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1 Calibrating an evapotranspiration model using radiometric surface temperature, 2 vegetation cover fraction and near-surface soil moisture data 3

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11 Key Points:

- 12
- 13 • TSEB model is enhanced to TSEB-SM model by using surface biophysical
14 characteristics
- 15 • Calibration method is developed to retrieve parameters affecting evapotranspiration
- 16 • The performance of TSEB and TSEB-SM models is evaluated over irrigated wheat
17 fields
- 18 • The Priestley-Taylor coefficient is found to vary in time as a function of soil moisture
19

22 Abstract

23 An accurate representation of the partitioning between soil evaporation and plant transpiration
24 is an asset for modeling crop evapotranspiration (ET) along the agricultural season. The Two-
25 Surface energy Balance (TSEB) model operates the ET partitioning by using the land surface
26 temperature (LST), vegetation cover fraction (f_c), and the Priestley Taylor (PT) assumption
27 that relates transpiration to net radiation via a fixed PT coefficient (α_{PT}). To help constrain the
28 evaporation/transpiration partition of TSEB, a new model (named TSEB-SM) is developed by
29 using, in addition to LST and f_c data, the near-surface soil moisture (SM) as an extra constraint
30 on soil evaporation. An innovative calibration procedure is proposed to retrieve three key
31 parameters: α_{PT} and the parameters (a_{RSS} and b_{RSS}) of a soil resistance formulation. Specifically,
32 a_{RSS} and b_{RSS} are retrieved at the seasonal time scale from SM and LST data with $f_c < 0.5$, while
33 α_{PT} is retrieved at the daily time scale from SM and LST data for $f_c > 0.5$. The new ET model
34 named TSEB-SM is tested over 1 flood- and 2 drip-irrigated wheat fields using in situ data
35 collected during two field experiments in 2002-2003 and 2016-2017. The calibration algorithm
36 is found to be remarkably stable as α_{PT} , a_{RSS} and b_{RSS} parameters converge rapidly in few (2-3)
37 iterations. Retrieved values of α_{PT} , a_{RSS} and b_{RSS} are in the range 0.0-1.4, 5.7-9.5, and 1.4-6.9,
38 respectively. Calibrated daily α_{PT} mainly follows the phenology of winter wheat crop with a
39 maximum value coincident with the full development of green biomass and a minimum value
40 reached at harvest. The temporal variations of α_{PT} before senescence are attributed to the
41 dynamics of both root-zone soil moisture and the amount of green biomass (vegetation water

42 content). Moreover, the overall (for the three sites) root mean square difference between the
43 ET simulated by TSEB-SM and eddy-covariance measurements is 67 W m^{-2} (24% relative
44 error), compared to 108 W m^{-2} (38% relative error) for the original version of TSEB using
45 default parameterization ($\alpha_{\text{PT}} = 1.26$). Such a calibration strategy has great potential for
46 applications at multiple scales using remote sensing data including thermal-derived LST, solar
47 reflectance-derived f_c and microwave-derived SM.

48 **1 Introduction**

49 A large variety of evapotranspiration (ET) models and measurements have been reported
50 in the literature (Allen et al., 2011). However, ET estimation over extended areas including
51 different biomes and climates is still subject to significant uncertainties (Pereira et al., 2004;
52 Ershadi et al., 2014). Although the main drivers of ET, such as atmospheric evaporative
53 demand, vegetation type, development stages and health, surface biophysical characteristics
54 and soil water availability (e.g. Federer et al., 2003), are now well identified, one major
55 difficulty in modeling this process lies in a lack of relevant input data available at the desired
56 space and time scales (Allen et al., 2011; Pereira et al., 2014). The accuracy of ET estimates at
57 a given scale thus currently represents a trade-off between model complexity and realism,
58 which is usually related to i) the number of model parameters and forcing variables and ii) the
59 availability of data that generally decreases with the spatial extent (Allen et al., 2011;
60 Gharsallah et al., 2014).

61 Regarding data availability over large areas and at multiple scales, remote sensing observations
62 provide very relevant information to feed ET models such as vegetation indices, land surface
63 temperature (LST) and near-surface soil moisture (SM). Especially, SM is one of the main
64 controlling factors of soil evaporation (e.g. Chanzy et al. 1993), vegetation cover fraction (f_c)
65 provides an essential structural constraint on evaporation/transpiration partitioning (e.g. Allen
66 et al. 2000) and LST is a signature of available energy and evapotranspiration (e.g. Norman et
67 al. 1995). For this reason, efforts have been made to integrate those data as additional and
68 complementary information on ET (e.g. Price et al., 1990). Through its link with ET under
69 moisture-limited conditions, LST has been extensively used to retrieve ET at a wide range of
70 spatial resolutions (Kalma et al., 2008). LST-based ET retrieval methods are generally
71 classified in two categories. The first one is the so-called “residual” method, which estimates
72 latent heat flux as a residual term of the surface energy balance (e.g. Norman et al., 1995; Su,
73 2002). The second one is named the “contextual” method based on the interpretation of the
74 LST versus vegetation index feature space (e.g. Moran et al., 1994 ; Long and Singh, 2012),
75 the interpretation of the LST versus albedo feature space (e.g. Roerink et al., 2000), or the
76 interpretation of both spaces (Merlin 2013; Merlin et al., 2014). The use of SM data, Jung et
77 al. (2010) related the global ET trend to the SM trend derived from TRMM (Tropical Rainfall
78 Monitoring Mission) microwave data. At regional scale, ET was found to have a correlation of
79 about 0.5 with the SM derived from airborne L-band data and a correlation even larger for f_c
80 values lower than 0.5 (Bindlish et al., 2001; Diarra et al., 2017). This was the basis for
81 developing ET models based on microwave-derived SM data (Kustas et al., 1998; Bindlish et
82 al., 2001; Kustas et al., 2003; Li et al., 2006; Gokmen et al., 2012; Li et al., 2015).

83 Among a wide panel of existing ET models, the Priestley Taylor (PT) assumption that
84 empirically relates ET to net radiation (Priestley and Taylor 1972) has shown a growing interest
85 (Norman et al., 1995, Kustas and Norman 1999, Li et al., 2005, Anderson et al., 2007, Fisher
86 et al., 2008, Agam et al., 2010, Jin et al., 2011, Yao et al., 2015, Ai et al., 2016). PT coefficient
87 noted α_{PT} directly relates latent heat flux to the energy available at the surface. Since neglecting
88 the aerodynamic resistance term included in the full Penman-Monteith equation (Monteith
89 1965), the PT formulation is relatively simple, requires less input data and has proven to be

90 remarkably accurate and robust for estimating potential ET in a wide range of conditions
91 (Fisher et al., 2008). It is therefore well suited for operational (McAneney et al., 1996) and
92 large scale (Anderson et al., 2008) applications. In addition, recent studies based on in situ
93 global data sets have reported a good robustness of the PT modeling approach over a variety
94 of biomes (Ershadi et al., 2014). Nevertheless, various theoretical (e.g. De Bruin, 1983) and
95 experimental (e.g. Fisher et al., 2008) studies have stressed that the PT coefficient is variable
96 under different surface and atmospheric conditions. In a literature review, the factors that
97 influence the variability of α_{PT} are: leaf area index (Fisher et al., 2008; Jin et al., 2011; Ai and
98 Yang, 2016), the green fraction of canopy (Norman et al., 1995; Fisher et al., 2008), soil water
99 availability (Davies and Allen, 1973; Mukammal and Neumann 1977; De Bruin, 1983;
100 Eichinger et al., 1996; Fisher et al., 2008; Jin et al., 2011; Perez et al., 2017; Yao et al., 2017),
101 vapor pressure deficit or advective conditions (Jury and Tanner, 1975; Kustas et al., 2000;
102 Agam et al., 2010; Colaizzi et al., 2014), wind speed (Mukammal and Neumann, 1977), air
103 temperature (Ai and Yang, 2016), air relative humidity (Er-Raki et al., 2010), plant temperature
104 (Fisher et al., 2008), surface sensible heat flux (Pereira and Nova 1992) and mulch fraction (Ai
105 and Yang, 2016). As a result of changes in the above ecophysiological and environmental
106 constraints, α_{PT} commonly varies in the range 0.5-2.0 with an average value estimated around
107 1.3 (above references).

108 Data available from space can help in implementing the PT approach from three distinct
109 perspectives: i) applying a constraint on vegetation transpiration using an a priori value for α_{PT}
110 (Norman et al., 1995; Kustas et al., 1999; Anderson et al., 2008), ii) applying a constraint on
111 soil evaporation using SM data (Bindlish et al., 2001; Yao et al., 2017), or iii) retrieving the
112 PT coefficient from vegetation indices (Fisher et al., 2008; Jin et al., 2011; Yao et al., 2015;
113 Yao et al., 2017) or from an interpretation of the LST-vegetation index feature space (Jiang
114 and Islam, 2001; Wang et al., 2006; Perez et al., 2017). While LST, vegetation indices and SM
115 are alternatively used by satellite-based PT approaches, few studies have combined all three
116 data types. In fact, most studies have compared LST-based versus SM-based ET models
117 separately (Kustas et al., 1998; Kustas et al., 2003; Li et al., 2006; Gokmen et al., 2012). Given
118 that SM controls the soil temperature (via the soil evaporation) and that LST integrates both
119 soil and vegetation temperatures, the main issue to integrate simultaneously SM and LST into
120 an unique model is to ensure a robust convergence of soil/vegetation temperatures (Kustas et
121 al., 2003; Li et al., 2006) and associated evaporation/transpiration fluxes. The recent studies of
122 Li et al.(2015) and Song et al.(2016) combined LST and SM to better constrain ET but both
123 approaches relied on a priori reduction coefficients of potential ET. Reduction coefficients of
124 potential ET are equivalent to the soil evaporative efficiency (defined as the ratio of actual to
125 potential evaporation, e.g. Merlin et al., 2016) and to the vegetation stress functions (defined
126 as the ratio of actual to potential transpiration, e.g. Hain et al., 2009) for the soil and vegetation
127 component, respectively. The point is there is no universal parameterization of both soil
128 evaporation efficiency and vegetation stress functions. Alternatively, Sun et al. (2012)
129 proposed an innovative assimilation method to calibrate the parameters of a SVAT (Soil
130 Vegetation Atmosphere Transfer) model from available remote sensing variables including
131 LST and SM. Assimilation results improved ET estimates but the retrieved parameters were
132 mostly conceptual due to the simplicity of the surface model used.

133 In this context, the objective of this paper is: (i) the modification of the PT-based TSEB
134 formalism (Norman et al., 1995; Kustas et al., 1999) to integrate LST and SM in situ data
135 simultaneously (the modified version is named TSEB-SM), and (ii) the development of a
136 calibration procedure of TSEB-SM to retrieve the main parameters of soil evaporation (soil
137 resistance) and plant transpiration (α_{PT}). The approach is tested over three irrigated wheat crops
138 in the Tensift basin, central Morocco. In each case, the calibration procedure is tested and the

139 TSEB-SM latent and sensible heat fluxes are evaluated and compared against the original
140 TSEB simulations.

141 **2 Methods**

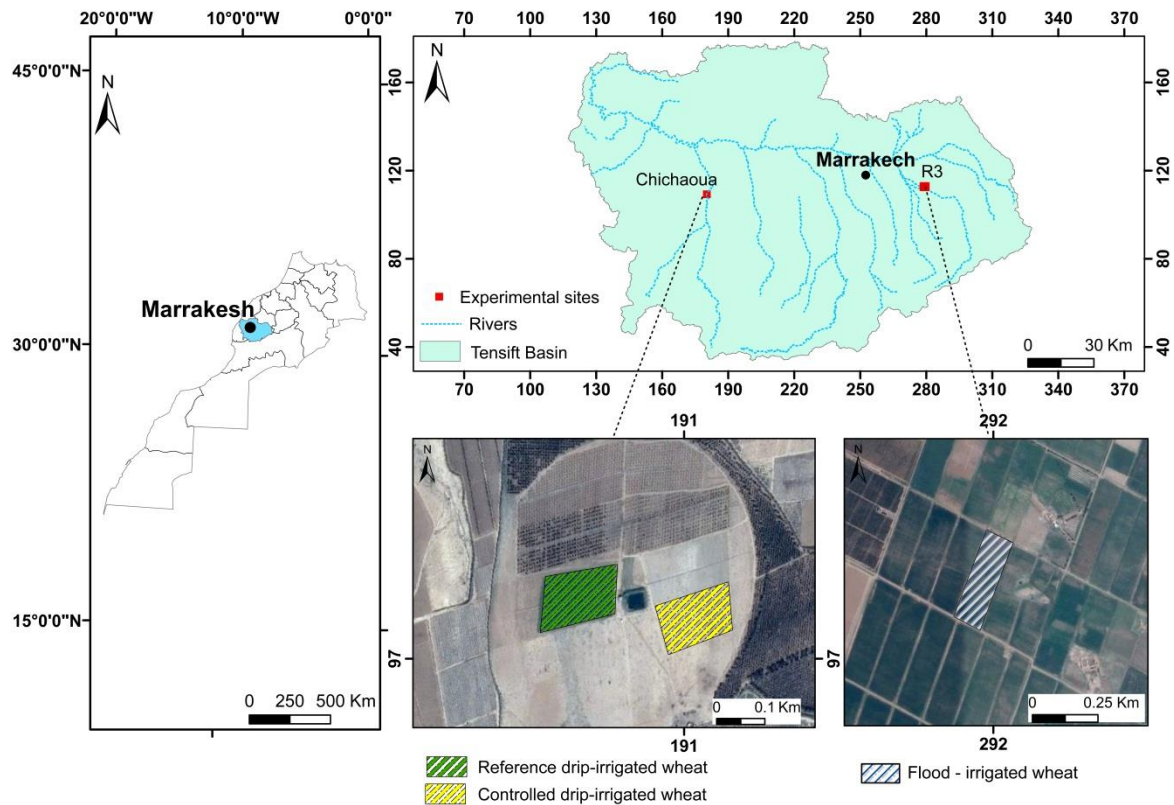
142 2.1 Data

143 2.1.1 Sites description

144 The study sites are located in irrigated agricultural areas east (R3 perimeter) and west
145 (Chichaoua area) of Marrakech city in the Tensift basin, central Morocco (see Figure 1). The
146 climate in the region is semi-arid, with an average yearly precipitation in the order of 250 mm,
147 of which approximately 75% falls during the winter and spring (November-April). The average
148 humidity of the atmosphere is 50% and the reference crop ET is estimated as 1600 mm per year
149 (Allen et al., 1998), greatly exceeding the annual rainfall.

150 Two data sets are used herein. The first data set was collected from December 2002 to May
151 2003 over a wheat crop in the R3 zone. The second one was collected from November 2016 to
152 May 2017 over two wheat crops near Chichaoua. Those experiments were carried out to
153 monitor the energy and water balance as well as the soil and vegetation characteristics and
154 conditions during the entire wheat growing cycle. The R3 crop field is 4 ha and is irrigated
155 through periodic (approximately every 3 weeks) flooding with a mean quantity of 30 mm
156 regardless of precipitation. Both Chichaoua crop fields are 1.5 ha and are irrigated by drip
157 technique. During the 2016-17 experiment, one (reference) field was irrigated according to the
158 crop water needs estimated by the FAO method every 3 to 4 days until mid-April while the
159 other (controlled) field was irrigated exactly the same way except during controlled stress
160 periods when irrigation was cut. The mean irrigation quantity was about 15 mm for both crop
161 fields, whereas the total water supply by drip irrigation was 374 and 504 mm for the controlled
162 and reference field, respectively.

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Figure 1. Location of the three study sites including a flood-irrigated wheat crop in the R3 zone (east of Marrakech) and two (controlled and reference) drip-irrigated wheat crops near Chichaoua city (west of Marrakech) in the Tensift basin, central Morocco. (Flat area)

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170 2.1.2 Surface fluxes

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An eddy covariance (EC) tower was installed over each field to measure the latent (LE) heat and sensible (H) heat fluxes at a 2-m height. EC systems included a CSAT3 3D sonic anemometer (Campbell scientific Ltd, Logan USA) over the three sites, a LICOR-7500 open-path infrared gas analyzer (Campbell scientific Ltd, Logan USA) installed over the R3 site and a KH20 Krypton hygrometer (Campbell Scientific Ltd, Logan USA) installed over both Chichaoua sites. The half-hourly fluxes were calculated off-line using the EC processing software ‘ECpack’, after performing all required corrections for planar fit correction, humidity and oxygen (KH20), frequency response for slow apparatus, and path length integration (Van Dijk et al., 2004). EC towers were also equipped with Kipp and Zonen CNR radiometers to measure net radiation (R_n) and heat flux plates (Campbell Scientific Ltd, Logan USA) to measure the soil heat flux (G). Analysis of the energy balance closure showed that the sum of latent and sensible heat flux measured independently by the EC systems was often lower than the available energy (R_n-G). The relative closure was satisfied by about 88%, 64% and 70% (of available energy) for the R3, controlled and reference sites, respectively. This problem could not be explained neither by the mismatch in the spatial extent of flux measurements, nor by the uncertainties associated with the measurements of soil heat flux and net radiation (Twine et al., 2000, Ezzahar et al. 2009, Hoedjes 2008). Correction was hence performed using the approach suggested by Twine et al. (2000). The energy budget closure was forced at the 30 min time step using the daily Bowen ratio (called $\beta = H/LE$). Corrected turbulent fluxes were

190 derived as $LE = \frac{\beta}{\beta+1} (Rn - G)$ and $H = \frac{(Rn-G)}{\beta+1}$, with β computed from the 30-min observed
 191 H and LE cumulated between 9 am and 5 pm. The Bowen ratio correction enhanced these
 192 turbulent fluxes by about 21, 39 and 50% for H and 20, 42 and 56% for LE, for R3 zone,
 193 controlled and reference sites, respectively.

194 2.1.3 Land surface temperature, soil moisture and vegetation cover fraction

195 Surface temperature was measured by using an infrared thermometer (IRTS-P) set up at a 2-m
 196 height above ground. Two sensors, oriented downwards, were used in each field. The measured
 197 LST is taken as the arithmetical mean of the two independent measurements.

198 Time Domain Reflectometry (TDR) probes (model CS615, CS655) were installed in a soil pit
 199 near the EC towers to measure soil water content at different soil depths of 5, 10, 20, 30, 50,
 200 100 cm and 5, 15, 25, 35, 50, 80 cm and 5, 15, 30, 50, 80 cm for the flood-, controlled drip-
 201 and reference drip-irrigated wheat, respectively. The TDR technique is based on the
 202 measurement of the soil dielectric constant to estimate its volumetric water content. An
 203 appropriate calibration of the TDR measurement is necessary because several factors as the
 204 electrical conductivity, bulk density and soil texture can affect the soil dielectric constant (Topp
 205 et al., 1980; Regalado et al., 2001; Roth et al., 1992; Tomer et al., 1999; Weitz et al., 1997).
 206 The field volumetric moisture content was determined using the gravimetric method; three
 207 samples were collected at installation depth of each TDR probe using a 392.5 cm³ aluminum
 208 core. A linear regression was established between the volumetric water content and the square
 209 root of the TDR time response (τ in s) ($SM = a_{TDR} * \sqrt{\tau} + b_{TDR}$).

210 The vegetation cover fraction -defined as the vegetated surface area projected on the ground at
 211 nadir, per soil surface area unit- was measured routinely within each field using a digital
 212 photography-based method. Hemispherical photographs were taken at various representative
 213 points of the field using a Nikon CoolPix camera equipped with a fisheye lens. This method
 214 binarizes digital photos, in vegetation and soil, based on thresholds in the green and red bands
 215 (Khabba et al., 2009).
 216

217 2.2 Models and calibration strategies

218 In this section, the main equations of the original version of TSEB model (Norman et al.,
 219 1995; Kustas et al., 1999) are briefly reproduced and the new TSEB-SM model is fully
 220 described. Note that the main difference between the two models concerns the treatment of soil
 221 evaporation, which is either estimated as a residual term for TSEB or explicitly represented
 222 through a soil resistance term for TSEB-SM.
 223

224 2.2.1 Models

225 A. TSEB model

226 The TSEB model was presented and described by Norman et al., (1995), Norman et al.
 227 (2000), Kustas and Norman (1999), Timmermans et al (2007), French et al. (2015) and Colaizzi
 228 et al. (2012). It produces two separate energy balances for the soil and vegetation and estimates
 229 evaporation and transpiration as residual term of the energy balance. Two variables derived
 230 from remote sensing instruments are key inputs for TSEB model: The first is the surface
 231 temperature, which is used to estimate the sensible heat flux and the second is the fraction
 232 cover, which controls the energy partitioning between surface vegetation and soil.

233 The PT coefficient (α_{PT}) is one of the most sensitive parameters of TSEB, because it drives the
 234 vegetation latent heat flux. Most studies conducted with TSEB have used its generic value
 235 around 1.3 (Norman et al., 1995; Kustas and Norman, 1999; Bindlish et al., 2001; Anderson et
 236 al., 2007; Colaizzi et al., 2014). Other studies have identified different values of α_{PT} depending
 237 on the vegetation cover fraction and particular forcing conditions. Notably, the PT coefficient
 238 was found to be smaller for dry surfaces and higher for humid conditions (Eichinger et al.,
 239 1996). Nevertheless the relative stability of α_{PT} in many conditions has led to set α_{PT} constant.
 240 Consistent with this assumption, α_{PT} is set to 1.26 in TSEB (Priestley and Taylor, 1972).

241 B. TSEB-SM model

242 The TSEB formalism is modified to integrate SM as an additional constraint on modeled
 243 ET. In practice, the energy balance for vegetation and soil in TSEB-SM is the same as in TSEB,
 244 but the soil evaporation is now explicitly represented as a function of SM via a soil resistance
 245 term. Note that Song et al. (2016) have recently introduced SM in TSEB using a formulation
 246 of soil evaporative efficiency. While there is partial equivalence between both formulations,
 247 the soil resistance formulation is preferred herein as its parameters can be calibrated either from
 248 soil texture information (Merlin et al., 2016) or from a combination of LST and SM data under
 249 bare soil conditions (Merlin et al., 2017).

250 The soil latent heat flux is estimated as:

$$LE_{soil} = \frac{\rho c_p}{\gamma} \cdot \frac{(e_s - e_a)}{r_{ah} + r_s + r_{ss}} \quad (1)$$

251 where e_s is the saturated vapor pressure at the soil surface, e_a is the air vapor pressure, and r_{ss}
 252 is the resistance to vapor diffusion in the soil. r_{ss} is expressed as follows (Passerat de Silans,
 253 1986) :

$$r_{ss} = \exp(a_{r_{ss}} - b_{r_{ss}} * \frac{SM}{SM_{sat}}) \quad (2)$$

254 with SM being the soil moisture in the 0-5 cm soil layer, $a_{r_{ss}}$ and $b_{r_{ss}}$ are two empirical
 255 parameters and SM_{sat} the soil moisture at saturation expressed as:

$$SM_{sat} = 0.1 * (-108 * f_{sand} + 49.305) \quad (3)$$

256 with f_{sand} is the percentage of sand in the soil.

257 The flowchart of Figure 2 summarizes the different steps followed to resolve the energy balance
 258 in TSEB-SM model. The algorithm is based on an iterative procedure that loops on the Monin-
 259 Obukhov length (MO length), which is a scale parameter that characterizes the degree of
 260 instability or stability of the boundary layer. MO length is approximately the height at which
 261 aerodynamic shear, or mechanical energy, is equal to the buoyancy energy. In practice, MO
 262 length is used as correction factor to determine the aerodynamic resistance r_{ah} . First, the
 263 algorithm starts by initializing the soil and vegetation temperatures, as well as sensible and
 264 latent heat fluxes. Then it calculates the available energy for the soil-vegetation-atmosphere
 265 interface by estimating the surface net radiation and its partition between the vegetation and
 266 the soil, as well as the soil heat flux. The way soil and vegetation temperatures are estimated is
 267 in fact a specificity of the new model, which is based on the explicit resolution of the energy
 268 balance for soil and vegetation respectively. Component temperatures are obtained by
 269 minimizing cost functions F_{soil} and F_{veg} :

$$F_{soil,k} = (R_{n,soil,k} - H_{soil,k} - LE_{soil,k} - G_k)^2 \quad (4)$$

270

$$F_{\text{veg},k} = (R_{\text{n,veg},k} - H_{\text{veg},k} - LE_{\text{veg},k})^2 \quad (5)$$

271 with k being a loop index. By using the formula of the Newton method:

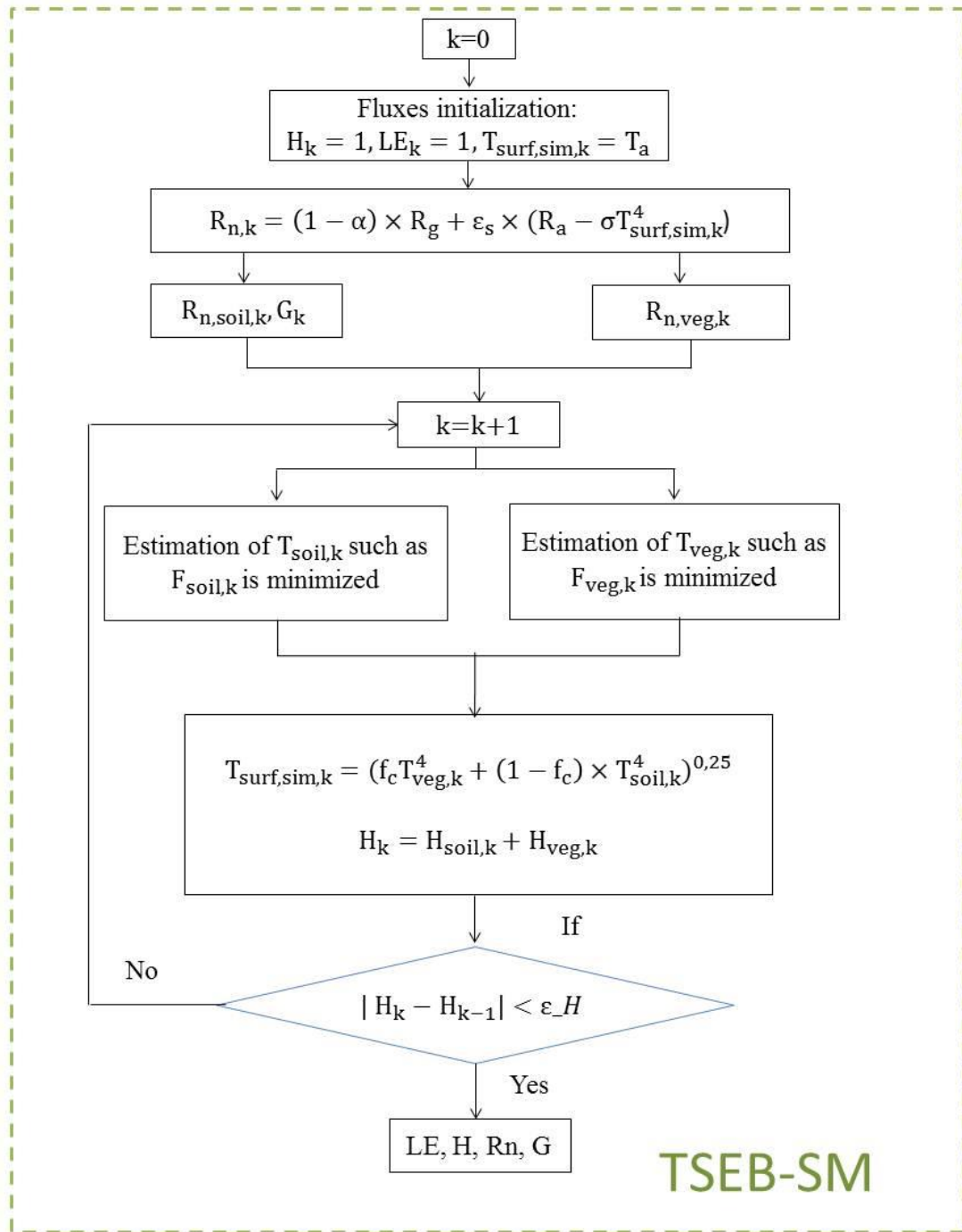
$$T_{\text{soil},k+1} = T_{\text{soil},k} - \frac{F_{\text{soil},k}}{dF_{\text{soil},k}} \quad (6)$$

$$T_{\text{veg},k+1} = T_{\text{veg},k} - \frac{F_{\text{veg},k}}{dF_{\text{veg},k}} \quad (7)$$

273 where dF_{soil} and dF_{veg} are the first derivative of the cost function for soil and vegetation,
274 respectively.

275 At the end of each iteration, the simulated LST (noted $T_{\text{surf},\text{sim}}$ Figure 2) and heat fluxes are
276 used to recalculate the MO length iteratively. The iterative procedure is repeated until MO
277 length (and H) converges, meaning that the difference between two successive values is smaller
278 than a given threshold (numerical uncertainty).

279



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Figure 2. Schematic diagram of TSEB-SM model.

282

283 2.2.2 Calibration strategies

284 The calibration approach of TSEB-SM is presented below. In this case, the calibration
285 strategy is tightly coupled to the model formalism and the availability of input data (LST in the
286 former case and both LST and SM in the latter).

287 C. TSEB-SM

288 The calibration procedure of TSEB-SM is presented in the schematic diagram of Figure
 289 3. It is done in two steps: the first aims to provide first guess estimates of $a_{r_{ss}}$ and $b_{r_{ss}}$ (named
 290 $a_{r_{ss},FG}$ and $b_{r_{ss},FG}$) as input to the second step that aims to provide the final values of ($a_{r_{ss},cal}$,
 291 $b_{r_{ss},cal}$) and $\alpha_{PT,cal,daily}$.

292 Given that soil evaporation and plant transpiration may compensate each other to result in
 293 similar total ET values, it is important to ensure that the calibration procedure is well defined,
 294 meaning that a unique triplet ($a_{r_{ss}}$, $b_{r_{ss}}$, α_{PT}) is systematically obtained at the desired time scale.
 295 In order to do so, the calibration data set is divided into two regions with specific behaviors: i)
 296 data with $f_c \leq 0.5$ for which ET is mainly controlled by soil evaporation and ii) data with $f_c >$
 297 0.5 for which ET is dominated by plant transpiration. In both data sets, soil evaporation and
 298 plant transpiration may occur simultaneously but the LST over the mixed surface is expected
 299 to be more sensitive to soil evaporation and plant transpiration for $f_c \leq 0.5$ and $f_c > 0.5$,
 300 respectively (Moran et al. 1994; Merlin et al. 2012).

301 The first calibration step initializes $\alpha_{PT}=1.26$ and inverts r_{ss} at each time (30-min) step for data
 302 with $f_c \leq 0.5$. The r_{ss} is first adjusted to minimize the following cost function:

$$F_{inst} = (T_{surf,sim} - T_{surf,mes})^2 \quad (8)$$

303 using the Newton method:

$$r_{ss,k+1} = r_{ss,k} - \frac{F_{instk}}{dF_{instk}} \quad (9)$$

304 where $T_{surf,sim}$ and $T_{surf,mes}$ are the LST simulated by TSEB-SM model and observed over the
 305 crop field at the 30-min time step, respectively. The inverted r_{ss} is then correlated to the
 306 observed SM to estimate $a_{r_{ss}}$ and $b_{r_{ss}}$. In practice, $a_{r_{ss}}$ and $-b_{r_{ss}}/SM_{sat}$ are the intercept and the
 307 slope of the linear regression of the $\ln(r_{ss})$ versus SM relationship (see Equation 2). As the
 308 retrieved pair ($a_{r_{ss}}$, $b_{r_{ss}}$) depends on the α_{PT} value, an iterative loop is run on $a_{r_{ss}}$, $b_{r_{ss}}$ and α_{PT}
 309 until convergence of $a_{r_{ss}}$ and $b_{r_{ss}}$ is achieved. At each iteration, the inverted $a_{r_{ss}}$ and $b_{r_{ss}}$ are used
 310 as input to invert α_{PT} for data with $f_c > 0.5$. The PT Taylor coefficient is adjusted, at the daily
 311 time scale, to minimize the following cost function:

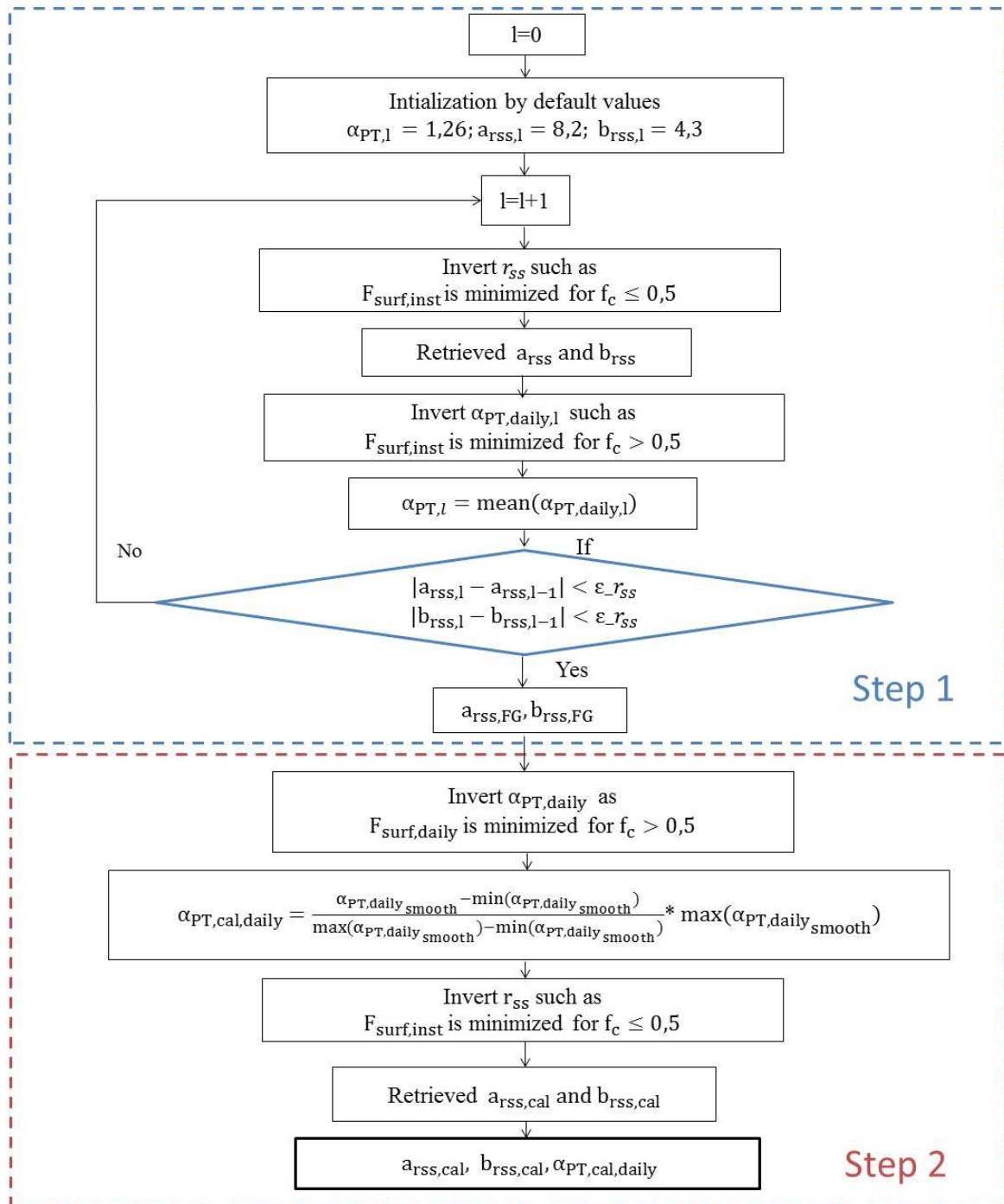
$$F_{daily} = \sum_{i=1}^N (T_{surf,sim,i} - T_{surf,mes,i})^2 \quad (10)$$

312 with N being the number of 30-min LST measurements available for a given day. To keep a
 313 (time) scale consistency between all three retrieved parameters in calibration step 1, the daily
 314 inverted α_{PT} is averaged at the seasonal time scale before being used as input to the following
 315 (next iteration) inversion of $a_{r_{ss}}$ and $b_{r_{ss}}$. To further assess the model's stability, the initial values
 316 of ($a_{r_{ss},k=0}$, $b_{r_{ss},k=0}$) were randomly set to a range of values between 1 and 13 and the results (not
 317 shown) confirmed the robustness of the calibration approach, regardless of the initialization.

318 The second calibration step refines the estimation of α_{PT} at the daily scale. The first guess $a_{r_{ss},FG}$
 319 and $b_{r_{ss},FG}$ obtained in step 1 are first used as input to the retrieval procedure of daily α_{PT} for
 320 data with $f_c > 0.5$ (minimization of F_{daily}). Next, the daily retrieved α_{PT} is smoothed to remove
 321 outliers as well as to reduce random uncertainties in daily retrieved α_{PT} . Then, the smoothed
 322 α_{PT} is normalized between its minimum and maximum values reached during the agricultural
 323 season after having forced the minimum value of smoothed α_{PT} to 0 at harvest so that
 324 transpiration is zero at this time:

$$\alpha_{PT,cal,daily} = \frac{\alpha_{PT,daily,smooth} - \min(\alpha_{PT,daily,smooth})}{\max(\alpha_{PT,daily,smooth}) - \min(\alpha_{PT,daily,smooth})} * \max(\alpha_{PT,daily,smooth}) \quad (11)$$

325 Finally r_{ss} is calibrated a last time to ensure consistency between daily calibrated $\alpha_{PT,cal,daily}$
 326 and final $a_{rss,cal}$ and $b_{rss,cal}$ (see Figure 3).
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328
 329 *Figure 3. Schematic diagram of the two-step calibration strategy of TSEB-SM model.*

331 **3 Results and Discussions**

332 The proposed calibration of r_{ss} and α_{PT} is successively applied to the flood-irrigated (R3),
333 the controlled drip-irrigated (Chichaoua) and the reference drip-irrigated (Chichaoua) wheat
334 sites. The TSEB-SM approach is then assessed in terms of evapotranspiration. In practice, the
335 H and LE simulated at the half hourly time scale (between 11 am and 1:30 pm) by TSEB-SM
336 and by the original TSEB model (using an a priori default value for α_{PT}) are compared against
337 EC measurements at the three experimental sites.

338 5.1 Retrieved parameters

339 Figure 4 plots the iterative values of a_{rss} , b_{rss} and mean α_{PT} during calibration step 1.
340 Iteration 0 corresponds to default values. The convergence of all three parameters is very fast,
341 requiring only 2 or 3 iterations for achieving a relative error better than 1%. This result confirms
342 the appropriateness of separating the calibration range in f_c intervals where one parameter has
343 significantly more weight on simulation results (i.e. simulated LST and associated fluxes) than
344 the others. The calibrated pair (a_{rss} , b_{rss}) is (5.67, 1.40), (6.51, 3.82) and (9.47, 6.87) for the
345 flood-, controlled drip- and reference drip-irrigated field, respectively. The mean retrieved
346 values (7.2, 4.0) are relatively close to those estimated in Sellers et al. (1992) (8.2, 4.3). The
347 variability of a_{rss} and b_{rss} can be explained by numerous factors such as soil texture (Merlin et
348 al., 2016) and meteorological conditions (Merlin et al., 2011). Nevertheless, retrieved
349 parameters are significantly different for both drip sites whereas they i) are located about 200
350 m apart only and ii) have similar soil texture and meteorological conditions. In fact, retrieved
351 a_{rss} is an increasing function of retrieved b_{rss} due to compensation effects between a_{rss} and b_{rss}
352 for a given SM and LST observation pair and regardless of soil properties and meteorological
353 conditions. Such compensation reveals the empirical nature of the r_{ss} formulation in Sellers et
354 al. (1992).

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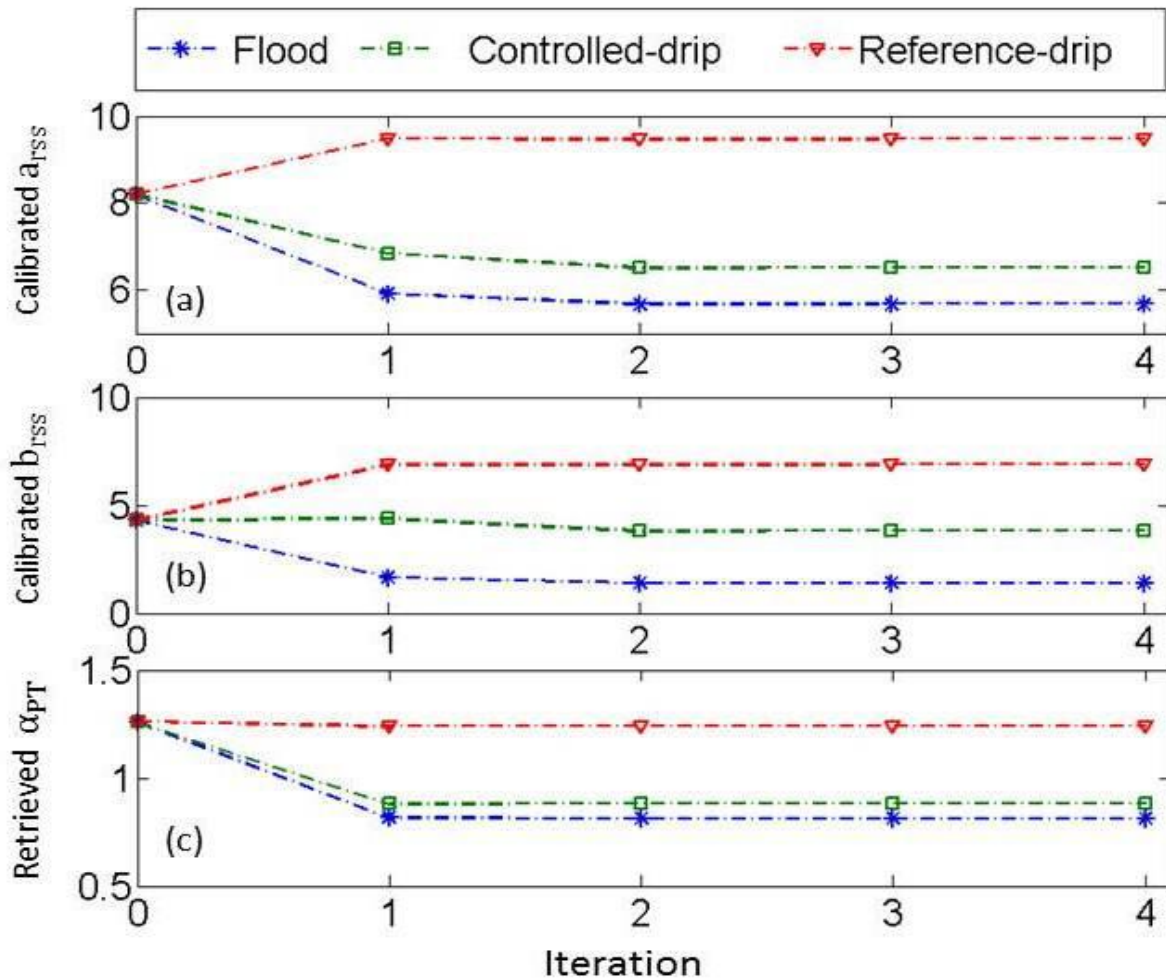


Figure 4. Iterative values of a_{RSS} , (a), b_{RSS} (b) and mean value of retrieved α_{PT} (c) for the flood-, controlled drip- and reference drip-irrigated wheat fields separately (calibration step 1).

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361 The mean value of α_{PT} at the semi-hourly time scale (see Figure 4) is 0.81, 0.88 and 1.24 for
362 the flood-, controlled drip- and reference drip-irrigated wheat fields, respectively. Note that the
363 mean value is very close to the theoretical α_{PT} value for the reference drip-irrigated field case.
364 It is suggested that f_g generally equals 1 at the maximum of α_{PT} (peak of ET), so that the
365 maximum α_{PT} value is directly comparable to its default value (1.26) corresponding to fully
366 unstressed conditions (Priestley and Taylor, 1972). Nonetheless, the mean α_{PT} is significantly
367 smaller than the default value for the flood- and controlled drip-irrigated cases. Lower values
368 can be associated with stress conditions that may have occurred during the crop development.

369 Figure 5 plots the time series of daily retrieved α_{PT} for each site separately. It can be seen that
370 the maximum value of daily α_{PT} varies from field to field. It is estimated as 1.8, 2.10 and 2.82
371 for the flood-, controlled drip- and reference drip-irrigated fields, respectively. It is clearly
372 observed that the values related to drip irrigation are significantly greater than the values related
373 to flood irrigation. This could be explained by the difference in agricultural practices of each
374 field (sowing date, irrigation events, rainfall and fertilization) as well as uncertainties in
375 retrieved α_{PT} . Two effects are likely to explain the highly variable and excessively high
376 retrieved α_{PT} values over the drip irrigated site for the first few daily retrievals. First, it is
377 reminded that α_{PT} is retrieved for $fc > 0.5$. When fc is slightly larger than 0.5 (that is on the first

378 few retrieval days of the season), large uncertainties in retrieved α_{PT} are expected because the
379 soil surface still plays a significant role in the observed LST. Little response is shown for the
380 first two months over the flood irrigation field, because the flux measurements over this site
381 started when wheat was already well developed (f_c significantly larger than 0.5). Second, the
382 R3 site is surrounded by homogeneous irrigated wheat fields while the drip irrigated fields are
383 surrounded by dryland, which potentially reinforces advection effects, leading to enhanced
384 retrieved α_{PT} . Note that the retrieved α_{PT} values above 2 and near 0 are due to the uncertainties
385 in LST-derived daily estimates, especially during the periods when wheat is partially covering
386 the soil.

387 As explained above, a smoothing function is applied to reduce uncertainties in daily α_{PT} . The
388 smoothing length (it is one parameter of the smoothing function) is set to 10% of the total time
389 series, that is about 10-20 days. Such a smoothing procedure is justified by the fact that both
390 biomass and root-zone soil moisture commonly change across the agricultural season with a
391 characteristic time of 1 to 2 weeks (Albergel et al. 2008). Furthermore, Figure 5 clearly shows
392 that the smoothing function removes all outliers while capturing significant patterns at the quasi
393 daily scale. The smoothed α_{PT} ranges from 0.03 to 1.22, 0.17 to 1.26 and 0.61 to 1.38 for the
394 flood-, controlled drip- and reference drip-irrigated wheat, respectively.

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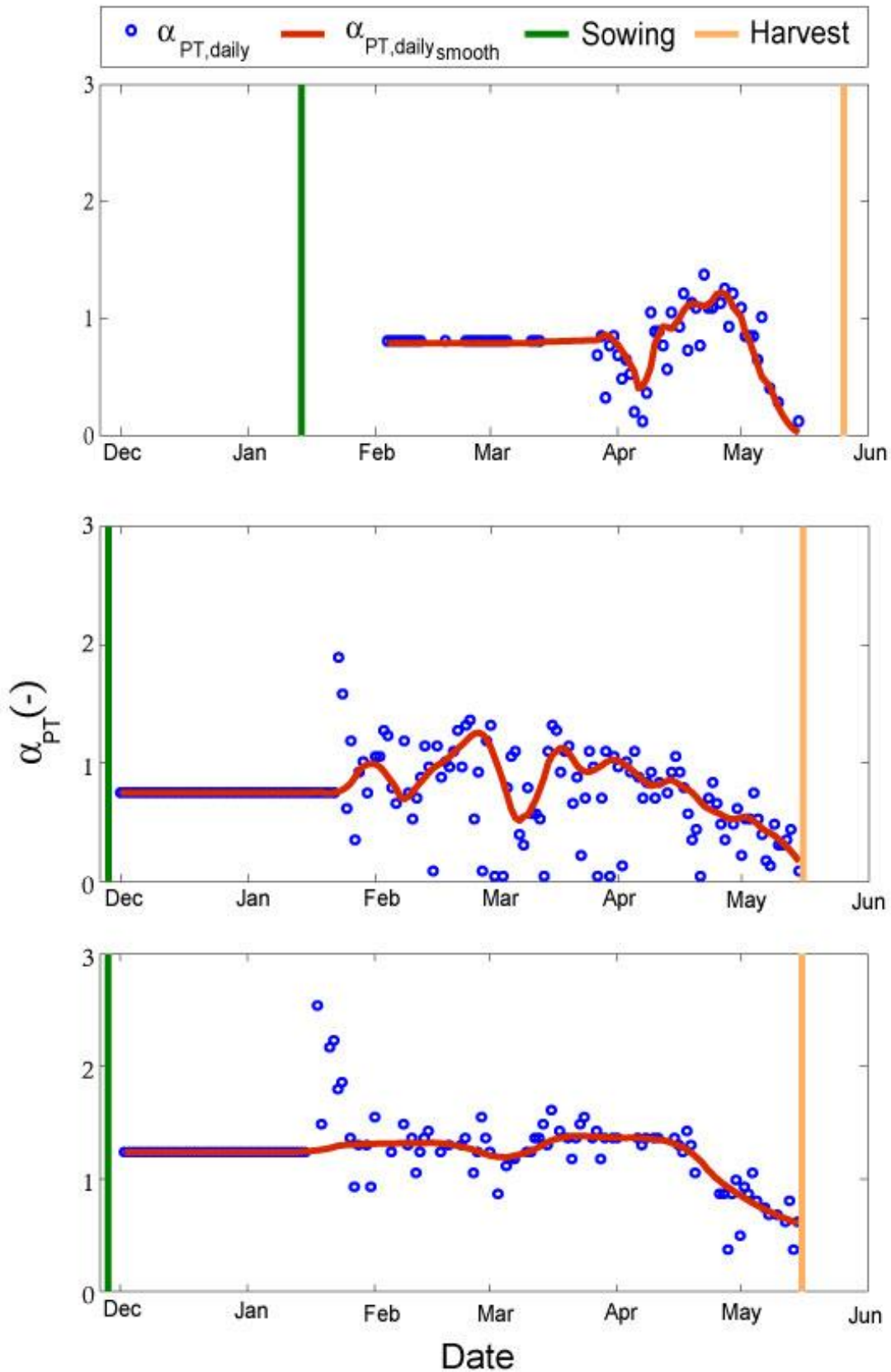
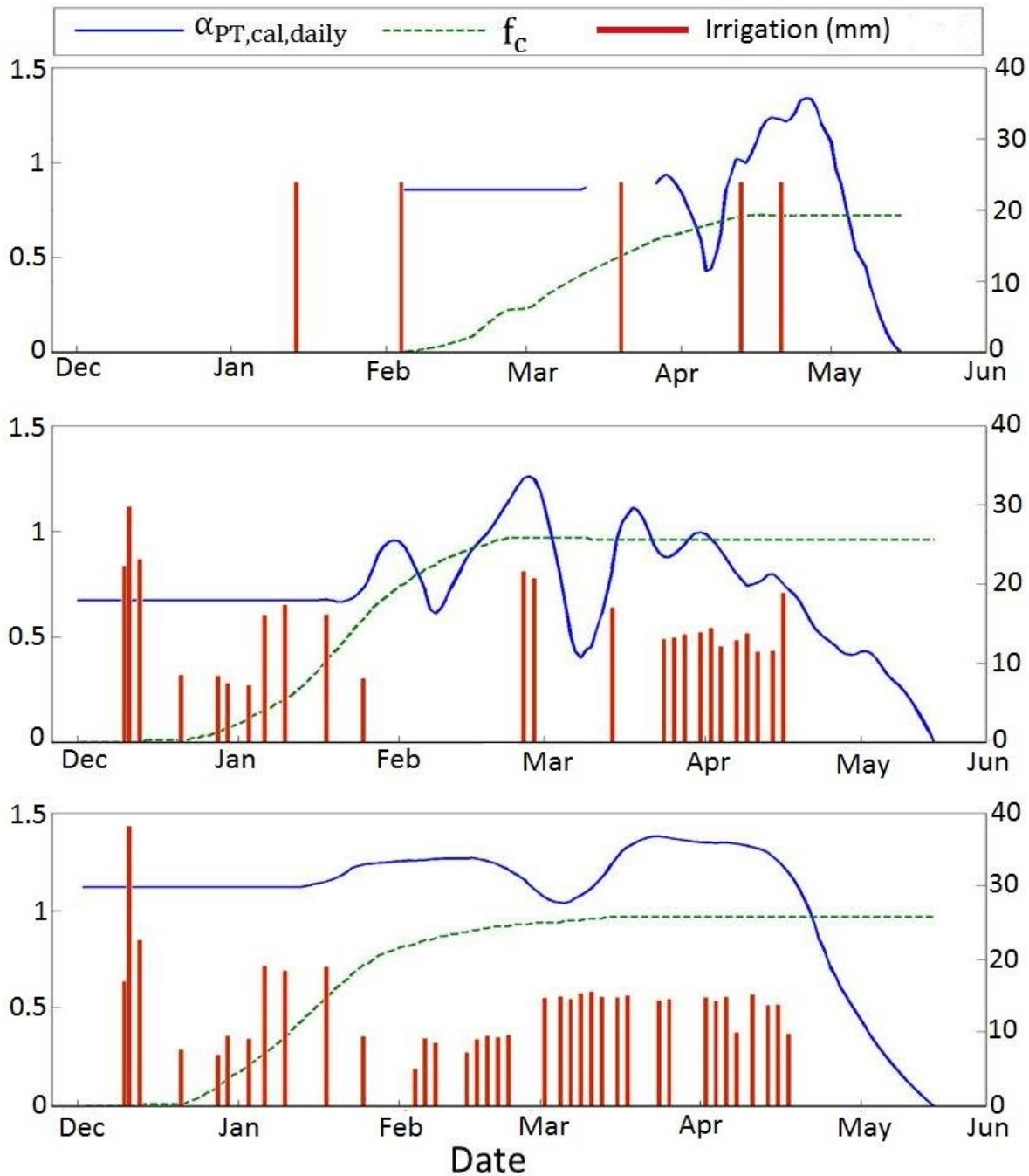


Figure 5. Time series of daily retrieved and smoothed α_{PT} for the (a) flood-, (b) controlled drip- and (c) reference drip-irrigated wheat fields, separately (calibration step 2).

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400 The normalization in Equation (11) of smoothed α_{PT} between its assumed minimum value (0)
401 and smoothed maximum value makes the calibrated daily α_{PT} range from 0 to 1.22, 0 to 1.26
402 and 0 to 1.38 for the flood-, controlled drip- and reference drip-irrigated fields, respectively.
403 Time series of calibrated daily α_{PT} are presented in Figure 6 superimposed with f_c for
404 comparison purposes. The maximum calibrated daily α_{PT} is close to the theoretical value of
405 1.26 in each case. However, its temporal variability is found to be significant even during the
406 growing stage of wheat. Calibrated daily α_{PT} is more stable for the reference drip field than for
407 both flood and controlled drip fields, with a relative change during the growing period of 8.08%
408 compared to 26.94% and 22.66% for the other two fields, respectively. This result is consistent
409 with the fact that the reference drip field had been irrigated according to the water needs
410 estimated by the FAO-56 method while the other two fields (flood and controlled drip) had
411 been under water deficit conditions for one or several periods during the growing stage. Note
412 that the controlled-drip field has a special feature in terms of α_{PT} daily dynamics. The maximum
413 value is reached by the beginning of March, which is much earlier than the α_{PT} peak observed
414 at the reference drip (around late April) and flood (beginning of May) fields, although wheat
415 was sowed on the same date as reference drip field. It is suggested that the controlled drip-
416 irrigated wheat did not recover well from the first (relatively long) stress period from
417 22/02/2017 to 06/03/2017. The irrigation water supplied after mid-March was probably not
418 sufficient for the wheat of controlled drip field to catch up with the reference drip-irrigated
419 wheat, even if the amount of water used for irrigation after this period was approximately the
420 same (about 166 mm).
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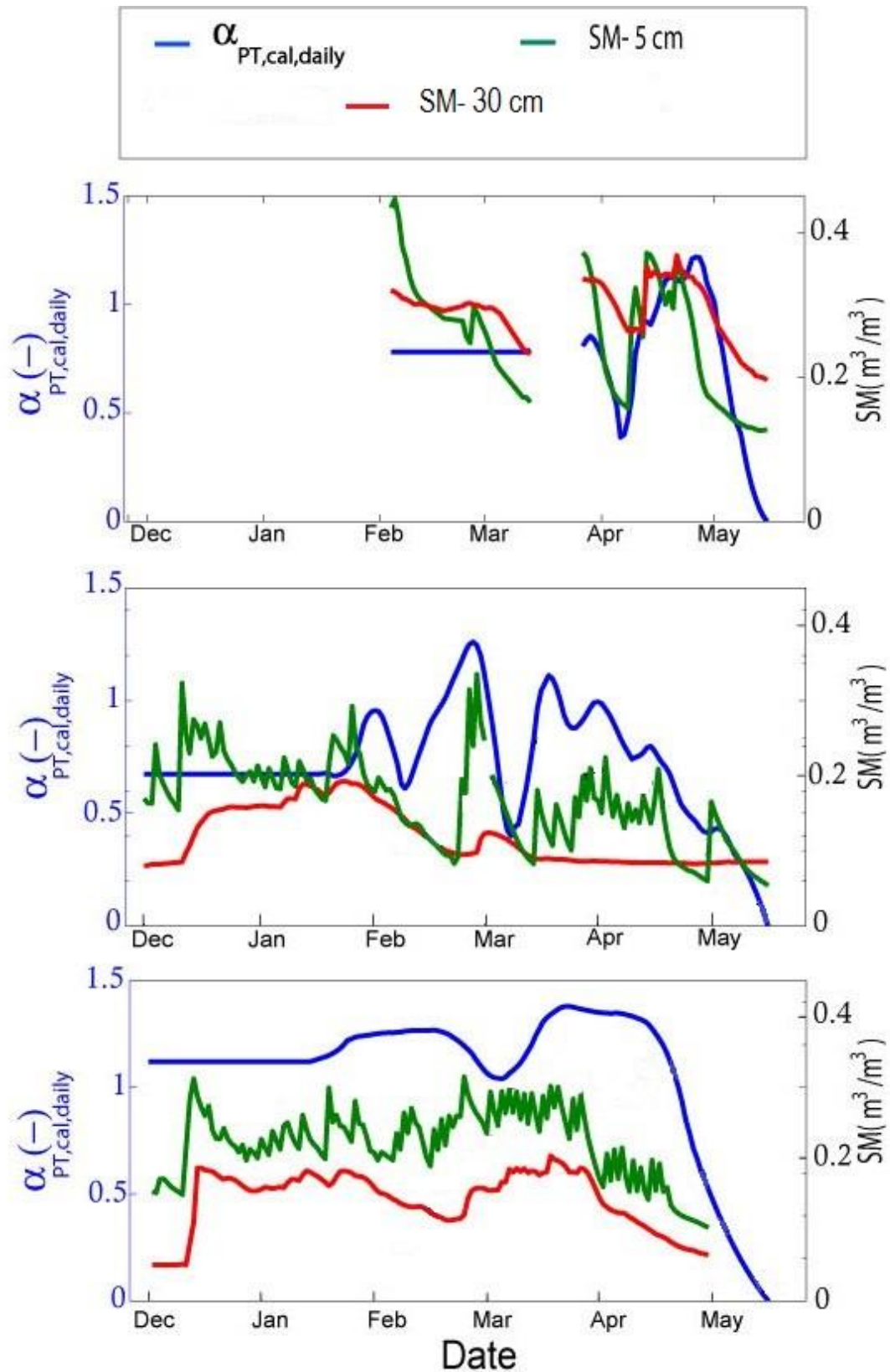
Figure 6. Time series of calibrated daily α_{PT} , superimposed with f_c for the (a) flood-, (b) controlled drip- and (c) reference drip-irrigated wheat fields, separately. The red segments represent irrigations during the season.

425

426 5.2 Interpretation of α_{PT} variabilities

427 α_{PT} is expected to vary according to several factors including LAI, green fraction cover and
 428 soil water availability. In order to verify the consistency of the variations in daily retrieved α_{PT} ,
 429 Figure 7 presents the time series of calibrated daily α_{PT} superimposed with near-surface (5-cm)
 430 soil moisture, deeper (30-cm) soil moisture. It is reminded that the daily α_{PT} for $f_c < 0.5$ is set
 431 to the mean daily α_{PT} obtained for $f_c > 0.5$ (see Figure 6). Therefore, the variability of α_{PT} should
 432 be interpreted for $f_c > 0.5$ only, that is from $f_c = 0.5$ until harvest. Figure 7 illustrates the expected
 433 relationships between α_{PT} and the water availability in the soil column. In each case, the α_{PT}
 434 dynamics are driven by soil moisture variations.

435 The qualitative analysis of α_{PT} variability in relation to soil water availability indicates that α_{PT}
436 cannot be considered as a constant. Large variations in this parameter are likely to occur during
437 the agricultural season, especially under stress conditions. Water deficit may happen with flood
438 irrigation when the frequency of water supplies (every 3 weeks on average over R3) is
439 relatively low compared to the water demand under such semi-arid conditions. Indeed the water
440 stress observed in the flood-irrigated wheat may be attributed to the increase in water depletion
441 at the root zone through a removal of water by transpiration and percolation losses (Er-Raki et
442 al., 2007). Water stress may also happen with drip when the technique is not appropriately
443 implemented or by applying regulated deficit irrigation.
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Figure 7. Time series of $\alpha_{PT,cal,daily}$ superimposed with 5-cm/30-cm soil moisture (SM) for: (a) flood-, (b) controlled drip- and (c) reference drip-irrigated fields, respectively.

448

449 5.3 Surface fluxes

450 The ability of TSEB and TSEB-SM for partitioning the available energy into H and LE
451 is assessed by forcing -in each case- R_n and G to their measured values. Note that the calibration
452 of TSEB-SM is still undertaken using observed LST, SM and f_c whereas the validation of TSEB
453 and TSEB-SM model output is undertaken using EC measurements of H and LE. The metrics
454 used to evaluate results comprise the determination coefficient (R^2), the root mean square error
455 (RMSE) and the mean bias error (MBE) between simulated and observed fluxes.

456 Figure 8 plots simulated versus observed LE for the three sites separately. TSEB provides
457 satisfying results for the flood site with a RMSE of 78 W/m^2 and a relative error (estimated as
458 RMSE divided by mean observed LE) of 27%. However, two notable features are observed for
459 the other two (controlled and reference drip) sites: i) the LE simulated by TSEB never exceeds
460 500 W/m^2 over the entire growing season ($f_c > 0.5$) although observations reach 700 W/m^2 and
461 ii) the overall MBE is about 29 W/m^2 and 66 W/m^2 for the controlled and reference drip field
462 respectively, meaning that TSEB also overestimates LE in the lower ET range. To dig deeper,
463 the performance of TSEB is now assessed by analyzing the metrics computed for three distinct
464 periods of the agricultural season: the period for $f_c \leq 0.5$, for $f_c > 0.5$ and the senescence
465 stage. Note that the senescence period is defined herein as starting after the last peak observed
466 on the calibrated daily α_{PT} (becomes remarkable after about one week) and finishing when
467 green fraction cover becomes zero, which corresponds to the last date of the three time series.
468 Hence the senescence starts on 27/04/2003, 19/04/2017 and 15/04/2017 for the flood-,
469 controlled drip- and reference drip-irrigated field, respectively. A visual assessment of scatter
470 plots in Figure 8 and the statistics presented in Table 1 clearly indicate that TSEB
471 underestimates LE fluxes at around the maximum of ET (well developed crop before
472 senescence) while it overestimates LE fluxes during senescence until harvest. The saturation
473 of TSEB in the higher range of ET is due to the fixed maximum value for α_{PT} (equal to 1.26).
474 The structure of the model cannot accommodate large evaporative demand conditions and
475 strong advective conditions (Song et al., 2016).

476 Both limitations identified in the TSEB formalism seem to be partly solved by the TSEB-SM
477 approach. In particular, the LE simulated by TSEB-SM (Figure 8) is closer to the 1:1 line in
478 each case ($f_c \leq 0.5$ and $f_c > 0.5$ and the senescence), providing a quite significant
479 improvement for drip sites. The simulated LE does not saturate as it reaches 700 W/m^2 over
480 the reference drip site. In fact, the retrieval of daily α_{PT} values larger than the theoretical
481 maximum 1.26 significantly improves ET estimates. Moreover, the overestimation of LE
482 during the senescence stage is much reduced for TSEB-SM. It is suggested that the decrease in
483 calibrated daily α_{PT} integrates the drop in green vegetation fraction that takes place during
484 senescence.

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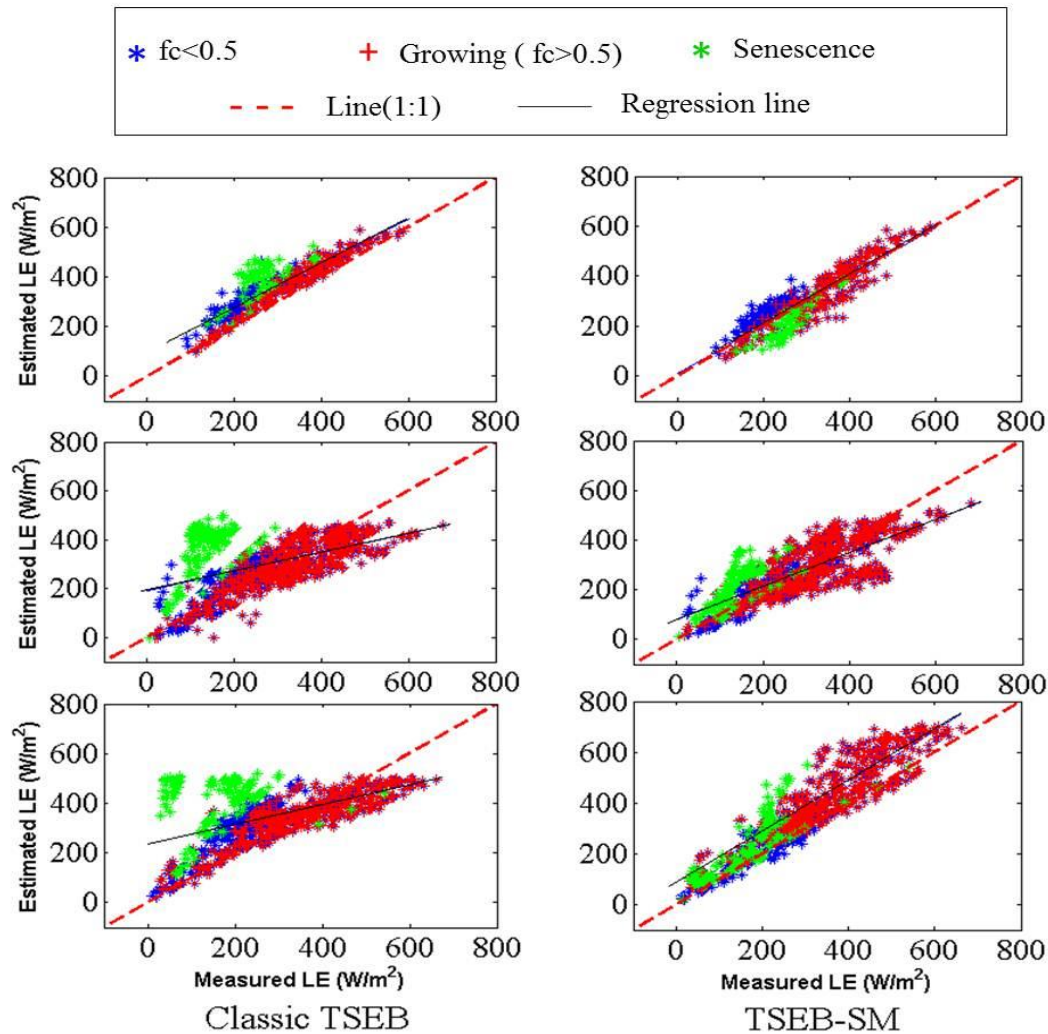


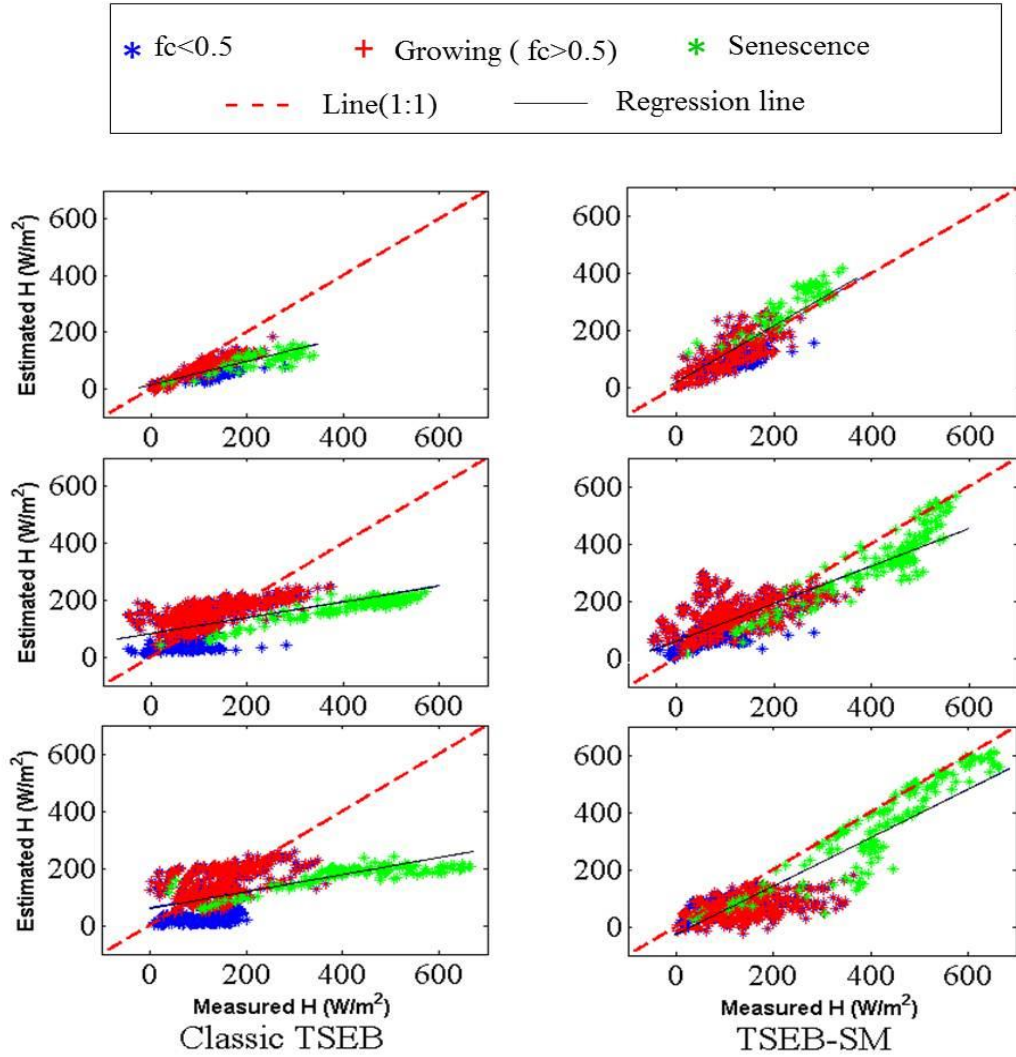
Figure 8. Scatterplot of simulated versus observed LE for the (top) food-, (middle) controlled drip- and (bottom) reference drip-irrigated fields and for (left) TSEB-SM and (right) TSEB models, respectively.

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490 The comparison between TSEB and TSEB-SM is continued by plotting simulated versus
491 observed H for each site in Figure 9. Consistent with previous results obtained for LE, the
492 calibration strategy within TSEB-SM provides in general a significantly improved RMSE
493 compared to the original TSEB. The RMSE is 49 W/m² instead of 73 W/m², 78 W/m² instead
494 of 78 W/m² and 119 W/m² instead of 128 W/m² for the flood-, controlled drip- and reference
495 drip-irrigated field respectively. The determination coefficient between simulated and observed
496 H is significantly improved from 0.61 to 0.67, from 0.37 to 0.75 and from 0.29 to 0.82,
497 respectively when including calibrated parameters to TSEB-SM.

498 One can observe that the slope of the linear regression between TSEB and in situ H is very low
499 in all cases. The modeled H does not seem to be sensitive enough to changes in surface and
500 atmospheric conditions during all three periods ($f_c \leq 0.5$, $f_c > 0.5$ and senescence).
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504 *Figure 9. Scatterplot of simulated versus observed H for the (top) flood-, (middle) controlled drip- and (bottom) reference*
 505 *drip-irrigated fields and for (right) TSEB and (left) TSEB-SM model, respectively.*

506 **Tableau 1:** Error statistics (RMSE, R^2 and MBE) between modeled and measured sensible and latent
 507 heat fluxes for the flood, controlled drip- and reference drip-irrigated fields, and for TSEB and TSEB-
 508 SM model, separately (Rn and G are forced to their measured value)

		TSEB-SM			TSEB		
		RMSE (W/m ²)	R ² (-)	MBE (W/m ²)	RMSE (W/m ²)	R ² (-)	MBE (W/m ²)
Latent heat flux (LE)	Flood	49	0.79	-4	78	0.79	66
	Controlled drip	73	0.64	-6	119	0.22	29
	Reference drip	78	0.86	56	128	0.28	66
Sensible heat flux (H)	Flood	49	0.67	4	78	0.61	-66
	Controlled drip	73	0.75	7	119	0.37	-29
	Reference drip	78	0.82	-56	128	0.29	-66

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511 The intercomparison between TSEB and TSEB-SM is finally undertaken by simulating the
 512 available energy, instead of forcing Rn and G to their measured values as in Table 1. Table 2
 513 reports the error statistics for the four energy fluxes separately. The larger discrepancies for LE
 514 estimated from TSEB-SM model in this case is likely due to greater scatter between modeled
 515 and measured Rn, which is related to the difference between simulated and observed LST. Note
 516 also that the determination coefficient between simulated and measured G is about 0.4-0.5 for
 517 both TSEB and TSEB-SM and all three sites. This is linked in part to the relatively small
 518 magnitude and range in the observed values combined with the simplicity of the approach used
 519 to estimate G. Overall, the simulations of LE and H when modeling Rn and G are fully
 520 consistent with those obtained when forcing Rn and G to their measured values. TSEB-SM still
 521 provides superior results to TSEB in terms of RMSE, R² and MBE between simulated and
 522 observed fluxes. Especially the sensible heat flux is significantly improved in all cases.

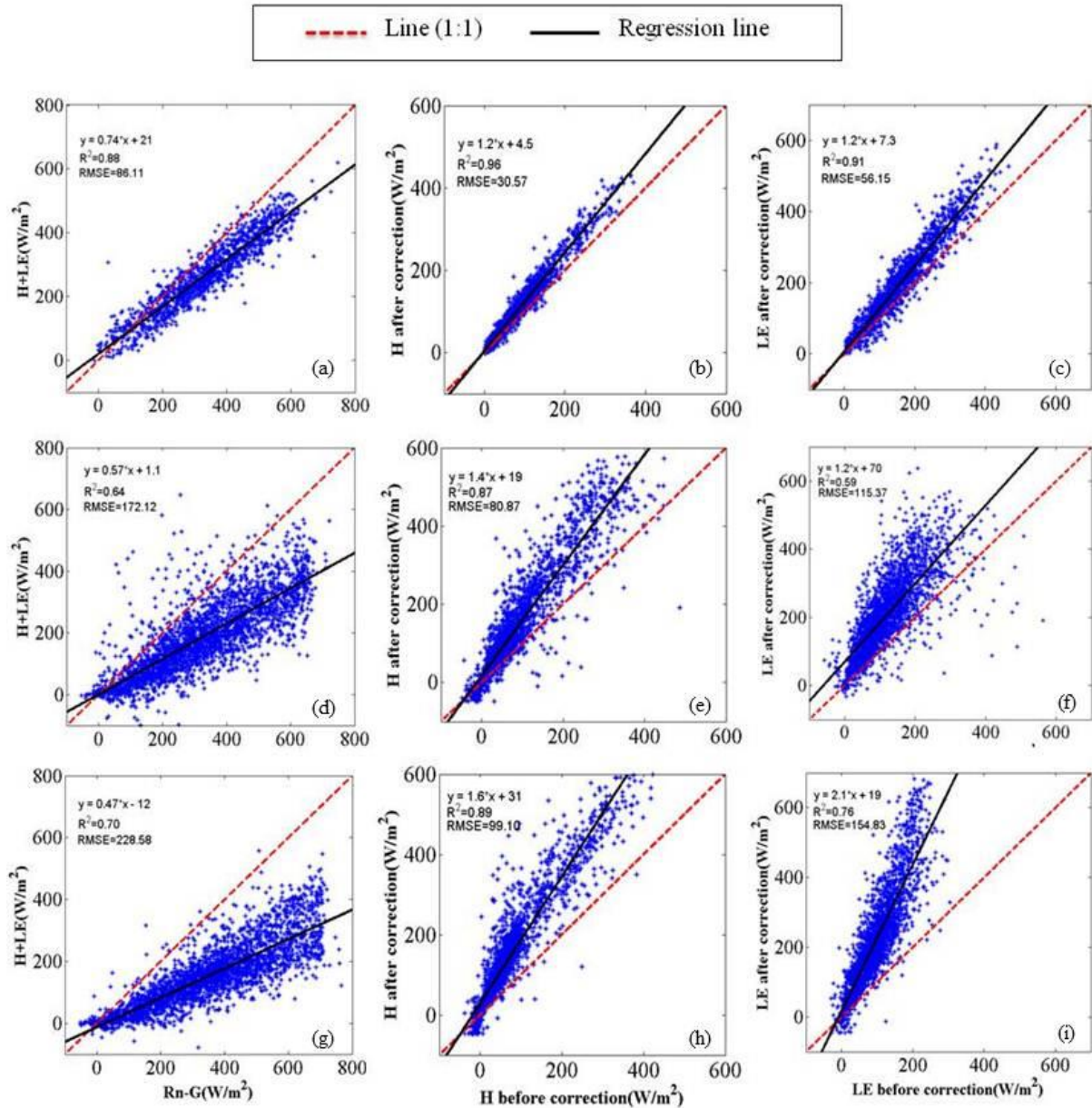
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524 Tableau 2: Error statistics (RMSE, R² and MBE) between modeled and measured net radiation,
 525 conductive flux, and sensible and latent heat fluxes for the flood, controlled drip- and reference drip-
 526 irrigated fields, and for TSEB and TSEB-SM model, separately.

		TSEB-SM			TSEB		
		RMSE (W/m ²)	R ² (-)	MBE (W/m ²)	RMSE (W/m ²)	R ² (-)	MBE (W/m ²)
Net radiation (Rn)	Flood	31	0.98	-25	18	0.99	-17
	Controlled drip	27	0.98	-10	16	0.99	1
	Reference drip	50	0.95	-32	9	0.99	1
Conductif flux (G)	Flood	23	0.41	2	22	0.43	1
	Controlled drip	20	0.5	9	25	0.48	12
	Reference drip	14	0.39	14	30	0.38	26
Sensible heat flux (H)	Flood	27	0.66	34	78	0.61	-67
	Controlled drip	61	0.82	8	118	0.38	-28

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530 *Figure 10. Scatterplot of observed H+LE versus observed Rn-G (left), corrected H versus observed H (center) and corrected*
531 *LE versus observed LE (right) the food- (top), controlled (middle) and reference drip-irrigated (bottom) fields respectively.*

532

533 4 Conclusions

534 A new evapotranspiration model named TSEB-SM is derived from the TSEB formalism by
535 explicitly representing soil evaporation using a soil resistance. An innovative calibration
536 approach is also developed to retrieve the main parameters of soil evaporation and plant
537 transpiration via the soil resistance and α_{PT} respectively. In practice the soil resistance
538 parameters are retrieved at the seasonal time scale from SM and LST data with $f_c \leq 0.5$. While
539 α_{PT} is retrieved at the daily time scale from SM and LST data for $f_c > 0.5$. The performance
540 of TSEB-SM and TSEB models is assessed in terms of LE and H partitioning using an in situ
541 data set collected over 1 flood- and 2 drip-irrigated wheat fields.

542 The convergence of the iterative calibration procedure on ($a_{r_{ss}}$, $b_{r_{ss}}$) and α_{PT} is successfully
543 tested when all three parameters are estimated at the seasonal time scale, as well as when

544 considering a daily variability of α_{PT} . The maximum calibrated daily α_{PT} is close to the
545 theoretical value of 1.26 for all three sites. However its temporal variability is found to be
546 significant even during the growing stage of wheat. A qualitative analysis of α_{PT} variabilities
547 in relation to soil moisture at 5 cm and 30 cm depth and to VWC indicates that α_{PT} cannot be
548 considered as a constant in the conditions of the experiments. Large deviations about the 1.26
549 value are likely to occur during the agricultural season especially under dry, water deficit and
550 advective conditions.

551 In terms of flux estimates, TSEB provides satisfying results for the flood site but not for the
552 other two (controlled and reference drip) sites. The saturation of TSEB in the higher range of
553 ET is due to the fixed maximum value for α_{PT} (equal to 1.26). Moreover, the overestimation of
554 LE by TSEB during senescence is associated with a very low sensitivity of simulated H to any
555 surface/atmospheric conditions. Both limitations identified in the TSEB formalism seem to be
556 partly solved by the TSEB-SM approach with a slope of the linear regression between
557 simulated and observed LE/H much closer to 1 in all cases. Such an evapotranspiration model
558 simultaneously constrained by LST, f_c and SM seems to respond robustly in terms of LE/H
559 partitioning for wheat crops under the conditions of the experiments. However, the calibrated
560 daily α_{PT} needed to be i) smoothed to reduce random uncertainties and ii) normalized between
561 its two extreme values since the 0 value was not necessarily reached at harvest. In the real
562 application the use of NDVI as a green vegetation index would provide complementary
563 information to constrain even more the drop in the retrieved “effective α_{PT} ” during senescence.
564 Further efforts should be made to investigate the variability of α_{PT} at the daily and finer time
565 scales and to relate its variations to variables other than biomass and soil water availability.
566 Reciprocally, the retrieved α_{PT} could serve as a basis for deriving a proxy for root zone soil
567 moisture and crop water needs. Last but not least estimates of SM are needed at the crop field
568 scale. Those data may be provided by satellite microwave data disaggregated at medium to
569 high spatial resolution (Merlin et al., 2013; Molero et al., 2016). Especially, the L4DIS
570 processor (Merlin et al., 2012; Molero et al., 2016) provides 1 km resolution SM data on a
571 routine basis from 40 km resolution Soil Moisture and Ocean Salinity (SMOS) and 1 km
572 resolution MODIS (Moderate resolution Imaging Spectroradiometer) data. Such a high-
573 resolution SM product would be fully compatible with future implementations of TSEB-SM
574 over large areas.

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