Geoinformation for European-wide Integration, Benes (ed.)

Object-oriented remote sensing tools for biodiversity assessment: A European approach

Eva Ivits & Barbara Koch
Department of Remote Sensing and Landscape Information Systems, Freiburg University, Freiburg, Germany
eva.ivits@felis.uni-freiburg.de

Keywords: remote sensing, biodiversity, landscape ecology, object oriented approach

ABSTRACT: In the framework of a European Union project, a method is needed that allows rapid, standardized, and comparable assessment of the recent state of biodiversity in several countries at the same time. Landscape ecological research in the last decades showed that diversity of species can be correlated to the diversity of their habitats, and that remote sensing images provide good basis for this assessment. Traditional image processing methods ordered pixels of the image into classes according to the habitat they represent. In order to calculate diversity of the habitats within a landscape however, it seems of advantage if habitats are defined as objects., Classification of these objects therefore seem appropriate for landscape ecological analysis. This paper presents an object-based assessment approach that was optimized for biodiversity studies and can be applied across several countries in different biogeographical regions.

1 BACKGROUND

In the last two decades, several investigations were focused on the interdependence between diversity of species and landscape characteristics. The main assumption in these studies is that flora and fauna species react on the extent and quality of their habitats. For instance, fragmentation of forest patches may hinder the interactions of two individuals from the same species. With quantitative landscape ecological methods, i.e. using landscape indices the size, number, and connectivity of the different habitat patches can be described and quantified. In this way, landscape characteristics can be turned into statistical-mathematical quantities, which can be used to compare different landscape types and different habitat qualities embedded in them. These studies, until recently, were mainly operated on a theoretical level. With the knowledge of whether bird species prefer edges or interior spaces, open grassland or forest, indices were developed that described habitats and landscape characteristics and thus, the diversity of the species. However, most of these studies were rarely supported with comprehensive field studies. Although recently there are several initiatives to correlate field data of species diversity with the derived landscape indices, there is still a considerable lack in this field of study. In the frame of a European project Biodiversity Assessment Tools (BioAssess), a method for biodiversity monitoring is developed which allows fast assessment in different regions of Europe. For this, selected indicator species based on terrestrial sampling and several remote sensing methods are studied. Test areas are selected in different biogeographical regions distributed over eight European countries (Finland, Ireland, UK, Hungary, Switzerland, France, Spain and Portugal). While biologists sample selected flora and fauna species in the field, remote sensing images are acquired from the area. In order to measure the impacts of major landuse on biodiversity in each bioregion six landscape units were selected representing a gradient from intensive to extensive landuse. Within the project a remote sensing methodology for the description of these landscapes is developed, indices will be calculated and correlated with the field data. This is supposed to bridge the missing linkage between remote sensing and ground based methods.

For the development of the remote sensing method, the six test sites in Switzerland and Hungary were selected, each with a 1x1 km^2 extent. The six test sites follow a gradient from extensively (old-growth forest) to intensively (agriculture) managed landscapes, which to some degree reflect differences in biodiversity. Based on practical considerations, mostly driven by costs, IRS panchromatic and Landsat ETM images were acquired for both countries covering all the six sampling areas. Later, the methodology will be transferred to the test areas in other bioregions.

2 AN OBJECT-ORIENTED ASSESSMENT FRAMEWORK

The main goal of the remote sensing research is to develop a standardized and half-automatic assessment method that can be transferred fast and effective to all countries in the project. The classification resulting from this method serves then as basis for the further landscape ecological analysis. To achieve comparability of remote sensing based biodiversity monitoring between different biogeographical regions, an image processing method is necessary that eliminates the subjectivity of the interpretation processes and the salt and pepper effects arising form pixel based methods.

The Fractal Net Evolution Approach (FNEA) commercially introduced by Baatz and Schäpe (1999) seems to be a suitable method to overcome the problems arising from the traditional pixel-based methods. The FNEA uses segmentation techniques in an object-oriented framework. Contrary to pixel-based methods, segmentation of images extracts objects of interest at the scale of the users' interest, where the finer scale corresponds to the resolution of the input data. FNEA starts with the upper left pixel in the image and compares it to its neighbors. The goal is to clump pixels with similar values to objects by minimizing the heterogeneity between them. As a result, the image is segmented into so-called object primitives. These can be grouped into meaningful objects by classifying them after user-defined rules by using fuzzy logic theory. Segmentation can be done on hierarchical scales, where a semantic net is built between the different levels and their objects. This allows the development of a hierarchical classification scheme where the delineated objects can be further ordered into finer classes. Since the user can define the scale, which influences the detail of objects segmentation, this method is very useful for landscape ecological analysis. For a more detailed description, see Baatz and Schäpe, 1999. The FNEA is incorporated in the commercially available software, eCognition.

Developing a remote sensing method for a European-scale usage is a challenging task, which requires standardization and optimization at different levels of image processing. In the following, those optimization steps will be described and some results presented.

2.1 *Optimization of input images*

Visual interpretation of satellite images is still a main approach to extract needed landscape information and/or define training areas for automatic supervised classification. Visual interpretation of the Landsat image itself does not provide appropriate information when considering the $1*1km^2$ test area. Therefore, an image fusion method was applied which allows better visual interpretation results. Additionally, segmentation and classification of the original Landsat and IRS data are expected to deliver unsatisfactory results. The low resolution of Landsat hinders the definition of objects, while the stripes coming from the IRS sensor change the object edges in the segmentation process. Therefore, besides image fusion several further image preprocessing steps were tested and applied.

To eliminate the IRS stripes, several filters were tested from which the modified sigma-filter delivered the best results. The stripes were smoothed out but the structural information of the image was practically not changed. The sigma filter has been widely used in radar remote sensing to eliminate the noise in SAR images. It applies a window moving across the image assuming, that the central pixel in the window is the mean of its Gaussian distribution. The filter averages pixels within two-sigma distance from the value of the central pixel. All pixels outside from this range are assumed to belong to another distribution, thus to be part of another object. The modified version of the sigma filter does not consider the mean but rather averages all pixels that could be part of the distribution of the central pixel. For a more detailed description, see Smith, 1996. This filter was used for eliminating the stripes existing in the IRS image (here: sigma-IRS).

To improve the visual quality, the Landsat and IRS images were then fused with the Adaptive Image Fusion (*AIF*) method developed by Steinnocher, 1999. The *AIF* uses the above-mentioned modified sigma filter for the fusion of the panchromatic (IRS) and the multispectral (Landsat) images. In this method, the local moving window selects those pixels in the higher resolution panchromatic image, which are located within two-sigma distance from the central pixel, i.e. belong to the same object. In the multispectral band, according to the position of the selected panchromatic ones, the respective pixels are averaged. An important advantage of the AIF method is, that no spectral information is transferred from the panchromatic image to the multispectral band (Steinnocher, 1999). Out of the several fusion methods tested (IHS, Brovey, Principal Component) the adaptive image fusion algorithm proved to deliver the best results.

The major limitation of AIF is the loss of texture information that is present in the panchromatic image, since the local variation of gray values in the higher resolution image cannot be reconstructed without distorting the spectral characteristics of the multispectral band (Alpmon project report, 1998). Therefore, an additional preprocessing step was needed to reimport the structural information from the IRS data. Fritz (Fritz, 1999) reported good results with the intensity, hue, and saturation (IHS) transformation of the *AIF* and the high resolution image. When compared to other methods, the “blockiness” from the Landsat 30m resolution pixels completely disappears from the *AIF-IHS* fused results. This is very important for the segmentation of objects, which form the basis for landscape indices calculations.

During the IHS transformation, the intensity channel has to be replaced with the panchromatic, high-resolution band, with the IRS band in the respective case. Since the IRS image contains the stripes described before, its inclusion in the transformation process would transfer the stripes back into the fused image. Therefore, for the IHS transformation after the *AIF* fusion, both the original IRS (here: *AIF-IHS image)* and the sigma-IRS (here: *AIF-sigma-IHS image*) was used, to test which method provides better segmentation results. Figure 1 shows the workflow of the AIF-sigma-IHS fusion.

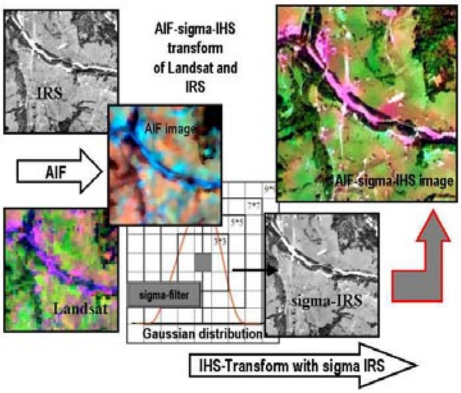

Figure 1. AIF-sigma-IHS transform

2.2 *Optimization of segmentation*

In eCognition there is the possibility to define which image channel should be included in the segmentation process: when considering Landsat and IRS as input images, one can segment on the basis of Landsat, IRS, or both. During segmentation, eCognition considers both structural and radiometric information contained in the images, therefore the use of a combination of high spatial and high multispectral resolution is advantageous. Although the 30m resolution of Landsat only allows very coarse object borders, its radiometric resolution gives rich assessment possibilities. The 5m resolution IRS image on the other, hand delivers fine object borders, but the panchromatic channel with low radiometric resolution restricts the assessment of different landuse categories.

In the following, an empirical method for optimization of the different input channels for the segmentation is described. The decision between the different methods was done with visual interpretation, deciding how well the delineation represented the objects in the image. The criteria for the decision were, how good

- the object edges follow the highest resolution panchromatic image,
- structure information is reflected in the segmentation, and
- the multispectral information is included in the object delineation process.

As a first step, segmentation was applied to the original Landsat image, resampled to 5m resolution. As expected, object edges followed the coarse Landsat pixels and object interiors showed homogeneous, not definable features (see Figure 2). Little openings in a forest patch or small forest habitats, which might have a decisive roll for biodiversity studies, were not displayed through segmentation based on Landsat. For this reason, other input channels were included in the segmentation process to refine the delineation of object. Secondly, segmentation was applied on the IRS image. This resulted in very good representation of clear object borders but fine multispectral information differences, e.g. between different grassland types were not reflected. Thirdly, the IRS panchromatic channel was segmented together with the Landsat image. With its 5m resolution, the IRS positively influenced the delineation results compared to plain Landsat data; small forest patches appeared as segments. However, Landsat still influenced object borders, as edges often followed the 30 m pixels. Since this method delivered still no satisfactory results, a fusion of the two images was included in the segmentation process.

As a fourth attempt, segmentation was based on the *AIF* fusioned Landsat and IRS image (see Figure 2). Object edges were delineated according to the panchromatic image, but some important details were lost. Little openings that are visible on the IRS image as well as other structural information inside objects were not delineated. Finally, the segmentation was applied to the *AIF-IHS* and *AIF-sigma-IHS* images. These fused images have very good visual appearance, the structural information contained in the IRS image is almost perfectly kept, and even the gray-level distribution provides a wide spectrum. Accordingly, the segmentation resulted in a very good delineation of object edges and inner structure realization. Differences between and within landuse types, e.g. intensively-extensively used meadows, and forest – greenland interfaces were also well segmented. Although the *AIF-IHS* fusion with the original IRS band allowed for a good recognition of patches, segmented objects were influenced by the stripes in the images. In the *AIF-sigma-IHS* image, based on sigma-filtered IRS, the stripes were reduced to such an extent that the shape of the segmented objects was not influenced anymore (see Figure 2). In other methods, like Principal Component Analysis, Brovey-, and IHS-fusions the blockiness from Landsat ETM data in the fused image could not be avoided which delivered bad segmentation results.

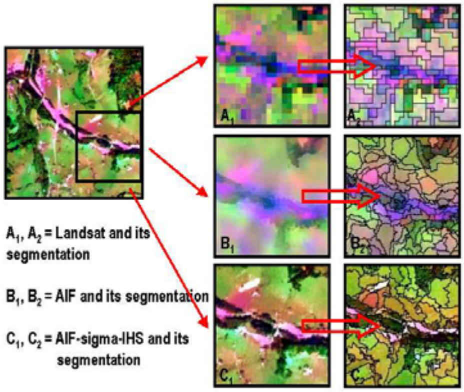

Figure 2. Selected segmentation results

2.3 *Optimization of classification inputs*

Since the CORINE classification system is too coarse for biodiversity studies in a 1km^2 test area, it was adjusted to the project. Some classes were added and others changed with respect to the selected indicator species, to better cover the small landuse differences that might be important for biodiversity studies. We used a hierarchical classification scheme, where the segments are classified in two levels. On the first level, an attempt was made to define coarse classes that can be uniquely applied all over the eight countries (here: *project level*). They are: urban, rock, bare-soil, gravel, asphalt, shadow, forest, and other vegetation areas. On the second level (here: *country level)*, forest and other vegetation areas were further classified to follow country specific characteristics. Based on their classification mask on the first level, forest areas were further divided into deciduous, evergreen, mixed, open forest classes and small forest habitats. Other vegetation classes were grouped into grassland and agricultural areas (Figure 4). Segments smaller then 1ha and not surrounded by other forest objects were classified in the category small forest habitats.

eCognition offers two types of supervised classifiers: one is the nearest-neighbor classifier, frequently used in traditional image processing steps, and the second one is membership functions. Membership functions are combinations of fuzzy sets of object features (spectral, shape, neighborhood characteristics) that require inclusion of expert knowledge to describe certain classes (eCognition User Guide, 2002). They are one-dimensional descriptions of class characteristics giving a discrete interval in the selected channel, whose values describe a certain class. However, the interval describing class A might also partly describe class B, which results in a considerable overlap between the feature spaces of the two classes (see Figure 3). When including several image channels in the process the dimensionality of the feature space increases. This might increase overlap between classes tremendously complicating the definition of classes. When using nearest neighbor classifiers on the other hand, the user has to mark objects in the image that typically describe the class of interest. Since nearest neighbor classifiers operate in a multidimensional feature space using factual distribution of image values the description of the selected objects is an easier task.

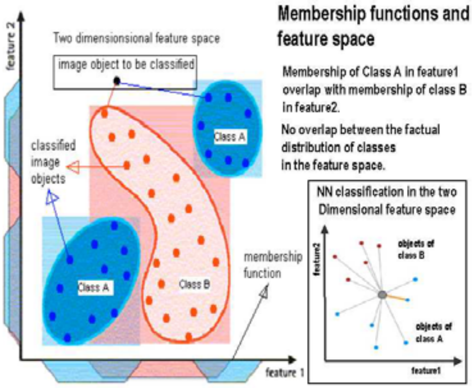

Figure 3. Membership functions and NN feature space. Modified from eCognition User Guide, 2002.

When only few, discrete features separate the classes from each other, the use of membership functions is the optimal choice. However, when several different features order objects into classes, the nearest neighbor method should be used. The usage of membership function is an inflexible classification method: once the discrete intervals are defined, it is not possible to apply the class-hierarchy on other areas. On the other hand, the nearest neighbor classifier only defines which image channels are used in the feature space; objects can be optionally selected from the image. The application of the nearest neighbor classifier seemed therefore the appropriate choice for a European approach.

For the classification of the segments, two types of nearest neighbor expression can be used in eCognition: the nearest neighbor (NN) and the standard nearest neighbor (Std. NN) expressions. The NN expression and its feature space can be individually adjusted to certain classes. For instance, classification of forest objects requires other image channels then classification of an urban area. On the contrary, the Std. NN expression and its defined feature space are valid for all the classes in the classification scheme. Using the Std. NN expression is often a better choice, because the separation of many classes is only meaningful when the samples are defined in the same feature space. We used both nearest neighbor expressions in the classification scheme. On a higher hierarchy level, classes were separated in a Std. NN feature space and on the lower one we adjusted the NN feature space to the classification of vegetated areas (see Figure 4).

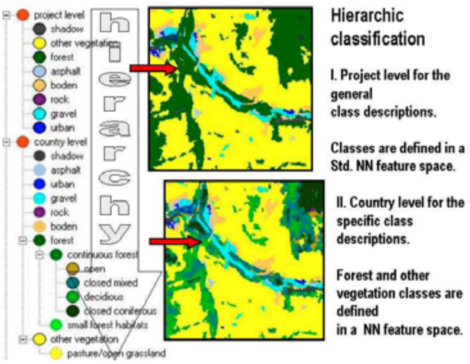

Figure 4. Classification hierarchy

The next optimization task was driven by the low input information and high quality output problem. Biodiversity studies often require the assessment of many small habitats from remote sensing images, in order to correlate the information with the field data. For this purpose not only the multispectral but also the structural information (texture or graininess) from the panchromatic IRS might be useful for the classification. The most often used method to measure texture is the so-called gray-level-coocurrence-matrix (GLCM). The GLCM is a two-dimensional histogram of gray levels for a pair of pixels, which are separated by a fixed spatial relationship. The matrix counts the joint probability distribution of a pair of pixels according to the spatial relationships direction, and neighboring pixel distance (Music and Grover, 1990, and Haralick et al., 1973). Additionally, some texture measures are computed from a gray level difference vector (GLDV), which counts the occurrence of reference to neighbor pixel absolute differences.

Nine GLCM and GLDV texture measures were calculated as follows: Homogeneity, Contrast, Dissimilarity, Standard Deviation, Entropy, Angular Second Moment, Correlation, GLDV Angular Second Moment, and GLDV Entropy. To test how much the stripes of the IRS sensor influence texture images, all measures were calculated from both the original and the *sigma-IRS* images. Several window sizes were tested for the texture calculation starting with 3x3 to 9x9 size. Window sizes bigger then that did not change the results significantly. In the four different window sizes all the possible neighborhood relationships were calculated: one for a 3x3, two for the 5x5, three for the 7x7, and four for the 9x9 window. These input parameter combinations resulted in 180 images.

Besides texture, several ratio and transformed channels were also computed from the multispectral Landsat images. Ratio transforms are often used in image processing to reduce radiometric effects of slope, sunlight angles or seasonal variability (in San Miguel-Ayanz and Biging, 1996). For the classification, we used the first principal component (PC) of the first three Landsat channels. These channels are highly correlated, therefore using those bands independently from each other would introduce redundancy and collinearity (San Miguel-Ayanz and Biging, 1996). We computed the normalized difference vegetation index (NDVI), and additionally three other ratio images: channels 5/3 and 7/3 for the differentiation of forest species and channel 5/4 for the definition of vegetation vigor. The Landsat channels were transferred into the brightness, greenness, and wetness axes of the Tasseled Cap calculation (Crist *et* al., 1986). The wetness channel has been shown to be insensitive to topographic variations and useful to differentiate between closed forest canopy conditions (Cohen and Spies, 1992). Although the brightness and greenness channels are highly sensitive to topography, they capture the rest of the spectral information associated with forest conditions. Additionally, slope derived from a 25m resolution digital elevation model was computed and included in the classification scheme.

Although eCognition uses fuzzy logic that allows classification of fine objects with a coarser resolution image, it was assumed that better results could be achieved when objects in the image used for classification correspond to those achieved during the segmentation. To test this assumption, the derived channels were calculated from both the Landsat and *AIF* images. Since the segments delineated from the *AIF-sigma-IHS* fused image represented best the real world appearance of the objects, only those were included in the further classification process.

2.4 *Object oriented signature analysis*

The 180 texture-, and the additional ratio and transform images deliver a huge source of information. Therefore, before including them into the classification, signature analysis was done to identify those images that best describe the classes of interest. The units of classification are the delineated segments, or objects primitives, rather then single pixels. Pixel based signature analysis therefore is not a possible solution since the spectral reflectance of the segments is needed.

One way eCognition classifies the delineated segments is calculating image layer mean values from all n pixels in the objects after the following criteria:

$$\bar{c}_L = \frac{1}{n} * \sum_{i=1}^{n} c_{Li}$$

where $\bar{c}_L$ is the layer mean value, c_{Li} is the layer value of an object, and n is the number of pixels building an object. This approach was simulated for the object oriented signature analysis. The delineated segments were exported to a GIS where the objects were clipped with the multispectral, panchromatic, and texture images. We used the “zonalmean” function of ArcInfo, that records in each output cell the mean of all cells in the input image, which belongs to the same zone as the segments. This way we had the same interpretation basis eCognition uses for classification. Signature analysis was then done with the simulated images to select those that best describe the respective classes (see Figure 5). In selecting the images on the *project level,* we focused on separating vegetation classes from non-vegetated once, since vegetation classes like forest or others are further classified in the *country level* with an adjusted NN feature space.

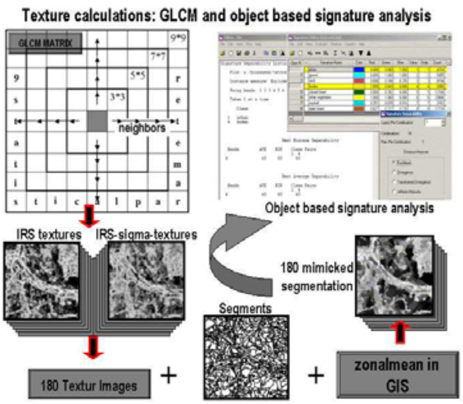

Figure 5. GLCM textures and their signature analysis

2.5 *Object oriented accuracy assessment*

Accuracy of classification may be defined as the degree or percentage of correspondence between the user’s observation on remote sensing images and the reality. In a pixel-based approach, mostly randomly selected reference pixels are compared to the classified ones to build the statistical background for the accuracy assessment. In our object-based method however, pixels in the reference image cannot be compared to the classified segments. eCognition offers two possibilities for object oriented accuracy assessment: in the first case the user selects objects in the segmented image which can be ordered into save classes and which eCognition then compares to the classification result. In the second case, the user can import a classified thematic layer prepared from any ground truth data, which serves as basis for accuracy assessment. However, in the first approach the users tend to select segments, which were used as training samples for the nearest neighbor classification. That calls a bias for the accuracy assessment. On the other hand, no thematic layer was at our disposal, therefore another approach was used.

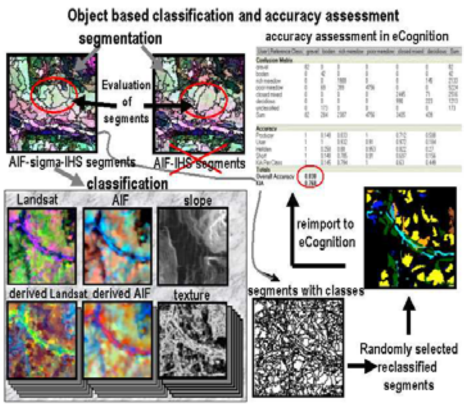

Figure 6. Classification of segments and object-based accuracy assessment

In eCognition, it is possible to export the objects to a GIS with their respective classification, where the classes are listed in the corresponding attribute table. As in the case of the texture images, we exported the segmentation results from eCognition into a GIS (this time with the corresponding classification results) and generated 250 random objects. The classification of the selected objects was then compared to color infrared aerial photos, and false classified objects corrected according to their real classes. This way reclassified objects were than reimported into eCognition for accuracy assessment (see Figure 6).

3 RESULTS OF THE OBJECT ORIENTED APPROACH

Segmentation based on the AIF-sigma-IHS images delivered in Hungary and Switzerland excellent results. Objects in the landscape were in both test sites accurately delineated according to the high resolution IRS images. Especially forest habitats, which are important landscape ecological units were well delineated according to the 5m resolution. Fine structures, like stand borders, little openings in a forest patch, or even smooth extensive-intensive grassland interfaces were in most cases identified. The identification of this structural information serves as important basis for landscape ecological analysis. Additionally, these findings might be very important for the design of an automated approach.

The object-oriented half-automatic classification proved to be very suitable for the different landscape types in Hungary and Switzerland. On the *project level*, accuracy was in both countries over 95%. On this scale the smallest forest object correctly recognized was 0.022ha (225m^2). With the help of the texture and slope images, non-vegetated features that reflect the incoming sun radiation on a very similar way were correctly identified. Homogeneity was very useful when separating homogeneous from heterogeneous non-vegetated areas like asphalt, bare soil and gravel surfaces from urban areas. Between homogeneous unvegetated surfaces, the Standard Deviation and the Dissimilarity measures delivered good results. For the classification based on the Std. NN feature space, the channels listed in table1 proved to be most suitable.

Table 1: Best channels for project level classification

	VEG			VEG-NonVEG	NonVEG		
Multispectral	IRS AIF5p3 AIF7p3 AIF, channel 6			AIFTC2 AIFTC3 AIFNDVI IRS AIF5p3 AIF5p4	AIF7p3 IRS SLOPE AIF, channel 3 AIF5p3 AIFNDVI AIFTC2 AIFTC3		
Texture	CF-OF	OtV-OF	CF-OtV	-	Ur-So	Gr-So	So-As
	Sgent9	Sasm5	Sasm5	-	Hom7	Std7	Dis7

Abbreviations: VEG = vegetation; NonVEG =non vegetated areas; CF = Closed Forest; OF = Open Forest; OtV=other vegetation; Ur=Uban; So = Soil; Gr = Gravel, As = Asphalt, Sgent9 = GLDV Entropy from sigma IRS, 9*9 window; Sasm5 = Angular Second Moment, sigma IRS, 5*5 window; Hom7=homogeneity, 7*7window; Std7=Stdandard Deviation, 7*7window; Dis7=Dissimilarity, 7*7 window.

The signature analysis proved the AIF images and its derived bands in all cases more suitable for class description, then the original Landsat channels. This can be explained with the fact, that objects in the AIF image follow the segments delineated from the AIF-sigma-IHS borders. Especially ratio images and the Tasseled Cap calculations showed high usability when separating the different vegetation classes from non-vegetation classes. Furthermore, while with Landsat a huge number of training areas had to be selected for class differentiation, classification with AIF images required fewer samples but provided a more stabile classification.

On the *country level*, the smallest correctly classified forest object was 0.025ha (250m^2) in the mixed forest category and 0.022ha (225m^2) in the small forest habitats category. In Hungary, the classification accuracy accounted to 87% with AIF and little above 80% with Landsat data. In Switzerland, both methods hardly reached 80%. The lower accuracy is not surprising, since the 30m multispectral Landsat bands serve only as poor information source in the 1km^2 test area. Additionally, in the Swiss test site, the lower accuracy can also be explained by the extreme topography that strongly influences the reflection values.

4 SUMMARY AND CONCLUSIONS

We presented an object-oriented approach to extract information from remote sensing data as basis for a European biodiversity monitoring system. The method was applied to Hungarian and Swiss test sites with very different landscape features. The main intention was to develop a mostly automatic and standardized methodology that facilitates a fast and effective evaluation of remote sensing images for biodiversity studies across different landscapes in different bioregions. Because of the small size of the test areas and the low resolution of the input remote sensing images, several preoptimization steps had to be performed to produce useful classification results for further landscape ecological assessments. Landsat ETM and IRS images were selected as standard dataset, the former for the radiometric resolution and the latter for the spatial resolution. The images were segmented following the FNEA approach that allows the delineation of object primitives at different scales. Several products were tested as basis for the segmentation where the use of the AIF-sigma-IHS method delivered the best results where segmentation delivered stable, meaningful object primitives with valuable structure information that proved the usefulness of the method for standardization.

For the classification of the object primitives, the original Landsat, IRS, AIF, derived channels, and 180 texture images were tested. Based on signature analysis, the appropriate channels were selected that best described the classes of interest. The signature analysis followed the object-oriented method where the segmentation was mimicked in a GIS environment. Objects, typical for certain classes, were selected from the exported segments and their spectral signature in the different input channels analyzed. Channels useful for class separation built the feature space for the nearest neighbor classification. Texture images that described classes like urban areas, asphalt, bare soil and gravel surfaces best were identified as well as spectral channels being most useful for vegetation classification. The classification was hierarchical, on the first level describing general classes and on the second level country specific ones. The classification scheme was applied to both the Swiss and the Hungarian dataset and resulted in very good accuracy for the general classes and in satisfactory accuracy for the finer classes.

The FNEA and its fuzzy logic method proved to be very useful when a flexible but stable classification has to be applied in different landscapes. Object primitives assure the creation of meaningful segments where the delineation is not biased by user errors. In case of a comparative landscape ecological analysis, where simple patch properties as area, perimeter, and neighborhood serve as basis for the assessment this object oriented method has an extreme importance. Additionally, the hierarchy of the classification allows flexibility when different landscapes with their characteristic vegetation cover have to be classified.

5 FUTURE WORK

In the ongoing studies, the accuracy of the country level classification will be improved. The input data set will be segmented on consecutively finer scales to test, which object primitive environment allows the best classification accuracy. For the forest classification, the usability of texture images will also be further tested. In the second phase of the project, landscape ecological analysis will be done based on classification results. Fragmentation and other indices will be calculated for the description of the landscapes. These results and other remote sensing derived indicators will then be correlated with the biological data. Additionally, for the Swiss test sites CIR aerial photos, Spot and Quickbird images will be processed for an object-based assessment.

ACKNOWLEDGEMENT

Special thanks go to the Institute of Ecology and Botany of the Hungarian Academy of Sciences, and for Andras Revesz for evaluating the Hungarian dataset. The study was carried out in the framework of the BioAssess (Biodiversity Assessment Tools, Project No. EVK2-CT1999-00041) research project in the Energy, Environment and Sustainable Development Program of the European Union. Reference data and the digital elevation model was provided from the Swiss Federal Institute for Forest, Snow and Landscape Research (WSL) whom also special thanks go for the support and discussions.

REFERENCES

ALPMON project report, 1998, ENV4-CT96-0359, European Commission, Directorate General XII, Science, Research and Development

Baatz, M. and A. Schäpe, 1999: Object-Oriented and Multi-Scale Image Analysis in Semantic Networks. In: Proc. Of the 2nd International Symposium on Operalization of Remote Sensing. August 16th-20th, 1999. Enschede. ITC.

Cohen, W. B., and Spies, T. A., 1992, Estimating structural attributes of Douglas-fir/western hemlock forests stands from Landsat and SPOT imagery. Remote Sensing of Environment. 41, 1-17.

Crist, E. P., Laurin, R., Cicone, R. A., 1986, Vegetation and soils information contained in transformed Thematic Mapper data. In: Proceedings, IGARSS '86 Symposium, Zürich, Switzerland, 8-11 September 1986 (Paris:ESA).

eCognition User Guide, 2002, http:\\www.definiens-imaging.com.

Fritz, R., 1999, Digitale Forstkartenerstellung und Feldgrenzendelinierung mit Hilfe hochauflösender Satellitensysteme. Ph.D. Thesis, Freiburg University.

Haralick, M. Robert, Shanmugam, K., Dinstein, Ist'hak, 1973, Textural Features for Image Classification, IEEE Transactions on Systems, Man, and Cybernetics, Vol. SMC-3, No. 6, November, 1973.

Musick, H. Brad and Grover, D. Herbert, 1990, Image Textural Measures as Indices of Landscape Pattern, In: Turner G. Monica and Gardner, H. Robert Edrs., Quantitative Methods in Landscape Ecology, 1990, Springer-Verlag New York, Inc.

San Miguel-Ayanz, J., Biging, G. S., 1996, An iterative classification approach for mapping natural resources from satellite imagery, International Journal of Remote Sensing, vol. 17, No. 5, pp. 957-981.

Smith, D. M., 1996, Speckle reduction and segmentation of synthetic aperture radar images. International Journal of Remote Sensing, 17(11), pp. 2043-2057.

Steinnocher, K., 1999, Adaptive Fusion of Multisource Raster Data Applying Filter Techniques, International Archives of Photogrammetry and Remote Sensing, Vol. 32, Part 7-4-3 W6, pp. 108-115.