Modified Penman–Monteith equation for monitoring evapotranspiration of wheat crop: Relationship between the surface resistance and remotely sensed stress index

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ABSTRACT

Evapotranspiration (ET) plays an essential role for detecting plant water status, estimating crop water needs and optimising irrigation management. Accurate estimates of ET at field scale are therefore critical. The present paper investigates a remote sensing and modelling coupled approach for monitoring actual ET of irrigated wheat crops in the semi-arid region of Tensift Al Haouz (Morocco). The ET modelling is based on a modified Penman-Monteith equation obtained by introducing a simple empirical relationship between surface resistance (r_c) and a stress index (SI). SI is estimated from Landsat-derived land surface temperature (LST) combined with the LST endmembers (in wet and dry conditions) simulated by a surface energy balance model driven by meteorological forcing and Landsat-derived fractional vegetation cover. The proposed model is first calibrated using eddy covariance measurements of ET during one growing season (2015-2016) over an experimental flood-irrigated wheat field located within the irrigated perimeter named R3. It is then validated during the same growing season over another drip-irrigated wheat field located in the same perimeter. Next, the proposed ET model is implemented over a 10 x 10 km^2 area in R3 using a time series of Landsat-7/8 reflectance and LST data. The comparison between modelled and measured ET fluxes indicates that the model works well. The Root Mean Square Error (RMSE) values over drip and flood sites were 13 and 12 W m^{-2}, respectively. The proposed approach has a great potential for detecting crop water stress and estimating crop water requirements over large areas along the agricultural season.

Keywords: Bulk surface resistance; Evapotranspiration; Crop water stress; Landsat; Penman-Monteith; Surface temperature.

NOMENCLATURE

Symbols	signification and unit
ET	Evapotranspiration, mm
rc	Surface resistance, s m^{-1}
r*	Critical bulk resistance, s m^{-1}
$\mathbf{R_n}$	Net radiation, W m^{-2}
G	Soil heat flux, W m^{-2}
$\mathbf{H_{EC}}$	Sensible heat flux (eddy covariance), W m^{-2}
$\mathbf{LE_{EC}}$	Latent heat flux (eddy covariance), W m^{-2}
$\mathbf{u_a}$	Wind speed, m s^{-1}
$\mathbf{R_g}$	Solar radiation, W m^{-2}
$\mathbf{rh_a}$	Relative humidity, %
$\mathbf{T_a}$	Air temperature, °C
$\mathbf{R^2}$	Determination coefficient
ρ_R	Red spectral reflectance, %
ρ_{PIR}	Near infrared spectral reflectance, %
ε	Surface emissivity
k	Attenuation coefficient
Δ	Slope of the saturation vapour pressure curve at air temperature, kPa $°C^{-1}$
γ	Psychrometric constant, kPa $°C^{-1}$
ρ	Mean air density at constant pressure, kg m^{-3}
$\mathbf{c_p}$	Stands for the specific heat of air, MJ kg^{-1} $°C^{-1}$
D	Vapour pressure deficit, kPa
$\mathbf{e_a}$	Actual vapour pressure, kPa
$\mathbf{e_s}$	Saturation vapour pressure, kPa
$\mathbf{r_{ah}}$,	Aerodynamic resistance, s m^{-1}
$\mathbf{z_r}$	Reference height, m
kar	Von Karman constant equal to 0.44
$\mathbf{h_c}$	Canopy height, m
d	Displacement height, m
$\mathbf{z_m}$	Height of the dynamic soil roughness, m
ψ_m	Atmospheric stability function
ψ_h	Sensitive heat stability function
α	Surface albedo
$\mathbf{R_{atm}}$	Atmospheric longwave radiation, W m^{-2}
σ	Stephan-Boltzmann constant equal to 5.67×10^{-8}, W m^{-2} K^{-4}
ε_a	Atmospheric emissivity
Γ	Fractional empirical coefficient set to 0.4
Fc	Fraction vegetation cover
a	Empirical coefficient equal to 0.17
b	Empirical coefficients equal to 0.8
c	Empirical coefficients equal to 0.8
F (LST)	Cost function
d	Calibration parameters equal to 3000, s m^{-1}

e	Calibration parameters equal to -1130, s m^{-1}
Abbreviation	
LST	Land Surface Temperature, °C
SI	Stress Index
IPCC	International Panel on Climate change
NDVI	Normalized Difference Vegetation Index
LAI	Leaf Area Index
SiSPAT	Simple Soil Plant Atmosphere
ISBA	Interaction Soil-Biosphere-Atmosphere
SVAT	Soil Vegetation Atmosphere Transfer
ICARE	Interactive Canopy Radiation Exchange
CERES	Crop Environment REsource Synthesis
STICS	Simulateur multidisciplinaire pour les Cultures Standard
Aquacrop	Crop-water productivity model
SEBS	Surface energy balance model
FAO-56	Food and Agriculture Organization. No 56
PM	Penman-Monteith
SEBI	Surface Energy Balance Index
WDI	Water Deficit Index
TVI	Temperature Vegetation Index
TVDI	Temperature Vegetation Dryness Index
VTCI	Vegetation Temperature Condition Index
ET_0	Evaporative demand, mm
KH21	Krypton hygrometer
HPF01	Soil heat flux plates
CSAT3	3D sonic anemometer
EC	Eddy covariance
L7	Landsat 7
L8	Landsat 8
NASA	National Aeronautics and Space Administration
USGS	United States Geological Survey
MODTRAN	MODerate resolution atmospheric TRANsmission
RMSE	Root Mean Square Error
IPI	Irrigated Priority Index
SLC	Scan line corrector
H2020	Horizon 2020
RISE	Research and Innovation Staff Exchange
REC	Root zone soil moisture Estimates at the daily and agricultural parcel scales for Crop irrigation management – a multi-sensor remote sensing approach
AMETHYST	Assessment of changes in MEdiTerranean HYdro-resources in the South: river basin Trajectories

1. INTRODUCTION

In arid and semi-arid regions, water scarcity is one of the main factors limiting agricultural development. Water scarcity is likely to be exacerbated in the near future under the combined effect of the alteration of the hydrological cycle, climate change and increasing water demand for agriculture, urban and industry (IPCC, 2009).

In Morocco, irrigation is the biggest consumer sector of water, in average, it has been estimated that about 85% of mobilised water resources is used by agriculture with an efficiency lower than 50 % (Plan bleu, 2009). The Tensift Al Haouz region, which is considered as a typical watershed of the Southern Mediterranean, is characterised by a semi-arid climate. Under these conditions, irrigation is inevitable for crop growth, development and yield. For that a good irrigation management requires an accurate quantification of crop water requirements which is assumed equivalent to evapotranspiration (ET) (Allen et al., 2011).

During the last decades, several techniques have been proposed to estimate ET from local to global spatial scales. At the local scale, ET can be measured by using the sap flow sensors (Smith and Allen, 1996) that can provide the individual plant transpiration rate when the tree capacitance is neglected. Based on three different tree crop species, Motisi et al. (2012) verified that transpirational flow at orchard level is regulated by tree conductance, whereas capacitance effects are related to tree size or to environmental demand. ET can be also estimate at local scale by lysimetry (Edwards, 1986; Daamen et al., 1993). Passing from local to integrated spatial scales, the eddy covariance technique (Bedouchi et al., 1988; Allen et al., 2011) is suitable for measuring ET at the field scale over an homogeneous fields (1 ha and above). The eddy covariance and sap flow techniques can be jointly use to partition the ET in plant transpiration and soil evaporation (Cammalleri et al., 2013; Er-Raki et al., 2010). Another technique, is the scintillometry that can provide the sensible and latent heat flux over a transect ranging from 250 m to 10 km even for heterogeneous fields (Kohsiek et al., 2002; Ezzahar and Chehbouni, 2009). At global scale, remote sensing data in the optical/thermal bands provide several ET-related variables such as the Normalized Difference Vegetation Index (NDVI), surface albedo, surface emissivity, LAI (Leaf Area Index) and Land Surface Temperature (LST) (Granger, 2000; Clarson and Buffum, 1989). Several Authors have proposed the use of these methodologies (Hatefield, 1983; Moran and Jackson, 1991; Kustas, 1996; Kalma et al., 2008; Li et al., 2009; Allen et al., 2011; Er-Raki et al., 2013). All these techniques provide ET estimates at a specific temporal and spatial scales and rely on particular assumptions. Interpolation or extrapolation is thus often necessary to infer ET rates outside application scales, which can be a source of additional uncertainty. Moreover, most *in situ* techniques are expensive, time consuming and need a well-trained staff to operate and maintain it.

As an alternative to observational methods of ET, numerous modelling methods have been proposed such as Simple Soil Plant Atmosphere (SiSPAT) (Braud et al., 1995), Interaction Soil-Biosphere-Atmosphere (ISBA) (Noilhan and Mahfouf, 1996) and simple SVAT (Soil Vegetation Atmosphere Transfer) (Boulet et al., 2000), Interactive Canopy Radiation Exchange (ICARE) (Gentine et al., 2007). Others models like Crop Environment REsource Synthesis (CERES) (Ritchie, 1986), Simulateur multidisciplinaire pour les Cultures Standard (STICS) (Brisson et al., 1998) and the crop-water productivity model (Aquacrop) (Raes et al., 2009) have combined the water balance with the crop growth, development and yield components. These modelling methods, whether complex or simple, are generally not easy to implement in an operational context as they require several parameters (e.g. soil and vegetation hydrodynamic properties) and forcing variables (e.g. climate and irrigation) that are often unavailable at the desired space and time scale. As a matter of fact, simpler models based on a few input data have been developed (Merlin, 2013; Merlin et al., 2014). Among them, the surface energy balance model (SEBS) estimates the turbulent fluxes and surface evaporative fraction (Su, 2002) by using remote sensing data (albedo, NDVI, emissivity and LST) in conjunction with meteorological forcing (solar radiation, air temperature, wind speed, air humidity) and surface parameters (e.g. roughness and stability correction functions for momentum and sensible heat transfer). In contrast, the FAO-56 model requires limited input parameters and it has been extensively and successful used for estimating ET over several agricultural areas such as : wheat (Er-Raki et al., 2007, 2010; Jin et al., 2017; Drerup et al 2017), olive (Er-Raki et al., 2008; Er-Raki et al., 2010; Rallo et al., 2014), citrus (Er-Raki et al., 2009; Rallo et al., 2017), table grapes (Er-Raki et al., 2013), sugar beet (Diarra et al., 2017; Anderson et al. 2017) and for different climate (Debnath et al., 2015; Ayyoub et al., 2017). It is based on the Penman-Monteith (PM) equation that has been formulated to include all the parameters that govern the energy exchange between vegetation and atmosphere. In the PM formulation, the extraction of water vapour from the surface is controlled by the surface resistance (r_c). However, the PM approach has been limited by the difficulties to estimate r_c as it depends on several factors related to pedological, biophysical and physiological processes, which are also related to agricultural practices (Katerji et al., 1991; Testi et al., 2004).

To overcome these difficulties, many authors have used the concept of "critical bulk resistance, r*", where r* is r_c when evapotranspiration is not affected by wind speed (Katerji and Perrier, 1983). The critical bulk resistance depends only on other local meteorological variables. Rana et al. (2005) and Ayyoub et al. (2017) showed that r_c is linearly related to r*, allowing the ET estimates even in water shortage conditions. It has been demonstrated that the use of the critical resistance approach to estimate canopy resistance that varies with local meteorology provides more accurate ET estimates than assuming a constant value of resistance for a given canopy (Katerji and Rana, 2006). Alves and Pereira (2000) further investigated the surface resistance in the PM equation and suggested that the surface resistance integrates the combined effects of stomatal, soil surface and canopy resistances. They also showed that the surface resistance depends on meteorological variables as in Jarvis (1976). This approach has then been confirmed by Katerji and Perrier (1983) who showed that decoupling the surface resistance (function of critical resistance), from atmospheric resistance effects improves ET estimates, and this is consistent with the study of Alves and Pereira (2000). All those methods estimate the surface resistance and ET at local scale but little attention has been paid on determining r_c at large scale from remote sensing data. Since the crop water stress is related to r_c through stomatal closure, one can estimate r_c from remotely sensed LST which can provide a good proxy for water stress level.

Several stress indexes have been developed such as the Surface Energy Balance Index (SEBI, Mensenti et al., 1993), Water Deficit Index (WDI, Moran et al., 1944; Moran, 2004), Temperature Vegetation Index (TVI, Prihodko et al., 1997), Temperature Vegetation Dryness Index (TVDI, Sandholt et al., 2002) and Vegetation Temperature Condition Index (VTCI, Wang et al., 2004; Wan et al., 2004). VTCI is defined as a ratio of the dry to actual LST difference to the dry to wet LST temperature difference, with wet/dry LST being estimated as the minimum/maximum LST that the surface can reach for a given meteorological forcing. Among existing thermal-based stress indexes, VTCI has two main advantages: 1) it is rather physically-based due to possibility of simulating wet/dry LST values using a surface energy balance model (Wang et al., 2001) and 2) it can be applied to mixed pixels including soil and vegetation components. In this context, the objective of this study is to model ET based on the modified PM equation by introducing a simple established relationship between r_c and a thermal-based proxy of vegetation water stress, since it was considered as the most relevant parameter for drought monitoring (Jakson et al., 1981; Wan et al., 2004). The surface water stress index (SI) will be derived from the VTCI estimated either from *in situ* or Landsat thermal/reflectance remote sensing data. After, the approach is calibrated and tested in terms of ET estimates over both flood and drip irrigated sites.

2. MATERIALS AND METHODS

2.1. Site description

A field experiment was conducted over wheat crops in the Tensift region in central Morocco. This area has a semi-arid Mediterranean climate, characterised by low and irregular rainfall with an annual average of about 240 mm, against an evaporative demand (ET_0) of 1600 mm year^{-1}. The study site is located in the irrigated zone R3 in the Haouz plain, approximately 40 km southwest of Marrakech city (see Figure 1). The experiment was carried out during the 2015-2016 growing season in two irrigated wheat fields: a 2 ha drip-irrigated field and a 4 ha flood-irrigated field. The surrounding of two fields is also cultivated with wheat and beans for the drip-irrigated one. The soil of both sites has low sand and high clay contents (47 % clay, 35 % silt, and 18 % sand). The sowing dates were the 13th and 22th December 2015 for the drip and flood irrigated sites, respectively.

2.2. Ground data description

During the investigated agricultural season, both wheat sites were equipped with all sensors necessary for measuring different water and heat fluxes exchanged between soil, vegetation and atmosphere. The net radiation (R_n) was measured by the net radiometer (Kipp and Zonen CNR4, Campbell Sci). Soil heat flux (G) was controlled at a 5 cm depth using soil heat flux plates (HPF01, Campbell Sci). Radiometric brightness temperature was measured using an Infra-Red Thermometer (IRTS-P's, Apogee) and then converted to LST using surface emissivity. An eddy covariance system, consisting of a 3D sonic anemometer (CSAT3, Campbell Scientific Ltd.) and a Krypton hygrometer (KH21, Campbell Scientific Ltd.), was installed to provide continuous measurements of vertical sensible heat (H_{EC}) and latent heat (LE_{EC}) fluxes. Half-hourly measurements of classical meteorological data were collected over a grass cover using an automatic meteorological weather station: wind speed (u_a), incoming solar radiation (R_g), air relative humidity (rh_a) and air temperature (T_a) at a reference height (2 m).

Before using the data of latent heat flux (equivalent to ET) measured by the eddy covariance system, it is important to check the reliability and the quality of these measurements. This is undertaken through the analysis of the energy balance closure. By ignoring the term of canopy heat storage and the radiative energy used by vegetation photosynthesis (Testi et al., 2004), the energy balance closure is defined as:

$$R_n - G = H_{EC} + LE_{EC} \tag{1}$$

To check the budget closure during the study period, we compared the available energy at the surface (R_n - G) with the sum of turbulent fluxes (H_{EC} + LE_{EC}) at half-hourly scale. The quality of the correlation between (R_n - G) and (H_{EC} + LE_{EC}) was evaluated by the regression line and the determination coefficient R^2. Figure 2 shows the energy budget closure for sub-hourly data during 2015-2016 growing season for both study sites separately.

Results show that the closure of the energy balance is relatively well verified by comparison with other studies (Testi et al., 2004; Ezzahar et al., 2009). The regression lines are close to the 1:1 line and R^2 values are generally close to 1 (0.91 and 0.88 for the flood and drip irrigated fields, respectively). However, the slope of the regression forced through the origin was about 1.3 for both sites, indicating some underestimation of turbulent fluxes (H_{EC} + LE_{EC}) by about 30% of the available energy (R_n - G). This due to the attenuation of turbulence at low or high frequency signals (Ezzahar et al., 2009). Also, the difference between the sensors source area has a very important impact on the energy balance closure. In fact, the surface area of the sensors measuring the available energy (net radiation and soil heat flux) is very small compared to that of EC system, which can quickly change depending on wind speed and direction and surface conditions. Moreover, the energy absorbed by the plant has not been considered in the energy balance. In this context, Scott et al. (2003) evaluated the storage in the biomass to about 5-10 % of the available energy, which could partially explain the overestimation of available energy at the surface.

2.3. Remote sensing data

Landsat 7 (L7) and Landsat 8 (L8) satellites were launched by NASA on April 1999 and February 2013, respectively. The combined use of both satellites potentially provides repetitive acquisitions every 8 days of high (30 -100 m) resolution multispectral data of the Earth's surface on a global basis. The data (available for download from the USGS website, https://earthexplorer.usgs.gov/) are resampled to 30 m resolution. A total of 14 images (6 and 8 images for L7 and L8, respectively) were used in this study. They were acquired from January 2016 until the end of the agricultural season (end of May).

Herein, Landsat data were used to estimate the NDVI, surface emissivity and LST over the R3 area overlaying both study sites. NDVI is calculated using the spectral reflectance measurements acquired in the visible ρ_R (red) and near-infrared regions ρ_{PIR}:

$$\mathrm{NDVI} = \frac{\rho_{PIR} - \rho_R}{\rho_{PIR} + \rho_R}\,. \tag{2}$$

The surface emissivity was estimated from an empirical relationship with NDVI and soil/vegetation emissivity components:

$$\varepsilon = \varepsilon_v - (\varepsilon_v - \varepsilon_s)\left(\frac{\mathrm{NDVI} - \mathrm{NDVI_v}}{\mathrm{NDVI_s} - \mathrm{NDVI_v}}\right)^k \tag{3}$$

where ε_v is the vegetation emissivity (set to 0.99), ε_s is the soil emissivity (set to 0.96), $\mathrm{NDVI_v}$ is NDVI for full vegetation (set to 0.99), $\mathrm{NDVI_s}$ is the NDVI for bare soil (set to 0.15). k is an attenuation coefficient relevant to the relation between LAI-NDVI and NDVI-emissivity ranging from 2 to 3. In Olioso et al. (2013) the value of k is derived from the shape of the NDVI-emissivity relationship for a range of soil moisture conditions and vegetation canopy emissivities. In our case, it was adjusted to 2 based on the NDVI-LAI relationship established in the same region by Er-Raki et al. (2007). Note that this value was used in Tardy et al. (2016) over the same (semi-arid) region.

LST was derived from the thermal infrared bands passing by different correction steps defined in Tardy et al., (2016). Those steps allowed to convert the Landsat digital number to the physical LST by inverting the Plank's low. An atmospheric correction of the thermal infrared bands data was firstly carried out using the MODTRAN atmospheric radiative transfer model software. For doing that, knowledge of the humidity and air temperature profile was needed. As second step, the at-sensor radiance was converted into surface radiance using the estimated surface emissivity. Then the LST was obtained by inverting the Plank's law. In order to evaluate the spaceborne LST, a comparison between the Landsat-derived against *in situ* LST measurements is presented in Figure 3.

According to this figure, a relatively good match between satellite and ground LST data is obtained for the flood irrigated wheat parcel with a determination coefficient (R^2) of 0.92 and a RMSE equal to 0.91 °C, whereas an R^2 of 0.80 and an RMSE equal to 2.36 °C are found for the drip-irrigated field. The systematic over-estimation observed in the drip site could be attributable to the spatial extent of *in situ* and spaceborne observations. In fact, the drip-irrigated site is small (in comparison with the flood one), and does not fully cover the Landsat thermal pixel size (100 m resolution). Moreover, some differences between *in situ* and Landsat data could be explained by the limited spatial representativeness of 2-m high *in situ* thermal data. In addition, the better results in flood irrigated field than in drip irrigated field is due to: 1) The irrigation system: as it is known, flood irrigation implies a homogeneous fraction of wetted areas, where all the pixels have the same percentage of irrigation water, which means an uniform LST within the site. In contrast, just a part of the soil surface is wetted in the drip irrigated site, which may lead to some heterogeneity in observed LST from one pixel to another. 2) The flood irrigated site is bigger (4 hectares) than the drip one (approximately 2 hectares with a surface area of 4 ha (35 Landsat pixels) and 2 ha (10 Landsat pixels), respectively. Note that several 60/100 m Landsat LST pixels were partly covering the surrounding fields, causing representativeness issues especially for the smaller (drip) field. In addition 3) for the flood site, the surrounding fields are similar with the same irrigation system and crop (wheat). Contrariwise, the drip one, was surrounded by fields with different crops (beans).

The observed overestimation of LST by Landsat could also be due to an overestimation of the surface emissivity. As soil emissivity is difficult to estimate without specific measurements (unavailable in this experiment), it was fixed arbitrarily to 0.95. Moreover, we would like to underline that the field measurements of LST are representative of a small square of the surface only, which is much smaller than a Landsat pixel. Last each crop field can include a mixture of wet and dry Landsat pixels, although an average of all LST values was computed at the field scale.

2.4. EVAPOTRANSPIRATION MONITORING APPROACH

2.4.1. Evapotranspiration modelling

The latent heat flux (LE (W m^{-2})) of wheat was modelled by using the following PM equation:

$$\mathbf{LE} = \frac{\Delta(R_n - G) + \rho c_p \frac{D}{r_{a,h}}}{\Delta + \gamma\left(1 + \frac{r_c}{r_{a,h}}\right)} \qquad (4)$$

where Δ stands for the slope of the saturation vapour pressure curve at air temperature (kPa °C^{-1}). The psychrometric constant (kPa °C^{-1}) and the mean air density at constant pressure (kg m^{-3}) are presented by γ and ρ respectively while c_p stands for the specific heat of air (MJ kg^{-1} °C^{-1}). The vapour pressure deficit; D (kPa) is obtained by calculating the difference between the air vapour pressure; e_a (kPa) and the saturated water vapour pressure; e_s (kPa) where the latter is calculated as addressed in equation 5.

$$e_s = 0.611 \times e^{\left(\frac{17.27 \times T_a}{T_a + 273.3}\right)} \quad (5)$$

In Equation (4), all parameters are deduced from the meteorological variables measured by the automatic meteorological station. However, the use of this model requires determining the aerodynamic resistance (r_{ah}, s m^{-1}) and bulk canopy resistance (r_c, s m^{-1}). r_{ah} is calculated at a reference height z_r in the boundary layer above the canopy by:

$$r_{ah} = \frac{(\log\left[{}^{(z_r - d)}/_{zm}\right] - \psi_m) \times (\log\left[{}^{(h_c - d)}/_{zm}\right] - \psi_h)}{kar^2 \times u_a} \quad (6)$$

where kar is the Von Karman constant equal to 0.44, h_c the canopy height, the displacement height (to adjust the effects of vegetation height on wind displacement) and the height of the dynamic soil roughness are presented as , $d = 2/3\ h_c$ and $z_m = h_c/8$ respectively. The ψ_m and ψ_h presents the atmospheric stability function and the sensitive heat stability function, respectively.

For irrigated crops, the canopy resistance r_c is not assumed to be constant. It changes according to available energy, vapour pressure deficit, and other environmental factors. In this study, we propose to use a simple empirical relationship between r_c and a vegetation water stress index (SI) which is calculated as:

$$SI = 1 - VTCI \quad (7)$$

where VTCI is calculated as follow:

$$VTCI = \frac{LST_{dry} - LST}{LST_{dry} - LST_{wet}} \quad (8)$$

where LST_{wet} and LST_{dry} are the LST simulated by an energy balance model in fully wet and dry surface conditions, respectively (Stefan et al., 2015; Merlin et al., 2016). We therefore distinguish between stressed and unstressed conditions via the VTCI. Especially, VTCI equals 1 (SI = 0) for $LST = LST_{wet}$ (energy-limited evaporation), which means that vegetation is unstressed and the value of r_c is low. In the opposite case, VTCI equals 0 (SI = 1) for $LST = LST_{dry}$ (soil-controlled evaporation), which means that vegetation is undergoing water stress and the value of r_c is large.

2.4.2. Energy balance Model

The two extreme temperatures (LST_{wet} and LST_{dry}) of Equation (8) are simulated by running an energy balance model forced by $r_c \approx 0$ s m^{-1} and $r_c \approx \infty$, respectively. The surface net radiation is expressed as:

$$R_n = (1 - \alpha)\ R_g + \varepsilon(R_{atm} - \sigma\ LST^4) \quad (9)$$

with α (-) being the surface albedo (set to 0.20), R_{atm} stands for the atmospheric longwave radiation (W m^{-2}) and $\sigma = 5.67 \times 10^{-8}$ the Stephan-Boltzmann constant (W m^{-2} K^{-4}). The downward atmospheric radiation at surface level is expressed as:

$$R_{atm} = \varepsilon_a \times \sigma T_a^4 \quad (10)$$

where ε_a is the atmospheric emissivity estimated as in Brutsaert (1975):

$$\varepsilon_a = 1.24 \times \left(\frac{e_a}{T_a}\right)^{\frac{1}{7}} \quad (11)$$

with $$e_a = e_s(T_a) \times \frac{rh_a}{100}$$

The ground flux G is estimated as a fraction of net radiation at the soil surface $R_{n,s}$:

$$G = \Gamma . R_{n,s} \quad (12)$$

with Γ being a fractional empirical coefficient set to 0.4, and $R_{n,s}$ is given by:

$$R_{n,s} = R_n \times (1 - Fc) \quad (13)$$

with Fc being the fraction vegetation cover calculated as:

$$Fc = \left(\frac{NDVI - NDVIs}{NDVI_V - NDVI_S}\right) \quad (14)$$

The sensible heat flux is given by:

$$H = \rho c_p \beta \frac{LST - T_a}{r_{a,h}} \quad (15)$$

where β is the "β function" calculated as follows as a function of LAI:

$$\beta = 1 - \frac{a}{LAI * b * \sqrt{2\pi}} e^{-\frac{(\ln(LAI) - c)^2}{2 * b^2}} \quad (16)$$

with *a*, *b* and *c* are empirical coefficients equal to 0.17 for *a* and 0.8 for *b* and *c* (Boulet et al., 2012). These values are calibrated for the wheat in the same study site.

The latent heat flux is estimated using the following equation:

$$LE = \frac{\rho c_p}{\gamma} \frac{e_s - e_a}{r_{a,h} + r_c} \quad (17)$$

Finally, for running the energy balance model, it was set LST = Ta and search for the value of LST that minimises the following cost function F (LST):

$$\mathbf{F\,(LST) = (Rn - G - H - LE)^2} \quad (18)$$

F (LST) is named "cost function" as it is the function to be minimised in order to find the LST value corresponding to the energy balance closure (e.g. Merlin et al., 2016).

3. RESULTS AND DISCUSSIONS

The PM equation is used in this study to estimate the surface ET of wheat over two different crop fields in terms of irrigation systems located in the R3 area. The proposed approach aims to modify the PM equation by expressing r_c, which is the main parameter controlling latent heat flux, as a function of a thermal-derived SI. The use of LST as an indicator of the surface resistance in order to estimate the ET, is assessed by using the *in situ* measurements collected in the flood-irrigated site. The "observed" r_c is estimated by inverting Equation (3) using ET measured by eddy covariance system. Then, a validation exercise is carried out over the drip irrigated-site using *in situ* data. Finally, an evaluation of the method is undertaken using Landsat data over both sites.

3.1 In situ evaluation of the proposed approach

The time series of retrieved SI and r_c over the flood site is shown in Figure 4. According to this figure, daily patterns of SI and r_c are similar and respond perfectly to the water supply (rainfall or irrigation). On one hand, after water supply, the soil moisture in the root zone increases and the plant transpirates at potential rate with no limitation and the values of r_c and SI tend to decrease. On another hand, the absence of irrigation and rainfall (dry condition, e.g. from the end of April) results in an increase in the root zone depletion and generates stress (SI increased). The increase in soil water depletion is due to the removal of water by ET that induces water stress conditions and then the stomatal closure which increases r_c. Consequently, it can be concluded that both the variables follow similar trends. This leads to look if there is any relationship between both terms. For this purpose, r_c is plotted against SI (Figure 5) by using *in situ* measurements (flood site). When SI ranges from 0 to 0.4 which corresponds to unstressed vegetation with low LST values, r_c values are scattered around a mean value of about 70 s m^{-1} which corresponds to the minimum bulk surface resistance (r_{cmin}).

The obtained value of r_{cmin} is in agreement with values obtained for wheat crop by Baldocchi (1994). When SI increases above a threshold value SI = 0.4, r_c increases linearly with SI. This confirms the results reported by Autovino et al. (2016) and Er-Raki et al. (2016) who found a similar shape for olive and orange orchards, respectively. The obtained relationship, which gives the best fit between both terms, is given by:

$$r_c = r_{cmin} = 70\ s.m^{-1} \qquad for\ SI < 0.4$$
$$r_c = d * SI + e \qquad for\ SI \geq 0.4 \qquad (19)$$

where d and e are the calibration parameters, which are equal to 3000 s m^{-1} and -1130 s m^{-1}, respectively. Note that the values of r_{cmin}, d and e are expected to depend on local meteorological data, crop and soil types.

The relationship of Equation (19) is validated by comparing the modelled and measured latent heat flux for the drip-irrigated wheat site at Landsat overpass time (Figure 6). According to this figure, an acceptable correlation is obtained between simulated and measured LE using the proposed approach (R^2 = 0.53). The scatter of modelled LE estimates is probably due to the uncertainties associated to the relatively small footprint of the *in situ* thermal radiometer. Looking at the dynamics of actual LE and r_c values estimated by Equation (19) (not showed in the manuscript), the proposed methodology for bulk resistance estimation allows for capturing the variability of measured LE. The significant bias in simulated LE is probably due to the underestimation of in situ LST, involving an overestimation of simulated LE especially during the dry period (Ramelo et al 2014; Ruhoff at al., 2013). Those explanations were added to the revised version.

3.2 Spatial analysis

To overcome the spatial representativeness issue of *in situ* measurements and for further evaluating the proposed model, Landsat data are used as input of the modified PM model. ET estimates are spatialized within a 10 × 10 km^2 area centred over the R3 sector which is mainly covered by wheat crops. The R3 perimeter is occupied by different cultures (wheat, alfalfa, orange, and olive), so before spatializing the ET, a land use has been performed in order to distinguish between wheat and other crops. Figure 7 shows the spatial and temporal variations of Landsat-derived LST and Fc over wheat crops. As the entire growing season of wheat was divided into four growth stages namely: the initial, the development, the mid-season and the late season, we choose to present one image for each stage (Figure 7). This figure shows that during the initial stage (06/01/2016), most of the fields were under bare soil conditions characterised by low Fc and high LST values depending spatially on the water supply and atmospheric conditions. In the development stage (07/02/2016) an effective full cover is reached in some parcels while other ones are characterized by low Fc depending on the sowing date and the development of vegetation. This spatial variability of Fc has a direct effect on the variability of LST. When Fc reaches the maximum value at the mid-season (18/03/2016), spatial LST values are similar around 20 °C except for some pixels where the LST values are relatively higher (about 35 °C), which correspond to the non-cultivated parcels. At the last stage (29/05/2016), from the beginning of maturity until harvest or full senescence, wheat fields are characterized by low Fc and high LST values.

Our approach involves the energy balance model in order to assess the variation of LST in space and time for two extreme dry and wet conditions which depend on climatological conditions. Figure 8 shows the dry and wet LST maps for the selected four dates. These maps show that, in the coldest days in winter (06/01/2016), the LST_{dry} oscillated between 15 and 30 °C and the LST_{wet} ranged from 10 to 17 °C. In the other hand, for the hottest days in summer (29/05/2016), the LST_{dry} reached its maximum (50 °C) as well as the LST_{wet} that reached 30 °C.

The use of LST time series extracted from Landsat satellite and the dry and wet LST values computed using the energy balance model appears to be a good way to monitor water stress index for irrigation scheduling. Figure 9 presents the spatial distribution of SI over R3 perimeter at the different growth stages. The maps of this figure show that Landsat-derived SI consistently ranges between 0 and 1 all along the agricultural season, regardless of the vegetation cover fraction and LST values (see Figure 7). In fact, the use of Fc and LST data as input variables of the energy balance model to estimates LST_{dry} and LST_{wet}, allows taking into account all the growing stages of wheat crop. In particular, we can distinguish between the small vegetation (tillering stage) and the full developed one (mid-season stage). In this regard Barbosa da Silva and Rao (2005) estimated SI of cotton crop using LST, r_c and R_n. However, they did not take into account the vegetation parameters and their variability during the agricultural season. These parameters affect the aerodynamic resistance and hence both the sensible and latent heat fluxes.

In Figure 9, the pixels having a SI value close to 1 (red colour) are characterised by a high vegetation stress due to the mismatch between water supply and water requirement (late irrigation). The values of SI ranging between 0.3 and 0.6 are characterised by the onset of vegetation stress. This is due to the difficulty of the irrigation distribution at the right moment. Indeed, the water transported by gravity across the R3 channels may arrive to the fields before or after the optimal date (Belaqziz et al., 2013; Belaqziz et al., 2014). Pixels with SI values around 0 correspond to un-stressed, meaning recently irrigated wheat. Following the evolution of SI, it appears that this index shows spatial and quantitative information about the method of irrigation distribution, and could be used to optimise the irrigation scheduling. Those results are consistent with the work of Belaqziz et al. (2013), who used another index named "Irrigated Priority Index (IPI)" in the same study area to manage the irrigation distribution. The IPI equation is mainly based on both the water stress level and irrigation dates of wheat crop. The main drawback of IPI is that it needs the amount of water supply as input, which is not the case of SI developed. This new index based on LST only might then be combined with IPI in order to detect and retrieve irrigation amount, information that is very difficult to obtain over large areas.

Figure 10 shows the spatial distribution of ET and its temporal variation across the season. We can observe a high variability of ET, which depends on the spatial heterogeneity of Fc, LST and SI over R3.

The spatial representation allowed to distinguish between the fields corresponding to stressed wheat (blue colour) where LE is lower and the field corresponding to un-stressed fields (other colour) that have been relatively well irrigated during the wheat growing stages, for high ET values. The obtained spatial and temporal variations of ET are in accordance with the spatio-temporal variability of Fc, LST and SI (see Figures 7, 9). To observe this more easily, the frequency histograms for remote sensing data (Fc, LST), SI and ET on one date 18/03/2016 are plotted in Figure 11. The choice of this date relies on the fact that the end of March summarises the history of wheat crop growth and its development from sowing date (Karrou., 2003; Hadria., 2006). By analysing the different histograms, one can be concluded that the estimates LE are coherent with other surface properties (Fc, LST, and SI). Fc values in the higher range (larger than 0.8) have a high frequency/percentage. They correspond to the fields with low LST values (lower than 25 °C), which are associated to small values of surface aerodynamic resistance (large crop height) rather than to large water availability for wheat. On this date, our model computes a large amount of un-stressed areas with relatively small SI and large LE values. Those results seem to be representative of the real situation.

The land surface parameters (LST, Fc, and emissivity) are obtained from Landsat data. Therefore all cloudy data (images) are discarded. In addition, the Landsat-7 images include data gaps due to scan line corrector (SLC) failure on May 31 2013, which on some dates unfortunately covered the irrigated sites. The selected data are used for validating the predicted ET (Equation 4) against *in situ* ET for both flood and drip sites (Figure 12). As it can be observed in this figure, the proposed approach allows to predict correctly the temporal dynamics of ET with an acceptable accuracy and a good correlation. The validations for the two sites resulted in R^2 of 0.76, 0.70 and a RMSE of 12, 13 W m^{-2} for flood-irrigated site and drip-irrigated site, respectively.

A further validation of the proposed approach was performed by comparing the measured ET with the ET simulated one under fully stressed (SI=1, r_c = 1870 s m^{-1}) and un-stressed (SI=0, r_c =70 s m^{-1}) conditions. The obtained results are presented in the same Figure 12 under real meteorological conditions. As expected, the model simulates very low values of ET for SI=1 whereas it simulates high values of ET for SI=0. On some dates, the ET simulations with SI=0 (r_c = 70 s m^{-1}) coincides with the ET estimated from Landsat-derived SI, which means that the fields were monitored in well-watered conditions (SI < 0.4). One key result is that the Landsat-derived SI (0< SI <1, 70< r_c <1870 s m^{-1}) provides much more accurate ET estimates over both validation sites than when assuming fully stressed (SI = 1, r_c = 1870 s m^{-1}) or fully unstressed (SI=0, r_c = 70 s m^{-1}) condition in the PM equation.

4. CONCLUSION

The aim of this study was to use the PM equation to estimate the evapotranspiration (ET) over irrigated wheat crops of semi-arid areas. As the PM approach has been limited by the difficulties to estimate the bulk surface resistance (r_c) since it depends on several factors related to crop characteristics and agricultural practices, we proposed in this study to link r_c to the stress index (SI) derived from remotely sensed LST and to implement the developed relationship in the PM model. SI was estimated as the observed LST normalized by the LST simulated in fully wet and dry conditions using a surface energy balance model forced by meteorological forcing and vegetation fraction.

The approach was tested over a 10 x 10 km^2 irrigated perimeter R3. The calibration/validation strategy implements two instrumented wheat sites with flood and drip irrigation and Landsat shortwave and thermal imagery during one growing season (2015-2016). The r_c retrieved from eddy covariance measurements over the flood-irrigated site (by inverting PM equation) was first correlated to SI. This relation was then tested over the drip-irrigated site using *in situ* measurements in order to simulate the surface ET. Next, this method was evaluated in terms of latent heat flux using Landsat temperature and reflectance data over both sites. The RMSE values over drip and flood sites are 13 and 12 W m^{-2}, which correspond to the relative errors of 5 and 4%, respectively.

The proposed relationship between r_c and SI employed in the PM model holds great potential for estimating crop ET using remote sensing data. Moreover, the results reached in terms of detecting crop water stress, can be helpful to distinguish between the irrigated and non-irrigated areas, which could give a prevision of the wheat yield based on the IPI developed by Belaqziz et al. (2013). Note however that the proposed methodology has been tested over two wheat parcels only. Further calibration studies should be undertaken to investigate and understand the variability of r_c parameters over different crop types and surface conditions.

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