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Calibrating an evapotranspiration model using radiometric surface temperature, vegetation cover fraction and near-surface soil moisture data

Bouchra Ait Hssaine[a,b,*], Olivier Merlin[a,b], Zoubair Rafi[a], Jamal Ezzahar[c], Lionel Jarlan[a,b], Saïd Khabba[a], Salah Er-Raki[d]

[a] LMME, Département de physique, Faculté des sciences Semlalia, Université Casi Ayyad, Marrakech, Morocco
[b] CESBIO, Université de Toulouse, IRD/CNRS/UPS/CNES, Toulouse, France
[c] Equipe de Mathématiques et traitement de l'information (MTI), Ecole Nationale des Sciences Appliquées, Université Cadi Ayyad, Safi, Morocco
[d] LP2M2E, Département de Physique Appliquée, Faculté des Sciences et Techniques, Université Cadi Ayyad, Marrakech, Morocco

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ABSTRACT

An accurate representation of the partitioning between soil evaporation and plant transpiration is an asset for modeling crop evapotranspiration (ET) along the agricultural season. The Two-Surface energy Balance (TSEB) model operates the ET partitioning by using the land surface temperature (LST), vegetation cover fraction (fc), and the Priestley Taylor (PT) assumption that relates transpiration to net radiation via a fixed PT coefficient (α_{PT}). To help constrain the evaporation/transpiration partition of TSEB, a new model (named TSEB-SM) is developed by using, in addition to LST and fc data, the near-surface soil moisture (SM) as an extra constraint on soil evaporation. An innovative calibration procedure is proposed to retrieve three key parameters: α_{PT} and the parameters (a_{rss} and b_{rss}) of a soil resistance formulation. Specifically, a_{rss} and b_{rss} are retrieved at the seasonal time scale from SM and LST data with $f_c < 0.5$, while α_{PT} is retrieved at the daily time scale from SM and LST data for $f_c > 0.5$. The new ET model named TSEB-SM is tested over 1 flood- and 2 drip-irrigated wheat fields using in situ data collected during two field experiments in 2002–2003 and 2016–2017. The calibration algorithm is found to be remarkably stable as α_{PT}, a_{rss} and b_{rss} parameters converge rapidly in few (2–3) iterations. Retrieved values of α_{PT}, a_{rss} and b_{rss} are in the range 0.0–1.4, 5.7–9.5, and 1.4–6.9, respectively. Calibrated daily α_{PT} mainly follows the phenology of winter wheat crop with a maximum value coincident with the full development of green biomass and a minimum value reached at harvest. The temporal variations of α_{PT} before senescence are attributed to the dynamics of both root-zone soil moisture and the amount of green biomass (vegetation water content). Moreover, the overall (for the three sites) root mean square difference between the ET simulated by TSEB-SM and eddy-covariance measurements is 67 W m^{-2} (24% relative error), compared to 108 W m^{-2} (38% relative error) for the original version of TSEB using default parameterization (α_{PT} = 1.26). Such a calibration strategy has great potential for applications at multiple scales using remote sensing data including thermal-derived LST, solar reflectance-derived f_c and microwave-derived SM.

1. Introduction

A large variety of evapotranspiration (ET) models and measurements have been reported in the literature (Allen et al., 2011; Subedi and Chávez et al., 2015; Guerra et al., 2015). However, ET estimation over extended areas including different biomes and climates is still subject to significant uncertainties (Pereira, 2004; Ershadi et al., 2014). Although the main drivers of ET, such as atmospheric evaporative demand, vegetation type, development stages and health, surface biophysical characteristics and soil water availability (e.g. Federer et al., 2003), are now well identified, one major difficulty in modeling this process lies in a lack of relevant input data available at the desired space and time scales (Allen et al., 2011; Pereira et al., 2015). The accuracy of ET estimates at a given scale thus currently represents a trade-off between model complexity and realism, which is usually related to i) the number of model parameters and forcing variables and ii) the availability of data that generally decreases with the spatial extent (Allen et al., 2011; Gharsallah et al., 2013).

Regarding data availability over large areas and at multiple scales, remote sensing observations provide very relevant information to feed ET models such as vegetation indices, land surface temperature (LST) and near-surface soil moisture (SM). Especially, SM is one of the main

* Corresponding author at: LMME, Département de Physique, Faculté des Sciences Semlalia, Université Cadi Ayyad, Marrakech, Morocco.
E-mail address: bouchra.aithssaine@ced.uca.ma (B.A. Hssaine).

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controlling factors of soil evaporation (e.g. Chanzy and Bruckler, 1993), vegetation cover fraction (f_c) provides an essential structural constraint on evaporation/transpiration partitioning (e.g. Allen, 2000) and LST is a signature of available energy and evapotranspiration (e.g. Norman et al., 1995). For this reason, efforts have been made to integrate those data as additional and complementary information on ET (e.g. Price, 1990). Through its link with ET under moisture-limited conditions, LST has been extensively used to retrieve ET at a wide range of spatial resolutions (Kalma et al., 2008). LST-based ET retrieval methods are generally classified in two categories. The first one is the so-called "residual" method, which estimates latent heat flux as a residual term of the surface energy balance (e.g. Norman et al., 1995; Su, 2002). The second one is named the "contextual" method based on the interpretation of the LST versus vegetation index feature space (e.g. Moran et al., 1994; Long and Singh, 2012), the interpretation of the LST versus albedo feature space (e.g. Roerink et al., 2000), or the interpretation of both spaces (Merlin et al., 2013, 2014). The use of SM data, Jung et al. (2010) related the global ET trend to the SM trend derived from TRMM (Tropical Rainfall Monitoring Mission) microwave data. At regional scale, ET was found to have a correlation of about 0.5 with the SM derived from airborne L-band data and a correlation even larger for f_c values lower than 0.5 (Bindlish et al., 2001; Diarra et al., 2017). This was the basis for developing ET models based on microwave-derived SM data (Kustas et al., 1998; Bindlish et al., 2001; Kustas et al., 2003; Li et al., 2006; Gokmen et al., 2012; Li et al., 2015).

Among a wide panel of existing ET models, the Priestley Taylor (PT) assumption that empirically relates ET to net radiation (Priestley and Taylor, 1972) has shown a growing interest (Norman et al., 1995; Kustas and Norman, 1999; Li et al., 2005; Anderson et al., 2007; Fisher et al., 2008; Agam et al., 2010; Jin et al., 2011; Yao et al., 2015; Ai and Yang, 2016). PT coefficient noted α_{PT} directly relates latent heat flux to the energy available at the surface. Since neglecting the aerodynamic resistance term included in the full Penman-Monteith equation (Monteith, 1965), the PT formulation is relatively simple, requires less input data and has proven to be remarkably accurate and robust for estimating potential ET in a wide range of conditions (Fisher et al., 2008). It is therefore well suited for operational (McAneney and Itier, 1996) and large scale (Anderson et al., 2007) applications. In addition, recent studies based on in situ global data sets have reported a good robustness of the PT modeling approach over a variety of biomes (Ershadi et al., 2014). Nevertheless, various theoretical (e.g. De Bruin, 1983) and experimental (e.g. Fisher et al., 2008) studies have stressed that the PT coefficient is variable under different surface and atmospheric conditions. In a literature review, the factors that influence the variability of α_{PT} are: leaf area index (Fisher et al., 2008; Jin et al., 2011; Ai and Yang, 2016), the green fraction of canopy (Norman et al., 1995; Fisher et al., 2008), soil water availability (Davies and Allen, 1973; Mukammal and Neumann, 1977; De Bruin, 1983; Eichinger et al., 1996; Fisher et al., 2008; Jin et al., 2011; Martínez Pérez et al., 2017; Yao et al., 2017), vapor pressure deficit or advective conditions (Jury and Tanner, 1975; Kustas et al., 2000; Agam et al., 2010; Colaizzi et al., 2014), wind speed (Mukammal and Neumann, 1977), air temperature (Ai and Yang, 2016), air relative humidity (Er-Raki et al., 2010), plant temperature (Fisher et al., 2008), surface sensible heat flux (Pereira and Nova, 1992)

) and mulch fraction (Ai and Yang, 2016). As a result of changes in the above ecophysiological and environmental constraints, α_{PT} commonly varies in the range 0.5–2.0 with an average value estimated around 1.3 (above references).

Data available from space can help in implementing the PT approach from three distinct perspectives: i) applying a constraint on vegetation transpiration using an a priori value for α_{PT} (Norman et al., 1995; Kustas et al., 1999; Anderson et al., 2007), ii) applying a constraint on soil evaporation using SM data (Bindlish et al., 2001; Yao et al., 2017), or iii) retrieving the PT coefficient from vegetation indices (Fisher et al., 2008; Jin et al., 2011; Yao et al., 2015, 2017) or from an interpretation of the LST-vegetation index feature space (Jiang and Islam, 2001; Wang et al., 2006; Martínez Pérez et al., 2017). While LST, vegetation indices and SM are alternatively used by satellite-based PT approaches, few studies have combined all three data types. In fact, most studies have compared LST-based versus SM-based ET models separately (Kustas et al., 1998, 2003; Li et al., 2006; Gokmen et al., 2012). Given that SM controls the soil temperature (via the soil evaporation) and that LST integrates both soil and vegetation temperatures, the main issue to integrate simultaneously SM and LST into an unique model is to ensure a robust convergence of soil/vegetation temperatures (Kustas et al., 2003; Li et al., 2006) and associated evaporation/transpiration fluxes. The recent studies of Li et al. (2015) and Song et al. (2016) combined LST and SM to better constrain ET but both approaches relied on a priori reduction coefficients of potential ET. Reduction coefficients of potential ET are equivalent to the soil evaporative efficiency (defined as the ratio of actual to potential evaporation, e.g. Merlin et al., 2016) and to the vegetation stress functions (defined as the ratio of actual to potential transpiration, e.g. Hain et al., 2009) for the soil and vegetation component, respectively. The point is there is no universal parameterization of both soil evaporation efficiency and vegetation stress functions. Alternatively, Sun et al. (2012) proposed an innovative assimilation method to calibrate the parameters of a SVAT (Soil Vegetation Atmosphere Transfer) model from available remote sensing variables including LST and SM. Assimilation results improved ET estimates but the retrieved parameters were mostly conceptual due to the simplicity of the surface model used.

In this context, the objective of this paper is: (i) the modification of the PT-based TSEB formalism (Norman et al., 1995; Kustas et al., 1999) to integrate LST and SM in situ data simultaneously (the modified version is named TSEB-SM), and (ii) the development of a calibration procedure of TSEB-SM to retrieve the main parameters of soil evaporation (soil resistance) and plant transpiration (α_{PT}). The approach is tested over three irrigated wheat crops in the Tensift basin, central Morocco. In each case, the calibration procedure is tested and the TSEB-SM latent and sensible heat fluxes are evaluated and compared against the original TSEB simulations.

2. Methods

2.1. Data

2.1.1. Sites description

The study sites are located in irrigated agricultural areas east (R3 perimeter) and west (Chichaoua area) of Marrakech city in the Tensift basin, central Morocco (see Fig. 1). The climate in the region is semi-arid, with an average yearly precipitation in the order of 250 mm, of which approximately 75% falls during the winter and spring (November-April). The average humidity of the atmosphere is 50% and the reference crop ET is estimated as 1600 mm per year (Allen et al., 1998, Jarlan et al., 2015), greatly exceeding the annual rainfall.

Two data sets are used herein. The first data set was collected from December 2002 to May 2003 over a wheat crop in the R3 zone. The second one was collected from November 2016 to May 2017 over two wheat crops near Chichaoua. Those experiments were carried out to monitor the energy and water balance as well as the soil and vegetation characteristics and conditions during the entire wheat growing cycle. The R3 crop field is 4 ha and is irrigated through periodic (approximately every 3 weeks) flooding with a mean quantity of 30 mm regardless of precipitation. Both Chichaoua crop fields are 1.5 ha and are irrigated by drip technique. During the 2016–17 experiment, one (reference) field was irrigated according to the crop water needs estimated by the FAO method every 3–4 days until mid-April while the other (controlled) field was irrigated exactly the same way except during controlled stress periods when irrigation was cut. The mean irrigation quantity was about 15 mm for both crop fields, whereas the total water supply by drip irrigation was 374 and 504 mm for the controlled and reference field, respectively.