Evapotranspiration and Evaporation/Transpiration retrieval using dual-source surface energy balance models integrating VIS/NIR/TIR data with satellite surface soil moisture information

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EVAPOTRANSPIRATION AND EVAPORATION/TRANSPIRATION RETRIEVAL USING DUAL-SOURCE SURFACE ENERGY BALANCE MODELS INTEGRATING VIS/NIR/TIR DATA WITH SATELLITE SURFACE SOIL MOISTURE INFORMATION

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ABSTRACT:

Evapotranspiration is an important component of the water cycle. For the agronomic management and ecosystem health monitoring, it is also important to provide an estimate of evapotranspiration components, i.e. transpiration and soil evaporation. To do so, Thermal InfraRed data can be used with dual-source surface energy balance models, because they solve separate energy budgets for the soil and the vegetation. But those models rely on specific assumptions on raw levels of plant water stress to get both components (evaporation and transpiration) out of a single source of information, namely the surface temperature. Additional information from remote sensing data are thus required. This works evaluates the ability of the SPARSE dual-source energy balance model to compute not only total evapotranspiration, but also water stress and transpiration/evaporation components, using either the sole surface temperature as a remote sensing driver, or a combination of surface temperature and soil moisture level derived from microwave data. Flux data at an experimental plot in semi-arid Morocco is used to assess this potentiality and shows the increased robustness of both the total evapotranspiration and partitioning retrieval performances. This work is realized within the frame of the Phase A activities for the TRISHNA CNES/ISRO Thermal Infra-Red satellite mission.

1. INTRODUCTION

There is an increasing need for spatially distributed estimates of agricultural water requirements and therefore evapotranspiration (ET). Estimating evapotranspiration, and, in turn, water stress, is important for irrigation monitoring and drought assessment. To do so, Remote Sensing provides an important array of data and solutions. Three spectral domains are concerned: solar (Visible/Near InfraRed spectrum, e.g. NDVI), thermal (Thermal InfraRed, e.g. surface temperature) and microwave (Radar data mostly). NDVI quantifies the amount of green vegetation, the largest water user in most areas since plants assess a larger fraction of the soil water through roots than what contributes to evaporation. Surface temperature is related to water stress through the energy budget, and gives a clue about the difference between actual and potential ET rates. Finally, radar data is related to surface soil moisture and thus evaporation. While NDVI and radar, on the one hand, and NDVI and surface temperature, on the other, are frequently used together to estimate ET, the three sources of information have rarely been combined together (Ait Hssaine et al. 2018).
If total ET is interesting for water management, drought assessment and irrigation control (esp. for drip or complementary irrigation), one must also estimate separately its components, i.e. evaporation and transpiration (the later representing the plant water uptake and the eco-agro system health). An estimate of the separate contribution of E and T to ET can be deduced from dual-source energy balance models such as TSEB (Kustas et al., 1999) or SPARSE (Boulet et al., 2015), but retrieving two unknowns (E and T) out of a single source of information (surface temperature T_{surf}) means that an additional assumption is laid down. In TSEB or SPARSE, the initial guess on the plant water stress is that, in most cases, there is none, and T_{surf} is used to estimate E while T is computed by solving the plant energy budget in potential (i.e. unstressed) conditions. If the vegetation is suffering from water stress, its temperature will be higher than what is deduced from the energy budget in potential conditions. Consequently, the soil temperature that corresponds to the observed surface temperature and the underestimated vegetation temperature will be overestimated, and at some point this leads to a negative E retrieval. In that case TSEB and SPARSE assume that, if the vegetation is suffering from stress, the soil surface is already long dry, and E is close to zero. T_{surf} is thus used to retrieve T. But how robust is this ? Can we improve the robustness by forcing E and T by two RS data, T_{surf} and a relative soil moisture level deduced from radar data ? This is the purpose of the present paper. It is organized in two main sections: the first summarizes the retrieval and prescribed algorithms of SPARSE as well as the dataset used to evaluate the various forcing configurations, while the second presents the comparison in the retrieval performance of total ET, total water stress and the T/ET ratio when using the sole surface temperature forcing or the combination of surface temperature and soil moisture forcing.

2. MATERIAL AND METHODS

2.1 The SPARSE Model

SPARSE solves the dual-source energy budget of the soil and the vegetation. The model can be run in two modes: a retrieval mode to simulate evaporation and transpiration from TIR data, and a prescribed mode which simulates evaporation and transpiration rates for known stress levels (from fully stressed, i.e. E=T=0 to fully potential). This enables to simulate not only fluxes in actual conditions but also surface and plant water stress since potential E and T are also computed. The prescribed (or direct) mode simulates fluxes and component (soil and vegetation) temperatures from known water stress conditions corresponding to relative levels between unstressed (potential rate) to fully stressed (minimum ET). The retrieval (or inverse) mode infer E and T from surface temperature observations using a decision tree (Figure 1).

As said in introduction, SPARSE, like TSEB, assumes in a first place that the vegetation is unstressed and transpires at maximum (potential) conditions. The information on surface temperature is thus translated into the reduced evaporation rate. If this rate is negative, the unstressed transpiration rate is challenged. One assumes then that if the vegetation, which extracts water from the whole root zone, is starting to suffer from water stress, then the soil surface is already long dry and does not evaporate (E=0, meaning that the corresponding soil latent heat flux component LE_s is also 0). The information contained in the surface temperature is thus passed on the transpiration reduction due to moisture limitation. If, in turn, transpiration drops below zero, then one assumes there is a mismatch between the surface temperature and the various potential energy status in the two previous configurations, and a new surface temperature is retrieved while LE_s=LE_v=0 are imposed. A critical assessment of this assumption is provided in Boulet et al., 2018. In particular, slightly stressed vegetation and evaporating bare soil conditions are rare but can coexist (i.e. after a very small rainfall event for instance). In complement to TSEB, SPARSE has a post-processing step that ensures consistency of outputs by imposing that all individual rates (soil and vegetation latent heat fluxes LE_s and LE_v) are below their corresponding maximum (potential) levels. A similar check is carried out for the sensible heat: the soil (H_s) and vegetation (H_v) sensible heat components must lie below their corresponding rates in fully stressed conditions. It is thus important to add an additional constraint on the relative importance of E and T within the energy budget forced by a single source of information. We propose here to constrain directly E by a fixed rate determined by the surface soil moisture available from, say, radar data.

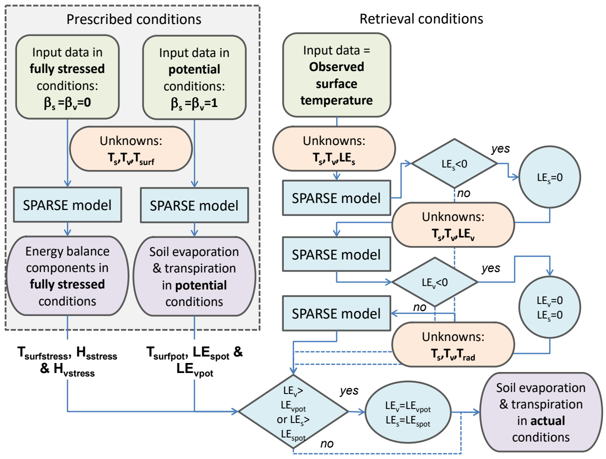

Figure 1. Flowchart of the SPARSE model (T is the element skin temperature, T_{surf} is the surface radiative temperature, LE is the latent heat flux and H the sensible heat flux, subscript "s" for soil and "v" for vegetation are used to characterize the component fluxes, subscripts "stress" for stressed and "pot" for potential are used to describe the water status; β is the efficiency, i.e. the ratio between actual and potential latent heat fluxes; from Saadi et al. (2018).

2.2 The dataset

ET, T and E data have been acquired over a drip irrigated wheat field in the Haouz plain in Morocco during the 2016-2017 growing season. The study field has been stressed voluntarily during 3 periods. ET was estimated with a standard eddy-covariance tower (CSAT3 sonic anemometer and KH20 krypton hygrometer) completed by a CNR1 net radiometer and HFT3 soil hat flux plates buried at 5 cm. Surface temperature was measured by using an infrared thermoradiometer (IRTS-P) and surface soil moisture by CS615 TDR probes at 5 cm. EC data were corrected by forcing the Bowen ratio closure. T was measured with the SHB micro-sap flow method using Dynagage SF sensors. E was estimated by a SFL lysimeter at a 30 cm depth with special treatment to prevent plant transpiration while capturing plant shadowing effect on the ground. The complete dataset, including the E/T partitioning, has been fully presented and analysed in Rafi et al. (2019) and Hssaine et al. (2018).

2.3 Additional constrain on E using observed surface soil moisture

An estimate of E (or its latent heat flux equivalent LE_s) is derived from the observed topsoil volumetric surface soil moisture and the formulation from Merlin et al. (2011):

$$LE_s = \left[0.5 - 0.5\cos\left(\pi \frac{\theta_{0-5cm}}{\theta_{sat}}\right)\right] \cdot LE_{spot} \tag{1}$$

where $\theta_{0\text{-}5cm}$ and θ_{sat} are the measured topsoil (0-5cm) and the saturation soil moisture respectively; LE_{spot} is the potential evaporation rate computed by SPARSE in potential conditions (cf. Figure 1). SPARSE can thus be run in two configurations: in the classic mode when only the surface temperature is imposed, and in a new mode when both the surface temperature and the surface soil moisture are imposed (i.e. no initial guess is

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made on the water stress level of the vegetation, unlike the classic mode). In this new mode, the decision tree is directly entered into the second configuration (LE_v, i.e. T is retrieved while LE_s, ie. E, is imposed), but instead of imposing LE_s=0, the constrained rate derived from Eq. (1) is imposed.

3. SIMULATION PERFORMANCE WITH OR WITHOUT E(θ) FORCING

3.1 Total LE retrieval performance

SPARSE is run with default parameters for herbaceous vegetation in both modes. Table 1 displays the RMSE values at midday, and shows a very large improvement when the new mode is used. In fact, as can be observed in Figure 2, at most times both modes show satisfying performances, but the classic mode has many outliers that decrease a lot the overall performance statistics. It turns out that these outliers correspond mostly to situations when both LE_s and LE_v are first set to 0, as well as situations when LEs is very large. Overall, there is a tendency to underestimate LE, as shown in Figure 3 for a subset corresponding to midday values.
What happens mostly is that in the new version the mode LE_s=LE_v=0 is rarely reached, meaning that the intermediate mode with an intermediate level of LEs is already good whereas in the classic mode when LE_s=0 is imposed (see Figure 1) the results in negative values of LE_v and a subsequent correction.

RMSE (W/m^2) at midday	T_{surf} only	T_{surf} and $\theta_{0\text{-}5cm}$
LE	125	64
H	131	60
G	43	34
Rn	114	36

Table 1. RMSE of the energy balance components at midday

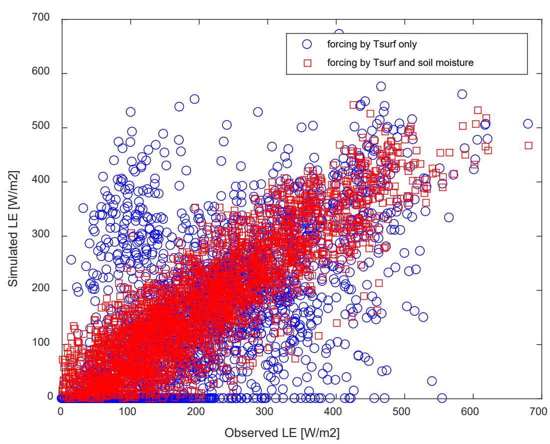

Figure 2. Scatter plot of simulated versus observed half hourly latent heat flux in both configurations

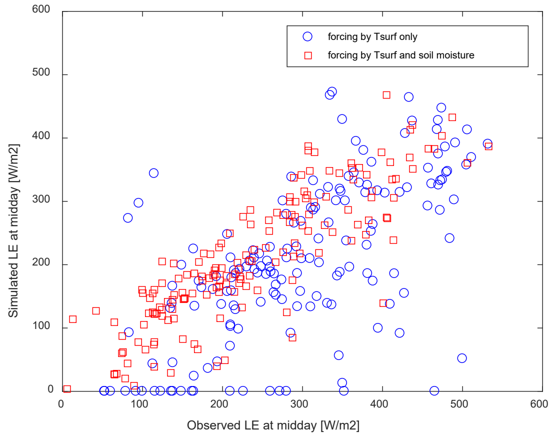

Figure 3. Same as Figure 2 for midday values

3.2 Total stress

Stress is computed by using the simulated potential latent heat. Figure 4 shows midday stress values. Overall tendencies, including dates of stress onset or stress removal, are reasonably well reproduced by both modes, except for the late season (from DOY 115). Stress is overestimated in mid-season (DOY 70 till 90) with values going up to 0.95, but order of magnitudes are well simulated in the later stages. Only the new mode is able to reproduce satisfactorily the late season, with very good performances for both drydowns DOY 110-122 and DOY 122-140.

3.3 Partitioning : T/ET

Lysimeter data (through ET-T) and sap flow data allow to compute the transpiration partitioning ratio T/ET. Figure 5 shows the evolution of T/ET during the period when measurements are available. As for the stress, the ratio is overestimated in mid-season (DOY 70-90). After this period, both models are consistent with the measurements, even though the classic mode predicts a decreasing trend of T/ET in advance of what is measured, while the new mode follows more closely the observations, with a small delay however.

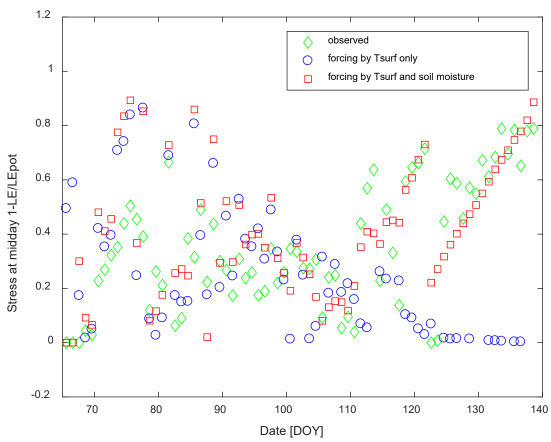

Figure 4. Time series of observed vs simulated total stress

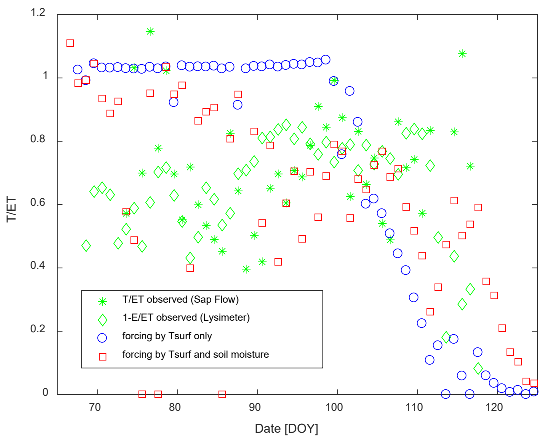

Figure 5. Time series of observed vs simulated T/ET ratios

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