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Katalin Varga*, Szilárd Szabó, Gergely Szabó, György Dévai, and Béla Tóthmérész

Improved land cover mapping using aerial photographs and satellite images

Abstract: Manual Land Cover Mapping using aerial photographs provides sufficient level of resolution for detailed vegetation or land cover maps. However, in some cases it is not possible to achieve the desired information over large areas, for example from historical data where the quality and amount of available images is definitely lower than from modern data. The use of automated and semi-automated methods offers the means to identify the vegetation cover using remotely sensed data. In this paper automated methods were tested on aerial photographs and satellite images to extract better and more reliable information about vegetation cover. These tests were performed by using automated analysis of LANDSAT7 images (with and without the surface model of the Shuttle Radar Topography Mission (SRTM)) and two temporally similar aerial photographs. The spectral bands were analyzed with supervised (maximum likelihood) methods. In conclusion, the SRTM and the combination of two temporally similar aerial photographs from earlier years were useful in separating the vegetation cover on a floodplain area. In addition the different date of the vegetation season also gave reliable information about the land cover. High quality information about old and present vegetation on a large area is an essential prerequisites ensuring the conservation of ecosystems.

Keywords: LANDSAT; vegetation season; vegetation type; maximum likelihood; mapping accuracy; SRTM

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***Corresponding Author: Katalin Varga:** Department of Ecology, University of Debrecen, Egyetem tér 1, Debrecen, H-4032 Hungary, E-mail: varg.kata@gmail.com
Szilárd Szabó, Gergely Szabó: Department of Physical Geography and Geoinformatics, University of Debrecen, Egyetem tér 1, Debrecen, H-4032 Hungary
György Dévai: Hydrobiology Department, University of Debrecen, Egyetem tér 1, Debrecen, H-4032 Hungary
Béla Tóthmérész: MTA-DE Biodiversity and Ecosystem Services Research Group, Debrecen, Egyetem tér 1, H-4032 Hungary

1 Introduction

Recently the use of remotely sensed data and land cover change detection techniques has attracted greater attention than ever [1–4]. Landscape parameters can be estimated with a variety of modern techniques and landscape indices [5–9]. Nowadays the rapid development of land surface detection and analysis techniques motivate researchers to find a simple objective method to estimate the changes of land cover and the effects of changes on the pattern and structure of land cover [10–12]. Spatially explicit information about landscapes and vegetation cover, both in small and large scales, are increasingly sought by biodiversity modelers and by management and restoration programs [13–16]. Furthermore, assessing and monitoring the state of the Earth's surface is a key requirement for global change research [14, 17–19].

Altogether, satellite based landcover mapping is a well known issue in remote sensing and the capture of high spatial and thematic accuracy information about vegetation across a large areas is usually difficult from old data due to their coarse resolution, limited number of spectral bands, lack of near-infrared bands or weak quality (i.e. blurred contours of map objects). They do not offer accurate and detailed information compared to the results obtained from modern images, but data extraction from these data sources is important for long-term land cover change analysis and for historical ecology [16, 20–22]. Therefore, it is an important task to test how to get more reliable and accurate prediction from their analysis.

Aerial photographs are coupled with a relatively small area of the ground which typically gives a detailed picture of the earth's surface [23, 24]. Theoretically, aerial photos are accessible any time, but there are limitations because of financial support, weather or license of the national aviation authorities; thus, their availability is also limited. On the other hand, remote sensing technology extends possible data archives from the present time to decades in the past. As a result, the data archives are continuously updated.

Several studies have been focused on comparisons between classification accuracies based on satellite images and aerial photographs since the ability to accurately monitor land surface or vegetation cover is important [4, 25–28]. Modern remote sensing imagery offers a practical and economical meaning to study land and vegetation cover changes and present valuable information for understanding natural and man-made environments. Remote sensing imagery is also very important in the diagnostic of ecosystem response to global changes, especially from local to global scales at a given time or over a continuous period [29, 30].

For example, the Shuttle Radar Topography Mission (SRTM) data provides a high quality surface model which is widely utilized in many studies, in geography [31], in geomorphology [32, 33] and to estimate vegetation height across the landscape [34, 35]. The use of SRTM could improve the vegetation and land cover detection, and in some cases it can modify the absolute accuracy [31, 36]. It is the first near-global spaceborne mission which provides fine resolution estimates of three-dimensional forest structure across the Earth's land surface [37–39]. The vertical accuracy of SRTM is widely analyzed by testing the differences between SRTM and Digital Elevation Models (DEMs) [40, 41].

Land cover maps are based on remotely sensed data; they are usually the outcomes of image classifications that may be achieved by either manual or automated computer-aided analysis. It is well known that usually, the manually vectorized aerial photographs and satellite images (complemented with auxiliary data and field experiences) allow a verified, more controlled and detailed land cover classification than any automated computer classification [42, 43], even if some semi-automated method with automated segmentation can be more accurate than manual vectorization [44–46]. Nevertheless, numerous automated and semi-automated methods can help identifying and mapping land cover using remotely sensed data [47]; furthermore, gradually replacing classical techniques due to the increasing classification accuracy [48]. The characterization of areas traditionally involves either expensive manual interpretation of aerial photographs or field investigation. In some cases field work is not possible, for example in analysis of historical data.

The main focus of this study was to obtain better results from older satellite images and low quality aerial photographs using auxiliary data sources from a floodplain area. It was studied how the accuracy of automated vegetation mapping could be increased in both cases. The first aim of our research was to test the automated methods on Landsat images evaluated with and without SRTM surface elevation data, to determine whether the SRTM could help us to interpret vegetation better on a flat area. Additionally, we tested whether seasonality or a short time period has an effect on the results of the automated analysis of vegetation cover on satellite images (due to the differences between the beginning and the end of summer). Furthermore, it was also tested whether better results could be obtained for vegetation and land cover classification by merging two aerial photographs. In this way it was analyzed the reliability of satellite images and aerial photographs in the automated analysis in cases when dense and impenetrable vegetation does not allow the extraction of information from the vegetation and the fieldwork is not possible.

2 Materials and Methods

2.1 Study area

The study area was a floodplain area (17 km^2) on the Upper-Tisza Region in North-Eastern Hungary near to the border where the Tisza River enters the country (Fig. 1). The study area is located on the right and left bank of the river, in the vicinity of four villages (Jánd, Gulács, Olcsvaapáti, Panyola). One part of these floodplains has conservation priority and another part is a Natura-2000 site within the Hortobágy National Park (48°4'58"N, 22°24'6"E). It is located at 104-111 m altitude above Baltic sea-level. The geological substrate is a Quaternary loess strata with alluvial silt. The climate is continental (mean annual temperature above 9-10 °C, annual precipitation of 600-700 mm), cool and dry temperate. Due to frequent floods on this area, a large river canalization and floodplain drainages were attempted between 1846 and 1880. There are five backwaters and some marsh patches in the studied area. Historically the marsh patches belonged to a backwater which was considerably altered in flood protection work. Today, the dominant land use types are arable lands, orchards, riparian forests and economic plantations.

2.2 Satellite images and aerial photographs

The first type of data sets were LANDSAT7 Enhanced Thematic Mapper (ETM+) images of two dates (03.06.2000 – D1 and 22.08 2000 – D2; NASA Landsat Program), with a spatial resolution of 30×30 meters. A color composite (RGB) was generated from bands 4 (near-infrared), 5 and 7 (mid-infrared ranges of the electromagnetic spectrum). This combination of color composite was ideal for detecting healthy green vegetation and the water-land

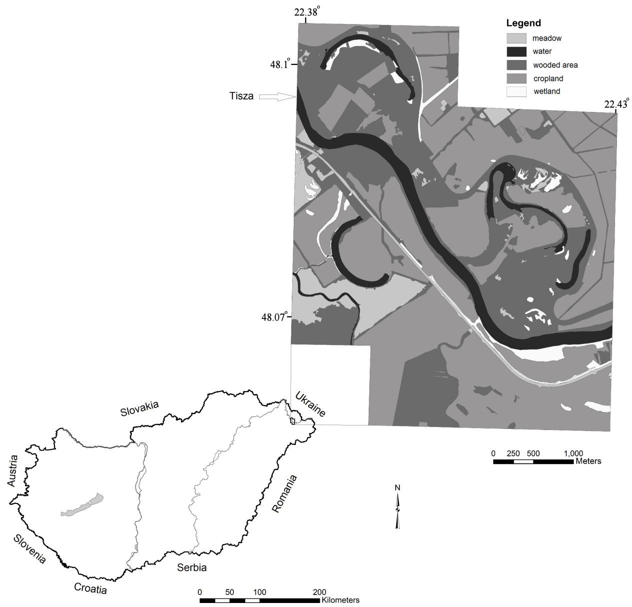

Figure 1: Location of the study site in Hungary.

border-line, which constituted necessary information for our analysis. The SRTM surface model, which original resolution of 90×90 m was resampled to 30×30 m, was integrated as a 4th band besides the 3 LANDSAT bands combination (RGB=457) to estimate geomorphometric parameters and to improve the land and vegetation cover analyses of the study area (Fig. 3). Absolute height error of SRTM is 6.6±3.7 m for Eurasia [49].

In addition, two aerial photographs from April 2004 and 2005, provided by the National Hungarian Mapping Agency (http://www.fomi.hu/portal/index.php/termekeink/legifelvetelek) were used to obtain detailed land cover information of floodplain. A Leica RC20, RC30 aerial camera was employed when acquiring the aerial photographs. The original resolution of the aerial photos was 0.63×0.63 m but it resulted noisy and unusable outcomes during our data processing. To overcome this issue, resampling was implemented using the nearest neighbor method improving (i.e. to remove/decrease noise from) the outcomes of the aerial photographs (with 0.63×0.63 m resolution). The resampling produced photos with a resolution of 2×2 meters that were separated in the visual spectral range into RGB channels and used for automated evaluation. We had six (2 ×RGB) channels after the RGB channel separation with the use of the two aerial photographs which were used in the automated evaluation together. Then, supervised classification methods were applied on training sites and provided real information categories. Five different combinations of the six aerial photos bands were tested: The first combination comprised only the bands from 2004. The second one comprised only the bands from 2005. The third one comprised the bands from 2004 and 2005 together without modification. The fourth one comprised the bands from 2004 and 2005 together but with bands multiplied (a pair wise multiplication of each band) (Fig. 3). Finally, the fifth combination contained the bands from 2004 and 2005 together with stretched values (linear stretch with 1% saturation). It is not common to use altered values in the analysis; however, these aerial photos did not have radiometric correction. Thus, this procedure can increase contrast and potentially improve the classification.

2.3 Manual interpretation

A habitat map of the study area was constructed to present the vegetation cover and type of these regions of Hungary. Vegetation was classified using the Hungarian General National Habitat Classification System (Á-NÉR) [50]. The habitat types were estimated in units of 20×20 m; 27 categories were found on the study area during our field work and the adjacent patches with similar category were merged (Table 1, Fig. 2). Aerial photos were used as reference information for these most accurate thematic map variants.

Nevertheless, the categories of the Hungarian General National Habitat Classification System were useless for automated mapping of satellite images and aerial photographs because of the similarities of the classes (e.g. forest and orchard). Therefore, their number was reduced into five easier-to-handle classes which were recognizable in this area with automated classification. On satellite images the follow five categories were suitable for the analysis: meadow, water, wooded area, croplands, and marshes. On aerial photos also five classes were considered due to the spectral information (only three bands in the visible range): Tisza, backwater, wooded area, arable land, other. This allowed us to construct simplified manual vectorized maps (MVM) of 2000, 2004 and 2005 with these five categories for automated satellite image classification (Table 1).These land cover maps were converted into a stratified random point map with the values of the land use codes and served as the reference in the accuracy assessment. All details of the vegetation and land cover maps could be controlled because the area had a manageable size and field observations were performed to rectify our MVMs (vegetation type, land cover classes). The maps of current vegetation in the different years were made with ArcGIS 9.3. (Fig. 2).

Table 1: Vegetation cover and types of the study area in the analyzed years.

Land cover classes	Á-NÉR (National Habitat Classification System of Hungary)
Cropland	Arable land (T1, T2 (forage plantation))
Meadow	Mesotrophic meadow (D4), Tall herb meadow (D6), Ruderal and semiruderal vegetation on floodplain and marsh (O3), Semiruderal vegetation on floodplain (O4), Seminatural grassland on fallow (O11), Seminatural vegetation on dike (O10), Dirt road vegetation (O13).
Water (Tisza, backwaters)	Standing water (U9), Running water (U8)
Marshes	Standing water vegetation with *Trapa*, *Lemna*, *Salvinia* and *Ceratophyllum* (A1), Floating vegetation of *Utricularia spp*. and *Stratiotes sp*.(A2), Submers or emerse rooted pioneer plant communities with *Potamogetonspp*. and *Nymphoidessp*.(A3), Marshy vegetation with *Thypaspp., Phragmites spp.*(B1), Assemblages of *Glyceria maxima*, *Sparganium erectum* and *Schoenoplectuslacustris*(B2), The water-fringing helophyte assemblageswith *Butomus sp.*, *Eleocharisspp*. and *Alisma spp.* (B3)
Wooded area	Riverine willow scrub (J3), Riverine willow-poplar woodland (J4), Riverine oak-elm-ash woodland (J6), Spontaneously afforested (P2) Lands forest with non-native wood, shrub and grassland level (R2), Locust tree plantation (S1), Poplar plantation (S2), Large orchard (T7), Little orchard (T8), Abandoned orchard (O12)

2.4 Automated image classification

IDRISI Taiga software was used for land cover classification and for comparison of the accuracy of assessment. In case of satellite images, spectral bands were analyzed with several methods like isodata, minimum distance, maximum likelihood, linear discriminant analysis classification, k-nearest neighbour classification, fuzzy image classifier. In the analysis, the maximum likelihood classifier gave better estimate than other methods (the total accuracy was more than 50%) and it was used separately in each date. This supervised classification method based on training sites and mean and variance/covariance statistics and provided real information categories [51, 52]. Training areas for land cover classification were designated on homogenous land cover units according to Cambell (2002) [53]. Also, MVM maps from 2000 provided preliminary information for training areas as auxiliary data.

The accuracy assessment of satellite images was estimated using 250 points chosen with the stratified random method to represent different land cover classes of the area with the same probability of selection within the classes [54–56]. The accuracy of classification estimated from the satellite images being compared by using the cross tabulation matrix in all compared pairs. The cross tabulation matrix was applied to calculate the error of omission [PA] and the error of commission [UA]. While PA showed the ratio of pixels where the classification was successful concerning the omissions (e.g. pixels claimed to be water surface are classified as water). UA showed the rate of accuracy concerning the commissions (e.g. which are the pixels actually classified as water) [57]. Furthermore, the Kappa Index of Agreement (overall and per categories), and Cramer's V were applied to estimate the spatial distribution of different vegetation and land cover classes. Cross-classification was also run showing multiple overlaps of all combinations (Fig. 3). Through the overlay process, areas which were misclassified in the cropland, wooded area, marshes and water classes were relabeled into the correct classes using the manual interpretation layer.

For aerial photographs, two different images were used and needed a control layer that showed the same land cover information in both years [58]. A stratified random sampling was defined and was overlapped with the land cover maps based on aerial photos and field observations. A cross tabulation image showed the points where the land cover type was the same in 2004 and 2005. This layer was reclassified to a binary image showing only the pixels where the land cover is the same in both years (Fig. 3). The study area had non-regular shape and the random point generation produced sampling points in the whole area. Hence, the original 1000 points were decreased to 609 due to differences. In accuracy assessments the values of the mask image with one of the hand-digitized land cover maps were updated providing a point layer with land cover data. This layer was used as a ground truth image in the verification procedure. The classification results of aerial photos were also controlled by using the confusion matrices (total accuracy [TA], error of omission [PA], error

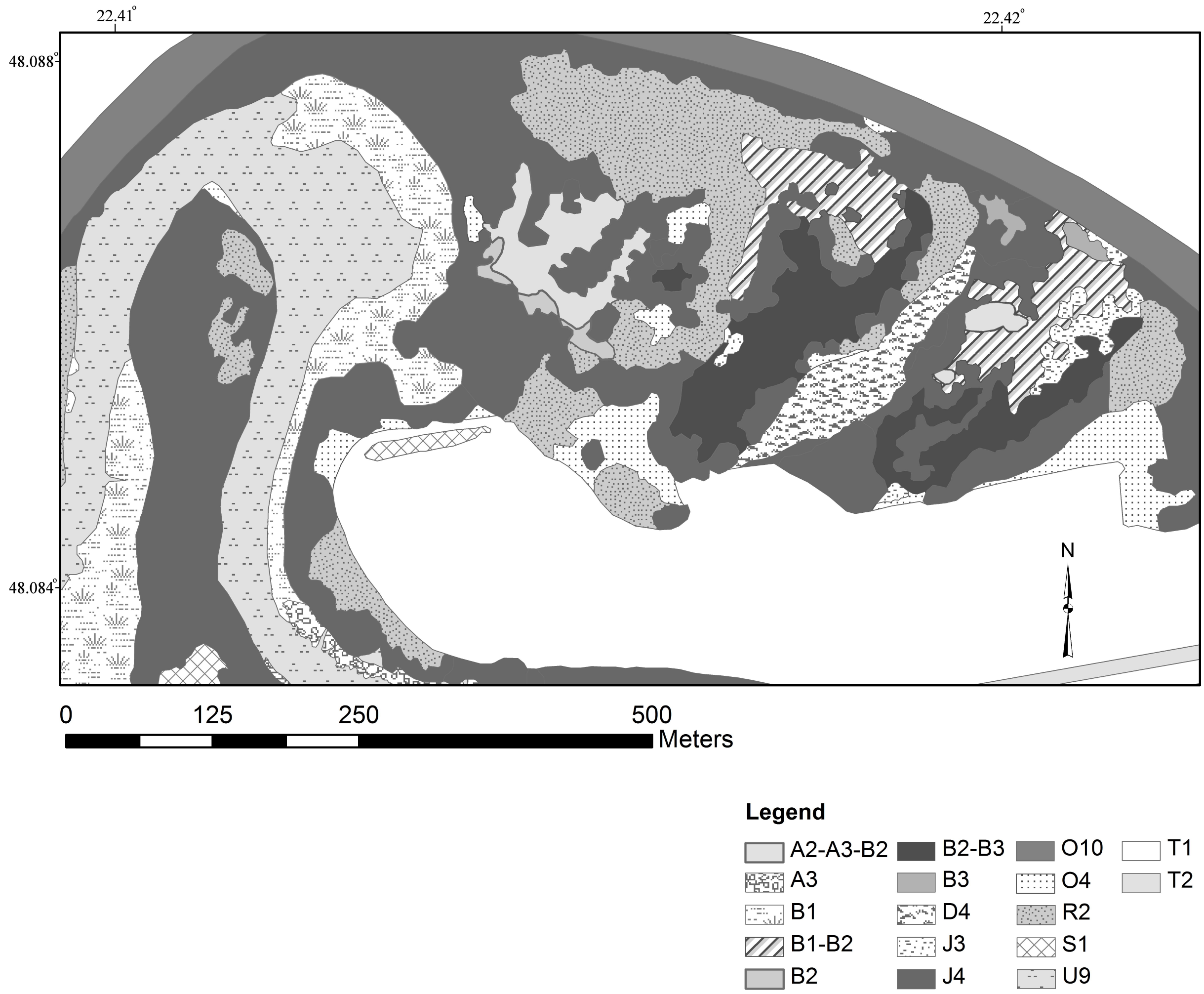

Figure 2: Vegetation types map in accordance with Á-NÉR on a part of the study area. Notations: A2 Floating vegetation of *Utriculariaspp*. and *Stratiotessp*., A3 Submers or emerse rooted pioneer plant communities with *Potamogetonspp*. and *Nymphoidessp*., B1 Marshy vegetation with*Thypaspp., Phragmites spp.*,B2 Assemblages of *Glyceria maxima*, *Sparganiumerectum* and *Schoenoplectuslacustris*, B3 The water-fringing helophyte assemblages, D4 Mesotrophic meadows, J3 Riverine willow scrub, J4 Riverine willow-poplar woodland, J6 Riverine oak-elm-ash woodland, O4 Semiruderal vegetation on floodplain, O10 Seminatural vegetation on dikes, R2 Forest with non-native wood, shrubby grassland level, S1 Locust tree plantations, T1 Arable lands, T2 Arable land (forage plantation), U9 Standing water).

of commission [UA]) and Kappa Index of Agreement (overall and per categories) [49].

3 Results

3.1 Automated interpretation of satellite images

The evaluation of the classification (or accuracy assessment) of satellite images showed small differences between the comparing pairs (Table 2). The total accuracy (TA) for reclassified images and MVM (estimated from the habitat map) was between 76 and 77% with SRTM and without SRTM.

In contrast, details of single class accuracy for all compared pairs showed that the SRTM presented higher accuracy by a comparison of MVM in various land cover classes (Table 3).

Five categories (meadow, water, wooded area, croplands, and marshes) were identified with varying success through the automated mapping technique. Cropland and water had the highest accuracy within the single land

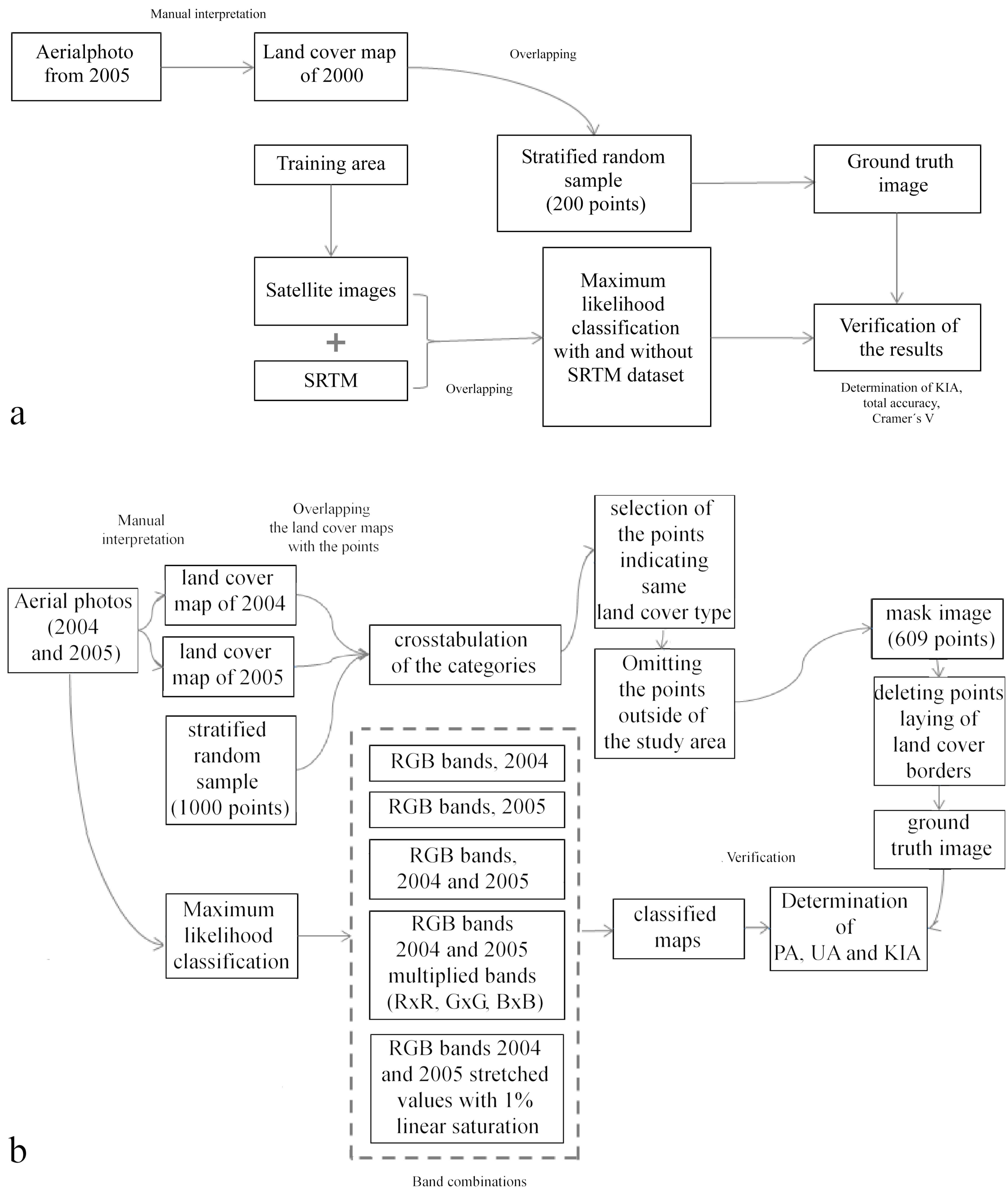

Figure 3: Scheme of delineating the mask image for the accuracy assessment, a) analysis of satellite images, b) analysis of aerial photographs.

cover class accuracies by MVM vs. reclassified images. The lowest accuracy belonged to marsh and meadow.

A post-classification detection technique was implemented with the cross tabulation matrix. Interpretation of the same land cover class by the comparison of different reclassified images estimated in different percentages of the surface area (Table 4). In the same classes, higher percentages were obtained, except for marsh. The identification of land cover classes was better when using the image classification pair of MVM vs. D1+SRTM and MVM vs. D1 reclassified image (Table 4) except class of water and forest. The misclassifications were predominantly under or around 10%. Higher misclassified values occurred in marsh-wooded area pairs (30-45%) as well as in marsh-

Table 2: Accuracy statistics of reclassified images for the classifications Notation: MVM - manual vectorized map; D1 – satellite image from 03.06.2000, D2 - satellite image from 22.08 2000.

	Total Accuracy	Cramer's V*	Kappa*
MVM vs. D1+SRTM	77.18	0.57	0.63
MVM vs. D1	77.27	0.58	0.63
MVM vs. D2+SRTM	75.94	0.56	0.62
MVM vs. D2	77.5	0.57	0.64

*Cramer's V show the association and Kappa Index show the agreement between images, 0=poor, 1=perfect

water pairs identification (17-28%) at MVM and in comparing pairs of reclassified images. A high value (18-40%) in meadows – cropland pairs was also obtained in the case of MVM and D2+SRTM and without a SRTM comparing pair.

3.2 Automated mapping of aerial photographs

The difference between the maps obtained from the two aerial photographs was minimal: Fuzzy Kappa [59] was 0.92 using a 10 meter neighborhood radius (which is about the same as the error of georeferenced images), thus the similarity was enough for their parallel application. The pixel values were similar in the case of water bodies, arable land and wooded area; they all had green toned colors and fine differences were impossible to discriminate accurately (e.g. between trees and bushes).

The error of omission was the highest in case of Tisza River in all cases. Backwater showed the lowest PA. Besides, arable lands and wooded area showed a constant UA but they had the highest error of commission. If only the River Tisza, the backwater, the arable lands and the green wooded area were distinguished, in that case the river (Tisza), arable lands and wooded area could be obtained an acceptable classification.

4 Discussion

The main focus of the current paper was to obtain better results from older satellite images and lower quality aerial photographs using auxiliary data sources from a floodplain area. In land and vegetation cover analyses of satellite images with and without SRTM surface elevation data, it could be observed that wooded area had the most distinct vegetation type, but the difference between an orchard and a wooded area was limited because of their color.

Given that forest and orchard textures were different, but we could not use this attribute by pixel-based classification. SRTM was useful in separating the land cover classes on the floodplain area in case of wooded area, but for the other categories it did not contribute to the identification accuracy. The lowest accuracy belonged to marsh and meadow by satellite image analysis which was explained by the fact that these areas were too small and the vegetation appearance (color composition) led to their misclassification as wooded area. Moreover, misclassifications occurred due to the fact that in some cases the croplands were spectrally interchangeable with the meadow class, and water areas could be interchangeable with wooded area as well as with some marsh patches. Ji (2000) [60] and Kokalj (2007) [61] reported the same conclusion that forests could be identified better than arable lands and orchards during the image processing. Open spaces are most commonly misclassified land cover type such different type of wooded area. The automated identification of vegetation patches can be difficult due to their heterogeneity and the sporadic influence of water that can cause spectral interchanges.

The further analysis of satellite image composition from different dates during the vegetation season showed that both dates gave reliable information regarding land cover. Altogether, classification at the beginning of summer could be more accurate, but the differences between the seasons were not considerable. During this part of analysis the differences were more significant when considerable taking into account the land cover types at summer in case of the satellite images with SRTM. Differences of seasonal vegetation could be demonstrated very well using of Landsat (ETM) Imagery [62], however in our study we did not find considerable differences.

In the test of the third hypothesis, whether better results could be gained for vegetation and land cover classification by merging two aerial photographs, the automated image classifications of the aerial photos were not acceptable in all categories (PA or UA were below 50%, Table 5). For example, the backwaters land cover types cannot be differentiated by automated methods because of their green tones as a consequence the biological processes of the water surface (PA was <40%). All methods in which the two aerial photographs were used together provided better results than the stand-alone tests (TA values were larger with 4-7%). The results could not be improved when the raw data were manipulated (e.g. multiplication; Table 5). Taken together, the results of the classification

Table 3: Accuracy statistics of reclassified images estimated to various land cover classes. Notations: MVM - manual vectorized map; D1 – satellite image from 03.06.2000, D2 - satellite image from 22.08 2000; UA - User's Accuracy; PA - Producer's Accuracy; KIA - Kappa Index of Agreement.

	MVM vs. D1+SRTM			MVM vs. D1			MVM vs. D2+SRTM			MVM vs. D2		
	PA	UA	KIA	PA	UA	KIA	PA	UA	KIA	PA	UA	KIA
meadow	71.43	32.08	0.30	32.62	84.72	0.31	42.24	48.24	0.39	43.3	45.5	0.40
water	81.12	77.69	0.76	74.61	82.2	0.73	76.9	83.7	0.75	77.3	86.6	0.75
wooded area	75.81	73.06	0.60	73.84	74.72	0.61	74	77.9	0.62	73.5	80.78	0.62
cropland	81.9	90.05	0.79	90.05	81.22	0.78	86.2	80.45	0.71	89.45	79.4	0.77
marsh	12.15	12.38	0.09	14.28	16.13	0.12	4.8	5.5	0.02	6.66	16.28	0.05

Table 4: Results of image classification technique in percent of surface area. Matching of various land cover classes identification by comparison of different reclassified images. Notations: MVM - manual vectorized map; D1 – satellite image from 03.06.2000, D2 - satellite image from 22.08 2000; C - cropland, F - wooded area, M - meadow, MA - marsh, W – water.

Misidentified Lclass1 as Lclass2		MVM vs. D1+SRTM	MVM vs.D1	MVM vs. D2+SRTM	MVM vs. D2
M	**M**	**71.43**	**84.72**	**48.17**	**45.51**
M	W	2.38	1.39	0.61	0.56
M	F	7.14	6.94	9.15	10.67
M	C	17.86	5.56	38.41	39.89
M	MA	1.19	1.39	3.66	3.37
W	M	1.20	0.85	0.00	0.00
W	**W**	**81.12**	**82.20**	**83.68**	**86.64**
W	F	12.45	12.29	9.62	9.05
W	C	1.20	0.42	1.67	0.43
W	MA	4.02	4.24	5.02	3.88
F	M	7.76	7.66	4.24	5.29
F	W	1.43	1.89	1.24	1.73
F	**F**	**75.82**	**74.73**	**77.87**	**80.78**
F	C	10.92	11.94	12.41	8.53
F	MA	4.08	3.78	4.24	3.67
C	M	2.67	2.71	3.86	3.20
C	W	1.46	1.32	1.56	1.78
C	F	11.48	12.28	11.58	12.74
C	**C**	**81.91**	**81.22**	**80.45**	**79.38**
C	MA	2.49	2.47	2.55	2.90
MA	M	3.74	2.15	5.49	6.98
MA	W	16.82	25.81	24.18	27.91
MA	F	44.86	30.11	43.96	32.56
MA	C	22.43	25.81	20.88	16.28
MA	**MA**	**12.15**	**16.13**	**5.49**	**16.28**

could be improved by using a combination of two temporally similar aerial photographs to map vegetation covers.

Since the spectral information could be obtained by the separation of visible (RGB) bands and had no infra-red (IR) bands, possibilities to extract features were limited. While Palandro (2003) [27] applied this method successfully in the study of coral reef changes.

Many studies deal with accuracy and issues such as, extracting better information from satellite images, aerial photographs and other remote sensing data sources [63–67]. Some studies also discuss how classifications of satel-

Table 5: Accuracy assessment of the maps classified with aerial photographs. Notations: UA - User's Accuracy; PA - Producer's Accuracy.

Land cover unit	2004		2005		2004 and 2005		2004 vs. 2005		2004 and 2005 stretched	
	PA	UA	PA	UA	PA	UA	PA	UA	PA	UA
Tisza	93	49	100	47	93	85	95	59	93	67
backwater	25	6	41	46	16	71	34	20	19	46
wooded area	68	61	57	66	94	62	82	64	89	63
arable land	52	81	69	66	65	82	64	79	66	79
other	7	29	15	33	20	23	11	35	15	24
Total accuracy	53		61		68		65		67	

lite images with automated classification methods could not perform satisfactorily accurate and reliable classification categories in some cases. Nevertheless, this classification could be improved as presented by Manandhar et al. (2009) [68] who also discussed how to improve the accuracy of land cover classification of LANDSAT data and they were able to improve accuracy by incorporating additional data (DEM, spatial texture, NDVI etc.).

In the same way, several land cover maps and vegetation maps of large projects were constructed based on satellite images due to the fact that they can cover large areas [69–71]. An example is the International Geosphere-Biosphere Program, which pioneered a global land cover mapping in the development of the Global Land Cover Characterization (GLCC). Their database was based on 1-km Advanced Very High Resolution Radiometer (AVHRR) in 1992 (http://edcsns17.cr.usgs.gov/glcc/). It must be mentioned that the Global Land Cover 2000 (GLC2000) (http://www-gvm.jrc.it/glc2000/) and other smaller scale programs were also developed such as the Pan-European Land Cover Monitoring project and Corine Land Cover (CLC50) which is based on the photo interpretation of SPOT4 images [72].

Our study established that more accurate information of vegetation type or land cover could be obtained with an automated analysis of satellite images than with an automated analysis of aerial photographs using old data. While Hyyppä et al. (2000) [73] found that aerial photographs could give comparable results to satellite images; it seems that in some cases this includes more information for forest inventory than satellite radar images.

Also, these techniques were applied in many studies using the two data source parallel and they produced useful information from structural plant diversity, land cover and from effects of land use on forest ecosystem [13, 43, 72].

5 Conclusions

In conclusion, the automated methods on remote sensing data sources with SRTM can give an accurate and useful opportunity to extract information from the vegetation (mainly from wooded area class) if the fieldwork is not possible. Analysis of satellite image with SRTM using automated methods also can help us to better interpret vegetation on a flat area. Nevertheless, the use of auxiliary data might be helpful (e.g. maps, field observations) and more than one aerial photograph could also improve the classification accuracy.

This selections are generally determined by different factors: the mapping objective, the cost of images, climate conditions and technical issues regarding image interpretation [47, 74, 75]. The selection of appropriate images [74, 76, 77] image pre-processing and the classification procedures are very important for mapping vegetation cover and land cover. These are important elements in long-term time series research where it is needed to analyze old images and to extract information from vegetation, in cases where field work is not possible. High quality information about old and present vegetation on a large area is an essential prerequisite for ensuring the conservation of ecosystems.

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