# Remote Sensing Based Energy Balance Algorithms for Mapping ET: Current Status and Future Challenges

P. H. Gowda, J. L. Chávez, P. D. Colaizzi, S. R. Evett, T. A. Howell, J. A. Tolk

**Abstract.** *Evapotranspiration (ET) is an essential component of the water balance and a major consumptive use of irrigation water and precipitation on cropland. Remote sensing based agrometeorological models are presently most suited for estimating crop water use at both field and regional scales. Numerous ET models have been developed in the last three decades to make use of visible, near-infrared (NIR), shortwave infrared (SWIR), and most importantly, thermal data acquired by sensors on airborne and satellite platforms. In this article, a literature review is done to evaluate numerous remote sensing based algorithms for their ability to accurately estimate regional ET. The remote sensing based models generally have the potential to accurately estimate regional ET; however, there are numerous opportunities to further improve them. The spatial and temporal resolution of currently available remote sensing data from the existing set of earth-observing satellite platforms are not sufficient enough to be used in the estimation of spatially distributed ET for on-farm irrigation scheduling purposes, especially at the field scale (~10 to 200 ha). This will be constrained further if the thermal sensors on future Landsat satellites are abandoned. Research opportunities exist to improve the spatial and temporal resolution of ET by developing algorithms to increase the spatial resolution of surface temperature data derived from ASTER/MODIS thermal images using same/other-sensor high-resolution visible, NIR, and SWIR images.*

***Keywords.*** *ET mapping, Irrigation scheduling, Surface energy balance, Water management.*

Evapotranspiration (ET) has been long been recognized as playing an essential role in determining exchanges of energy and mass between the hydrosphere, atmosphere, and biosphere (Sellers et al., 1996). In agriculture, it represents a major consumptive use of irrigation water and precipitation. Any attempt to improve water use efficiency must be based on reliable estimates of ET, which includes water evaporation from land and water surfaces and transpiration by vegetation. ET varies spatially and seasonally according to weather and vegetation cover conditions (Hanson, 1991).

At the field scale, ET can be measured over a homogenous surface using conventional techniques such as Bowen ratio (BR), eddy covariance (EC), and lysimeter systems. However, these systems do not provide spatial trends at the regional scale, especially in heterogeneous landscapes with advective climatic conditions. Remote sensing based ET models are better suited for estimating crop water use at both field and regional scales (Allen et al., 2007a). This article discusses some of the common remote sensing based land surface energy balance (EB) algorithms for mapping regional ET and their limitations, data needs, knowledge gaps, and future opportunities and challenges with respect to agriculture.

## Remote Sensing Based EB Algorithms

EB algorithms are based on the rationale that ET is a change of the state of water using available energy in the environment for vaporization (Su et al., 2005). Remote sensing based EB algorithms convert satellite sensed radiances into land surface characteristics such as albedo, leaf area index, vegetation indices, surface roughness, surface emissivity, and surface temperature to estimate ET as a "residual" of the land surface energy balance equation:

$$LE = R_n - G - H \tag{1}$$

where $R_n$ is the net radiation resulting from the budget of shortwave and longwave incoming and emitted radiation, $LE$ is the latent heat flux from evapotranspiration, $G$ is the soil heat flux, and $H$ is the sensible heat flux (all in W m$^{-2}$ units). $LE$ is converted to ET (mm h$^{-1}$ or mm d$^{-1}$) by dividing it by the latent heat of vaporization ($\lambda_v$, ~2.45 MJ kg$^{-1}$). Net radiation and soil heat flux, which is a function of $R_n$ and vegetation indices (Chávez et al., 2005; Daughtry et al., 1990), may be estimated using meteorological measurements (Allen et al., 1998) and by incorporating spatially distributed reflected and emitted radiation (Jackson et al., 1985; Jackson et al., 1987; Kustas et al., 1989; Daughtry et al., 1990) as:

Submitted for review in May 2007 as manuscript number SW 6919; approved for publication by the Soil & Water Division of ASABE in July 2007 as a contribution to the ASABE 100th Anniversary Soil and Water Invited Review Series.

The authors are **Prasanna H. Gowda, ASABE Member Engineer,** Agricultural Engineer, **Jose Luis Chávez, ASABE Member Engineer,** Agricultural Engineer, **Paul D. Colaizzi, ASABE Member Engineer,** Agricultural Engineer, **Steven R. Evett, ASABE Member,** Soil Scientist, **Terry A. Howell, ASABE Fellow,** Research Leader, Agricultural Engineer, and **Judy A. Tolk,** Crop Physiologist, USDA-ARS Conservation and Production Research Laboratory, Bushland, Texas. **Corresponding author:** Prasanna H. Gowda, USDA-ARS-CPRL, P.O. Drawer 10, Bushland, TX 79012-0010; phone: 806-356-5730; fax 806-356-5750; e-mail: pgowda@cprl.ars.usda.gov

$$R_n = (1-\alpha)\, R_s + \varepsilon_a\, \sigma\, T_a^4 - \varepsilon_s\, \sigma\, T_s^4 \quad (2)$$

where $\alpha$ is surface albedo; $R_s$ is incoming shortwave radiation (W m$^{-2}$) measured with pyranometers or calculated using the solar constant, the cosine of the solar incidence angle, the inverse squared relative earth-sun distance, and atmospheric transmissivity based on the ground elevation of the area of interest (image) with respect to mean sea level; $\sigma$ is the Stefan-Boltzmann constant (5.67E–08 W m$^{-2}$ K$^{-4}$); $\varepsilon$ is emissivity; and $T$ is temperature (K) with subscripts $a$ and $s$ for air and surface, respectively. $T_s$ is the remotely sensed radiometric surface temperature, which is obtained after correcting the brightness temperature imagery for atmospheric effects and surface emissivity. Other authors (Trezza, 2002; Allen et al. 2007a) have included an extra term in equation 2 to account for reflection of incoming longwave radiation in the form: $-(1 - \varepsilon_s)T_a^4$.

Some early applications of remote sensing based EB models include Brown and Rosenberg (1973), Stone and Horton (1974), Idso et al. (1975), Heilman et al. (1976), and Jackson et al. (1977). Most of these studies used airborne scanners, as first demonstrated by Bartholic et al. (1972). Price (1982) and Seguin and Itier (1983) were among some of the first to use thermal data obtained from satellites to estimate ET. They proposed to use surface temperature derived from remotely sensed data to estimate regional ET in the form:

$$LE = R_n - G - \frac{\rho_a\, C_p (T_s - T_a)}{r_{ah}} \quad (3)$$

where $\rho_a$ is air density (kg m$^{-3}$), $C_p$ is specific heat capacity of the air (J kg$^{-1}$ K$^{-1}$), and $r_{ah}$ is aerodynamic resistance for heat transfer (s m$^{-1}$). $T_s$ and $T_a$ are expressed in K. For example, Brown and Rosenberg (1973) and Brown (1974) used the surface radiometric temperature and air temperature difference ($T_s$ – $T_a$) and the aerodynamic resistance ($r_{ah}$) to estimate $H$, where the canopy or surface temperature was obtained from remotely sensed radiometric temperature using thermal scanners having a bandwidth mostly in the range of 10 to 12 μm. Later, Rosenberg et al. (1983) incorporated the term surface aerodynamic temperature ($T_o$) in the $H$ model, instead of $T_s$, considering that the temperature gradient (for $H$) was a gradient between the air temperature within the canopy (at a height equal to the zero plane displacement plus the roughness length for heat transfer) and the air temperature above the canopy (at a height where wind speed was measured or height for $r_{ah}$). They indicated that for partially vegetated areas and water-stressed biomass, the radiometric and aerodynamic temperatures of the surface were not equal.

Accurate estimates of $H$ are very difficult to achieve using a direct, absolute equation for $H$ (eq. 3) when $T_s$ is used instead of $T_o$ and atmospheric effects and surface emissivity are not considered properly. In such cases, $H$ prediction errors have been reported to be around 100 W m$^{-2}$ (Chávez and Neale, 2003). Consequently, more recent EB models differ mainly in the manner in which $H$ is estimated. These models include the Two-Source Model (TSM; Kustas and Norman, 1996), where the energy balance of soil and vegetation are modeled separately and then combined to estimate total $LE$; the Surface Energy Balance Algorithm for Land (SEBAL; Bastiannesen et al., 1998) that uses hot and cold pixels within the satellite images to develop an empirical temperature difference equation; and the Surface Energy Balance Index (SEBI; Menenti and Choudhury, 1993) based on the contrast between wet and dry areas. Other models include the Simplified Surface Energy Balance Index (S-SEBI; Roerink et al., 2000), the Surface Energy Balance System (SEBS; Su, 2002), the excess resistance (kB$^{-1}$; Kustas and Daughtry, 1990; Su, 2002), the aerodynamic temperature parameterization models proposed by Crago et al. (2004) and Chávez et al. (2005), the beta ($\beta$) approach (Chehbouni et al, 1996), and most recently the ET Mapping Algorithm (ETMA; Loheide and Gorelick, 2005) and Mapping Eva–potranspiration with Internalized Calibration (METRIC™; Allen et al., 2007a). The sections below discuss the main models in detail.

## SEBI, SEBS, and S-SEBI

SEBI, proposed by Menenti and Choudhury (1993), is based on the Crop Water Stress Index (CWSI; Jackson et al., 1981) concept in which the surface meteorological scaling of CWSI is replaced with planetary boundary layer (PBL) scaling. It uses the contrast between wet and dry areas appearing within a remotely sensed scene to derive ET from the relative evaporative fraction ($\Lambda_r$). The $\Lambda_r$ is calculated by relating surface temperature observations to theoretical upper and lower bounds on the difference between $T_s$ and $T_a$ (Menenti et al., 2003). Evaporative fraction ($\Lambda$), as utilized by Bastiaanssen et al. (1998), is defined as the ratio of latent heat flux to the available energy ($AE = R_n - G$) and is assumed to remain nearly constant during the day.

SEBS (Su, 2002) was developed using the SEBI concept. It uses a dynamic model for aerodynamic roughness length for heat (Su et al., 2001), bulk atmospheric similarity (BAS; Brutsaert, 1975) and Monin-Obukhov similarity (MOS) theories for PBL to estimate regional ET, and atmospheric surface layer scaling for estimating ET at local scale. SEBS requires theoretically defined wet and dry boundary conditions to estimate $H$. Under dry conditions, the calculation of $H_{dry}$ is set to the $AE$ as evaporation becomes zero due to the limitation of water availability and $H_{wet}$ is calculated using Penman-Monteith parameterization (Monteith, 1981). The main limitation with SEBS is that it requires aerodynamic roughness height. A potential weakness in the SEBS approach is the neglect of heat flux absorption along the temperature profile when extrapolating to and from the blending layer. The absorption, over a dry condition, can be large, and it disrupts the assumption of a smooth $T$ gradient that conveys the $H$ flux estimate all the way to the blending height. This results in an overstatement of the surface temperature for the dry condition and must be accounted for somehow empirically.

S-SEBI (Roerink et al., 2000) is a simplified method derived from SEBS to estimate surface fluxes from remote sensing data. Consequently, this model is based on $\Lambda$ and the contrast between the areas with extreme wet and dry temperature. The disadvantage of this method may be that it requires extreme $T_s$ values, which cannot always be found on every image. However, the major advantages are that it is a simpler method that does not need additional meteorological data, and it does not require roughness length as in the case of SEBS.

### TSM

The TSM considers the energy balance of the substrate (e.g., soil) and vegetation components separately, and then combines these components to estimate total ET. Norman et al. (1995) and Kustas and Norman (1996) developed operational methodology for the two-source approach proposed by Shuttleworth and Guerney (1990). This methodology generally does not require additional meteorological information over single-source models; however, it requires some parameterizations governing the partitioning of composite radiometric surface temperature into soil and vegetation components, turbulent exchange of mass and energy at the soil level, and coupling/decoupling of energy exchange between vegetation and substrate (i.e., parallel or series resistance networks). The energy exchange in the soil-plant-atmosphere continuum is based on resistances to heat and momentum transport, and sensible heat fluxes are estimated by the temperature gradient-resistance system. Radiometric temperatures, resistances, sensible heat fluxes, and latent heat fluxes of the canopy and soil components are derived by iterative procedures constrained by composite directional radiometric surface temperature, vegetation cover fraction, and maximum potential canopy transpiration flux.

Although this method is more physically based, it still incorporates a number of semi-empirical submodels, such as the clumping factor (a function of LAI and soil fraction cover), extinction coefficients for canopy and wind function, solar transmittance in the canopy, canopy emissivity, etc. Because of the semi-empirical submodels, the underlying assumptions, and the number of inputs/steps in the TSM algorithm, it may be subject to errors if not carefully applied.

### SEBAL

Bastiaanssen et al. (1998, 2005) described SEBAL in detail. Briefly, SEBAL is essentially a single-source model that solves the EB for *LE* as a residual. $R_n$ and $G$ are calculated based on $T_s$ and reflectance-derived values for albedo, vegetation indices, LAI, and surface emissivity. $H$ is estimated using the bulk aerodynamic resistance model and a procedure that assumes a linear relationship between the aerodynamic near-surface temperature-air temperature difference ($dT$) and $T_s$ calculated from extreme pixels. Basically, extreme pixels showing cold and hot spots are selected to develop a linear relationship between $dT$ and $T_s$, where the $dT$ parameter eliminates the need for $T_a$ and knowledge of $T_o$. It also provides for some bias compensation for errors in $R_n$ and $G$. At the pixel with cold condition, $H$ is assumed non-existent (i.e., $H_{cold} = 0$), and at the hot pixel, *LE* is commonly set to zero, which in turn allows $H_{hot} = (R_n - G)_{hot}$. Then $dT_{cold} = 0$, and $dT_{hot}$ can be obtained by inverting the bulk aerodynamic resistance equation. The $dT$ artifice is expected to compensate for bias in surface temperature estimates due to atmospheric correction, and it does not assume that radiometric and aerodynamic temperatures are equivalent. SEBAL has been tested extensively in different parts of the world (Bastiannesen et al., 2005).

### METRIC™

A full description of METRIC™ can be found in Allen et al. (2007a). The main difference between SEBAL and METRIC™ is that the latter does not assume $H = 0$ or $LE = R_n - G$ at the wet pixel. Instead, it calculates the ET of the hot pixel by performing a soil water budget, using meteorological data from a nearby weather station, to verify that ET is indeed zero for that pixel. For the wet pixel, *LE* is set equal to 1.05 $ET_r\ \lambda_v$, where $ET_r$ is the hourly (or shorter time interval) tall crop reference (like alfalfa) ET calculated using the standardized ASCE Penman-Monteith equation applied to local meteorological observations. The second difference is that METRIC™ selects extreme pixels purely in an agricultural setting, where particularly the cold pixel needs to have biophysical characteristics ($h_c$, LAI) similar to the reference crop (alfalfa). The third difference is that METRIC uses the alfalfa reference evapotranspiration fraction ($ET_rF$) mechanism to extrapolate instantaneous *LE* flux to daily ET rates instead of using the $\Lambda$. The $ET_rF$ is the ratio of $ET_i$ (remotely sensed instantaneous ET) to the reference $ET_r$ that is computed from weather station data at overpass time. The benefits of using $ET_r$ are the calibration around biases in $R_n$ and $G$ estimates at both ends of the temperature range (i.e., at the cold and hot pixels) as well as calibration around biases in $T_s$. An additional benefit of using $ET_r$ and $ET_rF$ is the ability to account for general advection impacts on ET. Disadvantages are the requirement for relatively high-quality weather data on an hourly or shorter time step and reliance on the accuracy of the $ET_r$ estimate.

## Limitations and Future Challenges

### $T_s$ vs. $T_o$

It was recognized that $T_s$ is sensitive to crop conditions and management practices (Kimes et al., 1980; Kimes, 1983) regardless of the type of platform used (i.e., ground, airborne, or satellite) or sensor characteristics (i.e., bandpass response, field of view, internal calibration). Most single-source EB methods use $T_s$ as a surrogate for $T_o$, although they may not be equal. Greater differences between $T_s$ and $T_o$ may be found with larger BRs (i.e., when the sensible heat flux is much larger in proportion to latent heat flux) and with partial vegetation (Hatfield et al., 1984; Jackson et al., 1987) and dry or water-stressed vegetation (Kalma and Jupp, 1990). Alves et al. (2000) found that the $T_s$ for dry conditions greatly departed from the $T_o$, which in turn will result in considerable errors in the estimation of sensible heat flux unless an inverted calibration scheme such as in SEBI, SEBAL, METRIC, etc., is employed.

#### Spatial and Temporal Resolution

In many EB models, $T_s$ is one of the key boundary conditions for estimating spatially distributed ET. In other EB models, $T_s$ is used more as an index for spatial distribution of $H$ rather than as an absolute boundary condition. Numerous remote sensing satellites provide thermal images that can be used to derive $T_s$. However, the spatial resolutions of these thermal images are nearly always coarser than that acquired in other wavelengths such as visible, near-infrared (NIR), and shortwave-infrared (SWIR). For example, the Moderate Resolution Imaging Spectrometer (MODIS) provide thermal images that are at 1000 m resolution (at near nadir), compared with 250 m resolution for images acquired in other bandwidths on the same satellite platform. Further, the time interval between successive satellite overpasses (repeat cycle) over the same geographic area varies from satellite to satellite. For more frequent coverage, the spatial resolution of the acquired images becomes coarser. For example, the Landsat 5 satellite has a repeat cycle of 16 days with 30 to 120 m spatial resolution, compared with daily coverage of MODIS with 250 to 1000 m.

The ET maps derived from remote sensing data acquired by satellite-based sensors with daily coverage such as MODIS and Advanced Very High Resolution Radiometer (AVHRR) are not sufficient to satisfy most agricultural management needs as their pixel size is larger than individual fields, causing significant errors in ET estimation at the field scale (Tasumi et al., 2006). The errors in the estimated ET are partly due to the presence of contaminated pixels, i.e., pixels with multiple land uses/vegetation types with significant differences in cover, roughness, and/or moisture content (Kustas et al., 2004). This condition is more common in arid and semi-arid regions where fully irrigated fields are usually surrounded by extremely dry landscape. However, a research opportunity exist to utilize simultaneously acquired high-resolution visible, VNIR, and SWIR images from MODIS as well as data from other sensors such as AVHRR, Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), or Landsat 5 TM for spatial sharpening of relatively low-resolution thermal imagery (Agam et al., 2007; Kustas et al., 2003) that would be useful for developing high-resolution ET maps for irrigation scheduling purposes. Limited research has been done to evaluate the scale influences on the estimation of ET using multiple aircraft and satellite sensors (McCabe and Wood, 2006).

### Data Accuracy

One main drawback of EB methods such as METRIC, SEBAL, SEBS, SEBI, S-SEBI, and ETMA is that they rely on the presence of extreme $T_S$ (hot and cold or dry and wet) pixels in the imagery. Without the presence of high water use crops in the imagery, these methods may under-scale if not adjusted to the true potential surface temperature range, thus leading to errors in the spatial ET estimation. Allen et al. (2007a) suggested a method to assign an adjusted ET to the cold extreme condition for when vegetation conditions are not at potential and for application to MODIS when thermal pixels are too large to contain only the cold condition. These methods reduce the need for accurate atmospheric correction of remote sensing data and surface emissivity to accurately estimate $H$. TSM does not require identifying extreme temperature pixels and appears to perform very well over heterogeneous surfaces with daily ET estimate errors lower than 15%. However, it requires atmospheric correction of images with atmosphere radiative transfer models and local radiosonde data and assumptions on planetary boundary layer development. The magnitude of errors in the calibration of radiometric temperature values depends mainly on the availability and accuracy of local atmospheric relative humidity profile and visibility data close to the time of remote sensing data acquisition. Other errors with the EB models may relate to the spatial validity of weather station data, such as air temperature, dewpoint temperature, and wind speed, in highly advective arid and semi-arid regions, as well as the submodels used to derive LAI, crop height, and fraction cover from remote sensing data.

### Data Processing Time and User Friendliness

Timeliness of information products derived from remotely sensed data remains an unresolved issue since Park et al. (1968) and others first envisioned applications for agricultural management. This has been revisited numerous times during the intervening four decades (e.g., Jackson, 1984; Moran et al., 1997). To reiterate, the usefulness of remote sensing in the estimation of irrigation water demand for direct water management depends on the turnaround time between image acquisition and the dissemination of derived ET information. At present, the turnaround time is anywhere from 1 to 3 weeks depending on the remote sensing platform/sensor, the algorithm utilized, and the technician's experience and expertise in applying such algorithms. However, for most agricultural applications, ET maps should be delivered within hours, and almost instantaneous (i.e., real-time) timeliness is required for irrigation scheduling. Research should include programs geared towards rapid processing and analysis of remotely sensed imagery with the aid of artificial intelligence, to make ET maps readily available to producers, researchers, and the general public by publishing daily digital ET maps over the internet. For many water rights determination applications, water transfers, hydrology studies, and planning studies, longer turnaround times are tolerable, and in fact, historical archives of satellite images are often employed to determine historical usage and trends (Allen et al., 2007b).

## Conclusions

Reliable regional ET estimates are essential to improve spatial crop water management. Land surface energy balance (EB) models, using remote sensing data from ground, airborne, or satellite platforms at different spatial resolutions, have been found to be promising for mapping daily and seasonal ET at a regional scale. In this article, a brief review of numerous remote sensing based models was made to assess the current status of research, the underlying principle for each method, their data requirements, and their strengths and weaknesses. Although the remote sensing based ET models have been shown to have the potential to accurately estimate regional ET, there are opportunities to further improve these models through (1) developing methods to accurately estimate aerodynamic temperature, (2) testing the spatial validity of the meteorological data such as air temperature and wind speed used in the EB models, and (3) testing the submodels used to estimate soil heat flux, LAI, crop height, etc., for their accuracy under various agrometeorological/environmental conditions.

The spatial and temporal remote sensing data from the existing set of earth-observing satellite sensors are not sufficient enough to use their ET products for irrigation scheduling. This will be constrained further by the possible disappearance of thermal sensors on future Landsat satellites. However, research opportunities exist to improve the spatial and temporal resolution of ET by developing data fusion/subpixel extraction algorithms to improve spatial resolution of surface temperature data derived from Landsat/ASTER/MODIS thermal images using same/other-sensor high-resolution visible, NIR, and SWIR images.

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