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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_s) 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 km² 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.

Symbols	signification and unit
ET	Evapotranspiration, mm
rc	Surface resistance, $s m^{-1}$
r*	Critical bulk resistance, $s m^{-1}$
R_n	Net radiation, $W m^{-2}$
G	Soil heat flux, $W m^{-2}$
H_{EC}	Sensible heat flux (eddy covariance), $W m^{-2}$
LE_{EC}	Latent heat flux (eddy covariance), $W m^{-2}$
u_a	Wind speed, $m s^{-1}$
R_g	Solar radiation, $W m^{-2}$
rh_a	Relative humidity, %
T_a	Air temperature, °C
R²	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, $kg m^{-3}$
c_p	Stands for the specific heat of air, $MJ kg^{-1} °C^{-1}$
D	Vapour pressure deficit, kPa
e_a	Actual vapour pressure, kPa
e_s	Saturation vapour pressure, kPa
r_{ah,}	Aerodynamic resistance, $s m^{-1}$
z_r	Reference height, m
kar	Von Karman constant equal to 0.44
h_c	Canopy height, m
d	Displacement height, m
z_m	Height of the dynamic soil roughness, m
ψ_m	Atmospheric stability function
ψ_h	Sensitive heat stability function
α	Surface albedo
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
F_c	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, $s m^{-1}$

<i>e</i>	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
ET₀	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

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

38 In Morocco, irrigation is the biggest consumer sector of water, in average, it has been estimated
39 that about 85% of mobilised water resources is used by agriculture with an efficiency lower than
40 50 % (Plan bleu, 2009). The Tensift Al Haouz region, which is considered as a typical watershed
41 of the Southern Mediterranean, is characterised by a semi-arid climate. Under these conditions,
42 irrigation is inevitable for crop growth, development and yield. For that a good irrigation
43 management requires an accurate quantification of crop water requirements which is assumed
44 equivalent to evapotranspiration (ET) (Allen et al., 2011).

45 During the last decades, several techniques have been proposed to estimate ET from local to
46 global spatial scales. At the local scale, ET can be measured by using the sap flow sensors (Smith
47 and Allen, 1996) that can provide the individual plant transpiration rate when the tree capacitance
48 is neglected. Based on three different tree crop species, Motisi et al. (2012) verified that
49 transpirational flow at orchard level is regulated by tree conductance, whereas capacitance effects
50 are related to tree size or to environmental demand. ET can be also estimate at local scale by
51 lysimetry (Edwards, 1986; Daamen et al., 1993). Passing from local to integrated spatial scales,
52 the eddy covariance technique (Bedouchi et al., 1988; Allen et al., 2011) is suitable for measuring
53 ET at the field scale over an homogeneous fields (1 ha and above). The eddy covariance and sap
54 flow techniques can be jointly use to partition the ET in plant transpiration and soil evaporation
55 (Cammalleri et al., 2013; Er-Raki et al., 2010). Another technique, is the scintillometry that can
56 provide the sensible and latent heat flux over a transect ranging from 250 m to 10 km even for
57 heterogeneous fields (Kohsiek et al., 2002; Ezzahar and Chehbouni, 2009). At global scale, remote
58 sensing data in the optical/thermal bands provide several ET-related variables such as the
59 Normalized Difference Vegetation Index (NDVI), surface albedo, surface emissivity, LAI (Leaf
60 Area Index) and Land Surface Temperature (LST) (Granger, 2000; Clarson and Buffum, 1989).
61 Several Authors have proposed the use of these methodologies (Hatefield, 1983; Moran and
62 Jackson, 1991; Kustas, 1996; Kalma et al., 2008; Li et al., 2009; Allen et al., 2011; Er-Raki et al.,
63 2013). All these techniques provide ET estimates at a specific temporal and spatial scales and rely
64 on particular assumptions. Interpolation or extrapolation is thus often necessary to infer ET rates

65 outside application scales, which can be a source of additional uncertainty. Moreover, most *in situ*
66 techniques are expensive, time consuming and need a well-trained staff to operate and maintain it.

67 As an alternative to observational methods of ET, numerous modelling methods have been
68 proposed such as Simple Soil Plant Atmosphere (SiSPAT) (Braud et al., 1995), Interaction Soil-
69 Biosphere-Atmosphere (ISBA) (Noilhan and Mahfouf, 1996) and simple SVAT (Soil Vegetation
70 Atmosphere Transfer) (Boulet et al., 2000), Interactive Canopy Radiation Exchange (ICARE)
71 (Gentine et al., 2007). Others models like Crop Environment REsource Synthesis (CERES)
72 (Ritchie, 1986), Simulateur multidisciplinaire pour les Cultures Standard (STICS) (Brisson et al.,
73 1998) and the crop-water productivity model (Aquacrop) (Raes et al., 2009) have combined the
74 water balance with the crop growth, development and yield components. These modelling
75 methods, whether complex or simple, are generally not easy to implement in an operational
76 context as they require several parameters (e.g. soil and vegetation hydrodynamic properties) and
77 forcing variables (e.g. climate and irrigation) that are often unavailable at the desired space and
78 time scale. As a matter of fact, simpler models based on a few input data have been developed
79 (Merlin, 2013; Merlin et al., 2014). Among them, the surface energy balance model (SEBS)
80 estimates the turbulent fluxes and surface evaporative fraction (Su, 2002) by using remote sensing
81 data (albedo, NDVI, emissivity and LST) in conjunction with meteorological forcing (solar
82 radiation, air temperature, wind speed, air humidity) and surface parameters (e.g. roughness and
83 stability correction functions for momentum and sensible heat transfer). In contrast, the FAO-56
84 model requires limited input parameters and it has been extensively and successful used for
85 estimating ET over several agricultural areas such as : wheat (Er-Raki et al., 2007, 2010; Jin et al.,
86 2017; Drerup et al 2017), olive (Er-Raki et al., 2008; Er-Raki et al., 2010; Rallo et al., 2014),
87 citrus (Er-Raki et al., 2009; Rallo et al., 2017), table grapes (Er-Raki et al., 2013), sugar beet
88 (Diarra et al., 2017; Anderson et al. 2017) and for different climate (Debnath et al., 2015; Ayyoub
89 et al., 2017). It is based on the Penman-Monteith (PM) equation that has been formulated to
90 include all the parameters that govern the energy exchange between vegetation and atmosphere. In
91 the PM formulation, the extraction of water vapour from the surface is controlled by the surface
92 resistance (r_c). However, the PM approach has been limited by the difficulties to estimate r_c as it
93 depends on several factors related to pedological, biophysical and physiological processes, which
94 are also related to agricultural practices (Katerji et al., 1991; Testi et al., 2004).

95 To overcome these difficulties, many authors have used the concept of “critical bulk resistance,
96 r^* ”, where r^* is r_c when evapotranspiration is not affected by wind speed (Katerji and Perrier,
97 1983). The critical bulk resistance depends only on other local meteorological variables. Rana et
98 al. (2005) and Ayyoub et al. (2017) showed that r_c is linearly related to r^* , allowing the ET
99 estimates even in water shortage conditions. It has been demonstrated that the use of the critical
100 resistance approach to estimate canopy resistance that varies with local meteorology provides
101 more accurate ET estimates than assuming a constant value of resistance for a given canopy
102 (Katerji and Rana, 2006). Alves and Pereira (2000) further investigated the surface resistance in
103 the PM equation and suggested that the surface resistance integrates the combined effects of
104 stomatal, soil surface and canopy resistances. They also showed that the surface resistance
105 depends on meteorological variables as in Jarvis (1976). This approach has then been confirmed
106 by Katerji and Perrier (1983) who showed that decoupling the surface resistance (function of
107 critical resistance), from atmospheric resistance effects improves ET estimates, and this is
108 consistent with the study of Alves and Pereira (2000). All those methods estimate the surface
109 resistance and ET at local scale but little attention has been paid on determining r_c at large scale
110 from remote sensing data. Since the crop water stress is related to r_c through stomatal closure, one
111 can estimate r_c from remotely sensed LST which can provide a good proxy for water stress level.

112 Several stress indexes have been developed such as the Surface Energy Balance Index (SEBI,
113 Mensenti et al., 1993), Water Deficit Index (WDI, Moran et al., 1944; Moran, 2004), Temperature
114 Vegetation Index (TVI, Prihodko et al., 1997), Temperature Vegetation Dryness Index (TVDI,
115 Sandholt et al., 2002) and Vegetation Temperature Condition Index (VTCI, Wang et al., 2004;
116 Wan et al., 2004). VTCI is defined as a ratio of the dry to actual LST difference to the dry to wet
117 LST temperature difference, with wet/dry LST being estimated as the minimum/maximum LST
118 that the surface can reach for a given meteorological forcing. Among existing thermal-based
119 stress indexes, VTCI has two main advantages: 1) it is rather physically-based due to possibility of
120 simulating wet/dry LST values using a surface energy balance model (Wang et al., 2001) and 2) it
121 can be applied to mixed pixels including soil and vegetation components. In this context, the
122 objective of this study is to model ET based on the modified PM equation by introducing a simple
123 established relationship between r_c and a thermal-based proxy of vegetation water stress, since it
124 was considered as the most relevant parameter for drought monitoring (Jakson et al., 1981; Wan et
125 al., 2004). The surface water stress index (SI) will be derived from the VTCI estimated either from

126 *in situ* or Landsat thermal/reflectance remote sensing data. After, the approach is calibrated and
127 tested in terms of ET estimates over both flood and drip irrigated sites.

128 **2. MATERIALS AND METHODS**

129 **2.1. Site description**

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

140 **2.2. Ground data description**

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

153 Before using the data of latent heat flux (equivalent to ET) measured by the eddy covariance
154 system, it is important to check the reliability and the quality of these measurements. This is

155 undertaken through the analysis of the energy balance closure. By ignoring the term of canopy
156 heat storage and the radiative energy used by vegetation photosynthesis (Testi et al., 2004), the
157 energy balance closure is defined as:

$$158 \quad R_n - G = H_{EC} + LE_{EC} \quad (1)$$

159 To check the budget closure during the study period, we compared the available energy at the
160 surface ($R_n - G$) with the sum of turbulent fluxes ($H_{EC} + LE_{EC}$) at half-hourly scale. The quality of
161 the correlation between ($R_n - G$) and ($H_{EC} + LE_{EC}$) was evaluated by the regression line and the
162 determination coefficient R^2 . Figure 2 shows the energy budget closure for sub-hourly data during
163 2015-2016 growing season for both study sites separately.

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

177 **2.3. Remote sensing data**

178 Landsat 7 (L7) and Landsat 8 (L8) satellites were launched by NASA on April 1999 and
179 February 2013, respectively. The combined use of both satellites potentially provides repetitive
180 acquisitions every 8 days of high (30 -100 m) resolution multispectral data of the Earth's surface
181 on a global basis. The data (available for download from the USGS website,
182 <https://earthexplorer.usgs.gov/>) are resampled to 30 m resolution. A total of 14 images (6 and 8
183 images for L7 and L8, respectively) were used in this study. They were acquired from January
184 2016 until the end of the agricultural season (end of May).

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

$$188 \quad \text{NDVI} = \frac{\rho_{PIR} - \rho_R}{\rho_{PIR} + \rho_R}. \quad (2)$$

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

$$191 \quad \varepsilon = \varepsilon_v - (\varepsilon_v - \varepsilon_s) \left(\frac{\text{NDVI} - \text{NDVI}_v}{\text{NDVI}_s - \text{NDVI}_v} \right)^k \quad (3)$$

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

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

209 According to this figure, a relatively good match between satellite and ground LST data is
210 obtained for the flood irrigated wheat parcel with a determination coefficient (R^2) of 0.92 and a
211 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
212 drip-irrigated field. The systematic over-estimation observed in the drip site could be attributable
213 to the spatial extent of *in situ* and spaceborne observations. In fact, the drip-irrigated site is small
214 (in comparison with the flood one), and does not fully cover the Landsat thermal pixel size (100 m
215 resolution). Moreover, some differences between *in situ* and Landsat data could be explained by

216 the limited spatial representativeness of 2-m high *in situ* thermal data. In addition, the better
 217 results in flood irrigated field than in drip irrigated field is due to: 1) The irrigation system: as it is
 218 known, flood irrigation implies a homogeneous fraction of wetted areas, where all the pixels have
 219 the same percentage of irrigation water, which means an uniform LST within the site. In contrast,
 220 just a part of the soil surface is wetted in the drip irrigated site, which may lead to some
 221 heterogeneity in observed LST from one pixel to another. 2) The flood irrigated site is bigger (4
 222 hectares) than the drip one (approximately 2 hectares with a surface area of 4 ha (35 Landsat
 223 pixels) and 2 ha (10 Landsat pixels), respectively. Note that several 60/100 m Landsat LST pixels
 224 were partly covering the surrounding fields, causing representativeness issues especially for the
 225 smaller (drip) field. In addition 3) for the flood site, the surrounding fields are similar with the
 226 same irrigation system and crop (wheat). Contrariwise, the drip one, was surrounded by fields with
 227 different crops (beans).

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

234 **2.4. EVAPOTRANSPIRATION MONITORING APPROACH**

235 **2.4.1. Evapotranspiration modelling**

236 The latent heat flux (LE (W m⁻²)) of wheat was modelled by using the following PM equation:

$$237 \quad \mathbf{LE} = \frac{\Delta(\mathbf{R}_n - \mathbf{G}) + \rho c_p \frac{\mathbf{D}}{r_{a,h}}}{\Delta + \gamma \left(1 + \frac{r_c}{r_{a,h}}\right)} \quad (4)$$

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

244
$$e_s = 0.611 \times e^{\left(\frac{17.27 \times T_a}{T_a + 273.3}\right)} \quad (5)$$

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

249
$$r_{ah} = \frac{(\log[(z_r - d)/z_m] - \psi_m) \times (\log[(h_c - d)/z_m] - \psi_h)}{k a r^2 \times u_a} \quad (6)$$

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

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

258
$$SI = 1 - VTCI \quad (7)$$

259 where VTCI is calculated as follow:

260
$$VTCI = \frac{LST_{dry} - LST}{LST_{dry} - LST_{wet}} \quad (8)$$

261 where LST_{wet} and LST_{dry} are the LST simulated by an energy balance model in fully wet and dry
 262 surface conditions, respectively (Stefan et al., 2015; Merlin et al., 2016). We therefore distinguish
 263 between stressed and unstressed conditions via the VTCI. Especially, VTCI equals 1 (SI = 0) for
 264 $LST = LST_{wet}$ (energy-limited evaporation), which means that vegetation is unstressed and the
 265 value of r_c is low. In the opposite case, VTCI equals 0 (SI = 1) for $LST = LST_{dry}$ (soil-controlled
 266 evaporation), which means that vegetation is undergoing water stress and the value of r_c is large.

267 **2.4.2. Energy balance Model**

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

271
$$R_n = (1 - \alpha) R_g + \varepsilon(R_{atm} - \sigma LST^4) \quad (9)$$

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

$$275 \quad R_{\text{atm}} = \varepsilon_a \times \sigma T_a^4 \quad (10)$$

276 where ε_a is the atmospheric emissivity estimated as in [Brutsaert \(1975\)](#):

$$277 \quad \varepsilon_a = 1.24 \times \left(\frac{e_a}{T_a} \right)^{\frac{1}{7}} \quad (11)$$

$$278 \quad \text{with} \quad e_a = e_s(T_a) \times \frac{rh_a}{100}$$

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

$$280 \quad G = \Gamma \cdot R_{n,s} \quad (12)$$

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

$$282 \quad R_{n,s} = R_n \times (1 - Fc) \quad (13)$$

283 with Fc being the fraction vegetation cover calculated as:

$$284 \quad Fc = \left(\frac{NDVI - NDVI_s}{NDVI_V - NDVI_s} \right) \quad (14)$$

285 The sensible heat flux is given by:

$$286 \quad H = \rho c_p \beta \frac{LST - T_a}{r_{a,h}} \quad (15)$$

287 where β is the “ β function” calculated as follows as a function of LAI:

$$288 \quad \beta = 1 - \frac{a}{LAI * b * \sqrt{2\pi}} e^{-\frac{(\ln(LAI) - c)^2}{2 * b^2}} \quad (16)$$

289 with a , b and c are empirical coefficients equal to 0.17 for a and 0.8 for b and c ([Boulet et al.,](#)
 290 [2012](#)). These values are calibrated for the wheat in the same study site.

291 The latent heat flux is estimated using the following equation:

$$292 \quad LE = \frac{\rho c_p}{\gamma} \frac{e_s - e_a}{r_{a,h} + r_c} \quad (17)$$

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

$$295 \quad \mathbf{F(LST)} = (\mathbf{Rn} - \mathbf{G} - \mathbf{H} - \mathbf{LE})^2 \quad (18)$$

296 F (LST) is named “cost function” as it is the function to be minimised in order to find the LST
297 value corresponding to the energy balance closure (e.g. [Merlin et al., 2016](#)).

298 3. RESULTS AND DISCUSSIONS

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

308 3.1 In situ evaluation of the proposed approach

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

322 The obtained value of r_{cmin} is in agreement with values obtained for wheat crop by [Baldocchi](#)
323 [\(1994\)](#). When SI increases above a threshold value $SI = 0.4$, r_c increases linearly with SI. This
324 confirms the results reported by [Autovino et al. \(2016\)](#) and [Er-Raki et al. \(2016\)](#) who found a

325 similar shape for olive and orange orchards, respectively. The obtained relationship, which gives
326 the best fit between both terms, is given by:

$$\begin{aligned} 327 \quad r_c &= r_{cmin} = 70 \text{ s.m}^{-1} && \text{for } SI < 0.4 \\ 328 \quad r_c &= d * SI + e && \text{for } SI \geq 0.4 \end{aligned} \quad (19)$$

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

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

343 3.2 Spatial analysis

344 To overcome the spatial representativeness issue of *in situ* measurements and for further
345 evaluating the proposed model, Landsat data are used as input of the modified PM model. ET
346 estimates are spatialized within a $10 \times 10 \text{ km}^2$ area centred over the R3 sector which is mainly
347 covered by wheat crops. The R3 perimeter is occupied by different cultures (wheat, alfalfa,
348 orange, and olive), so before spatializing the ET, a land use has been performed in order to
349 distinguish between wheat and other crops. Figure 7 shows the spatial and temporal variations of
350 Landsat-derived LST and F_c over wheat crops. As the entire growing season of wheat was divided
351 into four growth stages namely: the initial, the development, the mid-season and the late season,
352 we choose to present one image for each stage (Figure 7). This figure shows that during the initial
353 stage (06/01/2016), most of the fields were under bare soil conditions characterised by low F_c and
354 high LST values depending spatially on the water supply and atmospheric conditions. In the

355 development stage (07/02/2016) an effective full cover is reached in some parcels while other
356 ones are characterized by low Fc depending on the sowing date and the development of
357 vegetation. This spatial variability of Fc has a direct effect on the variability of LST. When Fc
358 reaches the maximum value at the mid-season (18/03/2016), spatial LST values are similar around
359 20 °C except for some pixels where the LST values are relatively higher (about 35 °C), which
360 correspond to the non-cultivated parcels. At the last stage (29/05/2016), from the beginning of
361 maturity until harvest or full senescence, wheat fields are characterized by low Fc and high LST
362 values.

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

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

381 In Figure 9, the pixels having a SI value close to 1 (red colour) are characterised by a high
382 vegetation stress due to the mismatch between water supply and water requirement (late
383 irrigation). The values of SI ranging between 0.3 and 0.6 are characterised by the onset of
384 vegetation stress. This is due to the difficulty of the irrigation distribution at the right moment.
385 Indeed, the water transported by gravity across the R3 channels may arrive to the fields before or
386 after the optimal date ([Belaqziz et al., 2013](#); [Belaqziz et al., 2014](#)). Pixels with SI values around 0

387 correspond to un-stressed, meaning recently irrigated wheat. Following the evolution of SI, it
388 appears that this index shows spatial and quantitative information about the method of irrigation
389 distribution, and could be used to optimise the irrigation scheduling. Those results are consistent
390 with the work of [Belaqziz et al. \(2013\)](#), who used another index named “Irrigated Priority Index
391 (IPI)” in the same study area to manage the irrigation distribution. The IPI equation is mainly
392 based on both the water stress level and irrigation dates of wheat crop. The main drawback of IPI
393 is that it needs the amount of water supply as input, which is not the case of SI developed. This
394 new index based on LST only might then be combined with IPI in order to detect and retrieve
395 irrigation amount, information that is very difficult to obtain over large areas.

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

399 The spatial representation allowed to distinguish between the fields corresponding to stressed
400 wheat (blue colour) where LE is lower and the field corresponding to un-stressed fields (other
401 colour) that have been relatively well irrigated during the wheat growing stages, for high ET
402 values. The obtained spatial and temporal variations of ET are in accordance with the spatio-
403 temporal variability of Fc, LST and SI (see Figures 7, 9). To observe this more easily, the
404 frequency histograms for remote sensing data (Fc, LST), SI and ET on one date 18/03/2016 are
405 plotted in Figure 11. The choice of this date relies on the fact that the end of March summarises
406 the history of wheat crop growth and its development from sowing date ([Karrou., 2003](#); [Hadria.,
407 2006](#)). By analysing the different histograms, one can be concluded that the estimates LE are
408 coherent with other surface properties (Fc, LST, and SI). Fc values in the higher range (larger
409 than 0.8) have a high frequency/percentage. They correspond to the fields with low LST values
410 (lower than 25 °C), which are associated to small values of surface aerodynamic resistance (large
411 crop height) rather than to large water availability for wheat. On this date, our model computes a
412 large amount of un-stressed areas with relatively small SI and large LE values. Those results
413 seem to be representative of the real situation.

414 The land surface parameters (LST, Fc, and emissivity) are obtained from Landsat data. Therefore
415 all cloudy data (images) are discarded. In addition, the Landsat-7 images include data gaps due to
416 scan line corrector (SLC) failure on May 31 2013, which on some dates unfortunately covered the
417 irrigated sites. The selected data are used for validating the predicted ET (Equation 4) against *in*
418 *situ* ET for both flood and drip sites (Figure 12). As it can be observed in this figure, the proposed

419 approach allows to predict correctly the temporal dynamics of ET with an acceptable accuracy and
420 a good correlation. The validations for the two sites resulted in R^2 of 0.76, 0.70 and a RMSE of
421 12, 13 $W m^{-2}$ for flood-irrigated site and drip-irrigated site, respectively.

422 A further validation of the proposed approach was performed by comparing the measured ET
423 with the ET simulated one under fully stressed ($SI=1$, $r_c = 1870 s m^{-1}$) and un-stressed ($SI=0$, r_c
424 $=70 s m^{-1}$) conditions. The obtained results are presented in the same Figure 12 under real
425 meteorological conditions. As expected, the model simulates very low values of ET for $SI=1$
426 whereas it simulates high values of ET for $SI=0$. On some dates, the ET simulations with $SI=0$
427 ($r_c = 70 s m^{-1}$) coincides with the ET estimated from Landsat-derived SI, which means that the
428 fields were monitored in well-watered conditions ($SI < 0.4$). One key result is that the Landsat-
429 derived SI ($0 < SI < 1$, $70 < r_c < 1870 s m^{-1}$) provides much more accurate ET estimates over both
430 validation sites than when assuming fully stressed ($SI = 1$, $r_c = 1870 s m^{-1}$) or fully unstressed
431 ($SI=0$, $r_c = 70 s m^{-1}$) condition in the PM equation.

432 4. CONCLUSION

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

441 The approach was tested over a $10 \times 10 km^2$ irrigated perimeter R3. The calibration/validation
442 strategy implements two instrumented wheat sites with flood and drip irrigation and Landsat
443 shortwave and thermal imagery during one growing season (2015-2016). The r_c retrieved from
444 eddy covariance measurements over the flood-irrigated site (by inverting PM equation) was first
445 correlated to SI. This relation was then tested over the drip-irrigated site using *in situ*
446 measurements in order to simulate the surface ET. Next, this method was evaluated in terms of
447 latent heat flux using Landsat temperature and reflectance data over both sites. The RMSE values

448 over drip and flood sites are 13 and 12 W m⁻², which correspond to the relative errors of 5 and
449 4%, respectively.

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

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