 %) were correctly classified.

Linear elements

Hedges and tree rows are theoretically detectable, if neighbourhood rules can be applied successfully. But this requires relevant objects (e. g. corn field and hedge objects)

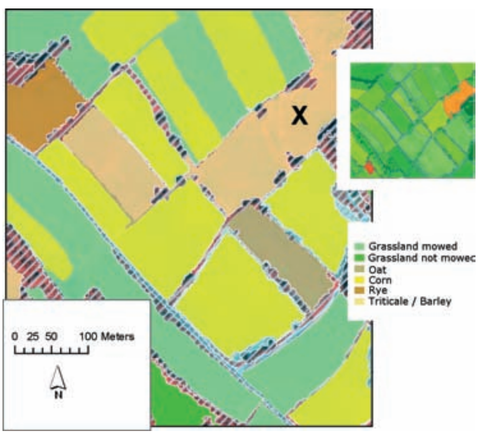

Fig. 5: Automated delineation of agricultural fields and differentiation of crop types. Note that assignment of the field X is ambiguous due to its reflection behaviour (*left*). Analysis of classification stability revealing high uncertainty for field X (orange colour) (*top right*).

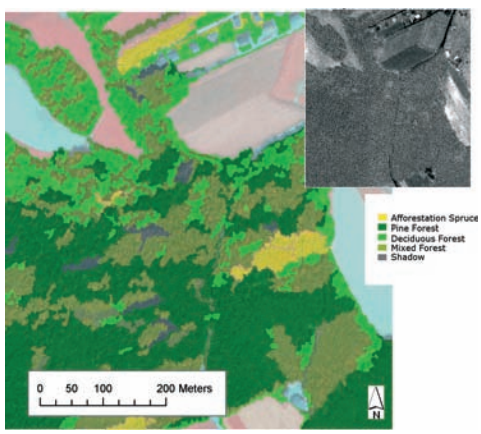

Fig. 6: Classification of different forest types. A texture image of PC-3 of the QuickBird data (*upper right corner*) was used to identify afforestation areas (spruce).

to be produced directly adjacent to each other. Due to graded transitions between the dark shaded areas and the bright neighbouring field, the neighbour-rule often fails. Problems of aggregation will arise, if on higher levels of segmentation the desired boundaries of the entire hedge are not produced.

Hybrid approaches

Manually delineated outlines of an orchard are used as predefined boundaries in the segmentation process. Alternatively, in this case, a convex hull could have been created around the trees using a certain buffer size. Using LIST, the number of deciduous trees and their averaged distance is then determined automatically (Fig. 7).

A similar procedure has been used to distinguish between forest classes, where aggregation would be difficult without visual delineation (e. g. mixed woodland). Deciduous and coniferous trees, which are classified automatically, were used for quantification and structural analysis of the delineated units (see Fig. 7, right).

Classification of degradation stages using ORM on MSS data layers

The classification results of the degradation stages in the Wenger Moor is shown in Fig. 8 and Tab. 2. In 1999 bush encroachment has increased significantly as compared to the situation in 1976, where the different degradation stages have yet to show. Accuracy assessment has been performed using a random selection of 93 centroids of randomly selected 25 m² cells. The same set of points has been used for both time slices. Since the data show a past status of the mire and due

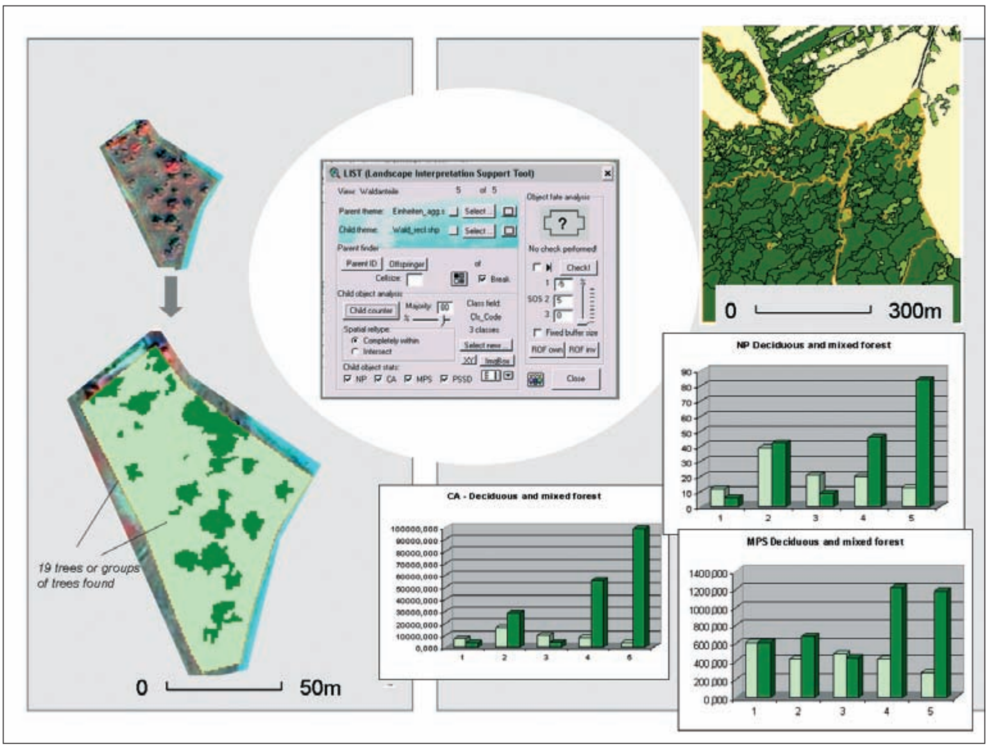

Fig. 7: Quantitative analysis using the ArcView extension LIST. *Left*: counting of trees within a manually delineated orchard. *Right*: Forest composition of manually defined units, being analyzed by the number of sub-objects (NP) of deciduous or coniferous/mixed woodland. Furthermore the respective total area (CA) and mean patch size (MPS) were calculated.

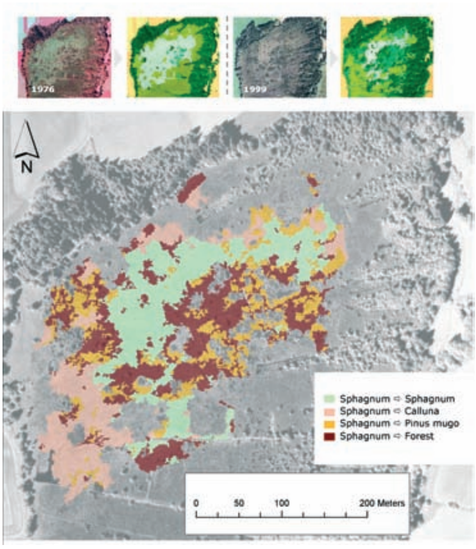

Fig. 8: Classification and quantification of changes in the Wenger Moor study. *Top row*: classification of false-colour air-photo from 1976 and colour air-photo from 1999. *Below*: Post classification change detection with transitions of Sphagnum to three different degradation stages.

to restricted access, ground truthing has been done by visual interpretation. However, assigning the correct reference values is problematic, since smooth transitions occur, when degradation stages gradually transform from one to another. Therefore 1st and 2nd choice has been accepted in these transition zones (the class "Active raised bog' has been excepted from this rule). 1st choice acceptance led to percent correct values smaller than 80% in either case (1976: 77.4%; 1999: 73.1%). 2nd choice acceptance led to 87.6% 1976 and 83.7% in 1999 when allowing bush and tree confusion in transition zones; 82.8 % in 1976 and 83.8% in 1999, when allowing heath and bush confusion. Taking both cases we finally reached 83.9% in 1976 and 89.3% in 1999. In 1976 slight overestimation of active raised bog was observed. Note that this could also refer to an underestimation in the reference interpretation. Point-based accuracy assessment seems to be very limited in scenes of high complexity and smooth transitions.

Quantification of changes

The change map (Fig. 8) shows the respective transitions from the original *Sphagnum* area towards each of the designated degradation stages in the Wenger Moor test site within the 23 years between 1976 and 1999. Pink tones indicate change from *Sphagnum* towards *Calluna vulgaris*, orange towards *Pinus mugo*, and red towards forest. Loss of the core bog area has been calculated as 3.3 ha in favour of the degradation stages heath (0.2 ha), bushes (2.1 ha) and trees (1.0 ha).

Discussion

We demonstrated to which extent approaches and strategies based on remotely sensed data can be used for fine-scaled classifications in the context of Natura-2000

Tab. 2: Results of the bog classification of two time slices 1976 and 1999. DG = degradation stage (0-III); CA = entire class area, NP = number of patches, MPS = mean patch size.

	1976			1999		
Class (DG)	*CA (ha)*	*NP*	*MPS (ha)*	*CA (ha)*	*NP*	*MPS (ha)*
Active Raised Bog (0)	5.98	3	1.99	2.13	17	0.13
Heath Bog (I)	7.51	8	0.94	4.85	25	0.19
Bush Bog (II)	0.48	21	0.02	3.59	207	0.02
Tree Bog (III)	10.11	15	0.67	14.57	95	0.15

habitat mapping. The potential of an object-based classification for deriving relevant target classes from VHSR data in a semi-automated manner has been examined, and critical issues and limits have been shown. Possibilities to facilitate the classification by rule sets or additional data derived by image processing were discussed. Using segmentation-based classification approaches, changes have been detected and spatially analyzed on aggregated levels. Monitoring and change detection methodologies are required in nature conservation, e. g. for the regular assessment of the conservation status of Natura-2000 sites all over Europe. In some cases this approach will be able to complement or even replace fieldwork, and at least enable better targeting the areas that warrant further study (Weiers et al. 2004).

Data material and usability

QuickBird data with an enhanced spatial resolution of 0.6 m and the spectral range including the VNIR band provide means to classify habitats and land use types in a target scale dimension reaching up to 1:10,000. The pan-sharpening product has proved to be suitable for increasing spatial resolution while at the same time maintaining spectral behaviour for detecting the target classes to be addressed. The majority of the target classes can therefore be derived from QuickBird data. But still the difference between a 0.25 m aerial photograph and a 0.6 m QuickBird image can be critical when trying to identify single trees or plant species, even if satellite data have high radiometric resolution (11 bit). A reasonable cost-benefit ratio and the possibility to order and program user-defined areas by polygonal boundaries are further assets making QuickBird attractive for studies that focus on a rather small overall study area. As compared to the usage of aerial photographs, the entire work flow from ordering to processing is digital, i. e. no information is lost due to analogue procedures and mosaicking. Continuing monitoring and change detection is supported by high repeating rates. However, receiving the data is depending on data providers and can be influenced by the political situation or other uncontrollable factors such as unfavourable weather conditions.

OLR, ORM and methodological constraints

OLR has turned out to be suitable for delineating landscape elements with rather distinct boundaries. Even in seemingly heterogeneous (forest) habitats specific forest types in OLR could be identified due to texture homogeneity. Semi-automated classification to a certain degree allows for delineating different forest types. This applies to deciduous forest, mixed woodland, coniferous forest and spruce afforestation. Image processing techniques, such as PCA, provide additional data layers, which can be used for class definition. Also larger single trees, e. g. individual oaks within a pine forest can be detected, but due to its high structural heterogeneity of coniferous forest with mixed ages it remains a domain of manual interpretation, though supplemented by quantification of the portion of deciduous trees. Approaches using crown shapes for classification (see Hirschmugl et al. 2004) appear to be promising when applied on images with spatial resolution smaller than 0.3 m.

Some classes turned out to be rather problematic for verification on the ground. This mainly applies for land-uses that showed a wide range of spectral signatures due to different land management on the different parcels. Classification based on samples using nearest neighbour classifiers and a uniform set of features proved to be successful in crop type differentiation on a limited area. At the very point of data capturing (beginning of May) a clear distinction is possible for corn against other crop species due to the phenology of growth. Judging hedges in terms of their suitability as habitats for bird species in the study area is likewise limited. The specific composition and the proportion of larger trees in relation to the under storey is relevant. While tree rows can be differentiated from lower hedges with ease, the species composition is hardly derivable from the QuickBird data.

The *gradient problem* occurs when features seem to have distinct boundaries, but transitions are being produced by the region-based segmentation algorithm. These transition zones may only be several pixels in width, but often cause segments to be generated. These small and elongated objects lead to a situation in which neighbouring objects are in fact not strictly adjacent. In some cases acceptable, e.g. when considering gradients (MÜLLER 1998) or ecotones (ODUM 1959) in the landscape, they usually hinder the application of spatial rules like 'is adjacent' or 'is surrounded by'. In this case the arrangement can only be modelled by distance rules, which are very processing-time intensive.

Another problem is concerned with the delineation of aggregated target classes like an orchard (*orchard problem*). The automated delineation of an orchard will fail, where an outer limiting polygon is missing on any of the segmentation levels. The individual trees are spectrally separable from the surrounding meadow, but the outline border of the orchard itself (which is considered a conceptual border) cannot be delineated automatically. The surrounding grassland is spectrally nearly identical to the meadow within the orchard. Such a task is accomplished by the human brain without major effort (although the human ability to aggregate suffers from subjectivity). If such classes shall be included, we suggest combining the strengths of human aggregation with the power of machine-based delineation and quantification. As an operational solution for integration advantages of either approach, we used manually derived geometry from visual interpretation as a) predefined outlines for the segmentation or b) spatially coinciding features on different scales, the hierarchical relationships of which can be analyzed.

At the same time we realize that this hybrid approach can only be seen as a step on the way towards developing fully automated image analysis. This brings up the question whether full automation is feasible at all, given the relatively high expenditure of time for the implementation of the rule sets.

Cross-study usability and transferability

By making expert knowledge explicit the process of classifying becomes more transparent. Object-based mapping in general is a means of semi-automatically providing landscape units and the respective labels in an objective manner. In case of the Wenger Moor the spatial distribution of the four degradation stages has been generated by a rule set, which can be fully reconstructed. Based on a production system the outcome strictly depends on the underlying object relationship model. At the same time it is flexible for adaptations by changing the parameterization. The establishment of a cognition network encapsulates the required knowledge for building up a rule set. Though not empirically proved as yet in this case, the transferability seems to be rather a matter of adapting the parameterization (SCHÖPFER et al. 2005).

When modeling aggregated and complex classes, difficulties arise in assessing the accuracy in the end, because working over several scales is required. In the end accuracy has to be judged on the reporting level. Getting visual prove from an expert may be easy, but to perform a quantitative assessment sophisticated methods of locational, attributive and geometrical accuracy have to be included.

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