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1 Evapotranspiration estimates in a traditional irrigated area in semi-arid 2 Mediterranean. Comparison of four remote sensing-based models

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16 Keywords: Evapotranspiration modelling, Remote sensing, Energy balance, FAO-56, Irrigation

17

18 Research Highlights

- 19 ● Four crop evapotranspiration estimates approaches based on remote sensing were compared
- 20 ● Eddy-Covariance and Scintillometer measurements were used for models' assessment
- 21 ● The four models estimate correctly the seasonal variations of actual crop ET
- 22 ● FAO-56 and METRIC GEE show the best results over a mixed irrigated area

23 Abstract

24 Quantification of actual crop evapotranspiration (ET_a) over large areas is a critical issue to manage
25 water resources, particularly in semi-arid regions. In this study, four models driven by high resolution
26 remote sensing data were intercompared and evaluated over an heterogeneous and complex traditional
27 irrigated area located in the piedmont of the High Atlas mountain, Morocco, during the 2017 and 2018
28 seasons: (1) SATellite Monitoring of IRrigation (SAMIR) which is a software-based on the FAO-56 dual
29 crop coefficient water balance model fed with Sentinel-2 high-resolution Normalized Difference
30 Vegetation Index (NDVI) to derive the basal crop coefficient (K_{cb}); (2) Soil Plant Atmosphere and
31 Remote Sensing Evapotranspiration (SPARSE) which is a surface energy balance model fed with land
32 surface temperature (LST) derived from thermal data provided from Landsat 7 and 8; (3) a modified
33 version of the Shuttleworth–Wallace (SW) model which uses the LST to compute surface resistances
34 and (4) METRIC-GEE which is a version of METRIC model (“Mapping Evapotranspiration at high

35 Resolution with Internalized Calibration”) that operates on the Google Earth Engine platform, also
36 driven by LST. Actual evapotranspiration (ET_a) measurements from two Eddy-Covariance (EC)
37 systems and a Large Aperture Scintillometer (LAS) were used to evaluate the four models. One EC was
38 used to calibrate SAMIR and SPARSE (EC1) which were validated using the second one (EC2),
39 providing a Root Mean Square Error (RMSE) and a determination coefficient (R) of 0.53 mm/day
40 (R=0.82) and 0.66 mm/day (R=0.74), respectively. SW and METRIC-GEE simulations were obtained
41 respectively from a previous study and Google Earth Engine (GEE), therefore no calibration was
42 performed in this study. The four models predict well the seasonal course of ET_a during two successive
43 growing seasons (2017 and 2018). However, their performances were contrasted and varied depending
44 on the seasons, the water stress conditions and the vegetation development. By comparing the statistical
45 results between the simulation and the measurements of ET_a it has been shown that SAMIR and
46 METRIC-GEE are the less scattered and the better in agreement with the LAS measurements (RMSE
47 equal to 0.73 and 0.68 mm/day and R equal to 0.74 and 0.82, respectively). On the other hand, SPARSE
48 is less scattered (RMSE = 0.90 mm/day, R = 0.54) than SW which is slightly better correlated (RMSE
49 = 0.98 mm/day, R = 0.60) with the observations. This study contributes to explore the complementarities
50 between these approaches in order to improve the evapotranspiration mapping monitored with high-
51 resolution remote sensing data.

52 1 Introduction

53 The Mediterranean region suffers from drought and increasing depletion of water resources due to the
54 effect of climate change and of the increasing anthropic water demand (Le Page et al., 2012). However,
55 agricultural production continues to increase and is the largest consumer of available water resources
56 (Boukhari et al., 2015). In order to achieve a balance between agricultural production and water
57 availability, a good monitoring of the crop hydric conditions is necessary. Numerous studies have been
58 conducted on the measurement and estimation of the water balance components of the crops in the semi-
59 arid region of Tensift Al Haouz but most of these studies were carried out in the plain (Amazirh et al.,
60 2017; Aouade et al., 2020; Diarra et al., 2017; Er-Raki et al., 2010; Ezzahar et al., 2007a; Ait Hssaine,
61 Merlin, et al., 2018; Ouaadi et al., 2020; Rafi et al., 2019). By contrast, the mountain foothills in semi-
62 arid regions are potential recharge areas for the groundwater table (Blasch & Bryson, 2007; Bouimouass
63 et al., 2020; Liu & Yamanaka, 2012; Martinez et al., 2017). This recharge is poorly known but could be
64 quantified by residual balance term. However, the uncertainty on the water balance variables in these
65 regions such as the precipitation and evapotranspiration (ET) increase the uncertainty on the estimation
66 of recharge. Hence there is a need for an accurate estimate of ET. In the last decades, a number of studies
67 focused on developing several methods for measuring and estimating ET_a based on remote sensing that
68 provides valuable data to assess its spatial and temporal variation.

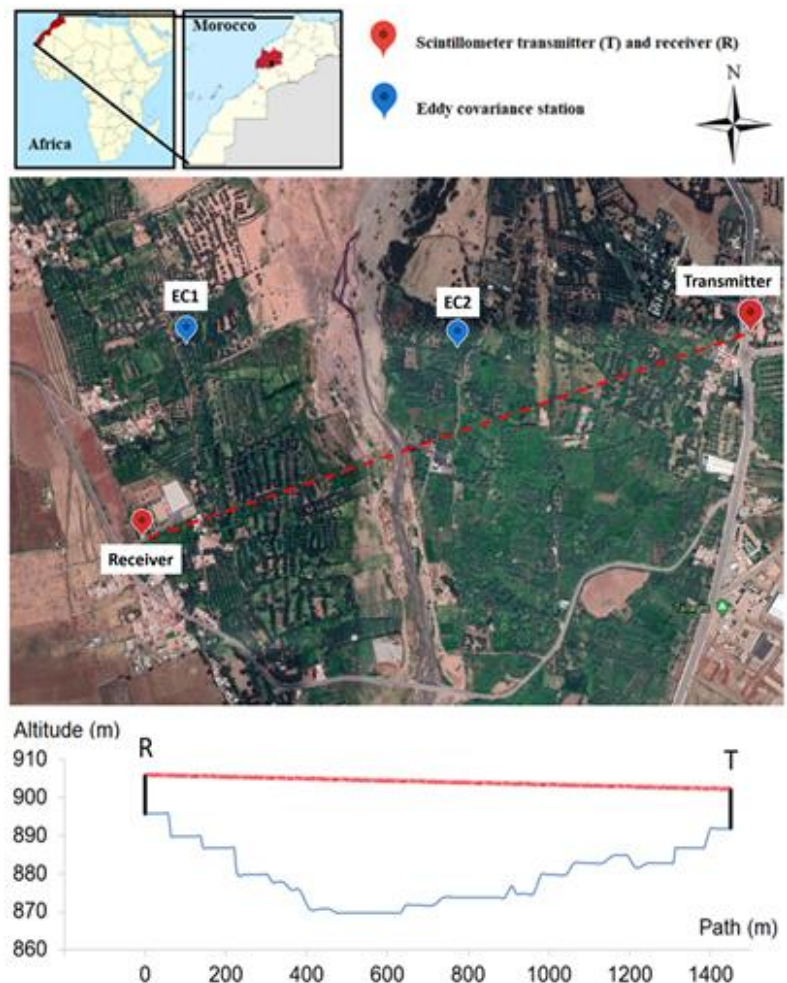
69 There is a variety of methods allowing direct or indirect ETa measurement in the field with variable
70 spatial and temporal representativeness (Allen et al., 2011; Er-Raki et al., 2013). The most used methods
71 are the lysimeter (Sánchez et al., 2019; Widmoser & Wohlfahrt, 2018) and the eddy covariance system
72 (Anapalli et al., 2020; Fang et al., 2020), both provide typically hectometric scale measurements, and
73 the scintillometer allowing measurements over transects of several kilometers (Duchemin et al., 2008;
74 Elfarkh et al., 2020; Ezzahar et al., 2007a; 2007b; 2009a; 2009b; 2009c; Isabelle et al., 2020; Zhao et
75 al., 2018). While these devices are the most accurate way to measure ET, their use over large areas is
76 limited due to their cost and their limited spatial representativity, especially in Mediterranean landscapes
77 known by heterogenous crops and water status. Major efforts to develop methods for ETa mapping have
78 been undertaken during the last decades, particularly with the development of remote sensing data
79 providing land surface characteristics using multi-spectral data from optical bands. The most physical
80 approaches are based on Soil-Vegetation-Atmosphere Transfer (SVAT) models, coupling the soil water
81 balance and the surface energy balance for soil-plant-atmosphere system and to quantify the amount of
82 ETa released in the atmosphere (Montes et al., 2014). These models offer an accurate estimates of ETa
83 but are complex because in addition to meteorological forcing (i.e., air temperature and humidity, wind
84 speed, incident radiation, rainfall), they require a large number of parameters such as information on
85 vegetation structure (i.e., leaf area index, LAI, height) and vegetation functioning (i.e., stomatal
86 conductance), on thermal and hydraulic properties of the soil (Olioso et al., 1999). To overcome these
87 constraints, simplified water balance models have been proposed like the FAO-56 dual crop coefficient
88 approach (Allen et al., 1998). This model requires a lower number of parameters and some of the main
89 ones, the crop coefficients, can be related to the amount of active vegetation present in the surface so
90 that they can be estimated from remote sensing using vegetation indices. On the other hand, another
91 category of ETa estimation method is based on the surface energy balance (SEB). SEB type models are
92 usually constrained by satellite land surface temperature observations, which are considered as a good
93 indicator of the water status of the surface, allowing to take into consideration the stress condition in
94 estimating actual ET. They calculate the sensible heat flux (H) from which the latent heat flux (LE)
95 associated with ETa is estimated as a residual term of the energy balance equation (Chirouze et al.,
96 2014). These models are a good indicator of the crop water status, but they basically provide
97 instantaneous estimates of ETa at the time of the satellite acquisition. SEB models can be divided into
98 two levels of complexity (Li et al., 2009): 1) single-source models that consider the surface as a big leaf
99 (Allen et al., 2007; Bastiaanssen et al., 1998; Roerink et al., 2000; Su, 2002) and 2) dual-source models
100 distinguishing between soil and vegetation processes (Anderson et al., 1997; Boulet et al., 2015; Norman
101 et al., 1995). Numerous authors have compared these two approaches, showing that dual-source models
102 show better performance over sparse vegetation. However, several authors have also found that with a
103 correct calibration even a single-source model can properly simulate the energy fluxes (Bastiaanssen et
104 al., 1998; Kustas & Norman, 1996).

105 The main objective of this study was to test the performance of different approaches used for estimating
106 ETa over a heterogeneous landscape of traditional irrigated agriculture in a semi-arid area located in the
107 piedmont of the High Atlas Mountains (Morocco). A simplified water balance model SAMIR
108 (Simonneaux et al., 2009), SPARSE model (Boulet et al., 2015), the modified Shuttleworth-Wallace
109 model (Elfarkh et al., 2021) and METRIC model (Allen et al., 2007) were compared during two seasons,
110 2017 and 2018. This study is a preliminary step to build an hybrid approach that could benefit from both
111 the continuity of water budget based estimates and the accuracy of thermal based ones.

112 2 Material and methods

113 2.1 Study area

114 The experiment was carried out over the piedmont of the High Atlas Mountain near the Marrakech city
115 in the center of Morocco (31°22'1.19"N, 7°56'47.21"O) (Figure 1). The climate in this area is semi-arid
116 with irregular and low rainfall especially during the study period with a total rainfall of 157 mm for
117 2017 and 384 mm for 2018. The study site is characterized mainly by traditional olive trees of various
118 ages, with some other species (apple, apricot, plum, orange, peach, ETa) and a frequent understory of
119 annual crops below the trees, mainly cereals. Crops are irrigated by the traditional flooding technique
120 using water diverted from the river issued from the mountains. Some patches of bare soils are also
121 present especially at the surrounding of the irrigated area.



122

123 *Figure 1: Eddy covariance and the scintillometer stations superimposed on an image of the study site from Google Earth. The*
 124 *plot at the bottom shows the scintillometer path and elevation along the path*

125 2.2 Experimental data

126 Both EC stations (EC1 and EC2) were equipped by meteorological instruments to measure the net
 127 radiation components (CNR4 radiometer, Campbell scientific) at a height of 17 m, air temperature and
 128 humidity (Vaisala HMP155, Campbell scientific) at height of 16 m (Figure 1). Also, the soil heat flux
 129 was measured at a depth of 5 cm using two heat flux plates (HPF_01, Campbell Scientific), one shaded
 130 by trees and the other one exposed to solar radiation. The rainfall was recorded using a rain gauge
 131 (ARG100/EC) installed close to the scintillometer receiver (Figure 1).

132 Flux stations were installed during 2017 and 2018 over two olive tree plots located in the study area on
 133 17.5 m height towers (EC1 and EC2 sites) (Elfarkh et al., 2020). The land cover of these two sites is
 134 supposed to be representative of the entire site, namely traditional olive plantations of 7 to 10 meters
 135 height with an understory of herbaceous vegetation, mainly wheat. EC2 shows more heterogeneity than
 136 EC1 since it includes olive trees, other fruit trees (mainly apple trees) and annual crops (Elfarkh et al.,
 137 2020). They measured the sensible and latent heat fluxes using the eddy correlation method, consisting
 138 of a 3D sonic anemometer (CSAT3, Campbell Scientific Ltd.) and a Krypton hygrometer (KH20,

139 Campbell Scientific Ltd.). The raw data were sampled at a rate of 20Hz and then used to calculate
140 sensible (H) and latent (LE) heat fluxes offline using the EC processing software 'ECpack' (Van Dijk et
141 al. 2004). The energy balance closure analysis showed that the sum of the turbulent fluxes only reaches
142 60% of the available energy (Elfarkh et al., 2020) which can be considered acceptable due to the
143 complexity of the study sites. Therefore, the correction of EC data was performed using the approach
144 suggested by Twine et al. (2000), which assumes the non-closure energy balance is due to
145 underestimates from EC measurements while the corresponding Bowen ratio (H/LE) is correctly
146 estimated. However, the reliability of ETa after this correction still affected by some uncertainty given
147 the assumptions taken in the Bowen correction namely the assumption that the difference between the
148 net radiation (Rn) and the soil heat flux (G) is equal to the sum of H and LE neglecting the energy stored
149 in the canopy. In addition, the footprint of the devices that measure both energy quantity Rn-G and
150 H+LE are different and that can generate an error especially in heterogeneous areas such as our study
151 site.

152 In addition to the EC towers, a Large Aperture Scintillometer (LAS) was installed over a 1464 m
153 transect, consisting of a receiver installed on a tower of about 10 m and a transmitter over a building of
154 about 10.5 m in the city (Elfarkh et al., 2020). Due to topography, the height between the LAS path and
155 the ground varied between 10 and 50 m and the effective height computed was around 26 m (Hartogensis
156 et al., 2003). The measurement of the refraction phenomena produced by the air turbulence allow the
157 calculation of the variation of the structure parameter of the refractive index C_n^2 along the path (Wesely,
158 1976). The sensible heat flux (H) was calculated iteratively based on the Monin-Obukhov theory (De
159 Bruin et al., 1993). The latent heat flux (LE) was obtained as the residual term of the energy balance,
160 where available energy was computed from the ground measurements (Elfarkh et al., 2020). For the LE
161 computation, we used the Rn and G measured at the EC1 site which is considered representative of the
162 land cover present in the LAS footprint. However, this remains an approximation and one possible
163 improvement would be to multiply measurements of Rn and G along the LAS path but this is
164 operationally difficult to achieve. For the sake of simplicity, we also didn't compute MODIS estimates
165 of daily Rn (Saadi et al., 2015).

166 2.3 Remote sensing data

167 2.3.1 Sentinel-2 data

168 The Normalized Difference Vegetation Index (NDVI) was computed using Sentinel-2 Red (R, band 4)
169 and Near-Infrared (NIR, band 8) reflectances at 10 meters resolution (Eq. 1). The Sentinel-2 images
170 were downloaded from the THEIA web site, a French open-source land data service center
171 (<https://www.theia-land.fr/>) providing cloud-free and atmospherically corrected surface reflectance
172 images. NDVI is closely related to vegetation cover (Tucker, 1979). Sentinel 2 images have the
173 advantage of constant viewing angles, limiting its impact on the same site. In addition, as images used

174 were radiometrically corrected, the effect of atmosphere was very limited. Although NDVI saturates
 175 regarding leaf area index (LAI), this is less of a problem regarding crop coefficient, which also saturates
 176 with LAI due to shading effect. As a result, it has been shown in many studies that crop coefficient can
 177 be linearly related to NDVI (Choudury et al., 1994). This index has been widely used in the region of
 178 our study area to characterize vegetation development and crop coefficients (Amazirh et al., 2022; Rafi
 179 et al., 2019; Duchemin et al., 2006; Er-Raki et al., 2007, 2010).

$$NDVI = \frac{NIR - R}{NIR + R} \quad \text{Eq: 1}$$

180 2.3.2 Landsat data

181 Both Landsat 7 and 8 satellites data were used in this study for the period 2017 and 2018 with a revisit
 182 time up to 8 days thanks to their shifted overpasses. The area is located in the center of the Landsat 7
 183 scene not affected by the SLC-off problem. Land Surface Temperature (LST) data was acquired from
 184 the web application (http://rslab.gr/downloads_LandsatLST.html) developed by Parastatidis et al.
 185 (2017). This application provides LST estimates using the single channel algorithm. The Landsat LST
 186 values were compared to measurement values from the CNR4 instrument over both stations EC1 and
 187 EC2. This comparison displayed in Figure 2a shows acceptable agreement between measured and
 188 Landsat LST with an RMSE of about 5 K for EC1 and 6.6 K for EC2, with a moderate but significant
 189 bias. However, despite the good correlation between ground and satellite data, we chose not to correct
 190 satellite data considering the low representativity of our local measurements as compared to satellite
 191 pixels (30 m) in this heterogeneous land cover context. The optical Landsat bands were downloaded in
 192 level 2 from the web site (<https://earthexplorer.usgs.gov/>) with atmospheric correction included.

193 Surface emissivity, albedo and the leaf area index (LAI) were computed using the optical Landsat data.
 194 The surface emissivity was calculated based on Tardy et al. (2016) as follows:

$$\varepsilon = \varepsilon_v - (\varepsilon_v - \varepsilon_s) \left(\frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \right)^k \quad \text{Eq: 2}$$

195 ε_v and ε_s are the soil and the vegetation emissivity. Their values are 0.96 and 0.99 respectively (Sobrino
 196 et al., 2004; Tardy et al., 2016). The $NDVI_{min}$ is the minimum value of NDVI representing bare soil
 197 and the $NDVI_{max}$ is the maximum value of NDVI representing dense vegetation, determined by
 198 examination of the images NDVI distribution. The k parameter was fixed arbitrarily to 2 according to
 199 Tardy et al. (2016). LAI was computed based on Landsat NDVI following (Wang et al., 2008):

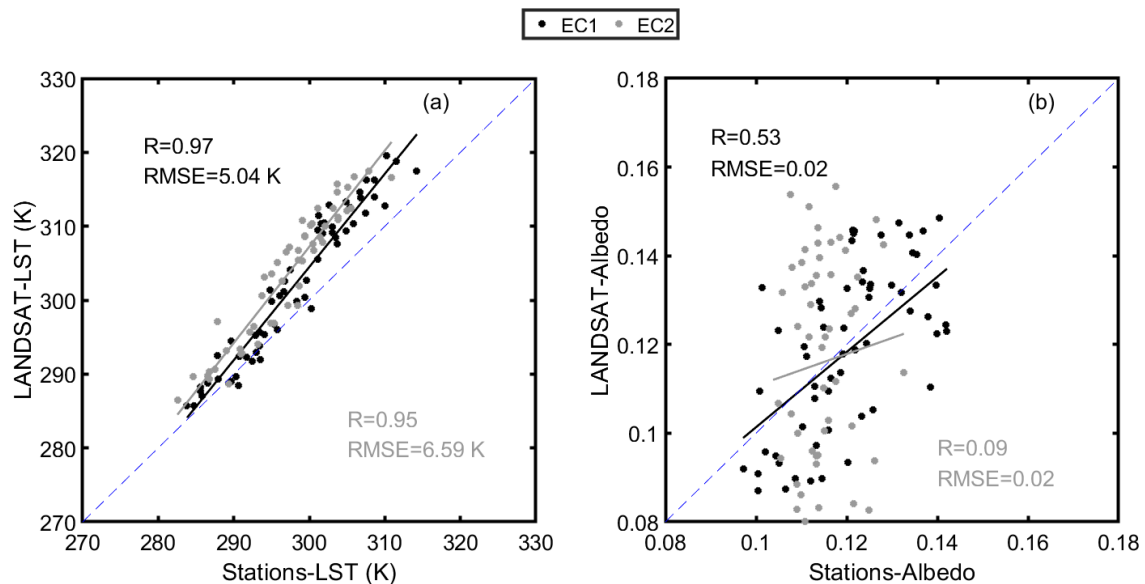
$$LAI = \sqrt{NDVI \frac{1 + NDVI}{1 - NDVI}} \quad \text{Eq: 3}$$

200 The visible and the near-infrared bands are used to retrieve the albedo (α) from Landsat data. The best
 201 combinations compared to in-situ measurement were obtained from the Red (R) and the Near-InfraRed
 202 (NIR) bands which is in-line with results obtained with other sensors including SPOT4 (Diarra et al.,
 203 2017) and FORMOSAT (Courault et al., 2008).

$$\alpha = 4.16 * 10^{-5} * R + 3.28 * 10^{-5} * NIR \quad \text{for Landsat 7} \quad \text{Eq: 4}$$

$$\alpha = 2.72 * 10^{-5} * R + 3.80 * 10^{-5} * NIR \quad \text{for Landsat 8} \quad \text{Eq: 5}$$

204 Figure 2b shows a large discrepancy between measured and estimated albedo. The errors can be
 205 explained by the high heterogeneity of the pixel area while point-scale albedo is measured by the
 206 stations. As long as the regression linear equation obtained from satellites data was not good, a fixed
 207 value of about 0.12 was adopted for the study site.



208

209 *Figure 2: Scatterplot of Landsat LST (a) and albedo (b) versus in-situ data for EC1 and EC2 stations.*

210 2.4 Evapotranspiration Modeling

211 Four models are used in this study. SAMIR is a software simulating crop water budget and
 212 evapotranspiration at daily scale based on the FAO-56 approach. It is fed with Sentinel-2 Normalized
 213 Difference Vegetation Index (NDVI) images used to compute both the basal crop coefficient (K_{cb}) and
 214 the vegetation fraction cover (fc). A soil water budget allows to automatically trigger irrigations based
 215 on simulated soil moisture. The SPARSE model solves the surface energy budget to provide
 216 instantaneous latent heat flux (LE) estimates using the Landsat 7 and 8 thermal data. Both models were
 217 tested over different crops and climates and have shown acceptable performance in estimating ETa
 218 (Boulet et al., 2015; Delogu et al., 2018; Saadi et al., 2015; Simonneaux et al., 2009). The Shuttleworth-
 219 Wallace and METRIC models have been added to this study to enrich the comparison of different
 220 approaches to estimating ETa using the same input data. For the Shuttleworth-Wallace model the version

221 used here is the modification proposed by Elfarkh et al., (2021) where they use thermal remote sensing
 222 data to spatialize ET. SPARSE, SW and SAMIR were calibrated and validated over the same study area
 223 using eddy covariance and scintillometer measurements. Regarding METRIC, its automated version
 224 featured on the Google Earth Engine Evapotranspiration Flux (EEFlux) platform is used. More details
 225 on each model are presented in the appendix. A summary of the inputs required and the parameters
 226 calibrated for each model is depicted in table 1.

227 *Table 1: Summary table of the inputs required and the parameters calibrated for each model.*

| Models | Inputs variables | Calibrated parameters | Calibration approach |
|------------|--------------------------------|--|---|
| SPARSE | - NDVI and Albedo | - Minimum stomatal resistance (rst_{min}) | - Minimization of the RMSE between the estimated and measured ETa |
| | - LST and emissivity | - Leaf width (w) | |
| | - Air temperature and humidity | - Ratio relating the soil net radiation to the heat soil flux (ξ) | |
| | - Wind speed | - Extinction coefficient (k) in the LAI equation | |
| | - Solar radiation | - Coefficient in the aerodynamic resistance (n_{SW}) | |
| SAMIR | - NDVI | - NDVI- K_{cb} relation's slope | - Minimization of the RMSE between the estimated and measured ETa |
| | - ET_0 | - NDVI- K_{cb} relation's intercept | |
| | - Rainfall | - Readily evaporable water (REW) | |
| | | - Maximum root depth (Zr_{max}) - Water diffusion coeff. between surface and root layers (Dif_{er}) | |
| SW | - NDVI and Albedo | - Coefficients in the soil and vegetation resistances | - Minimization of the RMSE between the estimated and measured ETa |
| | - LST and emissivity | | |
| | - Air temperature and humidity | | |
| | - Wind speed | | |
| | - Solar radiation | | |
| METRIC-GEE | - NDVI and Albedo | - No calibration | |
| | - LST and emissivity | | |
| | - Air temperature and humidity | | |
| | - Wind speed | | |
| | - Solar radiation | | |

229 2.5 Models evaluation

230 The evaluation of results was achieved using standard criteria, namely the correlation coefficient (R),
 231 the bias and the root mean square error (RMSE).

$$R = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}} \quad \text{Eq: 6}$$

$$bias = \frac{1}{n} \sum_{i=1}^n (y_i - x_i) \quad \text{Eq: 7}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - x_i)^2} \quad \text{Eq: 8}$$

232 where x_i is the measured values, y_i is the estimated values and n is the number of observations.

233 2.6 Extrapolation of instantaneous ETa to daily value

234 Thermal remote sensing-based ETa models like SPARSE and SW basically provide an instantaneous
 235 ETa value at the satellite overpass time. However, these instantaneous values are not useful for practical
 236 purposes which support water resources management such as irrigation scheduling. Many authors
 237 evaluated different temporal upscaling methods from instantaneous to daily ETa values (Xu et al., 2015;
 238 Saadi et al., 2018). One of the methods widely used is the evaporative fraction (EF). This latter supposes
 239 that the evaporative fraction remains almost constant during the day. However, Gentine et al. (2007)
 240 reported that EF depends on soil moisture and is not always satisfied for a fully vegetated surface. Here,
 241 we applied the method parametrized by Delogu et al. (2012) based on an improvement of EF method.
 242 This improvement is based on the diurnal variations of EF derived by Hoedjes et al. (2008) using an
 243 empirical relationship. This relation parameterized EF diurnal trend as a function of incoming solar
 244 radiation and relative humidity as follows.

$$LE_{day} = EF * AE_{day} \quad \text{Eq: 9}$$

$$AE_{day} = AE_{inst} * \frac{Rg_{day}}{Rg_{inst}} \quad \text{Eq: 10}$$

$$EF = \left(1.2 - \left(0.4 \frac{Rg_{day}}{1000} + 0.5 \frac{RH_{day}}{100} \right) \right) * \frac{EFsat_{inst}}{EFbase_{inst}} \quad \text{Eq: 11}$$

$$EFsat_{inst} = \frac{LE_{inst}}{AE_{inst}} \quad \text{Eq: 12}$$

$$EFbase_{inst} = 1.2 - \left(0.4 \frac{Rg_{inst}}{1000} + 0.5 \frac{RH_{inst}}{100} \right) \quad \text{Eq: 13}$$

245 where AE is the available energy ($Rn - G$), Rg is the solar radiation (W/m^2), RH is the relative humidity,
 246 EF is the evaporative fraction and $EFsat_{inst}$ and $EFbase_{inst}$ are the evaporative fraction observed at
 247 the satellite overpass time and calculated at the satellite overpass with the first part of the Eq. 11,
 248 respectively.

249 2.7 Footprint computation

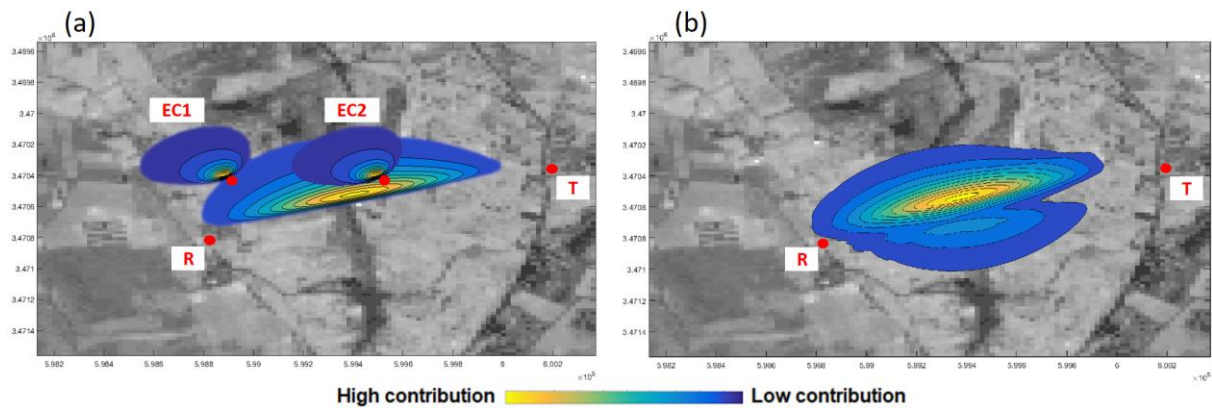
250 The LAS or EC measurements are influenced by an area, or footprint, where the contribution of each
 251 point is determined by its position, the wind speed and direction. Numerous models of footprint have
 252 been developed (Horst & Weil, 1992; Rannik et al., 2000; Schuepp et al., 1990). In our case, Horst and
 253 Weil (1992) model was used for the EC measurements, where the measured F flux is related to the
 254 surface elementary fluxes distribution (Eq. 14).

$$F(x, y, z_m) = \int_{-\infty}^{\infty} \int_{-\infty}^x F_0(x', y') f(x - x', y - y', z_m) dx' dy' \quad \text{Eq: 14}$$

255 where f is the footprint function figuring the spatial weighting of elementary surface fluxes,
 256 $F(x, y, (z = 0)) = F_0(x, y)$. x and y are the downwind and crosswind distances (m) from the
 257 measurement's points, respectively. For the LAS, the spatial weighting function is used to weight each
 258 point (Meijninger, 2003) (Eq. 15).

$$F_{LAS}(x, y, Z_{LAS}) = \sum_{i=1}^N F(x, y, Z_{LAS}) G(d_i) \quad \text{Eq: 15}$$

259 where $F_{LAS}(x, y, Z_{LAS})$ is the LAS integrated measurement, and $F(x, y, Z_{LAS})$ and $G(d)$ are the
 260 equivalent EC footprint and the scintillometer path-weighting function, respectively, for a given point
 261 distanced from the transmitter by d_i . The EC and LAS footprints were calculated for each half-hour
 262 (Figure 3a). To compare the measured flux with daily model outputs, daily footprints were calculated
 263 as the sum of the half-hourly footprints weighted by the net radiation values. As shown on the figure 3b,
 264 the daily footprint has a more complex form than the instantaneous ones because half-hourly footprints
 265 have different direction and form depending on the wind.



266

267 *Figure 3: (a) Instantaneous footprint of both stations (EC1 and EC2) and LAS, (b) daily LAS footprint. R and T means the*
 268 *receiver and the transmitter of scintillometer, respectively.*

269 3 Results

270 In this section the ETa estimations by the four models are presented. Only the calibration and the
 271 validation of SAMIR and SPARSE are shown here. The calibration of SW is detailed over the same site
 272 in Elfarkh et al. (2021). METRIC is downloaded from a Google Earth Engine platform. After that, the
 273 four models' estimations are evaluated and compared with the LAS and the EC measurements and the
 274 errors and domains of validity are discussed.

275 3.1 SAMIR calibration

276 The main parameters of SAMIR are basically related to crop types and to the soil. Thus, a land cover
 277 map of the study area was generated from the NDVI time series using the algorithm developed by
 278 Simonneaux et al., (2007). The main classes were trees, annual crops and bare soil. A Sentinel-2 NDVI
 279 time series was extracted by averaging pixel values in a 50*50 meters area centered on the EC1 site.
 280 The meteorological forcing, namely precipitation and ET_0 were obtained from our in-situ measurements.
 281 The SAMIR model was calibrated for the tree class using latent heat flux measured over EC1 for the
 282 two seasons 2017 and 2018, through minimizing the Root Mean Square Error (RMSE) computed
 283 between measured and modeled ET. The main calibrated parameters are listed in table 2. The rooting
 284 depth (Zr_{max}) obtained after calibration (4.9 m) is much larger than usual values proposed in the FAO-
 285 56 paper (1.6 m) for irrigated olive trees. This is not surprising considering that these trees are very old
 286 and periodically under stress, which causes deep rooting. The olive tree root system is adapted to water
 287 scarcity frequent in the mediterranean areas (Fernández 2014). In aerated soils of light texture, olive
 288 trees roots may reach depths of 7 m (Lavee, 1996). For the annual crops, no calibration was possible
 289 since no EC station was installed over such class. Instead, we used the parameters obtained by Saadi et
 290 al. (2015) after calibration of SAMIR over wheat plots in central Tunisia that we consider similar to our
 291 site. Irrigation was simulated assuming that the farmer avoid stress, triggering input just before stress
 292 and bringing the water amount required to fill the soil holding capacity. The irrigation simulations were

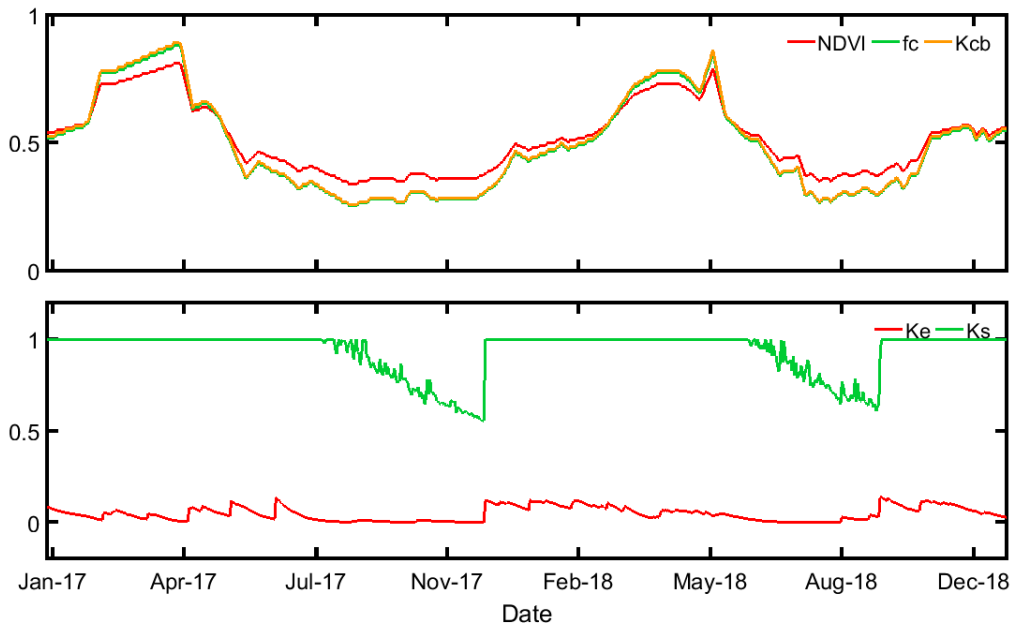
293 stopped from 16 July to 30 November 2017 and from 21 May to 26 September 2018, according to ground
 294 observation.

295 *Table 2: Main Calibrated Parameters used for the tree class.*

| Parameter | Definition | Value | Source |
|-----------------------------|--|-------|--------------------|
| a_{fc} | NDVI- fc relation's slope | 1.33 | Satellite imagery |
| b_{fc} | NDVI- fc relation's intercept | -0.20 | Satellite imagery |
| $a_{K_{cb}}$ | NDVI- K_{cb} relation's slope (Eq. A.2) | 1.35 | Calibrated |
| $b_{K_{cb}}$ | NDVI- K_{cb} relation's intercept (Eq. A.2) | -0.20 | Calibrated |
| Ze (mm) | depth of the soil evaporation layer | 125 | FAO-56 |
| REW (mm) | Readily evaporable water | 0 | Calibrated |
| m | Reduction coefficient (Torres et al. 2010) | 0.185 | Calibrated |
| Zr_{max} (mm) | Root depth (assumed constant for trees) | 4900 | Calibrated |
| p | root zone water depletion fraction before stress | 0.65 | FAO-56 |
| Dif_{er} | Diffusion between surface and root layers | 0 | Calibrated |
| ω_{fc} (m^3/m^3) | Volumetric water content at field capacity | 0.4 | Ground observation |
| ω_{wp} (m^3/m^3) | Volumetric water content at wilting point | 0.2 | Ground observation |
| $K_{c_{max}}$ | Maximum value of crop coefficient (following rain or irrigation) which is determined by the energy available for ETa at the soil surface | 1.15 | Ground observation |

296

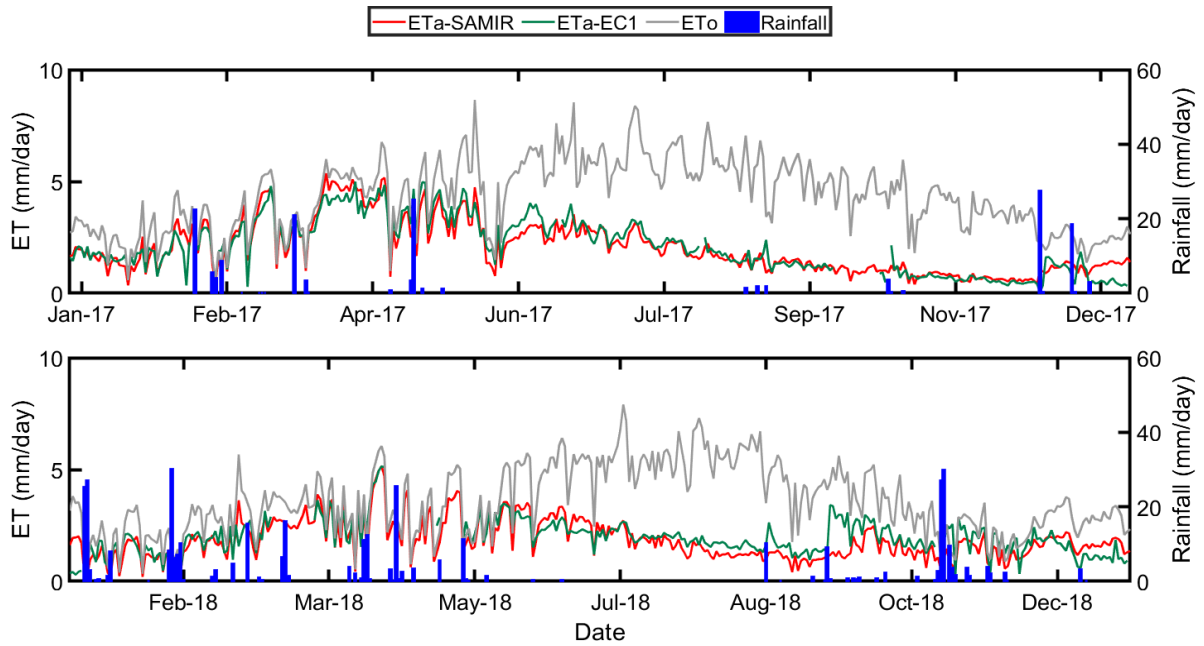
297 Figure 4 shows the temporal variations of the computed basal crop coefficient K_{cb} and the fraction cover
 298 (fc) values using the NDVI relationships with NDVI averaged over the EC1 station. Peak K_{cb} and fc
 299 values were observed at the beginning of spring for both years 2017 and 2018, while minimum K_{cb} and
 300 fc values were recorded in summer and early autumn. These variations are linked to the vegetative cycle
 301 of the olive tree itself, but they may be amplified by the understory of annual crops often observed in
 302 this area in spring and early summer, when water is available from the river. Conversely, the K_e values
 303 don't exhibit the same seasonality and are only linked to water inputs (irrigation or rainfall). It is
 304 remarkable to note that the resistance to evaporation is much increased as compared to FAO standards,
 305 with $REW = 0$ and $m = 0.185$, which is coherent with previous studies (Saadi et al., 2015; Torres &
 306 Calera, 2010). Thus, K_e values are on the whole quite low (below 0.2), which can be explained by the
 307 important canopy shading, modifying significantly the meteorological forcing at the soil level. The K_s
 308 values show non-stressed conditions during vegetation developments (i.e., $K_s = 1$), while stress appears
 309 in late summer and autumn justified by the insufficient irrigation due to water shortage in the river.



310

311 *Figure 4: Simulation of the evaporative coefficient (K_e), the stress coefficient (K_s), the crop coefficient (K_{cb}) and the fraction*
 312 *cover (fc) during the study period 2017 and 2018, as obtained from SAMIR modelling on the EC1 site.*

313 The SAMIR ETa simulations are in good agreement with observed values with an RMSE, bias and R of
 314 about 0.50 mm/day, -0.11 mm/day and 0.87, respectively (Figure 5). The simulated values reproduce
 315 well the seasonal cycle. During the development stage of wheat in spring, ETa was higher in the dry
 316 season (2017) than the wet one (2018) which is strongly related to the higher reference
 317 evapotranspiration in 2017. Despite the lack of rainfall, water is still available for irrigation in spring
 318 because water comes from the mountains and is not affected directly by drought occurring downstream.
 319 However, the gap between ETa and ET_0 during summer and autumn can be related to the water supply.
 320 This gap is large in 2017 when compared to 2018 since the first year is dry with 157 mm whereas 2018
 321 is wetter with 384 mm. However, even in these stressed conditions, the olive trees managed to keep a
 322 high level of transpiration due to the deep rooting of the trees.



323

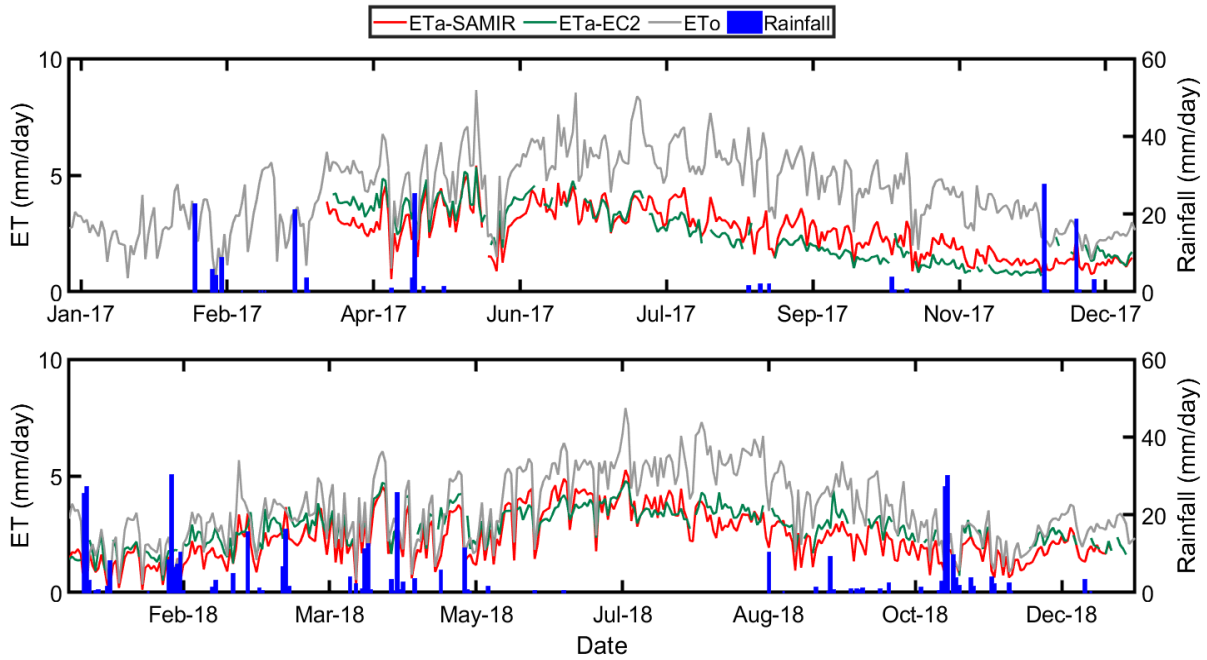
324 *Figure 5: Daily ETa measured by EC1 and estimated over the EC1 footprint by SAMIR during the study periods 2017 and 2018.*

325 **3.2 SAMIR validation**

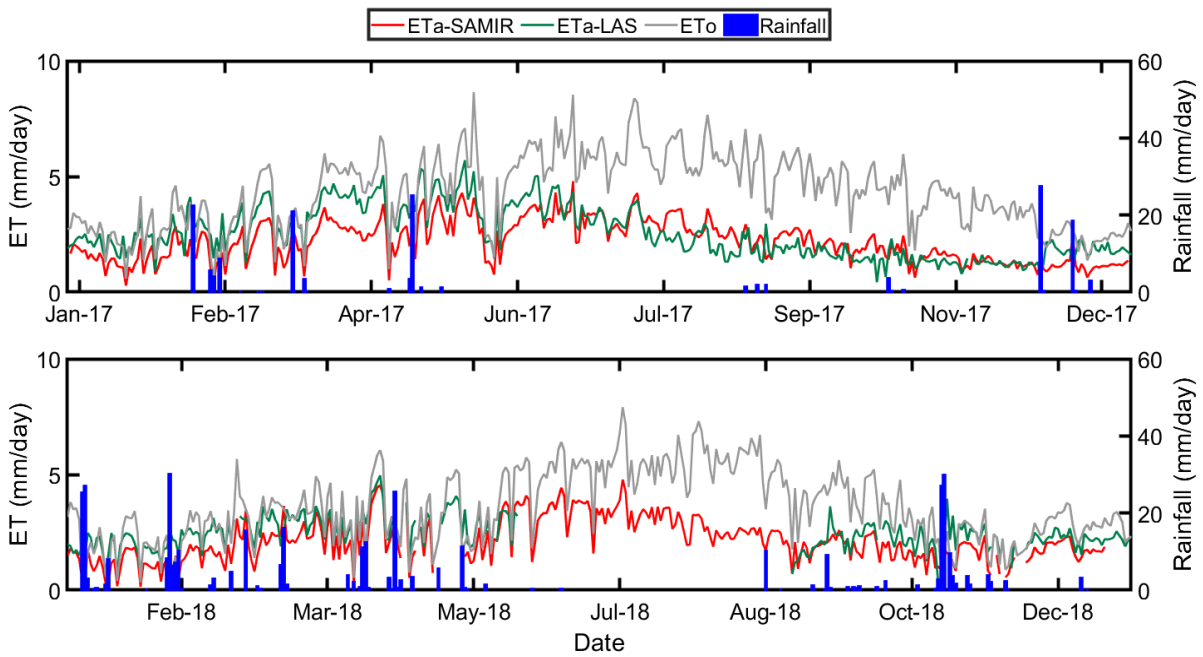
326 Using the calibrated parameters (Table 1), SAMIR was run over the study area using the Sentinel-2
 327 NDVI time series. The simulated SAMIR ETa values were validated using measurements provided by
 328 the EC2 and the LAS. For the latter, SAMIR daily ETa outputs were weighted according to the daily
 329 footprint computed as explained previously. The comparison between SAMIR daily ETa and ETa
 330 measured by EC2 in 2017 and 2018 shows a good agreement with an RMSE, bias and R of about 0.53
 331 mm/day, -0.12 mm/day and 0.82 (Figure 6), very close to the values obtained during the calibration
 332 stage on EC1. However, in 2017 SAMIR overestimated ETa during the dry period from July to
 333 November. This is because a spatialized version of the SAMIR tools is used in this study and it doesn't
 334 allow to stop irrigation while no water is available at this time of the season. By contrast, no
 335 overestimation of ETa was observed in summer 2018, as the year was wet and there was less water
 336 shortage in the root zone despite the lack of irrigation.

337 The comparison between SAMIR daily ETa and the LAS measurements in 2017 and 2018 is presented
 338 on figure 7. Due to technical problems, the LAS measurements are lacking from June to August 2018.
 339 On average, a good concordance is noticed between the simulations and the measurements with an
 340 RMSE, bias and R of 0.73 mm/day, -0.45 mm/day and 0.74, respectively. However, between January
 341 and June 2017, SAMIR underestimated ETa. One possible explanation for this gap is that during this
 342 period, since there is enough rainfall and no stress, SAMIR doesn't apply any irrigation which is not the
 343 case for the farmers who do not hesitate to bring water when it is available in the river. Indeed, as shown
 344 by Bouimouass et al., (2020) who studied irrigation in a very similar watershed neighboring the study
 345 site, overirrigation is very frequent as is driven by water availability and not by the crop requirements.

346 In 2018, this discrepancy between simulated and measured ETa is also visible but to a lesser extent;
 347 possibly because the precipitation was relatively high and consequently the impact of irrigation on ETa
 348 was lower.



349
 350 *Figure 6: ETa measured by EC2 and estimated over the EC2 footprint by SAMIR during the study period 2017 and 2018.*

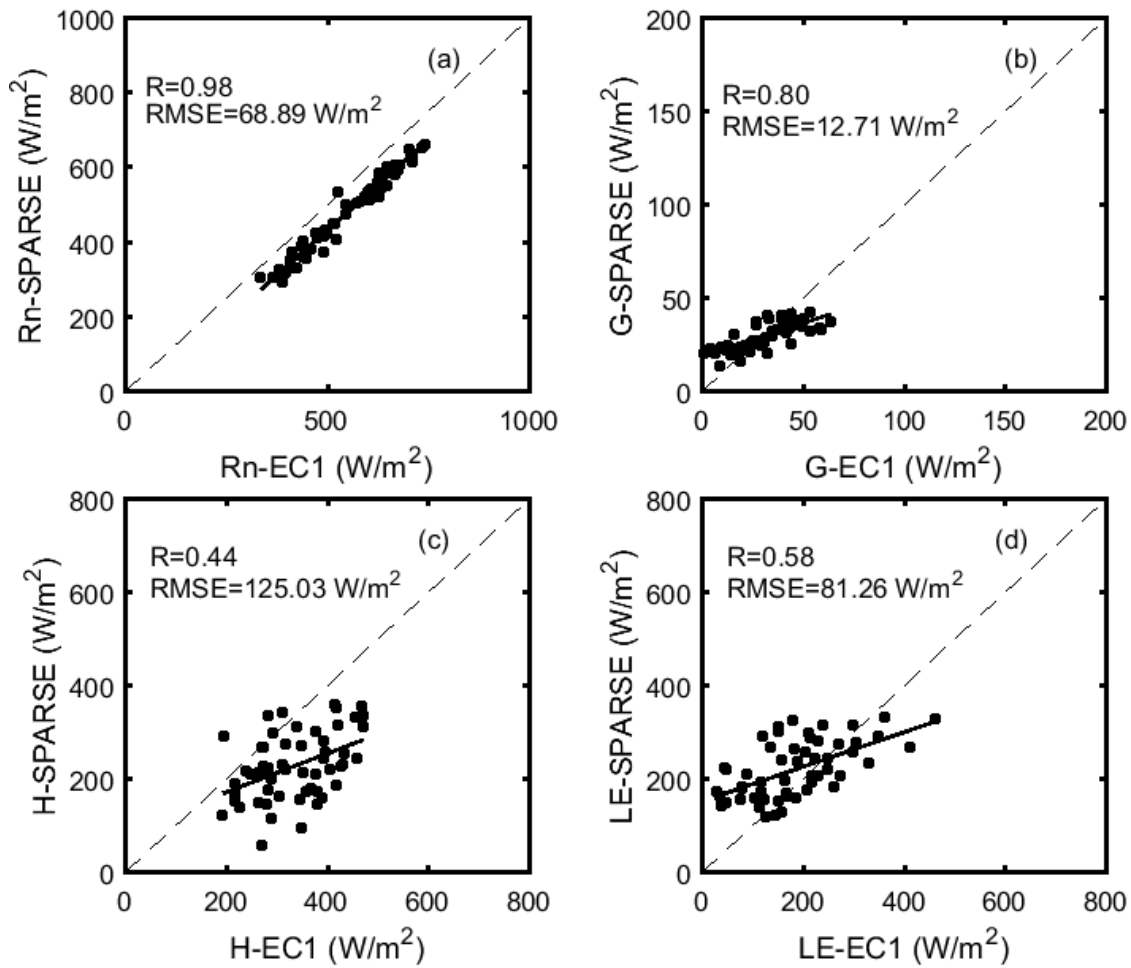


351
 352 *Figure 7: ETa measured by LAS and estimated over the LAS footprint by SAMIR during the study period 2017 and 2018.*

353

354 3.3 SPARSE calibration

355 As for SAMIR, the SPARSE model was calibrated over the EC1 station, by minimizing the RMSE
356 between simulated and observed LE . The SPARSE results were weighted by the EC and LAS
357 instantaneous footprints at the time of Landsat overpass. From a sensitivity study (Boulet et al., 2015),
358 five parameters of SPARSE having a significant impact on simulated ET_a were calibrated : the minimum
359 stomatal resistance ($r_{st_{min}}$) which was set to 260 s/m, As reported by Zhu et al. (2014) $r_{st_{min}}$ varies
360 for many natural and cultivated plants it ranges considerably from 20 to 100 s/m for crops and from 200
361 to 300 s/m for many types of trees (Zhu et al., 2014). Leaf width (w) set to 0.03 m is within the range
362 found in the literature (Saadi et al., 2018; Ait Hssaine et al., 2018; Braud et al., 1995). The ratio relating
363 the net radiation of the soil to the heat soil flux (ξ) set to 0.13. In fact, Kustas et al. (1993) pointed that
364 ξ is driven by several factors namely the time of day, the soil moisture and the thermal properties, as
365 well as the vegetation density and its value ranges between 0.05 and 0.5. The extinction coefficient (k)
366 in the equation where the fraction cover is calculated in term of LAI which is set to 0.6 which is in
367 conformity with the values found by Connor et al. (2012) and Srinet et al. (2019). The empirical
368 coefficient in the aerodynamic resistance (n_{SW}) set to 2.5 which is the same value stated by Boulet et al.
369 (2015). The calibration shows an acceptable agreement with an RMSE and R of about 81.3 W/m² and
370 0.58, respectively (Figure 8).



371

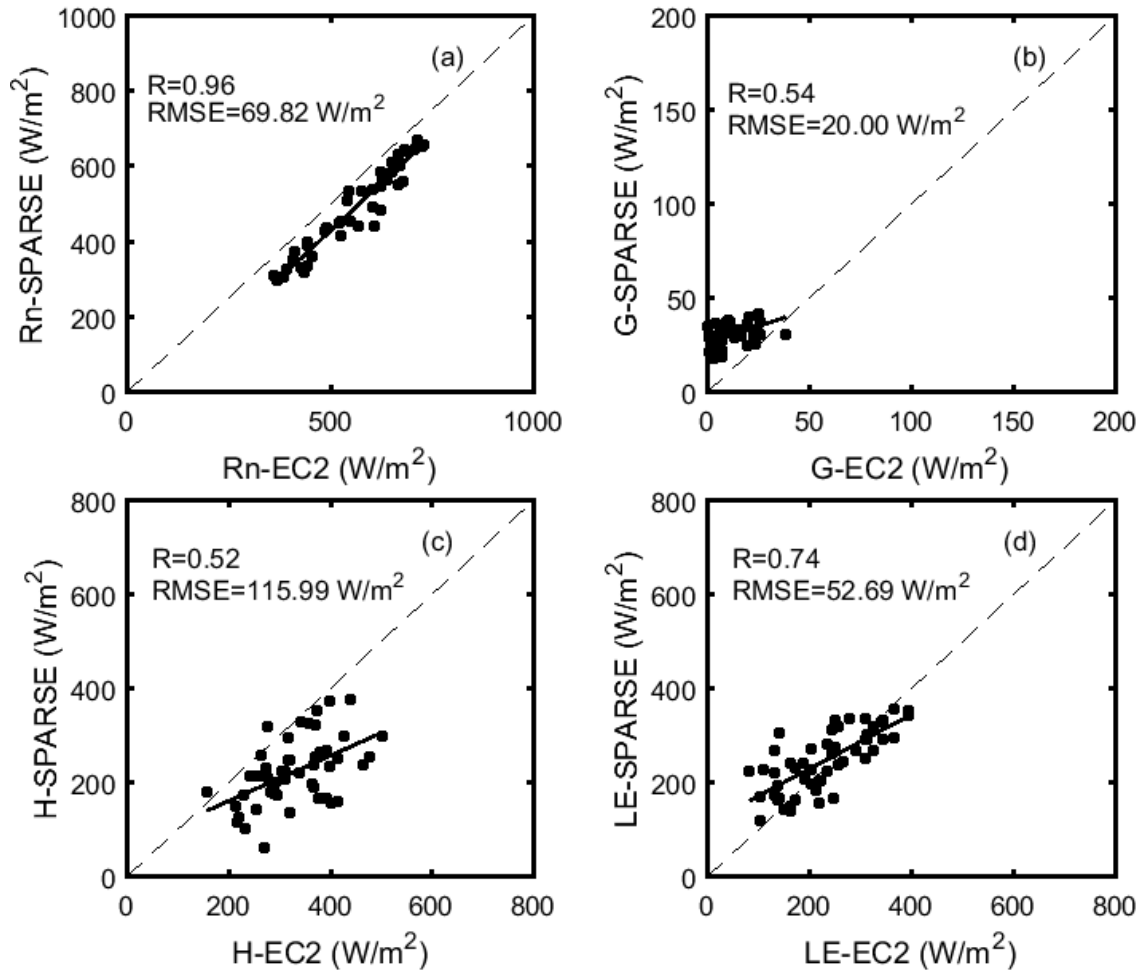
372 *Figure 8: Comparison between the EC1 measurements and SPARSE estimations (Net radiation (Rn), soil heat flux (G), sensible*
 373 *heat flux (H) and latent heat flux (LE)) using Landsat products.*

374 3.4 SPARSE validation

375 The parameters obtained over EC1 were validated locally over EC2 and spatially using the LAS
 376 measurements. Scatter plots of modeled available energy, sensible and latent heat fluxes for Landsat
 377 overpass dates, averaged over the EC2 and LAS footprints versus measurements are displayed at figures
 378 9 and 10. Net radiation values were accurately estimated by SPARSE with RMSE of about 69.8 W/m²
 379 for EC2. However, they show an underestimation compared to the two stations measurements which is
 380 expected since the Landsat LST overestimates the surface temperature as shown in figure 2. This is in-
 381 line with the same bias observed in the calibration phase. *Rn* measurement over a complex surface is a
 382 difficult task as many authors reported (Anthoni et al., 2000; Byun et al., 2014) due to the influence of
 383 the vegetation structure on the albedo. Comparison between observed and simulated soil heat flux shows
 384 lower agreement than for *Rn* which can be explained in one hand by the accuracy of the measurements
 385 since it gathers several difficulties as reported in the literature (Ezzahar et al., 2009b; Ait Hssaine et al.,
 386 2018). These difficulties lay in the plate protection from direct sunlight especially for the one at 5 cm
 387 and choosing the representative position which takes into consideration the vegetation intercept of the

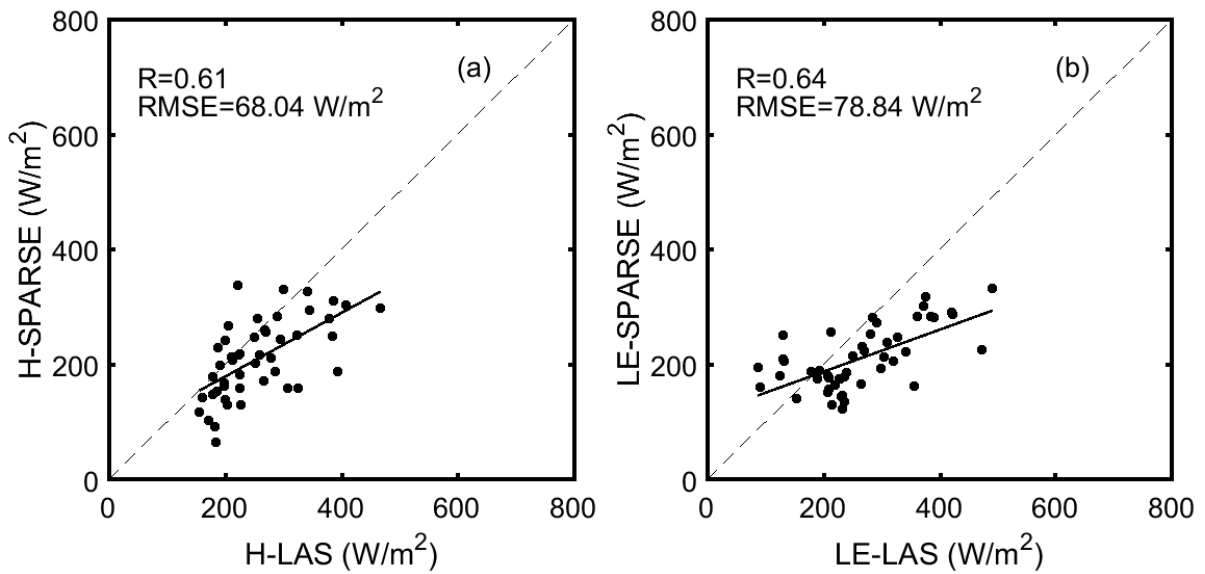
388 incoming radiation. On the other hand, SPARSE calculates G as a fraction of R_{ns} inducing the
389 transmission of the error on R_{ns} to G . Furthermore, for ease of implementation, a constant fraction value
390 was adopted in this study, whereas many studies have related the value of this fraction to the variation
391 of the surface cover (Diarra et al., 2017; Kustas, 1990; Saadi et al., 2018). Sensible heat flux simulations
392 show acceptable agreement over EC2 and LAS with an RMSE of about 116 W/m^2 and 68 W/m^2 ,
393 respectively. The discrepancy showed in the figures between modeled and observed H can be attributed
394 to numerous factors, particularly the accuracy of LST data. In addition, the calculation errors on the
395 surface resistances are strongly affecting the H estimation. Also, one potential source of error is the
396 accuracy of the displacement height (d) and roughness length (Z_0) which were estimated in this work as
397 a fraction of the vegetation height using the rule of thumb ($Z_0 = 0.14 \cdot h_{veg}$ and $d = 0.66 \cdot h_{veg}$, h_{veg} is
398 the vegetation height) following Brutsaert and Kustas (1987). The method used to approximate these
399 parameters are adapted to dense and homogeneous areas whereas the experimental field is
400 heterogeneous and sparse. Finally, the model provides good estimates of LE over EC2 and LAS with an
401 RMSE of about 52.7 W/m^2 and 78.8 W/m^2 , respectively. The discrepancy in LE can be related to the
402 uncertainty on H and AE ($R_n - G$) which is directly transmitted to LE values since it's a residual term
403 of the energy balance (Kalma et al., 2008; Morillas et al., 2013; Saadi et al., 2018). Moreover, using
404 constant parameters during the whole year despite vegetation and environmental changes can causes
405 some errors, especially for the minimum stomatal resistance ($r_{st_{min}}$). As reported by Boulet et al.
406 (2015) an inadequate value of $r_{st_{min}}$ increases automatically H and LE errors.

407



408

409 *Figure 9: Same as figure 8 but for EC2.*



410

411 *Figure 10: Comparison between the LAS measurements and SPARSE estimations (H and LE) using Landsat products.*

412 3.5 Model's validation and intercomparison

413 The comparison of the four models and LAS and EC2 measurements was done at the daily scale. The
414 instantaneous ETa estimates provided by SPARSE and SW were extrapolated to a daily value using the
415 *EF* method presented in section 2.5. Then, daily ETa maps provided by all models were weighted using
416 the daily footprint of the LAS and EC2 measurements in order to be compared with them.

417 Figure 11 and 12 presents the scatterplots of the four models ETa estimates compared to the EC2 and
418 LAS measurements, respectively. The four models underestimate the LAS measurements which is
419 strange and raises the question on the LAS accuracy. However, the LAS values were validated while
420 comparing them with the EC1 and EC2 values in a previous study (Elfarkh et al., 2020) and the results
421 were good. SPARSE and SW are more scattered which can be related to the large number of their
422 parameters that are taken constant throughout the season. Nevertheless, these parameters are variable in
423 space depending on the soil and vegetation characteristics. In addition, the sensibility of both models to
424 the LST data errors can also generate this bias. The METRIC and SAMIR ETa estimates are less
425 scattered and show better statistical results compared to SPARSE and to SW. The time series of the
426 daily ETa values obtained with the LAS and the four models are illustrated in figure 13. Overall, the
427 LAS and the four models ETa show similar seasonal dynamics. They increase with the begin of the
428 growing season in January, reach maximum values during growth peak in April-May, and then decrease
429 until December. Since precipitation and canopy development greatly affect ET, its rates decrease during
430 dry conditions and increase immediately after each rainfall event. The ETa values of winter are higher
431 in 2018 than in 2017 due to the higher precipitations in 2018. However, the ETa spring values are low
432 in 2018 compared to 2017, which can be attributed to the low available energy received due to more
433 frequent cloudy days.

434 During summer 2017, SW was close to the LAS measurements. SPARSE underestimates ETa values,
435 which may be due to the already observed overestimation of Landsat LST (Figure 2) that signify stress
436 conditions for the model. In contrast, the effect of the LST error on the SW estimations was not as strong
437 as for SPARSE, which can be attributed to fact that the absolute values of LST are used in SPARSE,
438 whereas LST was used in a relative manner in SW model to compute stress indexes related to the
439 resistances of vegetation and soil. Regarding SAMIR, the estimated ETa values were overestimated
440 which is expected since SAMIR doesn't stop irrigation in summer despite the water shortage. METRIC
441 in this period shows a slight overestimation that can be linked to wet edge detection error under these
442 stress conditions. The RMSE and the R of the models show that SAMIR and METRIC-GEE are the
443 least scattered and the most correlated to the measurements. On the other hand, SPARSE shows less
444 bias and dispersion than SW while the latter is better correlated.

445 In order to further compare the models and illustrate the discrepancies, ETa images of the four models
446 are shown for three dates illustrating contrasted conditions (Figure 14). The accuracy of each image is

447 assessed through the bias with the LAS measurements (Figure 15); keeping in mind that the LAS
448 measurements represent only the irrigated area in the center of the image. For the 16th of January 2017,
449 the model providing the best estimates is SPARSE, and the other models strongly underestimate ETa (-
450 1.5 to -1 mm bias). SAMIR shows low values of ET, especially over the bare soil supposedly not
451 irrigated and also over the wheat plots which were bare soil at this time (Figure 14). SW model also
452 underestimates ETa which can be explained by the non-representativeness of the relation established
453 between the stress indexes and the resistances over the bare soil since these relations were calibrated
454 over olive trees (EC1). In contrast, thanks to the thermal information which is highly correlated to the
455 soil moisture, SPARSE shows less bias compared to the LAS. Finally, METRIC-GEE underestimates
456 the most ETa although it is based on thermal remote sensing that should capture soil moisture conditions.
457 Indeed, the METRIC approach forces the flux computation to be bounded between wet and dry extreme
458 conditions, although these extreme conditions are not always present on every image and may thus
459 induce a wrong scaling. For the summer date of 20 August 2017, SW and SAMIR models provide the
460 best results. METRIC-GEE shows the higher bias which can be explained by the error on determining
461 the wet and dry temperatures which are not well identified in such dry uniform conditions. SPARSE
462 also underestimates ETa measurements which may be related to the LST reliability. On first April 2018,
463 during the development stage of annuals and no stress conditions, SAMIR model is close to the LAS
464 observations, whereas SW shows a strong underestimation. The SW and SPARSE underestimation can
465 be explained by the fact that several parameters, especially the minimal stomatal conductance, are set
466 constant during the entire season regardless of the seasonal changes. This assumption can lead to
467 erroneous ETa estimates. In fact, Zhu et al., (2013) and Hu et al., (2009) noted that over/underestimation
468 of ETa can occur when using constant parameters for long-term simulations using SW over different
469 vegetation and environmental conditions. Finally, for METRIC-GEE, we observe a strong contrast
470 between vegetation area with very high ETa and bare soil areas with low ET, which is a characteristic
471 of METRIC always stretching ETa between dry bare soil and wet vegetated areas (Tasumi, 2019).
472 However, despite a strong ETa in vegetated areas, the model predictions are still underestimated at the
473 scale of the LAS footprint, due to the underestimation of evaporation in the riverbeds (see below).

474 Another difference between the models is linked to riverbed. SAMIR shows low ETa for all dates in the
475 river, assuming a non-irrigated bare soil, without taking into consideration the evaporation due to
476 capillary rise from the shallow aquifer associated with riverbeds. This is well visible on the April image
477 and to a lesser extent in January, in contrast, SPARSE accounts for the soil moisture related to surface
478 temperature and shows higher ETa in riverbeds for these two dates. Although based on thermal data,
479 SW also underestimates ETa in this area, which is explained by the fact that the resistance calibrations
480 were done mainly on olive trees (EC1). This calibration may not be representative of the entire study
481 area, in particular the fields of annual crops. Calibration of the resistance's equation in the SW model
482 on different land uses is necessary to improve its performance.

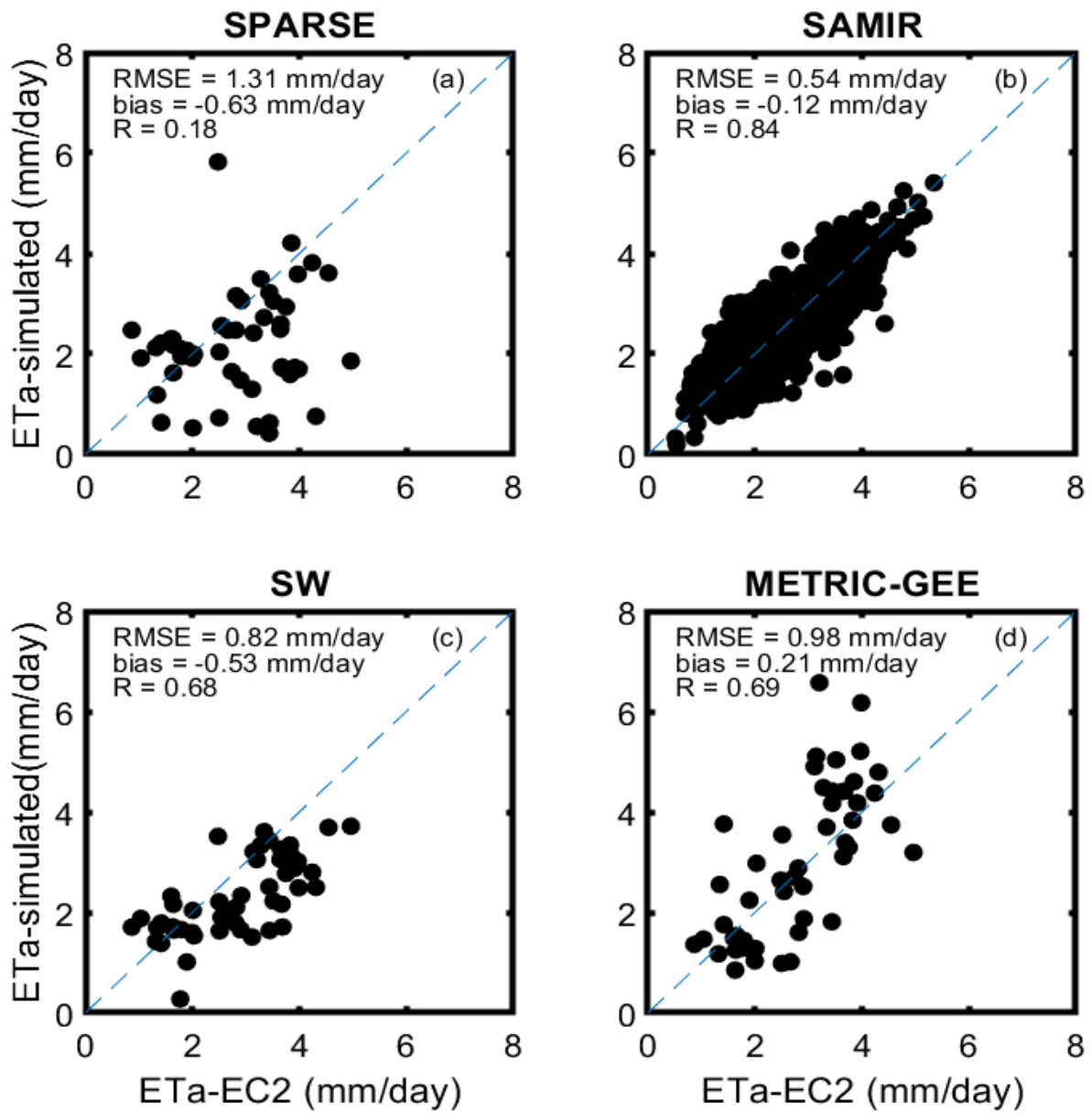
483 On the whole, the accuracy of the four approaches for predicting ETa was acceptable despite some
484 discrepancies observed in specific conditions but not at the same time depending on the model. There is
485 no unique method for evaluating models, so there is no easy answer to the question of which model is
486 most accurate. It seems that the SPARSE model, like other models based on thermal remote sensing,
487 even if it is based on physical assumptions, remains sensitive to the quality of the input variables on one
488 hand (e.g. the accuracy of the surface temperature), and on the other hand to the setting of the different
489 physical parameters required by the model. The latter parameters are very variable in space and their
490 calibration may suffer from equifinality problems as shown by the calibration of SPARSE. The errors
491 of the three energy balance models, SPARSE, SW and METRIC-GEE seem uncorrelated which lead to
492 a logical hypothesis of testing the potential benefit of computing their average value. As shown in figure
493 16, the correlation coefficient obtained between this average ETa value and the measurements shows an
494 improvement of 36%, 29% and 3% as compared to SPARSE, SW and METRIC-GEE, respectively.
495 However, this average is underestimated with a bias of about -0.63 mm/day which is expected since the
496 three model estimations are underestimated. Given that the bias can be corrected based on the linear
497 relation obtained, the improvement in the correlation between ETa values average and the LAS
498 measurements may be exploited for operational ETa estimates in this area. This approach of averaging
499 different methods is a technique that has been used in different works such as the EVASPA model that
500 includes several algorithms for calculating ETa in order to assess the uncertainties in ETa estimates.
501 (Gallego-Elvira et al., 2013).

502 In comparison with thermal approaches, SAMIR provides a good ETa because it is computed on a robust
503 base which is the slowly changing NDVI and accurately measured ET_0 , however it suffers from a major
504 drawback which is the lack of control of soil water conditions. Thus, water stress affecting both
505 transpiration (K_s) and evaporation (K_e) is poorly represented. Models do not have the same advantages
506 and weaknesses and each may be suitable under certain conditions (Table 3). The major constraint is the
507 need of user calibration each time the environmental conditions are different except for METRIC-GEE
508 for which there are achieved automatically. In addition, the availability of the model's input is a
509 paramount element to choose a model especially in traditional complex areas. For instance, it is
510 impossible to have spatial information about the irrigation of each plot. Consequently, SAMIR is not
511 the best choice in stress conditions where soil moisture strongly influences ET. On the other hand, the
512 difficulty to calculate accurate LST from the satellite's thermal bands is an issue for the energy balance
513 models due to their high sensitivity to this variable. However, these models are not equally affected by
514 LST accuracy. SPARSE is highly sensitive to LST accuracy since the error directly impacts H and LE.
515 In contrast, the contextual approach of METRIC-GEE "scaling" LST relatively to extreme values of the
516 image reduces problems. Also, for SW, the relative variation of LST between its maximum and
517 minimum is used to calculate the soil and the vegetation resistances. This means that the error on LST
518 will not have the same effect on METRIC-GEE and SW as compared to SPARSE. One advantage of

519 SAMIR is to produce continuous daily ETa estimates which is valuable in assessing the basin water
 520 budget (Simonneaux et al., 2007; Le Page et al., 2012; Diarra et al., 2017). SPARSE is a model that can
 521 be used accurately to detect stress conditions if properly calibrated (Boulet et al., 2015). Consequently,
 522 ETa estimated by SPARSE can be used to calculate stress indices. The modified SW model is a new
 523 approach that must be tested under different conditions in order to find a robust relationship that
 524 accurately represents the variation in resistance as a function of stress indices. Finally, METRIC-GEE
 525 showed a good agreement with the LAS measurements, which is very good news since it is available
 526 freely and it does not require in-depth technical knowledge.

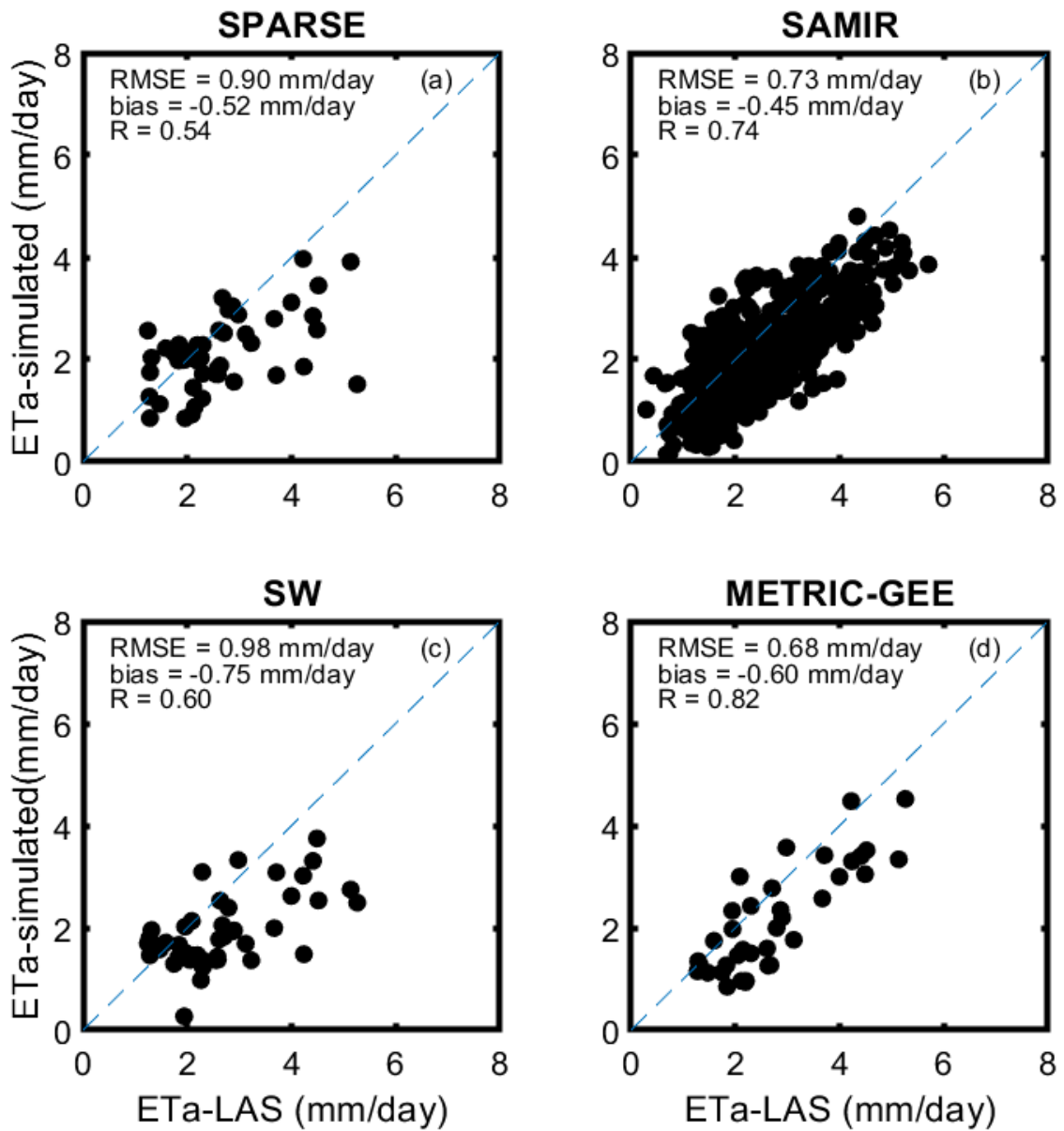
527 *Table 3: Summary table of the advantages and disadvantages for the four models.*

| Models | Disadvantages | Advantages |
|------------|--|---|
| SPARSE | <ul style="list-style-type: none"> - Very sensitive to LST accuracy - Many physical parameters required - Need of calibration - Extrapolation instantaneous ETa to daily values add errors | <ul style="list-style-type: none"> - Few inputs needed - Reliable in stress condition |
| SAMIR | <ul style="list-style-type: none"> - Irrigations are necessary and are estimated - Need of calibration (especially for the soil evaporation component) | <ul style="list-style-type: none"> - Provide continuous daily ETa values - It can provide accurate ETa values in no or limited stress conditions. |
| SW | <ul style="list-style-type: none"> - It is a new approach that need calibration / validation on other sites | <ul style="list-style-type: none"> - Few inputs needed |
| METRIC-GEE | <ul style="list-style-type: none"> - Sensitive to the error in the dry/wet edges detection - You cannot download large zone from the platform | <ul style="list-style-type: none"> - No calibration needed - Available to download freely - Ease of access. No need for in-depth technical knowledge |



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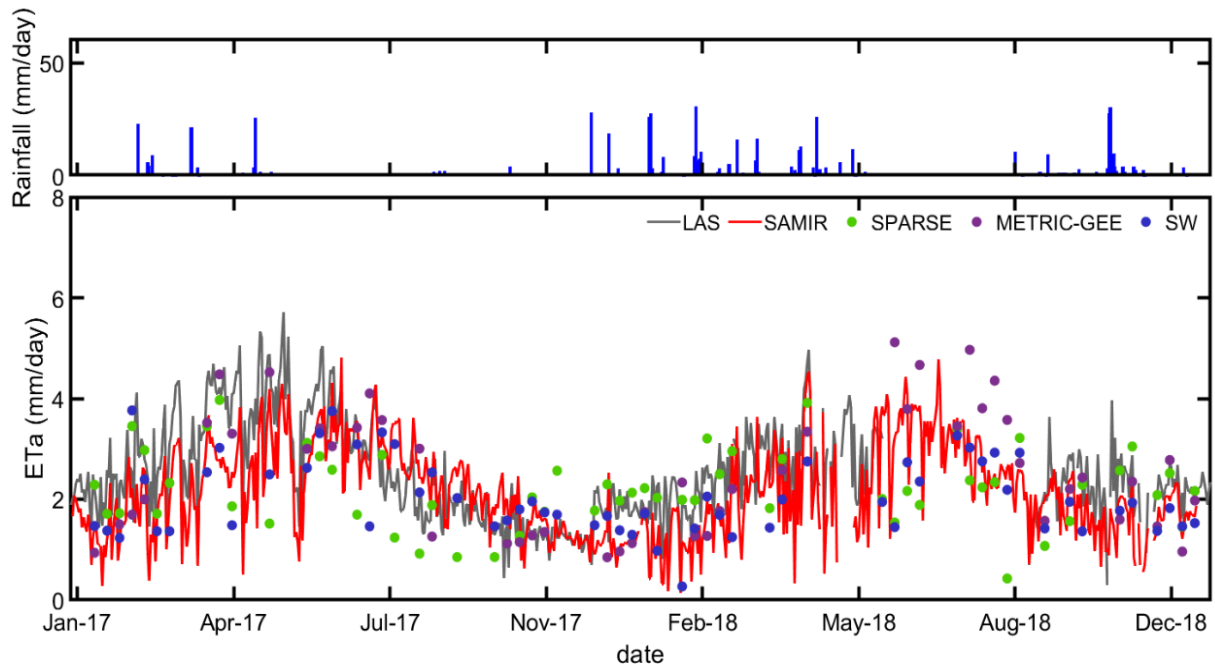
530 *Figure 11: Comparison between ETa measured by EC2 and estimated by SPARSE (a), SAMIR (b), SW (c) and METRIC-GEE (d).*



531

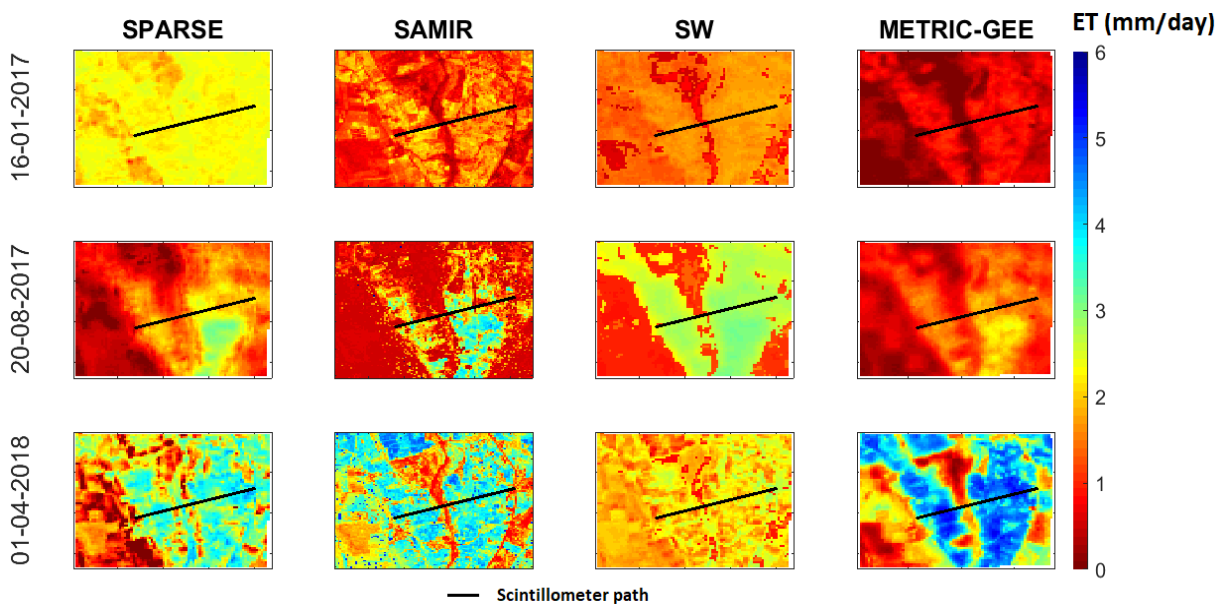
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Figure 12: Comparison between actual ETa measured by the LAS and estimated by SPARSE (a), SAMIR (b), SW (c) and METRIC-GEE (d).



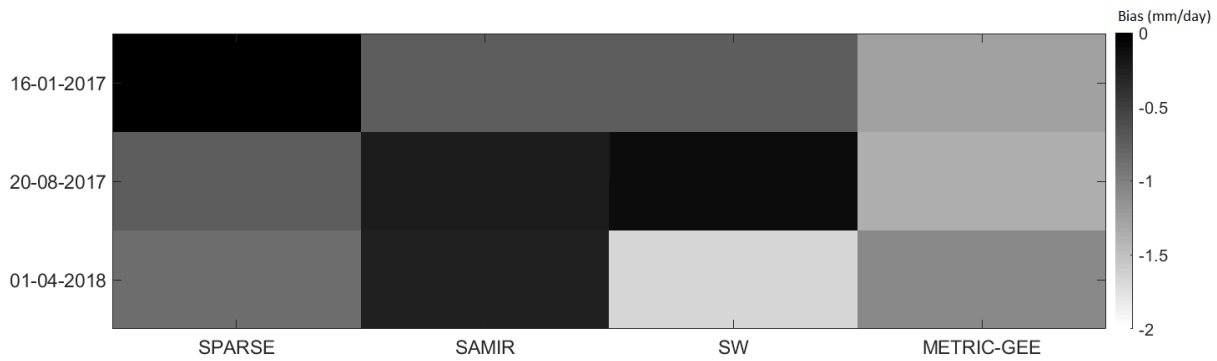
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535 *Figure 13: Daily series of the rainfall, ETa measured by LAS and estimated over the LAS footprint by SAMIR, SPARSE, SW and*
 536 *by METRIC-GEE during the study period 2017 and 2018.*



537

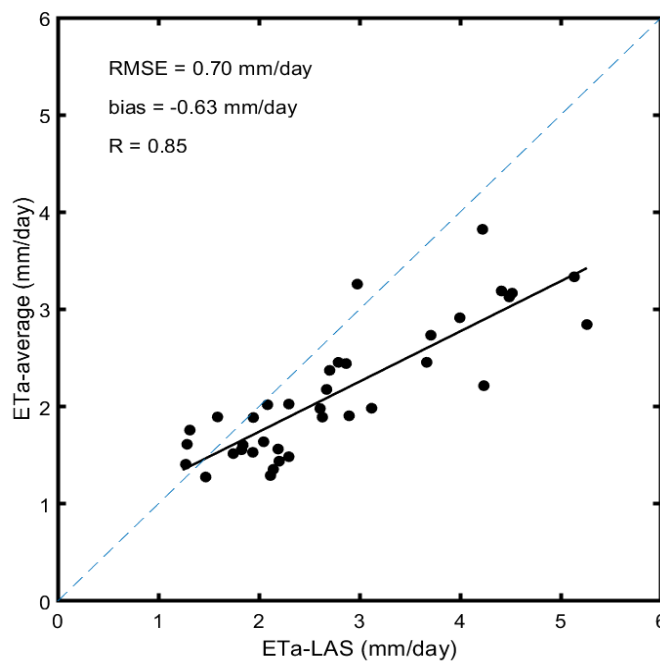
538 *Figure 14: ETa maps for three days of contrasting climate conditions estimated by SPARSE, SAMIR, SW and METRIC-GEE.*
 539 *SAMIR outputs have a 10 m spatial resolution whereas the other models' outputs have a 30 m pixel)*



540

541

Figure 15: Bias in mm/day between the model maps shown in Figure 13 and LAS measurements.



542

543

544

Figure 16: Comparison between the ETa measured by the LAS and the average of SPARSE, SW and METRIC-GEE ETa estimation.

545 4 Conclusion

546 The objective of this study was to map distributed actual crop evapotranspiration (ETa) at high
 547 resolution using different approaches based on different remote sensing data. We used the SAMIR
 548 model based on water budget as proposed by the FAO-56 approach, and three approaches based on
 549 thermal remote sensing, namely the SPARSE model, a modified version of Shuttleworth-Wallace (SW)
 550 model and an operational version of METRIC available on Google Earth Engine (METRIC-GEE). The
 551 comparison has been performed over an heterogeneous and complex irrigated agricultural area. Landsat
 552 7 and 8 products were used for SPARSE, SW and METRIC-GEE and Sentinel 2 products were used for
 553 SAMIR. The models' performance is evaluated using two Eddy covariance (EC) systems and
 554 scintillometer (LAS) measurements. The seasonal variability of ETa is correctly predicted by the four
 555 models throughout 2017 and 2018 agricultural seasons. However, SAMIR and METRIC-GEE, with an

556 RMSE of 0.73 and 0.68 mm/day respectively as compared to LAS measurements showed slightly better
557 performances in estimating ETa than SPARSE and SW which show an RMSE of 0.90 and 0.98 mm/day
558 compared to LAS measurements, respectively. Finally, when averaging the estimates of the three
559 thermal based models, the correlation coefficient with measurements was improved by 36%, 29% and
560 3% compared to SPARSE, SW and METRIC-GEE, respectively.

561 This study has shown the accuracy of different approaches and highlights the importance of remote
562 sensing data which allow highly spatial and temporal resolution of ETa estimation. SAMIR has
563 represented good estimation of ETa but its dependence for water input data (irrigation and rainfall) limit
564 its applicability especially over traditional irrigated areas. On the other hand, thermal approaches may
565 detect water stress but they have shown to be very sensitive to parameterization and to uncertainties in
566 input data. This is the case for the remotely sensed surface temperature and for parameters like the
567 stomatal resistance, sensitive to environmental conditions. Interestingly enough, METRIC-GEE ETa
568 products showed good agreement with the LAS measurements without any calibration and are freely
569 available online. These results confirm the idea that to move forward, the combination of these models
570 can be applied. For instance, assimilating the ETa estimates of METRIC-GEE, SW or SPARSE into
571 SAMIR which showed a good temporal consistency but whose widespread application may be limited
572 by lack of available, spatially-explicit data on irrigation amount. This potential synergy is expected to
573 be improved in the next few years with the LSTM mission of ESA and the TRISHNA mission
574 (Lagouarde et al., 2018) which will provide high spatial-temporal resolution land-surface temperature
575 at a resolution of 50 m, every 3 days, which is a significant step forward as compared to the actual
576 Landsat data (100 m, every 16 days). This will allow accurate monitoring of spatio-temporal changes in
577 the water status of surfaces, including crop stress detection, and will open great opportunities to improve
578 these models to be more adapted for assessing crops water demand at field scale.

579

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586

587 Appendix 1: SAMIR model

588 SAMIR, is a tool to compute ETa and water budget at the daily time step using the FAO method (Allen
589 et al., 1998). The soil model has been slightly modified to include three compartments, namely the
590 evaporation, root and deep soil compartments (Saadi et al., 2015). Between these compartments, water
591 can move down by gravity or up and down by diffusion processes. These fluxes are linked to the soil
592 moisture of the compartments. In this work, FAO dual crop approach implemented in the SAMIR tool
593 was used to calculate ETa as follows:

$$ETa = (K_s K_{cb} + K_e) ET_0 \quad \text{Eq: A.1}$$

594 The reference evapotranspiration (ET_0) was calculated using meteorological measurements based on the
595 FAO Penman-Monteith equation and the crop coefficient K_{cb} was estimated using a $NDVI - K_{cb}$
596 relationship based on satellite time series imagery:

$$K_{cb} = a * NDVI + b \quad \text{Eq: A.2}$$

597 Parameters a and b are related mainly to land cover type and climatic conditions and can be calibrated
598 or/and taken from previous studies (Duchemin et al., 2006; Er-Raki et al., 2007; Saadi et al., 2015).

599 K_e is the evaporation coefficient. When the depletion in the evaporation layer (i.e., void volume, De)
600 exceeds a threshold (i.e., readily evaporable water, REW), a reduction factor K_r is applied to reduce
601 evaporation following Eq. A.4.

$$K_e = \min(K_r(K_{c_{max}} - K_{cb}), f_{ew} \cdot K_{c_{max}}) \quad \text{Eq: A.3}$$

$$K_r = m \frac{TEW - De}{TEW - REW} \leq 1 \quad \text{Eq: A.4}$$

602 where $K_{c_{max}}$ and f_{ew} are the maximum capacity of water evacuation by atmosphere and the fraction of
603 soil wetted, respectively. TEW is the total evaporable water in the evaporation layer. In order to estimate
604 K_r , we used the formalism proposed by (Torres & Calera, 2010), namely the introduction of the m
605 parameter which allows more reduction of evaporation as compared to the original FAO-56 formalism.
606 The m coefficient initially set to 1 allows to further reduce the evaporation level with m values
607 potentially decreasing until 0. This choice was made because, like Torres et al., we observed a strong
608 overestimation of ETa especially after wetting events which was supposed to be due to higher
609 evaporation (Saadi et al. 2015). After introducing the m parameter and calibration, better estimates of
610 ETa were obtained (Saadi et al., 2015). The combination of REW and m are functionally defining the
611 surface resistance to the soil evaporation.

612 The stress coefficient K_S is computed when depletion in the root compartment (Dr) is higher than the
 613 readily available water (RAW), limiting the root uptake (Eq. A.5). RAW is a fraction of the TAW , the
 614 total available water available for vegetation.

$$K_S = \frac{TAW - Dr}{TAW - RAW} \leq 1 \quad \text{Eq: A.5}$$

615 In addition to NDVI time series, SAMIR uses as forcing the daily reference evapotranspiration (ET_0)
 616 values and water input. In fact, rainfall can be measured using the meteorological station, whereas
 617 irrigation cannot be easily observed for each plot in an area. Thus, SAMIR simulated the water inputs
 618 based on an assumed behavior of the farmer, regarding the threshold in soil moisture to trigger irrigation,
 619 and the water depth brought. A detailed explanation of SAMIR functioning may be found in (Saadi et
 620 al., 2015).

621 Some parameters were fixed according to the guideline of the FAO-56 paper (the depth of the soil
 622 evaporation layer (Ze), the root zone water depletion fraction before stress (p) and the maximum value
 623 of crop coefficient (following rain or irrigation) which is determined by the energy available for ETa at
 624 the soil surface (Kc_{max})), or were based on ground data (the volumetric water content at field capacity
 625 (ω_{fc}) and the volumetric water content at wilting point (ω_{wp})). Vegetation fraction cover values were
 626 computed based on a linear relationship with NDVI where the slope (a_{fc}) and the intercept (b_{fc}) were
 627 set assuming an NDVI value for the bare soil ($fc = 0$) and full coverage ($fc = 1$) equal to 0.15 and 0.9,
 628 respectively. fc was used to calculate the root zone depth (Zr) using a linear relation and assuming that
 629 the crop will reach its full rooting depth at maximum fc . The remaining parameters (the slope and the
 630 intercept of the NDVI- K_{cb} linear relationship (a_{Kcb} and b_{Kcb}), the readily evaporable water (REW), the
 631 root depth (Zr_{max}) and the diffusion between surface and root layers ($Diff_{er}$)) were calibrated using the
 632 flux data (Table 2).

633 Appendix 2: SPARSE model

634 The SPARSE model is a two-source model solving separately the energy budget of the soil and the
 635 vegetation (Boulet et al., 2015), where both of them are connected to the atmosphere separately. The
 636 model solves a system of equations regarding sensible and latent heat flux for soil and vegetation
 637 respectively (Eq. A.6 and A.7) and the energy balance of the soil and the vegetation (Eq. A.8 and A.9).
 638 Eq. A.10 describes the link between the average surface temperature and longwave radiative fluxes.

$$H = H_S + H_V \quad \text{Eq: A.6}$$

$$LE = LE_S + LE_V \quad \text{Eq: A.7}$$

$$Rn_s = G + H_s + LE_s \quad \text{Eq: A.8}$$

$$Rn_v = H_v + LE_v \quad \text{Eq: A.9}$$

$$\sigma \varepsilon LST^4 = \varepsilon R_{atm} - R_{an} \quad \text{Eq: A.10}$$

639 H is the sensible heat flux, LE is the latent heat flux, Rn is the net radiation and G is the soil heat flux;
 640 indexes “s” and “v” are for the soil and the vegetation, respectively. ε is the surface emissivity. R_{atm} is
 641 the incoming atmospheric longwave radiation, R_{an} is the net longwave radiation, LST is the radiative
 642 surface temperature (K) and σ is the Stefan-Boltzmann constant. To solve these equations, the model is
 643 first run in prescribed mode for two extreme configurations, namely fully unstressed and fully stressed
 644 vegetation (i.e. for a minimum and a maximum surface resistances), computing theoretical evaporation
 645 and transpiration fluxes based on the same method as the TSEB model (Kustas & Norman, 1999). These
 646 potential fluxes are then used as thresholds in the retrieval mode. In this mode, LE_v is calculated first
 647 considering unstressed conditions, deducting LE_s using the measured surface temperature. If the
 648 obtained LE_s value is negative, the unstressed vegetation assumption is invalid. In that case, the
 649 vegetation is assumed to suffer from water stress and the soil surface is assumed to be dry. Consequently,
 650 LE_s is set to 30 W/m² to account for the remaining slow vapor diffusion within the soil (Boulet et al.,
 651 1997) and the vegetation latent heat flux (LE_v) is recalculated. If LE_v is also negative, both LE_s and LE_v
 652 components are given zero independently of LST .

653 Appendix 3: Shuttleworth–Wallace model

654 This model is developed by Shuttleworth and Wallace in 1985 (Shuttleworth & Wallace, 1985). It
 655 estimates two separate fluxes one for soil and the other for the vegetation using the following formulas:

$$ETa = E + T = C_s PM_s + C_v PM_v \quad \text{Eq: A.11}$$

$$PM_s = \frac{\Delta A + \left[(\rho C_p D - \Delta r_a^s (A - A_s)) / (r_a + r_a^s) \right]}{\Delta + \gamma [1 + r_s^s / (r_a + r_a^s)]} \quad \text{Eq: A.12}$$

$$PM_v = \frac{\Delta A + \left[(\rho C_p D - \Delta r_a^v A_s) / (r_a + r_a^v) \right]}{\Delta + \gamma [1 + r_s^v / (r_a + r_a^v)]} \quad \text{Eq: A.13}$$

656 where A_s and A are available energy above soil surfaces and canopy (W/m²), respectively. Δ is the slope
 657 of saturation vapour pressure curve (kPa/K), ρ is the air density (kg/m³), C_p is the specific heat of dry
 658 air at constant pressure (J/kg/K), D is the water vapor deficit (kPa), γ is the psychrometric constant
 659 (Pa/K).

660 In this study a modified version of SW model is used. This version used the thermal data to provide
661 spatial ETa estimation as described by Elfarkh et al., (2021). In this approach the vegetation and soil
662 resistances were related to the stress indexes as follow:

$$r_s^s = ae^{b*SI_{ss}} \quad \text{Eq: A.14}$$

$$r_s^v = ce^{d*SI_{sv}} \quad \text{Eq: A.15}$$

663 where a, c, b and d are the calibration parameters set to 160.25 and 36.02 s/m, 2.62 and 1.30,
664 respectively. r_s^s and r_s^v are the resistances for soil and for vegetation, respectively. SI_{ss} and SI_{sv} are the
665 stress indexes for soil and vegetation, respectively. This approach was calibrated and validated in the
666 same study area (Elfarkh et al., 2021).

667 Appendix 4: METRIC-GEE model

668 METRIC-GEE is a version of METRIC (Allen et al., 2007) that operates on the Google Earth Engine
669 system (<https://eeflux-level1.appspot.com/>). The surface energy balance in this model is derived by
670 Landsat thermal band while the surface roughness, vegetation amounts and albedo are retrieved from
671 short-wave bands. The instantaneous evaporative fraction estimated at the time of satellite overpass is
672 extrapolated at daily scale to provide daily ETa value using reference ET computed by the Penman-
673 Monteith and GridMET weather data sets.

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