

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

Jamal Elfarkh, Vincent Simonneaux, Lionel Jarlan, Jamal Ezzahar, Gilles Boulet, Adnane Chakir, Salah Er-Raki

► To cite this version:

Jamal Elfarkh, Vincent Simonneaux, Lionel Jarlan, Jamal Ezzahar, Gilles Boulet, et al.. Evapotranspiration estimates in a traditional irrigated area in semi-arid Mediterranean. Comparison of four remote sensing-based models. Agricultural Water Management, 2022, 270, pp.107728. 10.1016/j.agwat.2022.107728. ird-03701664

HAL Id: ird-03701664 https://ird.hal.science/ird-03701664

Submitted on 14 Mar 2024 $\,$

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers. L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

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

Jamal Elfarkh^{1,2}, Vincent Simonneaux³, Lionel Jarlan³, Jamal Ezzahar^{4,5}, Gilles Boulet³, Adnane
Chakir⁶, Salah Er-Raki^{1,5}

- 5 (1) ProcEDE/AgroBiotech center, Département de Physique Appliquée, Faculté des Sciences et Techniques,
- 6 Université Cadi Ayyad, Marrakech, Maroc
- 7 (2) Hydrology, Agriculture and Land Observation Group, Water Desalination and Reuse Center, Biological and
- 8 Environmental Science and Engineering Division, King Abdullah University of Science and Technology, Thuwal,
 9 Saudi Arabia
- 10 (3) Centre d'Etudes Spatiales de la BIOsphère, CESBIO, Toulouse University, CNRS, CNES, IRD, UPS, INRAE,
- 11 Toulouse, France
- 12 (4) Département IRT, Laboratoire MISCOM, Ecole Nationale des Sciences Appliquées, Université Cadi Ayyad,
 13 Safi, Maroc
- 14 (5) Mohammed VI Polytechnic University (UM6P), Morocco, Center for Remote Sensing Applications (CRSA)
- 15 (6) LMFE, Département de Physique, Faculté des Sciences Semlalia, Université Cadi Ayyad, Marrakech, Maroc
- 16 Keywords: Evapotranspiration modelling, Remote sensing, Energy balance, FAO-56, Irrigation17
- 18 Research Highlights
- Four crop evapotranspiration estimates approaches based on remote sensing were compared
- Eddy-Covariance and Scintillometer measurements were used for models' assessment
- The four models estimate correctly the seasonal variations of actual crop ET
- FAO-56 and METRIC GEE show the best results over a mixed irrigated area

23 Abstract

24 Quantification of actual crop evapotranspiration (ETa) 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 Vegetation Index (NDVI) to derive the basal crop coefficient (K_{cb}) ; (2) Soil Plant Atmosphere and 30 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

Resolution with Internalized Calibration") that operates on the Google Earth Engine platform, also 35 36 driven by LST. Actual evapotranspiration (ETa) 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 ETa 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 ETa it has been shown that SAMIR and 46 METRIC-GEE are the less scattered and the better in agreement with the LAS measurements (RMSE equal to 0.73 and 0.68 mm/day and R equal to 0.74 and 0.82, respectively). On the other hand, SPARSE 47 is less scattered (RMSE = 0.90 mm/day, R = 0.54) than SW which is slightly better correlated (RMSE 48 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., 2017; Aouade et al., 2020; Diarra et al., 2017; Er-Raki et al., 2010; Ezzahar et al., 2007a; Ait Hssaine, 60 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 et al., 2020; Liu & Yamanaka, 2012; Martinez et al., 2017). This recharge is poorly known but could be 63 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 of recharge. Hence there is a need for an accurate estimate of ET. In the last decades, a number of studies 66 67 focused on developing several methods for measuring and estimating ETa based on remote sensing that 68 provides valuable data to assess its spatial and temporal variation.

There is a variety of methods allowing direct or indirect ETa measurement in the field with variable 69 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 approaches are based on Soil-Vegetation-Atmosphere Transfer (SVAT) models, coupling the soil water 80 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 conductance), on thermal and hydraulic properties of the soil (Olioso et al., 1999). To overcome these 86 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.



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

122

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

Flux stations were installed during 2017 and 2018 over two olive tree plots located in the study area on 17.5 m height towers (EC1 and EC2 sites) (Elfarkh et al., 2020). The land cover of these two sites is supposed to be representative of the entire site, namely traditional olive plantations of 7 to 10 meters height with an understory of herbaceous vegetation, mainly wheat. EC2 shows more heterogeneity than EC1 since it includes olive trees, other fruit trees (mainly apple trees) and annual crops (Elfarkh et al., 2020). They measured the sensible and latent heat fluxes using the eddy correlation method, consisting 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 sensible (H) and latent (LE) heat fluxes offline using the EC processing software 'ECpack' (Van Dijk et 140 141 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 calculation of the variation of the structure parameter of the refractive index C_n^2 along the path (Wesely, 157 158 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

The Normalized Difference Vegetation Index (NDVI) was computed using Sentinel-2 Red (R, band 4) and Near-InfraRed (NIR, band 8) reflectances at 10 meters resolution (Eq. 1). The Sentinel-2 images were downloaded from the THEIA web site, a French open-source land data service center (https://www.theia-land.fr/) providing cloud-free and atmospherically corrected surface reflectance images. NDVI is closely related to vegetation cover (Tucker, 1979). Sentinel 2 images have the 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 at al. 2010; Duchemin et al. 2006; Fe Babi et al. 2007, 2010)

179 et al., 2019; Duchemin et al., 2006; Er-Raki et al., 2007, 2010).

$$NDVI = \frac{NIR - R}{NIR + R}$$
 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 EC2. This comparison displayed in Figure 2a shows acceptable agreement between measured and 187 Landsat LST with an RMSE of about 5 K for EC1 and 6.6 K for EC2, with a moderate but significant 188 bias. However, despite the good correlation between ground and satellite data, we chose not to correct 189 satellite data considering the low representativity of our local measurements as compared to satellite 190 191 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.

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

$$\varepsilon = \varepsilon_{v} - (\varepsilon_{v} - \varepsilon_{s}) \left(\frac{NDVI - NDVI_{max}}{NDVI_{min} - NDVI_{max}} \right)^{k}$$
 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):

$$LAI = \sqrt{NDVI \frac{1 + NDVI}{1 - NDVI}}$$
 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).

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

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

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





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 Difference Vegetation Index (NDVI) images used to compute both the basal crop coefficient (K_{ch}) and 213 214 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 used here is the modification proposed by Elfarkh et al., (2021) where they use thermal remote sensing data to spatialize ET. SPARSE, SW and SAMIR were calibrated and validated over the same study area using eddy covariance and scintillometer measurements. Regarding METRIC, its automated version featured on the Google Earth Engine Evapotranspiration Flux (EEFlux) platform is used. More details on each model are presented in the appendix. A summary of the inputs required and the parameters 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 LST and emissivity Air temperature and humidity Wind speed Solar radiation 	 Minimum stomatal resistance (<i>rst_{min}</i>) Leaf width (<i>w</i>) Ratio relating the soil net radiation to the heat soil flux (ξ) Extinction coefficient (<i>k</i>) in the LAI equation Coefficient in the aerodynamic resistance (<i>n_{SW}</i>) 	- Minimization of the RMSE between the estimated and measured ETa
SAMIR	- NDVI - <i>ET</i> ₀ - Rainfall	 NDVI-K_{cb} relation's slope NDVI-K_{cb} relation's intercept Readily evaporable water (<i>REW</i>) Maximum root depth (<i>Zr_{max}</i>) Water diffusion coeff. between surface and root layers (<i>Dif_{er}</i>) 	- Minimization of the RMSE between the estimated and measured ETa
SW	 NDVI and Albedo LST and emissivity Air temperature and humidity Wind speed Solar radiation 	 Coefficients in the soil and vegetation resistances 	- Minimization of the RMSE between the estimated and measured ETa
METRIC- GEE	 NDVI and Albedo LST and emissivity Air temperature and humidity Wind speed Solar radiation 	- No calibration	

229 2.5 Models evaluation

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

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

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

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

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 empirical relationship. This relation parameterized EF diurnal trend as a function of incoming solar 243 244 radiation and relative humidity as follows.

$$LE_{dav} = EF * AE_{dav}$$
 Eq: 9

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

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

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

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

where *AE* is the available energy (Rn - G), Rg is the solar radiation (W/m²), RH is the relative humidity, *EF* is the evaporative fraction and *EF* sat_{inst} and *EF* base_{inst} are the evaporative fraction observed at the satellite overpass time and calculated at the satellite overpass with the first part of the Eq. 11, respectively.

249 2.7 Footprint computation

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

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

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

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

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



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

269 3 Results

267

268

In this section the ETa estimations by the four models are presented. Only the calibration and the validation of SAMIR and SPARSE are shown here. The calibration of SW is detailed over the same site in Elfarkh et al. (2021). METRIC is downloaded from a Google Earth Engine platform. After that, the four models' estimations are evaluated and compared with the LAS and the EC measurements and the 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. The meteorological forcing, namely precipitation and ET₀ were obtained from our in-situ measurements. 280 281 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 depth (Zr_{max}) obtained after calibration (4.9 m) is much larger than usual values proposed in the FAO-284 56 paper (1.6 m) for irrigated olive trees. This is not surprising considering that these trees are very old 285 286 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 trees roots may reach depths of 7 m (Lavee, 1996). For the annual crops, no calibration was possible 288 289 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

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

Parameter	Definition	Value	Source
a _{fc}	NDVI- <i>fc</i> relation's slope	1.33	Satellite imagery
b _{fc}	NDVI- <i>fc</i> relation's intercept	-0.20	Satellite imagery
a_{Kcb}	NDVI- K_{cb} relation's slope (Eq. A.2)	1.35	Calibrated
b_{Kcb}	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
$\omega_{fc} (m^3/m^3)$	Volumetric water content at field capacity	0.4	Ground observation
$\omega_{wp} (m^3/m^3)$	Volumetric water content at wilting point	0.2	Ground observation
Kc _{max}	Maximum value of crop coefficient (following rain	1.15	Ground observation
	or irrigation) which is determined by the energy		

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

available for ETa at the soil surface

296

Figure 4 shows the temporal variations of the computed basal crop coefficient K_{cb} and the fraction cover 297 (fc) values using the NDVI relationships with NDVI averaged over the EC1 station. Peak K_{cb} and fc298 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.



Figure 4: Simulation of the evaporative coefficient (K_e), the stress coefficient (K_s), the crop coefficient (K_{cb}) and the fraction 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. This gap is large in 2017 when compared to 2018 since the first year is dry with 157 mm whereas 2018 320 321 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.



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 NDVI time series. The simulated SAMIR ETa values were validated using measurements provided by 327 328 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 period, since there is enough rainfall and no stress, SAMIR doesn't apply any irrigation which is not the 342 343 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;
- possibly because the precipitation was relatively high and consequently the impact of irrigation on ETawas lower.



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



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

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 instantaneous footprints at the time of Landsat overpass. From a sensitivity study (Boulet et al., 2015), 357 358 five parameters of SPARSE having a significant impact on simulated ETa were calibrated : the minimum 359 stomatal resistance (rst_{min}) which was set to 260 s/m, As reported by Zhu et al. (2014) rst_{min} varies 360 for many natural and cultivated plants it ranges considerably from 20 to 100 s/m for crops and from 200 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 361 362 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 well as the vegetation density and its value ranges between 0.05 and 0.5. The extinction coefficient (k)365 in the equation where the fraction cover is calculated in term of LAI which is set to 0.6 which is in 366 conformity with the values found by Connor et al. (2012) and Srinet et al. (2019). The empirical 367 coefficient in the aerodynamic resistance (n_{SW}) set to 2.5 which is the same value stated by Boulet et al. 368 (2015). The calibration shows an acceptable agreement with an RMSE and R of about 81.3 W/m² and 369 370 0.58, respectively (Figure 8).



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

374 3.4 SPARSE validation

371

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 Rns inducing the transmission of the error on Rns to G. Furthermore, for ease of implementation, a constant fraction value 389 390 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/m² and 68 W/m², 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 surface resistances are strongly affecting the H estimation. Also, one potential source of error is the 395 396 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 ($Z_0 = 0.14$ *hveg and d = 0.66*hveg, hveg 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 heterogeneous and sparse. Finally, the model provides good estimates of LE over EC2 and LAS with an 400 RMSE of about 52.7 W/m² and 78.8 W/m², respectively. The discrepancy in LE can be related to the 401 uncertainty on H and AE (Rn - G) which is directly transmitted to LE values since it's a residual term 402 of the energy balance (Kalma et al., 2008; Morillas et al., 2013; Saadi et al., 2018). Moreover, using 403 404 constant parameters during the whole year despite vegetation and environmental changes can causes 405 some errors, especially for the minimum stomatal resistance (rst_{min}) . As reported by Boulet et al. 406 (2015) an inadequate value of rst_{min} increases automatically H and LE errors.





H-LAS (W/m²)

LE-LAS (W/m²)

412 3.5 Model's validation and intercomparison

The comparison of the four models and LAS and EC2 measurements was done at the daily scale. The instantaneous ETa estimates provided by SPARSE and SW were extrapolated to a daily value using the *EF* method presented in section 2.5. Then, daily ETa maps provided by all models were weighted using 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 daily ETa values obtained with the LAS and the four models are illustrated in figure 13. Overall, the 426 427 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.

In order to further compare the models and illustrate the discrepancies, ETa images of the four modelsare 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 be explained by the fact that several parameters, especially the minimal stomatal conductance, are set 465 466 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 transpiration (K_s) and evaporation (K_e) is poorly represented. Models do not have the same advantages 505 506 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 will not have the same effect on METRIC-GEE and SW as compared to SPARSE. One advantage of 518

SAMIR is to produce continuous daily ETa estimates which is valuable in assessing the basin water budget (Simonneaux et al., 2007; Le Page et al., 2012; Diarra et al., 2017). SPARSE is a model that can be used accurately to detect stress conditions if properly calibrated (Boulet et al., 2015). Consequently, ETa estimated by SPARSE can be used to calculate stress indices. The modified SW model is a new approach that must be tested under different conditions in order to find a robust relationship that accurately represents the variation in resistance as a function of stress indices. Finally, METRIC-GEE 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.

Models	Disadvantages	Advantages
SPARSE	 Very sensitive to LST accuracy Many physical parameters required Need of calibration Extrapolation instantaneous ETa to daily values add errors 	Few inputs neededReliable in stress condition
SAMIR	 Irrigations are necessary and are estimated Need of calibration (especially for the soil evaporation component) 	 Provide continuous daily ETa values It can provide accurate ETa values in no or limited stress conditions.
SW	- It is a new approach that need calibration / validation on other sites	- Few inputs needed
METRIC-GEE	 Sensitive to the error in the dry/wet edges detection You cannot download large zone from the platform 	 No calibration needed Available to download freely Ease of access. No need for in- depth technical knowledge

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



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



532 Figure 12: Comparison between actual ETa measured by the LAS and estimated by SPARSE (a), SAMIR (b), SW (c) and 533 METRIC-GEE (d).



534

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.



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)



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



543 Figure 16: Comparison between the ETa measured by the LAS and the average of SPARSE, SW and METRIC-GEE ETa 544 estimation.

545 4 Conclusion

The objective of this study was to map distributed actual crop evapotranspiration (ETa) at high 546 resolution using different approaches based on different remote sensing data. We used the SAMIR 547 model based on water budget as proposed by the FAO-56 approach, and three approaches based on 548 549 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 represented good estimation of ETa but its dependence for water input data (irrigation and rainfall) limit 563 its applicability especially over traditional irrigated areas. On the other hand, thermal approaches may 564 565 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

580 Acknowledgments

This research was conducted within the Joint International Laboratory TREMA (https://lmi-trema.ma).
Setup was funded by CNRST SAGESSE project and German Cooperation Giz within the frame of the
Hydraulic Basin Agency of the Tensift (ABHT). The authors wish to thank the projects: RISE-H2020ACCWA (grant agreement no: 823965), PHC TBK/18/61, PRIMA-IDEWA, PRIMA-ALTOS and
ERANETMED03-62 CHAAMS for partly funding the experiments.

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:

$$ETa = (K_s K_{cb} + K_e) ET_0$$
 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:

$$K_{cb} = a * NDVI + b$$
 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.

$$K_e = min(K_r(Kc_{max} - K_{cb}), f_{ew}.Kc_{max})$$
 Eq: A.3

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

602 where Kc_{max} and f_{ew} are the maximum capacity of water evacuation by atmosphere and the fraction of soil wetted, respectively. TEW is the total evaporable water in the evaporation layer. In order to estimate 603 604 Kr, 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 overestimation of ETa especially after wetting events which was supposed to be due to higher 608 609 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.

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

In addition to NDVI time series, SAMIR uses as forcing the daily reference evapotranspiration (ET_0) values and water input. In fact, rainfall can be measured using the meteorological station, whereas irrigation cannot be easily observed for each plot in an area. Thus, SAMIR simulated the water inputs based on an assumed behavior of the farmer, regarding the threshold in soil moisture to trigger irrigation, and the water depth brought. A detailed explanation of SAMIR functioning may be found in (Saadi et 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 computed based on a linear relationship with NDVI where the slope (a_{fc}) and the intercept (b_{fc}) were 626 set assuming an NDVI value for the bare soil (fc = 0) and full coverage (fc = 1) equal to 0.15 and 0.9, 627 628 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 (Dif_{er})) were calibrated using the 632 flux data (Table 2).

633 Appendix 2: SPARSE model

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

$$H = H_S + H_V$$
 Eq: A.6

$$LE = LE_S + LE_V$$
 Eq: A.7

$$Rn_S = G + H_S + LE_S$$
 Eq: A.8

$$Rn_V = H_V + LE_V Eq: A.9$$

$$\sigma \varepsilon LST^4 = \varepsilon R_{atm} - R_{an}$$
 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; indexes "s" and "v" are for the soil and the vegetation, respectively. ε is the surface emissivity. R_{atm} is 640 the incoming atmospheric longwave radiation, R_{an} is the net longwave radiation, LST is the radiative 641 642 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, LE_S is set to 30 W/m² to account for the remaining slow vapor diffusion within the soil (Boulet et al., 650 1997) and the vegetation latent heat flux (LE_V) is recalculated. If LE_V is also negative, both LE_S and LE_V 651 652 components are given zero independently of LST.

653 Appendix 3: Shuttleworth–Wallace model

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

$$ETa = E + T = C_s PM_s + C_v PM_v$$
 Eq: A.11

$$PM_{s} = \frac{\Delta A + \left[\left(\rho C_{p} D - \Delta r_{a}^{s} (A - A_{s}) \right) / (r_{a} + r_{a}^{s}) \right]}{\Delta + \gamma \left[1 + r_{s}^{s} / (r_{a} + r_{a}^{s}) \right]}$$
Eq: A.12

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

where A_s and A are available energy above soil surfaces and canopy (W/m²), respectively. Δ is the slope of saturation vapour pressure curve (kPa/K), ρ is the air density (kg/m³), C_p is the specific heat of dry air at constant pressure (J/kg/K), D is the water vapor deficit (kPa), γ is the psychrometric constant (Pa/K). 660 In this study a modified version of SW model is used. This version used the thermal data to provide

spatial ETa estimation as described by Elfarkh et al., (2021). In this approach the vegetation and soil
 resistances were related to the stress indexes as follow:

$$r_s^s = a e^{b * S I_{ss}}$$
 Eq: A.14

$$r_s^{\nu} = c e^{d * S I_{s\nu}}$$
 Eq: A.15

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

667 Appendix 4: METRIC-GEE model

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

674

675 References

- Allen, R. G., Pereira, L. S., Howell, T. A., & Jensen, M. E. (2011). Evapotranspiration information
 reporting: I. Factors governing measurement accuracy. *Agricultural Water Management*, *98*(6),
 899–920. https://doi.org/10.1016/j.agwat.2010.12.015
- Allen, R. G., Pereira, L. S., Raes, D., & Smith, M. (1998). Crop evapotranspiration: Guidelines for
 computing crop requirements. *Irrigation and Drainage Paper No. 56, FAO*.
 https://doi.org/10.1016/j.eja.2010.12.001
- Allen, R. G., Tasumi, M., & Trezza, R. (2007). Satellite-based energy balance for mapping
 evapotranspiration with internalized calibration (METRIC) Model. *Journal of Irrigation and Drainage Engineering*, 133(4), 380–394. https://doi.org/10.1061/(ASCE)07339437(2007)133:4(380)
- Amazirh, A., Er-Raki, S., Chehbouni, A., Rivalland, V., Diarra, A., Khabba, S., Ezzahar, J., & Merlin,
 O. (2017). Modified Penman–Monteith equation for monitoring evapotranspiration of wheat crop:

- Relationship between the surface resistance and remotely sensed stress index. *Biosystems Engineering*, 164(0), 68–84. https://doi.org/10.1016/j.biosystemseng.2017.09.015
- Amazirh, A., Er-Raki, S., Ojha, N., Bouras, E. houssaine, Rivalland, V., Merlin, O., & Chehbouni, A.
 (2022). Assimilation of SMAP disaggregated soil moisture and Landsat land surface temperature
 to improve FAO-56 estimates of ET in semi-arid regions. Agricultural Water Management, 260.
 https://doi.org/10.1016/j.agwat.2021.107290
- Anapalli, S. S., Fisher, D. K., Pinnamaneni, S. R., & Reddy, K. N. (2020). Quantifying
 evapotranspiration and crop coefficients for cotton (Gossypium hirsutum L.) using an eddy
 covariance approach. *Agricultural Water Management*, 233.
 https://doi.org/10.1016/j.agwat.2020.106091
- Anderson, M. C., Norman, J. M., Diak, G. R., Kustas, W. P., & Mecikalski, J. R. (1997). A two-source
 time-integrated model for estimating surface fluxes using thermal infrared remote sensing. *Remote Sensing of Environment*, 60(2), 195–216. https://doi.org/10.1016/S0034-4257(96)00215-5
- Anthoni, P. M., Law, B. E., Unsworth, M. H., & Vong, R. J. (2000). Variation of net radiation over
 heterogeneous surfaces: Measurements and simulation in a juniper-sagebrush ecosystem.
 Agricultural and Forest Meteorology. https://doi.org/10.1016/S0168-1923(00)00104-0
- Aouade, G., Jarlan, L., Ezzahar, J., Er-raki, S., Napoly, A., Benkaddour, A., Khabba, S., Boulet, G.,
 Garrigues, S., Chehbouni, A., & Boone, A. (2020). Evapotranspiration partition using the multiple
 energy balance version of the ISBA-A-gs land surface model over two irrigated crops in a semiarid Mediterranean region (Marrakech, Morocco). Hydrol. Earth Syst. Sci., 24, 3789–3814, 2020.
 https://doi.org/10.5194/hess-24-3789-2020
- Bastiaanssen, W. G. M., Pelgrum, H., Wang, J., Ma, Y., Moreno, J. F., Roerink, G. J., & Van Der Wal,
 T. (1998). A remote sensing surface energy balance algorithm for land (SEBAL): 2. Validation. *Journal of Hydrology*, 213–229. https://doi.org/10.1016/S0022-1694(98)00254-6
- Belaqziz, S., Khabba, S., Er-Raki, S., Jarlan, L., Le Page, M., Kharrou, M. H., Adnani, M. El, &
 Chehbouni, A. (2013). A new irrigation priority index based on remote sensing data for assessing
 the networks irrigation scheduling. *Agricultural Water Management*, *119*, 1–9.
 https://doi.org/10.1016/j.agwat.2012.12.011
- Blasch, K. W., & Bryson, J. R. (2007). Distinguishing sources of ground water recharge by using δ2H
 and δ18O. *Ground Water*, 45(3), 294–308. https://doi.org/10.1111/j.1745-6584.2006.00289.x
- Bouimouass, H., Fakir, Y., Tweed, S., & Leblanc, M. (2020). Groundwater recharge sources in semiarid
 irrigated mountain fronts. *Hydrological Processes*, 34(7), 1598–1615.

720 https://doi.org/10.1002/hyp.13685

- Boukhari, K., Fakir, Y., Stigter, T. Y., Hajhouji, Y., & Boulet, G. (2015). Origin of recharge and salinity
 and their role on management issues of a large alluvial aquifer system in the semi-arid Haouz plain,
 Morocco. *Environmental Earth Sciences*, 73(10), 6195–6212. https://doi.org/10.1007/s12665014-3844-y
- Boulet, G., Braud, I., & Vauclin, M. (1997). Study of the mechanisms of evaporation under arid
 conditions using a detailed model of the soil-atmosphere continuum. Application to the EFEDA I
 experiment. *Journal of Hydrology*, *193*(1–4), 114–141. https://doi.org/10.1016/S00221694(96)03148-4
- Boulet, G., Mougenot, B., Lhomme, J. P., Fanise, P., Lili-Chabaane, Z., Olioso, A., Bahir, M., Rivalland,
 V., Jarlan, L., Merlin, O., Coudert, B., Er-Raki, S., & Lagouarde, J. P. (2015). The SPARSE model
 for the prediction of water stress and evapotranspiration components from thermal infra-red data
 and its evaluation over irrigated and rainfed wheat. *Hydrology and Earth System Sciences*, 4653–
 4672. https://doi.org/10.5194/hess-19-4653-2015
- Braud, I., Dantas-Antonino, A. C., Vauclin, M., Thony, J. L., and Ruelle, P. (1995). A simple soil-plantatmosphere transfer model (SiSPAT) development and field verification, J. Hydrol., 166, 213–250.
 https://doi.org/10.1016/0022-1694(94)05085-C, 1995.
- Brutsaert, W., & Kustas, W. P. (1987). Surface water vapor and momentum fluxes under unstable
 conditions from a rugged-complex area. *Journal of the Atmospheric Sciences*, *44*(2), 421–431.
 https://doi.org/10.1175/1520-0469(1987)044<0421:SWVAMF>2.0.CO;2
- Byun, K., Liaqat, U. W., & Choi, M. (2014). Dual-model approaches for evapotranspiration analyses
 over homo- and heterogeneous land surface conditions. *Agricultural and Forest Meteorology*, *197*,
 169–187. https://doi.org/10.1016/j.agrformet.2014.07.001

Chehbouni, A., Escadafal, R., Duchemin, B., Boulet, G., Simonneaux, V., Dedieu, G., Mougenot, B.,
Khabba, S., Kharrou, H., Maisongrande, P., Merlin, O., Chaponnière, A., Ezzahar, J., Er-Raki, S.,
Hoedjes, J., Hadria, R., Abourida, A., Cheggour, A., Raibi, F., ... Sobrino, J. A. (2008). An
integrated modelling and remote sensing approach for hydrological study in arid and semi-arid
regions: The SUDMED programme. *International Journal of Remote Sensing*, *29*(17–18), 5161–
5181. https://doi.org/10.1080/01431160802036417

Chirouze, J., Boulet, G., Jarlan, L., Fieuzal, R., Rodriguez, J. C., Ezzahar, J., Er-Raki, S., Bigeard, G.,
Merlin, O., Garatuza-Payan, J., Watts, C., & Chehbouni, G. (2014). Intercomparison of four
remote-sensing-based energy balance methods to retrieve surface evapotranspiration and water
stress of irrigated fields in semi-arid climate. *Hydrology and Earth System Sciences*, *18*(3), 1165–

- 753 1188. https://doi.org/10.5194/hess-18-1165-2014
- Choudhury, B. J., Ahmed, N. U., Idso, S. B., Reginato, R.J., and Daughtry, C.S.T. (1994). Relations
 Between Evaporation Coefficients and Vegetation Indices Studied by Model simulations. Remote
 Sensing of Environment, 50:1-17.
- Connor, D.J., Gómez-del-Campo, M., Comas, J. (2012). Yield characteristics of N–S oriented olive
 hedgerows, cv. Arbequina. Sci. Hortic. 133, 31–36. https://doi.org/10.1016/j.scienta.2011.10.008.
- Courault, D., Bsaibes, A., Kpemlie, E., Hadria, R., Hagolle, O., Marloie, O., Hanocq, J. F., Olioso, A.,
 Bertrand, N., & Desfonds, V. (2008). Assessing the potentialities of FORMOSAT-2 data for water
 and crop monitoring at small regional scale in South-Eastern France. *Sensors*, *8*, 3460–3481.
 https://doi.org/10.3390/s8053460
- De Bruin H.A.R., Kohsiek W., van den Hurk B.J.J.M., (1993). A verification of some methods to
 determine the fluxes of momentum, sensible heat and water vapour using standard deviation and
 structure parameter of scalar meteorological quantities. Boundary Layer Meteorol 63: 231–257.
- Delogu, E., Boulet, G., Olioso, A., Coudert, B., Chirouze, J., Ceschia, E., Le Dantec, V., Marloie, O.,
 Chehbouni, G., & Lagouarde, J. P. (2012). Reconstruction of temporal variations of
 evapotranspiration using instantaneous estimates at the time of satellite overpass. *Hydrology and Earth System Sciences*, *16*, 2995–3010. https://doi.org/10.5194/hess-16-2995-2012
- Delogu, Emilie, Boulet, G., Olioso, A., Garrigues, S., Brut, A., Tallec, T., Demarty, J., Soudani, K., &
 Lagouarde, J. P. (2018). Evaluation of the SPARSE dual-source model for predictingwater stress
 and evapotranspiration from thermal infrared data over multiple crops and climates. *Remote Sensing*, *10*(11). https://doi.org/10.3390/rs10111806
- Diarra, A., Jarlan, L., Er-Raki, S., Le Page, M., Aouade, G., Tavernier, A., Boulet, G., Ezzahar, J.,
 Merlin, O., & Khabba, S. (2017). Performance of the two-source energy budget (TSEB) model for
 the monitoring of evapotranspiration over irrigated annual crops in North Africa. *Agricultural Water Management*, *193*, 71–88. https://doi.org/10.1016/j.agwat.2017.08.007
- 778 Duchemin, B., Hadria, R., Erraki, S., Boulet, G., Maisongrande, P., Chehbouni, A., Escadafal, R., 779 Ezzahar, J., Hoedjes, J. C. B., Kharrou, M. H., Khabba, S., Mougenot, B., Olioso, A., Rodriguez, 780 J. C., & Simonneaux, V. (2006). Monitoring wheat phenology and irrigation in Central Morocco: 781 On the use of relationships between evapotranspiration, crops coefficients, leaf area index and 782 vegetation indices. Agricultural Water 79. 1 - 27. remotely-sensed Management, 783 https://doi.org/10.1016/j.agwat.2005.02.013
- 784 Duchemin, B., Hagolle, O., Mougenot, B., Simonneaux, V., Benhadj I., Hadria, R., Ezzahar, J., Hoedjes,

- J., Khabba, S., Kharrou, M.H, Boulet, G., Dedieu, G., Er-Raki, S., Escadafal, R., Olioso, A.,
 Chehbouni, A.G. (2008). Agrometerological study of semi-arid areas: an experiment for analysing
 the potential of FORMOSAT-2 time series of images in the Tensift-Marrakech plain. International
 Journal of Remote Sensing, 29: 5291-5299.
- Elfarkh, J., Er-Raki, S., Ezzahar, J., Chehbouni, A., Aithssaine, B., Amazirh, A., Khabba, S., & Jarlan,
 L. (2021). Integrating thermal stress indexes within Shuttleworth–Wallace model for
 evapotranspiration mapping over a complex surface. *Irrigation Science*, 39(1), 45–61.
 https://doi.org/10.1007/s00271-020-00701-3
- Elfarkh, J., Ezzahar, J., Er-raki, S., Simonneaux, V., Hssaine, B. A., Rachidi, S., Brut, A., Vincent, R.,
 & Khabba, S. (2020). Multi-Scale Evaluation of the TSEB Model over a Complex Agricultural
 Landscape in Morocco. *Remote Sensing*, *1*. https://doi.org/10.3390/rs12071181
- Fr-Raki, S., Chehbouni, A., Boulet, G., & Williams, D. G. (2010). Using the dual approach of FAO-56
 for partitioning ET into soil and plant components for olive orchards in a semi-arid region. *Agricultural Water Management*, 97(11), 1769–1778.
 https://doi.org/10.1016/j.agwat.2010.06.009
- 800 Er-Raki, S., Chehbouni, A., Guemouria, N., Duchemin, B., Ezzahar, J., & Hadria, R. (2007). Combining 801 FAO-56 model and ground-based remote sensing to estimate water consumptions of wheat crops 802 in semi-arid 87. 41–54. а region. Agricultural Water Management, 803 https://doi.org/10.1016/j.agwat.2006.02.004
- Er-Raki, S., Ezzahar, J., Khabba, S., Jarlan, L., Kharrou, M. H., & Chehbouni, G. (2013).
 Micrometeorology tools for measuring evapotranspiration from the leaf to the region. In *Evapotranspiration: Processes, Sources and Environmental Implications* (pp. 1–22). Nova
 Science Publishers, Inc.
- Ezzahar, J., Chehbouni, A., Er-Raki, S., & Hanich, L. (2009a). Combining a large aperture scintillometer
 and estimates of available energy to derive evapotranspiration over several agricultural fields in a
 semi-arid region. *Plant Biosystems*, 143, 209–221. https://doi.org/10.1080/11263500802710036
- Ezzahar, J., Chehbouni, A., Hoedjes, J. C. B., Er-Raki, S., Chehbouni, A., Boulet, G., Bonnefond, J. M.,
 & De Bruin, H. A. R. (2007a). The use of the scintillation technique for monitoring seasonal water
 consumption of olive orchards in a semi-arid region. *Agricultural Water Management*, 89(3), 173–
 184. https://doi.org/10.1016/j.agwat.2006.12.015
- Ezzahar, J., Chehbouni, A., Hoedjes, J. C. B., & Chehbouni, A. (2007b). On the application of
 scintillometry over heterogeneous grids. *Journal of Hydrology*, *334*(3–4), 493–501.
 https://doi.org/10.1016/j.jhydrol.2006.10.027

- Ezzahar, J., Chehbouni, A., Hoedjes, J., Ramier, D., Boulain, N., Boubkraoui, S., Cappelaere, B.,
 Descroix, L., Mougenot, B., & Timouk, F. (2009b). Combining scintillometer measurements and
 an aggregation scheme to estimate area-averaged latent heat flux during the AMMA experiment. *Journal of Hydrology*, 375(1–2), 217–226. https://doi.org/10.1016/j.jhydrol.2009.01.010
- Ezzahar, J.; Chehbouni, A. (2009c). The use of scintillometry for validating aggregation schemes over
 heterogeneous grids. Agricultural and Forest Meteorology, 149, 2098–2109.
 https://doi.org/10.1016/j.agrformet.2009.09.004
- Fang, B., Lei, H., Zhang, Y., Quan, Q., & Yang, D. (2020). Spatio-temporal patterns of
 evapotranspiration based on upscaling eddy covariance measurements in the dryland of the North
 China Plain. Agricultural and Forest Meteorology, 281.
 https://doi.org/10.1016/j.agrformet.2019.107844
- Fernández J. E., 2014. Understanding olive adaptation to abiotic stresses as a tool to increase crop
 performance. Environmental and Experimental Botany. 103 158-179.
- Gallego-Elvira, B., Olioso, A., Mira, M., Castillo, S. R.-, Boulet, G., Marloie, O., Garrigues, S.,
 Courault, D., Weiss, M., Chauvelon, P., & Boutron, O. (2013). EVASPA (EVapotranspiration
 Assessment from SPAce) Tool: An overview. *Procedia Environmental Sciences*, *19*, 303–310.
 https://doi.org/10.1016/j.proenv.2013.06.035
- Gentine, P., Entekhabi, D., Chehbouni, A., Boulet, G., & Duchemin, B. (2007). Analysis of evaporative
 fraction diurnal behaviour. *Agricultural and Forest Meteorology*, *143*(1–2), 13–29.
 https://doi.org/10.1016/j.agrformet.2006.11.002
- Hartogensis, O. K., Watts, C. J., Rodriguez, J.-C., & De Bruin, H. a. R. (2003). Derivation of an Effective
 Height for Scintillometers: La Poza Experiment in Northwest Mexico. *Journal of Hydrometeorology*, 4(5), 915–928. https://doi.org/10.1175/15257541(2003)004<0915:DOAEHF>2.0.CO;2
- Hoedjes, J.C.B., Chehbouni, A., Jacob, F., Ezzahar, J., & Boulet, G. (2008). Deriving daily
 evapotranspiration from remotely sensed instantaneous evaporative fraction over olive orchard in
 semi-arid Morocco. *Journal of Hydrology*, *354*(1–4), 53–64.
 https://doi.org/10.1016/j.jhydrol.2008.02.016
- Horst, T. W., & Weil, J. C. (1992). Footprint estimation for scalar flux measurements in the atmospheric
 surface layer. *Boundary-Layer Meteorology*, 59(3), 279–296.
 https://doi.org/10.1007/BF00119817
- 849 Hssaine, B. A., Ezzahar, J., Jarlan, L., Merlin, O., Khabba, S., Brut, A., Er-Raki, S., Elfarkh, J.,

- Cappelaere, B., & Chehbouni, G. (2018). Combining a two source energy balance model driven
 by MODIS and MSG-SEVIRI products with an aggregation approach to estimate turbulent fluxes
 over sparse and heterogeneous vegetation in Sahel region (Niger). *Remote Sensing*, 10(6).
 https://doi.org/10.3390/rs10060974
- Hssaine, B. A., Merlin, O., Rafi, Z., Ezzahar, J., Jarlan, L., Khabba, S., & Er-Raki, S. (2018). Calibrating
 an evapotranspiration model using radiometric surface temperature, vegetation cover fraction and
 near-surface soil moisture data. *Agricultural and Forest Meteorology*, 256–257(August 2017),
 104–115. https://doi.org/10.1016/j.agrformet.2018.02.033
- Hu, Z., Yu, G., Zhou, Y., Sun, X., Li, Y., Shi, P., Wang, Y., Song, X., Zheng, Z., Zhang, L., & Li, S.
 (2009). Partitioning of evapotranspiration and its controls in four grassland ecosystems:
 Application of a two-source model. *Agricultural and Forest Meteorology*, *149*(9), 1410–1420.
 https://doi.org/10.1016/j.agrformet.2009.03.014
- Isabelle, P. E., Nadeau, D. F., Perelet, A. O., Pardyjak, E. R., Rousseau, A. N., & Anctil, F. (2020).
 Application and Evaluation of a Two-Wavelength Scintillometry System for Operation in a
 Complex Shallow Boreal-Forested Valley. *Boundary-Layer Meteorology*, *174*, 341–370.
 https://doi.org/10.1007/s10546-019-00488-7
- Jackson, R. D., Moran, M. S., Gay, L. W., & Raymond, L. H. (1987). Evaluating evaporation from field
 crops using airborne radiometry and ground-based meteorological data. *Irrigation Science*, 8(2),
 81–90. https://doi.org/10.1007/BF00259473
- Kalma, J. D., McVicar, T. R., & McCabe, M. F. (2008). Estimating land surface evaporation: A review
 of methods using remotely sensed surface temperature data. *Surveys in Geophysics*, 29(4–5), 421–
 469. https://doi.org/10.1007/s10712-008-9037-z
- Kustas, W. P. (1990). Estimates of evapotranspiration with a one- and two-layer model of heat transfer
 over partial canopy cover. *Journal of Applied Meteorology*, 29(8), 704–715.
 https://doi.org/10.1175/1520-0450(1990)029<0704:EOEWAO>2.0.CO;2
- Kustas, W.P., Daughtry, C.S.T., Van Oevelen, P.J., (1993). Analytical treatment of the relationships
 between soil heat flux/net radiation ratio and vegetation indices. Remote Sensing of Environment,
 46, 319–330.
- Kustas, W. P., & Norman, J. M. (1996). Use of remote sensing for evapotranspiration monitoring over
 land surfaces. *Hydrological Sciences Journal*, 41, 495–516.
 https://doi.org/10.1080/02626669609491522
- 881 Kustas, William P., & Norman, J. M. (1999). Evaluation of soil and vegetation heat flux predictions

using a simple two-source model with radiometric temperatures for partial canopy cover. *Agricultural and Forest Meteorology*, 94(1), 13–29. https://doi.org/10.1016/S01681923(99)00005-2

Lagouarde, J. P., Bhattacharya, B. K., Crébassol, P., Gamet, P., Babu, S. S., Boulet, G., Briottet, X.,
Buddhiraju, K. M., Cherchali, S., Dadou, I., Dedieu, G., Gouhier, M., Hagolle, O., Irvine, M.,
Jacob, F., Kumar, A., Kumar, K. K., Laignel, B., Mallick, K., ... Ramakrishnan, R. (2018). The
Indian-French Trishna mission: Earth observation in the thermal infrared with high spatio-temporal
resolution. *International Geoscience and Remote Sensing Symposium (IGARSS)*, 4078–4081.
https://doi.org/10.1109/IGARSS.2018.8518720

- Lavee, S., 1996. Biology and physiology of the olive tree. In: Lavee, S., Barranco, D., Bongi, G., Jardak,
 T., Loussert, R., Martin, G.C., Trigui, A. (Eds.), World Olive Encyclopaedia. International Olive
 Council, Madrid, Spain, pp. 61–110.
- Le Page, M., Berjamy, B., Fakir, Y., Bourgin, F., Jarlan, L., Abourida, A., Benrhanem, M., Jacob, G.,
 Huber, M., Sghrer, F., Simonneaux, V., & Chehbouni, G. (2012). An Integrated DSS for
 Groundwater Management Based on Remote Sensing. The Case of a Semi-arid Aquifer in
 Morocco. *Water Resources Management*, 26(11), 3209–3230. https://doi.org/10.1007/s11269012-0068-3
- Li, Z. L., Tang, R., Wan, Z., Bi, Y., Zhou, C., Tang, B., Yan, G., & Zhang, X. (2009). A review of
 current methodologies for regional Evapotranspiration estimation from remotely sensed data. In *Sensors* (pp. 3801–3853). https://doi.org/10.3390/s90503801
- Liu, Y., & Yamanaka, T. (2012). Tracing groundwater recharge sources in a mountain-plain transitional
 area using stable isotopes and hydrochemistry. *Journal of Hydrology*, 464–465, 116–126.
 https://doi.org/10.1016/j.jhydrol.2012.06.053
- Martinez, J. L., Raiber, M., & Cendón, D. I. (2017). Using 3D geological modelling and geochemical
 mixing models to characterise alluvial aquifer recharge sources in the upper Condamine River
 catchment, Queensland, Australia. *Science of the Total Environment*, 574, 1–18.
 https://doi.org/10.1016/j.scitotenv.2016.09.029
- Meijninger, W. M. L. (2003). Surface fluxes over natural landscapes using scintillometry. In
 Wageningen UR publication.
- Montes, C., Lhomme, J. P., Demarty, J. Ô., Prévot, L., & Jacob, F. (2014). A three-source SVAT
 modeling of evaporation: Application to the seasonal dynamics of a grassed vineyard. *Agricultural and Forest Meteorology*, *191*, 64–80. https://doi.org/10.1016/j.agrformet.2014.02.004

- Morillas, L., Leuning, R., Villagarcía, L., García, M., Serrano-Ortiz, P., & Domingo, F. (2013).
 Improving evapotranspiration estimates in Mediterranean drylands: The role of soil evaporation. *Water Resources Research*, 49(10), 6572–6586. https://doi.org/10.1002/wrcr.20468
- Norman, J. M., Kustas, W. P., & Humes, K. S. (1995). Source approach for estimating soil and
 vegetation energy fluxes in observations of directional radiometric surface temperature.
 Agricultural and Forest Meteorology, 77(3–4), 263–293. https://doi.org/10.1016/0168 1923(95)02265-Y
- Olioso, A., Chauki, H., Courault, D., & Wigneron, J. P. (1999). Estimation of evapotranspiration and
 photosynthesis by assimilation of remote sensing data into SVAT models. *Remote Sensing of Environment*, 68(3), 341–356. https://doi.org/10.1016/S0034-4257(98)00121-7
- Ouaadi, N., Jarlan, L., Ezzahar, J., Zribi, M., Khabba, S., Bouras, E., Bousbih, S., & Frison, P. L. (2020).
 Monitoring of wheat crops using the backscattering coefficient and the interferometric coherence
 derived from Sentinel-1 in semi-arid areas. *Remote Sensing of Environment*, 251(15).
 https://doi.org/10.1016/j.rse.2020.112050
- Parastatidis, D., Mitraka, Z., Chrysoulakis, N., & Abrams, M. (2017). Online global land surface
 temperature estimation from landsat. *Remote Sensing*, 9(12). https://doi.org/10.3390/rs9121208
- Rafi, Z., Merlin, O., Le Dantec, V., Khabba, S., Mordelet, P., Er-Raki, S., Amazirh, A., Olivera-Guerra,
 L., Ait Hssaine, B., Simonneaux, V., Ezzahar, J., & Ferrer, F. (2019). Partitioning
 evapotranspiration of a drip-irrigated wheat crop: Inter-comparing eddy covariance-, sap flow-,
 lysimeter- and FAO-based methods. *Agricultural and Forest Meteorology*, 265, 310–326.
 https://doi.org/10.1016/j.agrformet.2018.11.031
- Rannik, U., Aubinet, M., Kurbanmuradov, O., Sabelfeld, K. K., Markkanen, T., & Vesala, T. (2000).
 Footprint analysis for measurements over a heterogeneous forest. *Boundary-Layer Meteorology*,
 97(1), 137–166. https://doi.org/10.1023/A:1002702810929
- Roerink, G. J., Su, Z., & Menenti, M. (2000). S-SEBI: A simple remote sensing algorithm to estimate
 the surface energy balance. *Physics and Chemistry of the Earth, Part B: Hydrology, Oceans and Atmosphere*, 25(2), 147–157. https://doi.org/10.1016/S1464-1909(99)00128-8
- Ryu, Y., Baldocchi, D. D., Black, T. A., Detto, M., Law, B. E., Leuning, R., Miyata, A., Reichstein, M.,
 Vargas, R., Ammann, C., Beringer, J., Flanagan, L. B., Gu, L., Hutley, L. B., Kim, J., McCaughey,
 H., Moors, E. J., Rambal, S., & Vesala, T. (2012). On the temporal upscaling of evapotranspiration
 from instantaneous remote sensing measurements to 8-day mean daily-sums. *Agricultural and Forest Meteorology*, *152*(1), 212–222. https://doi.org/10.1016/j.agrformet.2011.09.010

- Saadi, S., Boulet, G., Bahir, M., Brut, A., Delogu, É., Fanise, P., Mougenot, B., Simonneaux, V., &
 Chabaane, Z. L. (2018). Assessment of actual evapotranspiration over a semiarid heterogeneous
 land surface by means of coupled low-resolution remote sensing data with an energy balance
 model: Comparison to extra-large aperture scintillometer measurements. *Hydrology and Earth System Sciences*, 22(4), 2187–2209. https://doi.org/10.5194/hess-22-2187-2018
- Saadi, S., Simonneaux, V., Boulet, G., Raimbault, B., Mougenot, B., Fanise, P., Ayari, H., & LiliChabaane, Z. (2015). Monitoring irrigation consumption using high resolution NDVI image time
 series: Calibration and validation in the Kairouan plain (Tunisia). *Remote Sensing*, 7(10), 13005–
 13028. https://doi.org/10.3390/rs71013005
- Sánchez, J. M., López-Urrea, R., Valentín, F., Caselles, V., & Galve, J. M. (2019). Lysimeter assessment
 of the Simplified Two-Source Energy Balance model and eddy covariance system to estimate
 vineyard evapotranspiration. *Agricultural and Forest Meteorology*, 274, 172–183.
 https://doi.org/10.1016/j.agrformet.2019.05.006
- Schuepp, P. H., Leclerc, M. Y., MacPherson, J. I., & Desjardins, R. L. (1990). Footprint prediction of
 scalar fluxes from analytical solutions of the diffusion equation. *Boundary-Layer Meteorology*,
 50(1–4), 355–373. https://doi.org/10.1007/BF00120530
- Shuttleworth, W. J. (1989). FIFE: The variation in energy partition at surface flux sites. *IAHS. Third Int*,
 67–74.
- Shuttleworth, W. James, & Wallace, J. S. (1985). Evaporation from sparse crops-an energy combination
 theory. *The Quarterly Journal of the Royal Meteorological Society*, *111*(465), 839–855.
 https://doi.org/10.1002/qj.49711146510
- 967 Simonneaux, V, Thomas, S., Lepage, M., Duchemin, B., Kharrou, M. H., Berjamy, B., Boulet, G., & 968 Chehbouni, G. (2007). «SAMIR», A tool for irrigation monitoring using remote sensing for 969 landcover mapping and evapotranspiration estimates. 2nd International Symposium on Recent 970 Advances 597-601. in Quantitative Remote 2(1),Sensing, 971 http://www.iwra.org/congress/2008/resource/authors/abs642 article.pdf
- Simonneaux, Vincent, Lepage, M., Helson, D., Metral, J., Thomas, S., Duchemin, B., Cherkaoui, M.,
 Kharrou, H., Berjami, B., & Chehbouni, A. (2009). Spatialized estimates of evapotranspiration of
 irrigated crops using remote sensing: Application to irrigation management in the Haouz plain
 (Marrakech, Morocco). *Secheresse (Montrouge)*, 20(1), 123–130.
- Sobrino, J. A., Jiménez-Muñoz, J. C., & Paolini, L. (2004). Land surface temperature retrieval from
 LANDSAT TM 5. *Remote Sensing of Environment*, 90, 434–440.
 https://doi.org/10.1016/j.rse.2004.02.003

- Srinet R., Nandy S., Patel N.R. (2019). Estimating leaf area index and light extinction coefficient using
 Random Forest regression algorithm in a tropical moist deciduous forest, India. Ecological
 Informatics, 52, 94-102. https://doi.org/10.1016/j.ecoinf.2019.05.008.
- Su, Z. (2002). The Surface Energy Balance System (SEBS) for estimation of turbulent heat fluxes.
 Hydrology and Earth System Sciences, 6(1), 85–100. https://doi.org/10.5194/hess-6-85-2002
- Tardy, B., Rivalland, V., Huc, M., Hagolle, O., Marcq, S., & Boulet, G. (2016). A software tool for
 atmospheric correction and surface temperature estimation of Landsat infrared thermal data. *Remote Sensing*, 8(9). https://doi.org/10.3390/rs8090696
- Tasumi, M. (2019). Estimating evapotranspiration using METRIC model and Landsat data for better
 understandings of regional hydrology in the western Urmia Lake Basin. Agricultural Water
 Management, 226. https://doi.org/10.1016/j.agwat.2019.105805
- Torres, E. A., & Calera, A. (2010). Bare soil evaporation under high evaporation demand: a proposed
 modification to the FAO-56 model. *Hydrological Sciences Journal*, 55(3), 303–315.
 https://doi.org/10.1080/02626661003683249
- 993 Tucker, C.J., (1979). Red and photographic infrared linear combinations for monitoring vegetation.
 994 Remote Sens Environ 8:127-150.
- Twine, T. E., Kustas, W. P., Norman, J. M., Cook, D. R., Houser, P. R., Meyers, T. P., Prueger, J. H.,
 Starks, P. J., & Wesely, M. L. (2000). Correcting eddy-covariance flux underestimates over a
 grassland. *Agricultural and Forest Meteorology*, *103*(3), 279–300. https://doi.org/10.1016/S01681923(00)00123-4
- Van Dijk, A., Moene, A.F., De Bruin, H.A.R. (2004). The principles of surface flux physics: theory,
 practice and description of the ECPACK library, Internal report 2004/1, Meteorologyand Air
 Quality Group Wageningen University, pp. 97
 (http://www.met.wur.nl/internal_reports/ir2004_01.pdf)
- 1003 Van Niel, T. G., McVicar, T. R., Roderick, M. L., van Dijk, A. I. J. M., Renzullo, L. J., & van Gorsel,
 1004 E. (2011). Correcting for systematic error in satellite-derived latent heat flux due to assumptions
 1005 in temporal scaling: Assessment from flux tower observations. *Journal of Hydrology*, 409(1–2),
 1006 140–148. https://doi.org/10.1016/j.jhydrol.2011.08.011
- 1007 Wang, L., Parodi, G. N., & Su, Z. (2008). SEBS module beam: A practical tool for surface energy
 1008 balance estimates from remote sensing data. *European Space Agency, (Special Publication) ESA*1009 SP.

- Wesely, ML., (1976) Combined effect of temperature and humidity fluctuations on refractive index. J
 Appl Meteorol 15:43–49. https://doi.org/10.1175/15200450(1976)015<0043:TCEOTA>2.0.CO;2
- Widmoser, P., & Wohlfahrt, G. (2018). Attributing the energy imbalance by concurrent lysimeter and
 eddy covariance evapotranspiration measurements. *Agricultural and Forest Meteorology*, 263,
 287–291. https://doi.org/10.1016/j.agrformet.2018.09.003
- Xu, T., Liu, S., Xu, L., Chen, Y., Jia, Z., Xu, Z., & Nielson, J. (2015). Temporal upscaling and
 reconstruction of thermal remotely sensed instantaneous evapotranspiration. *Remote Sensing*, *7*,
 3400–3425. https://doi.org/10.3390/rs70303400
- Zhao, J., Olivas, P. C., Kunwor, S., Malone, S. L., Staudhammer, C. L., Starr, G., & Oberbauer, S. F.
 (2018). Comparison of sensible heat flux measured by large aperture scintillometer and eddy
 covariance in a seasonally-inundated wetland. *Agricultural and Forest Meteorology*, 259, 345–
 354. https://doi.org/10.1016/j.agrformet.2018.05.026
- Zhu, G., Li, X., Su, Y., Zhang, K., Bai, Y., Ma, J., Li, C., Hu, X., & He, J. (2014). Simultaneously
 assimilating multivariate data sets into the two-source evapotranspiration model by Bayesian
 approach: application to spring maize in an arid region of northwestern China. Geoscientific Model
 Development, 7, 1467-1482. https://doi.org/10.5194/GMD-7-1467-2014
- 1027 Zhu, G., Su, Y., Li, X., Zhang, K., & Li, C. (2013). Estimating actual evapotranspiration from an alpine
 1028 grassland on Qinghai-Tibetan plateau using a two-source model and parameter uncertainty analysis
 1029 by Bayesian approach. *Journal of Hydrology*, 476, 42–51.
 1030 https://doi.org/10.1016/j.jhydrol.2012.10.006