

Remote Sensing Land Surface Temperature-Based ET Algorithms

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Evapotranspiration (ET) is a process that includes evaporation from the surface, such as open water bodies, soil and vegetation, and transpiration as the water released mostly by the plant leaves transported from the root system. ET is a key factor in the hydrological cycle, since it describes the mechanism and energy needed to transport the liquid water stored in the soil-watershed-canopy system to the atmosphere, converted into water vapour. Remote sensing technology is a globally consistent and economically feasible means to estimate ET values at regional and meso-scales on the Earth's surface, since the approach directly links surface radiances and the components of the surface energy balance. Over the past, combined use of satellite remote sensing data from optical and thermal infrared sensors has provided substantial progress in the estimation of ET. Based on the concept of surface energy balance and net radiation, most remote sensing models have estimated ET for application studies such as water consumption, water resources planning and management over watersheds or modeling ecological processes and analyzing biophysical characteristics of landscape.

ET

remote sensing

land surface temperature (LST)

atmospheric surface layer

1. Introduction

Evapotranspiration (ET) is a process that includes evaporation from the surface, such as open water bodies, soil and vegetation, and transpiration as the water released mostly by the plant leaves transported from the root system. ET is a key factor in the hydrological cycle, since it describes the mechanism and energy needed to transport the liquid water stored in the soil-watershed-canopy system to the atmosphere, converted into water vapour.

In the broader context, irrigated agriculture still accounts for 70% of freshwater withdrawals [1]. This is a serious problem noticed by the Horizon Europe program. In this framework, ET plays an important role as a controlling factor of the water cycle and energy transport among the biosphere, atmosphere and hydrosphere. The importance of ET has been evidenced from the very beginning of the Remote Sensing discipline, in application fields such as hydrology, for instance for the scheduling of field-scale irrigations and tillage [2] or in meteorology and climatology, for prediction of natural hazards such as floods and droughts [3] or in agriculture, where for vegetated surfaces, ET can be used as an indicator of plant water stress [4].

In situ ET field retrievals from ground instrumentation, based on conventional techniques (e.g., Eddy covariance, Bowen ratio, lysimetry, etc.), offer the advantage of a direct determination of the value of ET for a measuring site [5].

However, these instruments are often costly, their data require an adequate treatment which is quite time-consuming, and instrumental problems may happen [6]. A commonly-used alternative for the estimation of ET is the Penman-Monteith equation, which uses monitored variables (e.g., air temperature or humidity), very convenient with basic meteorological stations, especially in the form suggested by Food and Agriculture Organization (FAO) [7] [8]. Furthermore, for an area which is spatially heterogeneous, measurements made in a single location may not be representative of the full area [9]. For a given area in a humid climate, annual ET can be as large as half of the precipitation, whereas for arid and semi-arid areas ET is almost equivalent to the total annual rainfall [10].

In summary, even if accurate ET estimates can be obtained for the instrumented sites, these values are not useful at larger scales due to the usual heterogeneity of the landscape and the complexity of the hydrological processes [2]. Conventional ground measurement techniques do not appreciate spatial distribution at large-scales, especially in regions composed of well-contrasted areas where advection may be important.

2. Single-Source Energy Balance Models

2.1. Surface Energy Balance Index (SEBI) and Simplified-SEBI (S-SEBI) Models

Originally proposed by [11], the physically-based assumption is that ET varies with the T_s for a homogeneous surface. For a given surface albedo and boundary layer conditions, there exists a temperature gradient between the surface and the atmosphere ($T_s - T_a$) at some crop height, that ranges from a maximum value for which ET is assumed to be zero, to a minimum value for which the potential ET (ET_p) is taken, as given by the Penman-Monteith equation [7].

There exists a correlation between T_s and the surface reflectance (albedo), where for low reflectance values T_s remains constant with the progressive increase of such reflectance. This phenomenon is attributed to presence of body water or well-watered surfaces, where all the available energy is used for the evaporation. From certain reflectance threshold T_s increases with the reflectance, inducing a decrease in the evaporation, in the so-called "evaporation controlled" range. From another higher reflectance threshold, T_s decreases with the increase of the reflectance, because the R_n decreases due to the high reflection of the energy received, a process known as "radiation controlled".

Based on the previous assumptions, for a specific surface given T_s , [11] provided a value for ET by means of an interpolation expression:

$$ET_i = \left(1 - \frac{\frac{(T_s - T_{pbl})}{r_{aH}} - \frac{(T_{s,min} - T_{pbl})}{r_{aH,min}}}{\frac{(T_{s,max} - T_{pbl})}{r_{aH,max}} - \frac{(T_{s,min} - T_{pbl})}{r_{aH,min}}} \right) ET_p = (1 - SEBI) ET_p$$

where T_{pbl} is the average air potential temperature at higher elevation or at the top of the Planetary Boundary Layer (pbl) and $r_{aH,min}$ and $r_{aH,max}$ are the minimum and maximum aerodynamic resistance in the sensible heat flux

H [12].

A simplified version of the SEBI method (S-SEBI) was proposed by [13] with the advantage that no additional meteorological data are needed if the hydrological conditions of the surface are extreme enough to observe a significant range of gradient temperatures for the corresponding reflectance spectra.

Therefore if for a given α_s value the two extremes of T_s exist, that is for $H_{max}(T_{s,max}, \alpha_s)$ and $LE_{max}(T_{s,min}, \alpha_s)$, [13] expressed the ET value as:

$$\lambda ET_i = \frac{T_{s,max} - T_s}{T_{s,max} - T_{s,min}} (R_n - G)$$

The method is called simplified if the wet and dry pixel conditions are observed for a specific albedo value in a satellite scene. But [13] simplified even more Equation (19) by adjusting linearly the trends of maximum and minimum T_s with the albedo, according the following equations:

$$T_{s,min} = a_{min} + b_{min} \alpha_s$$

where a_{max} and b_{max} are the slope and offset coefficients for the linear regression of the maximum temperature values with the albedo and a_{min} and b_{min} are the corresponding coefficients for the linear regression of the minimum temperatures, also with the albedo. These four parameters must be adjusted in each individual satellite scene. Including Equations, ET expression from S-SEBI model can be defined then as:

$$\lambda ET_i = \frac{a_{max} + b_{max} \alpha_s - T_s}{a_{max} - a_{min} + (b_{max} - b_{min}) \alpha_s} (R_n - G)$$

Very few modifications have been proposed in the literature for the S-SEBI model. One of them is made by [14], which in order to avoid using the LE and H fluxes, it is proposed using instead the evaporative fraction (EF), that can be extracted from the T_s - α scatterplot shape.

A recently study [15] proposed an adaptation of EVapotranspiration Assessment from SPAce (EVASPA) tool [16] to S-SEBI model. This model, denoted as E3S (for EVASPA S-SEBI Sahel), proposes two relevant changes. The first one is related to the handling of the algorithms determining the wet and dry edges, since in some regions like the Sahel with strong seasonal contrast only one edge may be identified. This led to the introduction of twelve additional seasonally-dependent algorithms to estimate the dry and wet points, using an ensemble member weighting. Secondly a cloud edge filtering method was implemented, to avoid that pixel outliers can distort the T_s scatterplot shape. The cloud edge filtering was developed in two levels: (1) the first level filter was based on the quality flag provided by the MODIS land surface temperature (LST) products. Thus, all pixels bordering clouds and associated with an LST error >1 K were removed; (2) a second level filter consisted in extending the first level filter to cloud-bordering pixels with LST below the first LST quartile in the entire image. This quantile level selection could be site and climate-specific.

2.2. Surface Energy Balance System (SEBS) Model

Proposed by [17] the SEBS method is based, as it is S-SEBI, SEBAL and METRIC (to be described below), on the same main concept as SEBI. The difference of SEBS from the rest is that it deals with estimating the ET fluxes at large scales, therefore considering heterogeneous surfaces.

Therefore, the assumption of constant atmospheric conditions for the whole scene is not applicable. Moreover, spatial variation of roughness height for different surfaces is allowed.

The SEBS is an extended model that defines the surface roughness length in the heat fluxes, reformulating the EF at the limiting cases. To this end in the SEBS theory the dry and wet case limits are:

Dry limit:

$$LE_{dry} = 0$$

$$H_{dry} = R_n - G$$

$$LE_{wet} = R_n - G - H_{wet}$$

$$H_{wet} = \frac{R_n - G - \frac{\rho C_p VPD}{r_a H \gamma}}{\left(1 - \frac{\Delta}{\gamma}\right)}$$

where VPD is the vapor pressure deficit (difference between saturated and non-saturated vapor pressure), Δ is the slope of the curve relating temperature difference ($T_s - T_a$) with VPD , and γ is the psychrometric constant.

As an intermediate step SEBS method defines a relative EF (EF_r) as:

$$EF_r = 1 - \frac{H - H_{wet}}{H_{dry} - H_{wet}}$$

Some studies presented a modification of the SEBS inner structure in terms of: (i) momentum roughness length and zero plane displacement; (ii) an empirical relationship between land surface temperature and air temperature; and (iii) designing a new input interface of meteorological field at reference, with the objective of representing land surface and climatic changes of a specific region. These studies adapted SEBS to be applicable in different countries like Taiwan (SEBS-Taiwan, [18]), China (SEBS-China, [19]) or Iran (SEBS-Iran, [20]). SEBS was also modified at local scale (SEBS-Urban, [21]) after including the anthropogenic heat flux in the SEB equation to estimate the ET of Beijing city. This hypothesized that ET was equal to the water consumption in the study area.

An improvement of SEBS method was suggested by [22] by correcting the excess resistance with a scale factor dependent on soil moisture (SM), following:

$$\left(\frac{\kappa}{B}\right)_{corr} = \left[a + \frac{1}{1 + \exp(b - cSM_{rel})} \right] \frac{\kappa}{B}$$

where a , b and c are coefficients of the sigmoid function and SM_{rel} is a relative soil moisture defined as:

$$SM_{rel} = 1 - \frac{SM - SM_{min}}{SM_{max} - SM_{min}}$$

SM_{max} and SM_{min} values can be obtained using a time series analysis of the soil moisture data on annual or long-term basis [22]. Wu et al. [23] suggested the use of the Normal Differential Water Index (NDWI) instead of SM_{rel} in Equations. Yi et al. [24] also recommended replacing SM_{rel} by the inverse of the modified perpendicular drought index (MPDI).

It is also worth mentioning the study of Chen et al. [25], in which the excess resistance is internally modified to be robust for heat flux calculation for high and low canopies, since it has been proved its depends on environmental conditions, surface types, canopy structure and vegetation surface geometry. kB^{-1} structure was adjusted from a one-foliage layer to a multi-foliage layer, which provides the possibility of including the impact of vertical variations in foliage leaf area density, foliage shelter factor, and foliage heat transfer coefficient.

2.3. Surface Energy Balance Algorithm for Land (SEBAL) Model

Proposed by [26], SEBAL is an iterative and feedback-based numerical procedure that deduces the radiation, heat and evaporation fluxes. SEBAL estimates LE with the residual of Equations in a pixel by pixel satellite scene, just considering two anchor points (dry and wet points) for the full scene. At the dry point $LE = 0$ and $H = R_n - G$, and at the wet point $H = 0$ and LE can be considered either $R_n - G$ or a reference ET [2].

The main consideration of SEBAL is to establish a linear regression between T_s and difference of T_s with the air temperature at the crop height z (δT_a), as follows:

$$\delta T_a = c_1 T_s - c_0$$

where c_1 and c_0 are the empirical coefficients derived from anchored conditions of wet ($\delta T_{a,wet} = 0$, $T_{s,wet}$) and dry points ($T_{s,dry}$), for which the temperature difference is expressed as: $\delta T_{a,dry} = \frac{(R_n - G)r_{aH}}{\rho C_P}$

A first modification of SEBAL was proposed by [27] after introducing Digital elevation model (DEM) data to account for impacts of slope aspect on incident solar radiation. But the main subject of modification of SEBAL model is related with the choice of endmembers or anchor points (i.e., “hot” and “wet” points in the satellite scene). A Modified version of SEBAL (M-SEBAL) was proposed by [28], that based the election of the anchor (dry/wet) points on the type of surface, defined by the FVC. They adjusted Equations for every specific surface defined by FVC and

subsequently estimated H and LE. Feng et al. [29] derived geo-mathematically four reference dry and wet limits, instead of the classical option of two anchor points.

Another modification is addressed in [30], where researchers deal with the endmember pixel selection process, proposing an automated procedure by introducing an exhaustive search algorithm (ESA), in which all possible candidates are systematically considered and checked to determine if the solution is satisfied, based on two steps: (1) create a binary map of candidate pixels that are identified using a simple rule-based classifier, and (2) apply ESA to identify hot and cold pixels that meet the defined criteria. In this sense, [31] created the automated SEBAL (ASEBAL) model that allows automatic selection of the endmember pixels according to criteria based on the variation in biophysical parameter values retrieved from satellite products.

It is also worth mentioning the study of [32], where researchers found more appropriate to combine the capabilities of Synthetic Aperture Radar (SAR) with optical remote sensing technique in the applications where soil moisture conditions to locate anchor pixels, since SAR is more suitable to detect soil moisture conditions.

Two interesting studies that suggested modifications of SEBAL ET model were related with changes in the SEB equation, by introducing new fluxes terms that must be accounted in certain situations. Mkhwanazi et al. [33] proposed a modified version of SEBAL model (SEBAL-A), that is capable of accounting for advection flux term, estimated with a wind function which included a daily mean or extreme temperatures parametrization, which is incorporated it into the original SEBAL daily ET sub-model. [34] also suggested enhancing the SEBAL model when it is applied in a heterogeneous urban environment (uSEBAL), after considering urban land surface parameters and including the urban anthropogenic heat flux in the SEB budget.

Finally, it is worth to note that recent open access software code versions of SEBAL are accessible. One of them is a new python version of SEBAL (pySEBAL), which incorporates an automated pixel selection procedure and is currently under development and testing at the IHE-Delft Institute [35]. In addition, a new tool based on the SEBAL algorithm, modified with a simplified version of the Calibration using Inverse Modeling at Extreme Conditions process [36] for the endmembers selection, was developed within the Google Earth Engine (geeSEBAL) environment [37].

2.4. Mapping Evapotranspiration at High Resolution and with Internalized Calibration (METRIC) Model

METRIC was proposed by [38], based almost completely on SEBAL method. The main differences with SEBAL are that R_n and T_s are corrected topographically using a Digital Elevation Model. Both methods differ in the calculation of H as in METRIC the temperature gradient of the wet point is expressed as:

$$\delta T_{a,dry} = \frac{(R_n - G - 1.05ET_r)r_{aH}}{\rho C_P}$$

The assumption that ET rate (ET_r) is about 5% above that of the standard ET_r in the METRIC model is assumed because, for a large population of fields, some fields will have a wet soil surface beneath a full vegetation canopy that will tend to increase the total ET rate [38].

Since METRIC is directly based on SEBAL model, all the modifications previously discussed in [Section 3.1.3](#) can also apply to METRIC. However, it is interesting to note a recent study [39], where calibration variability in METRIC is examined through the anchor pixels selection. Following METRIC original procedure to detect “cold” and “hot” pixel in a scene, the researchers detected a range of different “cold” and “hot” pixels that conformed a total of five sets of calibration pixel pairs (based on combination of maximum and minimum “cold” and “hot”, as well as values closest to the flux station). So, different slopes and intercept values were retrieved from the plot δT vs. T_s . In summary, researchers observed significant spatial differences in ET across the study area, which suggested that candidate calibration pixels cannot be completely quantified using only NDVI and T_s . Therefore, it can be presumed that the large differences in δT among the candidate pixels were not random noise, and that the inclusion of available energy into the calibration pixel selection process could potentially improve the calibration process and provide better estimates of ET.

3. Land Surface Temperatures–Vegetation Index Triangle/Trapezoidal ET Models

Vegetation Indices (VIs) offer important information from T_s –VI triangle/trapezoidal relationship. These diagrams can be useful for estimating regional ET values under the condition that full ranges of SM content and vegetation are present in the remote sensing scene.

The Triangle method was described by [40], and provides a biophysical justification for the combination of T and vegetation indices (VI) time series for land-cover mapping and land-cover change analysis. The lower envelope represents the wet edge, which is nearly constant and represents the lowest T_s for the different types of surfaces, assuming here that the ET is potential. Theoretically the two envelopes (dry and wet edges) intersect in a point of full cover vegetation and maximum ET.

Based on the Priestley-Taylor formulation [41] and fully remotely sensed data, an expression proposed by [42] allows estimating the LE according to the T_s –VI triangular relationship as:

$$LE = \varphi \left[(R_n - G) \frac{\Delta}{\Delta + \gamma} \right]$$

where φ varies from 0 to 1.26, and it is estimated with a two-step linear interpolation. This interpolation consists in: (1) once set a $\varphi_{min} = 0$ (driest bare soil) and $\varphi_{max} = 1.26$ (largest VI and lowest T_s), for each intermediate VI a $\varphi_{min,i}$ is estimated by interpolation between φ_{min} and φ_{max} and a $\varphi_{max,i}$ is assigned to the minimum T_s value of such VI (usually 1.26), (2) Different φ_i can be estimated from the T_s range at each VI. VI can be either the NDVI, FVC, the Soil Adjusted Vegetation Index (SAVI), Enhanced Vegetation Index (EVI), etc.

The T_s -VI Trapezoidal method based on the proposed Water Deficit Index (WDI) by [43], an index related to the ratio of actual and potential evapotranspiration, which evaluates the evapotranspiration rates of both full-cover and partially vegetated sites. WDI based T_s -VI Trapezoidal method considers that full covered vegetation can both water-stressed and well-watered in a satellite scene, so there is no intersect in a point of full cover vegetation and the T_s -VI diagram become a trapezoid. Moran et al. [43], extended the ET estimation from full to partially vegetated surface areas, considering that temperature gradient ($T_s - T_a$) varies linearly with the vegetation status. So, WDI is linearly related at each VI to the maximum (dry bare soil) and minimum (probably well-watered full-cover vegetation) gradient temperature, taking values between 0 and 1 and LE is calculated similar to Equation as the ratio of potential ET calculated from Penman-Monteith equation [7], LE for the trapezoidal method is expressed as:

$$LE = (1 - WDI)LE_P = \left(1 - \frac{[(T_s - T_a)_{min} - (T_s - T_a)_i]}{[(T_s - T_a)_{min} - (T_s - T_a)_{max}]}\right)LE_P$$

Stinsen et al. [44], combined the triangle method with thermal inertia information obtained from MSG-SEVIRI sensor, by changing the surface temperature over time. Researchers also applied a slightly modified version of the two-step interpolation scheme to obtain φ , based on a interpolation where the decomposition is regarded as non-linear with the argument that non-linear intersections are observed in the dry edge and in the iso-lines of equal moisture availability of the T_s -VI triangle feature. Adopting equations, [45] proposed a Time-Domain Triangle Method (TDTM), based on a pixel by pixel T_s -VI feature space, obtained by exploring the temporal domains over each single image pixel, since the triangle contains the whole climatic variability of the T_s -VI. Also, in [46], an algorithm to determine quantitatively the dry and wet edges for the T_s -VI triangular space in arid and semi-arid areas, where wet pixels are not generally easily identified, was developed with an iterative process that automatically retrieve the two edges in the T_s -FVC triangle space in ten steps. The process starts dividing the range of FVC in the T_s -FVC triangle space into M intervals evenly and ends with a linear regression to obtain the dry edge.

Another interesting modification of the T_s -VI triangle method is proposed by [47] that estimate daily ET directly using the top of atmosphere (TOA) radiances without performing atmospheric correction or other processes, to avoid the uncertainty associated with the estimation of ET, attributed to satellite data products. Furthermore, a recent study [48] estimates the soil heat flux (G) in the trapezoidal space of T_s -FVC, prior to apply the original T_s -VI trapezoidal method afterwards.

4. Dual (Two)-Source Energy Balance (TSEB) Model

A two-layer model of turbulent exchange that includes the view geometry associated with directional radiometric surface temperature was developed and evaluated by [49]. The main assumption of TSEB model is that T_s estimated from remote sensing measurements is the composite of soil and canopy surfaces, and it can be expressed as:

$$T_s = [FVCT_c^4 + (1 - FVC)T_{soil}^4]$$

where T_c is the temperature of the canopy and T_{soil} is the temperature of the non-vegetated soil. Note the term FVC in this Equation is a function of LAI and sensor viewing angle [50]. The original TSEB does not consider the weighting by the emissivities of each component, but some researchers have claimed for its importance [51][52][53].

The key of the TSEB model is the partition of sensible heat flux into the canopy and soil layers. If there is an interaction between the fluxes of both components, due to a heating of the in-canopy air by heat transport from the soil, the resistance framework in TSEB can be considered to be in series [49][54][55][56]. A parallel configuration was also introduced [49], based on the assumption that the resistance of each source interacts independently with respect to the surface-atmosphere, although the canopy still has an effect on the radiation transmitted towards the soil and the wind attenuation through the canopy to the soil surface. Each component has its own SEB equation expressed as: $R_{n,soil} = H_{soil} + LE_{soil} + GR_{n,c} = H_c + LE_c$

A variety of radiative transfer models have been implemented within TSEB to estimate R_n components. Traditional versions of TSEB estimate R_n using the physically-based radiative transfer model described in [57], first implemented within TSEB by [58]:

In this revised two-source model, the separation of net radiation between canopy and soil can be expressed as:

$$R_{nc} = L_{nc} + (1 - \tau_s)(1 - \alpha_c)S$$

$$R_{ns} = L_{ns} + \tau_s(1 - \alpha_s)S$$

where S is solar radiation, τ_s is solar transmittance in the canopy, α_s is soil albedo, α_c is canopy albedo, L_{ns} and L_{nc} are longwave radiation for soil and canopy, respectively, and are estimated via the following expression:

$$L_{ns} = \exp(-\kappa_L \Omega LAI) L_{sky} + (1 - \exp(-\kappa_L \Omega LAI)) L_c - L_s$$

$$L_{nc} = (1 - \exp(-\kappa_L \Omega LAI)) (L_{sky} + L_s - 2L_c)$$

where L_{sky} , L_s , and L_c are longwave radiation from the sky, soil, and canopy, and can be calculated from air, soil, and canopy temperature, Ω is the clumping factor, and κ_L is an extinction coefficient. Campbell and Norman [57] described how to estimate the transmittance, albedo, and extinction coefficients for soil and canopy.

Soil and canopy sensible heat fluxes H of Equations, can be deduced easily as:

$$H_{soil} = \rho C_P \frac{T_{soil} - T_a}{r_{aH} + r_s}$$

$$H_c = \rho C_P \frac{T_c - T_a}{r_{aH}}$$

where the parameter r_s is the resistance to the heat flow in the boundary layer immediately above the soil surface, and it can be expressed as:

$$r_s = \frac{1}{0.0025(T_s - T_c)^{1/3} + 0.012u_s}$$

where u_s is the wind speed at a height above the soil surface where the effect of soil surface roughness is minimal (i.e., 0.05–0.1 m).

Latent heat fluxes for soil (LE_s) and canopy (LE_c) are calculated as residuals of Equations.

Another type of two-source model formulation is the so-called patch model where it is assumed that all the fluxes act vertically and that there is no interaction between soil and canopy components (i.e., a complete energy balance between the atmosphere and each element [58][59]).

There exist modifications on the TSEB model, like the Two-Source Time-Integrated Model (TSTIM) proposed by [60], lately called Atmosphere-Land Exchange Inverse (ALEXI) in [61], which relates time-differential T_s observed (1.5–5.5 h after sunrise) from geostationary satellites to the time-integrated energy balance within the surface-atmospheric boundary layer system.

ALEXI has minimal reliance on absolute (instantaneous) air or surface temperature input data, and therefore provides a relatively robust flux determination at the coarse geostationary pixel scale (5–10 km). For finer scale ET applications, ALEXI flux fields can be spatially disaggregated using higher resolution T_s information from polar orbiting systems (e.g., Landsat or MODIS) in an algorithm referred to Disaggregated ALEXI (DisALEXI) model [62].

Another modified TSEB model is the Simplified TSEB (STSEB) model proposed by [63], which suggests dividing the R_n , H and LE fluxes in soil and canopy weighted values, according to the FVC. The scheme proposed by [64], which is based on canopy conductance by means of a formulation that has sound parameterizations of transpiration and evaporation, that links soil surface temperature and soil evaporation eliminating the need of using soil moisture as input, and allowing the model predicting surface temperature and energy fluxes simultaneously. Furthermore, it can be calibrated using remotely sensed LST data.

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