***3\_\_\_\_\_***

***Remote Sensing of Evapotranspiration from Cropland***

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* 1. **Introduction**

Agriculture accounts for the majority of human water use and for more than 90% of global fresh water consumption during the 20th century (Hoekstra and Mekonnen, 2012; Shiklomanov, 2000). Despite this, estimates of the location and temporal dynamics of evapotranspiration (ET) from croplands are often uncertain at a variety of spatial and temporal scales. Better information on ET can be useful in several applications at a range of spatial scales. At the scale of irrigation projects, maps of ET can assist with irrigation scheduling and demand assessment. The estimation of ET is of practical value in studies of water resources, agronomy and meteorology (e.g. Rivas and Caselles, 2004). Measurements of are required for monitoring plant water requirements, plant growth and productivity, as well as for irrigation management and deciding when to carry out cultivation procedures (e.g. Consolli et al., 2006; Glenn et al. 2007; Yang et al., 2010). Estimation of is very important in planning and management of water resources, particularly in many arid and semi-arid regions where water is a limiting resource.

Accurate knowledge of ET is of great importance in a large number of regional and global scale applications. ET estimates can assist with water allocation decisions to support agriculture and ecosystems, including strategies for drought management. Global ET assessments can help understand, for example, how the global food production system may respond to global climate change. Data on the energy equivalent of ET (latent heat flux) are also of key significance in the numerical modelling and prediction of atmospheric and hydrological cycles, and in improving the accuracy of weather forecasting models (Jacob et al., 2002). ET (latent heat) is the single most important mechanism of mass (energy) exchange between the hydrosphere, biosphere and atmosphere, playing a critical role in both water cycle and energy balance (Sellers et al., 1996) and regional circulation patterns (Lee et al., 2011, 2009). Quantitative information on ET is also important for understanding the processes that control ecosystem carbon dioxide (CO2) exchange (Scott et al., 2006) as well as the interactions between parameters in different ecosystem processes (Wever et al., 2002).

ET can be measured in the field with different types of instruments including lysimeters, eddy covariance systems, surface renewal, and flux variance (French et al., 2012; Petropoulos et al., 2013). Field methods estimate ET over a range of spatial scales, from ~1m for lysimeters and up to ~100-1000 m for eddy covariance towers. While field data are the most direct way to measure ET, their use for the measurement of ET over large areas is limited due to the expense of maintaining the field equipment and to the large spatial variability in ET, particularly in agricultural settings (Ershadi et al., 2013; McCabe and Wood, 2006a). For example, eddy covariance towers are one of the most widely used methods for estimating energy fluxes above a canopy (Swinbank, 1951), but the global inventory of eddy flux towers (FLUXNET) (Baldocchi et al., 2001) reports data for fewer than 500 active towers with most towers concentrated in the United States and Europe and no towers in some countries where knowledge of ET is critical to water management (Jung et al., 2009).

In the absence of in-situ data on ET, crop models are often used to estimate ET under different crops and soil moisture conditions (Allen, 2000). Application of crop models to a new location and at regional scales suffers from several difficulties. Required input data, including crop growth stage and cropping calendars, may be difficult to determine in large areas with heterogeneous cover and intra-seasonal or inter-annual variability in cropping patterns. The model parameters are often functions of relative humidity and wind speed, resulting in corrections of up to 30% for tall crops growing in conditions of low humidity and high wind speeds (Allen, 2000). Crop models of ET may be difficult to parameterize during the initial growth stages, which are particularly sensitive to environmental conditions like wetting frequency and soil texture, which introduces uncertainty where soil evaporation is an important component of total ET.

Given the limitations of field measurements and the difficulty of estimating the parameters in crop models without additional data on crop calendars and condition, Earth Observation (EO) technology provides an opportunity to estimate ET at a variety of spatial and temporal scales. EO is defined here as the collection of imagery from aerial and satellite platforms. EO technology is recognized as the only viable solution for obtaining estimates of ET at the spatiotemporal scales and accuracy levels required by many applications (Glenn et al., 2007; Melesse et al., 2008). Several techniques have been proposed to estimate ET using different types of EO datasets, which often require some ancillary data for implementation. Previous reviews of remote sensing for ET estimation are available (Courault et al., 2005; Gonzalez-Dugo et al., 2009; Kalma et al., 2008; Kustas and Norman, 1996; Petropoulos, 2013; Verstraeten et al., 2008). Gowda et al (2008) provided an overview of ET estimation in agriculture, but focused on enery-based methods, which is one of several methods available (Table 1).

The present Chapter provides a critical and systematic overview of different modeling approaches to derive regional estimates of ET from EO data, with a focus on agriculture. The chapter is structured as follows: First we review methods for estimating net radiation (Rn), which is required by all ET modelling techniques. We then discuss three families of methods used to estimate ET using EO: 1) vegetation-based methods, 2) temperature-based methods, and 3) scatterplot inversion methods. We use common mathematical symbols for each method to facilitate intercomparison, and highlight similarities in the conceptual foundations of the various methods. Sufficient detail is provided to implement and compare some of the most commonly used algorithms and recommendations for the application of each method are also given, discussing any special issues related to estimating seasonal ET in agriculture. The accuracy of the methods is then compared, special problems in application of the methods to crops are discussed, and future research directions are highlighted.

* 1. **Overview of methods for ET calculation using remote sensing**

Several different terms are used to describe the water demand of the atmosphere and the actual use of water by crops (Allen et al, 1998). Potential evapotranspiration is the amount of water lost to both evaporation from the soil surface and from transpiration though the leaves of vegetation not experiencing soil moisture stress. Potential ET is a function of climatic variables like net radiation, temperature, and humidity, and of vegetation characteristics. For a well-watered crop grown under optimal conditions, potential ET can vary with leaf area, stage of development, photosynthetic pathway, and rooting depth, so a second term, reference ET (ETo) is defined as the amount of water used by a specific reference crop, usually a well-watered grass 12 cm tall with specific characteristics (see Section 3.2.2). Finally, actual ET is the amount of water that is lost via both evaporation from the soil surface and transpiration from a specific vegetation cover under actual field conditions, including limitations to ET caused by soil moisture stress, nutrient limitation, and pathogens. In this Chapter we use the symbol ET and the term evapotranspiration to represent actual evapotranspiration of a given land surface. The latent heat flux associated with ET is written as λET, and is simply the product of ET and the latent heat of vaporization of water at a given temperature (λ). It is sometimes used instead of ET because it is a rate that can be expressed for a given instant in time, and is also the variable measured by several field techniques. We use ET and λET interchangeably depending on the method being described.

***Table 1 here. Three families of methods used to calculate ET and their advantages and disadvantages.***

Remote sensing radiometers do not directly measure ET or λET. The spectral radiance measures they provide have to be combined in some form of retrieval algorithm or model in order to estimate the surface fluxes. Several algorithms have been developed in the last four decades for estimating ET using either space- or airborne systems. The available EO-based methods can be broadly grouped into three basic families of methods : 1) vegetation-based methods, 2)temperature-based methods , and 3) triangle/trapezoid or scatterplot inversion methods. Each of these methods is reviewed in turn, following a review of methods to estimate net radiation (Rn), which is required by all methods reviewed in the Chapter. Descriptions of Rn calculations are also included because, in agricultural applications, special adaptations are often required to calculate outgoing radiation at high spatial resolution in order to capture the heterogeneity of the land surface. While microwave (MW)-based methods have been developed, and could be particularly useful for areas with cloud-cover, the spatial resolution of MW imagery, at 35-65 km2, is deemed too coarse for application to agricultural areas (Petropoulos, 2013).

**3.2.1 Net radiation**

EO-based methods for estimating ET, including all methods reviewed in this Chapter depend on accurate determination of net radiation (Rn; W/m2), which is calculated as:

|  |  |
| --- | --- |
|  | **( 1 )** |

where *α* is broadband blue-sky albedo (dimensionless), *SW↓* is incoming shortwave radiation (W/m2), *LW↓* is downwelling longwave radiation and *LW↑* is upwelling longwave radiation (W/m2). For field-scale applications or watershed studies, Rn is often estimated with meteorological data alone. The specific method will depend on the availability of meteorological data. A variety of methods for small geographical areas with meteorological data are available and reviewed in several publications (e.g. Allen et al., 1998).

Rn can be calculated from well-established approaches based on primarily EO data. An excellent review of the different methods for the estimation of the different components of the radiation budget from EO sensors, including the operationally distributed products available, was provided recently by Liang et al. (2013). *SW↓* and *LW↓* depend on atmospheric properties that can be estimated accurately with coarse-resolution datasets (1 degree). *α* and *LW↑* depend on surface conditions, including reflectivity and temperature, which are more spatially variable. Below we review global datasets for *SW↓* and *LW↓* and other methods to estimate *α* and *LW↑*.

* + - 1. ***Regional and global datasets for net radiation***

At regional and global scales, Rn can be estimated with gridded data from surface climate reanalysis that assimilate remote sensing data or from EO data alone, with errors of ±10-20% compared to ground measurements (Bisht et al., 2005). Gridded datasets used for regional to global scale Rn estimation can be separated into two spatiotemporal categories: 1979-present (1° spatial resolution) and 2000-present (0.25° spatial resolution). The higher spatial resolution post-2000 is due to the launch of the MODIS satellites and other EO systems that facilitate the downscaling of the surface energy budget (Gottschalck et al., 2005). Liang et al. (2010) and Liang et al. (2013) provide good introductions to commonly used Rn datasets and associated uncertainties. For 1979-present, several coarse resolution and downscaled sources exist. The most commonly used is the Global Energy and Water Cycle Experiment Surface Radiation Budget (SRB) (Gupta et al., 1999), which provides 3-hourly shortwave and longwave radiation fluxes at one degree resolution. These data are generated primarily from the International Satellite Cloud Climatology Project (Rossow and Schiffer, 1999, 1991; Schiffer and Rossow, 1983) and Global Modeling and Assimilation Office (http://gmao.gsfc.nasa.gov/) meteorology. The original dataset covering 1983 to 2007 has been expanded to cover from 1979 to present, as part of the Modern ERA-Retrospective Analysis for Research and Applications (MERRA) (Rienecker et al., 2011) dataset. MERRA is updated regularly with remote sensing and observed data and fed through a land surface catchment hydrology model, which provides additional outputs and further reduces inconsistencies. Another one degree resolution surface reanalysis dataset is the Global Land Data Assimilation (GLDAS) (Rodell et al., 2004) product. GLDAS assimilates NOAA/GDAS atmospheric fields, Climate Prediction Center Merged Analysis of Precipitation fields, and observation-driven shortwave and longwave radiation using the Air Force Weather Agency’s AGRicultural METeorological (AGRIMET) modeling system to parameterize three land surface realizations ((1) NCEP, Oregon State University (OSU), Air Force, and Hydrology Research Laboratory at NWS- NOAH, (2) Community Land Model, Mosaic, and (3) Variable Infiltration Capacity model). The forcing data for GLDAS, like MERRA, is produced at 3-hourly intervals at one degree resolution from 1948 to present (Bosilovich, 2008). Although at much coarser spatial resolution, two other datasets are commonly used: National Centers for Environmental Prediction–National Center for Atmospheric Research (NCEP-NCAR) (Kalnay et al., 1996) and European Centre for Medium-range Weather Forecasts (ECMWF) interim reanalysis (Morcrette, 1991, 2002). NCEP-NCAR shortwave and longwave fluxes are available at 6-houlry intervals from 1948-present at 2.5 degree resolution, while the ECMWF interim shortwave and longwave flux is available at 6-houlry intervals spanning1979-present at 1.5 degree resolution. Sheffield et al. (2006) uses surface elevation to downscale the NCEP-NCAR to one degree resolution. Other downscaled Rn products can be found on the corresponding Princeton University Terrestrial Hydrology Research Group webpage (http://hydrology.princeton.edu/data.php).

For regional estimation of Rn after 2000, EO data are incorporated directly or indirectly into one of the aforementioned reanalysis datasets. These methods involve several assumptions or ground-based estimates of albedo, land surface temperature, and emissivity for model calibration (Bisht et al. 2005). Since 2000, land surface products from the Moderate Resolution Imaging Spectroradiometer (MODIS), including aerosol depth, temperature, emissivity, air temperature, dew point temperature, and albedo, have been combined and extrapolated from once-a-day measurements to daily flux at a quasi-1km resolution. The Clouds and Earth's Radiant Energy System (CERES) initially aboard NASA’s Tropical Rainfall Measurement Mission (TRMM) platform and later placed on NASA’s Terra and Aqua platforms, is a radiometer which collects solar-reflected, Earth-emitted, and total radiation to determine Earth’s radiation budget. Data is available from 2000-present at a 3-houlry, 1 degree resolution. Data is available from 2000-present as monthly or monthly hourly averages at 1 degree resolution. The Land Surface Analysis Satellite Applications Facility (LSA-SAF) (<http://landsaf.meteo.pt/>) has also developed a radiation budget for the land surface using The Spinning Enhanced Visible and Infrared Imager (SEVIRI) radiometer on board the Meteosat Second Generation (MSG) satellite. The MSG/SEVIRI platform provides 30-minute 3km resolution albedo, land surface temperature, emissivity, *SW↓*, and *LW↓* information from 2004-present. Unlike CERES, which is a global product, MSG/SEVIRI operational window includes primarily the African and European continents.

Satellite methods to estimate components of Rn are continually evolving and being evaluated against each other, including for SW↓?? (Ma and Pinker, 2012), LW (Gui et al., 2010), and Rn (Bisht and Bras, 2010), and it can be anticipated that re-analysis datasets that incorporate satellite imagery will continue to be improved.

ET mapping often uses vegetation indices (VI?) or land surface temperature at higher resolution (e.g. 30m, 250m, 1km) than is available from the global grids of radiation, but not all parts of the radiation budget need to be downscaled in detail. Incoming shortwave () and incoming longwave () are determined primarily by atmospheric properties and are therefore often assumed homogeneous over a given cell in the global gridded products, so they can be taken directly from the gridded data, though some applications (e.g. MOD16) interpolate to the resolution of the other satellite imagery used to map vegetation indices or radiometric surface temperature (Mu et al., 2011). MOD16 calculates net longwave as a function grid-cell average air temperature, which is in turn taken from the global gridded dataset (GMAO MERRA) and interpolated to 1km using non-linear interpolation on the four nearest neighbors (Mu et al, 2007).

***3.2.1.2 Outgoing shortwave and longwave at high spatial resolution***

In contrast to incoming radiation, outgoing shortwave and outgoing longwave depend on land surface properties and so may exhibit significant spatial variation over short distances, particularly in agricultural areas with sharp boundaries in vegetation with different levels of soil moisture stress. Algorithms for calculating albedo from Landsat imagery are included in several ET estimation models, including METRIC (Allen et al., 2007) and an albedo product is directly available for MODIS (MOD43B3). A review of the methods is also presented in Liang et al (2013). Outgoing longwave radiation can be calculated at high spatial resolution using surface radiometric temperature from satellite imagery and an estimate of the surface emissivity. This approach is used in the METRIC and SEBAL models (Allen et al., 2007) and in many other applications (Bisht et al., 2005; Tang and Li, 2008):

|  |  |
| --- | --- |
|  | ( 2 ) |

where εo is the broad-band surface emissivity, σ is the Stefan-Boltzmann constant (5.67 x 10-8 W m-2 K-1, and TR is the radiometric surface temperature, which is often assumed equal to the surface temperature. Some remote sensing products include estimates of εo, including MODIS and ASTER, though there may be significant errors over heterogeneous landscapes(Liang et al., 2013).

***3.2.1.3. Available energy and the ground heat flux***

Available energy is the amount of Rn left over after accounting for the ground heat flux (G; W/m2), and is calculated as Rn-G. G is usually close to zero over 24-hour periods and is assumed to be zero in several methods (e.g. ***Table 2***), but G can be significant at the instant of satellite overpass and is particularly important for energy-based methods. Instantaneous G can account for up to 50% of Rn for sparse vegetation and can average 20-30% for NDVI values up to around 0.6 (Bastiaanssen et al., 1998), so it cannot be neglected unless there is a high canopy cover fraction. Instantaneous G can be calculated with a variety of algorithms (Murray and Verhoef, 2007), the simplest of which is to assume that G is a constant fraction of Rn, usually between 0.2 and 0.5 at midday (Choudhury, 1989), with specific model applications using constant values of, for example, 0.35 (Norman et al., 1995) or 0.31 (Anderson et al., 1997). Other models include those where G/Rn is a function of NDVI, which is applicable over vegetated areas but not water (Morse et al., 2000):

|  |  |
| --- | --- |
|  | ( 3 ) |

G can also be estimated by a more complicated empirical equation (Table 3) that describes heat transfer using TR,albedo and an extinction factor that describes attenuation of radiation through canopies using NDVI (Choudhury, 1989; Clothier et al., 1986; Kustas and Daughtry, 1990; Van Oevelen, 1991). More detailed approaches incorporate soil properties (Murray and Verhoef, 2007). Using empirical equations, the error in G is often around 20-30% (Petropoulos, 2013). Over water bodies, G is usually larger and requires a different equation, often calibrated to local measurements (Morse et al., 2000). There has been no systematic comparison of the equations in different climatic and land surface conditions, so the user is recommended to try a few equations for G to test the sensitivity of Rn-G to the equation used.

**3.2.2 Vegetation-based methods for ET estimation**

Vegetation-based methods to estimate ET use an index of vegetation biomass or leaf area index to calculate crop ET. One of the most widely available global ET datasets, MOD16, uses a variant of the Penman-Monteith equation to estimate ET (Leuning et al., 2008; Mu et al., 2011, 2007; Nishida and Nemani, 2003). MOD16 is also referred to as PM-Mu in the literature. MOD16 and several other vegetation-based methods use the Penman-Monteith equation to calculate ET from crop canopies and soil surfaces (Mu et al., 2011):

|  |  |
| --- | --- |
|  | ( 4 ) |

where λET is latent heat flux (W m-2), ET is mean daily evapotranspiration (mm s-1, converted to mm d-1 by multiplying by 86400 s d-1), λ is the latent heat of vaporization (~2.26 x 106 J kg-1), s is the slope of the curve relating saturated vapor pressure (esat in Pa) to air temperature (Pa K-1), ρ is air density (kg m-3), Cp is the specific heat capacity of air (J kg-1 K-1), D is the vapor pressure deficit (esat-e, where e is actual vapor pressure in Pa), ra is the aerodynamic surface resistance (s m-1), γ is the psychrometric constant (∼0.066 kPa °C−1 or as calculated in Mu et al, 2007), and rs is the resistance of the land surface or plant canopy to ET (s m-1). Rn-G is for the 24-hour period, so G is usually close to zero. Several of these parameters (s, γ, ρ, Cp, e, esat) are determined from either global gridded or local meteorological data or elevation and do not depend on satellite-derived vegetation characteristics. The two main parameters that control ET for different vegetation types and different levels of soil moisture stress are ra and, more importantly, rs. The meteorological inputs are taken from either local meteorological stations or gridded global meteorological datasets, and include air temperature, which is used to calculate esat, and relative humidity, which is used to calculate e. Both temperature and RH are measured at a specified height, usually 1.25, 2, or 3 m above the ground.

Alternatively, the Priestley-Taylor equation has been used in global models, particularly the PT-JPL model (Fisher et al., 2008), and in several scatterplot methods (Jiang and Islam, 2001):

|  |  |
| --- | --- |
|  | ( 5 ) |

where αPT (unitless) is an empirical coefficient. For open water and vegetation without soil moisture limitation, αPT is 1.26, though adjustments may be applied in different environments. λET can be converted to ET in mm by dividing by the latent head of vaporization (λ = 2.45 MJ/kg) (Allen et al., 1998) and an appropriate time constant (e.g. to convert from mm s-1 to mm d-1, κ below).

Reference ET (ETo) is calculated using either Equation ( 5 ) or Equation ( 4 ), with ra and rs parameters for a reference surface, for example a grass 12 cm tall with an rs of 70 s m-1 and albedo 0.23 (Allen et al., 1998). Two basic approaches are used in their application to estimate actual ET: crop coefficient methods, and canopy resistance methods.

***3.2.2.1. Empirical vegetation methods: Crop coefficients***

*3.2.2.1.1. Calibration methods*

Crop coefficient methods calculate ET as the product of potential ET for a reference crop, also called the reference ET (ETo) and a crop coefficient. In the original FAO-56 model of crop ET (Allen et al., 1998) , the crop coefficient is separated into a coefficient describing the effect of crop type and growth stage (Kc) and the effect of soil moisture stress (Ks). The product (KcKs) is the combined crop coefficient. Most satellite methods estimate the combined coefficient, which is also sometimes called the reference evapotranspiration fraction (*ETf*). In order to simplify the notation, and because the method is often used for other vegetation types besides crops, here we use the term “reference ET fraction” and the symbol *ETf* to represent the combined crop coefficient throughout the Chapter.

The crop coefficient (ETf or Kc?) is modelled as a function of the vegetation index (VI?) using several possible empirical equations (Eq 5-7), including as a power function (Nagler et al., 2013):

|  |  |
| --- | --- |
|  | ( 6 ) |

where aK is an empirical coefficient determined by regression, and η is a coefficient that varies by the vegetation index. Alternatively, *ETf* can be modelled by first normalizing by extreme VI values in the image (Glenn et al., 2010):

|  |  |
| --- | --- |
|  | ( 7 ) |

where VImax is the VI value when ET is at a maximum, and VImin is the VI of bare soil (VI=0). η is often close to 1 for some vegetation indices (EVI, SAVI) but may be less than 1 for NDVI due to NDVI’s lack of sensitivity for leaf area indices greater than ~3 (Glenn et al., 2011). Note that this equation assumes evaporation is zero when VI equals VImin, which may not be the case for irrigated fields at initial growth stages, which may have wet soil but low crop cover. Soil evaporation can be included by introducing a second coefficient Ke that is determined by modelling the soil drying curve after precipitation or irrigation events, which is independent of remote sensing data(Glenn et al., 2010).

Other formulations of the *ETf* -VI relationship include those derived from Beer-Lambert Law of absorption of light by a canopy, assuming a linear relationship between EVI and the leaf area index (LAI) (Nagler et al., 2013) (Figure 1):

|  |  |
| --- | --- |
|  | ( 8 ) |

where aK, bK and cK are the coefficients determined by regression.

**Figure 1** here. *ETf-EVI.*

Implementation of the crop coefficient method depends on availability of ground data of ET from lysimeters, eddy flux correlation towers, sap flow measurements or other methods in order to calibrate the *ETf* -VI relationship. If lysimeters or towers are used, the equation estimates ET, and if sapflow measurements are used, the equation estimates transpiration only. The method assumes that all crops with identical VI have the same *ETf* values; while the *ETf* -VI relationship may be conserved over several vegetation types (Nagler et al., 2013, 2009), it may vary under different soil types or soil moisture stress conditions. The coefficients of Equations 6-8 may vary spatially and temporally, and so the method is typically used to estimate ET over relatively small areas with available data. Regional *ETf* -VI curves have been constructed for various locations in the western United States (Nagler et al., 2013), though the spatial and temporal variability in the *ETf* -VI relationships and the size region they can be applied with a given accuracy needs further documentation.

The accuracy of empirical crop coefficient methods has been assessed using flux towers, soil water balances, and annual water balances. Nagler et al. (2013) reported a standard mean error in *ETf* of 0.12 in the application of Equation **( 8 )** to MODIS EVI data compared to flux towers (riparian areas and irrigated alfalfa) and soil moisture balance (cotton). Glenn et al (2010), in a review of numerous applications of empirical *ETf* methods, report that the empirical methods have RSMD in the range of 10-30% of mean ET across several different biomes. The main disadvantage of the crop coefficient method is the requirement of meteorological data and some measure of ET to calibrate the *ETf*-VI equations.

*3.2.2.1.2 Application of the crop coefficient approach to agricultural crops*

Bausch and Neale (1987) and Neale et al. (1989) first established the validity of the VI-crop coefficient (Kc-VI) method at two experimental farm sites in Colorado. They grew irrigated corn in fields equipped with weighing lysimeters, and Kc was calculated with alfalfa grown at the same facility as the reference crop (i.e., Kc = ETcorn/ETalfalfa). NDVI was measured with radiometers suspended over corn canopies. NDVI was strongly correlated with LAI and fractional cover (fc), and Kc-VI derived from radiometric measurements closely tracked measured Kc over the crop cycle. Choudhury et al. (1994) used a modelling approach to show the theoretical justification for replacing Kc with Kc-VI, with Kc-VI replacing canopy resistance terms in the Penman-Monteith equation for ET. The Kc-VI method has since been successfully applied to a wide variety of crops as outlined in the following examples.

Vineyards and orchards are difficult to model with normal crop coefficients due to differences in plant spacing and other crop variables among plantings. By using NDVI and SAVI from satellite images Campos et al. (2010) accurately predicted actual ET by simple linear regression equations in grape orchards in Spain. Samani et al. (2009) used NDVI from Landsat imagery to develop field-scale Kc-VI values for pecan orchards in the lower Rio Grande Valley, New Mexico, USA. Their estimates of ET were within 4% of values measured at an eddy covariance flux tower. ET over 279 fields varied from 498 - 1259 mm yr-1. Only 5% of fields were within the range of ET and Kc set by expert opinion, indicating the potential for significant water savings over 11,000 ha of orchards.

Wheat has been extensively studied due to its importance as an irrigated or dryland crop around the world. Duchemin et al. (2006) used NDVI from Landsat images to map LAI and ET in irrigated wheat fields in Morocco, and reproduced ground measurements of ET within 15%. Wheat fields varied widely in ET, opening up the possibility of improving irrigation efficiency by tailoring water applications to actual crop needs determined by satellite imagery. Gontia and Tiwari (2010) developed field-specific crop coefficients for wheat field in West Benhal, India, using Kc-VI values determined from NDVI and SAVI from satellite sensors.

Extensive work on wheat has been conducted by the USDA-ARS in a desert irrigation district in Maricopa, Arizona, USA (Hunsaker et al., 2007a, 2007b; D. J. Hunsaker et al., 2005). They developed NDVI-derived Kc-VI values that tracked within 5% of measured Kc for wheat grown in weighing lysimeters. Wheat was then grown in field plots for two seasons under stress and non-stress conditions. The NDVI method gave more accurate predictions of actual irrigation demands than the FAO-56 method under all treatment conditions with a root mean square error of about 15% of measured water use with no bias towards under or overestimation across treatment.

Similar studies have been conducted with cotton in the southwestern U.S. (Hunsaker et al., 2003, 2005, 2009) (D. Hunsaker et al., 2005; Hunsaker et al., 2003, 2009) and Spain (González-Dugo and Mateos, 2008a). The latter study was conducted in a large irrigation district and the results showed that considerable water savings could be achieved by scheduling irrigations based on NDVI-derived crop models rather than Kc values determined for crops grown under optimal conditions. Kc-VI methods have been developed for other crops, including potato (Jayanthi et al., 2007), broccoli (El-Shikha et al., 2007), sugarbeet (González-Dugo and Mateos, 2008b), soybean (Gonzalez-Dugo et al., 2009), the oilseed crop camelina (Hunsaker et al., 2011), sorghum (Singh and Irmak, 2009) and alfalfa (Singh and Irmak, 2009). All these studies reported positive results and pointed to the possibility of considerable water savings by replacing static FAO-56 crop coefficients with locally-derived Kc-VI values.

Often the main interest is determining district-wide water demand, which requires estimating ET over mixed crop areas. Choudhury et al. (1994) pointed out that the ET:VI relationship was not necessarily crop-specific, and that the Kc-VI approach might be used over mixed crops without a serious loss of accuracy. Allen and Pereira (2009) found a reasonable agreement between measured Kc and fc over a wide range of tree crops, and the relationship was improved by including plant height in the regression. Similar findings were reported by Trout et al. (2008) for tree and vegetable crops, and a close correlation was noted between Landsat-derived fc based on NDVI, and fc measured on the ground over 30 fields with crops ranging from trees (almonds, pistachios), to vines (grapes), and row crops (onions, tomatoes, cantaloupes, watermelon, beans, pepper, garlic and lettuce. The only aberrant crop was red lettuce, which has a low NDVI due to reflection of red light from anthocyanin in the leaf cell vacuoles. They developed an operational ET-monitoring program for California’s irrigation districts based on Landsat-derived NDVI and ETo from the California Irrigation Management Information System’s network of micrometeorological stations (Johnson and Trout, 2012).

Rafn et al. (2008) compared an NDVI method for deriving Kc with the energy balance METRIC method over mixed crops in an Idaho irrigation district. They concluded that the Kc-VI method was a fully objective and repeatable process that was fast, easy and less costly to employ than the METRIC method. They projected that the method could be applied outside the area where it was developed. Similarly, Gonzalez-Dugo et al. (2008) found that NDVI-derived crop coefficients combined with ETo measurements predicted ET of corn and soybean crops as well as thermal-band methods in Central Iowa, although it over-estimated ET of corn during a dry-down period. Nagler et al. (2013) showed that a MODIS EVI-based algorithm could estimate ET over seven mixed irrigation districts in the U.S., Spain and Australia with an accuracy of within 5% of measured values on an annual basis. These findings open up the possibility of monitoring ET without field-by-field knowledge of cropping patterns.

### 3.2.2.2. Physically-based vegetation methods: PT-JPL model

For regional or global application, ground reference data are often not available at sufficient spatial density to support local calibration of the *ETf*-VI relationship, so more physically-based models that require minimum calibration have been developed for large geographic scales. The PT-JPL model of Fisher et al (2008) is designed to estimate ET directly from satellite imagery with minimal ground data requirements. In the PT-JPL algorithm, λET is calculated as the sum of evaporation of water intercepted by the canopy (λEI) and soil (λEs) and transpiration from the dry canopy (λEc) (***Table 2***), where a “dry canopy” has no liquid water on the surface of the leaves. In the PT-JPL model, *ETf* for transpiring vegetation is assumed to be the product of four coefficients that account for variations in surface wetness (fwet), fraction of the canopy transpiring (fg), a temperature constraint (fT), and a plant moisture constraint (fM):

|  |  |
| --- | --- |
|  | **( 9 )** |

where Rns is Rn at the soil surface and is a function of vegetation cover (***Table 2***). Alternate formulations are available that use fractional vegetation cover without calculating Rns separately (Marshall et al., 2013). The variable descriptions and their equations are listed in Table 2. Evaporation from intercepted water on a wet canopy is:

|  |  |
| --- | --- |
|  | ( 10 ) |

Soil evaporation (λETs) is calculated separately, but also has limitation factors related to surface wetness and soil moisture:

|  |  |
| --- | --- |
|  | ( 11 ) |

Several of the parameters in Table 2 may be adjusted according to local conditions. See Fisher et al. (2008) for more detail.

Fisher et al (2008) compared the PT-JPL model predictions to measurements at FLUXNET eddy covariance towers, and report an RMSE of 16 mm/month, and an error in annual ET of 12 mm/yr or 13% of the observed mean. The flux sites covered a range of biomes, including temperate C3/C4 crops, but did not include irrigated cropland, which might be expected to have higher error due to high evaporation from inundated and wet soil at the beginning of the growing season (Yilmaz et al., 2014).

*Table 2 here. PT-JPL model calculation steps.*

***3.2.2.3. Physically based vegetation methods: Canopy resistance and MOD16***

In order to overcome the limitations of empirical methods, which require ground-level reference data for calibration, canopy resistance methods predict the resistance parameters in the Penman-Monteith equation (ra, rc in Equation **( 4 )**) directly from satellite imagery. Several resistance methods, including MOD16, are based on the model of Cleugh et al. (2007). MOD16 is vegetation-based in that the primary inputs driving ET for a given amount of Rn are derived from vegetation-indices (VI). The fraction of photosynthetically active radiation (FPAR) is used to determine the fraction of the surface covered by crop canopy (Fc) and soil (1-Fc). The leaf area index (LAI) is used to determine the dry canopy resistance to transpiration (rs\_c), the aerodynamic resistance (ra) and wet canopy resistance (rs\_wetC) to evaporation.

Dry canopy resistance to transpiration (rs\_c) is calculated using LAI, minimum air temperature and vapor pressure deficit:

|  |  |
| --- | --- |
|  | ( 12 ) |

where cL is the mean potential stomatal conductance per unit leaf area, and m(Tmin) and m(D) are multipliers (range 0.1-1) that limit stomatal conductance by minimum air temperature (Tmin) and D. The specific equations for m(Tmin) and m(D) are given in Mu et al (2007).

***3.2.2.4. Vegetation-based methods and soil evaporation***

In both the PT-JPL and MOD16 methods, ET increases with VI. Soil evaporation, including from both saturated and unsaturated surfaces, is assumed to increase with the fourth power of relative humidity (RH) (see Table 2, Figure 2). In MOD16, evaporation from saturated and unsaturated soils is calculated separately. The water cover fraction or fraction of the soil that is saturated at the surface (*Fwet*) is assumed zero for relative humidity (RH) less than 70% (0.7) (Mu et al, 2011 eq 15):

|  |  |
| --- | --- |
|  | ( 13 ) |

In MOD16, potential evaporation from soils, both saturated and unsaturated, is:

|  |  |
| --- | --- |
|  | ( 14 ) |

where rtot is the total aerodynamic resistance to vapor transport and ra\_s is the aerodynamic resistance at the soil surface (Mu et al, 2011), and total evaporation from both saturated and unsaturated soils is:

|  |  |
| --- | --- |
|  | ( 15 ) |

where fSM is the same as fSM in the PT-JPL method (Table 2). A sample plot for a range of air temperatures shows that soil evaporation as a fraction of potential soil evaporation is very small (<0.2) for RH less than 0.4, particularly for high temperatures (Figure 2). At 40°C and RH = 0.5, for example, soil evaporation is less than 0.1 of the potential. The plot highlights the assumption that soil evaporation is predicted to be very low in arid and semi-arid environments with low RH and high daytime temperature, since the model assumes that soil evaporation is a function of the regional climate, with more soil evaporation in humid regions. While this assumption may be accurate in rainfed systems, it may be problematic in irrigated areas in arid and semi-arid climates, because soil moisture may be high due to irrigation, even if the grid-cell average RH is low. This could be a problem in particular for ET estimation in areas cultivated in rice or other crops that have a significant period of inundation or wet, bare soil.

*Figure 2 here. Soil moisture function.*

The authors of the MOD16 algorithm have recognized problems with its performance in irrigated areas and wetland, and have updated the algorithm in an application in the Nile River Delta (Mu, 2013). The revised MOD16 uses radiometric land surface temperature (TR) to calculate a revised surface resistance to ET. In early 2014, NASA has officially approved this as the revised MOD16 product (Mu et al., 2013), and future evaluations of the algorithm should include irrigated and wetland environments.

Mu et al (2011) validated MOD16 against eddy flux covariance towers, and report mean absolute bias in daily ET of 0.31-0.40 mm/d, or 24-25% of observed daily ET when using GMAO MERRA for meteorological input. Their flux towers were located in a range of biomes in the United States and at several sites in the Brazilian Amazon. The validation included two irrigated sites, both of which had higher error (1.2 mm/d, 72-76% of the observed mean) compared to the mean RMSE for all sites with flux tower data.

***3.2.2.5. Comparison of vegetation-based methods***

Vegetation-based methods have gained great appeal, because they can be run globally and continuously with remote sensing and surface climate reanalysis at low computational cost. The PT-JPL model was evaluated against several other vegetation-based approaches in the humid tropics, given its simplicity and strong dependence on Rn. In regions where light limits carbon assimilation, such as the humid tropics, Rn is the dominant control on λET (Fisher et al. 2009). The PT-JPL model performed best overall, as Penman-Monteith (resistance-based) methods include more parameters, and therefore may be inherently more uncertain and more strongly coupled to the atmosphere. A comparison of PT-JPL and MOD16 show that PT-JPL overpredicted ET, while MOD16 had lower bias but higher overall error (Chen et al., 2014). Vinukollu et al. (2011a) and Marshall et al. (2013) point out that the performance of these models has been evaluated primarily with eddy covariance flux tower data and their performance can significantly degrade at larger spatial scales, due to the large uncertainties in surface climate reanalysis products, in particular RH.

**3.2.3 Temperature- and energy-balance methods for ET estimation**

Temperature- and energy-based approaches are based on the fact that ET is a change of state of water that uses energy in the environment for vaporization and reduces surface temperature (Su et al., 2005). Energy balance methods have been used as early as the 1970s, when Stone and Horton (Stone and Horton, 1974) used a thermal scanner to estimate ET, and Verma et al. (1976) developed a resistance model with thermal imagery inputs. Since then a variety of methods have been developed, including the Surface Energy Balance Algorithm (SEBAL) (Bastiaanssen et al., 2002, 1998), Mapping EvapoTranspiration at high Resolution with Internalized Calibration (METRIC™), the Surface Energy Balance System (SEBS) (Su, 2002), ALEXI (Anderson et al., 1997), DisALEXI (Norman et al., 2003) and Operational Simplified Surface Energy Balance (SSEBop) (Senay et al., 2013). Most methods in this category use surface temperature to estimate components of the energy balance, though some simplified methods (e.g. SSEB) use temperature directly without solving for the energy balance. Below we summarize the theoretical foundations of the energy balance methods, describe simplified approaches based on temperature, and highlight key differences in the most-used algorithms.

In energy-balance methods, λET is computed as a residual of the energy balance equation:

|  |  |
| --- | --- |
|  | ( 16 ) |

where G is soil heat flux, and H is the sensible heat flux (all in W/m2). While there may be some energy exchange from photosynthesis, it is usually a small fraction of Rn, is not easily measured even by ground instrumentation (Wilson et al., 2001), and assumed to be zero (Meyers and Hollinger, 2004). In vegetation having significant amount of canopy, such as forests, energy exchange from photosynthesis can become high (7-15%), particularly over short time intervals (Meyers and Hollinger, 2004).

The variables in **( 16 )** are estimated at the time of satellite overpass. In order to calculate daily total ET, most energy balance models use (18) to calculate an evaporative fraction (SEBAL, ALEXI) or a reference ET fraction (METRIC) and multiply those fractions by Rn-G or reference ET. Section 3.3.2.3.5 below details these methods, their assumptions and limitations.

*Table 3 here. Steps in the SEBAL method.*

The most important term in the energy balance equation after Rn-G is H, which, for a one-source model (***Figure 3***) is calculated as:

|  |  |
| --- | --- |
|  | ( 17 ) |

where *ρair*is the density of air (kg/m3), *Cp* is the specific heat of air (J/kg/K), T1 is the aerodynamic temperature (K) of the evaporating surface at height z1, which is the height of the zero-plane displacement (d) plus the surface roughness height? for momentum transport (z0m), T2 is the air temperature at height z2, which is usually the height where air temperature is measured (2 m or 3 m above the evaporating surface), and Rah is the aerodynamic resistance to turbulent heat transport from z1 to z2 (***Figure 3***). The model assumes that evaporating surfaces have a temperature equal to or hotter than the air above (T1 >=T2), resulting in a non-negative sensible heat flux (H). The zero-plane displacement height (d) is the mean height where momentum is absorbed by the canopy, typically around 2/3 of the vegetation height (h), and z0m is a relatively small fraction of the height of vegetation (0.03h to 0.1h, or 0.123h in Morse et al, 2000), and so is around 0.03 m over grassland, 0.10-0.25 m over cropland, and 0.5-1.0 m over forest or shrubland. In practice, z0m is estimated as a function of NDVI or with a land cover map (see Table 3).

*Figure 3 here. 1, 2 source schematic*

There are two main uncertain variables in the calculation of *H* in Equation **( 17 )**. First, the satellite directly senses the radiometric surface temperature (TR) based on thermal radiation reaching the sensor from the combined soil and canopy surfaces, which may differ from the actual aerodynamic temperature (T1). . The correspondence between TR and air temperatures at either z1 or z2 varies by surface type, roughness, and crop canopy structure. Different temperature-based models have different strategies for estimating the temperature difference between z1 and z2. Some models (which?) include an extra term in Rah, while others (e.g. SEBAL, METRIC) calibrate an empirical linear model relating T1-T2 to TR. Second, Rah has high spatial variability and may be difficult to predict.

The sensible heat flux H in Equation **( 17 )** may be estimated using either one- or two-source models (***Figure 3***). One source models, including SEBAL (Bastiaanssen et al., 1998), METRIC (Allen et al., 2007), and SEBS (Su, 2002), estimate evapotranspiration from the surface as a whole. Two-source models (ALEXI/DisALEXI) (Anderson et al., 1997) separate ET into E from soil and ET from the vegetation canopy, which is sometimes further separated into evaporation of intercepted water from a wet canopy and transpiration from a dry canopy as in the PT-JPL and MOD16 models. The separation into two sources results in two additional resistance variables that need to be estimated: Rx, the total boundary layer resistance of the canopy, and Rs, the sensible heat exchange resistance of the soil surface (***Figure 3***). The next two sections describe how one- and two-source models estimate T1-T2 and Rah, and a comparison of the performance of the two methods is presented below.

***3.2.3.1 One-source models:* SEBAL, METRIC and SEBS**

In one-source models (SEBAL, METRIC, SEBS), a linear model predicts the difference between T1 and T2 as a function of the radiometric surface temperature (***Figure 4***, ***Table 3***):

|  |  |
| --- | --- |
|  | ( 18 ) |

where a and b are empirical parameters determined from the imagery in a process called ‘internalized calibration” (Allen et al., 2007). Field investigations suggest that Equation **( 18 )** holds under a variety of conditions (***Figure 4***). Note that in applications of the method, a and b are determined from the wet and dry pixels only, with no field data of air temperatures for calibration and therefore no estimate of error of Equation ( 18 ).

Combining Equation **( 17 )** with Equation **( 18 )** gives:

|  |  |
| --- | --- |
|  | **( 19 )** |

Identifying the parameters a, b and Rah requires calculating ρair and Cp (***Table 3***) and identifying some pixels where H and TR are known. First, one pixel is selected that is “wet”, where H=0 and λE = Rn-G, and another that is “dry”, where H=Rn-G and λE =0 (***Figure 4***). Initial guesses of Rah and are calculated for wet and dry pixels, and a and b determined from the observed TR at each pixel (Table 3). The initial guess of Rah is based on literature values by land cover type, and the initial guess of is made by solving for it in Equation **( 17 )**. H is then calculated again, this time accounting for unstable atmospheric conditions using the Monin-Obukhov (MO) equations (Table 3) (Allen et al., 2011; Bastiaanssen et al., 2002, 1998). The values of a, b, and Rah are then solved iteratively by updating the values of each until the result converges on H=0 for the wet pixel and H=Rn-G for the dry pixel. The internal calibration of SEBAL and METRIC allows estimation of ET without knowing either T1 or T2, which is an advantage in data-scare regions.

*Figure 4 here. TR-dT*

Sensitivity analysis suggests that TR at the hot and cold pixels are the most important controls on H and λET estimates for a given image, followed by Rn at the hot pixel (Long et al., 2011). Since H is assumed to be zero at the cold pixel, Rn at the cold pixel does not influence the resulting model parameters and calculated H. Given the importance of TR at the wet and dry pixels, the criteria for selection are important for SEBAL and METRIC ET estimates. The selection of the “dry” and “wet” pixels in SEBAL and METRIC can prove problematic, and there is no generally agreed upon? method for selecting them (Long et al., 2011). Past applications of SEBAL and METRIC have used manual pixel selection, since some user experience in the study area is useful for selecting the appropriate pixels that represent typical field conditions in the image. This manual pixel selection can add significantly to the processing time of SEBAL and METRIC. More recently, the wet and dry pixel selection has been semi-automated, where the dry pixel is the pixel with the highest TR in the subset of pixels with specified land use (bare, urban, or dry cropland), and the wet pixel is the pixel with the lowest TR, after screening for cloud contamination using the MOD11\_L21 quality information in MODIS (Long et al., 2011). The procedure can be automated using a VI to choose pixels, which reduces variability among users and allows for more rapid implementation (Conrad 2007, Kjaersgaard et al., 2009; Messina, 2012). Automation of pixel selection in METRIC (Allen et al., 2013) selects wet and dry pixels through a combination of NDVI, TR and albedo. Other semi-automated approaches simply select the highest and lowest TR in a given image, using masks to exclude either clouds or non-representative land covers. The reasons for excluding certain land covers for the wet and dry pixel selection are often not explicit and vary by application. For the wet pixel, some studies advocate excluding water bodies since they have different aerodynamic properties than agricultural fields where ET is being estimated (Conrad et al., 2007; Morse et al., 2000) while others include water bodies, particularly if vegetated pixels have much higher temperatures than open water bodies. For dry pixels, some studies exclude urban environments (Conrad et al., 2007) while others include them (Long et al., 2011). The impact of different selection rules, including which surfaces should or should not be included, has not been determined for a range of surface types and geographic regions.

One-source models have the convenience of being relatively simple to use, and are calibrated to wet and dry pixels, reducing the need for meteorological data. However, the calibration is performed on a single image, and the a and b parameters from Equation ( 19 ) may only be valid for that image. While this may not be a problem for study areas the size of a single scene, areas that cover multiple scenes may suffer from problems of merging along scene boundaries. To the authors’ knowledge, at the date of publication there have not been any efforts to determine the spatial and temporal variability in the a and b parameters, or evaluations of the extent and magnitude of scene boundary problems. The SSEBop model (Section 3.2.3.1.1) was designed to address scene boundary problems by estimating T1-T2 for each pixel under dry and wet conditions.

Summaries of the accuracies of SEBAL are available in Bastiaanssen et al (2005) and Kalma et al. (2008), with numerous case studies (Teixeira et al., 2009). In general, the reported errors are higher for smaller spatial scales and small time intervals, and are within the errors of measurements of the device used for validation, which is typically 10-15%. Reported accuracies from numerous validation exercises using point- and field-scale instruments suggest that remote sensing-based ET estimates have errors around 50 W m-2, or a maximum error of around 15-30% for daily estimates (Kalma et al., 2008), though the errors may vary with the spatial resolution of the input data. Errors over long time scales, including the seasonal estimates of importance to water managers and assessments of water productivity, are typically lower (RMSE~5%) due to cancelling out of daily errors (Bastiaanssen et al., 2005).

Most validation sites, both for SEBAL/METRIC and for EO-based ET methods in general, are located in relatively large plots of homogeneous vegetation, which facilitates comparison with satellite imagery but may not assess accuracy well over heterogeneous landscapes. SEBAL, for example, assumes minimal advection of energy among pixels, which is likely valid over large homogenous vegetation but may not be valid in heterogeneous irrigated landscapes in semi-arid and arid climates. Advection may double the amount of ET in situations of extreme humidity gradients and high winds (Allen et al., 2011), which motivated the use of ETo and *ETf* in METRIC in place of Rn-G as used in SEBAL. For small irrigated plots in semi-arid or arid climates, the assumption of no advection may be especially problematic, though this has not been systematically quantified using one-source models.

Water balance measurements have also been used to validate remotely sensed ET at the scales of individual fields, watersheds, or irrigation projects (Bastiaanssen et al., 2005, 2002). Validation using water balances at the watershed scale is difficult in rainfed systems in arid and semi-arid environments, since streamflow as a percentage of precipitation is often within the error of ET estimated by any method. Water balance validation is more feasible in surface irrigated systems, where inflows and outflows are large relative to ET (Bastiaanssen et al., 2002).

**3.2.3.2. Two source models: ALEXI, *DisALEXI***

Two source models account for the differences in aerodynamic resistance between soil and vegetation, which are lumped into a single resistance parameter in single-source models. Two source models require estimation of the energy balance and therefore of T1 and T2 over vegetation and soil separately, and so cannot use internal calibration to wet and dry pixels like in SEBAL. One popular two-source model, the Atmosphere-Land Exchange Inverse (ALEXI) model uses the Two Source Energy Balance model (TSEB) of Norman et al. (1995). In ALEXI, T1 of the soil (T1s) and canopy (T1c) are estimated by separating radiometric temperature (TR) by the vegetation cover fraction:

|  |  |
| --- | --- |
|  | ( 20 ) |

where fc is the fractional vegetation cover at a given view angle, calculated as:

|  |  |
| --- | --- |
|  | ( 21 ) |

where Ω is an index of the degree of clumping from the given view angle, and θ is the view angle.

T2 is estimated using an atmospheric boundary layer (ABL) model (Anderson et al., 2013) calibrated to the observed increase in temperature during the morning hours (from 1-1.5 hours after sunrise to before local noon), which is obtained from geostationary satellites such as the GOES satellite (Anderson et al., 2013). Like SEBAL, the use of temperature difference instead of absolute temperature avoids the need for in-situ measurements of air temperatures or estimates of atmospheric corrections, and is a significant advantage in data-scarce regions. The ABL model used in ALEXI is a relatively simple one that can be programmed as a system of equations.

The spatial resolution of the ALEXI model is constrained by the resolution of geostationary satellites (5-10 km), so a different algorithm, DisALEXI, uses higher-resolution imagery from MODIS (1km) or Landsat (30m) to generate higher resolution ET maps? using ALEXI results (Norman et al., 2003). DisALEXI utilizes the temperature and wind speed at the blending height (~50m above the land surface) and downwelling short- and longwave radiation from ALEXI as input, assuming those four variables are spatially uniform over the resolution of the ALEXI model (usually 5-10 km). The high-resolution thermal imagery is then adjusted to the view angle of the GOES satellite to ensure consistency in the radiometric temperature. The angle-adjusted radiometric temperature, vegetation cover, and land use maps from the high-resolution imagery are then used to calculate Rn at high resolution, and the two-source model run on each high-resolution pixel with the ALEXI-derived temperature at 50m as the upper boundary condition (Norman et al., 2003). The DisALEXI values are adjusted to match the mean ALEXI values by iteratively altering the air temperature map (T2) until the aggregated DisALEXI values match the ALEXI ET values, ensuring consistency across scales.

Methods for fusing DisALEXI results using both MODIS for daily resolution and Landsat for high spatial resolution have been developed and tested over rainfed (Cammalleri et al., 2013) and irrigated areas (Cammalleri et al., 2014), based on a data fusion strategy for MODIS and Landsat (Gao et al., 2006). The Spatial and Temporal Adaptive Reflectance Fusion Model (STARFM) finds the date with the highest correlation between Landsat- and MODIS-derived ET, and uses that correlation structure to predict Landsat-scale ET on dates with only MODIS data available (***Figure 7***). The use of MODIS improves the estimation of ET over the use of a simple spline function on ET using available Landsat dates. The results highlight the importance of having daily MODIS estimates for some locations where vegetation responds to changes in moisture (***Figure 8***). At some sites (162), little difference was observed between the interpolated Landsat ET and the MODIS-Landsat fusion product, but at other sites (161), ET increased rapidly and was higher than the interpolated Landsat values for a 15-20 day period following a rainfall event.

Anderson et al. (1997) compared DisALEXI model estimates of λET with eddy covariance towers and found RMSD of 40 W/m2, MAD of 30 W/m2, and R2 of 0.77. Norman et al. (2003) also found RMSD of 40-50 W/M2 compared with eddy covariance towers, but recent implementations of DisALEXI (Anderson et al. 2013) produced lower error with MAD of 15-20% for 30 min. avg, 10% for daily, and ~5% for seasonal λET.

*Figure 7 here. STARFM*

***3.2.3.2.1. Other TSM models***

Another TSM model, the dual-temperature-difference (DTD) model (Norman et al., 2000) was based on the time rate of change in TR and T2, where the equations in ALEXI model (Anderson et al., 1997) were used to form a dual-difference ratio of radiometric and air temperatures. The H flux is then calculated from temporal measurements of T2, TR and wind speed. An ABL model was not required in implementing the model, so the calculations can be made efficiently with minimal ground-based data. Various studies have evaluated the ability of DTD TSM for deriving surface heat fluxes over dissimilar testing conditions. Generally those studies have indicated an agreement between the model-predicted λET and corresponding ground observations in the order of ~50 Wm-2 (1.9 mm/d)(Gowda et al., 2008).

Sun et al (2009) proposed another TSM energy balance model, the Simple Remote Sensing Evapotranspiration Model (Sim-ReSET). The major difference in their model compared to other TSMs was that the aerodynamic resistance (Rah) was calculated using a reference dry bare soil and canopy height, assuming homogeneous wind speed in the upper boundary layer. Unlike ALEXI, Sim-ReSET is based on a single image, and, like SEBAL and METRIC, is based on internal calibration to dry soil and wet vegetated pixels. Evaluation of Sim-ReSET was performed for a region in north China using MODIS data. Comparisons of the predicted λET fluxes by Sim-ReSET versus concurrent ground measurements from 12 experimental days showed a RMSD for instantaneous values of ~42 Wm-2 (1.6 mm/d) and a MAE of 34 Wm-2 (1.3 mm/d). Error in the mean daily ET over a six day period was lower (MAD=0.26 mm day-1, RMSD=0.30 mm day-1) as observed in other applications. Two of the key advantages of Sim-ReSET were that it avoids the direct computation of the aerodynamic resistance, and that all the model inputs required can be estimated from remote sensing data alone.

**3.2.3.3. Simplified temperature-based approaches: SSEB and SSEBop**

Several other temperature-based methods have been developed, including the Simplified Surface Energy Balance (SSEB) model (Senay et al., 2007). Similar to the crop coefficient methods in section 3.2.2.1., SSEB calculates ET as the product of? reference ET (ETo, Equation **( 4 )** or **( 5 )**) and the reference ET fraction (*ETf*). The SSEB model assumes that *ETf* for a given pixel can be estimated from the radiometric temperatures at the hot, cold, and observed pixels alone, without explicitly solving the energy balance equation:

|  |  |
| --- | --- |
|  | ( 22 ) |

where Th is the radiometric temperature of the hot pixel and Tc is the radiometric temperature of the cold pixel. Since the maximum ET of a crop with a high leaf area index may be higher than that of the reference grass, the ETo parameterized for the reference grass is multiplied by a correction factor, usually 1.2 (Senay et al, 2007). Similar to other energy balance methods, the temperatures at the hot and cold pixel are derived from the image, assuming that pixels where ET=0 and ET=1.2ETo exist in the image.

While the original formulation of SSEB is easy to implement and produces estimates for regions with a uniform hydroclimate such as irrigated districts, an improvement was necessary to account for land surface temperature differences caused by spatial variation in elevation and albedo. An enhanced version of SSEB was introduced by Senay et al (2011) to adjust the radiometric temperature (TR?) using a lapse rate correction before using it in Equation **( 22 )**. A similar lapse-rate adjustment is also performed in other temperature-based methods, including SEBAL and METRIC. A comparison between the enhanced SSEB and METRIC showed a strong relationship at elevations below 2000 m (R2 =0.91) compared to elevations lower than 2000 m (R2 = 0.52) in Central Idaho (Senay et al., 2011). The original SSEB model also calculates ETo using a fixed value for albedo (0.23). While incoming shortwave and net longwave radiation can vary by pixel under the original SSEB method, using the fixed albedo ignores the impact of spatial variability in albedo and ground heat flux on ET, which could result in overestimation of ET at pixels with high albedo, and overestimation of ET at pixels with high and positive ground heat flux. An improved version of SSEB (Senay et al., 2011) adjusts *ETf*by a factor that varies with NDVI, and ranges from 0.65 to 1.0 (Equation 6 in Senay et al. 2011). The adjustment is designed to account for generally higher albedo and ground heat flux for pixels with low NDVI, though the relationship between the adjustment factor and NDVI may vary spatially? and is not derivable from other measurements.

The original SSEB model required the selection of hot and cold pixels in the image, as in the SEBAL and METRIC models. This selection process generally inhibits operational application of such models over large areas and introduces problems along scene boundaries. The SSEBop ET algorithm is an operational parameterization of the Simplified Surface Energy Balance (SSEB) model (Senay et al., 2007), renamed SSEBop because of its operational capability (Senay et al., 2013) (*Table 4*). SSEBop proposes that the hot and cold temperatures can be determined separately for each pixel, rather than for each image. SSEBop is based on two main assumptions. The first assumption is that for each day of the year, the temperature difference (*dT*), between a hot-dry reference condition and cold-wet reference condition is unique for each pixel and day of the year. The dry-minus-wet temperature difference (*dT*) is calculated for each day and pixel by assuming G is zero for a dry surface (Rn=H, ET=0), and solving the equation (17) for the temperature difference (*dT*) for a dry pixel:

|  |  |
| --- | --- |
|  | ( 23 ) |

where the variables definitions are the same as those in Equation ( 19 ). Since T1-T2 is assumed to be zero at a wet pixel, then dT is equivalent to T1-T2 at the hot pixel. Rah is assumed to have a constant value of 110 s m-1 for a bare, dry soil based on model inversion to field data in the Western United States (Senay et al, 2013). The constant value of Rah is used for all pixels regardless of actual cover, because dT represents the temperature difference between a hypothetical bare, dry soil surface and a well-vegetated surface at each pixel. The temperature difference parameter, *dT* can be calculated for each pixel for each day of the year, and generally ranges between 5 and 25 K depending on location and season.

***Table 4 here. Steps in the SSEBop model.***

The second important assumption in SSEBop is that for a given well-vegetated cold-wet pixel or location, the theoretical cold-wet surface temperature of a given pixel can be estimated using the air temperature, *T2* as

|  |  |  |
| --- | --- | --- |
|  |  | ( 24 ) |

where T2 is the air temperature at the height of the temperature measurement, usually 2 or 3 m and *c* is a temperature correction factor estimated as the ratio of surface temperature at the time of satellite overpass to the daily maximum air temperature () for a well vegetated wet surface (*NDVI* >= 0.8). Equation **( 24 )** is based on the premise that for a given clear-sky day, the land surface will experience an ET rate equal to the potential rate (healthy, well watered vegetation, or well-watered bare soil) when its surface temperature (*TR*) is close to the near-surface air temperature (*T2*) (i.e., negligible sensible heat flux). T2 is the observed air temperature at the time of satellite overpass obtained from station data or gridded weather fields. When the temperature corresponding to the satellite overpass is not available, daily maximum air temperature can be used, and c calculated as the ratio of daily maximum air temperature and daily temperature. The use of daily maximum air temperature offers an advantage when modeling over large areas (such as regional to global modeling) as exact time of satellite overpass could be different for different locations.

Once *dT* and *Tc* are calculated, theoretical surface temperature of a hot/dry surface/pixel can be estimated as . This simplification permits the estimation of the combined coefficient as:

|  |  |
| --- | --- |
|  | ( 25 ) |

Evapotranspiration at a given pixel (λET) is calculated by multiplying *ETf* by the maximum reference ET0 or potential ET. The advantage of this approach is the simplification of the model that enables operational application over large areas with limited data requirements. SSEBop relies on the accuracy of the *TR* and *dT* estimation, so it can produce inaccurate *ET* estimates on surfaces with high albedo and emissivity values that are different from the soil-vegetation complexes found in agricultural settings. To improve the accuracy of *ET* estimates, please refer to Senay et al. (2013) for suggested methods to condition *Ts* over surfaces with high albedo and emissivity.

***3.2.3.4. From instantaneous to daily ET***

Temperature- and energy-based methods provide instantaneous estimates of ET, but instantaneous estimates may be of little use for mapping seasonal crop water use (Petropoulos, 2013). A large number of methods have been proposed for the retrieval of daytime and daily average ET from instantaneous estimates derived from EO methods?. Those methods utilise spectral information acquired in the very near infrared (VNIR) and thermal infrared (TIR) parts of the electromagnetic spectrum, and generally vary widely from purely empirical to physically-based. This section of the chapter provides an overview of some of the key approaches developed in temporally extrapolating the instantaneous energy fluxes derived from remote sensing observations to estimates of daily and seasonal ET. Analogous detailed reviews on the topic have been provided in the past by a number of investigators (Crago, 1996; Kalma et al., 2008; Petropoulos, 2013).

Satellite methods estimate ET at a single instant (SEBAL, METRIC) or over the morning hours (ALEXI). Several approaches may be used to calculate daily total ET from the instantaneous imagery (Chávez et al., 2008), though two methods are most commonly applied: the evaporative fraction approach (EF) and the crop coefficient approach. The evaporative fraction approach uses the satellite-derived ET to calculate ET as a fraction of available energy (Rn-G):

|  |  |
| --- | --- |
|  | **( 26 )** |

The evaporative fraction at the time of overpass (Λop) is assumed equal to Λ for the daytime (Λd) or during a 24 hour period (Λ24). Either daytime or 24-hour total ET is calculated as the product of Λop and the daytime net available energy (Rn-G) or 24-hour net radiation (Rn24), since G is assumed to be zero over 24 hours. The assumption that Λop equals Λd or Λ24 is justified by some field measurements (Hall et al., 1992; Jackson et al., 1983), though clouds can change the temporal stability of Λ (Crago, 1996), and modelling studies suggest there may be diurnal variation in Λ, with minimum values during mid-day that can result in underestimation of the daily mean Λ of up to 20-40% when using overpass times between 11am and 3pm (Gentine et al., 2007; Lhomme and Elguero, 1999). Clouds reduce Rn-G, but typically H decreases more than λE, resulting in an increase in Λ during cloudy periods, though this difference was not statistically significant in field studies, and the assumption of constant Λ over daytime hours is “surprisingly robust” (Crago, 1996). Other studies suggest that a correction factor should be applied that varies with time of overpass and soil moisture (Gentine et al., 2007), though in practice, a constant Λ is often assumed.

Either daytime available energy (Ad = Rn-G) or 24-hour total net radiation (Rn24) is used as the multiplier to calculate total ET from Λop. Rn24 is most commonly used to estimate ET24 given the (near) zero G term, though Van Niel et al (2011) caution that, in addition to the assumption that the evaporative fraction is constant over a 24 hour period, the use of Rn24 also assumes that net available energy (Rn-G) and latent heat flux (λET) are zero or near zero at night (Van Niel et al., 2011). Rn-G is commonly negative at night due to longwave emission from the surface. While the latent heat flux can also be negative at night, corresponding to condensation or dew formation, much of the negative available energy changes the sensible heat flux rather than the latent heat flux. The latent heat flux can also be positive at night if sensible heat is advected onto a given location, which can occur where irrigated vegetation may have heat advected to it from surrounding hotter rainfed vegetation. In an irrigated alfalfa plot, nighttime ET was >7% of total daily ET (Tolk et al., 2006). This zero or positive nighttime latent heat flux can result in significant underestimation of daily ET when using Rn24, of up to -24% to -38% when using the mid-morning value of Λop and lower errors when using mid-afternoon values (-5% to -21%). The main contributor to the error of using Rn24 was the non-zero nighttime available energy flux, which was sometimes nearly equal to the daytime available energy in a wet forest site (Van Niel et al., 2011). The error was smaller at the drier savanna site. More documentation is needed about how the magnitude of errors incurred by using Rn24 instead of (Rn-G)d to calculate daily ET depend on season, climate, and vegetation.

Other methods, including the original METRIC model (Allen et al., 2007), use the crop coefficient approach, which calculates the ratio of actual to reference ET at the time of satellite overpass, then multiplies that fraction by reference ET for the day:

|  |  |
| --- | --- |
|  | ( 27 ) |

where ET24 is ET over the 24-hour period, Crad is an adjustment applied to sloped surfaces, *ETf* is the ratio of actual to reference ET at the time of satellite overpass, and ETo24 is reference ET for the 24-hour period. Crad is likely to be close to 1 for most crops, which are mostly grown on flat surfaces, but there may be local exceptions for agroforestry crops in mountainous terrain.

The crop coefficient method was advocated over the Evaporative Fraction (EF) method by Allen et al (2007) who suggested that advection, which is not included in the EF method, is important for heterogeneous irrigated landscapes and is accounted for by the Penman-Monteith equation. A review of field studies suggested that *ETf* is relatively constant over a 24-hour period in irrigated plots (Romero, 2004), cited in (Allen et al., 2007). In one comparison study, the EF method had a lower RMSE (7.0%) than the crop coefficient method (16.6%) (Chávez et al., 2008), but the accuracies of each method likely change with meteorological conditions, vegetation, and soil moisture.

***3.2.3.5. Comparison of temperature-based methods***

As energy balance methods gained popularity for their simplicity and accuracy in measuring energy fluxes across landscapes, the merits of one-source and two-source approaches were scrutinized. Timmermans et al. (2007) compared two common energy-based methods: one-source (SEBAL) and two-source (ALEXI). SEBAL accuracy declined over hot, dry, heterogeneous terrain, because of the difficulty in selecting a dry end-member pixel within the boundaries of the remote sensing image, which is then used to calibrate an assumed linear relationship between surface temperature and aerodynamic temperature. Two-source models, on the other hand, which rely heavily on vegetation fraction, tended to be less accurate in densely vegetated areas, where small changes in vegetation cover can have significant impact on canopy and temperature estimation. Other studies suggest that two source models may perform better in conditions of either dense or sparse vegetation, or extremes of soil moisture (Anderson et al., 2013) (p212), and field-scale comparisons suggest that two-source models outperform single source models (Gonzalez-Dugo et al., 2009), though both were found to produce acceptable results.

Gonzalez-Dugo et al. (2009) used data collected during the SMACEX/SMEX02 field experiments (Kustas et al., 2005) to evaluate instantaneous λET fluxes derived from an empirical one-layer energy balance model (Chávez et al., 2005), METRIC (Allen et al., 2007) and the two-source model of Kustas and Norman (1999), the latter being an updated version of the Norman et al. (1995) TSM model that forms the basis of ALEXI (Section 3.2.3.1 One-source models). The authors reported a RMSD of less than 50 Wm-2 and less than 33 Wm-2 in the estimation of the instantaneous λET and H fluxes respectively by all methods. The fluxes predicted by the two-source model of Kustas and Norman (1999) had the closest agreement to the ground observations (RMSD of 30 Wm-2, R2=0.83), followed by METRIC (RMSD of 42 Wm-2 , R2=0.70), and last by the empirical one-layer model (RMSD of 50 Wm-2, R2=0.70). Gonzalez-Dugo et al. (2009) underlined as a major disadvantage of both the two-source model and the empirical one layer model the requirement of both models for accurate emissivity and atmospheric correction of the thermal infrared imagery used subsequently for computing the land surface temperature. METRIC had a very important disadvantage in the requirement for scene internal calibration each time, which, although it reduces the need for accurate temperature retrieval, significantly diminishes the use of this model for operational application and introduces subjectivity in the pixel selection, though recent advances at automated pixel selection may reduce problems with application and subjectivity. Gonzalez-Dugo et al. (2009) also evaluated the performances of three modelling schemes for interpolating instantaneous to daily fluxes. The schemes evaluated included the evaporative fraction (EF) method (Crago, 1996), the adjusted EF method (Anderson et al., 1997) and the reference evapotranspiration fraction (Doorembos and Pruitt, 1977 – in Gonzalez-Dugo et al., 2009). Authors reported similar accuracy among the three models. The daily λET fluxes by the adjusted EF method returned the closest agreement to the reference measurements (RMSD=0.74 mm day-1, R2=0.76). The daily λET fluxes predicted by the reference evapotranspiration method were found to be overestimated during conditions of prolonged dry down period.

Senay et al. (2007) used MODIS data for two irrigated regions in Afghanistan to compare the performances of SSEB and METRIC energy balance models in deriving spatially distributed maps of λET at 1 km spatial resolution for a time period of six years. Due to the lack of ground observations, the authors focused on evaluating the agreement between the two products. Both methods captured the patterns of seasonal variability of λET for all years compared, including the different water management scenarios applied by the farmers.

**3.2.4 Scatterplot-based methods for ET estimation**

Scatterplot methods, also called triangle methods (Gillies et al., 1997) or trapezoidal methods (Moran and Jackson, 1991), combine features of the vegetation-based and energy-based methods. Like the vegetation-based methods, they use a vegetation index (VI), but also incorporate radiometric surface temperature (TR) to account for spatial variability in soil evaporation and in evaporation from vegetation experiencing varying soil moisture stress. Scatterplot methods are based on the relationships between TR and some other satellite-derived variable, often a vegetation index (VI) or albedo, when these are plotted in a scatterplot (*Figure* ***5***). The method places theoretical boundary lines on the observed inverse relationship between TR and VI or albedo, and uses the position of a pixel in the TR-VI or TR-α space relative to those boundary lines to calculate either the evaporative fraction (Λ) as in the energy-based methods (3.2.3), or the reference evapotranspiration fraction (*ETf*) as in the empirical vegetation-index methods (section 3.2.2.1). A review of these methods including the theoretical basis of the principles underlying the scatterplot methods can be found in Petropoulos et al. (2009).

*Figure 5 here. Scatterplot illustration*

Briefly, assuming that cloud-contaminated pixels and pixels containing standing water have been masked, per pixel-level values of TR and VI usually fall within a triangular (or trapezoidal) shape in the TR-VI feature space (***Figure 5***). In Figure 5, each yellow circle represents the measurements from a single image pixel, and includes the main properties believed to be represented by the TR-VI pixel envelope. The triangular or trapezoidal shape in TR-VI feature space is the result of the low variability of TR and its relative insensitivity to soil water content variations over areas covered by dense vegetation, and its increased sensitivity to soil moisture and larger spatial variation over areas of bare soil. The right-hand side border, the “dry edge” or “warm edge” is defined by the image pixels of highest temperature for the differing amounts of bare soil and vegetation and is assumed to represent conditions of limited surface soil water content and near-zero evaporative flux from the soil. The left hand border, the so-called “wet edge” or “cold edge”, corresponds to cooler pixels with varying amounts of vegetation cover and represents the limit of maximum surface soil water content. Variation along the triangle’s base represents pixels of bare soil and is assumed to reflect the combined effects of soil water content variations and topography. The triangle apex equates to full vegetation cover. Similar to single-source temperature-based methods, pixels with minimum TR represent the strongest evaporative cooling (point A in *Figure* ***5***), while those with maximum TR represent the weakest evaporative cooling and low ET (point B in *Figure* ***5***). The triangle method defines vegetation cover directly from NDVI, whereas the trapezoid method uses fractional cover (fc?). Several methods then calculate *ETf* as the ratio of distances CB and AB (Jiang and Islam, 2001; Moran et al., 1996), though a variety of methods are used to relate the position of a pixel in the scatterplot to ET.

Scatterplot methods for the estimating ET can be divided into four groups based on the variables used in the scatterplot, namely: 1) TR-VI scatterplots; 2) Surface-to-air temperature difference and VI scatterplots; 3) TR-albedo scatterplots; and 4) day-night temperature difference and VI scatterplots. A fifth method couples the TR-VI scatterplot with a Soil Vegetation Atmosphere Transfer (SVAT) model. In the remainder of this section each of the above groups of methods is reviewed, providing some information on the methods’ principles and operation, as well as examples from its implementation in different ecosystems. A summary of the strengths and limitations of the different groups of approaches is also provided in *Table 1*.

***3.2.4.1 TR-VI scatterplot methods***

A number of methods have been proposed to retrieve regional maps of ET from the TR-VI triangular space over a number of different land cover types. Jiang and Islam (1999; 2001) suggested a technique based on an extension of the Priestley-Taylor equation and a relationship between remotely sensed TR and VI. Jiang and Islam (2001) and Tang et al (2010) use the TR-VI scatterplot? to determine the αPT value from Equation **( 5 )** by assuming it is maximum on the wet edge and minimum on the dry edge, with global maxima at the minimum TR and maximum TR. αPT is calculated for a given pixel as 1.26 times the ratio of distance CB to AB in ***Figure 5***. A key assumption in the method is that pixels with ET=0 and ET=ETo could be identified from the remotely sensed data. Jiang and Islam (2001) showed an RSMD in ET around 30% of the observed mean.

Jiang and Islam (2001) assume that dense vegetation transpires at the potential rate (ET0 or PET?), which may not be the case for soil moisture stress. Nishida et al. (2003a, 2003b) addressed this problem by estimating the evaporative fraction (Λ) with MODIS data for vegetation and soil separately, where ET from vegetation is calculated from a combination of the Penman-Monteith equation and the complimentary relationship between potential ET and actual ET, and soil evaporation is calculated using the triangle method. Λ was computed every eight days for a range of climate and biome types, and validated at selected Ameriflux sites, with good agreement (RMSD= 45.1 Wm-2 or 1.7 mm/day, bias=5.6 Wm-2 or 0.2 mm/day, R2=0.86).

Critical to successful implementation of the TR-VI methods is identification of the wet and dry edges. Zhang et al. (2006) proposed using the VI for estimating the dry and wet edges of the scatterplot. Tang et al. (2010) emphasized the importance of the accurate determination of the wet and dry edges in the accurate retrievals of the λET fluxes by the TR/VI method of Jiang and Islam et al. (2001), and proposed a novel technique for determining quantitatively the dry and wet edges over a homogenous agricultural area.

***3.2.4.2 Surface-to-air temperature difference and VI scatterplot methods***

Surface-to-air temperature difference methods (TR-T2 and VI) are similar to TR-VI methods, but replace TR with the difference between TR and air temperature above the evaporating surface (z2). Moran et al. (1994) introduced the “vegetation index–temperature trapezoid” (VITT) for estimation of λET from the dT-VI domain in areas of partial vegetation cover, based on the Penman-Monteith (PM) equation ( **4** ) and the crop water stress index (CWSI = 1-*ETf*) (Jackson et al., 1981). The PM equation is inverted following Jackson et al (1981) to estimate TR at the four vertices of the dT-VI trapezoid, and 1-*ETf* is calculated as ratio of the difference in temperature between a given pixel and the dry temperature (CB in ***Figure 5***) to the difference in temperature between the dry edge and wet edge at the pixel’s NDVI value (AB in ***Figure 5***). Inversion of the PM equation to determine TR at the four corners of the trapezoid avoids the requirement that there be a pixels in the image where ET=ETo and another where ET=0 like in SEBAL and METRIC?. Validation of the VITT method was carried out using a number of techniques over various land cover types. Moran et al. (1994) performed validation studies over both agricultural and semi-arid grasslands in Arizona, USA, using model simulations and airborne data from the Modular Multispectral Radiometer (MMR) and ground-based measurements respectively. Moran et al. (1996) used Landsat TM data to estimate ET for all grassland sites within their study region (Arizona, USA), and reported a RMSD of 29 Wm-2 in the estimation of the instantaneous λET and a consistent overestimation of λET in most sites.

Jiang and Islam (2003) modified the Jiang and Islam (1999) method, using TR- T2, also known as dT, in place of TR and also by using the fractional vegetation cover (Fr) parameter, as a proxy for vegetation amount in place of NDVI. This method was validated in various sites across the USA. In some of those validation studies, λET flux estimates were predicted with a RMSD and bias of 58.6 (2.2 mm/d) and -42.4 Wm-2 (1.6 mm/d) respectively. Venturini et al. (2004) validated the method utilizing the same sensors for a region over South Florida, with RMSD in Λ prediction varying from 0.08 to 0.19, and a R2 ranging from 0.4 to 0.7. Stisen et al. (2008) modified the method proposed by Jiang and Islam (2003) by combining it with thermal inertia information obtained from the geostationary MSG-SEVIRI sensor to estimate regional evaporative fraction (Λ) for a semi-arid region in South Senegal in Africa. Comparisons performed by the authors showed a close agreement for both EF (RMSD of 0.13 and R2 of 0.63) and the instantaneous λET (RMSD of 41.45 Wm-2 and R2 of 0.66). Shu et al. (2011) performed further validation of the Stisen et al. (2008) method using observations from the Fengyun-2C (FY-2C) satellite in combination with the MODIS satellite products over a subtropical region in the North China Plain. Authors reported an R2 equal to 0.73 and a RMSD of 0.92 mm d-1 for daily ET and R2= 0.55 and RMSE= 0.14 for Λ. A very important advantage of the Jiang and Islam (2003) method included its independence from absolute accuracy of the TR measures, since DT equal to zero in their technique always represented the true cold edge of the triangle space where Λ equals zero. Nonetheless, this method also assumed a linear variation in Λ across the triangular/trapezoid domain of (Fr, DT) feature space for each class of Fr, which might not be so realistic approximation, an issue which in part tried Stisen et al. (2008) tried to address by assuming non-linear relationships between the biophysical properties encapsulated in the TR/VI scatterplot.

3.2.4.3 TR-albedo scatterplot methods

A different group of triangle methods is based on the correlation between TR and albedo. Roerink et al. (2000) proposed the Simplified Surface Energy Balance Index (S-SEBI) method for mapping ET based on the estimation of the evaporative fraction (Λ). S-SEBI calculates Λ using the same equation that SSEB uses to calculate *ETf* ( **22** ), but in S-SEBI, Th and Tc are linear functions of albedo, where the linear function coefficients are determined from the boundaries of the TR-albedo plot. Gómez et al. (2005) extended S-SEBI to the retrieval of daily evapotranspiration (λET) from high spatial resolution data (20m) from PoLDER (Polarization and Directionality of Earth Reflectance) airborne instrument and a thermal infrared camera (20 m), with an error of 90 Wm-2 and 1 mm day-1 in the estimates of instantaneous and daily total λET respectively. The method was evaluated further by Sobrino et al. (2005) using high spatial resolution airborne images from the Digital Airborne Imaging Spectrometer (DAIS) over agricultural areas in Spain. Authors reported accuracy in daily ET prediction higher than 1 mm d-1. Sobrino et al. (2008, 2007) subsequently adapted this methodology to the low spatial resolution data provided by the AVHRR and in the framework of the SEN2FLEX (field measurements, airborne data) project for similar sites in Spain. Authors reported a mean RMSD of ~1 mm d-1 in the estimation of daily λET by S-SEBI in comparison to ground λET measurements from lysimeters. Garcia et al. (2007) evaluated three operative models for estimating the non-evaporative fraction (NEF) as an indicator of the surface water deficit in a semiarid area of southeast Spain. Other studies, such as by Zahira et al. (2009) monitored the drought status in Algerian forest covered areas with the combined use of S-SEBI with the visible, near infrared and thermal infrared bands of Landsat ETM+ imagery. Comparisons performed between the instantaneous λET fluxes predicted by S-SEBI and corresponding in-situ showed a R2 of 0.85 and a RMSD of 64 Wm-2 (2.4 mm/d). Bhattacharya et al. (2010) suggested a technique for the estimation of regional λET fluxes from remote sensing data based on the computation of the EF from the TR/albedo plot, validated over an agricultural region in India from the Indian geostationary meteorological satellite Kalapana-1. They reported an overall RMSE in the predicted daily ET estimates in the range of 25–32% of measured mean. Comparisons of the 8-day ET product over agricultural land uses yielded RMSD of 26% (0.45 mm d-1) with r = 0.8 (n = 52,853) as compared to daily ET. An important advantage of the technique of Bhattacharya et al. (2010) was that it could be implemented without the need of any ground observations, making it potentially a very good choice for operational use. Also, in contrast to some other methods discussed so far their method avoided the H flux computation prior to ET flux estimation. A limitation is the assumption of uniform atmospheric conditions, and the method cannot be implemented if contrasting features (wet and dry pixels) are not present within the image.

***3.2.4.4 Day-night temperature difference and VI scatterplot methods***

Another variant of the triangle method uses the difference between the day and night TR versus the VI. Chen et al. (2002) were the first to propose the Diurnal Surface Temperature Variation (DSTV) approach. DSTV is based on the observed relationship between the difference between the day and night time temperatures and the soil moisture and thermal inertia (Engman and Gurney, 1991; Van de Griend et al., 1985) . The technique first implements a simple linear mixture model to determine the fractional contribution of vegetation, dry soil surfaces and wet soil surfaces to the observed values of NDVI and TR. The vegetation and moisture coefficient (VMC), which is the same as *ETf* in the crop coefficient methods (section 3.2.2.1), was then expressed at each pixel as the sum of the VMC for each of the three surface types weighted by the fraction contribution at the given pixel. They implemented the algorithm with AVHRR data for a site in South Florida, USA, and showed percentage errors in the prediction of ET compared to lysimeter measurements between 2.8% to 23.9% with RMSD’s varying from 3.08 to 5.74 mm day-1. An important advantage of the Chen et al. (2002) method was its requirement for only a small number of ground parameters. However, main limitations included the constraint to assume only three land cover types in the mixture modelling and the need for two satellite derived TR values to calculate the DSTV. Similar to Jiang and Islam (2001), this required assuming that ET was the same for all dense vegetation. Also, the fact that the method required identification of areas of the three distinct land use/cover types that are required to be homogeneous and of sufficiently large spatial extend for the VMC to be estimated can be attributed as a limitation for its implementation.

Wang et al. (2006) proposed a modification to the method of Jiang and Islam (2003) using the day–night TR difference and NDVI (ΔTR–NDVI), in place of the daytime TR. Wang et al. (2006) determined spatial variations of the ΔTR/NDVI space using data from MODIS global 1km daily products collected by the Aqua and Terra satellites which were used to estimate Ʌ (parameterized as a function of air temperature and the Priestley-Taylor parameter αPT), that was then compared to observations taken during 16 days in 2004, again at the SGP site, USA. The accuracy of the retrieved Λ was significantly better than that derived from the ΔTs/NDVI measure, whilst statistical comparisons showed that the ΔTs–NDVI Λ retrievals showed marked improvement compared to those retrieved from the daytime temperature alone. The mean relative accuracy in the estimation of Λ using the new method with Aqua day/night images was reported to produce a RMSD of 0.106, a bias of -0.002 and an R2 of 0.61, which was deemed satisfactory, especially after taking into account the simplicity of the approach and the requirement for only a small number of input parameters for its implementation. However, a possible constraint for the practical implementation of the method, also reported in Wang et al. (2006), included the method requirement for spatially derived temperatures available for both day and nighttime conditions.

***3.2.4.5 Coupling TR-VI scatterplots with SVAT models***

The outputs from a SVAT model can be coupled with the TR and VI, where VI is replaced by the fractional vegetation cover (Fr). Overviews of this technique can be found in Carlson (2007) and Petropoulos and Carlson (2011). First, both NDVI and TR are scaled to the maximum and minimum values in the image:

|  |  |
| --- | --- |
|  | ( 28 ) |

where the subscripts s and o indicate dense vegetation and bare soil, respectively. Fractional vegetation cover (Fr) is calculated as the square of NDVI\* following the methods of Gillies & Carlson (1995) and Choudhury et al. (1994). In an image with a full range of vegetation cover, N\* and Fr will range from zero to one. Fr allows us to plot both the SVAT-simulated and the measured surface radiant temperatures (TR)? from the satellite sensor on the same scale. Scaled temperature is calculated as:

|  |  |
| --- | --- |
|  | ( 29) |

where TRmax and TRmin are the maximum and minimum TR for wet vegetated pixels and for the dry, bare soil respectively interpolated from the scatterplot bounds.

In the next step, the SVAT model is combined with Tscaled and Fr in order to derive the inversion equations that will provide the spatially explicit maps of ET. Initially, the SVAT model is parameterized using the time and geographic location and the site-specific atmospheric, biophysical and geophysical characteristics. Subsequently, the SVAT model is iterated until the simulated and observed extreme values of Fr and Tscaled in the Tscaled/Fr scatterplot are matched. Initial model simulations aim to align observed Tscaled with two end points (NDVIo, NDVIs) where they intersect the “dry” edge. This extrapolation to NDVIo and NDVIs guarantees that the implied temperatures along the “dry” edge for bare soil and full vegetation cover are consistent with simulations for soil moisture (Mo) of zero. Once the model tuning is completed, the simulation time corresponding to the satellite overpass is kept the same as the SVAT model is ran repeatedly, varying Fr and Mo over all possible values (0-100 % and 0-1 respectively), for all possible theoretical combinations of Mo and Fr. The result is a matrix of model outputs for a number of simulated parameters: Mo, Fr, Tscaled, λET and H. Finally, this output matrix is used to derive a series of linear or quadratic equations, relating Fr and Tscaled to each of the other variables of interest: H, λET, and Λ. The SVAT model outputs are then used to derive a series of simple, empirical relations relating each of these parameters to Fr and Tscaled recorded at that location as quadratic polynomial equations:

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where the coefficients ap,q are derived from non-linear regression between the matrix values of Fr, Tscaled and ET, and p and q vary from 0 to 3. Since these variables of Fr and Tscaled are derivable from EO data, empirical equations such as these can then be used to obtain the required spatially explicit maps of the λET?and H fluxes as well as of Mo from the satellite observations.

Gillies and Carlson (1995) first applied the technique using AVHRR images for a region in the United Kingdom. Carlson et al. (1995b) then utilized the technique to derive daily estimates of ET for a site in Pennsylvania, USA, and validated the results using ground-based measurements from the Push Broom Microwave Radiometer (PBMR) and the NS001 instrument (30 m spatial resolution). Gillies et al. (1997) validated their method using high resolution airborne data from the NS001 instrument and observations collected from the FIFE (Vernekar et al., 2003) and MONSOON 90 (Kustas et al., 1991) field campaigns. The RMSD was ±10% for ET. Brunsell and Gillies (2003) implemented the method using satellite data from the TMS/TIMS airborne (12 m) and coarse AVHRR (1 km) radiometers. Predicted fluxes from the implementation of the triangle method using the different remote sensing data were compared versus in-situ observations from the SGP test site (USA). A close agreement for the high-resolution airborne data, within ~ 15% for λET, was reported, but results from the satellite data were in poor agreement with both the observations and the airborne data (50% difference for λET). Recently, Petropoulos et al. (2010) and Petropoulos and Carlson (2011) evaluated the triangle-SVAT method at several CarboEurope sites using ASTER data. Closer agreements with the ground observations were generally found when comparisons were limited to cloud-free days at flat terrain sites. Under such conditions the triangle-SVAT method estimated instantaneous λET with a mean RMSD of 27 Wm-2.

The triangle-SVAT method has several advantages over the other scatterplot methods. First, it provides a non-linear interpretation of the TR/VI space, which can be a more realistic assumption than the linear assumption in the empirical triangle methods. The triangle-SVAT method offers the potential for relatively easy transformation of the instantaneous-derived ET fluxes to daytime averages, and allows regional estimates of the H flux and the surface soil moisture content together with the ET fluxes, potentially very useful parameters to have information for many practical applications. In addition, it offers the possibility to extrapolate the instantaneous measurements of the computed energy fluxes from one time of day to another (see Brunsell and Gillies, 2003) and to times with clouds. A disadvantage is that the SVAT requires a large number of input parameters and its parameterization also requires user expertise, complicating its implementation over large geographic areas.

**3.2.5. Seasonal ET estimates and cloud cover issues**

All three families of satellite methods for estimating ET reviewed in this Chapter (vegetation-based, temperature- or energy-based, and scatterplot-based) produce daily maps of ET that can be temporally interpolated to estimate seasonal ET, which is often the main output of concern to water managers and agriculturalists. Interpolation is necessary because the satellite platforms that generate high-resolution imagery often have long overpass return periods (e.g. Landsat at 2 weeks), and because of clouds, which compromise the generation of daily ET maps even when daily imagery are potentially available (MODIS). Cloud cover may be less of a problem in arid and some semi-arid climates, but is a significant obstacle for determining season-total ET in semi-humid and humid climates. In regions with Mediterranean climates, the main growing season in summer corresponds to cloud-free conditions and satellite methods work well for determining seasonal ET from daily values. In other locations, where the growing season coincides with the wet season, such as monsoon-dominated areas, cloud-free imagery is often not available during the main crop growing season and EO-based methods for ET estimation may need to be supplemented with other modeling approaches like the FAO-56 method (Allen et al., 1998).

Three methods to interpolate ET maps for days without cloud-free imagery are 1) the evaporative fraction (EF) method, 2) the crop coefficient method (ETf or Kc?), and 3) the simulation model method (Long and Singh, 2010). The EF and crop coefficient methods for estimating seasonal ET are very similar to the methods for generating daily estimates from instantaneous estimates, but there are special problems with cloud cover when interpolating over longer time scales that are discussed further in this section.

The EF method, which is also used to calculate daily ET from instantaneous values of the evaporative fraction (Λop) (Section 3.2.3.5), calculates ET for a date without cloud-free imagery as the product of Rn for the day without cloud-free imagery and Λop from the date with cloud-free imagery. The EF method assumes that Λop is constant between the dates of cloud-free imagery which is more likely to be violated over several days than for a single day, especially if cloud cover changes significantly. Farah et al (2004) found that Λ does not vary with cloud cover over short (weekly) time intervals over woodland and grassland in central Kenya, which encourages the use of the evaporative fraction method (Farah et al., 2004). The method may produce accurate ET values over periods of 5-10 days (Farah et al., 2004), but over many areas, cloudy conditions persist much longer. Others have found that Λ increases during cloudy periods due to a larger proportionate reduction in available energy (Rn-G) than in latent heat flux (Van Niel et al., 2011).

The crop coefficient approach calculates the ratio of actual to reference ET on the day of satellite imagery, then multiplies that fraction by reference ET for each day without imagery (Long and Singh, 2010):

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where ET24d is 24-hour total ET on the date with satellite-derived ET, ETod is reference ET on the day with satellite-derived ET, and EToi is reference ET on day i, which does not have imagery, d1 is the beginning day without ET data, and n is the end day without ET data. The ET24d/ET0d fraction can be assumed constant between images, or could be linearly varied between available ET images. Allen et al. (2007) suggest that one ET image per month is sufficient to estimate seasonal total ET, though this may not be the case under conditions of rapidly varying soil moisture conditions or surface saturation, as might be expected in irrigated areas. The crop coefficient method has been applied using the METRIC model (Allen et al., 2007) and in northern China (Li et al., 2008).

The third approach to estimating ET on days without cloud-free imagery, the simulation model method, uses satellite-based ET on clear days to calibrate a soil-vegetation-atmosphere transfer (SVAT) model or some simplified version of a SVAT model, which is then run for all days including cloudy days. Simplified models of the relationship between meteorological conditions and ET, such as the Granger and Gray (GG) model (Granger and Gray, 1989), have been used in combination with SEBAL to estimate ET during cloudy periods (Long and Singh, 2010). The GG model uses the complimentary relationship between actual and potential ET to estimate actual ET when imagery are not available. One major limitation of the GG model as currently applied is that the spatial resolution and accuracy of the ET estimates depend on the availability of meteorological data at a comparable resolution to the observed heterogeneity in ET. Other simple models of soil moisture stress have been developed that use ET derived from remote sensing to estimate model states on clear days, and extrapolate those state variable values to dates with clouds (Anderson et al., 2007).

* 1. **ET methods intercomparison studies**

Each of the three families of methods used to estimate ET has different strengths and weaknesses (*Table 1*). Temperature- and energy based methods were developed to estimate ET from irrigated agriculture, and therefore are more likely to perform best there, but are often sensitive to how they are calibrated, and sometimes depend on the existence of extreme values of ET in the image. Vegetation-based methods were developed for global application, with a focus on rainfed systems, and may have lower accuracy in irrigated systems where ET may be decoupled from a vegetation index, particularly on the shoulders of the growing season. Scatterplot methods incorporate both temperature and vegetation, but usually require internal calibration and like temperature-based methods often depend on extremes of ET to be present in the image. Studies that compare vegetation-, temperature-, and scatterplot based methods together are not common, and here we review some recent examples. Such intercomparisons are important, because vegetation and temperature-based methods have strengths in different environments, and quantitative information on which does better under what climate and land use conditions can guide the user in method selection.

Vinukollu et al. (2011b) compared three different models: Surface Energy Balance System (SEBS; Su, 2002), MOD16 (Mu et al., 2007), and PT-JPL (Fisher et al., 2008). The focus of their study was to compare the instantaneous (W/m2) and daily ET (mm) fluxes predicted by the three models implemented with data from sensors on the MODIS-Aqua satellite augmented by AVHRR data for vegetation characterization. Vinukollu et al. (2011b) compared the three models at three spatial scales. At the first spatial scale, λET from the three models was compared to and parameterized by eddy covariance flux tower data. At the second scale, a basin-scale water balance validation was performed using the models parameterized by remote sensing data. Finally, the models were compared against a hydrologic model driven by surface climate reanalysis at a global scale and on a latitudinal basis. For towers where soil evaporation plays an important role following precipitation events, SEBS and PT-JPL showed the highest and similar correlations, though large differences occurred during the primary growing season. Correlations between λET measured at towers in densely vegetated areas, such as evergreen and deciduous broadleaf forests, were highest for PT-JPL, reflecting again the importance of Rn in modulating λET in these areas. At the basin scale, however, the performance of each model was comparable. At the global scale, the vegetation and energy-based ET methods tended to underestimate simulated soil moisture storage in water-limited (arid) regions of the world. In conclusion, the PT-JPL was deemed the most accurate of the competing methods.

Ershadi et al. (2014) evaluated the PT-JPL model against SEBS, the 2011 updated MOD16 (Mu et al, 2011), and a complementary approach (Advection-Aridity model) against ET observed at FLUXNET towers. The PT-JPL model had the closest correlation with the FLUXNET-estimated ET, but compared closely with SEBS. The PT-JPL model did particularly well in densely vegetated areas and was comparable to SEBS over croplands and grasslands. On a seasonal basis, all of the models, except the PT-JPL model, exhibited strong seasonality. The poor performance of MOD16 and SEBS in densely vegetated areas was attributed to the uncertainties that arise from a large number of model input requirements and complexity, including the sensitivity of their ET estimates to resistance parameters. All of the models did poorly over shrublands and evergreen needle leaf forests, reflecting the difficulty of NDVI in capturing vegetation dynamics for these land cover types. In conclusion, the authors suggested that, for regional to global studies, an ensemble of models, weighted by the success of contributing models for each land cover type be employed, given that no one single model performs consistently well across all land cover types.

Velpuri et al. (2013) compared SSEBop ET (Senay et al., 2013) with point and gridded flux tower observations and water balance ET, gridded FLUXNET ET (Jung et al., 2011) and MOD16 ET (Mu et al., 2011) over the conterminous United States (CONUS). Point scale validation using data from 60 FLUXNET tower locations against monthly SSEBop and MOD16 ET data aggregated by years revealed that both ET products showed overall comparable annual accuracies with mean errors in the order of 30-60%. Although both ET products showed comparable results for most land cover types, SSEBop showed lower RMSE than MOD16 for grassland, irrigated cropland and forest classes, while MOD16 performed better than SSEBop in rainfed croplands, shrublands and woody savanna classes. Basin scale validation of MOD16, SSEBop and gridded FLUXNET ET data against water balance ET indicated that both MOD16 and SSEBop ET matched the accuracies of the global gridded FLUXNET ET dataset at different scales. Both MODIS ET products effectively reproduced basin scale ET response (up to 25% uncertainty) compared to CONUS-wide point-based ET response (up to 50–60% uncertainty) illustrating the potential for MODIS ET products for basin scale ET estimation. The apparent CONUS-wide uncertainties (up to 50–60%) for monthly MODIS ET represented an overall error using data from several FLUXNET stations. The uncertainty for individual stations over time is much lower as shown from previous studies, including Mu et al. (2011) and Senay et al. (2013) who reported uncertainties up to 20% (MOD16) and 30% (SSEBop), on individual station-based FLUXNET validation, and Singh et al. (2013) reported uncertainties as low as 10% for individual stations in the Colorado River basin. Thus, despite an apparent high level of uncertainty at the CONUS-scale, the spatially explicit monthly SSEBop ET products can be useful for localized applications.

Choi et al. (2009) compared three models for estimating spatially distributed λET fluxes over a region in Iowa, USA using Landsat TM/ETM+ imagery and ancillary observations from the SMACEX 2002 field experiment. The modelling schemes compared included specifically TSEB, METRIC and the Ts/VI method of Jiang and Islam (2001). TSEB and METRIC yielded similar and reasonable agreement with measured λET and H fluxes, with RMSD of 50–75 W/m2 (1.9-2.9 mm/d) whereas for the Ts/VI method RMSE was over 100 Wm-2 (3.8 mm/d). Although TSEB and METRIC were in good agreement at the point comparisons performed, a spatial intercomparison of their results of gridded model output (i.e., comparing output on a pixel-by-pixel basis) revealed significant discrepancies in modelled turbulent heat flux patterns that correlated with vegetation density, particularly for H fluxes.

**3.4. Special problems in cropped areas**

**3.4.1 Landscape heterogeneity and spatial disaggregation**

Estimation of ET from croplands using remote sensing is particularly challenging in heterogeneous landscapes where agricultural plots are small (***Figure 6***). In India, for example, there are large areas of homogeneous irrigated cropping in canal irrigated systems, but more than 50% of the irrigated area is supplied from groundwater wells, which are typically individually owned bore wells supplying small plots (<1ha). The small groundwater-irrigated plots are often topographically organized, occurring mostly near stream channels where the water table is shallow, resulting in narrow bands of irrigation (***Figure 6***), which requires mapping irrigated areas as fractional cover of 1km MODIS pixels (Biggs et al., 2006). Most globally-available datasets are at a resolution of 1km (MOD16) or coarser (PT-JPL, MOD16, GLEAM, SEBS-LF), which is significantly larger than irrigated patches in many areas. Even in the United States, where agricultural fields are large, 1 km resolution can be too coarse to resolve individual fields and to map ET differences by crop (Kustas et al., 2004). The global datasets were designed for ET estimation over large spatial scales, often as input to community land surface models, rather than to assess crop-specific ET. In heterogeneous irrigated landscapes in semi-arid climates, extreme spatial variability in soil moisture and ET means that extremes of low and high ET may occur in a single 1km pixel, which significantly reduces ET estimates in the 1km aggregated average. This could result in an underestimation of ET from irrigated cropland if no further disaggregation technique were applied. High resolution imagery (<100m, e.g. Landsat 30m) is only available at 2 weeks or greater temporal resolution, which makes its application problematic in areas with high cloud cover and dynamic land cover. Some efforts have focused on combining imagery from different platforms to generate high-resolution maps of seasonal ET. Here we review a few select studies to illustrate the potential for cross-platform downscaling.

*Figure 6 here. SEBAL high low resolution.*

Thermal imagery typically has a coarser resolution than visible and near-infrared (NIR) bands for a given spectroradiometer. For the MODIS sensor, visible and NIR bands are available at 250m resolution, while the thermal band is at 1km. For Landsat, visible and NIR are at 30m, while the thermal infrared band is 120m but has been resampled to either 60m (before February 25, 2010) or 30m (after February 25, 2010). The higher-resolution bands can be used to sharpen the coarse resolution thermal band using the inverse relationship between TR and NDVI (Agam et al., 2008; Kustas et al., 2003). The correlation between TR and NDVI may break down over irrigated areas in either the beginning or end of the growing season, where high soil moisture or standing water and therefore low TR can co-occur with low vegetation cover, so Kustas et al (2003) proposed using both NDVI and TR to downscale TR:

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|  | ( 32 ) |

whereis the predicted radiometric temperature at high spatial resolution, is the predicted radiometric temperature using high-resolution NDVI, TRlow is the observed radiometric temperature at low resolution, and is the predicted radiometric temperature using low resolution NDVI. The function of NDVI is determined from the low-resolution NDVI and TR as a quadratic equation:

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|  | ( 33 ) |

Where ads, bds and cds are empirical coefficients determined through least squares regression, and the ds subscript designates downscaling to differentiate the coefficients from the a and b parameters of the SEBAL algorithm. More complex algorithms that use all visible and NIR bands to model TR in a moving window may be more successful in irrigated landscapes (Gao et al., 2012) . Sharpening may also be attempted by combining imagery from different satellite platforms, for example by using Landsat to sharpen MODIS imagery, though this has similar problems as the intra-platform sharpening technique in areas where TR-NDVI relationships are complicated by surface irrigation (Anderson 2014).

One downscaling method, DisALEXI, was discussed in Section 3.2.3.2. DisALEXI ensures consistency in aggregated ET across scales by adjusting the high-resolution estimates to match the low resolution average, though comparisons using ET algorithms forced by imagery with different resolutions have found disagreement among imagery with different resolutions. For example, a comparison of SEBS-ET calculated using Landsat, ASTER, and MODIS data showed consistency in SEBS-ET using the high-resolution imagery (Landsat and ASTER) but much worse agreement between Landsat or ASTER and MODIS, even when the Landsat and ASTER ET were aggregated to MODIS scale (McCabe and Wood, 2006b) (***Figure 9***). This is likely due to non-linear averaging of important inputs to the energy balance equations, and needs to be acknowledged when using moderate resolution (1km) data to estimate ET. The spatial average ET from all three image sources matched to within 10-15%, suggesting that the low-resolution MODIS imagery were useful for watershed-scale estimates of ET (50 km2), but the MODIS data underestimated the variability present in the landscape. McCabe and Wood (2006) conclude that MODIS data are sufficient for estimating ET at watershed scales, but are likely not accurate for estimating crop ET at resolutions that resolve ET from individual fields.

*Figure 8 here. ET/ETo Landsat and MODIS*

*Figure 9 here. SEBS-ET, ASTER and Landsat data (top) and MODIS, ASTER, and Landsat (bottom).*

Other algorithms have been developed to downscale TR by fusing MODIS and Landsat, including those that use Artificial Neural Network (ANN) models (Bindhu et al., 2013).

**3.4.2. High-resolution ET mapping: New and upcoming platforms**

There is a pressing need for datasets that allow mapping of ET at the spatial resolution of individual fields. In developing countries, field sizes may be very small (<1 ha), requiring high resolution data for field-scale mapping (~101 m). While high resolution data exist in historical archives (Landsat, 30m) and contemporary datasets (Landsat 8, ASTER), the overpass frequency (~2 weeks for Landsat) may not be sufficient to capture high-quality data in areas with either dynamic land cover or cloud cover during the cropping season. Data from new remote sensing platforms could prove very useful for downscaling ET estimates to scales that more closely approximate actual agricultural fields. Satellites such as Sentinels 2 and 3, planned for launch in 2014 by the European Space Agency (ESA), and NASA’s Hyperspectral Infrared Imager (HyspIRI, launch date unknown at time of publication) (Hook and Green, 2013) hold promise for providing high resolution data at high temporal frequency. Sentinel-2 will provide data on visible, near infrared and shortwave infrared wavelengths at 10 or 20 m with a revisit time of 5 days at the equator and 2-3 days at mid-latitudes. This will provide unprecedented data for vegetation-based ET models, including NDVI and the leaf area index. Sentinel-3 will provide thermal imagery at 1km resolution with revisit times of approximately 1 day at the equator. This temporal and spatial resolution is similar to existing MODIS data, so the additional gains for temperature-based methods may come in downscaling the 1km data using Sentinel-2 data.

Other high resolution datasets include the Landsat series (30m), with the latest Landsat 8 data beginning in June 2013, with 14-day overpass. The Landsat archive can provide historical imagery to the late 1970s, and it has been used in many ET applications (Ahmad et al., 2006; Allen et al., 2013; Anderson et al., 2012; Glenn et al., 2011; Kjaersgaard et al., 2011; Norman et al., 2003) though problems with cloud cover may be encountered, particularly where the rainy season coincides with the cropping season. The Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) generates data with 15m resolution in the visible and 90 m in the thermal infrared bands, but the image footprints and times of acquisition are often irregular, complicating its use for seasonal ET estimation (Er-Raki et al., 2008; Galleguillos et al., 2011). NASA’s HyspIRI Mission will provide visible to shortwave infrared (VSWIR: 380 nm-2500 nm) at 60 m resolution with a revisit time of 19 days, and mid and thermal infrared (TIR, 3-12 μm) at 60 m resolution and revisit time of 5 days (Hook and Green, 2013). The high-resolution TIR data, in particular, generated by HyspIRI will be valuable for mapping ET from irrigated croplands in heterogeneous landscapes.

## 3.4.3   Limitations to Current ET Methods and Future Directions

Equifinality and other sources of error in ET models

            Equifinality arises in process-based models that have many variables in the determining equations but few actual data to populate the equations (Beven, 2006; Franks et al., 1997; Medlyn et al., 2005). These models are frequently “parameterized” (made to fit) to calibration data sets using approximated or assumed values for unmeasured variables. As a result, different models with different assumptions and levels of complexity can converge on the same output values. Equifinality in hydrological models makes the choice of a model for a given application problematical, and makes the use of models for hypothesis testing difficult, because they all tend to give the same answers. Medlyn et al. (2005) gave an example of two models for soil respiration, one based on temperature and the other on substrate availability. They were parameterized to give the same predictions for a calibration data set, but they made different predictions about impacts of global warming on soil respiration, and there was no simple way to choose between models.

In the case of remote sensing of ET, problems of equifinality can occur in process-based models for use over mixed landscapes of natural and agricultural areas, for which few spatially distributed ground data are available. Remote sensing data usually consists only of radiance values from two or three optical bands (Blue, Red, NIR), and an imperfect estimate of land surface termperature (LST) from thermal bands. However, the determining equations generally have numerous variables, including fractional cover, LAI, roughness lengths for mass and momentum transfer, albedo, emissivity, net radiation and ground heat flux (e.g., Bastiaanssen et al., 1998; Kustas and Norman, 1999). All of these are related in some way to vegetation cover, so they are often estimated by the use of vegetation indices. However, this introduces the problem of collinearity among what are supposed to be independent variables. VIs cannot be used to uniquely determine separate biophysical variables; rather, they give an integrated measure of canopy "greenness" (Baret and Buis, 2008; Glenn et al., 2008). Equifinality can be suspected to apply to surface energy balance methods as well as to VI methods that attempt to parameritize numerous variables with limited remote sensing data.

Another problem is error and uncertainty in the ground data used for calibration and validation. Ground measurements usually come from eddy covariance flux tower measurements, and these have typical errors on the order of 15-30% when compared to lysimeters or other highly accurate measurements of ET (Allen et al., 2011). A particular problem with eddy covariance data is the "energy closure" error, where the sum of measured λE + H does not equal measured Rn − G.  λE and H are usually increased to force closure (Twine et al., 2000), but usually there is no way to check if this correction improves the ET estimates. Scott (2010) compared eddy covariance results at three flux tower sites in a semiarid rangeland, at which precipitation, infilatration and runoff were also measured. Uncorrected eddy covariance data gave ET values close to precipitation minus runoff and infiltration, where data corrected to force closure overestimated ET at each site by 10-20%.

A further problem is the mismatch between scales of measurement. Evett et al. (2008) compared surface energy balance components used to calculate ET at scales ranging from weighing lysimeters (4.7 m diameter), to small plots, to whole fields (several hundred ha) captured by aerial and satellite imagery.   They concluded that even with the best equipment and expertise, it was difficult to measure ET accurately using moisture flux towers. Advection led to underestimates of ET by tower sensor systems compared to lysimeters even after correcting for energy closure. This inaccuracy affected the interpretation of remote sensing results, which depended on flux tower data for validation. They urged caution in interpreting ET data from semiarid environments with advective conditions, especially those with mixes of irrigated and dryland crops and native vegetation. In dryland areas in Spain, Morillas et al. (2013) found that a two-source energy balance model had errors of up to 90% in estimating latent heat flux compared to eddy covariance data. This was because latent heat flux is estimated as a residual and was a small component of the overall energy budget. Glenn et al. (2013) reported that both energy balance and vegetation-based remote sensing methods overestimated ET of salt-stress shrubs by 50% or more in a riparian corridor.

As this review shows, there has been a proliferation of remote sensing ET methods, most of which have uncertainty or errors of 10-30% compared to ground measurements. As also seen in this review chapter, comparison studies often do not point to a clear choice of methods due to the problem of equifinality and errors and uncertainties in ground data (e.g., Gonzalez-Dugo et al., 2009). Simple methods tend to perform as well as more complex methods (e.g., Jiang et al., 2009). Reducing the error and uncertainty in remote sensing estimates of ET must depend in part on improving ground methods for measuring ET. Furthermore, Medlyn et al. (2005) and Beven et al. (2006) recommended more rigorous sensitivity analyses of ET models. Both studies proposed statistical tests that can be used to evaluate models. They concluded that simplistic comparisons of ET models with eddy covariance data could lead to errors due to problems of equifinality, insensitivity and uncertainty in both the models and the ground data. Their main concern was Soil-Vegetation-Atmosphere-Transfer models but their conclusions can also be applied to remote sensing methods for estimating ET (Glenn et al., 2008).(Glenn et al., 2008)

**3.5 Conclusions**

This chapter provided an overview of methods for estimating ET from Earth Observing (EO) platforms, with a focus on croplands. The Chapter used consistent mathematical symbols across all methods, facilitating intercomparison of multiple techniques. The hope in providing a single comparison of multiple methods in one text is that practitioners and researchers can see the similarities among different methods and potentially see how their particular model choice could be extended to include other methods, as well as to more clearly identify the assumptions, strengths and weaknesses of each family of methods. There are many different methods that are available to use with different degrees of complexity, utilizing EO data acquired from different platforms at different regions of the electromagnetic spectrum. Techniques are also characterized by different strengths and limitations related to their practical implementation and have varying accuracy. Many validation studies have, however, confirmed at least the potential for regional- and global-scale mapping at 1 km spatial resolution, and in some cases, operational implementation.

Methods to map global ET are becoming widely available and permit estimation of ET at monthly or seasonal scales at 1 km. The global models are typically vegetation-based methods, and their ability to perform in irrigated areas, where soil evaporation may occur in dry environments, has not been extensively tested. By contrast, temperature-based methods, especially those requiring internal calibration, have been widely tested in irrigated environments but face challenges in application for geographic scales larger than a single satellite image. On this basis, we encourage further intercomparison of the different EO-based modelling schemes for deriving ET in croplands and, for operational purposes, EO-based model ensembles that integrate the spatio-temporal benefits of each method.

Most studies that evaluate the ability of different techniques to predict ET have been based on direct comparisons between predicted fluxes and corresponding in-situ measurements. Other modeling approaches, such as uncertainty or sensitivity analysis, have so far been little incorporated in such studies, despite their importance for any all-inclusive model validation/verification (Petropoulos et al., 2013b).

Remote sensing of ET has reached a certain degree of maturity. Methods that apply to global mapping of ET are widely available, and permit estimation of ET at monthly or seasonal scales at 1km. However, this resolution may not be sufficient for estimating ET from specific crops in specific locations, requiring the use of downscaling techniques. The global models are also mostly vegetation-based methods, and their ability to perform in irrigated areas, where soil evaporation may occur in dry environments, has not been extensively tested. By contrast, temperature-based methods, especially those requiring internal calibration, have been widely tested in irrigated environments but face challenges in application for geographic scales larger than a single satellite image. More validation studies for operationally distributed products need to be conducted in different ecosystems globally. Such studies, if conducted in a systematic way following an acceptable protocol, will identify issues in the algorithmic design of these products which will improve our capability to operationally estimate ET from EO sensors. More work should be directed towards the development of schemes for the temporal interpolation of the instantaneous ET estimates, as well as of downscaling approaches of ET to the resolution of individual fields where possible. We encourage further intercomparison of vegetation and temperature-based methods, and further research on downscaling to the resolution of individual fields. We anticipate that EO data from new satellite platforms planned already to be launched in the next few years alone or in synergistic use to each other will help to meet some but not all of these needs.

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**Figure captions**

Figure 1. Empirical relationship between the reference ET fraction (*ETf*) (dimensionless) and EVI (dimensionless) for a mixture of ***riparian vegetation and crops***. The sites span a range of geographic locations (San Pedro River, AZ; Imperial Irrigation district, CA; Palo Verde irrigation district, CA; Texas). The line is the best fit regression line. Reprinted from (Nagler et al., 2013) with permission from MDPI.

Figure 2. The soil moisture function used in both the PT-JPL (Fisher et al, 2008) and MOD16 (Mu et al., 2011) versus relative humidity for a range of air temperature.

Figure 3. Schematic of one (left) and two-source (right) models for temperature-based ET calculations. TR is the radiometric surface temperature detected at the satellite, and the grey lines indicate thermal radiation emission from the combined soil and canopy.

Figure 4. Example of the assumption of the linear relationship between radiometric temperature (TR) and the temperature difference between heights z1 and z2. Data are from Bastiaanssen (1998), and dry and wet pixels are added for illustration of the concept. Permissions pending from Elsevier.

Figure 5. Example of the TR-VI relationship used in TR-VI scatterplot methods. Permissions pending (necessary?).

Figure 6. Maps of SEBAL ET (mm d-1) in a groundwater irrigated area in southern India at 30m (left) and aggregated to 1 km (right). The grid in both panels represents 1 km pixels. Based on data from Ahmad et al (2006).

Figure 7. Schematic of the STARFM method for fusing MODIS and Landsat imagery for high spatial and temporal resolution of ET. {permission needed Cammalleri et al, 2013)}.

Figure 8. Time series of ET/ETo estimated using Landsat alone and using MODIS downscaled to Landsat resolution using STARFM algorithm over rainfed soybeans in Iowa. Observations are from eddy flux towers (from Cammalleri et al. 2013, need permissions).

Figure 9. Comparison of SEBS-ET calculated using ASTER and Landsat data (top) and MODIS, ASTER, and Landsat (bottom). In the top panel, tower scale refers to individual pixels of Landsat or ASTER, while aggregated are the Landsat and ASTER SEBS-ET aggregated to MODIS resolution (1km). Reprinted from McCabe and Wood (2006), {{permission needed}}