Improving evapotranspiration estimates in Mediterranean drylands: The role of soil evaporation

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[1] An adaptation of a simple model for evapotranspiration (E) estimations in drylands based on remotely sensed leaf area index and the Penman-Monteith equation (PML model) (Leuning et al., 2008) is presented. Three methods for improving the consideration of soil evaporation influence in total evapotranspiration estimates for these ecosystems are proposed. The original PML model considered evaporation as a constant fraction (f) of soil equilibrium evaporation. We propose an adaptation that considers f as a variable primarily related to soil water availability. In order to estimate daily f values, the first proposed method (fSWC) uses rescaled soil water content measurements, the second (fZhang) uses the ratio of 16 days antecedent precipitation and soil equilibrium evaporation, and the third (f_drying), includes a soil drying simulation factor for periods after a rainfall event. E estimates were validated using E measurements from eddy covariance systems located in two functionally different sparsely vegetated drylands sites: a littoral Mediterranean semiarid steppe and a dry-subhumid Mediterranean montane site. The method providing the best results in both areas was f_drying (mean absolute error of 0.17 mm day⁻¹) which was capable of reproducing the pulse-behavior characteristic of soil evaporation in drylands strongly linked to water availability. This proposed model adaptation, f_drying, improved the PML model performance in sparsely vegetated drylands where a more accurate consideration of soil evaporation is necessary.


1. Introduction

[2] Evapotranspiration (E), is the largest term in the terrestrial water balance after precipitation. Additionally, its energetic equivalent, the latent heat flux (λE), plays an important role in the surface energy balance affecting terrestrial weather dynamics and vice versa. The importance of E in drylands, covering 45% of the Earth surface [Asner et al., 2003; Schlesinger et al., 1990], is critical since it accounts for 90–100% of the total annual precipitation [Glenn et al., 2007]. Therefore, an accurate regional estimation of E is crucial for many operational applications in drylands: irrigation planning, management of watersheds and aquifers, meteorological predictions, and detection of droughts and climate change.

[3] Remote sensing has been recognized as the most feasible technique for E estimation at regional scales with a reasonable degree of accuracy [Kustas and Norman, 1999; Mu et al., 2011]. Several methods have been developed for estimating regional E in the last decades. Many of them are based on the indirect estimation of E as a residual of the surface energy balance equation (SEB) using direct estimates of the sensible heat flux (H) derived from remotely sensed surface temperatures [Glenn et al., 2007; Kalma et al., 2008]. However, residual estimation of E in Mediterranean drylands remains problematic due to the reduced magnitude of λE in conditions where H is the dominant flux [Morillas et al., 2013]. Reduced inaccuracies affecting estimates of Rn and H derived from surface temperature measurements (~10 and ~30%, respectively) strongly affected the residually estimated values of λE (~90% of error) in such conditions [Morillas et al., 2013]. This suggests that direct estimation of E might be more advisable in Mediterranean drylands.

[4] Cleugh et al. [2007] presented a method for direct estimation of E based on regional application of the Penman-Monteith (PM) equation [Monteith, 1964] using leaf area index (LAI) from MODIS (Moderate Resolution Imaging Spectrometer) and gridded meteorological data. This work stimulated a number of later studies [Leuning...
et al., 2008; Mu et al., 2007, 2011; Zhang et al., 2008, 2010) that have demonstrated the potential of the PM equation as a robust and biophysically based framework for estimating evapotranspiration using remote-sensing inputs [Leuning et al., 2008].

[5] The key parameter of the PM equation is the surface conductance ($G_s$), the inverse of the resistance of the soil-canopy system to lose water. A simple linear relationship between $G_s$ and LAI was initially proposed by Cleugh et al. [2007] to estimate $E$ at two field sites in Australia. Mu et al. [2007, 2011] took one step forward with separate estimations for the two major components of $E$: canopy transpiration ($E_c$) and soil evaporation ($E_s$), both controlled by different biotic and physical processes in sparse vegetated areas [Hu et al., 2009]. Mu et al. [2007, 2011] included a formulation for $E_c$, considering the effects of vapor pressure deficit ($D_v$) and air temperature ($T_a$) on canopy conductance ($G_s$) but assumed constant parameters for each vegetation type. Based on these studies, Leuning et al. [2008] developed a less empirical formulation for $G_s$ to apply the PM equation regionally. This new formulation also considers both $E_c$ and $E_s$. For $G_s$, a more biophysical algorithm based on radiation absorption and $D_v$ was proposed by Leuning et al. [2008] based on Kellihier et al. [1995]. In this case, $E_s$ is estimated as a constant fraction, $f$, of soil equilibrium or potential evaporation [Priestley and Taylor, 1972] defined as the evaporation occurring under given meteorological conditions from a continuously saturated soil surface [Donohue et al., 2010; Thornthwaite, 1948]. Application of the Penman-Monteith-Leuning, PML model, as it was named by Zhang et al. [2010], requires commonly available meteorological data (more details in section 2), LAI data from MODIS or other remote-sensing platforms and two main parameters, considered by Leuning et al. [2008] to be constants: $g_{so}$, maximum stomatal conductance of leaves at the top of the canopy and $f$, representing the ratio of soil evaporation to the equilibrium rate. The potential of the PML for global estimates of $E$ is promising as shown by accurate estimates (systematic root-mean-square error of 0.27 mm day$^{-1}$) found in 15 Fluxnet sites located across a wide range of climatic conditions, from wetlands to woody savannas [Leuning et al., 2008]. Nonetheless, the latter model has not been tested in Mediterranean drylands characterized by strongly reduced magnitudes of $E$ (mean annual $E$ values ranging 0.5 mm day$^{-1}$) resulting from the typical asynchrony of energy and water availability in these environments [Serrano-Ortiz et al., 2007].

[6] In drylands, where water availability is the main controlling factor of biological and physical processes [Noy-Meir, 1973], evaporation from soil can exceed 80% of total $E$ [Mu et al., 2007]. Soil water availability, the main factor controlling $E_s$ in water-limited areas [McVicar et al., 2012] is highly variable in these ecosystems and, therefore, assuming $f$ as constant, as the original PML model of Leuning et al. [2008] did, is inadequate. Leuning et al. [2008] acknowledged this limitation and recommended that remote-sensing or other techniques should be developed to treat $f$ as a variable instead of a parameter, especially for sparsely vegetated sites ($LAI < 3$). Many authors have also claimed the necessity to increase the efforts to carefully quantify the $E_c$ contribution to total $E$ in low LAI ecosystems as semiarid grasslands and shrublands [Hu et al., 2009; Kuc and Small, 2004]. Numerous $E$ models that include specific methods for $E_s$ estimation, from the simplest to the most complex formulations, exist [Allen et al., 1998; Fisher et al., 2008; Kite, 2000; Mu et al., 2007; Shuttleworth and Wallace, 1985]. Special attention has been paid to this topic in the agronomy sector because from an agronomic point of view, soil evaporation is considered an unproductive use of water that requires quantification [Kite and Droogers, 2000]. Thus, many efforts have been devoted to improve $E_s$ formulation in croplands [Kite, 2000; Lagos et al., 2009; Snyder et al., 2000; Torres and Calera, 2010; Ventura et al., 2006]. The FAO 56 methodology [Allen et al., 1998] is one of the most used methods in agricultural areas due to its capacity to estimate both $E_c$ and $E_s$ beyond standard conditions (well-watered conditions) and some subsequent refinements have been proposed [Snyder et al., 2000; Torres and Calera, 2010; Ventura et al., 2006]. However, when applying this method, detailed local soil characteristics, such as depth of soil or soil texture, are needed for estimating $E_s$. This limits the regional application of this model beyond agricultural areas where little detailed soil information is available. There are other types of models partitioning the total $E$ by considering a different number of layers or sources like the sparse-crop model of Shuttleworth and Wallace [1985] or the model from Brenner and Incol [1997]. The layers are defined depending on the site-specific surface heterogeneity (i.e., canopy, bare soil, under plant soil, residue covered soil, etc.). These models have provided successful results in sparsely vegetated areas such as irrigated agricultural scenarios [Lagos et al., 2009; Ortega-Farias et al., 2007] and natural conditions [Domingo et al., 1999; Hu et al., 2009]. Yet, they require specific information regarding the vegetation physiology and the substrate. Furthermore, complex modeling of aerodynamic and surface resistances governing the flux from each layer is necessary, limiting its regional application. From another perspective, the distributed hydrological models also deal with $E_s$ estimation. These models consider all the water reservoirs, modeling runoff and infiltration processes in a basin scale using satellite data [Kite, 2000; Kite and Droogers, 2000] to offer $E$ estimates at macroscale basins. However, these models require the measurements of all the terms of the hydrological balance to be validated. Those measurements are not routinely available for many macroscale basins.

[7] From a more regionally operative point of view, several models designed for global $E$ estimation have also successfully estimated $E_s$ as a fraction, $f$, of soil equilibrium evaporation, as the PML model proposed. That soil equilibrium evaporation rate has been estimated using the PM equation [Mu et al., 2007, 2011] or the Priestley-Taylor equation [Fisher et al., 2008; Garcia et al., 2013; Zhang et al., 2010] but all these models considered $f$ as temporally variable. $f$ has been estimated as a function of $D_v$, relative humidity and a locally calibrated parameter $\beta$ (which indicates the relative sensitivity of soil moisture to $D_v$) every month or 8 days periods [Fisher et al., 2008; Mu et al., 2007, 2011]. Garcia et al. [2013] proved that such approach is very sensitive to $\beta$ parameter in a daily time basis and consequently proposed an alternative formulation for $f$ based on Apparent Thermal Inertia using surface...
temperature and albedo observations. Finally, Zhang et al. [2010] used the ratio between precipitation and equilibrium evaporation rate as an indicator of soil water availability to obtain $f$ values over successive 8 days intervals.

[9] Because Mediterranean drylands are characterized by irregular precipitation which causes rapid increases in soil moisture during rain followed by extended drying periods, we considered it important to develop a specific formulation for $f$ that models the soil drying process after precipitation. Black et al. [1969] and Ritchie [1972] presented a simple formulation to model the soil drying process as a function of the time (in days) following precipitation that we adapted for daily $f$ estimation.

[10] The objective of this paper was to adapt and evaluate the PML model for estimating daily $E$ in Mediterranean drylands where a more precise consideration of $E_i$ is necessary. To achieve this goal, we tested three different approaches to estimate the temporal variation of $f$: (i) using direct soil water content measurements; (ii) adapting Zhang et al.’s [2010] method for daily application; and (iii) including a simple model for soil drying after precipitation based on Black et al. [1969] and Ritchie [1972]. The PML model performance using the three $f$ approaches was evaluated by comparison with $E$ measurements obtained from eddy covariance systems at two functionally different Mediterranean drylands: (i) a littoral semiarid steppe and (ii) a shrubland montane site.

### 2. Model Description

#### 2.1. Penman-Monteith-Leuning Model (PML) Description

[10] Actual evapotranspiration ($E$) is the sum of canopy transpiration ($E_c$), soil evaporation ($E_s$), and evaporation of precipitation intercepted by canopy and litter ($E_i$) [D’Odorico and Porporato, 2006]. Despite the fact that $E_i$ has been shown to account for up to 30% of the annual rainfall in some arid communities [Dunkerley and Booth, 1999], the magnitude of $E_i$ is considered a small amount of the total water losses in areas with low ecosystem LAI or short vegetation because of the reduced fraction cover of plants in comparison with forests [Mu et al., 2007; Muzylo et al., 2009]. Moreover, in Mediterranean areas, a reduced relative magnitude of $E_i$ can be expected because precipitation events are intense and they occur mainly in the lower available energy seasons (autumn and winter), both factors decreasing the interception fraction [Domingo et al., 1998]. In this regard, García et al. [2013] reported no improvements in actual $E$ estimation by considering $E_i$ in two natural semiarid sites, one of them included in this work. Therefore, in the present work, only $E_c$ and $E_s$ were considered for actual $E$ estimation following the expression,

$$E = E_c + E_s$$

(1)

[11] The fluxes of latent heat associated with $E_c$ and $E_s$ were written by Leuning et al. [2008] as

$$\lambda E = \frac{\varepsilon A_c + (\rho c_p/\gamma) D_s G_s}{\varepsilon + 1 + G_s/G_c} + f \frac{\varepsilon A_s}{\varepsilon + 1}$$

(2)

where the first term is the PM equation written for the plant canopy and the second term is the flux of latent heat from the soil expressed as a fraction of potential. The variables $A_c$ and $A_s$ (W m$^{-2}$) are the energy absorbed by the canopy and soil, respectively. $G_s$ and $G_c$ (m s$^{-1}$) are the aerodynamic and canopy conductances, as defined below. $\varepsilon$ (KPa K$^{-1}$) is the slope ($s$) of the curve relating saturation water vapor pressure to air temperature divided by the psychrometric constant ($\gamma$), $\rho$ (kg m$^{-3}$) is air density, $c_p$ (J kg K$^{-1}$) is the specific heat of air at constant pressure, and $D_s$ (KPa) is the vapor pressure deficit of the air, computed as the difference between the saturation vapor pressure at air temperature, $e_{sat}$, and the actual vapor pressure, $e$ ($D_s = e_{sat} - e$). The factor $f$ in the second term of equation (2) modulates potential evaporation rate at the soil surface expressed by the Priestley-Taylor equation, $E_{pot} = \varepsilon A_s/\varepsilon + 1$, by $f = 0$ when the soil is dry, to $f = 1$ when the soil is completely wet. In spite of the Priestley-Taylor formulation was designed to estimate potential evaporation in energy-limited ecosystems [Priestley and Taylor, 1972], recent works have demonstrated that accurate estimates of actual $E$ can be determined in water-limited conditions by

### Table 1. Details of Field Sites Used to Evaluate the PML Model Performance

<table>
<thead>
<tr>
<th>Field Site</th>
<th>Balsa Blanca</th>
<th>Llano de los Juanes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Latitude/Longitude</td>
<td>36°56’21”39”N; 2°02’012”W</td>
<td>36°55’41.7”N; 2°48’1.7”W</td>
</tr>
<tr>
<td>Study period</td>
<td>Oct 2006 to Dec 2008</td>
<td>Apr 2005 to Dec 2007</td>
</tr>
<tr>
<td>Elevation (m)</td>
<td>196</td>
<td>1600</td>
</tr>
<tr>
<td>Vegetation classification (IGBP Class)</td>
<td>Stipa tenacissima</td>
<td>Festuca scariosa, Genista pumila, Hormathophylla spinosa</td>
</tr>
<tr>
<td>Dominant species</td>
<td>Stipa tenacissima</td>
<td>Closed shrubland</td>
</tr>
<tr>
<td>LAI (MODIS)</td>
<td>0.19–0.67</td>
<td>0.12–0.56</td>
</tr>
<tr>
<td>Cover fraction</td>
<td>0.6</td>
<td>0.5</td>
</tr>
<tr>
<td>Mean canopy height (m)</td>
<td>0.7</td>
<td>0.5</td>
</tr>
<tr>
<td>Mean annual precipitation (mm)</td>
<td>319</td>
<td>326</td>
</tr>
<tr>
<td>Temperature (°C)</td>
<td>Min 33</td>
<td>31</td>
</tr>
<tr>
<td></td>
<td>Mean 17</td>
<td>13</td>
</tr>
<tr>
<td></td>
<td>Max 4</td>
<td>–7</td>
</tr>
<tr>
<td>Dryness index*</td>
<td>2.8</td>
<td>2.3</td>
</tr>
<tr>
<td>Soil depth (m)</td>
<td>0.15–0.25</td>
<td>0.15–1.00 (highly variable)</td>
</tr>
</tbody>
</table>

*Quantitative data were derived using data from the entire study period (Table 2).

*Dryness index calculated as the average of the annual dryness index ($E_{eq}/P$) [Budyko, 1974] for the total study period (Table 2).
downscaling Priestley-Taylor potential evapotranspiration according to multiple stresses at daily time scale [Fisher et al., 2008; Garcia et al., 2013] as the PML model does through $f$. To estimate partitioning of available energy between soil and canopy surfaces, the Beer-Lambert law has been applied by many authors even in sparse vegetated areas [Hu et al., 2009; Leuning et al., 2008; Zhang et al., 2010]. Based on Beer-Lambert law, soil available energy can be estimated as $A_s = A / C_28$ and canopy available energy is $A_c = A(1/C_0/C_28)$, where $A/C_28 = \exp(-k_A l / A)$ and $k_A$ is the extinction coefficient for total available energy $A$. When eddy co-variance data are used for validation, $A = H + \lambda E$ can be assumed in order to ensure internal consistency in relation to eddy covariance closure error [Leuning et al., 2008]. Kustas and Norman [1999] have, however, questioned the reliability of the Beer-Lambert approach in sparse vegetation. Alternatively, they proposed a more complex method for energy partitioning based on surface temperature and shortwave incoming radiation retrievals that accounts for the different behavior of soil and canopy for the visible and near infrared regions of spectrum. Preliminary analyses included in Appendix A showed that mean absolute differences between daytime averages of $A_s$ and $A_c$ estimated by those two energy partitioning approaches were minor (18 and 32 W m$^{-2}$ for $A_s$ and $A_c$, respectively) over 144 days in 2011 when infrared sensors were available to measure surface temperature and shortwave incoming radiation. Because of these reduced differences (Figure A1) at daytime scale, the Beer-Lambert method was used to maintain the reduced number of PML model inputs. Of far greater importance is correctly estimating $f$, as discussed below.


$$G_a = \frac{k^2 u}{\ln(z_r - d)/z_{om}\ln(z_r - d)/z_{om}}$$

(3)

where $k$ is Von Karman’s constant (0.40), $u$ (m s$^{-1}$) is wind speed, $d$ (m) is zero plane displacement height, $z_{om}$ and $z_{ov}$ (m) are roughness lengths governing transfer of momentum and water vapor and $z_r$ (m) is the reference height where $u$ is measured. In this version of equation (3), the influence of atmospheric stability conditions over $G_a$ has been neglected for two reasons: (i) in dry surfaces where $G_a << G_{ir}$, $E$ is relatively insensitive to errors in $G_a$ [Leuning et al., 2008; Zhang et al., 2008, 2010] and (ii) in semiarid areas, where highly negative temperature gradients between surface and air temperature are found, correction for atmospheric stability can cause more problems than it solves for estimating $G_a$ [Villagarcia et al., 2007]. The variables $d$, $z_{om}$ and $z_{ov}$ were estimated via the canopy height ($h$) in m, using the

Figure 1. Time series of (a and b) 8-day accumulated precipitation (P) in mm, actual volumetric soil water content (SWC) in mm$^3$ mm$^{-3}$ and 8-day averages of LAI, (c and d) 8-day averages of observed $E$ and potential $E$ in mm day$^{-1}$, (e and f) 8-day averages of observed $E$ and estimated $E$ using PML model with $f_{dryng}$, $f_{SWC}$, and $f_{Zhang}$, respectively, during the validation period in Balsa Blanca site (a, c, and e) and in Llano de los Juanes site (b, d, and f). The legends in Figures 1b, 1d, and 1f apply to Figures 1a, 1c, and 1e, respectively.
general relations given by Allen [1986]: \( d = 0.66 \) h, \( z_{cm} = 0.123 \) h, and \( z_{av} = 0.1 \).

Canopy conductance was estimated using Leuning et al. [1995] formulation, based on Kellihar et al. [1995], as follows,

\[
G_c = \frac{g_{ss}}{k_Q} \ln \left[ \frac{Q_h + Q_{so}}{Q_h \exp(-k_Q LAI) + Q_{so}} \right] \left[ 1 + \frac{1}{D_s/D_{so}} \right]
\]

(4)

where \( k_Q \) is the extinction coefficient of visible radiation, \( g_{ss} \) is the maximum conductance of the leaves at the top of the canopy, \( Q_h \) is the visible radiation reaching the canopy surface that can be approximated as \( Q_h = 0.8A \) [Leuning et al., 2008] and \( Q_{so} \) are values of visible radiation flux and water deficit, respectively, when the stomatal conductance is half of its maximum value. We used \( Q_{so} = 30 \text{ Wm}^{-2} \) and \( D_{so} = 0.7 \text{ kPa} \), and \( k_Q = k_1 = 0.6 \) following the sensitivity analysis presented in Leuning et al. [2008].

The PML model (equations (2)–(4)) includes factors controlling canopy transpiration and soil evaporation but accurate estimation of \( g_{ss} \) and \( f \) is crucial for model success. Three methods for estimating \( f \) with increasing complexity, presented in section 2.2 were evaluated for improving PML performance in drylands.

2.2. Methods for \( f \) Estimation

Evaporation from soil surfaces is mainly controlled by volumetric soil water content in the top soil layer [Anadranitisakos et al., 2000; Farahani and Bausch, 1995] and has been traditionally described occurring in three stages. An energy-limited stage (Stage 1) when enough soil water is available to satisfy the potential evaporation rate \( (f = 1) \), a falling-rate stage (Stage 2) when soil is drying and water availability limits the soil evaporation rate \( (0 < f < 1) \) and a third stage (Stage 3) when soil is dry and it can be considered negligible \( (f = 0) \) [Idso et al., 1974; Ventura et al., 2006]. We tested three different methods to capture this dynamic of \( f \).

2.2.1. \( f \) As a Function of Soil Water Content Data \((f_{SWC})\)

We used measured values of volumetric soil water content measured at 4 cm depth (\( \theta_{obs} \)) rescaled between a minimum (\( \theta_{min} \)) and a maximum (\( \theta_{max} \)) threshold value to estimate \( f \) following the expression,

\[
f_{SWC} = \begin{cases} 
1 & \text{when, } \theta_{obs} > \theta_{max} \\
0 & \text{when, } \theta_{obs} < \theta_{min} \\
\theta_{obs} - \theta_{min} & \text{when, } \theta_{min} \leq \theta_{obs} \leq \theta_{max} 
\end{cases}
\]

(5)

\( \theta_{min} \) was experimentally estimated as the minimum value of the dry season and \( \theta_{max} \) as the value of \( \theta \) in the 24 h after a strong rainfall event, which can be considered as an estimate of the field capacity [Garcia et al., 2013], using data measured during the study period.

2.2.2. \( f \) as Function of Precipitation and Equilibrium Evaporation Ratio \((f_{Zhang})\)

We tested the method proposed by Zhang et al. [2010] to estimate \( f \) using the ratio of accumulated values of precipitation \( (P) \) and \( E_{eq,s} \), both in \( \text{mm day}^{-1} \), over \( N \) days. While the original formulation of Zhang et al. [2010] was designed to estimate the averaged value of \( f \) over successive 8 day intervals using accumulated values of \( P \) and \( E_{eq,s} \) in \( N = 32 \) days (covering 16 days prior and 16 days after the current day), we adapted this method for daily estimates of \( f \). After a sensitivity analysis, included in Appendix B, here we set \( N = 16 \), between day \( i \) and 15 preceding days \( (i - 15) \), to estimate daily \( f \) using measured values of \( P \) and \( E_{eq,s} \) and it is expressed as,

\[
f_{Zhang} = \min \left( \frac{\sum_{i=1}^{15} P_i}{\sum_{i=15}^{30} E_{eq,i}}, 1 \right)
\]

(6)

where \( P_i \) is the accumulated daily precipitation and \( E_{eq,i} \) is the daily soil evaporation and it can be considered negligible when \( f = 0 \).

2.2.3. \( f \) as a Function of Soil Drying After Precipitation \((f_{drying})\)

Black et al. [1969] formulated the cumulative evaporation in terms of the square root of time after precipitation considering the soil drying process after rain and Ritchie [1972] used the same approach for modeling the Stage 2 of soil evaporation. Thus for daily \( f \) estimation, we proposed to add use a similar formulation for the soil drying periods during dry days in combination with the \( f_{Zhang} \) method (equation (7)) used here to estimate \( f \) during the effective precipitation days \( (P_i > P_{min} = 0.5 \text{ mm day}^{-1}) \). This is,

\[
f_{drying} = \begin{cases} 
\min \left( \frac{\sum_{i=15}^{30} P_i}{\sum_{i=15}^{30} E_{eq,i}}, 1 \right) & \text{when } P_i > P_{min} \\
f_{LP} \exp(-\alpha \Delta t) & \text{when } P_i > P_{min}
\end{cases}
\]

(7)

where \( f_{LP} \) is the value for the last effective precipitation day, \( \Delta t \) is number of days between this and the current day \( i \) and \( \alpha \) \( (\text{day}^{-1}) \) is a parameter controlling the rate of soil drying, higher \( \alpha \) values reflecting higher soil drying speed. For simplicity, \( \alpha \) was considered a constant estimated by optimization, even though it is known that \( \alpha \) is related to air temperature, wind speed, vapor pressure deficit, and soil hydraulic properties [Ritchie, 1972].

3. Material and Methods

3.1. Validation Field Sites and Measurements

The PML model was evaluated at two experimental sites located in southeast Spain characterized by Mediterranean climate, sparse vegetation \( (\text{LAI} < 1) \) and winter rainfall (see Table 1). Both sites are water-limited areas, following the classification proposed by McVicar et al. [2012], with dryness index \( (\text{Diudyko, 1974}) \) of 2.8 and 2.3, respectively, during the study period. These are stronger aridity conditions than where the PML model has been previously tested [Leuning et al., 2008; Zhang et al., 2010].

Water vapor fluxes were measured at each site using eddy covariance (EC) systems consisting of a three axis sonic anemometer (CSAT3, Campbell Scientific Inc., USA) for wind speed and sonic temperature measurement and an open-path infrared gas analyzer (Li-Cor 7500,
Table 2. Optimization and Validation Periods Used in Both Field Sites

<table>
<thead>
<tr>
<th>Experimental Field Site</th>
<th>Optimization Period</th>
<th>Validation Period</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>18 Oct 2007</td>
<td>31 Dec 2008</td>
</tr>
<tr>
<td></td>
<td>N = 365 days</td>
<td>N = 440 days</td>
</tr>
<tr>
<td>Llano de los Juanes</td>
<td>27 Mar 2007</td>
<td>4 Apr 2005</td>
</tr>
<tr>
<td></td>
<td>31 Dec 2007</td>
<td>24 Mar 2006</td>
</tr>
<tr>
<td></td>
<td>N = 279 days</td>
<td>N = 355 days</td>
</tr>
</tbody>
</table>

Campbell Scientific Inc., USA) for variations in H2O density. EC sensors were located above horizontally uniform vegetation at 3.5 m at Balsa Blanca and at 2.5 m at Llano de los Juanes (zr = 3.5 and zr = 2.5, respectively). Data were sampled at 10 Hz and fluxes were calculated and recorded every 30 min. Corrections for density perturbations [Webb et al., 1980] and coordinate rotation [Kowalski et al., 1997; McMillen, 1988] were carried out in postprocessing, as was the conversion to half-hour means following Reynolds' rules [Moncrieff et al., 1997]. The slope of the linear regressions between available energy (Rn - G) and the sum of the surface fluxes (H + E) yields a slope ~0.8 in Balsa Blanca and ~0.7 in Llano de los Juanes. This is consistent with the ~20% of energy imbalance found in the European FLUXNET stations [Frennessen et al., 2010].

[23] Complementary meteorological measurements were also made at each field site. An NR-Lite radiometer (Kipp & Zonen, Netherlands) measured net radiation over representative surfaces at 1.9 m height at Balsa Blanca and 1.5 m at Llano de los Juanes. Soil heat flux was calculated at both sites following the combination method [Fuchs, 1986; Massman, 1992], as the sum of averaged soil heat flux measured by two flux plates (HFT-3; REBS, Seattle, WA, USA) located at 0.08 m depth, plus heat stored in upper soil measured by two thermocouples (TCAV; Campbell Scientific LTD) located at two depths 0.02 and 0.06 m. Air temperature and relative humidity were measured by thermohygrometers located at 2.5 m height at Balsa Blanca field site and 1.5 m at Llano de los Juanes (HMP45C, Campbell Scientific Ltd., USA). A 0.25 mm resolution pluviometer (model ARG100 Campbell Scientific Inc., USA) was used to measure precipitation at Balsa Blanca and a 0.2 mm resolution pluviometer was used at Llano de los Juanes (model 785, Davis Instruments Corp. Hayward, California, USA). Soil water content was measured at both sites using water content reflectometers (model CS616, Campbell Scientific INC., USA) located at 0.04 m depth with a reported accuracy by the manufacturer of ~2.5% volumetric water content. Due to the high soil heterogeneity, three randomly located sensors were averaged to obtain a representative SWC value at Llano de los Juanes, while at Balsa Blanca, one sensor located in bare soil was used. All complementary measurements were recorded every 30 min using data loggers (Campbell CR1000 and Campbell CR3000 data loggers, Campbell Scientific Inc., USA) and daytime (from sunrise to sunset) averages were used for model running.

3.2. Remotely Sensed Data

[24] LAI estimates were level 4 Moderate Resolution Imaging Spectrometers (MODIS) composite products provided by the ORNL-DAAC (http://daac.ornl.gov): (i) MOD15A (collection 5) from the Terra satellite and (ii) MYD15A2 from the Aqua satellite, both with a temporal resolution of 8 days. The averaged value of LAI reported from MOD15A and MYD15A2 for the 3 km × 3 km area centered on each site EC tower was computed. Filtering was performed according to MODIS quality assessment (QA) flags to eliminate poor quality data (affecting five and three observations at Balsa Blanca site and Llano de los Juanes, respectively) which were replaced by the average of previous and subsequent LAI values.

3.3. Model Performance Evaluation

[25] Average daytime E measurements were used to validate daily estimates of E derived from the PML model run using average daytime micrometeorological data [Clough et al., 2007; Leuning et al., 2008; Zhang et al., 2010]. The measurement data sets were divided into an optimization period, to estimate locally specific gsr and α values using the rgenoud package for the R software environment [Meheane and Sekhon, 2011], and a validation period, to validate PML model outputs at both field sites (see Table 2). The optimization was performed to find the values of gsr and α that minimized the cost function F for the total sample number, N, included in the optimization period (See N values in Tables 2 and 4), that is:

\[ F = \frac{\sum_{i=1}^{N} |E_{est,i} - E_{obs,i}|}{N} \]  

where E_{est,i} is estimated E for day i and E_{obs,i} is observed E for same day.

[26] Standard Major Axis Regression (SMA) type II [Warton et al., 2006] was used for comparing daily measurements and model estimates of E during the validation period. SMA regression attributes error in the regression line to both the X and Y variables, a method which is recommended when the X variable is subject to measurement errors, as is assumed for the EC system measurements used in this work. Slope, intercept, and coefficient of determination (R²) computed using SMA regression were reported in XY plots. Mean absolute difference (MAD) [Willmott and Matsuura, 2005] is used for quantitative evaluation of PML model results, while root mean square difference (RMSD) is also presented for comparison with previous works. Systematic and unsystematic components of RMSD [Willmott, 1982] are also reported. A low systematic difference indicates model structure adequately captures the system dynamics [Choler et al., 2010].

4. Results

[27] The two studied sites are Mediterranean drylands with clear functional differences (Figures 1a and 1b). Both sites presented a very different temporal pattern in phenology (LAI) with an early spring maximum at Balsa Blanca and a late-spring maximum at Llano de los Juanes. Balsa Blanca presented intermittent rainfall throughout the year causing a more fluctuating SWC pattern than at Llano de los Juanes which had distinct wet and dry seasons. These functional differences were also found in the temporal E pattern, that was more fluctuating at Balsa Blanca where E
Table 3. Optimized Model Parameters and Statistic of Model Performance for the Whole Validation Period (N = 440 Days in Balsa Blanca and N = 355 Days in Llano de los Juanes)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Balsa Blanca</th>
<th>Llano de los Juanes</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>fSWC</td>
<td>fZhang</td>
</tr>
<tr>
<td>g_{sx}</td>
<td>0.0097</td>
<td>0.0067</td>
</tr>
<tr>
<td>α</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>MAD</td>
<td>0.32</td>
<td>0.25</td>
</tr>
<tr>
<td>RMSE</td>
<td>0.41</td>
<td>0.34</td>
</tr>
<tr>
<td>% Syst. difference</td>
<td>52</td>
<td>5</td>
</tr>
<tr>
<td>% Unsys. difference</td>
<td>49</td>
<td>95</td>
</tr>
<tr>
<td>E_{avg}^* (0.49 ± 0.28)</td>
<td>0.78 ± 0.42</td>
<td>0.58 ± 0.42</td>
</tr>
</tbody>
</table>

*Estimates of daily evapotranspiration (mm day\(^{-1}\)) during the validation period in brackets and mean estimated values from each f approach. N/A, not applicable parameter.

Table 4. Estimated Model Parameters by Optimizing Using the Original Optimization Period, the Growing Season or the Nongrowing Season

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Optimization Period</th>
<th>Dates</th>
<th>N</th>
<th>fSWC</th>
<th>fZhang</th>
<th>fDrying</th>
</tr>
</thead>
<tbody>
<tr>
<td>g_{sx}</td>
<td>Original</td>
<td>27 Mar 2007</td>
<td>279</td>
<td>0.0076</td>
<td>0.0093</td>
<td>0.0109</td>
</tr>
<tr>
<td>α</td>
<td>Growing season</td>
<td>31 Dec 2007</td>
<td>109</td>
<td>N/A</td>
<td>N/A</td>
<td>0.478</td>
</tr>
<tr>
<td>g_{sx}</td>
<td>Nongrowing season</td>
<td>18 Apr 2007</td>
<td>134</td>
<td>0.0088</td>
<td>0.0098</td>
<td>0.0105</td>
</tr>
<tr>
<td>α</td>
<td>5 Aug 2007</td>
<td>134</td>
<td>0.0015</td>
<td>0.0055</td>
<td>0.0099</td>
<td></td>
</tr>
<tr>
<td>α</td>
<td>10 Aug 2007</td>
<td>134</td>
<td>N/A</td>
<td>N/A</td>
<td>0.500</td>
<td></td>
</tr>
<tr>
<td>α</td>
<td>22 Dec 2007</td>
<td>134</td>
<td>N/A</td>
<td>N/A</td>
<td>0.434</td>
<td></td>
</tr>
</tbody>
</table>

*Abreviations as follows: g_{sx}, maximum conductance of leaves; α, soil drying speed; and N/A, not applicable parameter.
optimized specifically for those conditions (Figure 3b). This test also showed a low sensitivity of the optimization method to the time period used especially using $f_{\text{drying}}$ (Table 4).

5. Discussion

[34] Important functional differences were observed between the two field sites, with an $E$ pattern more strongly linked to SWC at Balsa Blanca but better explained by pheno-

logy in Llano de los Juanes (Figure 1). These results can be understood considering the vegetation composition and geo-
morphological characteristics of both field sites.

[35] At Balsa Blanca, the vegetation is dominated by the perennial grass $S. \text{tenacissima}$ (57.2%) that is well adapted to aridity and shows opportunistic growth patterns with leaf conductance and photosynthetic rates largely dependent on water availability in the upper soil layer \cite{Haase et al., 1999; Pugnaire and Haase, 1996}. This explains the observed link between $E$ and SWC pattern here, where both $E_s$ and $E_c$ are controlled by water availability in the upper soil layer. In contrast, the vegetation at Llano de los Juanes is codominated by perennial grasses, $Festuca \text{scariosa}$ (Lag.) Hackel (19%), and shrubs, $Genista \text{pumila}$ ssp $pumila$ (11.5%) and $Hormatophylla \text{spinosa}$ (L.), P. Kipfer (6.3%) \cite{Serrano-Ortiz et al., 2007, 2009}. At this montane site, extraction of water by shrubs from deep cracks and fissures in the bedrock has been previously detailed \cite{Cantón et al., 2010} explaining the phenological control of $E$ during the dry period and the coincidence of the dry and growing seasons. These functional considerations of the sites help to understand the performance of the three proposed methods to improve $E$ estimates by the PML model.

![Figure 2.](image)

Figure 2. Scatterplots of estimated $E$ using (a, b) $f_{\text{drying}}$, (c, d) $f_{\text{SWC}}$, and (e, f) $f_{\text{Zhang}}$, respectively, versus observed $E$ in mm day$^{-1}$. Gray dashed line is 1:1 line and the black line is the line of best fit for the equation provided in the subplot by SMA.
The legends in Figure 3a also apply to Figures 3b and 3c.

5.1. Using Soil Water Content Data to Estimate Soil Evaporation ($f_{SWC}$)

Despite the fact that the energy consumed by $E_s$ mainly depends on the moisture content of the soil near the surface in water-limited areas [Leuning et al., 2008; McVicar et al., 2012], the PML model using $f_{SWC}$ (equation (5)) provided unsatisfactory estimates of $E$ (Table 3). This method tended to systematically overestimate $E$ at Balsa Blanca (Figure 2a) and presented a poor linear agreement with measured $E$ at Llano de los Juanes (Figure 2b). A similar approach to $f_{SWC}$ was used by García et al. [2013] to estimate $E_s$ at Balsa Blanca and another woody savanna site but using a different approach to estimate daily $E_s$ based on Fisher et al. [2008]. These authors found better $E_s$ estimates using $f_{SWC}$ with $R^2$ values ranging from 0.74 to 0.86. Our poorer results may be due to inaccuracies affecting the experimental threshold values $\theta_{\text{min}}$ and $\theta_{\text{max}}$. In the present study, these values were estimated using data from the study period (Table 2), whereas García et al. [2013] used a more extended study period (6 years) to estimate $\theta_{\text{min}}$ and $\theta_{\text{max}}$. Nevertheless, as only estimates of total $E$ were evaluated in both studies, it is difficult to conclude that the disparity between both studies derives from better $E_s$ estimates, since more accurate estimates of $E_s$ obtained through their daily adapted version of Fisher et al. [2008] model may also explain these differences. At the mountain site Llano de los Juanes, different reasons may explain the poor performance of $f_{SWC}$. $E$ underestimates found during the growing season using $f_{SWC}$ were a consequence of an underestimated value of $g_{\text{ax}}$ ($g_{\text{ax}} = 0.0076 \text{ m s}^{-1}$) found from optimization using $f_{SWC}$. This $g_{\text{ax}}$ value was lower than the one obtained using $f_{\text{Zhang}}$ and $f_{\text{drying}}$ (Table 3) resulting in stronger underestimates of $E$ during this period than the other two methods (Figure 1f). As Figure 3b shows, a higher $g_{\text{ax}}$ value ($g_{\text{ax}} = 0.0088 \text{ m s}^{-1}$) derived from optimization in the growing season (Table 3) reduced the aforementioned underestimates during that period using $f_{SWC}$ (Figure 3b). In contrast, during the wet season (November to March 2006) using $f_{SWC}$ led to overestimates of $E$ (Figure 1f) that we attributed to an effect of the high stoniness and frequent rock outcrops (30–40% rock fragment content) found in this field site [Serrano-Ortiz et al., 2007]. This high percentage of rock coverage reduces the effective soil surface described by the SWC data and results in $E_s$ overestimations. Consequently, our results suggest the necessity to adjust the fraction of transpiring soil surface in order to use SWC measurements to estimate $E_s$ as a portion of the equilibrium rate in areas with an important percentage of rocks.

5.2. Using Precipitation and Equilibrium Evaporation to Estimate Soil Evaporation ($f_{\text{Zhang}}$)

Use of $f_{\text{Zhang}}$ in the PML model resulted in a strong overestimation of $E$ during periods following heavy or intermittent rain events (Figures 1e and 1f). Thus, we found generally low correlations with observations at both field sites (Figures 2c and 2d). This occurred because $f_{\text{Zhang}}$ (equation (6)) assumes that the effect of rain over the soil water availability is limited to a time period of $N$ days ($N = 16$). As a result, after precipitation the model predicts that $f$ reaches high values remaining high for “$N$” days, after which an artificial drop takes place or, when rainfall is heavy and intermittent, the model predicts $f = 1$ during maintained periods of time. This is not an accurate representation of the real SWC pattern, which actually increases during rain and decreases progressively after rain events. Originally Zhang et al. [2010] used this approach to estimate $f$ over 32 day intervals for which a coarse resolution could be effective. They obtained an RMSD of 0.56 mm day$^{-1}$ for a sparsely vegetated savanna site in Australia (Virginia Park) where the mean annual $E$ (1.20 mm day$^{-1}$)

Figure 3. Time series of 8 day averages of observed $E$ and estimated $E$ in mm day$^{-1}$ using $f_{\text{drying}}$ $f_{SWC}$, and $f_{\text{Zhang}}$, respectively, using (a) the total optimization period, (b) the growing season of the optimization period, (c) or the non-growing season for optimization of parameters $g_{\text{ax}}$ and $\alpha$. The legends in Figure 3a also apply to Figures 3b and 3c.
was higher than that of our field sites. When we applied our proposed daily version of \( f_{\text{Zhang}} \) to our sites, we obtained an RMSE of 0.34–0.31 mm day\(^{-1}\). Since the mean annual was 0.49 mm day\(^{-1}\) at Balsa Blanca and 0.56 mm day\(^{-1}\) at Llano de los Juanes (Table 3) this RMSE is relatively larger than the reported by Zhang et al. [2010]. In other words, these results showed that the \( f_{\text{Zhang}} \) method did not improve PML model performance in Mediterranean drylands. The increase of SWC as a result of a rain event depends on the prior rain SWC level. Zhang et al. [2010] tried to incorporate this concept using the ratio of accumulated values of \( P \) and \( E_{\text{eq},t} \) during \( N \) previous days for modeling \( f \). However, this method is unable to record rapid decreases of SWC following rain in Mediterranean drylands where a higher temporal resolution is necessary to capture the daily variation of SWC.

### 5.3. Modeling the Soil Drying Process to Estimate Soil Evaporation (\( f_{\text{drying}} \))

[38] Adoption of the \( f_{\text{drying}} \) method clearly improved PML model performance at both sites (Table 3), outperforming the other two approaches (\( f_{\text{SWC}} \) and \( f_{\text{Zhang}} \)) (Figures 1e and 1f). \( E \) estimated using \( f_{\text{drying}} \) did not show the strong overestimation obtained using \( f_{\text{SWC}} \) or \( f_{\text{Zhang}} \) after rainfall, showing a better capacity to describe the gradual drying of soil following rainfall. This method uses the formulation based on Zhang et al. [2010] to estimate the increment of SWC as result of each precipitation event but it included a simple method to model the decrease of SWC during Stage 2 as a function of time after the last precipitation (equation (7)). Considering the difficulties associated with \( E \)-modeling in Mediterranean drylands, where measured \( E \) rates are especially low, often not exceeding the error range of methods for estimating \( E \) from remote sensing [Domingo et al., 2011], using \( f_{\text{drying}} \) the PML model achieved reasonable agreement with EC-derived daily \( E \) rates. This method showed an RMSE of 0.22–0.24 mm day\(^{-1}\) and \( R^2 \) from 0.47 to 0.59 (Figures 2e and 2f). This accuracy level is similar or slightly better than the results found by Leuning et al. [2008] and Zhang et al. [2010] in the Australian woody savanna sites Tonzi and Virginia Park. Fisher et al. [2008] found better correlation between estimates and EC-derived monthly averages of \( \lambda E \) (\( R^2 \sim 0.8 \)) at those two same Australian sites. However, their model overpredicted \( \lambda E \) during low \( \lambda E \) periods [Fisher et al., 2008] similarly to the overestimations that we found at Balsa Blanca site (when \( E \) was lower than 0.2 mm day\(^{-1}\)) (Figure 1e). Garcia et al. [2013] found \( R^2 \) values of 0.58 and 0.82 at two drylands (including Balsa Blanca site) using the same approach to estimate \( E \) as Fisher et al. [2008] but including a different approach for \( f \) based on Apparent Thermal Inertia derived from in situ surface temperature and albedo measurements. However, their results deteriorated further than ours (\( R^2 = 0.32 \)) when remote sensed surface temperature and albedo from SEVIRI (Spinning Enhanced Visible and Infared Imager) were used to estimate \( f \) at Balsa Blanca site. Improved MODIS global terrestrial \( E \) algorithm combined with tower meteorological data found RMSE values of 0.67–0.91 mm day\(^{-1}\) and \( R^2 \) values ranging from 0.24 to 0.78 in three woody savannas (including Tonzi site) where observed \( E \) was 0.94–2.08 mm day\(^{-1}\) [Mu et al., 2011]. Even though, in two shrubland sites, where observed \( E \) was 1.04 and 0.19 mm day\(^{-1}\), respectively, the same model reached higher inaccuracies than ours, with RMSE values of 1.10 mm day\(^{-1}\) (\( R^2 = 0.02 \)) and 0.31 mm day\(^{-1}\) (\( R^2 = 0.35 \)). These previous results demonstrate that the accuracy level found by the PML model using \( f_{\text{drying}} \) was similar or even outperformed previous models to estimate \( E \) using remote-sensing data in drylands where \( E \) modeling is still a challenging task [Domingo et al., 2011].

[39] Like \( f_{\text{Zhang}}, f_{\text{drying}} \) shares the advantage of only requiring widely available precipitation and equilibrium evaporation data, with the expense of a single additional parameter \( \alpha \). With the use of \( f_{\text{drying}} \), the PML model was able to capture the varying controls on \( E \), at both field sites (Figures 1e and 1f). Thus, the optimized value of the \( \alpha \) parameter, representing the speed at which soil reduces the capacity to evaporate water, was lower at Balsa Blanca (\( \alpha = 0.137 \) day\(^{-1}\)) than at Llano de los Juanes (\( \alpha = 0.478 \) day\(^{-1}\)). This implies that \( E \) at Balsa Blanca has a longer period of influence on total \( E \) than at Llano de los Juanes where the soil is assumed to dry more quickly. This is in agreement with the fact that Llano de los Juanes is a karstic area characterized by infiltration occurring in preferential flows through the abundant cracks, joints and fissures [Can- tôn et al., 2010; Contreras, 2006].

[40] Overall, the stronger phenological control over \( E \), the reduction of effective evaporative soil surface due to stoniness and rocky soil features and the importance of infiltration at Llano de los Juanes, contribute to \( E \), having a less important role in total \( E \) dynamics than at Balsa Blanca. This explains the higher systematically percentage differences found at Llano de los Juanes (Table 3) where all three adapted model versions, including \( f_{\text{drying}} \) were less effective at capturing the system dynamics because they were designed to improve \( E \), a less crucial factor at this site.

[41] The systematic underestimation of \( E \) by the PML model at the beginning of the dry season observed at Llano de los Juanes (Figure 2d) using \( f_{\text{drying}} \) (and also with \( f_{\text{Zhang}} \)) was proven not to be a consequence of underestimates of \( E \), resulting from failed optimized values of \( g_{\text{sw}} \), (Figure 3). In fact, tests optimizing model parameters using different optimization periods showed consistency for \( g_{\text{sw}} \), especially using \( f_{\text{drying}} \), the method less sensitive to changes in the optimization period (Table 4). Therefore, underestimates of \( E \) by the PML model using \( f_{\text{drying}} \) (and \( f_{\text{Zhang}} \)) at the beginning of the dry season were explained instead by errors in \( E \) caused by low \( f \) values. During this period, the effect of precipitation from the preceding wet season (finishing 20 days before our validation period) was not considered by \( f_{\text{drying}} \) (or \( f_{\text{Zhang}} \)) because these methods assume that the effects of rain over SWC only persist during \( N \) days (\( N = 16 \), in this case). In summary, underestimates of \( E \) along the dry and growing seasons at our montane site showed the limitation of \( f_{\text{drying}} \) and \( f_{\text{Zhang}} \) to capture high soil water availability levels originated by the cumulative effect of a long prior wet season.

### 6. Conclusion

[42] The capacity of Penman-Monteith-Leuning model (PML model) to estimate daily evaporation in sparsely vegetated drylands is demonstrated through the
development of methods for temporal estimation of the soil evaporation parameter $f$. We advanced Leuning et al. [2008] who found that estimating soil evaporation parameter $f$ as a local time constant produced poor results in sparsely vegetated areas ($\text{LAI} < 2.5$). Out of three proposed methods, $f_{\text{drying}}$, showed the best results for PML model adaptation at two experimental sites and was able to capture the daily pattern of near surface soil moisture content. This proposed method considers the soil water availability conditions previous to rainfall to estimate the SWC increment derived from rain and explicitly models the progressive soil drying process following precipitation. This way, the $f_{\text{drying}}$ method avoided the strong overestimates of $E$ obtained with two other $f$ estimation approaches, $f_{\text{SWC}}$ and $f_{\text{Zhang}}$. Nevertheless, the $f_{\text{drying}}$ method showed some limitations in its ability to model the soil evaporation rate when this was influenced by high soil water availability levels during the growing season from the cumulative effect of a long prior wet season at Llano de los Juanes.

The use of time-invariant parameters for evaporation modeling is a delicate issue in drylands and other extreme ecosystems where vegetation and soil are exposed to strong fluctuations in environmental conditions. Where a simplifying compromise is required in the design of operational and regionally applicable models, we showed here that reasonable results can be obtained using temporally constant estimates of $g_{s}$ and $\alpha$ in the PML model and the robustness of optimization period to estimate model parameters.

**Appendix A**

To evaluate the differences in available energy ($A$) partitioning between soil ($A_s$) and canopy ($A_c$) using the Beer-Lambert law (BL) or the method proposed Kustas and Norman [1999] specifically designed for sparse vegetation (K&N), daytime estimates of $A_s$ and $A_c$ obtained following these two different methods were compared at Balsa Blanca during a 144 days (15 January to 8 June 2011). During this time period, one Pyranometer (LPO2, Campbell Scientific, Inc., USA) and two broadband thermal infrared thermometers (Apogee IRT-S, Campbell Scientific, Inc., USA) were available at this site to measure incoming short-wave radiation and surface temperatures necessary for K&N method application. Measurements of: (i) composite soil-vegetation surface ($T_R$) and (ii) pure bare soil surface ($T_s$) at the field site were obtained using Apogee IRT-S, and canopy temperature ($T_c$) was derived from both applying the nonlinear relation between $T_R$, $T_s$, and $T_c$ based on vegetation cover fraction proposed by Norman et al. [1995]. Further details can be found in Morillas et al. [2013].

To estimate $A_s$ and $A_c$ using the Beer-Lambert law, $A_{\text{BL,s}}$ and $A_{\text{BL,c}}$ were estimated as follows

$$A_{\text{BL,s}} = A \exp \left(-k_s \text{LAI}\right)$$

$$A_{\text{BL,c}} = A \left[1 - \exp \left(-k_c \text{LAI}\right)\right]$$

where $k_s = 0.6$ and $A = H + \lambda E$ using daytime measured averages of $H$ and $\lambda E$ [Leuning et al., 2008].

To estimate $A_s$ and $A_c$ using the method proposed Kustas and Norman [1999], $A_{\text{K&N,s}}$ and $A_{\text{K&N,c}}$ where estimated following equations (A3) and (A4)

$$A_{\text{K&N}} = R_n - G$$

$$A_{c,\text{K&N}} = R_n$$

where $R_n$ and $G$ are daytime averaged estimates from equations (A5) and (A6) and $G$ is daytime averaged soil heat flux from measurements (section 3.1).

$$R_n = R_{n_s} + \tau_s (1 - \alpha_s) S$$

$$R_n = R_{n_c} + (1 - \tau_c)(1 - \alpha_c) S$$

where $S$ (W m$^{-2}$) is the incoming shortwave radiation, $\tau_s$ is solar transmittance through the canopy, $\alpha_s$ is soil albedo, $\alpha_c$ is the canopy albedo. Estimates of $\tau_s$, $\alpha_s$, and $\alpha_c$ are computed following the equations (15.4)--(15.11) in Campbell and Norman [1998] and based on LAI, the reflectances and transmittances of soil and a single leaf, and the proportion of diffuse irradiation, assuming that the canopy has a spherical leaf angle distribution.

$L_n$ and $L_c$ (W m$^{-2}$) are the net soil and canopy long-wave radiation, respectively, estimated using the following expressions:

$$L_n = L_{n_s} + \tau_s (1 - \alpha_s) S$$

$$L_c = L_{n_c} + (1 - \tau_c)(1 - \alpha_c) S$$

**Figure A1.** Scatterplots of (a) estimated canopy available energy, $A_c$, using Kustas and Norman [1999] method (K&N) versus the Beer-Lambert Law (BL) and (b) soil available energy, $A_s$, estimated by the same two methods. Gray dashed line is 1:1 line and the black line is the line of best fit for the equation provided in the subplot.
\[
L_{n} = \exp(-k_L \Omega LAI) L_{sky} + |1 - \exp(-k_L \Omega LAI)| L_{c} - L_e \quad (A6)
\]
\[
L_{n} = |1 - \exp(-k_L \Omega LAI)| [L_{sky} + L_s - 2L_e] \quad (A7)
\]

where \(k_L (k_L \approx 0.95)\) is the long-wave radiation extinction coefficient, which is similar to the extinction coefficient for diffuse radiation with low vegetation, i.e., \(LAI\) lower than 0.5 [Campbell and Norman, 1998]. \(\Omega\) is the vegetation clumping factor proposed by Kustas and Norman [1999] for sparsely vegetated areas, which can be set to one when measured \(LAI\) implicitly includes the clumping effect (i.e., \(LAI\) from the Moderate Resolution Imaging Spectroradiometer, MODIS) [Anderson et al., 1997; Norman et al., 1995; Timmermans et al., 2007], and \(L_{s}, L_{c},\) and \(L_{sky}\) (W m \(^{-2}\)) are the long-wave emissions from soil, canopy and sky computed by the Stefan-Boltzman equation based on measured \(T_s\) derived \(T_c\) and measured air temperature and vapor pressure [Brutsaert, 1982]. For further details about Kustas and Norman [1999] partitioning of \(R_n\) used here see Morillas et al. [2013].

[48] The linear agreement between daytime estimates of \(A_s\) and \(A_c\) from both methods was high with a determination coefficient \((R^2)\) of 0.92 for \(A_s\) and 0.79 for \(A_c\) (Figures A1a and A1b). Mean absolute differences between estimates of \(A_s\) and \(A_c\) from both methods were 31.74 and 17.97 Wm \(^{-2}\) for \(A_s\) and \(A_c\), respectively, during the 144 days tested. Considering these small differences, the higher complexity of K&N method and the increment of model inputs that this method implies, we decided that using the LB method for \(A\) partitioning between \(A_s\) and \(A_c\) at daytime scale was efficient and consistent.

**Appendix B**

To determine the optimal number of days, \(N\), to consider in equations (6) and (7) for estimating \(f_{\text{zhang}}\) and \(f_{\text{dry}}\) a sensitivity analysis was performed using data of Balsa Blanca field site. We obtained statistics of PML model performance using \(f_{\text{zhang}}\) and \(f_{\text{dry}}\) estimated using \(N\) values from 4 to 25 and also considering the time period including four 4 days previous and the 4 days after the current one (signed as 4_4). Effects over RMSD and MAD values (mm day \(^{-1}\)) of (a) model performance and (b) over the linear agreement, represented by slope, intercept, and \(R^2\), between estimates and EC-derived \(E\) values are shown.

\[
(0.30–0.34 \text{ mm day }^{-1}) \quad (\text{Figure B1a})
\]
\[
(0.40–0.42, \text{ slope range } 1.32–1.51, \text{ and intercept values from } -0.07 \text{ to } -0.16) \quad (\text{Figure B1b})
\]

Considering the modeling of the soil drying process included in \(f_{\text{dry}}\), the PML model performance also obtained better results using high values of \(N\) (Table B2), but the lowest mean inaccuracies were obtained using \(N\) values from 16 to 20 (Figure B2a) with MAD \(\sim 0.17\) mm day \(^{-1}\).

**Figure B1.** Sensitivity of the PML model performance using \(f_{\text{zhang}}\) to the \(N\) value considered for computing \(f_{\text{zhang}}\). \(N\) values ranged from 4 to 25 and also considering the time period including four 4 days previous and the 4 days after the current one (signed as 4_4). Effects over RMSD and MAD values (mm day \(^{-1}\)) of (a) model performance and (b) over the linear agreement showing a \(R^2\) range of 0.40–0.42, slope range of 1.32–1.51, and intercept values from \(-0.07\) to \(-0.16\) (Figure B1b).

**Table B1. Statistics of PML Model Performance With \(f_{\text{zhang}}\) Using Different \(N\) Values**

<table>
<thead>
<tr>
<th>(N)</th>
<th>4</th>
<th>6</th>
<th>8</th>
<th>10</th>
<th>12</th>
<th>14</th>
<th>16</th>
<th>18</th>
<th>20</th>
<th>25</th>
<th>4_4^a</th>
</tr>
</thead>
<tbody>
<tr>
<td>(g_a)</td>
<td>0.0095</td>
<td>0.0089</td>
<td>0.0085</td>
<td>0.0079</td>
<td>0.0076</td>
<td>0.0076</td>
<td>0.0067</td>
<td>0.0065</td>
<td>0.0061</td>
<td>0.0058</td>
<td>0.0087</td>
</tr>
<tr>
<td>(R^2)</td>
<td>0.26</td>
<td>0.30</td>
<td>0.32</td>
<td>0.33</td>
<td>0.34</td>
<td>0.34</td>
<td>0.39</td>
<td>0.41</td>
<td>0.41</td>
<td>0.42</td>
<td>0.40</td>
</tr>
<tr>
<td>Intercept</td>
<td>-0.16</td>
<td>-0.22</td>
<td>-0.24</td>
<td>-0.27</td>
<td>-0.27</td>
<td>-0.22</td>
<td>-0.18</td>
<td>-0.16</td>
<td>-0.12</td>
<td>-0.10</td>
<td>-0.07</td>
</tr>
<tr>
<td>Slope</td>
<td>1.38</td>
<td>1.58</td>
<td>1.67</td>
<td>1.75</td>
<td>1.66</td>
<td>1.60</td>
<td>1.51</td>
<td>1.44</td>
<td>1.37</td>
<td>1.32</td>
<td>1.58</td>
</tr>
<tr>
<td>RMSD</td>
<td>0.34</td>
<td>0.38</td>
<td>0.40</td>
<td>0.41</td>
<td>0.39</td>
<td>0.37</td>
<td>0.34</td>
<td>0.32</td>
<td>0.31</td>
<td>0.30</td>
<td>0.41</td>
</tr>
<tr>
<td>MAD</td>
<td>0.26</td>
<td>0.27</td>
<td>0.27</td>
<td>0.27</td>
<td>0.27</td>
<td>0.26</td>
<td>0.25</td>
<td>0.24</td>
<td>0.23</td>
<td>0.23</td>
<td>0.29</td>
</tr>
</tbody>
</table>

---

^a^The value of \(g_a\) obtained by optimization in the optimization period (Table 2) is also presented for each \(N\) value used for \(f_{\text{zhang}}\) estimation. RMSD and MAD values in mm day \(^{-1}\).

^b^\(N = 4_4\) considers the time period including four 4 days previous and the 4 days after the current one.
day$^{-1}$ and RMSD $\sim 0.21$ mm day$^{-1}$. Using $N$ from 16 to 20 also the linear agreement between model outputs and measured $E$ was improved (Figure B2b) but the best linear agreement was obtained using $N=16$ showing $R^2=0.47$ and the best slope and intercept values ($\text{slope}=0.97$ and $\text{intercept}=0.02$).

[52] Based on these results, we decided that $N=16$ was the more suitable value for daily estimation of $f_{\text{Zhang}}$ and $f_{\text{dry}}$ for PML model performance included in this paper. However, it is important to notice that the model accuracy did not show a strong variation of model accuracy under the range of $N$ values studied (Tables B1 and B2) with a maximum difference on accuracy of $\pm 0.1$ mm day$^{-1}$ depending on $N$. This suggests a low sensitivity of the PML model using $f_{\text{Zhang}}$ and $f_{\text{dry}}$ to the $N$ value and that alternative $N$ values could be used without a strong effect on model performance.

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