Chapter 8

Remote Sensing Based Crop Coefficients for Water Management in Agriculture

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Additional information is available at the end of the chapter

http://dx.doi.org/10.5772/48561

1. Introduction

The climatic factors and their variability, both spatial and temporal, linked to precipitation decreasing and irregular distribution, due to climatic changes, have been gathering a higher weight in the definition of water management policies. These policies have important implications on agriculture. Using new technologies that allow a better use of water requires institutional changes in major areas. The first point is the need for base information with an adequate spatial and temporal resolution. The work we have done includes itself in the water efficient and sustained use, allowing the improvement of irrigation systems and it's the result of a jointly effort of several teams based on an international project.

PLEIADES (Participatory multi-Level EO-assisted tools for Irrigation water management and Agricultural Decision-Support) is a research and technological development project co-funded by the European Commission's Sixth Framework Programme within its Sustainable Development, Global Change and Ecosystems Priority. The project responds to the identified need for targeted research in the area of Integrated management strategies and mitigation technologies, topic Water in Agriculture: new systems and technologies for irrigation and drainage. A set of pilot Case Studies represents a sample of the wide range of conditions found in the European and Southern Mediterranean and in the Americas, covering Portugal, Spain, Italy, Greece, Turkey, Morocco, Mexico, Peru, and Brazil.

The Portuguese working area was the Caia irrigation area, a subsystem of Guadiana basin, located in the southeast of Portugal, near the border with Spain. PLEIADES was expected to generate new knowledge on the functioning and performance of these pilot areas. This in turn aimed at providing the knowledge and information base for decision makers at all levels on agricultural water needs and consumption. It also set out to provide the basis for assessing the benefits and threats potentially brought about by new technologies to all actors in changing environments. The project was also expected to generate new tools for irrigation water management, combining innovative sensor technology with flexible easy-to-use Decision-Support Systems for adaptive management. These tools were designed to help farmers to control water more efficiently and improve the environmental and economic performance of their irrigation systems.

In our work, we address the efficient and sustainable use of water for food production in water-scarce environments. We consider the economic, environmental, technical, social, and political dimensions through a synergy of leading-edge technologies and participatory approaches. These technologies provide easy access to information for all stakeholders while active participation will be effected by spatial information and innovative networking tools. Our aim is to improve the performance of irrigation schemes by means of a range of measures. Major technical innovation is made possible by the comprehensive space-time coverage of *EO* data and the interactive networking/connecting capabilities of Information and Communication Technologies (*ICT*).

The project was designed to assess and demonstrate in an operational perspective how the integration of Earth observation (*EO*) techniques in routine Irrigation Advisory Services (*IAS*) can improve the efficiency in the use of water for irrigation. The use of leading-edge Information and Communication Technology (*ICT*) tools in the generation and distribution of information makes the *EO* easily available to *IAS* and the farmers. The project WebGIS (www.pleiades.es) was one of the central outcomes of our project. Its key feature is the operational generation of irrigation scheduling information products from a virtual constellation of *EO* satellites and their delivery to farmers in near-real-time using leading-edge on-line analysis and visualization tools. It is supported by a methodology package to derive crop coefficients and further advanced parameters from *EO* satellite images in an operational processing chain.

The overall goal is to improve and optimise irrigation and drainage systems by means of new technologies. In this context, New Technologies (*NT*) include Earth observation, Geographical Information Systems, Information and Communication Technologies, and Decision-Support systems. In order to achieve this overall goal 3 specific objectives have been set:

1. In accordance with the identified needs of stakeholders, multi-level NT-assisted tools will be adapted and developed for farmers and other water managers to optimise their water use at farm, irrigation scheme and at river-basin levels.
2. To conduct trial campaigns in pilot areas with the active participation of users at farm and irrigation scheme level.
3. To evaluate the performances of the NT-assisted tools using an extended evaluation system covering technical, economic, environmental, social and political dimensions and involving stakeholders at all levels over the whole lifetime of the project.

PLEIADES aims to demonstrate that New Technologies (*NT*) can effectively support the optimisation of irrigation schemes and in the long run foster sustainability by providing comprehensive and timely spatial information that supports decisions made at many levels: farms, irrigation schemes and river-basins.

We recognise that improvements will come not only from technical innovations but also from changes in social factors related to water governance, participation and social learning. Thus the NT-assisted tools will be deployed to facilitate technical and social learning enabling farmers to act responsibly by fine tuning their on-farm practices in accordance with the river-basin water status.

This work addresses the efficient and sustainable use of water for food production in water scarce environments. It aimed to improve the performance of irrigation schemes by means of a range of measures that consider the economic, environmental, technical, social, and political dimensions through a synergy of leading-edge technologies and participatory approaches. Major social and technical innovation was made possible by the comprehensive space-time coverage of Earth observation (*EO*) data and the interactive networking/connecting capabilities of Information and Communication Technologies. The system we developed stands mainly over *FAO* normative, about culture water needs and the calculation of cultural coefficient (K_c) in a simple way, directly from remote sensing data. For that we simply use radiometric parameters derived from visible and infrared bands. Crop evapotranspiration can be calculated using the crop coefficient (K_c) defined as the ratio of total evapotranspiration (ET) by reference evapotranspiration (ET_0).

Earth Observation (*EO*) provides an objective evaluation of crop water demand; this information can be used at different decision levels (from the farmers to the river basin authorities) to promote a more efficient use of water resources in agriculture. A rational management of water resources for irrigation requires information characterized by high temporal and spatial variability, which cannot be monitored with traditional field inspections. *EO* is a mature technology, ready for being transferred to operational applications in agricultural water management. Detailed data on crop development and irrigation needs are timely distributed to final users by means of modern Information and Communication Technologies.

Three main usages of *EO* based products have been conceived:

1. Distribution of personalized information to a range of stakeholders (i.e. landowners, irrigation farmers and their associations) concerning crop and water status;
2. Integration in *GIS* based river-basin water management tool, for distributed water balance calculations.
3. A portfolio of *EO* based products has been set-up, and the methodologies for their retrieval have been defined, starting from past experiences and scientific knowledge available among the partners in the Consortium. *FAO*. methodology has been adopted as the standard procedure for computing crop water requirements from *EO* based products.

Three different levels of *EO* based products are distinguished:

1. Land-use (irrigated vs. non irrigated crops; crop inventory maps);
2. Basic (vegetation cover, Leaf Area Index, Crop Coefficients, potential evapotranspiration, Crop Water Requirements among others);

3. Advanced (reference and actual evapotranspiration, biomass, yield).

The conceptual approach for the derivation of *EO* model of the service is split up into the following steps:

1. Acquisition and analysis of high resolution satellite images in the visible and infrared spectrum;
2. Local agro-meteorological data acquisition (e.g. temperature, humidity, wind speed, sun radiation, rainfall);
3. Field validation through measurements in selected areas;
4. Elaboration of *EO* based products;
5. Data quality check and integration in a dedicated Geographical Information Systems (*GIS*) for irrigation management from field to district and hydrological basin scale;
6. Real-time distribution of personalized irrigation advices on a weekly basis directly to farmers by means of different communication systems (Internet, text and graphical messages by using *GSM*/*UMTS*).

The validation of the different methodologies for the retrieval of *EO* based products has been an important part of the work carried out within all the pilot areas. Intensive field campaigns carried out simultaneously to satellite acquisitions have produced a large dataset for calibration and validation purposes. Micrometeorological instrumentations have been installed for comparison between field measurements of crop water use and estimates from *EO* processing. New methodologies have been set-up i.e. for improving the estimation of canopy parameters and for calculating reference evapotranspiration from geostationary satellites (of particular relevance in areas with very limited meteorological data).

2. Virtual constellation and space segment operationality

Farm management requires monitoring of agricultural crops at high spatial resolution and frequent temporal coverage during the entire growing season. The necessary spatial resolution can be provided by the current high-resolution sensors (20-30m pixel size), like TM, ETM+, SPOT, LISS, ASTER, ALI, or in the case of agricultural plots with special spatial requirements by very-high resolution sensors (like Quickbird, Ikonos). However, canopy architecture and biophysical parameters describing the canopy, like leaf area index, fractional ground cover, biomass, evapotranspiration, water stress, evolve continuously during the crop growing season.

A single satellite with a 16 day repeat time (like Landsat) would provide little useful information, considering also that cloud conditions may increase the time period between useable images. The critical requirement of frequency of coverage combined with high spatial resolution has not been satisfied after more than thirty years of Landsat mission launching. Satellite constellations have been proposed for this purpose by some studies, but a practical solution for the near future is not at hand. Our solution is a virtual constellation of EO satellites that corresponds to the needs and user requirements of irrigation scheduling and precision agriculture. Therefore, we have developed a unified procedure to obtain consistent time series of vegetation parameters of interest from this virtual constellation.

2.1. Definition and operational aspects

The virtual constellation (*VC*) is defined as a set of *EO* satellites, each of which provides the necessary data to derive *NDVI* and other vegetation parameters at the spatial resolution required for the given application. In our case, for irrigation scheduling a spatial resolution of at least 30 m is imperative to resolve the major part of agricultural fields (plots). An additional key selection criterion is near-nadir observation, such that bi-directional effects are minimized. Landsat is the backbone of this *VC*, because of its excellent operational availability and low cost.

Due to the technical failure in Landsat7 all images taken on/after 31 May 2003 have no useable data in a significant part of each image. The software correction offered by USGS involves spatial degradation, which moves the spatial resolution of ETM+ out of the interest margin of our *VC*, except for areas located directly in the centre of a scene (non-affected area). This sensor failure clearly demonstrates the vulnerability of the operational space segment for this and similar applications.

Currently available alternative platforms are less ideal for operations, since they are either much more expensive (IRS, ALI, Spot), more complicated (Spot, due to changing view angles), and/or not operational (Aster, no rush service). A number of emerging platforms may add more elements to the *VC*. Our experience in PLEIADES has shown that all can be used to complete the TM time series. Ikonos and Spot were successfully tested in the Italian pilot area. The experience of Spot programming for this area showed that on average 5-6 images per month can be obtained (fairly cloud free and with incidence angles less than 15º).

We want to stress here again that the space segment is the most vulnerable part of the entire operational system. For this reason, urgent actions are required to ensure the capability to obtain adequate *EO* images at the adequate coverage frequency and low cost. As a practical near-term solution for the case of cloudiness and/or satellite sensor failure, a contingency scenario was developed to base the PLEIADES operational system on a synergistic combination of *EO* data, field data, and an expert system of local crop coefficient (K_c) curves.

These curves have been developed from the synthesis of previous campaigns, specially tailored to the crops and climatology of a given area. In the case of an *EO* data failure (either missing image or clouds), the system would draw on a default list of K_c curves (per crop, crop cycle, sowing date) from (in order of priority) field data, the local expert system data base, and the look-up tables recommended by the Food and Agriculture Organization (FAO) [1]. Medium-resolution sensors (like AVHRR or MODIS) are also used to derive support data for this purpose.

2.2. Methodology to derive PLEIADES parameters from EO data

All biogeophysical parameter calculation from EO starts with a pre-processing of EO data, composed of three main steps: i) Geometric correction and image re-sampling; ii) Cross-satellite intercalibration; iii) Atmospheric correction.

Semi-automatic procedures have been developed in order to elaborate K_c maps from *EO* data in the minimum possible time. Pre-processing requires approximately half of the elaboration time of the entire process. Once georeferenced surface reflectance has been calculated in each pixel, the algorithms for determining K_c are quite straightforward.

The elaboration for step (i) is based on consolidated procedures available in each pilot zone. This step does not necessary requires a standardization, and it strictly linked to the topographical mapping standard adopted in each area. The principal recommendation coming from PLEIADES is to adopt procedures that do not alter substantially the radiometric content of data; as such, first-degree relationships should be preferentially used for coordinates transformation and nearest neighbour techniques for pixel resampling.

2.3. Cross-sensor intercalibration

When using different sensors from our virtual constellation to generate time series of maps of geobiophysical parameters, a reliable methodology is needed to intercalibrate the observations from different sensors at different observation scales in different platforms. Intercalibration between observations or cross-calibration of sensors aims at developing relationships that allow to translate reflectances and spectral vegetation indices from one sensor to another.

For this purpose, we have performed an observational study, comparing reflectances and *NDVI* from near-synchronous image pairs of ETM+ as the reference sensor and TM, LISS, Aster, Quickbird, and AVHRR. Linear relationships were found for the intercalibration of reflectances and *NDVI* from one sensor to another, for all sensors, provided that some spatial aggregation is performed.

The main source of data dispersion in our linear cross-sensor translation equations is the geolocalization uncertainty inherent in the process of geometric correction. Consequently, spatial aggregation needs always to be performed if (different or the same) sensors are to be used to derive time-series of biogeophysical parameters over heterogeneous areas.

The homogenous zone approach developed here is recommended as an excellent tool for deriving robust new cross-sensor relationships, provided that the selected homogeneous crops cover the full *NDVI* range. The linear cross-sensor relationships derived from one image pair are shown to be valid for the whole season and for all areas with similar vegetation and climate. We recommend repeating the procedure once or twice a year in order to check the temporal stability of the radiometric calibration coefficients.

Although the differences in most cases are small, we maintain different equations for different spatial aggregation sizes. Table 1 gives the coefficients of the resulting equations for the example of 100 m grid cell side length (except for 75 m for Aster), which is the minimum recommended grid size.

Sensor	Coefficients of linear equation $NDVI - ETM = a \cdot NDVI(sensor) + b$	
	a	**b**
TM	1.0336	+0.0128
LISS III 1D	1.1672	-0.0454
Quickbird	1.0443±0.008	+0.0191±0.005
Aster L1B	1.1304±0.022	-0.0002±0.019

Table 1. Summary of NDVI cross-sensor translation equations for elements in our virtual constellation. Measure of uncertainty is defined as deviation from the mean.

2.4. Operational atmospheric correction

An automatic procedure has been developed for atmospheric correction. This procedure uses parameters extracted directly from the image instead of recurring to external data on synchronous on-site vertical profiles of atmospheric data, which are usually difficult to obtain. It results in a substantial reduction of processing time as compared to approaches based on radiative transfer calculations. It was found that approach (i) for *NVDI* K_c calculation is less sensitive than approach of analytical K_c (ii) for the effects related to the atmospheric correction.

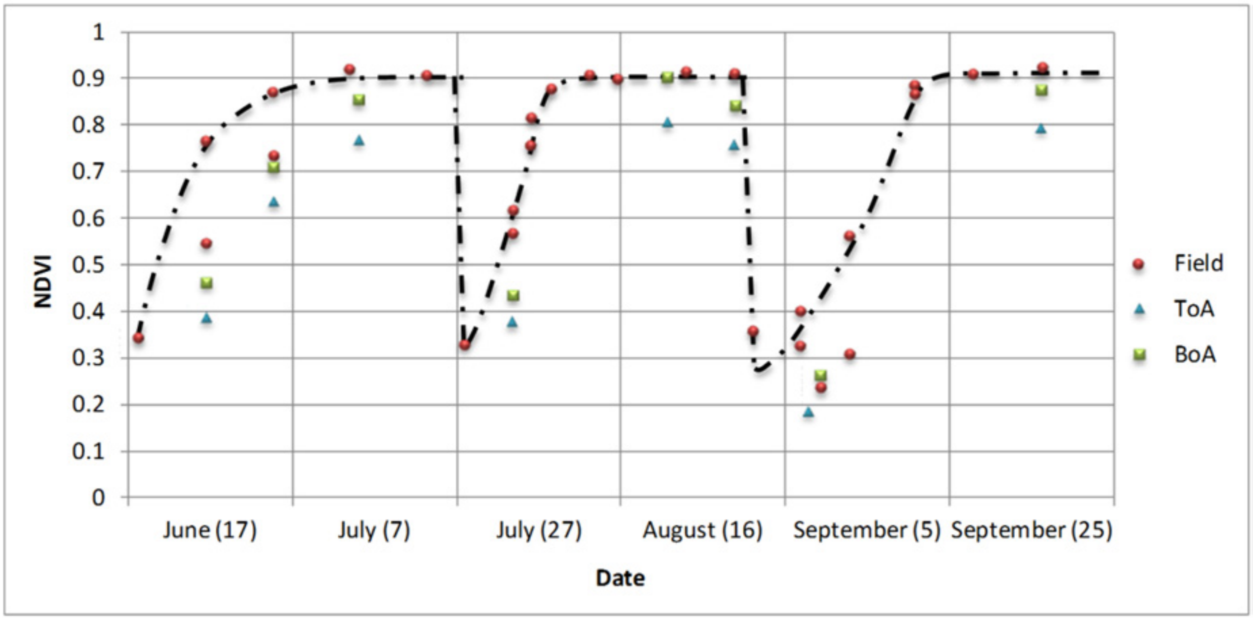

Figure 1. Example of the implementation of the atmospheric correction (*AC*) module on the satellite derived NDVI for an alfalfa plot. Top of atmosphere (*ToA*) *NDVI* refers to the *NDVI* without *AC*, whereas of atmosphere (*BoA*) *NDVI* corresponds to *NDVI* with *AC*. The reference field measurements of *NDVI* are shown as solid circles.

A validation of the performance of this module has been performed by using field measurements of spectral reflectance carried out with the spectroradiometer GER 3700 (331 - 2509 nm spectral coverage, 1.5 - 9.5 nm resolution) for two land uses: (i) an alfalfa plot and (ii) a bare soil. Figure 1 illustrates the outcome of the AC-module in terms of the *NDVI* values for the alfalfa plot. Field measurements of *NDVI* showed the greatest scattering due to both, heterogeneity of the canopy cover in the alfalfa field and, the small field of view of the spectroradiometer in comparison to Landsat pixel size. Taking into account this variability, we can conclude that atmospherically corrected *NDVI* values are in agreement with in field measured *NDVI*. Similar results are obtained for the bare soil plot.

3. Crop coefficient and reference evapotranspiration

Crop evapotranspiration can be calculated using the crop coefficient (K_c) (1) defined as the ratio of total evapotranspiration (ET) by reference evapotranspiration (ET_0). Combining K_c (from field measurements or from satellite images) with ET_0 from agrometeorological station observations allows us to calculate crop evapotranspiration. This coefficient integrates the effect of characteristics that distinguish a typical field crop from the grass reference, which has a constant appearance and a complete ground cover.

Factors that determine the crop coefficients are crop type, climate, soil evaporation and crop growth stages [1, 2]. For this purpose FAO has proposed tabulated average values distinguishing by crops that can be applied knowing its phenology.

In case of annual crops under standard conditions (disease-free, well fertilized, grown in large fields, under optimum soil water conditions and achieving full production under the given climatic conditions), the K_c curve for the whole growing season can be calculated considering the initial (K_{cINI}), medium (K_{cMID}) and end stage (K_{cEND}).

$$K_c = \frac{ET}{ET_0} \tag{1}$$

Mainly at the initial and end period, due to lower values of crop cover, soil evaporation has a large effect on K_{cINI} and K_{cEND} [3, 1, 4]. Therefore, vegetation indices (VI) are better related to transpiration of crop than to K_c [5] in those periods. This introduces a great variation in K_{cINI} and K_{cEND} daily values depending on soil water status, i.e. on frequency of wetting by irrigation and rainfall.

The dual crop coefficient approach proposed by [6] splits K_c into separate coefficients, one for crop transpiration K_{cb} (basal crop coefficient), and one for soil evaporation (K_e). The soil evaporation coefficient, K_e, describes the evaporation component of ET. When topsoil is wet, after irrigation or rainfall, K_e is maximal.

Estimation of K_e requires knowledge of soil water balance [1]. Wright [6] introduced the idea of a basal crop coefficient in which the soil evaporation component of ET was minimal due to a dry soil surface but adequate soil moisture in the crop root zone was available.

$$ET = \left(K_{cb} + K_e\right) \cdot ET_0 \tag{2}$$

In PLEIADES we use two approaches to obtain the crop coefficient from satellite imagery: one, directly from *NDVI*, named K_c - *NDVI*, based on the relationship between *NDVI* and the basal crop coefficient, and another, named analytical K_c, is based on the direct application of the Penman-Monteith equation. The *NDVI* is the main operational parameter to monitor vegetation status using Earth Observation.

4. Crop coefficient from NDVI and canopy biophysics parameters

Relevant canopy biophysics parameters are green fractional cover, fraction of absorbed photosynthetically active radiation, primary production, Leaf Area Index (*LAI*), basal crop coefficient. All they are involved in canopy evapotranspiration. The ability of *NDVI* to describe canopy biophysics parameter has been shown as follows:

1. *NDVI* is related linearly with green fractional cover [7, 8];
2. *NDVI* is related linearly with the fraction of absorbed photosynthetically active radiation (*fAPAR*) [9];
3. *NDVI* is related with primary production (dry biomass) by means of Light Use Efficiency (*LUE*) models [10, 11, 12]:

$$P = \int_0^t \left(a \cdot NDVI + b\right) \cdot PAR \cdot \varepsilon \cdot W \cdot dt \tag{3}$$

where P is primary production, PAR is Photosynthetically Active Radiation, ε is the efficiency of crop to transform PAR into dry mass, W is a water stress coefficient, and a, b are constants. Using these *LUE* models we can consider that, under non-water stress, *NDVI* on plateau stage can be seen as a good estimator of the dry matter accumulation rate, depending on crop and environmental variables [13].

It establishes a relationship between *NDVI* and crop growth rate (*CGR*) which agrees with the idea that considers *NDVI* as an estimator of the canopy photosynthetic power. This way, [14] consider that vegetation index can be legitimately used to provide an estimate of growth rate.

1. *NDVI* is related exponentially with Leaf Area Index (*LAI*) [15]. Is well known that *NDVI* begins to saturate for a value of *LAI* equal to 3 reaching a plateau for $LAI > 3$ (Figure 2 a);
2. *NDVI* is related linearly with the basal crop coefficient K_{cb} [16]. This relationship is a relevant basis for the K_c – *NDVI* approach.

The facts pointed out in (3) and (4) may appear contradictory (saturation of *NDVI* for $LAI > 3$ on one hand and the linear relation of *NDVI* with K_{cb} on the other). This seeming paradox is due to the usual reasoning that relates higher *LAI* with higher evapotranspiration. This reasoning arises from associating more leaf surface with more transpiration. However, already [17] stated that the evidence seems conclusive that transpiration in most mesophytic crop plants and other mesophytic vegetation well supplied with water increases with leaf area to *LAI* of about three (Figure 2 b).

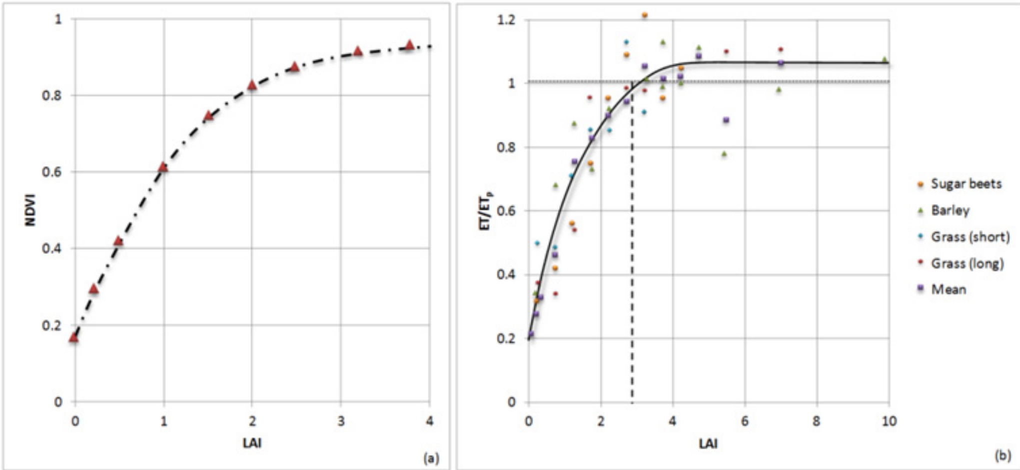

Figure 2. Typical *NDVI-LAI* curve (a), and ratio of actual to potential evapotranspiration (ET/ET_p) as a function of the *LAI* (b).

Accounting the *LAI* saturation in the relation with evapotranspiration has lead to the concept of active *LAI* (Allen et al., 1998). The active *LAI* is defined as the index of the leaf area that actively contributes to the surface heat and vapour transfer. It is generally the upper, sunlit portion of a dense canopy. For practical applications, however, the active *LAI* is an ambiguous concept due its dependence on canopy architecture and its interaction with sunlight.

The basal crop coefficient is clearly related with green fractional cover (f_c) (Figure 3). In fact, the procedure to estimate K_{cb} is based in the knowledge of f_c [1], despite of ambiguities of the green f_c concept, mainly in the maturation stage. The relationship between *NDVI* and *CGR* for well watered crops is based on the ability of *NDVI* to estimate *fAPAR*, introducing this fact in the *LUE* model. *CGR* is also related with the transpiration rate.

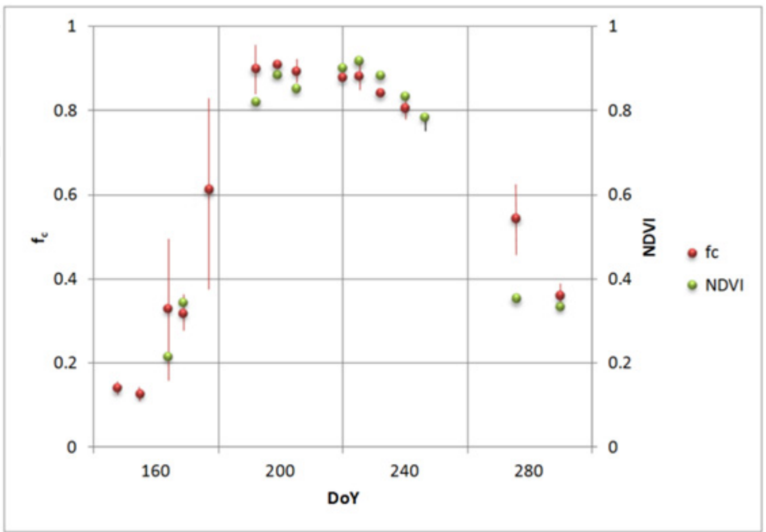

Figure 3. Green Fraction Coverand *NDVI* versus *DoY* at field scale for corn.

The relationship between *NDVI* and *CGR* exhibits a strong dependence on crop and environmental variables (solar radiation, temperature, etc.) [13]. This is due to the different nature of *NDVI* and *CGR*. *NDVI* depends only on canopy characteristics, while *CGR* and so the transpiration rate, are strongly also dependent on surface and environmental variables. The basal crop coefficient is the ratio of canopy transpiration rate over the reference canopy transpiration rate.

So, the empirical relationship between *NDVI* and K_{cb} shown by many authors, e.g. [18] and [19], (Figure 4) could be explained by considering *NDVI* as a measurement of relative *CGR*. Further research will be need in this subject. Despite limitations due to variability associated with canopy structure, background soil, and calibration uncertainties, *NDVI* can be used advantageously to estimate crop water requirements [20] in accounting its relationship with K_{cb}.

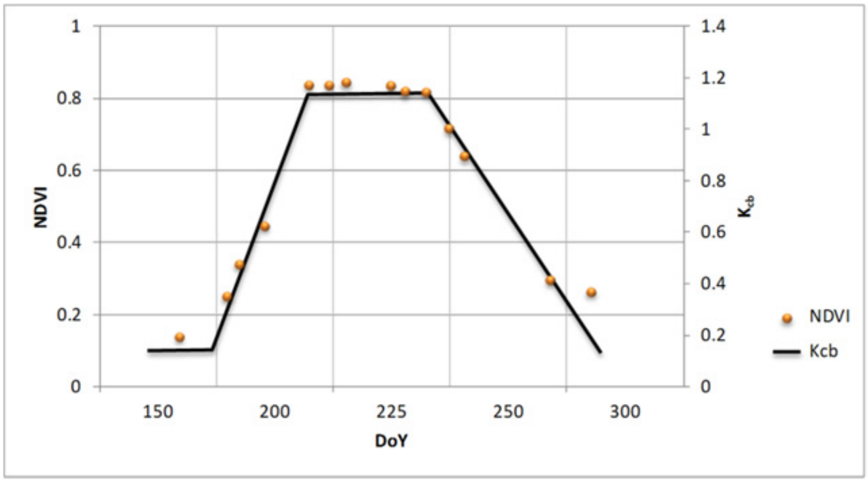

Figure 4. Temporal evolution of crop coefficient (K_{cb}) and *NDVI*, in maize. K_{cb} is estimated from green plant cover using FAO methodology [19].

Taking into account similarities between the crop coefficient curve and vegetation index, [21] established the potential for modelling crop coefficient as a function of vegetation index. This relation was derived from reflectance observations at field scale in the wavelengths ranges [0.63, 0.69 μm] and [0.76, 0.90 μm], measured at nadir and two meters above corn. A linear transformation of the *NDVI* was developed by equating the *NDVI* at effective cover and for dry, bare soil at the experimental site to the K_{cb} at effective cover and for dry soil evaporation, respectively. Similarly, [22] obtained (4) for two research sites in Colorado using alfalfa as reference evapotranspiration surface

$$K_{cb} = 1.181 \cdot NDVI - 0.026 \tag{4}$$

In order to minimize the presence of soil background, other vegetation indices (*VI*) have been used to compute K_{cb} [23]. This provides a particularly useful tool for satellite images where soil brightness and colour can vary. One of these *VIs* used is Soil Adjusted Vegetation Index (*SAVI*) [24] which for the same conditions as (4) gives the relationship [5]:

$$K_{cb} = 1.69 \cdot SAVI - 0.16 \tag{5}$$

Thus, crop coefficients derived from spectral measurements (K_{cs}) are independent of the time parameters, day of planting and effective cover, and represent a real-time crop coefficient. The use of spectral crop coefficients facilitates irrigation scheduling on a field-to-field basis over a large region if the fields can be observed spectrally, because planting and assumed effective cover dates are not required.

The spectral information would be sensitive to leaf loss due to hail, stress caused by disease and water deficit, cold or wet conditions that delay early growth, and warm temperatures and drought that speed senescence [16]. At field scale, further work was performed in order to improve scheduling irrigation events on corn compared to other traditional *DoY* based methods resulting in estimated crop water use reduced by 15% [25].

5. Crop coefficient and NDVI relation from field observations

Intensive experimental campaigns were conducted within pilot zones. The research field has a permanent lysimeter station and it is water controlled following FAO 56 specifications [26]. Coinciding in time with spectral acquisitions, biomass ($kg.m^{-2}$), Leaf Area Index (*LAI*), and Green Fraction Cover (f_c) were measured to describe the phenology of crops.

By the knowledge of crop stages, K_{cb} values have been estimated taking into account the effect of varying relative humidity and wind velocity from standard conditions ($RH = 40\%$, $v = 2\ m.s^{-1}$) (Allen et al., 1998). Reflectance in red and near infrared to compute *NDVI* is obtained by integrating spectral reflectance in the range of ranges [0.63, 0.69 μm] and [0.76, 0.90 μm].

Evolution in time of *NDVI* and f_c for maize is represented in Figure 5. *NDVI* reaches its maximum value, when crop reaches also full effective green cover in coincidence to maximum of K_{cb}. As can be seen in Figure 3 for maize, ranges of maximum and minimum values for f_c and *NDVI* coincide in time obtaining comparable curves.

Variation in behaviour of f_c allows determining K_{cbINI} (0.15), and K_{cbMID} (1.15). To determine K_{cbEND} it is necessary to estimate water content of plant. The resulting 54% on $DoY = 277$ suggest a value of $K_{cbEND} = 0.5$. The average curve for K_{cb} adapted for crop height, minimum relative humidity and wind velocity is represented in Figure 5 along with *NDVI*.

From linear regression we obtain the equations for the reflected-based crop coefficients for corn (Figure 6) in case of *NDVI* and *SAVI*:

$$K_{cbNDVI} = 1.37 \cdot NDVI - 0.017 \qquad \left(R^2 = 0.99\right) \tag{6}$$

$$K_{cbSAVI} = 1.76 \cdot SAVI - 9.10^{-2} \qquad \left(R^2 = 0.99\right) \tag{7}$$

To perform the comparison between (6) and (7), which are grass based reference evapotranspiration, and (4), which is alfalfa based reference evapotranspiration, we have realized the following steps:

1. Derive from (4) a new *SAVI* based equation, using the relationship NDVI = 1.2735•*SAVI*+0.02106, obtained from the definition of *SAVI* with a value for L = 0.5 (where L is the adjusting factor to account for f_c in the *SAVI* definition equation), the same as used for (7);
2. Multiply alfalfa-based K_{cb} by a factor 1.15 to convert them in grass based K_{cb}, according the procedure described in [27]. Equations (8) and (9) show that the obtained results are very similar to (6) and (7).

$$K_{cb,grass} = 1.36 \cdot NDVI - 0.031 \tag{8}$$

$$K_{cb,grass} = 1.73 \cdot SAVI - 0.009 \tag{9}$$

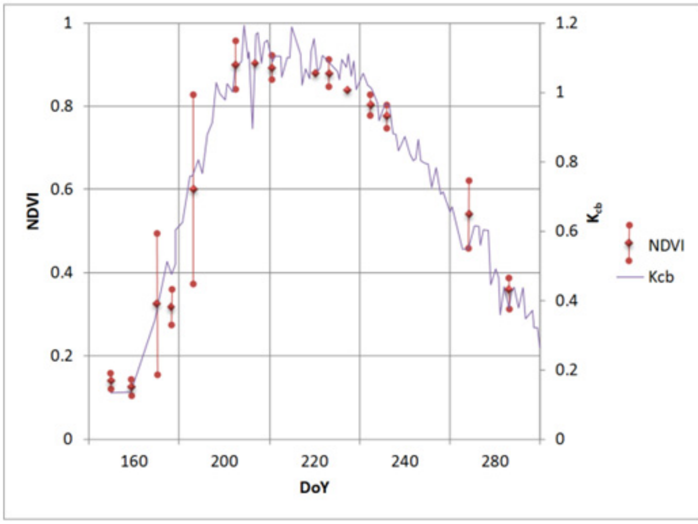

Figure 5. Field observations of K_{cb} and *NDVI* versus *DoY* for corn.

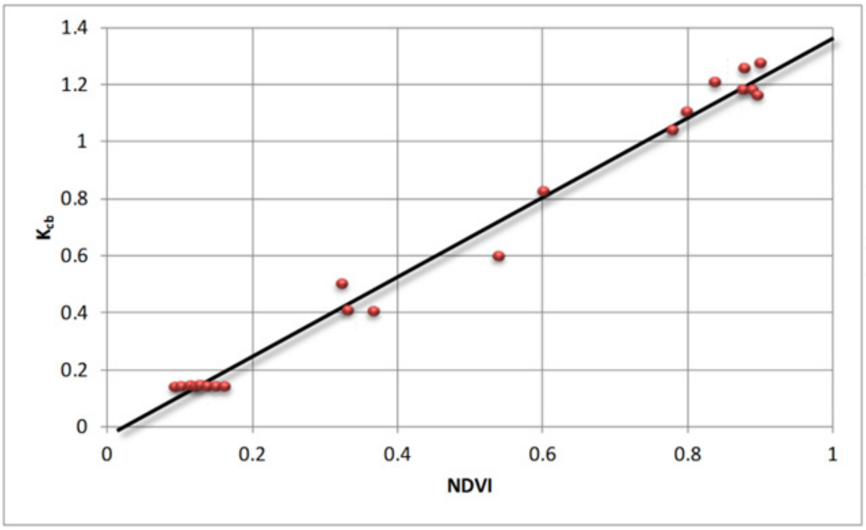

Figure 6. Linear regression between values of K_{cb} and measured *NDVI* for maize.

In the case of wheat, the evolution in time is not as representative as in maize. We observe in Figure 3 that on *DoY* = 95, f_c reaches a first local maximum before it continues growing in coincidence with emerging ears (with active photosynthesis), supposing a rapid increase in f_c, and thus in K_{cb} and spectral indices.

Applying (6) and (7) to data obtained for wheat, we see in Figure 7 that K_{cb} obtained from *NDVI* reproduces the evolution in time of f_c.

This relationship facilitates calculations of transpiration taking into account that only points over dry soil were considered, but without limiting crop transpiration. Evaporation of soil introduces an important contribution to K_c during days after irrigation or rainfall.

This means that water soil balance must be taken into account to get the contribution of evaporation in K_c. Over large areas, where variability of soil colour and brightness can influence the *NDVI*, *SAVI* and other *Vis* designed to normalize soil background effect should be used.

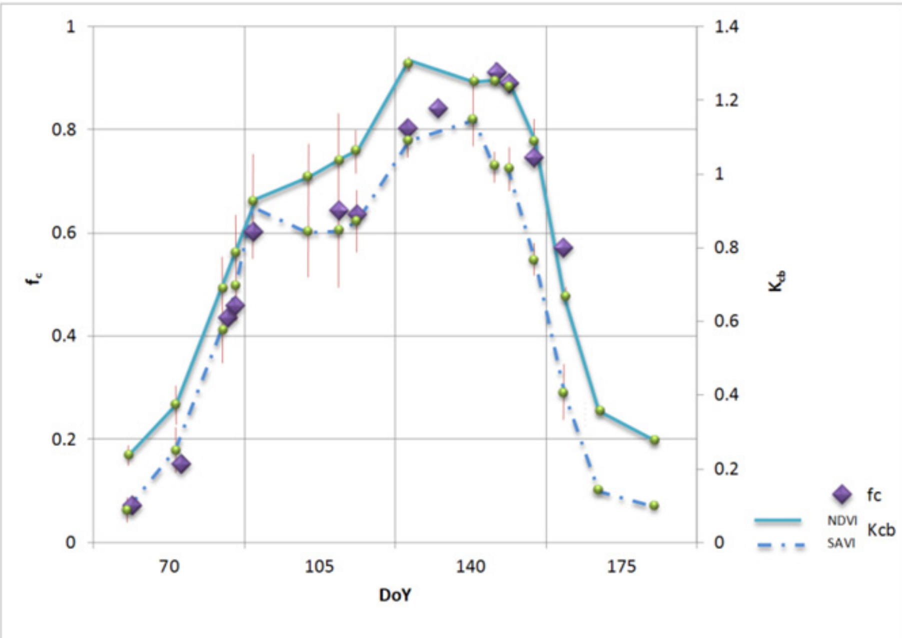

Figure 7. Evolution in time of observed f_c for wheat. The K_{cb} *NDVI* and K_{cb} *SAVI* values for wheat have been obtained from the linear relationships in (6) and (7).

6. Crop coefficient from NDVI: Operational point of view

Equations (6) and (7) provide the grass based basal crop coefficient from *NDVI* and *SAVI* data. These *VIs* are calculated for Landsat TM broadband from field radiometry data. Equation (4) provides alfalfa-based basal crop coefficient from *NDVI*.

Neale et al. [28] review the use of canopy reflectance observations to obtain crop coefficients over large areas. Similarities were found between the mean crop coefficient for small grain to the ratio of the perpendicular vegetation index (*PVI*) for wheat to *PVI* of wheat at full canopy cover. Heilman et al. [3] investigated the relationship between percent cover and reflectance-based perpendicular vegetation index (*PVI*) for alfalfa.

Neale et al. [22] related the crop canopy reflectance to basal crop coefficient for corn, developing an operational technique for estimating actual crop *ET*. The reflectance based crop coefficient (K_{cr}) was derived by nearly transforming the seasonal normalized difference vegetation index (*NDVI*) using the percent shading and leaf area measurements to establish the *EFC* and relate it to the basal crop coefficient by [6]. In several studies, *NDVI* has been directly used to predict K_c [5, 22, 23, 29, 30].

The operational procedure to estimate K_c from satellite imagery is based on the linear relationship between *NDVI* and basal crop coefficient described earlier. Landsat is the reference imagery to estimate *NDVI* (spectral broadband calibration). The attractiveness of Landsat is the high resolution (30 m in the visible and near infrared bands and 60 to 120 m in the thermal band) so that individual fields can be observed. The methodology that is described here has been checked against the preliminary results of all PLEIADES pilot areas for the following crops: Barley, wheat, maize, opium plant, sugar beet, alfalfa, pea, potato, onion and garlic. So we can establish the limits of applicability of this approach.

6.1. Dual crop coefficient NDVI approach

Wright [6] proposed a dual basal crop coefficient approach which splits the total crop coefficient into crop transpiration (K_{cb}) and soil evaporation (K_e) fractions, see Figure 8. The K_{cb} component represents the crop evaporative conditions from soil conditions whose surface is dry (direct evaporation from soil surface is minimum), and the crop growth is not limited by water, insect, climatological or physiological factors. The dual crop coefficient concept (see also equation (2)) expressed as

$$K_c = K_{cb} + K_e \tag{10}$$

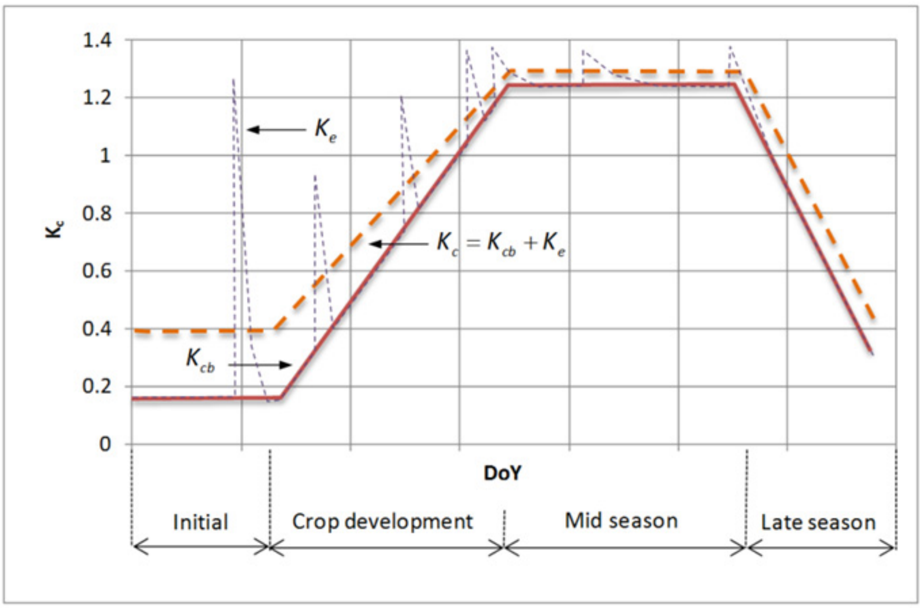

Figure 8. Crop coefficient curves showing the basal K_{cb}, soil evaporation K_e and the corresponding single $K_{cb} = K_{cb} + K_e$ curve [1].

We assume that there is a linear relationship between K_{cb} and *NDVI* as stated earlier. This time, however, the linear relationships are adjusted to values of $NDVI_{MAX}$ and $NDVI_{MIN}$ from satellite imagery rather to those from field radiometry. Table 2 gives the corresponding values.

	NDVI	K_{cb}	f_c	K_c
Minimum	0.16	0.15	0.0	0.4
Maximum	0.80	1.15	0.8	1.2

Table 2. Maximum and minimum values of NDVI and derived parameters observed in set of Landsat images.

The resulting linear relationship is:

$$K_{cb} = 1.5625 \cdot NDVI - 0.1 \tag{11}$$

The soil evaporation part in (10), K_e, is related with bare soil fraction, and is strongly dependent on wetting state of bare soil fraction, because the evaporative power of soil changes strongly if the soil is wetted or if the soil is dry. Irrigation system (gravity, sprinkler, drip, etc) and irrigation frequency, coupled with type and stage of crop, are the factors that determine the time of different bare soil wetting states. We propose a first approach to take into account these factors assuming *NDVI* as a good estimator of ground fractional cover, f_c, (and so, of bare soil fraction, 1 - f_c). The other factors are parameterized by means of a parameter β:

$$K_e = \left(1 - f_c\right) \cdot \beta \tag{12}$$

The parameter β is estimated empirically, from the values of K_{cINI} or K_{cMID} and can be modified on the basis of ancillary or local information. It is crop (and stage) dependent. Assuming a linear relationship between *NDVI* and f_c for all crops, and considering again the *NDVI* maximum and minimum values from satellite imagery and the corresponding f_c as given in Table 1, we obtain the relationship

$$f_c = 1.3514 \cdot NDVI - 0.2811 \tag{13}$$

6.2. Single crop coefficient NDVI approach

A common β parameter value is 0.25, obtained considering an f_c value of 0.8, K_c equal to 1.2, and K_{cb} equal to 1.15. Taking β as 0.25 and combining (10), (11), (12), and (13), we obtain a direct relationship K_c - *NDVI*

$$K_c = 1.2246 \cdot NDVI + 0.2203 \tag{14}$$

We also obtain a relationship K_c - *NDVI* directly from Table 1 in the same way as above, by considering a linear relationship between the maximum *NDVI* and the maximum K_c (at effective full cover) and the minimum (bare soil) *NDVI* and bare soil K_c, respectively. The resulting relationship is:

$$K_c = 1.25 \cdot NDVI + 0.2 \tag{15}$$

Equations (14) and (15) are very similar. By its simplicity we assume (15) as the operational formula to derive K_c from *NDVI*.

Table 3 shows the comparison between K_c values obtained from *NDVI* by means of (15), and the values for K_{cINI}, K_{cMID} from [1] for the crops studied in the field during the pilot campaign. We observe good agreement for crops with higher effective ground cover, although (15) seems to overestimate K_{cINI} slightly for spring crops.

Crop	NDVI min	NDVI max	K_{cINI} (15)	K_{cINI} FAO56	K_{cMID} (15)	K_{cMID} FAO56
Alfalfa	0.16	0.80	0.40	0.40	1.20	1.20
Barley	0.16	0.80	0.40	0.30	1.20	1.15
Garlic	0.16	0.44	0.40	0.70(0.40)*	0.75	1.00
Maize	0.16	0.78	0.40	0.30(0.40)*	1.17	1.20
Onion	0.16	0.53	0.40	0.70(0.50)*	0.86	1.00
Opium poppy	0.16	0.80	0.40	No reference	1.20	No reference
Pea	0.16	0.77	0.40	0.50(0.40)*	1.16	1.15
Potato	0.16	0.78	0.40	0.50(0.45)*	1.17	1.15
Sugar beet	0.16	0.78	0.40	0.35(0.45)*	1.17	1.20
Wheat	0.16	0.80	0.40	0.30	1.20	1.15

Table 3. Comparison between the averaged K_c values obtained from *NDVI* by means of (15), and the values for K_{cINI}, K_{cMID} from FAO56 [1] for the main crops in the pilot zone.

Significant deviations between *NDVI* based and FAO56 based K_{cMID} are found for crops like garlic and onion, which exhibit low ground cover in the stage of maximum development, in contrast with the rest of crops studied. The higher bare soil proportion of those crops can introduce and reinforce effects on K_c related with irrigation frequency, irrigation system utilized, environmental aspects and others. Further research is under way to study this behaviour.

It should be also noted that (14) and (15) are applicable for the initial crop development and mid-season phases only. The application for the late season phase, when the crop is maturing, requires a slight correction because ground cover (green and dry) remains nearly constant in that phase. Assuming a constant value of 0.8 for ground cover (Table 1) and combining (11) and (12), we obtain:

$$K_c = 1.5625 \cdot NDVI - 0.05 \tag{16}$$

Summarizing, the operational equations will be (15) for the initial, development and mid season and (16) for the late season.

7. Caia (Portugal)

The Caia irrigation scheme is located in the Caia watershed in east-central Portugal close to the Spanish border. The Caia river is a tributary to the transnational Guadiana river basin. It is a relatively flat area at a mean elevation of 200 m above sea level, with mean annual precipitation of 537 mm. The irrigation infrastructure was established in 1967, with a central dam of 203 hm^3 capacity and a metered canal network serving 7,237 ha. Except for a concentrated small-scale plot area of 600 ha, the fields are generally large, on average 35 ha. The main crops are corn, wheat, tomato, and sugarbeet, which are all grown for industrial commercialization.

The water resources from the dam are mainly used for irrigation (over 90%) and population supply (less than 10%). Pressure on water quantity is increasing and water quality is already under pressure, as ecological standards are very close to the regulatory limits.

The Associação de Beneficiários do Caia (ABCaia) is the local water user association (Irrigation District Board). It has the mandate for water management in the irrigation scheme and represents the local farmers in the River Basin Council. At the beginning of PLEIADES, there was an incipient traditional IAS (provided by the Centro Operativo de Técnicas de Rega, COTR) with a newly installed agrometeorological station and a small GIS facility at the Irrigation District Board. The goal was to build up an innovative irrigation advisory capacity, in order to cope with the rapidly increasing pressure on water quantity and quality.

7.1. Local crop expert database and field protocols

The first pilot campaign was a fruitful training and learning phase that consolidated the local team and established local field sampling protocols. It also laid the foundations for the local GIS-based expert database on crop phenology. Figure 9 shows the crop coefficient curves for the major crops. An important emphasis in the Caia pilot zone is on tomato, which has phonological cycles that can vary enormously between plots.

During the following pilot campaign, extensive field data were collected to extend the expert database for all major crops of the area. They were also used for validation and local calibration of EO-derived products.

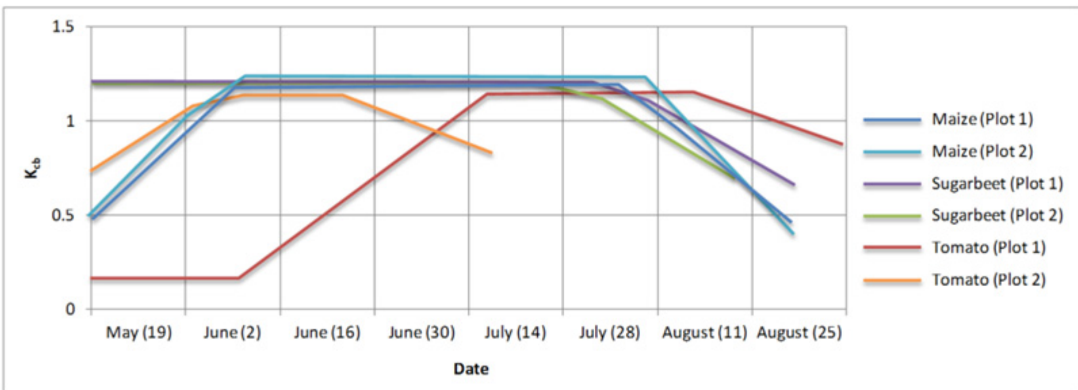

Figure 9. Crop coefficient curves for major crops in Caia area, from field campaign.

The local team developed and implemented a work strategy having as objective to be close to satellite overview conditions. In that sense nadir pictures of crop canopy have been taken as close as possible to overpass satellite period, to determine Green fraction cover, and the crop coefficient has been calculated using farming information concerning amount of used irrigation water, agrometeorological data and field phenological stage to correct and calibrate K_{cb} curve.

For this campaign a spatial extrapolation of the crop coefficients was performed, based on field work land use maps. Figure 10 shows the temporal and spatial evolution of crop coefficient in the pilot zone, for the three studied crops.

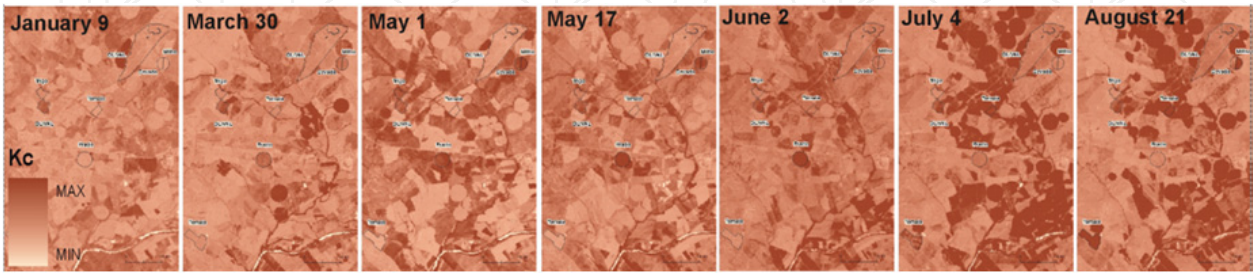

Figure 10. Spatial and temporal evolution of crop coefficient in Caia pilot Zone.

7.2. Calibration and validation of FAO and *EO* derived crop coefficients

The crop coefficient has been calculated in three different ways: the first (line in Figure 11) is based on the concepts of the FAO-56 (Allen et al., 1998) methodology for K_{cb} calculation, with its general tabulated values; the second is K_c *NDVI* calculated with *EO* PLEIADES methodology (circles and squares, from Landsat 7 and 5, respectively); third way is K_{cb} from field observations, adjusted with additional field data (triangles). Figure 11 shows maize monitored on "Melinho" and "Botafogo" test fields. The length of the "Initial stage" of phenological development is based on information concerning seeding dates, but FAO-56 standard methodology stipulates that crop green development occurs earlier than has been observed in the field. The EO-derived data are rather close to the field observations. The slight scatter indicates that the crop stage have several variations, depending on soil and crop water stress parameters.

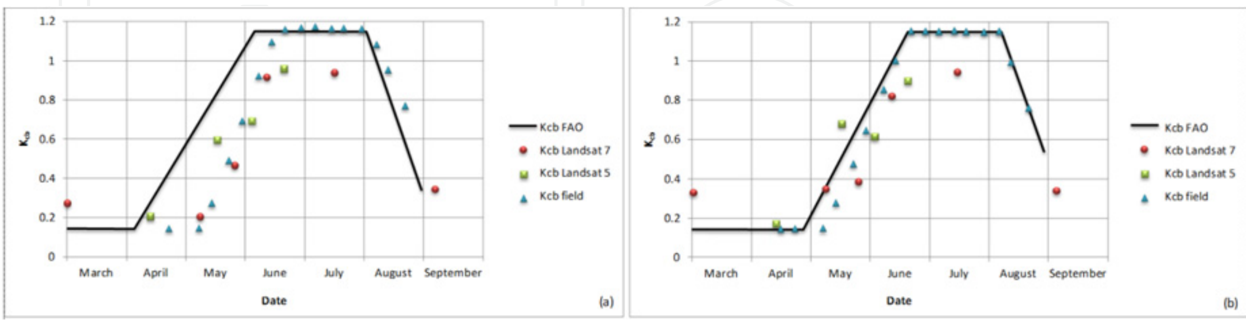

Figure 11. Maize field K_c evolution during campaign versus *EO* derived and FAO-56: Melinho plot area (a) and Botafogo plot area (b).

Tomato is planted in a way that full canopy is not reached in any growing stage. This means that soil evaporative fraction is always present, resulting in a better water management at plot level. Due to the fact that it is a multi-stage plant, i.e. one plant can be on multiple phenological stages at the same period, irrigation must be a compromise for the average stage of the field. Based on the experience of field technicians, the different K_{cb} curves (Figure 12) have been calculated with data obtained at plot level, FAO-56 methodology and *EO* derived data.

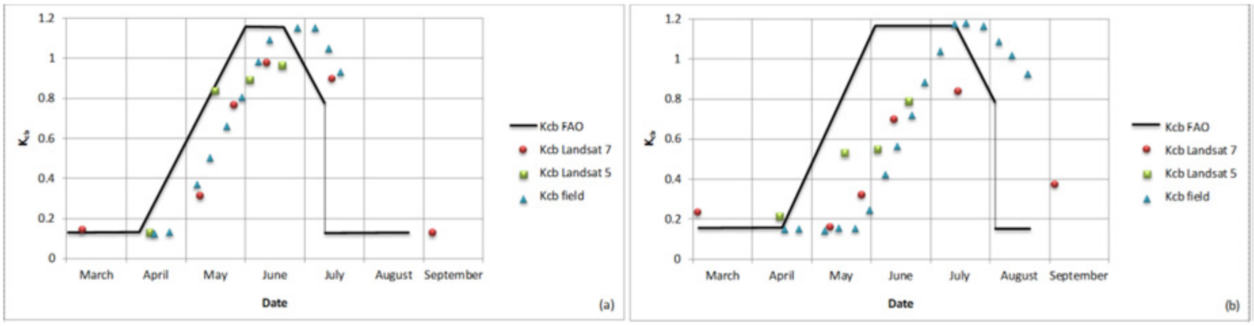

Figure 12. Tomato field K_c evolution during campaign versus *EO* derived and FAO-56: D. Joana plot area (a) and Sta. Isabel plot area (b).

The results demonstrate again a huge difference between standard FAO-56 values (line) and the K_c values obtained from field survey (triangles). As with maize, the *EO* derived data present closer values to what has been observed on the plots. Given the huge deviation of actual crop coefficients from FAO-56 values the local expert database on crop phenology plays a crucial role in the quality of an *IAS* under implementation.

7.3. Real-time demonstration and participatory evaluation with farmers

Field monitoring has been carried from seeding until harvesting dates, only during the months of July, August and September of 2005. A real-time on-place demonstration campaign of PLEIADES took place, surveying hot spots in each of the 6 pilot fields and delivering *IAS* information to farmers.

A "Farmer Report" was supplied to each individual land owner covered by the ground truth operation (Figure 13). In Figure 13 is clearly identified the difference in corn maturation in July, using drop-to-drop irrigation (a) and pivot irrigation (b).

Several meetings were organized to promote and explain the content of the information to the farmers and to get their feedback. The farmers found that the *EO* derived information, along with field survey data, can be very useful for them and that such an irrigate advisory service can help them with irrigation and farming strategies at their farm holding level.

Although, one of the monitored fields had a change for sugar beet with a winter variety, with impacts on data correlation, on the other two the same season of maize and tomato has been used.

The weekly procedure has been maintained in order to collect phenological stages data to define K_{cb} field curves, for evaluation of EO-derived data. For the demonstration campaign the Portuguese Meteorological Institute provided K_c *NDVI* data, obtained from Landsat 5, in almost real time, so that they could be compared with field data. The local team made their spatial integration and data extrapolation based on ABCaia GIS tools and related geographical information data available for this pilot zone.

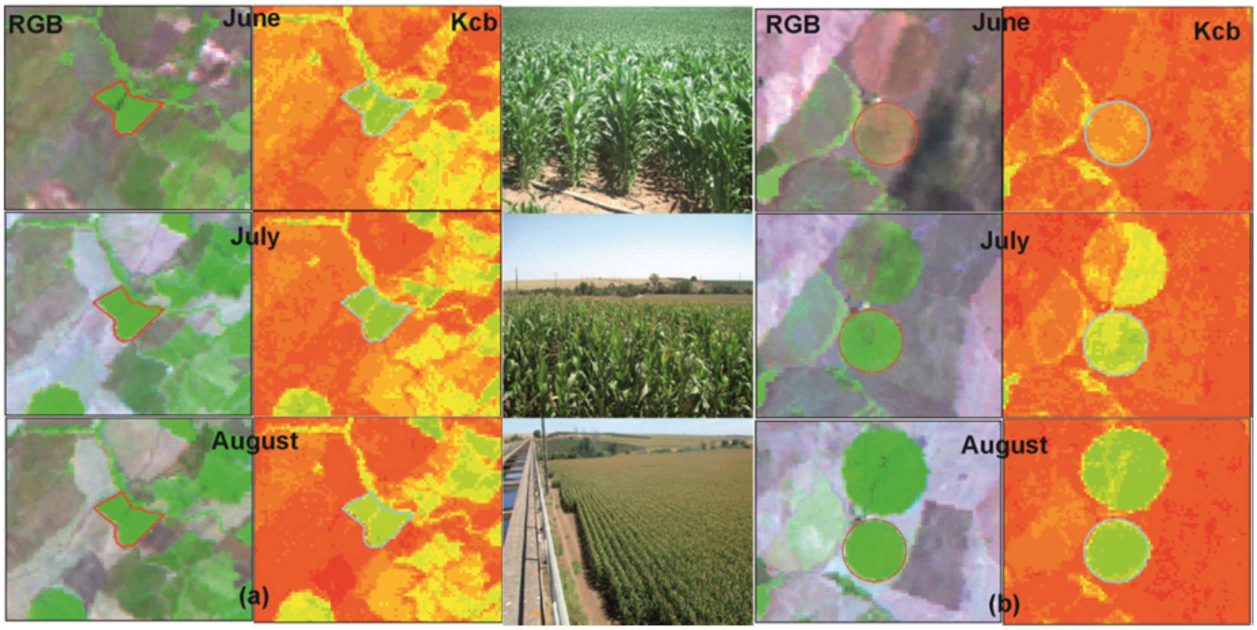

Figure 13. Farmer report from D. Isabel (a) and Melo (b) fields.

Knowing, through data from the meteorological station at Caia (Figure 14), the relationship between potential evapotranspiration (ET_p) and evapotranspiration measured from *EO* (ET_{EO}), it is possible to establish the relationship expressed in (2).

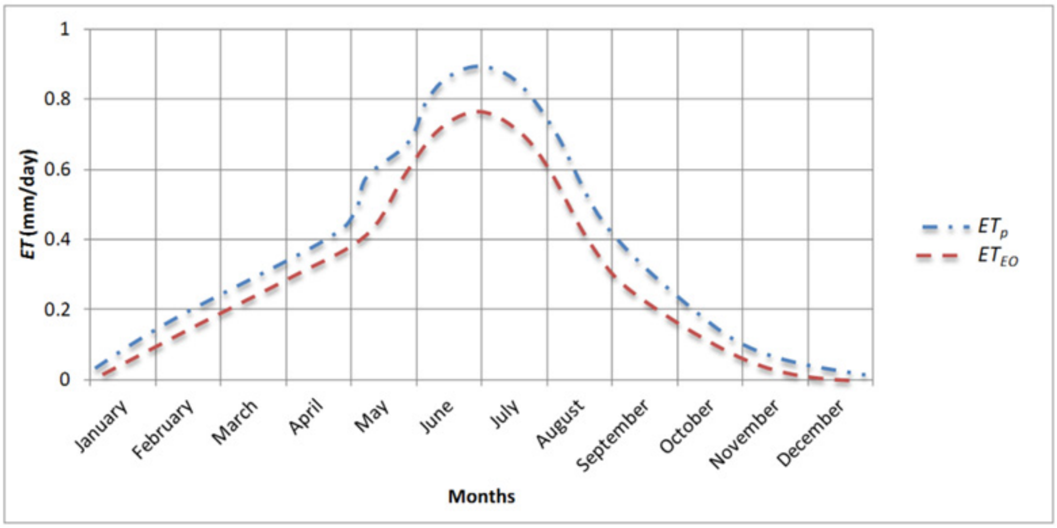

Figure 14. Evapotranspiration in Caia area.

Hence, having a value of, for example, ET_0 = 7.2 for the 2nd of June we can make the correspondence for the all area (Figure 15). This kind of data is very important to farmers because there is a well known relation where precipitation plus irrigation is equal to evapotranspiration plus terrain drainage.

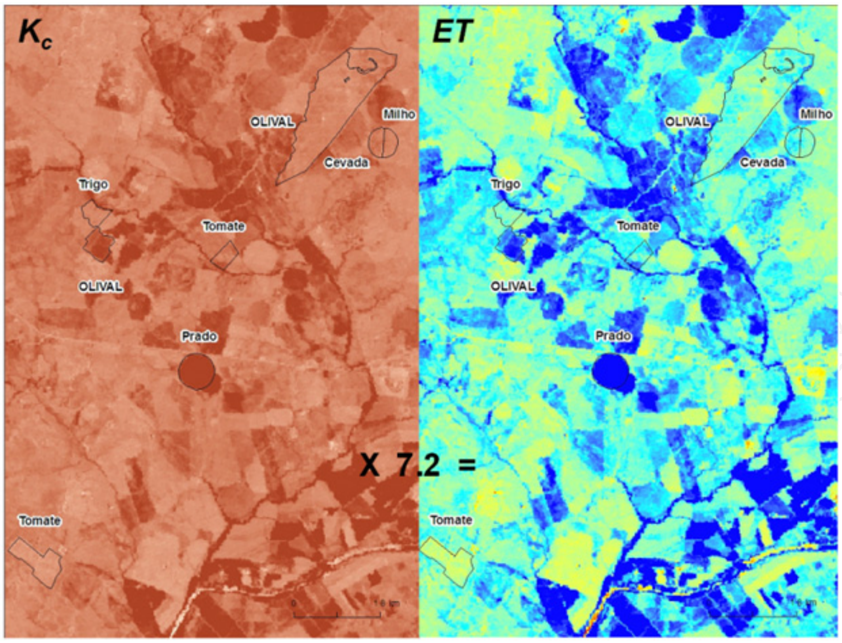

Figure 15. Crop coefficient and Evapotranspiration in Caia area at 2 of June.

7.4. Future perspectives

For the intensive and extensive campaign the local ground team has been organised and defined protocols and set up a strategy to collect data as close as possible to satellite overpass conditions. During the project period a local effort has been made to implement irrigation advisory services on the pilot zone area, resulting in ongoing use of agrometeorological station data provided by the Centro Operativo de Técnicas de Rega (COTR) and the Farmer Association (ABCaia) supplying information on irrigation parameters. Survey data have been available due to the cooperation of the Agronomy School of Elvas University (ESA) and also made available to them jointly with with ABCaia aiming to set up strategies for development of local technical skills to support irrigation development in accordance with environmental requirements.

The foundations have been laid for the PLEIADES prototype to start being operative in the Caia pilot zone. An efficient and dedicated local operating team has been consolidated, with collaborating entities. A local *GIS* based expert database on crop phenology and *EO* methodology calibration has been developed and the necessary *ICT* infrastructure has been established (Figure 15). The user participation is incipient but promising. A funding model still needs to be found for further sustainable implementation. Increasing pressure on water quantity and quality may provide an important motivation.

The Server is based on leading edge online GIS Technology. The system architecture is web based and composed by a modular group of components, which makes maintenance of the system easy. Those components are based on the XML language.

The web services have been programmed also to let the server be distributed in different *PCs* to share the load of the system. The server has been programmed for a Windows system, using open source libraries and toolkits like FOP, Xerces C++, GDAL, GD, MapServer, SWFF, etc. GDAL has been used for obtaining the satellite images information, getting the pixel value and creating charts with GD showing the time evolution.

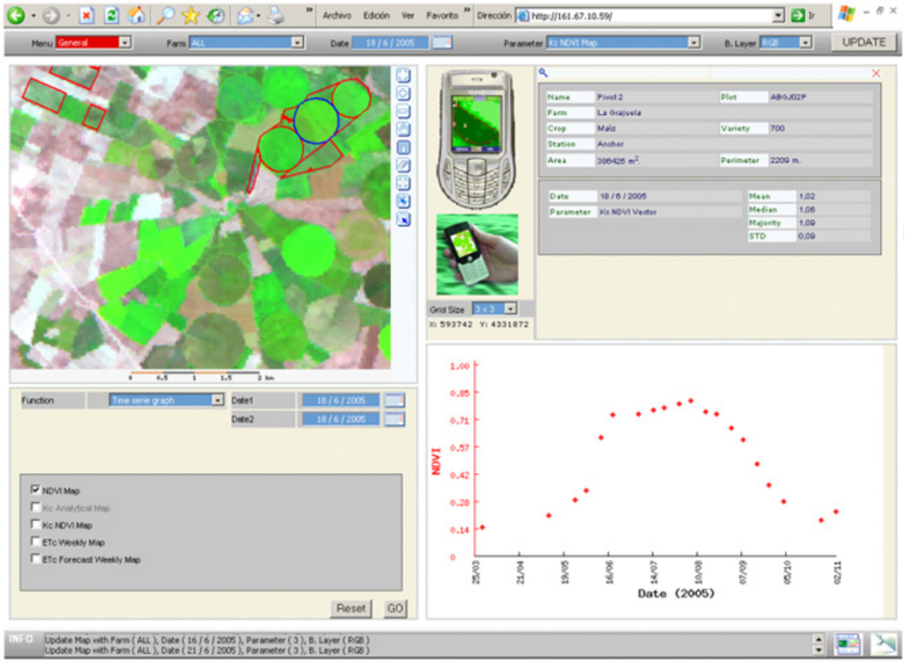

Figure 16. PLEIADES WebGIS and mobile applications example.

This toolkit, as well as the queries form, helps the user in taking decisions about water, crops, etc. MapServer lets the system offer a visual support for the user, supporting a wide variety of image formats, as well as vector format and databases. Xercess is the parser for the XML messages that implements the DOM interface providing quite an easy interface for the programmer for accessing the XML information.

The system receives information from images and stations, pre-processing some of them to provide formatted data. It also offers a Quality Control (QC) interface for the IAS manger to control the information for the farmer, so that the final information distributed to the user ("published") includes only correct and accurate information. The system is prepared for assimilating the satellite image as far as possible, so that the system gives a real time toolkit for analysing the satellite information with the spatial information.

The mobile phone client has been programmed in Flash. A simpler interface has been designed because of the limitations of the mobile technologies. This client lets the farmers access the information of the satellite wherever they are without needing a computer or an internet connection and with an easy interface that lets them zoom into the image or ask for parameters information.

8. Conclusions

PLEIADES was designed to assess and demonstrate in an operational perspective how the integration of Earth observation (*EO*) techniques in routine Irrigation Advisory Services

(*IAS*) can improve the efficiency in the use of water for irrigation. The use of leading-edge Information and Communication Technology (*ICT*) tools in the generation and distribution of information makes the *EO* easily available to *IAS* and the farmers.

The PLEIADES WebGIS (www.pleiades.es) is the central outcome of the project. Its key feature is the operational generation of irrigation scheduling information products from a virtual constellation of *EO* satellites and their delivery to farmers in near-real-time using leading-edge on-line analysis and visualization tools. It is supported by a methodology package to derive crop coefficients and further advanced parameters from *EO* satellite images in an operational processing chain.

PLEIADES basic products were generated and transmitted to a sample of farmers normally within 2 days from overpass, thus completely matching the weekly operational irrigation scheduling cycles.

Participatory evaluation with selected farmers shows that the farmers feedback is very positive, both on the information quality as on the added value of the spatial information (within-plot heterogeneity and between-plot variations). The reliability and accuracy of the information has been con-firmed by the comparison of different approaches to derive crop coefficients from EO and validation with field data in all pilot zones.

The major improvement achieved by the use of *EO* in the generation of basic IAS information products like crop coefficients is twofold. Firstly, the spatial coverage is enhanced significantly, both extending to larger areas and providing within-field heterogeneity information. Secondly, the spatially resolved *EO* data can easily be combined with cadastral information in a geographical in-formation system (*GIS*), which allows for personalization of the irrigation scheduling recommendation.

Conventional *IAS* provides average irrigation recommendations per crop type, while the new space-assisted *IAS* is able to provide specific recommendations for each individual plot, based on the actual state of that plot.

The fast image delivery and quality controlled operational processing make the EO-based crop coefficient maps available at the same speed and quality as ground-based data (point samples), while significantly extending the spatial coverage and reducing service cost. The uptake of users at *IAS* and farmer level is encouraging.

Advanced products have made a significant step towards operationality while maintaining satisfactory levels of accuracy. First exploitation steps including full operational implementation are indicators of the success of the prototype and the project.

The space segment is the most vulnerable part of the entire operational system. After the sensor failure of Landsat 7, the backbone of the actual system is Landsat 5, due to its excellent operationality and low cost (22 years old, with no replacement in sight). Urgent actions are required to ensure the capability to obtain adequate *EO* images at the adequate coverage frequency and low cost.

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9. References

[1] Allen, R.G, Pereira, L.S., Raes, D. y Smith, M. (1998). Crop evapotranspiration. Guidelines for computing crop water requirements. *UN-FAO, Rome, Italy*.

[2] Bailey, J.O. (1990). The Potential Value of Remotely Sensed Data in the Assessment of Evapotranspiration and Evaporation. *Remote Sensing Reviews*, 4(2):349-377.

[3] Heilman, J.L., Heilman, W.E. and Moore, D.G. (1982). Evaluating the Crop Coefficient Using Spectral Reflectance. *Agronomy Journal*, 74:967-971.

[4] Allen, R.G., Morse, A., and Tasumi, M. (2003). Application of SEBAL for western US water rights regulation and planning. University of Idaho, Kimberly, Idaho, USA. *Proceedings of ICID-CIID International Workshop: Use of remote sensing of crop evapotranspiration for large regions*: *September 17, Montpellier, FRANCE.*

[5] Choudhury, B. J., Ahmed, N. U., Idso, S. B., Reginato, R.J., and Daughtry, C.S.T. (1994). Relations Between Evaporation Coefficients and Vegetation Indices Studied by Model simulations. *Remote Sensing of Environment*, 50:1-17.

[6] Wright, J.L. (1982). New Evapotranspiration Crop Coefficients, *Journal of Irrigation and Drainage*, 108(1):57-74.

[7] Calera, A., Martínez, C., Meliá, J. (2001). A procedure for Obtaining Green Plant Cover: Relation to NDVI in a Case of Study for Barley. *International Journal of Remote Sensing*, vol 22, no 17, 3357-3362.

[8] Carlson, T.N., Ripley, D. (1997). On the Relation between NDVI, Fractional Vegetation Cover, and Leaf Area Index. *Remote Sensing of Environment*, 62:241-252.

[9] Sellers, P.J., Dickinson, R.E., Randall, A., Betts, A.K., Hall, F.G., Berry, J.A., Collatz, G.J., Denning, A.S., Mooney, H.A., Nobre, C.A., Sato, N., Field, C.B., Henderson- Sellers, A. (1997). Modelling the Eschanges of Energy, Water, and Carbon between Continents and the Atmosphere. *Science,* Vol 275, 52-509.

[10] Monteith, J. L. (1977). Climate and Efficiency of Cropproduction in Britain. *Phil. Trans. Res. Soc., London, SeriesB.* 281, pp. 277 - 329.

[11] Asrar, G., Fuchs, M., Kanemasu, E.T., and Hatfield, J.L. (1984). Estimating absorbed photosynthetic radiation and leaf area index from spectral reflectance in wheat. *Agronomy Journal* 76:300-306.

[12] Gower, S. T., Kucharik, C. J., and Norman, J. M. (1999). Direct and indirect estimation of leaf area index, fapar, and net primary production of terrestrial ecosystems. *Remote Sensing of Environment,* 70: 29-51.

[13] Calera, A., González-Piqueras, J., Meliá, J. (2004). Monitoring barley and corn growth from remote sensing data field scale. *International Journal of Remote Sensing*, vol. 25, no 1, 97-109.

[14] Monteith J.L., Unsworth M.H. (1990). Principles of Environmental Physics., *E.Arnold Ed., London,* pp.290

[15] Gilabert, M.A., Gandía, S., Meliá, J. (1996) Analyses of Spectral-Byophysical Relationships for a Corn Canopy. *Remote Sensing of Environment,* 55: 11-20.

[16] Bausch, W.C. and Neale, C.M.U. (1987). Crop Coefficients Derived from Reflected Canopy. *Transactions of the ASAE*, 30(3):703-709.

[17] Rosenberg, N.J., Blad, B.L., and Verma, S.B. (1983). Microclimate; The biological environment 2nd ed. *New York; John Wiley & sons*, pp.13-15,170.

[18] Calera, A., A. Jochum, and A. Cuesta (2003): Earth observation techniques to improve Irrigation Advisory Services. Proc. Envirowater, Albacete, 4-6 September.

[19] Jochum, A.M., A. Calera, and A. Cuesta (2003): Irrigation management from space: Towards user-friendly products. Proc. ICID Workshop "Use of Remote Sensing of Crop Evapotranspiration fro Large Areas", 17 September, Montpellier. (submitted *Int'l J. Irrigation & Drainage*)

[20] Moran, M.S., Inoue, Y., Barnes, E.M. (1997). Opportunities and Limitations for Image-Based Remote Sensing in Precision Crop Management. *Remote Sensing of Environment,* 61, 319-346.

[21] Bausch, W.C. and Neale, C.M.U. (1987). Crop Coefficients Derived from Reflected Canopy. *Transactions of the ASAE*, 30(3):703-709.

[22] Neale, C.M. U., Bausch, W.C., and Heermann, D.F. (1989). Development of Reflectance-Based Crop Coefficients for Corn. *Trans. ASAE* 32(6):1891-1899.

[23] Bausch, W.C. (1993). Soil Background Effects on Reflectance-Based Crop Coefficients for Corn. *Remote Sensing of Environment*, 46:213-222. 46:213-222.

[24] Huete, A.R. (1988). A Soil Adjusted Vegetation Index (SAVI). Remote Sensing of Environment, 25:295-309.

[25] Bausch, W.C. (1994). Remote Sensing of Crop Coefficients for Improving the Irrigation Scheduling of Corn. *Agricultural Water Management*, 27:55-68.

[26] Gonzalez-Piqueras, J., Calera, A. and Gilabert, M.A. (2003). Estimation of Crop Coefficients by Means of Optimized Vegetation Indices for Corn, *Proceedings of the SPIE, Barcelona, September, 8-11th.*

[27] ASCE Hydrology Handbook 2nd Ed . (1996). Chapter 4: Evaporation and Transpiration. *ASCE Manuals and Reports on Engineering* Practice No.28.

[28] Neale, C.M.U., Jayanthi, H., and Wright, J.L. (2003). Crop and irrigation water management using high resolution airborne renote sensing. Utah State University, Logan, Utah, USA. *Proceedings of ICID-CIID International Workshop: Use of remote sensing of crop evapotranspiration for large regions*: *September 17, Montpellier, FRANCE.*

[29] Bausch, W.C. and Neale, C.M.U. (1989). Spectral inputs improve corn crop coefficients and irrigation scheduling. *Transactions of the ASAE,* 32(6):1901-1908.

[30] Bausch, W.C. (1995). Remote sensingof crop coefficients for improving the irrigation scheduling of corn. *Agricultural Water Management*. 27:55-68.