AGRICULTURAL CROP MAPPING USING OPTICAL AND SAR MULTI-TEMPORAL SEASONAL DATA: A CASE STUDY IN LOMBARDY REGION, ITALY

G. Fontanelli, A. Crema, R. Azar, D. Stroppiana, P. Villa, M. Boschetti

Institute for Electromagnetic Sensing of the Environment (CNR IREA), Via Bassini 15, Milan (Italy)

ABSTRACT

This paper describes a mapping project carried out using both optical and SAR data on an agricultural area in northern Italy where the main crops are corn, rice and wheat. Temporal trends of backscatter and reflectance, given by the variations in vegetation growth, soil conditions and agricultural practices were analyzed and interpreted thanks to the ground-measured data. Information extracted from both optical and SAR data (vegetation indices, backscatter and texture features) were used to create training sets for implementing three different classification approaches. The work aimed at comparing early crop maps with maps derived at the end of the season. Results show that the classification accuracy obtained using only multispectral optical data is higher than the one reached using only SAR as input. Integrating both optical and SAR multitemporal features provides some advantages in terms of a more reliable crop map, especially during an early temporal stage scenario. Among the supervised algorithms tested, Maximum Likelihood shows the best overall accuracy performances at each thematic level, time step and using both optical and SAR input data.

Index Terms - SAR, Optical, Agriculture, Mapping.

1. INTRODUCTION

The availability of information about agricultural crops (i.e. typology, phenology, productivity, health) is crucial for a proper agronomic planning and management, especially for end users such as farmers and public administration.

Remotely sensed data acquired from space sensors, both optical and SAR, have long demonstrated their capability in providing such information in a timely and reliable fashion [1]. In particular, this data have proved to be very effective for assessing crop intra-annual cycles with high temporal resolution, mainly using moderate geometric resolution MODIS and SPOT Vegetation data [2]. In order to fulfil a multi-temporal monitoring with a higher spatial resolution, such data can be integrated with data acquired from the last generation of EO satellites, equipped with optical (e.g., Landsat 8 OLI, WorldView-3 and the foreseen Sentinel-2 MSI) and SAR sensors (e.g. COSMO-SkyMed, TerraSAR-X, RADARSAT-2 and the most recent, Sentinel-1). The integration of SAR and optical sensors data allow us to take advantage by the different sensitivity of both the technologies toward environmental parameters: e.g. soil roughness and moisture, plant water content and biomass for SAR and photosynthetically related vegetation features for the optical sensors [3], [4]. Moreover, exploiting both optical and SAR images, increases the frequency of observation, that, in case of optical data, can be reduced by cloud cover.

This work aims at mapping crops in Lombardy region (northern Italy) for the year 2013, by using multi-temporal, intra-annual series of SAR and optical satellite data. Moreover, our results provide a performance comparison between different supervised classification algorithms at different temporal periods during the growing season.

2. STUDY AREA AND DATASET

The study area is located in the southern part of Lombardy region, framed within the Po river plain and the Ticino river basin. This is a highly intensive agricultural area, with major crops consisting of both winter (wheat and other cereals) and summer (rice and maize) crops.

For this study both optical and SAR data were used. For the optical, 13 Landsat 8 OLI (Operational Land Imager; L8 OLI) scenes from May to December 2013 were used, taking advantages of two overlapping frames (path/row: 194/029 and 194/028) that can guarantee a theoretical 8 days revisiting cycle on the study area. Data are provided as Level 1 product, UTM-WGS84 geocoded, with 30 m spatial resolution and 8 reflective bands.

For the SAR, 15 Cosmo-SkyMed (CSK) X-band images were acquired for the period February-October 2013. These data are Stripmap Himage mode, with HH polarization and incidence angle of 24.13 degrees (nominal pixel spacing 3 m). Temporal granularity is not regular, varying from 16 to 32 days. Reference data on crops all over Lombardy region, used for training and validation of crop classification were extracted from the official 2013 crop thematic map of the Lombardy Region, named Sistema Informativo Agricolo della Regione Lombardia (SIARL; https://www.siarl.regione.lombardia.it/index.htm).

Dates of remote sensing images acquisition are shown in figure 1 together with crop development temporal behavior of the main targets: summer crop (rice and maize about 33% of total cultivated area) and winter crop (wheat 16%).

3. METHODS

The L8 OLI data were converted to surface reflectance through atmospheric correction performed with Atmospheric/Topographic CORrection for Satellite Imagery (ATCOR) [5]. Three different vegetation indices were extracted from each scene as features to be used for classification: i) Enhanced Vegetation Index (EVI) [6]; ii) Normalized Difference Flood Index (NDFI) [7] and iii) Red Green Ratio Index (RGRI) [8]. Eight different time series, of each of these indices, were created and used in the classification test (starting from T1, which represents the early stages of summer crops growth for 2013 and adding one date, for each sensor, at a time to the temporal series until T8, when the entire growth season is covered.

CSK images were pre-processed with Sarmap-Mapscape software: they were filtered with De Grandi multitemporal speckle filter [9], geocoded to UTM-WGS84 and radiometrically calibrated to Sigma Nought ($\sigma°$) by using elevation data coming from a SRTM DEM. Occurrence and Co-occurrence texture filters were then applied on the data [10]; variance feature from the occurrence filter, and contrast feature from the co-occurrence filter were also extracted and used along with the $\sigma°$ for crop classification. The data was then spatially resampled to the same geometric resolution of L8 OLI sensor (30 m). Similarly to L8 OLI, all the three features coming from the SAR data processing were finally composed into time series covering the Spring-Summer of 2013 from T1 to T7.

For the data integration of L8 OLI and CSK, only the more relevant time ranges were considered for both the sensor, namely T1 (early season), T3 (peak of season) and T8 (end of season).

In order to produce crop maps from the described time series of multi-sensor features, three different supervised classification methods were tested and compared: Maximum Likelihood (MLC) [11], Minimum Distance (EMD) [11] and Spectral Angle Mapper (SAM) [12]. All the three classification methods were applied separately to each time series for OLI (T1-T8) and CSK (T1-T7) and the combine OLI+CSK (T1, T3 and T8). The latter is the combination of CSK T7 an L8 OLI T8.

For training the classifiers, a set of pixels was selected based on the reference 2013 SIARL product. A mask derived from SIARL was used to exclude water bodies, urban areas and natural vegetation.

Two thematic levels of the crop maps were considered: a more general Level 1 (L1) which has 6 classes and a more detailed Level 2 (L2), as shown in the legend of Figure 2. SIARL crop map for 2013 was also used for extracting an independent validation sample of pixels, for both L1 and L2, which was used to assess the classification accuracy of the produced crop maps (see Figure 2a).

Confusion matrices were created for each of the classified maps over the different time ranges (T1-T8), and the two thematic levels (L1-L2).

Accuracy metrics were derived for each class as overall accuracy (OA), kappa coefficient (K), commission and omission errors.

4. RESULTS AND DISCUSSION

According to the approach described in the previous section, crop maps were produced through the classification of each combination of thematic level (L1 and L2), supervised algorithm (MLC, EMD, SAM) and different input time series derived by single OLI or CSK sensors and their combination.

Figure 2b, c, d, gives an overview of the classification results derived with MLC over different time ranges and over a subset of the study area, located around the province of Pavia, using L8 OLI and CSK data combined. By a visual comparison with the SIARL reference data (Figure 2a) it is evident that the classification at the end of the season (Figure 2d) provide better mapping results respect to the crop maps derived by using only the early season section of the features time series, represented by T1 (Figure 2b).

Such qualitative assessment of the classification performance is enforced by the results of crop maps validation performed against reference crop data gathered again from the SIARL database for 2013. Figure 3 shows the plot of variations in OA at both L1 and L2 for each of the three supervised algorithms and input time series tested. Here we can see, in the specific condition of our experiments, that according to the validation performed using MLC, accuracy ranges from 82.1% at T1 to 92.3% at T8 for L8 OLI and 94% at T8 for L8 OLI + CSK for L1 (Figure 3b, c).

Among the supervised algorithms tested, MLC is the best performing in terms of OA at each time step and using both L8 OLI and CSK as input data.

The integration of both L8 OLI features (EVI, NDFI, RGRI) and CSK $\sigma°$ provide some advantages in terms of more reliable crop maps especially at the thematic Level 2 and for the early temporal stage T1, marking an OA increment of 2.5% over the MLC classification's accuracy.

In other combinations of temporal series, thematic levels and classification algorithms, the gain in OA granted by the integrated use of both L8 OLI and CSK features is less significant (see Table 1).

Looking at the results plotted in Figure 3 and highlighted in Table 1 it is worth mentioning that a great part of the increment in OA along the considered temporal steps for the MLC classifiers, is occurring from T1 to T3, with only minor enhancements achieved from T3 to T8. By using L8 OLI features only, in fact, one can score an OA of 88.9% for L1 at T3 (compared to 82.1% at T1), and an OA of 84.9% for L2 at T3 (compared to 74.9% at T1). This means that from our dataset, a satellite based crop mapping of the area can be produced with a satisfying level of overall reliability at the end of June (T1) for L1and at the end of July (T3) for L2.

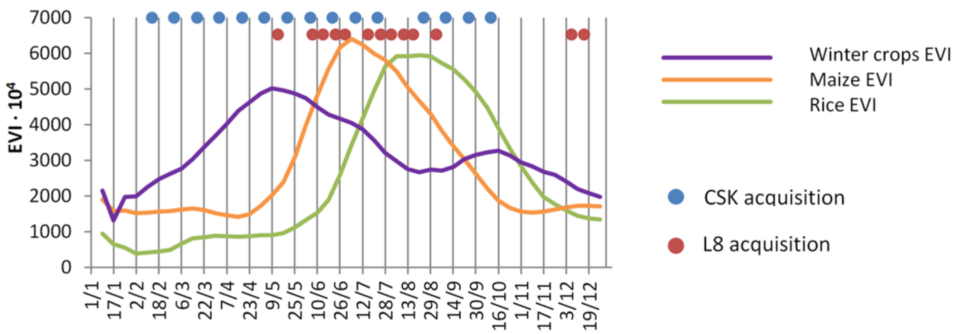

Figure 1. Temporal trends of EVI during 2013 for three different group of crops (winter crops, maize and rice) gathered from MODIS (250m) on the test area, plotted together with the dates of acquisition of CSK and L8 OLI.

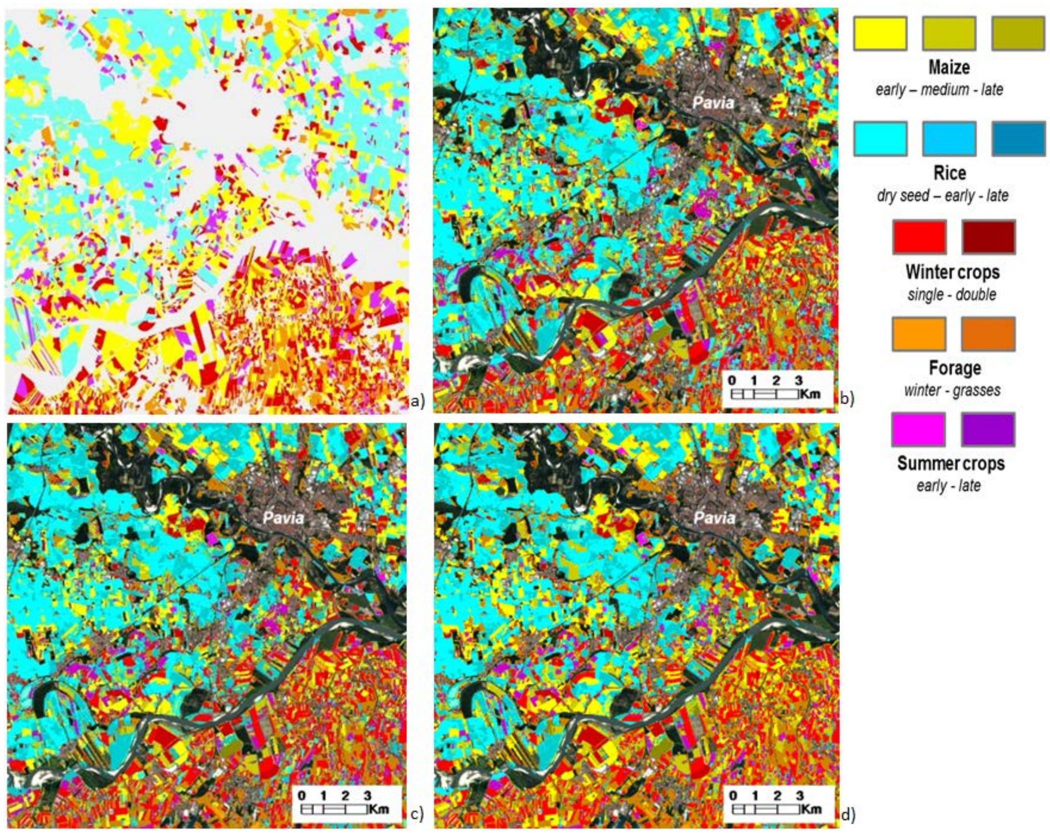

Figure 2. SIARL database used as reference for the classification testing and validation (a); L2 crop maps of 2013 of a subset of the study area located around the province of Pavia (highlighted in the images), derived by MLC classification of multitemporal features coming from the integration of L8 OLI and CSK data at T1 (b), at T3 (c), at T8 (d).

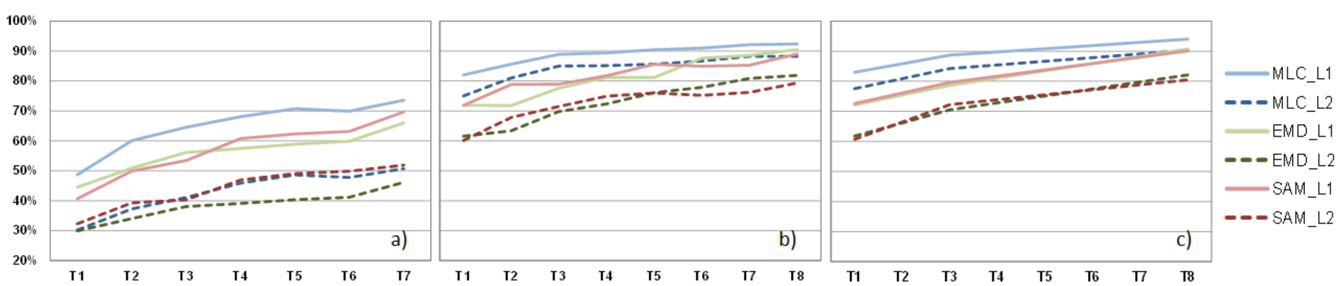

Figure 3. Variations of Overall Accuracy for crop maps produced at Level 1 and 2, by using MLC, EMD and SAM algorithms applied to: CSK HH features time series (a), L8 OLI features time series (b) and both CSK HH and L8 OLI features time series.

Table 1. Difference between crop map accuracies (OA) derived using integrated L8 OLI - CSK HH multitemporal features, and only L8 OLI multitemporal features as classification input.

Thematic level	Class. algorithm	Early season (T1)	Peak of season (T3)	End of season (T8)
Level 1	**MLC**	+0.97%	-0.19%	+1.65%
	EMD	+0.25%	+1.06%	+0.22%
	SAM	+0.78%	+0.72%	+1.06%
Level 2	**MLC**	+2.53%	-0.75%	+2.09%
	EMD	+0.22%	+0.69%	+0.25%
	SAM	+0.53%	+0.72%	+1.15%

5. CONCLUSIONS

In this work, crop mapping of an agricultural area in northern Italy, using optical and SAR satellite data was carried out.

Classification accuracy obtained using only optical data is higher than the one reached using only SAR. It is important to underline that the OLI dataset is composed by multispectral data with an almost weekly revisiting cycle during the summer vegetated season thanks to the exploitation of two overlapping frames. On the contrary the acquisition plan of the CSK dataset is quite irregular, with several images (5 on 15) acquired only in the pre-season (bare soil condition, as shown in Figure 1. In this condition more sophisticated approaches able to synthetize the temporal variability of the signal should be further investigated. Input features for a classification could be, in the future, temporal synthetized by the σ° such as the ones proposed in [13] that demonstrated good performance in crop classification. A further comment on the CSK data set is related to the steep look angle (24.13 degrees), this acquisition geometry doesn't guarantee the best sensitivity toward the vegetation biomass and features.

Despite this aspect, the integrated use of features from optical and SAR sensor provides advantages especially during the early stage temporal scenario. The information at this stage of the crop season is extremely important to create crop masks to be used in early warning monitoring system that exploit for quasi-real time monitoring moderate resolution satellite data.

Among the supervised algorithms tested, MLC shows the best overall accuracy performances at each thematic level, time step and using both optical and SAR input data.

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