Irrigation water use monitoring at watershed scale using series of high-resolution satellite images

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ABSTRACT

The integration of time series of high-resolution remote sensing images in the FAO crop evapotranspiration (ET) model is receiving growing interest in the last years, specially for operational applications in irrigated areas. In this study, a simplified methodology to estimate actual ET for these areas in large watersheds was developed. Then it was applied to the Guadalquivir river watershed (Southern Spain) in the 2007 and 2008 irrigation seasons. The evolution of vegetation indices, obtained from 10 Landsat and IRS images per season, was used for two purposes. Firstly, it was used for identifying crop types based on a classification algorithm. This algorithm used training data from a screened subset of the information declared by farmers for EU agriculture subsidies purposes. Secondly, the vegetation indices were used to obtain basal crop coefficients ($K_{cb}$, the component of the crop coefficient that represents transpiration). The last step was the parameterization of the influence of evaporation from the soil surface, considering the averaged effect of a given rain distribution and irrigation schedule. The results showed only small discrepancies between the crop coefficients calculated using the simplified model and those calculated based on a soil water balance and the dual approach proposed by FAO. Therefore, it was concluded that the simplified method can be applied to large irrigation areas where detailed information about soils and/or water applied by farmers lacks.

Keywords: evapotranspiration, irrigation, crop coefficients, Landsat, vegetation indices

1. INTRODUCTION

Integrated water management including sustainable use of irrigation water requires understanding the hydrological relationships at different scales. Water management assessment relies on the ability to precisely determine the water balance components, which in irrigated areas is particularly complex because of their high spatial variability. Evapotranspiration is the main component of the water balance in irrigated land. The integration of remotely sensed data into water balance models helps to better estimate evapotranspiration under heterogeneous cropping patterns. Time series of satellite images allow crop type identification and frequent monitoring of crop growth, key information for estimating evapotranspiration.

This work presents an approach for ET estimation based on the ability of vegetation indices to trace crop growth and thus to derive basal crop coefficients ($K_{cb}$) [1]. If weather stations providing reference evapotranspiration are locally available, then the FAO methodology [2,3] may be used to estimate field-specific, spatially distributed crop evapotranspiration [4]. The objective of this work was simplifying the approach proposed by Gonzalez-Dugo and Mateos [4] to make it applicable to irrigation areas at regional scale. The new approach was then applied to irrigation schemes within the watershed of the Guadalquivir River, Spain. This methodology means to become a planning and operational tool to be used by technical personnel of the Guadalquivir River Basin Authority.

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2. METHODOLOGY

2.1 Study area

The Guadalquivir River watershed (Fig. 1) is located in Southern Spain. The irrigated area in the watershed is around 700,000 ha. The study presented herein was restricted to the area comprised in the yellow rectangle in Fig. 1, which covers 232,500 ha of irrigated land. The application was performed for 2007 and 2008 with the aim of extending it to the whole watershed in 2009.

![Study area in Andalusia, Spain. Irrigated fields (green areas) are shown inside the Guadalquivir River watershed (brown area). Provincial limits are in black line. Red symbols represent the location of the stations in the Andalusian network of agroclimatic stations.](image)

Fig. 1. Study area in Andalusia, Spain. Irrigated fields (green areas) are shown inside the Guadalquivir River watershed (brown area). Provincial limits are in black line. Red symbols represent the location of the stations in the Andalusian network of agroclimatic stations.

2.2 Model description

Evapotranspiration (ET, mm) was computed using FAO methodology, which is based on the concepts of crop coefficient and reference evapotranspiration [2]. Reference evapotranspiration (ET\(_o\), mm), calculated using Penman-Monteith equation [3,5], was obtained from 26 stations (part of the Andalucian network of agroclimatic stations) that are located in the study area (Fig. 1). The crop coefficient (K\(_c\)) relates the evapotranspiration of a given crop to that of the reference surface. It may be computed using the single approach [2] or the dual approach [3,6]. The later separates crop transpiration (represented by the basal crop coefficient, K\(_{cb}\)) from soil surface evaporation as follows:

\[
ET = (K_{cb}K_s + K_e)ET_o
\]

(1)

where K\(_e\) is the soil evaporation coefficient and K\(_s\) quantifies the reduction in crop transpiration due to soil water deficit. K\(_c\) is determined based on the relative root zone soil water deficit, computed daily, and the soil evaporation coefficient is obtained by calculating the amount of energy available at the soil surface as follows:

\[
K_e = K_r (K_{e,max} - K_{cb})
\]

(2)

where K\(_r\) is a dimensionless evaporation reduction coefficient dependent on topsoil water depletion [3] and K\(_{e,max}\) is the maximum value of K\(_e\) following rainfall or irrigation.

Following the procedure described in [4], K\(_{cb}\) can be calculated as a function of a spatially distributed vegetation index (VI) provided by remote sensors. VI are transformations of two or more spectral bands designed to assess vegetation
condition, foliage and processes related to the fraction of photosynthetically active radiation absorbed by a canopy [7].

The basal crop coefficient can be estimated from vegetation indices because both are sensitive to leaf area index (LAI) and ground cover fraction ($f_c$) variations [8]. The VI adopted in this application is the Soil Adjusted Vegetation Index (SAVI, [9]) using the following linear approach:

\[
K_{cb} = K_{cb,max} \frac{SAVI - SAVI_{min}}{SAVI_{max} - SAVI_{min}}
\]

where subscripts max and min refer to the values of SAVI for very large LAI and bare soil, and $K_{cb,max}$ is the basal crop coefficient at effective full ground cover.

The water balance used to compute $K_e$ and $K_s$ requires daily rainfall and irrigation data, irrigation system characteristics and information regarding physical properties of the soil and crop response to water deficit.

The dual approach is more precise than the single approach because it accounts for variations of soil surface evaporation due to the occurrence of rainfall or irrigation events. However, keeping root zone water balances in large, heterogeneous areas may be impractical or inaccurate because of lack of soil and rainfall or irrigation data. The single approach becomes in those cases more appropriate.

What here is proposed is the use of the dual approach to parameterize the single approach according to local conditions. Then, the single approach may be applied at large scale distinguishing among regions for which the parameters have been determined.

2.3 Data acquisition and pre-processing

The primary sensor selected for this application was Thematic Mapper, on-board of Landsat-5 satellite. When cloud cover prevented using Landsat-5 images, the image series was completed with other sensors with similar spatial resolution. LISS and AWIFS sensors, on board of IRS satellite, were such sensors. The complete series of images is presented in table 1.

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Acquisition day</th>
<th>Sensor</th>
<th>Acquisition day</th>
</tr>
</thead>
<tbody>
<tr>
<td>L5-TM</td>
<td>18-03-07</td>
<td>IRS-Awifs</td>
<td>05-03-08</td>
</tr>
<tr>
<td>IRS-P6-Liss III</td>
<td>30-03-07</td>
<td>L5-TM</td>
<td>05-04-08</td>
</tr>
<tr>
<td>L5-TM</td>
<td>19-04-07</td>
<td>IRS-Awifs</td>
<td>01-05-08</td>
</tr>
<tr>
<td>L5-TM</td>
<td>05-05-07</td>
<td>L5-TM</td>
<td>08-05-08</td>
</tr>
<tr>
<td>L7-ETM SLC-off</td>
<td>29-05-07</td>
<td>L5-TM</td>
<td>24-06-08</td>
</tr>
<tr>
<td>L5-TM</td>
<td>22-06-07</td>
<td>L5-TM</td>
<td>10-07-08</td>
</tr>
<tr>
<td>L5-TM</td>
<td>08-07-07</td>
<td>L5-TM</td>
<td>26-07-08</td>
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<tr>
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<td>L5-TM</td>
<td>11-08-08</td>
</tr>
<tr>
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<td>L5-TM</td>
<td>27-08-08</td>
</tr>
<tr>
<td>L5-TM</td>
<td>10-09-07</td>
<td>L5-TM</td>
<td>12-09-08</td>
</tr>
</tbody>
</table>

All images were geometrically corrected using a 20-m resolution digital elevation model and a 1-m resolution color ortho-photograph (taken in 2004) for ground control point location. An atmospheric correction, using the MODTRAN [10] based Fast Line-of-Sight Atmospheric Analysis of Spectral Hypercube (FLAASH) and monthly-simulated aerosol and atmospheric water vapour contents, was applied.
2.4 Image classification for crop mapping

Crop type identification was assessed following procedures that differed for permanent and non-permanent crops. Citrus, fruit trees and olive trees were obtained from existing GIS databases (LPIS). Non-permanent crops were identified each year using a supervised image classification algorithm, applied to a set of 5 images from March, June, July and August 2007, and 8 images from April, June, July, August and September 2008.

The training and validation dataset for each crop was derived from a screened subset of the information declared by farmers for the control of EU agricultural subsidies. The screening process applied the Spectral Angle Mapper (SAM) algorithm to the multitemporal SAVI composed using the selected images. The average SAVI temporal trend for each crop, obtained from all the fields declared with that crop in that year, was compared with the temporal trend of each individual field. Based on the result of this comparison, the crop of each declared field was confirmed and used in the classification training or rejected.

A set of 700 accepted fields (100 per crop) were selected for training purposes and an equivalent subset was used to validate the final classification map.

3. RESULTS AND DISCUSSION

3.1 Parameterization of the single crop coefficient approach

The root zone soil water balance described in [4] was ran multiple times using weather data from several meteorological stations in the study watershed, using soil parameters characteristics of soils in the region; considering the most common irrigation methods in the study area; and scheduling optimum irrigation (in order to avoid water stress). Figure 2 shows $K_c$ for varying $K_{cb}$ assuming sprinkler, drip irrigation and using 2007 climatic data from 3 weather stations. A family of rather linear curves bounded by the curves corresponding to the driest and the rainiest months (July and February, respectively) was obtained.

In the light of these results, the relationship between $K_c$ and $K_{cb}$ was described mathematically as two lines joined at point $(1,1)$, the first with intercept $a$ and the second with maximum coordinates equal to the maximum values of $K_c$ and $K_{cb}$.
\[ K_c = a + (1-a)K_{cb} \quad \text{if} \quad K_{cb} < 1 \quad (4a) \]

\[ K_c = \frac{K_{c\text{max}} - 1}{K_{cb\text{max}} - 1} K_{cb} + \frac{K_{cb\text{max}} - K_{c\text{max}}}{K_{cb\text{max}} - 1} \quad \text{if} \quad K_{cb} > 1 \quad (4b) \]

Fig. 3. Simplified representation of \( K_c-K_{cb} \) relationship

Therefore, the simplification from the dual to the single approach was reduced to determining \( a \) for the rainfall, soil and irrigation conditions of interest. Note that the water balance simulation that has to be performed for determining \( a \) does not imply any crop assumption, i.e., it is for bare soil (\( a \) is \( K_c \) for zero \( K_{cb} \)). However, assumptions about irrigation frequency and soil surface wetting are required.

The performance of the simplified methodology was assessed by comparing ET simulated following the dual and simplified approaches using a large set of field data obtained in 2004 over an irrigation district located in the lower Guadalquivir valley, inside the study area (data description in [4]). The data corresponded to fields grown with sugarbeet and cotton crop, thus the results could be considered as representative of winter and summer crops.

The results showed that both models simulated similar seasonal ET (Fig. 4). The root mean square difference (RMSD) was 23 mm (3.5% of mean seasonal ET), correlation was high, and there was no bias in the whole dataset. The agreement between both models was for sugarbeet (RMSD = 17 mm) better than for cotton (RMSD = 28 mm), even though drip irrigation and irrigation frequency typical of cotton were assumed for determining \( a \). This different performance was likely due to winter and early spring weather conditions, when sugarbeet ground cover is increasing. During that period water was supplied mostly by rainfall. After, when irrigation started, the plants covered then soil almost completely, becoming evapotranspiration rather insensitive to irrigation frequency and soil wetting.

![Figure 4](image.png)

Figure 4. Comparison between seasonal ET calculated by the simplified method and by the FAO dual method, for cotton and sugar beet plots in 2004 irrigation season.
3.2 Crop type identification

The crop map obtained for the 2008 irrigation season is shown in Fig. 5; and the distribution of crops is presented in Table 2.

![Crop map for 2008 irrigation season](image)

Figure 5. Crop map for 2008 irrigation season

The validation of the non-permanent crops classification resulted in global success of 88%, with the best results obtained for cotton (92%) and the poorest for other uses (70%).

<table>
<thead>
<tr>
<th>Crop type</th>
<th>Surface (ha)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Citrus fruit tree</td>
<td>16.300</td>
</tr>
<tr>
<td>Other fruit tree</td>
<td>13.400</td>
</tr>
<tr>
<td>Olive tree</td>
<td>38.600</td>
</tr>
<tr>
<td>Cotton</td>
<td>27.450</td>
</tr>
<tr>
<td>Rice</td>
<td>12.300</td>
</tr>
<tr>
<td>Sunflower</td>
<td>22.700</td>
</tr>
<tr>
<td>Maize</td>
<td>12.100</td>
</tr>
<tr>
<td>Sugar beet</td>
<td>9.100</td>
</tr>
<tr>
<td>Cereals</td>
<td>35.700</td>
</tr>
<tr>
<td>Other uses</td>
<td>43.950</td>
</tr>
</tbody>
</table>

Table 2. Surface distribution of crops in the study area

3.3 Seasonal ET estimation

The simplified model was run on a daily basis for 2007 and 2008 irrigation seasons; 10-day aggregations were recorded; and seasonal maps were produced.
Fig. 6 presents ET maps corresponding to the 2007 and 2008 irrigation seasons. The highest ET obtained for both irrigation seasons (1042 and 1164 mm, respectively) corresponded to rice plots located at the lower areas of the watershed. Maize followed with 678 and 732 mm in 2007 and 2008, respectively. It is important to note that the period of analysis was slightly different in the two seasons because of the imagery availability in those years. The period lasted from 5 March to 12 September in 2007 and from 18 March to 10 September in 2008.

Fig. 7 shows in detail a subset of the lower Guadalquivir area, where differences between individual plots can be observed. The high spatial variability among fields highlighted the importance of high spatial resolution of the input data required to adequately characterize these areas.

The combination of ET and crop classification maps allowed the analysis of the results by crop type (Fig. 8). It was possible to monitor the temporal evolution of ET for each field as well. However, field monitoring is limited by the spatial resolution of the satellite images, therefore the estimation of ET of small fields may contain large errors.
Following the same procedure and aggregating ET data across the irrigation districts limits, sector or district statistics were obtained, but are not presented here.

Fig. 8. Average ET by crop type for 2007 and 2008 irrigation seasons in the studied area.

4. CONCLUSIONS

The estimation of ET by the simplified approach was satisfactory when compared to the FAO dual procedure; i.e., the main effects of rain and irrigation soil wetting on seasonal ET were modelled adequately. It was then concluded that the simplified method may be used to estimate evapotranspiration of irrigated land at regional scale. The spatial resolution of the satellite images permitted individual characterization of the irrigated fields for the typical field size in the area, and its temporal resolution allowed regular monitoring of crop growth. It is important to point that data coming from more than one satellite was required to obtain the desired temporal resolution.

Crop identification based on temporal trends of SAVI provided good success in the classification of non-permanent crops. Training datasets derived from crop declarations by farmers was critical to achieve this success, proving the great value of this kind of data for purposes different to those for which they were acquired.
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REFERENCES