KARTIRANJE SPREMEMB RABE ZEMLJIŠČ IZ NJIVSKIH POVRŠIN V TRAJNE TRAVNIKE Z NAPREDNIMI METODAMI

CHANGE DETECTION WORKFLOW FOR MAPPING CHANGES FROM ARABLE LANDS TO PERMANENT GRASSLANDS WITH ADVANCED BOOSTING METHODS

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IZVLEČEK

Ugotavljanje sprememb rabe oziroma pokrovnosti zemljišč na satelitskih posnetkih je zahtevna naloga, še posebej pri spremembah iz njivskih v travniške površine. Fenološke faze njivskih površin se namreč spreminjajo zelo hitro, medtem ko so pri travnikih stabilnejše. Zaradi spektralne podobnosti poljščin v najvišji vegetacijski dobi in trav je zelo težko ločiti med njivami in travniki. V članku predstavljamo relativno preprost postopek za ugotavljanje sprememb njivskih površin v travnike z dobro učinkovitostjo in točnostjo. Pri predlagani metodi se uporablja kombinacija algoritma za prepoznavanje sprememb MAD (angl. multivariate alteration detection*) in obstoječe metode strojnega učenja boosting, kot sta algoritma AdaBoost z različnimi šibkimi učenci in Extreme Gradient Boosting, ki je precej nov pristop na področju daljinskega zaznavanja. Glede na rezultate raziskave znaša točnost rezultatov 89,51 %. Predlagani postopek je bil testiran na podatkih Landsat s 30-metrsko prostorsko ločljivostjo, pri čemer je bila uporabljena prosto dostopna programska oprema: R in GRASS GIS ter knjižnica Orfeo Toolbox.*

ABSTRACT

The necessity of mapping changes in land cover categories based on satellite imageries is a challenging task especially in terms of arable land and grasslands. The phenological phases of arable lands change quickly while grasslands is more stable. It might be hard to capture these changes regarding the spectral overlap between crops in full growth and grass itself. We have introduced a relatively simple processing workflow with good efficiency and accuracy. Our proposed method utilises the combination of a Multivariate Alteration Change Detection Algorithm and an existing boosting method, such as the AdaBoost *algorithm with different weak learners and the most recent one –* Extreme Gradient Boosting *that is actually a relatively new approach in remote sensing. According to the results, the highest overall accuracy is 89.51 %. The proposed process workflow was tested on Landsat data with 30 m spatial resolution, using open-source software:* R *and* GRASS GIS, Orfeo Toolbox library.

KLJUČNE BESEDE

daljinsko zaznavanje, strojno učenje, MAD, boosting, AdaBoost, strojno učenje, objektna analiza podob

KEY WORDS

Remote Sensing, Machine Learning, MAD, Boosting, AdaBoost, Machine Learning, Object-Based Image Analysis

1 INTRODUCTION

In terms of arable lands and permanent grasslands, it is not easy to capture changes with methods dedicated to remote sensing. Many crops in fields have a variable spectral response (Peng et al., 2013; Wang et al., 2017). In the Czech Republic, permanent grasslands include many plant species. Definition of land cover category permanent grasslands is determined by LPIS (Land Parcel Identification System, www.lpis.eu). Permanent grasslands are defined as dedicated sort of agricultural lands, where grass species and other types of forage crops are grown longer than five years (Elbersen et al., 2014). A detailed description of common vegetation species including grasslands can be found in Vegetation Science Group (Vegetation Science Group, 2005). Capturing changes between the arable lands and permanent grasslands is a challenging task because the spectral response of grass species and cereal may overlap especially during the time of maximum growth in vegetation season (Pakzad et al., 2001). Permanent grasslands (Carleier et al., 2009) are a stable part of the landscape but arable lands are very variable due to crop rotation during vegetation season (Esch et al., 2014). Therefore, there is a growing requirement in monitoring the changes between these land cover categories, especially when subsidies are taken into consideration due to biofuel management and decreasing biodiversity (Stoate et al., 2001; Stoate et al., 2009).

Fast and accurate evaluations allow remote sensing technologies that enable one to monitor these changes in a short time and over large areas (Atzberger, 2013). They appear to be quite popular in discriminating crops and grasslands (Helmholz et al., 2014; Smith and Buckley, 2001; Müller et al., 2015). On the other hand, studies specially dedicated to mapping change transitions between crops and grassland are not so common (Weeks et al., 2014; Klouček et al., 2018; Yang et al., 2017).

When changes between crops and permanent grasslands are to be mapped, it is better to be focused on land parcels where transitions from crops to permanent grasslands are more common. In addition to this fact, the focus on land parcels where investigated land cover changes occur leads to a higher level of accuracy (Lobo et al., 1996; Conrad et al., 2010). For now, several studies exist related to the monitoring of crops (Stefanski et al., 2013; Esch et al., 2014; Belgiu and Csillik, 2018) using high and moderate resolution optical images.

However, the most recent studies focus on the utilisation of multitemporal data (Chen et al., 2018; Yin et al., 2018; Pflugmacher et al., 2019; Xu et al., 2018). Mapping transitions between crops and grasslands that only utilises bitemporal data are quite rare (Helmholz et al., 2014; Yang et al., 2017; Klouček et al., 2018). The advantage of using bi-temporal images is simplicity in the amount of data acquisition and speed of processing in comparison to image time series.

In this study, we present hybrid change detection method based on MAD (Multivariate Alteration Detection) transformation (Nielsen et al., 1998) in connection with boosting methods that have the ability to reduce bias and variance (Breiman, 1996) in order to capture transitions from arable lands to permanent grasslands. The ability of boosting methods to reduce bias and variance might be very efficient in order to generalize crop phenology rotations. These parameters are requested when spectral fluctuations occur very often and they need to be reduced in order to obtain accurate results. This is especially in the case when mapping vegetated areas with changes between them. In order to monitor changes from arable lands to permanent grasslands we have chosen study area (See section 2) in the north of the Czech Republic where these changes are certain. This fact was validated by the overlaying of vector layers from LPIS (www.lpis.eu).

MAD transformation only brings about binary information on the change so that there is a request to label the change information in order to obtain the standard land cover transitions 'from – to', therefore it means to select proper classifiers. Boosting ones can handle this task very well.

The core of MAD transformation is a canonical correlation analysis (Hotelling, 1936), which creates orthogonal image differences called MAD variates that contain different sorts of changes and are uncorrelated with each other. It has been proven that this method is really efficient in detecting changes (Aleksandrowicz et al., 2014; Ma et al., 2016; Canty and Nielsen, 2012; Niemeyer et al., 2008). A few years later, the original MAD was enhanced with an iteration scheme (Nielsen, 2005; Nielsen, 2007) that appears to be able to detect changes in agricultural areas reliably (Nielsen et al. 2010). But we preferred testing the original MAD transformation due to its implementation in the open-source library *Orfeo Toolbox* (Christophe et al., 2008; Inglada and Christophe, 2009) in comparison to the *IR-MAD* algorithm (Canty and Nielsen, 2012).

2 STUDY AREA

The study area is located in the north of the Czech Republic (Figure 1), in the northern foothills of Jizerské hory (Jizera Mountains) near Frýdlant, Hejnice, and Raspenava, roughly 30 km from the regional capital of Liberec. The area is largely covered by vast expanses of meadows, pastures and arable land and coniferous forests. In the data model, the whole area of approximately 189 km^2 is bordered by a polygon in the WGS 84 UTM 33N coordinate reference system. The study area is located in a mild climate with an average annual temperature of 8 ^{0}C. The average annual precipitation is 800 mm and the average sunshine is 1400 hours per year.

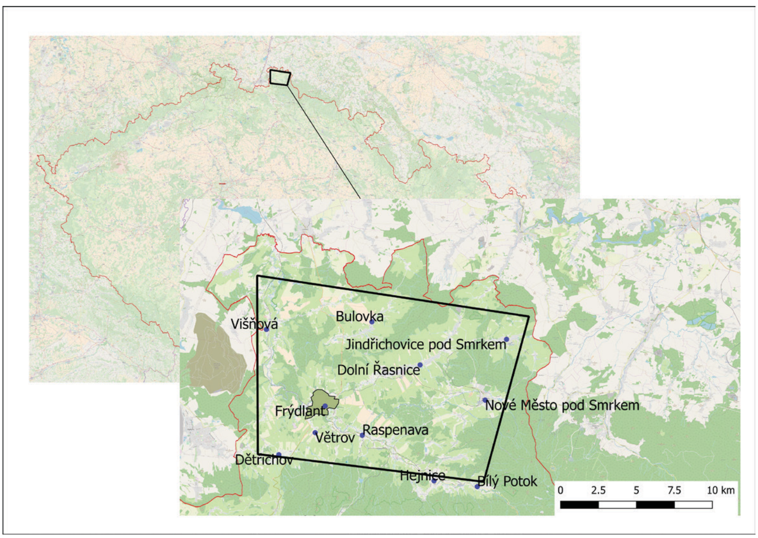

Figure 1: The detail of the selected study area in the north of the Czech Republic.

3 MATERIALS AND METHODS

3.1 Research aims

The aim of the research has been to introduce and test our process workflow (Figure 2) for mapping changes from arable lands to permanent grasslands. It utilises a combination of the original MAD (Multivariate Alteration Detection) transformation (Nielsen et al., 1998) and one of the advanced boosting algorithms. The main task is to choose the most suitable one with the highest accuracy and reliability in connection with the MAD transformation and bitemporal optical imagery.

3.2 Why boosting methods?

There are plenty of machine learning algorithms, but one specific method has been developed to reduced bias and variance in the form of boosting (Breiman, 1996). The history of boosting technique arises from the *AdaBoost.M1* algorithm (Freund and Schapire, 1996) that uses the output from weak classifiers (weak learners) to create a strong one – the core of the boosting technique. As it was mentioned above, the spectral signatures of the vegetation are quite variable so that boosting algorithms are the best solution in order to reduce the bias in phenological stages, especially when it is hard to distinguish between the different sorts of crops and grasslands. Their spectral signatures may overlap and it might be challenging to recognise them. In general, boosting algorithms show very good results in terms of accuracy in remote sensing (Zhou et al., 2015) especially when a combination of different weak learners is utilised (Dhou et al., 2018). Due to their general reliability in remote sensing tasks we decided to test their performance in our land cover change detection workflow. The advantage of the *AdaBoost* algorithm (Freund and Schapire, 1996; Schapire, 2003) is the possibility of changing weak learners. We tested the performance of the *AdaBoost* algorithm with different weak learners. Firstly, we tested *AdaBoost* with C4.5 decision trees (Salzberg, 1994), the *Random Forest classifier* (Breiman, 2001) and *Decision Stumps* (Iba and Langley, 1992), which are simple forms of standard decision trees (Breiman et al., 1984) including the modified version of the *AdaBoost* algorithm – *MultiBoost AdaBoost* (Webb, 2000). All forms of the *AdaBoost* algorithms were tested in the *WEKA* software package (Eibe et al., 2016) that was accessed through the *RWeka* package (Hornik et al., 2009) in R software (R Core Team, 2017).

The latest advanced boosting algorithm is *Extreme Gradient Boosting* (*XGboost*). It appears that this boosting algorithm is a robust and highly accurate classifier in the field of remote sensing (Georganos et al., 2018). *XGboost* utilises standard decision trees as weak learners and uses the gradient boosting technique (Breiman, 1997). The difference between *AdaBoost* and *Gradient Boosting* technique is in the approach, how these classifiers identify weak learners. *AdaBoost* finds weak learners based on high weights on weak learners in comparison to *Gradient Boosting* algorithm that identifies weak learners by gradients in the loss function. The loss function in terms of boosting is a measure to indicate the efficiency of weight coefficients that fit underlying data.

Implementation of *XGboost* algorithm was undertaken with the help of the *xgboost* package (Chen et al., 2017). Tuning of the *XGBoost* algorithm was executed with the help of the *caret* package (Wing et al., 2017) in *R*. All models were tuned with ten-fold cross-validation and repeated five times.

3.3 Data used and data processing

3.3.1 Data pre-processing

For the purpose of the analysis, we used a pair of optical images, the Landsat 5 ETM+ and the Landsat 8 OLI, both downloaded from the USGS archive. The first image (Landsat 5) was captured on 3. 7. 2010 and the second one on 6. 6. 2015. We used two methods of atmospheric correction schemes – the first one was the dark object subtraction method – DOS1 (Chavez et al., 1996) and the second one the LEDAPS (Landsat Ecosystem Disturbance Adaptive Processing System) algorithm (Masek et al., 2013) to calculate the surface reflectance. MAD (Multivariate Alteration Detection) transformation is insensitive to the differences in gain and the offset and different atmospheric conditions, therefore, it is suitable for change detection with different sensors (Aleksandrowicz et al., 2014). Its insensitivity to gain and offset differences arises from similarity to standard Principal Component Analysis (PCA). MAD variates are calculated as orthogonal differences between both images. These orthogonal differences are created as linear combinations from original images similar to PCA transformation. PCA offers generalized information obtained from original image separated from the noise dedicated to higher components. Then analogously similar principal is valid for MAD variates, where each MAD variate contains different intensity of change information and noise. Then both scenes were co-registered with each other and resampled with the nearest neighbour algorithm with the help of a third-degree polynomial transformation in ENVI 5.2. The root mean square error was less than 1 m.

3.3.2 Ancillary data

We used vector layers from LPIS for the years 2010 and 2015 as the ancillary data. LPIS is a geographical information system to monitor agricultural subsidies and it is administered by the Ministry of Agriculture of the Czech Republic (http://eagri.cz/public/app/lpisext/lpis/verejny2/plpis/). LPIS data is periodically updated and controlled via in situ inspections. LPIS database contains information about crop types and agricultural areas. From the point of view of this study, we extracted classes that are registered within LPIS database – *Arable lands* and *Permanent grasslands*. These classes were extracted in polygon format for further processing and investigations. In terms of LPIS *Arable lands* are defined as areas where agricultural crops are grown and they are not utilised for growing grass species. On the other hand, *Permanent grasslands* are known as areas where grass species are grown for a period of more than five years and follow the rules of subsidy policy from the European Union. LPIS vector layers served as the reference for the creation of the training and validation datasets in the form of spatial points as well as masks for crops and grassland areas.

3.3.3 Description of the process workflow

From the standardised images from the previous steps, we calculated several vegetation indices (Table 1) for both Landsat scenes. These indices were put into MAD (Figure 2) transformation (Nielsen et al., 1998) and post-processed with the Maximum Autocorrelation Factor (MAF) (Switzer, 1985) as it was recommended to further enhance the change information (Canty and Nielsen, 2012). From the conditional existence of the MAD transformation, we reached the same amount of MAF components. These MAF components contain different change information types. Then it was decided to choose the best combination of the three MAF components. We calculated the Optimum Index Factor (OIF) (Jensen, 1986):

$$OIF = \frac{\sum_i S_i}{\sum_i \sum_j R_{ij}} \quad (1)$$

S_i standard deviation of the *i* spectral band

R_i correlation coefficient for all possible combinations of the *i*, *j* spectral bands

Table 1: Calculated vegetation indices.

Vegetation Index	Equation	
Difference Vegetation Index	DVI=NIR-RED	(Foley et al., 1998)
Green Difference Vegetation Index	GDVI=NIR-GREEN	(Sripada et al., 2005)
Green Ratio Vegetation Index	$GRVI = \frac{NIR}{GREEN}$	(Sripada et al., 2005)
Infrared Percentage Vegetation Index	$IPVI = \frac{NIR}{NIR + RED}$	(Crippen, 1990; Kooistra et al., 2003)
Modified Non-Linear Vegetation Index	$MNLI = \frac{(NIR^2 - RED) * (1 + 0,5)}{NIR^2 + RED + 0,5}$	(Yang et al., 2008)
Modified Simple Ratio	$MSR = \frac{\left(\frac{NIR}{RED} - 1\right)}{\left(\sqrt{\frac{NIR}{RED}}\right) + 1}$	(Chen, 1996)
Normalized Difference Vegetation Index	$NDVI = \frac{NIR - RED}{NIR + RED}$	(Rouse et al., 1974)
Non-Linear Index	$NLI = \frac{NIR^2 - RED}{NIR^2 + RED}$	(Goel and Qin, 1994)
Optimized Soil Adjusted Vegetation Index	$OSAVI = \frac{1,5 * (NIR - RED)}{(NIR + RED + 0,16)}$	(Rondeaux et al., 1996)
Renormalized Difference Vegetation Index	$RDVI = \frac{(NIR - RED)}{\sqrt{(NIR + RED)}}$	(Roujean and Breon, 1995)
Soil Adjusted Vegetation Index	$SAVI = \frac{1,5 * (NIR - RED)}{(NIR + RED + 0,5)}$	(Roujean and Breon, 1995)
Simple Ratio	$SR = \frac{NIR}{RED}$	(Birth and McVey, 1968)
Transformed Vegetation Index	$TVI = \sqrt{0,5 + \frac{(NIR - RED)}{(NIR + RED)}}$	(Deering, 1975)

The higher the OIF is (1), the better it is for change detection purposes. All MAF components were then directly classified (without OIF) using the pixel-based approach and then with the highest OIF. The first dataset for the pixel-based classifications was the full MAF difference image obtained from the calculated vegetation indices (Table 1) then with OIF reduction. For the object-based approach, the best combination of the MAF components obtained with the highest OIF was imported into *GRASS GIS* (GRASS Development Team, 2017) and segmented. The parameters of the segmentation algorithm were selected automatically (Lennert, 2016). We calculated the spectral (minimum, maximum, average, range), the shape (area, perimeter, compact circle, compact square, fractal dimension) and all the textural features (Haralick and Shanmugam, 1973) in all directions. Feature extraction was undertaken through the *i.segment.stats* module (Lennert, 2018). All the features were exported and classified in *R* software (R Core Team, 2017) using the tested boosting algorithms.

We defined three land cover classes: *1. Arable land – Arable land*, *2. Grassland – Grassland*, *3. Arable land – Grassland*. In the first round, the full dataset of the exported features was used with a total count of 584 and directly classified. In the second round, dimensionality reduction was performed with the help of the Correlation Feature Selection (CFS) algorithm (Hall, 1999; Hall and Holmes, 2003). We used the CFS algorithm for its fast computation and efficiency (Georganos et al., 2018).

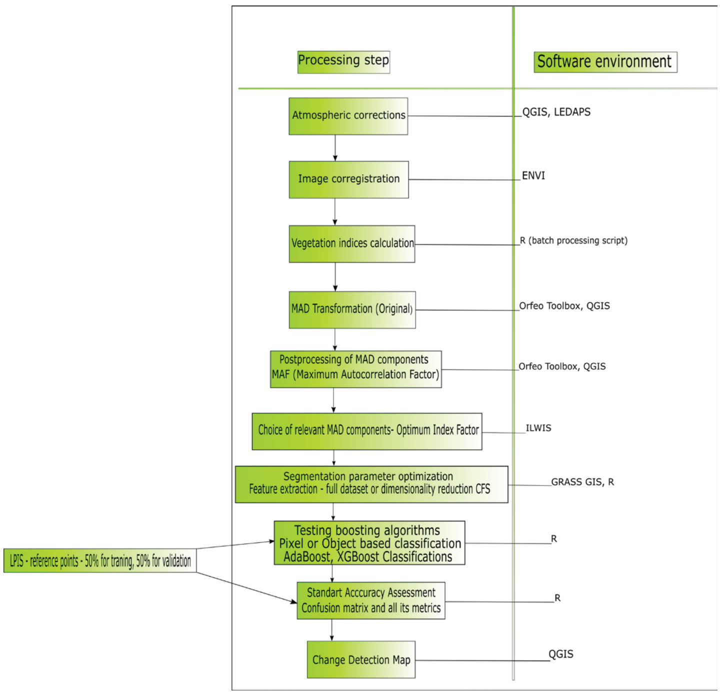

Figure 2: Overview of the proposed change detection workflow.

As a reference, we used LPIS polygons to create 3000 spatial reference points with a stratified random sampling strategy. 50% was used as the training dataset and the second half was used as a validation dataset. For each class, we used an equal size of samples – 1000 points. For the purposes of 10-fold cross-validation, 70 % of the total 1500 training points from training dataset were used for training and 30 % for validation. The accuracy assessment process was implemented in the classification process to quickly validate the results. We used the standard error matrix with the overall, the producer's and the user's accuracy metrics (Congalton, 1991; Congalton and Green, 2008) and with the kappa coefficient (Cohen, 1960).

Finally, we statistically evaluated all the classifications accuracies. As a statistical criterion, we used Friedman's test (Friedman, 1937; Friedman, 1940; Demšar, 2006) that revealed statistically significant differences between the means of the overall accuracies of all the classifiers. As a post hoc test, the Nemenyi statistical test (Demšar, 2006; Nemenyi, 1962) was used in order to discover the differences between each pair of the classifiers. We implemented it in R software (Pohler, 2014).

4 RESULTS

Five different boosting classifiers and two different atmospheric correction methods were tested. The results show that all algorithms perform equally well, however, one exception appears. It is the most often used AdaBoost with the Decision Stump as a weak classifier. It can be seen that this most frequently utilised version of the AdaBoost algorithm with decision stumps produces unstable results for all cases (Figure 3). On the other hand, the Extreme Gradient Boosting algorithm and AdaBoost with the Random Forest as a weak classifier perform equally well for mapping changes from arable land to grassland. As for the pixel-based classifications, it can be seen that no dimensionality reduction is required (Figure 3 A and B). OIF dimensionality reduction leads to a decrease by 10 % on average for the overall, the user's and the producer's accuracies for DOS1 and almost 20 % for the pixel classifications of the products corrected with LEDAPS (Figure 3 E and F). Therefore, dimensionality reduction in case of pixel-based classifications of MAF components is not recommended. It leads to a loss of a significant amount of important information.

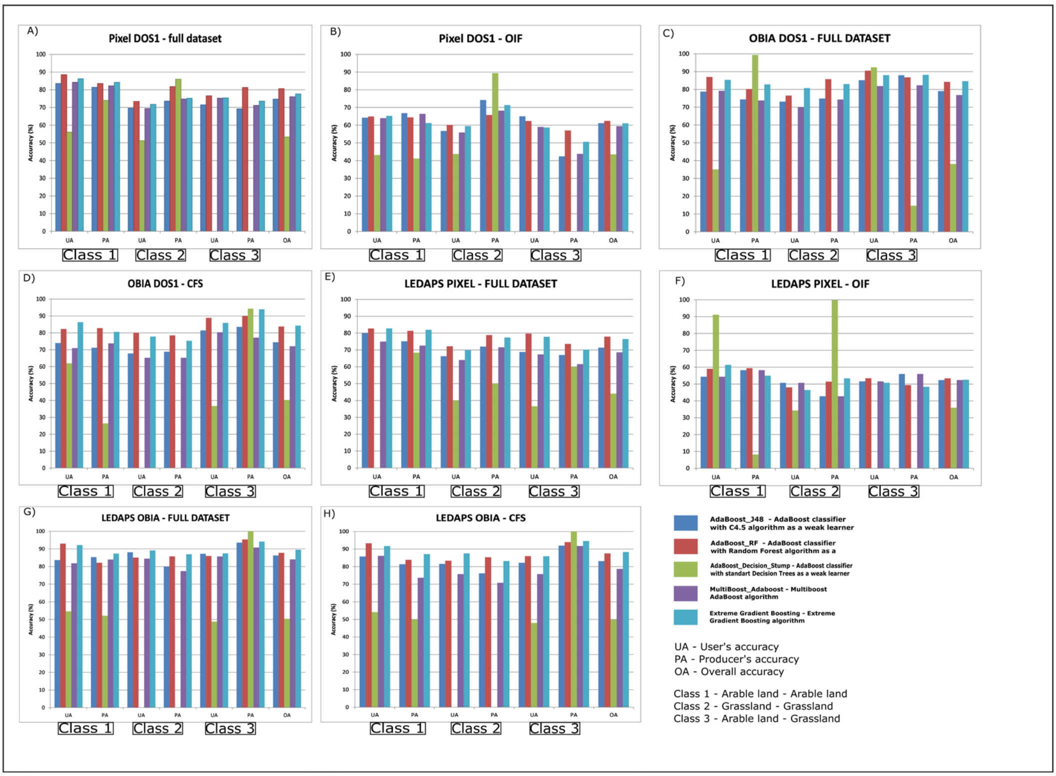

Figure 3: The producers', users' and overall accuracies for all the tested algorithms.

On the other hand, object-based classifications produce more stable results without a salt and pepper effect (Figure 4). DOS1 data correction (Figure 3 C and D) with a full feature set and after the CFS feature selection provides similar results. The highest user's, producer's and overall accuracies are given by the object-based image analysis of the products processed by LEDAPS with all 584 features (Figure 3 G). When these features were reduced (Figure 3 H), the accuracies are similar, therefore, it is recommended to use an additional feature selection, as the CFS algorithm.

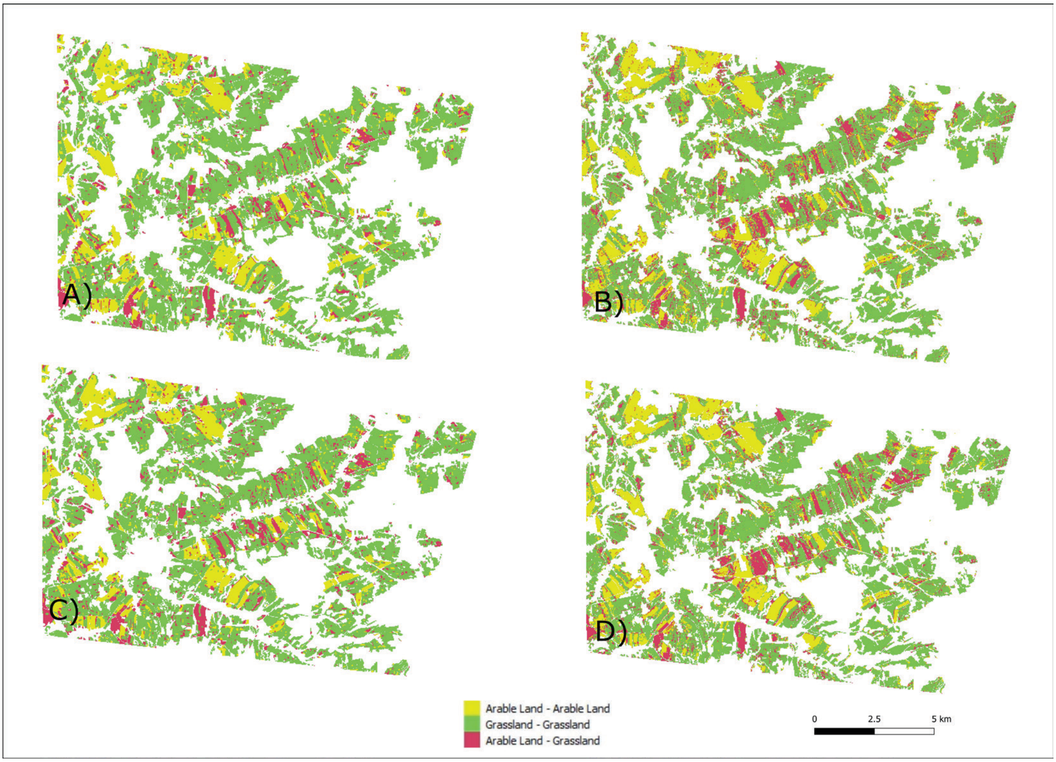

Figure 4 The results of the pixel-based (right column) and object-based (left column) classifications for the products corrected with the LEDAPS algorithm (a) Extreme Gradient Boosting OBIA (b) Extreme Gradient Boosting Pixel (c) AdaBoost with Random Forest OBIA (d) AdaBoost with Random Forest Pixel

A statistical evaluation shows obvious differences between AdaBoost with the Decision Stump (Table 3) and the other tested AdaBoost algorithms including the Extreme Gradient Boosting. However, other values indicate that the differences are not statistically significant. Though, in terms of speeding up the computations and efficiency, it is advisable to use the Extreme Gradient Boosting algorithm including the feature selection. The Extreme Gradient Boosting algorithm – 89.51 % (Table 2) reached the absolute highest overall accuracy, the second one was AdaBoost with the Random Forest as the weak classifier – 87.78 % which appears to be a relevant alternative for classifying changes from arable land (Table 2) to permanent grasslands. These two highest overall accuracies were reached for the products corrected by LEDAPS algorithm in connection with object-based classifications.

Table 2: Overall accuracies for all the tested boosting algorithms (%)

	DOS1 - PIXEL - FULL DATASET	DOS1 - PIXEL - OIF	LEDAPS - PIXEL - FULL DATASET	LEDAPS - PIXEL - OIF	DOS1 – OBJECT-BASED, FULL DATASET	DOS1 – OBJECT-BASED, CFS	LEDAPS – OBJECT-BASED FULL DATASET	LEDAPS – OBJECT-BASED, CFS
AdaBoost_J48	75	61	71	52	79	74	86	83
AdaBoost_RF	**81**	**62**	**78**	**53**	84	84	88	88
AdaBoost_DS	53	44	44	36	38	40	50	50
MultiBoost_ AdaBoost	76	59	69	52	77	72	84	79
Extreme Gradient Boosting	78	61	77	53	**85**	**84**	**90**	**88**

Table 3: Pairwise comparison for all boosting algorithms – p values after the post hoc Nemenyi test for critical level α = 0,05 (p value less than α means statistically significant result)

	AdaBoost_J48	AdaBoost_RF	AdaBoost_DS	Multiboost_AdaBoost
AdaBoost_RF	0.56109	-	-	-
AdaBoost_DS	0.04485	0.00019	-	-
Multiboost_AdaBoost	0.71282	0.04485	0.56109	-
Extreme Gradient Boosting	0.66359	0.99986	0.00038	0.06872

Legend:

AdaBoost_J48 *– AdaBoost algorithm with C4.5 classifier as a weak learner*

AdaBoost_RF *– AdaBoost classifier with the Random Forest algorithm as a weak learner*

AdaBoost_DS *– AdaBoost classifier with standard Decision Trees as a weak learner*

MultiBoost_AdaBoost*– Multiboost AdaBoost classifier itself*

Extreme Gradient Boosting *– Extreme Gradient Boosting classifier itself*

DOS1 dataset in the object domain reached less accurate results without and with CFS feature selection (Table 2) in comparison to the dataset corrected by the LEDAPS algorithm. This fact shows that it is better to use surface reflectance products created by LEDAPS algorithm than doing simple atmospheric correction in the form of dark object subtraction.

5 DISCUSSION

We demonstrated the effectiveness of boosting classifiers for mapping changes from arable lands to permanent grasslands with utilisation of MAD transformation algorithm (Nielsen et al., 1998). Our results show that boosting algorithms provide efficient tool for high dimensional datasets especially in object-based image analysis (584 features extracted). Novelty of Extreme Gradient Boosting algorithm proves here its merits as well as in urban areas (Georganos et al., 2018) with help of CFS feature selection algorithm (Hall and Holmes, 2003; Hall, 1999).

The limitations of our tested methodology arise from bitemporal imagery, where the biggest issue is to find the proper combination cloud-free imagery. On the other hand, once this is managed, our results show the effectiveness of our proposed methodology. There are other similar studies to our work and they appear to be effective in terms of providing accurate results as well (Helmholz et al., 2014; Klouček et al., 2018; Yang et al. 2017).

Here we tested the Landsat satellite imagery that has a spatial resolution 30 m. Nowadays there are satellites with better spatial resolution such as Sentinel-2. Sentinel-2 satellites have the best spatial resolution of 10 m for the spectral bands B2, B3, B4, B8 (ESA 2019). Even if their red-edge bands B5, B6, B7, B8A (ESA, 2019; Qiu et al., 2019) have a worse pixel size 20 m it is quite a big advantage over the Landsat satellite used in this study. From this point of view, Sentinel-2 can bring an improvement in our proposed approach especially in the case of the utilisation of its red-edge bands. Its spectral bands with better spatial resolution of 10 m might bring an improvement, especially for object image analysis.

As a simple input dimensionality data reduction, we used the Optimum Index Factor (Ren and Abdelsalam, 2001) but a more traditional way for such a task is to use the Principal Component Analysis. Therefore, there is space for further investigations. Similar research should be concentrated on other feature selection methods other than CFS algorithm used in our study. A Recursive Feature Elimination algorithm implemented in the caret package for R (Wing et al., 2017) or the Boruta algorithm (Kursa et al., 2010) can serve as such examples. Both algorithms show good results (Duro et al., 2012; Ma et al., 2017).

The most important thing is that the boosting methods have the ability to extract the relative importance of each input variable. This is possible in the case of the Extreme Gradient Boosting algorithm that is implemented in the xgboost package (Chen et al., 2017) or the H2O api (LeDell et al., 2019) also available for R, Python or Java. This is not possible for the AdaBoost.M1 algorithm because we used the RWeka (Hornik et al., 2009) package. It is a wrapper package for R that allows one to use limited functions instead of the WEKA software (Eibe et al., 2016) itself where this functionality is fully available. However, we do not recommend one to use the WEKA software directly because it can use a lot of system memory in the case of large datasets. This limitation has been empirically tested during the computation process of our study. When one is not familiar with R or Java, the Python programming language and its scikit-learn library (Buitinck et al. 2013) offers a good alternative. We must highlight that our process workflow requires decent programming skills because the boosting methods are not implemented in the common proprietary software such as ENVI or ERDAS Imagine. The open-source library Orfeo Toolbox (Inglada and Giros, 2008) offers a user-friendly alternative but there is a limitation in terms of the inability to change weak learners and the proper parameter tuning of each classifier. The results show that it is good to do a feature selection (Ma et al., 2017) especially for the OBIA approach in order to reduce the computation time and improve the accuracy because less is sometimes more (Georganos et al., 2018). Therefore, selecting the most important variables is a necessary step similar to how as Klouček et al. (2018) showed. They demonstrated that a combination of different vegetations indices brings redundant information for the change detection from grasslands to arable lands when the bi-temporal Landsat scenes were tested as well, as in our study. However we still recommend using the feature selection (Ma et al., 2017) regardless if the boosting methods have the ability to work with large datasets. The choice of the proper feature selection method is still a challenge that remains to be solved.

If we look at the tested boosting classifiers, AdaBoost algorithm with Random Forest as a weak learner offers superior results in terms of accuracy. The Random Forest classifier itself (Breiman, 2001) showed superior results in remote sensing (Belgiu and Dragut, 2016) so that an excellent performance could have been expected even when the Random Forest classifier was used as a weak learner. The boosting classifiers are more computationally demanding than the standalone Random Forest algorithm, but, on the other hand, the boosted Random Forest offers immunity to overfitting thanks to its randomness (Breiman, 2001) and has the ability to reduce the bias and variance. We recommend using boosted Random Forest for smaller study areas due to its computational demands on the contrary to the standard Random Forest algorithm. In general, the computational demands of the boosting algorithms are perpendicular to the input amount of data to be analysed. However computational demands are not only derived from amount of input data but it also depends on the implementations of each algorithm which can differ significantly in the terms of speed. Therefore, a decent working station with a multicore CPU and a lot of RAM is recommended. Our computations were executed on an AMD Ryzen 1700 CPU with 32 GB RAM.

Extreme Gradient Boosting and AdaBoost with Random Forest are less vulnerable to overfitting on the contrary to AdaBoost with Decision Stump which was shown here. Potential improvements of our method arise from additional data – a creation of multitemporal datasets for each year for the sake of capturing temporal changes in reflectance. MAD algorithm is superior in handling different data from different sensors (Aleksandrowicz et al., 2014; Nielsen 2005) so that there may be another opportunity for improvement. We demonstrated effectiveness in obtaining reliable accurate results for mapping changes from arable land to grasslands only with bitemporal imagery. Many studies use multitemporal data, our approach uses only bitemporal data. This helps to overcome common issues such as availability of cloudless scenes and time-saving in terms of preprocessing and calibrating all input data when time series is used. Our process workflow utilises the most open-source software solutions and guarantees every interested person to replicate our experiments or adapt for own needs. However, all tested boosting algorithms perform really well and provide similar results, especially in object domain so that it is up to producer's choice and experience, time and fund possibilities which boosting algorithm to choose.

6 CONCLUSION

We successfully demonstrated the effectiveness of boosting methods in order to classify changes from arable lands to permanent grasslands in connection with MAD transformation. Our hybrid change detection workflow offers highly accurate results with high overall, producer's and user's accuracies when Landsat satellite data are used. We demonstrated that accurate results can be achieved with only two bitemporal scenes instead of standard image time series. We tested only optical data with spatial resolution of 30 m. Further improvement can be expected from Sentinel-2 satellites that have better spatial resolution than Landsat satellites and contain red-edge bands dedicated to vegetation mapping. Therefore, future research should be concentrated on Sentinel-2 data or other upcoming satellites that will have similar temporal, spatial and radiometric resolutions similar to Landsat satellite family.

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