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A phenomenological model of soil evaporative efficiency using surface soil moisture and temperature data

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Abstract

Modeling soil evaporation has been a notorious challenge due to the complexity of the phenomenon and the lack of data to constrain it. In this context, a parsimonious model is developed to estimate soil evaporative efficiency (SEE) defined as the ratio of actual to potential soil evaporation. It uses a soil resistance driven by surface (0 – 5 cm) soil moisture, meteorological forcing and time (hour) of day, and has the capability to be calibrated using the radiometric surface temperature derived from remotely sensed thermal data. The new approach is tested over a rainfed semi-arid site, which had been under bare soil conditions during a 9-month period in 2016. Three calibration strategies are adopted based on SEE time series derived from 1) eddy-covariance measurements, 2) thermal measurements, and 3) eddy-covariance measurements used only over separate drying periods between significant rainfall events. The correlation coefficients (and slopes of the linear regression) between simulated and observed (eddy-covariance-derived) SEE

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are 0.85, 0.86 and 0.87 (and 0.91, 0.87 and 0.91) for calibration strategies 1, 2 and 3, respectively. Moreover, the correlation coefficient (and slope of the linear regression) between simulated and observed SEE is improved from 0.80 to 0.85 (from 0.86 to 0.91) when including hour of day in the soil resistance. The reason is that, under non-energy-limited conditions, the receding evaporation front during daytime makes SEE decrease at the hourly time scale. The soil resistance formulation can be integrated into state-of-the-art dual-source surface models and has calibration capabilities across a range of spatial scales from spaceborne microwave and thermal data.

Key words: Soil evaporation, soil resistance, soil moisture, surface temperature, calibration, remote sensing.

1 **1. Introduction**

2 To better understanding the water fluxes of crops, and optimizing irriga-
3 tion in water-limited environments, efforts are being made to estimate both
4 the plant consumption by transpiration (through stomata) and the water
5 losses by evaporation (from soil and in some instances from canopy via in-
6 terception) (Agam et al., 2012). The partitioning of evapotranspiration into
7 soil evaporation and plant transpiration is needed to assess the crop water
8 use efficiency through its transpiration rate (Hain et al., 2009), as well as
9 to evaluate how much production is derived per unit of crop transpiration
10 (Molden et al., 2010). Such information is also needed at multiple spatial
11 scales, from the field scale where agronomic practices are carried out (Allen,
12 1990), to the catchment scale where land and water management is operated
13 (Zhang et al., 2001).

14 Field instrumentation for measuring soil evaporation and plant transpi-
15 ration separately includes eddy covariance, micro Bowen-ratio energy bal-
16 ance, micro lysimeter, soil heat pulse probe, chamber, isotope and sap flow
17 techniques (Kool et al., 2014). Although those instrumentations have much
18 evolved since the initial experimentations in the 1970s, data collected *in*
19 *situ* are still very scarce (Schlesinger and Jasechko, 2014) and are generally
20 representative of the local conditions, that is from the leaf/stem to approxi-
21 mately the 100-m scale. This results in a large uncertainty of the transpira-
22 tion/evapotranspiration ratio (estimated in the range 0.35 – 0.80) associated
23 with a current lack of observation at the catchment scale (Coenders-Gerrits
24 et al., 2014).

25 To help evaluate the evaporation/transpiration partitioning at multiple
26 space-time scales, advanced land-surface models are available to simulate en-
27 ergy, water, and carbon fluxes at the land surface-atmosphere interface (Ole-
28 son et al., 2013; Boone et al., 2017, e.g.). Simpler models such as two-source
29 surface energy balance models (Lhomme and Chehbouni, 1999) require less
30 input parameters. In general, state-of-the-art models rely on specific assump-
31 tions on either the soil evaporation (Caparrini et al., 2004) or the plant tran-
32 spiration (Kustas and Norman, 1999), or base their two-source representation
33 on semi-empirical or semi-physical resistances. Whereas semi-empirical resis-
34 tances are difficult to generalize in a range of agro-environmental conditions
35 (Ershadi et al., 2014), semi-physical resistances generally depend on soil hy-
36 drodynamic properties (Decker et al., 2017), which are highly variable and
37 yet unavailable over large areas (Gutmann and Small, 2007).

38 To address the above-described difficulties in representing the evapora-

39 tion/transpiration components across a range of space-time scales using a
40 two-source resistance-based formulation, remote sensing data have great po-
41 tential. In fact, one way of separating soil evaporation and plant transpiration
42 is to estimate one component independently from the total evapotranspira-
43 tion. In this regard, the soil evaporation process is quite well constrained
44 by available remote sensing observations. Surface soil moisture derived from
45 microwave data is one main controlling factor of evaporation (Prévot et al.,
46 1984), and the radiometric soil temperature derived from thermal data in
47 the absence of dense vegetation cover is, under non-energy-limited condi-
48 tions, a signature of the evaporation rate (Norman et al., 1995). However,
49 although thermal-microwave data combining approaches have been imagined
50 since the 1990s (Chanzy et al., 1995; Li et al., 2006), none has been imple-
51 mented yet. One of the reasons is the lack of remote sensing sensors with
52 sufficient spatio-temporal resolution. Especially, the operational extraction
53 of surface soil moisture at high-spatial resolution remains delicate and there
54 is no thermal mission providing data at high spatio-temporal resolution. As
55 a step forward, recently launched/future satellite missions such as Sentinel-1
56 (Paloscia et al., 2013) and Trishna (Lagouarde et al., 2013) as well as disag-
57 gregation techniques (Peng et al., 2017; Zhan et al., 2013) could solve this
58 issue in the near future.

59 Another major issue when attempting to integrate thermal data in an
60 evaporation model is the drying (usually around noon) of the top few mil-
61 limeters of soil which inhibits evaporation, regardless of the availability of the
62 soil water underneath (Mahrt and Pan, 1984; Dickinson et al., 1986; Soares
63 et al., 1988; Wetzal and Chang, 1988; Van de Griend and Owe, 1994; Heitman

64 et al., 2008; Shahraeeni et al., 2012). Or et al. (2013) identify two regimes:
65 Stage I when both liquid phase continuity and capillary forces sustain evap-
66 oration at the top soil and Stage II when the drying front is deeper in the
67 soil and evaporation is mainly controlled by diffusion (Haghighi et al., 2013).
68 In fact, the soil drying during daytime and the uniform rewetting of soil via
69 capillary rises during nighttime is a cyclic phenomenon that is expected to
70 affect the evaporation resistance at the hourly time scale (Tuzet et al., 2003).
71 One challenge is that the radiometric soil temperature is highly variable in
72 time as a result of the diurnal dynamics of meteorological forcing (i.e. solar
73 radiation, wind speed, air temperature, air humidity) and the evolution of
74 soil moisture. Additionally, it is representative of the physical characteristics
75 of the soil skin only. A direct consequence is that a thermal-based evapo-
76 ration model should beneficially take into account the drying of the top soil
77 during daytime.

78 This was the rationale for developing a formulation of soil evaporative
79 efficiency (SEE, defined as the ratio of actual to potential soil evaporation)
80 with a shape that adapts to the soil moisture gradient. Given that the soil
81 moisture profile is generally unknown, and that the drying of the top soil is
82 related to the evaporative demand (in addition to the soil moisture value),
83 Merlin et al. (2011) considered potential evaporation as a proxy for the soil
84 moisture gradient in the topsoil. In fact, a large potential evaporation is
85 associated with a strong moisture gradient in the top soil, which implies
86 a decrease of SEE regardless of the moisture content integrated over the
87 0 – 5 cm soil layer. Such a phenomenological modeling approach allows for
88 implicitly representing the drying of the top soil during daytime. The SEE

89 formulation of Merlin et al. (2011) was derived at the daily scale only, which
90 is inconsistent with the subdiurnal availability of thermal data.

91 In this context, this paper aims to develop a quasi instantaneous model
92 of SEE that has the ability to consistently integrate both near-surface soil
93 moisture and radiometric soil temperature data. In practice, the recent SEE
94 modeling approach of Merlin et al. (2016) is improved by adding a temporal
95 dependence, as well as an additional parameter controlling the cyclic phe-
96 nomenon of the drying/rewetting of the top soil during daytime/nighttime.
97 The new resistance model is tested in terms of SEE estimates using eddy
98 covariance measurements collected over a bare soil site in central Morocco,
99 and its performance is assessed against two benchmark models. Calibration
100 capabilities of the SEE model from thermal (instead of eddy covariance) data
101 are also investigated.

102 2. Modeling approach

103 Soil evaporation can be modeled using a resistance approach:

$$LE = \frac{\rho C_P}{\gamma} \times \frac{e_{sat}(T) - e_a}{r_{ah} + r_{ss}} \quad (1)$$

104 with LE (W m^{-2}) being the soil latent heat flux, r_{ss} (s m^{-1}) the resistance
105 to the diffusion of vapor in soil pores, ρ (kg m^{-3}) the density of air, C_P (J
106 $\text{kg}^{-1} \text{K}^{-1}$) the specific heat capacity of air, γ (Pa K^{-1}) the psychrometric
107 constant, $e_{sat}(T)$ (Pa) the saturated vapor pressure at the soil surface, T (K)
108 the soil surface temperature, e_a (Pa) the vapor pressure of air and r_{ah} (s
109 m^{-1}) the aerodynamic resistance to heat transfer from the soil surface to the
110 reference height.

111 Based on Equation (1), one may also derive a potential soil evaporation,
 112 defined as the soil evaporation that would occur in fully saturated soil con-
 113 ditions so that $r_{ss} = 0$:

$$LEp = \frac{\rho C_P}{\gamma} \times \frac{e_{sat}(T_{wet}) - e_a}{r_{ah,wet}} \quad (2)$$

114 with T_{wet} (K) and $r_{ah,wet}$ (s m^{-1}) being the soil temperature and aerodynamic
 115 resistance in saturated soil conditions, respectively. The parameters used as
 116 input to the LEp model are presented in the Appendix A. The ratio of actual
 117 to potential soil evaporation, i.e. the SEE, can then be expressed as:

$$SEE = \frac{e_{sat}(T) - e_a}{e_{sat}(T_{wet}) - e_a} \times \frac{r_{ah,wet}}{r_{ah} + r_{ss}} \quad (3)$$

118 The soil resistance in Equation (3) is expressed as a function of soil mois-
 119 ture following Merlin et al. (2016):

$$r_{ss,M16} = r_{ss,ref} \exp(-\theta/\theta_{efolding}) \quad (4)$$

120 with $r_{ss,ref}$ being a hypothetical soil resistance corresponding to dry soil con-
 121 ditions and $\theta_{efolding}$ the soil moisture value at which r_{ss} is equal to $r_{ss,ref}/e$.
 122 The present paper aims to intercompare three evaporation models based on
 123 the following assumptions for the r_{ss} formulation:

- 124 • both $r_{ss,ref}$ and $\theta_{efolding}$ of Equation (4) are set to constant values
 125 (depending on soil texture and structure) as in Passerat de Silans (1986)
 126 and Sellers et al. (1992).
- 127 • $r_{ss,ref}$ and $\theta_{efolding}$ of Equation (4) are analytically expressed as a func-
 128 tion of meteorological forcing and two observable parameters as in Mer-
 129 lin et al. (2016).

130 • a correction term ($\delta r_{ss,t}$) is added to $r_{ss,M16}$ to account for diurnal
 131 variations in SEE associated with top-soil drying (receding evaporation
 132 front) during daytime (Mahrt and Pan, 1984; Dickinson et al., 1986;
 133 Soarès et al., 1988; Wetzal and Chang, 1988; Van de Griend and Owe,
 134 1994; Heitman et al., 2008; Shahraeeni et al., 2012).

135 For clarity, the three above models are named in the following as PdS86,
 136 M16 and new model, respectively.

137 The third and new soil resistance model is written as:

$$r_{ss,t} = r_{ss,M16} + \delta r_{ss,t} \quad (5)$$

138 with $r_{ss,M16}$ the soil resistance of Equation (4) and $\delta r_{ss,t}$ a correction term
 139 that includes the effect of the receding evaporation front during daytime on
 140 quasi-instantaneous SEE. A phenomenological expression of $\delta r_{ss,t}$ is proposed
 141 below as a function of time of day centered at solar noon ($\delta t = t - 12$ with
 142 t in unit of hour). The SEE difference between time t and 12 pm (δSEE_t)
 143 can be expressed as:

$$SEE_t = SEE_{12} + \delta SEE_t \quad (6)$$

144 Now, we assume (this assumption will be shown to be valid in section 4) that
 145 the relative diurnal variations in SEE are linearly dependent on the time of
 146 day δt :

$$\delta SEE_t = -SEE_{12} \times \delta t / \tau_{hyst} \quad (7)$$

147 with τ_{hyst} being a parameter (unit of hour) that characterizes the hysteretic
 148 time scale associated with the evaporative front drying during daytime, and
 149 the uniform rewetting of soil via capillary rises during nighttime. A rela-
 150 tionship between δSEE_t and $\delta r_{ss,t}$ is then built through the derivative of

151 Equation (3):

$$\delta SEE_t = -\frac{SEE_{12}}{r_{ah,12} + r_{ss,12}} \times \delta r_{ss,t} \quad (8)$$

152 with $r_{ss,12}$ and $r_{ah,12}$ being the soil and aerodynamic resistance estimated at
153 noon, respectively. Herein, $r_{ss,12}$ is approximated by the M16 soil resistance
154 (noted $r_{ss,M16}$) by assuming that θ does not vary much at the subhourly time
155 scale (a reasonable assumption), and $r_{ah,12}$ is approximated by r_{ah} at time t ,
156 so that $\delta r_{ss,t}$ can be instantly (not recursively) computed regardless of the
157 conditions at noon. Hence, by substituting δSEE_t in the above equation,
158 one obtains:

$$\delta r_{ss,t} = (r_{ah} + r_{ss,M16}) \times \delta t / \tau_{hyst} \quad (9)$$

159 **3. Data**

160 *3.1. Sidi Rahal site*

161 The Sidi Rahal site (-7.3535 E; 31.7035 N) is located east of the Tensift
162 basin in central Morocco (see Figure 1). The climate is semi-arid with an
163 annual precipitation of about 250 mm mostly concentrated between Novem-
164 ber and April and a reference crop evapotranspiration of 1600 mm per year.
165 The Sidi Rahal monitoring station was set up in a rainfed wheat field in De-
166 cember 2013 in the framework of a joint international project (Khabba et al.,
167 2013; Jarlan et al., 2015). Due to an unusual lack of precipitation late 2015,
168 the winter wheat crop had not been planted during the 2015-2016 season.
169 As a result, the crop field remained in bare soil conditions from January to
170 September 2016, which we took advantage of to test evaporation models in
171 ideal conditions. The soil texture is predominantly loam.

172 The station is equipped with an eddy-covariance (EC) system, radiome-
173 ters operating in the short and long wavelengths, heat flux plates and soil
174 moisture probes. The net radiation is measured by a Kipp & Zonen CNR1.
175 The soil heat flux is estimated with Hukseflux HFP-01 plates buried at 5
176 cm depth. Those data are collected with a time step of 10 s and then av-
177 eraged and recorded every 30 minutes. Latent and sensible heat fluxes are
178 estimated with a Campbell Scientific KH20 fast response hygrometer and a
179 Campbell Scientific CSAT3 anemometer at a frequency of 10 Hz and then
180 converted to a 30-minute average. Both latent and sensible heat fluxes are
181 corrected for energy balance lack of closure using the Bowen ratio method.
182 The daily (computed using 30-minute estimates between 9 am and 5 pm)
183 Bowen ratio and the 30-minute flux estimates are combined to derive the
184 corrected 30-minute latent and sensible heat fluxes. The 5-cm soil moisture
185 is measured by a Campbell Scientific CS616 calibrated using periodic gravi-
186 metric measurements. The radiometric surface temperature is derived from
187 an Apogee instruments 8-14 μm thermal infrared (TI) radiometer set up at a
188 2-m height. Meteorological forcing data including air temperature, solar radi-
189 ation, relative humidity, wind speed and rainfall are monitored continuously
190 at a semihourly time step at 2 m as well.

191 *3.2. SEE estimates*

192 Given the bare soil conditions of the Sidi Rahal site during the study pe-
193 riod, evapotranspiration originates only from soil in this experiment. There-
194 fore, evapotranspiration and soil evaporation, as well as potential evapotran-
195 spiration and potential soil evaporation, are assumed to be the same. An
196 estimate of SEE can hence be obtained by dividing the measured latent heat

197 flux by potential (soil) evaporation:

$$SEE_{EC} = \frac{LE_{EC}}{LEp} \quad (10)$$

198 with SEE_{EC} being the EC-derived SEE, LE_{EC} the evaporation measured by
199 EC and LEp the evaporation in saturated soil conditions (Equation 2).

200 Another relatively independent, indirect, estimate of SEE is derived from
201 the radiometric soil temperature:

$$SEE_{TI} = \frac{T_{dry} - T_{TI}}{T_{dry} - T_{wet}} \quad (11)$$

202 with SEE_{TI} the TI-derived SEE, T_{TI} the surface soil temperature retrieved
203 from TI measurements, and T_{dry} and T_{wet} the soil temperature in bone-dry
204 and saturated soil conditions, respectively (Merlin, 2013; Stefan et al., 2015).
205 In practice, T_{dry} and T_{wet} (together with LEp) are simulated by the same
206 soil energy balance model by setting $r_{ss} = \infty$ and $r_{ss} = 0$ in Equation
207 (1), respectively. The reader is advised to refer to Appendix A for more
208 information on the energy balance model.

209 Figure 2 plots the half-hourly surface soil moisture and EC- and TI-
210 derived SEE (for data collected between 6 am and 6 pm with $LEp > 100$
211 Wm^{-2}) as a function of day of year (DOY) 1 to 243 in 2016. One observes
212 a strong correlation between SEE estimates and θ , as all drying periods are
213 visible in the SEE time series. However, the TI-derived SEE is more scat-
214 tered than the EC-derived SEE. As mentioned above, one major objective
215 of this study is to assess the calibration capabilities of a SEE model using
216 consistent but uncertain TI-derived estimates. A total of 9 study periods are
217 defined for calibration and validation purposes: the whole study period noted
218 $P0$ (DOY 1 – 243) and 8 subperiods $P1 - 8$ bounded by significant rainfall

219 events. The start and end DOY of each subperiod P_i for $i = 1, \dots, 8$ are
 220 listed in Table 1. Note that many points corresponding to TI measurements
 221 exhibit a SEE larger than 1 or smaller than 0 in Figure 2. It means that
 222 the modeled T_{dry} and T_{wet} can be smaller and larger than the observed tem-
 223 perature, respectively. This may be due to several factors: uncertainties in
 224 thermal data, uncertainties in modeled T_{wet} and T_{dry} , and/or uncertainties in
 225 the model linking SEE to soil temperature. SEE_{TI} values larger than 1 and
 226 smaller than 0 mostly correspond to the early (before noon) and late (after
 227 noon) hours of dates with very wet and very dry conditions, respectively.

228 Figure 3 illustrates the variations during daytime of potential soil evapora-
 229 tion, the soil evaporation measured by the EC system and the soil evaporation
 230 derived as TI-derived SEE times potential evaporation for a relatively wet
 231 ($\theta \sim 0.18 \text{ m}^3\text{m}^{-3}$) and dry ($\theta \sim 0.05 \text{ m}^3\text{m}^{-3}$) day separately. Both EC- and
 232 TI-derived estimates are rather close, especially at around 12 pm. However,
 233 the time at which the maximum LE value is reached is about 11:00-11:30
 234 am for TI-derived estimates, 12:15-12:45 pm for EC-derived estimates and
 235 1:15-1:30 pm for potential evaporation. Differences in the time of maximum
 236 latent heat flux value can be interpreted as the impact of top-soil drying i.e.
 237 the downward-moving drying front that counters the evaporation process (Or
 238 et al., 2013). The maximum of LE_{EC} logically appears sooner than that of
 239 LE_p , due to the decrease of soil evaporation associated with the receding
 240 of evaporation front in the top soil at around noon. Such phenomenon is
 241 visible in both relatively wet and dry conditions as illustrated in Figure 3.
 242 The fact that the maximum of $SEE_{TI} \times LE_p$ appears sooner than that of
 243 LE_{EC} is explained by the difference in the depth (within the top 0 – 5 cm

244 layer) at which the actual soil evaporation occurs and that (near-surface) of
245 TI data. Hence, the thinner the soil layer used to represent evaporation, the
246 more sensitive the evaporation model is to the daytime top-soil drying.

247 Figure 3 also presents the hysteretic behavior of radiometric temperature
248 as a function of LEp . For a given level of LEp , the surface soil is cooler in the
249 morning than in the afternoon, explaining the decreasing rate of TI-derived
250 evaporation ($SEE_{TI} \times LEp$) during daytime. Note that the simulated ex-
251 treme temperatures T_{dry} and T_{wet} do not follow the same hysteretic behavior,
252 as similar values are obtained (for $LEp > 200 \text{ Wm}^{-2}$) before and after the
253 time of LEp maximum value. Hysteresis effects are nill in dry conditions
254 because when the soil is completely dry, evaporation stops. Hysteresis effects
255 are also theoretically nill in fully wet conditions, because when the soil is
256 maintained permanently wet, evaporation is at its potential rate at any time
257 of day. Another interesting feature of the temporal signature of radiometric
258 temperature is its link with wind speed. Whereas the increase of the drying
259 front intrusion during the day makes T increase, an increase in wind speed
260 has instead the effect of decreasing T (increasing SEE_{TI}) due to the drop
261 in r_{ah} . Nonetheless, extreme temperatures T_{wet} and T_{dry} are estimated using
262 quasi instantaneous wind speed as input to the energy balance model, and
263 therefore, the TI-derived SEE is less influenced by wind speed than the un-
264 normalized T . For instance, the correlation coefficient between unnormalized
265 T and wind speed is 0.85 (0.69) for the wet (dry) date of Figure 3 while it is
266 -0.03 (-0.06) between normalized T and wind speed, respectively.

267 **4. Calibration strategies**

268 Various calibration strategies of M16 (Equation 4) and the new r_{ss} model
 269 (Equation 5) are investigated depending on the nature of SEE estimates
 270 (derived either from EC or TI data) and on the length of observed SEE time
 271 series.

272 *4.1. Calibrating $r_{ss,ref}$ and $\theta_{efolding}$*

273 In Merlin et al. (2016), the $r_{ss,ref}$ and $\theta_{efolding}$ parameters of Equation
 274 (4) are analytically expressed as a function of meteorological forcing, cut-
 275 off soil moisture value $\theta_{1/2}$ at which $SEE=0.5$ and first derivative of SEE
 276 at $\theta_{1/2}$, named $\Delta\theta_{1/2}^{-1}$. The main equations are reminded in Appendix B.
 277 In fact, both parameters $\theta_{1/2}$ and $\Delta\theta_{1/2}^{-1}$ are estimated directly from a time
 278 series of SEE and θ observations. Merlin et al. (2016) developed a specific
 279 calibration approach to take into account the non-linearity of the $SEE(\theta)$
 280 relationship, as well as to adapt for data sets with soil moisture values that
 281 may not be uniformly distributed around the targeted $\theta_{1/2}$ value. In the
 282 same way as in Merlin et al. (2016), the full SEE range $[0 - 1]$ is split into
 283 20 (0.05-wide) bins, and the SEE and θ values falling into each SEE bin are
 284 averaged separately to provide a pair (SEE_k, θ_k) per bin. Then, 10 segments
 285 are computed by joining the two points (SEE_k, θ_k) and $(SEE_{k+10}, \theta_{k+10})$ for
 286 $k = 1, \dots, 10$. Nevertheless, an improvement is made herein to 1) estimate the
 287 pair $(\theta_{1/2}, \Delta\theta_{1/2}^{-1})_k$ for each segment k and 2) weight the pair $(\theta_{1/2}, \Delta\theta_{1/2}^{-1})_k$
 288 according to the mean difference between the ordinate of the center of the
 289 segment k and 0.5. In practice, we define the weight w_k such as: i) $w_k = 1$
 290 for $\overline{SEE}_k = 0.5$ and ii) $w_k = 0$ for $\overline{SEE}_k = 0.25$ or $\overline{SEE}_k = 0.75$, with

291 $\overline{SEE}_k = (SEE_k + SEE_{k+10})/2$. A general equation of w_k is obtained by
 292 considering a linear interpolation between extreme values:

$$w_k = 1 - 4 \times |0.5 - \overline{SEE}_k| \quad (12)$$

293 Note that the values allocated for the weighting function correspond to the
 294 simplest (triangular) function with a weight set to 0 and 1 for the extreme
 295 (one end point of a segment is associated to $SEE \sim 0$ or $SEE \sim 1$) and
 296 middle (mean $SEE = 0.5$) case, respectively. The new calibration procedure
 297 aims to give a larger weight to the segments that are close to the inflexion
 298 point of the $SEE(\theta)$ relationship and a smaller weight to the segments that
 299 are located in a region where the nonlinearity of the $SEE(\theta)$ relationship is
 300 more prominent. The quasi linearity of the $SEE(\theta)$ relationship around $\theta_{1/2}$
 301 is indeed an assumption of the above calibration strategy.

302 By way of illustration, Figure 4 plots EC-derived SEE versus θ and TI-
 303 derived SEE versus θ for data with $LEp > 400 \text{ Wm}^{-2}$ (arbitrary threshold)
 304 during the whole time period $P0$. **Such a threshold is chosen to separate**
 305 **between relatively low and high LEp conditions.** The above described cal-
 306 ibration procedure of $(\theta_{1/2}, \Delta\theta_{1/2}^{-1})$ is applied to both time series separately.
 307 Although the TI-derived SEE values appear to be more scattered than the
 308 EC-derived SEE, calibrated parameters have similar values in both cases: $\theta_{1/2}$
 309 is 0.129 and 0.125 m^3m^{-3} , and $\Delta\theta_{1/2}^{-1}$ is 4.01 and 4.21 m^3m^{-3} for EC and TI
 310 case, respectively. Note that $\theta_{1/2}$ and $\Delta\theta_{1/2}^{-1}$ may vary with parameters other
 311 than θ and texture (Merlin et al., 2016). For instance, the work in Chanzy
 312 and Bruckler (1993), a theoretical analysis supported by experimental evi-
 313 dences, has shown the role of LEp and wind velocity in the determination
 314 of $\theta_{1/2}$. Therefore, applying the calibration approach over several shorter

315 periods $P1 - 8$ may help improving model performances.

316 Once $\theta_{1/2}$ and $\Delta\theta_{1/2}^{-1}$ values have been retrieved, two different strategies
317 are investigated to estimate $r_{ss,ref}$ and $\theta_{efolding}$ parameters of Equation (4):

- 318 • For M16, $r_{ss,ref}$ and $\theta_{efolding}$ are derived from the analytical expressions
319 given in Appendix B (Equations 27 and 29). Therefore, both $r_{ss,ref}$ and
320 $\theta_{efolding}$ vary with meteorological conditions at the 30-minute time step.
- 321 • For PdS86, $r_{ss,ref}$ and $\theta_{efolding}$ are set to the average of the M16 values
322 during the whole time period. Therefore, both $r_{ss,ref}$ and $\theta_{efolding}$ are
323 constant in this case.

324 4.2. Calibrating τ_{hyst}

325 Figure 5 plots the 30-minute EC-derived SEE as a function of $\delta t = t - 12$
326 for two days of period $P0$. The linear fit of the daily relationship is superim-
327 posed for each day separately. The slope (noted $\delta SEE/\delta t$) of the relationship
328 observed at the daily time scale between SEE_t and δt is a decreasing function
329 of the daily mean SEE. The correlation coefficient between daily $\delta SEE/\delta t$
330 and daily SEE is -0.90 . Figure 5 also plots the 30-minute TI-derived SEE
331 as a function of δt . Although the data points are more scattered around the
332 daily linear fit than for EC case, the daily slope $\delta SEE/\delta t$ is consistently
333 decreasing with the daily mean SEE, as for EC case, with a correlation co-
334 efficient of -0.68 .

335 Based on the daily relationships discussed above, the time parameter τ_{hyst}
336 of Equation (9) is calibrated in a three-step procedure:

- 337 • The daily slope $\delta SEE/\delta t$ is computed for each day of the study period.

- 338 • The daily slope $\delta SEE/\delta t$ is correlated with the daily mean SEE for
339 each day of the study period. The daily mean is obtained by averaging
340 the 30-minute SEE estimates during daytime.
- 341 • The calibrated τ_{hyst} is equal to minus the inverse of the slope of the
342 relationship between $\delta SEE/\delta t$ and the daily mean SEE (see Equation
343 7). Note that SEE_{12} in Equation (7) is replaced by the daily mean
344 SEE to reduce uncertainties in quasi instantaneous SEE estimates. The
345 calibrated value of τ_{hyst} is 11 and 9 hours for the EC-derived and TI-
346 derived SEE case, respectively.

347 Note that the above calibration strategy is valid if the observed relation-
348 ships between SEE_t and δt and between $\delta SEE/\delta t$ and the daily mean SEE
349 are linear as a first approximation. Moreover, we assume herein that the SEE
350 at noon (SEE_{12} in Equation 7) is close to the daily mean SEE. In fact, such
351 a hypothesis relies on the above linearity assumptions. As a linearity assess-
352 ment of the $SEE_t(\delta t)$ relationship, the coefficient of determination (ordinary
353 R-squared) between EC-derived SEE and time of day is estimated as 0.99
354 and 0.93 for the wet and dry date of Figure 5 respectively. The R-squared is
355 slightly degraded to 0.93 and 0.73 respectively for the TI case, due to larger
356 uncertainties in TI-derived SEE estimates.

357 5. Results and discussions

358 The proposed $r_{ss,t}$ model (Equation 5) is applied to the Sidi Rahal'16 data
359 set and its performance in terms of SEE estimates is compared with that of
360 two benchmark models: the M16 (Equation 4) and PdS86 r_{ss} models. It

361 is reminded that PdS86 and M16 differ with regard to the values of $r_{ss,ref}$
 362 and $\theta_{efolding}$, which vary in time in M16 (according to Equation 27 and 29
 363 respectively) while they are set to a constant value in PdS86. Results are
 364 presented and discussed below for a calibration undertaken using EC- and
 365 TI-derived SEE estimates separately.

366 5.1. Models calibrated using EC measurements

367 5.1.1. Calibration parameters

368 The calibration algorithm of $(\theta_{1/2}, \Delta\theta_{1/2}^{-1})$ is run over each period $P0-8$ us-
 369 ing EC-derived SEE estimates. Note that diurnal patterns are not accounted
 370 for in the determination of $\theta_{1/2}$ and $\Delta\theta_{1/2}^{-1}$ parameters. The rationale is that
 371 both parameters are largely independent of τ_{hyst} : $\theta_{1/2}$ and $\Delta\theta_{1/2}^{-1}$ make SEE
 372 vary at the daily scale while τ_{hyst} makes SEE vary at the hourly scale around
 373 the daily mean SEE. Retrieved parameters are reported in Table 2 for data
 374 with a minimum LEp value of 400 Wm^{-2} and 100 Wm^{-2} separately. The
 375 main idea of those empirical thresholds is 1) to remove SEE estimates under
 376 low ($< 100 \text{ Wm}^{-2}$) evaporative demand conditions and 2) to qualitatively
 377 distinguish between relatively low and relatively high demand conditions.
 378 For data with $LEp > 100 \text{ Wm}^{-2}$, a pair $(\theta_{1/2}, \Delta\theta_{1/2}^{-1})$ is obtained for each
 379 period $P0 - 8$. However there are too few data points with $LEp > 400$
 380 Wm^{-2} during the winter months, hence no parameter is retrieved for $P1 - 4$
 381 in this case. EC-derived $\theta_{1/2}$ and $\Delta\theta_{1/2}^{-1}$ vary in the range $0.07 - 0.16 \text{ m}^3\text{m}^{-3}$
 382 and $4 - 11 \text{ m}^3\text{m}^{-3}$ respectively, with smaller values of $\theta_{1/2}$ being associated
 383 with larger values of $\Delta\theta_{1/2}^{-1}$ and reciprocally. Note that the extreme values
 384 of $\theta_{1/2} = 0.07 \text{ m}^3\text{m}^{-3}$ and $\Delta\theta_{1/2}^{-1} = 11 \text{ m}^3\text{m}^{-3}$ are both obtained during the
 385 hottest and driest subperiod $P7$ (see Table 1).

386 Figure 6 compares the retrieved values of $\theta_{1/2}$ and $\Delta\theta_{1/2}^{-1}$ in both cases:
 387 $LEp > 100 \text{ Wm}^{-2}$ versus $LEp > 400 \text{ Wm}^{-2}$. The correlation coefficient (and
 388 root mean square difference) between both data sets (for EC-derived SEE)
 389 is 0.97 (0.006 m^3m^{-3}) and 1.0 (0.46 m^3m^{-3}) for retrieved $\theta_{1/2}$ and $\Delta\theta_{1/2}^{-1}$,
 390 respectively. The calibration results when discarding the data with $LEp <$
 391 400 Wm^{-2} are very close to those obtained when including all data with
 392 $LEp > 100 \text{ Wm}^{-2}$. Therefore, the calibration parameters are found to be
 393 quite stable with respect to the evaporative demand conditions. Given that
 394 calibration results using EC-derived SEE estimates are very consistent for
 395 two different minimum LEp values, the lower (and less restrictive) threshold
 396 value $LEp > 100 \text{ Wm}^{-2}$ is chosen to assess model results in the rest of the
 397 paper.

398 The definition of 9 study periods and the application of the same calibra-
 399 tion procedure to data with $LEp > 100 \text{ Wm}^{-2}$ and data with $LEp > 400$
 400 Wm^{-2} also allow for evaluating the uncertainties in retrieved parameters.
 401 The relative uncertainty in $\theta_{1/2}$ (and $\Delta\theta_{1/2}^{-1}$) for a given time series is esti-
 402 mated as the absolute difference of the values obtained for data with $LEp >$
 403 100 Wm^{-2} and data with $LEp > 400 \text{ Wm}^{-2}$ divided by the average. The
 404 mean relative uncertainty for $P0$, $P5 - 8$ (see Table 2) is 3% and 7% for
 405 retrieved $\theta_{1/2}$ and $\Delta\theta_{1/2}^{-1}$, while the temporal variability (relative to the mean
 406 value for all periods) is estimated as 19% and 40%, respectively. Such results
 407 further confirm the robustness of the calibration procedure.

408 5.1.2. SEE results

409 $\theta_{1/2}$ and $\Delta\theta_{1/2}^{-1}$ are set to 0.12 m^3m^{-3} and 4.6 m^3m^{-3} respectively as es-
 410 timated previously for $P0$ data with a minimum LEp value of 100 W m^{-2} ,

411 and τ_{hyst} is set to 11 h. Figure 7 plots the SEE simulated by the calibrated
 412 PdS86, M16 and new r_{ss} models as a function of EC-derived SEE. The new
 413 model outperforms M16 and M16 outperforms PdS86 (statistics are provided
 414 in Table 3). Especially, the correlation coefficient (and RMSD) between sim-
 415 ulated and observed SEE is improved from 0.80 to 0.85 (from 0.12 to 0.10)
 416 with the new model. The representation of SEE at the subhourly time scale
 417 has also an impact on the slope of the linear regression between modeled
 418 and observed SEE, increasing from 0.86 to 0.91 for M16 and new model re-
 419 spectively. The new parameterization thus allows for simply representing the
 420 SEE decrease associated with the receding evaporation front during daytime.

421 Table 3 also lists the error statistics for each subperiod Pi ($i = 1, \dots, 8$) us-
 422 ing model parameters retrieved from Pi data (from $P0$ data in parenthesis).
 423 A lower RMSD is generally obtained by the new model using the subperiod
 424 calibration, except for $P3$ when the $P0$ calibration provides a significantly
 425 improved RMSD (0.18 instead of 0.24). To further explore the case of $P3$,
 426 we investigate the SEE simulated by M16 and new model separately as a
 427 function of EC-derived SEE for data with $LEp > 100 \text{ W m}^{-2}$ during $P2$, $P3$
 428 and $P7$ (Figure 8). Several different behaviors of the $SEE(\theta)$ relationship
 429 are observed during $P3$, as evidenced by the presence of three groups of data
 430 points located significantly above, significantly below and around the 1:1 line
 431 respectively. Given that the calibration method is dedicated to find the best
 432 slope ($\Delta\theta_{1/2}^{-1}$) at $\theta_{1/2}$, one expects to obtain the best slope of the linear regres-
 433 sion between simulated and observed SEE by calibrating the model over each
 434 subperiod separately. Table 3 clearly shows that the slope is systematically
 435 improved in all cases, including the case of $P3$. However, a better slope does

436 not necessarily mean an improved RMSD between simulated and observed
437 SEE.

438 In summary, it is found that 1) both $\theta_{1/2}$ and $\Delta\theta_{1/2}^{-1}$ vary between suc-
439 cessive drying periods, 2) the representation of this temporal variability by
440 means of a periodic calibration of $(\theta_{1/2}, \Delta\theta_{1/2}^{-1})$ enhances SEE estimates, and
441 3) the long-term calibration (during $P0$) of the SEE model still provides re-
442 liable results that are generally more accurate than those of the PdS86 and
443 M16 formulations.

444 5.1.3. Evaporation results

445 Since the target is evaporation, rather than SEE, results are also pre-
446 sented in terms of evaporation estimates in Figure 7. It is reminded that LE
447 is derived as $SEE \times LEp$. Therefore, given that the same energy balance
448 model is used to simulate both LEp and LE , there should be a perfect equiv-
449 alence between simulated LE and simulated SEE . In practice, if simulated
450 SEE is accurate compared to SEE_{EC} ($=LE_{EC}/LEp$), then simulated LE
451 ($=SEE \times LEp$) should be accurate compared to LE_{EC} . To further assess the
452 consistency between SEE and evaporation results, Table 4 reports the corre-
453 lation coefficient, slope of the linear regression and RMSD between simulated
454 and measured evaporation at Sidi Rahal site for all data with $LEp > 100$
455 Wm^{-2} . Statistics are presented for PdS86, M16 and new models separately,
456 all three models being calibrated with the same input data set (EC data for
457 $LEp > 100 Wm^{-2}$). While the RMSD is relatively low ($\leq 35 Wm^{-2}$) in all
458 cases, the correlation coefficient (and slope of the linear regression) increases
459 from 0.81 (0.89) to 0.85 (0.96) for the PdS86 and new model, respectively.
460 Such improvement is fully consistent with previous results in terms of SEE

461 estimates.

462 5.2. Models calibrated using TI measurements

463 5.2.1. Calibration parameters

464 Given that EC measurements are available at few locations only, we now
465 investigate the applicability of the calibration algorithm of $(\theta_{1/2}, \Delta\theta_{1/2}^{-1})$ to
466 TI data. In practice, the calibration procedure is applied to TI-derived SEE
467 estimates over each period $P0 - 8$. Retrieved parameters are reported in
468 Table 5 for data with a minimum LEp value of 400 Wm^{-2} and 100 Wm^{-2}
469 separately. TI-derived $\theta_{1/2}$ and $\Delta\theta_{1/2}^{-1}$ vary in the range $0.06 - 0.16 \text{ m}^3\text{m}^{-3}$
470 and $4 - 23 \text{ m}^3\text{m}^{-3}$ respectively. Consistent with EC case, smaller values
471 of TI-derived $\theta_{1/2}$ are associated with larger values of TI-derived $\Delta\theta_{1/2}^{-1}$ and
472 reciprocally. However, in contrast to EC case, the TI-derived $\Delta\theta_{1/2}^{-1}$ for data
473 with $LEp > 100 \text{ Wm}^{-2}$ is about twice the value obtained for data with
474 $LEp > 400 \text{ Wm}^{-2}$, while the TI-derived $\theta_{1/2}$ for data with $LEp > 100 \text{ Wm}^{-2}$
475 is about one third lower than the value obtained for data with $LEp > 400$
476 Wm^{-2} (see Figure 6).

477 Figure 9 plots TI-derived versus EC-derived $\theta_{1/2}$ and $\Delta\theta_{1/2}^{-1}$ for all periods
478 $P0 - 8$ and for data with a minimum LEp value of 100 and 400 Wm^{-2}
479 separately. It is clear that a better match of retrieved parameters is obtained
480 when $LEp > 400 \text{ Wm}^{-2}$ than when $LEp > 100 \text{ Wm}^{-2}$. In fact, the TI-
481 derived SEE greatly overestimates the EC-derived SEE in conditions of low
482 LEp values. In relatively wet conditions for instance (see Figure 3), the
483 TI-derived evaporation (estimated as $SEE_{TI} \times LEp$) can even exceed the
484 potential evaporation. The above results confirm the applicability domain of
485 the energy balance model to conditions with $LEp > 400 \text{ W m}^{-2}$. Therefore

486 the calibration of the pair $(\theta_{1/2}, \Delta\theta_{1/2}^{-1})$ using TI-derived SEE data should be
487 carried out under relatively large LEp conditions only.

488 The systematic difference between EC- and TI-derived SEE under low
489 LEp conditions can be explained by the inconsistency between the soil tem-
490 perature modeled at the evaporation front (Equation 1) and the remotely
491 sensed radiometric temperature that is representative of the surface skin
492 temperature only. In fact, the soil temperature modeled in dry conditions
493 T_{dry} is expected to deviate from the top soil temperature in the presence of
494 a receding evaporation front (Or et al., 2013). There are methods to correct
495 this inconsistency. For instance two distinct approaches have been devel-
496 oped to relate the observed superficial temperature to deeper soil tempera-
497 tures, either by implementing a physically-based heat diffusion model (Bateni
498 et al., 2013) to dynamically constrain the modeled surface temperature from
499 deeper temperatures or by smoothing/lagging the surface temperature using
500 a Fourier dissipation (Heusinkveld et al., 2004; Gentine et al., 2011) or lag
501 (Gentine et al., 2012) model.

502 The relative uncertainty in the $(\theta_{1/2}$ and $\Delta\theta_{1/2}^{-1})$ parameters retrieved from
503 TI data is estimated by computing the absolute difference of the values ob-
504 tained for TI data with $LEp > 400 \text{ Wm}^{-2}$ and for EC data with $LEp > 100$
505 Wm^{-2} divided by the average. The mean relative uncertainty for $P0$, $P5 - 8$
506 (see Tables 2 and 5) is 8% and 21% for retrieved $\theta_{1/2}$ and $\Delta\theta_{1/2}^{-1}$, respectively.
507 Although EC-retrieved parameters (3% and 7% relative error, respectively)
508 are more accurate than TI-derived parameters, the temporal variability in
509 retrieved parameters (19% and 40%, respectively) remains larger, i.e. cali-
510 bration using TI data is still effective and meaningful. Such results further

511 confirm the consistency between TI- and EC-derived SEE estimates when
512 $LEp > 400 \text{ Wm}^{-2}$.

513 5.2.2. SEE results

514 The hysteretic parameter τ_{hyst} is set to 9 h and the pair $(\theta_{1/2}, \Delta\theta_{1/2}^{-1})$ is
515 set to (0.085, 10.0) and (0.125, 4.21) as estimated with the P0 TI data for a
516 minimum LEp value of 100 and 400 W m^{-2} , respectively. Table 6 reports
517 error statistics in terms of correlation coefficient, slope of the linear regression
518 and RMSD between simulated and EC-derived SEE for all LEp conditions
519 ($LEp > 100 \text{ W m}^{-2}$). Best results are highlighted in bold. Consistent
520 with EC case, the correlation coefficient between simulated and observed
521 SEE is improved from 0.77 to 0.81 and from 0.80 to 0.86 when including
522 time of day in the soil resistance for data with $LEp > 100$ and $LEp > 400$
523 Wm^{-2} , respectively. Moreover, the error statistics for data with $LEp > 400$
524 Wm^{-2} are very similar to those obtained with the EC, with a correlation
525 coefficient of 0.86 and a RMSD of 0.10. Only the slope of the linear regression
526 between simulated and observed SEE is degraded from 0.91 (EC case) to
527 0.87 (TI case). Results in terms of SEE estimates are logically superior when
528 calibrating the model using TI data with $LEp > 400 \text{ Wm}^{-2}$ than using TI
529 data with $LEp > 100 \text{ Wm}^{-2}$, as the actual to wet temperature difference is
530 a good indicator of water stress when energy is not limiting (Boulet et al.,
531 2007).

532 Table 6 also lists the error statistics for each subperiod Pi ($i = 1, \dots, 8$)
533 using model parameters retrieved from the data set corresponding to sub-
534 period Pi and $LEp > 100 \text{ Wm}^{-2}$ and from the data set corresponding to
535 P0 and $LEp > 400 \text{ Wm}^{-2}$ (in parenthesis). The new SEE formulation gen-

536 erally provides best results in terms of correlation coefficient, slope of the
 537 linear regression and RMSD between simulated and observed SEE. However,
 538 the calibration of $(\theta_{1/2}, \Delta\theta_{1/2}^{-1})$ by subperiod does not succeed in representing
 539 the temporal variability of model parameters, which is due to the system-
 540 atic bias in TI-derived SEE for low LEp values. The relatively large slope
 541 (1.25 for $P0$) of the linear regression between simulated and observed SEE
 542 for data with $LEp > 100 \text{ Wm}^{-2}$ also reflects the overestimation of SEE by
 543 using TI data under low evaporative demand conditions. On the contrary,
 544 the calibration of $(\theta_{1/2}, \Delta\theta_{1/2}^{-1})$ over the whole period $P0$ using TI data with
 545 $LEp > 400 \text{ Wm}^{-2}$ provides good results at the subperiod scale (during each
 546 period $P1 - 8$).

547 In summary, the above results indicate that 1) the calibration of model
 548 parameters is feasible using TI data and 2) selecting TI data collected under
 549 relatively high evaporative demand conditions ($LEp > 400 \text{ Wm}^{-2}$ herein) is
 550 required for obtaining similar accuracy to the EC-based calibration case.

551 *5.3. Applicability to temporally-sparse thermal data*

552 The new r_{ss} formulation of Equation (5) is based on three parameters:
 553 τ_{hyst} , $\theta_{1/2}$ and $\Delta\theta_{1/2}^{-1}$. Validation results at Sidi Rahal site have shown that
 554 all three parameters can be efficiently calibrated using TI data combined
 555 with meteorological forcing and near-surface soil moisture observations. This
 556 opens up the path for model calibration using spaceborne thermal-derived
 557 radiometric surface temperature. However, the spatio-temporal resolution
 558 of available remote sensing products may be in some cases inadequate for
 559 implementing such a calibration. In particular, the thermal data available at
 560 high (100 m) spatial resolution have a repeat cycle of 8 days (by combining

561 Landsat-7 and Landsat-8) only or more, depending on cloudy/non-cloudy
562 conditions on Landsat overpass dates.

563 This subsection aims to assess the applicability of the calibration ap-
564 proach of $(\theta_{1/2}, \Delta\theta_{1/2}^{-1})$ to temporally sparse thermal data. In practice, pa-
565 rameter τ_{hyst} is set to 9 hours (as retrieved from high frequency TI data) and
566 the observation cycle of available TI data is increased from the hourly time
567 scale (previous results) to the 1-day, 2-day, 3-day, 4-day, 5-day, 6-day, 7-day
568 and the 8-day period (Landsat repeat cycle), and model results are evalu-
569 ated in each case. Note that the 1-day repeat cycle mimics the availability of
570 MODIS (MODerate resolution Imaging Spectroradiometer) TI data collected
571 onboard Terra and Aqua at 1 km resolution. To quantitatively evaluate the
572 uncertainty in retrieved parameters and model outputs (SEE and LE), an
573 input ensemble is built at a given TI observation cycle by extracting the TI
574 data at 11:30am, 12:00pm and 12:30pm separately and, for observation cycles
575 larger than 1 day, by including all the possible independent time series shifted
576 by 1 day from one another. The acquisition time approximately corresponds
577 to the overpass time (from 10:30am to 1:30pm) of available thermal sensors
578 at 100 m and 1 km resolution. For the hourly observation cycle, the ensemble
579 of input parameter sets is composed of the 3 $(\theta_{1/2}, \Delta\theta_{1/2}^{-1})$ pairs retrieved dur-
580 ing the whole study period using EC data with $LEp > 100 \text{ Wm}^{-2}$, EC data
581 with $LEp > 400 \text{ Wm}^{-2}$ and TI data with $LEp > 400 \text{ Wm}^{-2}$. For the other
582 cases (observation cycles equal to 1 day or more), TI data with $LEp > 400$
583 Wm^{-2} are used.

584 Figure 10 presents model results as a function of an increasing TI ob-
585 servation cycle. The calibration results in terms of retrieved $\theta_{1/2}$ and $\Delta\theta_{1/2}^{-1}$

586 correspond to data with $LEp > 400 \text{ Wm}^{-2}$ while the model output results
 587 in terms of SEE and LE correspond to all data with $LEp > 100 \text{ Wm}^{-2}$.
 588 The mean retrieved $\theta_{1/2}$ is found to be remarkably stable for all observation
 589 cycles ranging from 0 to 8 days, although its standard deviation significantly
 590 increases for an observation cycle changing from 1 to 2 days. The mean re-
 591 trieved $\Delta\theta_{1/2}^{-1}$ is systematically biased by about +20% for an observation cycle
 592 ranging from 1 to 8 days, and the variability of the retrieved $\Delta\theta_{1/2}$ within
 593 each input ensemble is relatively large (20–50%) for observation cycles 2-8
 594 days. The relatively large variability of $\Delta\theta_{1/2}^{-1}$ is attributed to the lack of ther-
 595 mal observations with both wet soil and $LEp > 400 \text{ Wm}^{-2}$ conditions. Note
 596 that such a limitation is specific to rainfed semi-arid areas like the Sidi Rahal
 597 region. Finally, as an assessment of the calibration strategy, LE estimates
 598 are compared for three different calibration approaches of $r_{ss,ref}$ and $\theta_{efolding}$:
 599 the fixed parameters (S92) of Sellers et al. (1992), the pedotransfer function
 600 (M16) in Merlin et al. (2016) and the proposed TI-based calibration. The
 601 mean root mean square error (RMSE) between simulated and EC-derived
 602 LE is about 60, 50 and 40 Wm^{-2} for the S92, M16 and TI-based calibra-
 603 tion strategy, respectively. Such results emphasize the utility of calibrating
 604 evaporation models using thermal data, even when TI data are temporally
 605 sparse.

606 6. Conclusions and perspectives

607 A new r_{ss} formulation is proposed to improve soil evaporative efficiency
 608 (SEE) estimates at the subhourly time scale given the near-surface (0 – 5
 609 cm) soil moisture, time of day and meteorological forcing data. The model

610 builds on the recent M16 SEE model and integrates time of day to implicitly
 611 represent the impact of the receding evaporation front on quasi instantaneous
 612 SEE during daytime. The three model parameters namely $\theta_{1/2}$, $\Delta\theta_{1/2}^{-1}$ and
 613 τ_{hyst} are calibrated using Eddy-covariance (EC) measurements collected at a
 614 bare soil field (Sidi Rahal site) in central Morocco. Results in terms of corre-
 615 lation coefficient, slope of the linear regression and RMSD between simulated
 616 and observed SEE indicate that the new model clearly outperforms both M16
 617 and also PdS86, which is classically used in many land surface models. Given
 618 that EC measurements are available at few locations only, the applicability
 619 of the calibration approach is also tested using thermal infrared (TI) instead
 620 of EC data. It is found that TI-derived SEE overestimates EC-derived SEE
 621 under low LEp ($< 400 \text{ Wm}^{-2}$) conditions. However, the model calibration
 622 using TI data under relatively high LEp ($> 400 \text{ Wm}^{-2}$) conditions provides
 623 very similar SEE results to the EC-based calibration case.

624 The phenomenological modeling approach allows to represent instanta-
 625 neous SEE over long time periods using a limited number (3) of input pa-
 626 rameters. Moreover, the hysteretic parameter τ_{hyst} (controlling the intrusion
 627 of evaporation front during daytime under given LEp and θ conditions) re-
 628 trieved at the Sidi Rahal site is found to be fairly stable during the 9-month
 629 study period. Both $\theta_{1/2}$ and $\Delta\theta_{1/2}^{-1}$ parameters (controlling the nonlinear SEE
 630 response to θ) vary between two successive drying periods, but accurate SEE
 631 estimates are still obtained when considering those paramaters as constant
 632 during the whole study period. An alternative calibration scheme could be
 633 the calibration of a single parameter (τ_{hyst}), while the others ($\theta_{1/2}, \Delta\theta_{1/2}^{-1}$)
 634 being estimated using pedotransfer functions as proposed in (Merlin et al.,

635 2016). Nonetheless, two questions that still remain open are the spatial vari-
636 ability of τ_{hyst} and the temporal variability of $(\theta_{1/2}, \Delta\theta_{1/2}^{-1})$. **Additional vali-**
637 **dation under different conditions is needed as a single site under the semi-arid**
638 **climate of Morocco is used in this study to develop and evaluate the method.**
639 Also, it is difficult to provide a deep, and quantitative, physical understand-
640 ing of the origin of this variability using a downward/semi-empirical modeling
641 framework solely. Future studies based on a mechanistic model could address
642 the issue of interpreting temporally-variable parameters. Moreover, the en-
643 ergy balance model used in this study to relate SEE to evaporation has been
644 successfully evaluated in terms of T_{wet} and T_{dry} in Stefan et al. (2015) but
645 not in terms of LEp directly. Although simulated LEp values are very con-
646 sistent with EC LE observations ($SEE_{EC} = LE_{EC}/LEp$ consistently ranges
647 between 0 and 1), further research should be undertaken to quantitatively
648 evaluate LEp estimates. This would require a specific experiment where soil
649 is maintained at field capacity under various atmospheric forcing conditions
650 (during several weeks).

651 The coupling of the new r_{ss}/SEE formulation with microwave-derived
652 soil moisture and thermal-derived radiometric temperature would allow soil
653 evaporation to be estimated at multiple scales over large areas. **However, the**
654 **concurrent requirements -to calibrate the model's parameters- of high evap-**
655 **orative demand (a threshold of 400 W m^{-2} is used in this study), rainfall**
656 **or irrigation events (enough to produce soil moisture variability) but lack of**
657 **clouds, so that thermal satellite images can be acquired, and bare soil sur-**
658 **faces for relatively long periods are difficult to reach with current satellites.**
659 **In fact, the model calibration over areas of agricultural or ecological interest**

660 requires remote sensing data at high spatio-temporal resolution (Lagouarde
661 et al., 2013, e.g.). As a long-term vision, the integration of the r_{ss} parameter-
662 ization in state-of-the-art dual-source surface models (Norman et al., 1995,
663 e.g.) has great potential to help separate soil evaporation and plant transpi-
664 ration components of agricultural crops (Merlin et al., 2014, e.g.), and hence
665 to better assess the crop water use efficiency. Under vegetated surface, soil
666 evaporation would be affected not only by the soil available energy but also
667 by the heat and vapor transfer coefficients between the soil, vegetation and
668 atmosphere (Shuttleworth and Wallace, 1985; Haghghi and Or, 2015). In
669 the recent study of Hssaine et al. (2018), the soil resistance’s parameters were
670 calibrated over partially covering wheat by implementing a network of soil,
671 vegetation and air resistances and by separating phenological stages with
672 fractional vegetation cover smaller and larger than 0.5. Further research
673 should tackle the structural (radiation interception) and functional (tran-
674 spiration rate) vegetation effects of different biomes on the soil evaporation
675 underneath. Last but not least, future studies should investigate the impact
676 on evaporation estimates (and calibration parameters) of uncertainties in in-
677 put soil moisture data sets derived from active microwave, passive microwave,
678 disaggregation and/or assimilation techniques (Peng et al., 2017).

679 **A. Soil energy balance model**

680 The evaporation model classically solves the energy budget equation over
681 bare soil:

$$LE = Rn - G - H \quad (13)$$

682 with LE (W m^{-2}) being the soil latent heat flux, H (W m^{-2}) the soil sensible
683 heat flux, Rn (W m^{-2}) the soil net radiation and G (W m^{-2}) the ground
684 conduction at 5-cm depth. The soil net radiation is expressed as:

$$Rn = (1 - \alpha)R_g + \epsilon(R_a - \sigma T^4) \quad (14)$$

685 with α (-) being the soil albedo, R_g (W m^{-2}) the incoming solar radiation,
686 ϵ (-) the soil emissivity (set to 0.95), R_a (W m^{-2}) the atmospheric longwave
687 radiation, σ ($\text{Wm}^{-2}\text{K}^{-4}$) the Stefan-Boltzmann constant and T (K) the soil
688 skin temperature. For simplicity, α is set to a constant value (0.20) as in
689 (Merlin et al., 2016). When applied to low resolution remote sensing data,
690 albedo could be made variable as a function of surface soil composition and
691 moisture (Liu et al., 2014). The downward atmospheric radiation at ground
692 level is expressed as:

$$R_a = \epsilon_a \sigma T_a^4 \quad (15)$$

693 with ϵ_a (-) being the effective atmospheric emissivity, and T_a (K) the air
694 temperature. The emissivity of clear skies is estimated as in Brutsaert (1975):

$$\epsilon_a = 0.553(e_a/100)^{1/7} \quad (16)$$

695 with:

$$e_a = e_{sat}(T_a)(h_a/100) \quad (17)$$

696 with h_a (%) being the air relative humidity and:

$$e_{sat}(T_a) = 611 \exp \left[17.27 (T_a - 273.2)/(T_a - 35.9) \right] \quad (18)$$

697 with T_a in K. The ground conduction is estimated as a fraction of soil net
698 radiation (Choudhury et al., 1987; Kustas and Daughtry, 1990):

$$G = C_G Rn \quad (19)$$

699 with C_G (-) a coefficient (set to 0.20). The sensible heat flux is expressed as:

$$H = \rho C_P \frac{T - T_a}{r_{ah}} \quad (20)$$

700 with the aerodynamic resistance being estimated as in Choudhury et al.
701 (1986):

$$r_{ah} = \frac{r_{ah0}}{(1 + Ri)^\eta} \quad (21)$$

702 with r_{ah0} (s m^{-1}) being the neutral aerodynamic resistance and Ri (-) the
703 Richardson number, which represents the importance of free versus forced
704 convection, and η (-) a coefficient set to 0.75 in unstable conditions ($T > T_a$)
705 and to 2 in stable conditions ($T < T_a$). The neutral r_{ah0} is computed as:

$$r_{ah0} = \frac{1}{k^2 u_a} \left[\ln \left(\frac{Z}{z_{0m}} \right) \right]^2 \quad (22)$$

706 with k (-) being the von Karman constant, u_a (m s^{-1}) the wind speed mea-
707 sured at the reference height Z (m) and z_{0m} (m) the momentum soil rough-
708 ness (set to 0.001 m (Yang et al., 2008; Stefan et al., 2015; Merlin et al.,
709 2016)). The Richardson number is computed as:

$$Ri = \frac{5gZ(T - T_a)}{T_a u_a^2} \quad (23)$$

710 with g (m s^{-2}) being the gravitational constant. The energy balance of
711 Equation (13) is solved by initializing the surface soil temperature $T = T_a$,
712 and by looking for the value of T that minimizes the cost function $F(T)$:

$$F(T) = (LE + H - Rn + G)^2 \quad (24)$$

713 with LE being expressed as in Equation 1.

714 **B. Analytical expressions of $r_{ss,ref}$ and $\theta_{efolding}$**

715 As an attempt to approximate SEE over its full range $[0 - 1]$, SEE is
 716 approached linearly at the mid-value (0.5). The linear approximation of
 717 $SEE(\theta)$ at $SEE = 0.5$ sets two constraints on the model. First, the soil
 718 moisture value at which $SEE = 0.5$ is noted $\theta_{1/2}$:

$$SEE(\theta_{1/2}) = 0.5 \quad (25)$$

719 Second, the first derivative of SEE at $\theta_{1/2}$ is set to the slope ($\Delta\theta_{1/2}^{-1}$) of the
 720 linear regression between SEE and θ observations:

$$\left(\frac{\partial SEE}{\partial \theta}\right)(\theta_{1/2}) = \Delta\theta_{1/2}^{-1} \quad (26)$$

721 The combination of the above two equations allows to estimate both $r_{ss,ref}$
 722 and $\theta_{efolding}$ parameters given a time series of SEE and θ observations. Pa-
 723 rameters $r_{ss,ref}$ and $\theta_{efolding}$ in Equation (4) are analytically expressed as a
 724 function of $\theta_{1/2}$, $\Delta\theta_{1/2}^{-1}$, soil temperature (T_{wet} and $T_{1/2}$) and aerodynamic
 725 resistance ($r_{ah,wet}$ and $r_{ah,1/2}$) values corresponding to $r_{ss} = 0$ and $\theta = \theta_{1/2}$,
 726 respectively. The soil energy balance model described in Appendix A is used
 727 to estimate both pairs ($T_{wet}, r_{ah,wet}$) and ($T_{1/2}, r_{ah,1/2}$) for a given meteorolo-
 728 gical forcing.

729 Briefly, $r_{ss,ref}$ is derived by inverting Equation (4):

$$r_{ss,ref} = r_{ss,1/2} \exp(\theta_{1/2}/\theta_{efolding}) \quad (27)$$

730 with $r_{ss,1/2}$ being the soil resistance at $\theta_{1/2}$ obtained by combining Equations
 731 (3) and (25):

$$r_{ss,1/2} = 2 \frac{e_{sat}(T_{1/2}) - e_a}{e_{sat}(T_{wet}) - e_a} r_{ah,wet} - r_{ah,1/2} \quad (28)$$

732 $\theta_{efolding}$ is obtained by applying the first derivative at $\theta = \theta_{1/2}$ to the soil
 733 energy balance equation:

$$\theta_{efolding} = \frac{\frac{r_{ss,1/2}}{r_{ss,1/2}+r_{ah,1/2}}(e_{sat}(T_{1/2}) - e_a) + f(\theta_{1/2})\dot{e}_{sat}(T_{1/2})}{\frac{r_{ss,1/2}+r_{ah,1/2}}{r_{ah,wet}}(e_{sat}(T_{wet}) - e_a)} \times \frac{1}{\Delta\theta_{1/2}^{-1}} \quad (29)$$

734 with \dot{e}_{sat} being the derivative of saturated vapor pressure with respect to T
 735 and $f(\theta_{1/2})$ expressed as:

$$f(\theta_{1/2}) = -\frac{\frac{r_{ss,1/2}r_{ah,1/2}}{(r_{ss,1/2}+r_{ah,1/2})^2}(e_{sat}(T_{1/2}) - e_a)}{\gamma + \frac{r_{ah,1/2}}{r_{ss,1/2}+r_{ah,1/2}}\dot{e}_{sat}(T_{1/2}) + 4\frac{\gamma}{\rho C_P}\epsilon\sigma(1 - C_G)T_{1/2}^3 r_{ah,1/2}} \quad (30)$$

736 Note that the full analytical development of $\theta_{efolding}$ is described in Merlin
 737 et al. (2016).

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Table 1: Start and end day of year (DOY) of the 9 study periods, including the whole bare soil period ($P0$) at Sidi Rahal site in 2016 and its 8 subperiods ($P1 - 8$) bounded by significant rainfall events. The soil moisture range, mean soil moisture, mean EC-derived SEE and mean potential evaporation are also listed for each period.

Period	Start (DOY)	End (DOY)	θ range (m ³ m ⁻³)	mean θ (m ³ m ⁻³)	mean SEE_{EC} (-)	mean LEp (Wm ⁻²)
$P0$	1	243	0.03–0.38	0.06	0.24	354
$P1$	1	8	0.05–0.24	0.10	0.38	238
$P2$	9	45	0.04–0.23	0.08	0.33	242
$P3$	46	57	0.05–0.25	0.10	0.40	283
$P4$	58	80	0.05–0.33	0.10	0.32	286
$P5$	81	95	0.07–0.38	0.14	0.46	313
$P6$	96	125	0.04–0.22	0.07	0.27	342
$P7$	126	234	0.03–0.12	0.04	0.16	398
$P8$	235	243	0.03–0.16	0.05	0.20	386

Table 2: List of $\theta_{1/2}$ and $\Delta\theta_{1/2}^{-1}$ parameters retrieved from EC measurements for data with $LEp > 100 \text{ Wm}^{-2}$ (for data with $LEp > 400 \text{ Wm}^{-2}$ in parenthesis) and for periods $P0-8$ separately.

Period	$\theta_{1/2}$ (m^3m^{-3})	$\Delta\theta_{1/2}^{-1}$ (m^3m^{-3})
$P0$	0.119 (0.129)	4.58 (4.01)
$P1$	0.129 (NA)	4.72 (NA)
$P2$	0.126 (NA)	4.54 (NA)
$P3$	0.112 (NA)	8.41 (NA)
$P4$	0.140 (NA)	5.61 (NA)
$P5$	0.156 (0.146)	4.49 (3.77)
$P6$	0.136 (0.136)	3.90 (3.51)
$P7$	0.073 (0.073)	11.0 (11.2)
$P8$	0.120 (0.120)	5.40 (5.22)

Table 3: Correlation coefficient (R), slope of the linear regression (S) and root mean square difference (RMSD) between modeled and EC-derived SEE for study periods $P0 - 8$ separately. Model parameters are calibrated using EC measurements for data with $LEp > 100 \text{ Wm}^{-2}$ during corresponding period $P0 - 8$ (during period $P0$ in parenthesis).

Period	R (-)			S (-)			RMSD (-)		
	PdS86	M16	New	PdS86	M16	New	PdS86	M16	New
$P0$	0.75 (0.75)	0.80 (0.80)	0.85 (0.85)	0.74 (0.74)	0.86 (0.86)	0.91 (0.91)	0.13 (0.13)	0.12 (0.12)	0.10 (0.10)
$P1$	0.94 (0.94)	0.94 (0.94)	0.97 (0.97)	0.82 (0.82)	0.85 (0.83)	0.87 (0.85)	0.11 (0.11)	0.11 (0.12)	0.08 (0.08)
$P2$	0.84 (0.84)	0.85 (0.84)	0.92 (0.92)	0.99 (0.99)	0.95 (0.95)	1.01 (1.02)	0.12 (0.12)	0.10 (0.11)	0.08 (0.07)
$P3$	0.55 (0.55)	0.57 (0.55)	0.63 (0.64)	0.57 (0.57)	0.89 (0.60)	0.98 (0.70)	0.21 (0.21)	0.25 (0.19)	0.24 (0.18)
$P4$	0.64 (0.64)	0.66 (0.66)	0.72 (0.73)	0.73 (0.73)	0.84 (0.74)	0.88 (0.80)	0.21 (0.21)	0.22 (0.22)	0.19 (0.19)
$P5$	0.78 (0.78)	0.85 (0.80)	0.92 (0.88)	0.82 (0.82)	0.95 (0.77)	1.03 (0.86)	0.19 (0.19)	0.15 (0.20)	0.12 (0.16)
$P6$	0.69 (0.69)	0.72 (0.70)	0.84 (0.81)	0.87 (0.87)	0.85 (0.96)	1.01 (1.11)	0.12 (0.12)	0.11 (0.13)	0.09 (0.11)
$P7$	0.30 (0.30)	0.79 (0.71)	0.87 (0.77)	0.12 (0.12)	0.80 (0.29)	0.91 (0.41)	0.10 (0.10)	0.07 (0.08)	0.05 (0.07)
$P8$	0.85 (0.85)	0.82 (0.82)	0.83 (0.83)	0.83 (0.83)	0.78 (0.71)	0.89 (0.84)	0.08 (0.08)	0.08 (0.07)	0.08 (0.08)

Table 4: Correlation coefficient (R), slope of the linear regression (S) and root mean square difference (RMSD) between simulated and measured evaporation at Sidi Rahal site.

Model	R (-)	S (-)	RMSD (Wm^{-2})
PdS86	0.81	0.89	34
M16	0.83	0.96	35
New	0.85	0.96	32

Table 5: Same as for Table 2 with model parameters calibrated using TI measurements.

Period	$\theta_{1/2}$ (m^3m^{-3})	$\Delta\theta_{1/2}^{-1}$ (m^3m^{-3})
<i>P0</i>	0.085 (0.125)	10.0 (4.21)
<i>P1</i>	0.086 (NA)	9.31 (NA)
<i>P2</i>	0.086 (NA)	12.7 (NA)
<i>P3</i>	0.093 (NA)	23.3 (NA)
<i>P4</i>	0.108 (0.128)	10.1 (5.63)
<i>P5</i>	0.143 (0.164)	9.86 (3.95)
<i>P6</i>	0.102 (0.150)	10.5 (3.52)
<i>P7</i>	0.055 (0.063)	20.1 (19.9)
<i>P8</i>	0.080 (0.111)	17.7 (6.46)

Table 6: Same as for Table 3 with model parameters calibrated using TI measurements for data with $LEp > 100 \text{ Wm}^{-2}$ during corresponding period $P0 - 8$ (for data with $LEp > 400 \text{ Wm}^{-2}$ during period $P0$ in parenthesis).

Period	R (-)			S (-)			RMSD (-)		
	PdS86	M16	New	PdS86	M16	New	PdS86	M16	New
$P0$	0.77 (0.75)	0.77 (0.80)	0.81 (0.86)	1.15 (0.71)	1.23 (0.82)	1.25 (0.87)	0.18 (0.13)	0.19 (0.11)	0.17 (0.10)
$P1$	0.89 (0.94)	0.89 (0.94)	0.92 (0.98)	1.02 (0.81)	0.96 (0.79)	0.97 (0.82)	0.20 (0.11)	0.21 (0.11)	0.17 (0.08)
$P2$	0.81 (0.86)	0.77 (0.85)	0.82 (0.94)	1.32 (1.02)	1.36 (0.90)	1.42 (0.98)	0.20 (0.12)	0.22 (0.10)	0.19 (0.07)
$P3$	0.43 (0.26)	0.48 (0.55)	0.52 (0.65)	0.71 (0.31)	1.04 (0.56)	1.08 (0.68)	0.32 (0.28)	0.37 (0.19)	0.35 (0.17)
$P4$	0.68 (0.82)	0.63 (0.65)	0.67 (0.74)	1.01 (0.82)	1.02 (0.70)	1.03 (0.77)	0.28 (0.14)	0.29 (0.21)	0.26 (0.18)
$P5$	0.60 (0.72)	0.77 (0.81)	0.82 (0.90)	0.55 (0.76)	1.17 (0.78)	1.21 (0.89)	0.35 (0.20)	0.25 (0.18)	0.22 (0.14)
$P6$	0.60 (0.70)	0.64 (0.71)	0.70 (0.83)	1.22 (0.85)	1.36 (0.91)	1.44 (1.09)	0.22 (0.12)	0.22 (0.12)	0.21 (0.10)
$P7$	0.77 (0.40)	0.76 (0.70)	0.82 (0.69)	0.52 (0.15)	1.24 (0.26)	1.37 (0.42)	0.08 (0.10)	0.12 (0.08)	0.12 (0.07)
$P8$	0.87 (0.85)	0.84 (0.81)	0.86 (0.79)	1.55 (0.78)	1.85 (0.64)	1.85 (0.80)	0.13 (0.07)	0.19 (0.07)	0.18 (0.08)

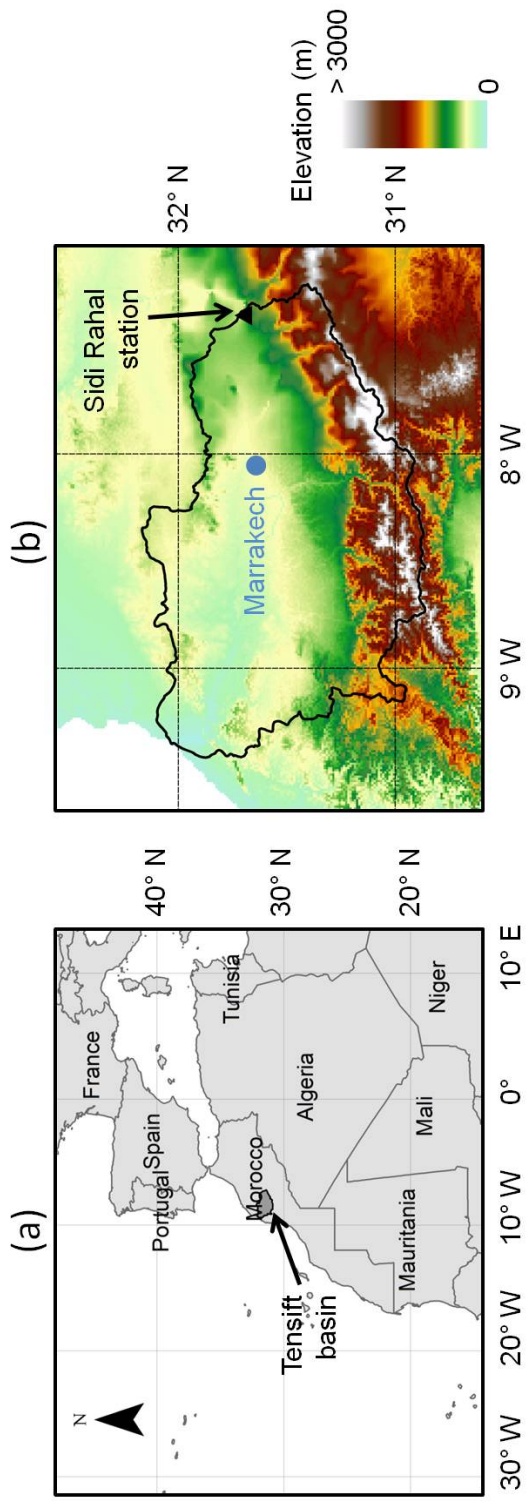


Figure 1: Geographic location of the Tensift basin in Morocco (a) and the Sidi Rahal flux site within the catchment (b).

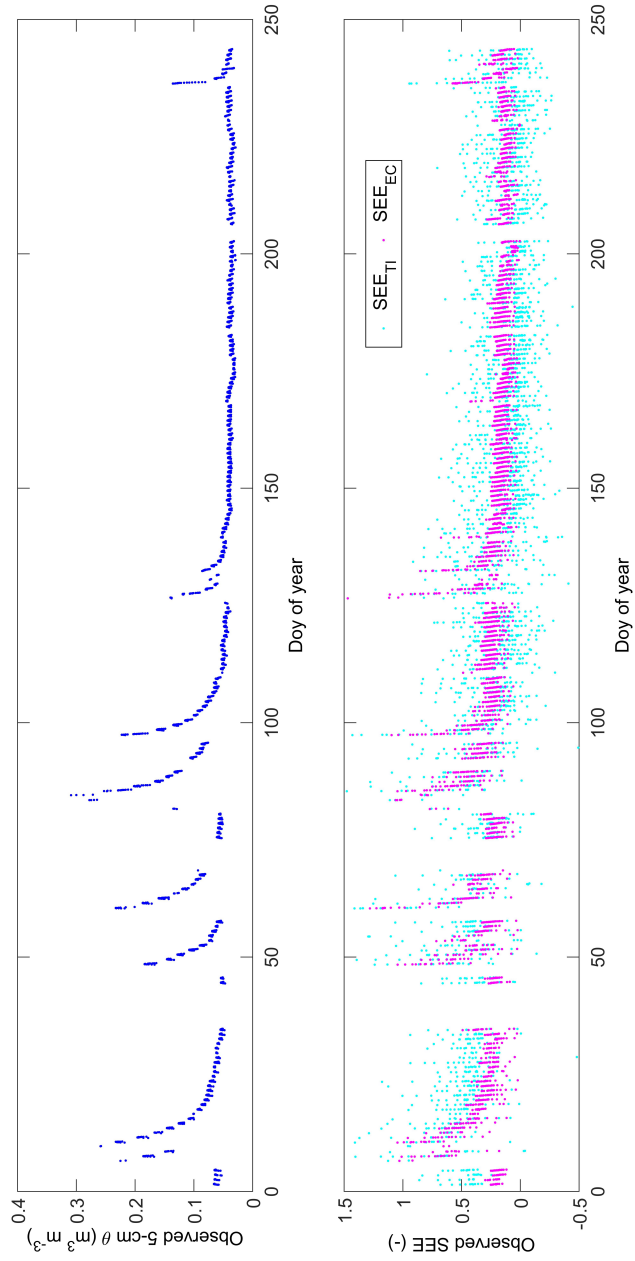


Figure 2: Time series of near surface soil moisture (θ) and EC-derived (SEE_{EC}) and TI-derived (SEE_{TI}) SEE in 2016 at the Sidi Rahal site.

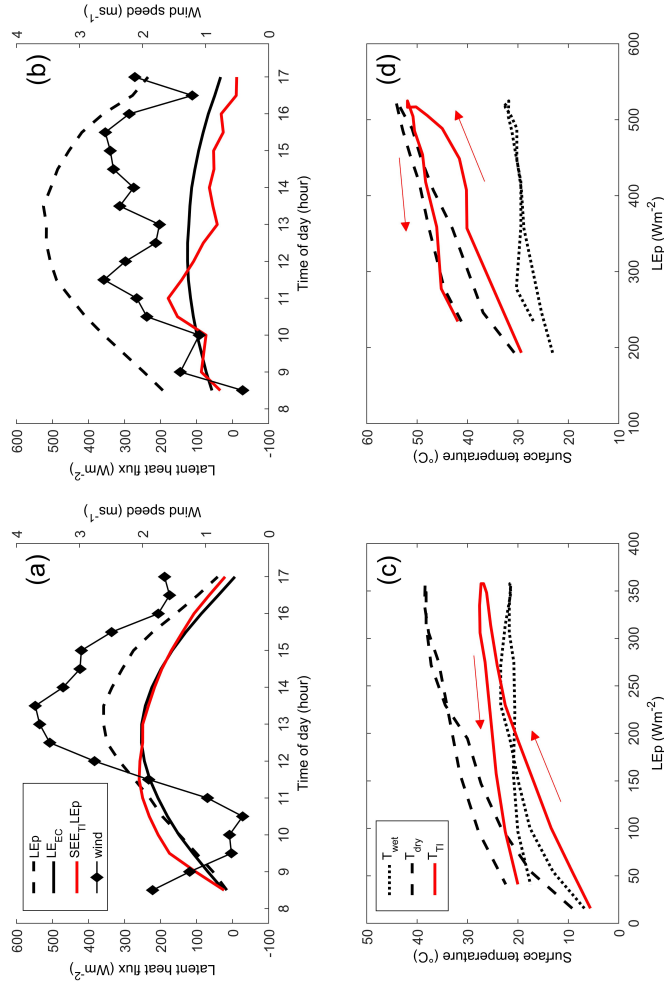


Figure 3: Variations between 8:30 am and 5:00 pm of the potential soil evaporation (LE_p), the soil evaporation measured by the EC (LE_{EC}), the soil evaporation estimated as the TI-derived SEE (SEE_{TI}) times LE_p and wind speed in relatively wet (a) and dry (b) conditions, on January 7th and May 1st 2016 respectively. The hysteresis behavior of radiometric temperature is also shown as a function of LE_p on the wet (c) and dry (d) date, respectively.

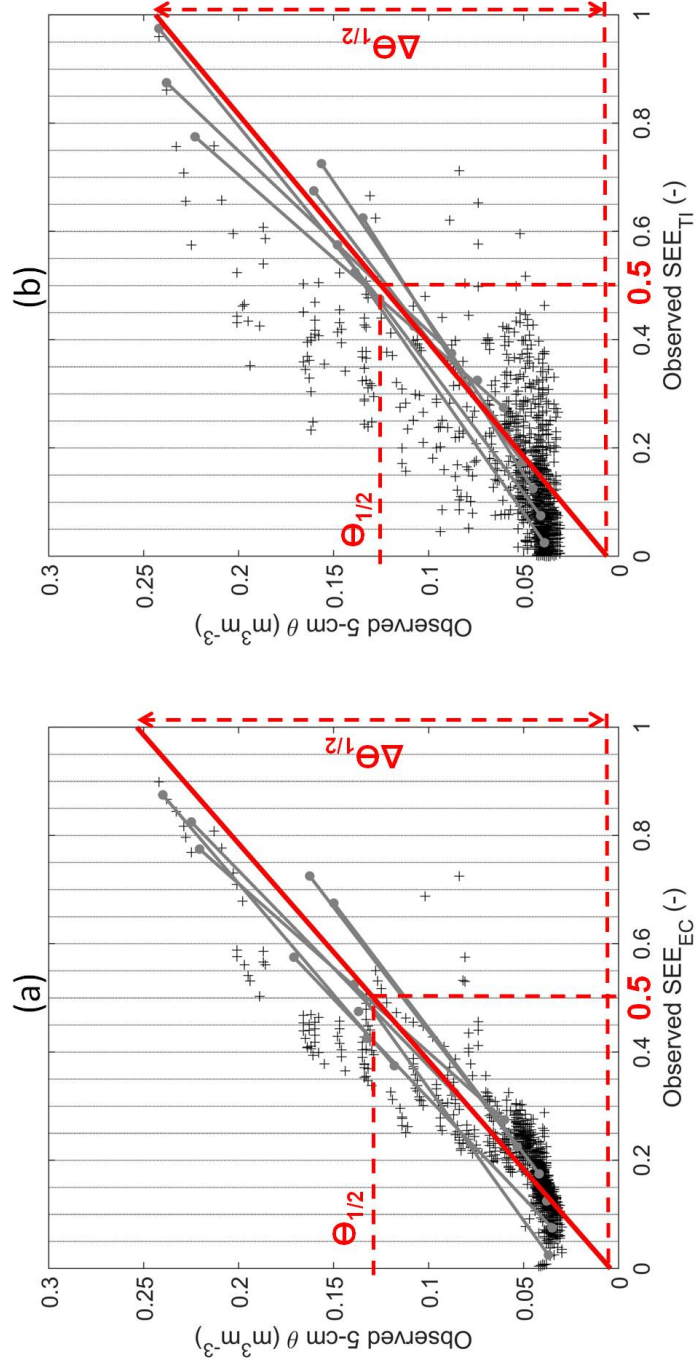


Figure 4: Retrieval of the pair $(\theta_{1/2}, \Delta\theta_{1/2}^{-1})$ during period $P0$ for data with $LEp > 400 \text{ W m}^{-2}$ and for EC-derived (a) and TI-derived (b) SEE separately.

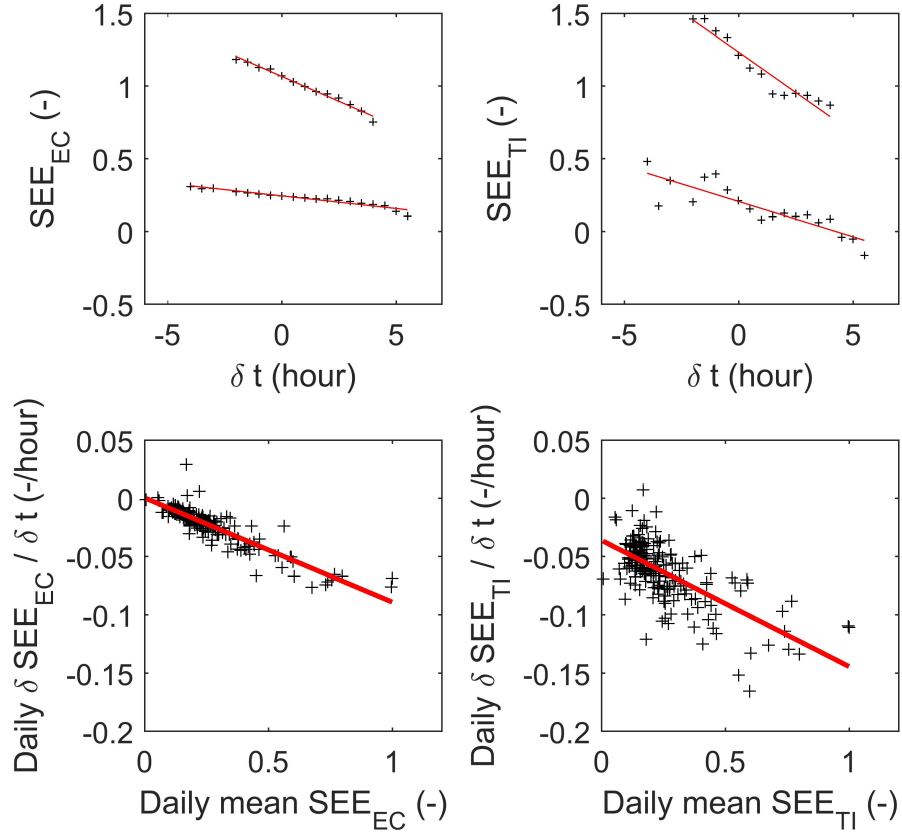


Figure 5: The observed SEE for data with $LEp > 100 \text{ Wm}^{-2}$ is plotted as a function of δt at the daily time scale for a wet (January 7th) and dry (May 1st 2016) day (top) and the estimated daily slope $\delta SEE / \delta t$ is plotted as a function of the daily mean SEE (bottom) for each day of period $P0$ and for the EC-derived (left) and TI-derived (right) SEE case separately.

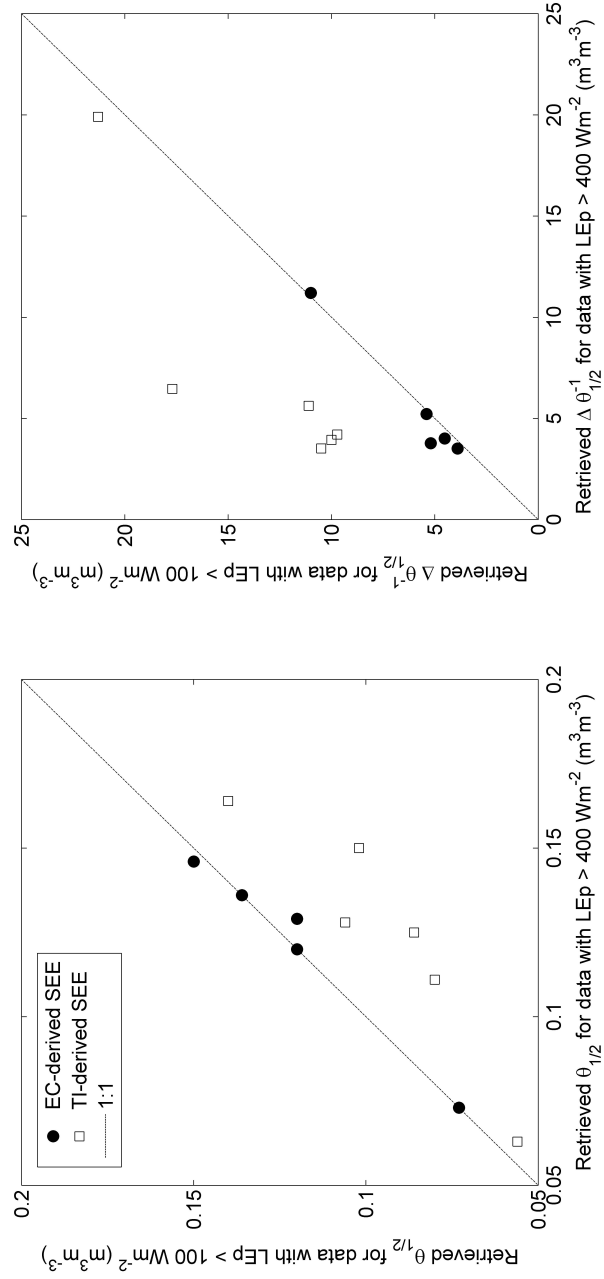


Figure 6: Retrieved $\theta_{1/2}$ (left) and retrieved $\Delta\theta_{1/2}^{-1}$ (right) for data with $LEp > 100 \text{ Wm}^{-2}$ versus the same parameter retrieved for data with $LEp > 400 \text{ Wm}^{-2}$.

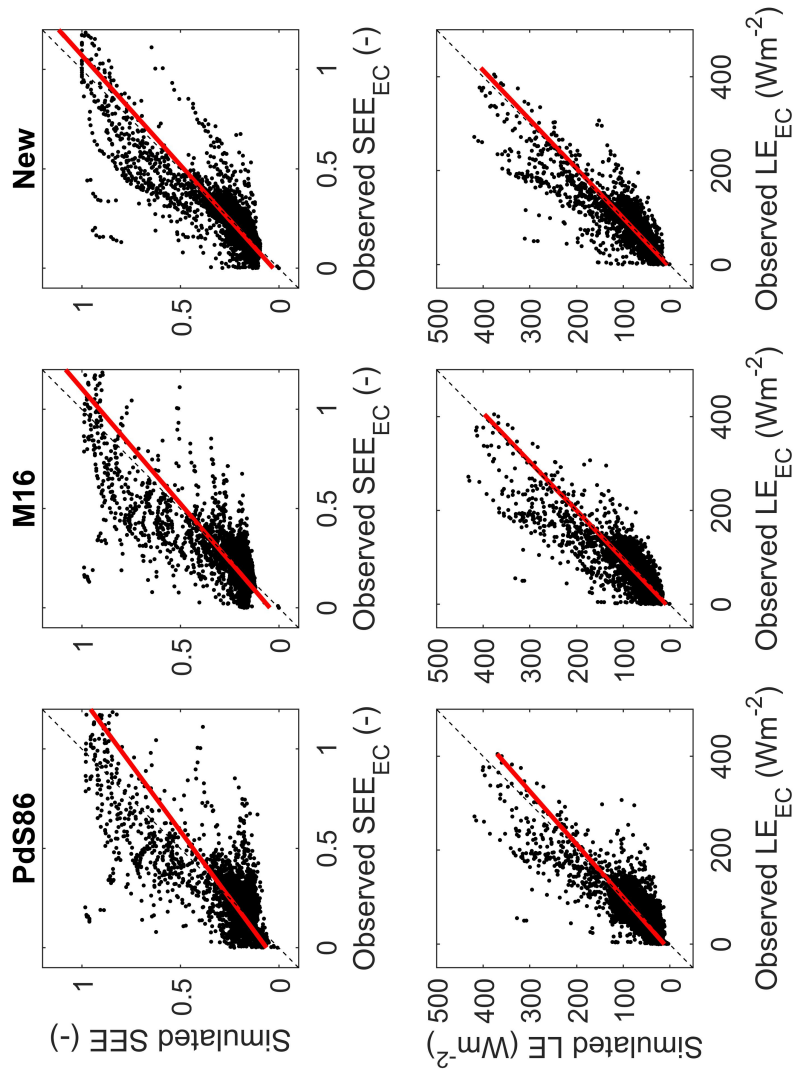


Figure 7: Simulated versus observed (EC-derived) SEE (top) and evaporation (bottom) for $P0$ data with $LEp > 100 \text{ W m}^{-2}$ and for three (PdS86, M16 and new) τ_{ss} models separately. In all three cases, both $\theta_{1/2}$ and $\Delta\theta_{1/2}^{-1}$ are calibrated during $P0$ from EC-derived SEE data with $LEp > 100 \text{ W m}^{-2}$.

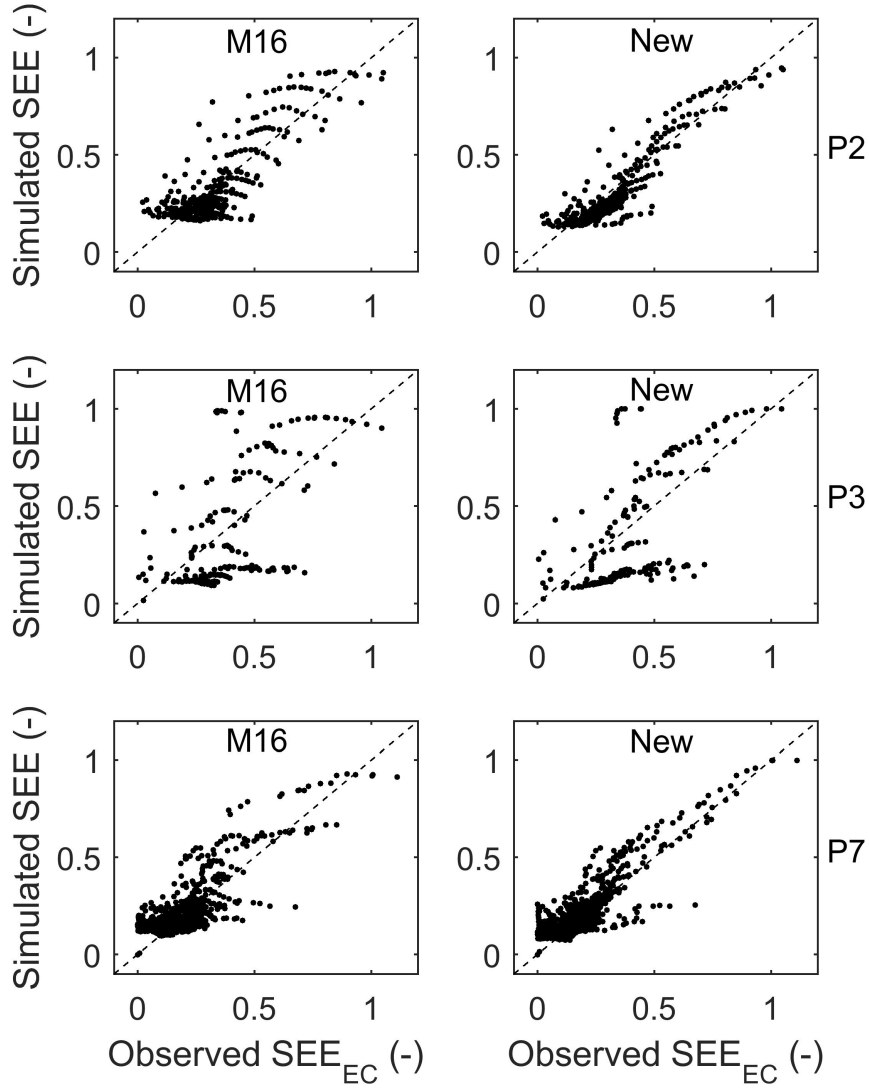


Figure 8: Simulated versus observed (EC-derived) SEE for data with $LEp > 100 \text{ W m}^{-2}$ during P2 (top), P3 (middle) and P7 (bottom) period and for M16 and new models separately. In all six cases, both $\theta_{1/2}$ and $\Delta\theta_{1/2}^{-1}$ are calibrated during $P0$ from EC-derived SEE data with $LEp > 100 \text{ W m}^{-2}$.

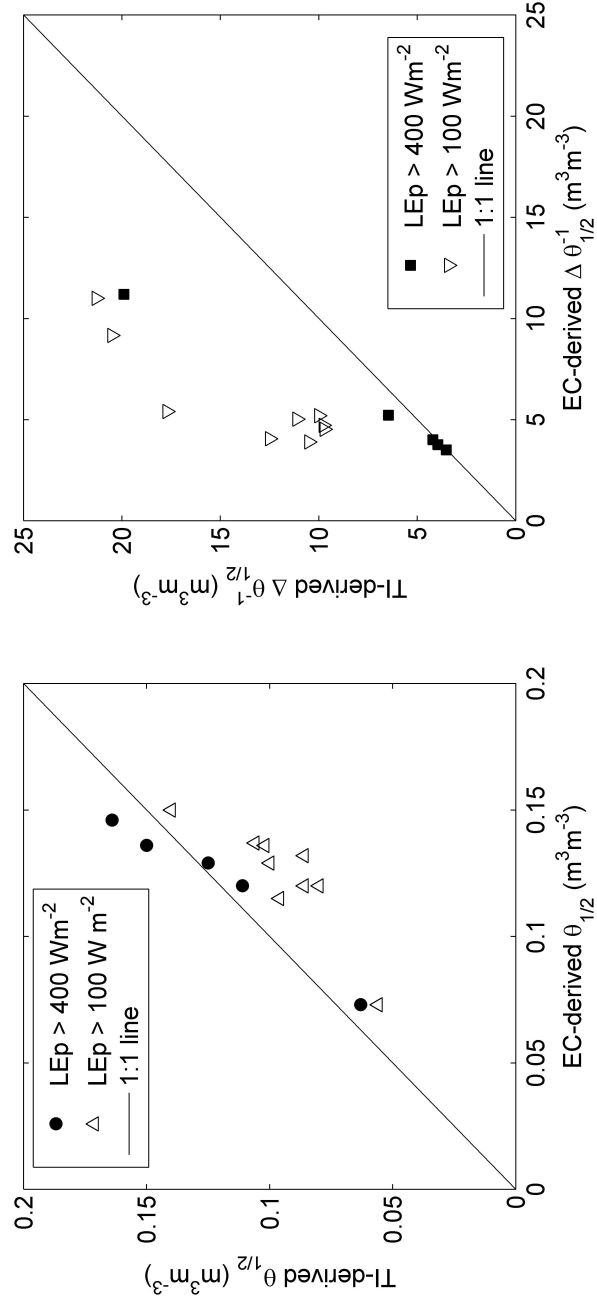


Figure 9: TI-derived versus EC-derived $\theta_{1/2}$ (left) and TI-derived versus EC-derived $\Delta \theta_{1/2}^{-1}$ (right) for data with a minimum LEp value of 100 and 400 Wm^{-2} separately.

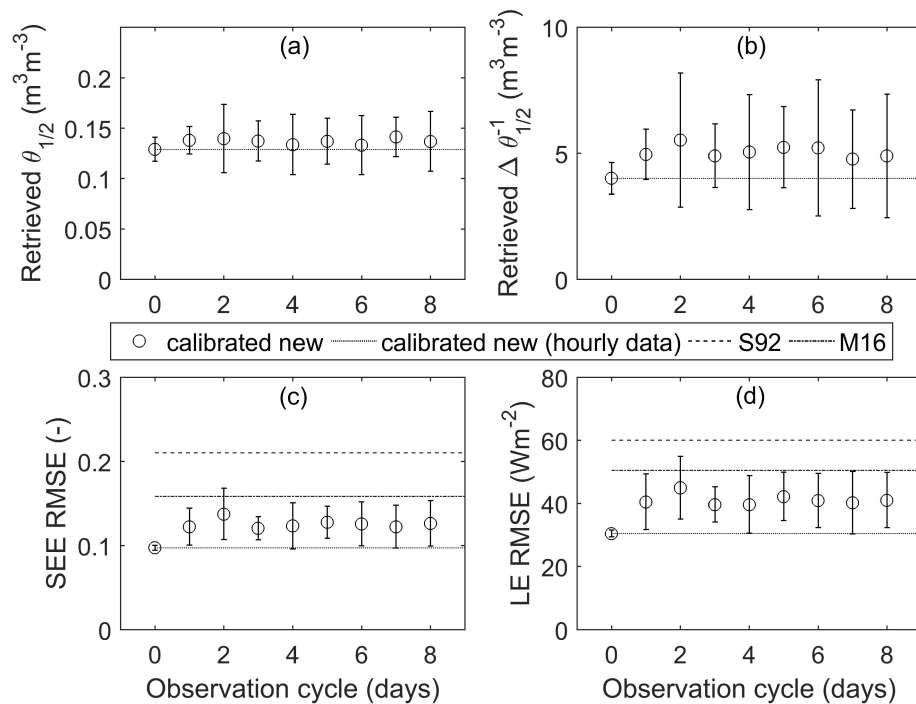


Figure 10: Model results in terms of (a) retrieved $\theta_{1/2}$, (b) retrieved $\Delta\theta_{1/2}^{-1}$, (c) RMSE in simulated SEE and (d) RMSE in simulated evaporation are presented for an increasing observation cycle –ranging from the hourly to the 8-day period– of TI calibration data. The mean (circles) and standard deviation (errorbars) of retrieved parameters are computed from an ensemble of input TI data sets (with $LEp > 400 \text{ Wm}^{-2}$) collected at 11:30 am, 12:00pm and 12:30pm separately and, for observation cycles longer than 1 day, on all possible observation cycles shifted by 1 day. The mean (circles) and standard deviation (errorbars) of RMSE in SEE/LE are computed from data (with $LEp > 100 \text{ Wm}^{-2}$) during the whole study period using the ensemble of parameter pairs $(\theta_{1/2}, \Delta\theta_{1/2}^{-1})$ retrieved previously. For comparison purposes, the RMSE of the SEE/LE estimated by M16 (pedotransfer function) and S92 (fixed parameters) is also plotted.