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# Aerial Image Classification for the Mapping of Riparian Vegetation Habitats

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**Abstract –** In the current study, aerial image analysis has been applied to map vegetation communities in a riparian wetland ecosystem, Szigetköz (Hungary). Remote sensing offers an objective and time-effective method for the detection of detailed vegetation habitats with the use of high resolution aerial photos combined with ancillary botanical and silvicultural data. Three images of the same test site, acquired in three different years have been analysed by sample-based semi-automated image classification technique. Due to the heterogeneous nature of the target vegetation classes, besides using spectral features (e.g. vegetation indices) textural descriptors were also involved in the classification procedure. The most appropriate parameters have been chosen using a statistical feature selection method based on the Jeffries-Matusita distance. The accuracy assessment proved for each scene that the combined use of spectral and textural features gave the best classification results in comparison to the exclusive use of spectral or textural measures. The here-applied feature set can be applied for the analysis of similar riparian sites.

**remote sensing / high resolution imagery / riparian wetland / texture analysis**

**Kivonat – Légifelvételek osztályozása vizes élőhelyek térképezése céljából.** A tanulmány célja légifelvételek elemzésére szolgáló módszer kidolgozása vizes élőhelyek vegetációtérképezéséhez, melyet a szigetközi folyómenti mintaterületen vizsgáltunk. A hagyományos terepi felméréssel szemben a távérzékelés lehetővé teszi vizes élőhelyek megközelítően objektív és gyors térképezését nagy felbontású légifelvételek és kiegészítő botanikai és erdészeti adatok felhasználásával. A mintavételen alapuló fél-automatikus képosztályozás eredményesnek bizonyult a kiválasztott három képre alkalmazva (adott tesztterület három időpontra). A vegetációs célosztályok heterogén természetéből adódik, hogy a spektrális jellemzők (vegetációs index) vizsgálata mellett texturális jellemzők bevonására is szükség van az osztályozási algoritmusok kialakításához. A legjelentősebb paramétereket a Jeffries-Matusita statisztikai kiválasztó módszer segítségével határoztuk meg. Megbízhatósági elemzés alapján a spektrális és texturális jellemzők együttes alkalmazása adta a legjobb osztályozási eredményeket a kizárólag spektrális vagy texturális paraméterek felhasználásával szemben. Hasonló ártéri területek növényzeti térképezéséhez a kiválasztott jellemzők alapértelmezett alkalmazása javasolt.

**távérzékelés / nagy felbontású felvétel / folyómenti vizes élőhely / texturális elemzés**

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## 1 INTRODUCTION

Rapid and extensive change of ecosystems in the last 50 years induced a significant decrease in the variety of life forms (Millennium Ecosystem Assessment 2005). Since by the end of 2010 it became clear that the loss of biodiversity could not be stopped, a new strategy (EU 2020 biodiversity strategy) has been developed, linked to the European Habitats Directive and the Birds Directive (Lang et al. 2013). Besides this policy framework, appropriate technology is needed for observation, where satellite Earth Observation (EO) emerged as a powerful monitoring device. Beyond satellite imagery, the use of archive aerial photography is essential, for the historical characterization of variability within ecosystems and hereby for the development of strategies related to the management of ecological integrity (Landres et al. 1999). The analysis of high resolution images with additional in-situ measurements can compete with traditional field surveying of complex vegetation communities considering cost- and time-effectiveness. The visually-based, solely manual interpretation of imagery is inefficient due to its high subjectivity, as well as due to the rapid development of digital image analysis techniques and automated information extraction methods which result in feasible investigation of larger areas with high spatial resolution. Nevertheless, the image classification techniques of high resolution images for vegetation habitats are not straightforward. Due to the heterogeneous nature of these communities at high geometric resolution, traditional pixel-based digital image classifiers do not give satisfactory results (Levick – Rogers 2008, Kamagata et al. 2008, Addink et al. 2007, Johansen et al. 2010). Therefore, the application of object-based algorithms, after appropriate segmentation approaches, emerged (Blaschke et al. 2011). In addition to that, numerous studies have postulated that a supplementary approach is needed to spectral classification regarding vegetated areas and forest structures from high resolution images (Lévesque – King 2003, Zhang 2001), since target features cannot be differentiated on the sole basis of spectral reflectance. The characterization of image texture became the backbone of various remote sensing related applications, e.g. the analysis of landscape heterogeneity, biophysical parameters, forest structural characteristics, prediction of species distribution and biodiversity patterns (Morgan et al. 2010). Many texture features can be added to a certain study, however, since classification cost increases with the number of features, it is reasonable to reduce this number and utilize only the necessary features for performing a classification (Richards − Jia 2006). In other words, finding the best suited characteristics is a prerequisite for an efficient classification approach, therefore, statistical feature separability methods have been applied aiming at emerging those parameters which have high significance and could be best used in the differentiation of diverse vegetation habitats (Bindel et al. 2011, Mahmoud et al. 2011).

The present study aims at finding an appropriate semi-automated classification method with the use of texture characteristics in order to map predefined vegetation habitats based on high resolution aerial imagery. The analysis is based on a test site in a riparian wetland ecosystem (Szigetköz, Hungary) applied to three different years. Image classifications are carried out independently, however, their comparable use by transferring the descriptive measures from the recent image into another is investigated as well.

## 2 STUDY SITE

Wetlands in general are among the world's most productive ecosystems and reached a critical vulnerable state recently, wherefore their conservation and sustainable development strategy has been formulated in the Ramsar Convention on Wetlands (1971).

The Szigetköz Danubian floodplain together with the Slovakian Csallóköz is the most extensive riparian wetland in the Upper-Danube region, displaying a high species diversity of flora and fauna (Illés − Szabados 2008). The region is part of the Fertő-Hanság National Park (FHNP) with 37 500 ha area, of which 9157 ha became landscape protected in 1987 and nowadays it is included in the list of NATURA 2000 SPA (special protected area) and IBA (important bird areas) (Szabó 2005).

Due to the diversion of the Danube into a side channel in 1992, related to the construction of the Gabčikovo Hydroelectric Power Plant, severe changes occurred in the discharge pattern of the old riverbed of the Danube, with a decrease of the average discharge approximately to 20% (Ijjas et al. 2010). It has been reported in the same study of Ijjas et al. (2010) that the unique diverse pattern of habitat types have been significantly affected by the changed flow and sediment regime, and an alteration has been detected from aquatic or aquatic-related species to more terrestrial ones. Medium resolution Landsat satellite image analysis showed negative changes of the normalized vegetation indices in short-term (1992–1993) (Smith et al. 2000), caused by dropping groundwater levels, as were documented and modelled in the region (Vekerdy – Meijerink 1998). Similarly to that, changes were detected in the wetness values based on the Tasseled Cap transformation of Landsat, however, from 1997 a continuous regeneration is experienced, except for older willow species (Kristóf 2005).

Blaschke et al. (2011) listed numerous vegetation studies, where advanced remote sensing techniques have been applied to the analysis of high resolution imagery (≤10 m/pixel) in the recent years, though, in the test site of the present research, vegetation habitat classifications have been mainly based on traditional field survey. Available archive aerial imagery has been often used as unprocessed background information for visualization purposes as a basic layer for vector data representation (Takács − Molnár 2009). While land use/land cover classification of such images has been mainly based on visual image interpretation (Licskó 2002), in the field of forestry Illés − Somogyi (2005) have given an example for the application of a supervised digital image processing algorithm for the detection of different species and their state of health, but they did not reach satisfactory results.

In our research, for detailed vegetation analysis an approximately 2.5 km$^2$ area has been chosen as a test site, near to the village Dunaremete *(Figure 1)*.

## 3 DATA

Archive aerial photo series with high spatial resolution (≤ 5 m/pixel) are available at more Hungarian institutions about the chosen test site. For our experiment we used the ones summarized in *Table 1*.

As a pre-processing phase, imagery from 2008 and 2005 has been resampled to the coarser geometric resolution of the image 1999 (1.25 m/pixel) in order to support comparable image analysis techniques for all dates, since textural parameters depend on the spatial resolution of the imagery.

Any kinds of vegetation-related studies need the support of in-situ measurements as reference data. Therefore, botanical maps have been gathered, where the field survey was based on the framework of the National Biodiversity Monitoring System (Takács − Molnár 2009) focusing on the mapping of Á-NÉR types (Á-NÉR = the Hungarian abbreviation of General National Habitat Classifying System) (*Figure 1*, *Table 2*). Besides the botanical view of habitat complexes, it was also essential to involve silvicultural databases (*Figure 1*, *Table 2*), in order to aid the selection of target vegetation classes. Personal field inspection of a part of the test site has been carried out in November, 2010. Nevertheless, it has to be mentioned, that the ancillary data have been acquired in different time from the image dataset, and this brings some additional uncertainties into the image interpretation procedure.

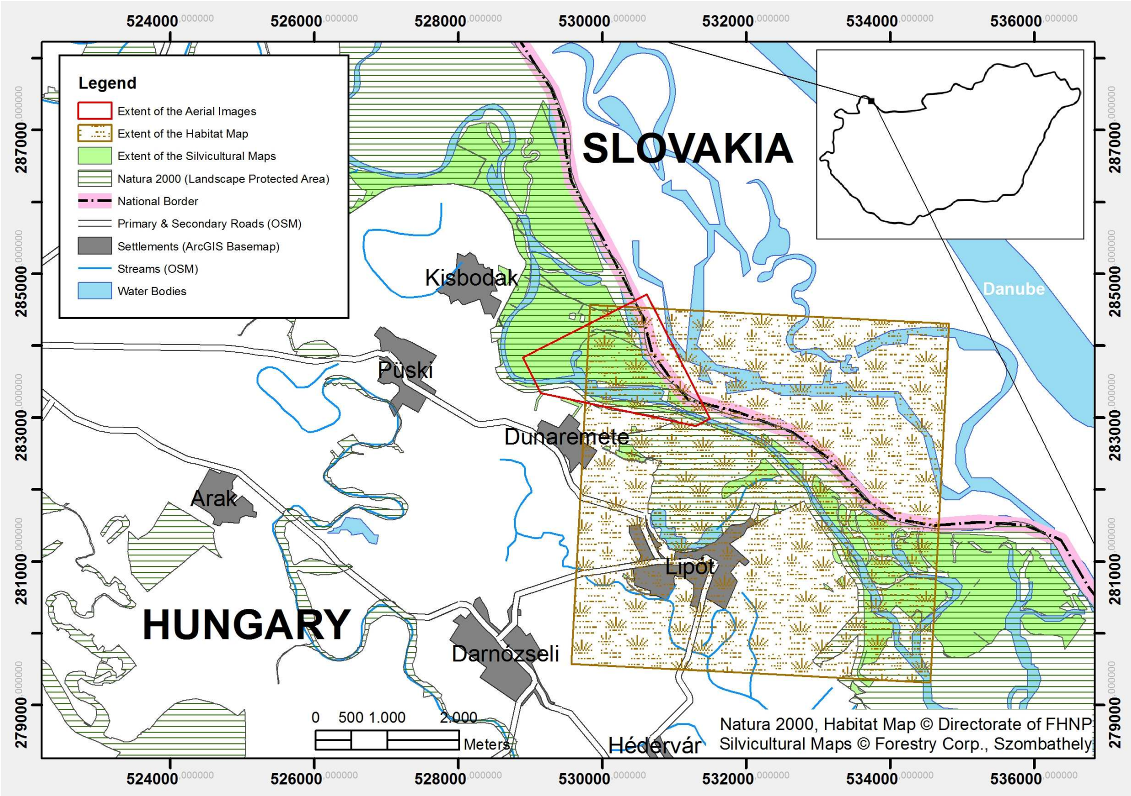


*Figure 1. Test site in the Szigetköz Danubian floodplain*

*Table 1. Aerial imagery*

| Imagery | Orthophoto 2008 | Orthophoto 2005 | Orthophoto 1999 |
|---|---|---|---|
| Source | Institute of Geodesy, Cartography and Remote Sensing (FÖMI), Budapest | | University of West Hungary, Phare CBC Project, EUROSENSE* |
| Scale | 1 : 74 000** | 1 : 30 000 | 1 : 30 000 |
| Original Ground Spatial Resolution | 0.5 m/pixel | 0.5 m/pixel | 1.25 m/pixel |
| Spectral Resolution | NIR, G, B | RGB | NIR, R, G |
| Camera Type | UltraCamX | RC 20 | Wild RC 20 |
| Applied Film Type | Digital, Color IR | Color | Color IR |
| Acquisition time | 06.08.2008 | 29.07.2005 | 03.08.1999 |
| Solar azimuth angle | 125.6° | 209.4° | 111.6° |

* CBC: Cross-Border-Cooperation; EUROSENSE: http://www.eurosense.com
** However, because of the digital camera, the given scale cannot be directly compared to the others.

*Table 2. Ancillary data*

| Ancillary data | Habitat map | Silvicultural map |
|---|---|---|
| Thematic information | Á-NÉR habitat type | First type of forest stand |
| Scale | 1 : 12 500 | 1 : 10 000 |
| Acquisition year | 2000, 2004 | 2003 |
| Acquisition time period | July-October | Spring-sommer-autumn |
| Source | Directorate of FHNP | Forestry Directorate, Szombathely |

# 4 METHODS

## 4.1 Object-based image analysis

Object-based image analysis (OBIA) technique, contrary to pixel based approaches, offers an efficient solution for high spatial resolution mapping with a potential extension for larger areas in a relatively rapid manner, due to the integration of spatial complexity. OBIA consists of (1) image segmentation: clustering of pixels into homogeneous objects, (2) classification: labeling of objects and (3) modeling based on the characteristics of objects (Johansen et al. 2010b). As the first step, the segmentation approach is mainly based on the concept from Tobler (1970), also known as the first law of geography, saying that “everything is related to everything else, but near things are more related than distant things”.

According to that, images of each year have been firstly analysed concentrating on the separation of`the spectrally differentiable ‘Water bodies’, like the first part of a hierarchical classification. In that case, after quadtree and multi-resolution segmentation approaches, the classification was based on vegetation indices (*Table 3*) and brightness values (average of the three original bands). In addition, manual corrections were needed, especially concerning the image from 2005.

*Table 3. Vegetation indices applied to images with different spectral resolutions*

| Orthophoto | 2008 | 2005 | 1999 |
|---|---|---|---|
| Spectral bands | NIR, G, B | R, G, B | NIR, R, G |
| Vegetation Index | modified NDVI: (NIR-B)/(NIR+B) | (G-R)/(G+R) (Gitelson et al. 2002) | NDVI: (NIR-R)/(NIR+R) |

## 4.2 Target vegetation classes

Further classes are related to vegetation habitats, where the selection of target classes was based on a synoptic view of the aerial photos (2008, 2005, 1999) and additional information, concentrating on the most occurring and characteristic vegetation patterns which can be “easily” identified by human eye in the visual image interpretation process. Reed (R), Hybrid Poplar (HP), Domestic Poplar (DP), Willow (W) and Willow & Poplar (WP) classes (*Figure 2*) have been defined as target classes for the image classification for each year, except for class Domestic Poplar (in the Hungarian designation “hazai nyáras”) which was only present in 2008. It has not been intended to identify each of the occurring classes in the test site, but those ones which cover an area with a significant size.

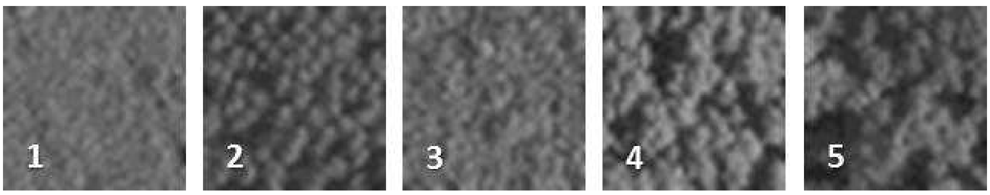


*Figure 2. Target vegetation classes represented by 40 m * 40 m square samples (2008, PC1, GSR: 1.25 m/pixel)*
*1: Reed, 2: Hybrid Poplar, 3: Domestic Poplar, 4: Willow, 5: Willow & Poplar*

### 4.3 Analysis of textures

In case of very high resolution (VHR) imagery the spectral characteristics (radiometric values in various bands) of a single pixel cannot describe forest stands or even an individual tree, therefore, information is needed on the local neighborhood of each pixel, either by the generalization for the stand (substand) or by the analysis of the texture of larger spatial units, like square-shaped windows/polygons. Local textures can be described by spatial statistical measures, grouped into three types, (1) first-order statistics, e. g. standard deviation, (2) second-order statistics based on co-occurrences and (3) semi-variances or autocorrelations within a pixel neighborhood (Tuominen − Pekkarinen 2005).

#### *4.3.1 The grey-level co-occurrence matrix*

Grey-level co-occurrence matrices (GLCM) belong to second-order statistics and have been successfully applied in numerous studies for land-cover/vegetation analysis of remotely sensed imagery (Berberoglu et al. 2007; Hájek 2008), showing significant improvements in the classification accuracies (Franklin et al. 2000; Carleer − Wolff 2006). Taking a grey-scale image with a given brightness value range (in our case $L = 256$ *due to the* 8 bit data), the GLCM is an $L \times L$ matrix, where the value for each cell is defined by the number of occurrences of a given grey-level-combination of 2 pixels (a pixel pair, with a defined $h$ distance and $\theta$ direction which are given for a concrete matrix) divided by the total possible number of grey level pairs (Richards − Jia 2006). Depending on the various $h$ and $\theta$ chosen, there are different GLCMs. Haralick et al. (1973) defined 14 various metrics derived from each matrix to use as texture measures.

In summary, variables which have to be defined for GLCM calculations are (1) moving window (object) size; (2) direction of the offset (mentioned as $\theta$ before); (3) distance of the offset ($h$); (4) image channel used; (5) specific metrics as defined by Haralick et al. (1973). Regarding the direction of the offset, the all directional feature is often applied, meaning the average of all the directions (0°, 45°, 90°, 135°), especially when the observed classes are not directionally biased (Laliberte − Rango 2009). The distance of pixels is normally set to 1, i.e. for the comparison of direct neighbours (Trimble 2013). We applied GLCM on the first principal component (PC1) calculated from the three bands of each aerial photo to best represent the texture of the photo (coefficients for PC1 *regarding 2008*: 0.659, 0.485, 0.575; *regarding 2005*: 0.579, 0.590, 0.563; *regarding 1999*: 0.685, 0.488, 0.541).

Similar to the case described above regarding the image analysis of VHR imagery, by the application of object-based image analysis technique the core of the analysis procedure is not any more the pixel itself, but “an extended neighborhood”, the image segments or objects, which are typically the sets of spectrally similar pixels coming from a multi-resolution segmentation approach (Benz et al. 2004). However, due to the fact that target vegetation communities are spectrally heterogeneous, another type of segmentation (“chessboard”) is privileged in our investigations, where the image scene is divided into unique-sized objects (squares) with a predefined size. This means actually that the minimum mapping unit of the classification has changed from 1.25 m/pixel to 20 m/pixel, but with additional information on the texture.

#### *4.3.2 The semi-variogram*

Moving window sizes or in our example, the square image object sizes are critical for any texture analyses. The internal spatial variability of the target class(es) will determine the ground resolution element (here the grid size), before unnecessary intra-parcel variability would be detected (Curran 1988). In this regard, semi-variogram analysis has been applied in numerous studies to choose the most appropriate window size for GLCM computation (Carr −

Miranda 1998; Treitz − Howarth 2000; Tsai − Chou 2006; Szantoi et al. 2013). The variogram (or semi-variogram) is frequently used as a measure of spatial continuity, as well as a multiscale directional measure of surface roughness (Trevisani et al. 2009). The mathematical structure model of the empirical semi-variogram is defined as (Curran 1988):

$$\gamma(h) = \frac{1}{2m}\sum_{i=1}^{m}\left[z(x_i) - z(x_{i+h})\right]^2 \tag{1}$$

where $x$ is a geographic point, $z(x)$ is its attribute value (in our case, the radiometric value, DN) and $m$ is the number of point pairs separated by vector $h$. For the graphs of the semi-variograms $\gamma(h)$ is visualized for increasing $h$**.** The larger $\gamma(h)$ is, the less similar are the pixels divided by a given $h$ vector (often named as *lag*). Range is one of the most important characteristics of the semi-variogram, which is a point on the $h$ axis where $\gamma(h)$ reaches its maximum, or rather for sample data where $\gamma(h)$ reaches approximately 95% of the sill - which is the maximum level of $\gamma(h)$ (Curran 1988).

In the current research, since target classes are vegetation habitats with repetitive patterns, their semi-variograms are rather periodical, but anisotropic. The visualization of the semi-variogram graphs help to identify approximately one period as the appropriate size for further texture investigations. Semi-variograms for 4 window sizes (*10 × 10, 20 × 20, 30 × 30, 40 × 40 m*) have been compared for the image 2008 calculated on the PC1, choosing certain samples from the predefined target vegetation classes (*Figure 2*). Corresponding to the solar azimuth angle of the image acquisition of 2008, directional variograms have been computed along the direction of the supposed minimum continuity (126°) in order to describe variability and as well along the direction of maximum continuity (perpendicular to 126°, thus 36°). These analyses (*Figure 3*) proved that the use of around *20 m × 20 m* (16 × 16 pixels for the 1.25 m/pixel GSR) square-objects is reasonable as basis for the texture analysis.

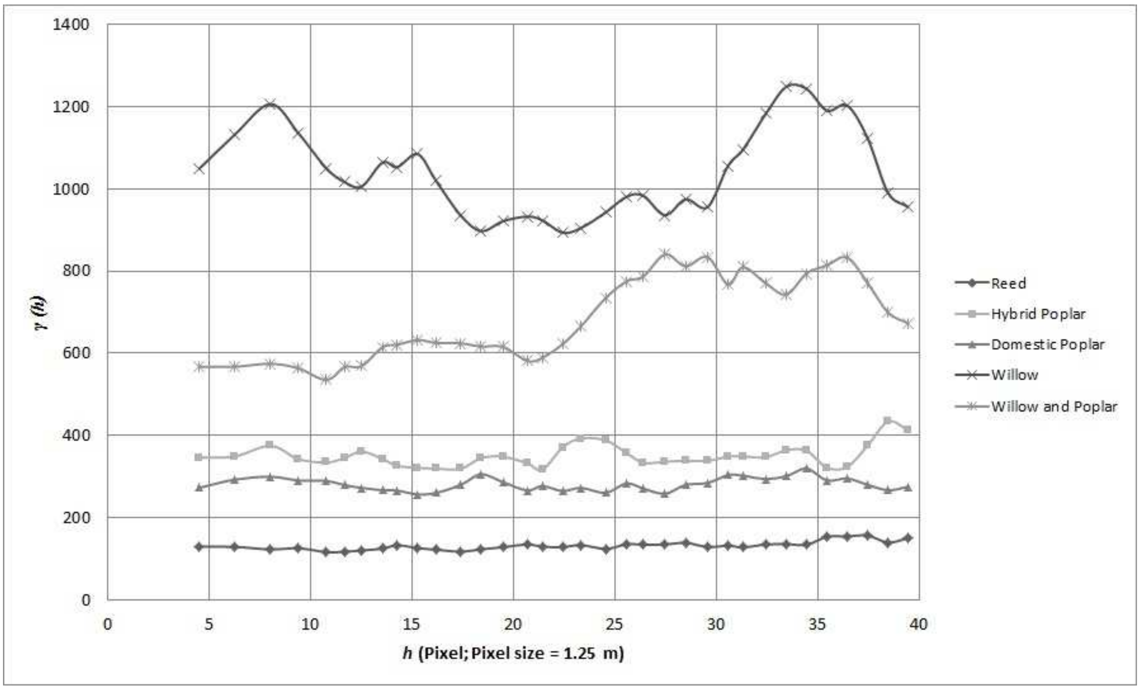


*Figure 3. Directional semi-variograms (regarding the solar azimuth angle: 126° of the image acquisition 2008) for different vegetation classes*

This was supported by the findings of Tuominen − Pekkarinen (2005) who applied 20 m $\times$ 20 m square-shaped windows, stating that this size would lead to near-optimal results regarding forest stand inventories based on the analysis of aerial photography.

### 4.4 Statistical feature selection method

In a recent study (Kollár et al. 2013) related to the present research project GLCM entropy (ENT), correlation (CORR) and standard deviation (STDEV) have been chosen from the texture measures based on literature references (Hall-Beyer 2007) and empirical observations by the comparison of feature value ranges of certain class-pairs. There, besides the all-directional type, directional textures have been analyzed as well, applied to those angles which were the nearest to the solar azimuth angle of each image acquisition (*Table 1*). For 2008 the use of the all-directional, for 2005 and 1999 the directional textures in the combined feature set (together with vegetation index) provided the best classification accuracies (Kollár et al. 2013).

The current attempt aimed at a statistically based feature selection method for the analysis and the choice of the most appropriate textural features from a larger number of measures, which have been analysed as well in the study of Laliberte − Rango (2009) complemented with two other measures. The issue of feature selection has been a general problem in image analysis methods, more specifically in pattern recognition related applications in order to minimize the classification error (Peng 2005, Pereira et al. 2007, Laliberte et al. 2012, Silva et al. 2012). Besides aiming at higher classification accuracies, the application of feature selection methods has been related to the reduction of redundant information in order to speed up the classification approach by an optimal decrease in the evaluated features (Mahmoud et al. 2011, Bindel et al. 2011). Determination of the mathematical separability of classes has been a common procedure, where feature reduction is performed by checking how separable various spectral classes remain when reduced sets of features are applied (Richards − Jia 2006). From the group of probabilistic measures the Bhattacharyya distance (*B*) is one of the most popular measures (Mahmoud et al. 2011):

$$B = \frac{1}{8}(m_1 - m_2)^2 \times \frac{2}{\delta_1{}^2 + \delta_2{}^2} + \frac{1}{2}\ln\left[\frac{\delta_1{}^2 + \delta_2{}^2}{2\delta_1\delta_2}\right] \tag{2}$$

which has been stated as a convenient equation for normal distributions, but not rejecting the complete group of non-Gaussian cases and also discussed for a family of gamma distributions (Fukunaga 1990). However, the infinite nature of $B$ concerning a range of a half-closed interval $[0, \infty)$ makes its interpretation difficult. Therefore, a similar measure, but with a finite dynamic range has been introduced, called Jeffries-Matusita distance *(JM)* (Richards − Jia 2006).

$$JM = 2(1 - e^{(-B)}) \tag{3}$$

Silva et al. (2012) have summarized that generally $JM$ values above 1.8 are the indicators for a good separability, the distance value below 1.8 would mean the possibility of confusion in the classification process between classes.

In our study 8–8 GLCM features (all-directional and directional) and 4–4 GLDV (gray level difference vector) statistics have been analyzed for the best separability measures, where GLDV is a sum of the diagonals of the GLCM and a measure of the absolute differences of neighbors (Laliberte − Rango 2009). Target classes have had a minimum of 20 grid samples for each year. The basis for the texture calculations was the first principal component layer. As mentioned before, GLCM can be directional (related to the solar azimuth angle of each image) and non-directional (the average of the directional features) and here both have been applied. For *d* (distance), 1 has been chosen as default, calculated in the object-based image analysis software eCognition Developer 8.9. Besides textures, vegetation indices (*Table 3*) and two other spectral descriptors (average of PC1 and average of the Green band) have been added as well to the separability analysis.

*JM* measures for image 2008 are shown in detail in *Table 4* for the selected textures (each one of them is all directional, *Table 5*) next to one spectral characteristic. Although, the separability value for GLCM Mean was only bigger than 1.8 for 2 class pairs, one of them (HP-SP) represents a unique case since those classes have not been separable by any other texture features. Besides this consideration, we can also take into account, that there might be class pairs which are not clearly separable and the step concerning the selection of target classes should be revised. *Table 4* indicates an example where the class pairs SP-WP and W-WP are not separable without confusion (white fields, where *JM* is under 1.8). From the investigations regarding 2005, 1999 pairs of HP-WP and W-WP have been inseparable.

*Table 4. JM measures for vegetation class pairs, concerning the selected textural and spectral features*

| | HP-SP | HP-W | HP-WP | HP-R | SP-W | SP-WP | SP-R | W-WP | W-R | WP-R | Number of pairs where JM ≥ 1.8 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| GLCM STDEV | 0.0 | 1.9 | 1.6 | 1.8 | 2.0 | 1.7 | 1.8 | 0.5 | 2.0 | 2.0 | 6 |
| GLDV ENT | 0.7 | 1.6 | 0.4 | 0.9 | 1.9 | 0.5 | 1.8 | 1.4 | 2.0 | 1.8 | 4 |
| GLCM CONT | 0.5 | 1.6 | 0.4 | 1.0 | 1.8 | 0.7 | 1.9 | 1.3 | 1.9 | 1.8 | 4 |
| GLCM MEAN | 1.9 | 1.4 | 0.4 | 2.0 | 0.4 | 1.0 | 1.0 | 0.4 | 1.1 | 1.4 | 2 |
| mNDVI | 1.9 | 2.0 | 1.9 | 2.0 | 1.1 | 0.6 | 1.9 | 0.2 | 1.0 | 1.3 | 5 |

*Table 5. GLCM measures chosen after separability analysis*

| Texture Measure | Formula |
|---|---|
| GLCM Contrast (CONT) | $\sum_{i,j=0}^{N-1} P_{i,j}(i-j)^2$ |
| GLCM Mean (MEAN) | $\frac{\sum_{i,j=0}^{N-1} P_{i,j}}{N^2}$ |
| GLCM Standard Deviation (STDEV) | $\sum_{i,j=0}^{N-1} P_{i,j}(i,j-\mu_{i,j})$ |
| GLDV Entropy (ENT) | $\sum_{k=0}^{M-1} V_k(-\ln Vk)$ |

$P_{ij}$ is the normalized gray-level value in the cell $i,j$ of the matrix, N is the number of rows or columns, $\mu_{i,j}$ are the mean of row $i$ and column $j$, $V_k$ is the normalized gray-level difference vector, and $k = |i–j|$.

### 4.5 Semi-automated classification algorithm

The complete image analysis with texture calculations was performed using the object-based image analysis software eCognition Developer 8.9. The applied supervised classification algorithm is based on a membership value based fuzzy class evaluation, where the membership values concerning one specific feature from the selected feature set are computed from the training grid cells. The fuzzy nature of the algorithm means that there are three potential classes in the evaluation for a certain object (here: grid cell), with the label of the best class, calculated from the membership value based class descriptions for the selected feature set (Trimble 2013). Semi-automated refers to the general nature of classification approaches as part of the digital image analysis techniques where pixels or grid cells are classified in an almost automatic manner. Although the part of training sample selection is still subjective, chosen by the analyst, the labeling of objects later on is based on the derived characteristics and chosen algorithms.

In traditional supervised classifications, firstly training samples are chosen from a concrete image where, based on their characteristics (usually the statistical descriptions), the whole image can be classified into the groups of predefined classes. In case of aerial image time series regarding a certain test site and short time period, the following question arises: whether it is possible to classify different-year images based on the training samples from a given year. In the current study, training samples have been collected from the 2008 image and the derived class descriptions have been tested for the 1999 image, which has a different spectral, but due to the earlier resampling (regarding the 2008 image) the same geometric resolution.

## 5 RESULTS AND DISCUSSION

Due to the fact that the acquisition times of botanical and forest inventories did not overlap with the aerial images, reference data cannot be directly taken. Thus, just like for the training stage of the classification, samples for accuracy assessment were taken from the target classes at locations different from the training areas. *Table 6* summarizes the overall accuracies and Kappa coefficient measures for the 9 classifications, regarding the 3 different feature sets applied to each year.

*Table 6. Accuracy assessment of the fuzzy classification results concerning different feature sets*

| | Year 2008 (CIR) | | Year 2005 (RGB) | | Year 1999 (CIR) | |
|---|---|---|---|---|---|---|
| Features applied | Overall acc. | Kappa | Overall acc. | Kappa | Overall acc. | Kappa |
| Mean of PC1, VI | 0.78 | 0.72 | 0.50 | 0.35 | 0.60 | 0.47 |
| 4 textures only | 0.91 | 0.89 | 0.88 | 0.84 | 0.82 | 0.76 |
| 4 textures, VI | 0.96 | 0.94 | 0.90 | 0.87 | 0.84 | 0.79 |

Accuracy measures have shown that the use of texture parameters leads to significant improvements in comparison to solely spectral bands based classifications, however, best classification results were reached with the application of a combined set of spectral (vegetation index) and textural descriptors.

The following three maps in *Figure 4* present the best classification results for the test site (2008, 2005, 1999).

Classification results for the different images (2008, 2005, 1999) come from independent image analyses based on sample selection in each year. Nevertheless, after visual interpretation target vegetation classes regarding species composition remained nearly the same between 1999 and 2008 for the most of the site, that's why it was reasonable to analyse the classification algorithm based on the same class descriptions for the former year 1999.

The identification of water bodies in image 1999 worked well with the application of the "transferred" algorithm applied originally to image 2008 (a combination of the use of vegetation index and brightness). Contrary to that the predefined vegetation classes could not be detected in the 1999 image. Because of temporal differences "stable" vegetation classes are changing (growth) as well and any change in the texture patterns is critical for the given (transferred) membership functions in the classification algorithm. In addition, the here-applied classification scheme does not cover the complete test site (unclassified area covers more than 30% in case of image 2008 and more than 20% for images 2005, 1999) which leads to difficulties regarding class transferability for different years and sites, that's why the reconsideration of target classes is vital. However, an extension of the classification scheme without primary ground reference information (field survey concerning the last image, 2008) isn't straightforward either. Complementary classes could partly come from habitat maps (in the concrete example, Dunaremete, 2004: vegetation on edges and dams, other hardwood, arable land), from silvicultural inventory (domestic poplar-acacia) and from visual interpretation (bare soil mixed with grass, road, young stand, shadow). The application of the same supervised classification method described before, however, with additional samples, resulted in 87% overall accuracy and showed a significant decrease in the unclassified area. It has to be emphasized that although we have been concentrated on a classification scheme mainly based on species composition, one of the additional classes: domestic poplar-acacia has been classified into the same group as a certain hybrid poplar stand with the same age (referring to the silvicultural information), which leads to the consideration of forest stand classification based on age structure.

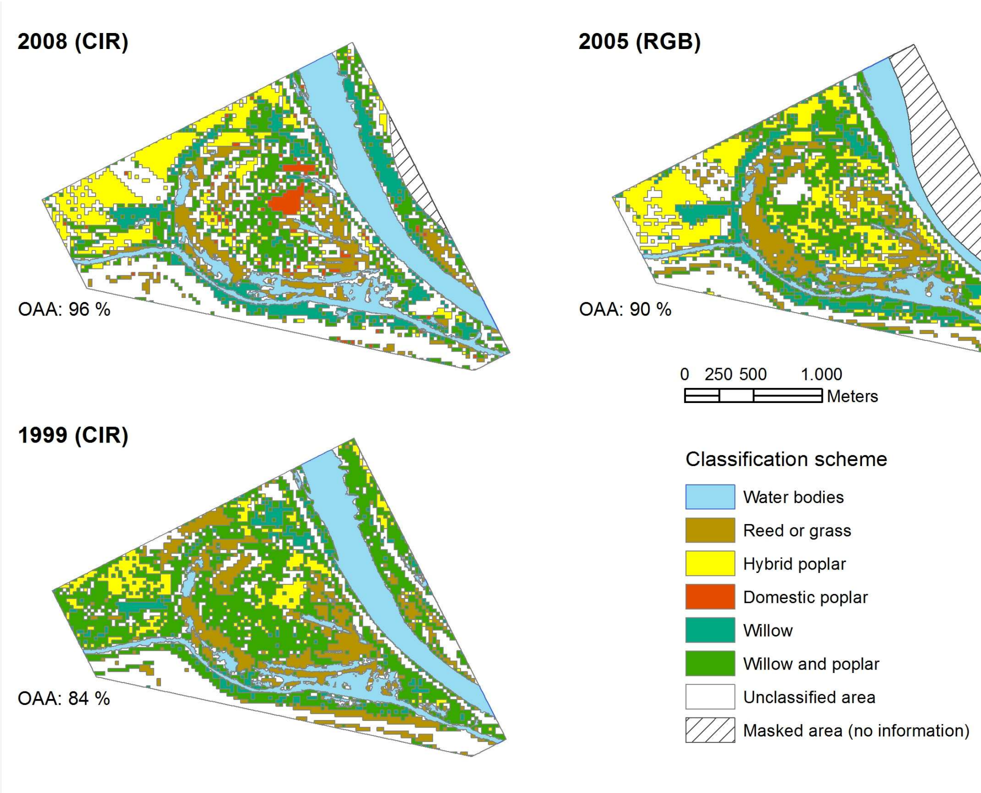


*Figure 4. Classification results based on the fuzzy (membership value based) classification, for three different years (2008, 2005, 1999) with the use of the combined (textural and spectral) feature set*

Beyond these aspects, the lack of reliable ancillary information for the former years makes it difficult to conduct a detailed analysis with appropriate accuracy. Monitoring approaches often apply post-classification change detection, which is an essential tool for the evaluation of quantitative and qualitative changes in the observed (vegetation) classes. Nevertheless, this type of analysis requires high classification accuracies for each analysed year. We have seen that overall classification accuracy decreases significantly from 2008 to 1999, however, for each scene it was higher than 80%. Considering the accuracy calculation procedure it is vital, that in the earlier-mentioned measures (*Table 6*) misclassification of the background (expected as unclassified area) has not been involved. Experimental accuracy calculations complemented with background reference samples, only applied to the 2008 image, have resulted in 9% decline (from 96% to 87%) regarding the overall accuracy and 0.10 decrease (from 0.94 to 0.84) concerning the Kappa index. These values emphasize the significance of more detailed accuracy assessment and the further improvement of classification results, before the application of reasonable change detection methods.

## 6 CONCLUSIONS AND FUTURE WORK

Generally speaking, aerial imagery based semi-automatic image analysis aids vegetation monitoring approaches, helps to understand the ecological structures (vegetation patches) in a faster manner and has the potential to analyse processes (temporal changes) and hereby, supports the work of botanical and silvicultural surveyors with habitat maps.

Based on the findings of the current study, the combined set of spectral (vegetation index) and textural (derived from GLCM/GLDV) features is suggested to be analysed and further involved in image classification algorithms for the mapping of riparian vegetation habitats. Based on the accuracy assessment the combination of spectral and textural features provided the best classification results in comparison to the sole use of spectral or textural descriptors. During the analysis of textural and spectral descriptors (features) the utilization of a statistical feature selection method (e.g. Jeffries-Matusita measure) has been proved to be essential in order to find the best fitting descriptors and to make reliable estimates of class signatures, especially in those cases where the selection of training pixels/objects is restricted due to the small size of the test site (Richards − Jia 2006). Regarding the remark (made in the previous section) concerning the similarities between different vegetation habitats (hybrid poplar and domestic poplar-acacia), it should be further investigated based on other test sites whether the age structure of forest stands significantly influences the vegetation habitat classification mainly based on species composition and if texture based image analysis could help to investigate forest stand ages.

Uncertainty originates from various sources in ecosystem mapping, already in the training phase of the supervised classification, e.g. definition of classes, subjectivity of the field surveying based reference data and the mixed pixel (in our case: mixed object) problem (Rocchini et al. 2013). In case of differing acquisition times in image and reference data, a significant difficulty is often present, since the identification of a certain land cover type cannot be precise. Accuracy assessment can only take into account those objects for proof where the identification of a given class is reliable.

The current study proved that the direct transfer of texture measures derived from one image transferred to a former one, and thereby the detection of the same or similar vegetation habitats in the former year cannot be worked out based on an incomplete classification scheme and the applied membership function based classification algorithm. For this reason and for the improvement of recent results, a complete cover of vegetation classes and the use of advanced classification algorithms have to be analysed in the further research.

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## REFERENCES

ADDINK, E. A. − JONG, S. M. de − PEBESMA, E. J. (2007): The Importance of Scale in Object-based Mapping of Vegetation Parameters with Hyperspectral Imagery. Photogrammetric Engineering & Remote Sensing 73 (8), 905–912.

BENZ, U. C. − HOFMANN, P. − WILLHAUCK, G. − LINGENFELDER, I. − HEYNEN, M. (2004): Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. ISPRS Journal of Photogrammetry and Remote Sensing 58 (3–4), 239–258.

BERBEROGLU, S. − CURRAN, P. − LLOYD, C. − ATKINSON, P. (2007): Texture classification of Mediterranean land cover. International Journal of Applied Earth Observation and Geoinformation 9 (3), 322–334.

BINDEL, M. − HESE, S. − BERGER, C. − SCHMULLIUS, C. (2011): Feature selection from high resolution remote sensing data for biotope mapping. In: C. Heipke, K. Jacobsen, F. Rottensteiner, S. Müller, U. Sörgel (Eds.): High-Resolution Earth Imaging for Geospatial Information. Hannover, June 14–17. ISPRS. XXXVIII-4/W19 (ISPRS Archives).

BLASCHKE, T. − JOHANSEN, K. − TIEDE, D. (2011): Object-Based Image Analysis for Vegetation Mapping and Monitoring. In: Q. Weng (Ed.): Advances in Environmental Remote Sensing: Sensors, Algorithms and Applications. United States: CRC Press Taylor & Francis Group, 241–271.

CARLEER, A. P. − WOLFF, E. (2006): Urban land cover multi-level region-based classification of VHR data by selecting relevant features. Int. J. of Remote Sensing 27 (6), 1035–1051.

CARR, J. R. − MIRANDA, F. P. de (1998): The semivariogram in comparison to the co-occurrence matrix for classification of image texture. Geoscience and Remote Sensing, IEEE Transactions on 36 (6), 1945–1952.

CURRAN, P. J. (1988): The semivariogram in remote sensing: An introduction. Remote Sensing of Environment 24 (3), 493–507.

FRANKLIN, S. E. − HALL, R. J. − MOSKAL, L. M. − MAUDIE, A. J. − LAVIGNE, M. B. (2000): Incorporating texture into classification of forest species composition from airborne multispectral images. International Journal of Remote Sensing 21 (1), 61–79.

FUKUNAGA, K. (1990): Introduction to Statistical Pattern Recognition. Second Edition. San Francisco San Diego: Morgan Kaufmann Academic Press.

GITELSON, A. A. – KAUFMAN, Y.J. – STARK, R. – RUNDQUIST, D. (2002): Novel algorithms for remote estimation of vegetation fraction. Remote Sensing of Environment 80, 76–87.

HÁJEK, F. (2008): Process-based approach to automated classification of forest structures using medium format digital aerial photos and ancillary GIS information. Eur J Forest Res 127 (2), 115–124.

HALL-BEYER, M. (2007): The GLCM Tutorial Home Page. Available online at http://fp.ucalgary.ca/mhallbey/tutorial.htm, updated on 21/02/2007, checked on 6/12/2012.

HARALICK, R. M. − SHANMUGAM, K. − DINSTEIN, I. (1973): Textural Features for Image Classification. Man and Cybernetics Systems 3 (6), 610–621.

IJJAS, I. − KERN, K. − KOVÁCS, GY. (Eds.) (2010): Feasibility Study. The Rehabilitation of the Szigetköz Reach of the Danube. Budapest.

ILLÉS, G. − SOMOGYI, Z. (2005): A szigetközi ártéri erdők egészségi állapotának ortofotókon alapuló elemzése és értékelése. [Health condition of the forests of Szigetköz based on orthophotos.] Tájökológiai Lapok 3 (2), 335–360. (in Hungarian)

ILLÉS, G. − SZABADOS, I. (2008): 20 éves az erdészeti monitoring a Szigetközben. [20 years of monitoring in Szigetköz.] Erdészeti Kutatások 2007–2008 92, 95–120. (in Hungarian)

JOHANSEN, K. − ARROYO, L. A. − PHINN, S. − WITTE, C. (2010a): Comparison of Geo-Object Based and Pixel-Based Change Detection of Riparian Environments using High Spatial Resolution Multi-Spectral Imagery. Photogrammetric Engineering & Remote Sensing 76 (2), 123–136.

JOHANSEN, K. − BARTOLO, R. − PHINN, S. (2010b): SPECIAL FEATURE – Geographic Object-Based Image Analysis. Journal of Spatial Science 55 (1), 3–7.

KAMAGATA, N. − HARA, K. − MORI, M. − AKAMATSU, Y. − LI, Y. − HOSHINO, Y. (2008): Object-based classification of IKONOS data for vegetation mapping in Central Japan. In: T. Blaschke, S. Lang, G. J. Hay (Eds.): Object-Based Image Analysis - Spatial Concepts for Knowledge-Driven Remote Sensing Applications. Berlin Heidelberg: Springer-Verlag, 459–475.

KOLLÁR, Sz. − VEKERDY, Z. − MÁRKUS, B. (2013): Geostatistical Characterization of Wetland Habitats. In: M. Neményi, L. Varga, F. Facskó, I. Lőrincz (Eds.): Science for Sustainability. International Scientific Conference for PhD Students. Győr, Hungary, March 19–20. Sopron: University of West Hungary Press, 106–111.

KRISTÓF, D. (2005): Távérzékelési módszerek a környezetgazdálkodásban. [Remote sensing methods in environmental management.] PhD thesis, University of Szent István, Gödöllő (in Hungarian)

LALIBERTE, A. − BROWNING, D. − RANGO, A. (2012): A comparison of three feature selection methods for object-based classification of sub-decimeter resolution UltraCam-L imagery. International Journal of Applied Earth Observation and Geoinformation 15, 70–78.

LALIBERTE, A. − RANGO, A. (2009): Texture and Scale in Object-Based Analysis of Subdecimeter Resolution Unmanned Aerial Vehicle (UAV) Imagery. IEEE Trans. Geosci. Remote Sensing 47 (3), 761–770.

LANDRES, P. B. − MORGAN, P. − SWANSON, F. J. (1999): Overview of the use of natural variability concepts in managing ecological systems. Ecological Applications 9 (4), 1179–1188.

LANG, S. − CORBANE, C. − PERNKOPF, L. (2013): Earth Observation for Habitat and Biodiversity Monitoring. T. Jekel, A. Car, J. Strobl, G. Griesebner (Eds.): GI_Forum 2013. Creating the GISociety. GI Forum. Salzburg. Berlin/Offenbach: Herbert Wichmann Verlag, 478–486.

LÉVESQUE, J. − KING, D. J. (2003): Spatial analysis of radiometric fractions from high-resolution multispectral imagery for modelling individual tree crown and forest canopy structure and health. Remote Sensing of Environment 84 (4), 589–602.

LEVICK, S. R. − ROGERS, K. H. (2008): Structural biodiversity monitoring in savanna ecosystems: Integrating LiDAR and high resolution imagery through object-based image analysis. In: T. Blaschke, S. Lang, G. J. Hay (Eds.): Object-Based Image Analysis - Spatial Concepts for Knowledge-Driven Remote Sensing Applications. Berlin Heidelberg: Springer-Verlag, 477–491.

LICSKÓ, B. (2002): A Szigetköz digitális felszínborítás térképeinek elkészítése légi felvételek kiértékelésével. [Digital mapping of Szigetköz by evaluating aerial photos.] Térinformatika (3), 13–15. (in Hungarian)

MAHMOUD, A. − ELBIALY, S. − PRADHAN, B. − BUCHROITHNER, M. (2011): Field-based landcover classification using TerraSAR-X texture analysis. Advances in Space Research 48 (5), 799–805.

MILLENNIUM ECOSYSTEM ASSESSMENT (Ed.) (2005): Ecosystems and Human Well-being: Synthesis. Washington, DC., Island Press

MORGAN, J. L. − GERGEL, S. E. − COOPS, N. C. (2010): Aerial Photography: A Rapidly Evolving Tool for Ecological Management. BioScience 60 (1), 47–59.

PENG, H. (2005): Feature Selection Based on Mutual Information: Criteria of Max-Dependency, Max-Relevance, and Min-Redundancy. IEEE Transactions on Pattern Analysis and Machine Intelligence 27 (8), 1226–1238.

PEREIRA, R. R. − AZEVEDO MARQUES, P. M. − HONDA, M. O. − KINOSHITA, S. K. − ENGELMANN, R. − MURAMATSU, C. − DOI, K. (2007): Usefulness of Texture Analysis for Computerized Classification of Breast Lesions on Mammograms. J Digit Imaging 20 (3), 248–255.

RICHARDS, J. A. − JIA, X. (Eds.) (2006): Remote Sensing Digital Image Analysis. An Introduction. 4th Edition. Heidelberg: Springer-Verlag

ROCCHINI, D. − FOODY, G. M. − NAGENDRA, H. − RICOTTA, C. − ANAND, M. − HE, K. S. et al. (2013): Uncertainty in ecosystem mapping by remote sensing. Computers & Geosciences 50, 128–135.

SILVA, C. − MARCAL, A. − PEREIRA, M. − MENDONÇA, T. (2012): Separability analysis of color classes on dermoscopic images. In: A. Campilho, M. Kamel (Eds.): ICIAR 2012. Part II. LNCS 7325. Berlin; Heidelberg: Springer-Verlag, 268–277.

SMITH, S. − BÜTTNER, G. − SZILAGYI, F. − HORVATH, L. − AUFMUTH, J. (2000): Environmental impacts of river diversion: Gabcikovo Barrage System. Journal of Water Resources Planning and Management 126 (3), 138–145.

SZABÓ, M. (2005): Vizes élőhelyek tájökológiai jellemvonásai a Szigetköz példáján. [Landscape ecological features of wetlands exemplified by the Szigetköz region] PhD thesis ELTE, Budapest, (in Hungarian)

SZANTOI, Z. − ESCOBEDO, F. − ABD-ELRAHMAN, A. − SMITH, S. − PEARLSTINE, L. (2013): Analyzing fine-scale wetland composition using high resolution imagery and texture features. International Journal of Applied Earth Observation and Geoinformation 23 (0), 204–212.

TAKÁCS, G. − MOLNÁR, ZS (Eds.) (2009): National Biodiversity Monitoring System XI. Habitat mapping. 2nd modified edition. Vácrátót; Budapest: Hungarian Academy of Sciences, Insitute of Ecology and Botany; Ministry of Environment and Water

TOBLER, W. (1970): A computer movie simulating urban growth in the Detroit region. Economic Geography 46 (2), 234–240

TREITZ, P. − HOWARTH, P. (2000): High Spatial Resolution Remote Sensing Data for Forest Ecosystem Classification: An Examination of Spatial Scale. Remote Sensing of Environment 72 (3), 268–289.

TREVISANI, S. − CAVALLI, M. − MARCHI, L. (2009): Variogram maps from LiDAR data as fingerprints of surface morphology on scree slopes. Nat.Hazards Earth Syst.Sci. (9), 129–133.

TRIMBLE (Ed.) (2013): eCognition Developer. Reference Book, Trimble Germany GmbH.

TSAI, F. − CHOU, M.-J. (2006): Texture augmented analysis of high resolution satellite imagery in detecting invasive plant species. Journal of the Chinese Institute of Engineers 29 (4), 581–592.

TUOMINEN, S. − PEKKARINEN, A. (2005): Performance of different spectral and textural aerial photograph features in multi-source forest inventory. Remote Sensing of Environment 94 (2), 256–268.

VEKERDY, Z. − MEIJERINK, A. M. J. (1998): Statistical and analytical study of the propagation of flood-induced groundwater rise in an alluvial aquifer. Journal of Hydrology (205), 112–125.

ZHANG, Y. (2001): Texture-Integrated Classification of Urban Treed Areas in High-Resolution Color-Infrared Imagery. Photogrammetric Engineering & Remote Sensing 67 (12), 1359–1365.