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Monitoring crop evapotranspiration with time series of MODIS satellite data in Northern Italy

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ABSTRACT: Crop water need is defined as the water needed to meet the loss through evapotranspiration (et). ET depends on meteorology and on the crop type, health and phenological stage. The fao methodology calculates crop et as the product of crop-specific coefficients (k_c) by the reference evapotranspiration (et_o) and has been widely applied for irrigation planning, using only three tabulated values of k_c referring to key phenological stages. This approach cannot always match the crop coefficient with the actual crop growth. On the other hand, previous research has shown a linear relationship between the k_c and vegetation indexes (v.i.) from remote sensing.

This relationship has already been used in recent studies with high resolution images. This work aims at exploring the usefulness of MODIS daily data to monitor K_c temporal and spatial variability and therefore crop water needs.

MODIS time-series of V.I. have been processed by means of Savitzky-Golay filters. K_c tabulated values corresponding to the beginning and the peak of the season can be linearly related with the corresponding V.I. values on the smoothed curve allowing us to obtain a continuous daily surface of K_c values. Daily K_c maps are then multiplied by the daily reference evapotranspiration surface (obtained with geostatistical methods from meteorological stations data) to obtain daily maps of potential crop ET, which is the crop water needed to meet the atmospheric water demand.

Given the MODIS moderate spatial resolution, this operational approach is addressed to authorities working at a territorial scale, such as irrigation consortia.

1 INTRODUCTION

Recent events of drought observed in Northern Italy (e.g. the 2003 summer drought) caused considerable damage to economic activities and in particular to agriculture. In fact, agriculture consumes for irrigation the greatest water share among the other uses. In Italy this share amounts to 50% of the overall water consumption, while in other European countries this percentage is even greater (88% in Greece, 72% in Spain, 59% in Portugal).

Agricultural drought is due to short-term precipitation shortages and temperature anomalies that cause increased evapotranspiration and soil water deficits that adversely affect crop production. Although there is still debate on the issue, climate change seems to play a role in these events and, with a warmer climate, droughts and floods could become more frequent, severe, and long-lasting.

This situation calls for the need of new tools to support the decision making process of authorities in charge of water management such as public authorities or irrigation consortia. The 2000/60/EC European Directive (the so-called ''Water Framework Directive'') underlined explicitly the need for new technologies of ''continuous monitoring'' to help a sustainable use of resources in order to mitigate the effects of droughts and floods. In particular, for agricultural water management there is a need for efficient operational technologies to monitor and estimate irrigation water needs for a more rationale allocation of water resources.

Recent research has shown the remarkable potential of the use of remote sensing in retrieving evapotranspiration in a spatially distributed way from natural and agricultural surfaces. The goal of this work is to develop an operational and low-cost tool to estimate crop water requirements at a territorial scale, making use of meteorological data and easily accessible satellite images to monitor real-time crop conditions and consequently crop water needs. Such a tool may prove to be useful to assist the decision-making process of authorities in charge of water resources management.

2 CROP WATER REQUIREMENTS, EVAPOTRANSPIRATION AND IRRIGATION WATER NEED

2.1 *The FAO methodology*

Crop water need is defined as the amount of water needed to meet the water loss due to evapotranspiration (ET). ET is usually expressed in mm/day and summarizes the transpiration from the plant tissues and the evaporation from the soil and other wet surfaces, as these two processes occur simultaneously. ET depends mainly on weather conditions, on the crop type and on the plant growth stage (phenology) (Brouver & Heibloem 1986).

The FAO methodology (Allen *et al.* 1998) calculates crop ET as the product of crop-specific coefficients (K_c), which take into account the crop species and the phenological stage, by the reference evapotranspiration (ET_o), which is the evapotranspiration from a well watered hypothetical grass reference crop (e.g. alfalfa) calculated from meteorological data by means of appropriate equations.

$$ET_c = K_c\, ET_o \tag{1}$$

ET_c is the crop ET under standard conditions, which refer to crops grown in large fields under excellent agronomic, soil and water conditions.

K_cs are defined as the ratio between the crop ET (ET_c) and the ET_o and are determined and tabulated in field studies. These coefficients integrate the effects of those characteristics that distinguish field crops from reference grass, and can therefore be used to estimate ET_c. This approach is known as the ''single coefficient approach'' because it integrates in a single crop coefficient K_c the effect of both crop transpiration and soil evaporation. In a second approach (''dual crop coefficient''), K_c is defined as the sum of two factors that separately describe the evaporation from the soil (K_e, soil evaporation coefficient) and the plant transpiration (K_{cb}, basal crop coefficient).

The ET_c is the ET that would be observed with water always available in the crop root zone. In this sense ET_c represents the maximum water uptake of the atmosphere for that crop in that phenological stage. Therefore ET_c is corresponding, in the final analysis, to the crop water requirement, or the optimal crop water need to meet the atmospheric demand (Doorenbos & Pruitt 1977).

In case of water stress, the actual ET is below the ET_c, and it is represented by an adjusted ET_c (ET_c adj) obtained with a stress coefficient (K_s). Beside water shortage, other hypothetical non standard conditions may influence the actual ET (e.g. salinity); however, in well-managed agricultural fields the standard conditions are generally the actual field conditions, at least in terms of agronomic management and soil conditions, and what generally may vary is the water availability.

Irrigation water need is defined as the difference between the crop water need and the proportion of the rainfall stored in the root zone and therefore available for the plants, (i.e. effective rainfall). Effective rainfall is the total rainfall minus the percolation below the root zone and the run-off. If the rainfall is sufficient to cover the water needs of the crops, irrigation is not required. The irrigation water need calculation requires the estimation of the crop water need and a soil water balance to obtain the effective rainfall.

2.2 *The reflectance-based crop coefficients approach*

The FAO approach has been widely used for irrigation planning purposes, using only three tabulated values of Kc for the initial stage (from bare soil to effective full cover), the mid-season stage (from effective full cover to the start of maturity) and the late season stage. Appropriate tables give for each crop indicative lengths of the different stages expressed in number of days from the planting date.

A major drawback of this "traditional" approach is that it cannot take into account the actual crop growing conditions and real-time vegetation variations. Consequently, it cannot always match the crop coefficient with the actual crop phenological stage and health condition (Bausch 1993; Hunsaker *et al.* 2005).

Remote sensing techniques provide tools to effectively monitor crop growth and photosynthetic activity, which is an indication of the health status of the plant. Both crop coefficients and canopy reflectance varies with the plant growth. Leaf area index (LAI) has a similar exponential relationship both with K_c and with Vegetation Indexes (VI) such as the NDVI (Duchemin *et al.* 2006).

Starting from these experimental observations, previous research has showed that the relationship between VIs and K_c is linear, and therefore it is possible to model a vegetation index into a crop coefficient by means of a linear regression. This method has been developed and validated in several studies and field experiments on different crops (Heilman *et al.* 1982; Bausch & Neale 1987; Bausch *et al.* 1989; Bausch 1991, 1993 & 1995; Choudhury *et al.* 1994). The coefficients obtained from remotely sensed data are called Reflectance-based Crop Coefficients (K_{cr}). This approach is considered one of the most promising for operational applications (Moran *et al.* 1997) because it overcomes some of the limitations of the "traditional" FAO approach. In fact, the reflectance-based coefficients are independent of the usual time-based parameters associated with traditional and published crop coefficients, such as the planting date and the effective cover date, which often do not allow matching the crop coefficient with actual crop growth. This is especially the case of anomalous climatic conditions and other stresses. Being vegetation indexes able to monitor photosynthetic activity, K_{cr} are sensitive to foliar stresses caused by insects, water shortages and diseases, and can detect abnormal growth induced by weather conditions. This makes K_{cr} representative of the actual field conditions.

This approach has already been used in different works with reflectance data collected by field radiometers or with airborne imagery (Neale *et al*. 2005, Hunsaker *et al*. 2005).

The increasing availability of Earth Observation satellite data has driven the research focusing on the operational use of these methodologies. The European project DEMETER (www.demeter-ec.net) used the K_{cr} approach to show the potential of the use of high-resolution imagery to support Irrigation Advisory Services (IAS) (Belmonte *et al*. 2005; Lopez *et al*. 2005).

The currently available satellites with high-resolution sensors (e.g. Landsat TM or TERRA-ASTER) have a spatial resolution which matches well the spatial resolution of IAS. However, their temporal resolution, which varies between 14 and 25 days (without considering cloudy days), is inadequate for the needs of a day-to-day use for the decision support to irrigation. This makes it necessary the integrated use of data coming from all the available sensors, by means of inter-satellite cross-calibration and coregistration procedures (Calera *et al*. 2001; Martinez *et al*. 2003).

The launch of the MODIS (Moderate-Resolution Imaging Spectroradiometer) sensor onboard the NASA EOS satellites Terra and Aqua, active respectively since 2000 and 2002, opened new perspectives for the operational use of these methods. MODIS has a high temporal resolution, providing a near daily global coverage of the Earth's surface. The sensor provides high radiometric sensitivity (12 bit) in 36 spectral bands ranging in wavelength from 0.4 µm to 14.4 µm and a spatial resolution of 250 m. at nadir in the Red and Near Infrared (NIR) wavelengths (the most used for vegetation studies), and of 500 m or 1 Km in the other bands. The NASA policy is to offer MODIS products free of charge, and this is an unprecedented opportunity for exploring operational, cost-efficient uses of remote sensing.

Obviously the moderate spatial resolution is an issue that must be carefully addressed when using MODIS, and makes the instrument unfeasible for certain fields of application, such as precision farming studies. However, when it comes to wider scales (e.g. irrigation consortia), this tool opens very interesting opportunities for daily monitoring of Earth surface.

3 MATERIALS AND METHODS

3.1 *Study area and land cover mapping*

The study area covers the South Milan area between Milan and Pavia, part of which belongs to the South Milan Agricultural Park, and the Eastern and Western surroundings of the town. The area is intensely cultivated, with an agricultural surface of 140000 ha.

Paddy rice is cultivated on the 18% of the agricultural area, summer cereals over the 58% and winter cereals on the 17% (ARPA Lombardia 2005). The land cover pattern is heterogeneous, with a strong presence of urban areas and road networks; therefore it is a good situation to test the use of MODIS in a real context. In this preliminary application, we studied the year 2003, when a drought took place in the summer season with serious economic damages.

A first phase of the work required the land cover mapping of the area and the supervised classification of the different cropping patterns, using Landsat TM and ETM+ satellite images acquired in 2003 (April 24th and July 5th) and georeferenced with the regional digital map. The resulting maps were integrated with GIS data from public authorities (Regione Lombardia 1998 & 2000; ARPA Lombardia 2005), obtaining a map of the 2003 cropping patterns.

From the land cover maps we obtained binary masks to identify areas homogeneous with reference to the cultivated crop.

3.2 *Satellite data processing*

NASA provides different MODIS products already processed with standard correction algorithms. MODIS 09 daily data (spectral reflectances) are corrected for the effects of gaseous and aerosol scattering and absorption as well as adjacency effects caused by variation of land cover, Bidirectional Reflectance Distribution Function (BRDF) and atmosphere coupling effects, and contamination by thin cirrus (Vermote & Vermeulen 1999). In particular, each MOD09Q1 data granule (MODIS/Terra Surface Reflectance 8-Day L3 Global 250m SIN Grid) offers a composite of the previous 8 daily surface reflectance products with the best observations for each pixel in the two MODIS bands at 250 m (Red and NIR). The goal is to obtain single cloud-free images with minimal atmospheric and sun-surface-sensor angular effects representative of the 8-day period. In this work we used the NDVI (Normalized Difference Vegetation Index), the most used VI, which is related with the plant fractional vegetation cover (Carlson & Ripley 1997).

MOD09Q1 images have been collected for the whole 2003 year (46 images) and reprojected using the NASA reprojection tool software (NASA-USGS 2006). NDVI values where computed for each image. Even though clouds should have been removed in the preparation of the MOD09Q1 sets, residual atmospherically related noises, as well as some noise due to other factors (e.g. surface anisotropy and sensor problems) remain in the data. Therefore, the temporal series were smoothed with a Savitzky-Golay filter algorithm (Savitzky & Golay 1964) implemented in IDL code, which replaces each data value I_i, $i = 1, \ldots,$ N by a linear combination of nearby values in a window:

$$\sum_{j=-n}^{n} c_j I_{i+j} \tag{2}$$

For each data value, the weights c_j are calculated by fitting a quadratic polynomial $f(t) = c_1 + c_2 t + c_3 t^2$ to all the 2n + 1 points in the moving window and replacing the value I_i with the value of the polynomial at position t_i (Press *et al.* 1992). This method preserves the area, the mean position, the width and the height of a seasonal peak in a series with data regularly spaced and requires as parameters the dimension of the moving window and the degree of the smoothing polynomial (between 2 and 4).

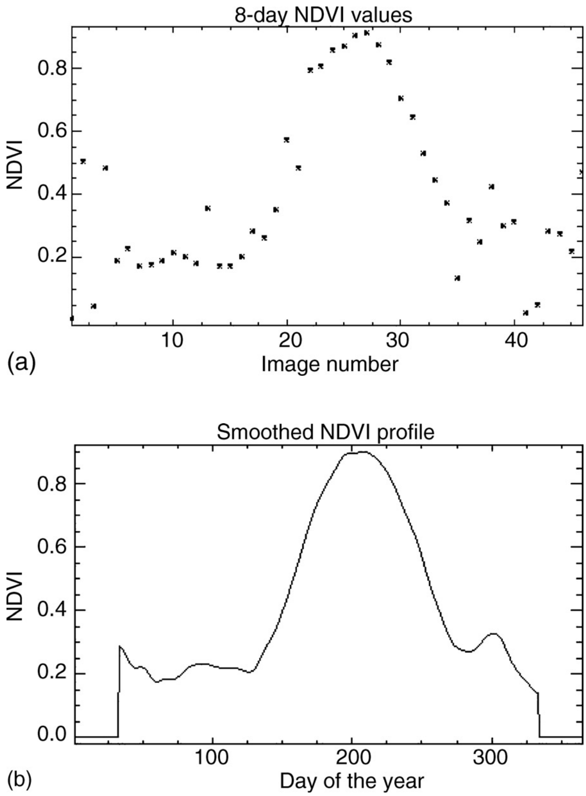

Figure 1. The interpolation and the smoothing of the NDVI time series with the Savitzky-Golay filter.

The result is a smoothed curve in each pixel, with daily NDVI images (Fig.1).

3.3 *Meteorological data processing*

Potential Evapotranspiration (ET_o) is calculated from meteorological data by means of appropriate equations. The FAO 56 paper (Allen *et al*. 1998), beside the recommended Penman-Monteith method, reports also the Hargreaves equation:

$$ET_o = 0.0023(((T_{max} + T_{min})/2) + 17.8)(T_{max} - T_{min})\, 0.5\, R_a \qquad (\text{mm day}^{-1}) \qquad (3)$$

This simplified method requires as input data only maximum and minimum temperature (T_{max} and T_{min}) and Extraterrestrial radiation (R_a), which can be estimated for each day of the year and for different latitudes from the solar constant, the solar declination and the time of the year.

For this work we used data coming from different networks of meteorological stations belonging to the University of Milan, the Regional Agency for the Protection of the Environment (ARPA Lombardia) and from the Italian Central Office for the

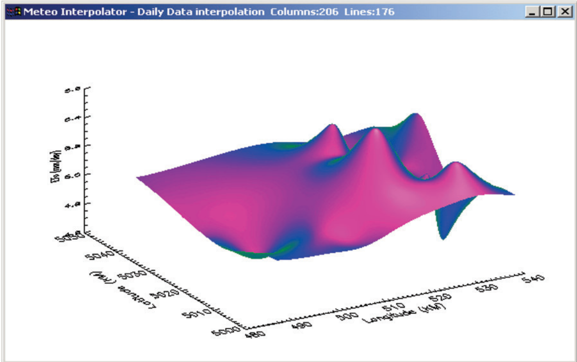

Figure 2. Daily spatial interpolation of ET_o values.

Agricultural Ecology (UCEA). In total we considered 16 agro-meteorological stations. Only in rare cases it was possible to obtain the full dataset required for the Penman-Monteith equation, and for this reason we used the Hargreaves equation to estimate ET_o. In fact, considering the characteristics of our study area (flat and not particularly windy) and the scale at which we are working, the Hargreaves equation can be considered as sufficiently reliable.

We calculated punctual daily values of ET_o for all the stations, then we created daily surfaces from the measured points by means of an interpolating application coded in IDL using the inverse distance weight method. For each pixel we obtained daily values as in the example in Fig. 2.

3.4 K_{cr} *surfaces*

Reflectance-based crop coefficients (K_{cr}) surfaces were obtained from the NDVI time series by means of a linear transformation (Bausch 1993; Belmonte *et al*. 2005) between maximum and minimum NDVI values (in areas where the cropping patterns were known to be homogeneous at a scale larger than the MODIS scale) and the FAO tabulated K_c values for effective full cover and initial conditions (bare soil for corn, paddy for rice). Pixels representing initial conditions were selected also using the Landsat image of April 24th 2003. In the case of corn, the relationship was as follows:

$$K_{cr} = 1.25\ \mathrm{NDVI} + 0.10 \tag{4}$$

This result appears to be consistent with those obtained in other works which studied corn (e.g. Lopez *et al*. 2005). In the case of rice:

$$K_{cr} = 0.20\ \mathrm{NDVI} + 1.02 \tag{5}$$

The equations reflect the significant difference in the initial K_c values of corn and rice due to the different initial conditions.

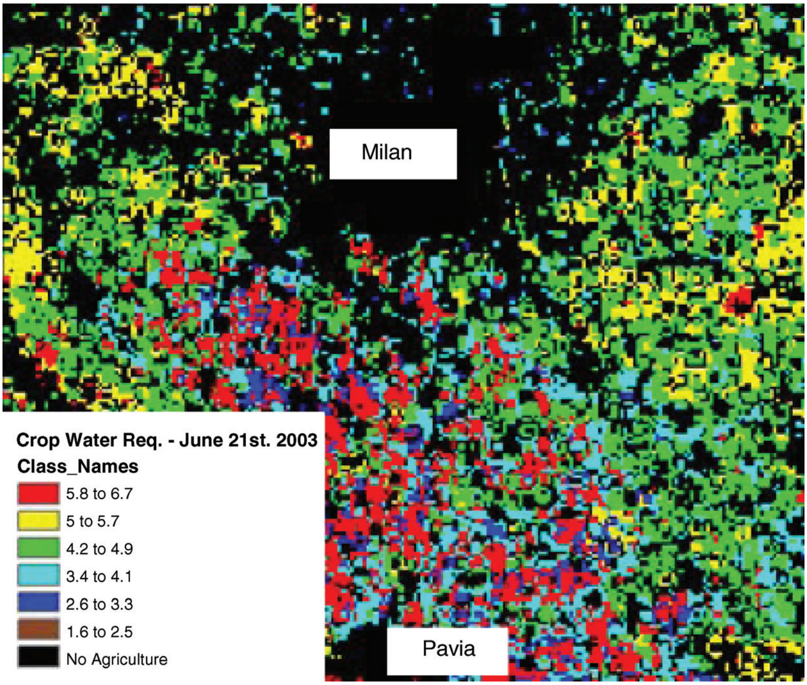

Figure 3. Daily crop water requirements map in mm day^{-1}.

3.5 *Results*

From the daily K_{cr} and ET_o maps we derived by means of the Eq.1daily potential crop ET maps with values expressed in mm day^{-1} (1 mm day^{-1} corresponds to 10 m^3 ha^{-1} day^{-1}). Maps obtained for the different crops were summarized to derive daily maps of crop water requirements for the whole agricultural area. Fig. 3 shows as an example the map of June 21st 2003.

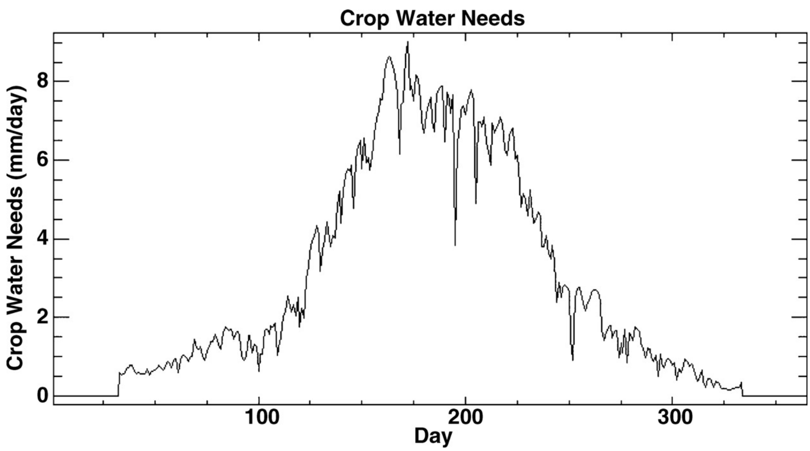

Figure 4. Corn water needs profile in a single pixel.

Potential crop ET is the crop water demand, or the optimal amount of water that the crop needs to face the atmospheric water demand. Having it been calculated from reflectance-based K_{cr}, it takes into account the actual crop conditions for each day in terms of phenological stage and photosynthetic activity, monitored by means of daily MODIS satellite data. The daily crop water needs values here obtained are consistent with those of other studies. As it was expected, areas with rice fields have in the summer season the greatest crop ET. Fig. 4 shows the profile in a pixel cultivated with corn.

4 CONCLUSIONS

In this work we tested the Reflectance-based crop coefficients approach with MODIS satellite data.

These preliminary results show that there is a potential to develop tools to monitor crop water needs at a regional scale by means of MODIS images. Although there is a solid bibliographic basis supporting the method, as far as we know this is the first attempt to use it with MODIS data and therefore it has to be tested in field experiments. Beside this, the method can be significantly improved working on different aspects.

The characteristics of the area of application influence the results in a decisive way, as the spatial resolution of MODIS poses limits to the degree of heterogeneity of the land cover patterns in the area of application. Future research will focus on improving the selection of pixels representative of agricultural areas, also by means of soft classification algorithms, and to assess for which maximum level of land cover heterogeneity the method can be used.

Beside the NDVI, other VIs exist which better describe vegetation status, in particular in conditions of moderate-to-high LAI, such as the WDRVI (Gitelson 2004). Other indexes, like the SAVI, better minimize soil background influences in sparse to dense vegetation conditions (Bausch 1993). Thus, other indexes will be tested and it is feasible to foresee the use of different indexes according to the phenological stage ‘‘before-full cover’’ or ‘‘after-full cover’’.

Also, in this work we used the single coefficient approach, while it is possible to use the dual coefficient approach focusing on the transpiration, as at full crop cover more than 90% of ET comes from transpiration (Allen *et al*. 1998).

Meteorological data availability is another important issue, as it determines the method chosen for the ET_o computation and therefore the reliability of the results. In particular in areas with a complex topography (e.g. hilly and windy areas), the Penman-Monteith equation might be the only reliable method to estimate ET_o, thus requiring more complete meteorological databases.

The results obtained in this work could be exploited with estimates of effective rainfall coming from a soil water balance model to estimate irrigation water needs, as described by Allen *et al*. (1998).

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