CROP EVAPOTRANSPIRATION ESTIMATION USING OPTICAL AND MICROWAVE REMOTE SENSING

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ABSTRACT

In 1994, Cemagref-ENGREF Remote Sensing Laboratory and U.S. Water Conservation Laboratory conducted an experiment called 'MAC VII' on Maricopa Agricultural Center, to demonstrate the ability of using combined optical and microwave remote sensing data for estimating the evapotranspiration of irrigated crops. Two approaches were developed on alfalfa and cotton crops. One is based on the combination of remotely sensed surface temperature and vegetation index representing both vegetation water stress and fractional cover, and providing a water deficit index (*WDI*), which has been demonstrated to be a reliable extension of the Crop Water Stress Index (CWSI) concept to partial coverage canopies. The estimation of *WDI* was improved here by using surface soil moisture derived from ERS-1 radar satellite C-Band data, which provided the ability to discriminate canopy transpiration from soil evaporation. The other approach is based on the combination of airborne Ku- and C-Band radar imagery, which represent both vegetation fractional cover and water stress, respectively. This new tool is useful for estimating plant water stress in partial coverage conditions, and has the advantage of being independent of atmospheric and cloudiness conditions, unlike approaches based on optical remote sensing data.
Keywords : Crop transpiration, Radar, Optical measurement, Plant Water Stress.

INTRODUCTION

It has been shown for a long time that remote sensing has good potential for evapotranspiration monitoring. However, this potential has been limited by a series of problems occurring when optical remote sensing data are used. Among the most common problems, one could mention the cloudiness limiting the acquisition frequency, the resolution of sensors, and the effects of soil on measured reflectance and thermal emission.

For the last few years, active microwave data from recently-launched ERS-1 and JERS-1 radar satellites have provided a solution to both cloudiness and resolution constraints, as radars get information independently of cloud coverage, and with a spatial resolution which is compatible with field sizes (30 m). When combining different wavelengths, these data can also provide independent information on vegetation and soil (Prevot et al., 1993a), that could be used to account for their effect on measured reflectance and thermal emission.

During the same period, an operational method was developed to account for these effects when using optical data (i.e. red/infrared reflectances derived *NDVI* - Normalized Difference Vegetation Index -, and thermal emission derived surface temperature). This approach, presented by Moran et al. (1994), is based on the representation of the soil-canopy continuum in a diagram of fractional vegetation cover vs. surface minus air temperature difference (*Ts-Ta*). Actually, its position is theoretically comprised within a trapezoidal pattern; Figure 1 presents such a pattern and the definition of its limits. These authors have shown the essence of this approach as:

- the limits of the trapezoids represent limit situations for the surface energy budget, that can be estimated using only meteorological data and a value of the aerodynamic resistance of the soil-canopy continuum;

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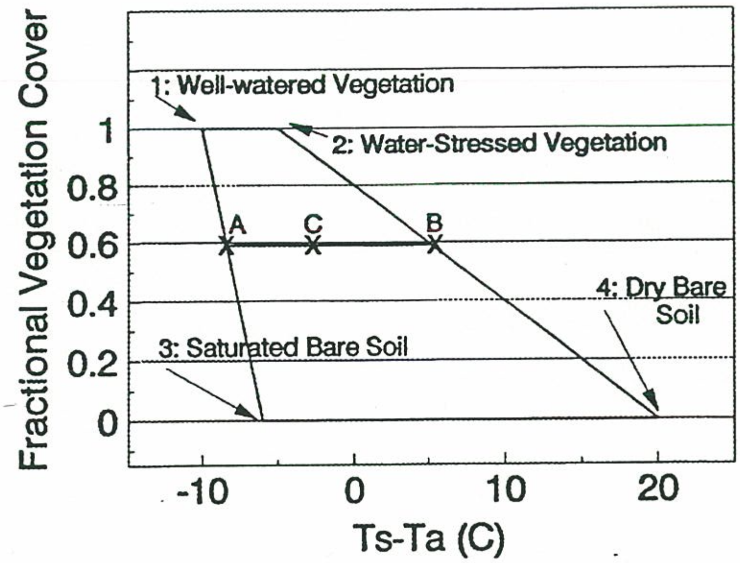
model simulations showed that hypotheses of linearity between the left (wet conditions) and right (dry conditions) limits of the trapezoid are valid under most



conditions.

Figure 1. The theoretical trapezoidal shape showing the different biomass vs. water stress conditions of the canopy-soil continuum (from Moran et al., 1994). The *WDI* (water deficit index) of point C is given by AC/AB as shown in Eq. 1.

The above considerations lead to both a theoretical and graphically simple estimation of the soil-canopy evaporation *LE* for a given Fractional Vegetation Cover, knowing its potential evaporation *Lep*:

$$\frac{LE}{LEp} = \frac{(Ts - Ta) - (Ts - Ta)_{dry}}{(Ts - Ta)_{wet} - (Ts - Ta)_{dry}} = \frac{BC}{AB} = 1 - WDI \qquad (1)$$

where *Ts* is the composite surface temperature of the soil-canopy continuum as estimated from thermal infrared measurements, *BC* and *AB* are the distances represented on Figure 1, and the *wet* and *dry* subscripts correspond to the left and right limits of the trapezoid. The main advantage of this approach is the possibility of estimating both *Ts-Ta* and Fractional Vegetation Cover from remote sensing measurements. Fractional Vegetation Cover can be estimated using the Normalized Difference Vegetation Index (*NDVI*) defined from ρ_{NIR} and ρ_R, the reflectances in the sensor's near infrared and red waveband :

$$NDVI = \frac{\rho_{NIR} - \rho_R}{\rho_{NIR} + \rho_R} \qquad (2)$$

In 1994, Cemagref-ENGREF Remote Sensing Laboratory and U.S. Water Conservation Laboratory conducted an experiment called 'MAC VII' on Maricopa Agricultural Center, to demonstrate the ability of using combined optical and microwave remote sensing data for estimating the evapotranspiration of irrigated crops (Moran et al., 1996a). Two approaches were developed on alfalfa and cotton crops. One is based on the water deficit index (*WDI*) presented above, whose estimation was improved by using surface soil moisture derived from ERS-1 radar satellite C-Band data. This provided the ability to discriminate canopy transpiration from soil evaporation. The other approach is based on the combination of airborne Ku- and C-Band radar imagery, which represent both vegetation fractional cover and water stress, respectively, and has been presented by Moran et al. (1996b).

The objective of this paper is to show how the *WDI* can be improved by the use of C-band radar data, and how multispectral microwave data can be used to replace optical/microwave combination for days where clouds interfere with the use of optical data, such as thermal infrared.

METHODS AND MATERIALS

The site for the experiment was MAC, a 770 ha research and demonstration farm located about 48 km S of Phoenix, owned and operated by the University of Arizona. The demonstration farm is composed of large fields (up to 0.27 x 1.6 km) used for demonstrating new farming techniques on a production scale. Alfalfa is grown year-round with about 7-8 harvests per year and, cotton is grown during the summer. Since the predominant irrigation method for the MAC demonstration farm is flooding, each field is dissected into level-basin borders. During a single irrigation, the borders are sequentially flooded with a 3-4 day progression from one end of a 1.6-km long field to the other.

This experiment was conducted on DOYs (Days Of Year) 165 to 175, directed at investigating the utility of multispectral remotely sensed data for day-to-day farm management. The European Remote Sensing (ERS-1) satellite supports an imaging SAR sensor operating at C-band (5.35 GHz), VV polarization and 23° incidence angle. A SAR image covering most of MAC was obtained on 15 June (DOY 166) during a descending pass at 10:00 p.m. Sandia National Laboratory (SNL) in Albuquerque, New Mexico provided an airborne imaging SAR sensor operating at Ku-band (14.85 GHz), VV polarization and 55° incidence angle. A SAR image covering most of MAC was obtained on 24 June (DOY 175) at 11 am MST. Scientists from Utah State University (USU) deployed a multi-spectral airborne video system with four spectral bands covering the visible to thermal spectral region on 15 June at 11 am (Neale and Crowther, 1994). Microwave data were calibrated using on-board calibration coefficients, and optical data using ground-measurements of reference targets reflectance and surface temperature. For each field border, values of Ts, ρ_{NIR} and ρ_R from the USU sensors and values of σ°_c and σ°_k from the ERS-1 and SNL sensors were computed by averaging the values for all pixels located within the border. During each overpass, detailed measurements were made in selected fields of such crop properties as density, biomass, and Green Leaf Area Index (*GLAI*).

Detailed vegetation measurements were made in selected cotton and alfalfa fields on a weekly basis during MAC VII. In the sample sites within the cotton fields, measurements were made of plant density, height, vegetation cover fraction, and number of squares/bolls/flowers. Five plants were weighed in each sample site and the plant of median weight was taken to the laboratory for measurement of wet and dry biomass and *GLAI*. In sample sites within the alfalfa fields, plant density, height and percent cover were measured. A 0.5-m^2 sample from each site was cut and taken to the laboratory for measurements of *GLAI* and wet and dry biomass. Such measurements in cotton and alfalfa fields were made coinciding with the SAR and optical instrument overpasses. In the early morning following the nighttime ERS-1 SAR overpass, gravimetric soil moisture samples to 5 cm depth were made in selected fields. The bulk density of the soil was computed for each sample based on the volume of the soil sample container and averaged to produce a bulk density estimate for the field. This was used to convert all gravimetric data to values of volumetric soil moisture. Several values were averaged to produce one estimate of soil moisture content for each of the selected borders.

The *WDI* was estimated from the trapezoid presented in the introductory section, based on hourly meteorological data collected on MAC. In order to separate crop transpiration from soil evaporation, the soil surface temperature was estimated from the surface soil moisture derived from ERS-1 C-band backscattering, and using the calibration equations of Moran et al. (1996b). Actually, Troufleau et al. (1996) have shown that an index that could be called the 'Soil Water Index' (*SWI*), i.e. a concept similar to the Crop Water Stress Index (CWSI) defined by Jackson et al. (1981), was related to surface soil moisture (0-5 cm) through an exponential relationship. This relationship is physically based on the resistance of soil surface to evaporation, and was shown to be only dependent on soil texture (Chanzy, 1991). *SWI* can be defined by:

$$SWI = \frac{T_s - T_a}{T_{s\,max} - T_a} \tag{3}$$

with Ta being air temperature, and Ts_{max} the maximum value of Ts, expressed as :

$$T_{s\,max} = T_a + \frac{r_a}{\rho C_p}(R_n - G) \tag{4}$$

where Rn is the net radiation flux, G the soil heat flux, ρCp is the volumetric heat capacity of air ($\approx 1200\ J\ m^{-3}\ K^{-1}$), ra is the aerodynamic resistance (s/m) corrected for stability/unstability effects and for the additional resistance effect due to the difference between radiative and aerodynamic surface temperature, usually referred as the kB^{-1} resistance (Prevot et al., 1993b).

Figure 2 shows how the ratio crop transpiration / potential transpiration can be derived from the above concepts. This ratio will be called from now on the *CWDI* (Crop Water Deficit Index).In another approach, Moran et al. (1996b) combined Ku- and C-band data to derive soil moisture and Green Leaf Area Index (*GLAI*), to estimate soil-vegetation variables on a cloudy day.

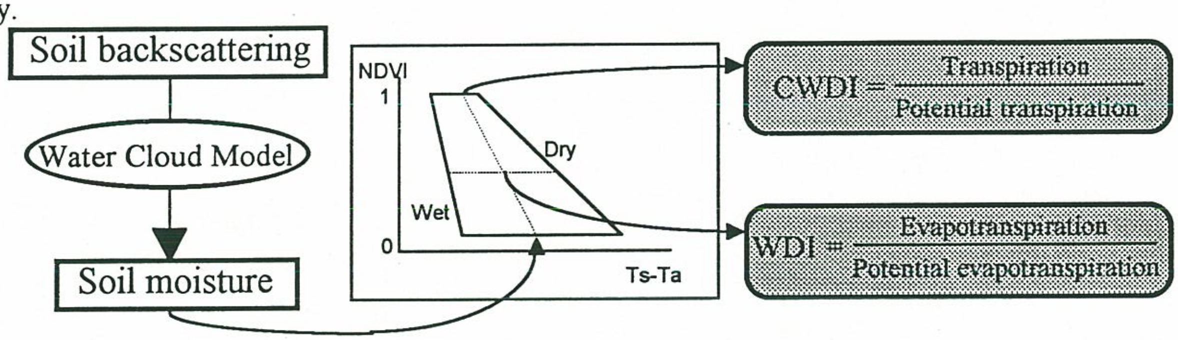


Figure 2. Combined use of active microwave and optical remote sensing data to derive soil moisture and evaporation in the trapezoid. Whereas optical data only allow estimation of soil-plant Water Deficit Index (*WDI*), microwave allows estimation of the so-called Crop Water Deficit Index (*CWDI*).

Finally, 6 fields (3 of cotton, 3 of alfalfa) were selected on MAC farm for DOY 165, in order to obtain a representative variability of soil moisture, vegetation coverage and water stress.

RESULTS AND DISCUSSION

A preliminary result concerns the relation between soil moisture and soil temperature for experimental conditions. It was calibrated on the experimental site for DOY 163 where measurements of both soil surface temperature and moisture were available : the calibration equation is given on Figure 3.

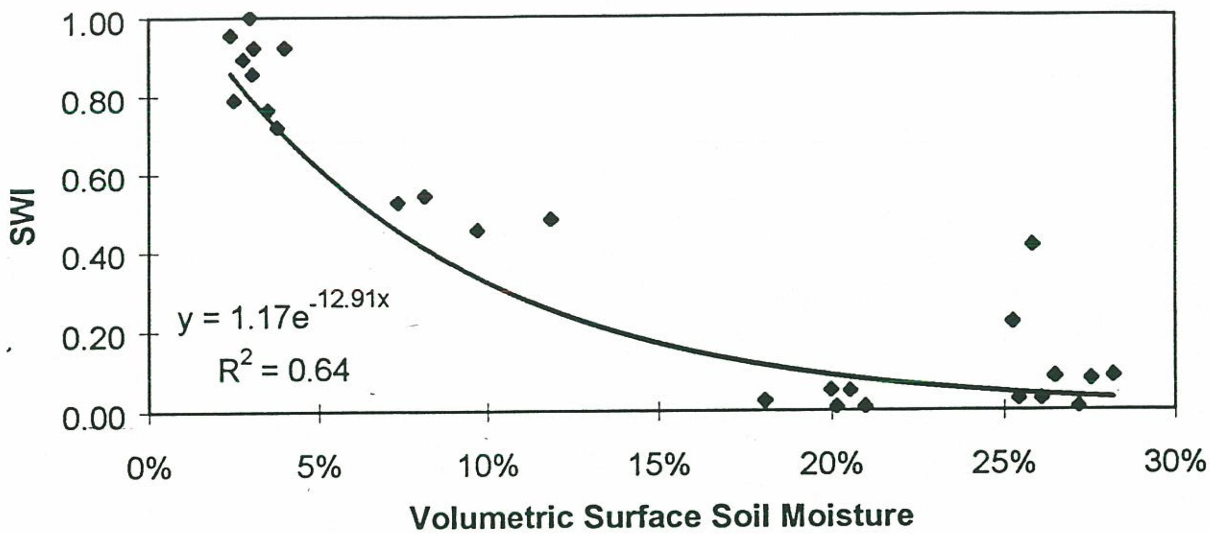


Figure 3. Calibration of the relationship between Soil Water Index (*SWI*) and surface soil volumetric moisture (0-5 cm). MAC Farm, fields 13 (Cotton), 17 (Alfalfa), 18 (Bare soil), 25 (Alfalfa) and 38 (Cotton), DOY 163.

In a second step, different variables were estimated for each subdivision (or *border*) of the 6 selected fields, i.e. *NDVI* and surface soil moisture *hv* as vegetation development and field wetness indicators, then surface minus air temperature difference *Ts-Ta*, Water Deficit Index *WDI* and Crop Water Deficit Index *CWDI* as various indicators of crop water stress. As no measurement of latent heat flux was available on all selected fields, we will consider in the following discussion the surface soil moisture variability as a reference for crop water stress variability. The values obtained appear on Figure 4. The main results are :

- Variations of *Ts-Ta* are related to both variations in water stress related to soil moisture and variations in *NDVI*;
- For fields with large variations of *NDVI* (e.g. Fields 17 and 25), *WDI* and *CWDI* better represent variations in water stress than *Ts-Ta* (these variations are small in Fields 17-25): this is particularly important because alfalfa is often not considered as a partial cover vegetation, and one could think that using *Ts-Ta* would be sufficient;
- For fields with high values of *NDVI*, *CWDI* is equivalent to *WDI* to represent variations in water stress, except in Field 15 where *CWDI* shows a better contrast when soils are particularly dry in the first centimeters;
- For fields with low values of *NDVI*, *CWDI* represents variation or absence of variation in water stress better than *WDI*; this clearly appears in Field 38 where large variations of *NDVI* occur.

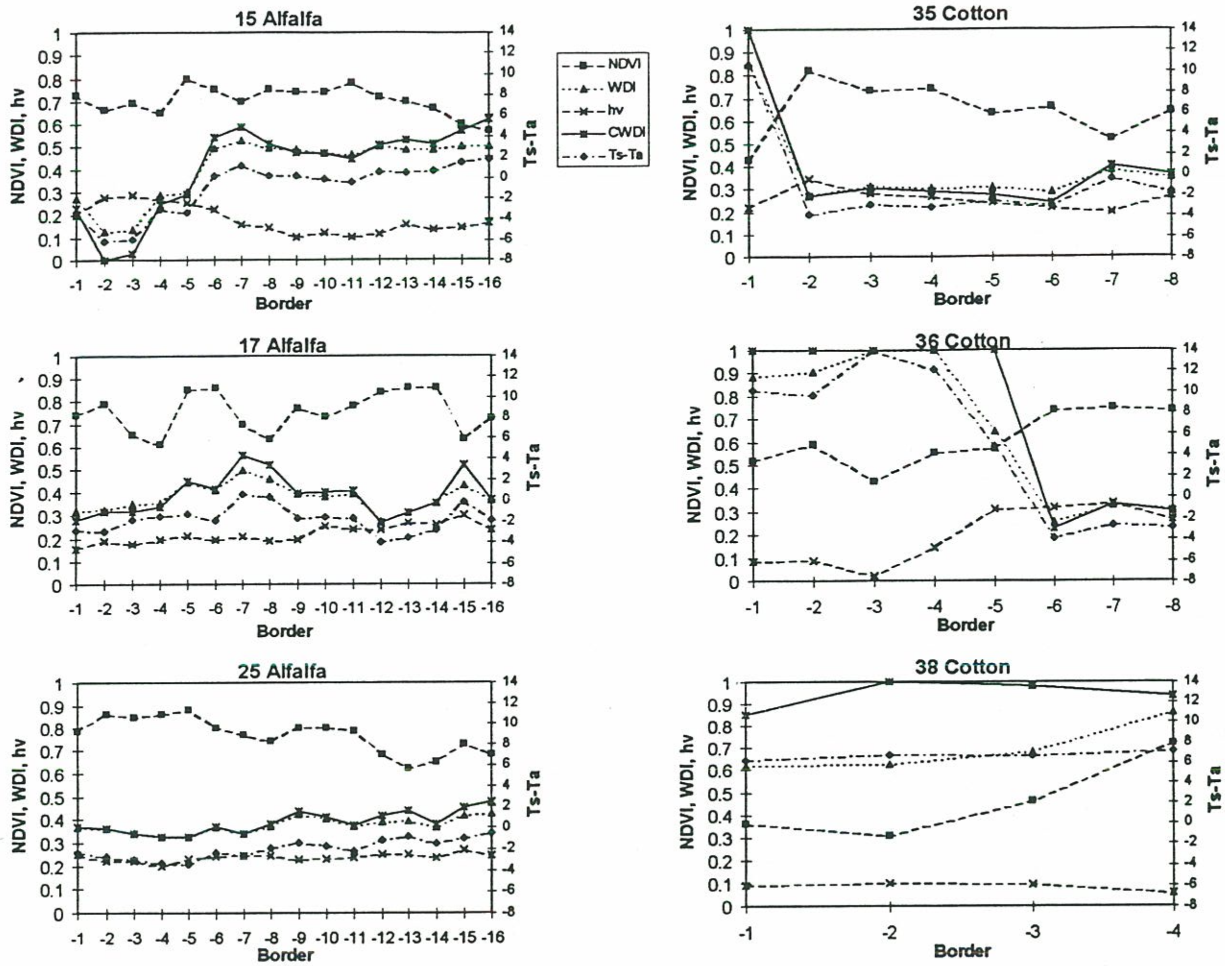


Figure 4. Variations of vegetation index *NDVI*, surface soil moisture hv, surface minus air temperature difference *Ts-Ta*, Water Deficit Index *WDI* and Crop Water Deficit Index *CWDI* inside the selected alfalfa and cotton fields. The left axis corresponds to all variables ranging from 0 to 1, such as *NDVI*, *WDI* and *CWDI* (adimensional) or hv (m^3/m^3). The right axis only corresponds to *Ts-Ta*.

WDI and *CWDI* are obtained using optical and optical-microwave data respectively. When no optical data is available, microwave data alone can be used to determine surface soil moisture and Green *LAI*. These latter variables were related for the selected fields to *CWDI* and *WDI*, using multiple linear regression (Table 1).

Table 1. Multiple and partial regression coefficients obtained when relating *CWDI* and *WDI* to Ku-band (resp. C-band) active microwave derived *GLAI* - Green Leaf Area Index (resp. *hv* - surface soil moisture 0 - 5cm).

	CWDI			*WDI*		
	Alfalfa	Cotton	All	Alfalfa	Cotton	All
Multiple regression coefficient	0.519**	0.572**	0.435**	0.614**	0.719**	0.570**
GLAI regression coefficient	0.270	0.328	0.189	0.377	0.517	0.324
hv regression coefficient	0.237	0.135	0.160	0.349	0.379	0.300
Standard-Error	0.107	0.303	0.162	0.070	0.165	0.098
Observations	48	10	58	48	10	58

In all cases, regression was significant with a 0.01 level. Except for cotton, where the number of observations was reduced from 20 to 10 due to a partial visibility of selected fields by the radar, the standard-error for the no-optical-data derived *CWDI* and *WDI* is close to or lower than 10 %. This clearly shows the potential of active multi-frequency microwave data for replacing optical or optical-microwave data for water stress monitoring.

CONCLUSIONS

The present analysis, which remains rather qualitative, shows that optical (vegetation index and surface temperature) and active microwave data can be combined to estimate precisely the crop water stress conditions, even for partial canopies. This approach uses two complementary indices, the Water Deficit Index (*WDI*) equal to the ratio 'evapotranspiration / potential evapotranspiration', and the Crop Water Deficit Index (*CWDI*), equal to the ratio 'crop transpiration / potential transpiration'. This combination is particularly efficient when the vegetation cover is low.

A strong relation exists between these water stress indices and soil-vegetation variables (Green *LAI* and surface soil moisture) derived only from multifrequency active microwave data (e.g. Ku- and C-band). This relation makes it possible to calibrate these variables for days where both optical and microwave data are available, and then to use microwave data only when clouds prevents from optical data acquisition. Both methods are of interest for operational monitoring of agricultural evapotranspiration rates, as most of the data used in this experiment could be available weekly in the near future, either on dedicated small airborne systems or on satellites like RADARSAT in C-Band and IRSUTE in thermal infrared, both with resolutions around 50 m and observation frequencies better than one week.

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