Cropland mapping from Sentinel-2 time series data using object-based image analysis

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Abstract

The increasing spatial and temporal resolution of Sentinel-2 data creates new premises for cropland mapping and monitoring at local, regional and global scale. This paper reports the results of a study dedicated to cropland mapping from Sentinel-2 time-series data using objects as spatial analysis units. The Sentinel-2 time-series data stack was automatically segmented using multi-resolution segmentation algorithm and the resulting image objects were classified using the Time-Weighted Dynamic Time Warping (TWDTW) method. We applied this approach to map wheat, maize, rice, sunflower and forest in an agricultural area situated in the south-eastern part of Romania. The implemented cropland mapping framework yielded an overall accuracy of 93.43% and a kappa index of 92%. It has the advantage of generating spatial vector dataset which can supports decision making in various agricultural management contexts.

Keywords: cropland, remote sensing, object-based image analysis, time-series data, Sentinel-2.

1 Introduction

Accurate and efficient cropland mapping is a pre-requisite for developing efficient agricultural management policies which facilitate the implementation of sustainable food supply systems worldwide.

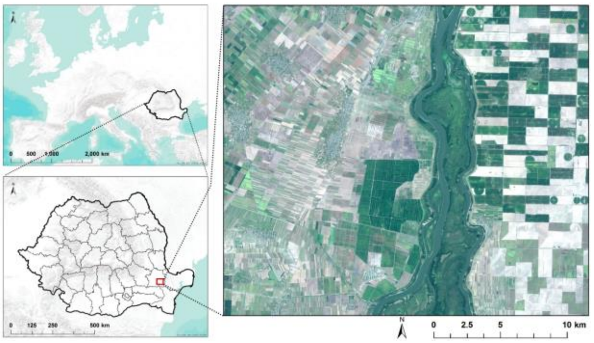
Remote sensing data has already been successfully used in different cropland monitoring programs due to their global coverage (Inglada et al., 2015). Existing studies dedicated to cropland mapping used MODIS data (Maus et al., 2016, Arvor et al., 2011, Pringle et al., 2012, Qiu et al., 2017), SPOT data (Desclée et al., 2006), Landsat data (Yan and Roy, 2015, Qiu et al., 2017) or, Landsat data combined with SPOT (Matton et al., 2015) or MODIS data (Jia et al., 2014). Since its launch, Sentinel-2 data gained the attention of the remote sensing community for cropland mapping and monitoring due to the high spatial resolution (e.g. 10 m spatial resolution of the blue, green, red and near-infrared spectral bands) and high temporal resolution (5 days revisiting time with twin satellites). The increased spatial resolution of the carried MultiSpectral Instrument (MSI) sensor allows the application of object-based image analysis (OBIA) method (Blaschke, 2010) for cropland mapping. This method has the advantage of generating ready-to-use spatial vector datasets which can be further used by decision-makers for developing sustainable agricultural management and monitoring policies (Matton et al., 2015). Immitzer et al. (2016) evaluated for example the suitability of single-date Sentinel-2 data for crops mapping by applying Random Forest algorithm (Breiman, 2001) using both pixel and object-based classifications. This study revealed that object-based and pixel-based Random Forest achieved comparable results. The authors concluded that multi-temporal Sentinel-2 images might increase the classification results, because the multi-temporal spectral and phenological indices can better describe the vegetation dynamics of the target crop types. Lebourgeois et al. (2017) used simulated Sentinel-2 time series data, SPOT digital elevation model (DEM) and very high resolution (VHR) Pleiades images for mapping smallholder agriculture in tropical areas. VHR images served as input data for delineating agricultural fields through segmentation, whereas the variables (spectral indices, reflectance) derived from simulated time-series Sentinel-2 data were used for the classification purpose. This study revealed that multi-temporal information is essential for cropland mapping in small-scale agricultural regions. Despite the increasing interest of the remote sensing community in using Sentinel-2 data for croplands mapping, none of the existing studies evaluated how OBIA method performs when applied to cropland mapping from time-series Sentinel-2 data. This study reports the classification results yielded for wheat, maize, rice, sunflower and forest mapping from a diverse agricultural landscape situated in Romania.

2 Study area and data

The study area is situated in the south-eastern part of Romania and it is divided into two sections by the Danube River (Fig. 1). As depicted in Figure 1, the eastern part of the study area comprises compact, relatively large agricultural fields, whereas the western part is characterized by a highly fragmented agricultural landscape. The study area have an extent of 2740×2335 pixels, covering 63.979 ha.

For the cropland classification purpose, we used 13 Sentinel-2 Level 1C images for the year 2016 (from February to September), well distributed across the agricultural calendar. The images were selected according to the cloud coverage: the images with cloud coverage greater than 10% were not used in the further classification framework. This study focuses only on the visible bands of the Sentinel-2 sensor (band 2, band 3 and band 4) and near-infrared band (band 8) for the segmentation process, while the phenological cycles of the land use/land cover classes of interest were computed using the Normalized Difference Vegetation Index (NDVI).

Figure 1: Study area localization in south-eastern part of Romania.



3 Methodology

This section introduces the methodological framework applied in this study: image segmentation, time-weighted dynamic time warping and evaluation of the final classification (Fig. 2).

3.1 Object-based image analysis framework

OBIA has gained an increasing attention in the last years due to the high classification accuracy yielded when applied to very high resolution satellite images (Blaschke, 2010). The method consists of two main steps: segmentation and classification.

Through segmentation the image is partitioned into contiguous spatial objects according to a homogeneity criteria defined by users. Resulting objects (referred into the OBIA literature as image objects) are classified using supervised or unsupervised image classification procedure. In our study, we applied the multi-resolution segmentation (Baatz and Schäpe, 2000) to segment the Sentinel-2 time-series data stack. To reduce the subjectivity and the time required for the segmentation algorithm tuning, we applied the Estimation of Scale Parameter 2 (ESP2) tool (Drăguţ et al., 2014), which automatically selects an objective scale parameter (SP) based on local variance of objects. The red, green, blue and near-infrared bands were used in the process of segmenting 13 different dates, resulting in a stack of 52 layers. We used all these layers in order to identify all meaningful boundaries which may appear during the timeframe of the analysis. In the end, 13 different raster datasets were exported, representing the mean NDVI values for each object. Resulting raster datasets were then stacked and ready to be analysed using Time-Weighted Dynamic Time Warping (TWDTW) approach (Maus et al., 2016) (Fig. 2).

3.2 Time-Weighted Dynamic Time Warping method

TWDTW is a supervised classification method that uses the temporal patterns of the training samples computed from different indices and/or spectral features to classify the agricultural fields of interest (Fig. 3). For this study, we randomly generated 2500 samples, resulting in 589 training samples and 1660 validation samples. These samples were classified through visual interpretation, relying on the visual interpretation keys developed using the European Land Use and Coverage Area Frame Survey (LUCAS) training samples for the land cover/land use classes of interest. This dataset was available only for 2015 and therefore, we could not use it directly as training samples for Sentinel-2 data which was available for 2016.

Figure 2: The methodological workflow used in this study.

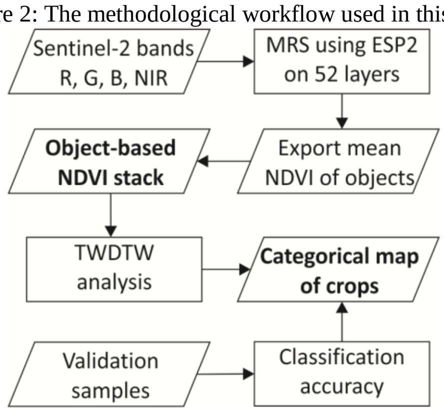
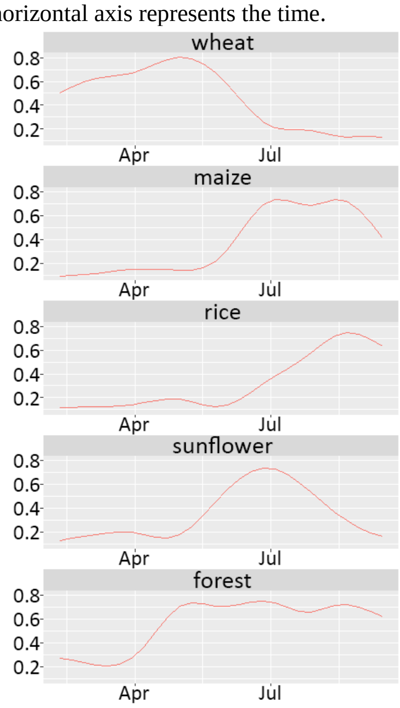


Figure 3: Temporal patterns of NDVI for wheat, maize, rice, sunflower and forest computed from Sentinel-2 NDVI time series data. The vertical axis represents the value of NDVI, while the horizontal axis represents the time.



Applying TWDTW method requires three main steps (1) generating the temporal patterns of the training samples based on the NDVI raster time series (Fig. 3), (2) applying the TWDTW analysis and (3) classifying raster time series (Fig. 2). In our study we used the R package called *dtwSat* (Maus et al., 2016) to execute the workflow towards obtaining a TWDTW classification based on objects.

We applied a logistic TWDTW with $\alpha = -0.1$ and $\beta = 50$, which means that we added a time-weight to the DTW with a low penalty for time warps smaller than 50 days and higher penalty for bigger time warps (Maus et al. 2016). Two raster datasets are created: the categorical map of classes of interest and the TWDTW dissimilarity measure of the scene classified.

3.3 Classification accuracy assessment

The accuracy of the obtained object-based classification was evaluated using overall accuracy, producer's accuracy, user's accuracy metrics (Congalton, 1991) and kappa coefficient (Cohen, 1960), using 1660 validation samples.

4 Results and discussions

The objective of this study was to evaluate the performance of OBIA method when applied to cropland mapping from Sentinel-2 time-series data. The image objects delineated by applying multi-resolution segmentation algorithm were further classified using the TWDTW method (Fig. 4). We obtained a classification accuracy of 93.43% and a kappa coefficient of 92% (Table 1). The lowest user's accuracy was yielded for the rice class (78.8%) because of the confusion with the maize class, whereas the highest user's accuracy was achieved by the wheat class (99.72%), followed by the forest, maize and sunflower classes. The lowest producer's accuracy was also obtained by the rice class (82.86%), followed by the maize class with 86.68%. The high misclassification rate of the maize class was caused by the confusion with rice and sunflower. Better results are expected by including the red-edge and SWIR bands in the image analysis procedure. Immitzer et al. (2016) showed in their study dedicated to cropland mapping from single-date Sentinel-2 data that among the five most important spectral bands two are located in the red-edge and one in the SWIR.

The most critical step of OBIA is the segmentation of the images into meaningful objects (Belgiu and Drăguţ, 2014). Most of the exiting segmentation algorithms require users' intervention for selecting the segmentation parameters. In our study, we used the ESP-2 tool to automatically identify the SP for crop fields delineation from time-series data. We applied the ESP-2 tool using a hierarchical segmentation approach to ensure a faster segmentation, because each of the iteration is built on the previous obtained level of segmentation. The final obtained SP was 186, using shape 0.1 and compactness 0.5, resulting in 4479 objects with a mean area of 1428 pixels of 10m resolution.

The diversity of the agricultural landscape can greatly impact the segmentation results obtained by applying the ESP-2 tool. The western part of our study area for example is characterized by small agricultural parcels (Fig. 5). Consequently, narrower and elongated fields were under-segmented. The under-segmentation increases the misclassification rate especially when smaller agricultural fields cultivated with different crops are merged together. In the eastern part of our study area, the agricultural fields were over-segmented, because of the utilization of irrigation systems that caused spectral variation within the same agriculture field (Fig. 5). Over-segmentation is preferable to under-segmentation (Gao et al., 2011), because smaller objects belonging to the same agriculture field can be easily

Figure 4: Object-based TWDTW classification of the study area. The settlements (gray color) are masked.

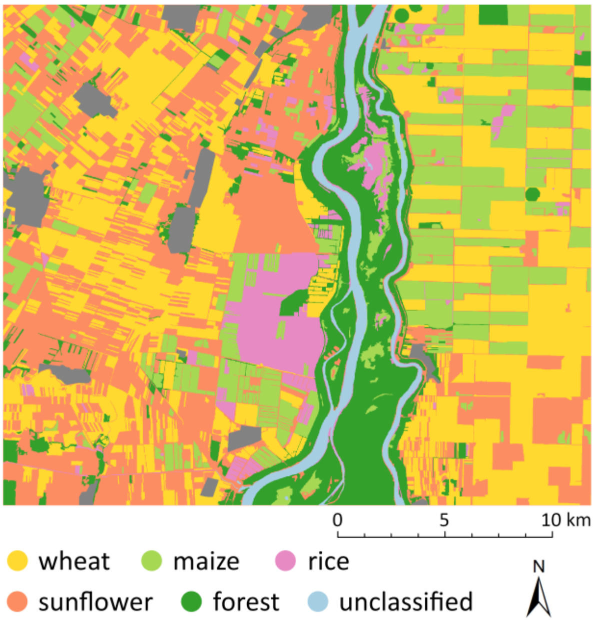


Figure 5: Two subsets of the study area showing the segmentation results superimposed on a RGB image from May: (A) highly fragmented agricultural landscape and (C) relatively large agricultural parcels. For the same two subsets, the object-based classification is showed in (B) for small parcels and (D) for large parcels.

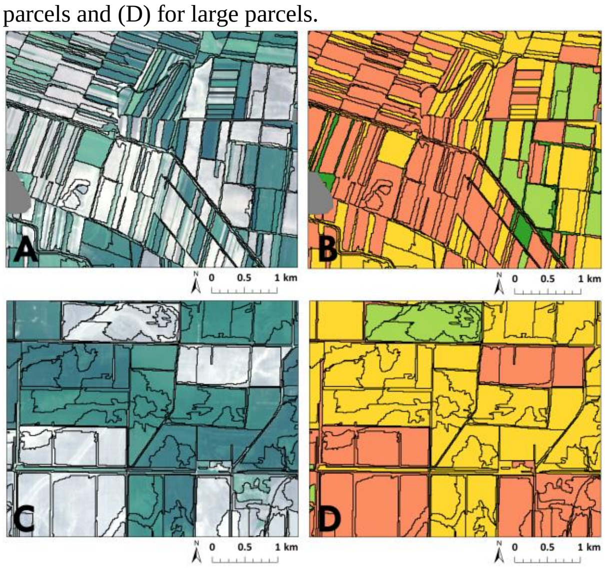


Table 1: Classification accuracy achieved by applying the TWDTW method to objects, as spatial analysis units. PA stands for Producer's accuracy, UA stands for User's accuracy and OA for Overall accuracy.

Map class	Reference class						Total	UA (%)
	Wheat	Maize	Rice	Sunflower	Forest	Unclassified		
Wheat	360	0	0	1	0	0	361	99.72
Maize	0	332	30	14	1	0	377	88.06
Rice	0	32	145	3	3	1	174	78.80
Sunflower	3	19	0	175	0	0	197	88.83
Forest	1	0	0	1	335	0	337	99.41
Unclassified	0	0	0	0	0	204	204	100
Total	364	383	175	194	339	205	1660	
PA (%)	98.90	86.68	82.86	90.21	98.82	99.51	**OA (%) = 93.43**	

merged together in the further image analysis steps. Under-segmentation results on the other hand cannot be easily ruled out. One possible solution to this problem could be the division of the study area into two regions based on the characteristics (and thus complexity) of the agricultural fields. In this way, the highly fragmented agricultural landscape present in the western part of the study area could be segmented independently from the eastern part, where larger agricultural fields dominate. The same procedure has been successfully implemented by d'Oleire-Oltmanns and Tiede (2014) for gully delineation from QuickBird image. In a previous study, Matton et al. (2015) argued that the slightly better classification results produced by the object-based method do not balance out the high processing time required for the segmentation step. In our case, the segmentation of time-series layers proved to be a less computationally-intensive process (1h 50min, using 16 cores with 2.90 GHz and 32GB memory).

In spite of the increasing temporal resolution of Sentinel-2 data, the presence of clouds significantly reduced the number of available scenes. To address the problem of cloud obscuration, radar data such as RADARSAT-2 or Sentinel-1 data can be used in combination with Sentinel-2 for cropland mapping.

Our study revealed also that TWDTW is an efficient method for cropland mapping using phenological pattern of target crops computed from NDVI time-series data. In the future study, we plan to evaluate how this method performs when additional indices such as Enhanced Vegetation Index (EVI) or Normalized Difference Water Index (NDWI) (McFeeters, 1996) and the vegetation red edge bands (band 5, 6, 7 and 8a, respectively) are used. Furthermore, we plan to evaluate how OBIA performs in different geographical regions where the agricultural fields have different spatial structures and where the agricultural practices differ.

5 Conclusion

This study showed that OBIA can be successfully used for cropland mapping from Sentinel-2 time-series data, achieving an overall accuracy of 93.43%. One of the advantages of this method consists in reducing the salt-and-pepper effect occurring usually in per pixel classifications and in generating ready-to-use spatial vector datasets. The availability of vector-based agricultural fields datasets at regional and global level could benefit agricultural management and monitoring agencies including the European Common Agriculture Policy (CAP) and its European Agricultural Guarantee Fund (EAGF) program towards developing sustainable agricultural practices and agricultural subsidies programs for food security.

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References

Arvor, D., Jonathan, M., Meirelles, M. S. P., Dubreuil, V. and Durieux, L. Classification of MODIS EVI time series for crop mapping in the state of Mato Grosso, Brazil. International Journal of Remote Sensing, 32: 7847-7871, 2011.

Baatz, M. and Schäpe, A. Multiresolution segmentation – an optimization approach for high quality multi-scale image segmentation. In: Strobl, J., Blaschke, T. and Griesebner, G., (eds.) *Angewandte Geographische Informations-Verarbeitung XII*, 12-23, 2000.

Belgiu, M. and Drăguţ, L. Comparing supervised and unsupervised multiresolution segmentation approaches for extracting buildings from very high resolution imagery. *ISPRS Journal of Photogrammetry and Remote Sensing*, 96: 67-75, 2014.

Blaschke, T. Object based image analysis for remote sensing. *ISPRS Journal of Photogrammetry and Remote Sensing*, 65: 2-16, 2010.

Breiman, L. Random Forest. *Machine Learning*, 45(1): 5-32, 2001.

Cohen, J. A coefficient of agreement for nominal scales. *Educational and psychological measurement*, 20(1): 37-46, 1960.

Congalton, R. G. A review of assessing the accuracy of classifications of remotely sensed data. *Remote sensing of environment*, 37(1): 35-46, 1991.

D'Oleire-Oltmanns, S. and Tiede, D. Specific target objects-specific scale levels? Application of the estimation of scale parameter 2 (ESP 2) tool for the identification of scale levels for distinct target objects. *South Eastern European Journal of Earth Observation and Geomatics*, 3(2S): 579-584, 2014.

Desclée, B., Bogaert, P. and Defourny, P. Forest change detection by statistical object-based method. *Remote Sensing of Environment*, 102: 1-11, 2006.

Drăguţ, L., Csillik, O., Eisank, C. and Tiede, D. Automated parameterisation for multi-scale image segmentation on multiple layers. *ISPRS Journal of Photogrammetry and Remote Sensing*, 88: 119-127, 2014.

Gao, Y., Mas, J. F., Kerle, N. and Navarrete Pacheco, J. A. Optimal region growing segmentation and its effect on classification accuracy. *International Journal of Remote Sensing*, 32, 3747-3763, 2011.

Immitzer, M., Vuolo, F. and Atzberger, C. First Experience with Sentinel-2 Data for Crop and Tree Species Classifications in Central Europe. *Remote Sensing*, 8(3): 166, 2016.

Inglada, J., Arias, M., Tardy, B., Hagolle, O., Valero, S., Morin, D., Dedieu, G., Sepulcre, G., Bontemps, S., Defourny, P. and Koetz, B. Assessment of an Operational System for Crop Type Map Production Using High Temporal and Spatial Resolution Satellite Optical Imagery. *Remote Sensing*, 7(9): 12356-12379, 2015.

Jia, K., Liang, S., Zhang, N., Wei, X., Gu, X., Zhao, X., Yao, Y. and Xie, X. Land cover classification of finer resolution remote sensing data integrating temporal features from time series coarser resolution data. *ISPRS Journal of Photogrammetry and Remote Sensing*, 93: 49-55, 2014.

Lebourgeois, V., Dupuy, S., Vintrou, É., Ameline, M., Butler, S. and Bégué, A. A Combined Random Forest and OBIA Classification Scheme for Mapping Smallholder Agriculture at Different Nomenclature Levels Using Multisource Data (Simulated Sentinel-2 Time Series, VHRS and DEM). *Remote Sensing*, 9(3): 259, 2017.

Matton, N., Canto, G. S., Waldner, F., Valero, S., Morin, D., Inglada, J., Arias, M., Bontemps, S., Koetz, B. and Defourny, P. An automated method for annual cropland mapping along the season for various globally-distributed agrosystems using high spatial and temporal resolution time series. *Remote Sensing*, 7: 13208-13232, 2015.

Maus, V., G, C., Cartaxo, R., Sanchez, A., Ramos, F. M. and Queiroz, G. R. D. A Time-Weighted Dynamic Time Warping Method for Land-Use and Land-Cover Mapping. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 9(8): 3729-3739, 2016.

McFeeters, S. K. 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.

Pringle, M. J., Denham, R. J. and Devadas, R. Identification of cropping activity in central and southern Queensland, Australia, with the aid of MODIS MOD13Q1 imagery. *International Journal of Applied Earth Observation and Geoinformation*, 19: 276-285, 2012.

Qiu, B., Luo, Y., Tang, Z., Chen, C., Lu, D., Huang, H., Chen, Y., Chen, N. and Xu, W. Winter wheat mapping combining variations before and after estimated heading dates. *ISPRS Journal of Photogrammetry and Remote Sensing*, 123: 35-46, 2017.

Yan, L. and Roy, D. P. Improved time series land cover classification by missing-observation-adaptive nonlinear dimensionality reduction. *Remote Sensing of Environment*, 158: 478-491, 2015.