PARCEL BASED CLASSIFICATION FOR AGRICULTURAL MAPPING AND MONITORING USING MULTI-TEMPORAL SATELLITE IMAGE SEQUENCES

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ABSTRACT

In this paper, we propose a new approach to pixel and parcel-based classification of multi-temporal optical satellite imagery. We first restore missing data due to clouds and shadows based on vector and raster data fusion in different phases of classification methodology. Pixel-based classification maps are derived from an ensemble of neural networks, in particular multilayer perceptrons (MLPs).. The proposed approach is applied for regional scale crop classification using multi-temporal Landsat-8 images for the JECAM site in the Kyivska oblast of Ukraine in 2013. The obtained results on crop area estimates are also compared to official statistics.

Index Terms — Classification, parcel-based, remote sensing, neural networks, agriculture, JECAM, Ukraine.

1. INTRODUCTION

Geographical location and distribution of crops at global, national and regional scale is an extremely valuable source of information for many applications [1]–[11]. Higher spatial, spectral and temporal resolution of satellite imagery allows to improve the quality of classification maps. Also, in order to discriminate different crop types, it is necessary to use multi-temporal images as opposed to a single imagery. New "free and open" data access policies, such as those for Landsat and Sentinel imagery, facilitate wide area mapping and continuous updating of agricultural crop maps. One of the main issues in utilizing optical imagery for crop mapping is the presence of clouds and shadows that introduce missing values. In order to deal with missing data in optical satellite imagery, a number of approaches have been proposed such as compositing [12] and filling in missing data [13]. Complementary use of optical and SAR imagery allow other gap-filling methods. Whereas classification accuracy could decrease for pixels with restored (filled) data, additional information, e.g. on field boundaries (or parcels), has the potential to boost the quality of the final maps. In this paper, we focus on comparison of pixel-based and parcel-based approaches to crop mapping using multi-temporal satellite imagery, in particular Landsat-8. Results are presented for the Joint Experiment of Crop Assessment and Monitoring (JECAM) test site in Ukraine [8], [14].

2. METHODOLOGY

One the main challenges in classification of multi-temporal optical satellite imagery is the presence of missing values caused by clouds and shadows. Therefore, in order to provide input to a classification algorithm, one should present valid values in the time-series satellite imagery. In this paper, it is proposed to restore such missing values. The proposed approach combines unsupervised and supervised neural networks for missing data restoration and supervised classification, respectively. First, self-organizing Kohonen maps (SOMs) are applied to restore missing pixel values in a time series of satellite imagery [13], [15]. Then, a supervised classification is performed to classify multi-temporal satellite images [16]–[18]. For this, a committee of NNs, in particular multi-layer perceptrons (MLPs), is utilized to improve performance of individual classifiers. The MLP classifier has a hyperbolic tangent activation function for neurons in the hidden layer and logistic activation function in the output layer. The committee is formed using MLPs with different parameters trained on the same training data. Outputs from different MLPs are integrated using the technique of average committee. Under this technique the average class probability over classifiers is calculated, and the class with the highest average posterior probability for the given input sample is selected.

In the study, two approaches are applied and compared for crop mapping: pixel-based (approach A) and parcel-based [19]. Within the latter approach, two options are exploited to decrease the impact of uncertain (restored from clouds) information (B and C). The main idea of the first approach (B) is vector information about parcels and raster pixel-based classification map data fusion. This approach was divided in two experiments (B1 and B2) depending on decision-making methods. In B1, we used only vector data and the classification map. Nevertheless, considering that our classification methodology to restore no-data pixels has non-perfect reliability we take into account the impact of information restored from clouds and shadows (Fig. 1). In the experiment B1 we use a map from pixel-based classification. A parcel is assigned to the class with maximum number of pixels within the parcel (restoring pixels and trustful pixels has the same impact). If more than half the pixels in the polygon have incorrect class, B1 method assigns to the parcel an incorrect class and decreases overall accuracy of the resulting classification map (Fig. 2). In the B2 approach, we propose to take into account restoring pixels class and decrease its impact on the result. We attributed to trustful pixels a weight equal to 1, and for each restored pixel the square of the ratio between the number of unclouded images and all images in time-series. B2 is more accurate than B1 but it is useful only for the classification of optical images time-series. The main advantage of the B1 approach is that it is universal.

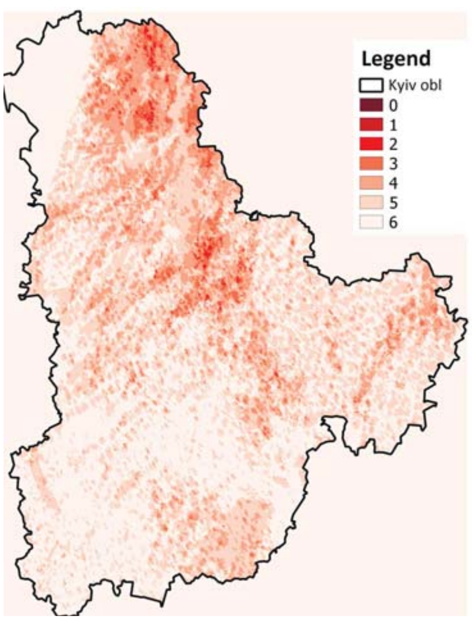

Fig. 1. Cloud cover score that shows number of cloud-free images (0 means no cloud-free images, while 6 shows that all 6 images were cloud-free). For majority voting incorporating cloud score, the cloud score value was normalized (in this case by 6) to ensure that coefficient values are in the range from 0 to 1.

Within the second approach (C), input features (e.g. surface reflectance values) are averaged within the parcel taking into account unclouded pixels, and are input to the classifier which assigns the corresponding class to the parcel. An alternative approach could be based on complementary use of SAR and optical time series [20]. This is particularly interesting after the successful launch of the new Copernicus Sentinel-1A satellite, which is already providing systematic coverage for some important agricultural production areas, including Ukraine.

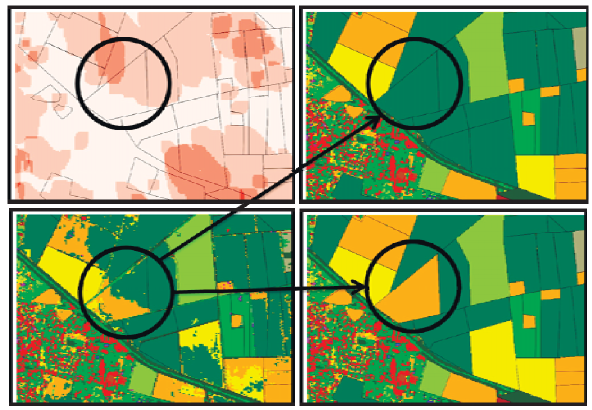

Fig. 2. An example of restoring pixels affected by cloud cover on the data fusion result. Top left is the cloud cover mask, bottom left the pixel-based classification. Parcel based classification results for the B1 and B2 experiments are in the top and bottom right, respectively.

The presented approaches, which are based only on optical images for now, are compared in terms of classification accuracy and crop areas that are estimated using a pixel counting technique and also compared to official statistics.

3. STUDY AREA AND MATERIALS DESCRIPTION

The JECAM test site in Ukraine was established in 2011 and covers the administrative region of Kyiv oblast with the geographic area of 28,100 km2 and almost 1.0 M ha of cropland. The northern part of the region is dominated by forests and grasslands, while the central and southern parts are agriculture intensive areas. The crop calendar is September-July for winter crops, and April-October for spring and summer crops. Major crop types include maize (25.1% of total cropland area in 2013), winter wheat (16.1%), soybeans (12.6%), vegetables (10.3%), sunflower (9.3%), spring barley (6.8%), winter rapeseed (4.0%), and sugar beet (1.3%). Fields in the region are quite large (except family gardens) with size generally ranging up to 250 ha.

Ground surveys were conducted in June 2013 to collect data on crop types and other land cover classes. The European Land Use and Cover Area frame Survey (LUCAS) nomenclature is used in this study as a basis for land cover /

land use types. In total, 386 polygons are collected covering the area of 22,700 ha.

Remote sensing images acquired by the Operational Land Imager (OLI) sensor aboard Landsat-8 satellite are used for crop mapping over the study region. Three scenes with path/row coordinates 181/24, 181/25 and 181/26 cover the test site region. Satellite images are pre-processed to remove the effect of atmosphere using the Simplified Model for Atmospheric Correction (SMAC). Therefore, each pixel value is converted to the surface reflectance (SR) value. Images acquired on April 16, May 02, May 18, June 19, July 05, and August 06 2013 are used in this study. Multi-temporal Landsat-8 images acquired in bands 2 through 7 are reconstructed using SOMs and used for classification of satellite imagery. The entire set of surveyed fields are randomly divided into training set (50% of polygons) to train the classifier and testing set (50%) for testing purposes. Polygons are selected in such a way so there is no overlap between training and testing sets. A parcel is considered to belong to a particular class based on the majority of pixel classifications within the parcel boundary.

Table 1. Comparison of crop area from official statistics with Landsat-8 derived using a pixel-based classification and parcel-based classification.

Crop	Official statistics (1000 ha)	Pixel-based app. A (1000 ha / error %)	Parcel-based (app. B1) (1000 ha / error %)	Parcel-based app. B2 (1000 ha / error %)
Winter wheat	187.3	184.5 / - 1.5	174.5 / -6.8	179.1 / -4.4
Winter rapeseed	46.7	59.9 / 28.3	54.3 / 16.3	52.4 / 12.2
Maize	291.7	342.4 / 17.4	373.8 / 28.1	368.3 / 26.2
Sugar beet	15.5	11.2 / -27.9	16.2 / 4.6	8.4 / -45.9
Sunflower	108.2	117.6 / 8.7	114.5 / 5.8	106.5 / -1.6
Soybeans	145.9	168.5 / 15.5	142.3 / -2.5	143.2 / -1.9

4. RESULTS

When comparing classification accuracy at pixel level, pixel-based classification (approach A) and parcel-based approaches (B1, B2 and C) yielded 85.32%, 87.70%, 89.30% and 78.18% overall accuracy on testing data set, respectively. When comparing classification accuracy at parcel level, parcel-based approaches B1, B2 and C yielded 84.0%, 84.5%, and 82.19% overall accuracy, respectively. Therefore, parcel-based classification derived from per-pixel classification map provided better results than classification at purely parcel level (Fig. 3). Note, however, that there were several cases where the parcel-based classification grouped distinct segments that showed different classification results in the pixel-based classification. These were typical connected segments that resulted from the second or third majority class within a parcel boundary that likely included crop sub-divisions. We are working on methods to resolve such cases. The derived classification maps were used for crop area estimation. Crop areas were estimated using a pixel counting method for classification approach A, and by estimating the areas of classified parcels in approach B. The obtained crop areas with comparison to official statistics are provided in Table 1. Parcel-based estimates were closer to the official estimates for most crops. The major inaccuracies were for summer crops as discrimination power of optical imagery was not enough. For this, we will use radar imagery to increase classification accuracy [20].

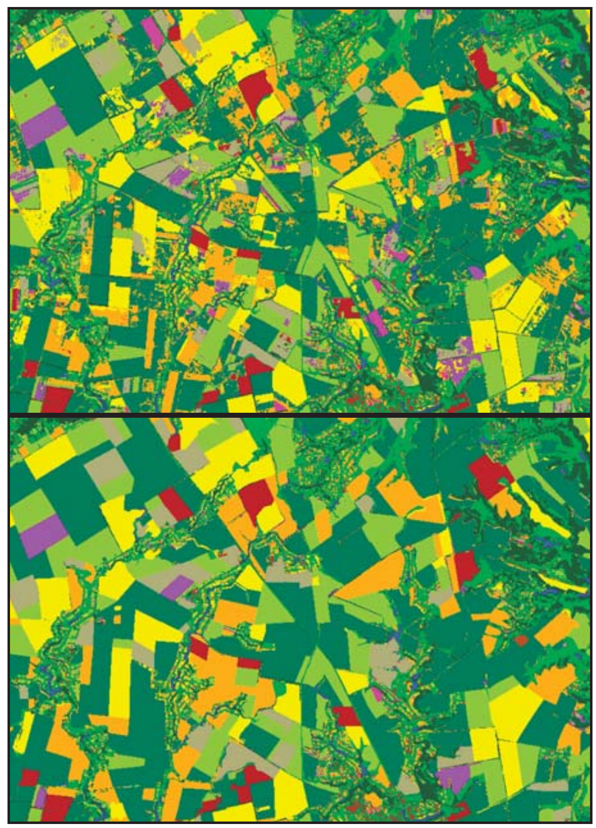

Fig. 3. Results of pixel-based (top) and parcel-based B2 (bottom) classification of Landsat-8 time-series.

5. CONCLUSIONS

In this paper, we addressed a problem of crop mapping from multi-temporal satellite imagery that are affected by clouds and shadows and introduce missing data. For this, a combination of unsupervised and supervised neural networks was applied. Pixel-based and parcel-based approaches were investigated. Different parcel-based approaches were assessed with the approach that uses per-pixel classification map with majority voting taking into account unclouded pixels shows better performance. Crop areas derived from parcel-based maps show better accuracy to pixel-based approach when comparing to official statistics. Our method is sufficiently generic to include further data set, and we hope to be able to present initial results for the 2015 season, possibly with the inclusion of Sentinel-1 time series. We also intend to experiment with Google Earth Engine to extend our methodology to large area crop classification.

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