

OBJECT-BASED CLASS MODELING FOR ASSESSING HABITAT QUALITY IN RIPARIAN FORESTS

T. Strasser^{a,b,*}, S. Lang^a, L. Pernkopf^a and K. Paccagnel^a

^a Centre for Geoinformatics (Z_GIS), Salzburg University, Schillerstraße 30, 5020 Salzburg, Austria – (stefan.lang, klaus.paccagnel, lena.pernkopf@sbg.ac.at)

^b Dept. of Organismic Biology, Salzburg University, Hellbrunnerstraße 34, 5020 Salzburg, Austria – * thomas.strasser2@stud.sbg.ac.at

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ABSTRACT:

This paper discusses conceptual elements and preliminary results of a workflow assessing habitat distribution and quality by means of object-based image analysis in a riparian forest. This follows the design of a 'site-level' service within the EC GMES project MS.MONINA to support the implementation of the Habitat Directive in Europe by providing dedicated EO-based services. We developed routines for (semi-) automated forest habitat delineation in the Natura 2000 site Salzach river floodplain using multi-level class modeling. Satellite data for the target level and the finer level -1 was WorldView-2 8-band multi-spectral data. We employed object feature libraries for the level -1 tree stand classification. Level +1 was created using SPOT-5 data, performing a EUNIS-3 visual interpretation. Class models were created for HabDir riparian and alluvial forest classes, by integrating both level -1 and level +1 object information.

1. INTRODUCTION

1.1 EO-based biodiversity monitoring

Since the UN Convention on Biodiversity (CBD), halting the loss of biodiversity is an international commitment. This entails a demand for regularly updated spatial information on habitat quality in order to fulfill monitoring requirements. The European initiative GMES (*Global Monitoring of Environment and Security*) strives to provide operational answers to such political agreements. With the help of Earth observation (EO) technology and ground measurements it will be a powerful and ubiquitous provider of accurate, timely and easily accessible information as soon as it enters the operational phase.

Services based on EO data which support habitat monitoring are currently developed in MS.MONINA (*Multi-scale Service for Monitoring NATURA 2000 Habitats of European Community Interest*, www.ms-monina.eu) – a GMES project funded within the EU's Seventh Framework Programme for Research (FP7). MS.MONINA aims at offering ready-to-use information to public authorities on European, national and local level in a multi-scale approach which reflects the specific information requirements on different (political) levels. The availability of very high spatial resolution (VHSR) data and advanced image analysis techniques facilitates the extraction of thematic information on biodiversity status. Object-based image analysis (OBIA) provides adequate and automated methods for the analysis of complex scene content (Lang, 2008). The image information is exploited more efficiently to reveal trends in habitat area and quality.

While specific information needs at the local level differ from one site to another, in general thorough knowledge of actual habitat locations and distributions is required, and the conditions in terms of overall quality, existing threats and pressures need to be known, as well as their trend of development (Lang et al., 2011). Such up-to-date information is also of high value to site managers, to make informed decisions about the measures to be applied, as well as the effects of such measures, in order to steer adaptations and improvements (Vanden Borre et al., 2011).

1.2 Delineation and assessment of riparian habitats

In the context of the MS.MONINA site level service we focus on the assessment of riparian forest habitats, their quality and conservation status, as well as their change over time. HR data such as SPOT-5 (5 m ground sample distance) and VHR data such as WorldView-2 (WV2) with 0.5 m resolution, coupled with a dedicated usage of OBIA methods offer new possibilities for addressing such habitats. In addition, we would expect from an OBIA approach, to discern habitats with different quality but similar spectral behavior. In other words we would like to distinguish riparian habitat types from forest management areas with a similar composition of dominating species. This requires a multi-level representation of the features composing such forest habitats, starting from singular homogeneous tree stands, over functional homogenous classes (including aspects of naturalness) up to broader alluvial or riparian forest classes with a specific groundwater regime and species composition. Here we clearly challenge the contribution that EO data can make, in terms of mixed spectral properties, but also the non-homogenous compositions of the classes. An OBIA approach can support this by aggregating high fidelity information on various levels and extracting the relevant information from these. Applying techniques of class modeling (Lang, 2008), we are able to interlink these levels and build up higher complex class descriptions.

Habitat types have distinctive structural and compositional features, which also relate to the conservation status of the habitat. Ecological classification schemes, such as the European Nature Information System (EUNIS) scheme, imply a kind of ordinal structure where classes are discerned according to some inherent quality measure. The spatial distribution of such habitat classes, which can be characterized by structural indicators, allows for an integrated assessment of conservation areas.

2. STUDY AREA

The MS.MONINA pilot site Salzachauen (Austria, Salzburg) [UL: N 47°56'12" / E 12°56'24"; LR: N 47°52'42" / E 12°59'21"] is located along the regulated river Salzach in a densely populated area of the alpine foreland at the Austrian-German border (Figure 1).

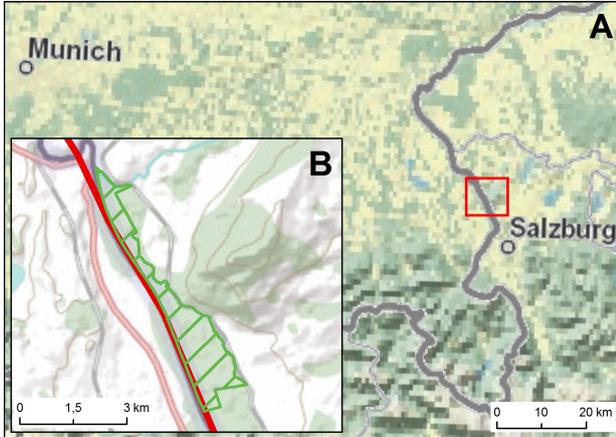


Figure 1. A) Location of the pilot site Salzachauen, at the Austrian-German border. B) Area of interest.

Dominating Natura 2000 habitat types are *alluvial forests* (habitat code: 91E0) and *riparian mixed forest* (habitat code: 91F0) featured by species-richness and endangered species. Prevalent tree-species are *Alnus incana*, *Salix alba*, *Fraxinus excelsior*, *Quercus robur* and *Acer pseudoplatanus*. Table 1 shows existing forest types (dominating tree species and mixtures) which are characteristic for the selected Natura 2000 habitat types.

| Natura 2000 habitat type | Forest types |
|--------------------------|---|
| 91E0 | <i>Salix alba</i> |
| | <i>Alnus incana</i> |
| | <i>Fraxinus excelsior</i> |
| | <i>Alnus incana</i> mixed with <i>Fraxinus excelsior</i> |
| | <i>Fraxinus excelsior</i> mixed with <i>Alnus incana</i> and <i>Acer pseudoplatanus</i> |
| 91F0 | <i>Fraxinus excelsior</i> mixed with <i>Acer pseudoplatanus</i> |
| | <i>Quercus robur</i> mixed with <i>Fraxinus excelsior</i> |

Table 1. Characteristic forest types for Natura 2000 habitat types.

Fragmentation is caused by forestry management and plantations with allochthonous tree-species such as *Picea abies*, *Populus canadensis* and *Populus balsamifera*. Modified hydrological conditions due to river regulation, continuous urbanization and related demands (power plant and bridge construction), the presence of invasive non-native species (neophytes) and fungal parasitism on ashes pressure the natural distribution of potential habitat types. Stepwise dismantling the river regulation, which reactivates former hydrological conditions, will lead to a succession of riparian forest. All in all large-scale changes on potential habitat type distribution

including species composition are expected. Therefore Salzachauen is a very suitable pilot case for EO-based long-time series monitoring.

3. DATA & METHODS

3.1 Data

3.1.1 Satellite data

Quantitative and qualitative changes of the habitat types under pressures are detected on pan-sharped satellite imagery with different spatial and spectral resolution (see Figure 2). For this study two WV-2 images were acquired in July and September 2011. The WV-2 sensor incorporates a high resolution panchromatic band (0.5 m ground sample distance), the common multispectral bands Red, Blue, Green, NIR1 and the new additional bands Coastal Blue (400 – 450 nm), Yellow (585 – 625 nm), Red Edge (705 – 745 nm), as well as an enlarged range NIR2 (860 – 1040 nm) with 2 m ground sample distance. These four supplementary bands are located at vegetation sensitive regions of the spectrum and are expected to provide important information for detecting fine differences between tree species (Sridharan, 2011). Ancillary information is provided by SPOT-5 imagery (acquired in June 2005). SPOT-5 features a spatial resolution of 5 m in panchromatic mode, 10 m in multispectral mode including Green, Red and NIR bands and a 20 m resolution for the Middle Infrared.

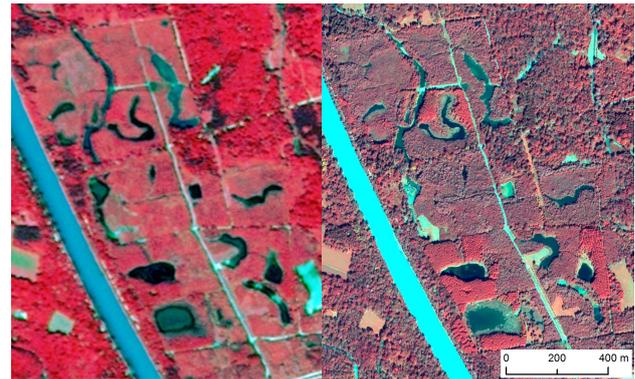


Figure 2. Spatial resolution of satellite data (NIR band combination). Left: SPOT-5 (June, 2005; 5 m GSD), right: WV-2 (September, 2011; 0.5 m GSD).

3.1.2 Ground data for validation

Ground data has been collected at randomized sample points for verification and validation of the results. Therefore tree species, predominance and vegetation density are documented within a square 10 by 10 m. DGPS-position, and pictures (to north, east, south and west) are collected as additional information.

3.2 Workflow

Habitat status and quality in the Salzachauen is analyzed using a multi-scale approach (Figure 3), consisting of two pillars: (1) thematic information extraction from satellite data, (2) calculation of habitat quality indicators for biodiversity assessment which is then provided as MS.MONINA site (sub-) service.

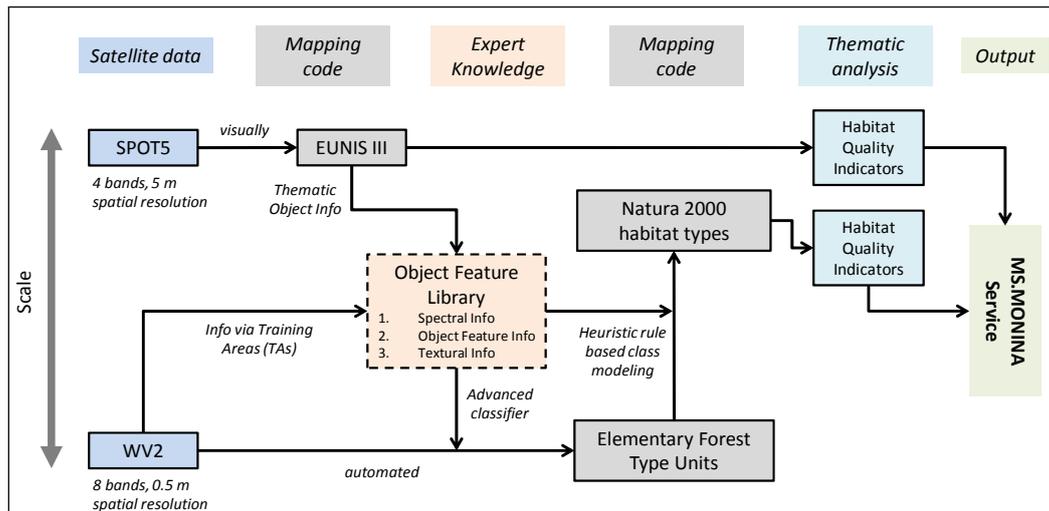


Figure 3. Workflow of thematic information extraction and habitat quality analysis.

Further, the thematic information extraction is separated into two steps. First visual delineation is done on SPOT-5 data using EUNIS-3 code, which (1) provides object feature information to calibrate and optimize automated habitat analysis on WV-2 data, (2) serves as control data (reference data set) for the interpretation of habitat quality indicators and (3) is used as benchmark for hot spot detection on large scales (e.g. European riverine landscape). Secondly, automated habitat extraction is performed on WV-2 data via multi-level class modeling. Class modeling requires expert knowledge, which is stored in an Object Feature Library (OFL). This contains (1) collected spectral behavior of WV-2 data using Training Areas (TAs), (2) thematic object feature and textural information derived from SPOT-5 data.

Based on the extracted habitat types, quality analysis will support the assessment of the biodiversity status on different scales.

3.3 Class modeling

3.3.1 Strategy

eCognition 8.7 class modeling software is used for composing Natura 2000 habitat types and forest management types, respectively (Figure 4). To achieve this, an OFL is set up. In a next step, an object hierarchy is created through multi-level segmentation. Based on this hierarchy, elementary forest type units are classified via spectral values and indices. Finally, Natura 2000 habitat types and forest management types are built out of previously classified elementary units incorporating expert knowledge.

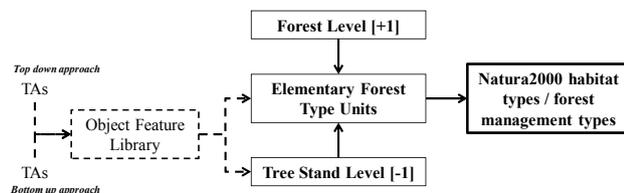


Figure 4. Strategy for class modeling. Information is collected via training areas on different scales (top down, bottom up) to simulate habitat class mixtures.

3.3.2 Object Feature Library

An OFL consists of structural, textural, as well as shape-related information derived from SPOT-5 data and spectral statistics, which are collected on WV-2 using a bottom up and top down approach (Figure 4). Such a two-way approach is necessary for the subsequent elementary forest type classification, where different tree species mixtures have to be simulated.

Bottom up approach: spectral statistics of areas with unmixed tree species are collected via two different squared TAs (for each representative forest type) with a size of 50 x 50 m (Figure 5). (2) Top down approach: spectral statistics of areas with exemplarily mixed tree species are collected respectively to (1), but within an increased search window. Next, class dependent spectral statistics (min, max, mean, median, standard deviation) and spectral indices (e.g. GreenNDVI, SPVI, TCARI), which have been selected according to a study by Main et al. (2011), are calculated for the whole TA. Because of shadow effects, additional statistics of local maxima are calculated within the TAs. A seed-point algorithm applied to the PAN-band (450 – 800 nm) detects local maxima. These bright reflecting values correspond to tree crowns and distinct spectral information of tree species (Figure 5).



Figure 5. Example of a training area for OFL. Left: sample site for *Populus canadensis*, right: seedpoint-algorithm for extracting distinct spectral information of tree crowns.

3.3.3 Multi-level segmentation

Following the structure of the proposed hierarchical system two different levels, namely the level of tree stands (level -1) and the level of elementary forest type units (focal level) are segmented using WV-2 data (Figure 4). On level -1, small regions with homogeneous pixel value distribution are assumed to represent tree stands with same tree species. On the focal level, tree stands are aggregated to larger regions, which will later be

classified into forest patches with unmixed or mixed forests (e.g. *Alnus incana* forest or *Fraxinus excelsior* mixed with *Acer pseudoplatanus*). The forest level (level +1) bridges object information between WV-2 and SPOT-5. Moreover, the forest level serves as a data mask to accelerate computational tasks for automated class modeling.

An initial segmentation is performed to detect tree stands. The segmentation parameters are mainly based on spectral values (shape factor = 0.1), because the shape of segments might be affected by neighboring trees, especially within heterogeneous structured forests (Förster and Kleinschmit, 2008). Another adverse effect on segmentation originates from shadow areas. To obtain meaningful objects, shadows are classified on the tree stand level and are excluded for higher level segmentation. A refinement of scale parameters is done using the ESP-Tool, which suggests appropriate parameters based on statistical analysis (Dragut et al., 2010).

3.3.4 Classification

First, a common classification is done on level -1 to separate woodland from other vegetation, water, or man-made features (Figure 6). Then elementary forest type units are determined with *advanced classifiers* (e.g. Bayes, Decision Tree algorithm). Therefore seed points (with local maxima) are detected within the forest mask (level +1). These points are classified according to the TAs. Representing tree crowns, seed points specify segments of the tree stand level that are modeled to elementary forest type classes according to dominant tree species and compositions. Resulting unmixed or mixed forest types units are aggregated in a cyclic hierarchical classification approach (Batz et al., 2008) to *alluvial forests* (91E0), *riparian mixed forest* (91F0) and forest management areas (potential species and allochthonous species). Required expert knowledge is provided by the OFL. Here, we focus on man-made forest structure features, which originate through regular tree planting to obtain optimal plant growth. These are expressed by textural and shape information. However natural succession causes a blurring of this information, thus differentiation between habitat types and forest management is a challenging task. Finally, extracted thematic classes are validated with collected ground data.

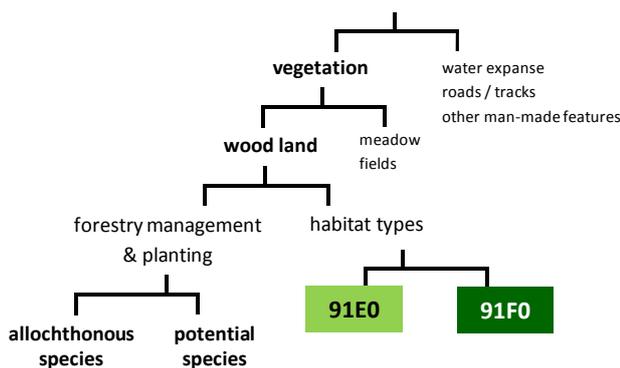


Figure 6. Scene classification. Riparian habitat types: *alluvial forests* (91E0), *riparian mixed forests* (91F0).

3.4 Habitat quality analysis

The resulting classification layer is further analyzed regarding structural habitat qualities. Landscape metrics quantifying habitat form, fragmentation, and diversity as well as the configuration of undisturbed core areas provide valuable information on habitat conditions. This analysis will be repeated for time-series analysis and change indication. Other habitat quality indicators derived from EO data could be: the distribution and extent of forest management areas and allochthonous tree species, vitality conditions of single trees, water and nutrition conditions.

4. RESULTS

4.1 Class modeling

4.1.1 Object Feature Library

Figure 7 shows spectral signatures of eight tree species extracted from the WV-2 September scene. Samples are based on seed points within representative training areas. *Populus canadensis* and *Picea abies* are easily distinguishable, featuring the highest and lowest value range in NIR-bands. *Salix alba* can be identified through highest reflection values in the Green, Yellow and Red band. Only the differentiation between *Fraxinus excelsior* and *Acer pseudoplatanus* is relatively tricky as they show similar spectral behavior.

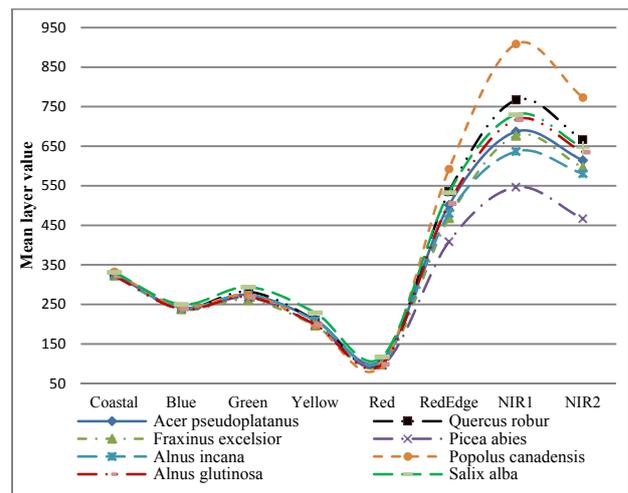


Figure 7. Spectral signature of sampled tree crowns within WV-2 bands (September scene).

4.1.2 Multi-level segmentation

Successful class modeling strongly depends on a well performed segmentation approach. Figure 8 illustrates levels of hierarchy (tree stand level and elementary forest type units) after the exclusion of shadow areas. Recognition of meaningful objects is possible on both levels. Elongated segments are visible within forest plantation areas (tree stand level: center to left). This shape-related information is collected to OFL. Due to the high spatial resolution of the sensor, both examples show highly irregular delineations.

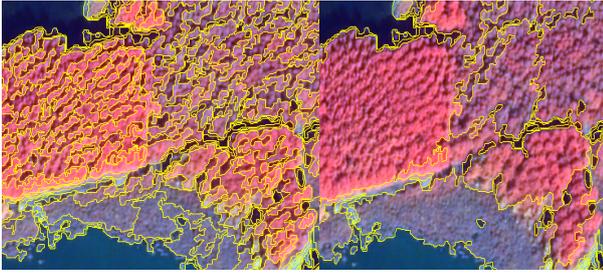


Figure 8. Segmentation hierarchy based on WV-2 (band combination: NIR1, Green, Blue). *Left*: Tree stand level, *right*: elementary forest type units.

4.2 Habitat quality analysis

The results derived from SPOT-5 data have been used to calculate a set of landscape metrics indicating the habitat quality of the EUNIS-3 units. Especially the shape-index, describing the complexity of patch form, is a good indicator for natural habitat conditions. The value of the index is increased e.g. by small creeks that contribute to optimal conditions in riparian forests. Small, compact forms are, in most cases, the result of anthropogenic use (see Figure 9 and Table 2).

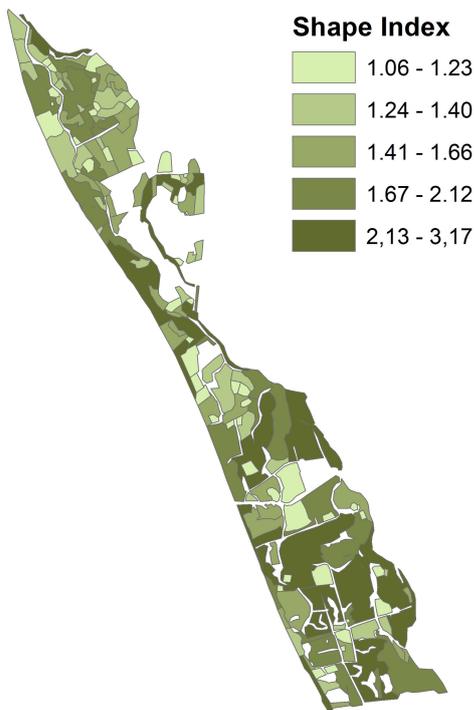


Figure 9. Shape-index values on patch level.

The parameters have been calculated using V-LATE, a vector-based landscape analysis tools extension for ArcGIS. Fragmentation and diversity measures (e.g. the effective mesh size and Shannon's diversity index) are particularly valuable in time-series analysis to evaluate changes in landscape pattern.

| | EUNIS-3 code | Number of patches | Shape-Index |
|----------------------|--------------|-------------------|-------------|
| Natural vegetation | G1.1 | 26 | 1.597 |
| | G1.2 | 14 | 1.644 |
| | G1.2/.A | 31 | 1.730 |
| Anthropogenic impact | G1.C | 27 | 1.382 |
| | G3.F | 15 | 1.438 |
| | G4.F | 15 | 1.600 |
| | G5.1 | 2 | 2.282 |
| | G5.2 | 3 | 1.146 |
| | G5.4 | 21 | 1.214 |
| | G5.5 | 2 | 1.352 |
| | G5.6 | 1 | 1.454 |
| | G5.7 | 1 | 1.124 |
| G5.8 | 4 | 1.241 | |

Table 2. Shape-index values aggregated on class level.

5. CONCLUSIONS & OUTLOOK

In this paper we discussed a workflow-based strategy for (semi-) automated habitat delineation and assessment. We applied a hierarchical class modeling scheme, integrating a lower-level single-tree/forest stand extraction and an upper-level broad habitat visual interpretation. While extensive ground samples have been used to test and verify the habitat class models, no validation has been performed so far, as the final results of this process are still due. We extensively investigated the potential of 8-band WorldView-2 scene, as being superior to standard NIR channel imagery. Further research is required to consolidate the class models in terms of robustness and transferability, for providing a solid geometry for the assessment of quality and dynamics in the study area.

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