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Review on estimation of evapotranspiration from remote sensing data: From empirical to numerical modeling approaches

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Abstract. Different methods have been developed to estimate evapotranspiration from remote sensing data, from empirical approaches such as the simplified relationship to complex methods based on remote sensing data assimilation along with SVAT models. The simplified relationship has been applied from small spatial scale using airborne TIR images to continental scale with NOAA data. Assimilation procedures often require remote sensing data over different spectral domains to retrieve input parameters which characterize surface properties such as albedo, emissivity or Leaf Area Index. A brief review of these different approaches is presented, with a discussion about the main physical bases and assumptions of various models. The paper reports also some examples and results obtained over the experimental area of the Alpilles Reseda project, where various types of models have been applied to estimate surface fluxes from remote sensing data.

Key words: evapotranspiration, operational application, remote sensing, simplified model, SVAT model

Introduction

Detailed knowledge of land surface fluxes, especially latent and sensible components, is important for monitoring the climate of land surface, for evaluating parameterization schemes in weather and climate models used to predict fluxes exchanges between the surface and the lower atmosphere, and for agricultural applications such as irrigation scheduling. The main methods classically used to measure evapotranspiration (ET) are available at the field scale (Bowen ratio, eddy correlation system, soil water balance), but do not allow estimating the fluxes when dealing with large spatial scales. For operational applications, water managers and irrigation engineers need to have accurate estimations of surface fluxes, and especially ET. Nowadays, the recommended FAO 56 method is used in numerous countries. This method consists of estimating crop evapotranspiration (Etc) for a crop canopy using a reference evapotranspiration (Etr) and a crop coefficient (Kc), where Etr is retrieved using the Penman–Monteith method (PM). The latter provides Etr over a grass under optimum soil moisture conditions with a constant value of the surface canopy resistance considering then the grass as a single big leaf (Allen et al., 1998, FAO 56 method). However, surface resistance can vary according to the day, the weather conditions, especially available radiation and vapor pressure deficit (Ortega et al., 2004). The determination of crop coefficients is also debatable because a lot of factors occur (Neale et al., 2005). The ET crop surfaces under non-standard conditions is adjusted by either a water stress coefficient or modifying the *Kc* coefficient. Actual evapotranspiration (Etact) corresponds to the real water consumption according to weather parameters, crops factors, management and environmental conditions. However, several other crop and surface characteristics have to be considered: crop type/variety/development stage, ground cover and root system development.

Remote sensing data with the increasing imagery resolution is a useful tool to provide such information over various temporal and spatial scales. Different methods have been developed to use this information in surface flux estimation schemes. It is always difficult to classify these methods, since their complexity depends on the balance between the empirical and physically based modules used. Nevertheless, we propose in this paper four model categories which are based on:

– *Empirical direct methods* where remote sensing data are introduced directly in semi-empirical models to estimate ET (for example, the simplified relationship using Thermal Infra Red (TIR) remote sensing and meteorological data). We will present the main assumptions of this approach in the first section of the paper. It allows characterizing crop water status both at the local scale using ground measurements and over large irrigated areas using satellite data using the cumulative temperature difference ($Ts - Ta$), also known as a stress degree day (SDD).
– *Residual methods of the energy budget* combining some empirical relationships and physical modules. Most current operational models (such as SEBAL, S-SEBI described further) use remote sensing directly to estimate input parameters and ET.
– *Deterministic methods* generally are based on more complex models such as Soil–Vegetation–Atmosphere Transfer models (SVAT), which compute the different components of energy budget (ISBA, Meso-NH). Remote sensing data are used at different modeling levels, either as the input parameters to characterize the different surfaces, or in assimilation procedures which aim at retrieving adequate parameters for the ET computation. Some examples of this approach will be shown in the third section.

– *And lastly vegetation index methods*, or inference methods based on the use of remote sensing to compute a reduction factor (such as *Kc* or Priestley Taylor-alpha parameters) for the estimation of the actual evapotranspiration. These approaches consider a potential or reference *ET* obtained from ground measurements. Differents papers deal with these approaches in this special issue (Allen et al., 2005; Neale et al., 2005; Garatuza et Watt, 2005).

Before presenting these different approaches, a brief review about energy budget is required for a better understanding of the relationships between ET and the driving variables such as surface temperature (*Ts*). Then we will describe some models using remote sensing to estimate ET. We note that this is not an exhaustive review since we have chosen to deal with widely used models. For more details, one can refer either to overviews on the use of remote sensing for evapotranspiration monitoring such as proposed by Kustas & Norman (1996), or to web sites such as: http://www.cgiar.org/iwmi. In conclusion, we will discuss about the application of these models for crop monitoring and water management, present potentialities and limits, and on future remote sensing tools.

Evapotranspiration and energy budget

Evapotranspiration estimation (corresponding to the latent heat flux *LE*) from remote sensing is based on assessing the energy balance through several surface properties such as albedo, leaf area index, vegetation cover, and surface temperature (Ts). When considering instantaneous conditions, the energy balance equation is written as:

$$Rn = LE + H + G \tag{1}$$

The available net radiant energy Rn is shared between the soil heat flux G and the atmospheric convective fluxes (sensible heat flux H and latent energy exchanges *LE*). Radiant and convective fluxes can be described either considering the observed surface as a single component (single layer approaches) or discriminating soil and vegetation components with different degrees of canopy description according to the number of vegetation layers (multilayer approaches, with those based on two sources that are widely used).

Rn depends on incident solar radiation (Rg), incident atmospheric radiation over the thermal spectral domain (Ra), surface albedo (α_s), surface emissivity (ε_s) and surface temperature (Ts):

$$Rn = (1 - \alpha_s)Rg + \varepsilon_s\, Ra - \varepsilon_s\, \sigma\, T_s^4 \tag{2}$$

where Rn is related to the whole surface for single layer models and to both soil and vegetation layers for multiple layer models.

For single approaches, sensible heat flux H is calculated using the aerodynamic resistance r_a between the surface and the reference heigth z_a in the lower atmosphere (commonly 2 m) above the surface

$$H = \rho cp(Ts - Ta)/r_a \tag{3}$$

r_a is a function of wind speed u_a, atmospheric stability and roughness lengths for momentum and heat (z_0, z_{0t}, respectively, depending on vegetation height and geometry). These last variables are then characterized using the kB^{-1} parameter given as $kB^{-1} = \log(z_0/z_{0t})$, which varies significantly according to characteristics of the observed surfaces: thin or medium (grass, soybean, wheat) or well developed crop with large values of vegetation height. Thus the surface temperature corresponds to the "aerodynamic surface temperature" which is defined by extrapolating air temperature profile down to the level z_{0t}. This surface temperature is generally different from the radiometric surface temperature measured with satellites (Norman & Becker 1995). Different models generally with 2 layers (described further) have integrated this difference to estimate ET.

For multiple layer models, H is characterized considering both a soil and canopy resistance, with the corresponding temperature.

Estimating *LE* can be performed using the residual method, which induces that *LE* is linearly related to the surface air temperature difference at the time of Ts measurement, if the second order dependence of r_a on this gradient is ignored.

$$LE = R_n - G - \rho cp(Ts - Ta)/r_a \tag{4}$$

This equation is widely used for the estimation of instantaneous *LE*. When estimated at midday, it provides a good indicator of plant water status for irrigation scheduling. When dealing with longer periods (seasonal, monthly, daily estimations), the use of ground-based ET from weather data is necessary to make temporal interpolation. Several papers have used the tendency for the evaporative fraction (*EF*, e.g. the ratio of latent heat flux to available energy for convectives fluxes) to be nearly constant during the daytime, which allows estimating daytime evaporation from one or two estimates only of *EF* at midday (e.g. at the satellite acquisition time) (Crago, 2000).

$$\begin{aligned} EF &= \frac{LE}{(Rn - G)} \\ \mathrm{ET}_{24} &= EF * Rn_{24} \end{aligned} \tag{5}$$

Another way to estimate ET is to compute this term according to the following equation from air vapor pressure e_a and a water vapor exchange coefficient (h_s). This last method is commonly used along with estimates of soil moisture in models simulating Soil–Vegetation–Atmosphere Transfers (SVAT) and defined in this paper as deterministic approaches.

$$LE = \rho c_p h_s (e_s^*(T_s) - e_a) \tag{6}$$

$e_s^*(T_s)$ is the saturated vapor pressure at the surface temperature T_s. h_s is an exchange coefficient, often represented in numerical model through a network of resistances more and less complex according to the vegetation layers considered in the canopy description (Figure 1). It depends on the aerodynamic exchange coefficient ($1/r_a$), soil surface and stomatal resistances of the different leaves in the canopy. A global canopy resistance (r^*) including both soil and canopy resistances can be estimated from the formulation proposed by Katerji & Perrier (1985):

$$r^* = \frac{1}{\frac{1}{r_{og}+r_g} + \frac{1}{r_0+r_s}} \tag{7}$$

r_{og} is the resistance due to the vegetation structure, r_g the resistance of the soil layer depending on the soil water content, r_0 the resistance due to the canopy structure and r_s the stomatal resistance. The calculation of the latter requires information on plant structure: leaf area index (*LAI*) and fraction of vegetation cover (*veg*), the minimum stomatal resistance ($rs_{\min}$). Several studies proposed different parameterisations of the stomatal resistance according to climatic and soil moisture (Jacquemin & Noilhan, 1990).

From these basic elements, it appears that the surface temperature (Ts) or more exactly ($Ts - Ta$) is related to ET, and that Ts can be estimated using thermal infrared measurements (either at local scale using ground radio thermometer, either at regional or global scale using satellite data).

In the next paragraph, we will present the main steps and assumptions of these methods using remote sensing data to estimate *LE*.

Direct simplified methods

The simplified relationship, firstly derived at field scale by Jackson et al. (1977) and later analyzed by Seguin & Itier (1983), has widely been used for mapping daily evapotranspiration over large areas from surface temperature measurements (Lagouarde & Brunet, 1991, Courault et al., 1994). This method assumes that it is possible to directly relate daily (ET$_d$) to the instantaneous

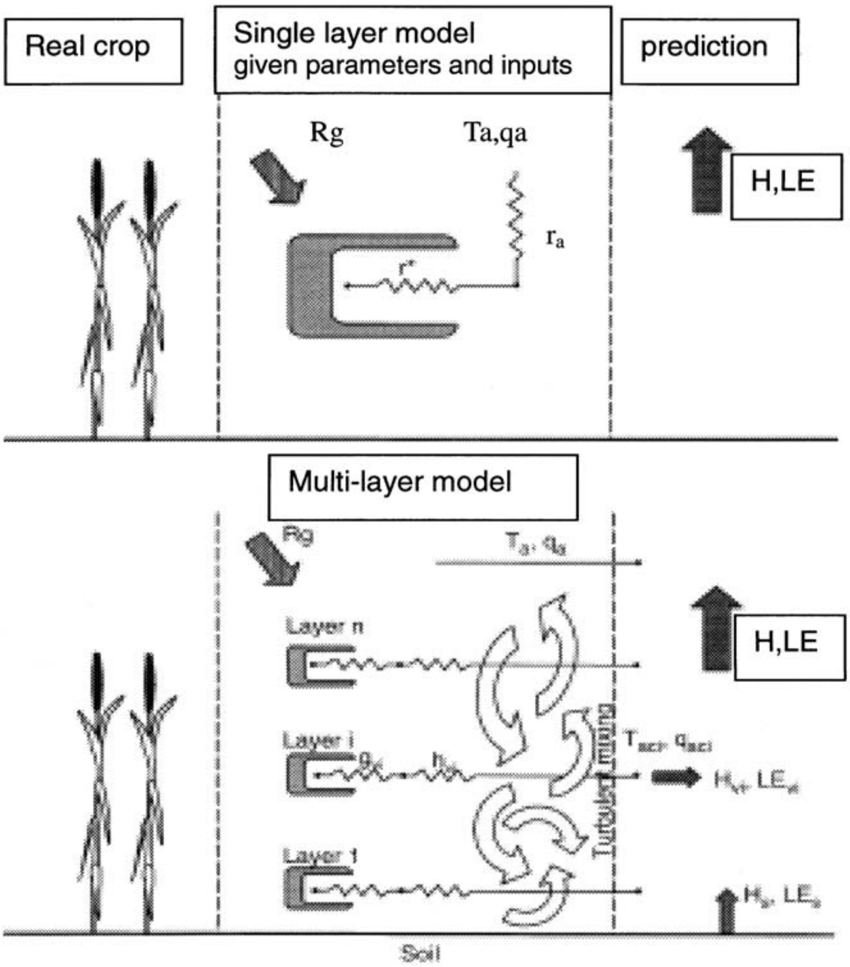


Figure 1. Schematic structure of single layer and multilayer models based on resistance network to represent the exchanges between vegetation and atmosphere (in Olioso et al., 1999). (H, LE: sensible and latent fluxes, Ta, qa: air temperature and humidity, r^*: surface resistance, ra: aerodynamic resistance).

difference $(Ts - Ta)_i$ measured around midday as follows:

$$\mathrm{ET}_d = Rn + A - B(Ts - Ta)_i \tag{8}$$

A and B being constant depending on the local situation. Many papers have dealt with the analysis of this relationship and their assumptions (Lagouarde, 1991; Seguin & Itier, 1983; Riou et al., 1988). The method relies on the assumptions that the ratio H/Rn is constant all along the day, and the daily value of soil heat flux is negligible ($G_d = 0$). Ts can be extracted from measurements

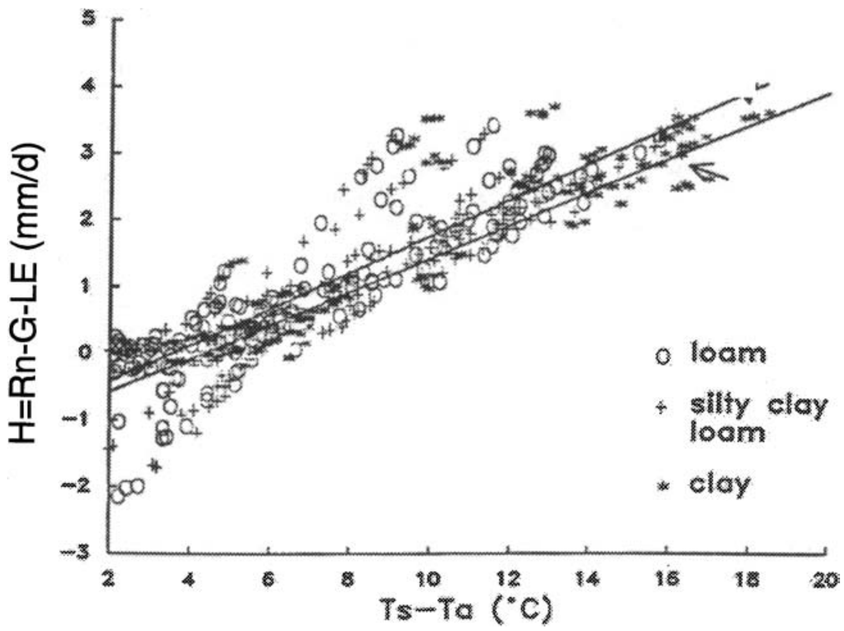


Figure 2. Simplified relationship obtained for different soil types between $(Ts - Ta)$ and H. (from Chanzy, 1991).

acquired in the thermal infrared range (TIR) with airborne or satellite sensors, after atmospheric corrections. Seguin et al. (1982) and Steinmetz et al. (1989) have shown that the accuracy could reach 10–15% at a local scale, but also that *A* and *B* coefficients varied according to the experiment (Figure 2). Other studies have introduced different parameterizations for these coefficients as function of wind speed, roughness and criterions of atmospheric stability (Vidal & Perrier, 1989; Lagouarde & McAneney, 1992).

The cumulative value of $(Ts - Ta)$ named stress degree day (*SDD*) appears as a significant tool for assessing the global water use of a given crop.

The application of this relationship requires two variables: the maximum air temperature and the daily net radiation. If the last one (R_n) can be obtained by remote sensing (for example incident solar and atmospheric radiations can be computed from the visible and thermal channels of Meteosat, see EARS[1] and EUMETSAT[2]), the problem of the spatial representativity of the air temperature (T_a) is more arguable and particularly acute for regional studies. Geostatistical models can be used to interpolate local measurements (Courault et al., 1994). Accuracy is then around 20 to 30%.

Carlson & Buffum (1989) have proposed to take air temperature at 50 m above the surface making the assumption that at this level, atmospheric conditions are more homogeneous. They considered the difference: $(Ts - Ta)^n$ and expressed *n* and *B* coefficients as function of *NDVI*.[3]

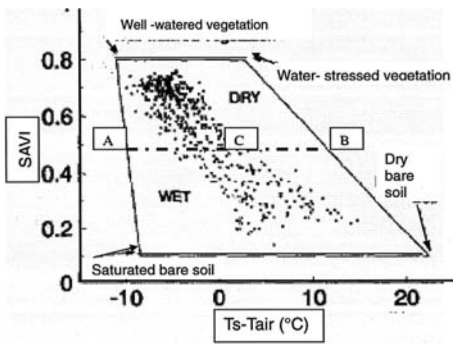


Figure 3. Trapezoidal scheme (from Moran et al., 1994) allowing one to compute a crop water stress index like CWI = AC/AB.

Other authors have used the relationship between Ts and a temperature of a well irrigated area (Nieuwenhuis et al., 1985; Thunissen & Nieuwenhuis, 1990).

Carlson et al. (1995), Moran et al. (1994) have explored the relationship between *Ts* and *NDVI*, because the amount of vegetative cover affects transpiration. Vegetation indices (like *NDVI* or *SAVI*) are also related to surface temperature, i.e. more evapotranspiration tends to be associated with lower temperatures. A trapezoid scheme appears in which the different soil moisture conditions can be classified (Figure 3). Carlson et al. (1990) have proposed a method of estimating root-zone moisture availability, soil surface moisture and vegetation fraction using *NDVI* and directional *Ts* combined with a transfer model. Water stress indices have been computed from this scheme and applied at large spatial scale for crop monitoring and water management.

Other residual methods of the energy budget

SEBAL

SEBAL is an intermediate approach using both empirical relationships and physical parameterizations (Bastiaanssen et al., 1998a, 1998b; Jacob et al., 2002b). This model has been designed to calculate the energy partitioning at the regional scale with minimum ground data. Atmospheric variables (air temperature and wind speed) are estimated from remote sensing data by considering the spatial variability induced by hydrological and energetic contrasts (Figures 4a–4b). The determination of wet and dry surfaces on the studied area is necessary to extract threshold values. The model requires incoming radiation, Ts, *NDVI* and albedo maps. Semi-empirical relationships are used to estimate emissivity, roughness length from *NDVI*. The sensible heat flux

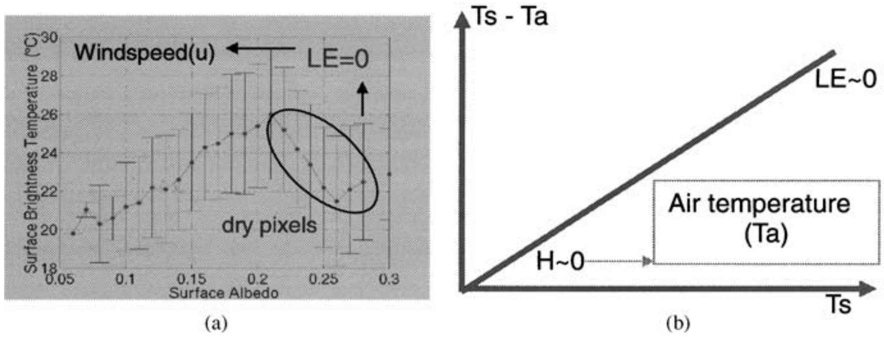


Figure 4. (a) Relation used in SEBAL between Albedo and brightness temperature obtained from POLDER (POLarization and Directionality of the Earth's Reflectances) and TIR measurements over the ALPILLES site in 1997, which allows one to derive windspeed (from Jacob, 1999). (b) Spatial relation used in SEBAL between *Ts* and *Ta* to estimate air temperature (when $(Ts - Ta) \sim 0$, $H \sim 0$, *Ta* can be estimated from *Ts* values from TIR images).

is computed inverting sensible heat flux expression over both dry ($LE = 0$) and wet ($H = 0$) land. Latent heat flux is computed as the residual of energy balance.

The model was validated on both intermediary variables and surface energy fluxes by Jacob et al. (2002b). It was also used for different applications to estimate monthly and seasonal ET. For several applications studies, ET for specific days has been extrapolated for the ET of the season by holding the ratio *Etact/Etref* constant between consecutive overpasses, where *ETref* was reference ET computed in different ways. In Bastiaanssen et al. (2002), *ETref* has been approximated by net radiation. In other applications, ET has been interpolated by using the Penman-Monteith equation with rs interpolated between images as determined by SEBAL (Bastiaanssen, 2000; Droogers & Bastiaanssen, 2002).

SEBI, S-SEBI, SEBS

Also based on the contrast between wet and dry areas, Menenti & Choudhury (1993) proposed a method to derive the evapotranspiration from the evaporative fraction. The concept was included by Su (2002a) in a more complex framework called SEBS which allows determination of the evaporative fraction by computing the energy balance in limiting cases. A simplified method derived from SEBI (S-SEBI) was further developed to estimate of surface flux from remote sensing data (Roerink et al., 2000). It consists of determining a reflectance dependant maximum (respectively minimum) temperature for dry (respectively wet) conditions, the major advantages being that no additional meteorological data are needed if the surface extremes are present on the images studied (Figure 5).

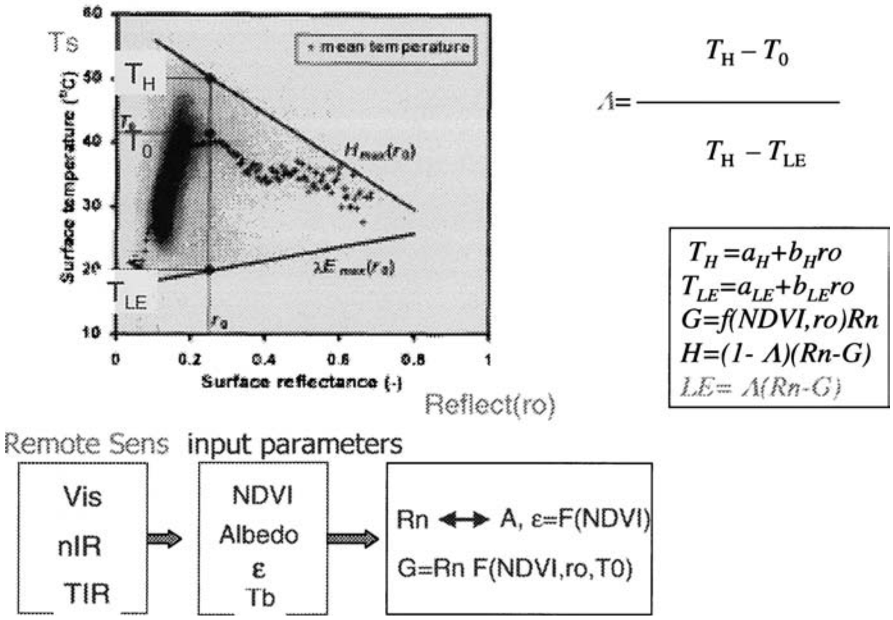


Figure 5. Schematic presentation of the S-SEBI model based on a graphic method, where no additional meteorological data are needed. The determination of wet (T_{LE}) and dry pixels (T_H) are necessary to compute LE, NDVI, albedo, emissivity (ε) and brightness temperature (Tb) are derived from remote sensing data (empirical relationships (F) are used to estimate emissivity, soil heat flux) (from Roenink et al., 2000).

Other models

Other approaches were proposed in the literature, such based on either surface single layer modeling as the excess resistance (or kB^{-1}) (Su, 2002b), the surface dual layer modeling (Norman et al., 1995; Chebhouni et al., 2001b) and the β approaches (Chebhouni et al., 1997). Some of them gave satisfactory results even on sparse vegetation (Zhan et al., 1996; Chehbouni et al., 1997; French et al., 2000). All these models presented in Table 1 can be operationally used for water management. The main problems for routine monitoring of surface energy fluxes is to get satellite observations with high spatial and temporal resolutions.

Problems linked to the surface temperature obtained from remote sensing

Most methods of the aforementioned types are based on the use of land surface temperature derived from TIR data. Atmospheric corrections and surface emissivity effect have to be removed for better temperature retrieval.

Table 1. Some semi-empirical models for LE and H fluxes.

Simplified relationship	
(Seguin & Itier, 1983)	$LE_d = Rn_d - A_1 - B_1(Ts_{14h} - Tamax)$
Methods based on excess resistance	
(Kustas, 1990)	$H_i = \rho cp(Ts - Ta)/(ra + rex)$
(Lhomme et al., 1992)	$LE_i = (1 - A_2)Rn_i - H_i$
(Moran et al., 1994)	
Approaches based on a relation between radiometric and a so-called aerodynamic temperature	
(Troufleau et al., 1997)	$H_i = \rho cp(Taer - Ta)/ra$
(Chehbouni et al., 1997)	$(Taer - Ta) = (1 - A_3)(Ts - Ta)$
Two source approach	
(Norman et al., 1993)	$H_i = \rho cp((Tv - Ta)/ra + (Tg - Ta)/(ra + rc))$

Symbols: A_1, A_2, A_3, B: empirical coefficients, cp: specific heat of air, i: instantaneous, d: daily, ra: aerodynamic resistance (above canopy), rc: aerodynamic resistance at the soil surface, rex: excess resistance, Ta: air temperature at some height above canopy (generally 2 m), $Taer$: aerodynamic temperature (mean temperature at some height in the canopy), Tv: vegetation surface temperature, Tg: soil surface temperature, Ts: radiometric surface temperature (from Olioso et al., 1999).

Therefore, the estimate accuracies depend on the performances of retrieval algorithms. The latter can be split in two categories: direct methods using atmospheric sounding combined with a radiative transfer model and indirect methods using only satellite observation (Tovs or split window method). The resulting uncertainties commonly range between 1 and 3 K. Dual angle observation (ATSR) improves the estimation. The effect of emissivity is important and can lead to significant error. The most promising method for obtaining both surface directional infrared temperature and surface directional emissivity is based on high spectral resolution (Norman et al. 1995a). The Table 2 shows the importance of error of $(Ts - Ta)$ on the sensible heat flux H.

Note that these difficulties on temperature estimation were taken into account by a few models which proposed using differential approaches. These can be spatial differential methods, such as SEBAL or the trapezoid – SVAT

Table 2. Error in sensible heat flux arising from a 1 °C error in $(Ts - Ta)$ for several conditions (in Norman et al., 1995b).

Canopy height (m)	Wind speed (m/s)	Error H ($Wm^{-2}\,C^{-1}$)
1	1	8
1	5	40
10	1	17
10	5	87

procedure proposed by Carlson et al. (1995) and Capehart (1996), or temporal differential methods such as the PBL integrating model proposed by Mecikalski et al. (1999) and Jacob et al. (2002b). These methods aimed at using an automatic internal calibration of a difference between Ts and α (where α is a given parameter) such as α determined from Ts given that the accuracy on $Ts - \alpha$ is good. This is a positive point for operational applications because it decreases the processing time.

Spatial and temporal resolution of TIR data

Frequent data acquisitions are needed for proper crop monitoring during the growing season, but only meteorological satellites offer the necessary frequency of measurements, and the spatial resolution remains still too coarse to define each type of crop. On the other hand, data in the visible and near-infrared wavelengths, used for computing vegetation indices, are available at resolutions an order of magnitude smaller than TIR, and hence provide higher resolution information on vegetation cover (Table 3). Recently Kustas et al. (2003) have explored the relationship between these two spatial and spectral resolution (*NDVI* and Ts) and proposed a disaggregating procedure for estimating the subpixel variation in Ts. They used then a remote sensing based energy balance model (DisALEXI) for estimating the surface fluxes. This disaggregation technique appears to be a promising way for evaluating Ts at the field scale.

Meteorological variables – models integrating the atmospheric boundary layer

In order to avoid the difficulties of obtaining meteorological variables on large areas, some models integrate the planetary boundary layer (PBL) to simulate the evolution of variables like air temperature, and wind speed. Radio soundings or outputs from GCM[4] are then required to initialize atmospheric

Table 3. Main characteristics for the satellites most used (repetivity and pixel resolutions) for normalized difference vegetation index (NDVI) and surface temperature (*Ts*) (from Kustas et al., 2003).

Satellite	Repeat Cycle (day)	NDVI pixel resolution (m)	*Ts* pixel resolution (m)
ASTER	16	15	90
AVHRR	2 im/day	1100	1100
GOES	1/4 h	4000	4000
LANDSAT 5	16	30	120
LANDSAT 7	16	30	60
MODIS	2 im/d	250	1000

parameters. 1D (Lagouarde & Brunet, 1991), 2D (Hasager et al., 2002) or 3D (Courault et al., 2003) approaches for estimating surface fluxes have used remote sensing data at different levels. The inclusion of energy balance in a PBL model has also been used for deriving the fluxes on the basis of the rate of change of surface temperature during the morning hours (Meciakalski et al., 1999).

The microscale aggregation model (2D) described by Hasager & Jensen (1999) uses surface temperature images. A roughness map is obtained from land use maps. A set of equations per land cover type defines the relation between thermal roughness and LAI (Hasager et al., 2002). The model solves the linearized atmospheric flow equations by Fast Fourier Transforms (FFT). The maps of friction velocity, u^*, and temperature scalar T^*, are calculated through iteration including the Monin–Obukhov stability functions. From the u^* and T^* maps, the effective values of z_{0m} and z_{0t} are calculated, and then the surface fluxes.

Although these methods have operational applications like drought detection at continental scale, or soil water reserve estimation for irrigation, the accuracy is always difficult to estimate. In order to get more realistic simulations, remote sensing data have been introduced at different levels. This is a reason why these last years, other numerical methods based on assimilation procedures have been developed, because they allow, among other things, to get intermediate variables linked to the crop development (like LAI) or to the soil water status.

"Deterministic" approaches

We find different model types in this category: remote sensing forced models, assimilation of numerical models. Generally these models (SVAT models) describe the exchanges between soil plant and atmosphere according to the physical processes occurring in each compartment with generally a fine time step (second, hour). Different complexity levels appear according to the process description: for example, if the vegetation and soil behavior are separated, then evaporation and transpiration are computed with a surface temperature for each part (it is more realistic for comparison with TIR data acquired at different hours and angles). Different schemes were developed to represent the vegetation layers (Figure 1): from simple descriptions such as the big leaf approach with one surface resistance, to multi-layer models, where radiative and energy budgets are computed for each layer (see Olioso et al., 2002a and Olioso et al., 1999 for more details). The finer the surface and the process description, the more parameters are needed. Some of them can be estimated by remote sensing data. There are three ways to use this spectral and spatial–temporal information.

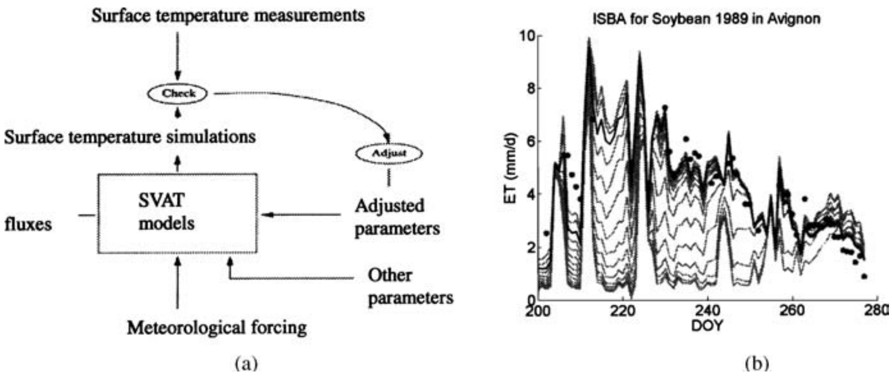


Figure 6. (a) Schematic representation of the assimilation method (in Olioso et al., 1999). In this example, comparisons are made between surface temperature estimated by the model with *Ts* measured. (b) Example of assimilation of remote sensing data in a SVAT model (ISBA) (different simulations have been done (green lines) adjusting the initial soil moisture after comparing *Ts* estimated and measured (in Olioso et al., 2002a).

– forcing the model input directly with the remote sensing measurements
– correcting the course of state variables in the model at each time remote sensing data are available (sequential assimilation)
– re-initializing or changing unknown parameters using data sets acquired over temporal windows of several days/weeks (variational assimilation) (Figure 6a).

Many works have been conducted on these assimilation procedures and have shown that the most adequate variables to be estimated from remote sensing, are surface/stomatal resistances, and soil moisture (Olioso et al., 1999, Figure 6b). Other works were focussed on using radiative surface temperature (Soer, 1980; Ottlé & Vidal Madjar, 1994), or microwave derived parameters such as vegetation water content (Wigneron et al., 2002). For example, Ts derived from NOAA data were used along with the SVAT called MAGRET to find parameters linked to the irrigation over the agricultural region "la Crau" in South-Eastern France (Courault et al., 1998). The predicted parameters were the beginning and the end of irrigation, frequency and water quantity diverted. The global method consisted of calibrating parameters by minimizing over a 10 day period within crop cycle the difference between MAGRET simulated and NOAA measured surface temperatures.

One of the main problems arising when using SVAT model is the remote sensing data spatial resolution. Indeed, the detailed process descriptions provided by these models are based on local parameters which are not systematically adequate with the information collected with several meter size pixels. These difficulties yield the development of several approaches which consisted in defining "effective" parameters corresponding to these

Table 4. Main biophysical variables derived from remote sensing data classified according to wavelength ranges and models, Fonct: crop model simulating the vegetation development (from Baret, INRA Avignon, personal communication). SVAT: Soil-vegetation-Atmosphere transfer model

Biophysical variables	Solar	IRT	Active μ waves	Passive μ waves	Process models
Albedo	++				SVAT
Vegetation cover	++	+			SVAT
FAPAR	++				Fonct
LAI	++	+	+	+	SVAT&Fonct
Water content in vegetation			++	++	Fonct
Temperature		++		+	SVAT&Fonct
Chlorophyl	++				Fonct
Leaf water content	++				Fonct
Soil water content	++		++	++	SVAT&Fonct
Soil roughness			++	++	SVAT
Vegetation height (roughness)	++	+	+		SVAT&Fonct

composite surfaces (Noilhan & Lacarrère, 1995). Other approaches aimed at disaggregating the pixel content into elementary responses for each landuse class (Courault et al., 1998). Some parameters like *LAI*[5] can be easily averaged using arithmetic laws. For surface temperature, however, aggregation schemes are more complex.

The main parameters extracted from remote sensing measurements are vegetation fraction (*veg*), LAI, albedo, emissivity, (most of them are estimated using information in the solar domain, Table 4). Roughness and parameters linked to the stomatal resistance are still difficult to access. They are often estimated from both knowledge of the type of canopy and the phenological stage. Some progresses were made in mapping roughness using either laser altimeter (LIDAR) data (Menenti et al., 1994), or relationships based on vegetation index (Olioso et al., 2002c). However, these latter relationships still remain applicable for particular conditions only. Therefore special caution must be exercised in applications to various crop types.

MESO-NH[6] is a 3D atmospheric model mainly developed by the Aerology Laboratory and the CNRM[7] from Toulouse. The surface scheme based on the force restore method is ISBA (Noilhan & Planton, 1989) which has been widely used in 1D version coupling assimilation methods with remote sensing data (Calvet et al., 1998; Olioso et al., 2002a). The assimilation procedures are not yet introduced in the 3D atmospheric model, but all input data may be derived from remote sensing. An example is shown on Figure 7 corresponding to the Alpilles area (5×5 km) where LAI and vegetation fraction were

Table 5. Summary of the advantages and disadvantages of the different approaches used to estimate ET from remote sensing data.

Methods-models	Advantage	Disadvantage
Simplified (Simplified Relationship.)	Operational from local to regional scale	spatial variations of coefficients
Inference models (Kc f(NDVI))	Operational if combined with ground measurements or models estimating accurate ETR	requires calibration for each crop type *Kc* varies according to water stress
Graphic (SEBAL, S-SEBI. . .)	Operational, low cost, need no additional climatic data, (Sebal: no atmospheric corrections for *Ts*)	requires presence of wet and dry pixels Some empirical relationships (z_0), Tair
Determinist (SVAT 1D) ISBA. . .	Estimation of intermediate variables (LAI), possible links with climate, hydrogical models, assimilation to find some parameters	requires more parameters ± easy to estimate Requires accurate remote sensing data
3D models: (PBL, MesoNH. . .)	Estimation of climatic data, lateral exchanges accounted, possible to simulate landuse modification (irrigation scenario. . .)	complex, and high cost for CPU, only short simulation for high spatial resolution

computed from POLDER images using a neural network (Weiss et al., 2002). Albedo in the visible and near infrared range were estimated using Liang's coefficients (Jacob et al., 2002), roughness and other parameters linked to the stomatal resistance were derived from the land use map obtained from SPOT images (Courault et al., 2002). The interest of such a 3D model is that it simulates not only the main energy fluxes like evapotranspiration (Figure 7c) over all the area but also the evolution of climatic variables like air temperature for different land use practices. Thus, the irrigation of all the wheat fields over the small agricultural area of Alpilles has been simulated with the Meso-NH model. The map of *Tair* estimated at 2 m above the surface was compared to the real situation without irrigation (Figure 8a, b). A significant temperature decrease was observed because of irrigation (as expected), not only over the wheat fields (-1.2 °C) but also over the other fields (-0.5 °C), that can induce significant differences for crop development. Among the different outputs, the surface temperature maps estimated by the model for several days were compared with TIR images acquired during the experiment. The results were globally satisfactory, even if the main difficulty still remains the determination of the initial soil moisture variability on the whole area (Courault et al., 2003).

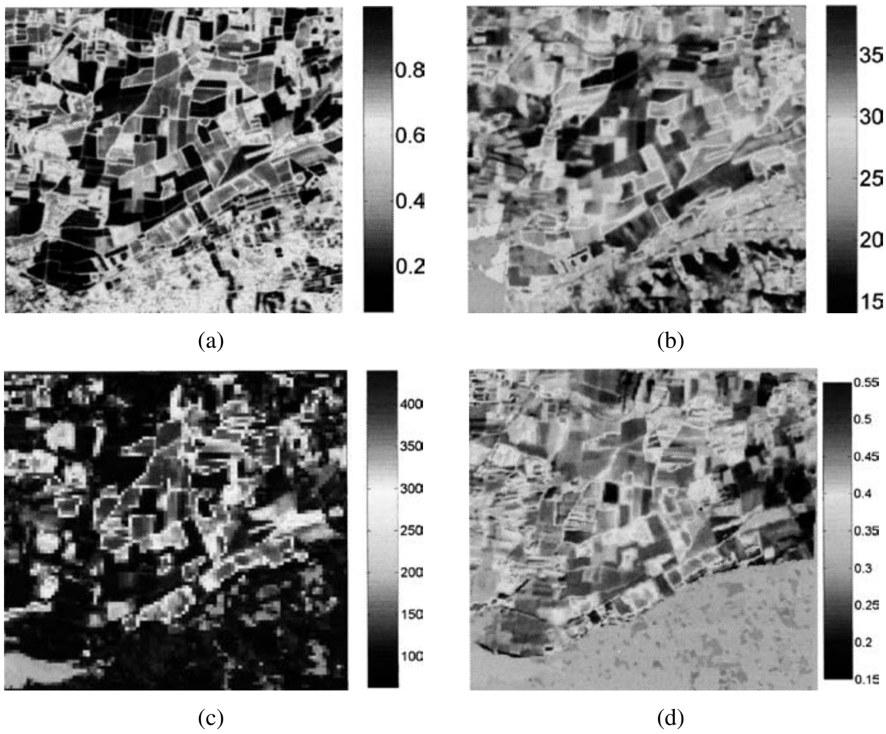


Figure 7. (a) NDVI computed from POLDER reflectances over the Alpilles area (5×5 km 20 m resolution) on April 18th 1997. (b) Surface temperature obtained with the airborne IRT camera over the Apilles area for the same date at 12:00UTM. (c) LE map estimated with the Meso-NH model over Alpilles on April 18 1997 at midday (hourly average, 50 m spatial resolution). (d) Near IR albedo derived from POLDER reflectance using Liang coefficients (from Jacob, 1999) on Ap18 97.

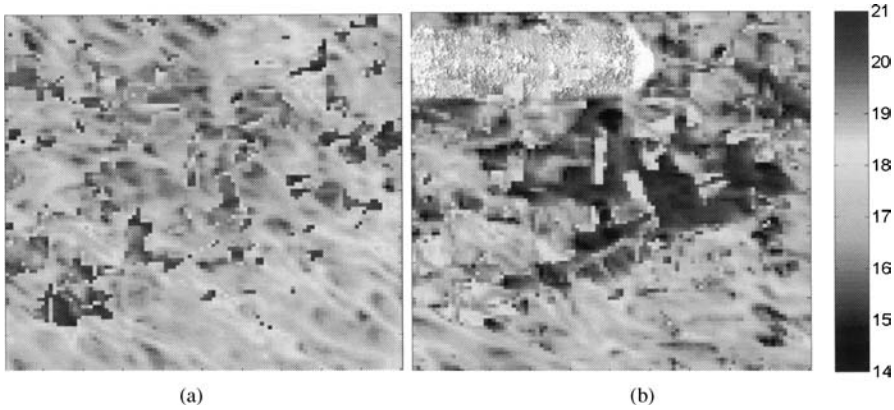


Figure 8. Maps of the air temperature (°C) estimated at 2 m above the surface with the Meso-NH model, over the Alpilles area (spatial resolution 50 m) on April 18th 1997. (a) real case without irrigation (b) irrigation of all wheat fields (30% of the whole area).

Comparison between models

During the Alpilles–Reseda[8] project, several models have been used to estimate the surface fluxes with remote sensing data (a direct flux equation using Ts, *Tair* and the exchange coefficient computed using the Monin–Obukhov theory, the SEBAL model which computed *Tair* and wind speed, the 2D aggregation model ("MAM model", Hasager et al., 2002 where *Tair* and wind speed were taken from radio sounding measurements, ISBA 1D and MESONH). Figure 7c shows the *LE* map obtained with Meso-NH on April 18th 1997 at midday. The fluxes showed a great spatial variability according to the development stage of the different crops as expected: high values for well developed crops (winter wheat in April, alfalfa well supplied in water), and low values for dry and bared soils (the last rain was in January). $(Ts - Ta)$ varied from 0 to 15 °C for this date.

Figures 9a–9b show the results obtained for 3 models compared against ground measurements (Olioso et al., 2002b). The estimations were globally satisfactory. The different models gave similar results. On the other hand, if the model outputs are compared with each other (Figures 10a and 10b), differences appear on flux estimation, mainly due to the way of obtaining the surface parameters and meteorological variables, especially air temperature and roughness (Olioso et al., 2002b). SEBAL and the 1D model were based on the same physic equations but had different input parameters, since MAM and 1D models had the same inputs but different physic equations. An accurate description of the model inputs (surface parameters and meteorological variables) is therefore a first stage for the estimation of surface fluxes, which is crucial to get realistic LE values. The other conclusions on the main results about this experiment can be found in the special issue of *Agronomie* (2002, vol. 22).

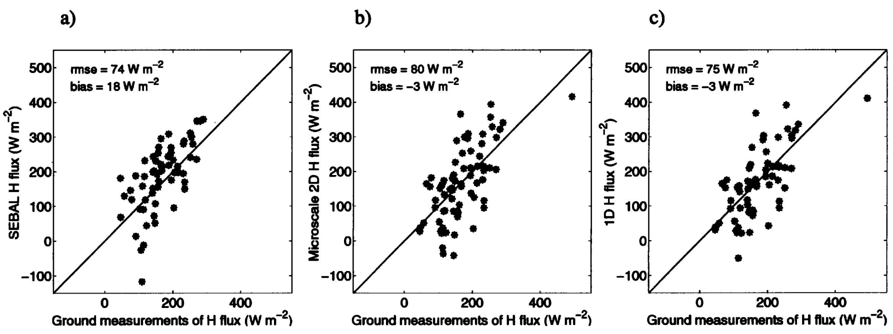
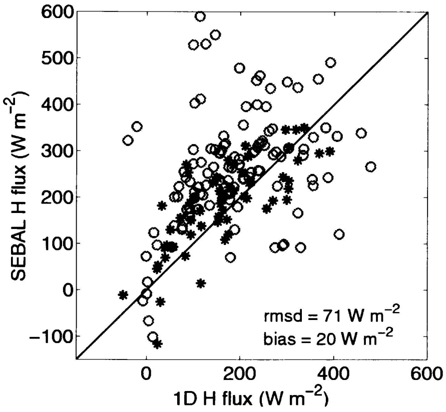
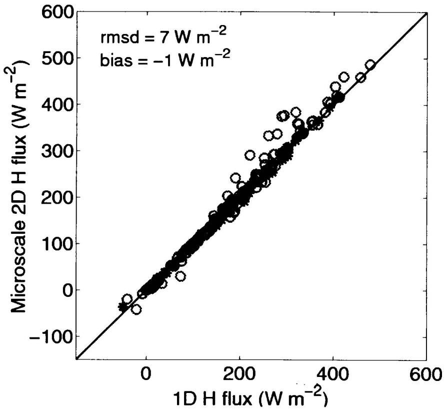


Figure 9. Comparison of sensible heat flux simulations to ground measurements for three models (a) SEBAL, (b) 2D MAM model (c) 1D model (rmse: root mean square error) (in Olioso et al., 2002b).



(a)



(b)

Figure 10. Comparison of sensible heat flux simulated by different models (a) 1D and SEBAL, these two models have the same physical components but different input parameters (b) 2D MAM and 1D model, these two models have different physical components but the same inputs (o corresponds to simulations without corresponding ground measurements, rmsd: root mean square difference) (in Olioso et al., 2002b).

Discussion and conclusion

An accurate estimation of evapotranspiration is very useful for an appropriate water management, both at the farm and the irrigation project level. In numerous countries, the method recommended by FAO is used. However, the spatial and temporal variations of the surface characteristics can't be taken into account with high accuracy by this method. The use of remote sensing brings a significant contribution for assessment of crop water status, either in view irrigation scheduling or in global assessment of crop water use and its spatial variations within an irrigated area (Vidal et al., 1987).

Evapotranspiration may be estimated from remote sensing data with different approaches: direct methods using *TIR* data, indirect estimates using assimilation procedures combining different wavelengths to get various input parameters (in particular related to vegetation water status). Some methods are based on the spatial variability present in remote sensed images (like the SEBAL or S-SEBI models), and try to use no additional meteorological data to estimate ET for routine application. The interest of using SVAT models is not only because they generally describe with more accuracy the crop functions, but also because they allow access to intermediate variables like soil moisture or LAI, which are related to physiologic and hydrologic processes that can be linked to other meteorological or hydrological models.

However, the use of remote sensing for operational applications presents still several problems (see Table 5). The determination of ET for crop monitoring requires the routine processing of images on a near-real-time basis. The relatively long turn-around time for image delivery and the cost involved with the acquisition of high-resolution imagery make their use for operational application often unattractive. Notice however, that since the rapid development of internet accessible archives, some remote sensing data (like Landsat images) can now be ordered in approximately 3 days after the overpass. Nevertheless images processing are then necessary to get reliable information overlaid to a reference map.

Data accuracy

Most methods use *TIR* data. Atmospheric corrections and surface emissivity are necessary to get accurate Ts. Some models like SEBAL with their internal calibration avoid this problem and are then more attractive for operational applications. Thus SEBAL has been applied on a near-real-time basis to estimate actual evaporation in Sri Lanka on a 10-day basis from June 1999 to 2000 using NOAA AVHRR radiances (Bastiaanssen, 2003).

Spatial and temporal resolution

The thermal infrared measurements appear as useful tools for water use in irrigated area. For a global monitoring purpose, the availability of advanced very high resolution radiometer (AVHRR) imagery from NOAA meteorological satellites series on a daily basis at most of the national meteorological services worldwide and at no extra cost, makes them a viable alternative for operational estimation of evaporation. But more detailed observations would be needed for analyzing the spatial distribution of water use in the irrigation network. The NOAA resolution (1 km) is too coarse for that purpose. A higher resolution can be achieved by Landsat (120 m in *TIR* for Landsat 5, 60 m for Landsat 7), but both the frequency (every 16 days) and time acquisition (for example 10:00 over France) are limiting factors. Moreover the future of Landsat is uncertain, because the cooling techniques are too heavy and that makes the payload too expensive. There are currently no operational solutions for this problem. So, we have to find methods for combining information at different wavelengths and resolutions.

The arrival of new satellites like ASTER (15 m in 3 visible near infrared bands and 90 m in 5 *TIR* band from 8.1 to 11.6 μm) may allow combining high spatial resolution with other sensors with high temporal resolution (like MODIS or GOES, see Table 3).

The method proposed by Kustas et al., (2003) to disaggregate the pixel to estimate subpixel Ts is promising and allows to estimate ET combining Ts with an energy balance model (DISALEXI).

Meteorological forcing

It is important also to take into account the spatial variability of climatic data, particularly air temperature, which is a key variable in the exchanges. Meteorological variables may be directly measured, but often the station density is poor. They can however be estimated by models simulating the evolution of the planetary boundary layer (PBL model, Carlson et al., 1995, MESONH). Some models like SEBAL use spatial information in images to derive air temperature, but their estimations depend on the spatial variability of the studied area. These simplified methods work correctly when the atmospheric conditions are relatively constant over the image and sufficient wet and dry pixels are present throughout the scene. When different wind speeds occur that change values of extreme Ts (min and max), or if wet and dry pixels cannot be found on the same images (e.g. England having no dry areas, Europe having variable atmospheric conditions) external meteorological data (radio soundings or weather prediction model output) are necessary (Roerink et al., 2003). Another way is to use Large Aperature Scintillometers (LAS, see Gieske et al., 2003; De Bruin et al., 1995). Iterative flux-profile methods allow calculation of sensible heat and momentum fluxes using temperature gradients and wind speed data obtained in the lower atmosphere. Flux-profile methods are also applied to the problem of regional evapotranspiration evaluation by the use of satellite imagery. An illustration is shown with AVHRR data for a case study from western Turkey (Gieske, 2003). Other models use air temperature at 50 m making the assumption that atmospheric conditions are more homogeneous at this level.

There is a critical need to understand the feedback between the land surface and atmosphere at various scales. The role of land surface modifying the climate is not yet adequately considered in climate models, however its effect like irrigation is significant for temperature (De Ridder et Gallée, 1998). The current parameterizations of land processes are still too coarse and currently the trend is to describe the different surfaces with more accuracy. The derivation of accurate surface parameters from remote sensing is a key for determining the main terms of the energy balance depending on the type of vegetation. It is also important for having an exhaustive view of the vegetation cover types in order to analyze in detail model results and evapotranspiration estimations. For that specific purpose, thermal infrared wavelengths appear as the best suited, and, coupled with shortwave channels, allow one to quantify the effect of water stress on biomass by the use of vegetation index. With the increasing spatial resolution and the sensor profusion, we can expect that remote sensing will continue to play an essential role in partitioning the surface energy budget into sensible heat and evapotranspiration, and to provide information at a low cost for improving the use of scare water resources.

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Notes

1. EARS: www.ears.nl/EWBMS.
2. EUMETSAT: www.eumetsat.de/fr.
3. NDVI: Normalized Difference Vegetation Index is defined as the following ratio between reflectances in the red (r) and near infrared (nir) range: $NDVI = (\rho_{\mathrm{nir}} - \rho_r)/(\rho_{\mathrm{nir}} + \rho_r)$.
4. GCM: global circulation model.
5. LAI: Leaf area index is the surface of leaves per surface of ground (m^2/m^2).
6. MESO-NH Non-Hydrostatic Mesoscale atmospheric model, http://www.aero.obs-mip.fr/~Meso-NH.
7. CNRM: Centre National de Recherches Météorologiques.
8. Alpilles Reseda: was an CEE project http://www.avignon.inra.fr/reseda.

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