The role of geostatistical measures in the classification of riparian vegetation – case study about a Hungarian floodplain

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The role of geostatistical measures in the classification of riparian vegetation - case study about a Hungarian floodplain

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Abstract

Archive aerial image databases are important sources of detailed vegetation information and its monitoring, however, a large amount of botanical and silvicultural mapping tasks are carried out solely by traditional field surveying or by the additional use of manual based remotely sensed image interpretation. Automatized digital image analysis techniques offer a potential tool for rapid mapping purposes of ecosystems, without strong limitations of areal extent and the interpreter's subjectivity. In this study a semi-automatic classification approach has been developed for the mapping of riparian vegetation habitats for a test area in the Szigetköz Danubian floodplain, based on aerial imagery from different years. In order to detect complex vegetation patches, textural information has been added to the analysis of spectral characteristics and hereby provided promising results due to the improved classification accuracies.

1. Introduction

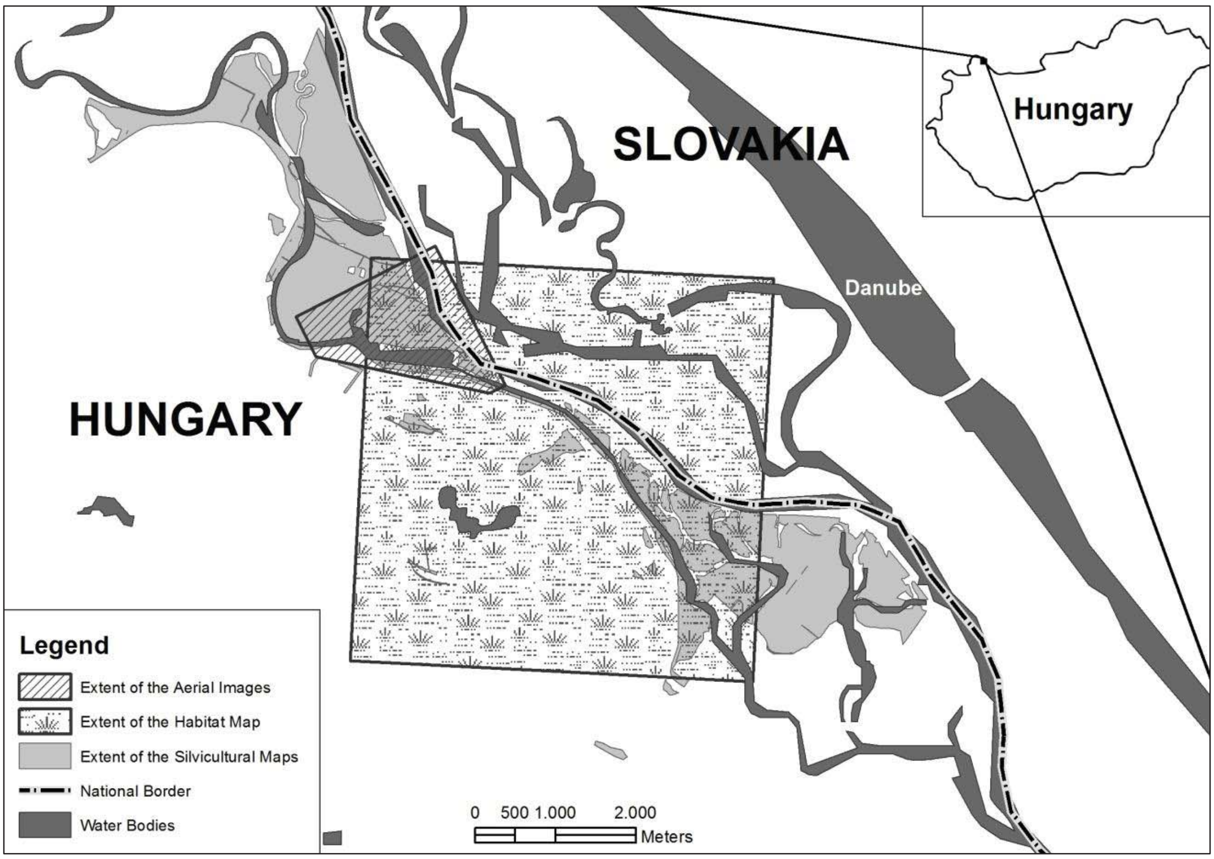
Aerial photography has a unique place within remote sensing and ecology (Morgan et al. 2010). With the use of archive imagery it is possible to reconstruct historic ecosystem conditions which are essential for characterizing the historic range of variability within ecosystems and hereby for developing strategies aimed at managing for ecological integrity (Landres et al. 1999). It can provide spatially and often also temporally continuous data which is extremely important for the monitoring of the most productive, but vulnerable ecosystems, the wetlands. They have a particular value between other ecosystems due to their high biodiversity, providing critical habitats for many plants and animals and being a natural element in the maintenance of water quality. Their conservation and sustainable development strategy has been the subject of the Ramsar Convention on Wetlands (1971), because of the vulnerable state mainly caused by human intervention. These areas are often inaccessible, therefore the analysis of available imagery has a high significance. Besides, remote sensing applications offer a cost-effective and time-efficient method with the development of automated (computer-assisted) image analysis techniques which have a great potential in the rapid processing of imagery, contrary to visual photo-interpretation based manual delineation. However, the mapping of complex vegetation patches can be hardly applied on a pixel-basis due to the high spectral variance of each vegetation class, that's why another technique based on the combination of spectral and texture characteristics on an object-basis, has to be tested for appropriate classification results.

The present study attempts to make a rapid classification of riparian wetland vegetation in a Hungarian floodplain based on archive aerial imagery and hereby prepare the monitoring of the test site for the recent years. We suppose that the additional use of texture measures will significantly improve the classification accuracies.

2. Study Site

The present study focuses on the Szigetköz Hungarian Danubian floodplain (Figure 2-1), which one together with the Slovakian Csallóköz is the most extended wetland in the Upper-Danube region with high biodiversity (Illés & Szabados 2008; Smith et al. 2000). It belongs to the Directorate of Fertő-Hanság National Park with 37 500 ha area, from which 9157 ha became landscape protected area in 1987 and nowadays including NATURA 2000 SCI (sites of community interest), SPA (special protected area) and IBA (important bird areas) (Szabó 2005). In 1992 severe changes have occurred in the region due to the Danube-diversion, leading approximately 80 % of the water discharge into the bypass canal of Gabčikovo Hydropower Plant. The changed flow and sediment regime has significantly affected the unique diverse pattern of habitat types, which have been altered from aquatic or aquatic-related forms to more terrestrial species (Ijjas et al. 2010). Due to its vulnerability Szigetköz has got national importance and the Hungarian Scientific Academy has built an interdisciplinary research group for continuous monitoring purposes concentrating on distinct fields. Regarding the former remote sensing related investigations land use maps have been created annually since 1996 with visual photo-interpretation technique and land use changes have been detected and according to this the effects of human intervention and natural events could be evaluated (Licskó 2008). Illés & Somogyi (2005) have monitored the floodplain forests from the silvicultural aspect, where they have already established the usefulness of supervised image classification for the separation of forest types (with different species), for the monitoring of spatial changes and mapping of spatial pattern based on 1991 and 1999 imagery, however, the separation between different health stages and various species with the use of those techniques was not possible with a satisfactory accuracy.

Figure 2-1: The Szigetköz Danubian floodplain in Hungary



3. Data

In our study CIR (colour infrared) aerial imagery from 2008 and from 1999 has been involved in the analysis about a test site (2.5 km^2) near to the village Dunaremete. Image 2008 is available at the Institute of Geodesy, Cartography and Remote Sensing (FÖMI, Budapest), the latter one (1999) is provided by the University of West Hungary, acquired in the framework of the Phare CBC Project by Eurosense Company. The most important characteristics of the photos are summarized in the Table 3-1.

Table 3-1: Aerial imagery

Imagery	Orthophoto 2008	Orthophoto 1999
Scale	1 : 74 000	1 : 30 000
Ground Spatial Resolution	0,5 m/pixel	1,25 m/pixel
Spectral Resolution	NIR, G, B	NIR, R, G
Acquisition time	06.08.2008	03.08.1999

The different ground spatial resolutions of aerial imagery affect the analysis and results, especially regarding comparability issues, therefore image 2008 has been resampled by bilinear interpolation to the coarser geometric resolution of image 1999 (1.25 m/pixel).

The detailed mapping of riparian vegetation is not concentrating on a general land cover classification scheme, rather on local characteristics, related to the certain riparian wetland area, presented by the sample site, spreading out until the dams. An exact description of local characteristics is possible in an approximate scale of 1:10 000, therefore botanical and silvicultural inventory data has been gathered about the region (Table 3-2) which have those appropriate scales.

Table 3-2: Ancillary data

Ancillary data	Habitat map	Silvicultural map
Number of classes (related to the test site)	13	8
Scale	1 : 12 500	1 : 10 000
Acquisition time	2000, 2004; July-Oct.	2003, with actualizations (until 2010)

Target classes for the vegetation classification have been defined based on these inventories, personal field survey and visual image interpretation.

4. Methods

Object-based image analysis (later: OBIA) method has been chosen for the study which is based on the principle of grouping pixels into meaningful objects before the classification. Besides tone or colour, size, shape, texture, shadow, landscape context and position can be involved in the analysis, and hereby OBIA mimics manual (human) interpretation to a certain extent, and suites better for the analysis of high or very high resolution data (e. g. aerial imagery) than pixel-based classifiers (Morgan et al. 2010). Cserhalmi et al. (2010) applied this technique to the analysis of archive black & white imagery in order to detect vegetation changes in a mire ecosystem in Hungary. Langanke et al. (2007) have investigated the conservation status of a bog site based on different types of aerial photographs (black & white, colour infrared and true colour) and combined standard photo-interpretation with multi-scale object-based classification besides landscape metric analysis, in the framework of the pan-European conservation programme Natura-2000, where they concluded that OBIA overcomes several problems of the solely manual based image interpretation.

In our study after the combination of quadtree and multi-resolution segmentation algorithms a prior classification of water bodies were applied based on vegetation indices which were defined differently for each year due to the distinct spectral resolutions (Table 4-1).

Table 4-1: The use of vegetation indices

Imagery	**Orthophoto 2008**	**Orthophoto 1999**
Spectral Resolution	NIR, G, B	NIR, R, G
VI (vegetation index)	modified NDVI	NDVI
Formula	(NIR-G)/(NIR+G)	(NIR-R)/(NIR+R)

Water image segments can be clearly identified based on this method, whilst the classification of the target vegetation classes remained difficult, because of their complex spectral characteristics. The result after the multi-resolution segmentation approach demonstrates the significance of the spectral behaviour during the segmentation procedure and that spectrally similar pixels belong to the same object and spectrally inhomogeneous fields are separated. The examination of object's neighbourhood-relationship could offer a potential solution, however, it would be very time-consuming because of the complex nature of the target classes.

In numerous studies related to the issue of sufficient mapping of vegetated areas and forest structures from high-resolution imagery, it has been presented that an additional approach is needed to the spectral classification (Zhang 2001; Lévesque & King 2003), because of those features which in general cannot be differentiated on the basis of spectral reflectance. Very much earlier Haralick et al. (1973) stated that there is an inextricable relationship between texture and tone, namely when a specific region shows a wide variation of features of discrete grey tone (spectrally heterogeneous), the dominant property of that area is texture. Contrary to spectral characteristics related to the average tonal variations, texture, as a context descriptor, provides information about the spatial statistical distribution of tonal variations within a certain band. The structural arrangement of surfaces and their relationship to the surrounding environment is described there (Haralick et al. 1973). Looking at the interdisciplinary field of sciences texture analysis plays an important role in human vision, computer vision, pattern recognition and digital image processing (Gotlieb & Kreyszig 1990). Morgan et al. (2010) have listed a number of remote sensing related applications with the use of image texture, e. g. the analysis of landscape heterogeneity, biophysical parameters, forest structural characteristics, prediction of species distribution and biodiversity patterns. A silvicultural study of medium format digital aerial photos about a South Moravian region (Czech Republic) has showed the significance of texture characteristics in order to discriminate prevailing forest types on the level of forest compartments (Hájek 2008). Laliberte et al. (2008, 2009) have analysed high spatial resolution imagery where they showed a significant improvement regarding classification accuracies with the use of GLCM features for rangeland classification. Su et al. (2008) have examined urban areas based on a QuickBird image scene and also got improved accuracies with the application of textural (including GLCM features) and local spatial statistics information.

Texture measures can be grouped as features based on local variation measures (first-order statistics) such as standard deviation, those based on second-order statistics (co-occurrence) and features based on spatial statistics, like local semi-variances or autocorrelations within a pixel neighbourhood (Tuominen & Pekkarinen 2005). In case of second-order statistics features are computed from angular nearest-neighbour grey-tone spatial dependence matrices or the so-called grey-level co-occurrence matrices (GLCM). Haralick et al. (1973) firstly defined 14 different features extracted from each of these matrices for various angular relationships and distances between neighbouring resolution cell pairs on the image. For the calculation of GLCM texture values the following variables have to be defined: (1) moving window size (in our study: the target object size), (2) direction of the offset (which means that pixels only in a specific direction will be compared, the 4 available directions are 0°, 45°, 90° and 135°, however, the use of the average is also possible), (3) distance of the offset (as default it is 1, which means the reference pixel and its immediate neighbour are taken into account), (4) image layer, (5) specific measure by equation (Haralick et al. 1973).

In the present analysis, for a consistent and objective study, the textures of unique image segments have been analysed. Those segments resulted from the so-called chessboard segmentation approach dividing the image into regular square-shaped objects with a user-defined size. Based on the literature (Tuominen & Pekkarinen 2005) and visual investigation of actual vegetation patterns 20 m x 20 m size (16x16 pixels due to the 1.25 m/pixel ground spatial resolution) has been chosen for the segments. Tuominen & Pekkarinen (2005) have stated for forest stands that a single pixel cannot represent the characteristics of vegetation habitats to be mapped and thus, generalized spectral information is needed regarding the local neighborhood of each pixel or as an alternative, larger analysis unit has to be introduced. Their statement is also applicable for riparian vegetation analysis. Regarding the GLCM direction, firstly, all directional GLCM features have been calculated, which means the average of each direction and later, due to the specific solar azimuth angles of the aerial images, directional GLCM measures have been defined, calculated and used for the classification separately. The offset-distance was 1 and as image layer the 1st principal component (PC1) has been chosen for both images.

Regarding the choice of certain GLCM features Hall-Beyer (2007) has recommended the use of one contrast measure (from Contrast, Dissimilarity, and Homogeneity), one orderliness measure (from Angular Second Moment, Maximum Probability, Entropy) and two or three of the descriptive statistics (from Mean, Variance or Standard Deviation, Correlation) for classification purposes. This was also corroborated by Laliberte & Rango (2008). Therefore, GLCM Contrast, Entropy, Mean, Standard Deviation and Correlation (Table 4-2) have been primarily tested for training samples and feature value ranges have been compared for each class-pair. GLCM Entropy, Correlation and Standard Deviation have provided the best results regarding the complete separability (no or minimal overlap between feature value ranges) of certain class-pairs and thus those have been chosen for further analysis.

Table 4-2: The tested GLCM measures

Texture measure	Formula
GLCM Contrast	$\sum_{i,j=0}^{N-1} P_{i,j}(i-j)^2$
GLCM Entropy	$\sum_{i,j=0}^{N-1} P_{i,j}(-lnP_{i,j})$
GLCM Mean	$\frac{\sum_{i,j=0}^{N-1} P_{i,j}}{N^2}$
GLCM Standard Deviation	$\sum_{i,j=0}^{N-1} P_{i,j}\ (i,j-\mu_{i,j})$
GLCM Correlation	$\sum_{i,j=0}^{N-1} P_{i,j} \frac{(i-\mu_i)(j-\mu_j)}{\sigma_i * \sigma_j}$ where $\sigma_i^2 = \sum_{i,j=0}^{N-1} P_{i,j}\ (i-\mu_i)^2$ $\sigma_j^2 = \sum_{i,j=0}^{N-1} P_{i,j}\ (j-\mu_j)^2$

For a supervised classification approach training samples from the square-shaped image objects have been chosen based on thematic maps and visual image interpretation, starting with the 1999 image. The number of training samples fitted to the size of the test area and to the target classes and thus, 20-20 samples have been defined for reed, poplar, special poplar and willow & poplar classes, 30 samples for willow class. The next step was the choice of features taken into account in the classification.

The first observed features concentrated solely on spectral characteristics (mean of PC1 and NDVI), secondly on GLCM textural measures (related to the average of all directions), the third group of features was the combination of spectral and textural without the mean of PC1, and the last one was a similar combination as in the 3rd case with the difference that directional GLCM features have been chosen there. The application of directional GLCM is reasonable due to the fact that the presence of different shadows coming from altering acquisition parameters (certain solar azimuth angles due to date and time of acquisition) has a great influence on the estimated texture characteristics. Because of these differences in the solar azimuth angle (2008: 125.6°; 1999: 111.6°) directional GLCM features have been tested with appropriate directions, which means choosing the nearest one from the 4 main directions defined for GLCM calculation (2008: 135°; 1999: 90°).

The classification algorithm was based on the membership values of certain image segments according to the class descriptions where the chosen features and value ranges came from the training samples for each class. The membership value of a specific image object is compared to a list of selected classes resulting in a fuzzy class evaluation with the first three best classes and the classification result is updated according to the first best class (Trimble 2012).

Although, image 2008 represents also a CIR image, it has a different spectral resolution (NIR, G, B). The appropriate tests showed that the same texture feature value intervals cannot be applied for the classification of the same or similar habitats as in 1999. Nevertheless, the definition of same or similar target classes with a 9-year difference is a complex problem, related to the question, under which circumstances we will or we could differentiate between vegetation habitats. Vegetation succession stages play also an important role in this. Based on new training samples for 2008, texture measure ranges have been updated for the same spectral and textural features applied before and the classification has been carried out with the new class descriptions.

5. Results

The study has concentrated on vegetation classification, not including water bodies, however, it was important, that water segments could be separated easily from any vegetation class. In each type of classifications water remained unclassified due to the inclusion of vegetation indices and besides having very different texture characteristic (plain surface).

As mentioned above, different combinations of features have been used for separate classifications in order to prove their significance regarding the accuracy of the classification results.

The essential values of accuracy assessment measures (overall accuracy, Kappa index) could be compared for each type of classification result related to a specific feature combination. For 1999, 'GLCM only' classification provided better accuracies than the sole use of spectral characteristics, however, the best result was reached by the combination of them, using GLCM directional features (Figure 5-1). In case of the 2008 image the application of spectral or textural characteristics only, provided similar accuracies (Kappa spectral = 0.704; Kappa textural = 0.691), whereas their combination: firstly GLCM (directional) with VI (vegetation index), then GLCM (average) with VI showed a significant improvement (overall: 0,936; Kappa: 0,920) (Figure 5-2).

Figure 5-1: Classification results (1999)

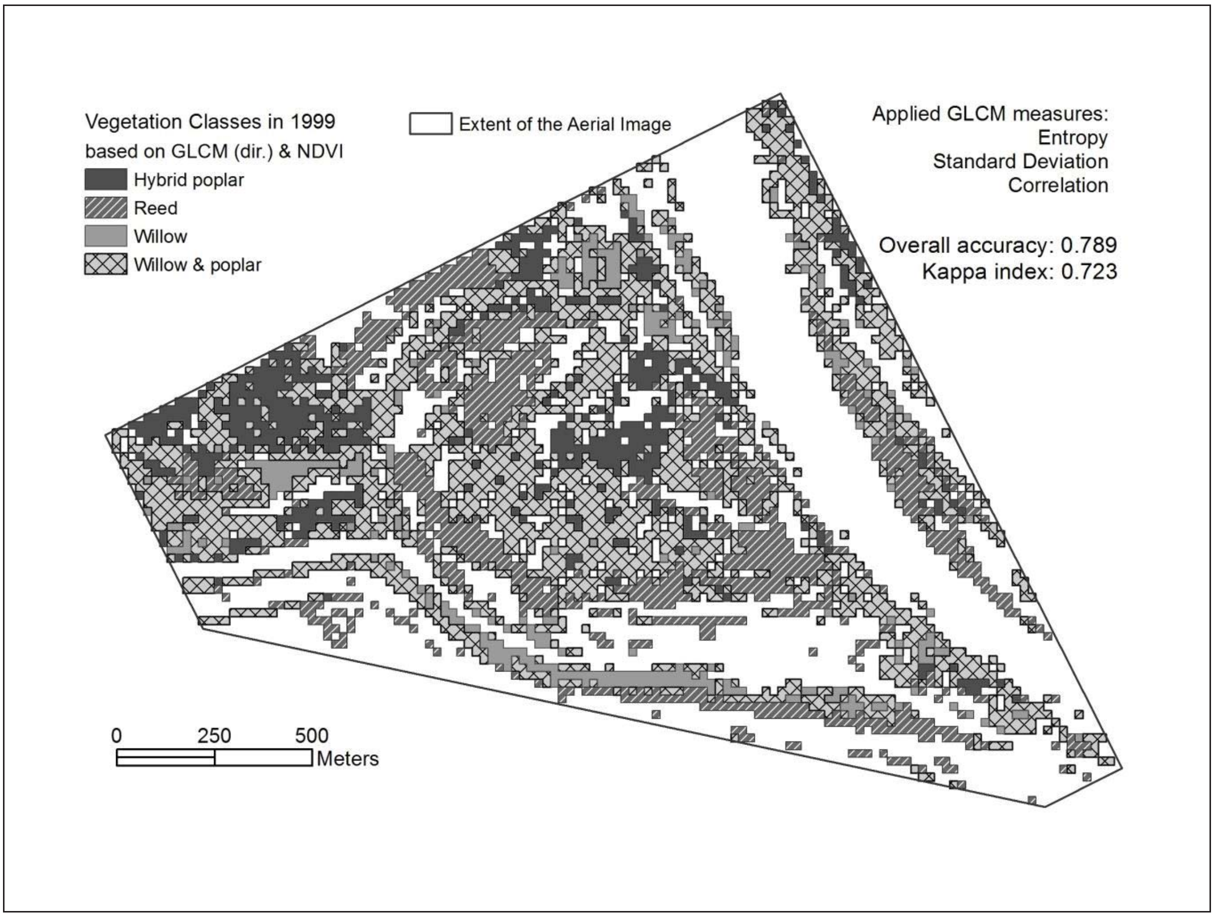
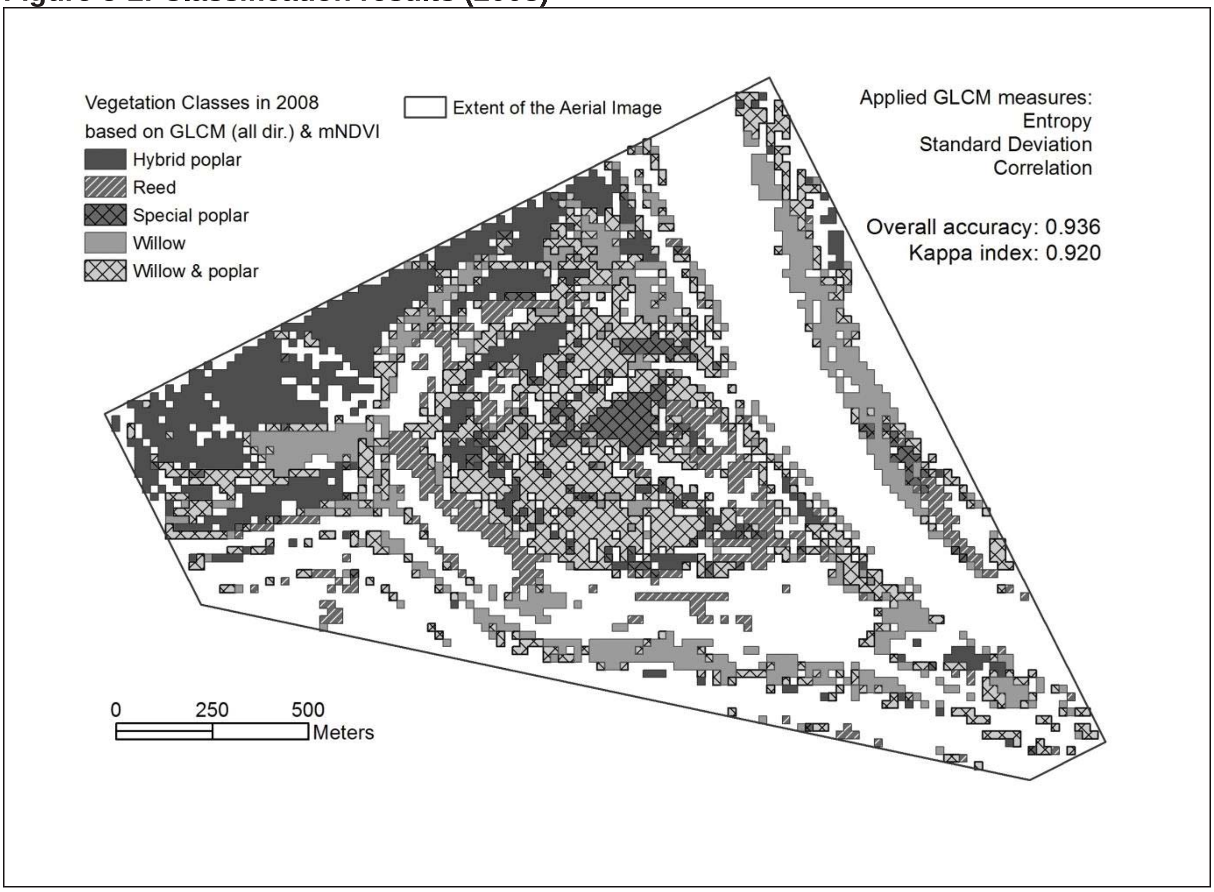


Figure 5-2: Classification results (2008)



6. Conclusions

Involving texture characteristics into the classification approach of riparian vegetation habitats apparently improved the classification accuracies, where the sole use of spectral descriptors, e. g. mean of a given layer, vegetation indices could not give sufficient results. However, classification accuracies have differed significantly for the two years (2008-overall: 0,936; 1999-overall: 0,789) because of the difference in the aerial image material (e. g. analogue versus digital, original spectral and spatial resolutions). In this case accurate vegetation change could be hardly reached based on post-classification-comparison. Future research is aiming at better classification accuracies for distinct years, involving the statistical separability analysis of best descriptors for vegetation habitats and besides, the development of an image segment based change detection analysis based on textural transitions.

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