



HAL
open science

Integrating thermal stress indexes within Shuttleworth–Wallace model for evapotranspiration mapping over a complex surface

Jamal Elfarkh, Salah Er-Raki, Jamal Ezzahar, Abdelghani Chehbouni, Bouchra Aithssaine, Abdelhakim Amazirh, Saïd Khabba, Lionel Jarlan

► **To cite this version:**

Jamal Elfarkh, Salah Er-Raki, Jamal Ezzahar, Abdelghani Chehbouni, Bouchra Aithssaine, et al.. Integrating thermal stress indexes within Shuttleworth–Wallace model for evapotranspiration mapping over a complex surface. *Irrigation Science*, 2020, 39 (1), pp.45-61. 10.1007/s00271-020-00701-3 . ird-04420881

HAL Id: ird-04420881

<https://ird.hal.science/ird-04420881>

Submitted on 27 Jan 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.



2 Integrating thermal stress indexes within Shuttleworth–Wallace 3 model for evapotranspiration mapping over a complex surface

4 Jamal Elfarkh¹ · Salah Er-Raki^{1,2} · Jamal Ezzahar^{2,3} · Abdelghani Chehbouni^{2,4} · Bouchra Aithssaine² ·
5 Abdelhakim Amazirh² · Saïd Khabba^{2,5} · Lionel Jarlan⁴

6 Received: 31 December 2019 / Accepted: 18 September 2020
7 © Springer-Verlag GmbH Germany, part of Springer Nature 2020

8 Abstract

9 The main goal of this work was to evaluate the potential of the Shuttleworth–Wallace (SW) model for mapping actual crop
10 evapotranspiration (ET) over complex surface located in the foothill of the Atlas Mountain (Morocco). This model needs
11 many input variables to compute soil (r_s^s) and vegetation (r_s^v) resistances, which are often difficult to estimate at large scale
12 particularly soil moisture. In this study, a new approach to spatialize r_s^s and r_s^v based on two thermal-based proxy variables
13 was proposed. Land Surface Temperature (LST) and Normalized Difference Vegetation Index (NDVI) derived from Landsat
14 data were combined with the endmember temperatures for soil ($T_{s_{\min}}$ and $T_{s_{\max}}$) and vegetation ($T_{v_{\min}}$ and $T_{v_{\max}}$), which
15 were simulated by a surface energy balance model, to compute the soil (T_s) and the vegetation (T_v) temperatures. Based on
16 these temperatures, two thermal proxies (SI_{ss} for soil and SI_{sv} for vegetation) were calculated and related to r_s^s and r_s^v , with
17 an empirical exponential relationship [with a correlation coefficient (R) of about 0.6 and 0.5 for soil and vegetation, respec-
18 tively]. The proposed approach was initially evaluated at a local scale, by comparing the results to observations by an eddy
19 covariance system installed over an area planted with olive trees intercropped with wheat. In a second step, the new approach
20 was applied over a large area which contains a mixed vegetation (tall and short) crossed by a river to derive r_s^s and r_s^v , and
21 thereafter to estimate ET. A Large aperture scintillometer (LAS) installed over a line transect of 1.4 km and spanning the
22 total area was used to validate the obtained ET. The comparison confirmed the ability of the proposed approach to provide
23 satisfactory ET maps with an RMSE, bias and R^2 equal to 0.08 mm/h, 0.06 mm/h and 0.80, respectively.

24 Introduction

25 The fast-growing population and economy in recent decades
26 are accompanied by an increase in agricultural production. Agricultural and irrigation techniques have been widely developed, but the deterioration and depletion of water resources remain a problem that threatens the future of food security, especially in arid and semi-arid zones (Plattner et al. 2009; Gohar et al. 2019). Rational management of water resources, which is a primary concern for the managers, requires a good knowledge of the water and energy processes taking place in the soil-vegetation-atmosphere continuum (Blinda 2012; Bhattarai et al. 2019). Indeed, the control of these processes allows to assess the exact amount of water that the plant requires overtime, which is similar to the field water loss through evapotranspiration (Allen et al. 2011). The process of evapotranspiration is difficult to determine because of various challenges, including the vegetation complexity, plant diversity, lack of available data and because the in-situ direct measurement of ET is difficult

A1 ✉ Salah Er-Raki
A2 s.erraki@uca.ma; s.erraki@gmail.com

A3 ¹ ProcEDE, Département de Physique Appliquée, Faculté des
A4 Sciences et Techniques, Université Cadi Ayyad, Marrakech,
A5 Morocco

A6 ² Mohammed VI Polytechnic University (UM6P), Center
A7 for Remote Sensing Applications (CRSA), Ben Guerir,
A8 Morocco

A9 ³ Département IRT, Laboratoire MISCOM, Ecole Nationale
A10 des Sciences Appliquées, Université Cadi Ayyad, Safi,
A11 Morocco

A12 ⁴ Centre d'Etudes Spatiales de La Biosphère, Toulouse,
A13 France

A14 ⁵ LMFE, Département de Physique, Faculté des Sciences
A15 Semlalia, Université Cadi Ayyad, Marrakech, Morocco

in complex surfaces like our study site. Then an accurate assessment of evapotranspiration (ET) is crucially needed at the basin scale for studying the hydrological processes and water balance especially from upstream to downstream and it is required for a good integrated water management. There is thus an imperative need to develop reliable computation method with a limited number of input parameters especially over complex surfaces.

Several methods have been used to measure ET and its components [plant transpiration (T) and soil evaporation (E)], which are different in complexity and/or in accuracy. The principles of these methods are various; they can be hydrological, physiological or micrometeorological. Based on the hydrological balance, the lysimeter provides direct evaporation or evapotranspiration measurements at a local scale and over homogeneous canopy (Allen et al. 2011; Sánchez et al. 2019). To assess the plant transpiration, the physiological approach has been used based on introducing a source of low-grade heat into the stem or the trunk of a plant. This approach known as the sap flow method, can be used in homogeneous crops but it requires an up-scaling procedures to extrapolate measurements from individual plants to the stand level transpiration (Green et al. 2003; Steppe et al. 2010; Er-Raki et al. 2010a; Rafi et al. 2019). Currently, around the world the micrometeorological techniques such as eddy covariance are widely used to measure ET over a scale of a few hectares, depending on the height of the measurements (Ezzahar et al. 2007; Allen et al. 2011; Fang et al. 2020). By contrast, the scintillometer technique that was recently developed allows for measurements of sensible (optical LAS) and latent (microwave LAS) heat fluxes over transects up to 10 km (Ezzahar and Chehbouni 2009; Ezzahar et al. 2009b, a; Zieliński et al. 2013, 2017; Yee et al. 2015). In addition, scintillometers are easy to install, to monitor and can provide measurements of the surface fluxes over complex surfaces which makes them suitable for validating remote sensing-based methods (Duchemin et al. 2008; Tang and Li 2015; Huang et al. 2016; Ait Hssaine et al. 2018; Saadi et al. 2018). The LAS applies the Monin–Obukhov Similarity Theory (MOST) to estimate the sensible heat flux. However, the applicability of MOST is limited when conditions are not favorable, which can happen for a number of reasons. Atmospheric conditions, instrumental setup, data processing and evaluation criteria (particularly choice of similarity function and variable of interest) can all affect the MOST applicability (Ward 2017).

With regard to modelling aspect, there are different types of models to estimate surface fluxes. They range from complex physically based, conceptual, to empirical ones. There are some models characterised by a simplified relation using thermal infrared and micrometeorological data (Jackson et al. 1977; Seguin and Itier 1983). Others are based on residual methods of the energy budget (Surface Energy

Balance Algorithm for Land (Bastiaanssen et al. 1998), Surface Energy Balance System (Su 2002), two-source energy balance (Norman et al. 1995), Mapping Evapotranspiration at a high-Resolution with Internalized Calibration (Allen et al. 2007)). A third one, more complex, characterizes the energy and water transfers in all the continuum soil-vegetation-atmosphere (Interaction Soil Biosphere Atmosphere (Noilhan and Mahfouf 1996; Aouade et al. 2020), Simple Soil-Plant-Atmosphere Transfer (Braud et al. 1995), Soil Plant Atmosphere and Remote Sensing Evapotranspiration (Boulet et al. 2015) and the Interactive Canopy Radiation Exchange (Gentine et al. 2007)). Compared to those based only on the energy budget, this category of models needs more input data which is often not available at large scale. Finally, some other approaches use a crop coefficient to provide actual ET from reference or potential one (Allen et al. 2005; Neale et al. 2005). These models can be extended to large areas when they are combined with remote sensing data (Duchemin et al. 2008; Er-Raki et al. 2010b; Diarra et al. 2017). Satellite products such as land surface temperature (LST), emissivity, albedo and vegetation indexes have been improving in their spatiotemporal resolution during the recent years, especially with the launch of Landsat 7 and 8 and Sentinel 2 satellites. Consequently, mapping and assessing ET over heterogeneous and large areas became a promising challenge which has been largely investigated in recent years (Albergel 2010; Singh et al. 2014; Semmens et al. 2016; Tan et al. 2019).

The two components of the ET are influenced differently by many factors which mean that the contribution of each one (E and T) to the total ecosystem ET is highly variable in time and space (Aouade et al. 2016). Consequently, estimating accurate ET over vegetation canopy using two-source models is necessary since this type of model computes each component distinctly. In this context, Shuttleworth and Wallace developed in Shuttleworth and Wallace 1985 a two-source model taking into account the interaction flux from vegetation and soil separately. It is characterized by a rigorous physically based framework which provides accurate ET estimation values especially for row crops (Ortega-Farias et al. 2007; Zhang et al. 2008). However, Shuttleworth–Wallace (SW) model is significantly sensitive to errors in the values of soil and vegetation resistances (Zhu et al. 2014). These resistances can be parameterized using measurements of E, T and ET (Samanta et al. 2007; Villagarcía et al. 2010; Zhu et al. 2014). Many authors have used empirical equations to compute these resistances based on surface and root-zone soil water content (Ramírez et al. 2007; Were et al. 2007). However, the soil water content is difficult to obtain at a large scale. Several methods were developed to estimate this variable but they are complex and need the knowledge of many physical soil parameters (Guswa et al. 2002; Verhoef et al. 2006; Merlin et al. 2016). For this reason and to

149 estimate spatial values of ET using the SW model, a param-
 150 eterization of the soil and vegetation resistances using a thermal-based proxy derived from Landsat was proposed in this
 151 paper. The stress indexes presented by this proxy reflect the
 152 hydric state of both soil and vegetation since the temperature
 153 variation of the soil or the vegetation can be attributed to
 154 change in the water content between dry and wet conditions.
 155 In this context, good results have been obtained by relating
 156 thermal-based proxy of vegetation water stress to canopy
 157 resistance (Amazirh et al. 2017) and to stress coefficient in
 158 FAO-56 (Olivera-Guerra et al. 2018, 2020). The novelty of
 159 the proposed approach is the link of both vegetation and
 160 soil resistances to the stress indexes which can provide an
 161 accurate estimation of spatial ET.

163 This paper is organized as follows: first, an overview of
 164 the study area, the experimental design and the proposed
 165 approach is presented. After, a description of the obtained
 166 results at a local scale is provided. Then, an illustration of
 167 the spatial results with a discussion about the potential of
 168 the developed approach to assessing the evapotranspiration
 169 over a heterogeneous semi-arid region is presented. Finally,
 170 a summary and conclusions are provided.

171 Materials and methods

172 Study area and data description

173 Study area description

174 An experiment was conducted over the piedmont of the
 175 Atlas mountain in the center of Morocco (Tahanaout city,
 176 Fig. 1). This area is characterized by a semi-arid climate
 177 with a low annual rainfall amount especially for 2017 where
 178 an annual cumulative value of about 157 mm compared to
 179 the cumulative value during last two decades (302 mm).
 180 The land use mapping of the experimental area is also pre-
 181 sented in Fig. 1a. According to this figure, one can remark
 182 clearly that the area is heterogeneous and composed of small
 183 fields planted by olive trees with a height ranging from 3 to
 184 12 m which were measured using the 45° Triangle method
 185 (Fig. 1b). Note that some farmers mix the olive trees with
 186 herbaceous crops such as wheat, alfalfa and/or corn. In the
 187 same area apricot, plum, orange and peach trees are also
 188 cultivated. The bare soil is mainly present on the sides of
 189 Rherhaya river and on the North-West part of the study area.
 190 Additionally, the heterogeneity of the site is amplified by the
 191 difference in the height between different trees and herba-
 192 ceous crops. All fields are irrigated using the flooding tech-
 193 nique. In general, the irrigation water comes from mountain
 194 (rainfall or melting snow) and is diverted to the study area
 195 through traditional networks (Bouimouass et al. 2020).

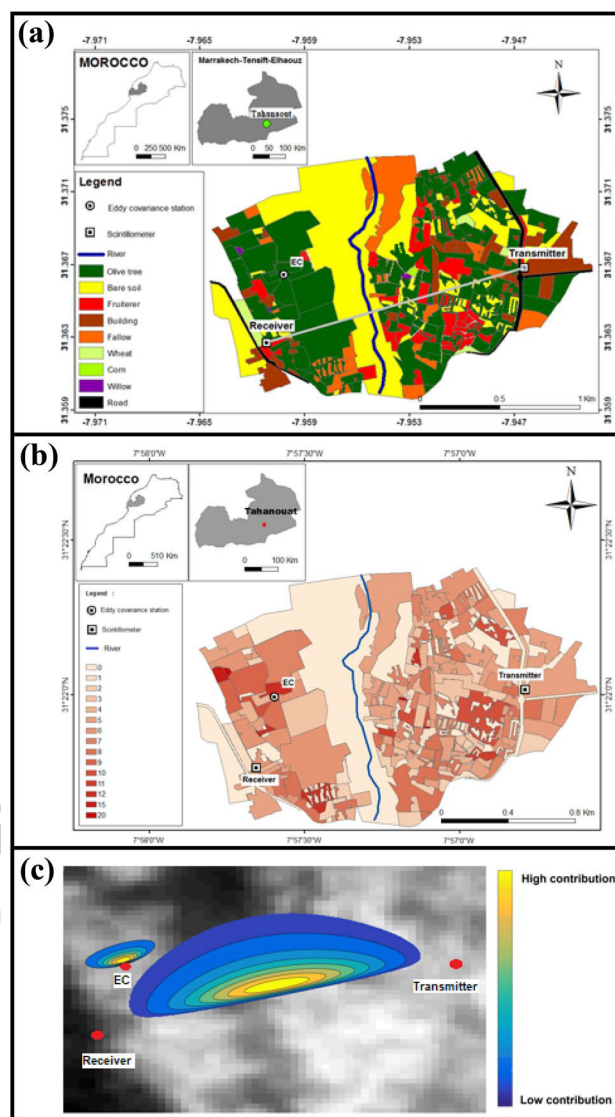


Fig. 1 Locations of the Eddy Covariance (EC) station, the scintillometer (transmitter and receiver) superimposed on the land use map (a), vegetation height map (b) and Landsat image with their footprint (c)

196 Meteorological data, eddy covariance and scintillometer 197 measurements

198 A set of instruments was deployed over the EC tower in the
 199 study site for measuring meteorological data, turbulent
 200 fluxes, soil moisture and surface temperature. Air tempera-
 201 ture and humidity were measured with a Vaisala (HMP155,
 202 Campbell scientific) at a height of about 15.6 m. The four
 203 components of the net radiation were measured using a
 204 CNR4 radiometer (Campbell scientific) at a height of about
 205 16.7 m. The soil heat flux was averaged using the measure-
 206 ment of two heat flux plates at 5 cm depths (HPF01, Hukse-
 207 flux) in two locations: one below the tree (always shaded)
 208 and the other between the trees (directly exposed to solar

radiation). Soil moisture was measured at different depths (5 and 15 cm) using CS655 water content reflectometers (Campbell Scientific). Radiometric brightness temperature was measured over the soil and the vegetation separately using an Infra-Red radiometer (IRTS-P's, Apogee) and then converted to land surface temperature (LST) using surface emissivity. One of the radiometers was positioned at height of about 11.7 m directed vertically towards the ground and the other one was positioned at height of about 6.5 m directed towards the vegetation with a view angle of about 60 degrees. An eddy covariance (EC) system was installed on 17.5 m height tower to measure the latent and sensible heat fluxes. It is composed of a three-dimensional sonic anemometer (CSAT3, Campbell Scientific Ltd.) and a Krypton hygrometer (KH20, Campbell Scientific Ltd.). Raw data were sampled at a rate of 20 Hz and processed using the ECPack software to compute turbulent fluxes. The comparison between available energy ($R_n - G$) and the sum of the sensible (H) and latent (LE) heat fluxes shows a non-closure of the energy balance which is expected given the high complexity of the surface. The turbulent flux values used in this work were corrected using the approach proposed by (Twine et al. 2000) which is based on the hypothesis that the ratio H/LE is accurately measured than H and LE separately. Then, corrected turbulent fluxes were derived as $LE = \frac{\beta}{\beta+1}(R_n - G)$ and $H = \frac{(R_n - G)}{\beta+1}$, with β computed from the 30-min observed H and LE. Additionally, a Large Aperture Scintillometer (LAS) was set up over a 1464 m transect spanning a representative area of the total site across the river between 10 and 50 m above the ground, with an effective height of ≈ 26 m. It consists of a transmitter installed at a height of 10.5 m and a receiver mounted at the height of 10 m (Fig. 1). Measurements were sampled at 1 Hz, averaged, and then stored at 30 min intervals on CR10X dataloggers. In this study, a footprint model proposed by Horst and Weil (1992, 1994) was applied to average the remote sensing data over the source areas where the turbulent fluxes were emanated (see Appendix 1).

Remote sensing data

In this study, 17 satellite images were collected from Landsat 7 and 8. Combining the two satellites, a repeatability of eight days was reached. The resolution of the acquired images ranges from 30 to 100 m, depending on the spectral bands. The satellites products were downloaded from the USGS website (<https://earthexplorer.com/>). Nevertheless, the radiation measured by Landsat 7/8 has to be corrected from the atmosphere. To overcome this issue and derive actual land surface temperature (LST), the images were corrected following the steps described in Tardy et al. (2016). The corrections associated with the radiation emitted by the

atmosphere and to the atmospheric attenuation were based on the vertical atmospheric conditions (pressure, temperature, water vapor and ozone) of the ERA-Interim dataset. The atmospheric correction parameters were finally computed using the commercial RTM software MODTRAN. The surface emissivity was determined based on the vegetation index (NDVI) according to Wittich (1997).

Evapotranspiration modelling

Shuttleworth–Wallace model

Shuttleworth and Wallace developed a parameterization of the canopy evapotranspiration in 1985. This model considers two sources of water transfer from the surface to the atmosphere, from the soil by the evaporation process and from the vegetation through transpiration. For each source, the model takes into account both aerodynamic and surface resistances and assumes that the two sources will interact at the effective canopy's height considering another aerodynamic resistance between this height and the reference height source. The model is represented as follows:

$$ET = E + T = C_s PM_s + C_v PM_v \quad (1)$$

where E is the soil evaporation, T is the vegetation transpiration, PM_s and PM_v are terms similar to the Penman–Monteith combination equation.

They are expressed by the two following equations:

$$PM_s = \frac{\Delta A + [(\rho C_p D - \Delta r_a^s (A - A_s)) / (r_a + r_a^s)]}{\Delta + \gamma [1 + r_s^s / (r_a + r_a^s)]} \quad (2)$$

$$PM_v = \frac{\Delta A + [(\rho C_p D - \Delta r_a^v (A - A_s)) / (r_a + r_a^v)]}{\Delta + \gamma [1 + r_s^v / (r_a + r_a^v)]} \quad (3)$$

where A and A_s are the available energy above canopy and the soil surfaces (W/m^2), respectively. Δ is the slope of saturation vapour pressure curve (kPa/K), ρ is the air density (kg/m^3), 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).

The coefficients C_s and C_v are given as follows:

$$C_s = \frac{1}{1 + [R_s R_a / R_v (R_s + R_a)]} \quad (4)$$

$$C_v = \frac{1}{1 + [R_v R_a / R_v (R_v + R_a)]} \quad (5)$$

where R_s , R_v , R_a are formulated as:

- 300 $R_s = (\Delta + \gamma)r_a^s + \gamma r_s^s$ (6) 343
 301 344
- 302 $R_v = (\Delta + \gamma)r_a^v + \gamma r_s^v$ (7) 345
 303 346
- 304 $R_a = (\Delta + \gamma)r_a$ (8) 347
 305 348
- 306 where r_a^v , r_a^s , and r_a are the aerodynamic resistance of the
 307 canopy, the aerodynamic resistance between the reference
 308 height and the effective height and from the effective height
 309 to the soil surface (s/m), respectively. Additionally, soil
 310 evaporation and plant transpiration are controlled by the
 311 soil surface resistance (r_s^s) and the canopy resistance (r_s^v),
 312 respectively. Both resistances are expressed as follow: 349
- 313 $r_s^s = r_{s\min}^s \left(2.5 \left(\frac{\theta_F}{\theta_s} \right) - 1.5 \right)$ (9) 350
 314 351
- 315 $r_s^v = \frac{r_{ST\min}}{\text{LAI} \prod_{i=1}^3 F_i(X_i)}$ (10) 352
 316 353
- 317 $F_1(S) = \left(\frac{S}{1100} \right) \left(\frac{1100 + a_1}{S + a_1} \right)$ (11) 354
 318 355
- 319 $F_2(T) = \frac{(T - T_L)(T_H - T)^{(T_H - a_2)/(a_2 - T_L)}}{(a_2 - T_L)(T_H - a_2)^{(T_H - a_2)/(a_2 - T_L)}}$ (12) 356
- 320 357
- 321 $F_3(\theta) = \begin{cases} 1, \theta \geq \theta_F \\ \frac{\theta - \theta_W}{\theta_F - \theta_W}, \theta_W < \theta < \theta_F \\ 0, \theta \leq \theta_W \end{cases}$ (13) 358
 322 359
- 323 where $r_{s\min}^s$ is the minimum soil surface resistance (taken as
 324 100 s/m (Zhang et al. 2008)) and $r_{ST\min}$ is the minimal stomatal
 325 resistance of individual leaves under optimal conditions (taken
 326 as 146 s/m (Zhang et al. 2008)). θ_s is the water content of the
 327 upper soil surface layer (cm^3/cm^3). LAI is the leaf area index,
 328 and $F_i(X_i)$ is the stress function of the incoming photosyntheti-
 329 cally active radiation flux (S), the air temperature (T) and the
 330 actual soil moisture content in the root-zone (θ). T_H and T_L
 331 are the upper and lower temperature limits outside of which
 332 transpiration is assumed to stop ($^\circ\text{C}$) and are set at values of
 333 40 and 0 $^\circ\text{C}$ (Harris et al. 2004). θ_W is the soil moisture con-
 334 tent at wilting point (cm^3/cm^3), θ_F is the soil water content at
 335 field capacity (cm^3/cm^3). The empirical coefficients a_1 and a_2
 336 were derived by optimization and were set to 57.67 and 25.78
 337 (Zhang et al. 2008), respectively.
- 338 The available energies above canopy and above the soil
 339 surface are defined by the following expressions: where G is
 340 the soil heat flux (W/m^2) and R_n is the net radiation (W/m^2).
- 341 $A = R_n - G$ (14) 389
 342 390
- $A_s = R_n - G$ (15) 343
 344
- R_n is the net radiation fluxes into the soil surface (W/m^2)
 345 which is parametrized as follows: where C is the extinction
 346 coefficient of light attenuation, that equal to 0.68 for the fully
 347 grown plant (Sene 1994). Moreover, resistance parameteriza-
 348 tions are detailed in Zhang et al. (2008). 349
- $Rn_s = R_n e^{-C \times \text{LAI}}$ (16) 350
 351
- Leaf area index (LAI) is derived from Landsat NDVI fol-
 352 lowing Wang et al. (2008): 353
- $\text{LAI} = \begin{cases} 0, \text{NDVI} < 0.2 \\ \sqrt{\text{NDVI} \frac{1 + \text{NDVI}}{1 - \text{NDVI}}}, \text{NDVI} \geq 0.2 \end{cases}$ (17) 354
 355
- Energy balance model and hourglass method** 356
- Soil energy balance model:* The soil energy balance model
 357 was implemented to compute the endmembers temperature
 358 ($T_{s\min}$, $T_{s\max}$, $T_{v\min}$ and $T_{v\max}$) further used in the Hourglass
 359 method. The extremes soil temperature $T_{s\min}$ and $T_{s\max}$ were
 360 simulated by forcing the surface resistances to 0 and ∞ ,
 361 respectively (Stefan et al. 2015; Merlin et al. 2016; Amazirh
 362 et al. 2017, 2018). The model was initialized by the observed
 363 air temperature and soil temperature is sought by minimiz-
 364 ing the following cost function F : where H and LE are the
 365 sensible and latent heat fluxes, respectively. 366
- $F = (R_n - G - H - LE)^2$ (18) 367
 368
- The $T_{v\min}$ was set to the air temperature measured over
 369 the studied areas (Carlson et al. 1995; Bastiaanssen et al.
 370 1998; Roerink et al. 2000; Merlin 2013; Stefan et al. 2015).
 371 For $T_{v\max}$, it was defined according to the assumptions
 372 described in Stefan et al. (2015), which considered the dif-
 373 ferences between the extreme soil temperatures is the same
 374 that between the extreme vegetation temperatures. 375
- Hourglass method:* Based on the strong relationship
 376 between the variation of the cover fraction (fc) and the sur-
 377 face temperature (LST), Moran et al. (1994) determined a
 378 polygon with four zones where each one is characterized
 379 by a range of values of fc and LST. Merlin et al. (2012)
 380 defined and separated four zones: transpiration- and evap-
 381 oration-controlled, stressed and unstressed mixed surface.
 382 The endmembers obtained with the soil energy balance were
 383 used in the Hourglass method to determine the four zones.
 384 Hereafter, the partitioning of LST into its soil and vegetation
 385 components is based on the LST and fc within the polygon
 386 to determine one of the temperature components T_v or T_s
 387 (see Appendix 2). 388
- Soil and vegetation temperature estimations:* A time series
 389 of vegetation and soil temperatures (T_v and T_s) and their
 390

391 corresponding endmembers ($T_{s_{\min}}$, $T_{s_{\max}}$, $T_{v_{\min}}$ and $T_{v_{\max}}$)
 392 from day of the year 45–60 (2017) are shown in Fig. 2. In this
 393 section, LST used in Eq. 32 was inverted from the longwave
 394 radiation emitted by the surface and measured using CNR4
 395 as follow:

$$396 \quad \text{LST} = \left(\frac{\text{LW}}{\varepsilon \sigma} \right)^{1/4} \quad (19)$$

397 where LW is the longwave radiation emitted by the surface,
 398 ε is the surface emissivity and σ is the Stefan-Boltzmann
 399 constant. This period was chosen to illustrate the variation
 400 of the different temperatures since it coincides with the
 401 development stage of the wheat that presents a mixture of
 402 soil and vegetation. The two temperatures T_v and T_s ranged
 403 between their minimum and maximum values supporting
 404 the good performances of the Hourglass method. To vali-
 405 date the two components T_v and T_s of the partition of the
 406

LST, both were compared against soil and vegetation tem-
 407 perature observations (Fig. 3). T_v is well reproduced with
 408 an RMSE and R^2 equal to 1.6 K and 0.94, respectively. By
 409 contrast, the simulated T_s is not as good with an RMSE and
 410 R^2 of about 3 K and 0.76, respectively. It is clearly seen that
 411 both temperatures T_s and T_v are overestimated, with a bias
 412 equal to -1.4 K and -1 K for T_s and T_v , respectively. This
 413 scattering can be justified by numerous factors. As T_v was
 414 computed first for most of the time while T_s was deducted
 415 from Eq. 32. Meaning that T_s accumulated errors of both T_v
 416 and LST. Likewise, the discrepancy can be related to the
 417 estimation of f_c from Landsat NDVI, as the Landsat pixel
 418 size is larger than the surface of view of the IRT-Apogee.
 419 This will obviously lead to some errors in the partition of
 420 temperature between soil and vegetation. Another reason
 421 that can probably explain the discrepancy is the location
 422 of the measurements. As reported by Olivera-Guerra et al.
 423 (2018) the youngest leaves of the plant are expected to be
 424

Fig. 2 Variation of soil (a) and vegetation (b) temperatures derived from Hourglass method, and their maximum and minimum computed from soil surface energy balance model, from DOY 45 to DOY 60

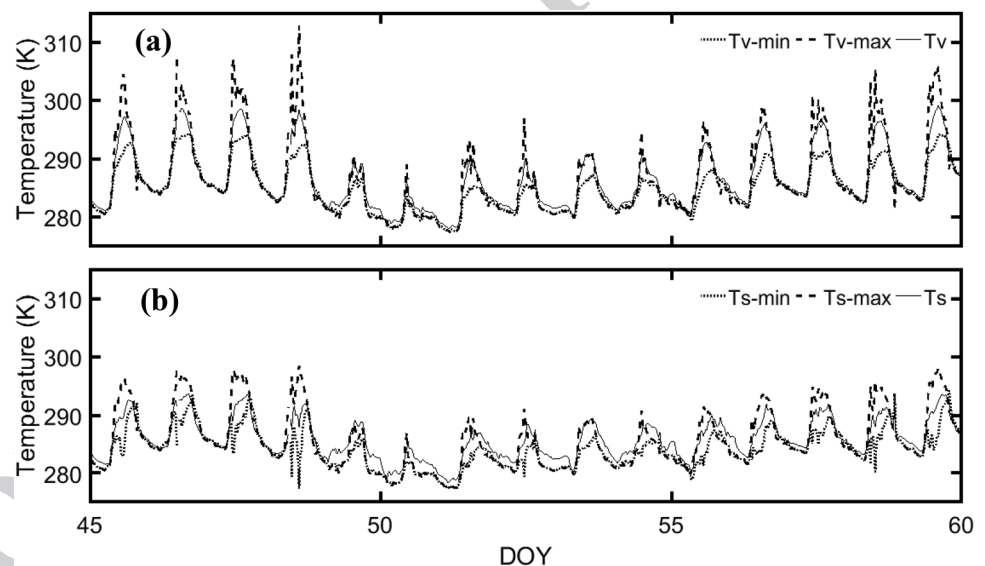
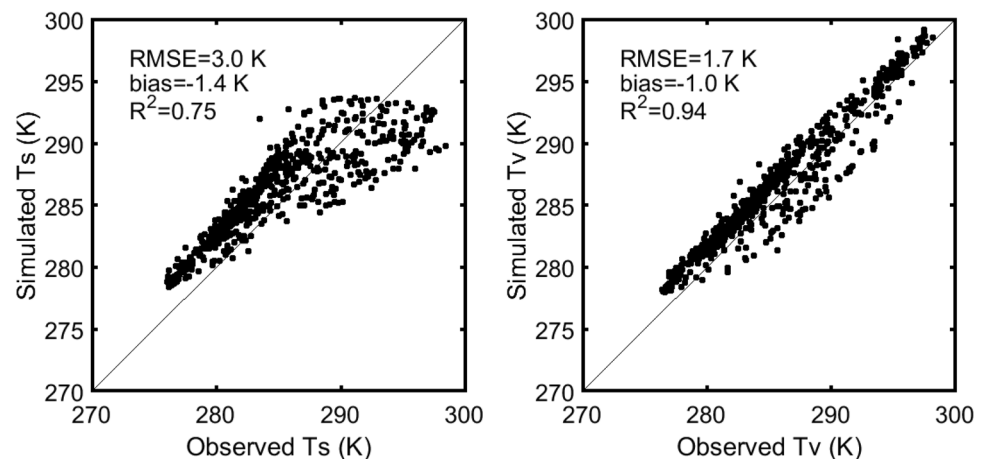


Fig. 3 Simulated soil and vegetation temperatures versus in situ measurements for the same period as Fig. 2



425 colder than the adult and senescing leaves, whose tempera-
 426 ture has not been measured. Otherwise, by comparing both
 427 simulated T_s and T_v temperatures in terms of magnitude it
 428 can notice that T_v is superior to T_s . T_s never exceeds 294 K
 429 although T_v reaches 300 K. This can be explained by the
 430 plotting period of T_s and T_v that coincides with the develop-
 431 ment stage of wheat planted under olive trees and thus there
 432 was no bare soil surface. As well as, T_s can be lower than
 433 T_v during rainfall or irrigation events. Overall, these results
 434 are in agreement with the values reported in the literature
 435 (Stefan et al. 2015; Olivera-Guerra et al. 2018). Soil and
 436 vegetation temperatures and their endmembers are used to
 437 calculate the two stress indexes related to the soil (SI_{ss}) and
 438 to the vegetation (SI_{sv}), and finally to estimate spatial ET by
 439 the SW model.

440 **Spatialization of the SW model**

441 ET derived by the SW model showed a good consistency at
 442 the local scale (Zhang et al. 2008; Zhu et al. 2013, 2014).
 443 However, to our knowledge, no study tried to spatialize the
 444 SW model since many variables are required especially, for
 445 the soil and the vegetation resistances (r_s^s and r_s^v) computa-
 446 tion. As mentioned above, this work aims to retrieve the
 447 resistances using accurate values of transpiration and evapo-
 448 ration and to suggest a relationship between the retrieved
 449 resistances and the stress indexes based on the measured
 450 LST. In fact, retrieving these resistances from measure-
 451 ments based on the equations of the SW model is very
 452 difficult mathematically. To overcome this issue, the Shut-
 453 tleworth–Wallace model has been used to retrieve the two

resistances values based on a very small threshold conver-
 454 gence (less than 2 W/m^2) defined as the absolute value of the
 455 difference between simulated (ET_{SW}) and measured (ET_{EC})
 456 evapotranspiration. This threshold is chosen based on the
 457 reliability of the simulated values and on their number to get
 458 enough points to develop the relationship between the indi-
 459 ces and the resistances. Hereafter, an empirical exponential
 460 relationship was developed between the retrieved resistances
 461 and the soil and the vegetation stress indexes (SI_{ss} , SI_{sv}).
 462 These latter were computed using the endmember tempera-
 463 tures deduced from the soil energy balance model and the
 464 vegetation and the soil temperature calculated using Hour-
 465 glass method as follow:

$$SI_{ss} = \frac{T_s - T_{s_{min}}}{T_{s_{max}} - T_{s_{min}}} \tag{20}$$

$$SI_{sv} = \frac{T_v - T_{v_{min}}}{T_{v_{max}} - T_{v_{min}}} \tag{21}$$

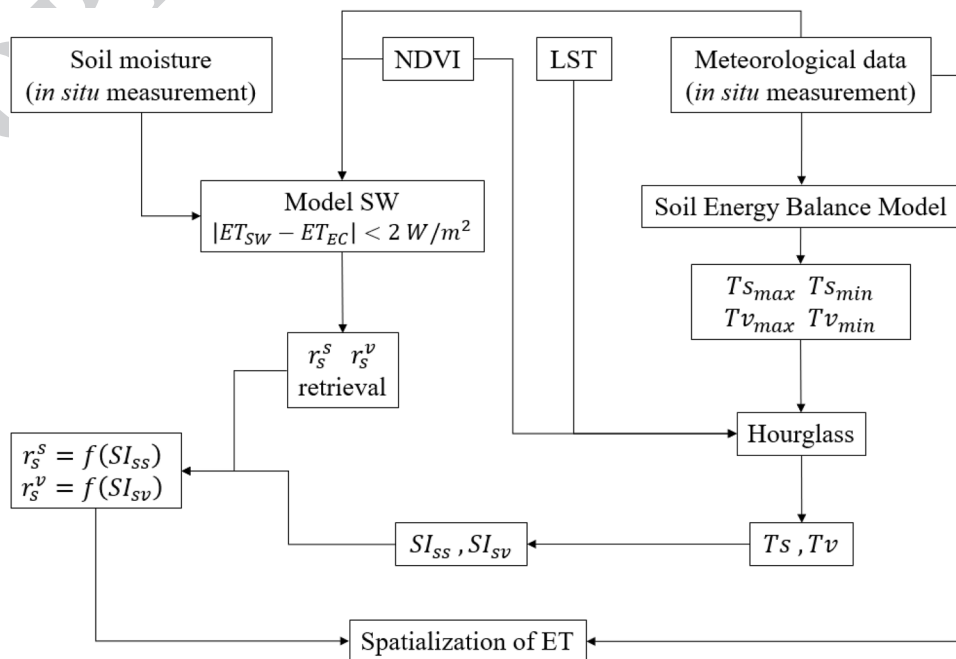
An overview of the methodology is summarized in Fig. 4.

Results

In situ evaluation of the SW model

Figure 5 presents a comparison between the half-hourly ET
 measured by eddy covariance system (average of 0.26 mm/h)
 and simulated (average of 0.30 mm/h) by the original SW
 model based on the soil moisture data to compute soil and

Fig. 4 Flowchart of the proposed approach



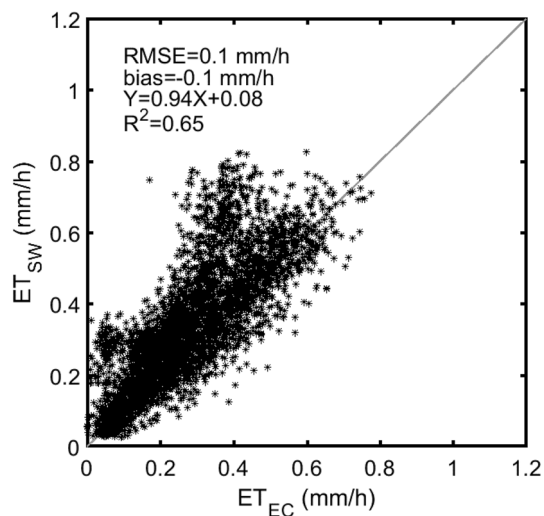


Fig. 5 Half-hourly comparison between evapotranspiration predicted by the Shuttleworth–Wallace model (ET_{SW}) and measured by the Eddy covariance system (ET_{EC}) during 2017

478 vegetation resistances, during the 2017 growing season. This
 479 figure shows that the linear regression between simulated
 480 and in situ ET is very encouraging with a slope and an inter-
 481 cept of about 0.94 and 0.08 mm/h, respectively. According
 482 to the statistical analysis depicted in this figure, the model
 483 simulations are acceptable with a relative RMSE, bias and
 484 R^2 of about 0.38, -0.1 mm/h and 0.65, respectively. The
 485 obtained results indicate that the model is able to predict
 486 ET over surface with a high degree of canopy cover hetero-
 487 geneity. The scatter of modeled ET is mainly due to canopy
 488 uniformity over the surface. Moreover, the experimental plot
 489 is irrigated differently during the season. In fact, the farmer
 490 irrigates the entire surface when the wheat was cultivated
 491 under the olive trees. By contrast, when there is no wheat,
 492 the irrigations were limited to the tree rows. This can create
 493 a large heterogeneity over the EC footprint. Additionally,
 494 this heterogeneity can affect the soil and vegetation resist-
 495 ances which were estimated using data acquired near the EC
 496 tower. Another major issue that can explain the differences
 497 between measured and simulated ET is the non-closure of
 498 the energy balance at the EC system level. The compar-
 499 ison between the available energy and the turbulent fluxes
 500 shows that the sum of the turbulent fluxes only reaches 60%
 501 of the available energy. This non-closure is similar to what
 502 has been observed in previous studies (Mauder et al. 2006;
 503 Liu et al. 2011) and can be considered acceptable due to
 504 the complexity of the study site. In fact, the EC measure-
 505 ments were corrected using Bowen ratio method (Twine
 506 et al. 2000). However, the correction was not ideal due to
 507 the storage and the photosynthesis terms which were not
 508 taken into consideration. Additionally, the footprint devices
 509 of the EC system, the CNR4 radiometer and the soil flux

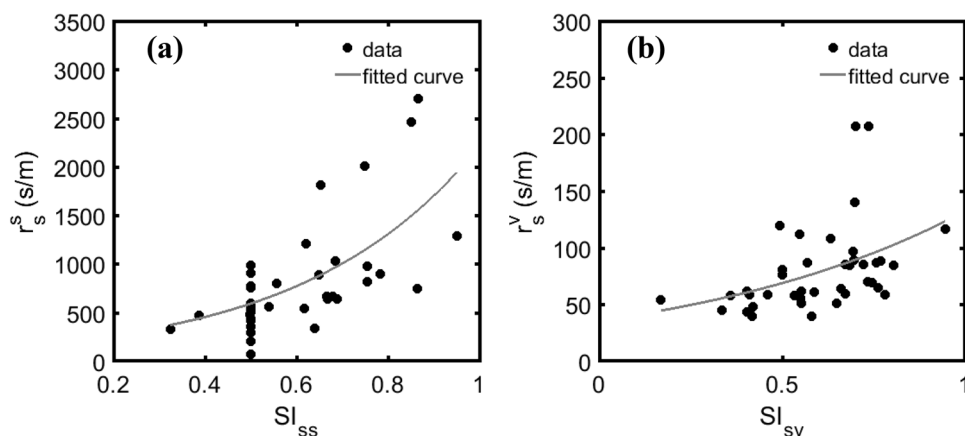
510 plaques were quite different. Furthermore, the soil heat flux
 511 was measured using a heat flux plate, which does not take
 512 into consideration the heat storage in the soil layer above
 513 it. This error related to the G measurements can affect the
 514 Bowen correction of the EC measurements and consequently
 515 the comparison between simulated and measured ET.

516 As reported by Zhang et al. (2009), when the soil was
 517 partially wetted the SW model tends to overestimate ET
 518 by 25.2% over a vineyard. Likewise, Zhang et al. (2008)
 519 found that this model overestimates the ET over a vineyard
 520 in an arid desert region with a mean absolute error (MAE)
 521 of about 0.057 mm/h. On the contrary, some studies showed
 522 that the SW model underestimated half-hourly ET. Zhu et al.
 523 (2014) indicated that the SW model tended to underestimate
 524 the half-hourly ET with a RMSE value of 0.12 mm/h and a
 525 maximum nearly equal to 0.88 mm/h over the spring maize
 526 in the arid desert oasis. Also, Ortega-Farias et al. (2010)
 527 reported that the SW model underestimated on half-hourly
 528 time intervals compared to the EC-measured ET over a
 529 drip-irrigated Merlot vineyard in a Mediterranean semi-
 530 arid region during the growing season in 2006/2007 with a
 531 RMSE equal to 0.046 mm/h and a maximum nearly equal
 532 to 0.59 mm/h. Therefore, the performance of the SW model
 533 seemed to be variable for different crops and places. Further-
 534 more, several parameters used in the model are set to con-
 535 stant values throughout the study period without considering
 536 the seasonal changes. This may impact the quality of the ET
 537 predictions, in particular for the physiology-related param-
 538 eters. In addition, Hu et al. (2009) and Zhu et al. (2013)
 539 reported that for long-term simulations of ET, a systematic
 540 overestimation or underestimation may occur when constant
 541 parameters are used during different vegetation and environ-
 542 mental conditions. The simulated values chosen to retrieve
 543 the soil and vegetation resistances were selected based on
 544 the good simulation of ET by the SW model when the gap
 545 between simulated and measured ET is less than 2 W/m^2 .

546 Local evaluation of the proposed approach

547 Figure 6 displays the relationship between the retrieved
 548 resistances (r_s^s and r_s^v) and the stress indexes (SI_{ss} and SI_{sv}),
 549 respectively. The values have been chosen between 12 and
 550 15 h which correspond to the maximum of radiation. The
 551 resistance variation ranges (0–3000 s/m for r_s^s and 0–250 s/m
 552 for r_s^v) presented in Fig. 6 are in good agreement with those
 553 obtained in the literature (Ortega-Farias et al. 2010; Zhu
 554 et al. 2014; Zhao et al. 2015). In addition, the obtained trend
 555 is similar to that found by Ortega-Farias et al. (2010), Bren-
 556 ner and Incoll (1997) and Zhao et al. (2015) between the
 557 soil resistance and the soil humidity which is replaced in
 558 this work by the stress indexes. Note, that the stress indexes
 559 represent dry conditions when they tend towards 1 and wet
 560 conditions when they are close to 0. Figure 6a presents some

Fig. 6 Relationships between the soil (a) and vegetation (b) resistances (r_s^s and r_s^v) and two stress indexes (SI_{ss} , SI_{sv}) derived from Eqs. 22, 23 for the values between 12 and 15 h. The best fit was also presented (solid line)



561 soil resistance corresponding to the same stress index value
 562 ($SI_{ss} = 0.5$). These (LST, f_c) points were situated in the
 563 transpiration-control zone (see Appendix 2). In this zone T_s
 564 was calculated as the average of their endmembers (Eq. 27).
 565 The stress index was calculated as the ratio of the differ-
 566 ence between T_s and $T_{s_{min}}$ and the difference between $T_{s_{max}}$
 567 and $T_{s_{min}}$. Consequently, the stress index will be continu-
 568 ally equal to 0.5 in this zone. This problem was not seen
 569 in Fig. 6b for the vegetation resistance since there are few
 570 (LST, f_c) points located in the evaporative control zone. The
 571 figure shows the best fits obtained between the soil and the
 572 canopy resistances and the stress indexes which are given by:

$$573 \quad r_s^s = ae^{b \times SI_{ss}}, \quad R = 0,6 \quad (22)$$

574

$$575 \quad r_s^v = ce^{(d \times SI_{sv})}, \quad R = 0,5 \quad (23)$$

576

577

578 Where the calibration parameters a, c, b and d are equal
 579 to 160.25 and 36.02 s/m, 2.62 and 1.30, respectively. Note
 580 that the values of these parameters are expected to depend
 581 on the canopy, on the local meteorological conditions and
 582 on the soil types. Exponential fitting was chosen after test-
 583 ing numerous fitting types given its good representativity of
 584 the points scatter.

585 For the validation of the proposed approach based on
 586 optical (NDVI) and thermal (LST) data to compute soil and
 587 vegetation resistances in SW model, a comparison between
 588 the predicted (average of 0.37 mm/h) and measured (aver-
 589 age of 0.34 mm/h) ET at the station scale was illustrated in
 590 Fig. 7. The obtained linear regression between simulated
 591 and in situ ET is very encouraging with a slope and an inter-
 592 cept of about 0.8 and 0.1 mm/h, respectively. The results
 593 are acceptable with a relative RMSE, bias and a R^2 of about
 594 0.29, -0.03 mm/h and 0.48, respectively. The discrepan-
 595 cies in the estimation of ET can be related to the error in
 596 the LST estimations and in its partitioning. The statistical
 597 performances obtained were in concordance with other

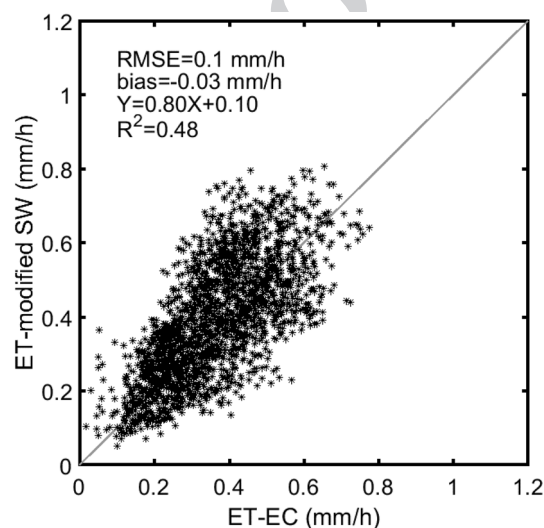


Fig. 7 Half-hourly comparison between estimated ET using the proposed approach and measured one by the Eddy covariance system from January to June 2017

588 studies that used the thermal proxy based on LST such as (i) 598
 599 FAO-2Kc model used by Olivera-Guerra et al. (2018), who 599
 600 found a RMSE of 0.08 mm/h and R^2 of 0.75 over a wheat 600
 601 plot using daily average values, (ii) Penman–Monteith equation 601
 602 used by Amzirh et al. (2017) who found a RMSE of 602
 603 about 0.12 mm/h and a R^2 of 0.53 over a wheat plot, and (iii) 603
 604 TSEB model where Diarra et al. (2017) obtained a RMSE 604
 605 of 0.10 mm/h and a R^2 of 0.67 over a sugar beet field and a 605
 606 RMSE of 0.11 mm/h and R^2 of 0.42 over a wheat field. 606

607 Spatial evaluation of the proposed approach

608 Stress indexes and resistances spatialization

609 The SW model has been used to spatialize the evapotranspi- 609
 610 ration over the piedmont zone. The inputs used in the calcu- 610
 611 lation of the soil and vegetation resistances are difficult to be 611

612 spatialized given the need for soil moisture (SM) maps with
 613 high spatial resolution. Indeed, global soil moisture prod-
 614 ucts are generally derived from passive microwave radiom-
 615 eters with a spatial resolution exceeding 10 km, largely too
 616 coarse for hydrological applications or from the active one
 617 which can provide soil moisture products with high spatial
 618 resolution but using complexed method. By contrast, opti-
 619 cal and thermal remote sensing data are available with high
 620 spatial resolution. Consequently, to overcome this issue the
 621 Landsat data have been used instead of the SM to calculate
 622 the soil and vegetation resistances using the new proposed
 623 approach. Figure 8 presents the spatial variation of the two
 624 stress indexes (SI_{ss} and SI_{sv}) at two dates in winter (2017-01-16)
 625 and summer (2017-06-09) periods. The stress indexes
 626 range between 0 (no stress) and 1 (severe stress) depend-
 627 ing on the hydric state of the surface. For both dates, the two
 628 indexes exhibited as expected values close to 1 at the river
 629 level since there were no growing plants. By contrast, the
 630 areas covered by vegetation are characterized by values of
 631 SI lower than 1. Both stress indexes achieved high values
 632 in summer (date 2017-06-09) exceeding 0.6 which can be
 633 justified by the absence of water supply. This is compat-
 634 ible with the available water since the irrigation system is
 635 based on surface water that occurs as a result of melting
 636 snow. Figure 9 represents the corresponding soil and vegeta-
 637 tion resistances, computed from two stress indexes through

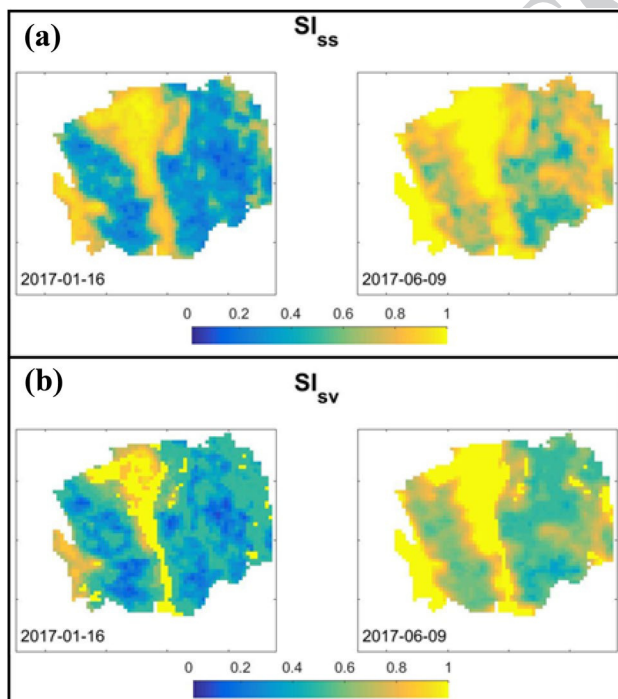


Fig. 8 Maps of the soil (SI_{ss}) and vegetation (SI_{sv}) stress index over the study area for two contrasted dates (2017-01-16) and (2017-06-09)

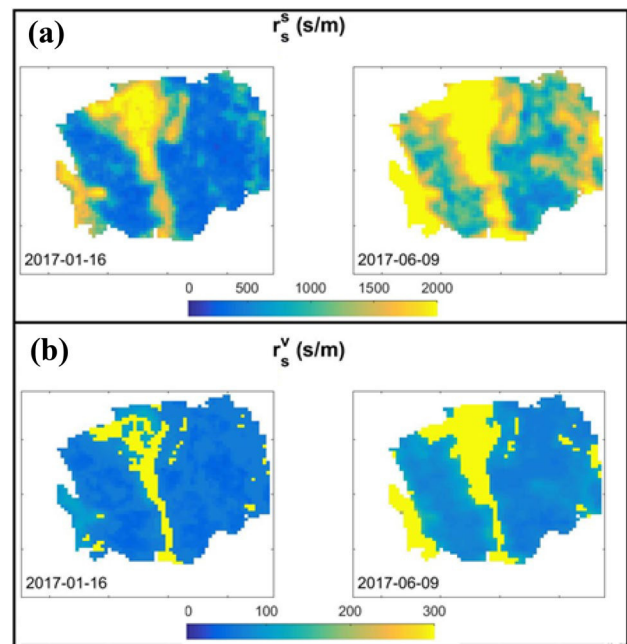


Fig. 9 Maps of the soil (r_s^s) and vegetation (r_s^v) resistance over the study area for two dates (2017-01-16) and (2017-06-09)

two relationships proposed above (Eqs. 22, 23). Vegetation resistance is obviously very high along the river bed since the LAI tends to zero and leads to negligible transpiration. Soil resistance reflects the temporal and spatial variation of the surface soil moisture on the study area. High soil resistance values lead to a sharp decrease in evaporation which is produced by the increase in solar radiation reaching the surface and the low irrigation supply.

Evapotranspiration mapping

Figure 10 displays the spatial and temporal distributions of ET from winter to summer of 2017. For that, 17 Landsat images have been used but only 9 images acquired by Landsat-7 are plotted for illustrating purpose. The spatial distribution of ET is tightly linked to the spatial variation of the fraction cover (Fig. 11), with low values along the river bed which represents a bare soil surface and higher overall the study site which contains a diversity of croplands and arboriculture especially olive trees. The use of an averaged fc value integrating different heterogeneous crops which are located within one Landsat pixel can generate some uncertainties in the ET estimates. Indeed, the transpiration for each type of crops is different and depends on its response to the stress conditions due to the difference of LAI and rooting depth. In practice, values of LAI should be calculated for each crop within one Landsat pixel and afterwards a specific formula should be used for deriving the correspondent fc of each LAI value. However, this solution cannot be applied in

Fig. 10 Evapotranspiration (mm/h) maps over the study area for the dates of the Landsat-7 overpass. The footprint of LAS and EC for the time of the satellite overpass is also represented

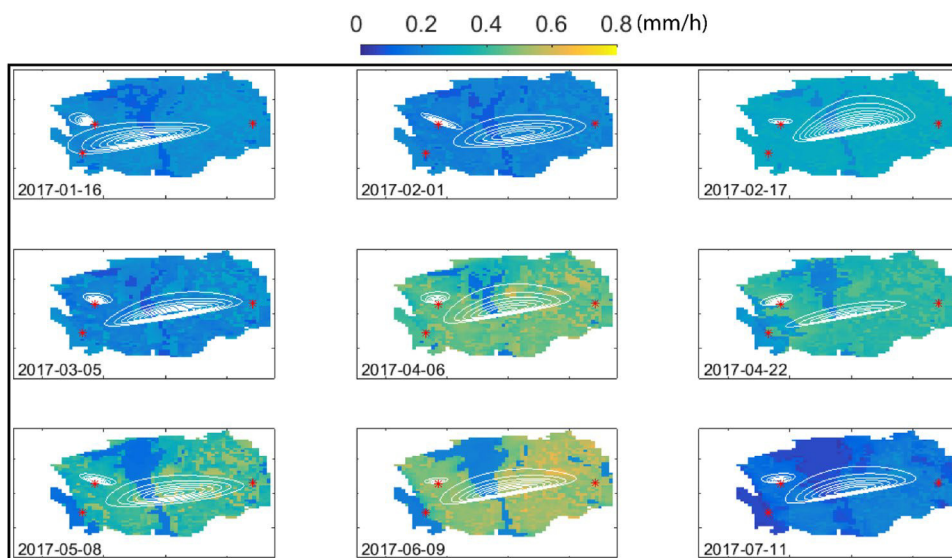
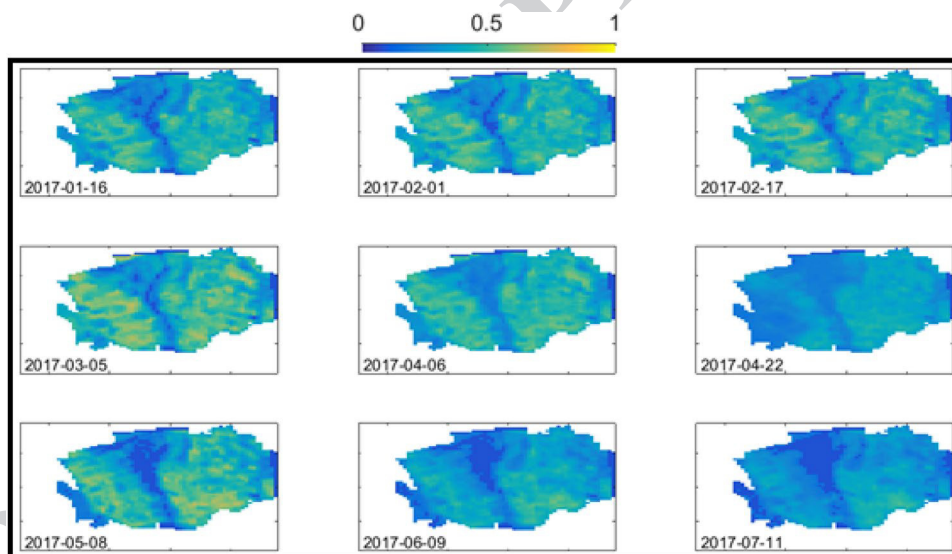


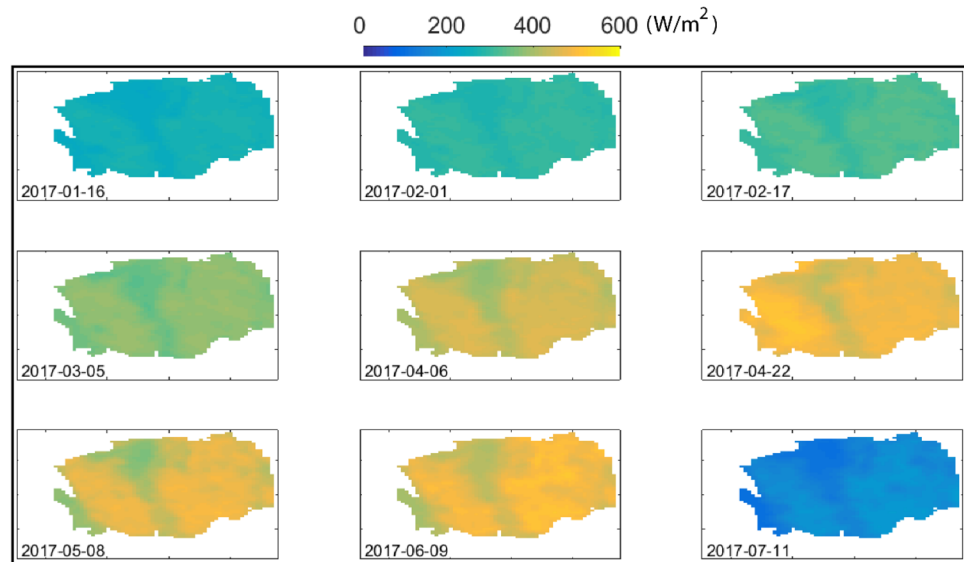
Fig. 11 Fraction cover maps over the study area for the dates that coincide with the overpass of Landsat-7



665 this study due to the complexity of the site. Therefore, it can
 666 be concluded that although great progress has been made
 667 in the development of the satellites particularly in terms of
 668 spatial resolution, the heterogeneity of our site is one of the
 669 major challenges that must be overcome to use the satellite
 670 data to assess evapotranspiration in that orchards. Another
 671 issue that can generate some uncertainties in the ET esti-
 672 mates over our site was the difficulties of measuring T_v . In
 673 fact, measured T_v used in this study was a value attributed
 674 to the whole vegetation which means that the same resist-
 675 ance value was attributed to the different crops. In practice,
 676 it is difficult to have an adequate place to install the Infra-
 677 Red radiometer sensor for providing measurements that can
 678 be representative of the whole vegetation in such complex
 679 area. To avoid this problem, we need to install an Infra-Red

radiometer over each crop which is not feasible as explained
 for f_c issue. Otherwise, the estimated T_v using the energy
 balance model and the hourglass method represents the
 whole vegetation, meaning that no separation between crops
 was considered. Consequently, to improve the transpiration
 estimates using the proposed model, as mentioned before,
 a high spatial resolution of satellite data is required over
 such complexity to distinguish between different types of
 crops. Figure 10 shows also a significant seasonal variation
 of ET values ranging from less than 200 to up to 520
 W/m^2 . This variation is mainly related to the available
 energy and the fraction cover which increase progressively
 in time from winter to early summer when wheat is
 harvested (Figs. 11, 12). However, in the fifth day of
 March, ET values were low even while the available energy
 was significant (an average

Fig. 12 Available energy (W/m^2) maps over the study area for the dates that coincide with the overpass of Landsat-7

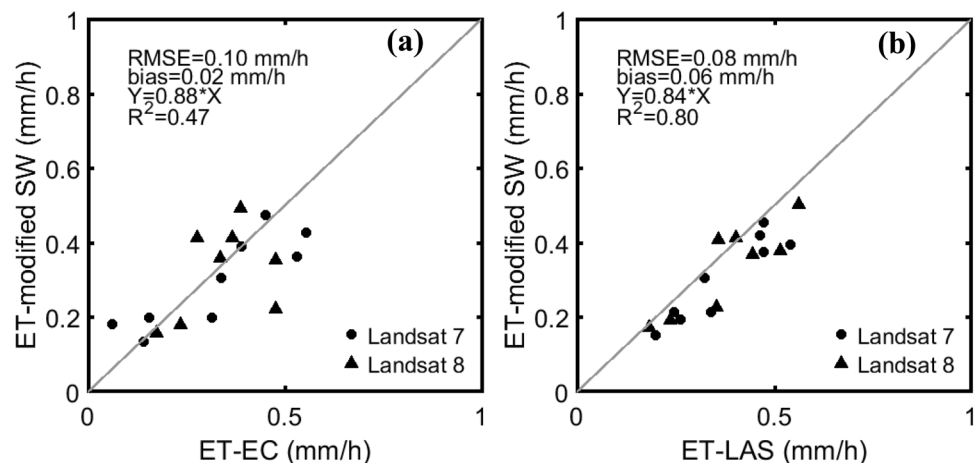


695 of about $420 \text{ W}/\text{m}^2$) and the fraction cover was high (an
696 average of about 0.65). This is attributed to the atmospheric
697 saturation, as the air temperature was low (about $14 \text{ }^\circ\text{C}$)
698 and the air humidity was high (71.45%). This drastically
699 decreased the amount of the evaporative demand.

700 The footprints of the scintillometer and EC were also
701 presented in Fig. 10 to show the variation of the source area
702 of the LAS and EC measurements. The footprint was used
703 to weight the ET values from the maps at the time of the
704 satellites overpass. The modeled ET values were validated
705 by comparing them to the measurements (over the LAS and
706 EC footprints). Figure 13 shows good consistency between
707 the simulated ET values, using SW model driven by Landsat
708 7 and 8 and observed one. The statistical analysis between
709 the model and the LAS measurements showed better agree-
710 ment than those obtained between the model and the EC
711 measurements with an RMSE and R^2 of about 0.08 mm/h
712 and 0.80, respectively, for the LAS and 0.1 mm/h and 0.47,

713 respectively, for the EC. This can be justified by the accu-
714 racy of the relation between the resistances and the stress
715 indexes which could be stronger over other plots than the
716 plot where the calibration was done. Otherwise, the com-
717 parison with EC and LAS measurements show an underesti-
718 mation with a slope of about 0.84 and 0.88 for LAS and EC,
719 respectively. This underestimation of the ET by the model
720 is probably justified by the error on the satellites LST. The
721 processing of this data as mentioned in Sect. (Remote sens-
722 ing data) can cause a surface temperature overestimation.
723 This will generate an overestimation of the resistances and
724 consequently, the ET will be underestimated. Additionally,
725 in our model, for an NDVI less than 0.2 the LAI is set to
726 0 while, some sparse vegetation can grow along the river
727 which is not enough to exceed the NDVI threshold. This
728 can provide low estimated ET. The results obtained are rel-
729 evant compared to other studies that used the scintillometry
730 method to evaluate the performance of the different model

Fig. 13 Comparison of esti-
mated evapotranspiration from
the modified SW model driven
by Landsat-7 and Landsat-8
and measured by the eddy
covariance system (a) and the
scintillometer (b)



731 in estimating ET. Ait Hssaine et al. (2018) have found an
 732 RMSE and R^2 of about 0.11 mm/h and 0.52, respectively,
 733 between scintillometer measurement and ET estimated using
 734 the Two-source Energy Balance model (TSEB) over an het-
 735 erogeneous area covered by Millet (58%), Fallow savannah
 736 (23%) and Degraded shrubs (19%) in the region of Niamey
 737 city, Niger. In the same vein, Saadi et al. (2018) have used
 738 an extra-large scintillometer to validate ET values estimated
 739 using Soil Plant Atmosphere and Remote Sensing Evapo-
 740 transpiration (SPARSE) model over a landscape dominated
 741 by agriculture products (cereals, olive groves, fruit trees,
 742 market gardening). They found a RMSE and R^2 of about
 743 0.06 mm/h and 0.55, respectively.

744 The proposed approach has some limitations compared
 745 to traditional models such as SEBAL or METRIC. In fact,
 746 these models don't need an accurate surface temperature
 747 which demands complicated treatments and corrections
 748 (Allen et al. 2007; Gonzalez-Dugo et al. 2009) or air tem-
 749 perature measurements. In contrary, our approach requires
 750 accurate values of surface temperature to correctly esti-
 751 mate the different resistances. Otherwise, Choi et al. (2009)
 752 reported that METRIC forces the predicted flux distributions
 753 to scale between wet and dry hydrologic conditions, which
 754 may not necessarily be present in every image. In contrast,
 755 the proposed approach does not make this assumption and
 756 depend only on moisture variability represented by the stress
 757 indexes in the model. In addition, the proposed approach
 758 is a two-source model which allows to the ET partitioning
 759 into soil evaporation (E) and plant transpiration (T). This is
 760 an important advantage that provides precise information
 761 about the real amount of water needs by crops. However, in
 762 this study, the partition of the soil evaporation and the tran-
 763 spiration was not evaluated given the unavailability of the
 764 measurement devices of separate E/T in the study area. The
 765 proposed approach was calibrated over olive tree with an
 766 understory of annual crops. The established relation between
 767 the stress indexes and the resistances (Eqs. 22, 23) over this
 768 type of cover may need to be adapted over other vegetation
 769 types which their sensitivity to the stress conditions is differ-
 770 ent. Otherwise, although the study site presents a high het-
 771 erogeneity of vegetation type, the proposed approach shows
 772 good consistency when the simulation values were compared
 773 to the LAS measurements. Overall, this modification of the
 774 SW model is needed to be tested with other data set and over
 775 other meteorological conditions to evaluate its robustness
 776 and improve the relation found between the resistances and
 777 the thermal stress indexes.

778 The proposed approach has a great potential for esti-
 779 mating ET over complex surface. This provides a precise
 780 information about the real amount of crops water needs
 781 for improving large scale sustainable irrigation strategy. In
 782 addition, the use of thermal/optical remote sensing data has
 783 proven to be remarkably accurate and robust for estimating

the ET over complex and heterogeneous area. However, test-
 ing this approach with other data set and over other meteoro-
 logical conditions to evaluate its robustness and improve the
 relation found between the resistances and the thermal stress
 indexes is necessary. Likewise applying other constraint on
 soil evaporation and plant transpiration as the soil moisture
 derived from the microwave data will be of great importance
 to improve the soil and vegetation resistances estimates.

Conclusion

Accurate and consistent estimation of evapotranspiration is
 essential in determining the crop water requirement. The aim
 of this work was to map the ET over a heterogeneous surface
 in the piedmont of Atlas mountain using the SW model.

The spatialization of this model requires knowledge of the
 spatial variation of certain inputs such as the soil moisture
 which is not easy to be obtained with high spatial resolution
 taking into account the heterogeneity of the site. The idea
 that has been proposed is to use the thermal and optical
 data provided from Landsat 7 and 8 instead to soil moisture
 which is difficult to obtain. Soil and vegetation resistances
 (r_s^s, r_s^v) were linked to the stress indexes which are computed
 from a normalization of vegetation and soil temperature by
 their endmembers. The vegetation and soil temperatures are
 derived using the Hourglass method forced by vegetation
 fraction and meteorological data. The endmembers of the
 two surface temperature components are simulated using a
 surface energy balance model. The following conclusions
 were drawn from the results of the study:

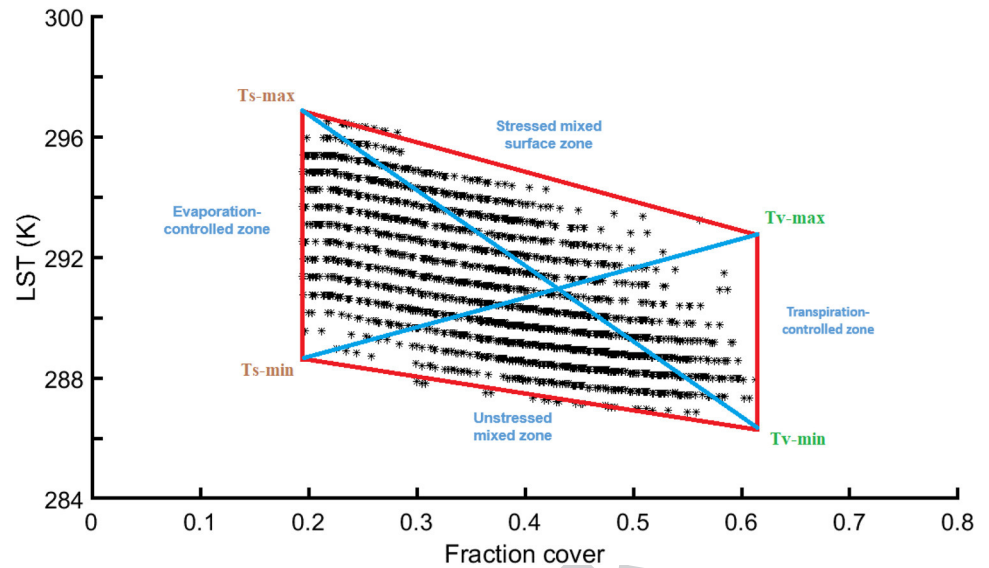
First, SW model was tested locally and acceptable results
 were obtained in estimating ET with a relative RMSE and
 bias are equal to 0.38 and -0.1 mm/h, respectively.

Second, the resistances values were inverted from the SW
 model and used to found the empirical relations based on
 the stress indexes. The method was validated at local scale
 by comparing the results with EC system and the statistical
 performance were encouraging with a relative RMSE and
 bias equal to 0.29 and -0.03 mm/h, respectively.

Finally, the proposed approach was spatialized using
 Landsat 7 and 8 data and confirmed its accuracy by compari-
 son to the LAS and EC measurements. The RMSE, bias and
 R^2 are equal to 0.08 mm/h, 0.06 mm/h and 0.80, respectively,
 compared to the LAS and equal to 0.1 mm/h, 0.02 mm/h and
 0.47, respectively, compared to the EC.

This approach proves the utility of thermal and optical
 remote sensing for estimating accurate ET at a regional
 scale. This will be even better if these data were provided
 with a high revisit time keeping the same spatial resolu-
 tion. Such improvement is possible with the advent of the
 TRISHNA mission as reported by Lagouarde and Bhat-
 tacharya (2018). In addition to optical and thermal data

Fig. 14 Illustration of a polygon defined in the land surface temperature-fractional vegetation cover space contains four distinct zones (Evaporation-controlled zone, stressed mixed surface zone, transpiration-controlled zone and unstressed mixed zone)



834 other relevant remote sensing product could be used to
835 feed the proposed approach. In particular, the microwave
836 data, which are strongly related to the soil hydric status,
837 can provide a promising issue to improve irrigation man-
838 agement. Finally, it should be noted that the procedure
839 proposed here has been solely tested during one growing
840 season. Further tests of this procedure with other data sets
841 and over other surface conditions are needed.

842 **Acknowledgments** This work was carried out within the frame of the
843 Joint International Laboratory TREMA (<https://lmi-trema.ma>). Setup
844 was funded by CNRST SAGESSE project and German Cooperation
845 Giz within the frame of the Hydraulic Basin Agency of the Tensift
846 (ABHT). PHC TBK/18/61 project is acknowledged for providing
847 Jamal Elfarkh a travel grant. The authors wish to thank the projects:
848 RISE-H2020-ACCWA (grant agreement no: 823965) and ERANET-
849 MED03-62 CHAAMS for partly funding the experiments.

850 Appendix 1

851 The LAS measurement is the average of an entire area
852 where each part of it contributes with a percentage
853 depends on its position, weight and wind speed. To obtain
854 this contribution several analytical and Lagrangian models
855 of footprint have been developed (Schuepp et al. 1990;
856 Horst and Weil 1992; Rannik et al. 2000). In this work,
857 we used the model of Horst and Weil (1992) that relates
858 the flux measured at z_m to the surface distribution of the
859 flux: where f is the footprint function relates the flux meas-
860 ured at z_m , $F(x, y, z_m)$ to the spatial distribution of surface
861 fluxes, $F(x, y, z = 0) = F_0(x, y)$. x and y are the downwind
862 and crosswind distances (m) from the point where the
863 measurements are taken, respectively.

$$F(x, y, z_m) = \int_{-\infty}^{\infty} \int_{-\infty}^x F_0(x', y') f(x - x', y - y', z_m) dx' dy' \quad (24)$$

864
865
866 As already mentioned, each point is weighted according
867 to the spatial weighting function of the LAS (Meijninger
868 2003): Where $F_{LAS}(x, y, Z_{LAS})$ is the LAS footprint, and
869 $F(x, y, Z_{LAS})$ is the flux footprint for a point located at d
870 distance from the transmitter. $G(d)$ is the scintillometer path-
871 weighting function for the position located at d distance.

$$F_{LAS}(x, y, Z_{LAS}) = \sum_{i=1}^N F(x, y, Z_{LAS}) G(d) \quad (25)$$

872 Appendix 2

873
874
875 The partitioning of LST into its soil and vegetation compo-
876 nents is based on the LST and fc within the polygon (Fig.
877 14) to determine one of the temperature components T_v or
878 T_s as follow:

879 For a given data point located in the evaporation-con-
880 trolled zone, T_v computed as:

$$T_v = \frac{T_{v_{\max}} + T_{v_{\min}}}{2} \quad (26)$$

881
882
883 For a given data point located in the transpiration-con-
884 trolled zone, T_s computed as:

$$T_s = \frac{T_{s_{\max}} + T_{s_{\min}}}{2} \quad (27)$$

887 For a given data point located in the stressed mixed sur-
888 face zone, T_v computed as:

$$889 \quad T = \frac{LST - T_{s_{\max}}}{fc} + T_{s_{\max}} \quad (28)$$

$$891 \quad T_v = \frac{T_{v_{\max}} + T}{2} \quad (29)$$

893 For a given data point located in the unstressed mixed
894 zone, T_v computed as:

$$895 \quad T = \frac{LST - T_{s_{\min}}}{fc} + T_{s_{\min}} \quad (30)$$

$$897 \quad T_v = \frac{T_{v_{\max}} + T}{2} \quad (31)$$

899 Then, the other component T_v or T_s was derived based on
900 a linear decomposition of the LST in its vegetation and soil
901 components as follows:

$$902 \quad LST = ((1 - fc)T_s^4 + fcT_v^4)^{1/4} \quad (32)$$

904 In what follows, fc is derived from Landsat NDVI using
905 the following equation:

$$906 \quad fc = 1 - e^{-0.5 \times LAI} \quad (33)$$

908 References

- 909 Ait Hssaine BA, Ezzahar J, Jarlan L et al (2018) Combining a two
910 source energy balance model driven by MODIS and MSG-
911 SEVIRI products with an aggregation approach to estimate tur-
912 bulent fluxes over sparse and heterogeneous vegetation in Sahel
913 region (Niger). *Remote Sens* 10(6):974. [https://doi.org/10.3390/](https://doi.org/10.3390/rs10060974)
914 [rs10060974](https://doi.org/10.3390/rs10060974)
- 915 Albergel C (2010) Assimilation de données de télédétection dans le
916 modèle ISBA-A-gs pour une analyse conjointe de la biomasse et
917 de l'état hydrique du sol. <https://www.theses.fr>
- 918 Allen RG, Pereira LS, Howell TA, Jensen ME (2011) Evapotran-
919 spiration information reporting: I. factors governing measure-
920 ment accuracy. *Agric Water Manag* 98:899–920. [https://doi.](https://doi.org/10.1016/j.agwat.2010.12.015)
921 [org/10.1016/j.agwat.2010.12.015](https://doi.org/10.1016/j.agwat.2010.12.015)
- 922 Allen RG, Tasumi M, Morse A et al (2007) Journal of irrigation and
923 drainage engineering satellite-based energy balance for Map-
924 ping Evapotranspiration with Internalized Calibration (MET-
925 RIC)—applications. *J Irrig Drain Eng*. [https://doi.org/10.1061/](https://doi.org/10.1061/(ASCE)0733-9437(2007)133)
926 [\(ASCE\)0733-9437\(2007\)133](https://doi.org/10.1061/(ASCE)0733-9437(2007)133)
- 927 Allen RG, Tasumi M, Morse A, Trezza R (2005) A landsat-based
928 energy balance and evapotranspiration model in Western US water
929 rights regulation and planning. *Irrig Drain Syst* 19:251–268. [https](https://doi.org/10.1007/s10795-005-5187-z)
930 [://doi.org/10.1007/s10795-005-5187-z](https://doi.org/10.1007/s10795-005-5187-z)
- 931 Amazirh A, Er-Raki S, Chehbouni A et al (2017) Modified Pen-
932 man-Monteith equation for monitoring evapotranspiration of
933 wheat crop: Relationship between the surface resistance and
934 remotely sensed stress index. *Biosyst Eng* 164:68–84. [https://doi.](https://doi.org/10.1016/j.biosystemseng.2017.09.015)
935 [org/10.1016/j.biosystemseng.2017.09.015](https://doi.org/10.1016/j.biosystemseng.2017.09.015)
- Amazirh A, Merlin O, Er-Raki S et al (2018) Retrieving surface
936 soil moisture at high spatio-temporal resolution from a synergy
937 between Sentinel-1 radar and Landsat thermal data: a study case
938 over bare soil. *Remote Sens Environ* 211:321–337
939
- Aouade G, Ezzahar J, Amenzou N et al (2016) Combining stable
940 isotopes and micrometeorological measurements for partition-
941 ing evapotranspiration of winter wheat into soil evaporation and
942 plant transpiration in a semi-arid region. *Agric Water Manag*
943 177(1):181–192. [https://doi.org/10.1016/j.](https://doi.org/10.1016/j.agwat.2016.07.021)
944 [agwat.2016.07.021](https://doi.org/10.1016/j.agwat.2016.07.021)
- Aouade G, Jarlan L, Ezzahar J et al (2020) Evapotranspiration parti-
945 tion using the multiple energy balance version of the ISBA-A-
946 gs land surface model over two irrigated crops in a semi-arid
947 Mediterranean region (Marrakech, Morocco). *Hydrol Earth*
948 *Syst Sci Discuss* 24(7):3789–3814. [https://doi.org/10.5194/](https://doi.org/10.5194/hess-24-3789-2020)
949 [hess-24-3789-2020](https://doi.org/10.5194/hess-24-3789-2020)
- Bastiaanssen WGM, Pelgrum H, Wang J et al (1998) A remote sensing
950 surface energy balance algorithm for land (SEBAL): 2. Validation
951 *J Hydrol*. [https://doi.org/10.1016/S0022-](https://doi.org/10.1016/S0022-1694(98)00254-6)
952 [1694\(98\)00254-6](https://doi.org/10.1016/S0022-1694(98)00254-6)
- Bhattarai N, Mallick K, Stuart J et al (2019) An automated multi-model
953 evapotranspiration mapping framework using remotely sensed and
954 reanalysis data. *Remote Sens Environ* 229:69–92. [https://doi.](https://doi.org/10.1016/j.rse.2019.04.026)
955 [org/10.1016/j.rse.2019.04.026](https://doi.org/10.1016/j.rse.2019.04.026)
- Blinda M (2012) Cahier 14 EAU EFFICIENCE Vers une meilleure
956 efficacité de l'utilisation de l'eau en Méditerranée
957
- Boulet G, Mougnot B, Lhomme, et al (2015) The SPARSE model for
958 the prediction of water stress and evapotranspiration components
959 from thermal infra-red data and its evaluation over irrigated and
960 rainfed wheat. *Hydrol Earth Syst Sci* 19(11):4653–4672. [https://](https://doi.org/10.5194/hess-19-4653-2015)
961 doi.org/10.5194/hess-19-4653-2015
- Bouimouass H, Fakir Y, Tweed S, Leblanc M (2020) Groundwater
962 recharge sources in semiarid irrigated mountain fronts. *Hydrol*
963 *Process* 34:1598–1615. [https://doi.org/10.1002/hyp.](https://doi.org/10.1002/hyp.13685)
964 [13685](https://doi.org/10.1002/hyp.13685)
- Braud I, Dantas-Antonino AC, Vauclin M et al (1995) A simple soil-
965 plant-atmosphere transfer model (SiSPAT) development and field
966 verification. *J Hydrol* 166:213–250. [https://doi.org/10.1016/0022-](https://doi.org/10.1016/0022-1694(94)05085-C)
967 [1694\(94\)05085-C](https://doi.org/10.1016/0022-1694(94)05085-C)
- Brenner AJ, Incoll LD (1997) The effect of clumping and stomatal
968 response on evaporation from sparsely vegetated shrublands.
969 *Agric For Meteorol* 84:187–205. [https://doi.org/10.1016/S0168-](https://doi.org/10.1016/S0168-1923(96)02368-4)
970 [1923\(96\)02368-4](https://doi.org/10.1016/S0168-1923(96)02368-4)
- Carlson TN, Capehart WJ, Gillies RR (1995) A new look at the sim-
971 plified method for remote sensing of daily evapotranspiration.
972 *Remote Sens Environ* 54:161–167. [https://doi.org/10.1016/0034-](https://doi.org/10.1016/0034-4257(95)00139-R)
973 [4257\(95\)00139-R](https://doi.org/10.1016/0034-4257(95)00139-R)
- Choi M, Kustas WP, Anderson MC et al (2009) An intercomparison
974 of three remote sensing-based surface energy balance algorithms
975 over a corn and soybean production region (Iowa, U.S.) dur-
976 ing SMACEX. *Agric For Meteorol* 149:2082–2097. [https://doi.](https://doi.org/10.1016/j.agrformet.2009.07.002)
977 [org/10.1016/j.agrformet.2009.07.002](https://doi.org/10.1016/j.agrformet.2009.07.002)
- Diarra A, Jarlan L, Er-Raki S et al (2017) Performance of the two-
978 source energy budget (TSEB) model for the monitoring of
979 evapotranspiration over irrigated annual crops in North Africa.
980 *Agric Water Manag* 193:71–88. [https://doi.org/10.1016/j.](https://doi.org/10.1016/j.agwat.2017.08.007)
981 [agwat.2017.08.007](https://doi.org/10.1016/j.agwat.2017.08.007)
- Duchemin B, Hagolle O, Mougnot B et al (2008) Agrometeorologi-
982 cal study of semi-ard areas: an experiment for analysing the
983 potential of time series of FORMOSAT-2 images (Tensift-
984 Marrakech plain). *Int J Remote Sens* 29:5291–5300. [https://doi.](https://doi.org/10.1080/01431160802036482)
985 [org/10.1080/01431160802036482](https://doi.org/10.1080/01431160802036482)
- Er-Raki S, Chehbouni A, Boulet G, Williams DG (2010a) Using
986 the dual approach of FAO-56 for partitioning ET into soil and
987 plant components for olive orchards in a semi-arid region. *Agric*
988 *Water Manag* 97:1769–1778. [https://doi.org/10.1016/j.](https://doi.org/10.1016/j.agwat.2010.06.009)
989 [agwat.2010.06.009](https://doi.org/10.1016/j.agwat.2010.06.009)
- Er-Raki S, Chehbouni A, Duchemin B (2010b) Combining satellite
990 remote sensing data with the FAO-56 dual approach for water use
991 1000
992 1001

- 1002 mapping in irrigated wheat fields of a semi-arid region. Remote
1003 Sens. <https://doi.org/10.3390/rs2010375>
- 1004 Ezzahar J, Chehbouni A (2009) The use of scintillometry for vali-
1005 dating aggregation schemes over heterogeneous grids. *Agric*
1006 *For Meteorol* 149:2098–2109. <https://doi.org/10.1016/j.agrfo>
1007 [rmet.2009.09.004](https://doi.org/10.1016/j.agrfo)
- 1008 Ezzahar J, Chehbouni A, Er-Raki S, Hanich L (2009a) Combining a
1009 large aperture scintillometer and estimates of available energy
1010 to derive evapotranspiration over several agricultural fields
1011 in a semi-arid region. *Plant Biosyst* 143:209–221. <https://doi.org/10.1080/11263500802710036>
- 1012 Ezzahar J, Chehbouni A, Hoedjes J et al (2009b) Combining scintillom-
1013 eter measurements and an aggregation scheme to estimate area-
1014 averaged latent heat flux during the AMMA experiment. *J Hydrol*
1015 375:217–226. <https://doi.org/10.1016/j.jhydrol.2009.01.010>
- 1016 Ezzahar J, Chehbouni A, Hoedjes JCB et al (2007) The use of the
1017 scintillation technique for monitoring seasonal water consump-
1018 tion of olive orchards in a semi-arid region. *Agric Water Manag*
1019 89:173–184. <https://doi.org/10.1016/j.agwat.2006.12.015>
- 1020 Fang B, Lei H, Zhang Y et al (2020) Spatio-temporal patterns of evapo-
1021 transpiration based on upscaling eddy covariance measurements
1022 in the dryland of the North China Plain. *Agric For Meteorol.* <https://doi.org/10.1016/j.agrformet.2019.107844>
- 1023 Gentine P, Entekhabi D, Chehbouni A et al (2007) Analysis of evapora-
1024 tive fraction diurnal behaviour. *Agric For Meteorol* 143:13–29.
1025 <https://doi.org/10.1016/j.agrformet.2006.11.002>
- 1026 Gohar AA, Cashman A, Ward FA (2019) Managing food and water
1027 security in small island states: new evidence from economic
1028 modelling of climate stressed groundwater resources. *J Hydrol*
1029 569:239–251. <https://doi.org/10.1016/j.jhydrol.2018.12.008>
- 1030 Gonzalez-Dugo MP, Neale CMU, Mateos L et al (2009) A comparison
1031 of operational remote sensing-based models for estimating crop
1032 evapotranspiration. *Agric For Meteorol* 149:1843–1853. <https://doi.org/10.1016/j.agrformet.2009.06.012>
- 1033 Green S, Clothier B, Jardine B (2003) Theory and Practical Applica-
1034 tion of Heat Pulse to Measure Sap Flow. In: *Agronomy Journal*.
1035 pp 1371–1379
- 1036 Guswa AJ, Celia MA, Rodriguez-Iturbe I (2002) Models of soil
1037 moisture dynamics in ecohydrology: a comparative study. *Water*
1038 *Resour Res* 38:5-1-5–15. <https://doi.org/10.1029/2001wr000826>
- 1039 Harris PP, Huntingford C, Cox PM et al (2004) Effect of soil mois-
1040 ture on canopy conductance of Amazonian rainforest. *Agric*
1041 *For Meteorol* 122:215–227. <https://doi.org/10.1016/j.agrfo>
1042 [rmet.2003.09.006](https://doi.org/10.1016/j.agrfo)
- 1043 Horst TW, Weil JC (1994) How far is far enough? The fetch require-
1044 ments for micrometeorological measurement of surface
1045 fluxes. *J Atmos Ocean Technol* 11:1018–1025. [https://doi.org/10.1175/1520-0426\(1994\)011<1018:hffet>2.0.co;2](https://doi.org/10.1175/1520-0426(1994)011<1018:hffet>2.0.co;2)
- 1046 Horst TW, Weil JC (1992) Footprint estimation for scalar flux measure-
1047 ments in the atmospheric surface layer. *Boundary-Layer Meteorol*
1048 59:279–296. <https://doi.org/10.1007/BF00119817>
- 1049 Hu Z, Yu G, Zhou Y et al (2009) Partitioning of evapotranspiration
1050 and its controls in four grassland ecosystems: Application of a
1051 two-source model. *Agric For Meteorol* 149:1410–1420. <https://doi.org/10.1016/j.agrformet.2009.03.014>
- 1052 Huang G, Li X, Huang C et al (2016) Representativeness errors of
1053 point-scale ground-based solar radiation measurements in the
1054 validation of remote sensing products. *Remote Sens Environ*
1055 181:198–206. <https://doi.org/10.1016/j.rse.2016.04.001>
- 1056 Jackson RD, Reginato RJ, Idso SB (1977) Wheat canopy temperature: a
1057 practical tool for evaluating water requirements. *Water Resour Res*
1058 13:651–656. <https://doi.org/10.1029/WR013i003p00651>
- 1059 Liu SM, Xu ZW, Wang WZ, Jia ZZ, Zhu MJ, Bai J, Wang JM (2011) A
1060 comparison of eddy-covariance and large aperture scintillometer
1061 measurements with respect to the energy balance closure problem.
1062 *Hydrol Earth Syst Sci* 15:1291–1306
- 1063 Mauder M, Liebenthal C, Göckede M, Leps JP, Beyrich F, Foken T
1064 (2006) Processing and quality control of flux data during LIT-
1065 FASS-2003. *Bound Layer Meteorol* 121:67–88
- 1066 Meijninger WML (2003) Surface fluxes over natural landscapes
1067 using scintillometry **AQ3** 1071–1072
- 1068 Merlin O (2013) An original interpretation of the wet edge of the
1069 surface temperature-albedo space to estimate crop evapotran-
1070 spiration (SEB-1S), and its validation over an irrigated area
1071 in northwestern Mexico. *Hydrol Earth Syst Sci* 17:3623–3637.
1072 <https://doi.org/10.5194/hess-17-3623-2013>
- 1073 Merlin O, Rüdiger C, Al Bitar A et al (2012) Disaggregation of
1074 SMOS soil moisture in Southeastern Australia. *IEEE Trans*
1075 *Geosci Remote Sens* 50:1556–1571. <https://doi.org/10.1109/TGRS.2011.2175000>
- 1076 Merlin O, Stefan VG, Amazirh A et al (2016) Modeling soil evapo-
1077 ration efficiency in a range of soil and atmospheric conditions
1078 using a meta-analysis approach. *Water Resour Res* 52:3663–
1079 3684. <https://doi.org/10.1002/2015WR018233>
- 1080 Moran MS, Clarke TR, Inoue Y, Vidal A (1994) Estimating crop
1081 water deficit using the relation between surface-air temperature
1082 and spectral vegetation index. *Remote Sens Environ* 49:246–
1083 263. [https://doi.org/10.1016/0034-4257\(94\)90020-5](https://doi.org/10.1016/0034-4257(94)90020-5)
- 1084 Neale CMU, Jayanthi H, Wright JL (2005) Irrigation water manage-
1085 ment using high resolution airborne remote sensing. *Irrig Drain*
1086 *Syst* 19:321–336. <https://doi.org/10.1007/s10795-005-5195-z>
- 1087 Noilhan J, Mahfouf JF (1996) The ISBA land surface parameteri-
1088 sation scheme. *Glob Planet Change* 13:145–159. [https://doi.org/10.1016/0921-8181\(95\)00043-7](https://doi.org/10.1016/0921-8181(95)00043-7)
- 1089 Norman JM, Kustas WP, Humes KS (1995) Source approach for
1090 estimating soil and vegetation energy fluxes in observations of
1091 directional radiometric surface temperature. *Agric For Meteorol*
1092 77:263–293. [https://doi.org/10.1016/0168-1923\(95\)02265-Y](https://doi.org/10.1016/0168-1923(95)02265-Y)
- 1093 Olivera-Guerra L, Merlin O, Er-Raki S et al (2018) Estimating the
1094 water budget components of irrigated crops: combining the
1095 FAO-56 dual crop coefficient with surface temperature and
1096 vegetation index data. *Agric Water Manag* 208:120–131. <https://doi.org/10.1016/j.agwat.2018.06.014>
- 1097 Olivera-Guerra L, Merlin O, Er-Raki S (2020) Irrigation retrieval
1098 from Landsat optical/thermal data integrated into a crop water
1099 balance model: a case study over winter wheat fields in a semi-
1100 arid region. *Remote Sens Environ.* <https://doi.org/10.1016/j.rse.2019.111627>
- 1101 Ortega-Farias S, Carrasco M, Olioso A et al (2007) Latent heat flux
1102 over Cabernet Sauvignon vineyard using the Shuttleworth and
1103 Wallace model. *Irrig Sci* 25:161–170. <https://doi.org/10.1007/s00271-006-0047-7>
- 1104 Ortega-Farias S, Poblete-Echeverría C, Brisson N (2010) Param-
1105 eterization of a two-layer model for estimating vineyard
1106 evapotranspiration using meteorological measurements. *Agric*
1107 *For Meteorol* 150:276–286. <https://doi.org/10.1016/j.agrfo>
1108 [rmet.2009.11.012](https://doi.org/10.1016/j.agrfo)
- 1109 Plattner G-K, Stocker T, Midgley P, Tignor M (2009) INTERGOV-
1110 ERNMENTAL PANEL ON CLIMATE CHANGE IPCC Expert
1111 Meeting on the Science of Alternative Metrics Meeting Report
1112 Supporting material prepared for consideration by the Intergov-
1113 ernmental Panel on Climate Change. This material has not been
1114 subjected to for **AQ4** 1123–1124
- 1115 Rafi Z, Merlin O, Le Dantec V et al (2019) Partitioning evapotran-
1116 spiration of a drip-irrigated wheat crop: Inter-comparing eddy
1117 covariance-, sap flow-, lysimeter- and FAO-based methods.
1118 *Agric For Meteorol* 265:310–326. <https://doi.org/10.1016/j.agrfo>
1119 [rmet.2018.11.031](https://doi.org/10.1016/j.agrfo)
- 1120 Ramírez DA, Bellot J, Domingo F, Blasco A (2007) Can water
1121 responses in *Stipa tenacissima*L. during the summer season be
1122 promoted by non-rainfall water gains in soil? *Plant Soil* 291:67–
1123 79. <https://doi.org/10.1007/s11104-006-9175-3>
- 1124 1125
1126
1127
1128
1129
1130
1131
1132
1133

- 1134 Rannik U, Aubinet M, Kurbanmuradov O et al (2000) Footprint analy- 1200
 1135 sis for measurements over a heterogeneous forest. *Boundary-Layer* 1201
 1136 *Meteorol* 97:137–166. <https://doi.org/10.1023/A:1002702810929> 1202
 1137 Roerink GJ, Su Z, Menenti M (2000) S-SEBI: A simple remote sens- 1203
 1138 ing algorithm to estimate the surface energy balance. *Phys Chem* 1204
 1139 *Earth Part B Hydrol Ocean Atmos* 25:147–157. [https://doi.](https://doi.org/10.1016/S1464-1909(99)00128-8) 1205
 1140 [org/10.1016/S1464-1909\(99\)00128-8](https://doi.org/10.1016/S1464-1909(99)00128-8) 1206
 1141 Saadi S, Boulet G, Bahir M et al (2018) Assessment of actual evapo- 1207
 1142 transpiration over a semiarid heterogeneous land surface by means 1208
 1143 of coupled low-resolution remote sensing data with an energy 1209
 1144 balance model: comparison to extra-large aperture scintillometer 1210
 1145 measurements. *Hydrol Earth Syst Sci* 22:2187–2209. [https://doi.](https://doi.org/10.5194/hess-22-2187-2018) 1211
 1146 [org/10.5194/hess-22-2187-2018](https://doi.org/10.5194/hess-22-2187-2018) 1212
 1147 Samanta S, Mackay DS, Clayton MK et al (2007) Bayesian analysis 1213
 1148 for uncertainty estimation of a canopy transpiration model. *Water* 1214
 1149 *Resour Res* 43:1–13. <https://doi.org/10.1029/2006WR005028> 1215
 1150 Sánchez JM, López-Urrea R, Valentín F et al (2019) Lysimeter assess- 1216
 1151 ment of the simplified two-source energy balance model and 1217
 1152 eddy covariance system to estimate vineyard evapotranspiration. 1218
 1153 *Agric For Meteorol* 274:172–183. <https://doi.org/10.1016/j.agrforrmet.2019.05.006> 1219
 1154 Schuepp PH, Leclerc MY, MacPherson JI, Desjardins RL (1990) Foot- 1220
 1155 print prediction of scalar fluxes from analytical solutions of the 1221
 1156 diffusion equation. *Boundary-Layer Meteorol* 50:355–373. [https](https://doi.org/10.1007/BF00120530) 1222
 1157 [://doi.org/10.1007/BF00120530](https://doi.org/10.1007/BF00120530) 1223
 1158 Seguin B, Itier B (1983) Using midday surface temperature to estimate 1224
 1159 daily evaporation from satellite thermal IR data. *Int J Remote Sens* 1225
 1160 4:371–383. <https://doi.org/10.1080/01431168308948554> 1226
 1161 Semmens KA, Anderson MC, Kustas WP et al (2016) Monitoring daily 1227
 1162 evapotranspiration over two California vineyards using Landsat 1228
 1163 8 in a multi-sensor data fusion approach. *Remote Sens Environ* 1229
 1164 185:155–170. <https://doi.org/10.1016/j.rse.2015.10.025> 1230
 1165 Sene KJ (1994) Parameterisations for energy transfers from a 1231
 1166 sparse vine crop. *Agric For Meteorol* 71:1–18. [https://doi.](https://doi.org/10.1016/0168-1923(94)90097-3) 1232
 1167 [org/10.1016/0168-1923\(94\)90097-3](https://doi.org/10.1016/0168-1923(94)90097-3) 1233
 1168 Shuttleworth WJ, Wallace JS (1985) Evaporation from sparse crops—an 1234
 1169 energy combination theory. *Q J R Meteorol Soc* 111:839–855. 1235
 1170 <https://doi.org/10.1002/qj.49711146510> 1236
 1171 Singh RK, Senay GB, Velpuri NM et al (2014) On the downscaling of 1237
 1172 actual evapotranspiration maps based on combination of MODIS 1238
 1173 and landsat-based actual evapotranspiration estimates. *Remote* 1239
 1174 *Sens* 6:10483–10509. <https://doi.org/10.3390/rs6110483> 1240
 1175 Stefan VG, Merlin O, Er-Raki S et al (2015) Consistency between 1241
 1176 In Situ, model-derived and high-resolution-image-based soil 1242
 1177 temperature endmembers: Towards a robust data-based model for 1243
 1178 multi-resolution monitoring of crop evapotranspiration. *Remote* 1244
 1179 *Sens* 7:10444–10479. <https://doi.org/10.3390/rs70810444> 1245
 1180 Steppe K, De Pauw DJW, Doody TM, Teskey RO (2010) A compar- 1246
 1181 ison of sap flux density using thermal dissipation, heat pulse 1247
 1182 velocity and heat field deformation methods. *Agric For Meteorol* 1248
 1183 150:1046–1056. <https://doi.org/10.1016/j.agrformet.2010.04.004> 1249
 1184 Su Z (2002) The Surface Energy Balance System (SEBS) for estima- 1250
 1185 tion of turbulent heat fluxes. *Hydrol Earth Syst Sci* 6:85–100. 1251
 1186 <https://doi.org/10.5194/hess-6-85-2002> 1252
 1187 Tan S, Wu B, Yan N (2019) A method for downscaling daily evapo- 1253
 1188 transpiration based on 30 m surface resistance. *J Hydrol.* <https://doi.org/10.1016/j.jhydrol.2019.06.054> 1254
 1189 Tang R, Li ZL (2015) Evaluation of two end-member-based models for 1255
 1190 regional land surface evapotranspiration estimation from MODIS 1256
 1191 data. *Agric For Meteorol* 202:69–82. [https://doi.org/10.1016/j.](https://doi.org/10.1016/j.agrformet.2014.12.005) 1257
 1192 [agrformet.2014.12.005](https://doi.org/10.1016/j.agrformet.2014.12.005) 1258
 1193 Twine TE, Kustas WP, Norman JM et al (2000) Correcting eddy-covar- 1259
 1194 iance flux underestimates over a grassland. *Agric For Meteorol* 1260
 1195 103:279–300. [https://doi.org/10.1016/S0168-1923\(00\)00123-4](https://doi.org/10.1016/S0168-1923(00)00123-4) 1261
 1196 Verhoef A, Fernández-Gálvez J, Diaz-Espejo A et al (2006) The diurnal 1261
 1197 course of soil moisture as measured by various dielectric sensors: 1262
 1198 effects of soil temperature and the implications for evaporation 1263
 1199 estimates. *J Hydrol* 321:147–162. <https://doi.org/10.1016/j.jhydrol.2005.07.039> 1264
 1200 Villagarcía L, Were A, García M, Domingo F (2010) Sensitivity of 1265
 1201 a clumped model of evapotranspiration to surface resistance 1266
 1202 parameterisations: application in a semi-arid environment. *Agric* 1267
 1203 *For Meteorol* 150:1065–1078. <https://doi.org/10.1016/j.agrformet.2010.04.006> 1268
 1204 Wang L, Parodi GN, Su Z (2008) SEBS module beam: A practical tool 1269
 1205 for surface energy balance estimates from remote sensing data. In: 1270
 1206 European Space Agency, (Special Publication) ESA SP **AQ5** 1271
 1207 Ward HC (2017) Scintillometry in urban and complex environments : 1272
 1208 a review. *Meas Sci Technol* 28:27. [https://doi.org/10.1088/1361-](https://doi.org/10.1088/1361-6501/aa5e85) 1273
 1209 [6501/aa5e85](https://doi.org/10.1088/1361-6501/aa5e85) 1274
 1210 Were A, Villagarcía L, Domingo F et al (2007) Analysis of effective 1275
 1211 resistance calculation methods and their effect on modelling 1276
 1212 evapotranspiration in two different patches of vegetation in semi- 1277
 1213 arid SE Spain. *Hydrol Earth Syst Sci* 11:1529–1542. [https://doi.](https://doi.org/10.5194/hess-11-1529-2007) 1278
 1214 [org/10.5194/hess-11-1529-2007](https://doi.org/10.5194/hess-11-1529-2007) 1279
 1215 Wittich KP (1997) Some simple relationships between land-surface 1280
 1216 emissivity, greenness and the plant cover fraction for use in satel- 1281
 1217 lite remote sensing. *Int J Biometeorol* 41:58–64. [https://doi.](https://doi.org/10.1007/s004840050054) 1282
 1218 [org/10.1007/s004840050054](https://doi.org/10.1007/s004840050054) 1283
 1219 Yee MS, Pauwels VRN, Daly E et al (2015) A comparison of opti- 1284
 1220 cal and microwave scintillometers with eddy covariance derived 1285
 1221 surface heat fluxes. *Agric For Meteorol* 213:226–239. [https://doi.](https://doi.org/10.1016/j.agrformet.2015.07.004) 1286
 1222 [org/10.1016/j.agrformet.2015.07.004](https://doi.org/10.1016/j.agrformet.2015.07.004) 1287
 1223 Zhang B, Kang S, Li F, Zhang L (2008) Comparison of three evapo- 1288
 1224 transpiration models to Bowen ratio-energy balance method for 1289
 1225 a vineyard in an arid desert region of northwest China. *Agric* 1290
 1226 *For Meteorol* 148:1629–1640. <https://doi.org/10.1016/j.agrformet.2008.05.016> 1291
 1227 Zhang B, Kang S, Zhang L et al (2009) An evapotranspiration model 1292
 1228 for sparsely vegetated canopies under partial root-zone irrigation. 1293
 1229 *Agric For Meteorol* 149:2007–2011. [https://doi.org/10.1016/j.](https://doi.org/10.1016/j.agrformet.2009.07.007) 1294
 1230 [agrformet.2009.07.007](https://doi.org/10.1016/j.agrformet.2009.07.007) 1295
 1231 Zhao P, Li S, Li F et al (2015) Comparison of dual crop coefficient 1296
 1232 method and Shuttleworth–Wallace model in evapotranspiration 1297
 1233 partitioning in a vineyard of northwest China. *Agric Water Manag* 1298
 1234 160:41–56. <https://doi.org/10.1016/j.agwat.2015.06.026> 1299
 1235 Zhu G, Su Y, Li X et al (2013) Estimating actual evapotranspiration 1300
 1236 from an alpine grassland on Qinghai–Tibetan plateau using a 1301
 1237 two-source model and parameter uncertainty analysis by Bayes- 1302
 1238 ian approach. *J Hydrol* 476:42–51. <https://doi.org/10.1016/j.jhydrol.2012.10.006> 1303
 1239 Zhu GF, Li X, Su YH et al (2014) Simultaneously assimilating multi- 1304
 1240 variate data sets into the two-source evapotranspiration model by 1305
 1241 Bayesian approach: application to spring maize in an arid region 1306
 1242 of northwestern China. *Geosci Model Dev* 7:1467–1482. <https://doi.org/10.5194/gmd-7-1467-2014> 1307
 1243 Zieliński M, Fortuniak K, Pawlak W, Siedlecki M (2013) Turbulent sen- 1308
 1244 sible heat flux in łódź, central poland, obtained from scintillometer 1309
 1245 and eddy covariance measurements. *Meteorol Zeitschrift* 22:603– 1310
 1246 613. <https://doi.org/10.1127/0941-2948/2013/0448> 1311
 1247 Zieliński M, Fortuniak K, Pawlak W, Siedlecki M (2017) Influence 1312
 1248 of mean rooftop-level estimation method on sensible heat flux 1313
 1249 retrieved from a large-aperture scintillometer over a city centre. 1314
 1250 *Boundary Layer Meteorol* 164:281–301. [https://doi.org/10.1007/](https://doi.org/10.1007/s10546-017-0254-1) 1315
 1251 [s10546-017-0254-1](https://doi.org/10.1007/s10546-017-0254-1) 1316

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Journal:	271
Article:	701

Author Query Form

Please ensure you fill out your response to the queries raised below and return this form along with your corrections

Dear Author

During the process of typesetting your article, the following queries have arisen. Please check your typeset proof carefully against the queries listed below and mark the necessary changes either directly on the proof/online grid or in the 'Author's response' area provided below

Query	Details Required	Author's Response
AQ1	Reference: Reference [Tardy et al. (2016)] was mentioned in the manuscript; however, this was not included in the reference list. As a rule, all mentioned references should be present in the reference list. Please provide the reference details to be inserted in the reference list.	
AQ2	Please provide publisher location and editor name for reference [Green et al., 2003].	
AQ3	Please provide journal title, volume number, issue number, page range/DOI for references [Meijniger, 2003].	
AQ4	Please provide full details and complete sentence for references [Plattner et al., 2009].	
AQ5	Please provide publisher location, editor name for references [Wang et al., 2008].	

Author Proof