Comparison of Object and Pixel-based Land Cover Classification through three Supervised Methods

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Summary

Land cover has undergone tremendous changes in the last century, with strong consequences on the environmental balance, therefore the classification of land cover using Earth Observation data is very important. Recently, the widely used pixel-based approach for land cover classification was questioned through the emergence of the object-based approach. The main objective of this paper is to evaluate the performances of pixel-based and object-based approaches through three classification methods, *Random Trees*, *Decision Tree* and *Kappa Nearest Neighbor*, for land cover classification using Landsat satellite imagery. Our results suggest that using methods based on decision trees (*Random Trees* or *Decision Tree*) the accuracy values are superior in the object-based approach compared to pixel-based approach. Instead, using KNN classification, accuracy values are superior in the pixel-based approach.

Zusammenfassung

Die Landbedeckung hat im letzten Jahrhundert enorme Veränderungen erfahren, mit starken Auswirkungen auf die Umweltbilanz. Daher ist die Klassifizierung der Landbedeckung unter Verwendung von Erdbeobachtungsdaten sehr wichtig. Vor kurzem wurde der weit verbreitete pixelbasierte Ansatz für die Klassifizierung der Landbedeckung durch das Auftauchen des objektbasierten Ansatzes in Frage gestellt. Das Hauptziel dieses Beitrags ist es, die Leistungsfähigkeit von pixelbasierten und objektbasierten Ansätzen anhand von drei Klassifikationsmethoden – Random Trees, Decision Tree *und* Kappa Nearest Neighbor *– für die Landbedeckung mit Landsat-Satellitenbildern zu bewerten. Unsere Ergebnisse zeigen, dass die Methoden, die auf Entscheidungsbäumen basieren* (Random Trees *und* Decision Tree)*, im Falle des objektorientierten Ansatzes eine höhere Genauigkeit ergeben als beim pixelbasierten Ansatz. Dagegen ergibt die Verwendung der KNN-Klassifikation genauere Werte für den pixelbasierten Ansatz.*

Keywords: OBIA, land cover, supervised classification

1 Introduction

Land cover has undergone tremendous changes in the last century, with strong consequences on the environmental balance. Classification and detection of land cover changes using Earth Observation data is important, having a great practical importance in various applications, such as analysis of deforestation, disaster monitoring and damage assessment, urban expansion, land planning and management.

Currently there is a debate about the two paradigms used in land cover classification, the pixel-based approach, generally accepted and most utilized or object-based approach, a relatively new approach. To date the most approaches classifying land cover and analyzing change detection using satellite images are pixel-based, meaning that classifications and change analysis is performed at the raster cell level. For example, Wilson and Sader (2002) used a simple technique for classifying time series Landsat TM images for detecting deforestation types concluding surprisingly, that the use of the less common *Normalized Difference Moisture Index* produced better results than the wildly used *Normalized Difference Vegetation Index*. Rogan et al. (2002) compared two classification methods, *Maximum Likelihood* and *Decision Tree*, concluding that the *Decision Tree* method is superior to *Maximum Likelihood* method, by 10 %. Xiuwan (2002) applied a post-classification method for detecting land cover changes in the Ansan City, Korea, between 1985 and 1990, using multitemporal Landsat TM satellite images, the authors emphasizing the importance of selecting the appropriate method for land cover classification.

Relatively recently, the pixel-based classifications were questioned through the emergence of an alternative paradigm, namely geographic object-based image analysis (GEOBIA) which delineate homogeneous objects in attribute and geographic space through various image segmentation algorithms (Blaschke et al. 2014). The basic idea is that objects are created using local homogeneity criteria, merging spatially contiguous pixels. The unit of analysis within GEOBIA is the object which includes information about texture, form and spatial relationships with adjacent objects, thus allowing operation on spatial context (Aguirre-Gutiérrez et al. 2012, Bock et al. 2005). For example, Dronova et al. (2011) applied GEOBIA and supervised classification of four satellite images to examine small-scale land cover and changes between 2007 and 2008, in the area of Poyang Lake, China. Tehrany et al. (2013) analyzed changes in urban areas in Klang Valley, Malaysia, between 2003 and 2010, using the *Nearest Neighbour* classification method and object-based analysis. Spiekermann et al. (2015) analyzed changes in forested areas, species and land cover between 1967 and 2011, in an area from Sahel, Mali, using object-based analysis and high resolution multispectral images. Besides these studies, Dingle Robertson and King (2011) compared classifications based on pixel and object

DOI 10.12902/zfv-0165-2017

of Landsat TM images for mapping and analyzing the land cover changes, concluding that the two methods do not produce significantly different results.

Land cover classification could be conducted through various methods, among the most utilized methods being *Random Trees*, *Decision Tree* and *Kappa Nearest Neighbor*. To our knowledge, no study evaluated the performances of the two fundamental approaches with different classification methods. The main objective of this paper is to evaluate the performance of pixel-based and object-based approaches through three classification methods, *Random Trees*, *Decision Tree* and *Kappa Nearest Neighbor*.

2 Methods

2.1 Study area

The study area for conducting the analyses is located in the north-eastern part of Banat Region, Romania, between 45° 24′ 25″ and 45° 58′ 01″ northern latitude, and 21° 09′ 55″ and 22° 13′ 37″ eastern longitude, occupying an area of 5,296 km^2 (Fig. 1). The area is situated at the interference between Banat Plain, Banat Hills, Poiana Ruscă Mountains and Dognecea Mountains, with elevations ranging from 80 m in the western part to 1,000 m in the eastern part.

As land cover classes, the study area is covered by agricultural land and built-up areas in the plains and by forests and pastures at higher altitudes. Therefore we focused our classification over five land cover classes: deciduous forest, pasture, built-up area, arable land and water.

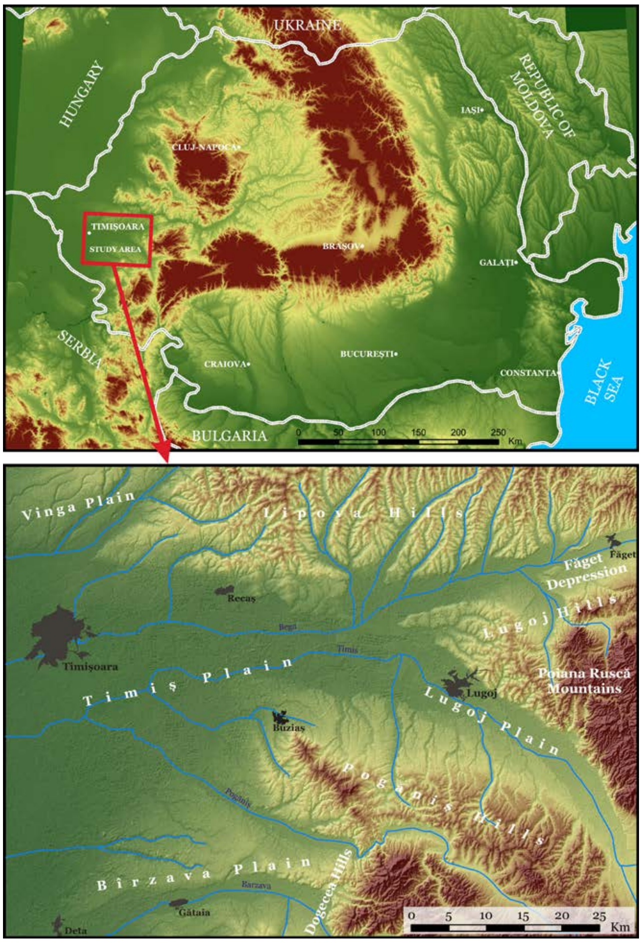

Fig. 1: Study area for land cover classification

2.2 Data

We used Landsat 8 OLI + TIRS satellite image for the year 2013 available in GeoTIFF format and having path 186 and row 028 (Tab. 1). We observed that the land cover classes in the study area are best differentiated based on image acquired in the summer. Besides satellite images we used a digital elevation model (DEM) SPOT with spatial resolution of 30 m.

2.3 Data pre-processing

To improve the quality of land cover classifications, numerous studies recommended corrections to be applied on images and the use of normalized indices.

Corrections applied to satellite image bands were conducted using *Image Processing* module within *Terrset* program. The image used in this study did not re-

Tab. 1: Details of the Landsat scene used for land cover classification

Attribute	Landsat scene	Attribute	Landsat scene
Scene identifier	LC81860282013205LGN00	Processing level	Level 1T
Mission identifier	LANDSAT 8	Projection system	UTM
Acquisition date	2013/07/24	Datum	WGS84
Quality	9	Elippsoid	WGS84
Could coverage	16 %	UTM Zone	34
Sun elevation	59,41944013	Latitude	46° 01′ 47,21″ N
Sun azimuth	141,92450098	Longitude	21° 20′ 13,16″ E

Tab. 2: Variables used for land cover classification

Variable	Description	Source
Blue band	Enhance the differences between forests and the other land cover classes.	Row values of Landsat satellite image
Green band	Used to assess the vitality of the plants.	Row values of Landsat satellite image
Red band	Used for monitoring the health of vegetation, enhancing the spectral differences between soil and vegetation.	Row values of Landsat satellite image
Near infrared (NIR) band	Highlights the biomass content of plants.	Row values of Landsat satellite image
Shortwave infrared 1 (SWIR1) band	Used for estimates of soil and vegetation moisture.	Row values of Landsat satellite image
Shortwave infrared 2 (SWIR2) band	Used for estimates of soil and vegetation moisture.	Row values of Landsat satellite image
Normalized difference vegetation index (NDVI)	Illustrates the consistency of green vegetation, higher values representing dense deciduous forests, average values representing herbaceous vegetation and lower values illustrating no vegetation. $NDVI = \frac{NIR - RED}{NIR + RED}$	Rouse et al. (1974)
Normalized difference water index (NDWI)	Illustrates the moisture content of trees and plant associations. $NDWI = \frac{NIR - GREEN}{NIR + GREEN}$	McFeeters (1996)
Normalized difference moisture index (NDMI)	Illustrates the moisture content in soil, rock and vegetation, helping to assess the hydric potential of vegetation and soil and moisture excess or deficit. $NDMI = \frac{NIR - SWIR\ 1}{NIR + SWIR\ 1}$	Wilson, Sader (2002)
Normalized difference built-up index (NDBI)	Enables automatic identification of settlements, dams, railways, roads, etc. $NDBI = \frac{SWIR\ 1 - NIR}{SWIR\ 1 + NIR}$	Zha et al. (2003)
Digital Elevation Model	Elevation above sea level in meters. Used to better differentiate pastures which are located at higher elevations.	–

quire geometrical corrections. We conducted atmospheric corrections through *Dark Object Subtraction Model* and topographic correction through *Illumination Modeling* method (Eastman 2015).

For land cover classification, in this study we used eleven variables listed and described in Tab. 2.

2.4 Land cover classification

We compared the two fundamental approaches, pixel-based and object-based, for each approach being tested three supervised classification methods: *Random Trees*, *Decision Tree* and *k Nearest Neighbor*.

2.4.1 Sample selection

Using supervised classification methods, they require a number of samples for training the method and for validation. On the color composite image we manually digitized a total of 106 samples, assuming that there are enough for our study area and land cover classes. The samples were divided into two subsets: 70 % as training samples used for the land cover classification and 30 % as validation samples used for accuracy assessment of the classification (Fig. 2).

2.4.2 Classification methods

As noted, in this study were compared three supervised classification methods implemented in the eCognition software: *Random Trees*, *Decision Tree* and *k Nearest Neighbor*.

Decision Tree (DT) use binary decision trees to divide the input data successively into more homogeneous subsets, based on independent variables (Lees and Ritman 1991).

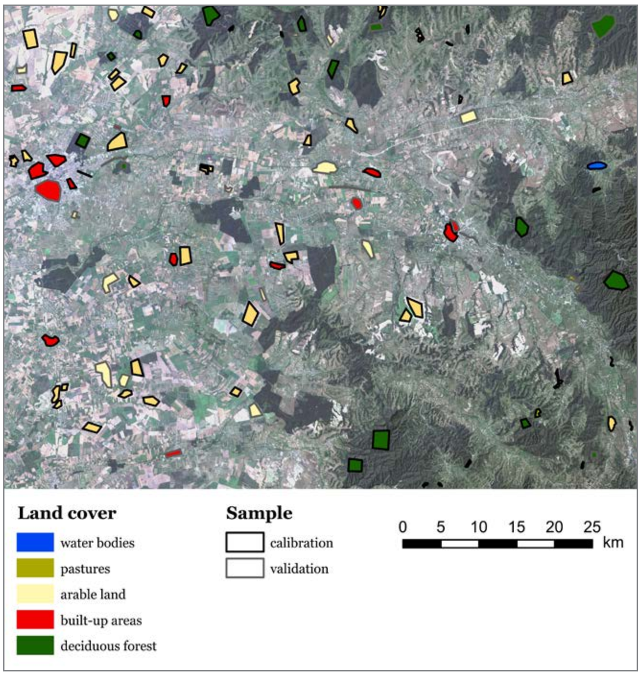

Fig. 2: The selected samples for land cover classification

Random Trees (RT) was developed by Breiman (2001) and is based on decision trees. It creates combinations of classification trees on the basis of independent and random selection of variables and samples, the final classification being much less influenced by the input data noise.

k Nearest Neighbor (KNN) classifies the objects based on the nearest sample in feature (attribute) space. KNN method returns a membership value, ranging from 0 to 1, based on the distance in feature space to the nearest neighbor. The membership value is 1 if the object is identical to a sample (Trimble Germany GmbH 2013).

2.4.3 Object-based classification

Object-based image analysis relies on the segmentation process, which aims to create objects (polygons) by merging adjacent pixels of one or more raster data set, subsequently the classification being performed on the resulting objects.

For segmentation, we used *multiresolution segmentation algorithm (MRS)*, implemented in the eCognition software, which iteratively merges adjacent pixels or objects. The fusion occurs only if the homogeneity of the resulting object is lower than the homogeneity threshold, called scale parameter (SP) (Baatz and Schäpe 2000).

To select the variable to be segmented, we analysed the mean and standard deviation of spectral values for land cover classes, the variables with high differences of the mean values and recording high values of standard deviation being considered the most suitable for segmentation since they best differentiates the land cover classes. The highest values of standard deviation was 0.19 recorded by NDWI and NDVI, two variables recording a standard deviation of 0.15 and the other six variables recording values of standard deviation lower than 0.07. Since the mean values of spectral variables are more similar for NDWI, the normalized difference vegetation index was segmented with MRS algorithm. After conducting several tests we decided that the most suitable value for scale parameter to delineate the five land cover classes in the study area was 3, used therefore for the segmentation of NDVI raster. The resulted objects were classified using the three methods, obtaining land cover maps.

2.4.4 Pixel-based classification

Pixel-based classifications were conducted in the eCognition Developer software, using chessboard segmentation algorithm with an object size of 1 that divides the scene into individual pixels.

Since the three methods are supervised classifiers, it could be defined the attributes that will be considered for classification as feature space. In this study having a total of eleven attributes, represented by the six spectral bands, the four normalized indices and the digital elevation model, we tested two configurations of feature space:

- mean and standard deviation of all eleven attributes;
- mean and standard deviation of attributes not used to derive the normalized indices. It is a well known fact that covariance of predictors could negatively influence the classification; therefore we excluded green, red, near infrared and short wave infrared bands from feature space.

Finally, we obtained six object-based and six pixel-based land cover classifications, the accuracy being evaluated using the validation samples.

2.5 Accuracy assessment

Accuracy assessment of classifications was conducted using validation samples regarding overall accuracy (OA) and kappa index of agreement (KIA). Overall accuracy is calculated by dividing the number of the correctly classified samples by the total number of validation samples (Congalton 1991). Kappa index is the coincidence of the validation samples and tested classification, after the coincidence by chance is eliminated (Cohen 1960).

3 Results and discussions

Tab. 3 presents the accuracy values of the twelve classifications. It can be noticed that using Random Trees and Decision Tree methods, the accuracy values are superior by 10 to 19 %, when the classification was conducted using an object-based approach compared to pixel-based approach. Instead, using KNN method, the accuracy

Tab. 3: Accuracy of land cover classifications

Feature space	Variables not used to calculate the normalized indices				All variables			
	OBIA		PIXEL		OBIA		PIXEL	
	OA	KIA	OA	KIA	OA	KIA	OA	KIA
RT	0.88	0.80	0.75	0.63	0.93	0.89	0.82	0.72
DT	0.92	0.86	0.82	0.72	0.91	0.85	0.86	0.77
KNN	0.65	0.46	0.70	0.56	0.65	0.46	0.76	0.63

RT – Random trees, DT – Decision tree, KNN – k nearest neighbor, OBIA – object-based classification, PIXEL – pixel-based classification

values are superior by 7 to 11 %, using pixel-based approach. It seems that KNN method is more appropriate for pixel-based approaches and methods based on decision trees are more suitable for object-based approach. It is worth mentioning the execution time of classifications, in the case of decision tree based methods and the KNN method conducted in an object-based manner, being about 13 to 15 minutes, while exceeding 7 hours in the case of KNN method conducted in a pixel-based manner.

Using all the variables as feature space led to higher accuracies for all the three methods in the pixel based-approach, but only for RT method in the object-based approach. It seems that RT method performs better when used with more variables, even if multicollinearity affects some of the variables. A possible explanation is related to the random selection of the variables, a larger range of variables positively influencing the results. The higher accuracies of pixel-based approach using as feature space all the variables over using only the uncorrelated variables could be explained by the large combinations of values, more variables allowing a better differentiation between classes.

Deciduous forests were best classified in all cases except object-based KNN and pixel-based DT, since they are distinguished easily from other classes. The forests were better classified in all cases using RT than KNN and in three cases using DT, KNN outperforming DT in the pixel-based approach using six variables in feature space.

The built-up areas and arable land present very good accuracy values in all cases, however overlapping to some extent in feature space. Arable land was better classified using DT in three cases and using RT in one case, KNN performing much worse. Water was poorly classified mainly because it covers small areas, and pasture because feature space overlap with arable land (Tab. 4).

The highest accuracy was obtained by the object-based approach in combination with the Random Trees method and using as feature space all the eleven variables, land cover classes recording the highest Kappa values, except water class. An interesting result is that the KNN method seems more appropriate for pixel-based approaches and methods based on decision trees more appropriate for object-based approaches.

The main problem encountered in land cover classification is that the built-up areas and pastures could not be clearly differentiated to some arable land, so that the built-up area was mapped on slightly wider areas than in reality. The use of elevation facilitated the differentiation of pastures, which are located at higher altitudes.

An unexpected result of this study relates to improving the quality of land cover classifications by applying atmospheric and topographic corrections to satellite images. Contrary to our expectations, these corrections did not improve the consistency of spectral bands, but actually worsened it. The lack of efficacy for the elimination of topographic effect can be explained by the morpho-

Tab. 4: Kappa index of agreement of land cover classess

Class	Feature space consisting from variables not used to calculate the normalized indices						Feature space consisting from all variables					
	OBIA			PIXEL			OBIA			PIXEL		
	RT	DT	KNN	RT	DT	KNN	RT	DT	KNN	RT	DT	KNN
Deciduous forest	1.00	1.00	0.48	0.97	0.79	0.89	1.00	1.00	0.48	0.99	0.99	0.98
Pasture	0.49	0.49	0.30	0.20	0.63	0.04	0.65	0.49	0.30	0.29	0.27	0.06
Water	0.48	0.48	0.18	0.44	0.75	0.16	0.68	0.68	0.18	0.43	0.44	0.19
Built-up area	0.82	0.93	0.77	0.85	0.86	0.75	0.89	0.85	0.77	0.81	0.75	0.81
Arable land	0.87	0.94	0.39	0.42	0.63	0.39	.0.94	0.91	0.39	0.58	0.74	0.47

RT – Random trees, DT – Decision tree, KNN – k nearest neighbor, OBIA – object-based classification, PIXEL – pixel-based classification graphy of the study area, which is dominated by plains, where other studies have noted that the application of such corrections may deteriorate spectral values.

Regarding the use of normalized indices, they improved classifications of some land cover classes, for example the NDVI enhancing the classifications of deciduous forests and pastures and NDWI and NDMI also enhancing the differentiation of forests. An unexpected result is that the NDBI failed to differentiate built-up areas which registered average values, as some arable land.

4 Conclusions

The main conclusion of this study is that for land cover classification, object-based approach is superior to pixel-based approach, if it is used the classification methods based on decision trees (*Random Trees* and *Decision Tree*). Instead, using KNN classification the accuracy is higher by pixel-based approach. Another conclusion of this study is that the atmospheric and topographic corrections did not improve the consistency of spectral bands, but actually deteriorated it.

References

Aguirre-Gutiérrez, J., Seijmonsbergen, A.C., Duivenvoorden, J.F.: Optimizing land cover classification accuracy for change detection, a combined pixel-based and object-based approach in a mountainous area in Mexico. Applied Geography, 34, 29–37, 2012.

Baatz, M., Schäpe, A.: Multiresolution Segmentation: an optimization approach for high quality multi-scale image segmentation. In: J. Strobl, T. Blaschke, G. Griesebner (eds.), Angewandte geographische Informationsverarbeitung. Wichmann-Verlag, Heidelberg, 2000.

Blaschke, T., Hay, G.J., Kelly, M., Lang, S., Hofmann, P., Addink, E., Feitosa, R.Q., Van Der Meer, F., Van Der Werff, H., Van Coillie, F., Tiede, D.: Geographic Object-Based Image Analysis – Towards a new paradigm. ISPRS Journal of Photogrammetry and Remote Sensing, 87, 180–191, 2014.

Bock, M., Xofis, P., Mitchley, J., Rossner, G., Wissen, M.: Object-oriented methods for habitat mapping at multiple scales – Case studies from Northern Germany and Wye Downs, UK. Journal for Nature Conservation, 13, 75–89, 2005.

Breiman, L.: Random forests. Machine learning, 45, 5–32, 2001.

Cohen, J.: A coefficient of agreement for nominal scales. Educational and psychological measurement, 20, 37–46, 1960.

Congalton, R.G.: A review of assessing the accuracy of classifications of remotely sensed data. Remote Sensing of Environment, 37, 35–46, 1991.

Dingle Robertson, L., King, D.J.: Comparison of pixel- and object-based classification in land cover change mapping. International Journal of Remote Sensing, 32, 1505–1529, 2011.

Dronova, I., Gong, P., Wang, L.: Object-based analysis and change detection of major wetland cover types and their classification uncertainty during the low water period at Poyang Lake, China. Remote sensing of environment, 115, 3220–3236, 2011.

Eastman, J.R.: TerrSet Manual. Clark University, 2015.

Lees, B.G., Ritman, K.: Decision-tree and rule-induction approach to integration of remotely sensed and GIS data in mapping vegetation in disturbed or hilly environments. Environmental Management, 15, 823–831, 1991.

McFeeters, S.: The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features. International Journal of Remote Sensing, 17, 1425–1432, 1996.

Rogan, J., Franklin, J., Roberts, D.A.: A comparison of methods for monitoring multitemporal vegetation change using Thematic Mapper imagery. Remote sensing of environment, 80, 143–156, 2002.

Rouse, J., Haas, R., Schell, J., Deering, D.: Monitoring vegetation systems in the Great Plains with ERTS. NASA special publication, 351, 309, 1974.

Spiekermann, R., Brandt, M., Samimi, C.: Woody vegetation and land cover changes in the Sahel of Mali (1967–2011). International Journal of Applied Earth Observation and Geoinformation, 34, 113–121, 2015.

Tehrany, M.S., Pradhan, B., Jebur, M.N.: Remote sensing data reveals eco-environmental changes in urban areas of Klang Valley, Malaysia: contribution from object based analysis. Journal of the Indian Society of Remote Sensing, 41, 981–991, 2013.

Trimble Germany GmbH: Definiens eCognition Developer 8.9 User Guide. München, Germany, 2013.

Wilson, E.H., Sader, S.A.: Detection of forest harvest type using multiple dates of Landsat TM imagery. Remote Sensing of Environment, 80, 385–396, 2002.

Xiuwan, C.: Using remote sensing and GIS to analyse land cover change and its impacts on regional sustainable development. International Journal of Remote Sensing, 23, 107–124, 2002.

Zha, Y., Gao, J., Ni, S.: Use of normalized difference built-up index in automatically mapping urban areas from TM imagery. International Journal of Remote Sensing, 24, 583–594, 2003.

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