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# 1 Assessment of an extended SPARSE model for estimating 2 evapotranspiration from directional thermal infrared data

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## 8 Abstract

9 The spatial distribution of evapotranspiration is often obtained from dual source energy balance  
10 models forced by surface temperature data. The use of multi-angular remotely-sensed thermal  
11 data in such methods makes them susceptible to directional-anisotropy/thermal-radiation  
12 directionality effects that may result from the satellite's position, relative to the Sun, at overpass  
13 time. It is therefore important to have these effects accounted for to ensure realistic flux  
14 retrievals irrespective of sensor viewing position. At present, dual source models generally  
15 interpret surface temperature according to two sources, representing the soil surface and the  
16 vegetation. This may be insufficient to adequately represent the limiting temperature conditions  
17 that not only depend on the source type but also their exposure to the Sun. Here, we present a  
18 modified version of the SPARSE (Soil Plant Atmosphere Remote Sensing Evapotranspiration)  
19 model, wherein the original SPARSE is modified to incorporate sunlit/shaded soil/vegetation  
20 elements and coupled with a radiative transfer model that links these four component emissions  
21 to out-of-canopy directional radiances as observed by remote sensors. An initial evaluation is  
22 carried out to check the model's capability in retrieving surface fluxes over diverse environments  
23 instrumented with in-situ thermo-radiometers. When run with nadir-acquired thermal data, both  
24 algorithms show no observable difference in their retrieval of total fluxes. We nonetheless show  
25 that by incorporating the solar direction and discriminating between sunlit and shaded elements,

26 the partitioning of these overall fluxes between the soil and vegetation can be improved  
27 especially in water-stressed environments. We also test the sensitivity of flux and component  
28 temperature estimates to the viewing direction of the thermal sensor by using two sets of TIR  
29 data (nadir and oblique) acquired simultaneously to force the models and show that sensitivity to  
30 viewing direction is significantly reduced. This is an important aspect particularly when using  
31 high resolution spatial and temporal data from Earth observation missions that inherently have to  
32 consider a wide-range of viewing angles in their design.

33 Keywords: Evapotranspiration, thermal infrared radiation (TIR), Soil Vegetation Atmosphere  
34 Transfer (SVAT), temperature inversion.

## 35 1. Introduction

36 Evapotranspiration (ET) plays a key role in mass and energy interactions in the soil-vegetation-  
37 atmosphere domain, making its estimation important in applications related to hydrology,  
38 agriculture, weather and climate studies. In crop water-use management, accurate ET translates  
39 to improved water stress detection, which is important especially in arid and semi-arid regions  
40 where ET has been shown to account for more than 90% of the precipitation (Huxman et al.,  
41 2005) hence to a large extent controlling the water budget. Transpiration has also been found to  
42 account for *ca.* 61% of the global terrestrial ET (Schlesinger & Jasechko, 2014) highlighting the  
43 importance of evapotranspiration partitioning. Operationally applicable ET models are therefore  
44 of key significance to water resource stakeholders for adequate water-use quantification and its  
45 efficient allocation particularly in water-limited areas.

46 Theoretically, one of the methods used to estimate evapotranspiration involves solving the  
47 surface energy budget equation for a surface temperature that results from the aggregation of the

48 various temperature sources within the soil-canopy system and observed by remote sensors. The  
49 energy partitioning can either be: single- (e.g., Surface Energy Balance System (SEBS, Su,  
50 2002)) if one single temperature is used to compute all fluxes; or dual-source if the surface is  
51 represented by two bulk temperature sources, one for the soil component considered as a  
52 homogeneous isothermal surface and another for the vegetation component seen as a big  
53 transpiring leaf, also isothermal (e.g., SPARSE, Boulet et al., 2015 and Two-Source Energy  
54 Balance, TSEB, Norman, Kustas, & Humes, 1995). In addition to allowing the partitioning  
55 between evaporation and transpiration, the development of dual source models was also meant to  
56 realistically address the contribution of varying soil and vegetation skin temperatures to the  
57 aerodynamic temperature, which influences the sensible heat flux (Boulet et al., 2012). While  
58 remotely-observed radiometric temperature can be defined as the soil and vegetation  
59 temperatures weighted by their relative cover fraction in the viewing direction, the link of these  
60 component temperatures to the aerodynamic temperature is described according to turbulence  
61 resistance between the aerodynamic level and the soil and the vegetation (Norman et al., 1995).  
62 Since source temperatures (i.e., sunlit and shaded elements of the soil or vegetation) may exhibit  
63 large differences depending on their exposure to the Sun, it is necessary to incorporate the source  
64 temperature variations to enable a more accurate representation of conditions at the aerodynamic  
65 level.

66 To drive such surface energy balance models, measurements from in-situ stations have primarily  
67 been used as forcing input. The advent of remote sensing (RS), which provides observations of  
68 Earth surface characteristics e.g. surface brightness temperature, soil moisture, vegetation  
69 indices, albedo etc., has made estimation of land surface fluxes at various spatial and temporal  
70 scales more practical. Of the terrestrial state variables retrievable from space, land surface

71 temperature (LST) is tightly linked to the surface turbulent fluxes and plant water stress hence its  
72 ubiquitous use in ET estimation methods. While in-situ thermal infra-red (TIR) sensors can  
73 provide point measurements from a fixed direction (generally from nadir or close to nadir),  
74 space-borne sensors, which provide observations at larger spatial scales, often view pixels on  
75 Earth from varying directions each observation instance. For example, the Moderate Resolution  
76 Imaging Spectroradiometer (MODIS) sensor aboard the Terra and Aqua satellites provides,  
77 among other products, global LST at a spatial resolution of ~1 km every 1 to 2 days and over a  
78 broad-range of viewing angles ( $\leq 65^\circ$ ). The newly proposed Thermal infRared Imaging Satellite  
79 for High resolution Natural resource Assessment (TRISHNA) mission, instituted by the French  
80 (CNES) and Indian (ISRO) Space Agencies, is also expected to provide global LST products  
81 with a revisit time of ~3 days (Lagouarde et al., 2019). Its high spatial resolution (~57m at nadir)  
82 and relatively wide field-of-view ( $\pm 34^\circ$ ) should enable multi-scale monitoring of the water and  
83 energy budgets. Directional effects can however impact the accuracy of surface state variables  
84 inferred from such thermal data.

85 The need to incorporate directional aspects has necessitated the use of simple radiative methods  
86 that link the observed brightness temperature with the prevailing component temperatures,  
87 particularly in dual-source models. These, however, do not account for the solar-Earth-viewing  
88 geometry, which can lead to significant thermal radiation directionality (TRD) effects (also  
89 referred to as TIR directional anisotropy); an extreme case of TRD is the hotspot effect that  
90 results from the syzygy Sun-satellite-Earth configuration, where the sensor mostly observes  
91 sunlit elements. According to Kimes & Kirchner (1983), Lagouarde et al. (2014) and Duffour et  
92 al. (2016), oblique-nadir temperature differences (i.e., thermal radiation directionality) can reach  
93 15 °C. Since LST uncertainties of 1-3 °C may in-turn result in flux errors in the order of ~100

94  $Wm^{-2}$  (Kustas & Norman, 1996), accounting for anisotropy in evapotranspiration models has the  
95 potential of significantly improving the derived estimates. Formulations that address thermal  
96 radiation directionality, and thus the hotspot phenomenon, are fundamentally extensions of the  
97 optical domain's reflectance theory. As detailed in Cao et al.'s (2019) review, they range from  
98 geometric, parametric, hybrid to 3-D radiative transfer models.

99 For dual-source evapotranspiration models, it is more suitable to invert component temperatures  
100 using radiative transfer or hybrid methods. Bian et al. (2018) recently developed the physically-  
101 based unified four-component (UFR97) model. Their radiative scheme is an extension of the  
102 two-component Francois et al.'s (1997) model and incorporates bi-directional aspects from Yan  
103 et al. (2012). They tested the model on homogeneous, row-crop and forest covers (assuming a  
104 spherical foliage projection) where they showed that it could satisfactorily simulate directional  
105 temperatures with component sunlit/shaded soil/vegetation temperatures used as input. The  
106 relatively easy to implement UFR97 method can thus be used for direct assimilation of  
107 directional TIR data and thereby help to address directional anisotropic issues in surface energy  
108 balance inversion schemes.

109 In this study, we present an evaluation of a coupled SPARSE-UFR97 model (hereafter  
110 SPARSE4) meant for inverting directionally anisotropic thermal data for evapotranspiration and  
111 water stress estimation. By coupling SPARSE with the UFR97 radiative method, the original  
112 scheme was extended from a two- (soil/vegetation) to a four-component (sunlit/shaded  
113 soil/vegetation) formulation. The dual-source SPARSE model, which inverts surface temperature  
114 for source emissions and separate retrieval of soil evaporation and vegetation transpiration  
115 fluxes, has already been extensively assessed and shown to be capable of reasonably estimating  
116 and partitioning turbulent fluxes. In the next section, we introduce the theoretical and

117 implementation aspects behind the original and extended SPARSE models. The formulations are  
118 then evaluated and their performance analyzed using field measurements collected from diverse  
119 environments, which include two olive Orchards and two other experimental sites (cultivated  
120 with soybean and wheat). Finally, conclusions are drawn and outlooks on continuing and future  
121 works with respect to thermal radiation directionality assessments are presented.

## 122 2. Materials and Methods

### 123 2.1. Theory: SPARSE and SPARSE4 model description

124 Radiation controls the turbulent fluxes at and near the Earth surface. For energy conservation, the  
125 net radiation ( $R_n$ ) is dissipated in turbulent and conduction heat flux exchanges as:

$$126 \quad R_n = (1 - \alpha_{sf})S \downarrow + L \downarrow - L \uparrow = H + G + \lambda E \quad (1)$$

127 where  $S \downarrow$  is the incoming shortwave radiation (bottom of atmosphere; BOA);  $\alpha_{sf}$  is the surface  
128 albedo;  $L \downarrow = \epsilon_a^{cs} \sigma T_a^4$  - incoming long wave radiation emitted by atmospheric constituents (a :  
129 clouds, aerosols and gasses); the apparent emissivity  $\epsilon_a^{cs}$  is derived according to Brutsaert (1975)  
130 in clear-sky situations (which are the relevant situations when using TIR data from satellites);  $\sigma$   
131 is the Stefan Boltzmann constant; and  $T_a$  the air temperature.  $L \uparrow = \sigma T_B^4 = \epsilon_{sf} \sigma T_{rad}^4 +$   
132  $(1 - \epsilon_{sf})L \downarrow$  - outgoing long-wave radiation corresponding to the emission by the surface and  
133 the reflected incoming long-wave radiation;  $\epsilon_{sf}$  is the surface emissivity and  $T_{rad}$  is the  
134 surface/radiative temperature;  $T_B$  is the brightness temperature as measured by a thermo-  
135 radiometer.  $H$  denotes the sensible heat flux,  $G$  the ground heat flux and  $\lambda E$  the latent heat flux.  
136 When dealing with remotely sensed thermal data, all used terms are instantaneous (as at the  
137 satellite overpass time).

138 Dual-source energy partitioning in SPARSE consequently involves splitting the single-source

139 energy balance (Equation (1)) between the vegetation and the soil. The out-of-canopy thermal  
 140 radiance as observed by a remote sensor is thus treated as a weighted composition of vegetation  
 141 and soil emissions. To calculate the emissions, and thus the net radiation, component  
 142 temperatures are required. These soil/vegetation temperatures can then be linked to the remote  
 143 thermal observation depending on their respective fractions in the viewing direction. In  
 144 SPARSE4, sunlit and shaded elements of the soil and vegetation sources are discriminated and  
 145 consequently linked to the measured directional temperature using the Unified Francois model  
 146 (UFR97, Bian et al., 2018). A synopsis of the similarities and differences between SPARSE and  
 147 SPARSE4 models is presented next starting with the radiative transfer scheme, the net radiation  
 148 partitioning, the other energy balance components and finally the implementation framework.

#### 149 2.1.1. Out-of-canopy radiance

150 The general form of the link between surface component temperatures and the out-of-canopy  
 151 radiance in the viewing direction of a remote sensor can be written as;

$$152 \quad L_{\text{rad},\lambda}^{\uparrow}(\theta_v) = \tau_{\omega}(\theta_v)\varepsilon_{g,\lambda}B(T_g) + (1 - \tau_{\omega}(\theta_v))\varepsilon_{v,\lambda}B(T_v) + (1 - \varepsilon_{\text{sf},\lambda})L_{\lambda}^{\downarrow}, \quad (2. a)$$

$$153 \quad = K_g\tau_{\omega}(\theta_v)\varepsilon_{g,\lambda}B(T_{gs}) + K_z\tau_{\omega}(\theta_v)\varepsilon_{g,\lambda}B(T_{gh}) + \omega_{\omega,s,\lambda}(\theta_v)B(T_{vs}) +$$

$$154 \quad \omega_{\omega,h,\lambda}(\theta_v)B(T_{vh}) + (1 - \varepsilon_{\text{sf},\lambda})L_{\lambda}^{\downarrow}, \quad (2.b)$$

155 SPARSE applies Equation (2.a) by considering the soil and vegetation sources whereas  
 156 SPARSE4 uses Equation (2.b) to separate sunlit/shaded elements in the viewing direction. In the  
 157 UFR97 model (Bian et al., 2018), Equation (2.b) acts as the main link between the separate  
 158 sunlit/shaded element emissions and the remotely-observed radiative temperature. The terms in  
 159 the effective emissivities for sunlit/shaded soil/vegetation ( $K_g\tau_{\omega}(\theta_v)\varepsilon_{g,\lambda}$ ,  $K_z\tau_{\omega}(\theta_v)\varepsilon_{g,\lambda}$ ,  
 160  $\omega_{\omega,s,\lambda}(\theta_v)$  and  $\omega_{\omega,h,\lambda}(\theta_v)$ , respectively) are given in Appendix A and further detailed in Bian et  
 161 al. (2018), Francois et al. (1997) and Yan et al. (2012) -  $K_g$  and  $K_z$  are the sunlit and shaded



162 fractions of the soil, respectively;  $\tau_\omega$  is the gap fraction;  $\varepsilon_{g,\lambda}$  the soil emissivity;  $\omega_{\omega,s,\lambda}$  and  
 163  $\omega_{\omega,h,\lambda}$  are the effective emissivities of sunlit and shaded vegetation.  $T_{v,s|h}$  and  $T_{g,s|h}$  are the,  
 164 vegetation and soil component temperatures, respectively; s – sunlit and h - shaded elements.  
 165  $B(\cdot)$  is the blackbody (Planck's or, as used herein, Stefan Boltzmann) function. Olioso (1995)  
 166 noted that significant errors could arise if the measuring spectral window of the sensor is not  
 167 taken into account. Scaling to within the 8-14  $\mu\text{m}$  spectral band (e.g., apogee radiometer  
 168 specification) is therefore implemented following Olioso (1995) (see Appendix B). Subscript  $\lambda$   
 169 holds for the IRT sensor spectral window.

170  $1 - \tau_\omega(\theta_v) = f(\theta_v)$  is the fraction of radiometer's field of view that is occupied by the canopy,  
 171 which is a function of view zenith angle ( $\theta_v = \cos^{-1}(\mu_v)$ ) and vegetation cover fraction ( $f_c =$   
 172  $1 - \tau_\omega = 1 - e^{-\mathcal{G} \cdot \text{LAI}}$  for a homogeneous cover – applied throughout this study), i.e.:

$$173 \quad f(\theta_v) = 1 - e^{-\mathcal{G} \cdot \text{LAI} / \mu_v} \quad (3)$$

174 LAI here is the effective leaf area index, which is the product of the clumping index and the real  
 175 LAI of the canopy (Nilson, 1971). It is important to account for the clumping index in non-  
 176 continuous canopies. For the leaf projection factor,  $\mathcal{G}$ , a spherical foliage ( $\mathcal{G} = 0.5$ ) is assumed  
 177 with formulations for other leaf inclination distributions defined following Nilson (1971). It  
 178 should be noted that for the vegetation fraction, the gap fraction ( $\tau_\omega$ ) is defined from nadir view  
 179 (i.e.,  $\cos^{-1}(\mu_v) = 0^\circ$ ), Emissivity of the entire canopy ( $\varepsilon_{sf,\lambda}$ ) is given by Francois et al. (1997)  
 180 as:

$$181 \quad \varepsilon_{sf,\lambda}(\theta_v) = 1 - \tau_\omega(\theta_v)M(1 - \varepsilon_{g,\lambda}) - \alpha[1 - \tau_\omega(\theta_v)M](1 - \varepsilon_{v,\lambda}) \quad (4)$$

182 where  $\alpha$  is the cavity effect factor (François, 2002; Francois et al., 1997), which defines part of  
 183 the incident radiation that is reflected by the leaves and finally absorbed by the canopy. Fitting

184 the  $\alpha$  vs  $\theta_v$  data provided in François (2002) yields  $\alpha = 0.3168 + 0.0029\exp(0.0605 \cdot \theta_v)$ ; an  
185 alternative option suitable for large view zenith angles, i.e. a regression based on the  $\alpha$ - $\theta_v$  data of  
186 the canopy-emissivity model (C-EP, Cao et al., 2018), is also included;  $M = \frac{1}{\pi} \int_{-\pi/2}^{\pi/2} \tau_\omega(\theta) d\theta$  is  
187 the hemispherical gap fraction (Francois et al., 1997). All other terms are as previously defined.

## 188 2.1.2. Net radiation and energy balance

### 189 *Global solar radiation partitioning, apparent atmospheric emissivity and net radiation*

190 The new formulation needs partitioning of the global solar radiation into its direct and diffuse  
191 components. The Erbs et al.'s (1982) clearness method summarized in Appendix C is utilized  
192 herein to disaggregate the global radiation into diffuse and direct short wave radiation. The gap  
193 fraction in the solar direction ( $\theta_i, \phi_i$ ) is then used to apportion the direct radiation between the  
194 sunlit sources. This gap probability is defined in the solar direction ( $\theta_i = \cos^{-1}(\mu_i)$ ) as  $\tau_\omega(\theta_i) =$   
195  $e^{-G \cdot LAI / \mu_i}$  for a homogeneous cover.

196 For the incoming sky radiance, Brutsaert's (1975) analytical method is used, i.e.,  $RA = \epsilon_a^{cs} \sigma T_a^4$ ;  
197 where  $\epsilon_a^{cs} = 1.24(e_a/T_a)^{1/7}$  is the apparent emissivity;  $e_a$  and  $T_a$  are the air vapor pressure and  
198 temperature, respectively. This method however only applies to clear skies and it is therefore  
199 necessary to have corrections for overcast days. Herein, the Meeus99 scheme detailed in Annear  
200 and Wells (2007) is first used to identify clear days. In the method, the clear-sky solar radiation  
201 is computed as a function of parameterized ground surface reflectivity, atmospheric albedo,  
202 direct and scattered radiation. While Brutsaert's (1975) method is kept for the clear days, it is  
203 modified according to Brutsaert (1982) as detailed in Herrero and Polo (2012) for the apparent  
204 emissivity in cloudy conditions. The method introduces a parameterized factor ( $F$ ) that scales the  
205 clear-sky emissivity to cloudy conditions, i.e.  $\epsilon_a = F \epsilon_a^{cs} = (1 + CN^2) \epsilon_a^{cs}$ ;  $C$  is a cloud dependent

206 coefficient (herein tuned using incoming longwave measurements) and  $N$ , also an atmosphere-  
207 dependent coefficient, is parameterized as a function of clearness and relative humidity  
208 following Herrero and Polo (2012).

209 The incoming solar and sky radiations serve as initial inputs for the net radiation terms. The  
210 sunlit and shaded contribution functions detailed for the solar domain in Yan et al. (2012) and  
211 also applied (with some modifications) in the thermal spectrum by Bian et al. (2018) are used to  
212 partition the incoming short- and long-wave radiations between the sunfleck/shaded components.  
213 Presently, the turbid canopy radiative method by Taconet et al. (1986), which is in use in the  
214 standard SPARSE model, has been extended to incorporate the sunlit/shaded components  
215 (Appendix C). The net short-wave ( $RG_{xx}$ ) and absorbed sky emission ( $RA_{xx}$ ) terms are separated  
216 from the unknown surface thermal emissions ( $L_{TIRxx}^{\uparrow} = f(T_{xx})$ ) for the net radiation terms:

$$217 \quad R_{n,xx} = RG_{xx} + RA_{xx} + L_{TIRxx}^{\uparrow} \quad (5)$$

218  $xx = v, g$  and  $xx = vs, vh, gs, gh$  for SPARSE and SPARSE4, respectively; “v” and “g” denote  
219 the vegetation and the soil/ground, which can either be sunlit (“s”) or shaded (“h”) in the  
220 extended formulation. Like in the original SPARSE, the surface emission terms ( $L_{TIRxx}^{\uparrow}$ ) are  
221 defined around air temperature through a Taylor expansion. Further details in Appendix C.

### 222 *Energy balance scheme*

223 The SPARSE model (Boulet et al., 2015) is based on the two-source TSEB (Norman et al., 1995)  
224 rationale. However, unlike in TSEB, where the potential canopy latent flux is estimated through  
225 the Priestley-Taylor method, SPARSE utilizes a Penman-Monteith approximation. It is argued  
226 that the Priestley-Taylor coefficient ( $\sim 1.3$ ) may not be reasonable for natural vegetation and  
227 regions with strong vapor pressure deficit (Colaizzi et al., 2012). Priestley-Taylor formulations

228 have been shown to consistently underestimate transpiration partitioning of total ET, especially  
 229 in semi-arid lands (Agam et al., 2010). SPARSE also employs bounding similar to SEBS (Su,  
 230 2002) where theoretical potential and fully stressed flux limits for the soil and vegetation are  
 231 derived.

232 The net radiation ( $R_{n,xx}$ ) terms according to Equation (5) are partitioned for retrieval of the soil  
 233 (G), sensible (H) and latent ( $\lambda E$ ) heat fluxes. The available energy is thus written as:

$$234 \quad R_{n,xx} - G = R_{n,xx}(1 - \xi) = \lambda E_{xx} + H_{xx} \quad (6)$$

235  $\xi$  is the fraction of soil/ground net radiation stored in the soil, i.e.,  $\xi = G/R_{ng}$ . Therefore,  $\xi = 0$   
 236 for the vegetation layers. For diurnal variations of the ground heat storage, the sinusoidal  
 237 function by Santanello and Friedl (2003) is also included, i.e.,  $\xi = \xi_{max} \cdot \cos[2\pi(t + 10800)/$   
 238  $B]$ ;  $t$  [s] is the time relative to solar noon,  $B$  [s] is a deviation minimization factor while 10800  
 239 [s] accounts for the three-hour lag between the maximum incoming radiation and maximum  
 240 fraction ( $\xi_{max}$ ).

241 Soil and vegetation component latent fluxes are treated as representative averages for the surface  
 242 (here  $g_x = g$  and  $v_x = v$  for SPARSE; and  $g_x = g_s, g_h$  and  $v_x = v_s, v_h$  for SPARSE4):

$$243 \quad \lambda E_g = \sum_{g_x} \frac{\rho C_p}{\gamma} \beta_s \frac{e_{sat}(T_{g_x}) - e_0}{r_{as}} \quad (7)$$

$$244 \quad \lambda E_v = \sum_{v_x} \frac{\rho C_p}{\gamma} \beta_v \frac{e_{sat}(T_{v_x}) - e_0}{r_{vv}} \quad (8)$$

245 likewise, the component sensible heat fluxes are defined as:

$$246 \quad H_g = \sum_{gx} \rho C_p \frac{T_{gx} - T_0}{r_{as}} \quad (9)$$

$$247 \quad H_v = \sum_{vx} \rho C_p \frac{T_{vx} - T_0}{r_{av}} \quad (10)$$

248 where  $\rho C_p$  denotes the volumetric heat capacity of air,  $\gamma$  the psychrometric constant,  $e_{sat}(T_{xx}) =$   
249  $e_{sat}(T_a) + \Delta(T_{xx} - T_a)$  is the saturated vapour pressure at temperature  $T_{xx}$ ,  $\Delta$  the slope of the  
250 vapour pressure-temperature curve at  $T_a$ ,  $e_0$  is the partial vapor pressure at the aerodynamic level;  
251  $r_{as}$  is the soil to aerodynamic level resistance and  $r_{vv} = r_{av} + r_{sto}$  the minimum total resistance  
252 for latent heat exchange between the vegetation and the aerodynamic level;  $r_{av}$  is the vegetation-  
253 to-aerodynamic level resistance;  $r_{sto}$  is the stomatal resistance (defined below).  $\beta_s$ ,  $\beta_v$  are the  
254 respective evaporation and transpiration efficiencies, defined as the ratio between actual and  
255 unstressed latent heat fluxes in actual surface conditions, functionally equivalent to soil and  
256 vegetation surface conductances, respectively. For the dependence of aerodynamic resistance to  
257 stability correction, the aerodynamic temperature ( $T_0$ ), component temperatures ( $T_{xx}$ ), energy  
258 fluxes and  $e_0$  are solved and updated iteratively (Richardson number) until convergence. Similar  
259 to SPARSE, aerodynamic resistances are expressed according to Shuttleworth and Gurney  
260 (1990). Surface components very often alternate between sun and shade and there is therefore no  
261 clear distinction between sunlit/shaded elements. For the evaporation/transpiration efficiencies,  
262 only the soil and vegetation sources are hence distinguished with similar  
263 (evaporation/transpiration) efficiencies applying to both sunlit/shaded sources.

#### 264 *Canopy stomatal conductance*

265 While Chen and Liu (2020) observe that shortcomings resulting from theoretical and practical  
266 issues are more serious in big-leaf photosynthesis than in big-leaf evapotranspiration models,

267 they recommend theoretical consistency in conductance formulation and aggregation. Owing to  
 268 the inter-dependence between stomatal conductance and assimilation rate in Ball-Berry schemes  
 269 (e.g., Collatz et al., 1991; Medlyn et al., 2011), and the necessity to have a method that is  
 270 theoretically consistent with the physics of the original model, we prefer and consequently retain  
 271 a conductance scheme that considers the product of several relevant environmental factors as  
 272 used in SPARSE (Boulet et al., 2015; Braud et al., 1995; Noilhan & Planton, 1989; Oliosio et al.,  
 273 1995). We follow the method by Sinclair et al. (1976) who implemented an irradiance-dependent  
 274 conductance method for sunfleck/shaded leaves, which is more compatible with SPARSE's  
 275 model structure. Of critical importance is the proper scaling from leaf to canopy stomatal  
 276 conductance using the respective sunlit/shaded leaf area indices ( $LAI_{vx}$ ). The stomatal resistance  
 277 ( $r_{sto}$ ) to be aggregated for the minimum resistance to latent heat ( $r_{vv} = r_{av} + r_{sto}$ ) as used in  
 278 Equation (8) is thus written as:

$$279 \quad r_{sto} = \frac{r_{stmin} \prod f}{LAI_{vx}} \quad (11)$$

280 where  $r_{stmin}$  is the minimum stomatal resistance;  $\prod f = f_{Rg} f_{ea}$  is the product of environmental  
 281 factors -  $f_{Rg}$  is the radiation factor, which measures the influence of photosynthetically active  
 282 radiation and  $f_{ea}$  is the vapor pressure deficit factor, which represents the effects of vapor  
 283 pressure deficit of the atmosphere on the surface resistance (Braud et al., 1995; Noilhan &  
 284 Planton, 1989; Oliosio et al., 1996).

285 In SPARSE (and hence SPARSE4), the stomatal conductance ( $g_{sto} = 1/r_{sto}$ ) is coupled with the  
 286 vegetation efficiency ( $\beta_v$ ), a term that is related to the plant-water stress, to derive the latent  
 287 fluxes. The efficiency can be viewed here as a separate conductance term that represents the  
 288 impact of water stress (related to soil moisture in the root zone) on the vegetation. Coupling the

289 two conductance terms allows the derivation of flux estimates in potential as well as in  
 290 prevailing/actual conditions.

### 291 2.1.3. Implementation

292 SPARSE (xx = v, g) separately solves the radiative and energy budgets for the soil (g) and  
 293 vegetation (v) sources. The two continuity equations (Equations (12.b) and (12.c)) and two  
 294 energy balance equations, together with the link between the component temperatures and the  
 295 out-of-canopy radiance (Equation (2.a)) are thus solved for the 6 unknowns, i.e.,  
 296  $T_{xx=g,v}$ ,  $T_0$ ,  $e_0$ ,  $\beta_v$  &  $\beta_s$ . For the new version SPARSE4, there are four components (xx =  
 297 vs, vh, gs, gh) since each source - soil (g) or vegetation (v) - is split into a sunlit (s) and a shaded  
 298 (h) component. This leads to four energy budget and two continuity equations, which together  
 299 with the out-of-canopy thermal link (Equation (2.b)) are to be solved to retrieve the 8 unknowns:  
 300  $T_{xx=vs,vh,gs,gh}$ ,  $T_0$ ,  $e_0$ ,  $\beta_v$  &  $\beta_s$ . Therefore, for both SPARSE and SPARSE4, the system of  
 301 equations is underdetermined and one unknown must be fixed a priori. The energy budget and  
 302 continuity equations are written as:

$$\left\{ \begin{array}{l} R_{n,xx}(1 - \xi) - (H_{xx} + \lambda E_{xx}) = 0 \\ \rho C_p \frac{T_0 - T_a}{r_a} = H = \sum_{xx} H_{xx} \\ \frac{\rho C_p}{\gamma} \frac{e_0 - e_a}{r_a} = \lambda E = \sum_{xx} \lambda E_{xx} \end{array} \right. \quad \begin{array}{l} (12.a) \\ (12.b) \\ (12.c) \end{array}$$

303 where  $r_a$  is the aerodynamic-to-reference level resistance; and as noted earlier in the section,  $\xi$   
 304 only applies to the soil and is set to zero for vegetation elements. Other terms are as defined  
 305 above.

306 SPARSE can be run in either 'retrieval' ('inverse') or 'prescribed' ('forward') modes. Similar to

307 TSEB, both modes assume the soil surface layer dries first while the vegetation transpires at  
308 potential rate ( $\beta_v = 1$ ). In the ‘prescribed’ mode, the soil evaporation and vegetation  
309 transpiration efficiencies are known and the SPARSE4 model uses a 4-by-4 (2-by-2 for  
310 SPARSE) energy budget matrix system to solve for the fluxes and temperatures directly. For  
311 consistency, the ‘prescribed’ mode is used herein as it allows a more straightforward separation  
312 of the interacting terms and thus get rid of the system’s under determination. The transpiration  
313 efficiency is therefore prescribed by initially setting it to ( $\beta_v = 1$ ) and the system of equations  
314 solved iteratively by decreasing  $\beta_s$  incrementally from ( $\beta_s = 1$ ) till a value that minimizes the  
315 difference between the observed and simulated  $T_{\text{rad}}$ . If a minimum difference is not reached and  
316 the soil is dry ( $\beta_s$ , thus evaporation, close to 0), then one assumes that the vegetation is  
317 undergoing stress.  $\beta_s$  is then at its minimum (e.g.,  $\beta_s \approx 0$ ) and, similarly,  $\beta_v$  is decreased  
318 incrementally until the difference between the observed and simulated radiative temperatures is  
319 minimal (i.e. simulated  $T_{\text{rad}} \approx$  observed  $T_{\text{rad}}$ ).

320 The simultaneous retrieval procedure of the fluxes and temperatures from the energy and  
321 radiative set of equations is illustrated by Figure 1 and summarized by Equations (12.a), (12.b)  
322 and (12.c). That is: the incoming short- and longwave radiation fluxes are partitioned between  
323 the components; a first guess of the aerodynamic temperature then provides a solution for the  
324 component emissions (thus temperatures) for onward derivation of the initial component fluxes;  
325 the temperature and partial vapor pressure at the aerodynamic level are then iteratively computed  
326 for stability convergence (Richardson number – see section 2.1.2). By modulating the  
327 evaporation/transpiration efficiencies, i.e. applying a linear decrement of the efficiencies, the  
328 procedure can be repeated until the surface temperature boundary condition is met (i.e. simulated  
329  $\approx$  observed surface temperature).



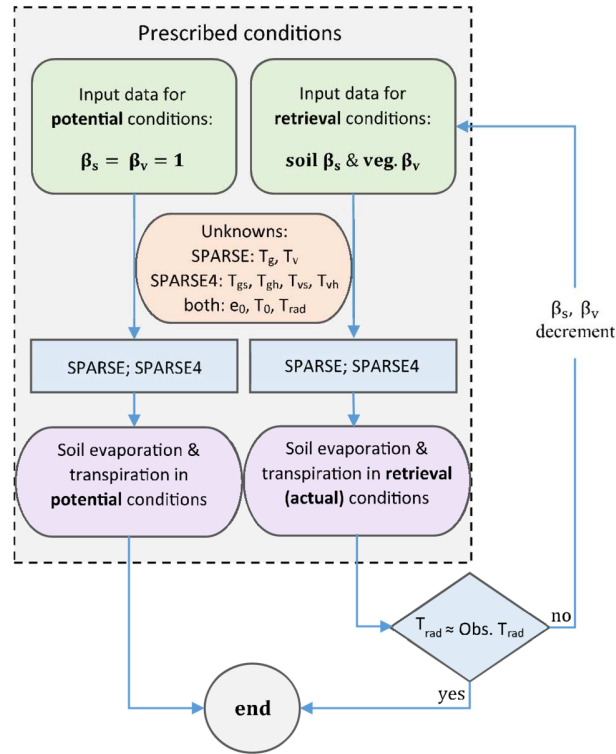


Figure 1: Model flow diagram (adapted from Boulet et al. (2015))

330

## 331 2.2. Data description

### 332 2.2.1. Study sites

333 The datasets used to run the models and for performance evaluations are drawn from four  
 334 contrasting sites. Two Olive Orchards located in: Nasrallah, Tunisia (Latitude, Longitude: 35.30°  
 335 N, 9.92° E: 2014) and Agdal, Morocco (31.60° N, 7.98° W: 2003) with vegetation cover  
 336 fractions of ~7% (Chebbi et al., 2018) and ~60% (Er-Raki et al., 2009), respectively.  
 337 Experimental datasets for the other two sites were collected during the growing periods of  
 338 Soybean: 1990 (Avignon: 43.90° N, 4.80° E, France; Olioso et al., 1996) and flood-irrigated  
 339 wheat: 2004 (R3: 31.67° N, 7.59° W, Morocco; Duchemin et al., 2006), hence varying  
 340 vegetation cover fractions. Table 1 provides a summary of the input data collected from the sites.

341 These can broadly be categorized into: data used for model runs – meteorological, biophysical  
 342 information; and evaluation data – flux measurements from the installed radiometers and eddy  
 343 covariance systems.

### 344 2.2.2. Meteorological and surface biophysical input variables

345 Forcing data collected from the meteorological stations at the four locations include air  
 346 temperature, relative humidity, wind speed and direction. These are recorded at heights of 9.2, 3,  
 347 9.8 and 2 m for Agdal, Avignon, Nasrallah and R3 sites, respectively. Surface temperature,  
 348 which is needed to force the surface energy balance, is also measured on-site using Apogee  
 349 Infra-red radiometers (Apogee Instruments Inc., UT, USA) observing from zenith. The R3 study  
 350 site is also equipped with an oblique-viewing radiometer (at 45° elevation). Surface temperature  
 351 in Avignon is measured using a Heimann kT17 thermal radiometer. Additionally, incoming solar  
 352 and sky radiation data from the installed pyranometers and pyrgeometers were available. See  
 353 Appendix D for a summary of the instruments. Except for Avignon, where recordings were made  
 354 at hourly intervals, measurements at the other sites were collected on half-hourly basis.

Table 1: Summary of meteorological, biophysical and flux information at the experimental sites (the instruments installed at the experimentation sites are detailed in Appendix D and also presented in the supplementary materials)

Data	Source	Range
<i>Characteristics (both model formulations)</i>		
Surface albedo [-]	<i>Field: i.e. S ↑/S ↓</i>	varying
Vegetation albedo; soil and vegetation emissivity [-]	<i>Literature</i>	~0.15-0.25; 0.96, 0.98
Bio-physical parameters: leaf area index (LAI – [m <sup>2</sup> m <sup>-2</sup> ]), leaf inclination distribution function (LIDF - spherical foliage assumed herein: i.e., $\bar{g} = 0.5$ [-]), vegetation height [m], minimum	<i>Field</i> Agdal: Avignon: Nasrallah:	LAI; height; $r_{stmin}^*$ ~1.8; ~6; 200 <sup>*a</sup> ~0.4 – 4.0; ~0.2 – 0.8; 80 <sup>*b</sup> ~0.21; ~5.8; 200 <sup>*a</sup>

stomatal resistance ( $r_{stmin}$  - [ s m<sup>-1</sup>]), R3: ~0 – 4.2; ~0.1 – 0.8; 100\*<sup>c</sup>

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*Forcing and fluxes (both formulations)*

Meteorological data: Incoming solar radiation (S ↓ - [W m <sup>-2</sup> ]), air & surface temperature [°C], relative humidity [-], wind speed [m s <sup>-1</sup> ]	<i>Field</i>	varying
Fluxes [W m <sup>-2</sup> ]: radiation; latent, sensible and ground heat	<i>Field</i>	varying

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*Other data*

Viewing direction: Zenith ( <i>SPARSE and SPARSE4</i> ) and Azimuth ( <i>SPARSE4</i> )	<i>Field</i>	nadir (all sites) and oblique (R3)
Solar direction [°]: Zenith and Azimuth ( <i>SPARSE4</i> )	<i>From local time &amp; geo. co-ord.</i>	as per solar algorithm: ~0 – 90; ~0 – 360

---

355 <sup>\*a</sup> Delogu et al. (2018); <sup>\*b</sup> Olioso et al. (1996); <sup>\*c</sup> Boulet et al. (2015), Gentine et al. (2007)

356 Other than angular data (i.e., viewing azimuth, solar zenith and azimuth angles), no additional  
 357 information is required to run the extended model for a homogeneous canopy that assumes a  
 358 randomly inclined foliage. The solar zenith and azimuth angles can be calculated from the local  
 359 time and geographic coordinates of an area of interest; the Sun angles and daylength algorithm  
 360 (Campbell & Norman, 1998; Iqbal, 1983) is used herein.

### 361 2.2.3. Observations used for evaluation

362 In all sites but Avignon, sensible and latent energy fluxes were measured using eddy covariance  
 363 (EC) systems, which consisted of temperature probes, hygrometers, and 3D sonic anemometers  
 364 that measured the fluctuations of air temperature, water vapor and wind velocity components.  
 365 The raw EC data at the Agdal site was processed using the ‘ECpack’ processing tool developed  
 366 by the Meteorology and Air Quality Group, Wageningen University (Hoedjes et al., 2007).  
 367 Nasrallah’s EC system data was analysed using the ‘eddy pro’ software developed and  
 368 maintained by LI-COR Biosciences and the ‘ReddyProc’ tool used for gap-filling (Chebbi et al.,

369 2018). For R3, processing of the raw data was done using the 'EdiRe' software package from the  
370 University of Edinburgh (Duchemin et al., 2006). The ground heat flux was measured using soil  
371 heat plates installed within a few centimeters depth (a correction is applied to account for the  
372 heat storage between the sensor and the soil surface). Net radiation was calculated as a residual  
373 from the incoming and outgoing short- and long-wave radiation observations from 4 component  
374 net radiometers; at Avignon, direct measurements of  $R_n$  were performed using 2 component net  
375 radiometers. In Avignon sensible heat flux was measured using 1D sonic anemometers and latent  
376 heat flux was computed as the residual of the energy balance equation. Latent heat flux was also  
377 measured using a Bowen ratio system providing results consistent with the residual method  
378 (Cellier & Olioso, 1993). Correction of latent heat fluxes at the R3 wheat field was similarly  
379 achieved by ensuring Bowen conservation (Boulet et al., 2015). There was a good daily energy  
380 budget closure at the Nasrallah Olive site, which was characterized by a slope of 98 % (Chebbi  
381 et al., 2018). An absolute energy closure of 90 % has also been reported for the Agdal Olive site  
382 (Er-Raki et al., 2009).

383 While overall fluxes are important, separating them between the soil and vegetation components  
384 is key particularly to users in water deficit regions who are faced with the need to allocate the  
385 scarce resource to the plant for optimal agricultural production. Transpiration data were however  
386 only available at the Nasrallah and Agdal orchard sites. To allow adequate representation of the  
387 olive trees at the Nasrallah site, rescaling of sap-flow observations was necessary. The rescaled  
388 measurements were calculated using parameters (i.e., trunk diameter, total stem section) taken  
389 from old and young olive trees (Chebbi et al., 2018). For Agdal, data filling was done using a  
390 linear regression for the site proposed in Er-Raki et al. (2009), i.e.  $0.44ET_0 + 0.49$ ; where  
391  $ET_0$  [ $\text{mm d}^{-1}$ ] is the daily reference evapotranspiration (estimated in their work using the FAO-

392 56 Penman-Monteith equation).

393 For Nasrallah, performance reporting primarily focuses on the dataset collected over the year  
394 2014 whereas some other evaluation variables are drawn from years 2013 and 2015. This is  
395 because continuous meteorological, EC and sap-flow data that had minimal errors were readily  
396 available for year 2014 while other data were collected in the other years. For instance,  
397 measurement of shaded soil temperatures only began in year 2015; however, the turbulent flux as  
398 well as sap flow measurements collected during that year had a lot of intermittent but frequent  
399 instrument-related errors. In this isolated tree agro-system, positioning an infrared thermometer  
400 in the shade or over the sunlit soil was technically straightforward, while the sunlit and shaded  
401 leaf elements were more homogeneously distributed and could not fall within the field-of-view  
402 (FOV) of a single instrument. We therefore interpreted the difference between a nadir-looking  
403 narrow-FOV TIR radiometer and the hemispherical radiometer to retrieve both elementary  
404 temperatures. The sunlit vegetation temperature was therefore recomputed from the outgoing  
405 longwave radiation (from the hemispherical radiometer), shaded vegetation temperature and  
406 sunlit/shaded soil temperatures (from the narrow-FOV TIR radiometers looking at the central  
407 canopy gap and bare soil, respectively). That is, the outgoing longwave radiation was assumed to  
408 be a function of the bare soil and vegetation (weighted by the gap fraction and foliage cover  
409 fraction, respectively) and a small contribution from the reflected sky emittance. From the  
410 calculated average foliage temperature, the sunlit vegetation temperature was indirectly solved  
411 for by weighting the sunlit/shaded vegetation elements using their respective contribution  
412 coefficients from UFR97.

#### 413 2.2.4. Evaporation proxy

414 Save for the hourly-retrieved measurements at the Avignon experimental site, edaphic variables

415 (i.e., soil moisture and soil temperature) are recorded every 30 minutes. We used the surface soil  
 416 moisture measurements as a proxy to estimate the evaporation efficiency. Soil evaporation  
 417 efficiency can be defined as the ratio between actual and potential/maximum evaporation. The  
 418 ‘reference’ soil evaporation efficiency (also ‘relative humidity at the ground surface’ according  
 419 to Noilhan and Planton (1989)) is given by a sinusoidal function described in Merlin et al. (2011)  
 420 as:

$$421 \quad \beta_s = \begin{cases} \left[ 0.5 - 0.5 \cos \left( \pi \frac{\theta_{0-5\text{cm}}}{\theta_{\text{max}}} \right) \right]^p, & \theta_{0-5\text{cm}} < \theta_{\text{max}} \\ 1, & \theta_{0-5\text{cm}} \geq \theta_{\text{max}} \end{cases} \quad (13)$$

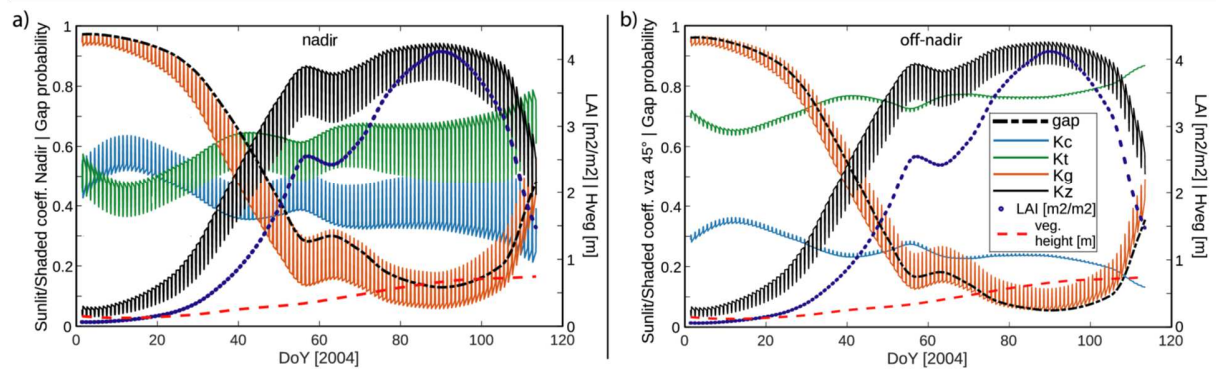
422 where  $\theta_{0-5\text{cm}}$  and  $\theta_{\text{max}}$  are the observed and saturation soil water contents at the surface layer  
 423 (here volumetric [ $\text{m}^3\text{m}^{-3}$ ] soil moisture at 5 cm depth is used);  $p$  [-] is a shape parameter related  
 424 to soil texture. Such a function can also act as an observation operator when assimilating satellite  
 425 acquisitions of surface soil moisture in soil-vegetation-atmosphere transfer algorithms.

## 426 3. Results

### 427 3.1. Sunlit and shaded contributions

428 The Unified Francois (UFR97) model, as detailed earlier, estimates contributions of sunlit and  
 429 shaded elements depending on the solar and viewing directions. Here we only present a  
 430 simulated example of the Morocco R3 site as it is the only one with oblique thermal  
 431 measurements. The site is instrumented with two Apogee Infrared radiometers viewing from  
 432 nadir and oblique (at  $45^\circ$  inclination). Figure 2 highlights the simulated contributions of the  
 433 sunlit and shaded soil and vegetation elements. The daily variations are more differentiable in the  
 434 nadir case where contribution of sunlit elements is highest around solar noon (peaks/troughs in  
 435 sunlit/shaded element envelopes in Figure 2). With the solar azimuths ranging from  $110^\circ$  -  $250^\circ$

436 (10 AM - 3 PM), the south-facing off-nadir thermal sensor is simulated to observe varying  
437 sunlit/shaded soil elements while mostly viewing the shaded vegetation over the experiment  
438 period. This observation is as expected for a site that is located in the Northern Subtropics.



439 Figure 2: Contributions of sunlit/shaded soil ( $K_g/K_z$ ) and sunlit/shaded vegetation ( $K_c/K_i$ )  
 440 components and gap fraction (probability) at the R3 wheat site (10 AM - 3 PM) as simulated by  
 441 the UFR97 method for a) Nadir-, and b) off-nadir/oblique-facing radiometer. Solar noon depicted  
 442 by peaks in sunlit elements and troughs in shaded elements.

### 443 3.2. Global fluxes and partitioning

444 In this and subsequent sections, the ‘prescribed’ model runs were forced with surface  
 445 temperature measurements acquired at nadir, except for the R3 site which also had oblique TIR  
 446 observations. Performance in estimating total fluxes is analyzed first, then we look at how those  
 447 fluxes were partitioned between the vegetation and soil sources, and finally on the estimated  
 448 evaporation efficiency. For an initial overview of how the models perform under different  
 449 atmospheric conditions, outputs from clear skies were distinguished from cloudy days following  
 450 the method detailed in section 2.1.2. However, throughout the rest of this study focus is mainly  
 451 on outcomes from the combined clear-sky and overcast datasets. Further reporting on the nadir-  
 452 and oblique-derived estimates at the R3 site is discussed in section 4.2. The objective functions  
 453 used for assessing the performance of the models include: the root mean square error/difference  
 454 (RMSE [variable’s units]), correlation coefficient ( $R$  [-]) and bias [variable’s units].

#### 455 3.2.1. Overall (global) fluxes

456 Daily RMSEs and correlation coefficients for the overall fluxes over the four sites are compared  
 457 in Table 2 with the columns denoted ‘All data’ reporting on the combined clear-sky and overcast



458 output. Similarly, Figure 3 illustrates comparisons of the combined data. From inspection of the  
459 tabulated metrics, it can be observed that even by applying relatively simple sky radiation scaling  
460 methods, clear-sky performances can be replicated, i.e., the respective model performances  
461 between cloudless and combined outcomes are comparable in all test sites. This highlights the  
462 utility of models meant to be used with all-weather remotely sensed data. While this may be  
463 desirable temporal-wise, their usage in cloudy conditions would require the use of thermal data  
464 that is less influenced by the atmosphere's visibility conditions (e.g. in-situ/field-collected data  
465 or unmanned aerial vehicles – UAV imagery), which typically have limited spatial coverage.

466 Some site-specific characteristics could also be observed to influence the overall results. In  
467 Nasrallah, for example, the prevailing dry conditions coupled with the fact that only around 7%  
468 of the surface is vegetated lead to the flux simulations being mostly attributed to the soil, and  
469 more so to the sensible heat flux. With much less available energy being assigned to latent  
470 fluxes, relatively low RMSEs could be achieved for the site. However, the latent flux goodness-  
471 of-fit for the site as described by the correlation coefficient was not as good although a small  
472 improvement could be observed with SPARSE4. Contrarily, at the Agdal orchard - which has a  
473 higher vegetation cover fraction and is frequently irrigated - the turbulent fluxes RMSEs are  
474 relatively higher but with much better correlation. The hourly performances are displayed in  
475 Figure 3 where both models demonstrate nocturnal equivalence with some differences being  
476 observed during the day. The relatively large early-morning biases of latent fluxes at the  
477 Nasrallah site, which are somewhat reduced in the new model formulation, can also be seen to be  
478 averaged out by the reduced nighttime biases.

Table 2: SPARSE and SPARSE4 global fluxes performance: RMSEs [ $\text{W m}^{-2}$ ], correlation coefficients -  $R$  [-] and bias [ $\text{W m}^{-2}$ ] for the four sites

		SPARSE				SPARSE4			
		RMSE/correlation/bias		RMSE/correlation/bias		RMSE/correlation/bias		RMSE/correlation/bias	
		Clear skies	All data	Clear skies	All data	Clear skies	All data	Clear skies	All data
Agdal	Rn	29/0.99/-19	34/0.99/-24	21/0.99/-4	23/0.99/-5				
	LE	64/0.83/11	63/0.82/8	61/0.83/9	57/0.83/6				
	H	75/0.87/-29	74/0.86/-28	63/0.88/-12	61/0.88/-11				
	G	27/0.88/15	25/0.88/14	27/0.84/2	26/0.84/2				
Avignon	Rn	43/0.98/-12	42/0.98/-11	36/0.98/7	38/0.98/7				
	LE	44/0.95/-12	43/0.95/-12	48/0.94/2	47/0.94/-1				
	H	41/0.90/-13	40/0.89/-14	42/0.78/-4	44/0.77/-3				
	G	39/0.89/16	38/0.86/16	39/0.82/11	38/0.80/11				
Nasrallah	Rn	35/0.98/-3	34/0.98/4	32/0.98/3	33/0.98/4				
	LE	38/0.59/6	39/0.56/7	35/0.62/2	36/0.60/3				
	H	48/0.93/-29	47/0.92/-26	44/0.94/-20	44/0.93/-19				
	G	42/0.94/13	41/0.93/14	43/0.93/9	41/0.93/12				
<i>TIR-view</i> →	<i>nadir</i>	<i>oblique</i>	<i>nadir</i>	<i>oblique</i>	<i>nadir</i>	<i>oblique</i>	<i>nadir</i>	<i>oblique</i>	
R3	Rn	35/0.98/6	36/0.99/7	39/0.98/1	38/0.98/1	41/0.99/13	41/0.99/12	42/0.98/12	43/0.98/11
	LE	48/0.84/-3	46/0.89/5	48/0.83/-6	48/0.87/-1	36/0.94/4	37/0.93/4	40/0.93/5	41/0.91/4
	H	59/0.82/-19	54/0.81/-27	59/0.83/-23	56/0.82/-28	49/0.84/-8	52/0.83/-8	49/0.85/-11	52/0.84/-10
	G	30/0.83/15	32/0.83/16	29/0.82/11	29/0.81/12	37/0.71/6	37/0.70/6	36/0.66/3	36/0.65/3

479 The net radiation, which is the main source of energy for the system, is observed to be increased  
480 with SPARSE4. This tends to reduce the bias (in absolute terms) and the RMSE except in R3.  
481 Changes are mostly significant in diurnal periods as shown in Figure 3 and also at night for  
482 Nasrallah. In Agdal, the reduced net radiation biases (lower negative biases according to Table 2)  
483 also appear to be partly contributed by the relatively higher net radiation for the vegetation  
484 (Figure 7). The turbulent fluxes RMSEs at Avignon are fairly higher for the new model. The  
485 differences, which can possibly be attributed to the added model complexities, are nonetheless  
486 counterbalanced by improved biases. In terms of mean errors, both model formulations appear to  
487 consistently overestimate the ground heat flux while generally underestimating the sensible heat  
488 fluxes. These biases can mainly be attributed to the estimates at nighttime when the ground

489 (sensible) heat fluxes are generally overestimated (underestimated). Night soil temperatures  
490 estimated by both models generally appear to be underestimated (Figure 5) thus explaining the  
491 biases since the low temperatures suggest less soil emissions and therefore more soil net  
492 radiation, which is then available for the soil energy fluxes and therefore partly explaining the  
493 overestimation of the soil heat flux. The inverse effect of the increased net radiation on sensible  
494 heat flux is likely as a result of the inherent/theoretical direct relation between sensible heat flux  
495 and temperature and the fact that latent fluxes are capped. The biases are nevertheless somewhat  
496 suppressed in SPARSE4 for all fluxes across all sites.

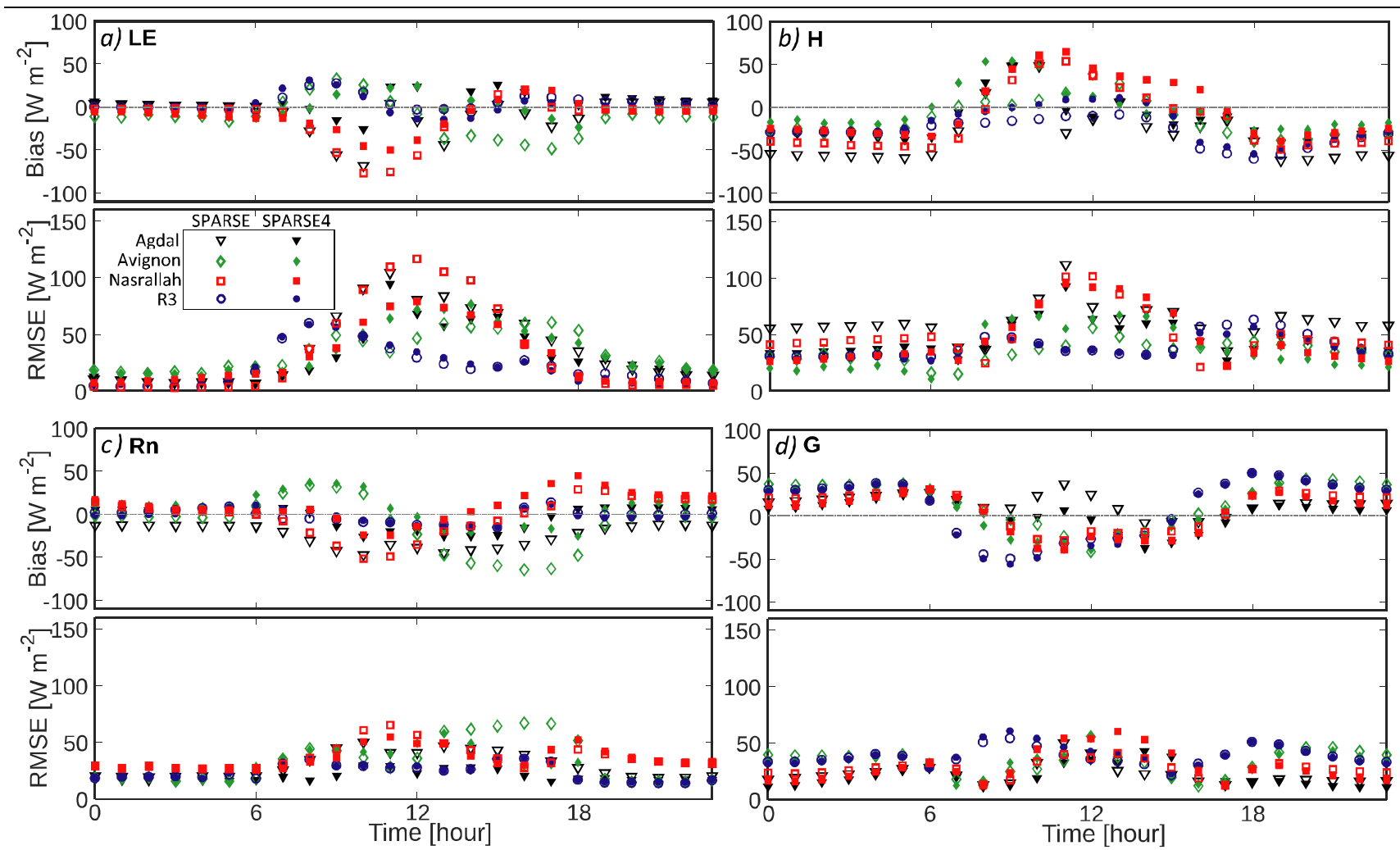


Figure 3: Nocturnal/diurnal trends of bias and RMSEs; for a) latent heat flux, b) sensible heat flux, c) net radiation, and d) ground heat flux. Hollow and solid shapes represent SPARSE and SPARSE4, respectively; shape/color (site): triangle/black (Agdal), lozenge/green (Avignon), square/red (Nasrallah), and circle/blue (R3)

497 3.2.2. Flux partitioning and temperatures

498 This sub-section reports on the partitioning of the total fluxes starting with the decomposition of  
499 evapotranspiration between the soil and vegetation at the Nasrallah and Agdal orchard sites. As  
500 previously noted, availability of sap-flow data is limited to these two sites. The daily  
501 transpiration rates simulated during the study periods are illustrated in Figure 4. For Nasrallah,  
502 the respective root mean square errors [mm/day], correlation [-] and bias [mm/day] for SPARSE  
503 were: 0.15, 0.91, -0.12; and for SPARSE4: 0.09, 0.90, -0.02. The models' RMSEs,  
504 correlations and bias for Agdal were 0.40, 0.96, -0.35 and 0.23, 0.96, -0.04, respectively. The  
505 overall reduction of the bias - by at least 40 % - translated to the transpiration in the new  
506 formulation being higher than in the standard SPARSE hence allowing the estimates to closely  
507 follow the reference observations particularly during the summer.

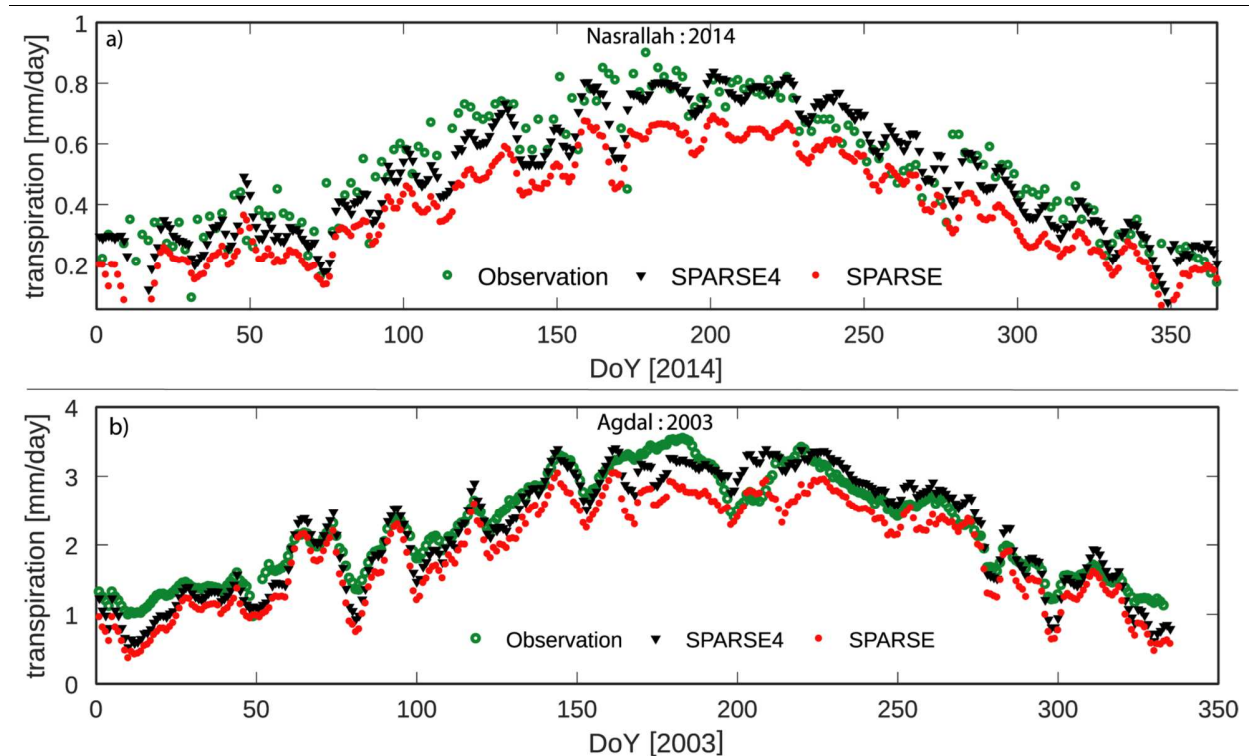


Figure 4: Observed (green  $\bullet$ ) and simulated (SPARSE: red  $\bullet$ , SPARSE4: black  $\blacktriangledown$ ) transpiration -time series' for a) Nasrallah and b) Agdal sites.

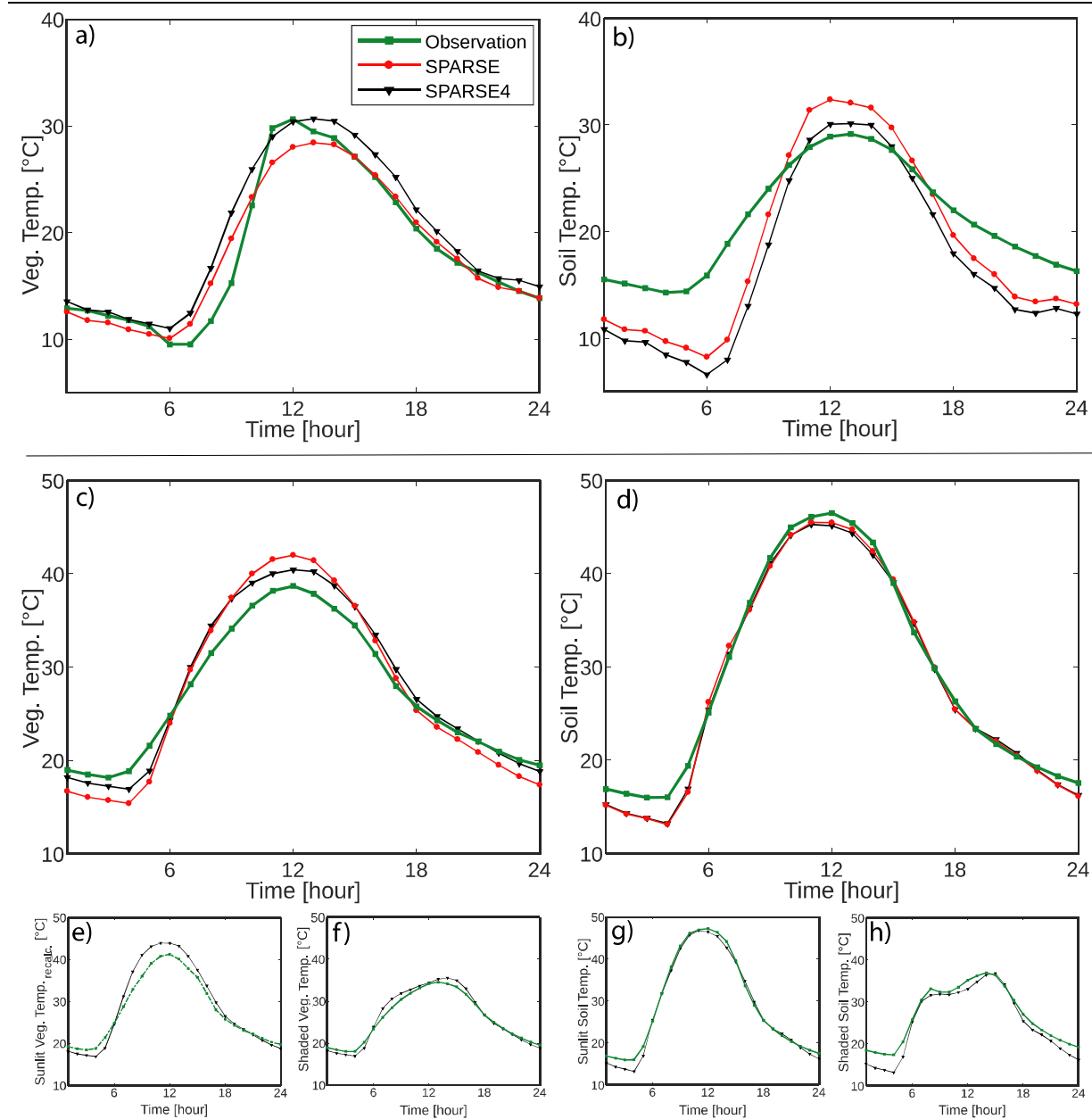


Figure 5: Vegetation and soil temperatures (estimated and observed) over the simulation period in Agdal (a, b) and Nasrallah (c, d); and e, f) sunlit and shaded vegetation elements; g, h) sunlit and shaded soil at the Nasrallah site (key applies to all figures)

508 The simulated temperatures for the Agdal and Nasrallah (2015) sites are shown in Figure 5. For  
 509 Agdal, the measurements were taken as the soil/vegetation averages. For Nasrallah, however, the  
 510 sunlit soil, shaded soil and shaded vegetation temperatures were available but only from year  
 511 2015. As detailed in section 2.2.3, the sunlit vegetation temperature was re-calculated from the

512 long-wave radiation observations and the measured sunlit/shaded soil and shaded vegetation  
513 temperatures. Estimates by SPARSE4, which outputs both shaded and sunlit temperatures, are  
514 compared to the observations in Figure 5. The nocturnal soil temperature estimates are generally  
515 underestimated resulting in the already noted biases on the soil energy fluxes. The TIR Apogee  
516 sensor that provides the shaded soil temperatures (installed under a tree) records slightly higher  
517 night temperatures when compared to the sensor in the open field (in the Sun during the day).  
518 This phenomenon is however not replicated by the model since the entire soil is considered  
519 shaded at night.

### 520 3.3. Soil evaporation efficiency

521 Unavailability of sap flow data due to complexities involved in collecting accurate measurements  
522 can make the assessment of evapotranspiration partitioning impractical for some sites.  
523 Nonetheless, how well a model estimates vegetation (latent heat) fluxes can be deduced from  
524 overall evapotranspiration and soil evaporation. This can practically be obtained as the difference  
525 between total evapotranspiration from eddy covariance measurements and soil evaporation  
526 inferred from surface soil moisture. Here, we compare the soil efficiencies retrieved by SPARSE  
527 to the proxy soil evaporation efficiency given by Equation (13) (Merlin et al., 2011). The  
528 modeled soil efficiencies are illustrated and compared to the proxy in Figure 6.

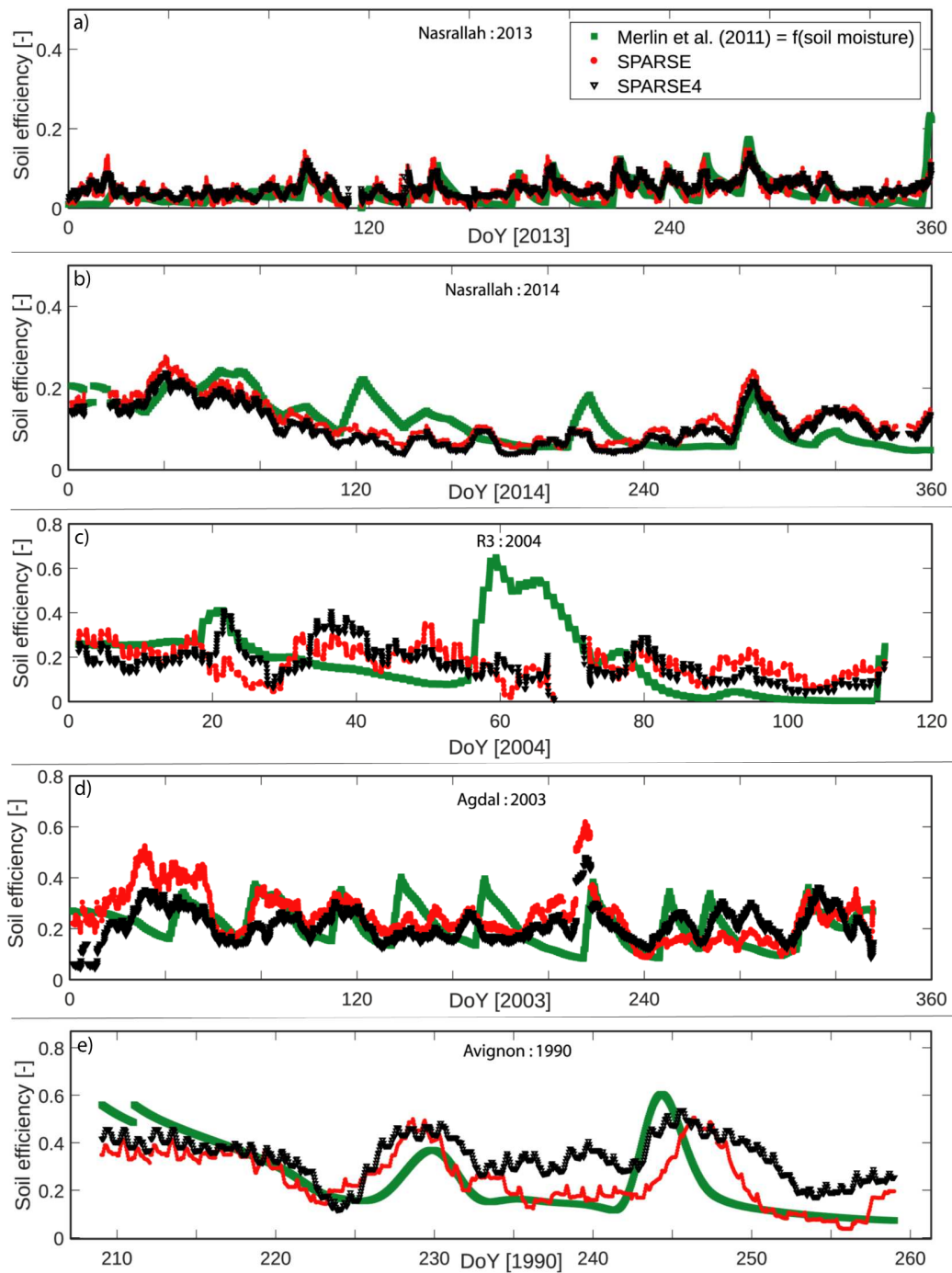


Figure 6: Time series' of soil evaporation efficiencies (SPARSE: red and SPARSE4: black) with Merlin et al.'s (2011) method as the proxy (in green) a, b) Nasrallah - 2013 and 2014, c) R3, d) Agdal, and e) Avignon

529 In Nasrallah, where the soil is greatly stressed, the models' soil efficiency simulations are able to  
 530 reproduce the 'observation' with both models generally showing a better fit with variations of the



531 soil moisture inferences. The new scheme appears to capture most peaks in R3 and Agdal,  
532 especially around the first soil water inputs, with slightly better timing. Otherwise, the soil  
533 efficiency estimations by the two models were almost similar in the four experiments. In addition  
534 to the peak in R3 at maximum vegetation development (from DoY ~55 to ~70 excluding missing  
535 simulations arising from a surface temperature data gap), some peaks in the evaporation  
536 efficiencies at the Agdal site corresponding to irrigation episodes are not well captured.

## 537 4. Discussion

### 538 4.1. Overall performance and the influence of direction on partitioning

539 The SPARSE and SPARSE4 energy balance schemes were evaluated over two orchards and two  
540 crop experimental sites. Overall, it was apparent that both models could satisfactorily estimate  
541 the global fluxes. While there was a general reduction of flux biases with SPARSE4,  
542 performance between the models was almost similar when using the nadir-retrieved temperature  
543 inputs since such measurements are generally not influenced by TRD effects. These results are  
544 expected as all the four sites are situated in relatively high latitudes where directionality effects  
545 on the nadir measurements are negligible due to the medium/low Sun angles throughout the  
546 simulation periods. R3, which was the only site with an oblique-viewing radiometer, also  
547 provided measurements that were simulated to originate from mostly shaded elements as  
548 illustrated in Figure 2.b. Consequently, the nadir- and oblique-derived total flux estimates were  
549 retrieved with reasonable accuracy by both schemes (Table 2). In order to derive differentiated  
550 and possibly improved total flux retrievals from the new model formulation, surface temperature  
551 differences arising from thermal radiation directionality effects should be present. As reported  
552 earlier, directionality effects can be quite large especially when viewing in the solar direction  
553 warranting the use of a directionality model to simulate out-of-canopy radiances. These thermal

554 directionality effects could however not be tested at present due to limitations related to  
555 unavailability of directional thermal measurements. SPARSE has also been shown to exhibit  
556 equifinality (Boulet et al., 2015; Boulet et al., 2018) where consistent/similar total fluxes can be  
557 estimated with different stress-level combinations of the individual sources. We acknowledge  
558 and expect that this aspect is also present in the new formulation.

559 Figure 7 illustrates the component net radiations as simulated by the two models. Also shown are  
560 the vegetation cover fractions in the solar as well as nadir directions. Consideration of the solar  
561 direction, i.e. where direct radiation is partitioned with respect to the solar elevation, ensures  
562 more radiation is apportioned to the vegetation in the new formulation. The rationale is twofold:  
563 1) the diffuse fraction ( $f_d$ ) as defined by Erbs et al. (1982) decreases with increase in the sky  
564 clearness index, therefore high global solar radiation will generally result in high direct radiation  
565 in the solar direction; and 2) gap fraction – complement to vegetation cover fraction as illustrated  
566 in Figure 7 - diminishes (hence canopy fraction increases) from nadir to the Sun's zenith (which  
567 is often oblique especially in the subtropics and temperate regions); this additional radiation  
568 received by the vegetation can then be partitioned between the turbulent fluxes. Indeed, this leads  
569 to the higher vegetation available energy in the Agdal site, which is then apportioned for the  
570 higher canopy turbulent fluxes thus the slightly higher transpiration. However, if one assumes  
571 minimal errors in the diffuse radiation measurements, then it should be acknowledged that the  
572 use of Erbs et al.'s (1982) method introduces additional partitioning uncertainties as depicted by  
573 the observed diffuse fraction band in Figure C1. With relatively more radiation reaching the soil,  
574 the classical SPARSE model attains a better simulation of the ground heat flux in terms of  
575 RMSE and correlation although this appears to in-turn lead to relatively higher positive biases.  
576 While the discrimination between shaded and sunlit elements likely results in better partitioning

577 of vegetation's available energy between sensible ( $H_v$ ) and latent ( $LE_v$ ) heat fluxes, the expected  
 578 impact of vegetation temperatures on the absolute  $H_v$  values is not apparent - especially for  
 579 densely vegetated scenes and unstressed vegetation. When the vegetation is unstressed, the new  
 580 formulation will generally apportion the relatively higher vegetation available energy as  
 581 unstressed  $H_v$  since  $LE_{vpot}/Rn_{vpot}$  is inherently similar to that simulated by SPARSE.

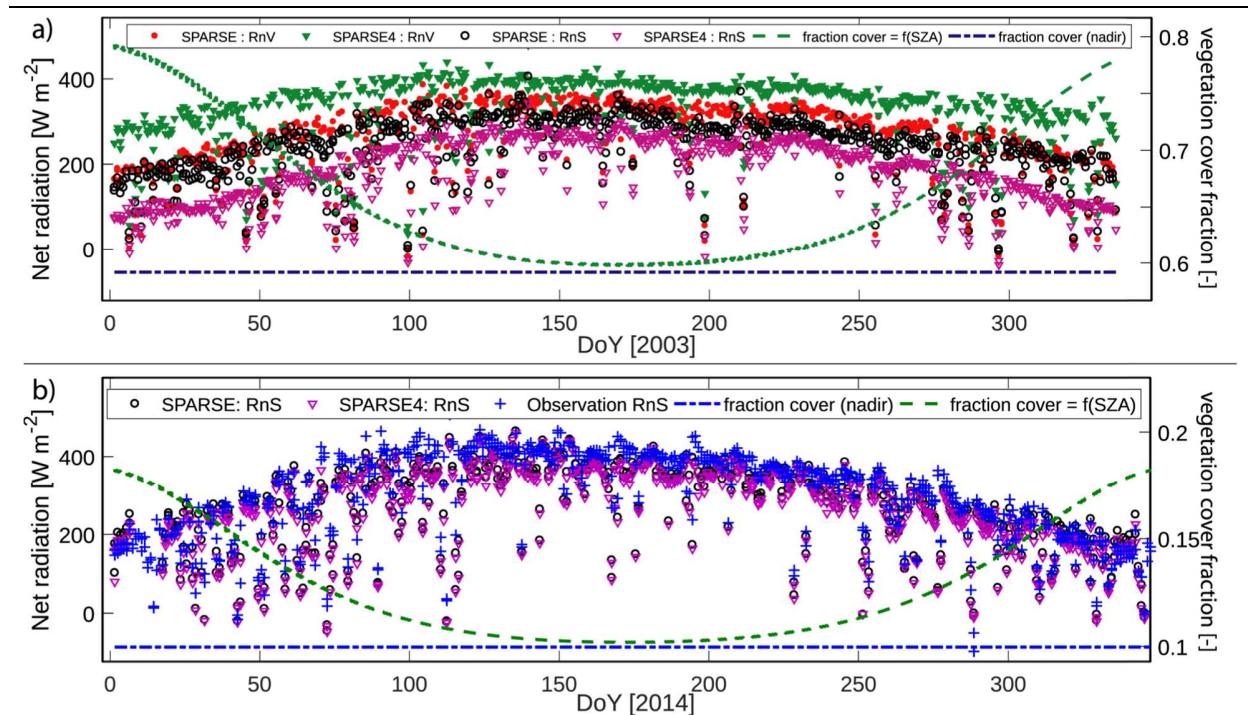


Figure 7: a) Vegetation/soil net radiation (noon) at the Agdal site and b) Nasrallah soil net radiation. Right axis: nadir vegetation cover fraction (only dependent on LAI and LIDF) and vegetation cover fraction in the Sun direction (dependent on LAI, LIDF and solar elevation).

582 While the UFR97 method provides gap frequencies treatment for homogeneous/continuous  
 583 covers, row (Yan et al., 2012) and forest (Bian et al., 2018; Li et al., 2017), this study applies the  
 584 homogeneous method across all sites since it ensured consistency with the observations. When  
 585 compared to the continuous cover method, Li et al.'s (2017) method has been shown to provide  
 586 significantly larger gap fractions especially at nadir (Bian et al., 2018). We also observe its  
 587 underestimation of vegetation cover fraction when compared to the observations at the orchards.

588 The radiative model could nonetheless be improved by using the discontinuous versions, which  
589 we expect can further improve the results. The method's suitability in surface energy balance  
590 partitioning however requires careful analysis before it can be properly applied. With respect to  
591 applying different cavity effect formulations (FR97 and C-EP), we observe that the differences in  
592 the resulting fluxes are very small (results not shown). This is because the orders of magnitude of  
593 both cavity effect formulations are quite close for nadir views with the differences in the  
594 resulting canopy emissivity being marginally higher for larger viewing zeniths.

#### 595 4.2. Sensitivity of estimates to nadir vs off-nadir viewing

596 It is important to test the sensitivity of evapotranspiration derivation methods to the sensor  
597 direction of view because prevailing surface condition retrievals (temperatures, radiation and  
598 turbulent fluxes) should essentially be similar whatever the geometry of data acquisition. This is  
599 a key consideration aspect since space-borne sensors, which presently act as essential sources of  
600 input data for Earth observation methods, generally observe terrestrial pixels from off-nadir  
601 directions, with the viewing orientations changing often depending on the satellite's location in  
602 its orbit. While the Sun-synchronous concept used in some missions (e.g., MISTIGRI,  
603 Lagouarde et al., 2013) minimizes the impact of thermal radiation directionality by allowing  
604 same viewing geometry for a given location, it cannot entirely eliminate effects resulting from  
605 solar position variations (Duffour et al., 2016; Duffour et al., 2015). For instance, future high  
606 resolution satellite missions in the TIR domain (e.g., TRISHNA, Lagouarde et al., 2019) will  
607 observe a given location with very different observation angles from one overpass to the other.  
608 This will allow frequent revisit capacities, which are indeed necessary for reasonable temporal  
609 upscaling of evapotranspiration estimates (Delogu et al., 2021). While the retrieval parameters  
610 (e.g. overpass time) can be duly chosen such that the hotspot is rarely observed, these

611 specifications mean that it is likely for the sensors to acquire remote sensing data close to the  
612 hotspot particularly over the tropics and subtropics (see for example Duffour et al. (2016)).  
613 Additionally, directionality is also an issue for current missions including MODIS, and is usually  
614 ignored (except for the amount of vegetation in the sensor's field of view). SPARSE 4 was  
615 designed to account for such differences in viewing direction and changes in Sun position, and it  
616 is important to evaluate potential improvements in this sense comparatively to SPARSE. We  
617 therefore test the models' output sensitivity to observation angle for the R3 site when forced with  
618 surface temperature observations acquired simultaneously either at nadir or from a 45° (south-  
619 facing) elevation angle.

620 Figure 8 plots the oblique- against nadir-retrieved model estimates for the two SPARSE  
621 formulations and the performance evaluation of the respective nadir and oblique simulation sets  
622 are tabulated in Table 2. The small differences between the temperatures observed from the two  
623 directions (within ~3°C) allow the overall fluxes to be satisfactorily reproduced by both models.  
624 Reproduced retrievals of vegetation fluxes by SPARSE4 however appear better and it can also be  
625 observed that angular surface temperature inputs have slightly more impact on SPARSE's  
626 retrieval of soil temperatures. This can in part be explained by the fact that the gap fraction  
627 reduces from nadir to off-nadir and the underlying physical assumption of the soil being stressed  
628 prior to vegetation. This lower oblique gap means that the fraction of soil (and hence its  
629 contribution to the signal) in the field of view of the sensor is reduced leading to variations in the  
630 simulated soil stress efficiency and thus the soil temperatures. Additionally, the coupling of the  
631 soil and vegetation in the net radiation scheme means any deviations in soil emissions ultimately  
632 influence the vegetation's radiative and energy budgets. The influence on soil fluxes in extended  
633 model can be interpreted the same way although its consideration of the shaded soil (which

634 reduces the average temperature variations) appears to diminish the overall effect. There is  
 635 consequently a tendency to simulate similar, albeit potential (*subscript pot*) or unstressed,  
 636 vegetation fluxes in both SPARSE4 scenarios.

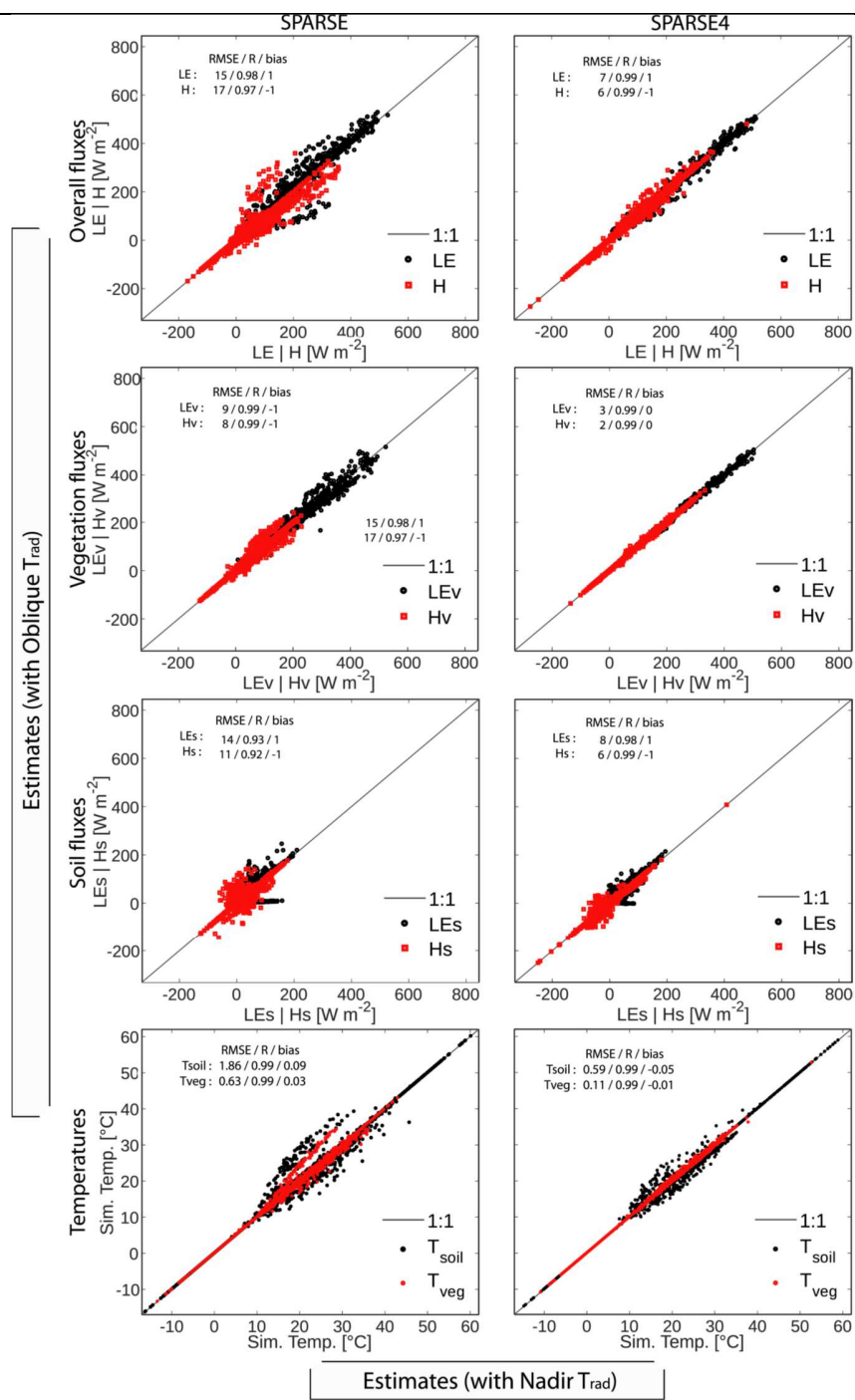


Figure 8: Sensitivity of estimates to angular thermal data. I.e.: estimates using oblique-observed

$T_{\text{rad}}$  (ordinate) vs estimates from nadir-observed surface temperature ( $T_{\text{rad}}$ ) input (abscissa). Inset: RMSE, R and bias of oblique-based estimates versus nadir-based estimates.

637 The inversion capabilities of the coupled model are quite promising since it is apparent that, even  
638 with thermal data measured from different directions, the prevailing component temperatures and  
639 fluxes (radiative and energy) at the land surface can satisfactorily be retrieved and reproduced  
640 with SPARSE4 estimates being more consistent when compared to SPARSE's retrievals.  
641 Nevertheless, the method's inversion and turbulent flux reproduction capabilities over the entire  
642 Sun-observer polar grid requires further verification. Since we also see no observable  
643 improvement in overall flux retrievals especially when thermal radiation directionality effects  
644 (oblique-nadir temperature differences) are negligible, a study that will encompass a wide-  
645 ranging combination of Sun-Earth-sensor geometries (including the hotspot region) is necessary.

## 646 5. Summary and Conclusions

647 In this study, we have presented an extended formulation of the Soil Plant Atmosphere Remote  
648 Sensing Evapotranspiration (SPARSE) model where sunlit and shaded elements have been  
649 distinguished in the energy and radiative balance schemes. A clearness index method was hence  
650 adopted to partition the incoming global solar radiation into its direct and diffuse components.  
651 Since remote thermal infra-red sensors usually observe within a narrow spectral window, a  
652 method that accounts for this important aspect has also been incorporated. For thermal radiation  
653 directionality effect accounting, coupling was done with the Unified Francois (UFR97) radiative  
654 transfer model that links the sunlit/shaded soil/vegetation surface emissions with out-of-canopy  
655 radiance in the viewing direction. A preliminary evaluation of the extended method was then  
656 carried out to assess its capability in estimating and partitioning overall fluxes on two orchards  
657 and over growing cycles of soybean and wheat.

658 We observed that the partitioning of total fluxes does improve when sunlit and shaded elements



659 are distinguished leading to better transpiration estimates especially in water stressed regions. By  
660 weighting between shaded/sunlit elements, the tendency by the original SPARSE model to  
661 simulate higher vegetation temperatures was also largely reduced. Since remotely sensed data are  
662 often acquired from oblique directions, models that invert the measured surface temperatures  
663 should be insensitive to any angular effects. It was thus observed that the extended formulation,  
664 coupled with an anisotropy model, resulted in better reproduction of flux and component  
665 temperature estimates from directional thermal data. This is particularly important when using  
666 data whose signal could be influenced by the Sun-Earth-sensor geometry particularly in the  
667 hotspot direction. Satellite missions whose objectives include ecosystem functioning and stress  
668 monitoring (e.g. TRISHNA, LSTM) can / will be able to provide thermal observations at  
669 relatively high spatial and temporal resolutions by proposing a wide range of viewing repeat-  
670 cycle angles. While we contend that the new formulation is not meant to replace the standard  
671 SPARSE algorithm especially when inverting thermal data less influenced by TRD, its  
672 consideration of directionality aspects/effects (which are not only limited to the hotspot region)  
673 as well as its demonstrated capabilities of flux partitioning in water-deficit terrains are worth  
674 further investigation. These should form part of a future study whose main focus will be thermal  
675 radiation directionality effects on turbulent flux estimation. Such analyses should also potentially  
676 be able to inform the selection of algorithms that normalize directionality-influenced remote  
677 sensing products to a particular standard direction. Introducing clumping index into the modified  
678 SPARSE model by considering non-continuous vegetation cover is another valuable work in the  
679 future.

680 *Supplementary material and code availability:* supplements are available as a separate file; the  
681 code can be accessed through: [osr-cesbio.ups-tlse.fr/gitlab\\_cesbio/mbugu/sparse4](https://osr-cesbio.ups-tlse.fr/gitlab_cesbio/mbugu/sparse4)

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692 comments and suggestions.

## 693 Appendix A: Contribution of sunlit and shaded elements

694 The sunlit ( $K_g$ ) fraction of visible soil is calculated as:

$$695 \quad K_g = \frac{\exp \left[ - \left( \Omega_i \frac{G_i}{\mu_i} + \Omega_v \frac{G_v}{\mu_v} - w \sqrt{\Omega_i \Omega_v \frac{G_i G_v}{\mu_i \mu_v}} \right) LAI \right]}{b(\theta_v)} \quad (A1)$$

696 and the complement is the shaded fraction of visible soil:

$$697 \quad K_z = 1 - K_g \quad (A2)$$

698  $G_{j=i,v}$  is the foliage projection factor in the viewing (v) or solar/illumination (i) direction;  $\mu_{j=i,v}$  is  
699 the cosine of an angle;  $\Omega_{j=i,v}$  is the clumping index derived by inverting the gap frequency  
700 ( $b(\theta_v) = \tau_\omega(\theta_v)$ ) Beer's exponential formula given in Nilson (1971); LAI is the leaf area index;  
701  $w = \frac{d}{h\delta} (1 - e^{-h\delta/d})$  is the hotspot function; d and h are the leaf width and canopy height,  
702 respectively;  $\delta = \sqrt{\tan^2(\theta_i) + \tan^2(\theta_v) - 2 \tan(\theta_i) \tan(\theta_v) \cos(\varphi)}$ ;  $\varphi$  – relative azimuth angle between

703 the solar and viewing directions.

704 Effective emissivity expressions of the sunlit ( $\omega_{\omega,s}(\theta_v)$ ) and shaded ( $\omega_{\omega,h}(\theta_v)$ ) leaves are:

705  $\omega_{\omega,s}(\theta_v) = [1 - b(\theta_v)]\varepsilon_v K_c + (1 - M)b(\theta_v)(1 - \varepsilon_g)\varepsilon_1 C_c + (1 - \alpha)[1 - b(\theta_v)M][1 - b(\theta_v)](1 - \varepsilon_v)\varepsilon_v C_c$  (A3)

706  $\omega_{\omega,h}(\theta_v) = [1 - b(\theta_v)]\varepsilon_v K_t + (1 - M)b(\theta_v)(1 - \varepsilon_g)\varepsilon_v C_t + (1 - \alpha)[1 - b(\theta_v)M][1 - b(\theta_v)](1 - \varepsilon_v)\varepsilon_v C_t$  (A4)

707 where  $\varepsilon_v$  and  $\varepsilon_g$  are the leaf and soil emissivities respectively;  $\alpha$  is the cavity effect factor  
708 (François, 2002; Francois et al., 1997) that defines part of the incident radiation that is reflected  
709 by the leaves and finally absorbed by the canopy.  $C_c$  and  $C_t$  respectively are the contribution of  
710 sunlit and shaded leaves inside the canopy to the radiation emitted from leaves and reflected by  
711 the soil. The same factors apply for radiance emitted from the leaves and reflected by other  
712 leaves (Bian et al., 2018; Francois et al., 1997).  $M$  is the hemispherical average gap frequency  
713 (Francois et al., 1997). The respective contributions of sunlit and shaded leaves are (Yan et al.,  
714 2012):

715 
$$K_c = \frac{\left[1 - \exp\left(-w\sqrt{\Omega_i\Omega_v\frac{G_i}{\mu_i}\frac{G_v}{\mu_v}}LAI\right)\right]}{[1 - b(\theta_v)]}$$
 (A5)

716 
$$K_t = 1 - K_c$$
 (A6)

717 For definition of some terms that were modified when formulating the UFR97 model (e.g.  
718 upper/lower layer height and leaf area terms for  $K_c$  and  $K_t$ ) see Bian et al.'s (2018) work.

## 719 Appendix B: Long-wave radiation in the narrow 8 – 14 $\mu\text{m}$ spectral band of 720 the observing thermal sensor

721 Field thermo-radiometers usually provide measurement in the 8 – 14  $\mu\text{m}$  spectral range (it is  
722 also common to have satellite radiometers observing in the 10.5 – 12.5  $\mu\text{m}$  band). The measured  
723 thermal radiation is given by (Oliosio, 1995):

724 
$$f_\lambda(T_B)\sigma T_B^4 = \varepsilon_{\text{surf},\lambda}f_\lambda(T_{\text{rad}})\sigma T_{\text{rad}}^4 + (1 - \varepsilon_{\text{surf},\lambda})L_\lambda^\downarrow$$
 (B1)

725 where  $\sigma$  is the Stefan Boltzmann constant,  $T_B$  is the measured brightness temperature,  $T_{\text{rad}}$  the  
 726 radiative surface temperature and  $L_{\lambda}^{\downarrow}$  is the down-welling atmospheric radiation in the narrow  
 727 observation band. By assuming  $f_{\lambda}(T_B) \approx f_{\lambda}(T_{\text{rad}})$ , the unknown  $T_{\text{rad}}$  can be solved for.  $f_{\lambda}(T)$  and  
 728  $L_{\lambda}^{\downarrow}$  for  $\lambda = 8 - 14 \mu\text{m}$  are expressed as:

$$729 \quad f_{\lambda:8-14}(T) = -0.6732 + 0.6240 \cdot 10^{-2}T - 0.9140 \cdot 10^{-5}T^2 \quad (\text{B2})$$

$$730 \quad L_{\lambda:8-14}^{\downarrow} = \varepsilon_{a,\lambda} f_{\lambda}(T_a) \sigma T_a^4 \quad (\text{B3})$$

731  $T_a$  is the air temperature. Likewise, the atmospheric apparent emissivity  $\varepsilon_{a,\lambda}$  in the  $8 - 14 \mu\text{m}$   
 732 window is given by:

$$733 \quad \varepsilon_{a,\lambda:8-14} = 0.15 + 5.03 \cdot 10^{-6} e_a \exp(2450/T_a) \quad (\text{B4})$$

734 All temperatures are in [K] and the atmospheric vapor pressure  $e_a$  in [hPa]. Further details  
 735 including formulations for the  $10.5 - 12.5 \mu\text{m}$  thermal band can be found in Idso (1981) and  
 736 Oliosio (1995).

## 737 Appendix C: Global solar radiation partitioning and radiative balance 738 terms

### 739 *Global solar radiation partitioning*

740 Fraction of incoming diffuse radiation (fd) is estimated following the sky clearness index ( $K_T$ )  
 741 method proposed in Erbs et al. (1982). Where the atmosphere's optical depth data is available, a  
 742 modified function according to Carrer et al. (2013) is applied for  $K_T > 0.80$ :

$$743 \quad \text{fd} = \begin{cases} 1 - 0.09K_T, & \leq 0.22 \\ 0.9511 - 0.1604K_T + 4.388K_T^2 - 16.638K_T^3 + 12.336K_T^4, & 0.22 < K_T \leq 0.80 \\ 0.165 \mid (1 - \exp(-\tau_{\text{opt}})) / (1 - (1 - \mu_s) \exp(-\tau_{\text{opt}})), & K_T > 0.80 \end{cases} \quad (\text{C1})$$

744 where  $K_T = \text{RG} / (C_s \mu_s)$  is the clearness index,  $\text{RG} = S \downarrow$  is the global solar irradiance at BOA,  
 745  $C_s = 1368 \text{ W m}^{-2}$  the terrestrial solar radiation constant,  $\mu_s$  is the cosine of the solar zenith

746 angle), and  $\tau_{\text{opt}}$  is the aerosol optical thickness. Consequently,  $RG = RG_{\text{dir}} + RG_{\text{diff}} = RG_{\text{dir}} +$   
 747  $fd \cdot RG$ .

748 Figure C1 illustrates the estimated compared to observed fraction of diffuse ( $fd$ ) radiation. The  
 749 sample data used for the diagram was collected at the Bensalem site in Tunisia. The global  
 750 incoming radiation was measured using a pyranometer with a hemispherical view while the  
 751 direct radiation was observed using a narrow-view pyrhelimeter.

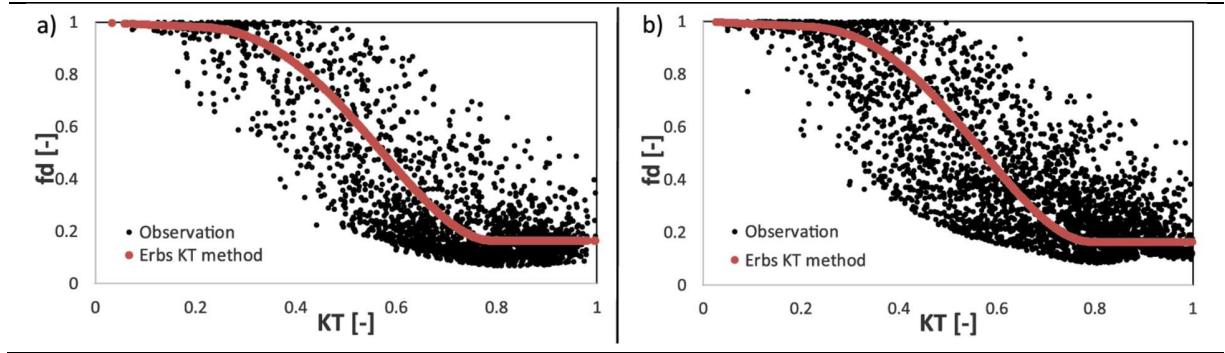


Figure C1:  $fd$  (fraction of incoming diffuse radiation) plots using Erbs et al.'s (1982) clearness index ( $K_T$ ) method on BenSalem dataset for years a) 2014 and b) 2016

752 *Net radiation terms*

753 The incoming solar and sky emission terms are partitioned as:

$$\begin{aligned}
 754 \quad RG_{vs} + RA_{vs} &= RG_{\text{dir}} \left[ f_{\text{sol}}(1 - \alpha_v) + \frac{f_{vs}\alpha_g(1 - f_{\text{sol}})[(1 - \alpha_v) + \alpha_v f_{vh}]}{1 - f\alpha_v\alpha_g} \right] \\
 755 \quad &+ f_{vs}RG_{\text{diff}} \left[ (1 - \alpha_v) + \frac{(1 - \alpha_v)[\alpha_v f_{vh}(1 - f_{vs}) + \alpha_g(1 - f)] + \alpha_v f_{vh}\alpha_g(1 - f)}{1 - f\alpha_v\alpha_g} \right] \\
 756 \quad &+ f_{vs}RA \left[ \varepsilon_v + \frac{\varepsilon_v[\rho_v f_{vh}(1 - f_{vs}) + \rho_g(1 - f)] + \rho_v f_{vh}\rho_g(1 - f)}{1 - f\rho_v\rho_g} \right] \quad (C2.1)
 \end{aligned}$$

$$\begin{aligned}
 757 \quad RG_{vh} + RA_{vh} &= RG_{\text{dir}} \left[ \frac{f_{vh}\alpha_g(1 - f_{\text{sol}})(1 - \alpha_v)}{1 - f\alpha_v\alpha_g} \right] + f_{vh}RG_{\text{diff}} \left[ \frac{(1 - \alpha_v)[1 + \alpha_g(1 - f)] + \alpha_v f_{vs}}{1 - f\alpha_v\alpha_g} \right] \\
 758 \quad &+ f_{vh}RA \left[ \frac{\varepsilon_v[1 + \rho_g(1 - f)] + \rho_v f_{vs}}{1 - f\rho_v\rho_g} \right] \quad (C2.2)
 \end{aligned}$$

$$\begin{aligned}
 759 \quad RG_{gs} + RA_{gs} &= \frac{(1 - \alpha_g) \left\{ (1 - f_{\text{sol}}) \left[ RG_{\text{dir}} \left( 1 + \alpha_v f_{vh} \alpha_g (1 - f_{\text{sol}}) \right) + \alpha_v f_{vh} \alpha_g (1 - f) RG_{\text{diff}} \right] + f_{gs} RG_{\text{diff}} \right\}}{1 - f\alpha_v\alpha_g} \\
 760 \quad &+ \frac{\varepsilon_g RA [f_{gs} + (1 - f_{\text{sol}}) \rho_v f_{vh} \rho_g (1 - f)]}{1 - f\rho_v\rho_g} \quad (C2.3)
 \end{aligned}$$

$$\begin{aligned}
761 \quad RG_{gh} + RA_{gh} &= \frac{(1 - \alpha_g)\{f_{gh}RG_{diff} + f_{sol}\alpha_v f_{vh}\alpha_g[(1 - f_{sol})RG_{dir} + (1 - f)RG_{diff}]\}}{1 - f\alpha_v\alpha_g} \\
762 \quad &+ \frac{\varepsilon_g RA[f_{gh} + f_{sol}\rho_v f_{vh}\rho_g(1 - f)]}{1 - f\rho_v\rho_g}
\end{aligned}$$

763 The grey-body thermal emission is defined around air temperature and estimated through a  
764 Taylor expansion:

$$765 \quad \sigma T_{x=vs,vh,gs,gh}^4 = \sigma(T_a + T_x - T_a)^4 \approx \sigma T_a^4 + \rho C_p \frac{4\sigma T_a^3}{\rho C_p} (T_x - T_a) \approx X_{\varepsilon 1} + \rho C_p \frac{X_{\varepsilon 2}}{\rho C_p} (T_x - T_a) \quad (C2.4)$$

766 Component emissions are:

$$\begin{aligned}
767 \quad L_{TIRvs}^{\uparrow} &\approx \frac{f_{vs}[(\varepsilon_v + \rho_v f_{vh})(\rho_g(1 - f_{vh})f_{vs}\varepsilon_v + \varepsilon_g) + \varepsilon_v(\rho_v f_{vh}f_{vs}\varepsilon_v + f_{vh}\varepsilon_v - 2)]}{1 - f\rho_v\rho_g} X_{\varepsilon 1} \\
768 \quad &+ \frac{X_{\varepsilon 2} f_{vs}}{(1 - f\rho_v\rho_g)} \{ \varepsilon_v[(\varepsilon_v + \rho_v f_{vh})\rho_g(1 - f_{vh})f_{vs} + \rho_v f_{vh}f_{vs}\varepsilon_v - 2](T_{vs} - T_a) + f_{vh}\varepsilon_v^2(T_{vh} - T_a) \\
769 \quad &+ (\varepsilon_v + \rho_v f_{vh})[(1 - f_{sol})\varepsilon_g(T_{gs} - T_a) + f_{sol}\varepsilon_g(T_{gh} - T_a)] \} \quad (C2.5)
\end{aligned}$$

$$\begin{aligned}
770 \quad L_{TIRvh}^{\uparrow} &\approx \frac{f_{vh}\varepsilon_v [(\rho_v f_{vs} + \rho_g)f_{vh} + f_{vs}]\varepsilon_v + \varepsilon_g - 2}{1 - f\rho_v\rho_g} X_{\varepsilon 1} \\
771 \quad &+ \frac{X_{\varepsilon 2} f_{vh}\varepsilon_v}{(1 - f\rho_v\rho_g)} \{ f_{vs}\varepsilon_v(T_{vs} - T_a) + [(\rho_v f_{vs} + \rho_g)f_{vh}\varepsilon_v - 2](T_{vh} - T_a) + (1 - f_{sol})\varepsilon_g(T_{gs} - T_a) \\
772 \quad &+ f_{sol}\varepsilon_g(T_{gh} - T_a) \} \quad (C2.6)
\end{aligned}$$

$$\begin{aligned}
773 \quad L_{TIRgs}^{\uparrow} &\approx \frac{(1 - f_{sol})\varepsilon_g[(f - f_{vh}f_{vs})\varepsilon_v + \rho_v f_{vh}\varepsilon_g - 1]}{1 - f\rho_v\rho_g} X_{\varepsilon 1} \\
774 \quad &+ \frac{X_{\varepsilon 2}(1 - f_{sol})\varepsilon_g}{(1 - f\rho_v\rho_g)} \{ (1 - f_{vh})f_{vs}\varepsilon_v(T_{vs} - T_a) + f_{vh}\varepsilon_v(T_{vh} - T_a) \\
775 \quad &+ [(1 - f_{sol})\rho_v f_{vh}\varepsilon_g - 1](T_{gs} - T_a) + \rho_v f_{vh}f_{sol}\varepsilon_g(T_{gh} - T_a) \} \quad (C2.7)
\end{aligned}$$

$$\begin{aligned}
776 \quad L_{TIRgh}^{\uparrow} &\approx \frac{f_{sol}\varepsilon_g[(f - f_{vh}f_{vs})\varepsilon_v + \rho_v f_{vh}\varepsilon_g - 1]}{1 - f\rho_v\rho_g} X_{\varepsilon 1} \\
777 \quad &+ \frac{X_{\varepsilon 2} f_{sol}\varepsilon_g}{(1 - f\rho_v\rho_g)} \{ (1 - f_{vh})f_{vs}\varepsilon_v(T_{vs} - T_a) + f_{vh}\varepsilon_v(T_{vh} - T_a) + \rho_v f_{vh}(1 - f_{sol})\varepsilon_g(T_{gs} - T_a) \\
778 \quad &+ (f_{sol}\rho_v f_{vh}\varepsilon_g - 1)(T_{gh} - T_a) \} \quad (C2.8)
\end{aligned}$$

779 where  $f = f_{vs} + f_{vh}$  (cover fraction) and  $1 - f = f_{gs} + f_{gh}$  (gap fraction equivalent to the  
780 transmissivity to the background soil) are defined at nadir ( $\cos(vza) = \cos(0^0) = 1$ );  $f_{sol} =$

$$781 \quad f(\theta_s) = 1 - e^{-\alpha \cdot LAI/\mu_s}, \quad f_{vs} = K_c f; \quad f_{vh} = K_t f; \quad f_{gs} = K_g(1 - f) \text{ and } f_{gh} = K_z(1 - f).$$

782  $K_c, K_t, K_g$  and  $K_z$  are sunlit/shaded contribution terms as previously defined.  $\alpha_v$  and  $\alpha_g$  are the

783 vegetation and soil albedos (reflectance in the optical domain) while  $\rho_v = 1 - \varepsilon_v$  and  $\rho_g = 1 - \varepsilon_g$

784 are the thermal reflectance for the vegetation and soil, respectively.

Table 3: Instrumentation (including manufacturer and model) at the experimentation sites

<b>Instrument; Manufacturer; Model</b>	<b>Agdal</b> <i>(Hoedjes et al., 2007; Williams et al., 2004)</i>	<b>Avignon</b> <i>(Cellier &amp; Olioso, 1993; Olioso et al., 1996)</i>	<b>Nasrallah</b> <i>(Chebbi et al., 2018)</i>	<b>R3</b> <i>(Boulet et al., 2015; Duchemin et al., 2006)</i>
<i>Radiation</i>	Net radiometer; Kipp & Zonen; CNR1	Net rad. differential pyrrometer; Crouzet, FR Rg; Kipp & Zonen; CM5	Net radiometer; Hukseflux, Delft, NL; NR01 :- SR01, IR01	Net radiometer; Kipp & Zonen; CNR1
<i>Turbulent fluxes</i>	Eddy Covariance (EC) system; Campbell Sci. Ltd., USA; 3D sonic anemometer CSAT3; Hygrometers - CS7500, KH20	1D sonic anemometer - <i>H</i> ; Campbell Sci., UK; CA27. Residual and Bowen ratio methods – <i>LE (home built based on a HMP35A Vaisala (Helsinki, Finland) humidity sensor, a differential air pumping system and type T thermocouples; cf. Cellier and Olioso (1993)</i>	EC system; Campbell, USA; 3D sonic anemometer CSAT3; Hygrometers - LI-COR7200, LI-COR7500	EC system; Campbell, USA; CSAT sonic anemometers; Krypton fast-response hygrometers
<i>Wind speed</i>	Wind vane/anemometer; R.M. Young Co.; WP200	CIMEL (Paris, France) cup anemometer	Anemometer; R.M. Young, USA	Anemometer; R.M. Young, USA; A100R
<i>Relative humidity</i>	Humidity probe; Vaisala, FI; HMP45C	Humidity probe; <i>HMP35A Vaisala (Helsinki, Finland)</i>	Humidity probe; Vaisala; HMP155/45	Humidity probe; Vaisala; HMP45C
<i>Air temperature</i>	Temperature probe; Vaisala, FI; HMP45C	Homemade temperature copper probe	Temperature probe; Vaisala; HMP155/45	Temperature probe; Vaisala; HMP45C
<i>Ground heat flux</i>	Heat flux plates; Hukseflux, Delft, NL;	Calorimetric method: i.e., from temperature profiles (type T thermocouples) down to 1 m and soil heat capacity calculated from soil moisture and soil density profiles	Heat flux plates; Hukseflux, Delft, NL; HFP01	Heat flux plates; REBS Inc., USA; HFP3
<i>Surface temperature</i>	Thermo-radiometer; Apogee Inc., UT, USA IRTS-Ps	Heiman KT17 thermo-radiometer, Wiesbaden, Germany	Thermo-radiometer; Apogee Inc., UT, USA IR120	Thermo-radiometers; Apogee Inc.; IRTP1541, IRTP1383

$\alpha$	Cavity effect factor [-]
$\alpha_g, \alpha_v$	Soil/ground (g) and vegetation (v) albedos [-]



$\beta_s, \beta_v$	Soil evaporation and vegetation transpiration efficiencies [-]
$\Delta$	Slope of the vapor pressure-temperature curve at $T_a$ [ $\text{Pa K}^{-1}$ ]
$\varepsilon_a = F \varepsilon_a^{\text{CS}}$	Apparent emissivity of the atmosphere [-]. $F$ – parameterization factor for conditions other than cs: clear-sky [-]
$\varepsilon_g, \varepsilon_v, \varepsilon_{\text{sf}}$	Emissivity of the soil, vegetation and entire surface, respectively [-]
$\varepsilon_{\text{TIRxx=vs,vh,gs,gh}}$	Emitted radiation forcing terms in the net radiation scheme; for sunlit (s) and shaded (h) soil (g) and vegetation (v) [ $\text{W m}^{-2}$ ]
$\gamma$	Psychrometric constant [ $\text{Pa K}^{-1}$ ]
$\omega_{\omega,s}(\theta_v), \omega_{\omega,h}(\theta_v)$	Effective emissivity of sunlit and shaded leaves, respectively [-]
$\phi_{j=i,v}$	Solar (i) and viewing (v) azimuth angles [ $^\circ$ ]
$\varphi$	Relative azimuth angle between solar and viewing directions [ $^\circ$ ]
$\rho C_p$	Product of air density [ $\text{kg m}^{-3}$ ] and the specific heat of air at constant pressure [ $\text{J kg}^{-1} \text{K}^{-1}$ ]
$\sigma$	Stefan Boltzmann constant [ $\text{W m}^{-2} \text{K}^{-4}$ ]
$\tau_\omega   b(\theta_v)$	The upward directional canopy transmittance / gap frequency/fraction in viewing direction [-]
$\theta_{j=i,v}; \mu_j$	Solar (i) and viewing (v) zenith angles; cosine of an angle j [ $^\circ$ ]
$\xi$	Fraction of soil/ground net radiation stored in the soil, i.e., $\xi = G/R_{\text{ng}}$ [-]
$C_c, C_t$	Contribution of sunlit and shaded leaves, respectively, to the emitted leaves radiation reflected by the soil (also apply for leaf emission reflected by other leaves) [-]
$e_a, e_0$	Air vapor pressure at the reference and aerodynamic levels, respectively [Pa].
$G, H, \lambda E$	Ground, sensible and latent heat fluxes [ $\text{W m}^{-2}$ ]
$h, d$	Vegetation height and leaf width [m]
$K_g, K_z$	Fractions/contribution of sunlit and shaded visible soil [-]
$K_c, K_t$	Contribution of sunlit and shaded leaves to out-of-canopy radiation [-]
$K_T; f d$	Clearness index [-] and fraction of diffuse radiation [-], respectively
$L(\theta_v), L_a^\perp$	Out-of-canopy radiance in the viewing direction and incoming sky radiation [ $\text{W m}^{-2}$ ]
$\text{LAI}, \sigma, \Omega$	Leaf area index [ $\text{m}^2 \text{m}^{-2}$ ], foliage projection factor [-] and clumping index [-]
$M$	Hemispherical average gap frequency [-]
$r_a$	Aerodynamic resistance between the aerodynamic level and the reference level [ $\text{s m}^{-1}$ ]
$r_{\text{as}}/r_{\text{av}}$	Aerodynamic resistance between the soil/vegetation and the aerodynamic level [ $\text{s m}^{-1}$ ]
$r_{\text{vv}}$	Surface resistance between the aerodynamic and the reference levels [ $\text{s m}^{-1}$ ]
$\text{RG}_{\text{dir}}, \text{RG}_{\text{diff}}, \text{RG}, C_s$	Direct, diffuse, total/global (BOA) and terrestrial (TOA) solar radiations, respectively [ $\text{W m}^{-2}$ ]
$R_n$	Total (overall) net radiation [ $\text{W m}^{-2}$ ]
$R_{\text{ng},s}; R_{\text{ng},h}$	Net radiation over the sunlit (s) and shaded (h) soil [ $\text{W m}^{-2}$ ]
$R_{\text{nv},s}; R_{\text{nv},h}$	Net radiation over the sunlit and shaded vegetation [ $\text{W m}^{-2}$ ]

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