

COMPARATIVE ANALYSIS OF LANDSAT TM, ETM+, OLI AND EO-1 ALI SATELLITE IMAGES AT THE TISZA-TÓ AREA, HUNGARY

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Abstract

Satellite images are important information sources of land cover analysis or land cover change monitoring. We used the sensors of four different spacecraft: TM, ETM+, OLI and ALI. We classified the study area using the Maximum Likelihood algorithm and used segmentation techniques for training area selection. We validated the results of all sensors to reveal which one produced the most accurate data. According to our study Landsat 8's OLI performed the best (96.9%) followed by TM on Landsat 5 (96.2%) and ALI on EO-1 (94.8%) while Landsat 7's ETM+ had the worst accuracy (86.3%).

Keywords: remote sensing, satellite images, land cover, thematic accuracy

1. Introduction

Remote sensing is one of the best ways to collect data simultaneously from large areas of the Earth's surface (Burai et al. 2015; Kohán et al. 2014; Szabó et al. 2013). Satellite images are taken with several multispectral bands based on the visual and infrared electromagnetic spectrum. The sensors are recording the radiance of the Earth's surface (Schowengerdt 2007).

There are several different methods to interpret the remotely sensed data, like generalization, which is well known from the Large Area Crop Inventory Experiment (LACIE). At the LACIE project the classifiers were trained with one segment of a wheat-growing region, and based on these classifiers they tried to determine wheat acreage, so they tested the spectral extendibility (Woodcock et al. 2001). We can also use segmentation combined with classifiers (Burai et al. 2015),

e.g. Maximum Likelihood, Minimum Distance, Support Vector Machines or Spectral Angular Mapper (Otukei 2010; Wacker – Landgrebe 1972; Yuhas et al. 1992). Based on these classifiers we can produce thematic land cover maps.

The knowledge of the land cover provides important information for several disciplines and practitioners (van Dessel et al. 2011; Kerényi – Szabó 2007; Móricz et al. 2005; Nagyvárad et al. 2011; Ortmann-Ajkai et al. 2014; Srivastava et al. 2015, Zlinszky et al. 2015). The comparison of the previous and current states can provide information about the changing trends (Balázs – Lóki 2014) but we can determine the area, spatial extent, or even the spread of only one land cover category (e.g. forests). The most common way to use these data is to determine the state of forests focusing on change-detection (Henits et al. 2016), monitoring of regrowth

in a defined timespan (Hansen et al. 2013; van Leuwen et al. 2012).

Depending on our requirements there are many sensors to choose from. One of the best known earth observing satellite family is the Landsat series (Wulder et al. 2007). During the Landsat Data Continuity Mission (LDCM), in 2013 the Landsat 8, as the newest member, was launched with two sensors on board. One is the Operational Land Imager (OLI) which collects data for nine multispectral bands (Table 1.), and the other sensor is the Thermal Infrared Sensor (TIRS) which has two thermal bands (Irons et al. 2012). In addition to the OLI, we studied two more Landsat sensors. The Landsat 5 – Thematic Mapper (TM) with 7 multispectral bands (Table 1.) (Gupta 2003), and the Landsat 7 – Enhanced Thematic Mapper Plus (ETM+) with 8 multispectral bands (Table 1.; Y. Lin –

G. Zhao 2014).

Besides, there are other satellites providing free images for landscape analysis. One is the Advanced Land Imager (ALI) on the Earth Observing-1 (EO-1) satellite, which was launched in 2000 as an experiment for its hyperspectral sensor (Hyperion) on board. The ALI was also constructed for an experimental purpose, it helped the scientists selecting the optimal bands for the OLI. It has 10 multispectral bands (Table 1.) which are, in conclusion, very similar to the OLI's bands. From 1999 EO-1 has continuously acquired quality data and follows Landsat 7 exactly one minute late it can be used to validate or compare to the data of other sensors, e.g. any member of the Landsat family as well (Zhang – Tian 2015). An other satellite providing free data is the new Sentinel 2A and the planned 2B (Drusch et al. 2012).

Table 1. Spectral bands of the sensors (Gupta, 2003; Chang, 2007; Lin – Zhao, 2014)

Band	Wavelength (µm)	Resolution (m)	Landsat 5 (TM)			Landsat 7 (ETM+)			Landsat 8 (OLI)		
			B.	W. (µm)	R. (m)	B.	W. (µm)	R. (m)	B.	W. (µm)	R. (m)
Band 1	0.48-0.69	10									
Band 2	0.433-0.453	30						Band 1	0.433-0.453	30	
Band 3	0.45-0.515	30	Band 1	0.45-0.52	30	Band 1	0.450-0.515	30	Band 2	0.450-0.515	30
Band 4	0.525-0.605	30	Band 2	0.52-0.60	30	Band 2	0.525-0.605	30	Band 3	0.525-0.600	30
Band 5	0.63-0.69	30	Band 3	0.63-0.69	30	Band 3	0.630-0.690	30	Band 4	0.630-0.680	30
Band 6	0.775-0.805	30	Band 4	0.76-0.90	30	Band 4	0.775-0.900	30	Band 5	0.845-0.885	30
Band 7	0.845-0.89	30	Band 5	1.55-1.75	30	Band 5	1.550-1.750	30	Band 6	1.560-1.660	30
Band 8	1.2-1.3	30	Band 6	10.40-12	120*(30)	Band 6	10.40-12.50	60*(30)	Band 7	2.100-2.300	30
Band 9	1.55-1.75	30	Band 7	2.08-2.35	30	Band 7	2.090-2.350	30	Band 8	0.500-0.680	15
Band 10	2.08-2.35	30				Band 8	0.520-0.900	15	Band 9	1.360-1.390	30

Table 2. Satellite images and recording dates

Spacecraft	Sensor	Date
EO-1	Advanced Land Imager (ALI)	2005. 09. 08.
Landsat 5	Thematic Mapper (TM)	2005. 08. 10.
Landsat 7	Enhanced Thematic Mapper Plus (ETM+)	2002. 09. 04.
Landsat 8	Operational Land Imager (OLI)	2013. 08. 16.

Classified land cover data always have uncertainty, which is caused by the geometric inaccuracy and the thematic (spectral) noise. The latter depends on the input data of the map, which can be greyscale, true or false color aerial photos or satellite images (Berke et al. 2013; Burai et al. 2015). Using supervised classification there may occur misclassification due to inaccurately selected training areas, atmospheric or sensor noise (Congalton 1991). For supervised classifications we can use almost exclusively multi-band images (since most algorithms require the total number of bands + 1 training pixels which cannot be achieved using a single band image), but in our case the sensor characteristics, such as spectral resolution,

the number of bands and the signal-to-noise ratio are also important (Deák et al. 2013; Tobak et al. 2013).

In this study we studied the datasets of four different spacecraft sensor to reveal their performance in supervised classification and evaluated the results from the aspect of thematic accuracy.

2. Material and method

Possible study areas were limited by the availability of the EO-1 ALI images and within those areas it was selected considering the land cover diversity. The additional sensors were selected from the Landsat series. The

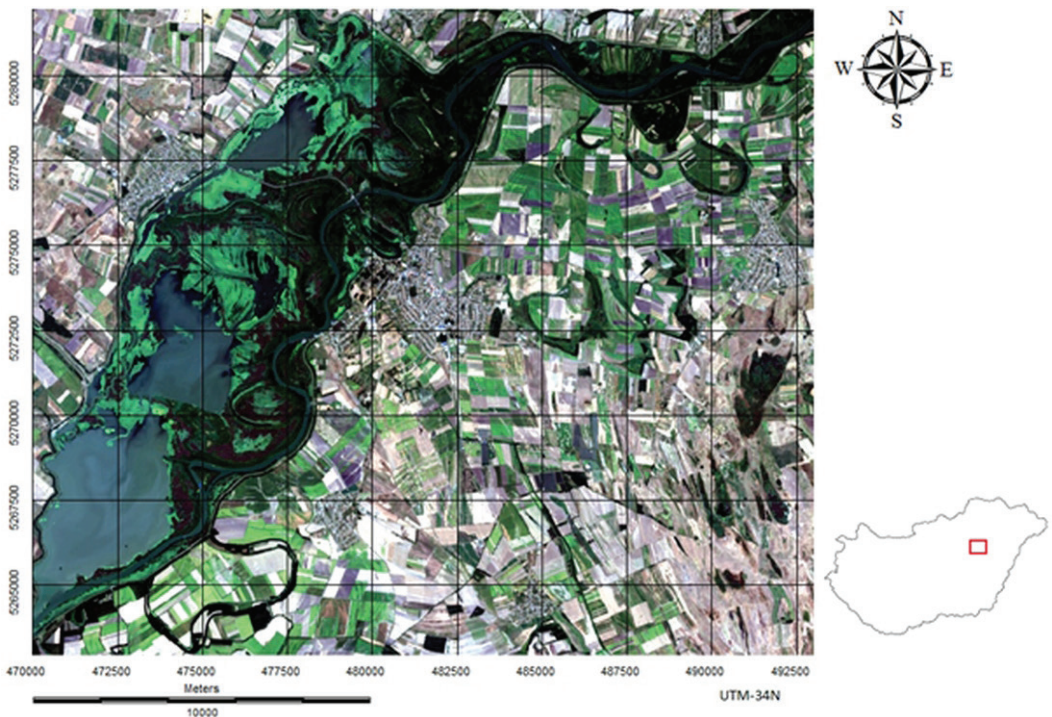


Figure 1. The location of the Tisza-tó area, Hungary on the OLI's true color composite

Landsat 5 – Thematic Mapper (TM), the Landsat 7 – Enhanced Thematic Mapper Plus (ETM+), and the Landsat 8 – Operational Land Imager (OLI) (Table 2.).

The Tisza-tó (Tisza Lake) area (Figure 1.) was a good candidate to be the study area which has open water surface (lakes and the river Tisza), reedy and sedgy vegetation and dryland forests as well. The dominating species in the water are *Phragmites australis*, *Typhetum angustifoliae* while the forests are mainly consisting of *Amorpha fructifosa*, *Populus alba* and *Salix purpurea* (Aradi 2007; Oláh – Tóth 2008). The area also contains meadows, pastures, grasslands, and various arable lands for agricultural cultivation.

For selecting the training areas for the maximum likelihood classification we used the segmentation technique (Dragut et al. 2010; Varga – Túri 2014) in the Idrisi Selva software. We performed the segmentation of the green, red and near-infrared (TM234) composites of each image. This method has the advantage that classifies the pixels based on their spatial homogeneity, thus, the adjacent pixel groups are clearly separated and they can be easily and efficiently used as training data in the classification process. We defined five land cover classes: arable lands, grasslands, forests, water surfaces and reedy-sedgy vegetations.

Accuracy assessment was conducted using a test database, i.e. we collected 60-100 pixels per categories to control the thematic accuracy. We checked the Overall Accuracy (OA), the User's Accuracy (UA) and the

Producer's Accuracy (PA; Congalton 1991).

3. Results

The thematic map derived from the ALI image (Figure 2.) had relatively good performance. According to the accuracy assessment (Table 3.), classification of water surfaces, reedy-sedgy vegetation and forests were successful. Classification conducted on the TM image (Figure 3.) showed that meadows contained several thematic error due to their interspersions with arable lands (Table 4.). The PA of the meadows was low and the arable lands produced lower accuracy regarding the UA. The map from the ETM+ images (Figure 4.) had the worst accuracy of all maps. Only the water surfaces were classified well (Table 5.). All other classes had lower accuracy regarding the UA or the PA. On the map from the OLI sensor's images (Figure 5.) the water surfaces, reedy-sedgy vegetation and the forests had almost perfect classification (Table 6.). Some interspersions can be observed between the meadows and arable lands caused by their spectral similarity.

The confusion matrices showed that the most accurate map was the OLI sensor's map (96.9%), and the least accurate map was derived from the ETM+ sensor's images (86.3%). Maps derived from the ALI and TM sensors' images based on the accuracies had average outcomes. The problem was mainly the misclassification of arable lands and grasslands.

Table 3. Accuracy Assessment of the ALI sensor's map

2002.09.04. ETM+	Water	R-S veg.	Forests	Meadows	Arable	Total	UA
Water	45	0	0	0	0	45	100.00
R-S veg.	1	47	0	0	0	48	97.92
Forests	0	22	71	0	1	94	75.53
Meadows	0	6	0	58	12	76	76.32
Arable	0	0	0	2	56	58	96.55
Total	46	75	71	60	69	321	
PA	97.83	62.67	100.00	96.67	81.16		86.29

Table 4. Accuracy Assessment of the TM sensor's map

2005.08.10. TM	Water	R-S veg.	Forests	Meadows	Arable	Total	UA
Water	60	4	0	0	0	64	93.75
R-S veg.	0	95	0	0	0	95	100.00
Forests	0	0	71	0	0	71	100.00
Meadows	0	0	0	53	2	55	96.36
Arable	0	1	0	7	72	80	90.00
Total	60	100	71	60	74	365	
PA	100.00	95.00	100.00	88.33	97.30		96.16

Table 5. Accuracy Assessment of the ETM+ sensor's map

2005.09.08. ALI	Water	R-S veg.	Forests	Meadows	Arable	Total	UA
Water	66	0	0	0	0	66	100.00
R-S veg.	0	95	0	0	0	95	100.00
Forests	0	0	70	0	0	70	100.00
Meadows	0	0	0	65	17	82	79.27
Arable	0	3	0	0	70	73	95.89
Total	66	98	70	65	87	386	
PA	100.00	96.94	100.00	100.00	80.46		94.82

Table 6. Accuracy Assessment of the OLI sensor's map

2013.08.16. OLI	Water	R-S veg.	Forests	Meadows	Arable	Total	UA
Water	65	0	0	0	0	65	100.00
R-S veg.	0	91	0	0	2	93	97.85
Forests	0	0	84	0	0	84	100.00
Meadows	0	0	0	62	5	67	92.54
Arable	0	0	0	6	103	109	94.50
Total	65	91	84	68	110	418	
PA	100.00	100.00	100.00	91.18	93.64		96.89

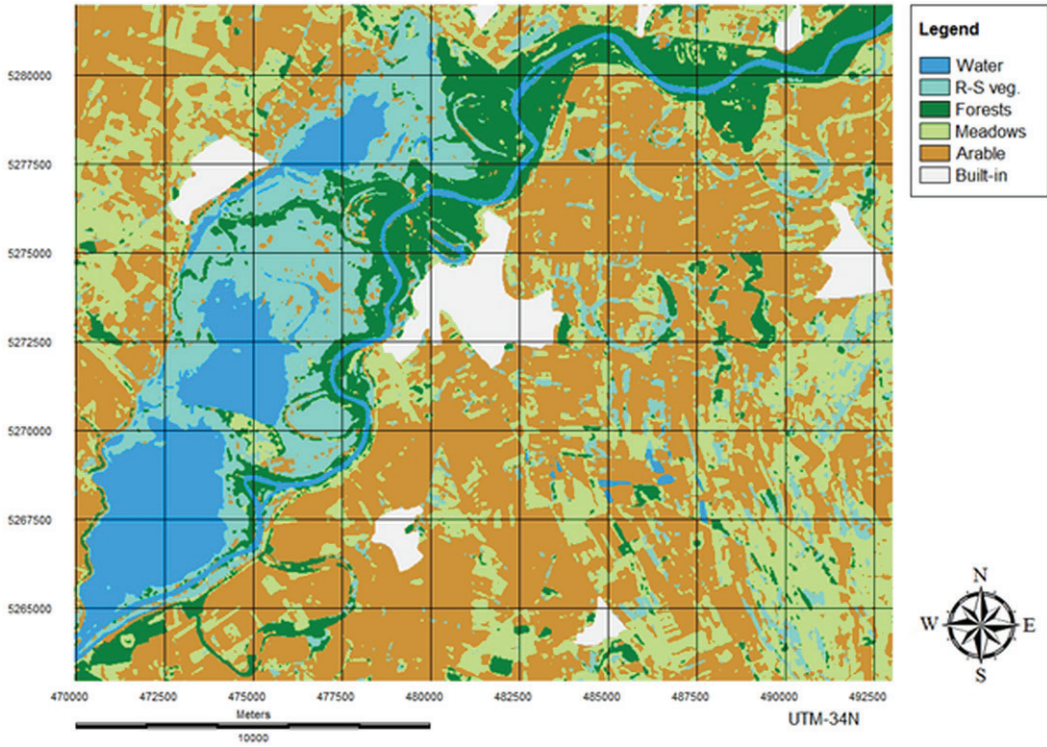


Fig. 2. Thematic land cover map from ALI sensor's images

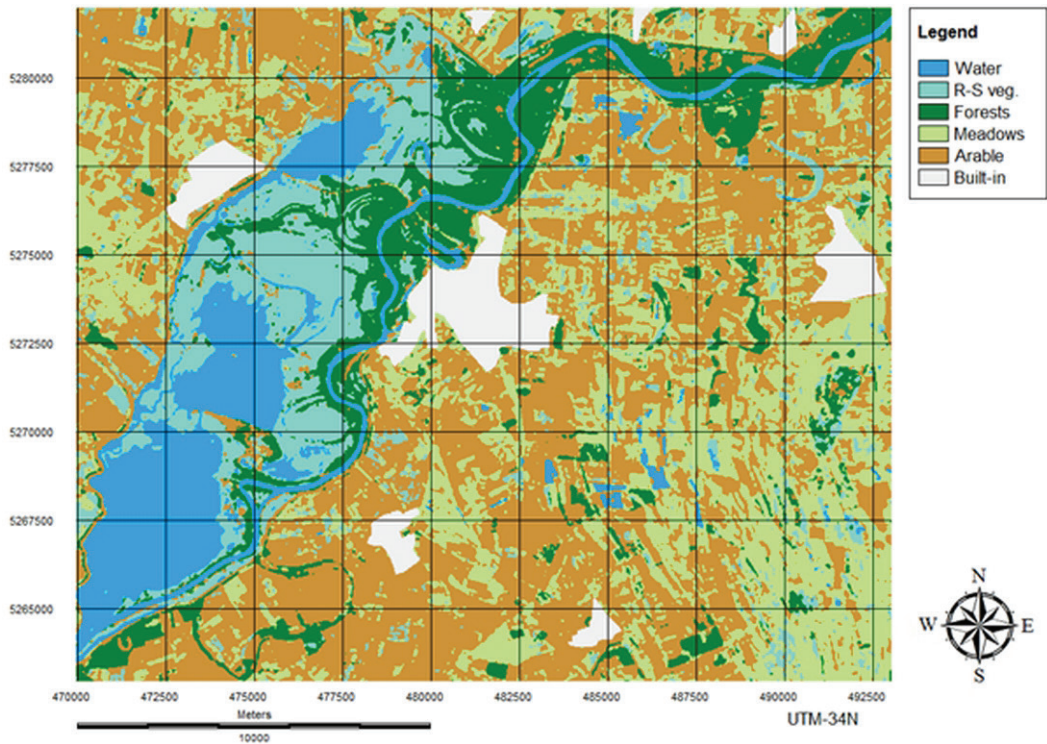


Fig. 3. Thematic map from TM sensor's images

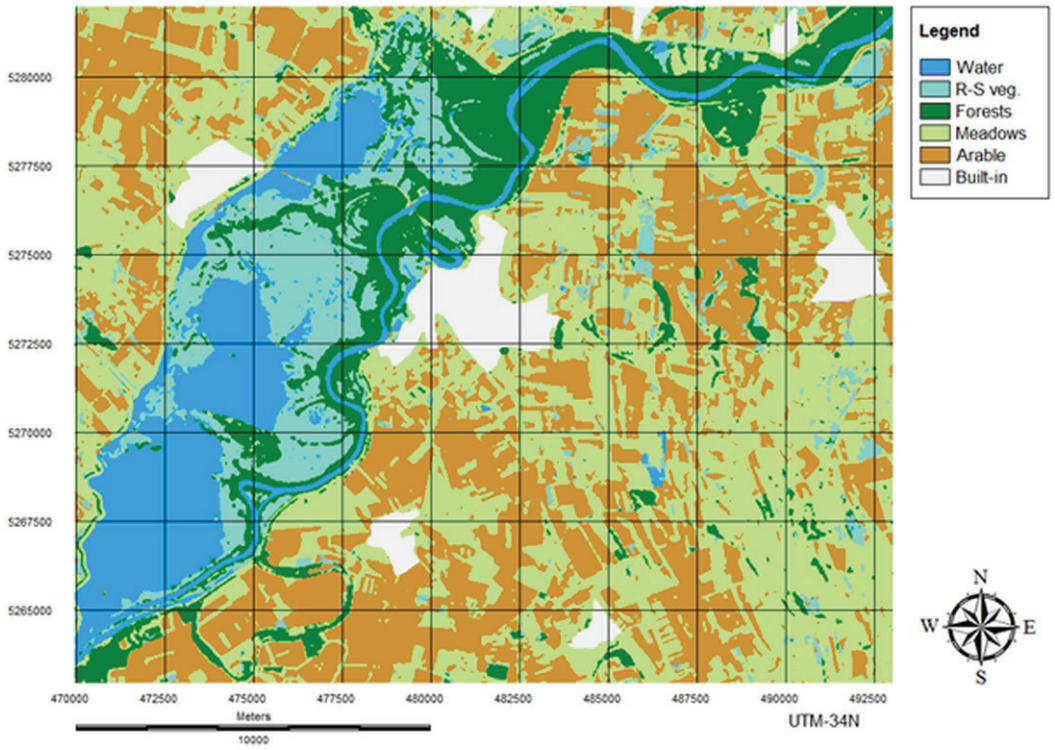


Fig. 4. Thematic map from ETM+ sensor's images

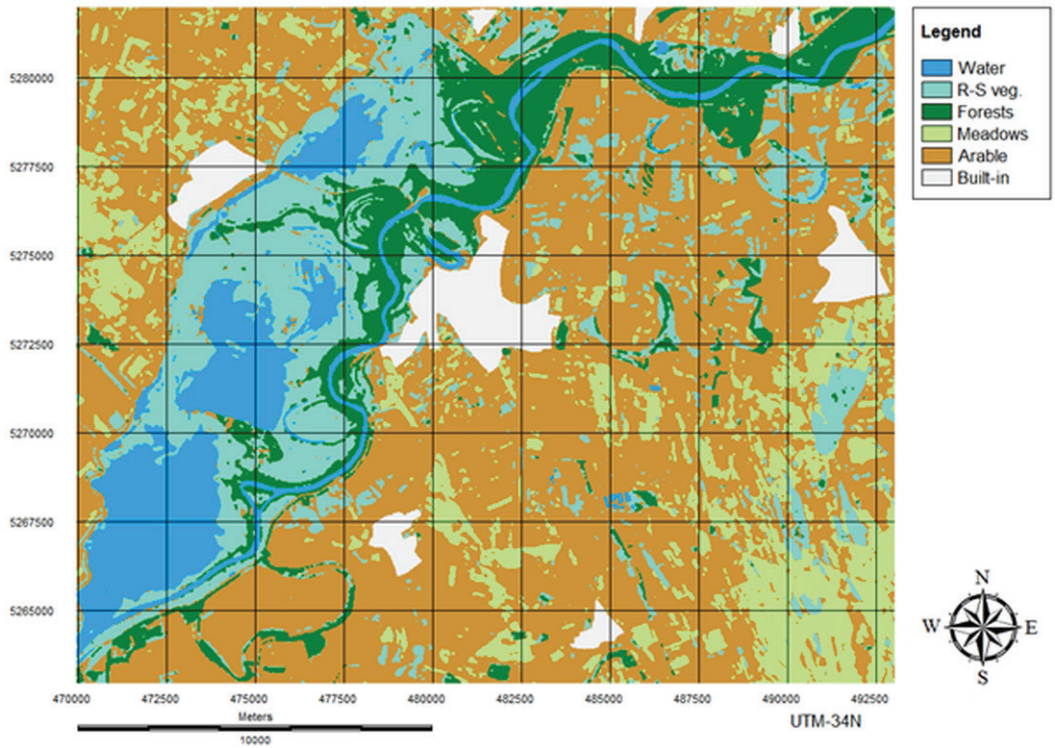


Fig. 5. Thematic map from OLI sensor's images

4. Discussion

Based on the sensors' similar spectral bands and spatial resolution they can be suitable for the same tasks, however, there are differences between each sensor considering the gained accuracy.

The ALI images are appropriate to classify the open water surfaces and the forests. Besides, for reedy-sedgy vegetation also we got acceptable results, but in case of grasslands or arable lands the accuracy was too low. There are spectral similarities between the grasslands and arable lands, thus, classifying these categories separately from the others can result good performance. Interspersion between these land cover units was found by Prishchepov et al. (2012), too. The TM sensor's images are perfect for classify forests, and also provided good results at classifying water surfaces and reedy-sedgy vegetation. The classification of grasslands and arable lands had low accuracy similarly to land cover maps derived from ALI's sensor. Price et al. (2002) also found that the raw bands are not performed relevantly well even with involving all the possible bands in case of TM bands. They enhanced the relevance of NIR band and the possible usage of Greenness Vegetation Index. The ETM+ image had some cloudy area that probably influenced our pixel values, thus, its accuracy was the worst of all. Only the water surfaces had accuracy with above 95%; other categories had misclassification or bad results based on the UA or the PA. The OLI sensor produced the best OA. Water surfaces and forests were perfectly classified and the reedy-sedgy vegetation also had the best results; thus, OLI is a good choice to classify these categories. Grasslands and arable lands have interspersion, caused by the spectral similarity as well.

Cunningham (2006) found that land cover databases classified from remotely sensed data were lower than it was reported in their documentation in case of grasslands, wetlands and woodlands. Similarity of spectral features cannot be avoided,

classification accuracy of grasslands and arable lands can be improved by preliminary field survey. Precisely structured training areas are important too, which we performed by the segmentation.

5. Conclusions

In conclusion, if we aim to examine current problems of remote sensing methods and if our goal is not the classification of the arable lands, then the results of the OLI sensor on Landsat 8 is the best, because in almost all cases this sensor's images performed the best. For dates before 2013, Landsat 5's TM provides satisfying results as well. For additional images we recommend the application of EO-1's ALI data. The ETM+ is also can be a good solution, in our case the full extent image was cloudy, so probably that caused the low accuracy. The Landsat Data Continuity Mission provides the future application of these quality data. Since the Landsat 8 there are freely available high quality satellite images of the Earth. In addition there is a plan of Landsat 9 and Sentinel 2B, which could improve the quality and accuracy of this segment of remote sensing technology.

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6. References

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