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Estimating actual irrigation application by remotely sensed evapotranspiration observations

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ABSTRACT

Water managers and policy makers need accurate estimates of real (actual) irrigation applications for effective monitoring of irrigation and efficient irrigation management. However, this information is not readily available at field level for larger irrigation areas. An innovative inverse modeling approach was tested for a field in an irrigation scheme in southern Spain where observed actual evapotranspiration by satellites was used to assess irrigation application amounts. The actual evapotranspiration was used as the basis for an optimization procedure using the physical based SWAP model and the parameter optimization tool PEST. To evaluate the proposed techniques two steps were taken. First, actual observed evapotranspiration from remote sensing was used to optimize two parameters of the SWAP model to determine irrigation applications. Second, a forward–backward approach was applied to test the minimum overpass return time of satellites and the required accuracy of remotely sensed actual evapotranspiration for accurate assessment of irrigation applications. Results indicate that irrigation application amounts can be estimated reasonably accurately, providing data are available at an interval of 15 days or shorter and the accuracy of the signal is 90% or higher.

1. Introduction

Appropriate planning in water resources, and more specifically in irrigation, is becoming increasingly important given the challenges of already-stressed water resources, climate change, growing population, increased prosperity, and potential food shortages. However, policy makers and water managers are often constrained in this context of increasing complexity by insufficient knowledge of current agricultural water management practices. Insufficient knowledge of actual irrigation applications in particular hampers the assessment of water management practices of different agricultural crops.

Global estimates of water consumption by sector indicate that irrigated agriculture is responsible for 85% of the water-use and that consumption in this sector will increase by 20% by 2025 (Shiklomanov, 1999). Gleick (2004) presented estimates of the amount of water required to produce daily food requirements per region. According to his figures there are large differences between regions, ranging from 1760 l per person per day for Sub-Saharan Africa to 5020 for North America. In 2050 the total amount of water evaporated in crop production would amount to 12,000–13,500 km^3, almost doubling the 7130 km^3 of today (Molden, 2007). The increase in food and water requirements coincides with evidence of increased water scarcity and thus the need for more accurate information on water consumption and especially on actual irrigation applications (Dam et al., 2006).

Irrigated agriculture is a very important global food producer. Irrigated land comprises less than one-fifth of the total cropped area of the world but produces about two-fifths of the world's food (WWAP, 2009). This sector however competes heavily for the already limited water resources in irrigation regions.

Closely related to food production and irrigation is the amount of actual water consumed in the form of evapotranspiration. Review papers on evapotranspiration mapping for water management have been prepared for Asia by Bastiaanssen and Harshadeep (2005) and for the Western US by Allen et al. (2005, 2007). Use of spatial estimates of actual evapotranspiration in climatic studies is reported by for instance van den Hurk et al. (1997), Mohamed et al. (2005), and Anderson et al. (2007). A number of studies deal with the assimilation of evapotranspiration data in hydrological models to facilitate model calibration (e.g. Schuurmans et al., 2003; Droogers and Bastiaanssen, 2002). The performance of hydrological models can also be improved by calibrating model parameters by optimizing the difference between modeled and remotely sensed observed evapotranspiration. Typical examples of model parameter optimization are provided by Ines and Honda

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(2005), Immerzeel et al. (2008), Immerzeel and Droogers (2008). Bastiaanssen et al. (2007) reviewed studies where remotely sensed evapotranspiration observations in irrigation systems were used to calibrate hydrological models.

Folhes et al. (2009) demonstrated that by combining observed irrigation applications and remotely sensed derived evapotranspiration a clear picture of the performance of systems can be obtained. However, in their approach it was assumed that the applied irrigation amount has to be known, which is as they admit, often not clear at field scale level. A comparable study was undertaken for the Gediz Basin in Turkey (Karatas et al., 2009), where irrigation performance was assessed using remotely sensed derived evapotranspiration. In this study it was also indicated that the actual irrigation application at field level was one of the missing data parameters.

A first attempt to assess actual irrigation applications based on remotely sensed evapotranspiration observations was presented by Ramos et al. (2006). The authors used the Surface Energy Balance Algorithm for Land (SEBAL) remote sensing technique to assess the actual evapotranspiration and to compute net water volumes and net irrigation volumes by introducing a water application efficiency factor. They concluded that it is possible to assess actual irrigation application based on actual evapotranspiration observations. One key question remained however: what is the required accuracy and temporal frequency for effective use of these techniques?

These kind of studies are often referred to as inverse modeling, which can be defined as the quintessential problem of determining an unknown parameter (e.g. hydraulic conductivity) from a set of observations (e.g. hydraulic head). This is usually achieved through systematic fitting of parameter values to match measured values (Pinault and Schomburgk, 2006). Substantial progress in inverse modeling in the domain of water resources has been achieved by obtaining soil characteristics based on observations of water, solutes and/or heat fluxes. A comprehensive overview is provided by Friedel (2005).

It should be emphasized that this inverse modeling approach is fundamentally different from calibration (Ines and Droogers, 2002). The latter has the sole objective of minimizing the difference between observed and simulated data by adjusting a set of calibration parameters (Droogers and Immerzeel, 2006). The objective of inverse modeling is to obtain the value of a physically defined parameter by automatically changing this physical parameter till observed and simulated values are within a defined minimum. The corresponding parameter value can be considered as the true value. Obviously, this approach requires a physically based simulation model.

For more theoretical studies on inverse modeling a synthetic set of "observed" values are sometimes used (e.g. Friedel, 2005; Feddes et al., 1993). The "observed" values are in these cases generated by a simulation model. One of the main advantages of such an approach is that the real parameter values are exactly known and the performance of the inverse modeling process can be assessed. This technique is often referred to as forward–backward approach (Feddes et al., 1993). Note that terms "inverse modeling" and "forward–backward approach" are not interchangeable. The first one refers to the technique of obtaining the value of a physically based parameter, while the latter is a testing methodology if measurements are lacking.

In summary the main objectives of the study are to evaluate what the impact of the observation interval and accuracy of remotely sensed evapotranspiration is on the determination of actual irrigation applications. This has been explored using a combination of observations of actual evapotranspiration from satellites and synthetically constructed actual evapotranspiration data from a validated physically based simulation model.

2. Materials and methods

2.1. General setup

The general setup of the study is based on three main tools applied to one irrigated field in an irrigation scheme in southern Spain. For this irrigated scheme SEBAL (Surface Energy Balance Algorithms for Land) was applied to assess the actual evapotranspiration based on Landsat remote sensing images. The model SWAP (soil–water–atmosphere–plant) was setup for one particular field to estimate the daily actual evapotranspiration based on the prevailing conditions of the field. However, since actual irrigation applications were unknown, the SWAP model was not able to estimate the same actual evapotranspiration as observed from the satellite. Using the PEST (Parameter ESTimation) package the SWAP input regarding irrigation applications were adjusted in order to obtain the same actual evapotranspiration as observed from the satellite. The derived input for SWAP can be considered as a representation of the real irrigation applications. Particulars of the applied tools will be described in more detail hereafter.

2.2. Genil-Cabra Irrigation Scheme

The Genil-Cabra Irrigation Scheme (GCIS) is located in the southern part of Spain, near the town of Cordoba (Fig. 1) and currently irrigates around 23,000 ha divided in three irrigation districts. The irrigation district called "Colectividad de Santaella" covers about 6800 ha of irrigated land and was developed around 1990, and 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 temperature ranges from 10 °C in winter to 27 °C in summer. The predominant soils in the district are loamy soils. Cropping patterns are fairly diverse. Dominant crops in the area during 2004/2005 were wheat, cotton and olive, representing 23, 18, and 14% of the irrigated area, respectively. Various other crops are grown including maize, sugar beet, beans, garlic, sunflower, and other vegetables. The area is serviced by a modern pressurized irrigation system, which allows complete flexibility in frequency, rate, and duration of water delivery as long as water is available. The irrigation application method is crop dependent. Thus, crops such as wheat or sunflower are irrigated with hand-move sprinkler systems, while horticultural crops or olives are mainly irrigated with drip systems. In maize and cotton, approximately half of the area is drip irrigated and the rest with sprinkler systems.

This study covered the year 2005 which was very dry; seasonal rainfall was 271 mm compared to an average of 529 mm over the previous 15 years. The average irrigation depth applied in the irrigation scheme during the 2005 irrigation season was 420 mm, which is much higher than the previous decade average of 260 mm.

Within the Colectividad de Santaella one field was selected for the study (Fig. 2). This field, locally known as 1086-C3 (16.8 ha), was selected because only one crop was grown during 2005, soils represent dominant soils in the area, and the field was well irrigated. The crop that was cultivated was cotton and the growing season was from 23 March to 1 October 2005.

Irrigation of the cotton field followed common practice in the region. At the onset of the growing season 4 times an amount of 25 mm was applied to ensure effective germination and crop establishment. During mid-season no irrigation was applied to support seedling establishment. Finally irrigation was resumed in July to support cotton lint growth. However, exact irrigation applications were not monitored for fields and the question is whether remote sensing can support monitoring of real irrigation applications. A

Fig. 1. Location of the Genil-Cabra Irrigation Scheme in southern Spain.

detailed description of the study area is beyond the scope of this paper but can be found elsewhere (Lorite et al., 2004, 2007).

2.3. Satellite observed actual evapotranspiration

Advances in remote sensing techniques for estimating actual evapotranspiration have been significant over the last decade and some of these techniques are applied operationally nowadays. Most of these techniques are based on a combination of various wavelengths of sensors, including thermal infrared to determine the energy balance and thus producing estimates of actual evapotranspiration (Bastiaanssen et al., 1998; Allen et al., 2007). METRIC (Mapping EvapoTranspiration with high Resolution and Internalized Calibration) is an evapotranspiration estimation model developed by the University of Idaho, USA (Allen et al., 2007) 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., 2005a,b) while METRIC has been applied in the western United States (Allen et al., 2005, 2007) to produce high resolution actual evapotranspiration maps. Estimates of actual evapotranspiration by METRIC have been compared with a series of lysimeter evapotranspiration measurements at two locations in the northwest US showing that satellite observed actual evapotranspiration can be considered as reliable (Tasumi et al., 2005). Gowda et al. (2008) reported overall estimation accuracy of various methods varying from 67 to 97% for daily evapotranspiration, and greater than 94% for seasonal evapotranspiration. SEBAL, and the derived METRIC is described in detail in more recent publications such as Bastiaanssen et al. (2002, 2005a,b) and Teixeira de Castro et al. (2008).

For the GCIS 11 Landsat 5 TM images were obtained, covering Landsat path 201 and row 34. The Landsat images originated from 5 March, 22 April, 8 May, 9 June, 25 June, 11 July, 12 August, 28 August, 13 September, and 29 September 2005. These images were processed using the METRIC energy balance computation procedure (2006 version) of Allen et al. (2007) to obtain daily actual evapotranspiration for each image date at a resolution of 120 m. Typical examples of these analyses are shown in Fig. 2. Spatial variation in actual evapotranspiration is quite high due to variation in crops and different timings of irrigation. Accuracy of the observed actual evapotranspiration was not determined, but given the fact that conditions and methods are similar to the ones described before, it is expected that accuracy will be greater than 90%. Further details of the evapotranspiration estimation are beyond the scope of this paper but can be found in Santos et al. (2008).

2.4. SWAP model

The SWAP (soil–water–atmosphere–plant) model was applied to explore the impact of temporal data resolution on estimating actual irrigation applications. SWAP is an integrated physically based simulation model for water, solute, and heat transport in the saturated–unsaturated zone in relation to crop growth. A first version of the SWAP model was developed in 1978 (Feddes et al., 1978) with continuous development since. The version used for this study is SWAP 3.2 and is described by Kroes et al. (2008).

The core part of the model is the modeling of vertical flow of water in the unsaturated–saturated zone, which can be described by the well-known Richards' equation:

$$\frac{\partial \theta}{\partial t} = \frac{\partial}{\partial z}\left[K(\theta)\left(\frac{\partial h}{\partial z}+1\right) - S(h)\right] \tag{1}$$

where θ denotes the soil water content (cm^3 cm^{-3}), t is the time (d), h (cm) is the soil matrix head, z (cm) is the vertical coordinate, taken positive upwards, and K is the hydraulic conductivity as a function of water content (cm d^{-1}). S (d^{-1}) represents the water uptake by plant roots (Feddes et al., 1978), and defined for a uniform root

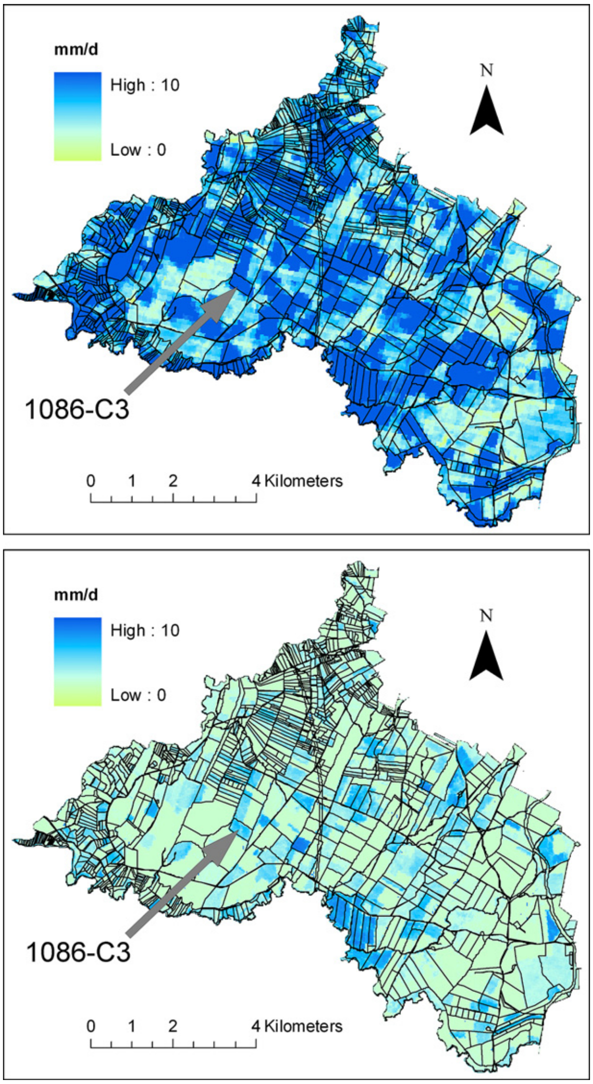

Fig. 2. Satellite derived actual evapotranspiration on 12 August 2005 (top) and 29 September 2009 (bottom).

distribution as:

$$S(h) = \alpha(h)\ \frac{T_{\text{pot}}}{|z_{\text{r}}|} \tag{2}$$

where T_{pot} is the potential transpiration (cm d^{-1}), z_{r} is the rooting depth (cm), and α (−) is a reduction factor as a function of h and accounts for water and oxygen deficit. Total actual transpiration, T_{act}, is calculated as the depth integral of the water uptake function S. Note that the potential transpiration is used here, which is defined as the amount of transpiration that would occur if the specific crop under the current conditions is fully watered.

The SWAP model has been applied and tested already for many different conditions and locations and has been proven to produce reliable and accurate results (e.g. Bastiaanssen et al., 2005a,b; Heinen, 2006; Varado et al., 2006; Droogers et al., 2000, 2008; Eitzinger et al., 2004). A more detailed description of the model and all its components are beyond the scope of this paper, but can be found in Kroes et al. (2008).

SWAP requires various data as input which can be divided into state variables, boundary conditions (model forcing) and calibration/validation data. The most important state variables are related to soil and crop characteristics.

The field selected for our study is locally known as 1086-C3. This specific field was selected as there was only one crop and the spatial variability within the field was low according to the satellite images (Fig. 2). The crop grown on this particular field in 2005 was cotton. It was known that irrigation applications of cotton in the area were divided into three stages, but the actual amount applied on the field was unknown. During the early crop stages (April–May) cotton is irrigated quite frequently for effective germination and crop establishment. During seedling establishment in early June irrigation stopped, but was resumed to ensure high cotton lint growth. Planting was done on 23rd of March and harvesting at 1st of October.

This irrigation practice was simulated using two of SWAP's irrigation simulation options. The first one is defining four fixed date pre-irrigation applications of 25 mm in April and May. Second, during cotton lint development irrigation was scheduled automatically using the SWAP's automatic irrigation scheduling option. The level of soil water shortage during drought was diagnosed from a threshold defined by the ratio of reduced transpiration (Tr) to potential transpiration (Tp). Irrigation was applied whenever reduced transpiration was lower than the threshold:

$$\text{Tr} <= \text{f1} \times \text{Tp}$$

where Tr is the transpiration reduced by drought (mm d^{-1}), Tp is the potential transpiration (m d^{-1}), f1 (−) is a user defined factor for allowable daily stress.

It should be emphasized that the irrigation application as referred to in this study is the actual amount delivered to the field and does not include any conveyance or other water requirements. Moreover, it is assumed that irrigation was provided completely homogenous to the field.

2.5. PEST

Model calibration was performed using the PEST program. PEST is a non-linear parameter estimation package that can be used to estimate parameters for just about any existing computer model (Doherty, 2005). PEST runs a model as many times as necessary to adjust its parameters until selected model outputs match a complementary set of field or laboratory measurements as closely as possible.

PEST uses the Gauss–Marquardt–Levenberg (GML) algorithm to optimize the model. The theory underlying the GML method is derived from the linear parameter estimation theory. The relation between a hydrological model (X), a set of parameters (p), a set of observations (H), and residuals in the observations (ε) can be described as:

$$X \cdot p = H + \varepsilon \tag{3}$$

The goal of PEST is to find that p value that minimizes the objective function, which is defined as the sum of squared deviations between model-generated values and experimental observations and is expressed as:

$$\Phi = (H - Xp)^t\ Q(H - Xp) \tag{4}$$

where Q is the proportional to the inverse of $C(\varepsilon)$, the covariance matrix of measurement noise. The objective function used in PEST can be converted to the commonly used root mean square error (RMSE) through:

$$\text{RMSE} = \left(\frac{\Phi}{N}\right)^{\frac{1}{2}} \tag{5}$$

Φ is minimized when

$$p = (X^t Q X)^{-1}\ X^t Q h \tag{6}$$

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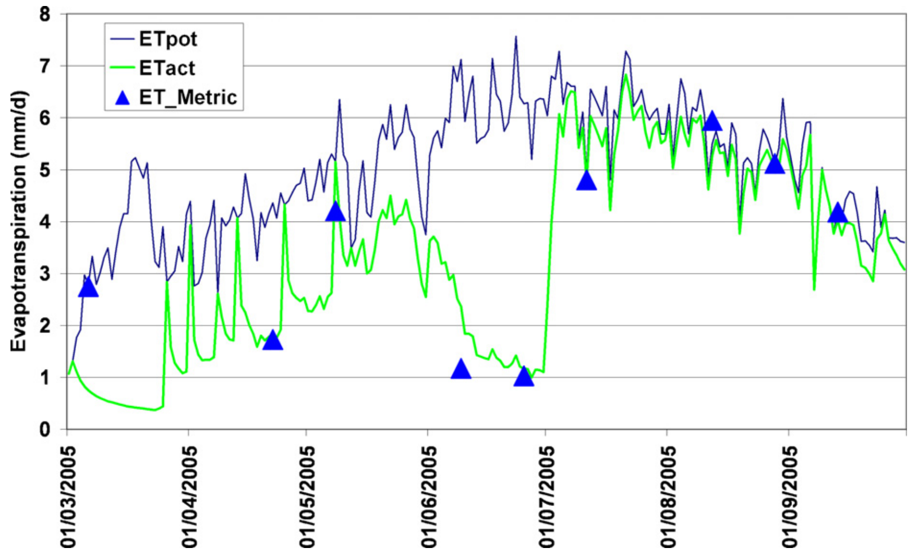

Fig. 3. Comparison between simulated actual evapotranspiration (ETact) and satellite derived evapotranspiration (ET_Metric).

Optimization of linear models can be achieved in one step, whereas for non-linear modeling an iterative process is required. At the beginning of each iteration the relationship between model parameters and model-generated outputs is linearized by formulating a Taylor expansion about the currently best parameter set; hence, the derivatives of all observations with respect to all parameters must be calculated. This linearized problem is then solved for a better parameter set, and the new parameters tested by running the model again.

However, one of the most relevant restrictions in the GML algorithm, a gradient based method, is sensitivity to local minima. Recent advances in the GML algorithm have improved the capability to identify the global minimum in surface water models (Skahill and Doherty, 2006). The most pronounced advantage of the GML method is that it can generally complete a parameter estimation process with an extremely high level of model run efficiency.

A detailed description of PEST is beyond the scope of this publication; however, PEST can be considered as the de facto standard in parameter estimation and is widely used in various water related applications, such as macropore flow (Schaik et al., 2010), variable saturated flow (Dam et al., 2008) and water quality modeling (Ellis et al., 2009).

2.6. Optimizations

This study includes two different optimization tests. The first one is a straightforward optimization of the SWAP model using the five daily remotely sensed derived actual evapotranspiration values as objective function. The two parameters to be optimized are: (i) initial pre-irrigation application during the first phase of the growing season in mm and (ii) threshold value for the daily stress (f1) when irrigation starts during growing season, expressed as the actual transpiration over potential transpiration.

The second optimization is referred to as the forward–backward optimization. Since continues daily estimates of remotely sensed actual evapotranspiration were not available and moreover, actual accuracy is impossible to assess, this so-called forward–backward approach has been applied. In such an approach model output is altered and used as input data for calibration. In this specific case the daily actual evapotranspiration during the cropping season was used to this end.

The following optimization tests were setup to meet the main objectives of the study:

- Actual evapotranspiration observations at an interval of 1, 2, 3,. . ., 40 days.
- Actual evapotranspiration observations with a random error of 1, 2, 3,. . ., 50%.

It is well known that optimization algorithms are sensitive for local optimizations, especially in non-linear systems and if calibration data are scarce. To avoid the effects of local minima, each optimization was performed five times using different initial parameter values. The best performing optimization was selected and used in the subsequent analysis.

The two parameters which were included in the inverse modeling and which largely determine actual applied irrigation are (i) initial pre-irrigation application during the first phase of the growing season in mm and (ii) threshold value for the daily stress (f1) when irrigation starts during growing season, expressed as the actual transpiration over potential transpiration.

3. Results

3.1. Initial runs

The SWAP model was setup for the year 2005 using existing data without performing any optimization. Examples of typical output of a SWAP run are plotted in Fig. 3, based on realistic estimates of four times a pre-irrigation value of 25 mm, and 0.95 for the stress threshold value. Clearly three crop stages can be observed during the growing season. At the beginning of the growing season the actual evapotranspiration is substantially lower than potential evapotranspiration as the crop is not yet fully developed. The figure indicates that the model simulated the observed satellite actual evapotranspiration well, based on the assumed pre-irrigation and stress threshold value. The r^2 of the observed and modeled actual evapotranspiration is 0.76, but when the first observation point, which is located before the actual growing season, is excluded r^2 increases to 0.91.

The extensive output of the SWAP model makes it possible to evaluate model performance in great detail and to understand the natural processes much better. A typical example is the soil moisture profile as shown in Fig. 4. During the beginning of the year relatively dry conditions occurred, followed by spring rains and initial irrigation for effective germination and crop establishment. During seedling establishment irrigation ceased and dry soil con-

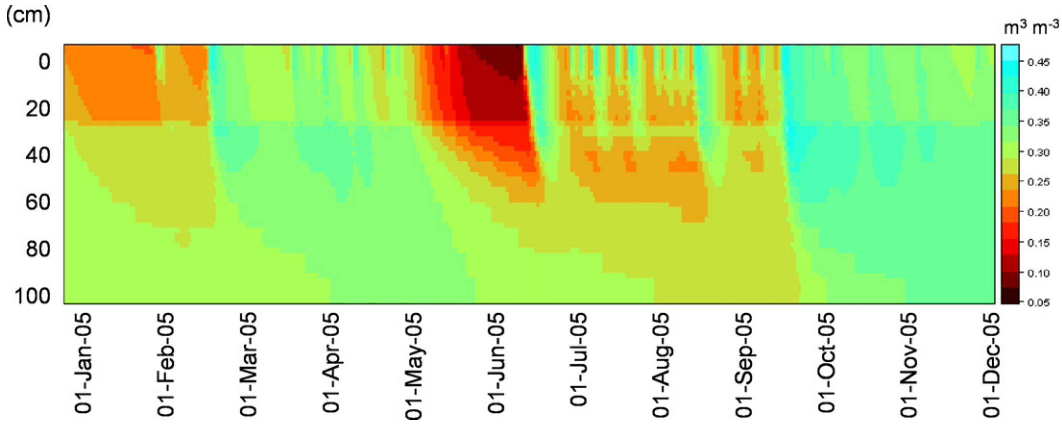

Fig. 4. Soil moisture profile ($m^3\ m^{-3}$) up to 1 m depth for the year 2005.

ditions occurred. Finally irrigation was resumed in July to support cotton lint growth resulting is fairly wet soil conditions.

3.2. PEST optimization

Optimization was performed using the PEST algorithm as explained before. Two parameters were optimized: pre-irrigation and daily stress irrigation threshold values. The pre-irrigation amount parameter range was set between 0 and 100 mm, and the range for daily stress irrigation threshold values between 0 and 1. A typical example of a PEST optimization, based on this forward–backward approach, is shown in Fig. 5. Two parameters were optimized using 214 daily actual evapotranspiration values as generated in the forward step. A total of 15 optimization steps were taken, requiring 84 model calls. After these 15 optimization steps the process terminated because relative parameter changes were less than 0.01 and no further improvement could be expected. Fig. 5 (top) shows a steady reduction in RMSE during the first seven optimization steps, followed by a somewhat more irregular pattern in RMSE improvement. The two parameters being optimized: pre-irrigation amount and stress threshold value, reflect a similar pattern. During the initial phase of optimization the parameters follow a more or less linear pattern towards the optimum value. Once these optimum values are within range, a more random behavior in the search process can be observed.

One of the advantages of the forward–backward approach is that the optimum parameter values are exactly known, since these are the parameters used to generate the calibration values. In this specific case the values are 25 mm for the pre-irrigation and 0.95 for the stress threshold value. In the example shown, the optimization resulted in a pre-irrigation value of 31 mm and a stress threshold value of 0.98. Although quite close to the original values, PEST was not able to find the optimum values exactly. A typical explanation often given is the non-uniqueness of the parameters involved. However, in this case a more physically based reason can be provided. The 25 mm pre-irrigation application used in the forward step is already sufficient to have almost no water stress conditions. Values higher than 25 mm will therefore have a limited effect on actual evapotranspiration. Also, the difference in the actual evapotranspiration caused by the threshold values of 0.95 (original) and 0.98 (optimized) to start irrigation is not very high. In other words, if the analysis is successful under these conditions, actual irrigation application estimates might even be better under dryer conditions since parameters will be more sensitive.

The overall objective of this research is to see whether actual irrigation applications can be observed using a combination of actual evapotranspiration and model optimization. For this example the estimated irrigation application was 652 mm, while the original application in the forward step was 600 mm. In other words, using actual evapotranspiration observations at this interval and accuracy, in combination with the SWAP–PEST approach, one is able to estimate the actual irrigation application within an accuracy of 90%.

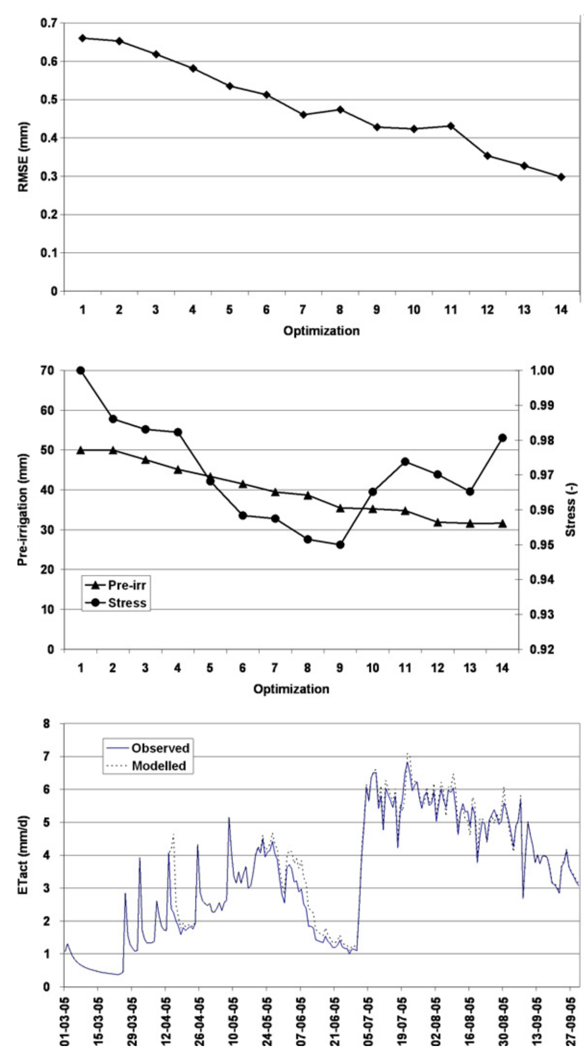

Fig. 5. Typical example of optimization results: reduction in RMSE (top), changes in parameters (middle) and performance of optimization (bottom).

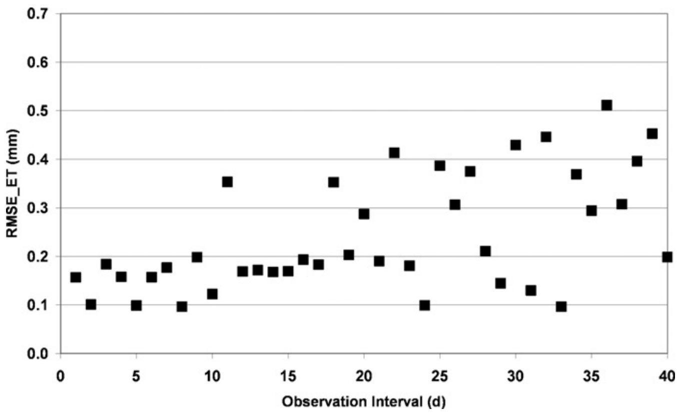

Fig. 6. RMSE as a function of the observation interval included in the optimization process.

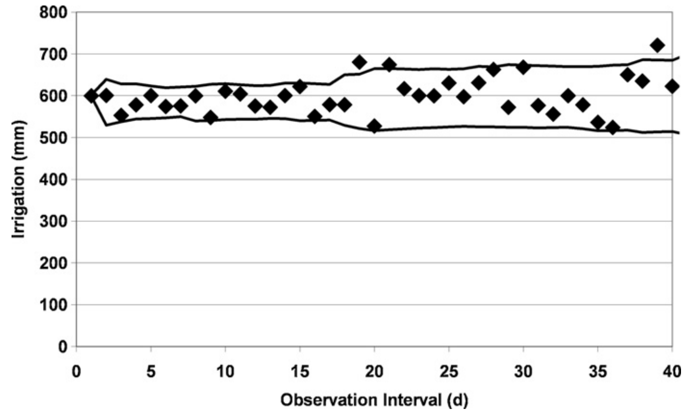

Fig. 8. Irrigation application as a function of observation interval. Lines indicate two times standard deviation based on a moving interval of 5.

3.3. Forward–backward optimization: observation interval

One of the restrictions in observing actual evapotranspiration by remote sensing is the return period of satellite overpasses. Although for some satellites the return period is small, e.g. 1 day for MODIS, these satellites have a resolution too coarse to be used for individual field observations. Satellites observing with resolutions higher than 50 m, such as Landsat, are still restricted in terms of return interval of overpass. It is therefore of interest to explore the relation between the so-called observation interval and the ability to use these data to monitor actual irrigation applications.

Observation intervals of actual evapotranspiration between 1 and 40 days have been used in the optimization process. Fig. 6 indicates that there is a clear trend in the RMSE (between actual evapotranspiration observed and the actual evapotranspiration simulated) with increasing observation intervals. As long as observation intervals are more frequent than 15 days, the RMSE is constant at a value of around 0.15 mm (is less than 4% error). The exception shown using intervals of 11 days is most likely the impact of a local minimum in which the optimization routine was trapped.

At intervals longer than 15 days RMSE increases and the model is less accurate in simulations of observed actual evapotranspiration. However, for some cases of more than 15 days the RMSE is also quite low (e.g. interval days 24 and 33), but given the big variation compared to other interval days this good fit can only be attributed to a coincidence, rather than to a stable optimization.

Since the observed actual evapotranspiration values were generated in the forward step, exact parameter values are known, and can therefore be compared with the optimized values as a function of the observation interval. From Fig. 7 it is clear that the parameter error is relatively low provided the observation interval is within 15 days (with the exception of day 11). Beyond this, parameters cannot be accurately optimized. Similar as to the RMSE, the parameter error is relatively small for some interval days. However, given the overall variation, these small parameter errors are probably coincidental.

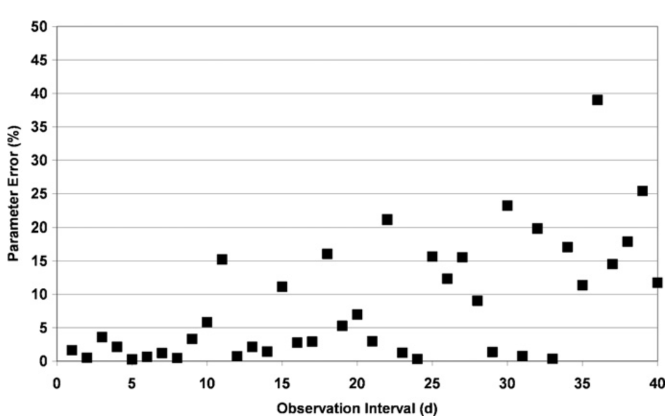

Fig. 7. Parameter error as a function of the observation interval.

The ultimate objective of this study is to evaluate the ability to assess actual irrigation applications as a function of the observation interval. The real irrigation obtained using the forward SWAP simulation was 600 mm. Fig. 8 indicates that independently to the observation interval all obtained irrigation applications, with the exception of one, are within 500–700 mm. There is however a clear trend which indicates that if the observation interval is shorter than 15 days, irrigation applications can be assessed at an accuracy of about 95%. If observations are less frequent than these 15 days accuracy decreases to about 85%.

3.4. Forward–backward optimization: signal accuracy

It is well known that, despite advances in the observation of actual evapotranspiration from satellites, accuracies can vary depending on the algorithm used, satellite sensor, and atmospheric conditions. The actual evapotranspiration values from the forward SWAP simulations, referred to as the actual evapotranspiration observed, were modified by imposing a random error ranging from maximum 1 to 50% on the daily actual evapotranspiration. Note that this random error can be positive or negative and was selected for each day independently. In other words, this error reflects a non-systematic error in the observation of actual evapotranspiration from satellites. It was selected to focus on non-systematic errors only as these occur regularly by clouds and atmospheric disturbance.

Fig. 9 (top) shows the resultant irrigation application, based on the daily observed actual evapotranspiration, with an error ranging from maximum 1% up to maximum 50% (positive or negative). It is clear that the original irrigation application of 600 mm can be assessed reasonably accurately even if error levels are up to 50%. It is somewhat surprising that even under these high error levels this result can be obtained. However, the random error was applied for every day which means that the total growing season error is close to zero.

The same random error between 1 and 50% was applied to actual evapotranspiration being observed only every 5 days. Reliable estimates of irrigation applications would than be possible as long as this error is smaller than about 10% (Fig. 9, middle). Higher random errors in the actual evapotranspiration observations make estimations of actual irrigation applications difficult.

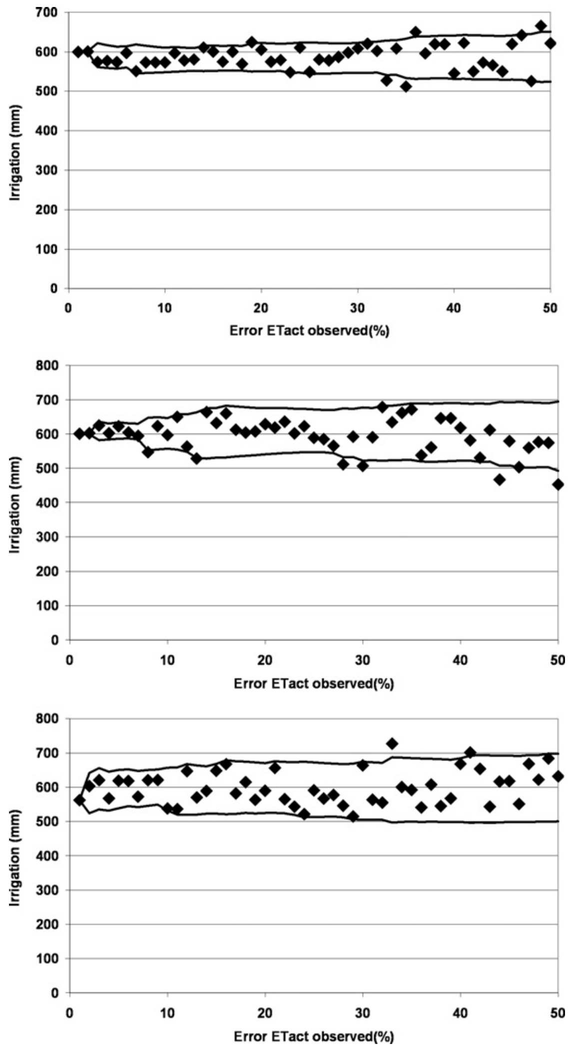

Fig. 9. Irrigation application as a function of error in observed actual evapotranspiration for observation intervals of 1 day (top), 5 days (middle) and 15 days (bottom). Lines indicate the running minimum and maximum based on two times the standard deviation.

If actual evapotranspiration is observed at intervals of 15 days (Fig. 9, bottom) actual irrigation applications can be assessed with an accuracy of about 90% provided the error in the actual evapotranspiration signal is below 10%. Lower accuracies in actual evapotranspiration observations result in errors of more than 20% in actual irrigation application assessments.

4. Conclusions

There is a clear need for water managers and policy makers to assess and monitor the amount of actual applied irrigation at field level. However, accurate observations are scarce and estimates are often crude and based on crop water requirements rather than on actual observations. Actual observations from e.g. pumping hours or from detailed irrigation canal monitoring are in most cases not available for entire irrigation districts. Water releases from reservoirs for large scale irrigation are usually known, but information at field level is lacking. In this research an innovative approach was explored, where actual evapotranspiration observations by remote sensing were used. These actual evapotranspiration observations by satellites are increasingly applied operationally and are becoming more accurate.

A forward–backward optimization approach was used for one field in an irrigation district in southern Spain to explore the minimal observation interval and the minimum required accuracy for actual evapotranspiration observations by satellites. It has been demonstrated that actual irrigation applications can be assessed relatively accurately provided actual evapotranspiration observations are available at intervals of 15 days or smaller. If observation intervals are less frequent than 15 days, assessment of irrigation applications is less accurate. In terms of practical applications this means that satellites should overpass an area at least twice a month, provided all images are cloud free. The Landsat satellite can therefore be used to monitor actual irrigation applications under cloud free conditions during the irrigation season.

The selection of SEBAL, SWAP and PEST as our main tools was based on three grounds. First, these tools are well known and described widely in the international literature. Second, the tools have been calibrated and validated extensively for a wide range of conditions. Finally, the tools were geared towards the tasks required. SEBAL is specifically developed to estimate actual evapotranspiration; SWAP is a physically based soil–water–plant simulation model with strong water management options; and PEST is the ultimate tool for model independent parameter estimation. Obviously, other tools might be used as well as long as they are similar in behavior as the ones used here.

The accuracy of the remotely sensed actual evapotranspiration signal was explored by distorting the signal with random errors between 1 and 50% for every observation. If daily actual evapotranspiration observations are available for the optimization process, these errors up to 50% are not effecting actual irrigation application assessments. However, daily actual evapotranspiration observations are scarce and in reality data at 15 days intervals are available only. Under these conditions actual irrigation applications can be assessed at an accuracy of about 90% provided the error in the actual evapotranspiration signal is below 10%. It is important to note that these imposed errors are non-systematic daily errors and not accumulative, so total actual evapotranspiration over the growing season is error free.

The advantage of generating a synthetic set of "observed" actual evapotranspiration values with the forward–backward optimization approach is that the "real" irrigation application is known. The ability of the inverse modeling method to generate a particular irrigation application can thus be tested. The forward–backward process has however a drawback in that model assumptions are reflected in the synthetically derived evapotranspiration data and in the optimization process as well. However, the applied model SWAP is physically based, so model assumptions are considered to be realistic.

For irrigation management in practice the developed approach brings significant advances in semi-real time applications. Managers could setup an operational system which provides not only the actual evapotranspiration and water shortage for the crop from remote sensing, but can also assess simultaneously the actual amount of irrigation applied. Accuracy of the method requires however additional research with preferable well monitored field calibration and validation data.

The study as presented here is valid for the particular field in southern Spain given the conditions prevailing in 2005. These conditions were: a relatively dry year with abundant irrigation water available. It would be valuable to extend the analysis to other environments and especially to conditions where available irrigation water is less, as water managers' interests in obtaining irrigation applications will be specifically high under such conditions. Moreover, the number of parameters used in the optimization, testing of parameter uniqueness, optimization techniques, etc. required further studies.

Finally, the study has practical application for water managers and policy makers in that assessment of actual applied irrigation amounts can be reasonably accurate, providing remotely sensed evapotranspiration data are available at an interval of 15 days or lower, and accuracy of the signal is 90% or higher.

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