TECHNICAL PAPER

CROP DATA RETRIEVAL USING EARTH OBSERVATION DATA TO SUPPORT AGRICULTURAL WATER MANAGEMENT

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ABSTRACT

Accurate crop data are essential for reliable irrigation water requirements (IWR) calculations, which can be acquired during the crop growth season for a given region using earth observation (EO) satellite time series. In addition, a relationship between crop coefficients and the NDVI can be established to allow for crop evapotranspiration estimation. The main objective of the present work was to develop a methodology, and its implementation in an application software, to extract crop parameters from EO image time series for a set of parcels of different types of crops, to be used as input data for a soil water balance model to compute IWR. The methodology was tested at two distinct test sites, the Vila Franca de Xira (site I) and Vila Velha de Ródão (site II) municipalities, Portugal. Landsat-7 and -8 images acquired from April to October 2013 were used for site I, while SPOT-5 Take-5 images from April to September 2015 were considered for site II. EO data were used to estimate the basal crop coefficients, planting dates, and crops growth stage lengths. Based on crop, soil and meteorological data, the IWR for the main crops of both test regions were estimated using the IrrigRotation model. The crop coefficient curves obtained from the EO data proved to be reliable for IWR estimation.

INTRODUCTION

Reliable IWR estimation requires available and accurate data (e.g., crop coefficients, planting dates, and crop growth stage lengths) to determine the soil water balance. Crop data can be estimated using acquired earth observation (EO) data, along the crop growth cycle, at time intervals suitable for the detection of changes in crop phenology (D'Urso & Calera Belmonte, 2006; Vilar, 2015; Vilar et al., 2015; Navarro et al., 2016; Rolim et al., 2016). Presently, the availability of free and open access to high spatial resolution EO data with a short revisit time allows for accurate crop parameter estimation as well as crop growth cycle characterization, improving the identification of each growth cycle stage, which is often imperceptible when lower temporal resolution data are used (El Hajj et al., 2009; D'Urso et al., 2010; Ramme et al., 2010; Johann et al., 2013; Johann et al., 2016; Navarro et al., 2016; Rolim et al., 2016; Grzegozewski et al., 2017; Toureiro et al., 2017).

EO methodologies have been widely used for crop evapotranspiration (ET_c) and IWR estimation because of the reflective properties of vegetation that allow one to estimate crop biophysical parameters and plant processes such as transpiration (Neale et al., 1989; Calera Belmonte et al., 2005; D'Urso et al., 2010; Paço et al., 2014; Vuolo et al., 2015; Ferreira et al., 2016; Oliveira et al., 2016). ET_c can be estimated from EO data using empirical methods based on the use of vegetation indices (VIs) to estimate crop coefficients (Neale et al., 1989; Calera Belmonte et al., 2005; D'Urso et al., 2010) or using physics-based methods based on the surface energy balance to estimate the latent heat flow based on EO thermal images (Bastiaanssen et al., 1998; Allen et al., 2007; Eldeiry et al., 2016). The empirical methods have been more widely used because of their simplicity, with the most common VI, the normalized difference vegetation index (NDVI), used to estimate several crop parameters, such as fraction of ground cover (f_c), single crop coefficient (K_c), and basal

crop coefficient (K_{cb}), among others, used as input data for soil water balance simulations (D'Urso et al., 2010).

IWR estimation is commonly performed using the crop coefficient approach (Allen et al., 1998), computing ET_c based on the use of crop coefficients that relate the ET_c to the reference evapotranspiration (ET_o). ET_o is calculated by using the standard FAO Penman–Monteith method (Allen et al., 1998). The crop coefficients can be estimated using the single crop coefficient (K_c) or the dual crop coefficient approach, based on K_{cb} and on the soil evaporation coefficient (K_e) (Allen et al., 1998). As proposed by several authors (Neale et al., 1989; Calera Belmonte et al., 2005; D'Urso & Calera Belmonte, 2006; D'Urso et al., 2010), the K_{cb}-NDVI approach establishes an empirical relationship between the K_{cb} values, obtained through field measurements (soil water balance, lysimeters, micrometeorological techniques, etc.), and NDVI values retrieved from optical EO time series. The equations used to estimate crop coefficient values based on VIs require field campaigns to be calibrated and validated for a given location. Once calibrated, they can accurately estimate ET_c, enabling one to replace in situ data, which are difficult and expensive to collect at field evaluations (D'Urso et al., 2010; Toureiro et al., 2017).

In both crop coefficient approaches the main source of uncertainty in the IWR estimation is the incorrect characterization of the crop growth stage lengths and hence of the crop coefficient curves (Allen et al., 1998; Toureiro et al., 2017). In fact, IWR estimation for water management purposes is often performed using FAO 56 tabulated crop coefficients values and lengths of crop growth stages that can lead to large errors (Allen et al., 1998). The uncertainty resulting from the use of these values is increasingly relevant because of climate change, with impacts on crop calendars and phenology, requiring field observations for new crop data collection. Therefore, EO techniques are a viable and cost-effective alternative to complement traditional field evaluations.

The main objective of this work was the development of a methodology to extract crop data from EO time series, for several crop parcels of an irrigation perimeter, to be used as input data for a soil water balance model, enabling crop IWR calculation at a regional level. More specifically, it was intended to use EO data to estimate basal crop coefficients, planting dates, and crop growth stage lengths. The developed methodology was implemented in an application software (Vilar, 2015) and applied to two different test sites in Portugal, the Vila Franca de Xira (site I) and Vila Velha de Ródão (site II) municipalities, where EO images of different spatial and temporal resolutions were used.

METHODOLOGY

NDVI TIME SERIES

NDVI values were calculated for each EO data acquisition date using the red and near infrared bands using [eq. (1)] (Rouse et al., 1974) as follows:

$$NDVI = \frac{\rho_{NIR} - \rho_R}{\rho_{NIR} + \rho_R} \tag{1}$$

in which ρ_{NIR} and ρ_R are the surface reflectance in the near infrared and red bands, respectively. Based on the NDVI time series, for each crop parcel, characterization of the behaviour of each crop type throughout the entire growing season and extraction of crop data were possible.

BASAL CROP COEFFICIENT CURVE

K_{cb} values are empirically determined from the K_{cb}-NDVI relationships applied within the PLEIADeS project using [eq. (2)] (Calera Belmonte et al., 2005; D'Urso & Calera Belmonte, 2006) as follows:

$$K_{cb} = 1.5625 \cdot NDVI - 0.1 \tag{2}$$

in which NDVI is the mean value of each parcel for each acquisition date. This equation was defined using several types of annual crops, including maize, in a pilot campaign in the Barrax municipality in Spain, with a Mediterranean climate, and showed good agreement between field measurements and estimated K_{cb}-NDVI values (Calera Belmonte et al., 2005; D'Urso, & Calera Belmonte, 2006). NDVI time series were used to define the crop coefficient curve, enabling one to identify the crop growth stage lengths (initial, crop development, mid-season and late season) and the corresponding K_{cb} coefficients for the initial ($K_{cb\ ini}$), mid-season ($K_{cb\ mid}$), and end of late season ($K_{cb\ end}$) stages (Figure 1), reflecting the actual crop growth conditions.
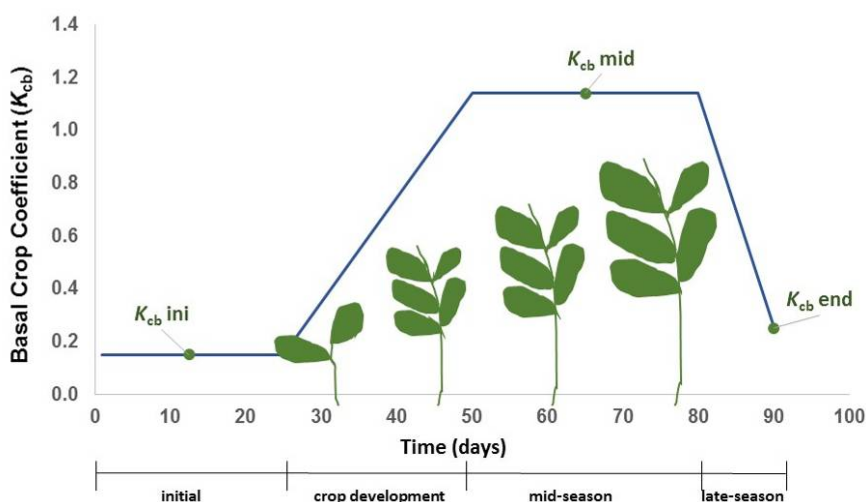

FIGURE 1. Basal crop coefficient (K_{cb}) curve (Navarro et al., 2016).

IRRIGATION WATER REQUIREMENTS (IWR)

IWR are defined as the net amount of water, expressed as the depth of water (mm), applied to the crop throughout the entire irrigation season to fully satisfy the water loss via evapotranspiration that is not satisfied by rainfall or soil water storage and not considering irrigation losses (Doorenbos & Pruitt, 1977; Allen et al., 1998). In this study, IWR were computed using the IrrigRotation soil water balance simulation model (Rolim & Teixeira, 2008). This model simulates the soil water balance using a daily time step and computes ET_c according to the dual crop coefficient approach proposed by Allen et al. (1998), as defined in [eq. (3)] as follows:

$$ET_c = \left(K_s \cdot K_{cb} + K_e \right) \cdot ET_o \tag{3}$$

in which ET_c is the crop evapotranspiration (mm·day^{-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 evapotranspiration (mm·day^{-1}). K_s describes the effect of water stress on crop transpiration, yet, in this case, no water stress was considered when simulating the soil water balance. Alternatively, K_{cb} values retrieved from EO data are already adjusted to the actual field conditions, which already incorporate water stress. ET_o was computed using the FAO Penman–Monteith (FAO-PM) method (Allen et al., 1998).

The soil water balance equation adopted in the IrrigRotation model is defined as follows:

$$\Delta R = \left(P - ET_c + R_g - E_s + A_c - D_r \right)_{\Delta t} \tag{4}$$

in which ΔR is the variation in the volume of water stored in the root zone (mm), Δt is the time step (day), P is the precipitation (mm·day^{-1}), R_g is the irrigation (mm·day^{-1}), A_c is the capillary rise (mm·day^{-1}), ET_c is the crop evapotranspiration (mm·day^{-1}), E_s is the runoff (mm·day^{-1}) and D_r is the drainage and deep percolation (mm·day^{-1}). In the present study, an irrigation strategy of no water restrictions was evaluated because the water deficit is included in the K_{cb} obtained using the EO data.

CROP DATA RETRIEVAL FROM EO DATA

A realistic estimate of the IWR depends on the choice of representative crop parcels. The analysis of just one or a few parcels for each type of crop might not allow for the identification of the standard pattern for each crop along its growth cycle, for one given region, because of noise and clouds in the satellite images and the lack of representativity. Thus, it is more useful to consider a broad set of crop parcels, with similar phenological behaviour, to extract average crop data values, as performed by Esquerdo et al. (2011) and Johann et al. (2013, 2016), which are more representative and reliable than those individually obtained, reducing uncertainty resulting from sensor errors and cloud cover and improving data reliability when IWR is calculated at a regional or irrigation perimeter level. Hence, two different approaches were adopted to retrieve crop data as follows:

Average curve: The average NDVI and K_{cb} values were obtained for each parcel and for each acquisition epoch. Based on these values, the crop growth cycle curves were defined by calculating the average NDVI and

K_{cb} values of all the crop parcels of the same type, also determining the maximum and minimum values, to present the dispersion of the values acquired by the satellite. This approach aimed to extract the K_{cb} time series and the identification of the crop growth stages dates using an average value for each crop to be used as an input for the soil water balance model.

A set of curves: The NDVI, and K_{cb} time series were determined for each individual parcel, as previously mentioned. The crop growth cycle curve of all parcels, of the same type of crop, were simultaneously plotted in one single chart, showing the dispersion of the results. This second approach allowed one to identify different crop growth behaviours, and consequently to detect different crop varieties or the presence of outlier parcels. Removing these parcels, or separating them into subsets, improved the representativeness of each type of crop data. Comparing the NDVI (or K_{cb}) curves obtained for several parcels enabled us to distinguish different crop developmental patterns, reflecting distinct crop growth and management conditions such as different crop varieties, planting date, plant density, irrigation, fertilization and pest and diseases control levels, allowing for the detection of different productivity levels. Esquerdo et al. (2011) generated NDVI time series for several soybean parcels in Brazil, aggregated at the municipality level, demonstrating the usefulness of adopting several parcels to generate an average NDVI profile allowing for an accurate characterization of this crop's phenological cycle.

COMPUTATIONAL APPLICATION DEVELOPED

APPLICATION STRUCTURE

A computational application was developed using MATLAB® 2014 to implement the proposed methodology (Vilar, 2015). This application was composed of three computational modules, including a Geographic Information System (GIS) graphical user interface and a geospatial database in ArcCatalog®. The database stores information regarding the crop parcels and crop biophysical parameters provided by the EO data. This application was developed to automate EO time series processing for a large number of crop parcels.

APPLICATION SOFTWARE WORKFLOW

The application comprises three modules (Figure 2) as follows:

- **Module I – Optical digital image processing for data extraction**: This module aims to extract information from EO optical images time series. NDVI values are calculated based on [eq. (1)]. Results, for each input file, are the NDVI images. Land Surface Temperature (LST) values are also calculated by this software for each crop parcel, despite not being used in this study.

- **Module II – K_{cb} calculation using the GIS interface**: This module performs the average K_{cb} calculation for each crop parcel based on the NDVI images using the ArcMap® Zonal Statistics tool. The K_{cb} estimation is performed based on the NDVI time series images using [eq. (2)]. K_{cb} values are then used to generate the crop growth curves (Figure 1).

- Module III – Crop growth stages estimation: This module plots the NDVI and K_{cb} time series curves graphs for each crop type based on the attribute table previously generated by module II and on the approach selected (*average curve* or a *set of curves*), allowing one to observe crop behaviour along the entire growing season.

INPUT DATA

The main input data used for this application software are composed of the following:
- Optical image time series acquired by the Landsat-7 Enhanced Thematic Mapper plus (ETM+)

sensor and the Landsat-8 Operational Land Imager (OLI) from April to October 2013 for test site I.
- Optical image time series acquired by the SPOT-5 Take-5 HRG (High Resolution Geometric) sensors, from April to September 2015, for test site II.
- Vector files extracted from the National Land Parcel Identification System (NLPIS) containing each agricultural parcel's limits, as well as the crop type, for the 2013 (site I) and 2015 (site II) subsidy control campaigns. These files were provided by the Portuguese Control and Paying Agency (Instituto de Financiamento da Agricultura e Pescas – IFAP).
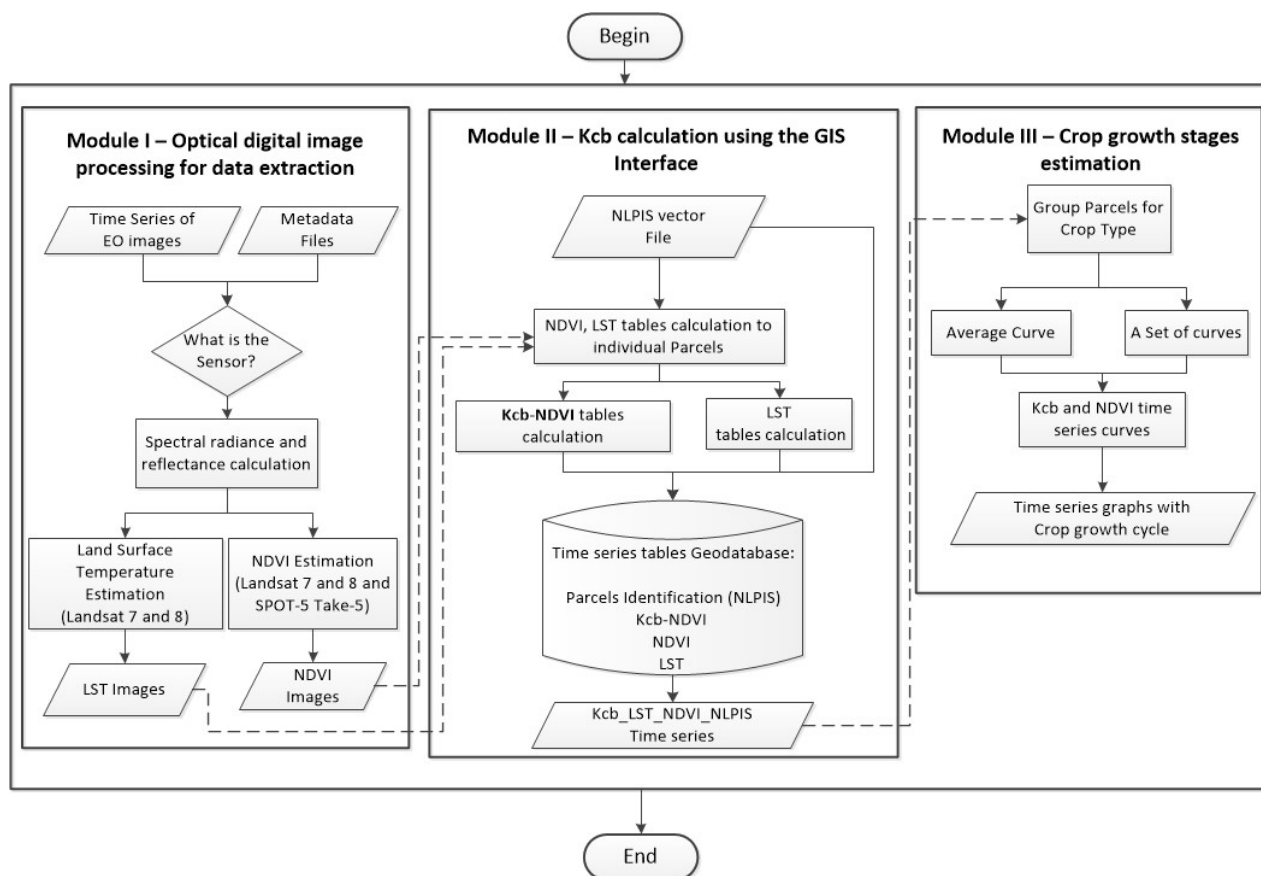

FIGURE 2. Flowchart of the application software.

OUTPUT DATA

- NDVI images generated, using module I, to be used as input to the K_{cb} calculation procedure (module II). The NDVI and LST images can also be used for other type of applications beyond the scope of IWR estimation, such as crop parcel classification (Vilar et al., 2015).
- NDVI and K_{cb} time series graphs that allow one to characterize the crop behaviour along the growth cycle and, consequently, distinguish the four different crop growth stages and the corresponding $K_{cb\ ini}$, $K_{cb\ mid}$ and $K_{cb\ end}$ values, enabling the definition of the crop coefficient curve as shown in Figure 1.

EXPERIMENTAL APPLICATION

The developed methodology was applied to evaluate its suitability to retrieve crop parameters from EO data to be used as input data for a soil water balance model to estimate IWR. This study was conducted at two test sites in central Portugal (Figure 3). For both sites, the location of the agricultural parcels belonging to the crop types of interest was selected based on the NLPIS data. For each acquisition date, and for every parcel, the average NDVI values were determined to estimate the K_{cb} values, planting dates and crop growth stage lengths. Based on crop, soil and meteorological data, the IWR were estimated using the IrrigRotation model for the main crops at both sites.

TEST SITE I – VILA FRANCA DE XIRA

The first test site is in the Vila Franca de Xira municipality, in the Lisbon District, Portugal, as shown in Figure 3. The main annual irrigated crops produced in this region are maize, tomato, rice and melon (Vilar et al., 2015). The Vila Franca de Xira climate, according to the Köppen classification system, is Csa, i.e., a temperate climate with a hot and dry summer. Climate normal data, from 1971 to 2000, for the Lisboa weather station (38º 43'

N, 9º 08' W, 77 m in altitude) of the Instituto Português do Mar e da Atmosfera (IPMA) network, show that the hottest month is August, with a monthly average temperature of 23ºC, and the lowest average temperature of 11.3ºC is observed in January. The highest monthly precipitation occurs in December (121.8 mm), while July is the driest month (6.1 mm). The average annual precipitation during the period of record is 725.8 mm.
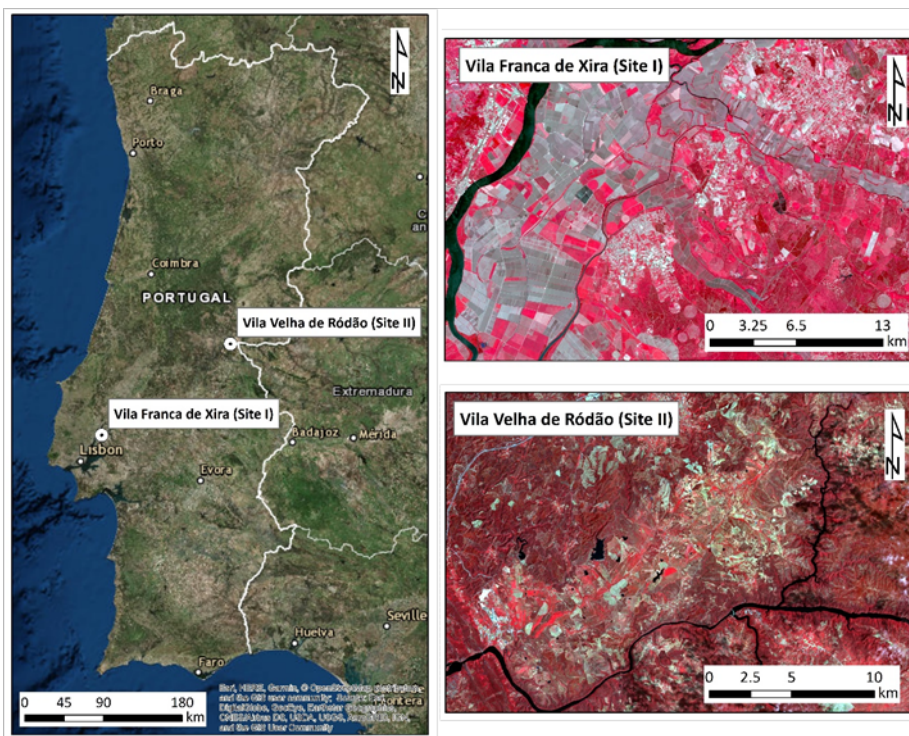

FIGURE 3. Location of the test sites: Vila Franca de Xira (test site I) and Vila Velha de Ródão (test site II) municipalities.

DATA

Earth Observation (EO) data

Two Landsat-7 satellite ETM+ and 9 Landsat-8 OLI/TIRS sensor images acquired from April to October 2013 were used (Vilar, 2015; Vilar et al., 2015), corresponding to the spring/summer crop growing season (Table 1). The spatial resolution of both images is 30 m with a revisit time of 16 days. The acquisition dates, and the corresponding day of the year (DOY) and type of image, are listed in Table 1.

TABLE 1. Landsat-7 (L7) and Landsat-8 (L8) images acquisition dates for site I (DOY - Day of the Year, 2013 in this case).

Satellite	L8	L7		L8							
Date	17/04	11/05	12/06	20/06	6/07	22/07	7/08	23/08	8/09	24/09	10/10
DOY	107	131	163	171	187	203	219	235	251	267	283

Radiometric calibration and normalization of the Landsat images

Landsat-7 and Landsat-8 data were downloaded as Level-1 data products consisting of quantized and calibrated scaled Digital Numbers (DN) representing the multispectral image data. All images were rescaled to top of atmosphere (TOA) reflectance using radiometric rescaling coefficients provided in the metadata file (MTL.txt) that is delivered with the Level-1 product. The conversion to TOA reflectance was performed using equations provided at the United States Geological Survey (USGS) website. Landsat-7 images were used in this study to fill missing data in the time series, as most of the crop parcels were covered by clouds in the Landsat-8 images

acquired during May (DOY 139) and in the first half of June (DOY 155), 2013. Despite the Landsat-7 Scan Line Corrector (SLC) malfunction, it was possible to use these images because Vila Franca de Xira (site I) is in the central part of the images not affected by the sensor error.

To compare data from different sensors (with slightly different wavelength intervals), a relative radiometric normalization was applied to both Landsat datasets (Du et al., 2002). The images normalization of the same region acquired at two different times (or by different sensors) is completed using a linear regression, assuming that the spectral reflectance properties of the sampled pixels did not change during the time interval. Based on two sets of pseudo-invariant features, bright (bare soil) and

dark (water), selected on both Landsat images (L7-DOY 131/L8-DOY 139 and L7-DOY 163 and L8-DOY 155) via visual inspection, it was possible to calculate the linear regression coefficients.

Soil Data

Sheets 390, 391 and 404 of the soil maps of Portugal, produced by the Instituto de Hidráulica, Engenharia Rural e Ambiente (IHERA), at a scale 1:25 000, were used for test site I to identify the soil types present in each crop parcel and consequently obtain the soil hydraulic characteristics to perform the soil water balance simulation.

Meteorological data

Climatic data was obtained from the Magos Dam weather station (38º 59' N, 8º 42' W, 43 m in altitude) belonging to the Sistema Nacional de Informação de Recursos Hídricos (SNIRH) for the period from April to October 2013 at a daily time step. The meteorological variables considered were the following: maximum air temperature (°C), minimum air temperature (°C), maximum relative humidity (%), minimum relative humidity (%), average wind speed at 2-m height (m·s^{-1}), solar radiation (MJ·m^{-2}·day^{-1}) and precipitation (mm·day^{-1}).

RESULTS AND DISCUSSION

NDVI time series

The time series of the mean NDVI for the selected crops (maize, tomato, rice, and melon) at test site I (Vilar et al., 2015) are shown in Figure 4, for the *set of curves* and *average curve* approaches, presenting the evolution of the crops' NDVI temporal profiles as described in Ramme

et al. (2010), Johann et al. (2013) and Oliveira et al. (2016). As shown in Figure 4 the NDVI time series show, for all the selected crops, a behaviour similar to the expected theoretical growing cycle of the spring/summer annual crops (Allen et al., 1998), previously shown in Figure 1, enabling identification of the crop growth stages, in line with the results obtained by D'Urso & Calera Belmonte (2006), D'Urso et al. (2010), Ramme et al. (2010) and Johann et al. (2013). Nevertheless, for all crops, except melon, some parcels show an anomalous behaviour. The *set of curves* approach (Figure 4a, c, e and g) enables the identification of outlier parcels, and consequently their removal from the analysis, which is extremely useful when applying the *average curve* approach (Figure 4b, d, f and h). As a result, average NDVI curves were calculated considering only a subset of crop parcels that show a standard behaviour, allowing computation of more accurate average K_{cb} curves to be used in the soil water balance simulation.

As shown in Figure 4, extracting crop data from a set of parcels improves identification of the crop growth stages for maize, rice and melon. In the case of tomato (tomato for industry), the *set of curves* approach (Figure 4c) allows the identification of different crop varieties with different cycles, with a broader range in the sowing and harvesting dates. This implies higher standard deviation values during the initial and late season stages, and consequently, the *average curve* will show a higher variability in minimum and maximum NDVI values (Figure 4d) when compared to the curves for the other three crops, indicating the existence of different crop development stages for a given date.
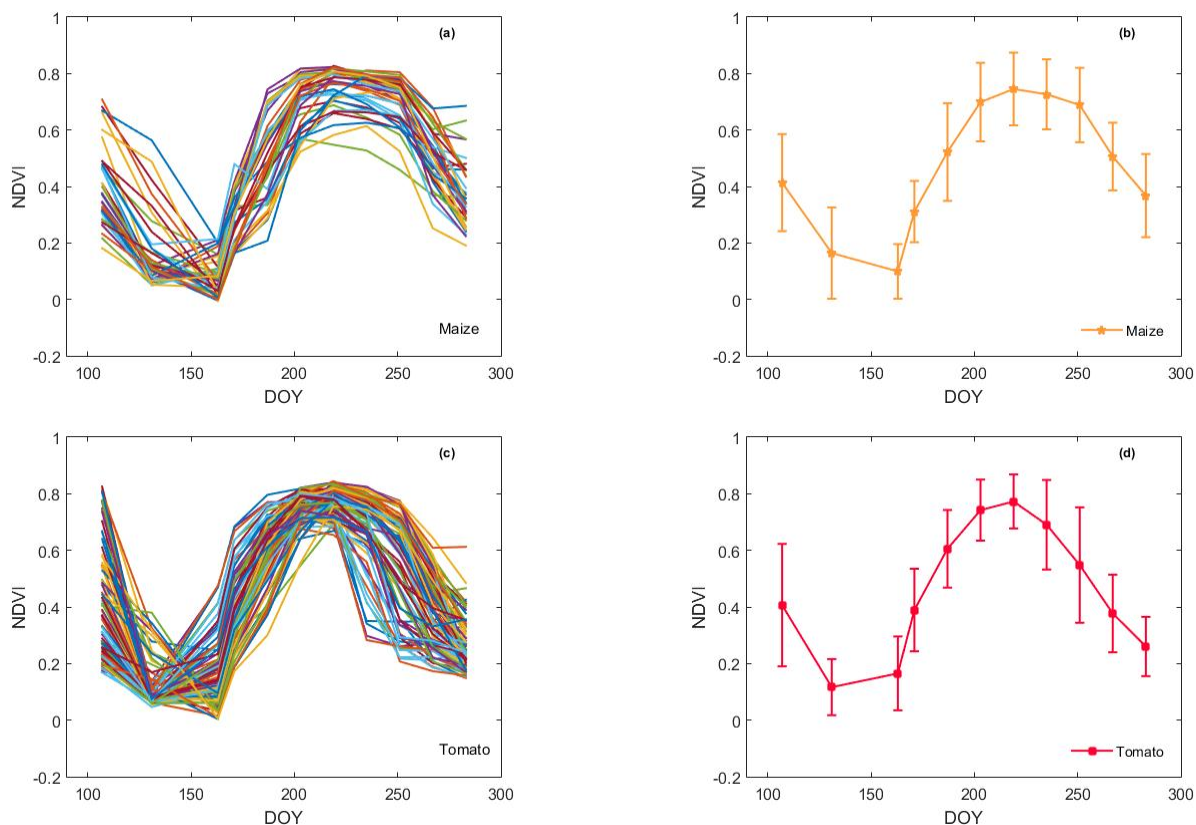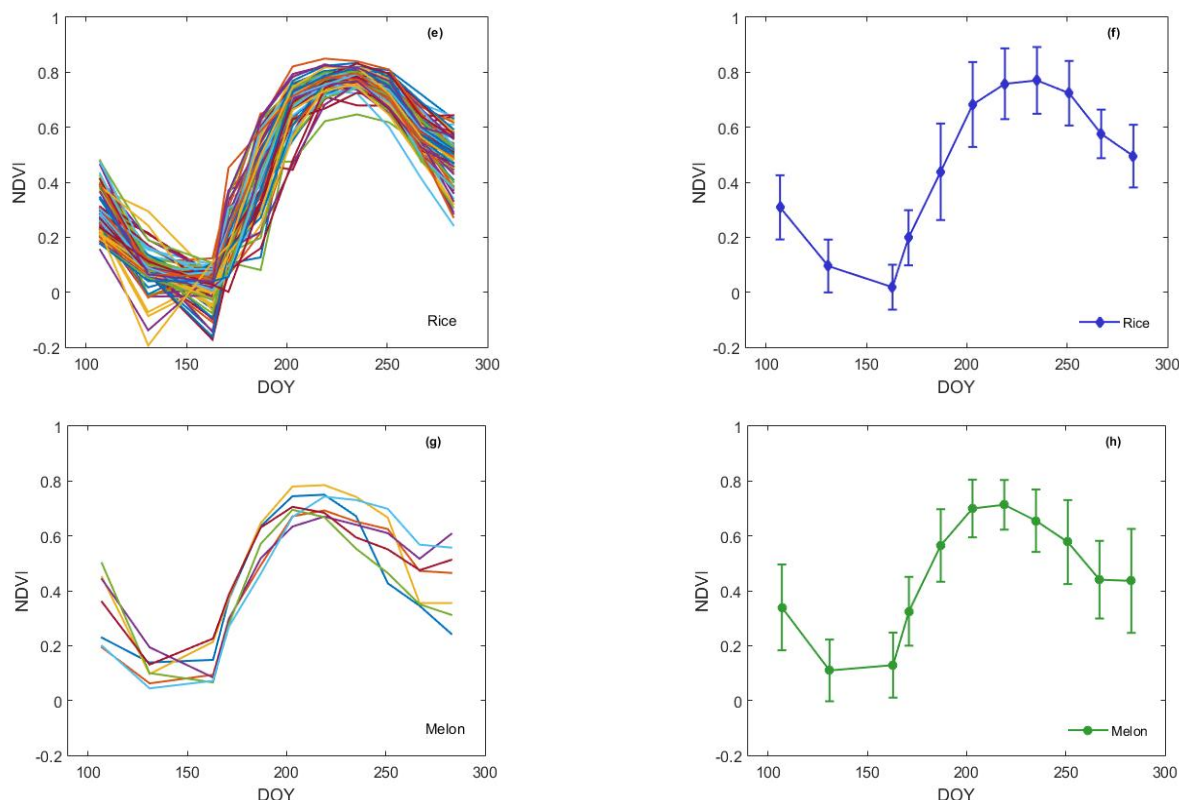
FIGURE 4. NDVI time series for maize (a), tomato (c), rice (e) and melon (g) crop parcels using the *set of curves* approach and mean NDVI curves obtained for maize (b), tomato (f), rice (h) and melon (d) using the *average curve* approach, after removing the outlier parcels (adapted from Vilar et al., 2015).

Basal crop coefficient (K_{cb}) curve

The crop parameters, K_{cb} and crop growth stage lengths, used to compute ET_c, were inferred from the average K_{cb}-NDVI curves obtained, for each crop, using the *average curve* approach. K_{cb} values obtained for each crop from EO data were compared to the FAO 56 tabulated values (Allen et al., 1998) to avoid large errors in the IWR estimation. Figure 5 shows a comparison of the maize crop between both data sets (Vilar et al., 2015), with the K_{cb}-NDVI time series presenting slightly lower values than those of the FAO 56. The produced K_{cb}-NDVI temporal profile is similar to the obtained Kcb curves for the maize crop from the field trials (Trout & DeJonge, 2018). Despite the overall good results obtained using the K_{cb}-NDVI relationship, the K_{cb} values obtained from the NDVI for

the initial stage are underestimated for all the crops considered, with the exception of melon. This can be explained by the soil's influence on the lower NDVI values, as during the initial stage the ground cover is less than 10% (Allen et al., 1998). Thus, for the IWR calculation the FAO 56 tabulated $K_{cb \; ini}$ values were used for the initial stage. An unexpected behaviour in the NDVI values was also observed for some parcels during the late season stage (Figure 4). As previously mentioned, the crop stage lengths used for the soil water balance simulation were inferred from the K_{cb}-NDVI curves; however, in the case of a 16-day revisit time, it is not possible to accurately identify each crop's growth stage length. Thus, EO data with higher time resolution for IWR calculation should be used as also referred by Toureiro et al. (2017).
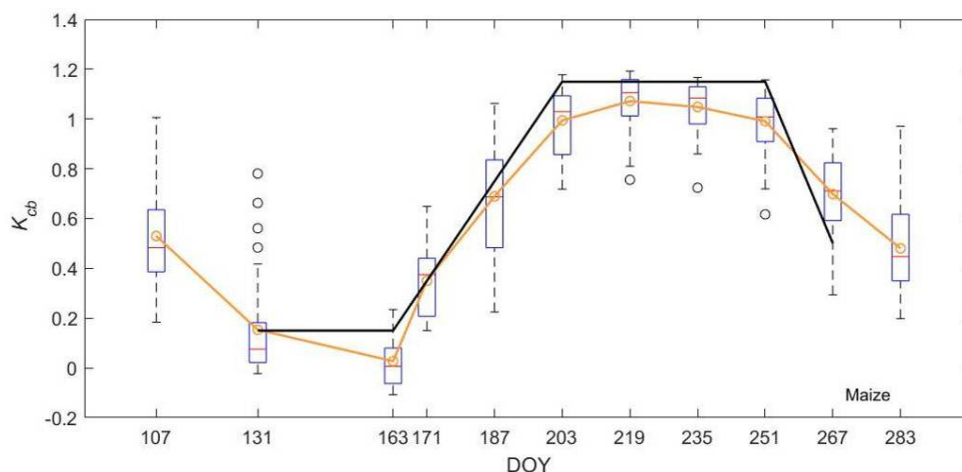

FIGURE 5. Average K_{cb}-NDVI (—) time series for maize parcels versus FAO 56 basal crop coefficient curve (—).

Irrigation Water Requirements (IWR)

The crop parameters used as input for the soil water balance model IrrigRotation to estimate the IWR are presented in Table 2 (Vilar et al., 2015), in which the K_{cb} values were empirically determined from the K_{cb}-NDVI relationship (Equation 2) with the exception of $K_{cb\ ini}$, which was obtained from FAO 56, as previously mentioned.

TABLE 2. Average crop parameters retrieved from EO data used to compute the IWR for the maize, tomato, rice and melon crops (adapted from Vilar et al., 2015).

Parameters	Crop			
	Maize	Tomato	Rice	Melon
$K_{cb\ ini}$*	0.15	0.15	0.15	0.15
$K_{cb\ mid}$	1.15	1.1	1.15	1
$K_{cb\ end}$	0.5	0.6	0.7	0.7
Planting date	11 May	11 May	11 May	11 May
L_{ini} (days)	32	32	32	32
L_{dev} (days)	40	40	40	40
L_{mid} (days)	48	48	48	48
L_{late} (days)	16	16	16	16

* FAO 56 tabulated values.

The seasonal IWR computed for the selected crops are presented in Table 3, corresponding to the average of the crop parcels in the region. The standard deviation values resulting from the different soil types existing in the Vila Franca de Xira region are also listed.

TABLE 3. Average seasonal IWR (mm) for the rice, tomato, maize and melon crops (adapted from Vilar et al., 2015).

	Seasonal crop irrigation water requirements (mm)			
	Maize	Tomato	Rice	Melon
average	639	611	835	587
standard deviation	15.1	15.3	0.2	26.4

TEST SITE II – VILA VELHA DE RÓDÃO

The second test site was in the Vila Velha de Ródão municipality, in the Castelo Branco district, east central Portugal (Figure 3). The main crops in the area are forage crops, maize, olive, permanent pasture and temporary pasture.

In this region, the climate according to the Köppen classification system is also Csa, i.e. a temperate climate with a hot and dry summer. Climate normal data, from 1971 to 2000, for the Castelo Branco weather station (39º 50' N, 7º 28' W, 386 m in altitude) of the IPMA network, show that the two hottest months are July and August, with monthly average temperatures higher than 24ºC, while winters are colder, with average temperatures lower than 10ºC from December to February. The highest monthly precipitation occurs in December (128.2 mm), while August is the driest month (8.4 mm). The average annual precipitation during the period of record is 758.3 mm.

This region was used by Rolim et al. (2016) to assess the use of both optical and Synthetic-Aperture Radar (SAR) data to estimate K_{cb} curves to be used for IWR calculation. In that study, SPOT-5 Take-5 and Sentinel-1A data were used to generate, respectively, NDVI and backscattering time series for maize. Since a significant correlation between both data sets was found, a preliminary empirical linear regression equation was proposed to estimate K_{cb} values from the SAR data, demonstrating that SAR data might be useful to compute the IWR.

The developed methodology, in this study, was applied to site II to identify the eligible crop parcels, as well as to evaluate the use of optical images with higher spatial and temporal resolutions (SPOT-5 Take-5) to define the K_{cb} curves.

DATA

Earth Observation (EO) data

SPOT-5 Take-5 images acquired from April to September 2015 were used for site II. These images were provided by the *Centre National d' Études Spatiales* (CNES) with a 10-m spatial resolution and 5-day revisit time. SPOT-5 Take-5 Level-2A images (orthorectified, bottom of atmosphere (BOA) reflectances) were used in this study because of their improved pre-processing level. Therefore, no further pre-processing steps were required. A total of 18 images without cloud cover were identified for the entire spring/summer crop growing season. The acquisition dates and the corresponding day of the year (DOY) are listed in Table 4.

TABLE 4. SPOT-5 Take-5 images acquisition dates for site II (DOY - Day of the Year, 2015 in this case).

Month	Apr			May			Jun			Jul					Aug			Sep
Day	13	23	28	18	23	28	17	22	27	2	7	12	22	27	1	11	26	10
DOY	103	113	118	138	143	148	168	173	178	183	188	193	203	208	213	223	238	253

RESULTS AND DISCUSSION

Using the *set of curves* approach, crop growth curves were generated for the main crops in the region. The average NDVI time series curves obtained for irrigated maize, irrigated pastures and non-irrigated meadow parcels are shown in Figure 6.

All parcels declared by the farmers as irrigated maize are plotted in Figure 6a, in which one can observe that some do not show the typical behaviour of this crop (Allen et al., 1998; Trout & DeJonge, 2018). After the removal of the outlier parcels, eight eligible maize parcels were obtained in which it was possible to identify, as shown in Figure 6b, different planting dates and lengths of the crop cycles. Therefore, it is demonstrated that it is possible to use NDVI time series with a short revisit time, 5 days in this case, to obtain better characterization of the crop growth cycle. Four parcels (sowed later) show an

anomalous behaviour during the late season (senescence), as well as an overestimation of the $K_{cb\ ini}$ values (Rolim et al., 2016). Both behaviours had already been observed for some parcels at site I, including for maize, using Landsat-8 data (Vilar et al., 2015). Ramme et al. (2010) also reported the occurrence of significant noise on crop NDVI temporal profiles, particularly for lower NDVI values because of the influence of soil and the need to filter the time series data. Uncertainties in the definition of the K_{cb} curve may also result from the use of K_{cb}-*NDVI* empirical formulas calibrated for other regions, and they should be validated for local conditions (D'Urso et al., 2010; Toureiro et al., 2017). However, despite these difficulties, the improved crop growth stages characterization, when using high spatial and temporal resolution satellite images such as SPOT5, is emphasized.
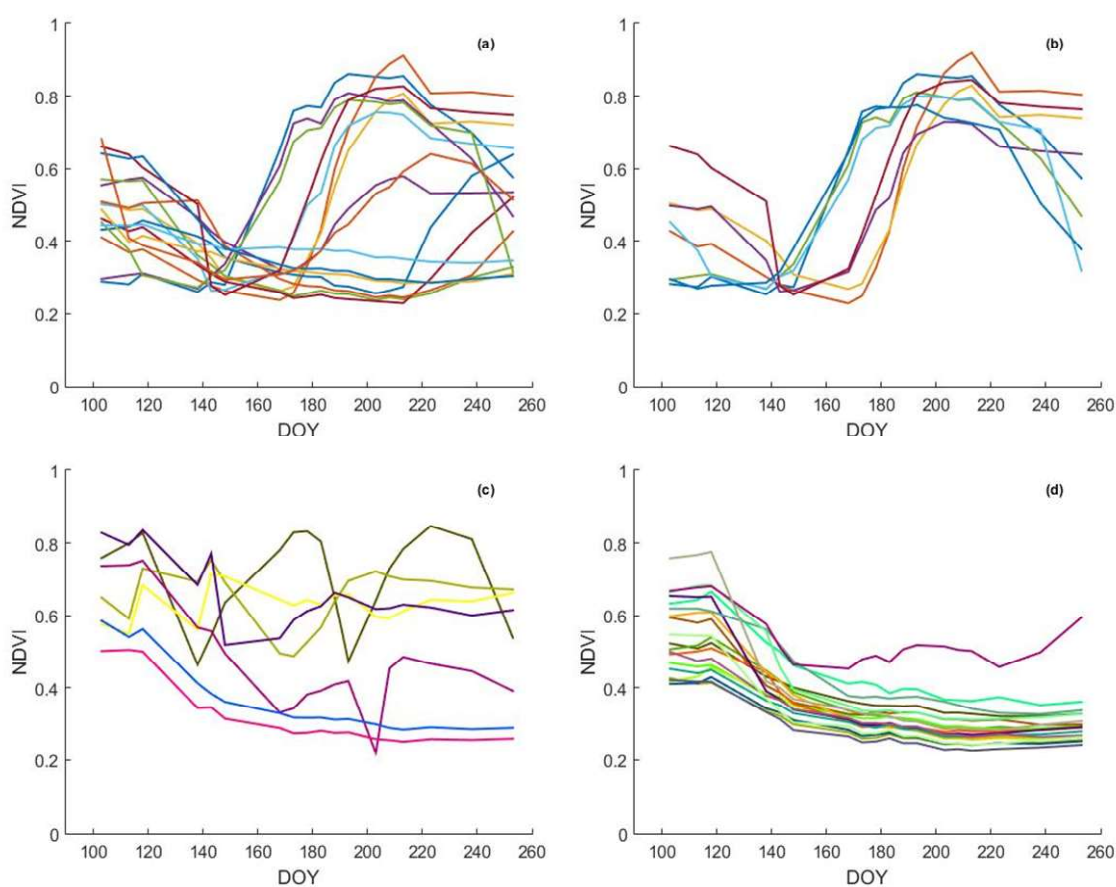

FIGURE 6. Mean NDVI time series for all parcels declared by the farmers as irrigated maize (a), after removing the outliers' parcels (b), irrigated pasture parcels (c), and non-irrigated meadow parcels (d) at site II.

For irrigated pasture (Figure 6c), it is possible to detect several forage cuts given the short revisit time of the SPOT-5 Take-5 images. The NDVI curves obtained for the non-irrigated meadow parcels, shown in Figure 6d, reveal a very different pattern when compared to those obtained for the irrigated crops because of the effect of the high water stress of rainfed crops induced by the hot and dry summers characteristic of the Mediterranean climate.

Comparing these results to those obtained for site I, using Landsat-7 and -8 images, it is possible to conclude that the obtained K_{cb} curves are less accurate than those for site II (SPOT5 Take-5) because of the reduced temporal resolution of the Landsat images. Therefore, it is

demonstrated that the use of EO data with higher spatial and temporal resolutions allows one to more reliably define detailed K_{cb} curves and consequently provide more accurate IWR estimation.

CONCLUSIONS

The proposed methodology was tested using the developed application software which proved to be suitable for the retrieval of crop data for IWR estimation at a regional level by providing accurate information relative to crop growth stages and crop coefficients. The determination of the K_{cb} curve using the EO-derived NDVI

time series allows for IWR estimation based on observations of the actual field crop growing conditions, and therefore, a more accurate soil water balance simulation is achieved.

This study demonstrated that the use of a single crop parcel or a small set of parcels may hamper crop behaviour characterization, particularly when the chosen parcel(s) is not representative of the crop pattern or of the management practices in the region. Considering a large sample of parcels for the estimation of crop parameters, it is possible to obtain a more representative and accurate crop coefficient curve, resulting in better ET_c estimation.

It was observed that a denser EO time series enables better identification of the crop phenological stage lengths and planting/sowing dates and thus overcomes one of the major sources of uncertainty in IWR estimation. Although the results obtained using this methodology are encouraging, some difficulties were found mainly concerning the estimation of the initial and end of the late season K_{cb} values obtained using the K_{cb}-NDVI approach. Caution should be exercised when using the K_{cb}-NDVI empirical formulas, and field observations are required to validate the obtained results.

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