



HAL
open science

Assimilation of SMAP disaggregated soil moisture and Landsat land surface temperature to improve FAO-56 estimates of ET in semi-arid regions

Abdelhakim Amazirh, Salah Er-Raki, Nitu Ojha, El Houssaine Bouras,
Vincent Rivalland, Olivier Merlin, Abdelghani Chehbouni

► **To cite this version:**

Abdelhakim Amazirh, Salah Er-Raki, Nitu Ojha, El Houssaine Bouras, Vincent Rivalland, et al.. 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*, 2022, 260, pp.107290. 10.1016/j.agwat.2021.107290 . hal-03878614

HAL Id: hal-03878614

<https://hal.science/hal-03878614v1>

Submitted on 14 Dec 2022

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.

1 **Assimilation of SMAP disaggregated soil moisture and**
2 **Landsat land surface temperature to improve FAO-56**
3 **estimates of ET in semi-arid regions**
4

5 **Abdelhakim Amazirh^{a,*}, Salah Er-Raki^{a,b}, Nitu Ojha^c, El houssaine Bouras^{b,c}, Vincent**
6 **Rivalland^c, Olivier Merlin^c. Abdelghani Chehbouni^{a,c}.**

7 *^aMohammed VI Polytechnic University (UM6P), Morocco, Center for Remote Sensing Applications*
8 *(CRSA).*

9 *^bProcEDE, Département de Physique Appliquée, Faculté des Sciences et Techniques, Université Cadi*
10 *Ayyad, Marrakech, Maroc.*

11 *^cCentre d'Etudes Spatiales de la Biosphère (CESBIO), Université de Toulouse, CNES, CNRS, IRD,*
12 *UPS, Toulouse, France.*

13
14
15 **Corresponding author*: Dr. Amazirh Abdelhakim**

16 **Email: abdelhakim.amazirh@um6p.ma/ abdelhakim.amazirh@gmail.com**

17 *Center for Remote Sensing Applications (CRSA), Mohammed VI Polytechnic University (UM6P), Hay*
18 *Moulay Rachid-Benguerir, Morocco.*

19

20 **Abstract**

21 Accurate estimation of evapotranspiration (ET) is of crucial importance in water science and
22 hydrological process understanding especially in semi-arid/arid areas since ET represents more
23 than 85% of the total water budget. FAO-56 is one of the widely used formulations to estimate
24 the actual crop evapotranspiration ($ET_{c\ act}$) due to its operational nature and since it represents
25 a reasonable compromise between simplicity and accuracy. In this vein, the objective of this
26 paper was to examine the possibility of improving $ET_{c\ act}$ estimates through remote sensing data
27 assimilation. For this purpose, remotely sensed soil moisture (SM) and Land surface
28 temperature (LST) data were simultaneously assimilated into FAO-dual K_c . Surface SM
29 observations were assimilated into the soil evaporation (E_s) component through the soil
30 evaporation coefficient, and LST data were assimilated into the actual crop transpiration ($T_{c\ act}$)
31 component through the crop stress coefficient. The LST data were used to estimate the water
32 stress coefficient (K_s) as a proxy of LST (LST_{proxy}). The FAO- K_s was corrected by assimilating
33 LST_{proxy} derived from Landsat data based on the variances of predicted errors on K_s estimates
34 from FAO-56 model and thermal-derived K_s . The proposed approach was tested over a semi-
35 arid area in Morocco using first, *in situ* data collected during 2002-2003 and 2015-2016 wheat
36 growth seasons over two different fields and then, remotely sensed data derived from
37 disaggregated Soil Moisture Active Passive (SMAP) SM and Landsat-LST sensors were used.
38 Assimilating SM data leads to an improvement of the $ET_{c\ act}$ model prediction: the root mean
39 square error (RMSE) decreased from 0.98 to 0.65 mm/day compared to the classical FAO-
40 dual K_c using *in situ* SM. Moreover, assimilating both *in situ* SM and LST data provided more
41 accurate results with a RMSE error of 0.55 mm/day. By using SMAP-based SM and Landsat-
42 LST, results also improved in comparison with standard FAO and reached a RMSE of 0.73
43 mm/day against eddy-covariance $ET_{c\ act}$ measurements.

44 *Key words:* Evapotranspiration; Data assimilation; FAO-dual K_c ; Soil moisture; Land surface
45 temperature.

46 **1. Introduction**

47 Accurate estimation of surface evapotranspiration (ET) is crucial to understand land-surface
48 interaction processes. Additionally, ET is the dominant factor in the water cycle, especially in
49 arid and semi-arid regions. About 85 to 90 % of precipitation returns to the atmosphere through
50 ET (Rosenberg et al., 1983). Moreover, ET estimates have an important role in monitoring
51 drought (Bhattarai et al., 2019; Gerhards et al., 2019) and other extreme climatic events (Littell

52 et al., 2016; Molden et al., 2010), as well as water resource management (Madugundu et al.,
53 2017; Tasumi, 2019). In this case the objective is to have accurate ET estimates that allow
54 computing irrigation requirements. Precise actual crop evapotranspiration ($ET_{c\ act}$) estimates are
55 the key for the quantification of crop water requirements, which allow the optimization of
56 irrigation especially in semi-arid and arid areas that suffer from a pronounced shortage of water
57 (Allen et al., 2011; French et al., 2015). Several techniques were developed and used to monitor
58 $ET_{c\ act}$ at different space-time scales. At plot or field scale, we found the eddy correlation system
59 (Allen et al., 2011; Baldocchi et al., 1988), while at a larger scale, the scintillometer can provide
60 $ET_{c\ act}$ over a transect up to 5 km (Ezzahar and Chehbouni, 2009; Kobsiek et al., 2002). Other
61 approaches for measuring $ET_{c\ act}$ were discussed in Alfieri et al. (2018) and Er-Raki et al.
62 (2013).

63 Concerning $ET_{c\ act}$ predictions, several models with different degrees of complexity have been
64 developed during the past 30 years (Li et al., 2009; Seguin and Itier, 1983). Note that, crop ET
65 (ET_c) refer to optimal, well-watered conditions and pristine cultivated crops, i.e. cropped in
66 conditions without any stress conditions and may be estimated with models while under field
67 conditions actual ET is estimated with models because crops are generally subject to water
68 (and/or other stress conditions). Some of these models use remotely sensed data such as surface
69 albedo, Leaf Area Index (LAI), Normalized Difference Vegetation Index (NDVI), Land Surface
70 Temperature (LST) (Allen et al., 2011; Granger, 2000; Kharrou et al., 2013; Kustas and
71 Norman, 1996; Li et al., 2009) and soil moisture (Elfarkh et al., 2021; Gokmen et al., 2012;
72 Walker et al., 2019). $ET_{c\ act}$ component can be predicted based on water balance at a daily time
73 scale. Among this family of models, the FAO dual crop coefficient model (FAO-dualK_c, Allen
74 et al., 1998) is the most common and operational model to retrieve $ET_{c\ act}$, which was
75 extensively used for modeling water consumption and growth of plants (e.g., Alberto et al.,
76 2014; Barker et al., 2018; Ko et al., 2009; Liu and Luo, 2010). The SIMDualK_c software (Paço
77 et al., 2014; Paredes et al., 2014; Pereira et al., 2020; Rosa et al., 2012b, 2012a) was set up
78 based on FAO-dualK_c to simulate $ET_{c\ act}$ and its components. In contrast with other models
79 based on energy balance theory, the FAO-56 model requires limited input parameters. Several
80 studies used the FAO model to retrieve $ET_{c\ act}$ over various crop types where wheat is the most
81 studied crop among small grain cereals (e.g. Amazirh et al., 2021; Drerup et al., 2017; French
82 et al., 2020; Rafi et al., 2019). Recently, Pereira et al. (2021) provides a review of the studies
83 using the FAO-dualK_c over wheat and other crop types. The FAO-dualK_c approach allows for
84 the partitioning of $ET_{c\ act}$ into soil evaporation (E_s) and plant transpiration ($T_{c\ act}$) by separating

85 the crop coefficients ($K_{c \text{ act}}$) into a basal crop ($K_{cb \text{ act}}$) and soil evaporation (K_e) coefficients.
86 Despite the operationality of the FAO-dual K_c , several studies stated that FAO-dual K_c tends to
87 under/overestimate soil evaporation (E_s) at the beginning or the end of the season when the
88 surface is under bare soil conditions (Amazirh et al., 2021; Boulet et al., 2019; Olivera-Guerra
89 et al., 2018). In this context, many papers deal with the use of soil moisture (SM) data to retrieve
90 soil evaporation under bare soil conditions (Amazirh et al., 2018; Zribi et al., 2011). Moreover,
91 the crop $T_{c \text{ act}}$ estimates is based on the root zone water balance reflecting the variation of the
92 root zone soil moisture (RZSM). Therefore, using RZSM measurements will improve the $T_{c \text{ act}}$
93 estimates. The root zone soil moisture is a state variable that is quite difficult to estimate from
94 meteorological data alone or remote sensing data. For this reason, as an attempt to improve $ET_{c \text{ act}}$
95 estimates, Kalma et al. (2008) and Li et al. (2009) used LST data to estimate water stress
96 indices. More recently, LST data were used to retrieve the stress coefficient (K_s) used by the
97 FAO approach (DeJonge et al., 2015; Ihuoma and Madramootoo, 2017; Kullberg et al., 2017).

98 Other techniques attempt to combine complementary information from hydrological models
99 and observed data for mapping $ET_{c \text{ act}}$. This technique is named data assimilation (Kumar et al.,
100 2008; McLaughlin et al., 2006). The data assimilation technique is based on minimizing the
101 mismatch between the model outputs and observations, by making the optimal use of all
102 available information. We distinguish between two categories of data assimilation schemes:
103 sequential assimilation like Ensemble Kalman Filter and optimal interpolation. The former
104 technique has been widely used in hydrology (Chen et al., 2013; Moradkhani et al., 2005; Wang
105 et al., 2009; Xie and Zhang, 2010). The latter is variational assimilation (e.g., 4-dimensional
106 variational assimilation (Caparrini et al., 2004; Courtier et al., 1993)). Several research works
107 used data assimilation techniques to estimate $ET_{c \text{ act}}$ at different levels (Er-Raki et al., 2008;
108 Merlin et al., 2006; Neale et al., 2012; Pipunic et al., 2008). Recently, many research works
109 used the variational data assimilation technique to update and improve the $ET_{c \text{ act}}$ estimates and
110 its components (e.g. Abdolghafoorian and Farhadi, 2020; Tajfar et al., 2020; Xu et al., 2019,
111 2016). For the sequential data assimilation technique, Kalman Filter (KF) and its variants are
112 the widely used techniques for the $ET_{c \text{ act}}$ retrieval due to their simple conceptual formulation
113 and relative ease of implementation compared to other techniques (Bateni and Entekhabi, 2012;
114 Er-Raki et al., 2008; He et al., 2019; Xu et al., 2011). KF provides a sequential, unbiased, and
115 minimum error variance estimate under the assumption of known statistics of system and
116 measurement errors for a linear problem. The KF provided a comparable result with other
117 popular assimilation methods, despite its simple conceptual formulation which did not require

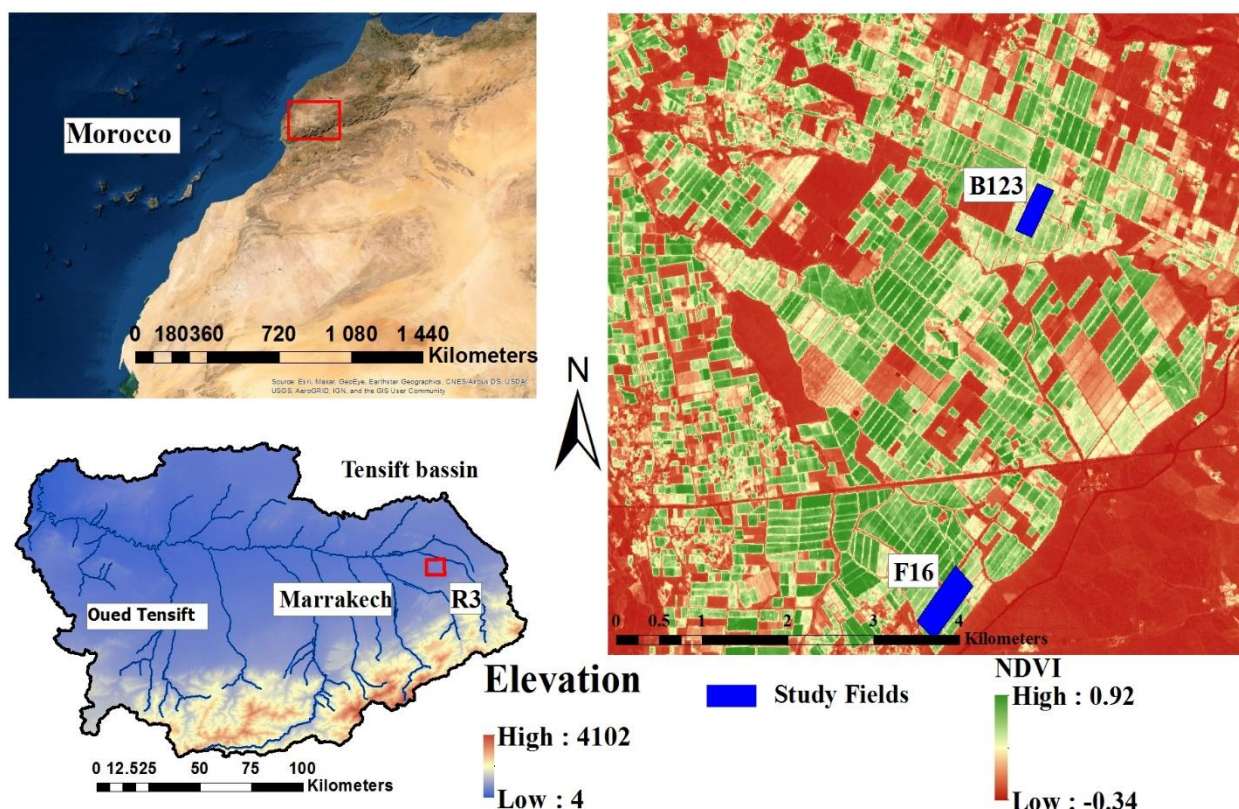
118 any integrations backward in time compared to other variational assimilation techniques
119 (4DVAR, 3DVAR...). However, KF does not account for nonlinearities in hydrological
120 systems, for this, a variant of KF (e.g. extended Kalman filters) could solve some nonlinear
121 problems. Even that, KF affords very good results compared to other complicated models such
122 as the variational method (Tian et al., 2008). In addition, KF requires few restrictive
123 assumptions which make it operational. Therefore, KF seems to be suitable for hydrological
124 linear problems such as modeling $ET_{c\ act}$. Data assimilation technique seems to be a promising
125 tool to improve the $ET_{c\ act}$ estimates when combining with FAO model. Er-raki et al. (2008)
126 have shown that assimilating LST data into FAO-56 single crop model improves the overall
127 $ET_{c\ act}$ estimates. Er-raki et al. (2008) in their paper reach a satisfactory result after assimilating
128 LST data in FAO single crop coefficient with RMSE values dropping down from 0.69 to 0.46
129 mm/day compared to open-loop FAO, which corresponds to an improvement of 40% when
130 assimilating LST into the FAO56 approach. In the same vein, the objective of this paper is to
131 use data assimilation in conjunction with FAO-dual K_c methods to improve $ET_{c\ act}$ estimates.
132 We first assimilate time domain reflectometry (TDR) near-surface SM (0-5cm) observations
133 into FAO-dual K_c to improve the soil E_s estimates. Then, TDR-SM and infrared thermal
134 radiometer (IRT) derived LST data were jointly assimilated to improve soil E_s and wheat crop
135 $T_{c\ act}$, respectively. A sequential assimilation scheme was applied to update the E_s and $T_{c\ act}$
136 estimates. Secondly, Landsat 7/8 derived-LST and disaggregated Soil Moisture Active Passive
137 (SMAP)-SM data at 100 m resolution were used in conjunction with a sequential assimilation
138 approach over two wheat fields named B123 and F16 near Marrakech city in central Morocco.

139 **2. Sites and data description**

140 **2.1. Sites description**

141 The present work was conducted over the Tensift region in central Morocco (Figure 1). This
142 area is known as a semi-arid area with low and irregular precipitation against high potential
143 ET_o . Numerous studies have been performed in this region since 2002-2003 to address various
144 problems regarding the use of water, understanding the integrated hydrological functioning of
145 the Tensift semi-arid basin, as well as improving our knowledge of fundamental hydrological
146 processes (Amazirh et al., 2017; Chehbouni et al., 2008; Merlin et al., 2018). The Tensift basin
147 receiving about 250 mm/year of rainfall, while the reference evapotranspiration (ET_o) is about
148 1600 mm/year, according to the FAO-56 model (Allen et al., 1998). Two study fields have been

149 monitored during 2002-2003 and 2015-2016 wheat agricultural seasons named by B123 and
 150 F16, respectively. Both fields were irrigated by flood gravitation irrigation systems. Flowmeters
 151 were used to collect precisely the irrigation volumes of the two irrigated fields. Irrigation was
 152 applied every 1 to 3 weeks from December 2015 to April 2016 during the 2015–2016 season.
 153 The 4 ha F16 field was irrigated 8 times with a volume of 64 mm each, while the B123 field
 154 was irrigated 4 times with a volume of 24 mm each. These fields are located in an irrigated
 155 perimeter named by R3 situated about 40 km east of the city of Marrakech (31°40'9.46"N,
 156 7°35'45.64"W). The B123 and F16 fields occupied an area of approximately 4 ha each (0.85
 157 km * 4.15 km) involving 7 pixels. The surrounding two fields were also cultivated with wheat
 158 crops and were similar to the same irrigation system. Both fields were known for high clay
 159 contents (47%) and 18% of sand fraction. The sowing dates were the 13th December 2015 and
 160 14th January 2003 for the F16 and B123 irrigated sites, respectively (Amazirh et al., 2017;
 161 Olivera-Guerra et al., 2018).



162
 163 *Figure 1: Location of the study area R3 (red rectangle). Study fields are illustrated with blue*
 164 *rectangles.*

165 2.2. Experimental data set

166 2.2.1. Weather station

167 During the investigated agricultural seasons, an experiment has been set up for each site. An
168 automatic weather station was set up, over an alfalfa cover near the studied wheat fields, to
169 provide continuous climatological data at a sub-hourly time step, including air temperature (T_a ,
170 HMP60, Vaisala, Oyj, Helsinki, Finland), relative humidity (rh_a , HMP60, Vaisala, Oyj,
171 Helsinki, Finland), solar radiation (R_g , pyranometer, LI-COR LI-200X, Lincoln, NE, USA),
172 wind velocity (u_a , anemometer, R.M. Young 3002, Traverse City, USA) and precipitation (P ,
173 automatic rain gauge, Texas Electronics TE525 MM, USA). Reference evapotranspiration
174 (ET_0) was calculated on a daily basis using the Penman-Monteith equation for short canopies
175 (Allen et al., 1998).

176 **2.2.2. Eddy covariance stations**

177 Each field was equipped with an eddy covariance station (EC) consisting of a 3D sonic
178 anemometer (CSAT3, Campbell Scientific Ltd. Logan, UT, USA) that measures the three
179 components of wind speed and a Krypton hygrometer (KH21, Campbell Scientific Ltd. Logan,
180 UT), providing continuous measurements of energy fluxes, vertical sensible heat (H_{obs}) and
181 latent heat (LE_{obs}) fluxes which is equivalent to $ET_{c act obs}$. The net radiometer (Kipp and Zonen
182 CNR4, Campbell Sci, Delft, The Netherlands) measured the surface net radiation (R_n) at 2.6 m
183 height and the soil heat flux (G) was measured at 5 cm depth by using two heat flux plates
184 (HPF01, Campbell Sci, Logan, USA) over the wheat crop fields. An average output of the two
185 plates was used. The two plates were buried with thermocouples at two depths to account for
186 heat storage. Note that, the EC systems were installed at a height of 2.6 m, and the maximum
187 height of wheat was 0.74 m and 0.90 m for B123 (2002-2003) and F16 (2015-2016) sites,
188 respectively. Therefore, the EC system was at least 1.70 m above the canopy. The choice of the
189 installation height actually resulted in a compromise between two constraints: 1) sampling
190 within the field for a range of wind directions and 2) measuring above the roughness layer all
191 along the agricultural season. The relative height of 1.70 m above the canopy ensures that the
192 EC is in the constant flux layer, which is located approximately 1.5-2 canopy heights above the
193 soil surface (Burba, 2013). The two energy fluxes were extracted from KH21 hygrometer
194 measurements, which quantify the fluctuations of atmospheric water vapor and temperature.
195 The collected raw EC data at 20 Hz are processed in the laboratory using the EC-pack software
196 developed by the Meteorology and Air Quality Group, Wageningen University (available for
197 download at <http://www.met.wau.nl/>). The flux tower $ET_{c act}$ is calculated as a multiplication of
198 the air density by the fluctuation of the mean density of water vapor in the air, the fluctuation
199 of the mean vertical wind velocity, and the latent heat of vaporization. Before using such an

200 energy flux data set, a verification of the reliability and the quality of these measurements is
201 needed. The energy balance closure is a way to assess that, by comparing the surface available
202 energy ($R_n - G$) to the sum of turbulent fluxes ($H_{obs} + LE_{obs}$). For the F16 field, the energy budget
203 closure was achieved in Amazirh et al. (2017). The ratio of the turbulent energy flux to available
204 energy (EBR) was 78%, with a strong coefficient of determination ($R^2=0.91$), while for B123
205 field, the EBR is equal to 80% with an R^2 equal to 0.92 (Er-Raki et al., 2011). The slope of the
206 regression forced through the origin was about 1.30 and 1.22 for F16 and B123 fields,
207 respectively. The closure error is close to 10 % for both field which is in the acceptable ranges
208 (from 10% to 30%) reported in Twine et al. (2000). The obtained results are relatively good and
209 the closure of the energy balance is relatively well verified in comparison with other studies
210 (Elfarkh et al., 2021; Testi et al., 2004; Twine et al., 2000). To correct some small uncertainties
211 of non-closure of the energy balance, the Bowen ratio was used to recompute H and LE by
212 forcing the energy balance closure with the measured values of Bowen ratio. The observed data
213 were carefully processed and rigorously screened, some gaps were observed in the collected
214 data, these data were excluded.

215 **2.2.3. In situ soil moisture and land surface temperature measurements**

216 Soil moisture data were also collected over both sites at different depths (5, 10, 20, 30, 50, 70
217 cm), at a half-hourly time step, using time-domain reflectometer (TDR) probes buried under
218 the eddy covariance system for each field. Only one point was selected under the eddy
219 covariance stations for each field. This is due to fact that the fields are irrigated with flooding
220 system which implies a homogeneous fraction of wetted areas, where all the pixels have the
221 same percentage of irrigation water, which means uniform soil moisture within the site. Also,
222 the wheat crop covers the field uniformly (uniform distribution of seeds), which means that the
223 shaded area within the field is uniform. This homogeneity all over the field could explain the
224 use of one location instead of several locations. Note that, SM was measured up to 0.7 m, but
225 only data from 0.05 to 0.5 m were used in this study. This is due to, the measured rooting depths
226 which are 0.52 and 0.50 m for F16 and B123 fields (Er-Raki et al., 2007). The collected SM
227 data were calibrated using the gravimetric technique by taking soil samples at each depth. SM
228 at the surface was used in this study to improve soil E_s through assimilation technic.

229 In addition, brightness surface temperature (T_{bs}) was measured by an Apogee 8–14 μm thermal
230 radiometer sensor (SI-121, Apogee IRTS-P's, Inc., Logan, Utah, USA) in each field, set up at a
231 2 m height looking at nadir. The T_{bs} is corrected from sensor errors using the sensor body

232 temperature, then was converted to surface temperature as in Tardy et al. (2016), using the
233 approach proposed by Olioso (1995). The thermal data were corrected from atmospheric effects
234 using the spectral atmospheric transmission and the atmospheric downwelling and upwelling
235 radiances. The atmospheric parameters are obtained from an atmospheric radiative transfer
236 model (MODTRAN, Berk et al., 2005). Finally, LST was estimated by inverting the simplified
237 Plank's law. The derived spectral atmospheric parameters and the surface emissivity permit the
238 conversion of the at-sensor radiance into the top of canopy radiance exempt from atmospheric
239 effects. The corrected temperature was used to improve $T_{c\ act}$ by updating the stress coefficient
240 (K_s).

241 **2.3. Remote sensing data**

242 In this work, Landsat-7 (L7) and Landsat-8 (L8) data were used to provide land surface
243 temperature (LST) while SMAP data were used to extract surface soil moisture (SM) Table (1).
244 Only data over the F16 field were derived because SMAP sensor was launched in 2015 and
245 B123 field was set in 2002.

246 **2.3.1. Landsat data**

247 L7 ETM+ and L8 OLI-TIRS were used in this study. The surface reflectance and thermal
248 radiance (TIR) were downloaded from the USGS website (<https://earthexplorer.usgs.gov/>). L7
249 provides one thermal band (band 6) while the L8 provides two thermal bands (bands 10 and 11)
250 but only band 11 was considered which is recommended to be used regarding the quality. TIR
251 data were freely acquired with a spatial resolution of 60 and 100 m for L7 and L8, respectively.
252 The revisit time for each sensor is 16 days with an 8-day offset between the two overpasses,
253 which offers TIR data every 8 days. 13 cloud-free images were collected in the 2015-2016
254 agricultural season over F16 study field. As mentioned in section 2.1, the F16 field occupied an
255 area of approximately 4 ha ($0.85\text{ km} \times 4.15\text{ km}$) involving 7 pixels. However, a selection of the
256 pixel where the eddy covariance system was installed has been performed to overcome the edge
257 problem, which can involve the pixels of the surrounded fields. Even if an average over the
258 field was made, it would not impact the results because the surrounding fields are also cultivated
259 with wheat crop with the same irrigation system (gravity) and at the same time.

260 L7 and L8 have different resolutions, a rescaling approach is needed. Since the spatial resolution
261 of L7 thermal data (60 m) is much finer than spatial resolution of L8 thermal data (100 m), the
262 60 m TIR data were resampled linearly to 100 m resolution which is the lowest spatial resolution
263 between L7 and L8. The 13 TIR data were then preprocessed to extract the LST. TIR data were

264 converted to LST data after applying atmospheric correction and correction of surface
265 emissivity. The followed steps are described in Tardy et al. (2016) and the same processing
266 chain was used in Amazirh et al. (2019, 2018). The different correction steps defined in Tardy
267 et al. (2016) allow converting the Landsat digital number to top of atmosphere radiance to top
268 of canopy radiance then, to the physical LST at the surface. An atmospheric correction of the
269 thermal infrared bands' data was firstly carried out using the MODTRAN atmospheric radiative
270 transfer model software. The atmospheric profile composition (vertical air temperature and
271 water content) needed as input to the model has been obtained from the ECMWF European
272 Reanalysis (ERA) Interim product (Dee et al., 2011). As the second step, the at-sensor radiance
273 was converted into surface radiance using the estimated surface emissivity. Then the LST was
274 obtained by inverting Plank's law.

275 **2.3.2. SMAP**

276 SMAP mission was launched in January 2015. This satellite was launched by the National
277 Aeronautics and Space Administration (NASA) with an L-band passive sensor onboard
278 (Entekhabi et al., 2014). SMAP satellite (Entekhabi et al., 2014) is the first L-band mission that
279 combines both radiometer (passive) and radar (active) data dedicated to the study of soil
280 moisture at a range of resolutions from 3 km (active) to 36 km (passive) with a revisit cycle of
281 2–3 days. It orbits at an altitude of 658 km and provides SM from both descending and
282 ascending overpasses. Despite the high frequency of SMAP data acquisition, the spatial
283 resolution is very low which limits their application, especially to agricultural fields. To fill the
284 gap, many disaggregation methodologies were developed to provide SM at high spatial
285 resolution (Abbaszadeh et al., 2019; Peng et al., 2017). Ojha et al. (2019) used DISPATCH
286 (DISaggregation based on Physical And Theoretical scale Change) method to disaggregate 36
287 km-SMAP SM resolution to 100 m resolution. All the followed disaggregation steps were
288 described in Ojha et al. (2019). Three steps were followed to downscale the 36 km SMAP SM
289 to 100 m. The 36 km SM is first disaggregated to 1 km resolution using MODIS LST and NDVI
290 (DISPATCH-1 km). The 1 km resolution disaggregated data is next aggregated to the
291 intermediate spatial resolution, and then further disaggregated to 100 m resolution using
292 Landsat-derived LST and NDVI (DISPATCH-100 m). The disaggregation approaches are
293 based on thermal-derived soil evaporative efficiency (SEE) which is a normalization of LST
294 data by its maximum and minimum values derived from the energy balance model. The
295 disaggregated $SM_{DISPATCH}$ products were evaluated over 22 irrigated fields in the same used
296 area. The *in situ* SM measurements have been collected and calibrated as in Amazirh et al.

297 (2018) during the 2015–2016 season. The disaggregation procedure was tested on 7 dates at
 298 Landsat overpass against *in situ* SM. The evaluation of disaggregated SM was done based on
 299 statistical results in terms of the correlation coefficient (R), the slope of the linear regression,
 300 absolute mean bias, and root mean square difference (RMSD). The results show good results in
 301 terms of R which is ranged between 0.6 and 0.9 with a relatively low absolute bias lower than
 302 0.03 m³/m³. This approach developed by Ojha et al. (2019), was applied during this work to 36
 303 km-SMAP resolution data products, and the disaggregated data set was used in this study. In
 304 this study, only 9 available dates were selected on the Landsat overpass, due to *in situ* data gaps.
 305 Another issue is that the evaluation was assessed from December 27, 2015 to January June 01,
 306 2016 (winter wheat growth season) which limit the number of satellite overpasses. In addition,
 307 the disaggregated SM products include data gaps, which on some dates unfortunately covered
 308 the wheat site.

309 Table 1 lists the characteristics and the selected dates of L7/8 and SMAP overpasses used in
 310 this work.

311 *Table 1: Technical characteristics of satellite products and the selected dates collected in clear*
 312 *sky conditions over the study site.*

Sensors /Mission	Acquisition Time	Bands	Spatial resolution (m)	Temporal resolution (Day)	Acquisition date of used data (2016)
Soil Moisture Active Passive (SMAP)	06:00 AM/PM	Brightness temperature	36 km*	2-3	14, 22, 30 January 02, 10 March 03, 27 April 13, 29 May
Landsat 7 and Landsat 8 (L7/L8)	~11:30 AM	- VNIR ⁺ (L7: B3 & B4; L8: B4 & B5) - TIR (B6 for L7 and B10 et B11 for L8)	60 m and 100 for TIR [×] 15 m for VNIR	8	06, 14, 22, 30 January 07, 23 February 02, 10, 18 March 03, 27 April 21, 29 May

313 * *SMAP data were disaggregated from 36 km to 100 m resolution.*

314 ⁺ *VNIR stands for Visible-near infrared. [×]TIR stands for Thermal infrared. B stands for Band.*

315 3. Methodologies

316 3.1. FAO-56: Dual crop coefficient

317 FAO-56 (Allen et al., 1998) was extensively used to retrieve ET and irrigation scheduling. This
318 is due to its operationality and its simplicity of implementation. The FAO dual crop coefficient
319 (FAO-dual K_c) comes to improve the ET estimates by partitioning ET into soil E_s and plant T_c
320 using reduction evaporation coefficient (K_e) and basal crop coefficient (K_{cb}), respectively, from
321 standard evapotranspiration (ET_0). Under well-watered condition ET_c is written as:

$$322 \quad ET_c = (K_{cb} + K_e)ET_0 \quad (1)$$

323 ET_0 being the ET rate over a well-watered crop land covered by a short green, grass-like crop
324 (reference ET), depending only on atmospheric conditions (ASCE-EWRI, 2004). Equation (1)
325 depends only on atmospheric conditions and is adapted to non-hydric stressed crops (standard
326 conditions). To take into account the crop water stress and to catch the real ET ($ET_{c\ act}$), a water
327 stress coefficient (K_s) was introduced into Equation (1) and it becomes:

$$328 \quad ET_{c\ act} = ET_{FAO} = K_{cb}K_sET_0 + K_eET_0 = T_{c\ act} + E_s \quad (2)$$

329 Where $ET_{c\ act} \equiv ET_{FAO}$ is the actual crop evapotranspiration under non-standard conditions.
330 K_{cb} , K_e , and K_s are basal crop $T_{c\ act}$ coefficient under non-standard conditions, soil evaporation,
331 and water stress coefficients, respectively.

332 The K_{cb} values are defined for each crop growth stage. The wheat growth stages are distinct by
333 their lengths (initial (L_{ini}), development (L_{dev}), mid-season (L_{mid}), and late (L_{late})). Lengths of
334 growth stages are usually calculated based on the fractional vegetation cover (f_c) derived from
335 normalized difference vegetation index (NDVI) as in Er-raki et al. (2008), Er-Raki et al. (2007),
336 Olivera-Guerra et al. (2018) and Rafi et al. (2019). During the initial stage, K_{cb} named $K_{cb\ ini}$,
337 mid-season named $K_{cb\ mid}$, and at the end of the growing season, K_{cb} named $K_{cb\ end}$ where the
338 values were taken from Allen et al. (1998). Local calibration of the FAO model has been
339 stressed in this work, by adjusting the default values of lengths of growth stages reported in
340 FAO based on the different equations provided in FAO-56 for adjusting the K_{cb} values. Lengths
341 of growth stages significantly differ from the FAO-56 default values, especially for the duration
342 of phenological phases. However, the calibrated lengths of growth stages were in accordance
343 with the NDVI measurements carried out on the site. Note that, the lengths of the growth stage
344 reported in FAO-56 are informative values which can only be used in locations with no data.
345 Also, the stages durations are changing from one year to another due to its dependence on the

346 thermal accumulation. The K_{cb} parameter was decomposed into $K_{cb\ ini}$, $K_{cb\ mid}$, and $K_{cb\ end}$. The
 347 $K_{cb\ dev}$ is the K_{cb} during the development stage and is estimated using linear interpolation
 348 between $K_{cb\ ini}$, and $K_{cb\ mid}$. The K_{cb} was interpolated at the daily scale between the start and
 349 end value ($K_{cb\ ini}$, $K_{cb\ mid}$, $K_{cb\ end}$) of each phenological phase as in the FAO-56 documentation.
 350 K_{cb} values were adjusted in each growing stage using climatic data. K_e is the evaporation
 351 coefficient which is calculated as:

$$352 \quad K_e = \min\{[K_r(K_{c\ max} - K_{cb})], [f_{ew}K_{c\ max}]\} \quad (3)$$

353 where $K_{c\ max}$ is the maximum value of crop coefficient (following rain or irrigation), ranged
 354 from 1.05 to 1.30 and estimated using meteorological data (Allen et al., 1998). f_{ew} is the fraction
 355 of exposed and wetted soil from which most E_s occurs. It is calculated as a function of fraction
 356 cover derived from NDVI as suggested by Er-raki et al. (2007). K_r is the reduction coefficient
 357 of evaporation. This coefficient depends on the amount of water that can be depleted by E_s
 358 during a complete drying cycle (TEW) and the cumulative depth of water depleted at the end
 359 of day $i-1$ ($D_{e,i-1}$). It is calculated as:

$$360 \quad K_{r,FAO} = \frac{TEW - D_{e,i-1}}{TEW - REW} \quad ; D_{e,i-1} > REW \quad (4)$$

$$361 \quad K_{r,FAO} = 1 \quad ; D_{e,i-1} < REW$$

362 where REW is the readily evaporated water, which is the maximum depth of water that can be
 363 easily evaporated without restriction. REW (mm) depends on soil properties. FAO provides
 364 REW value for each soil texture (Allen et al., 1998) ranging from 5 to 12 mm. To estimate the
 365 maximum amount of water that can be evaporated (TEW), the top layer depth that can be
 366 evaporated (Z_e), the soil moisture at field capacity (SM_{FC}), and the soil moisture at wilting point
 367 (SM_{WP}) are required. TEW is calculated as:

$$368 \quad TEW = 1000(SM_{FC} - 0.5SM_{WP})Z_e \quad (5)$$

369 SM_{FC} and SM_{WP} are reported for each soil texture classification in FAO-56.

370 A daily water balance is required to estimate the cumulative depth of E_s (depletion) from the
 371 soil surface layer (D_e). A simplification of the water balance equation was established, where
 372 runoff flux is ignored when working on a flat area.

$$373 \quad D_{e,i} = D_{e,i-1} - P_i - \left(\frac{I_i}{f_w}\right) + \frac{E_{s,i}}{f_{ew}} + DP_{e,i} \quad (6)$$

374 where P_i is precipitation input (mm) on day i and I_i is irrigation measured for each site (mm)
 375 on day i , $E_{s,i}$ is soil evaporation (mm) on day i , calculated as $K_e \times ET_0$ (Allen et al., 1998; Bos
 376 et al., 2008) and f_w is the fraction of soil surface wetted by irrigation. In case of irrigation event
 377 or precipitation more than 3 mm/day, f_w is taken equal to 1, otherwise, f_w is set to zero. In this
 378 study, fields are irrigated by flood-irrigation technique, therefore, f_w set to 1 during irrigation
 379 event. The $DP_{e,i}$ is deep percolation loss (downward drainage) from the topsoil layer on day i
 380 (mm). Deep percolation occurs when soil moisture exceeds field capacity following heavy rain
 381 or irrigation. The $DP_{e,i}$ equation assumes that water content is at field capacity so that $D_{e,i}$ set
 382 to zero and the E_s process switch off on the day of a complete wetting event. From equation (6),
 383 $DP_{e,i}$ then is calculated as follow:

$$384 \quad DP_{e,i} = P_i + \left(\frac{I_i}{f_w}\right) - D_{e,i-1} \quad (7)$$

385 The procedure to estimate the transpiration reduction factor K_s [0-1] is similar to K_r . K_s is
 386 calculated based on a daily computation of the water balance for the root-zone layer Z_r (m)
 387 which is written as follow:

$$388 \quad K_{s,FAO} = \frac{TAW - D_r}{TAW - RAW} = \frac{TAW - D_r}{(1-p)TAW} \quad (8)$$

389 When $D_r > RAW$ the stress is presumed to start, and K_s is calculated using Equation (8).
 390 Conversely, when $D_r \leq RAW$ then K_s is equal to 1.

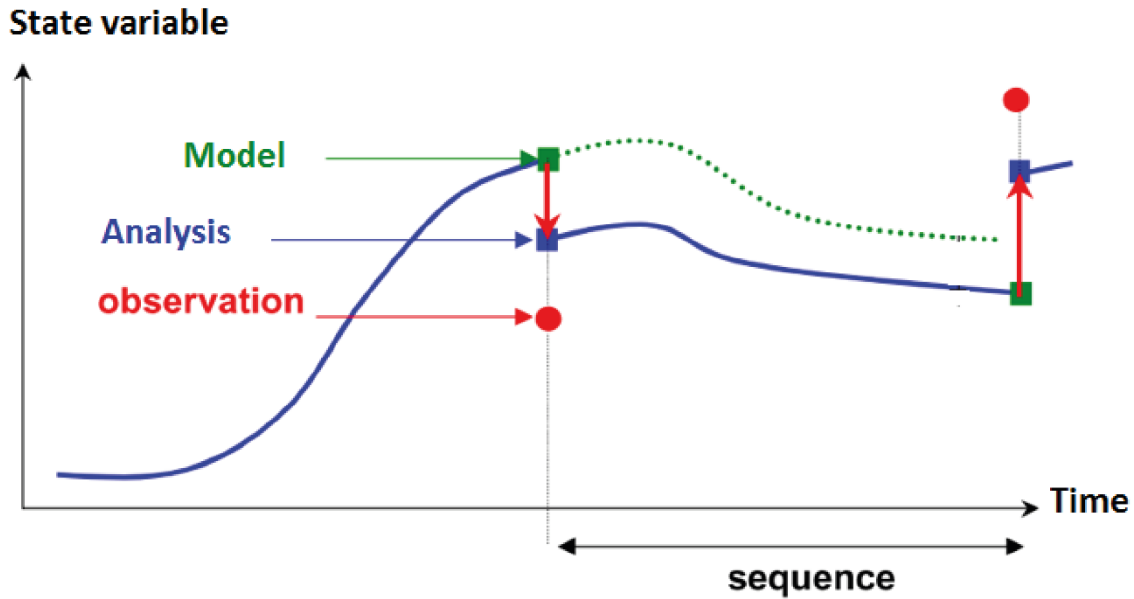
391 D_r is the root zone depletion (mm), TAW is total available water in the root zone [mm], RAW
 392 is readily available soil water of the root zone ($p \cdot TAW$) and p is the depletion fraction for no
 393 stress which is a fraction of TAW that a crop can extract from the root zone without causing
 394 water stress. The TAW is linked to the root depth and to the difference between the water
 395 content at field capacity and wilting point as expressed in Equation (9):

$$396 \quad TAW = 1000(SM_{FC} - SM_{WP})Z_r \quad (9)$$

397 **3.2. Assimilation approaches**

398 Through assimilation, we seek to improve first daily soil E_s by integrating observed and
 399 remotely sensed SM, then integrating observed and remotely sensed LST into the $T_{c \text{ act}}$ rate.
 400 Figure 2 presents an illustration of how the correction is performed using sequential
 401 assimilation to improve state variables using observations to correct the model. The state
 402 variables in our case are the soil E_s and the plant $T_{c \text{ act}}$. The used sequential assimilation

403 approach is based on generating an ensemble of perturbations, to obtain the forecast error
 404 covariance information required by the standard Kalman filter update equation.



405

406 *Figure 2: Sequential data assimilation principle to obtain corrected value (analysis) by*
 407 *updating model using observation (Stanev and Schulz-Stellenfleth, 2014).*

408 Two assimilation methods were used, the first one, by assimilating SM into FAO-dualK_c soil
 409 E_s component and the second, by assimilating jointly SM and LST into FAO-dualK_c soil E_s
 410 and wheat T_{c act}. Both approaches are detailed below.

411 3.2.1. Method 1: SM only

412 As a first step, SM was assimilated into the FAO model to improve the E_s component estimates.
 413 The data assimilation scheme is used to correct the depletion depth D_e used by the FAO-dualK_c
 414 by using first, *in situ* and then remote sensing SM at field scale integrated into K_e equation.
 415 Data assimilation is based on the use of an optimal and simple linear scheme to sequentially
 416 assimilate K_e as proposed by Schuurmans et al. (2003) and used by Er-Raki et al. (2008). This
 417 method has been chosen due to its simplicity and to keep FAO method operational. The
 418 assimilated K_e is written as:

$$419 \quad K_{e,New} = K_{e,FAO} + \mathbf{K}_{evap}(K_{e,SM} - K_{e,FAO}) \quad (10)$$

420 where \mathbf{K}_{evap} is the Kalman gain that minimizes the analyzed error covariance, calculated as:

$$421 \quad \mathbf{K}_{evap} = \frac{\sigma_{K_e,FAO}^2}{\sigma_{K_e,FAO}^2 + \sigma_{K_e,SM}^2} \quad (11)$$

422 $\sigma_{K_e,FAO}^2$ and $\sigma_{K_e,SM}^2$ are the variances of predicted errors on K_e estimates from FAO-dual K_c
 423 model and SM observations, respectively.

424 $K_{e,FAO}$ and $K_{e,New}$ are the estimated K_e by the FAO-dual K_c approach before and after data
 425 assimilation, respectively. While $K_{e,SM}$ is the K_e estimated from SM observations derived from
 426 *in situ* or SMAP disaggregated data. The $K_{e,SM}$ is calculated as Equation (3) except that the D_e
 427 equation is forced by SM data instead of using the water balance model at the surface. The D_e
 428 equation using SM information is written as follow:

$$429 \quad D_e = 1000(SM_{FC} - SM_{obs})Z_e \quad (12)$$

430 **3.2.2. Method 2: Combined assimilation of SM and Land Surface Temperature**

431 FAO-dual K_c model is based on water balance model to estimate K_s . In order to improve wheat
 432 crop $T_{c,act}$ estimates, surface temperature can be used to reflect the crop water status by
 433 calculating stress index for the root-zone layer. The used assimilation scheme is the same used
 434 for assimilating SM (sequential assimilation):

$$435 \quad K_{s,New} = K_{s,FAO} + \mathbf{K}_{stress}(K_{s,LST} - K_{s,FAO}) \quad (13)$$

436 where the \mathbf{K}_{stress} is the Kalman gain calculated as equation:

$$437 \quad \mathbf{K}_{stress} = \frac{\sigma_{K_s,FAO}^2}{\sigma_{K_s,FAO}^2 + \sigma_{K_s,LST}^2} \quad (14)$$

438 $K_{s,FAO}$ is the stress coefficient calculated by water balance in the root zone layer, While $K_{s,LST}$
 439 is estimated as a proxy of LST, where the LST is normalized by its maximal and minimal values
 440 as in Idso et al. (1981).

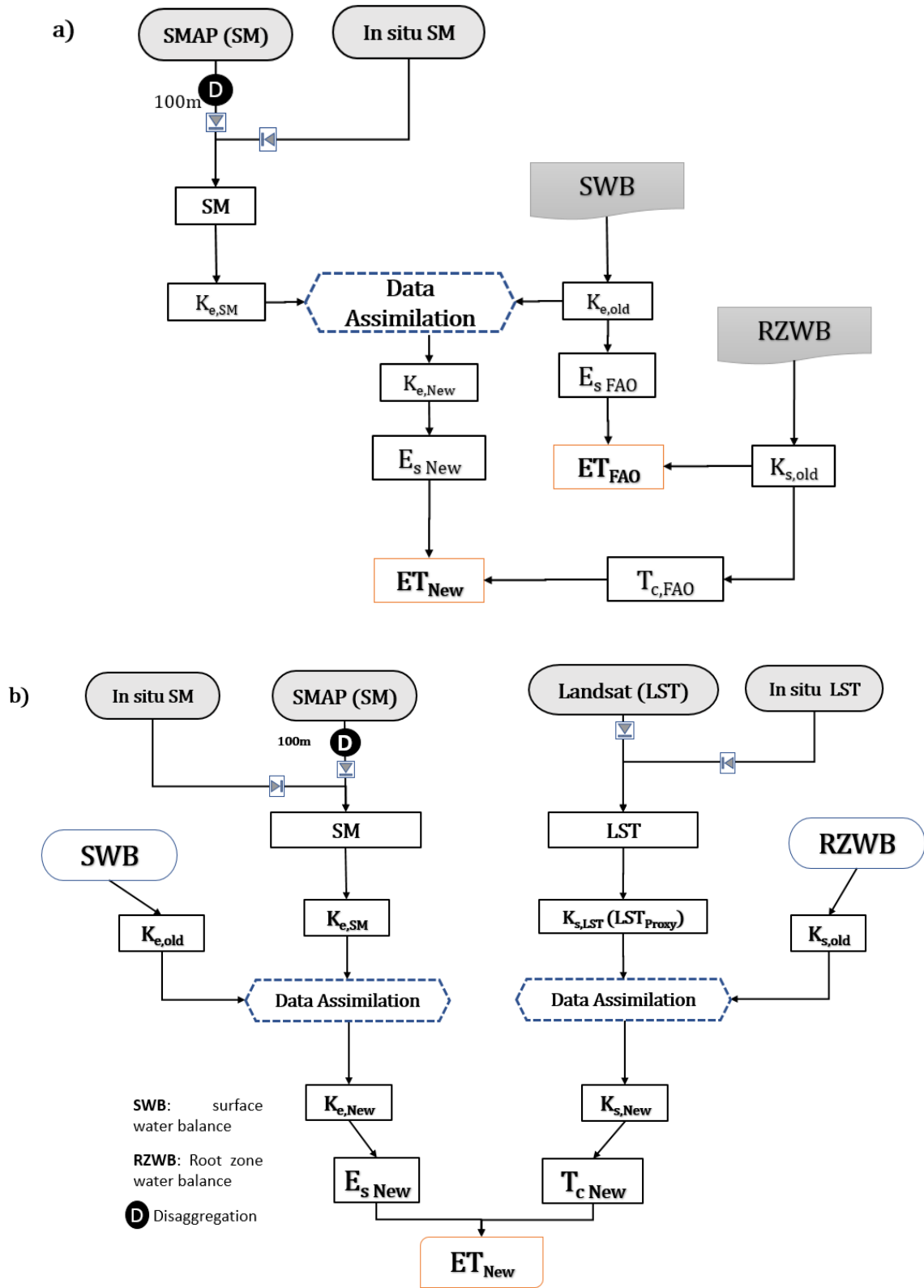
$$441 \quad K_{s,LST} = LST_{proxy} = \frac{(LST - T_a)_{max} - (LST - T_a)}{(LST - T_a)_{max} - (LST - T_a)_{min}} \quad (15)$$

442 where $LST - T_a$ is the difference between surface temperature and air temperature; $(LST - T_a)_{min}$
 443 is the lower limit of $(LST - T_a)$ of a surface which is transpiring at the potential rate, and
 444 $(LST - T_a)_{max}$ the expected differential in the case of a non-transpiring crop.

445 An overview of the methodologies using remote sensing data is represented in the flowcharts,
 446 Figure 3.

447

448



449

450 *Figure 3: Schematic diagrams presenting an overview of the main inputs, models and outputs*
 451 *of the assimilation of soil moisture into FAO-dualK_c (a) and SM & LST conjointly (b).*

452

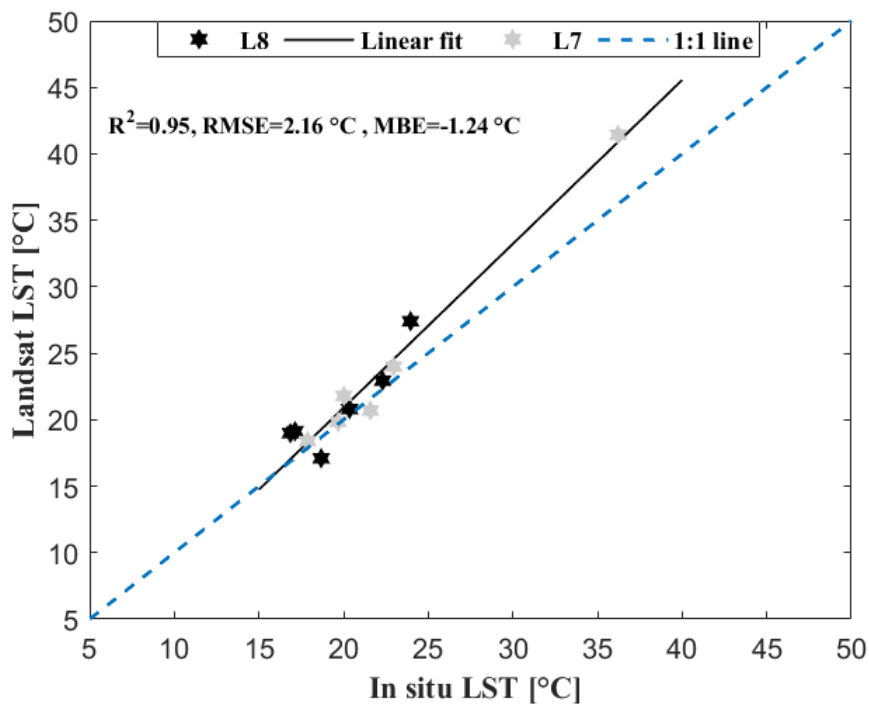
Standard FAO-dualK_c is also presented in (a).

453 **4. Results and discussions**

454 **4.1. Remote sensing data analysis**

455 **4.1.1. Landsat against in situ LST**

456 As an important step for investigating the use of LST data for the assimilation approach, it is
457 essential to investigate the relevance between the Landsat LST data and in situ measurements.
458 In this section a comparison between the 100 m Landsat LST and in situ TIR measurements
459 was performed. In Figure 4, Landsat LST is plotted against *in situ* LST data in order to check
460 the reliability of the remote sensed Landsat LST.



461

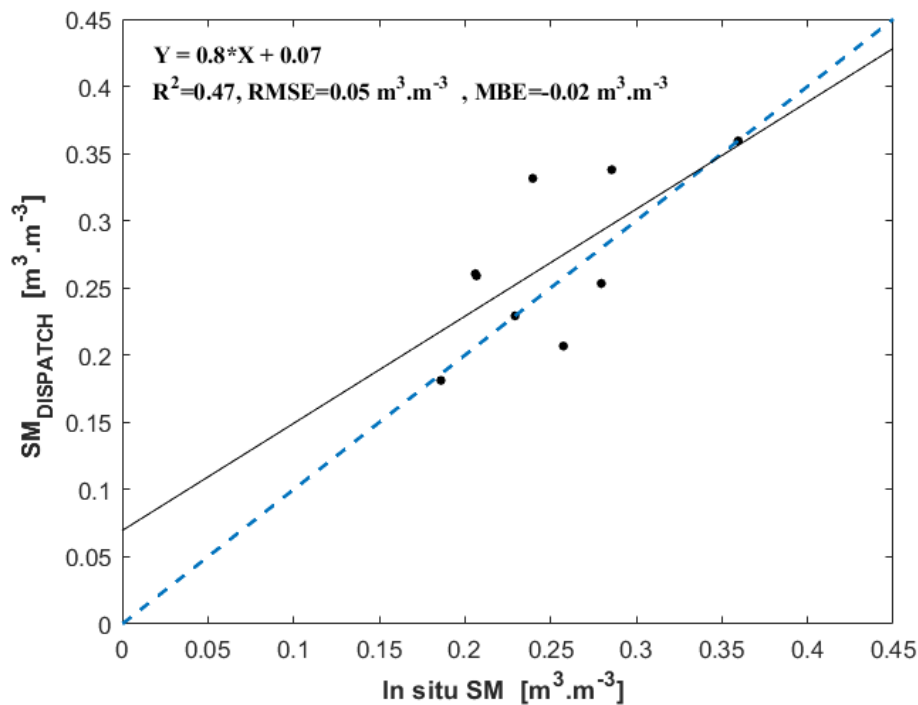
462 *Figure 4: Land surface temperature derived from Landsat-7 (L7) and -8 (L8) versus in situ*
463 *(In situ LST) measurements for F16 field. Line 1:1 (dotted blue line) and regression line*
464 *(black solid line) were also presented.*

465 The comparison between both temperatures showed good agreement, with a determination
466 coefficient equal to 0.95 and an error (RMSE) equal to 2.16 °C. The results are slightly
467 consistent with the one obtained in Amazirh et al. (2018), where they found an error close to 3
468 °C, over a field near the study field, by applying the same algorithm used in this work. Landsat
469 overestimates slightly LST. This is due to the difference in the spatial extent of remotely sensed
470 and *in situ* observations, where the Apogee radiometer was installed at a 2-m height, which
471 limits the spatial representativeness of its measurements. The observed underestimation is quite
472 similar for both L7 and L8 compared to in situ measurements. An RMSE of 2.33 °C and MBE

473 of -1.30 °C were obtained when comparing L-7 and in situ measurements, while when
474 comparing L8 against in situ LST, an RMSE of 1.98 °C and MBE of -1.18 °C were obtained.
475 This allows, to combine the both satellites to benefit from the temporal resolution of both
476 satellites.

477 4.1.2. TDR against disaggregated-SMAP soil moisture

478 Before using the 100 m resolution SMAP disaggregated SM ($SM_{DISPATCH}$), it is important to
479 check their reliability and quality. To this end, an evaluation against *in situ* SM over the F16
480 study field was performed. The comparison results are illustrated in Figure 5.



481

482 *Figure 5: Disaggregated SMAP-soil moisture ($SM_{DISPATCH}$) against in situ soil moisture (In*
483 *situ SM) over the F16 field. Line 1:1 (dotted blue line) and regression line (black solid line)*
484 *were also presented.*

485 The comparison results show that $SM_{DISPATCH}$ matches relatively well the TDR *in situ*
486 measurements with a root mean square error (RMSE) of $0.05 m^3 \cdot m^{-3}$ and mean bias error of -
487 $0.02 m^3 \cdot m^{-3}$. The regression line is close to the 1:1 line and the determination coefficient is
488 equal to 0.47 which corresponds to Pearson correlation coefficient (R) value equal to 0.69 that
489 lies in the results range [0.5-0.9] reached by Ojha et al. (2019) over the 22 fields in the same
490 area. This result is encouraging despite the acceptable statistics considering the localization of

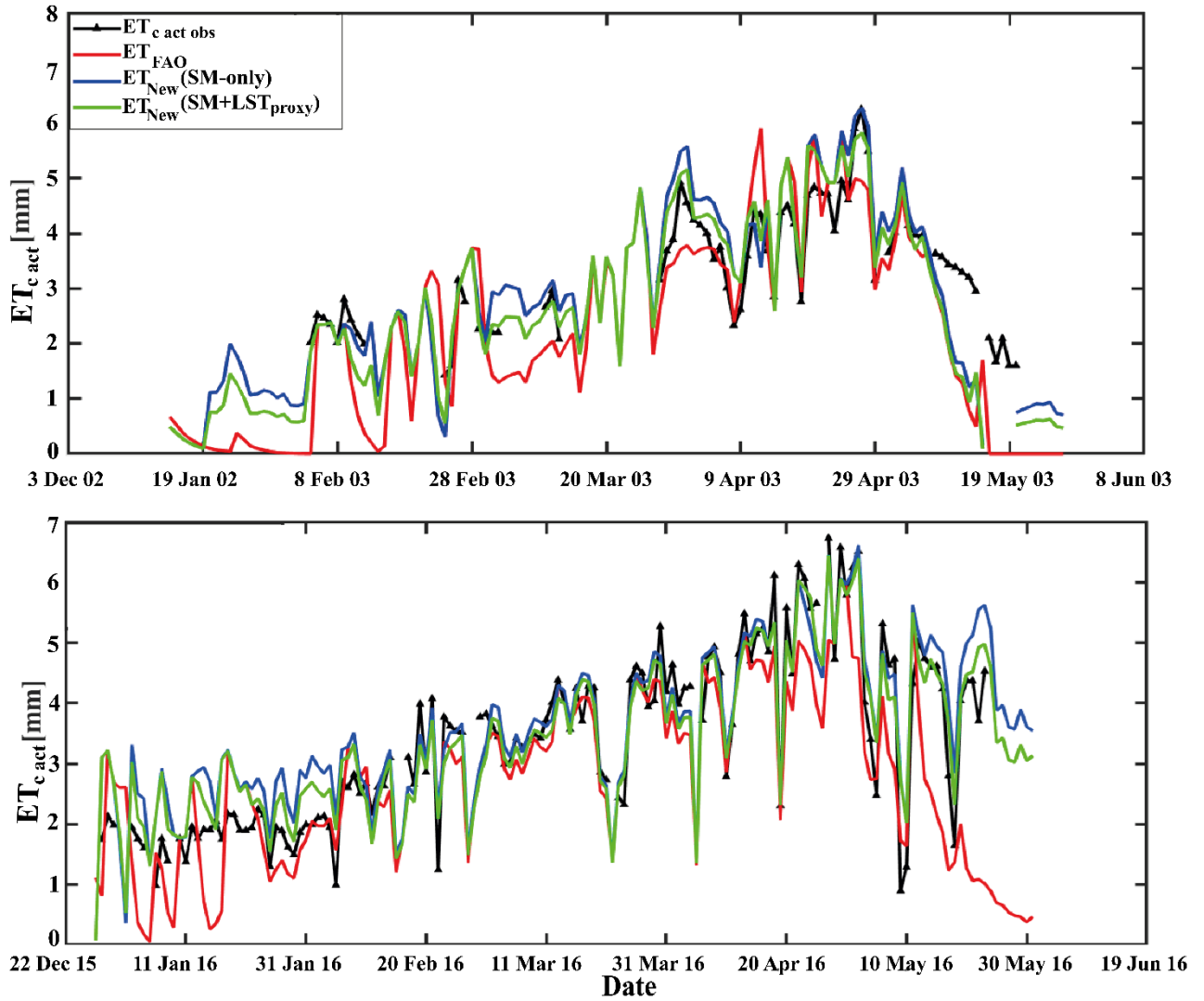
491 the *in situ* measurements within the disaggregated SMAP SM pixel. Moreover, another issue
492 that could lead to differences between the disaggregated and *in situ* SM is that the ground SM
493 sensors are buried at a depth of 5 cm, while the penetration of the L-band wave varies between
494 2 and 5 cm depending on soil conditions (eg. soil texture).

495 **4.2. In situ evaluation of the assimilation approaches**

496 As an assessment of the assimilation methodologies, this procedure was tested over both B123
497 and F16 sites. *In situ* SM and LST data are available over both sites. The first step was to test
498 the effect of near-surface SM assimilation alone into FAO-dualK_c E_s component. The second
499 step was to assess the performance of coupled assimilation of both SM and LST variables into
500 FAO-dualK_c ET_{c act}. Assimilating LST alone into the FAO model was also tested over both
501 sites. Results (results not shown) indicate that assimilating LST only, slightly improves the ET_c
502 _{act} estimations (an error difference of 0.92 mm/day) and an R² equal to 0.64 with and an MBE
503 less than 0.57 m/day for the F16 site. The slightly improvement of ET_{c act} estimates using LST
504 only is due to the fact that LST data is representing the soil and wheat temperatures and a
505 partition of LST is needed to incorporate LST data into FAO model. Otherwise, assimilating
506 LST data into FAO single approach coefficient could improve the ET_{c act} results significantly
507 as found in Er-Raki et al. (2008).

508 Figure 6 presents the daily temporal comparison of the ET_{c act} estimates using the assimilation
509 approaches and the observed ET_{c act}. The statistical results of the assimilation approaches and
510 the standard FAO-dualK_c are presented in Table 2. The ET_{c act} estimates are evaluated by
511 comparing them with the measured ET_{c act} by the Eddy covariance system from both wheat sites
512 (B123 and F16). Ground-based SM and LST data are available at a 30 min time scale, which
513 allows us to choose the number of assimilation dates without restrictions. In our case, an 8-day
514 frequency was used, which corresponds to the Landsat revisit time-frequency over our study
515 sites. First only SM data are assimilated (SM-only) then SM and LST couple are assimilated.

516



519 *Figure 6: Daily temporal comparison between FAO-dualK_c and observed ET_{c act} without*
 520 *assimilation (ET_{FAO}) and when assimilating SM-only and when assimilating SM and LST_{proxy}*
 521 *couple for B123 (top) and F16 (bottom) sites.*

522 *Table 2: Statistical analysis of ET_{c act} simulated by the FAO-dualK_c before assimilation and*
 523 *after assimilations for both wheat fields.*

Statistics	R ²		RMSE (mm/day)		MBE (mm/day)		
	<i>Fields</i>	B123	F16	B123	F16	B123	F16
Methods							
ET _{FAO} (no assimilation)		0.72	0.63	1.01	0.98	-0.44	-0.47
SM-only		0.77	0.85	0.73	0.65	-0.14	-0.32
SM+LST _{proxy}		0.77	0.87	0.71	0.55	0.03	-0.14

524 **NOTE. ET_{FAO} (no assimilation):** open loop FAO model. **SM-only:** assimilating only soil moisture data
525 into FAO model. **SM+LST_{proxy}:** Assimilating conjointly soil moisture and Land surface temperature
526 into FAO model.

527 From Table 2 the RMSE between measured and estimated $ET_{c\ act}$ using standard FAO-dual K_c
528 (no assimilation) for the F16 and B123 sites are, 0.98 and 1.01 mm/day, respectively. As seen
529 in Figure 6, without assimilation, standard FAO-dual K_c severely underestimates $ET_{c\ act}$ (see the
530 MBE values in Table 2). The assimilation of surface soil moisture alone is significantly
531 improving the estimate of soil E_s component, which ameliorates $ET_{c\ act}$ estimates at the field
532 scale. Without and with SM assimilation, the RMSE decreases from 0.98 and 1.01 to 0.65
533 mm/day and 0.73 mm/day, and the R^2 increases from 0.63 and 0.72 to 0.85 and 0.77 for F16
534 and B123, respectively. The classical FAO-dual K_c is based on an estimated SM from a
535 simplified water balance budget (Equation 6), where some water fluxes were neglected in our
536 case (runoff, deep percolation, and capillarity rise...). Where runoff flux takes place above a
537 certain threshold value of soil moisture present in the soil (Manabe, 1969), which can generate
538 some uncertainties. The underestimation of $ET_{c\ act}$ is observed at the beginning of the season,
539 during the germination and emergence stage of growing crops and at the end (senescent stage)
540 of the agricultural season, due to the limitation of the standard FAO-56 model in the estimation
541 of the E_s component where water is lost mainly by E_s .

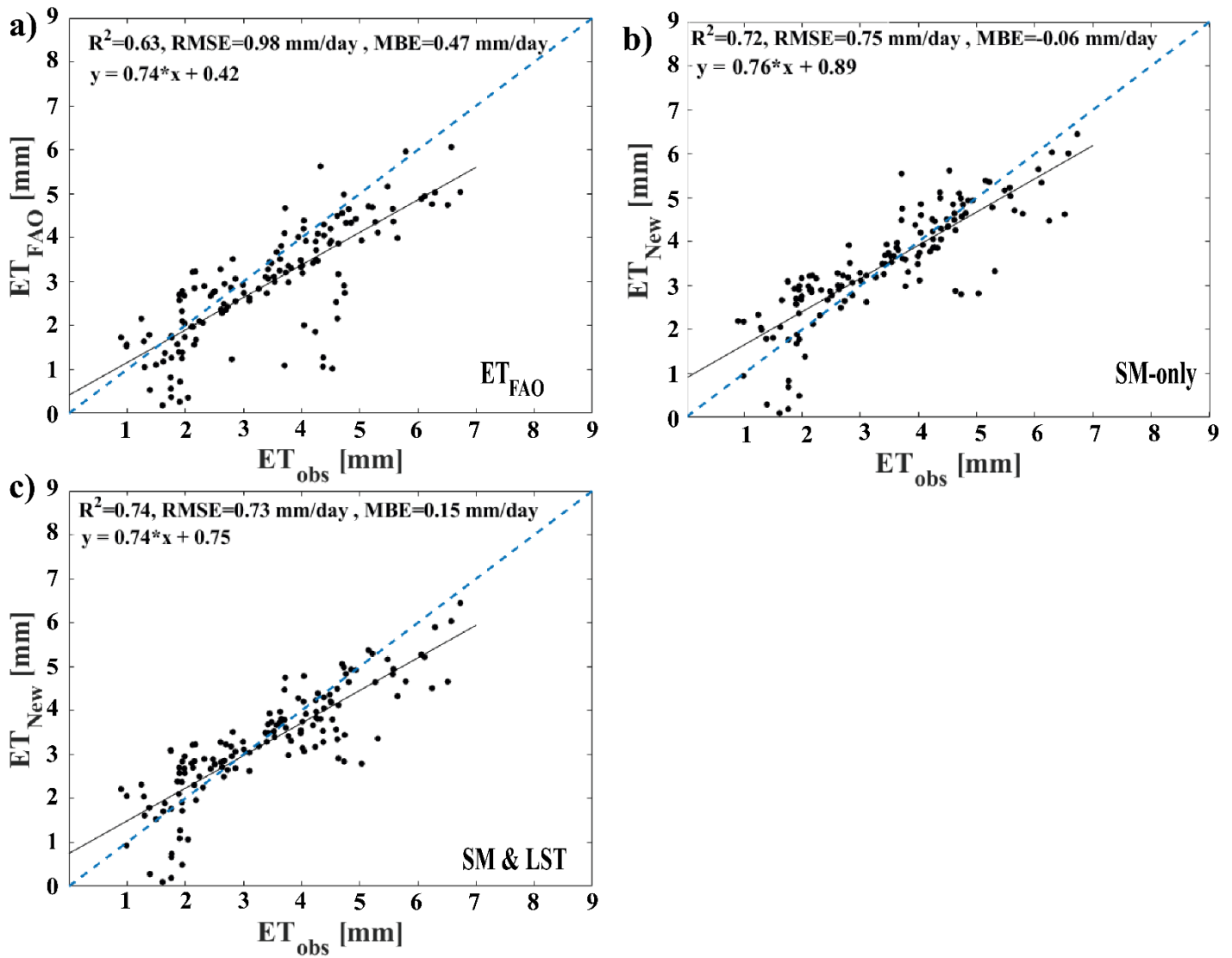
542 These results are in accordance with several works (Amazirh et al., 2021; Er-Raki et al., 2007;
543 Olivera-Guerra et al., 2018; Rafi et al., 2019). Realistic dynamics of SM allow reflecting
544 correctly the water budget closure to catch the variability of soil E_s . The better results obtained
545 when assimilating SM into FAO-dual K_c confirm this improvement where the integration of SM
546 data allows better control of the model variation, and by assimilation, we tend to adjust soil
547 water content and calibrating FAO-dual K_c model. In the classical FAO, the evaporation
548 coefficient K_e is linked mainly to soil texture based on a standard formulation using SM data
549 (*ad-hoc* relationship with soil texture). This could provide a limitation to some extent in the E_s
550 estimation over bare soil conditions (under/overestimation). By assimilating SM, we tend to
551 correct this issue by adjusting the soil evaporation coefficient, based on a relationship between
552 SM and E_s process taking into account soil types and surface conditions as in Merlin et al.
553 (2018, 2016).

554 Results of the coupled assimilation of SM and LST into FAO-dual K_c for both sites are also
555 given in Table 2. As seen from Table 2, combining LST and SM assimilation schemes provides
556 good results in comparison with standard FAO-dual K_c . The RMSE and the bias are reduced
557 from 0.98 mm/day and -0.47 mm/day to 0.55 mm/day and -0.14 mm/day while R^2 increases

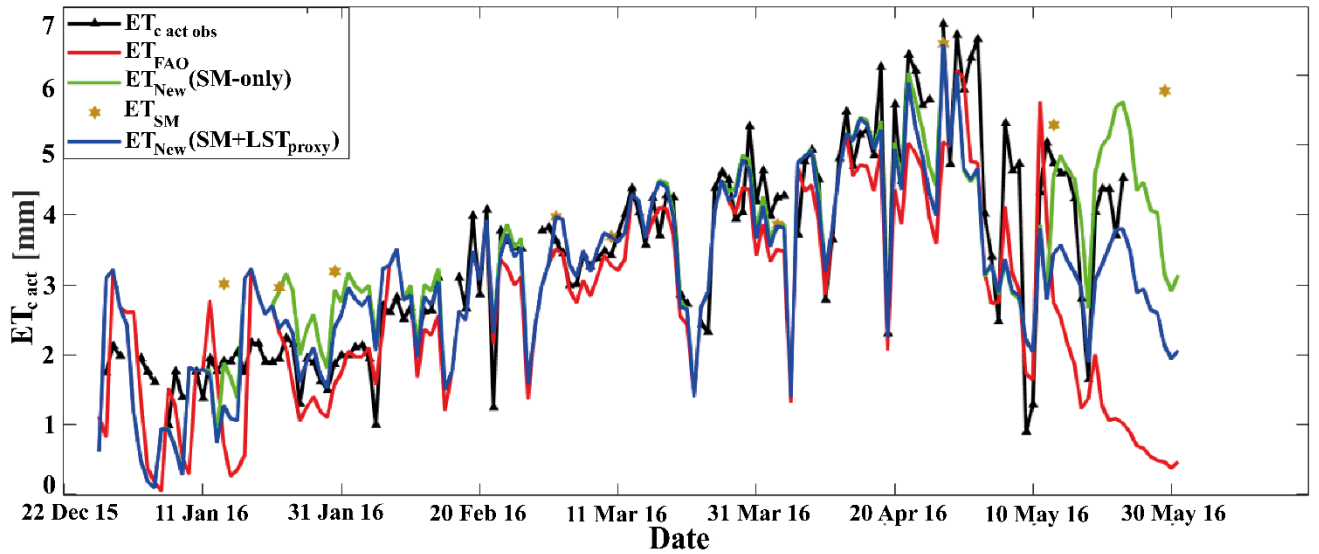
558 from 0.63 to 0.87 using FAO-dualK_c without assimilation and with assimilation of both SM and
559 LST-proxy conjointly, for F16 site, respectively. These results reveal that the best statistical
560 parameters are provided by jointly assimilating LST_{proxy} and SM data. Looking at the results,
561 for B123 site, it is noticed that the best results are provided when assimilating SM and LST
562 couple with an RMSE of 0.71 mm/day and MBE equal to 0.03 mm/day. While before
563 assimilation, the RMSE and MBE values for the ET_{c act} were 1.01 and -0.44 mm/day for the
564 B123 field, respectively. In the case of assimilating SM and LST couple, the effectiveness of
565 the assimilation process is mainly dominated by SM assimilation. Overall, the assimilation
566 approaches provide better results than the standard FAO-56. For F16 sites as an example, the
567 main discrepancies between ET_{c act} estimates before and after assimilation can be observed
568 during the development (between December 2015 to January 31, 2016) and late (from 10 May
569 to the end of the season) stages due to great differences in K_e estimates and thus in E_s. Late in
570 the season, a difference is observed between E_s estimates before and after the assimilation
571 procedure. In the standard FAO which is based on daily water balance, the water in the surface
572 evaporable layer is fully depleted means K_{e,FAO} ~ 0, and E_s ≈ 0. Whereas, when assimilating SM,
573 we tend to update the K_e, and then the evaporation increases to catch better the EC observations.
574 The increase in E_s can be explained by an increase of the sun-exposed soil due to the reduction
575 of vegetation and the capillary rise from the root zone, which can be detected from the SM
576 assimilated into the E_s estimates. Moreover, the underestimation of E_s by FAO-56 could be
577 explained by the definition of the depth of Z_e, where a 5 cm SM was used in this study to be
578 consistent with the remote sensing depth. As FAO suggested, Z_e should be ranging from 0.10-
579 0.15 cm based on the soil texture and this could affect the final result of E_s estimation as shown
580 previously in Amazirh et al. (2021).

581 **4.3. Assimilating remote sensing data into FAO-dualK_c**

582 To evaluate the spatial extensibility of the assimilation scheme, the daily ET_{c act} over the
583 selected F16 field during 2015–2016 was simulated at a spatial resolution of 100 m. Only F16
584 was chosen for the spatial analysis due to the availability of thermal data at high spatio-temporal
585 resolution as Landsat 7 and 8 data as well as SM data derived from SMAP. In this case, SM
586 data was derived from SMAP data product, which were disaggregated to 100 m (Ojha et al.,
587 2019), and LST data were derived from Landsat-7 and Landsat-8 data. As the *in situ* evaluation,
588 two assimilation techniques were tested: SM only and assimilating jointly SM and LST_{proxy}
589 couple into FAO model. Figures 7 and 8 present the scatter and time series plots of the obtained
590 results using the assimilation techniques, respectively.



592 *Figure 7: Scatter plot comparison between FAO-dualK_c and observed ET_{c act} (ET_{obs}) without*
 593 *assimilation 'ET_{FAO}' (a), when assimilating only soil moisture 'SM-only' (b) and conjointly*
 594 *soil moisture and land surface temperature 'SM and LST' (c).*

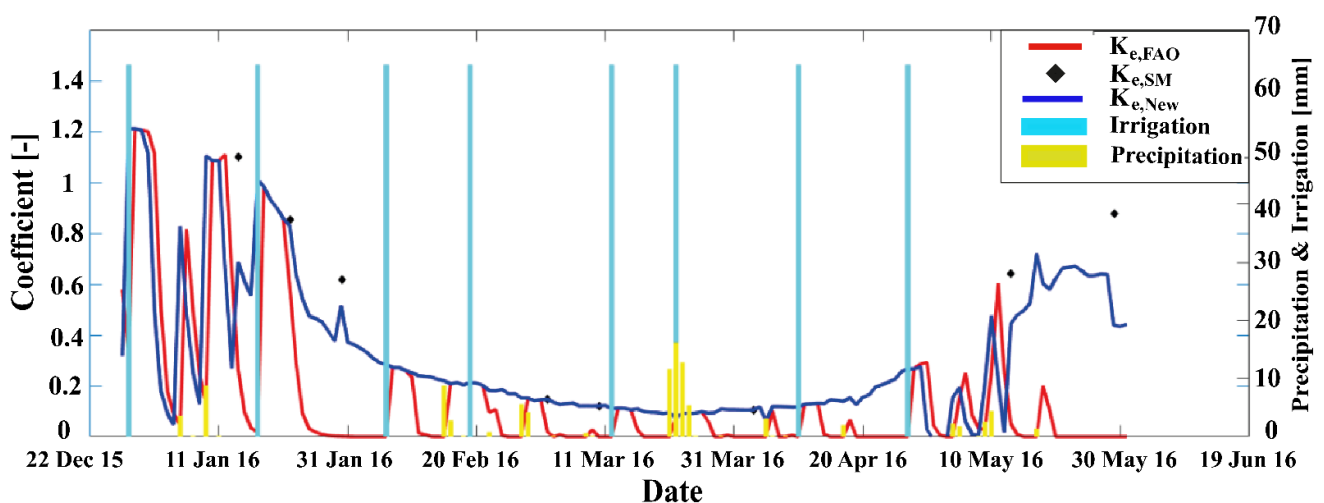


597 *Figure 8: Daily temporal comparison between FAO-dualK_c and observed ET_{c act} (ET_{obs})*
 598 *without assimilation and when assimilating SM-only (SM_{New} (SM-only)) and conjointly SM*
 599 *and LST-proxy (SM_{New} (SM + LST_{proxy})). The ET_{SM} is presented also (yellow hexagram)*
 600 *indicating the assimilation dates.*

601 From the obtained results in Figures 7 and 8, the assimilation approaches tend to improve the
 602 ET_{c act} estimates either using the proposed assimilation approaches. In the first case, the
 603 SM_{DISPATCH} products are only assimilated into FAO-dualK_c. Figures 7 and 8 compare the results
 604 of the assimilation procedure with the one from the open-loop ET_{FAO} (no assimilation, Figure
 605 7a and Figure 8 ‘red line’). When assimilating the SMAP based disaggregated SM_{DISPATCH}
 606 (Figure 7b and Figure 8 ‘green line’), the ET_{c act} estimates is improved where the error is reduced
 607 compared to ET_{FAO} from 0.98 mm/day to 0.75 mm/day, as well as the bias decreased from -
 608 0.47 mm/day to -0.06 mm/day. For the other case, when coupled assimilation of SM_{DISPATCH}
 609 and LST through using the normalized LST proxy, the RMSE is equal to 0.73 mm/day with a
 610 bias that doesn’t exceed 0.15 mm/day. Comparing both assimilation approaches, the lowest
 611 RMSE is assessed by assimilating both SM and LST into FAO model (Figure 7c and Figure 8
 612 ‘blue line’). Without assimilation (ET_{FAO}), FAO-dualK_c severely underestimates ET_{c act} during
 613 the senescence period (Figure 7a), where both assimilation experiments have slightly similar
 614 accuracy in ET_{c act} estimates. This is seen especially at the beginning and the end of the wheat
 615 growing season (Figure 8), where the SM improves the soil E_s when soil is under bare soil
 616 conditions.

617 We note that the assimilation using *in situ* data provided better and more accurate results than
 618 using remote sensing ones. This is due first to the data, where *in situ* data are the truth

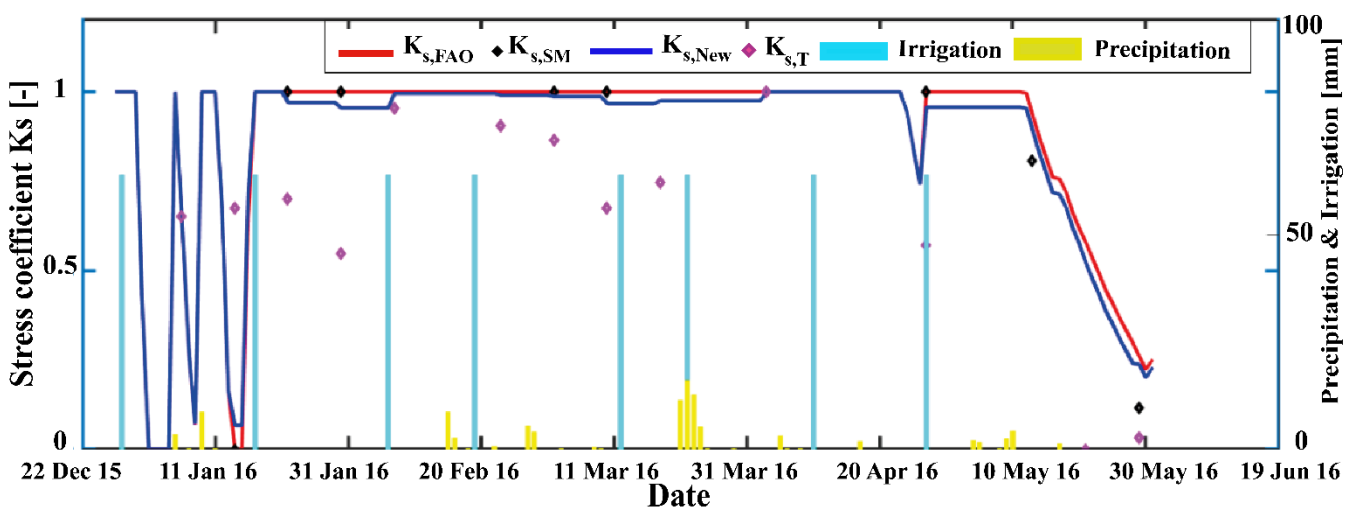
619 observations while the remotely sensed ones are estimated from model (Dispatch for SM) or
620 corrected (MODTRAN for LST) which generate a cumulated error. In this study a proxy of
621 LST was used, therefore the observed error of 2.16 °C when comparing Landsat LST and *in*
622 *situ* LST may less impact the $ET_{c\ act}$ results since a relative value of LST data (between 0-1)
623 was used. Then the frequency of the *in situ* perturbations (observations) is higher than the
624 remote sensing data (cloud effects and satellite revisit time). This could also impact the results,
625 where the higher assimilation frequency (sequence), the better the $ET_{c\ act}$ estimates are, as found
626 in Er-raki et al., (2008) and Fu et al. (2018). The assimilation of SM allows the updating of the
627 surface depletion (D_e), thus controlling the water budget at the surface then updating the K_e
628 coefficient of evaporation. By integrating the LST information, this allows the updating of the
629 root zone depletion D_r , which controls the temporal course of the root zone water budget, which
630 leads to correcting the K_s values. The idea of assimilating LST into the stress coefficient is to
631 improve the transpiration component. Both sites were well irrigated, and the stress appears just
632 in some periods during the investigated study. The real impact of LST on the water balance at
633 the root zone could be seen clearly in the case of a field that undergoes several stress periods
634 when irrigation is deliberately cut. In this study, just on some dates that the field is undergoing
635 stress period and by assimilating LST into FAO model we succeeded to capture the stress
636 periods. To better observe the difference on the assimilated $K_{e,SM}$ and the surface water balance
637 based $K_{e,FAO}$, Figure 9 illustrates the temporal course comparison between the estimated K_e by
638 FAO-dual K_c model without and with SM assimilation during 2015-2016 growing season for
639 F16 field.



641 *Figure 9: Comparison between the FAO-dual K_c evaporation coefficient $K_{e,FAO}$ before*
642 *assimilation (red line) and the updated one ($K_{e,New}$) after assimilation (blue line). The $K_{e,SM}$ is*

643 presented also (black rectangles) indicating the assimilation dates. Precipitation and
 644 irrigation events are shown as yellow and light blue bars, respectively.

645 As seen from Figure 9, K_e ranges from 0 to 1.2 for both cases. Nine available dates are used for
 646 the SM assimilation when SMAP $SM_{DISPATCH}$ data are available. For dry conditions (absence
 647 of irrigation or precipitation, e.g. from the 15th to 31st of January), an increase in the surface
 648 depletion leads to a decrease of both K_e and an increase of E_s surface resistance, which induces
 649 water stress at the surface. While, after an irrigation or rainfall, soil evaporates at a potential
 650 rate when the soil resistance is decreasing, which leads to an increase of K_e . From Figure 9, the
 651 daily pattern of $K_{e,FAO}$, and $K_{e,New}$ are similar and responds perfectly to water supply
 652 (precipitation or irrigation). Despite that, the assimilated $K_{e,New}$ is more physical which means
 653 it increased and decreased progressively, especially during the dryness period. This clearly
 654 appears at the 22nd and 11th of January, where the $K_{e,FAO}$ decreased sharply and suddenly than
 655 the $K_{e,New}$ that decreased gradually and slowly. It can be concluded that SM assimilation tends
 656 to adjust the duration of the dryness phenomena when the water content in the upper soil
 657 becomes limiting, taken into account the soil properties as shown in Amazirh et al. (2021).
 658 Especially in stage 2 when soil moisture is the limiting factor, the $K_{e,New}$ decreases progressively
 659 depending on the soil properties, this because of the response and the soil drying time which is
 660 well taken into account in the $K_{e,New}$ approach. For the coupled assimilation, the $K_{e,New}$ was
 661 taken to update the E_s component, while the introduction of LST data will update the stress
 662 coefficient K_s . Figure 10 shows the time variation comparison between the estimated K_s by
 663 FAO-56 model with assimilation ($K_{s,New}$) and without assimilation ($K_{s,FAO}$).
 664



665
 666 Figure 10: Comparison between the FAO-dual K_c stress coefficient $K_{s,FAO}$ before assimilation
 667 (red line) and the updated one ($K_{s,New}$) after assimilating LST_{proxy} and SM couple (blue line).

701 water balance models, given that forcing data (including irrigation) are accurately known. The
702 proposed study showed its capability to retrieve $ET_{c\ act}$ at field scale, a spatialization of $ET_{c\ act}$
703 is needed. This could be done by using LST and SM products at high resolution (Amazirh et
704 al., 2019; Ojha et al., 2019). Recently, Amazirh et al. (2021) proposed a new E_s formulation by
705 including the soil texture information into the reduction coefficient (K_r). The proposed
706 formulation demonstrates its better performance than the classical FAO. Combining the
707 assimilation of SM into E_s formulation developed in Amazirh et al. (2021) could provide more
708 accurate results by improving the E_s component.

709 **Declaration of competing interest**

710 The authors declare that they have no known competing financial interests or personal
711 relationships that could have appeared to influence the work reported in this paper.

712 **Acknowledgements**

713 This study was conducted within the Center of remote sensing applications
714 (<https://crsa.um6p.ma/>), at the Mohammed VI university-Morocco and funded by OCP (AS No
715 71). This work was also partly funded by the European Commission Horizon 2020 Programme
716 for Research and Innovation (H2020) in the context of the Marie Skłodowska-Curie Research
717 and Innovation Staff Exchange (RISE) action (REC project, grant agreement no: 645642),
718 followed by ACCWA project, grant agreement no. 823965). The *in situ* data set was provided
719 by the Joint International Laboratory TREMA (<http://trema.ucam.ac.ma>). PRIMA IDEWA and
720 ALTOS projects are also acknowledged.

721 **References**

- 722 Abbaszadeh, P., Moradkhani, H., Zhan, X., 2019. Downscaling SMAP Radiometer Soil
723 Moisture Over the CONUS Using an Ensemble Learning Method. *Water Resour. Res.* 55,
724 324–344. doi:10.1029/2018WR023354
- 725 Abdolghafoorian, A., Farhadi, L., 2020. LIDA: A Land Integrated Data Assimilation
726 Framework for Mapping Land Surface Heat and Evaporative Fluxes by Assimilating
727 Space-Borne Soil Moisture and Land Surface Temperature. *Water Resour. Res.* 56.
728 doi:10.1029/2020WR027183
- 729 Alberto, M.C.R., Quilty, J.R., Buresh, R.J., Wassmann, R., Haidar, S., Correa, T.Q., Sandro,
730 J.M., 2014. Actual evapotranspiration and dual crop coefficients for dry-seeded rice and
731 hybrid maize grown with overhead sprinkler irrigation. *Agric. Water Manage.* 136, 1–12.
732 doi:10.1016/j.agwat.2014.01.005
- 733 Alfieri, J.G., Kustas, W.P., Anderson, M.C., 2018. A Brief Overview of Approaches for
734 Measuring Evapotranspiration, in: *Agroclimatology: Linking Agriculture to Climate*. pp.
735 109–127. doi:10.2134/agronmonogr60.2016.0034

736 Allen, R.G., Pereira, L.S., Howell, T.A., Jensen, M.E., 2011. Evapotranspiration information
737 reporting: I. Factors governing measurement accuracy. *Agric. Water Manage.* 98, 899–
738 920. doi:10.1016/j.agwat.2010.12.015

739 Allen, R.G., Pereira, L.S., Raes, D., Smith, M., 1998. *Crop evapotranspiration - Guidelines for*
740 *computing crop water requirements - FAO Irrigation and drainage, Paper No. 56, FAO.*
741 *Rome, Italy.*

742 Amazirh, A., Er-Raki, S., Chehbouni, A., Rivalland, V., Diarra, A., Khabba, S., Ezzahar, J.,
743 Merlin, O., 2017. Modified Penman–Monteith equation for monitoring evapotranspiration
744 of wheat crop: Relationship between the surface resistance and remotely sensed stress
745 index. *Biosyst. Eng.* 164, 68–84. doi:10.1016/j.biosystemseng.2017.09.015

746 Amazirh, A., Merlin, O., Er-Raki, S., 2019. Including Sentinel-1 radar data to improve the
747 disaggregation of MODIS land surface temperature data. *ISPRS J. Photogramm. Remote*
748 *Sens.* 150, 11–26. doi:10.1016/j.isprsjprs.2019.02.004

749 Amazirh, A., Merlin, O., Er-Raki, S., Bouras, E., Chehbouni, A., 2021. Implementing a new
750 texture-based soil evaporation reduction coefficient in the FAO dual crop coefficient
751 method. *Agric. Water Manage.* 250, 106827. doi:10.1016/j.agwat.2021.106827

752 Amazirh, A., Merlin, O., Er-Raki, S., Gao, Q., Rivalland, V., Malbeteau, Y., Khabba, S.,
753 Escorihuela, M.J., 2018. Retrieving surface soil moisture at high spatio-temporal
754 resolution from a synergy between Sentinel-1 radar and Landsat thermal data: A study
755 case over bare soil. *Remote Sens. Environ.* 211, 321–337. doi:10.1016/j.rse.2018.04.013

756 ASCE-EWRI, 2004. *The ASCE Standardized Reference Evapotranspiration Equation.*
757 *American Society of Civil Engineers, Reston, VA.* doi:10.1061/9780784408056

758 Baldocchi, D.D., Hicks, B.B., Meyers, T.P., Hincks, B.B., Meyers, T.P., 1988. Measuring
759 biosphere-atmosphere exchanges of biologically related gases with micrometeorological
760 methods. *Ecology* 69, 1331–1340. doi:10.2307/1941631

761 Barker, J.B., Heeren, D.M., Neale, C.M.U., Rudnick, D.R., 2018. Evaluation of variable rate
762 irrigation using a remote-sensing-based model. *Agric. Water Manage.* 203, 63–74.
763 doi:10.1016/j.agwat.2018.02.022

764 Bateni, S.M., Entekhabi, D., 2012. Surface heat flux estimation with the ensemble Kalman
765 smoother: Joint estimation of state and parameters. *Water Resour. Res.* 48.
766 doi:10.1029/2011WR011542

767 Bhattarai, N., Mallick, K., Stuart, J., Vishwakarma, B.D., Niraula, R., Sen, S., Jain, M., 2019.
768 An automated multi-model evapotranspiration mapping framework using remotely sensed
769 and reanalysis data. *Remote Sens. Environ.* 229, 69–92. doi:10.1016/j.rse.2019.04.026

770 Bos, M.G., Kseklik, rob A.L., Allen, R.G., Molden, D.J., 2008. *Water Requirements for*
771 *Irrigation and the Environment.* doi:10.1007/978-1-4020-8948-0

772 Boulet, G., Rafi, Z., Le Dantec, V., Mallick, K., Olioso, A., Er-Raki, S., Merlin, O., 2019.
773 Evapotranspiration and Evaporation/Transpiration Retrieval Using Dual-Source Surface
774 Energy Balance Models Integrating VIS/NIR/TIR Data with Satellite Surface Soil
775 Moisture Information. *IGARSS 2019 - 2019 IEEE Int. Geosci. Remote Sens. Symp.* 6283–
776 6286. doi:10.1109/igarss.2019.8900333

777 Burba, G., 2013. *Eddy Covariance Method-for Scientific, Industrial, Agricultural, and*
778 *Regulatory Applications, LI-COR Biosciences.* doi:10.13140/RG.2.1.4247.8561

779 Caparrini, F., Castelli, F., Entekhabi, D., 2004. Estimation of surface turbulent fluxes through
780 assimilation of radiometric surface temperature sequences. *J. Hydrometeorol.* 5, 145–159.
781 doi:10.1175/1525-7541(2004)005<0145:EOSTFT>2.0.CO;2

782 Chehbouni, A., Escadafal, R., Duchemin, B., Boulet, G., Simonneaux, V., Dedieu, G.,
783 Mougnot, B., Khabba, S., Kharrou, H., Maisongrande, P., Merlin, O., Chaponnière, A.,
784 Ezzahar, J., Er-Raki, S., Hoedjes, J., Hadria, R., Abourida, A., Cheggour, A., Raibi, F.,
785 Boudhar, A., Benhadj, I., Hanich, L., Benkaddour, A., Guemouria, N., Chehbouni, A.H.,

786 Lahrouni, A., Oliosio, A., Jacob, F., Williams, D.G., Sobrino, J. a, 2008. An integrated
787 modelling and remote sensing approach for hydrological study in arid and semi-arid
788 regions: the SUDMED Programme. *Int. J. Remote Sens.* 29, 5161–5181.
789 doi:10.1080/01431160802036417

790 Chen, S., Qi, J., Sun, X., Deng, X., Tian, J., 2013. An evapotranspiration assimilation method
791 based on ensemble kalman filter and À trous wavelet. *Adv. Meteorol.* 2013.
792 doi:10.1155/2013/531810

793 Courtier, P., Derber, J., Errico, R., Louis, J., Vukicevic, T., 1993. Important literature on the
794 use of adjoint, variational methods and the Kalman filter in meteorology. *Tellus A* 45,
795 342–357. doi:10.1034/j.1600-0870.1993.t01-4-00002.x

796 Dee, D., Uppala, S., Simmons, A., Berrisford, P., Poli, P., Kobayashi, S., Andrae, U.,
797 Balmaseda, M., Balsamo, G., Bauer, P., 2011. The ERA - Interim reanalysis:
798 Configuration and performance of the data assimilation system. *Quarterly J. R. Meteorol.*
799 *Soc.* 137, 553–597. doi:10.1002/qj.828

800 DeJonge, K.C., Taghvaeian, S., Trout, T.J., Comas, L.H., 2015. Comparison of canopy
801 temperature-based water stress indices for maize. *Agric. Water Manage.* 156, 51–62.
802 doi:10.1016/j.agwat.2015.03.023

803 Drerup, P., Brueck, H., Scherer, H.W., 2017. Evapotranspiration of winter wheat estimated with
804 the FAO 56 approach and NDVI measurements in a temperate humid climate of NW
805 Europe. *Agric. Water Manage.* 192, 180–188. doi:10.1016/j.agwat.2017.07.010

806 Elfarkh, J., Er-Raki, S., Ezzahar, J., Chehbouni, A., Aithssaine, B., Amazirh, A., Khabba, S.,
807 Jarlan, L., 2021. Integrating thermal stress indexes within Shuttleworth–Wallace model
808 for evapotranspiration mapping over a complex surface. *Irrig. Sci.* 39, 45–61.
809 doi:10.1007/s00271-020-00701-3

810 Entekhabi, D., Yueh, Si., O’Neil, P.E., Kellogg, K.H., Allen, A., Bindlish, R., Administration,
811 N.A. and S., 2014. SMAP Handbook–Soil Moisture Active Passive: Mapping Soil
812 Moisture and Freezes/Thaw from Space. Jet Propulsion Laboratory, Pasadena, CA, USA.

813 Er-Raki, S., Chehbouni, A., Ezzahar, J., Khabba, S., Lakhal, E.K., Duchemin, B., 2011. Derived
814 crop coefficients for winter wheat using different reference evapotranspiration estimates
815 methods. *J. Agric. Sci. Technol.* 13, 209–221.

816 Er-Raki, S., Chehbouni, A., Guemouria, N., Duchemin, B., Ezzahar, J., Hadria, R., 2007.
817 Combining FAO-56 model and ground-based remote sensing to estimate water
818 consumptions of wheat crops in a semi-arid region. *Agric. Water Manage.* 87, 41–54.
819 doi:10.1016/j.agwat.2006.02.004

820 Er-Raki, S., Chehbouni, A., Hoedjes, J., Ezzahar, J., Duchemin, B., Jacob, F., 2008.
821 Improvement of FAO-56 method for olive orchards through sequential assimilation of
822 thermal infrared-based estimates of ET. *Agric. Water Manag.* 95, 309–321.
823 doi:10.1016/j.agwat.2007.10.013

824 Er-Raki, S., Ezzahar, J., Khabba, S., Jarlan, L., Kharrou, M.H., Chehbouni, G., 2013.
825 Micrometeorology tools for measuring evapotranspiration from the leaf to the region, in:
826 *Evapotranspiration: Processes, Sources and Environmental Implications.* New York :
827 Nova Science, (Environmental Science, Engineering and Technology), pp. 1–22.

828 Ezzahar, J., Chehbouni, A., 2009. The use of scintillometry for validating aggregation schemes
829 over heterogeneous grids. *Agric. For. Meteorol.* 149, 2098–2109.
830 doi:10.1016/J.AGRFORMET.2009.09.004

831 French, A.N., Hunsaker, D.J., Sanchez, C.A., Saber, M., Gonzalez, J.R., Anderson, R., 2020.
832 Satellite-based NDVI crop coefficients and evapotranspiration with eddy covariance
833 validation for multiple durum wheat fields in the US Southwest. *Agric. Water Manage.*
834 239. doi:10.1016/j.agwat.2020.106266

835 French, A.N., Hunsaker, D.J., Thorp, K.R., 2015. Remote sensing of evapotranspiration over

836 cotton using the TSEB and METRIC energy balance models. *Remote Sens. Environ.* 158,
837 281–294. doi:10.1016/j.rse.2014.11.003

838 Fu, X., Yu, Z., Ding, Y., Tang, Y., Lu, H., 2018. Analysis of influence of observation operator
839 on sequential data assimilation through soil temperature simulation with common land
840 model. *Water Sci. Eng.* 11, 196–204. doi:10.1016/j.wse.2018.09.003

841 Gerhards, M., Schlerf, M., Mallick, K., Udelhoven, T., 2019. Challenges and future
842 perspectives of multi-/Hyperspectral thermal infrared remote sensing for crop water-stress
843 detection: A review. *Remote Sens.* 11. doi:10.3390/rs11101240

844 Gokmen, M., Vekerdy, Z., Verhoef, A., Verhoef, W., Batelaan, O., van der Tol, C., 2012.
845 Integration of soil moisture in SEBS for improving evapotranspiration estimation under
846 water stress conditions. *Remote Sens. Environ.* 121, 261–274.
847 doi:10.1016/j.rse.2012.02.003

848 Granger, R., 2000. Satellite-derived estimates of evapotranspiration in the Gediz basin. *J.*
849 *Hydrol.* 229, 70–76. doi:10.1016/S0022-1694(99)00200-0

850 He, X., Xu, T., Bateni, S.M., Neale, C.M.U., Liu, S., Auligne, T., Wang, K., Zhu, S., 2019.
851 Mapping Regional Turbulent Heat Fluxes via Assimilation of MODIS Land Surface
852 Temperature Data into an Ensemble Kalman Smoother Framework. *Earth Sp. Sci.* 6.
853 doi:10.1029/2019EA000705

854 Idso, S.B., Jackson, R.D., Pinter, P.J., Reginato, R.J., Hatfield, J.L., 1981. Normalizing the
855 stress-degree-day parameter for environmental variability. *Agric. Meteorol.*
856 doi:10.1016/0002-1571(81)90032-7

857 Ihuoma, S.O., Madramootoo, C.A., 2017. Recent advances in crop water stress detection.
858 *Comput. Electron. Agric.* 141, 267–275. doi:10.1016/j.compag.2017.07.026

859 Kalma, J.D., McVicar, T.R., McCabe, M.F., 2008. Estimating land surface evaporation: A
860 review of methods using remotely sensed surface temperature data. *Surv. Geophys.* 29,
861 421–469. doi:10.1007/s10712-008-9037-z

862 Kharrou, M.H., Le Page, M., Chehbouni, A., Simonneaux, V., Er-Raki, S., Jarlan, L., Ouzine,
863 L., Khabba, S., Chehbouni, G., 2013. Assessment of Equity and Adequacy of Water
864 Delivery in Irrigation Systems Using Remote Sensing-Based Indicators in Semi-Arid
865 Region, Morocco. *Water Resour. Manage.* 27, 4697–4714. doi:10.1007/s11269-013-0438-
866 5

867 Ko, J., Piccinni, G., Marek, T., Howell, T., 2009. Determination of growth-stage-specific crop
868 coefficients (Kc) of cotton and wheat. *Agric. Water Manage.* 96, 1691–1697.
869 doi:10.1016/j.agwat.2009.06.023

870 Kohsiek, W., Meijninger, W.M.L., Moene, A.F., Heusinkveld, B.G., Hartogensis, O.K., Hillen,
871 W.C.A.M., De Bruin, H.A.R., 2002. An Extra Large Aperture Scintillometer For Long
872 Range Applications. *Boundary-Layer Meteorol.* 105, 119–127.
873 doi:10.1023/A:1019600908144

874 Kullberg, E.G., DeJonge, K.C., Chávez, J.L., 2017. Evaluation of thermal remote sensing
875 indices to estimate crop evapotranspiration coefficients. *Agric. Water Manage.* 179, 64–
876 73. doi:10.1016/j.agwat.2016.07.007

877 Kumar, S. V., Reichle, R.H., Peters-Lidard, C.D., Koster, R.D., Zhan, X., Crow, W.T.,
878 Eylander, J.B., Houser, P.R., 2008. A land surface data assimilation framework using the
879 land information system: Description and applications. *Adv. Water Resour.* 31, 1419–
880 1432. doi:10.1016/j.advwatres.2008.01.013

881 Kustas, W.P., Norman, J.M., 1996. Use of remote sensing for evapotranspiration monitoring
882 over land surfaces. *Hydrol. Sci. J.* 41, 495–516. doi:10.1080/02626669609491522

883 Li, Z.-L.L., Tang, R., Wan, Z., Bi, Y., Zhou, C., Tang, B., Yan, G., Zhang, X., Li, Z.-L.L.,
884 Tang, R., Wan, Z., Bi, Y., Zhou, C., Tang, B., Yan, G., Zhang, X., 2009. A review of
885 current methodologies for regional Evapotranspiration estimation from remotely sensed

886 data. *Sensors* 9, 3801–3853. doi:10.3390/s90503801

887 Littell, J.S., Peterson, D.L., Riley, K.L., Liu, Y., Luce, C.H., 2016. A review of the relationships
888 between drought and forest fire in the United States. *Glob. Chang. Biol.* 22, 2353–2369.
889 doi:10.1111/gcb.13275

890 Liu, Y., Luo, Y., 2010. A consolidated evaluation of the FAO-56 dual crop coefficient approach
891 using the lysimeter data in the North China Plain. *Agric. Water Manage.* 97, 31–40.
892 doi:10.1016/j.agwat.2009.07.003

893 Madugundu, R., Al-Gaadi, K.A., Tola, E.K., Hassaballa, A.A., Patil, V.C., 2017. Performance
894 of the METRIC model in estimating evapotranspiration fluxes over an irrigated field in
895 Saudi Arabia using Landsat-8 images. *Hydrol. Earth Syst. Sci.* 21, 6135–6151.
896 doi:10.5194/hess-21-6135-2017

897 McLaughlin, D., Zhou, Y., Entekhabi, D., Chatdarong, V., 2006. Computational issues for
898 large-scale land surface data assimilation problems. *J. Hydrometeorol.* 7, 494–510.
899 doi:10.1175/JHM493.1

900 Merlin, O., Chehbouni, A., Boulet, G., Kerr, Y., 2006. Assimilation of Disaggregated
901 Microwave Soil Moisture into a Hydrologic Model Using Coarse-Scale Meteorological
902 Data. *J. Hydrometeorol.* 7, 1308–1322. doi:10.1175/JHM552.1

903 Merlin, O., Olivera-guerra, L., Ait Hssaine, B., Amazirh, A., Ra, Z., Ezzahar, J., Gentine, P.,
904 Khabba, S., Gascoin, S., Er-raki, S., 2018. A phenomenological model of soil evaporative
905 efficiency using surface soil moisture and temperature data. *Agric. For. Meteorol.* 257,
906 501–515. doi:10.1016/j.agrformet.2018.04.010

907 Merlin, O., Stefan, V.G.V.G.G., Amazirh, A., Chanzy, A., Ceschia, E., Er-Raki, S., Gentine,
908 P., Tallec, T., Ezzahar, J., Bircher, S., Beringer, J., Khabba, S., Gentine, P., Er-Raki, S.,
909 Bircher, S., Khabba, S., 2016. Modeling soil evaporation efficiency in a range of soil and
910 atmospheric conditions using a meta-analysis approach. *Water Resour. Res.* 52, 3663–
911 3684. doi:10.1002/2015WR018233.Received

912 Molden, D., Oweis, T., Steduto, P., Bindraban, P., Hanjra, M.A., Kijne, J., 2010. Improving
913 agricultural water productivity: Between optimism and caution. *Agric. Water Manage.* 97,
914 528–535. doi:10.1016/j.agwat.2009.03.023

915 Moradkhani, H., Hsu, K.L., Gupta, H., Sorooshian, S., 2005. Uncertainty assessment of
916 hydrologic model states and parameters: Sequential data assimilation using the particle
917 filter. *Water Resour. Res.* 41, 1–17. doi:10.1029/2004WR003604

918 Neale, C.M.U., Geli, H.M.E., Kustas, W.P., Alfieri, J.G., Gowda, P.H., Evett, S.R., Prueger,
919 J.H., Hipps, L.E., Dulaney, W.P., Chávez, J.L., French, A.N., Howell, T.A., 2012. Soil
920 water content estimation using a remote sensing based hybrid evapotranspiration modeling
921 approach. *Adv. Water Resour.* 50, 152–161. doi:10.1016/j.advwatres.2012.10.008

922 Ojha, N., Merlin, O., Molero, B., Suere, C., Olivera-Guerra, L., Ait Hssaine, B., Amazirh, A.,
923 Al Bitar, A., Escorihuela, M., Er-Raki, S., 2019. Stepwise Disaggregation of SMAP Soil
924 Moisture at 100 m Resolution Using Landsat-7/8 Data and a Varying Intermediate
925 Resolution. *Remote Sens.* 11, 1863. doi:10.3390/rs11161863

926 Olioso, A., 1995. Estimating the difference between brightness and surface temperatures for a
927 vegetal canopy. *Agric. For. Meteorol.* 72, 237–242. doi:10.1016/0168-1923(94)02163-E

928 Olivera-Guerra, L., Merlin, O., Er-Raki, S., Khabba, S., Escorihuela, M.J., 2018. Estimating
929 the water budget components of irrigated crops: Combining the FAO-56 dual crop
930 coefficient with surface temperature and vegetation index data. *Agric. Water Manage.* 208,
931 120–131. doi:10.1016/j.agwat.2018.06.014

932 Paço, T.A., Pôças, I., Cunha, M., Silvestre, J.C., Santos, F.L., Paredes, P., Pereira, L.S., 2014.
933 Evapotranspiration and crop coefficients for a super intensive olive orchard. An
934 application of SIMDualKc and METRIC models using ground and satellite observations.
935 *J. Hydrol.* 519. doi:10.1016/j.jhydrol.2014.09.075

936 Paredes, P., Rodrigues, G.C., Alves, I., Pereira, L.S., 2014. Partitioning evapotranspiration,
937 yield prediction and economic returns of maize under various irrigation management
938 strategies. *Agric. Water Manage.* 135. doi:10.1016/j.agwat.2013.12.010

939 Peng, J., Loew, A., Merlin, O., Verhoest, N.E.C., 2017. A review of spatial downscaling of
940 satellite remotely sensed soil moisture. *Rev. Geophys.* 55, 341–366.
941 doi:10.1002/2016RG000543

942 Pereira, L.S., Paredes, P., Hunsaker, D.J., López-Urrea, R., Mohammadi Shad, Z., 2021.
943 Standard single and basal crop coefficients for field crops. Updates and advances to the
944 FAO56 crop water requirements method. *Agric. Water Manage.*
945 doi:10.1016/j.agwat.2020.106466

946 Pereira, L.S., Paredes, P., Jovanovic, N., 2020. Soil water balance models for determining crop
947 water and irrigation requirements and irrigation scheduling focusing on the FAO56
948 method and the dual Kc approach. *Agric. Water Manage.*
949 doi:10.1016/j.agwat.2020.106357

950 Pipunic, R.C., Walker, J.P., Western, A., 2008. Assimilation of remotely sensed data for
951 improved latent and sensible heat flux prediction: A comparative synthetic study. *Remote*
952 *Sens. Environ.* 112, 1295–1305. doi:10.1016/j.rse.2007.02.038

953 Rafi, Z., Merlin, O., Le Dantec, V., Khabba, S., Mordelet, P., Er-Raki, S., Amazirh, A., Olivera-
954 Guerra, L., Ait Hssaine, B., Simonneaux, V., Ezzahar, J., Ferrer, F., 2019. Partitioning
955 evapotranspiration of a drip-irrigated wheat crop: Inter-comparing eddy covariance-, sap
956 flow-, lysimeter- and FAO-based methods. *Agric. For. Meteorol.* 265, 310–326.
957 doi:10.1016/j.agrformet.2018.11.031

958 Rosa, R.D., Paredes, P., Rodrigues, G.C., Alves, I., Fernando, R.M., Pereira, L.S., Allen, R.G.,
959 2012a. Implementing the dual crop coefficient approach in interactive software. 1.
960 Background and computational strategy. *Agric. Water Manage.* 103.
961 doi:10.1016/j.agwat.2011.10.013

962 Rosa, R.D., Paredes, P., Rodrigues, G.C., Fernando, R.M., Alves, I., Pereira, L.S., Allen, R.G.,
963 2012b. Implementing the dual crop coefficient approach in interactive software: 2. Model
964 testing. *Agric. Water Manage.* 103. doi:10.1016/j.agwat.2011.10.018

965 Rosenberg, N.J., Blad, B.L., Verma, S.B., 1983. *Microclimate. The Biological Environment* (2
966 nd edition), Wiley–Blac. ed.

967 Schuurmans, J.M., Troch, P.A., Veldhuizen, A.A., Bastiaanssen, W.G.M., Bierkens, M.F.P.,
968 2003. Assimilation of remotely sensed latent heat flux in a distributed hydrological model.
969 *Adv. Water Resour.* 26, 151–159. doi:10.1016/S0309-1708(02)00089-1

970 Seguin, B., Itier, B., 1983. Using midday surface temperature to estimate daily evaporation
971 from satellite thermal IR data. *Int. J. Remote Sens.* 4, 371–383.
972 doi:10.1080/01431168308948554

973 Stanev, E., Schulz-Stellenfleth, J., 2014. *Methods of data assimilation.* Kuste 133–151.

974 Tajfar, E., Bateni, S.M., Lakshmi, V., Ek, M., 2020. Estimation of surface heat fluxes via
975 variational assimilation of land surface temperature, air temperature and specific humidity
976 into a coupled land surface-atmospheric boundary layer model. *J. Hydrol.* 583.
977 doi:10.1016/j.jhydrol.2020.124577

978 Tardy, B., Rivalland, V., Huc, M., Hagolle, O., Marcq, S., Boulet, G., 2016. A Software Tool
979 for Atmospheric Correction and Surface Temperature Estimation of Landsat Infrared
980 Thermal Data. *Remote Sens.* 8, 696. doi:10.3390/rs8090696

981 Tasumi, M., 2019. Estimating evapotranspiration using METRIC model and Landsat data for
982 better understandings of regional hydrology in the western Urmia Lake Basin. *Agric.*
983 *Water Manage.* 226, 105805. doi:10.1016/j.agwat.2019.105805

984 Testi, L., Villalobos, F., Orgaz, F., 2004. Evapotranspiration of a young irrigated olive orchard
985 in southern Spain. *Agric.For.Meteorol* 121, 1–18.

986 doi:10.1016/J.AGRFORMET.2003.08.005
987 Tian, X., Xie, Z., Dai, A., 2008. An ensemble-based explicit four-dimensional variational
988 assimilation method. *J. Geophys. Res. Atmos.* 113. doi:10.1029/2008JD010358
989 Twine, T.E., Kustas, W.P., Norman, J.M., Cook, D.R., Houser, P.R., Meyers, T.P., Prueger,
990 J.H., Starks, P.J., Wesely, M.L., 2000. Correcting eddy-covariance flux underestimates
991 over a grassland. *Agric. For. Meteorol.* 103, 279–300. doi:10.1016/S0168-
992 1923(00)00123-4
993 Walker, E., García, G.A., Venturini, V., Carrasco, A., 2019. Regional evapotranspiration
994 estimates using the relative soil moisture ratio derived from SMAP products. *Agric. Water*
995 *Manage.* 216, 254–263. doi:10.1016/j.agwat.2019.02.009
996 Wang, X., Ma, M., Han, X., Song, Y., 2009. Assimilation of soil moisture in LPJ-DGVM.
997 *Remote Sens. Agric. Ecosyst. Hydrol.* XI 7472, 747220. doi:10.1117/12.830312
998 Xie, X., Zhang, D., 2010. Data assimilation for distributed hydrological catchment modeling
999 via ensemble Kalman filter. *Adv. Water Resour.* 33, 678–690.
1000 doi:10.1016/j.advwatres.2010.03.012
1001 Xu, T., Bateni, S.M., Margulis, S.A., Song, L., Liu, S., Xu, Z., 2016. Partitioning
1002 evapotranspiration into soil evaporation and canopy transpiration via a two-source
1003 variational data assimilation system. *J. Hydrometeorol.* 17, 2353–2370. doi:10.1175/JHM-
1004 D-15-0178.1
1005 Xu, T., He, X., Bateni, S.M., Auligne, T., Liu, S., Xu, Z., Zhou, J., Mao, K., 2019. Mapping
1006 regional turbulent heat fluxes via variational assimilation of land surface temperature data
1007 from polar orbiting satellites. *Remote Sens. Environ.* 221. doi:10.1016/j.rse.2018.11.023
1008 Xu, T., Liang, S., Liu, S., 2011. Estimating turbulent fluxes through assimilation of
1009 geostationary operational environmental satellites data using ensemble Kalman filter. *J.*
1010 *Geophys. Res. Atmos.* 116. doi:10.1029/2010JD015150
1011 Zribi, M., Chahbi, A., Shabou, M., Lili-Chabaane, Z., Duchemin, B., Baghdadi, N., Amri, R.,
1012 Chehbouni, A., 2011. Soil surface moisture estimation over a semi-arid region using
1013 ENVISAT ASAR radar data for soil evaporation evaluation. *Hydrol. Earth Syst. Sci.* 15,
1014 345–358. doi:10.5194/hess-15-345-2011
1015