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Integrating Satellite-based Evapotranspiration with Simulation Models for Irrigation Management at the Scheme Level.

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Abstract

Improvements in irrigation management are urgently needed in regions where water resources for irrigation are being depleted. This paper combines a water balance model with satellite-based remote-sensing estimates of evapotranspiration (ET) to provide accurate irrigation scheduling guidelines for individual fields. The satellite-derived ET was used in the daily soil water balance model to improve accuracy of field-by-field ET demands and subsequent field-scale irrigation schedules. The combination of satellite-based ET with daily soil water balance incorporates the advantages of satellite remote-sensing and daily calculation time steps, namely, high spatial resolution and high temporal resolution. The procedure was applied to Genil – Cabra Irrigation Scheme of Spain, where irrigation water supply is often limited by regional drought. Compared with traditional applications of water balance models (i.e. without the satellite-based ET), the combined procedure provided significant improvements in irrigation schedules for both the average condition and when considering field-to-field variability. A 24% reduction in water use was estimated for cotton if the improved irrigation schedules were followed. Irrigation efficiency calculated using satellite-based ET and actual applied irrigation water helped to identify specific agricultural fields experiencing problems in water management, as well as to estimate general irrigation efficiencies of the scheme by irrigation and crop type. Estimation of field irrigation efficiency ranged from 0.72 for cotton to 0.90 for sugar beet.

1. Introduction

Irrigated agriculture currently faces the dilemma of meeting the increases in food demand associated with a growing world population that is changing its diet, while ensuring the sustainable use of an already scarce water resource and protecting the quality of the environment. Improving water management in irrigated areas and assessment of irrigation performance are critical activities for this endeavor. These activities are needed not only to improve water productivity (Hsiao et al., 2007), but also to increase the sustainability of irrigated agriculture, improving the irrigation efficiency in a situation of strong competition for the water resources.

Most of the consumptive use of irrigation water, defined as the water abstracted which is no longer available for use because it has evaporated, transpired or been incorporated into crops, is transferred to the atmosphere as evapotranspiration (ET), and therefore, the spatial and temporal quantification of ET is essential in agricultural water management, especially in areas experiencing scarcity in total fresh water resources. Estimates of ET at the regional scale are difficult to obtain and thus, spatial information is limited. Field techniques such as soil water balance residual methods, Bowen ratio and eddy covariance systems provide ET measurements (Dugas et al., 1991), but they are obtained at the plot scale or are limited to the local environment in which the instruments are installed. Methods used to obtain estimates of ET at large scales are often based on a physical-mathematical procedure, i.e., simulation models or remote sensing algorithms (Black et al., 1989; Kite and Droogers, 2000; Bastiaanssen et al., 2005).

Remote sensing techniques for estimating ET have been recently developed and are based on using satellite-based energy balance and thus producing estimates of actual ET (Bastiaanssen et al., 1998; Allen et al., 2007a). METRIC (*Mapping EvapoTranspiration with high Resolution and Internalized Calibration*) is an ET estimation model developed by the University of Idaho, USA (Allen et al., 2007a) and based on the SEBAL (*Surface Energy Balance Algorithms for Land*) model of Bastiaanssen et al. (1998). The SEBAL model has been applied and tested at a large number of locations around the world (Bastiaanssen et al., 2005) while METRIC has been applied in the Western United States (Allen et al., 2005; Allen et al., 2007b) to produce high resolution ET maps. Estimates of ET by METRIC have been compared favorably with a series of lysimeter ET measurements at two locations in the northwest US (Tasumi et al., 2005b).

Although satellites routinely measure surface reflectance and some measure surface temperature, none measure near surface vapor content. Therefore in METRIC, ET is determined from Landsat satellite imagery by applying an energy balance at the surface, where the energy consumed by the ET process is calculated as a residual of the surface energy balance equation. The energy balance is calibrated for each image using a reference ET calculation determined from weather data. Once crop ET is determined, it is possible to calculate the ratio between real crop evapotranspiration and reference crop evapotranspiration (ET_o). This ratio is termed the real crop coefficient ($K_{c\ act}$). Crop ET estimations based on $K_{c\ act}$ values derived from satellite images have been shown to be useful in field and regional water management (Tasumi and Allen, 2007).

Many models have been used to simulate components of the hydrologic cycle in irrigated agriculture, from empirical or functional (USDA-SCS, 1972; Williams, 1991; Allen et al., 1998) to mechanistic (Van Aelst et al., 1988). Water balance components, including ET, may be estimated with these models over a variety of time periods. When used with polar-orbiting satellites such as Landsat, ASTER and MODIS, or with aerial-based images, remote sensing provides only a snapshot (for Landsat images once in a period of 16 days and only if the atmosphere is free of clouds). However, images are generally produced with high spatial resolution. Combining hydrologic models and remote sensing can overcome many of the shortcomings associated with low spatial coverage of field scale models and with the low temporal resolution of high spatial resolution remotely sensed images (Droogers and Bastiaanssen, 2002). This combination can thereby facilitate detailed spatial and temporal analyses used to assess the performance of irrigation schemes (Kite 2000; Kite and Droogers 2000). To verify the accuracy of such an approach, it must be tested at the scale of an irrigation scheme where there is sufficient information (weather data, soil, cropping patterns, water use records and irrigation practices)

The opportunities to combine satellite-based ET data with soil water and ET estimates obtained with simulation models or with water use information collected in the field are numerous. Here, we have combined METRIC-derived estimates of ET in the Genil – Cabra Irrigation Scheme in southwest Spain with a water balance model by Lorite et al. (2004a) hereafter named LORMOD, to evaluate the potential of using near-real time ET estimates to update and correct irrigation scheduling predictions made with the model at the plot level and to assess its impact on scheme water use. Additionally, we show here that such ET estimates may be used together with on-farm measurements of applied irrigation water to provide reliable estimates of irrigation efficiency, thus identifying those plots within the scheme that require improvements to their irrigation management.

2. Material and Methods

a. Satellite-based energy balance estimation of crop ET (METRIC)

Eleven Landsat 5 TM images were used in this work, covering Landsat path 201 and row 34. The images have corner coordinates shown in Table 1. The Landsat image dates were November 13 of year 2004, and March 5, April 22, May 8, June 9, June 25, July 11, August 12, August 28, September 13, September 29 of year 2005. The images were processed using the METRIC energy balance computation procedure (2006 version) of Allen et al., (2007a) to obtain daily ET for each image date.

METRIC estimates ET as a residual of the energy balance at the surface, where energy consumed by the ET process is calculated as a residual of the surface energy equation:

$$LE = R_n - G - H \qquad (1)$$

where LE is the latent energy consumed by ET, R_n is net radiation, G is sensible heat flux conducted into the ground, and H is sensible heat flux to the air. Details of the METRIC model are given in Tasumi et al. (2005a) and Allen et al. (2007a).

Net radiation is computed by subtracting all outgoing radiant fluxes from all incoming radiant fluxes and includes solar and thermal radiation. Incoming shortwave radiation is calculated by analyzing solar position and intensity of radiation (Allen et al., 2006). Surface albedo is calculated by integrating reflectivities from bands 1–5 and 7 of Landsat. Incoming longwave radiation is estimated using a regionally calibrated equation, and outgoing longwave radiation is calculated by surface temperature (T_s) and emissivity.

Soil heat flux is estimated as a function of R_n, T_s, and vegetation indexes. Sensible heat flux is estimated by deriving a near surface air-temperature gradient (dT) and aerodynamic resistance between two near surface heights (0.1 and 2 m above zero plane displacement), assuming dT is linear to radiometric T_s. Calibration of the dT function is accomplished by selecting two extreme “calibration pixels” representing very dry and very wet agricultural surfaces, as described in Allen et al. (2007a). Some site-specific coefficients (e.g. surface roughness length by land use type) must be locally derived and were adapted here to Andalusian conditions. To sample ET by which to characterize each field, pixels located near the centers of fields were selected. In fields with enough size, more than one pixel was selected in order to develop analyses on ET variability within fields. For Landsat 5 TM, the thermal band resolution is 120 m x 120 m, thus sampled pixels locations were at least 120 m from field edges.

We define a crop coefficient, $K_{c\ act}$, as the ratio between actual ET estimated by METRIC, and the grass reference ET (ET_o) calculated following the ASCE standardized Penman- Monteith method (ASCE-EWRI, 2005). This $K_{c\ act}$ differs from the standard K_c (Allen et al., 1998) in that our actual ET estimate is usually below the maximum ET due to agronomic factors. Real crop coefficient ($K_{c\ act}$) images were created by dividing the ET images derived from METRIC by ET_o. Weather data for calculating ET_o were provided by five automatic weather stations located close to the GCIS. These weather stations are part of the Agroclimatic Information Network of Andalusia (Gavilán et al., 2006) and provide semi-hourly weather data including wind speed, air temperature, humidity and solar radiation. The weather information was evaluated and quality controlled following standardized procedures recommended by ASCE-EWRI (2005). The values obtained for $K_{c\ act}$ were interpolated between each image date (16 days at a minimum) using a spline, to define the temporal evolution of $K_{c\ act}$ values and to thus obtain the $K_{c\ act}$ curves.

b. Simulation model

A water balance model was used to calculate the fate of water applied to field. The water balance components include rain, irrigation, soil evaporation, transpiration, run-off and drainage. Details are provided in Lorite et al. (2004a). Surface run-off is estimated from daily precipitation using the USDA – Soil Conservation Service (1972) curve number method. The curve number method was modified to include the effect of field slope (Williams, 1991) in addition to considering precipitation, soil type, land use and management (Lorite et al., 2004a).

Three soil water thresholds are characterized in LORMOD (Lorite et al., 2004a) for each soil layer: the saturated water content, the drained upper limit or field capacity (FC) and the lower limit of plant extractable water or wilting point. Infiltrated water (precipitation minus run-off) is distributed within the soil profile following a cascading approach where the soil profile is divided into 20 layers. The amount of water above FC in any given layer is transferred to the layer immediately below. This procedure is repeated for all layers until drainage from a layer is less than the water deficit (below FC) of the layer below. Drainage below the profile is assumed to occur when the soil water content of the deepest layer is above FC.

Maximum crop evapotranspiration was calculated from the product of reference evapotranspiration and dual crop coefficients (Allen et al., 1998) where the dual K_c contains components for both evaporation and transpiration and is calculated on a daily timestep. Reference evapotranspiration was estimated using the FAO-56 Penman-Monteith method (Allen et al., 1998) which is identical, for 24-hour calculation timesteps, to the standardized Penman-Monteith method of ASCE-EWRI (2005) for ET_o.

Crop water extraction in each soil layer was calculated as a function of root density and water content in that layer (Coelho el al., 2003). Actual plant water uptake from each layer was linearly reduced after its soil water content decreased below a given fraction of the extractable water (the allowable depletion). Actual crop ET was then calculated as the sum of soil evaporation and plant water uptake from each layer. In the original formulation, the season length and the duration of each growth stage of the

K_c curve were based on Allen et al. (1998), but were adjusted with data collected locally. The magnitude of K_c was not varied from Allen et al. (1998).

The water balance model calculated required irrigation applications as the depth of irrigation water needed to refill the soil profile, termed net irrigation requirement (NIR). The NIR values derived for fields were divided by an irrigation efficiency accounting for deep percolation losses due to irrigation ununiformity (Wu, 1988) to obtain the gross irrigation requirement. Other specifics of the LORMOD model are described in Lorite et al. (2004a).

c. Integration of METRIC ET estimation with the simulation model for irrigation scheduling.

Figure 1 describes the procedure followed to integrate estimates of actual ET derived from METRIC with LORMOD simulation model, with the objective of including real $K_{c\ act}$ values over time and providing adjusted irrigation schedules of each field. In the procedure followed here, initially, LORMOD developed preliminary irrigation schedules for each field using the maximum $K_{c\ act}$ values that were obtained by METRIC over all the fields for each crop (values provided later in the Results section). Such values provide an upper limit of the $K_{c\ act}$ for each crop over the scheme, and were used to generate preliminary schedules instead of using K_c values from the literature, as in Lorite et al. (2004a) or rather than using the field specific $K_{c\ act}$ values from METRIC. Using the maximum calculated $K_{c\ act}$ values ensured that these preliminary irrigation schedules generated provided sufficient water to meet the full crop demands for all fields. However, in almost all the cases irrigation scheduled in this fashion would recommend watering in excess of the actual needs. To prevent excessive irrigation, the preliminary schedules were updated for each case using field-specific K_c

$_{act}$ information determined by METRIC. Soil water deficit (SWD) is the parameter used to determine the final irrigation schedule. For each satellite image available, a new daily ET rate was back-calculated using the $K_{c\ act}$ obtained via METRIC and the SWD of each field was recalculated for each day up to the previous image date. In that way, the SWD was updated using real $K_{c\ act}$ values for the plot (and actual ET) that was provided by METRIC instead of the maximum $K_{c\ act}$ values used initially. The LORMOD model adjusted the next irrigation date based on the updated SWD. Once the SWD was updated, the next irrigation event was delayed accordingly, if necessary.

d. Area description

The study area was located within the Genil – Cabra Irrigation Scheme (GCIS), near the town of Cordoba, Spain (4º 51' W, 37º 31' N). The area evaluated encompasses about 6,800 ha of irrigated land developed around 1990, being under full water supply since 1995. The climate is Mediterranean continental with an annual average precipitation of 610 mm, and a rainless summer. The average air temperature ranges from 10 ºC in winter to 27 ºC in summer. The predominant soils in the area are Chromic Haploxererts (35%) and Typic Xerorthent (34.7%).

Cropping patterns are fairly diverse. The most important crops in the area during 2004/05 were wheat, cotton and olive, representing 23%, 18%, and 14% of the irrigated area, respectively. Other crops in the area included, in order of importance, maize, sugar beet, beans, garlic, sunflower, and several vegetable crops.

The area is serviced by a modern pressurized irrigation delivery system, which allows complete flexibility in frequency, rate and duration of water delivery. The water application methods depend on the crop. Thus, crops such as wheat or sunflower are irrigated with hand-move sprinkler systems, while horticultural crops or olive are mainly irrigated with drip systems. In maize and cotton, approximately half of the area is drip irrigated and the rest with sprinkler systems. Land use has the following characteristics: there are 290 fields of less than 2 ha, occupying 4.3% of the area, about 360 fields between 2 and 10 ha, representing 22.6% of the area, and 190 fields between 10 and 100 ha (65.7% of the area). Three command areas serve fields that are over 100 ha, occupying 8.5% of the area. Over 90% of the individual fields are less than 20 ha in size. Every field outlet has a water meter that provides cumulative water delivery records. These records are compiled by the staff of the irrigation scheme, who read the meters at least four times throughout the irrigation season.

The 2004/05 irrigation season was very dry; seasonal rainfall was 271 mm while in the last fifteen years the average seasonal value in the area was 529 mm. The average irrigation depth applied in the irrigation scheme during the 2004/05 irrigation season was 417 mm, a value that was much greater than the average depth applied over the last ten years (261 mm).

3. Results

a. Seasonal ET and Crop Coefficients

The seasonal ET estimated with METRIC for all the plots in the Genil – Cabra Irrigation Scheme (GCIS) are depicted in Figure 2 for the 2004/05 irrigation season. Seasonal ET varied from more than 1000 mm for well-irrigated fields, to almost zero for non-agricultural areas. Rain fed areas surrounding the GCIS (in the north) had ET values around 200 mm, which were commensurable with the seasonal rainfall, while values comparable to those calculated for the GCIS were found towards the south, in another irrigation scheme (Fig. 2).

Crop coefficients calculated by dividing METRIC ET for individual fields by ET_o exhibited very high variability for the different crops (Fig. 3). Variability associated with irrigation and cropping practices (as in cotton) adds to the variability caused by different sowing dates (as in maize) and by different harvest dates (as in sugar beet and garlic). This high variability in actual ET can be explained in large part by the plot to plot variability in irrigation management in the GCIS, as characterized previously by Lorite et al. (2004b) in terms of the volume of irrigation water delivered to individual fields. Lorite et al. (2004b) found substantial variability in seasonal depth of irrigation delivery among fields of the same crop, leading to the conclusion that soil water deficits occurred in some fields, given that delivery records were significantly less than crop ET needs.

Traditionally, during the early crop stages (April-May), cotton is irrigated in the area using hand-move sprinkler systems (even in fields equipped with drip irrigation) for effective germination and crop establishment. Consequently, the initial $K_{c\ act}$ values for cotton were high after planting but then decreased after sprinkler irrigation applications ended, following seedling establishment in early June (Fig. 3a). For sugar beet and garlic, $K_{c\ act}$ s were high during the winter period (Nov 2004 thru March 05; Fig. 3c,d), a consequence of the dry winter that forced farmers to irrigate during that period, hence the high $K_{c\ act}$ values. The season length for sugar beets was extraordinarily long (more than 8 months until August; Fig. 3d) because, due to winter frosts, farmers had to replant several times. This long season caused a significant increase in total sugar beet ET and in irrigation requirements, as shown in Table 2. Actual irrigation water use for sugar beet was higher than for maize and cotton during 2004/05 (785 mm vs. 710 mm; Table 2).

The variability in ET among fields having the same crop type can be assessed by plotting the cumulative frequency of the observed field ET values for the different crops (Fig. 4). This distribution allowed the calculation of the percentage of fields that had ET values higher or lower than a fixed value. Crops differed in their ET variability; in some crops such as sunflower, variability was high (CV_s=0.28; Table 2) while average ET was low (378 mm; Fig. 4). Other crops such as maize or cotton, showed lower relative variability (CV_s=0.12) and high average ET (around 700 mm; Fig. 4). On an absolute basis, variability among fields was similar across all crop types, ranging from 70 to 110 mm.

3.2. ET Variability within Fields

In addition to the ET variability encountered among fields in the GCIS, it was possible to assess the ET variability within fields in those that had enough size to contain more than one thermal pixel with valid METRIC ET estimates (samples were taken far enough inside fields to avoid contamination of thermal pixels from areas outside the field). The coefficient of variation within fields (CV_w) varied from 0.03 for pepper to 0.13 for sunflower (Table 2), implying variations of more than 160 mm (44% of seasonal ET) within a sunflower field, while maximum variability in pepper fields was 70 mm (12% of seasonal ET) (Data not shown).

Additionally, the variability within fields (CV_w) was well correlated with variability among fields (CV_s): Crops with low ET variability among fields, such as cotton or maize showed low variability within fields (CV_s for cotton was 0.12 while CV_w was 0.05; Table 2), while sunflower had high values of CV_s and CV_w (0.28 and 0.13 respectively). Given the low input management practiced in this crop in the GCIS, variations in crop husbandry (seeding rates, fertilization, etc.) must have been largely responsible for the high CV's observed. NDVI was determined for the sunflower fields where ET was found to vary within the field. The level of variability in NDVI was similar to the level of ET variability (data not shown) suggesting that the main cause of ET variations in this case was the degree of ground cover by the crop.

3.3. Updating Irrigation Schedules with METRIC ET within the Simulation Model

Significant differences were found among the schedules generated using the standard methodology and using actual estimates of ET. For cotton, average seasonal irrigation depth calculated with the standard irrigation schedule was 733 mm while when the schedule was routinely updated using actual field-scale ET estimates from METRIC, the average depth decreased to 559 mm. Differences in seasonal irrigation demand were also found for the other crops, as shown in Figure 5 and in Table 3. The magnitude of differences depended on the crop. For some crops such as cotton or maize, where actual ET was less than maximum, the updated schedules generated important irrigation savings (around 24% for cotton and 10% for maize; Table 3 and Fig. 5). In other crops such as garlic or sugar beet, updated schedules required more irrigation water than that specified by the standard schedules (around 10% for garlic and 21% for sugar beet; Table 3 and Fig. 5), and would potentially increase crop yields for these crops by reducing water stress. These differences in the irrigation scheduling were caused by differences between the standard K_c values taken from the literature by Lorite et al. (2004a), and the real $K_{c\ act}$ values as determined by METRIC (Fig. 3) as discussed below.

When the irrigation schedules were developed using the uppermost values of the $K_{c\ act}$ curves in Figure 3, the seasonal irrigation depth required was even greater (766 mm for cotton or 843 mm for maize; Table 3) than that obtained with the standard K_c values from the literature used by Lorite et al. (2004a).

3.4. Estimation of irrigation efficiency using METRIC ET estimates.

Field irrigation efficiency (IE, Burt et al., 1997) was estimated for selected fields using the ET determined by METRIC, the effective rainfall, and the actual plot water use obtained from water meter records. Results are presented in Figure 6 and in Table 4. Two groups of efficiency values were found; one for summer crops such as cotton or maize, that had an average IE of around 0.75 (0.72 for cotton and 0.76 for maize; Table 4), and another for winter crops, such as garlic and sugar beet that had higher IE values of around 0.85 (0.82 for garlic and 0.90 for sugar beet; Table 4) .

The average IE for the area was 0.77. In terms of irrigation method, sprinkler systems had lower IE values than drip systems (0.71 vs. 0.75 in cotton, or 0.70 vs. 0.80 in maize; Table 4) and higher plot to plot variability (CV=0.17 vs. CV=0.09 in cotton). The variation in IE within each crop shown in Figure 6 confirms the high variability in irrigation management that exists among farmers in the area, as determined with other procedures by Lorite et al. (2004b).

To estimate the actual irrigation use associated with each field, we calibrated and validated a procedure using averages for IE values previously developed. An average IE value was determined for each crop by choosing at random 20% of the total number of fields for which there were ET estimates and water meter records. The value of IE thus obtained was used to estimate the actual water use of the remaining fields. This was done by dividing seasonal ET for each field, determined by METRIC, less effective rainfall, by the average IE. The results are shown in Figure 7. On average, estimation of irrigation water used by farms based on METRIC was quite accurate when compared with actual measurements; thus, while actual average water use was 699 mm, irrigation water use estimated by METRIC was 677 mm, implying an error in the estimation of 3%.

Many points in Figure 7 fall along a 1:1 line suggesting that this approach may be very useful to estimate the actual water use in fields, if a good estimate of IE is available. In some cases, field values departed from the 1:1 relationship (points lying within the black circle), because, either of over-irrigation or a low, actual IE value. In both cases these fields should be targeted for irrigation management improvements. A few other cases are above the 1:1 line possibly because the actual IE of the field was higher than the average estimate. Nevertheless, for more than 60% of the fields, METRIC ET provided accurate estimation of water use (Fig. 7) and allowed the labelling of fields that were over-irrigated (black circle in Fig. 7).

4. Discussion

A satellite-based energy balance process called METRIC was used to estimate seasonal ET and associated $K_{c\ act}$ curves for a number of fields within an irrigation scheme in southwest Spain. This approach, used previously by Tasumi et al. (2005a), is an alternative methodology to satellite-based vegetation index procedures used in other studies (Ray and Dadhwal, 2001). From the real ET values determined (Fig. 2), it was possible to quantify the variability in ET among fields and associated variation in crop coefficients (Fig. 3), and in seasonal ET (Fig. 4). In this study, eleven Landsat images were processed over the growing season. The relatively large number of available images during spring – summer allowed $K_{c\ act}$ peaks to be correctly detected and described. The winter period (from Nov. 2004 until March 2005) was uniquely described using two images. The relatively high frequency of images collected in this study produced a high level of confidence in ET estimates, especially during the period of high irrigation requirements. Thus, the quality of results were not impacted by infrequent timing of remote sensing data acquisition as other authors have previously referred to (Guerif and Duke, 2000). The seasonal ET estimates constitute an improvement in the temporal analysis of ET as compared with previous studies that have used as few as one satellite image (Consoli et al., 2006).

The determination of ET via remote sensing techniques can help to identify a number of factors that appear to have affected actual ET, such as disease, drought, limited irrigation, adverse weather conditions or planting date (Tasumi and Allen, 2007). These factors are difficult to detect with other methods (Burt et al., 1997). For example, during 2004/05 in the GCIS, winter frosts caused the need to replant sugar beet crops and that led to an important increase in ET for some fields due to the extension of the crop cycle (Fig. 4). This was confirmed by the records of actual sugar beet water use that were nearly double those of previous seasons (62% higher), while, in spite of the drought that caused a severe precipitation shortage in 2005, water use for maize and cotton increased only by 18% (Lorite et al., 2007).

The cumulative ET curves (Fig. 4) had similar shapes to those obtained by Mo et al. (2005) for maize and winter wheat in China. The variability of ET encountered in the GCIS (CV_s=0.12 for cotton and CV_s=0.28 for sunflower; Table 2) indicate significant variation in irrigation management among farmers. However, although a low spatial variability does not necessarily mean that there is proper system management (Sanaee and Feyen, 2001), in the case of the GCIS, where on-demand supply is practiced, the significant spatial variability is likely associated with suboptimal crop husbandry and/or deficit irrigation management. Similar values of ET variability (CV_s=0.25) were found for orange orchards irrigated with a suboptimal water supply, based on high resolution vegetation indexes and agro-meteorological data (Consoli et al., 2006). In general, variability is a suitable indicator for water supply equity (Bastiaanssen and Bos, 1999), but also, a large variability in performance among farmers may indicate a substantial potential for improvement in performance, even if the average performance values or seasonal ET are reasonable. The use of average performance values does not shed light on the actual level of scheme performance (Bastiaanssen et al., 2001; Bandara, 2003; Lorite et al., 2004b). Thus, the assessment of variability, as offered by satellite image processing, is essential for a thorough and revealing irrigation performance analysis.

The ET estimates for fields that had sufficient size to sample provided information on seasonal ET variability within fields (CV_w; Table 2). Such variability is attributed to problems associated primarily with irrigation uniformity. The within field variability detected in GCIS was lower than that obtained by Roerink et al. (1997). Those authors determined a level of variability under surface irrigation ranging from 9.2 to 18.6%, with a mean CV_w value of 14%, using remote sensing data from one image in an irrigation scheme. In the current work, a correlation between the variability among and within fields was noted, as in the case of sunflower (CV_s=0.28 and CV_w=0.13; Table 2). This high variability (among and within fields) suggests that irrigation and crop management were not optimal from the productivity standpoint. However, because the sunflower crop has generally low income and low water productivity, such practices probably lead to maximum profits (Lorite et al., 2004b).

In this work, we have applied a water balance model, similar to Droogers and Bastiaanssen (2002), to fill in temporal gaps between successive satellite overpasses, which can be a handicap of current satellite-based remote sensing techniques when applied to irrigation scheduling. The integration of the water balance model LORMOD with METRIC allowed the adjustment of irrigation schedules as the season progressed, considering the circumstances that the specific fields underwent through the irrigation season, in contrast with the traditional fixed schedules based on average data (Lorite et al., 2004a). In the GCIS, adjustments to ET demands using real time ET estimates reduced the average irrigation depth in cotton by 24%, while it increased 21% for sugar beet during the 2004/05 season to meet the unusually high ET demand (Table 3 and Fig. 5). The magnitude of these differences was directly related to the accuracy of the original, general K_c curves used, and the specific circumstances of each season. The integration methodology carried out in this work encapsulated nearly all of the field-specific characteristics that affect crop water requirements, and therefore, a greater variability among irrigation schedules was obtained (CV=0.21 for cotton; Table 3) than when schedules were calculated with the conventional methodology (CV=0.04), that considered standard K_c values (Allen et al., 1998).

When seasonal ET was transformed into actual irrigation water use (Fig. 6) it was possible to estimate values for field irrigation efficiencies (IE). This is an important application result, from combining plot water use information with satellite-based ET estimation, due to the scarcity of IE data worldwide and the difficulties in obtaining IE estimates using field evaluation (Mateos, 2006). In the analyzed area, sprinkler systems had lower IE values than drip systems (Table 4) and typically had higher values for winter crops such as sugar beets and garlic than for summer crops, due to lighter irrigation depths (around 40 mm) and more controlled irrigation in the winter crops (for sugar beet crops, full cover sprinkler systems with high distribution uniformity are promoted by the sugar industry). Thus, sprinkler systems in the area had relatively high IE values (around 0.75). A explanation for some low values in IE for some fields (Fig. 6) was the existence in the area of clay soils, hilly topography and poor irrigation management. Even drip systems installed in some of these cotton and maize fields contributed to the generation of significant irrigation runoff, causing a reduction in the irrigation efficiency. Additionally, some fields with cotton were over-irrigated (extreme values of Fig. 6a) decreasing the average IE for cotton to 0.72 (Table 4).

Finally, estimating water use by METRIC constitutes a useful tool to quantify and improve irrigation system performance on the field level and/or to quantify and control water consumption under restricted supplies and even to determine pumping extractions. Until now, several studies have estimated ET using remote sensing techniques applied to district areas (Mo et al., 2005; Er-Raki et al., 2007) and from those, water consumption was inferred. In our case, since water meter records of plot seasonal use were available, we were able to estimate the irrigation efficiency (IE) or, after assessing an average IE value (Fig. 6), we were able to compare actual water meter records to the estimated plot water use (Fig. 7). We are not aware of previous studies where both actual water use and spatially quantified ET have been computed over a large number of plots as has been done here. There is a dearth of field data on plot water use, as many schemes do not have water metering facilities at the plot scale. The methodology described in this paper for the determination of irrigation efficiencies or irrigation use can be a valuable tool for district and watershed managers, especially during drought periods, to first identify irrigators having low irrigation efficiency levels and to provide advice for improvement. Also, products can be used to spatially assess water requirements within an irrigation district or watershed.

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Figure 1. Flow chart describing the integration of the water balance simulation model LORMOD with METRIC ET estimation. SWD means soil water deficit.

Figure 2. Seasonal ET determined by METRIC for all field plots within the Genil – Cabra Irrigation Scheme for the irrigation season 2004/05.

Figure 3. Real crop coefficient curves for well-irrigated primary crops in individual fields within GCIS obtained with the METRIC estimate of ET. The solid line (FAO 56) indicates the standard crop coefficient values of Allen et al. (1998).

Figure 4. Curves of cumulative frequency of seasonal ET values for nine crops in GCIS during the 2004/05 irrigation season.

Figure 5. Irrigation depth calculated using the integration of METRIC with LORMOD (triangles) compared with values (squares) obtained with the standard FAO methodology (Allen et al., 1998) for four crops and 13 to 75 fields in GCIS during 2004/05.

Figure 6. a) Plot of the calculated ET by METRIC against the volume of irrigation water delivered to fields of four crops and, b) Curves of cumulative frequency of the estimated irrigation efficiency for four crops during 2004/05 in GCIS.

Figure 7. Comparison between irrigation water use estimated by METRIC and the measured irrigation water delivery in four crops. In grey, line 1:1. For additional explanation, see text.

Table 1. Coordinates for the four corners of the images used located in UTM Zone 30N.

Corner coordinates	UTM Zone 30N	
	X	Y
Upper Left	327567	4161534
Upper Right	341898	4161558
Lower Left	327543	4148815
Lower Right	341945	4148791

Table 2. Number of fields analyzed for variability within fields, seasonal ET, variability among fields (CV_s), variability within fields (CV_w) and irrigation delivery for the main crops during 2004/05 in GCIS.

	Analyzed Fields	Seasonal ET (mm)	CV_s	CV_w	Irrigation delivery (mm)
Sugar beet	5	829	0.11	0.09	785
Maize	16	733	0.12	0.04	754
Cotton	13	649	0.12	0.05	711
Pepper	3	641	0.04	0.03	-
Garlic	4	523	0.12	0.03	478
Bean	13	493	0.15	0.07	370
Onion	6	433	0.16	0.08	-
Wheat	49	424	0.09	0.06	218
Sunflower	9	378	0.28	0.13	279

Table 3. Average recommended irrigation depth and coefficients of variation (in parentheses) for the three irrigation schedules generated by integration of METRIC results (METRIC), using the maximum Kc act values observed via METRIC (ENV), and using the standard FAO 56 (Allen et al., 1998) K_c values (FAO).

	Fields number	**METRIC**	**ENV**	**FAO**
Cotton	75	560 (0.21)	766 (0.08)	733 (0.04)
Maize	33	663 (0.22)	843 (0.08)	738 (0.04)
Pepper	6	630 (0.01)	657 (0.01)	546 (0.02)
Garlic	13	548 (0.05)	557 (0.04)	497 (0.08)
Sugar Beet	24	882 (0.06)	953 (0.03)	730 (0.05)

Table 4. Average values of estimated irrigation efficiency for the main crops in GCIS. Coefficients of variation for each of the four crops are indicates in parentheses.

	Global	Sprinkler	Drip
Cotton	0.72	0.71	0.75
	(0.15)	(0.17)	(0.09)
Maize	0.76	0.70	0.80
	(0.11)	(0.09)	(0.08)
Garlic	0.82	0.82	-
	(0.13)	(0.13)	-
Sugar Beet	0.90	0.90	-
	(0.05)	(0.05)	-
Average	0.77	0.75	0.77
	(0.15)	(0.17)	(0.09)