LAND COVER MONITORING FOR WATER RESOURCES MANAGEMENT IN ANGOLA

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ABSTRACT

The aim of this paper is to assess the impact of improved temporal resolution and multi-source satellite data (SAR and optical) on land cover mapping and monitoring for efficient water resources management. For that purpose, we developed an integrated approach based on image classification and on NDVI and SAR backscattering (VV and VH) time series for land cover mapping and crop's irrigation requirements computation. We analysed 28 SPOT-5 Take-5 images with high temporal revisiting time (5 days), 9 Sentinel-1 dual polarization GRD images and in-situ data acquired during the crop growing season. Results show that the combination of images from different sources provides the best information to map agricultural areas. The increase of the images temporal resolution allows the improvement of the estimation of the crop parameters, and then, to calculate of the crop's irrigation requirements. However, this aspect was not fully exploited due to the lack of EO data for the complete growing season.

1. INTRODUCTION

Water resources management has become a challenging problem worldwide, especially in developing countries. The lack of information on land cover has a huge impact on the water resources management, since it may hamper the collection, treatment and distribution of water for human consumption and agricultural development. The potential of Earth Observation (EO) data and techniques has been widely acknowledged for the management of land and water resources mostly in agriculture sector [FAO, 1995; Schultz and Engman, 2000]. The repeatability of observations on a cyclic basis and the availability of high spatial resolution multispectral data, are particularly suitable for mapping crops and irrigated areas with satisfactory accuracy and in a cost-effective way [D'Urso *et al*., 2010]. Water requirements varies from crop to crop and also during the period of growth of an individual crop.

The amount of water required to compensate the evapotranspiration loss from cropped fields is defined as crop water requirements. As there is still a considerable lack of information for different crops, the Penman-Monteith method is used as the standard method for the definition and computation of the reference evapotranspiration (ET_o) [Allen *et al*., 1998]. The ET from crop surfaces under standard conditions is determined by crop coefficients (K_c) that relate ET_c to ET_o. The dual crop coefficient approach separates K_c into two separate coefficients, one for crop transpiration (K_{cb}, basal crop coefficient) and another for soil evaporation (K_e). As proposed by Osann Jochum *et al*. [2006], the K_c-NDVI approach establishes an empirical relationship between K_{cb} and NDVI values retrieved from EO optical data. This means that the knowledge of timely and accurate NDVI estimates would allow computing crop water consumption over the crop growth stages and improve water management on agriculture explorations.

With the ever-increasing number of satellites and the availability of data free of charge, the integration of multi-sensor images in coherent time series offers new opportunities for land cover and crop type classification [Waldner *et al*., 2015]. In addition, the launch of satellites with shorter revisit time (e.g. 6 days at the equator for the Sentinel-1 constellation and 5 days at the equator in cloud-free conditions for the Sentinel-2 constellation) and reconfigurable acquisitions (different viewing conditions can be operated for more frequent observation of a certain area) enables a better identification of the different growth cycle stages that are often imperceptible when using more sporadic data.

Many studies have combined optical and microwave images to improve mapping accuracy in agricultural scenarios [Brisco and Brown, 1995; Le Hegarat-Mascle *et al*., 2000; Ban, 2003; Blaes *et al*., 2005; Michael *et al*., 2005; McNairn *et al*., 2009]. SAR data is independent from solar illumination and its brightness depends on the roughness, geometry, and material contents of the targeted surface and the wavelength, while optical data is greatly influenced by cloud cover and its brightness represents the reflectance of solar

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energy from a target area.

This paper aims at assessing the potential of multi-temporal and multi-sensor EO data for crop type classification at high spatial (10 m) and temporal (5 days) resolution with a focus on agriculture, as crops are dynamic and require frequent observations. For this purpose, EO data (Sentinel 1 + SPOT-5 Take-5) are evaluated for the estimation of crop irrigation requirements based on a soil water balance model, IRRIGROTATION [Rolim and Teixeira, 2008]. Additionally, in-situ field data (crop patterns and planting dates) and also meteorological data are used to compute crop evapotranspiration. Reference evapotranspiration will be computed based on available meteorological daily data. In order to estimate the crop behaviour even in the presence of a cloud cover, the consistency of both optical and microwave time series is evaluated. In the other hand, the potential of crop's classification with Sentinel-1 data along the growing season is assessed and compared to accuracies obtained only with spectral information from SPOT-5. This allows the identification of: (1) band combinations that provide better classification results, (2) most critical dates for an improved crop´s class discrimination, (3) and how many observation are required, within a given growing season, for a good classification accuracy.

2. TEST AREA

The test area is located in Angola, in the South-Kwanza province and it covers an approximate area of 960 km^2 (24 x 40 km) on a plateau zone above 1200 m. The area covers an irrigation perimeter close to the town of Wako-Kungo (Figure 1).

Figure 1. Regional context of the test area (hatch lines rectangle) with the location of the Kibala and Wako Kungo weather stations of the SASSCAL WeatherNet.

This region has a warm temperate climate with a marked wet season, with an average annual precipitation of about 1250 mm, distributed over the months from October to April. The average annual temperature is about 21 °C, ranging between 22 °C in September and October and 18 °C in June [Diniz, 1998; Russo *et al*., 2011].

3. DATA

In order to achieve a high temporal resolution, Sentinel-1 and SPOT-5 Take-5 images were requested, respectively to ESA (European Space Agency) and to CNES (*Centre National d'ÉtudesSpatiales*), in the scope of the ESA Alcantara initiative project (Ref: 14-P13) and SPOT-5 Take-5 project ID: 29142, for the time period between March to September 2015. A total of 37 satellite images were made available for this study: 28 SPOT-5 Take-5 images from April, 10 to September, 12 and 9 Sentinel-1A from March, 26 and October, 4 (Table 1).

Table 1. *S*entinel-1 and SPOT-5 Take-5 acquisition dates. Sentinel-1 images are highlighted in grey and the date in bold corresponds both to a Sentinel-1 and SPOT-5 acquisition date.

Acquisition Date	DOY	Acquisition Date	DOY
26 March	85	30 June	181
10 April (*)	100	4 July	185
15 April (*)	105	9 July	190
19 April	109	14 July	195
30 April	120	19 July	200
5 May	125	**24 July (+)**	**205**
10 May	130	29 July (*)	210
13 May	133	8 August	220
15 May	135	13 August	225
20 May	140	17 August (+)	229
25 May	145	18 August	230
4 June	155	23 August (*)	235
6 June (+)	157	28 August	240
9 June	160	29 August	241
14 June	165	2 September (*)	245
19 June	170	7 September	250
24 June	175	12 September	255
29 June	180	4 October	277

(*) not used due to the existence of a significant cloud cover
(+) lack of the Northern part of the image

All Sentinel-1 C-band SAR images were made available in Interferometric Wide Swath (IW) mode with a dual polarisation scheme (VV+VH). These images were distributed as Single Look Complex (SLC), except for the first two acquisition dates, and Ground Range Detected (GRD) for all dates. SLC images ground resolution is 5 x 20 m, while for the GRD images is 10 m. All images were acquired in ascending mode with incidence angles ranging from 38°.87 to 39°.26.

SPOT-5 Take-5 images were distributed both at Level-

1C (orthorectified, Top of Atmosphere- TOA-reflectance) and Level-2A (orthorectified, Bottom of Atmosphere-BOA-reflectances), in 10 m spatial resolution such as the Sentinel-2 products. In analogy to the previous SPOT-4 Take-5 experiment, on 2 May 2015, SPOT-5 was placed in a 5 days cycle orbit, acquiring data over 150 selected sites every 5 days under constant angles. These Sentinel-2 type time series were made available by ESA and CNES to the scientific community to support the development of time series analysis in preparation for the exploitation of the Sentinel-2 mission.

Crops ground truth information was collected in the field from 15 to 30 of April 2015. A total number of 56 eligible parcels were mapped during the campaign. Crop types identified in the field were mainly maize, but soybean, bean and pasture were also observed (Table 2). Other crop types identified in the field were not considered in this study due their small number of parcels. The size of the parcels differs significantly, varying from a minimum of 0.43 to a maximum of 110.03 ha.

During the field campaign the local situation of crop type and its phenological growth stage, according to the BBCH scale [Meier and Bleiholder, 2006] was registered. For maize, most of the parcels were in the senescence (Sen) stage, while 1 parcel was in the flowering (Fl) stage and another one in the leaf development (Lf) stage (Table 2). All soybean parcels were in the senescence phase, whilst 1 parcel in Lf, 3 parcels in Fl and 1 parcel in the development of fruit (Fr) stage were observed for bean. Whenever possible, the planting date was also collected for each parcel.

Table 2. Crop type and number of parcels identified in the test area during the field work.

Crop Type	Nº of parcels	Min. area (ha)	Max. area (ha)	Phenological Growth Stage
Maize	28	4.48	110.03	1 Lf, 1 Fl and 26 Sen
Soybean	13	4.47	48.95	Sen
Pasture	5	9.64	14.79	-
Bean	5	0.43	42.31	1 Lf, 3 Fl and 1 Fr

4. METHODOLOGY

4.1 Images Pre-Processing

The pre-processing of SAR images includes radiometric calibration and coregistration to a common geometry. The radiometric calibration was preformed including the effect of local terrain slope on the pixel area (sigma naught). For that, the SRTM model and the calibration vector included in each product were used. Next, the sigma naught values were converted to logarithmic scale (dB). The corregistration was done using well establish routines used for interferometric processing attaining accuracies better than 0.5 pixels. The Range Doppler orthorectification method was used for geocoding all SAR images using available orbit state vector information in the metadata, radar timing annotations, slant to ground range conversion parameters together with the reference DEM data to derive the precise geolocation information.

Level-2A SPOT-5 images were used in this study due to its improved pre-processing level. Therefore, no further pre-processing steps were required for these images.

4.2 NDVI and VV and VH Backscattering Time Series

SPOT-5 bands B2 (Red) and B3 (NIR) were used to compute a NDVI image for each epoch [Rouse *et al*., 1974]. Based on these NDVI images it was possible to calculate the average NDVI and the standard deviation values for each crop parcel. SPOT-5 time series graphs, for each crop type (pasture, maize, soybean and bean) and for each epoch, were generated to assess the behaviour of each crop for the entire growing season from the trend analysis of the NDVI values. Likewise, the sigma VV and VH bands were used to determine the mean value for each crop parcel for 9 epochs.

4.3 Image Classification and Accuracy Assessment

Four combinations of bands were tested: (1) SPOT-5 bands; (2) SPOT-5 bands + Sentinel-1 VV band; (3) SPOT-5 bands + Sentinel-1 VH band and (4) SPOT-5 bands + Sentinel-1 VV and VH bands. All multispectral bands of the SPOT-5 HRG2 sensor, e. g. B1 (Green), B2 (Red), B3 (NIR) and SWIR bands, were considered for classification.

The Maximum Likelihood (ML) classifier was applied to each combination for the following image pairs: (A) SPOT-5 April, 30 and Sentinel-1 April, 19; (B) SPOT-5 May, 15 and Sentinel-1 May, 13; (C) SPOT-5 June, 29 and Sentinel-1 June, 30; and (D) SPOT-5 August, 28 and Sentinel-1 August, 29. For the first pair, the SPOT-5 image of April, 15 would be more suitable; however this image has an almost total cloud cover. Other possible pairs between SPOT-5 and Sentinel-1 images were not used because of the lack of the Northern part of the latter images for June, 6, July, 24 and August, 17.

About 50% of the ground truth parcels identified in the field per crop were chosen randomly to train the ML classifier and the rest was used to validate the classification results (Table 3). For the classification only 4 crop classes were considered: maize, soybean, pasture and bean. Confusion matrices were generated for each combination and for each image's pair as well as the overall accuracy, the kappa index, the producer's and user's accuracy for each class were calculated.

Table 3. Ground truth parcels used to train the classifier and to validate the classification results.

Crop Type	Nº of training parcels	Nº of validation parcels	Total of parcels
Maize	12	16	28
Soybean	5	8	13
Pasture	2	3	5
Bean	2	3	5

4.4 Crop Irrigation Requirements (CIR) Modelling

The crop irrigation requirements (CIR) are defined as the total amount of water, expressed in water height [mm], applied to the crop throughout the entire irrigation season to fully satisfy the crop water requirements. CIR are computed in this study according to the FAO 56 approach [Allen *et al*., 1998], through the use of the IrrigRotation soil water balance simulation model [Rolim and Teixeira, 2008].

In IrrigRotation, the crop evapotranspiration under standard conditions (ET_c) is calculated following the dual K_c approach, proposed by Allen *et al*. [2005, 2007], which is defined by:

$$ET_c = (K_s \cdot K_{cb} + K_e) \cdot ET_o \qquad (1)$$

where ET_c is the crop evapotranspiration [mm d^{-1}], K_{cb} is the basal crop coefficient, K_e is the soil evaporation coefficient, K_s is the water stress coefficient and ET_o is the reference crop evapotranspiration [mm d^{-1}]. K_s describes the effect of water stress on crop transpiration. For soil water limiting conditions, $K_s < 1$, while where there is no soil water stress, $K_s = 1$.

The ET_o is computed from meteorological data using the FAO Penman-Monteith (FAO-PM) method [Allen *et al*., 1998; 2007]. In this study, the K_{cb} is determined empirically from the K_{cb}-NDVI relationships applied within the PLEIADeS project, using the following equation [D'Urso and Calera Belmonte, 2006]:

$$K_{cb} = 1.5625 \cdot NDVI - 0.1 \qquad (2)$$

where NDVI are the mean values of a crop type for each acquisition date. The NDVI time series are used to identify the lengths of crop growth stages (initial, crop development, mid-season and late-season), and the corresponding K_{cb} coefficients for the initial, mid-season and late-season periods. This methodology was applied in the lower Tagus valley (central Portugal) showing a good agreement between the estimation of the K_{cb}-NDVI values and the K_{cb} recommended by FAO 56 [Vilar *et al*., 2015].

5. RESULTS AND DISCUSSION

The classification process was used to identify the crop type and to build a time series of land cover maps that, in conjunction with the NDVI time series, allowed to estimate the water requirements for each epoch. Four combinations were evaluated on four periods: SPOT, SPOT+VV, SPOT+VH, SPOT+VV+VH. The overall accuracy and kappa index values for the 4 image pairs are presented in Table 4. It is clear that the overall classification accuracy for all crop classes is highest when both polarizations are considered, except for Pair C (June 2015), though the decrease is less than 1%. The same trend is verified for the Kappa index. Besides, when a single polarizations is added to the optical data, overall classification accuracies for VH bands are slightly higher when compared with the ones for VV bands. This has already be concluded by Saraiva and Navarro [2015] and Karjalainen *et al*. [2008] when using dual-polarization (VV+VH) SAR images for agricultural monitoring. Accordingly to Karjalainen *et al*. [2004], the VV polarization might be used for detecting sowing dates while the VH cross-polarization is best for the crop biomass estimation.

Table 4. Overall accuracy (OA) and Kappa index (KI) values for different data combinations for the 4 image pairs considered.

(Pair A)	SPOT	SPOT+VV	SPOT+VH	SPOT+dual
OA (%)	72.68	72.79	73.27	73.47
KI (%)	51.99	52.67	53.17	53.51

(Pair B)	SPOT	SPOT+VV	SPOT+VH	SPOT+dual
OA (%)	78.97	79.97	80.41	80.80
KI (%)	60.87	62.22	62.92	63.40

(Pair C)	SPOT	SPOT+VV	SPOT+VH	SPOT+dual
OA (%)	64.98	64.41	69.57	68.80
KI (%)	37.04	37.44	43.71	43.19

(Pair D)	SPOT	SPOT+VV	SPOT+VH	SPOT+dual
OA (%)	48.18	47.09	48.27	48.30
KI (%)	18.17	19.10	19.86	21.00

The highest value obtained for the overall accuracy (80.8 %) was verified for combination (4) and pair (B). Combination (4) corresponds to all bands from both types of satellite imagery used in this study, which allows to conclude that the inclusion of SAR data, together with optical data, in the classification process improves the results accuracy. Regarding the acquisition time that enabled the best classification results, classifications based on images acquired in May 2015 returned the highest accuracies. From this date on, there is a substantial decay in the NDVI and VV and VH values indicating that the cultures are all at the last stage of senescence, being wilt and, sometimes, already harvested.

The time series of mean NDVI, VV and VH backscattering for the selected crop types are represented in Figure 2.

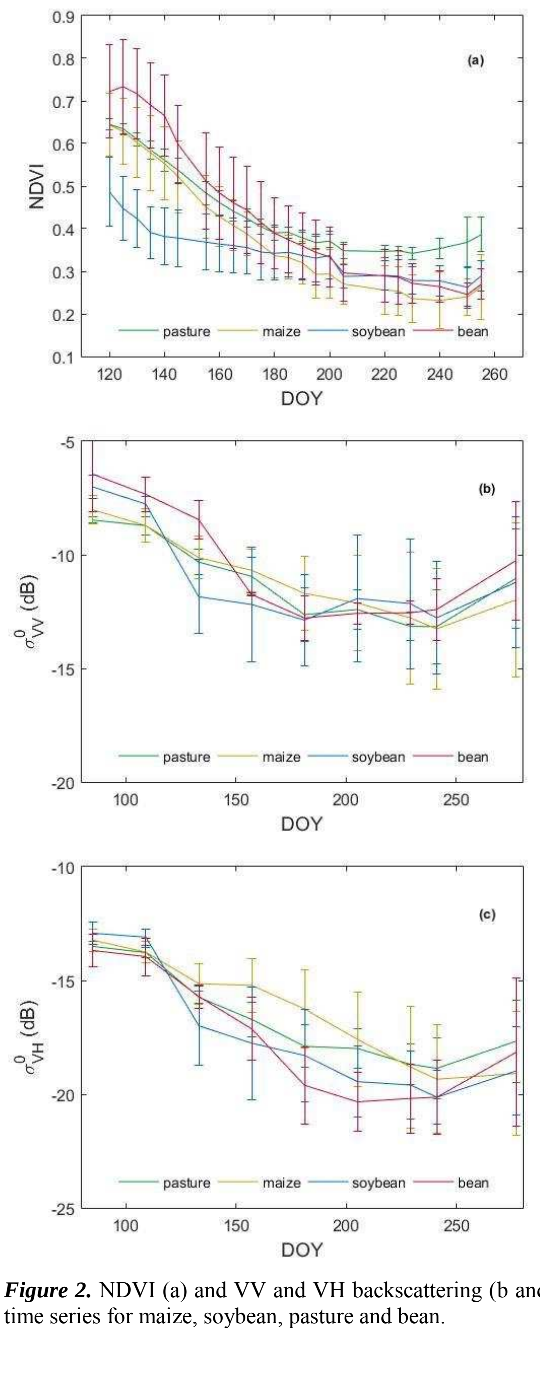

Figure 2. NDVI (a) and VV and VH backscattering (b and c) time series for maize, soybean, pasture and bean.

As can be seen from Figure 2, the average VV backscatter is higher than the average VH backscatter. The dynamic range of the VV backscatter is -13.26 dB to -7.34 dB while the range of VH backscatter is -20.34 dB to -13.09 dB. NDVI values range from 0.23 to 0.73. Most parcels of maize were sowed in September/October 2014, while first EO acquisition date is from 2015 March, 26 (DOY 85). In the graphs, the maize crop curve range from the end of the mid-season until harvesting, corresponding to the senescence stage. That is verified in the NDVI time series by the decrease trend for the maize crop. The same trend was also verified for the VV and VH backscatter time series indicating that both types of EO data are correlated. Although, only half crop growth cycle is retrieved from the EO data, results are promising once they prove that this correlation is also possible for the late season period when crop's height is relatively stable.

Bean parcels, which were sowed in late February 2015, exhibit higher NDVI values in the beginning of the curve once it corresponds to the leaf development stage. At the senescence stage, bean crop presents the same trend as maize. As soybean was sowed in December 2014, lower NDVI in the beginning of the curve are explained by its crop growth stage (senescence) and also by its typical height (around 0.45 m). Pasture crop shows a smoother curve for the three time series which is compatible with the fact that this crop is always in the leaf development stage due to several cuts during the growing season.

The behaviour of the Sentinel-1 backscattered signal was analysed as a function of the NDVI. For each crop considered in this study, the backscattering coefficients were compared to the NDVI index calculated from the SPOT-5 data with acquisition dates close to the Sentinel-1 acquisitions (Figure 3).

From Table 5 and Figure 3, a significant correlation between VV and VH and NDVI (higher than 67% and 88%, respectively) was observed for all classes, showing the consistency of both optical and microwave time series, proving that optical data can be replaced by microwave in the presence of a cloud cover. This result allows to overcome one of main limitations in these type of studies, i. e. the reduced amount of EO data due to meteorological conditions.

Table 5. R-squared values for each crop type when comparing the Sentinel-1 VV and VH bands with the NDVI band.

R^2	Maize	Soybean	Pasture	Bean
NDVI+VV	0.95	0.67	0.95	0.86
NDVI+VH	0.88	0.97	0.95	0.96

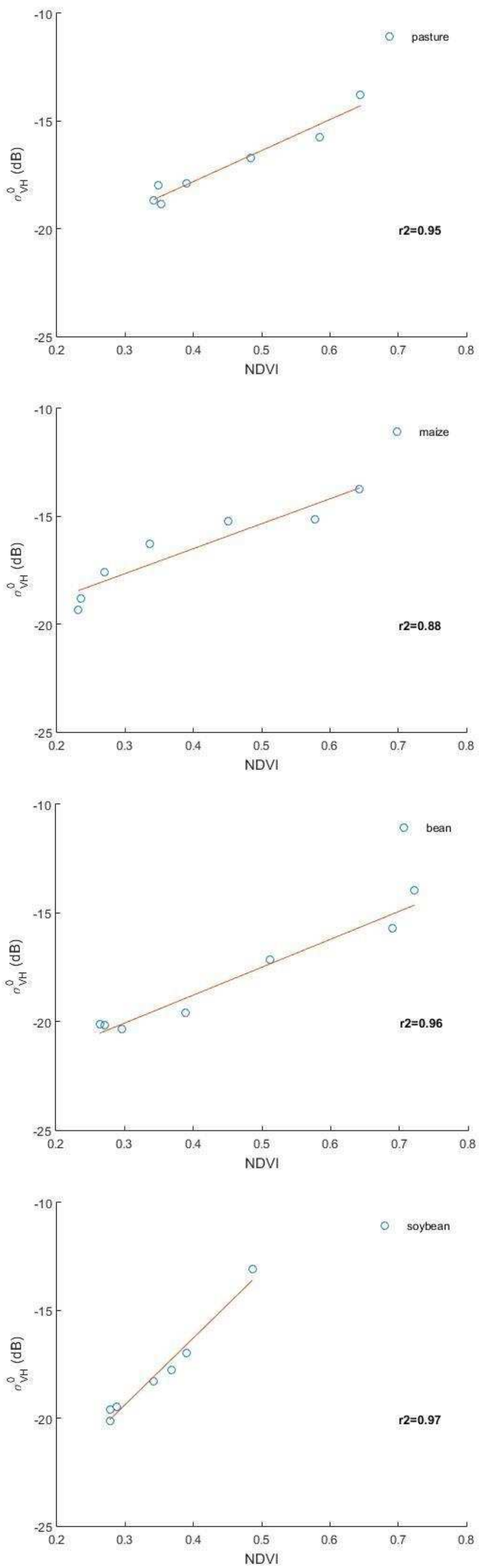

Figure 3. Scatterplots of a linear regression between the VH Sentinel-1 bands and the NDVI band for each crop type.

ET_o and ET_c values for each crop type, along the time series of this study, are shown in Figure 4. ET_c values exhibit a decay trend which is consistent with the senescence stage shown by most crops. Only crop water requirement values are presented, since during the late-season the irrigation is interrupted in order to allow the maturation of the crop. Additionally, in this study, the harvesting dates are unknown for all crop types. Thus, it was not possible to distinguish between the late-season and the off-season. Hence, without a through characterization of complete growing season and cultural and irrigation practices, in the region, it is difficult to accurately estimate the irrigation water requirements.

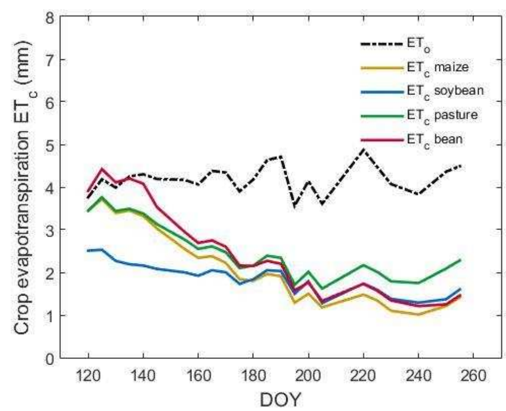

Figure 4. Reference evapotranspiration (ET_o) and crop evapotranspiration (ET_c) for each crop.

The crop water requirements were calculated for the crop parcels identified in-situ during the field work. The total volume of water withdrawn for irrigation in the test area was estimated multiplying the crop water requirements for the total area occupied by each crop type is listed in Table 6. The water volume (m^3) consumed by each crop were computed for each acquisition date. From the analysis of the calculated volumes, it is possible to verify the decrease in the values over time, again, due to the senescence stage shown by most crops.

Table 6. Total area of all parcels identified in the field for each crop type.

Crop type	Total area (ha)
Maize	1311.47
Soybean	302.87
Pasture	62.72
Bean	97.22

With EO data available for the entire crop growing season, better classifications results would have been obtained and therefore it would have been possible to estimate the crop irrigation requirements for the Wako Kungo agricultural perimeter.

6. CONCLUSIONS

The purpose of this study was to develop a framework for multi-source and multi-date crop classification along the growing season to support effective agricultural monitoring. Sentinel-1 and SPOT-5 Take-5 were used to evaluate their potential for extracting reliable land cover information to be used in water management in Angola.

The integration of optical (SPOT-5 Take-5) and microwave (Sentinel-1) data revealed only a slight improvement in land cover mapping. Higher classification accuracies were expected, however the fact that images were available only less than half crop cycle (end of the mid-season until harvesting), disabled the identification of critical dates for crop's discrimination. Those dates coincide with the mid-season period that can be recognized in the NDVI or VV and VH time series where the curves exhibit their maximum values for a certain crop. Nevertheless, independently of the crop type, and of the acquisition date, it is clear that the overall classification accuracy and Kappa index are highest when both polarizations (VV+VH) are considered together with the optical bands.

The improved temporal resolution of the SPOT-5 Take-5 images, used in this study to simulate the ESA Sentinel-2 time series, is relevant for a better identification of the different growth cycle stages that are often imperceptible when using more sporadic data. Higher temporal resolution time series allow the retrieval of realistic values for K_{cb}, instead of the standard values proposed by FAO 56 [Allen *et al*., 1998], and, consequently, a better estimation of the crop's irrigation requirements. However, this aspect was not fully exploited for the same reason as mentioned before, i. e. the lack of EO data for the complete growing season. Moreover, the consistency observed between the optical and microwave time series for all crop types, enables the replacement of optical data, affected by clouds, by microwave data in order to increase the temporal resolution of the time series.

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