Managing Water in Agriculture through Remote Sensing Applications

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Abstract. 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. The PLEIADES Project - Participatory multi-Level EO-assisted tools for Irrigation water management: and Agricultural Decision - Support, falls in the 6th Framework Programme, Priority 6 - Sustainable Development, Global Change and Ecosystems – CEC - Research Directorate-General-Integrating and Strengthening the European Research Area. 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. The system praised by PLEIADES 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.

Keywords. Agriculture, remote sensing, water managing,

Introduction

Crop evapotranspiration can be calculated using the crop coefficient (Kc) 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. 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. Therefore, vegetation indices (VI) are better related to transpira-

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tion of crop than to K_c 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 Wright [1] splits K_c into 2 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. Wright [1] 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.

1. K_c from NDVI: Foundations

1.1. NDVI and Canopy biophysics parameter

Relevant canopy biophysics parameters are green fractional cover, fraction of absorbed photosynthetically active radiation, primary production, Leaf Area Index, basal crop coefficient. All they are involved in canopy evapotranspiration.

The ability of NDVI to describe canopy biophysics parameter has been shown as follows: *i*) NDVI is related linearly with green fractional cover; *ii*) NDVI is related linearly with the fraction of absorbed photosynthetically active radiation (fAPAR); *iii*) NDVI is related with primary production (dry biomass) by means of Light Use Efficiency (LUE) models; *iv*) NDVI is related exponentially with Leaf Area Index (LAI). Is well known that NDVI begins to saturate for a value of LAI equal to 3 reaching a plateau for LAI > 3; *v*) NDVI is related linearly with the basal crop coefficient (K_{cb}). This relationship is a relevant basis for the "K_c-NDVI" approach.

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

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 this 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. 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, Monteith and Unsworth [2] consider that vegetation index can be legitimately used to provide an estimate of growth rate.

The facts pointed out in (*iii*) and (*iv*) may appear contradictory (saturation of NDVI for LAI above 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 Rosenberg et al. [3] 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 a LAI of about three". Accounting the LAI saturation in the relation with evapotranspiration has lead to the concept of active LAI. The active LAI is defined as the index of the leaf area that actively contributes to the surface heat and vapor 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). In fact, the procedure to estimate K_{cb} is based in the knowledge of f_c, 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.

The relationship between NDVI and CGR exhibits a strong dependence on crop and environmental variables (solar radiation, temperature, etc.). 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} 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 in accounting its relationship with K_{cb}.

Taking into account similarities between the crop coefficient curve and vegetation index, Bausch and Neale [4] established the potential for modeling crop coefficient as a function of vegetation index. This relation was derived from reflectance observations at field scale in the wavelengths ranges $[0.63,\ 0.69\ \mu m]$ and $[0.76,\ 0.90\ \mu m]$, 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, Neale et al. [5] obtained Eq. (4) for two research sites in Colorado using alfalfa as reference evapotranspiration surface.

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

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. At field scale, further work was performed in order to improve scheduling irrigation events on corn compared to other traditional Day of Year (DoY) based methods resulting in estimated crop water use reduced by 15%.

1.2. Kcb-NDVI relation from field observations

Intensive experimental campaigns were conducted 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=2ms^{-1}). Reflectance in red and near infrared to compute NDVI is obtained by integrating spectral reflectance in the range $[0.63,\ 0.69\ \mu m]$ and $[0.76,\ 0.90\ \mu m]$. NDVI reaches its maximum value, when crop reaches also full effective green cover in coincidence to maximum of K_{cb}. For maize, ranges of maximum and minimum values for f_c and NDVI coincide in time obtaining comparable curves. Variation in behavior of f_c allows determining K_{cb}INI (0.15), and K_{cb}MID (1.15). To determine K_{cb}END it is necessary to estimate water content of plant. The resulting 54% on

DoY=277 suggest a value of $K_{cb}END$ =0.5. From linear regression we obtain the equation for the reflected-based crop coefficients for corn.

$$K_{cb\,NDVI} = 1.37 \cdot NDVI - 0.017 \quad \left(R^2 = 0.99\right) \tag{5}$$

To perform the comparison between Eqs. (5), which is grass based reference evapotranspiration, and (4), which is alfalfa based reference evapotranspiration, we multiply alfalfa-based K_{cb} by a factor of 1.15 converting it in grass-based K_{cb}, according the procedure described in ASCE [6]. Comparing Eqs. (6) and (5), we saw they lead to very similar results.

$$K_{cb\,grass} = 1.36 \cdot NDVI - 0.031 \tag{6}$$

Applying Eq. (5) to data obtained for wheat, we observed 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.

2. Kc from NDVI: Operational point of view

Neale et al. [7] review the use of canopy reflectance observations to obtain crop coefficients over large areas. Related studies found similarities between the mean crop coefficient (K_c) 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. [8] investigated the relationship between percent cover and reflectance-based perpendicular vegetation index (PVI) for alfalfa. Neale et al. [5] 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 Wright [1]. In several studies, NDVI has been directly used to predict K_c.

2.1. Methodology

The operational procedure to estimate K_c from satellite imagery is based on the linear relationship between NDVI and basal crop coefficient. Eq. (5) provides the grass-based basal crop coefficient from NDVI. This VI is calculated for TM broadband from field radiometry data. Equation (4) provides alfalfa-based basal crop coefficient from NDVI. Landsat 5-TM are the reference images to estimate NDVI (spectral broadband calibration). The attractiveness of Landsat is the high resolution (30 m in the visible and near infrared bands and 120 m in the thermal band) so that individual fields can be observed.

The methodology that is described here has been checked against the results of the field campaigns for the following crops: wheat, tomato, alfalfa, and corn. So we can establish the limits of applicability of this approach. For further developments we will use corn as an example.

2.2. Dual crop coefficient NDVI approach

Wright [1] proposed a dual basal crop coefficient approach which splits the total crop coefficient into crop transpiration (K_{cb}) and soil evaporation (K_e) fractions. 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 expressed as:

$$K_c = K_{cb} + K_e \tag{7}$$

Again, we assume that there is a linear relationship between K_{cb} and NDVI. 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.

The soil evaporation part in Eq. (7), 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 :

$$K_e = (1 - f_c) \cdot \beta \tag{8}$$

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, we obtain the relationship:

$$f_c = 1.3514 \cdot NDVI - 0.2811 \tag{9}$$

2.3. 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 Eqs. (7), (8) and (9), we obtain a direct relationship K_c-NDVI:

$$K_c = 1.2246 \cdot NDVI + 0.2203 \tag{10}$$

We also obtain a relationship K_c-NDVI 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:

$$Kc = 1.25 \cdot NDVI + 0.2 \tag{11}$$

Eqs. (10) and (11) are very similar. By its simplicity we assume Eq. (11) as the operational formula to derive K_c from NDVI. The comparison between K_c values obtained from NDVI by means of Eq. (11), and the values for K_{cini}, K_{cmid}, from Allen et al. [9] for the crops studied in the field campaign shows good agreement for crops with higher effective ground cover; although it seems to slightly overestimate K_{cini} for spring crops. Figure 1 shows Eq. (11) results for corn in the area of Caia-Portugal, being perfectible visible the crop development, 15 of June to 2 of August, the mid season, 2 of August to 18 of August and finally, the late season, extending from 18 of August to 5 of October.

3. 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.

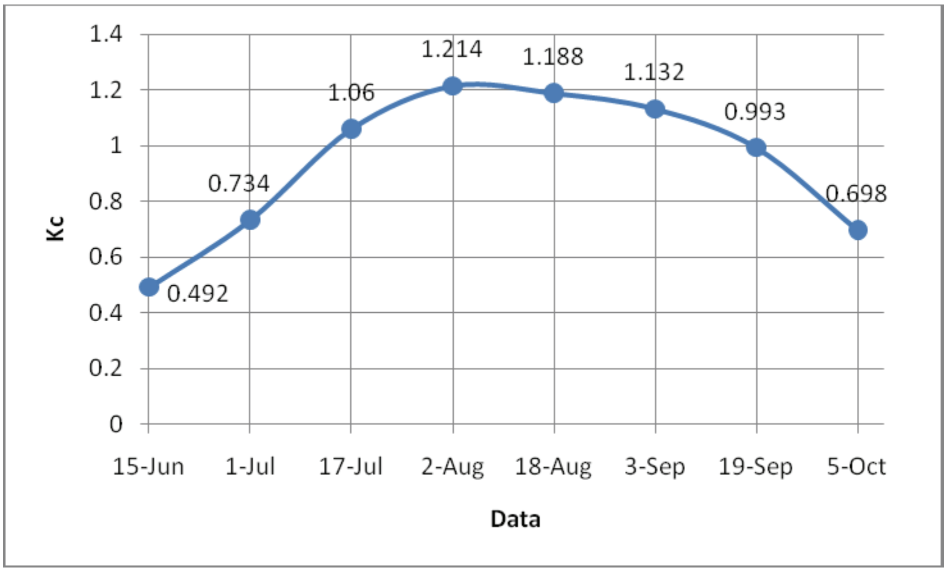

Figure 1. Evolution of corn K_c NDVI driven.

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 confirmed 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 information 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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