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ET mapping for agricultural water management: present status and challenges

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Abstract Evapotranspiration (ET) is an essential component of the water balance. Remote sensing based agrometeorological models are presently most suited for estimating crop water use at both field and regional scales. Numerous ET algorithms have been developed to make use of remote sensing data acquired by sensors on airborne and satellite platforms. In this paper, a literature review was done to evaluate numerous commonly used remote sensing based algorithms for their ability to estimate regional ET accurately. The reported estimation accuracy varied from 67 to 97% for daily ET and above 94% for seasonal ET indicating that they have the potential to estimate regional ET accurately. However, there are opportunities to further improving these models for accurately estimating all energy balance components. The spatial and temporal 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 management purposes, especially at a field scale level ($\sim$10 to 200 ha). This will be constrained further if the thermal sensors on future Landsat satellites are abandoned. However, research opportunities exist to improve the spatial and temporal resolution of ET by developing algorithms to increase the spatial resolution of reflectance and surface temperature data derived from Landsat/ASTER/MODIS images using same/other-sensor high resolution multi-spectral images.

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Introduction

Evapotranspiration (ET) has been long been recognized as the most important process that plays an essential role in determining exchanges of energy and mass between the hydrosphere, atmosphere and biosphere (Sellers et al. 1996). In agriculture, it is a major consumptive use of irrigation water and precipitation on agricultural land. 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 regionally and seasonally according to weather and wind conditions (Hanson 1991). Understanding these variations in ET is essential for managers responsible for planning and management of water resources especially in arid and semi-arid regions of the world where crop water demand generally exceeds precipitation and requires irrigation from surface and/or groundwater resources to meet the deficit.

At a 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 (or distribution) at the regional scale especially in regions with advective climatic conditions. Remote sensing based ET models are better suited for estimating crop water use at a regional scale (Allen et al. 2007a). Numerous remote sensing-based ET algorithms that vary in complexity are available for estimating magnitude and trends in regional ET. This paper discusses remote sensing based regional ET prediction algorithms and their limitations, data needs and availability, knowledge gaps, and future opportunities and challenges with respect to agriculture.

Remote sensing based ET algorithms

Remote sensing has long been recognized as the most feasible means to provide spatially distributed regional ET information on land surfaces (Park et al. 1968; Jackson 1984; Choudhury et al. 1987). The use of remote sensing to estimate ET is presently being developed along two approaches: (a) land surface energy balance (EB) method that uses remotely sensed surface reflectance in the visible (VIS) and near-infrared (NIR) portions of the electromagnetic spectrum and surface temperature (radiometric) from an infrared (IR) thermal band, and (b) Reflectance-based crop coefficient (generally denominated K_{cr}) and reference ET approach where the crop coefficient (K_c) is related to vegetation indices derived from canopy reflectance values. The first approach is 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 models convert satellite sensed radiances into land surface characteristics such as albedo, leaf area index, vegetation indices, surface emissivity and surface temperature to estimate ET as a "residual" of the land surface energy balance equation:

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

where, R_n is the net radiation resulting from the budget of short and long wave incoming and emitted radiation respectively, 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 day^{-1}) by dividing it by the latent heat of vaporization (λ_v; $\sim$2.45 MJ kg^{-1}) and an appropriate time constant. R_n and G may be estimated locally using meteorological measurements (Allen et al. 1998) and regionally by incorporating spatially distributed reflected and emitted radiation (Jackson et al. 1985) as:

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

where α is surface albedo, R_s is incoming short wave radiation (W m^{-2}) measured with pyranometers or calculated using the Angstrom formula based on the solar constant, location and time of the year (Allen et al. 1998) or by using the solar constant, the cosine of the solar incidence angle, the inverse squared relative earth–sun distance, and atmospheric transmissivity based on the area of interest (image) ground elevation respect to mean sea level (Allen et al. 2007a), σ is the Stefan–Boltzmann constant (5.67 E-08 W m^{-2} K^{-4}), ε is emissivity and T 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 sensor brightness temperature imagery for atmospheric effects and for surface emissivity considering, for example, procedures by Hipps (1989) and Brunsell and Gillies (2002). The surface emissivity correction is performed assuming typical bare soil and fully vegetated surface emissivities of 0.93 and 0.98, respectively, and the fractional vegetation cover from the scaled normalized difference vegetation index (NDVI). Alternatively, surface albedo for vegetated areas is generally estimated using the Brest and Goward (1987) model. This model is based on the red (R) and NIR band reflectance:

$$\alpha = 0.512\, R + 0.418\, \mathrm{NIR} \tag{3}$$

The emissivity of air can be obtained from the Brutsaert (1975) equation:

$$\varepsilon_a = 0.0172 \left(\frac{e_a}{T_a}\right)^{1/7} \tag{4}$$

where e_a is actual vapor pressure (kPa). G is commonly estimated as a fraction of R_n depending on leaf area index (LAI) or NDVI. Chávez et al. (2005) found that a combination of a linear and a logarithmic model could estimate G for soils planted to corn and soybean crops in central Iowa (r^2 = 0.73):

$$G = R_n\, (0.3324 - 0.024\, \mathrm{LAI})(0.8155 - 0.3032\, \mathrm{LN(LAI)}) \tag{5}$$

H is then estimated using the aerodynamic surface–air temperature gradient (or combination of gradients) and aerodynamic resistance, where generally radiometric temperature (T_s) has been used as a surrogate for aerodynamic temperature (T_o).

In the second approach, R and NIR reflectance measurements are used to compute a vegetation index such as NDVI (Rouse et al. 1974) or the soil adjusted vegetation index (SAVI; Huete 1988), and the vegetation index is then used in place of calendar days or heat units to drive or scale the crop coefficient. The reference ET is then computed using local meteorological measurements of incoming solar radiation, air temperature, relative humidity or dew temperature, and wind speed.

Some early applications of remote sensing based EB models include Brown and Rosenberg (1973), Brown (1974), Stone and Horton (1974), Idso et al. (1975), Heilman et al. (1976), Verma et al. (1976), Kanemasu et al. (1977), and Jackson et al. (1977). Most of these studies used airborne scanners as first demonstrated by

Bartholic et al. (1972). Price (1982), Seguin and Itier (1983), and Taconet et al. (1986) 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:

$$\mathrm{LE} = R_n - G - \frac{\rho_a C_p (T_s - T_a)}{r_{ah}} \tag{6}$$

where ρ_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 10–12 μm. Later, Rosenberg et al. (1983) incorporated the term surface aerodynamic temperature (T_o) in the H model, instead of surface radiometric temperature, considering that the temperature gradient (for H) was a gradient between air temperature within the canopy (at a height equal to the zero plane displacement plus the roughness length for heat transfer) and 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 for water stressed biomass, radiometric and aerodynamic temperatures of the surface were not equal. This inequality is discussed further in a later section.

Hatfield et al. (1983) evaluated the surface temperature with the energy balance approach at seven locations throughout the United States equipped with weighing lysimeters and ground-based instrumentation. In their study, daily G was assumed negligible. Crops were sorghum, alfalfa, tomato and wheat at full cover, and tomato at 80% cover. They concluded that remotely sensed T_s may be used in the EB model to estimate regional ET. Estimated LE values, using atmosphere stability corrected aerodynamic resistances, were very closely matched to those measured by the lysimeters. Reginato et al. (1985) refined estimates of R_n using reflected shortwave and emitted long wave measurements as outlined by Jackson et al. (1985). They also used ground-based instrumentation to estimate ET of wheat and achieved good agreement with lysimeters and neutron scattering. Later, Jackson et al. (1987) applied this procedure using an airborne radiometer and compared with BR measurements for cotton, alfalfa, and wheat with homogenous crop surfaces (full canopy with no contribution from soil background). Comparison of the remote sensing based LE estimates for 5 days with BR values resulted in a greatest difference of 12% while errors in daily ET estimates were less than 8% for 3 days and 25% on the other two. Moran et al. (1989) then applied this procedure using R/NIR (simple ratio) and thermal data from the Landsat Thematic Mapper (TM) satellite and reported agreement within 12% with the BR and airborne data from Jackson et al. (1987).

Accurate estimates of H are very difficult to achieve, mainly when T_s is used instead of T_o and when 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; Matsushima 2000). Consequently, more recent EB models differ mainly in the manner that H is estimated. These models included the two-source model (TSM; Norman et al. 1995; Kustas and Norman 1996; Chehbouni et al. 2001), where the energy balance of soil and vegetation are modeled separately and then combined to estimate total LE, surface energy balance algorithm for land (SEBAL; Bastiaanssen et al. 1998) that uses hot and cold pixels to develop an empirical temperature difference equation, and surface energy balance index (SEBI; Menenti and Choudhury 1993) based on the contrast between wet and dry areas. Other models include simplified surface energy balance index (S-SEBI; Roerink et al. 2000); 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); Beta (β) approach (Chehbouni et al. 1996); and most recently ET mapping algorithm (ETMA; Loheide and Gorelick 2005) and Mapping Evapotranspiration with Internalized Calibration (METRIC$^{\mathrm{TM}}$; Allen et al. 2002, 2005, 2007a). The sections below discuss the main models in detail.

SEBI, SEBS and S-SEBS: SEBI, proposed by Menenti and Choudhury (1993), is based on the crop water stress index (CWSI; Jackson et al. 1981) concept in which 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 (Λ_r). It determines Λ_r by relating surface temperature observations to theoretical upper and lower bounds on the difference between surface and air temperature (Menenti et al. 2003). Evaporative fraction (Λ), 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.

Surface energy balance system (Su 2002) was developed using the SEBI concept. It uses a dynamic model for thermal roughness (Su et al. 2001), bulk atmospheric similarity (BAS) (Brutsaert 1999) and Monin–Obukhov similarity (MOS) theories for regional ET estimation, and atmospheric surface layer (ASL) scaling for estimating ET at local scale. SEBS requires wet and dry boundary conditions to estimate H. Under dry conditions, the calculation of H_{dry} is set to the available energy AE as evaporation becomes zero due to the limitation of water availability and H_{wet} is calculated using the Penman–Monteith parameterization (Monteith 1965, 1981) as:

$$H_{\mathrm{wet}} = \mathrm{AE} - \frac{\left(\frac{\rho_{\mathrm{a}} Cp}{r_{\mathrm{ah}}}\right)\left(e_{\mathrm{s}} - \frac{e}{\gamma}\right)}{\left(1 + \frac{\Delta}{\gamma}\right)} \tag{7}$$

where e is the actual vapor pressure (kPa), e_{s} is the saturation vapor pressure (kPa), γ is the psychrometric constant (kPa °C^{-1}), Δ is the rate of change of saturation vapor pressure with temperature (kPa °C^{-1}) and r_{ah} is the bulk surface external or aerodynamic resistance (s m^{-1}) estimated under the assumption that the bulk internal resistance is zero. Finally, relative evaporative fraction (Λ_r), evaporative fraction (Λ) and LE for each pixel in the remote sensing image is calculated as:

$$\Lambda_r = 1 - \frac{H - H_{\mathrm{wet}}}{H_{\mathrm{dry}} - H_{\mathrm{wet}}} \tag{8}$$

$$\Lambda = \frac{\Lambda_r (R_{\mathrm{n}} - G - H_{\mathrm{wet}})}{R_{\mathrm{n}} - G} \tag{9}$$

and

$$\mathrm{LE} = \Lambda (R_{\mathrm{n}} - G) \tag{10}$$

The evaporative fraction ($\Lambda = \mathrm{LE}/(R_n - \mathrm{G})$) is used in the estimation of LE because it is assumed to remain constant through out the day and can be obtained for short periods and be used for LE extrapolation to daily values. Brutsaert and Sugita (1992) presented the assumption that the partitioning of available energy (AE) into H and LE is constant (self-preservation of the available energy partitioning) or that the evaporative fraction remains almost constant during the daytime. Zhang and Lemeur (1995) added that the evaporative fraction indicates how much of the available energy is used for ET and that the assumption that the instantaneous Λ is representative of the daily energy partitioning, is an acceptable approximation for clear-sky conditions. Crago (2000) concluded that the Λ has the tendency to be nearly constant during daytime, permitting the estimation of daytime evaporation from one or two estimates of the evaporative fraction during the middle of the day at the satellite overpass time.

Su et al. (2005) evaluated SEBS with two independent, high-quality datasets that were collected at a field scale during the soil moisture–atmosphere coupling experiment (SMACEX) in the Walnut Creek agricultural watershed near Ames, IA, USA. Meteorological and EC measurements from ten locations within the watershed were used to estimate and compare fluxes during a period of rapid vegetation growth and varied hydrometeorology. Results indicated that ET estimates from the SEBS were close to 85–90% of the measured ET values from EC systems for both corn and soybean surfaces. In the same study, regional fluxes were calculated using Landsat enhanced thematic mapper plus (ETM+) data for a clear day during the field experiment. Results at the regional scale showed that ET prediction accuracies were strongly related to crop type with improved ET estimates for corn surfaces compared to those of soybean. Differences between the observed and predicted ET values were approximately 5%. Further, McCabe and Wood (2006) used thermal data from Landsat ETM+ (60 m), advanced spaceborne thermal emission and reflection radiometer (ASTER; 90 m), and moderate resolution imaging spectrometer (MODIS; 1,020 m) sensors to independently estimate ET using SEBS. A high degree of consistency was observed between flux retrievals from ETM+ and ASTER data while MODIS data was unable to discriminate the influence of heterogeneity in land use at field scale. The main limitation with the SEBS is that it requires aerodynamic roughness height. Currently, several methods are available to estimate this variable using wind profile, vegetation index, and crop height (h_{c} in m) or by assigning nominal values based on the land use.

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 Λ and the contrast between the areas with extreme wet and dry temperature, T_{wet} and T_{dry}, respectively. The instantaneous LE is calculated as:

$$\mathrm{LE}_i = \Lambda_i (R_n - G)_i \tag{11}$$

where the subscript "i" means instantaneous. Λ_i is expressed as:

$$\Lambda_i = \frac{T_{\mathrm{Dry}} - T_S}{T_{\mathrm{Dry}} - T_{\mathrm{Wet}}} \tag{12}$$

Λ_i is assumed constant through the day. Daily LE (LE_d) is calculated as:

$$\mathrm{LE}_d = \frac{\mathrm{LE}_i \, R_{n,d}}{(R_n - G)_i} \tag{13}$$

where $R_{n,d}$ is daily net radiation (W m^{-2}), can be estimated from a known relationship at solar noon as:

$$C_{d,i} = \frac{R_{n,d}}{R_{n,i}} \tag{14}$$

where $R_{n,i}$ is the instantaneous net radiation, and $C_{d,i}$ is approximately 0.30 (±0.03) for summer months. Finally, ET_d can be estimated as:

$$ET_d = \frac{\Lambda_i\ C_{d,i}\ R_{n,i}}{\lambda^v} \tag{15}$$

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. Gómez et al. (2005) used the Λ concept based on S-SEBI for estimating ET_i and to extrapolate it to ET_d. The method was applied using airborne sensor: PolDER (polarization and directionality of earth reflectance) and a thermal camera. Validation with a BR system showed LE estimation error of 26% and 1 mm day^{-1} for ET_d over corn, alfalfa, wheat and sunflower crops.

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 (1999) developed operational methodology to the two-source approach proposed by Shuttleworth and Wallace (1985) and Shuttleworth and Gurney (1990). This methodology generally does not require additional meteorological or information over single-source models; however, it requires some assumptions such as 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 latent heat flux.

Kustas et al. (2004) applied TSM to Landsat TM and ETM+ images to evaluate the effect of sensor resolution on model output over corn and soybean fields in central Iowa. The pixel resolution was varied from 60–120, 240, and 960 m. Comparison of flux estimates with tower-based and aircraft-based flux measurements indicate that the TSM performed reasonably well. Gonzalez-Dugo et al. (2006) compared an EB single-source model with TSM to evaluate their ability to estimate surface fluxes. They found that both methods performed well (RMSD less than 31 W m^{-2}) in estimating the H using calibrated Landsat TM imagery. However, the TSM performed slightly better than the EB single source model with r^2 values of 0.87 and 0.94 for H and LE estimates, respectively. The EB single source model produced r^2 values of 0.78 and 0.91 for H and LE estimates, respectively. Colaizzi et al. (2006a) evaluated the TSM for alfalfa, corn, cotton, grain sorghum, soybeans, winter wheat, wheat stubble, and bare soil using large weighing lysimeters in Bushland, Texas. The TSM over-estimated LE for smaller observed LE ($<|400|$ W m^{-2}) by up to 200 W m^{-2}, but relative error improved for larger LE. Overall, RMSE ranged from 77 W m^{-2} for soybean to 135 W m^{-2} for winter wheat, and TSM performance was not influenced by regional advection.

Norman et al. (2000a, b) proposed a variation of the TSM called dual-temperature-difference (DTD) method using time rate of change in T_s and T_a to compute surface heat fluxes. This method reduced the effect of errors associated with radiometric calibration, emissivity variations, and use of non-local air temperature and wind speed data. Comparison of H estimates from DTD method with that from original TSM indicated that the DTD method had potential for regional-scale applications using geo-stationary satellites (like GOES) data with a synoptic weather network. H estimation errors were generally <50 W m^{-2}. The DTD approach was well suited for geostationary satellites with high temporal resolution but coarse (4 km) spatial resolution, and it conceivably could be applied to thermal pixel disaggregation schemes to improve spatial resolution such as those described in the below paragraph.

Using the TSM, Kustas et al. (2003) and Norman et al. (2003) developed a two-step approach called the Disaggregated Atmosphere Land EXchange Inverse model (DisALEXI) to combine low- and high-resolution remote sensing data to estimate ET on the 10–100 m scale without requiring local observations. The first step involves deriving surface fluxes from low spatial resolution but frequently available remote sensing data using a coupled TSM–ABL model known as ALEXI. The second step disaggregates those low spatial resolution surface flux estimates using vegetation index and surface temperature estimates derived from non-frequent high resolution remote sensing datasets. For example, one can derive average surface flux estimates from a 4-h repeat cycle GOES satellite data with a spatial resolution of 5 km and disaggregate into high spatial resolution flux maps using vegetation index and surface temperature data from Landsat (30 m) dataset with a repeat cycle of 16 days. They successfully demonstrated its application using data from the Southern Great Plains in central Oklahoma (Norman et al. 2003). The root mean square difference (RMSD) between remote sensing estimates of surface fluxes and ground-based measurements were within 10–

12%. Similar results were reported by Anderson et al. (2007).

SEBAL: Bastiaanssen (1995) and 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 of 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 surface temperature–air temperature difference (dT) and radiometric surface temperature (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. At the cold pixel in the satellite imagery, H is assumed non-existent i.e., $H_{cold} = 0$ and at the hot pixel, LE is set to 0 which in turn allows to set $H_{hot} = (R_n - G)_{hot}$. Then, $dT_{cold} = 0$ and dT_{hot} can be obtained by solving the bulk aerodynamic resistance equation for the hot pixel as:

$$H = \rho_a C_P \frac{dT}{r_{ah}} \tag{16}$$

After calculating dT at both cold and hot pixels, a linear relationship between dT and T_s is developed to estimate H iteratively correcting r_{ah} for atmospheric stability. This is done applying the MOS theory. This step requires T_a and u measured at a weather station and a mechanism that extrapolates wind speed to a blending height of 100–200 m. The dT artifice is expected to compensate for errors in surface temperature estimates due to atmospheric correction, and does not assume that radiometric and aerodynamic temperatures are equivalent.

SEBAL has been tested extensively in different parts of the world. Bastiaanssen et al. (2005) summarized SEBAL accuracy under several climatic conditions at both field and regional scales. For a range of soil wetness and plant community conditions, the typical accuracy at field scale was 85% for a single day and 95% for a seasonal scale. For large watersheds, on an annual basis, the ET prediction accuracy was up to 96%. However, application of SEBAL by Trezza (2002) for a variety of crops in Kimberly, ID resulted in ET estimation errors ranging from 2.7 to 35% with an average error of 18.2%.

METRIC™: A full description of the METRIC™ can be found in Allen et al. (2002, 2005, 2007a) who highlighted that METRIC™ uses remote sensing imagery in the visible, near-infrared and thermal portion of the electromagnetic spectrum along with ground-based horizontal wind speed and near surface dew point temperature measurements. This model is based on the SEBAL algorithm. The main difference between SEBAL and METRIC™ is that the latter does not assumes $H = 0$ or $LE = R_n - G$ at the wet pixel, instead a soil water budget is applied for the hot pixel to verify that ET is indeed zero and for the wet pixel, LE is set to 1.05 $ET_r\ \lambda_v$, where ET_r is the hourly (or shorter time interval) tall reference (like alfalfa) ET calculated using the standardized ASCE Penman–Monteith equation. The second difference is that it selects extreme pixels purely in an agricultural setting whereby the cold pixel should have biophysical characteristics (e.g., 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 Λ. ET_rF is the ratio of ET_i (remotely sensed instantaneous ET) to the reference ET_r (e.g., mm h^{-1}) that is computed from weather station data at overpass time.

Tasumi et al. (2003) validated METRIC™ for various crops grown on weighing lysimeters located at the USDA-ARS laboratory in Kimberly, Idaho. Allen et al. (2007b, 2005) compared seasonal ET estimated for two agroecosystems in Idaho: an irrigated meadow in the Bear River Basin and a sugar beet field near Kimberly, using METRIC™ with lysimeters measurements resulted in 4 and 1% errors, respectively; with ET overestimation errors as high as 10–20%. Errors in predicted monthly ET at Montpelier, ID averaged ±16% relative to a local lysimeter, although the difference for ET sums over a 4-month period was only 4%, according to the authors. Chavez et al. (2007) applied METRIC™ to the Texas High Plains using a Landsat 5 TM image acquired early in the cropping season. The performance of the METRIC™ was evaluated by comparing the predicted daily ET with values derived from a soil water budget at four different locations. ET estimates errors were below 15%. The use of METRIC™ for the advective conditions of the Texas High Plains is promising; however, more evaluation is needed using lysimeter or well-calibrated Scintillometer derived ET measurements for different agroclimatological conditions.

ETMA: The ETMA proposed by Loheide and Gorelick (2005) is based on the surface energy budget and requires only local weather data including G measurements and high-resolution airborne thermal imagery to estimate ET. It uses two surface temperature points, T_{LE} and T_H, at which all of the turbulent heat flux is attributed to the LE and H, respectively, to develop linear relationships between surface temperature and instantaneous ET (ET_i) at specified times as follows:

$$ET_i = AE \frac{\left(\frac{T_H - T_S}{T_H - T_{LE}}\right)}{\lambda^v}. \tag{17}$$

At $H = 0$, $T_{LE} = T_a$ and at LE = 0, the T_H is calculated as:

$$T_H = \frac{\text{AE}\,(r_{ah} + r_{ex})}{\rho_a\, C_p} + T_a \tag{18}$$

where r_{ex} is the excess resistance that is encountered for heat transfer compared to momentum transfer (Norman and Becker 1995). Daily ET will then be developed from two instantaneous ET maps using Penman–Montieth and Jarvis–Stewart models and surface resistance. ETMA was intended for application at the local scale where T_a, u, h_c, e, and T_{soil}, are uniform in space. This model may not work well for regions subject to advective conditions or may not be applicable on regions with significant surface heterogeneity.

EB methods based on relating T_o to T_s: Since T_o cannot be measured directly, it is usually derived by inverting some form of Eq. (6). Numerous studies have shown that T_s and T_o are neither equal nor do they have a unique relationship, as reviewed by Kustas et al. (2003, 2007). Kustas and Norman (1996) pointed out that the difference between T_s and T_o can be significant for relatively sparse vegetation cover (LAI < 1.5) and/or water stressed vegetation. Chehbouni et al. (1996) tried to compensate for the difference of these two temperatures by trying to relate ($T_s - T_o$) to ($T_s - T_a$) for grass and mesquite patches. They indicated that despite some scatters, especially for the mesquite site, the comparison showed that the ($T_s - T_o$) increased as T_o increased. Their model assumed that the relationship was not linear. Their results allowed the formulating of sensible heat flux (H) using T_s as:

$$H = \rho_a\, C_p\, \beta \left(\frac{T_s - T_a}{r_{ah}}\right) \tag{19}$$

where,

$$\beta = \frac{1}{\exp\left(\frac{L}{L - \text{LAI}}\right) - 1} \tag{20}$$

where L is a site-specific empirical factor. In Chehbouni et al. (1996), L was found to be 2.5 through least square regression. They calibrated the model for LAI values less than 1.0 $m^2\ m^{-2}$. A similar study by Matsushima (2005) over a wide range of rice density (LAI ranged from 0.04 to 5.4) indicated that the variation of β with LAI did not agree with the empirical parameterization proposed by Chehbouni et al. (1996). Instead, the author found that the logarithmic diurnal average of the thermal roughness lengths (Z_{oh}) was a function of LAI. While on the other hand, Colaizzi et al. (2004) compared ($T_s - T_a$) with ($T_o - T_a$) using weighing lysimeters planted with irrigated alfalfa, irrigated and dryland cotton, and dryland grain sorghum. They did not find a relationship between ($T_s - T_a$) and ($T_o - T_a$). They concluded that the difference might have been influenced by the different surface roughness of each crop type.

Zibognon et al. (2002) applied a land surface–atmosphere-radiometer model to convert T_s to an equivalent isothermal (or aerodynamic) temperature using data for one day at a grass site with LAI of 1.0. The model used variables that described the shape of the vertical foliage temperature profile. The model estimates were compared to the T_o reference values from the inversion of the MOS theory, obtaining good agreement. In this study, T_o over T_s resulted in an improvement by 3.6 K.

Crago et al. (2004) suggested calibrating the bulk aerodynamic resistance equation (Rosenberg et al. 1983) to estimate T_o, using estimated H values with the analytical land–atmosphere-radiometer model (ALARM). The model assumed the foliage had an exponential vertical temperature profile. They indicated that the same profile was felt by the within-canopy turbulence. The ALARM converted radiometric surface temperatures into T_o called the equivalent radiometric isothermal surface temperature and then calculated H using the MOS theory.

Chávez et al. (2005) linearly related aerodynamic temperature (T_o) to T_s, LAI, T_a and u for corn and soybean fields in central Iowa. The calibration equation resulted with an r^2 value of 0.77. The linear expression is shown below:

$$T_o = 0.534\ T_s + 0.39\ T_a + 0.244\ \text{LAI} - 0.192\ u + 1.67 \tag{21}$$

where T_s and T_a are in °C, LAI is in $m^2\ m^{-2}$, and u is in $m\ s^{-1}$. EC systems were used to extract values for u and T_a. The model was found to be valid for a LAI range of 0.3–5.0 and u values ranging from 1.5 to 7.3 $m\ s^{-1}$. T_a was measured approximately at a height of 2 m for soybean and 3 m for corn.

The evaluation of the T_o model was performed with inverted values from measured H using a different set of EC stations resulted in a mean bias error (MBE) and root mean square error (RMSE) values of 0.2 and 0.9 °C, respectively. The corresponding goodness of fit was $r^2 = 0.90$ which demonstrated the good agreement with measured values. The T_o model was used in the EB estimation of LE which was compared to EC measured values resulting in MBE and RMSE of –9.2 and 39.4 W m^{-2}, respectively. The errors were well within the margin of errors of the LE from EC ground station measurements. The comparison of estimated with measured values was performed taking into account the heat fluxes footprint by means of heat flux source area models that incorporate the analytical solution to the diffusion–dispersion–advection equation. However, note that the T_o model was developed using data over corn and soybean fields having relatively homogeneous surface canopies under unstable atmospheric conditions. Therefore, the proposed model requires further evaluation over heterogeneous surfaces and/or under stable/neutral atmospheric conditions of semi-arid regions.

Instantaneous to daily ET extrapolation

This technique was first introduced by Jackson et al. (1983) to calculate a coefficient to convert one-time-of-day remote sensing based ET estimates to daily total ET. It required geographic latitude, day of year, and time of day and diurnal solar radiation and ET were described by a sine function. They compared ET estimates with lysimetrically determined daily total ET for four crops at five different locations. Results indicated that reliable estimates of daily ET from one-time-of-day measurements could be made for cloud free days. For cloudy days, the results were less reliable, but the authors suggested that estimates could be improved by considering the amount and temporal distribution of cloud cover. They added that the one-time-of-day measurements should be made within about 2 h of solar noon.

In a recent study on fully irrigated alfalfa, partially irrigated cotton, dryland grain sorghum and bare soil (tilled fallow sorghum), Colaizzi et al. (2006b) found that the ET_rF approach could scale instantaneous LE to daily ET more accurately for cropped surfaces compared with evaporative fraction [$\Lambda = LE/(R_n - G)$]; however, Λ gave slightly better prediction for bare soil. The authors used the standardized ASCE-PM grass reference ET (ET_oF) to scale daily ET from one-time-of-day 0.5 h ET data from a lysimeter. They found daily ET underestimation errors were within the 10% for ET > 6 mm day^{-1}, within 20% for ET values between 3.9 and 5.8 mm day^{-1}, and >20% for ET values ranged 0.4–3.2 mm day^{-1}. In a airborne remote sensing study conducted in Walnut Creek watershed located south of Ames in central Iowa, Chavez and Neale (2007) compared evaporative fraction, the solar radiation method and the alfalfa and grass reference evapotranspiration fraction methods to extrapolate instantaneous to daily ET. Instantaneous ET estimates were made from aircraft imagery acquired at different times of the day. In the study area, plant available water was not a limiting factor and advection was not an issue. Results indicated that the Λ method performed better than the other two methods when compared to daily ET values measured by several EC systems. Better results were obtained for flight overpasses from local Noon to close to 2:00 PM CST.

Reflectance-based crop coefficient method

Reflectance based crop coefficient method has been studied, among others, by Reginato et al. (1985), Neale et al. (1989, 2003), and Hunsaker et al. (2005). Furthermore, crop coefficients (K_c) have been related to vegetation indices such as PVI (Jackson et al. 1980; Heilman et al. 1982), NDVI (Bausch and Neale 1987; Neale et al. 1989), and SAVI (Bausch 1993; Neale et al. 1996). D'Urso and Santini (1996) attempted to derive the crop coefficient analytically from remote sensing estimated albedo, surface roughness, and aerodynamic resistance (from LAI). This method does not require knowledge of crop development stage.

K_c is defined by the ratio of the crop ET_c to the reference crop ET (grass or alfalfa). According to Allen et al. (1998), K_c represents an integration of the effects of four characteristics that distinguish a given crop form the reference crop: crop height (affects aerodynamic resistance and vapor transfer), canopy-soil albedo (affects R_n), canopy resistance (to vapor transfer), and evaporation from soil. K_c is mainly directly derived from studies of the soil water balance determined from cropped fields or from lysimeters. K_c values are estimated under optimal agronomical conditions, i.e., no water stress, disease, weed/insect infestation, or salinity issues.

Neale et al. (1996), using multi-temporal airborne digital multi-spectral video imagery acquired over cotton crop through a growing season, obtained reflectance-based crop coefficients that were related to the SAVI. They maintained a water balance in the root zone of the cotton crop in three fields with ET estimates based on K_c derived using the spectral methods and K_c curves from FAO Paper No. 56 (Allen et al. 1998). Reflectance based K_c followed the actual cotton growth in the field. Their results indicated that the FAO's K_c procedure underestimated ET during the vegetative stage of growth and overestimated towards the latter in the cropping season. Based on a simulated irrigation schedule, they emphasized that water savings could have been up to 12%. Similarly, Harikishan et al. (2006) used the basal crop coefficient (K_{cb}) approach to estimate the crop ET from a non-water limited soil–plant environment showing a dry soil surface and plants free of pest/disease. They concluded that canopy reflectance-based crop coefficient is a practical and accurate indicator of the actual crop ET. They conducted root zone soil water balance simulations where the seasonal variations in the simulated soil water profiles in the root zone were compared to the actual soil water contents measured with a neutron probe. Results showed good agreement throughout the cropping season and validated the canopy reflectance-based crop coefficient for non-grain crops. A historical retrospective on the remote sensing based crop coefficients for ET can be found in Neale et al. (2003). They concluded that the remote sensing based crop coefficients can be accurately used for grain, non-grain and forage crops.

In Kenya, Michael and Bastiaanssen (2000) derived reflectance based crop coefficient (K_{cr}) from Landsat images using the simplified Priestley–Taylor equation for estimating crop ET. They obtained good results for unstressed crop where vapor pressure deficits remained within acceptable limits. Tasumi et al. (2005a, b, 2006) showed a method to estimate K_{cr} using a satellite-based EB model and a parameterization of K_{cr} (which in this case represented mean K_c) using NDVI to obtain daily ET. With this method traditional K_{cr} curves could be adjusted to reflect actual crop/weather/field/management conditions by shifting key crop development days (curve shifting) to better match the remote sensing based K_{cr} curve and to obtain improved ET estimates. With the parameterization of K_{cr} using NDVI, ET estimates for grass and sugar beets were compared to lysimeter measurements. The seasonal ET estimation errors for grass and sugar beets were 2 and 6%, respectively. The method of calibration was region specific and did not need a land use map showing crop types.

On a different approach, Zhang and Wegehenkel (2006) developed a regional ET model that integrates the MODIS vegetation data (VIS, NIR reflectance) with the FAO-56 Penman–Monteith reference ET model, where K_c was estimated based on the crop h_c and fractional vegetation cover (f_c). Fractional vegetation cover was related to NDVI values and root depth to LAI through the season. Estimated seasonal ET was compared with ET by twelve lysimeters (1 $m^2 \times 1.5$ m deep) in Berlin, Germany, resulting in an index of agreement above 0.87 and R^2 values higher than 0.59.

In a semi-arid region of Morocco, Er-Raki et al. (2007) compared estimates of actual ET for winter wheat under different irrigation treatments; using K_{cb} values from the FAO-56 procedure, locally measured K_{cb}, and K_{cb} and f_c derived from NDVI (reflectance values based on ground radiometer readings); with ET values derived from EC systems. At mid-season state, the K_{cb} values based on FAO-56 were found considerably less than the locally calibrated K_{cb} values. NDVI-based K_{cb} values were found acceptable especially when the soil evaporation was negligible suggesting that this method is promising for regional scale ET estimation. The locally developed K_{cb} values and the NDVI based values performed similarly with ET prediction errors of 0.16 ± 0.45 and 0.33 ± 0.51 mm day^{-1}, respectively, producing a model efficiency of 79 and 70%, respectively, compared to 44% with the FAO-56 procedure.

Limitations and future challenges

Radiometric versus aerodynamic temperature

It was recognized that radiometric temperature is sensitive to canopy structure (Kimes 1980), vertical vegetation temperature distribution (Kimes et al. 1980), and row spacing and soil–vegetation component temperatures (Kimes 1983), regardless of the type of platform used (i.e., ground, airborne, or satellite) or sensor characteristics (i.e., band pass response, field of view, internal calibration). Most single-source EB methods use radiometric temperature 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 (Kustas et al. 1989; Kalma and Jupp 1990). Norman et al. (1995) and Norman and Becker (1995) pointed out that when two targets (e.g., soil and vegetation) at different temperature levels are viewed by the sensor, their composite wavelength distribution is not that of a blackbody, meaning that there is no equivalent composite blackbody giving the same radiance at the given temperature. Hence, equality of radiometric and aerodynamic temperature, at least for composite surfaces, should not be expected. Supporting these findings, Alves et al. (2000) found that radiometric surface temperature for dry conditions greatly depart from the aerodynamic temperature, which in turn will result in considerable errors in the estimation of sensible heat flux.

Spatial and temporal resolution

There is usually a trade-off between spatial (i.e., pixel size) and temporal (i.e., repeat frequency) resolution for satellite platforms (Table 1). For example, the Landsat 5 has a repeat cycle of 16 days with 30–120 m spatial resolution compared with daily coverage of MODIS with 250–1,000 m. Furthermore, the spatial resolutions of thermal bands are often coarser than other wavelengths such as visible, NIR and SWIR (Shortwave-Infrared). For example, MODIS provides thermal images at 1,000-m resolution compared with 250-m resolution for images acquired in other bandwidths on the same satellite platform.

The ET maps derived from remote sensing data acquired by satellite-based sensors with daily coverage such as MODIS, geostationary environmental satellite (GOES), and advanced very high resolution radiometer (AVHRR) are too coarse to be useful in agricultural regions because their pixel size is larger than individual fields in most regions causing significant errors in ET estimation (Tasumi et al. 2006). The spatial errors in the estimated ET are partly due to presence of pixels having 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

Table 1 Repeat cycle, spectral and spatial resolution of spectral bands on ASTER, Landsat 5, and MODIS sensors

Satellite	Repeat cycle	Spectral band	Wavelength (μm)	Spatial resolution (m)
ASTER	16 days (nadir)	1	0.52–0.60 (green)	15
		2	0.63–0.69 (red)	
		3	0.76–0.86 (NIR)	
		5	1.600–1.700 (SWIR)	30
		6	2.145–2.185 (SWIR)	
		7	2.185–2.225 (SWIR)	
		8	2.235–2.285 (SWIR)	
		9	2.295–2.365 (SWIR)	
		10	2.360–2.430 (SWIR)	
		11	8.125–8.475 (TIR)	90
		12	8.475–8.825 (TIR)	
		13	8.925–9.275 (TIR)	
		14	10.25–10.95 (TIR)	
		15	10.95–11.65 (TIR)	
TM	16 days	1	0.45–0.52 (blue)	30
		2	0.52–0.60 (green)	
		3	0.63–0.69 (red)	
		4	0.76–0.90 (NIR)	
		5	1.55–1.75 (SWIR)	
		7	2.08–2.35 (SWIR)	
		6	10.4–12.5 (TIR)	120
MODIS	Daily	1	0.62–0.67 (red)	250
		2	0.841–0.876 (NIR)	
		3	0.459–0.479 (blue)	500
		4	0.545–0.565 (green)	
		5	1.230–1.250 (SWIR)	
		6	1.628–1.652 (SWIR)	
		7	2.105–2.155 (SWIR)	
		31	10.780–11.280 (TIR)	1,000
		32	11.770–12.270 (TIR)	

NIR Near infrared, *SWIR* shortwave infrared, *TIR* thermal infrared

by an extremely dry landscape. However, there is a research need to utilize simultaneously acquired high resolution visible, VNIR and SWIR images from the MODIS as well as data from other sensors such as ASTER and Landsat 5 TM to scale up the ET maps (in terms of frequency and spatial resolution). Most likely a combination of data from satellites/airborne remote sensing platforms (temporally coinciding/not coinciding), ET pixels scaling algorithms, and in between overpasses interpolation techniques will contribute towards improving the spatial and temporal resolution issues. Limited research (McCabe and Wood 2006; Kustas et al. 2003, 2004 for the humid Iowa region; Jacob et al. 2002 for Mediterranean Region) has been done to evaluate the scale influences on the estimation of ET using multiple aircraft and satellite sensors. However, no such study has been implemented in semi-arid and arid regions of the U.S. to evaluate scale influences on estimating ET using land surface EB models.

Success of remote sensing based ET models depends on the availability cloud-free remote sensing data. In areas such as semi-arid Southern and Central High Plains in the central U.S., there is a limited opportunity to obtain cloud free data at high spatial resolution from satellite platforms such as Landsat and ASTER. In addition, Landsat 5 is expected to be out of service in 2008, and chances of having a thermal sensor on future Landsat satellites are presently low. However, there is a possibility to use microwave data to estimate surface fluxes through computation of soil and canopy temperatures (Trofleau et al. 1997). Numerous field studies with microwave data (Moran et al. 1997; Diak et al. 1995) indicate that low frequency (~5 GHz) microwave backscatter may be related to ($T_s - T_a$) while high frequency (~15 GHz) microwave backscatter may be related to the NDVI. One main drawback at present with microwave data is that the spatial resolutions of passive microwave sensors are on the order of 10–100 km limiting their use to global scale applications. With the advent of improved algorithms, we may be able to use active microwave sensors that provide data at high spatial resolutions.

Data accuracy

One main drawback of existing 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 the true potential surface temperature range, thus leading to errors in the spatial ET estimation. However, these methods eliminate the need for accurate atmospheric correction of remote sensing data and surface emissivity to estimate H accurately. The 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 numerous inputs/steps and atmospheric correction of images with atmosphere radiative transfer models and local radiosonde data. 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, dew point temperature and wind speed in the highly advective arid and semi-arid regions as well as the sub-models used to derive LAI, crop height, 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 remote sensing applications for agricultural management. This has been revisited numerous times during the intervening four decades (e.g., Jackson 1984; Moran 1994; Moran et al. 1997). To reiterate, the usefulness of remote sensing in the estimation of irrigation water demand will depend on the turn around time between image acquisition and the dissemination of derived ET information. At present, the turn around time is anywhere from 1 to 3 weeks depending on the remote sensing platform/sensor, algorithm utilized, and technician's experience/expertise on 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 public by publishing daily digital ET maps over the Internet.

Review of different ET mapping algorithms presented in this paper show that most EB models are complex to use. Literature review indicated that there is an effort towards the simplification of the procedures to estimate regional ET mainly through the parameterization of crop coefficients using vegetation indices or the scaling of potential ET based on extreme surface temperature pixels. However, coefficients used in the simplified methods may vary spatially from one region to another. More research needs to be done in this direction, and some research efforts are presently underway to address the transferability of crop coefficients to different location (Howell et al. 2006).

Model validation

Literature review showed that most studies used BR and/or EC data for development and calibration of regional scale EB models. It is known that EC method has an energy balance non-closure problem i.e., $R_n \neq H + \mathrm{LE} + G$ (Oncley et al. 2000; Twine et al. 2000) of up to 20% even for non-advective conditions. Measurements of latent heat flux differed by up to 29% between BR and large, weighing lysimeters for irrigated alfalfa during advective conditions in the Southern High Plains of Texas (Todd et al. 2000). Therefore, calibration of the EB models against lysimetric and/or well-calibrated scintillometer measurements over irrigated and dryland conditions may enhance their ability to estimate regional ET accurately. In addition, heat flux source models should be utilized to properly weight and integrate LE pixels, for example, upwind of BR, EC, and/or scintillometer stations in the process of comparison of LE estimates with measured values (Chávez et al. 2005).

Conclusions

Reliable regional ET estimates are essential to improve spatial crop water management. Land surface EB models, using remote sensing data from ground to airborne to satellite platforms at different spatial resolutions, have been found to be promising for mapping daily and seasonal ET at a regional scale. In this paper, a thorough review of numerous remote sensing based models was made to understand the current status of the regional ET research, underlying principle for each method, data requirements, and their strengths and weaknesses. In all EB methods, thermal remote sensing data is one of the crucial inputs. In general, ET estimation errors associated with EB models were mostly found in the range of 2.7–35% for daily ET and less than 6% for seasonal ET, with larger errors associated with simplified methods. Reflectance based crop coefficient methods are relatively easy to use to estimate ET compared to EB models, however, crop coefficients must account for water stress and require calibration for each crop type. Further, a major limitation of this approach is the spatial validity of the estimated reference ET.

Although the remote sensing based ET models shown to have the potential to accurately estimate regional ET, there are opportunities to further improve these models through (1) developing methods for accurately estimating canopy temperature profiles, (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 sub-models used to estimate soil heat flux, LAI, crop height, etc., for their accuracy, under various agrometeorological/environmental conditions. In addition, further evaluation of different scaling methods to extrapolate remote sensing derived instantaneous ET to daily and seasonal ET values is needed.

The spatial and temporal remote sensing data from existing set of earth observing satellite sensors are not sufficient to use their ET products for irrigation scheduling. This may be constrained further by the disappearance of thermal sensors on future Landsat satellites. However, research opportunities exist to improve the spatial and temporal resolution of ET by developing algorithms similar to those by McCabe and Wood (2006), Kustas et al. (2003), Norman et al. (2003), Kustas et al. (2004), or Jacob et al. (2002) to improve spatial resolution of reflectance and surface temperature data derived from Landsat/ASTER/MODIS images using same/other-sensor high resolution visible, NIR and SWIR images. Finally, weighting and integrating remote sensing derived ET pixels should be done using footprint (heat flux source area) models for proper comparison to measured values by EC, BR or scintillometer energy balance stations.

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