Identifying crops in smallholder farms using time series of WorldView-2 images

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***Abstract*—A high heterogeneity in farming factors (soils, weather, inputs, practice) characterizes the typical smallholder farm landscapes of sub-Saharan Africa. This complicates automatic classification to crop when using only spectral information of very high spatial resolution image time series. This work addresses the crop identification problem in smallholder landscapes through three steps: features extraction, feature selection and classification. Feature extraction is used to exted the spatial-spectral information of the farm fields, with a substantial number of features considered through cloud computing. Feature selection is based on correlation between the features and the labels of the field's crops and it is applied to reduce the dimensionality of the data without lose information. Finally, a random forest classifier is applied to identify a crop class per field. Good preliminary results were obtained reducing the number of features from** 1638 **to** 66**. The overall accuracy achieves** 80% **in the test set using a random forest classifier.**

I. Introduction and Motivation

A strong demographic boom has taken place in sub-Saharan Africa in the last decades, and it is projected to continue until the 2080s [1], [2]. Given this development, governmental and non-governmental organizations alike are seeking ways to sustainably improve agricultural productivity in this part of the world. It is clear that the use of remote sensing technology may help in agricultural decision-making. Over the last decades, this technology has become a commomnly used tool in many projects that address food security and land resources [3]. However, its use in sub-Saharan Africa is challenging because of the types of crop grown and the cropping technique applied. Smallholder farms, which dominate the African agricultural landscape, are characterized by a heterogeneous mosaic of crops [4] and a huge variability that complicates the use of remotely sensed images, for instance in crop identification. Increased spatial resolution of the images helps to improve the detection and identification of crops. Nevertheless, Very High Spatial Resolution (VHSR) images typically come with limited spectral resolution and this negatively affects the potential for crop discrimination. This spectral limitation can be partially overcome by the acquisition of image time series from which meaningful spectral and spatial features can be derived.

In the work reported here, we use a combination of spatial-spectral features extracted from a VHSR image time series to classify crops in smallholder farm fields in sub-Saharan West Africa. Thanks to the use of cloud computing (Google Earth Engine), we generated a wide array of features. To reduce the dimensionality problem thus created, we applied feature selection before training the classifier. This work is a first step in the automatic recognition of smallholder crops in sub-Saharan Africa, a pre-requisite for the wide adoption of sustainable land management and for the development their (rural) cadastre.

II. Data

The multispectral images used in this study were acquired by *WorldView-2* [1]. The platform provides images with eight spectral bands and with a spatial resolution of 2 meters. The multispectral images were preprocessed using the satellite image workflow [2] developed in the STARS project [3]. With this workflow the images were mosaicked, orthorectified, co-registered with trees and clouds automatically masked out. The multispectral images cover 10km^2 near Sukumba, Koutiala district, Mali. A total of seven acquisition dates were available for the year 2014 (Fig. 1). The images were acquired from May to November, in correspondence with the crop season in this area [5]. A total of 201 farm field polygons, which were delineated during field work, were analysed at object-level (a farm field considered as a single entity) to extract and classify the smallholder crops. Five crop classes of interest were identified in the farm fields: Maize, Millet, Peanut, Sorghum and Cotton.

III. Methods

The approach used in this study consists of four steps: 1) spectral and spatial feature extraction, 2) selection of the most important features based on correlation, 3) lifting pixel-based feature values to object-based farm field values, and 4) classification of farm fields. First, the Normalized Difference Vegetation Index [6], the Enhanced Vegetation Index (EVI) [7], the Transformed Chlorophyll Absorption in Reflectance Index (TCARI) [8], the Soil-Adjusted Vegetation Index (SAVI) [9] and the Modified SAVI (MSAVI) [10] were calculated at pixel level, for each of the seven images in the

[1] http://www.satimagingcorp.com/satellite-sensors/worldview-2/
[2] http://web.natur.cuni.cz/gis/lucc/wp-content/uploads/2016/06/poster_2016_EARSeL_NASA_Prague_v3_printed.pdf
[3] http://www.stars-project.org/en/

978-1-5386-3327-4/17/$31.00

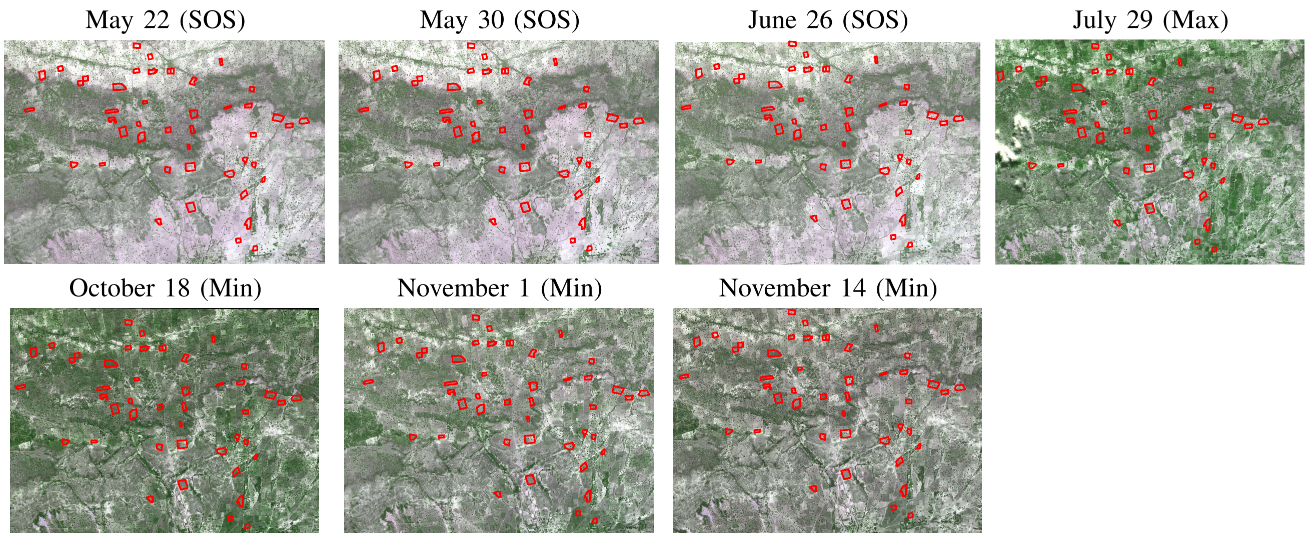

Fig. 1: Farm field polygons (red) overlapping RGB time-series composites of the study area [SOS: Vegetation start of season, Max: Maximum range and Min: minimum range of the vegetation].

time series. Then, 17 textures based on the Gray Level Co-occurrence Matrix [11] were extracted from all original image bands as well as from the derived vegetation index images. Subsequently, the average of each (pixel-based) feature was calculated per farm field. This process was done using the Google Earth Engine (GEE),[4] a cloud-based application that specializes in geospatial data processing. After that, we determined the correlation between per-field feature values and the land use crop labels. Next, we selected a set of features taking into account two standard deviations of the correlation per class. Finally, a Random Forest classifier was trained to identify the crops.

IV. Experiments and Results

The farm field polygons were split into a training (of 150 fields) and a test (of 51 fields) subset. The splitting of the data set was done in ten runs to obtain the best partitions to train the random forest classifier. After this, a total number of ten realizations were accomplished by the random forest to avoid biased results. The feature selection based on correlation reduced the dimensionality of the data from 1638 to 66 features. Both spectral and spatial features occur in this reduced set. However, the majority is spatial (i.e., textural based on GLCM). The average overall accuracy OA obtained is 80%, while the estimated Cohen's kappa statistic κ is 0.75 for the 66 features selected. These results are confirmed by visual inspection of the classification maps shown in Fig. 2. The Maize and Millet classes gave higher precision, whereas the Peanut class gave more errors, possibly because of a low number of ground truth samples. In further research efforts, we plan to use more powerful algorithms of feature selection, and to conduct a more detailed analysis of what causes features to be important.

[4]https://earthengine.google.com/

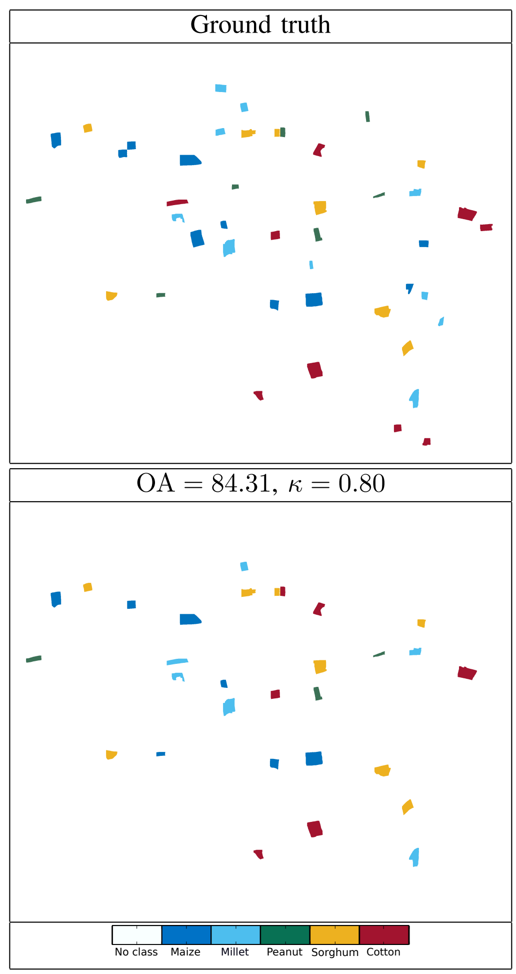

Fig. 2: Ground truth data (crop types) of study area, and the classification map with test set farm field polygons, with overall accuracy and kappa.

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