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Integrating Remote Sensing and Ground Methods to Estimate Evapotranspiration

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f_c and SR was near linear, the calculation of ET for large areas is essentially scale invariant. Hall *et al.* (1992) analyzing data from the same campaign, concluded that R_a could be estimated by VIs with an error of about 10%, and that VIs respond primarily to photosynthetically active radiation (PAR) absorbed by the live or green component of the canopy rather than dead tissue, soil or litter.

Studies by Xiao *et al.* (2004, 2005), however, in needleleaf and broadleaf forest canopies, have shown a high sensitivity of NDVI to the non-photosynthetic vegetation (NPV) fraction within canopies. They found the EVI to best depict seasonal variations in the chlorophyll-related absorbed fraction of PAR and the NDVI to best depict overall canopy absorbed PAR. It needs to be emphasized that a VI alone is not sufficient to estimate ET; the SVAT model used by Sellers *et al.* (1992) requires additional meteorological and canopy data to calculate ET_o by Equation (2).

Early studies showed good cross-site relationships between NDVI and ET when integrated over an entire growing season (Running and Nemani, 1988). More recent studies have noted a strong correlation of ET with NDVI or other VIs in agricultural (Bausch and Neale, 1987; Choudhury *et al.*, 1994; Penuelos *et al.*, 1994; Bausch, 1995; Neale *et al.*, 1996; Jayanthi *et al.*, 2001; Hunsaker *et al.*, 2003, 2005; Houborg and Soegaard, 2004) and natural ecosystems (Seevers and Ottomann, 1994; Szilagyi, 2000, 2002; Liu *et al.*, 2003; Nagler *et al.*, 2005a,b; Nagler *et al.*, 2006; Kim, 2006; Falge *et al.*, 2005). The best relationships use time series of VIs measured frequently over a crop cycle or annual growth cycle for natural vegetation. Frequently, the ET curve (measured on the ground) follows the VI curve (or VI combined with ground meteorological data to estimate ET_o) with a coefficient of determination (r^2) of 0.75 or higher, and within the measurement error of flux tower data or other ground methods for measuring ET. This applies to both agricultural crops and natural vegetation associations.

E. Application of VI Methods to Estimate ET for Agricultural Crops

The most direct application of remotely sensed VIs to ET estimation in agriculture is to substitute the VI for K_c in Equation (3). As mentioned, monthly values of K_c are now determined from tables for a pristine crop (Allen *et al.*, 1998; Allen, 2000). Typically, values of K_c for most agricultural crops increase from a minimum value at planting to a maximum value at full canopy, then K_c might decrease as the crop matures. The crop coefficient curve is the seasonal distribution of K_c expressed as a smooth, continuous function in time or some other time-related index, such as degree-days. However, the table values represent standard crop densities at a given location under optimum agronomic and water management practices, and FAO strongly recommends that they be locally modified to reflect crop development patterns and water needs under local conditions (Allen *et al.*, 2000).

Remotely sensed data for spectral reflectances can provide an indirect estimate for K_c because ET is dependent on f_c, k and LAI, and these can be integrated into a single estimate of absorbed photosynthetically active radiation by vegetation indices derived from reflectances. In an agricultural setting, ET-NDVI curves can have $r^2 > 0.90$ over a cropping season (e.g., Hunsaker *et al.*, 2003, 2005; Er-Raki *et al.*, 2007). Choudhury *et al.* (1994) modeled the relationship between K_c and ET_c and three vegetation indices for irrigated wheat in Arizona. ET_c modeled from vegetation indices compared well with lysimeter observations. Modeled results for 19 different soil types under both wet and dry conditions showed significant linear regressions between ET_c and vegetation indices, with r^2 ranging for 0.81 for NDVI and 0.88 for the Soil Adjusted Vegetation Index (SAVI). In fact, VIs were good predictors of ET across different crop types, with $r^2 > 0.80$.

Hunsaker *et al.* (2003) used NDVI measured daily over cotton fields with a hand-held radiometer to compute K_c under stressed and unstressed condtions. The NDVI-derived K_c was within 9% of the value derived from lysimeter studies, and offered a method for tailoring crop irrigation schedules to crops growing under less than pristine conditions (to prevent wasting water). The same group (Hunsaker *et al.*, 2005) derived wheat K_c from NDVI measured over different fields with different performance standards, and found that NDVI could predict K_c within 3–5% of the measured value, and offered an improved method for water allocation for actual crops (Figure 4). Similar applications of spectrally-derived K_c values were demonstrated for bean, corn, and cotton by Bausch and Neale (1987, 1989) and Neale *et al.* (1996). Most agricultural applications use ground or airborne sensor systems, because frequent-return satellite systems such as AVHRR do not have the resolution needed to monitor individual fields. However, MODIS resolution does approach the size range of individual farms. Typical plot size in western irrigation districts is 40–250 ha, which would encompass 6–40 MODIS VI pixels. MODIS imagery can be used to track the development of a crop at 16-ay intervals, while within-field variability can be tracked by less frequent Thematic Mapper or other higher resolution imagery.

F. Application of VI Method to Natural Ecosystems

The same approach can be extended to natural ecosystems if ground measurements of ET are available. Nagler *et al.* (2005a,c) correlated MODIS EVI with flux tower data from eddy covariance and Bowen ratio stations set in the major plant associations on the Upper San Pedro, Middle Rio Grande, and Lower Colorado Rivers in the southwestern United States. MODIS and flux tower data were available for nine towers covering the period 2000–2004 (although some tower sites did not cover all years). The individual pixel encompassing each flux tower was extracted. A statistical analysis showed that ET was more closely correlated with EVI than NDVI at each individual tower site and for all sites combined. The only meteorological variable that was

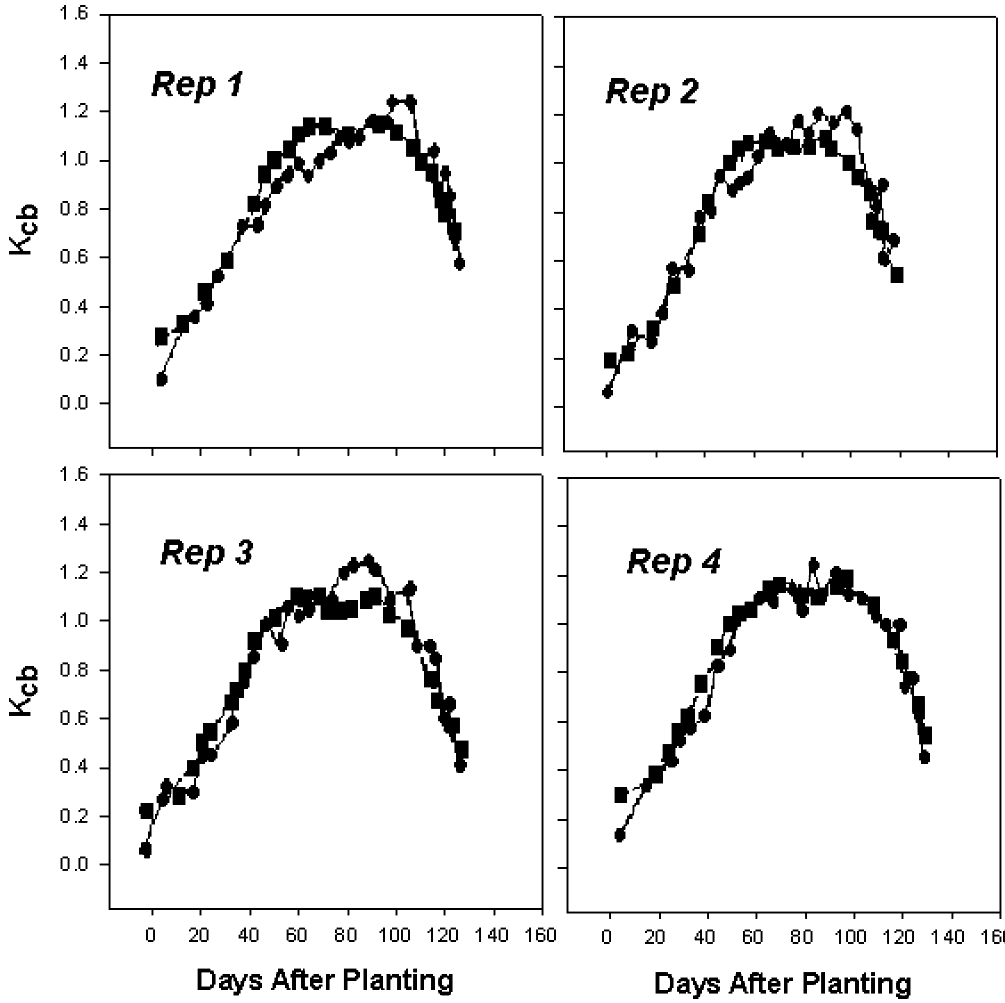

FIG. 4. Crop coefficient (K_c) values for wheat, relating actual ET to potential ET, as measured by water loss from crops grown in precision weighing lysimeters (measured K_c) (circles) vs. values calculated from an equation of best fit relating ET to NDVI measured over the crop (predicted values) (squares). The graphs show four individual replicate plots over a complete growing season. Redrawn from Hunsaker *et al*. (2005).

significantly correlated with ET was air temperature. A regression equation using EVI and meteorological station maximum daily air temperature (T_a) predicted ET with an r^2 of 0.76 across plant types, sites and river systems (Figure 5A). The ET:EVI:T_a relationship was then projected over large river stretches and multiple plant associations on each river. The study showed that riparian ET was considerably lower than had been estimated by indirect, water balance methods, and that the exotic shrub, saltcedar, that had been thought to be a high water user, was actually a low to moderate water user compared to native vegetation.

Nagler *et al*. (2007) extended the range of plant communities to include upland desert sites in the Upper San Pedro basin (Figure 5B). They correlated 16-Day, MODIS EVI values with ET from two moisture flux towers set in sparse grass and creosote shrub sites. The time series was from 2000 to 2004. ET was strongly correlated with EVI at both sites, and ET over combined sites was predicted with an r^2 of 0.74 by a simple multiple linear fit of ET to EVI and precipitation (P). The standard coefficients for ET on EVI and P were 0.78 and 0.14, respectively, indicating the fraction of the variability in ET that could be explained by each variable. EVI was considered a surrogate for T, since T is related to foliage density, whereas P was a surrogate for E, since bare soil evaporation only proceeds for a few days after a rain event in this environment. Hence, T dominated ET even in this sparse landscape, and over five years greater than 80% of P was consumed in ET.

Yang *et al*. (2006) combined MODIS EVI, LST, and land cover class data with ground-based estimates of R_s to scale ET measured at AmeriFlux sites over the continental U.S. They divided the data into training sets and validation sets, and found the equations of best fit with an inductive machine-learning technique that determined the best non-linear combination of independent variables to explain the dependent variable. They were

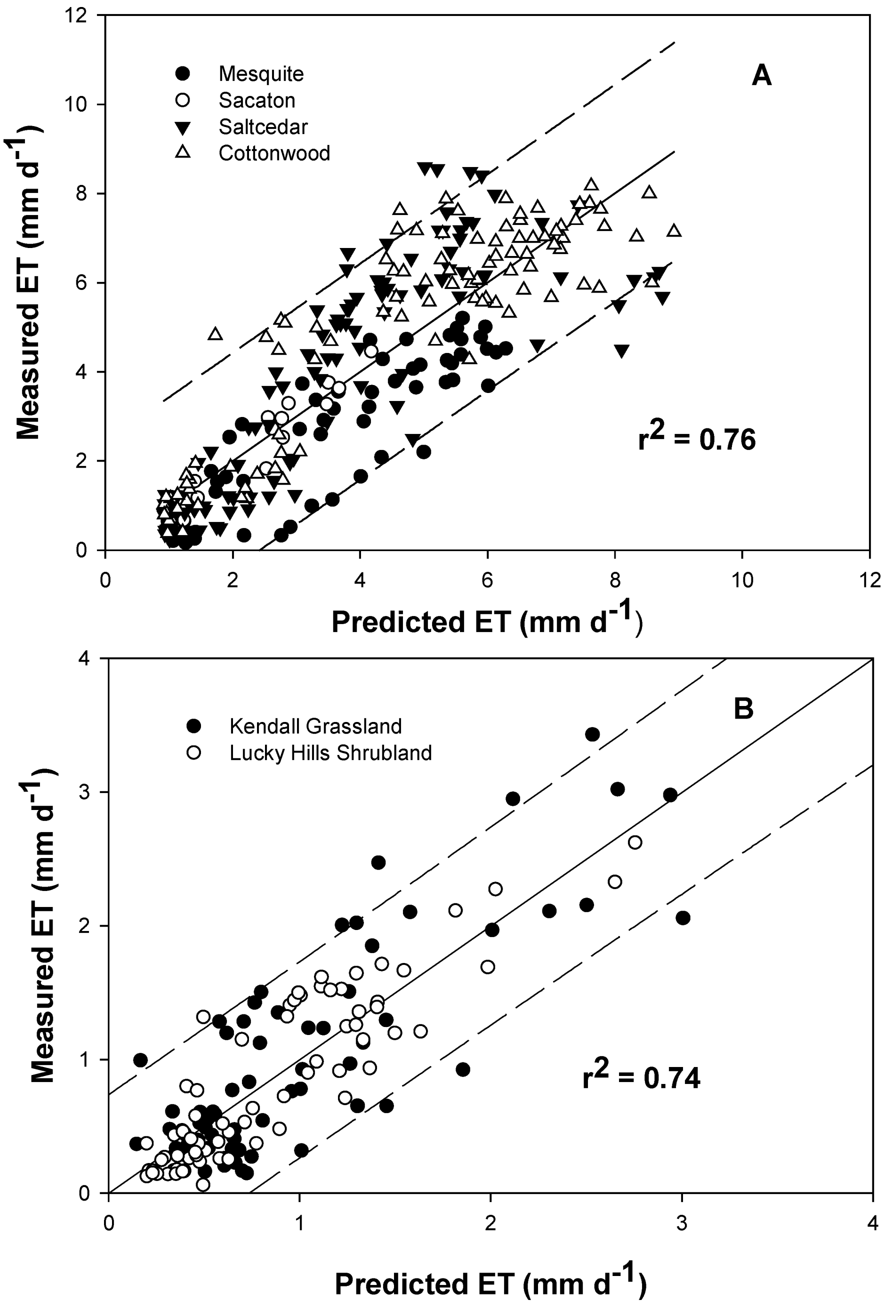

FIG. 5. (A) Measured vrs. Predicted ET at nine moisture flux tower sites on the Middle Rio Grande, Lower Colorado River, and San Pendro River in the western U.S. Results are presented by the dominant plant species at each tower site. ET was predicted from MODIS Enhanced Vegetation Index (EVI) and air temperature data measured on the ground. (B) Measured vrs. Predicted ET at grassland and shrubland moisture flux tower sites in a semiarid rangeland in Walnut Gulch, Arizona. ET was predicted from MODIS EVI and precipitation. Dashed lines show 95% prediction intervals. Data are 16-day means over 2000-2004 at each site. (A) is redrawn from data in Nagler *et al*. (2005c) and (B) is redrawn from Nagler *et al*. (2007).

able to predict ET at the validation sites over 16-day intervals with an r^2 of 0.75 and a mean square error of 23% of tower values, within the error range expected among flux towers. They then used the model to predict the spatial distribution of ET over the co-terminus U.S. for 2004, and showed that their model captured the spatial and temporal variations in ET determined by ground data.

A possible pitfall of time series studies is that both ET and VI can independently follow the same seasonal trend, producing a spurious autocorrelation. Szilagyi (2000, 2002) circumvented this problem by regressing annual rates of ET, measured over different catchments areas in Georgia over multiple years by water balance methods, against time-averaged NDVI values from AVHRR sensors. He obtained an r^2 of 0.88 between ET and NDVI over catchments and years, well within the error term of the ET estimation.

G. Limitations of VI Methods

Despite the good agreement between predicted and measured ET over diverse landscapes, VI-based scaling methods have limitations. Since they rely on foliage density as the main independent variable, they do not adequately account for direct evaporation from soil or leaves following rainfall events. Methods that are calibrated against flux tower data do incorporate both E and T into their overall estimate of ET, so annual estimates of ET are not biased, but the temporal response of E and T to precipitation are different. E is expected to be highest immediately following a rainfall event when the soil and leaves are wet, whereas T has a much more attenuated response to precipitation.

The linear regression model developed for semiarid grassland and shrublands (Nagler *et al*., 2007) incorporated precipitation as an independent variable, which can be regarded as a surrogate for E over the 16-day time steps of MODIS measurements. E can also be estimated by the FAO 56 method (Allen *et al*., 1998), based on precipitation and other meteorlogical data from micrometeorology stations.

Another limitation is that empirical VI models cannot be expected to work outside the application for which they were developed. The models have in common that they use VIs to estimate foliage density and micrometeorological data and flux tower data to calibrate VIs to ET for a particular application. However, they differ in the suite of variables that calibrate ET to meteorological conditions. In the continental-scale model of Yang *et al*. (2006), R_s was the most important explanatory variable after EVI, whereas in the riparian ecosystems, T_a was the second most important variable, and in agricultural crops, ET_o was the most important variable after NDVI (Hunsaker *et al*., 2003, 2005), while in semiarid rangelands (Nagler *et al*., 2007), precipitation was the second independent variable after EVI. These differences simply reflect the fact that different limiting factors for ET apply in different ecosystems. For example, at a continental scale, $R_s$differs widely over the U.S. and is the limiting factor for ET (Yang *et al*., 2006), whereas in western riparian corridors, R_s is not limiting, but rather atmospheric water demand, determined by T_a, is the main seasonal factor controlling ET (Nagler *et al*., 2005a,c). Hence, we cannot expect to develop a universal model for ET with VI-based empirical methods, and a given model will not be useful outside the range of conditions for which it was developed and validated.

Time-series VI methods are also limited by the coarse resolution of frequent-return satellite sensor systems. MODIS, with 250 m resolution in the Red and NIR, is an improvement over the AVHRR series of satellites with 1 km resolution. However, this resolution is too coarse to detect within-field variability in agricultural districts, or separate plant associations in patchy ecosystems.

Finally, VI-based models are useful at time scales of weeks to years, but they cannot capture changes in ET at time scales of hours or days needed to model ET as a function of micrometeorological conditions over the course of a day, or to detect incipient stress in plants. Therefore, VI-based methods are adequate for seasonal and annual monitoring of ET, but not for tasks that require an early detection of plant stress, such as irrigation scheduling. LST footprints can be used to detect stress effects on vegetation without the need to know absolute values of LST (e.g., Wan *et al*., 2004a; Park *et al*., 2005). Useful drought and stress detection algorithms have been developed as products for MODIS based on normalized LST data (Nishida *et al*., 2003a).

V. SURFACE ENERGY BALANCE METHODS TO ESTIMATE ET BY REMOTE SENSING DATA

A. General Approach

SEB methods were developed starting in the 1970s (Sone and Horton, 1974; Verma *et al*., 1976; Jackson *et al*., 1977; Price, 1982; Seguin and Itier, 1983; Jackson, 1986), and they have been the subject of many hundreds of papers and numerous NASA-sponsored field campaigns over three decades (reviewed in Kustas *et al*., 2003; Li and Lyons, 1999; Diak *et al*., 2004; Overgaard *et al*., 2006). They are physically-based models that have the potential to model ET over short or long time steps and over diverse sets of meteorological conditions. Most of these methods attempt to calculate λET as a residual of Equation (1), once R_n, G and H are determined through a combination of ground, remote sensing, and modeling techniques. R_n can be obtained from ground stations equipped with net radiometers, or estimated by remote sensing data (Jackson, 1984). The GOES sensors provide hourly solar insolation (R_s) values for the U.S. that take into account cloud cover and are accurate within 10% of ground measurements (Diak *et al*., 2004).

R_n is determined from R_s by subtracting out the shortwave and longwave radiation reflected or emitted from the canopy. Shortwave reflection is a function of the albedo of the surface, which differs for vegetation and bare soil. R_n can be determined in several ways, using ground or remote sensing data. A simple remote sensing method is to determine f_c by VIs, then to partition albedo into vegetation and soil fractions using measured or assumed albedo values for each fraction, such as 0.23 for vegetation and 0.15 for light colored soil (e.g., Jackson *et al*., 1985; Bastiaanssen, 2000). Albedo is also available from the GOES sensors as 20 day, clear-sky composites with 10 km resolution (Diak *et al*., 2004). Upward and downward long-wave radiation terms often result in a low residual term that is sometimes ignored in calculation of R_n, or modeled values can be used based on LST (Bisht *et al*., 2005). MODIS sensors can be used to provide an instantaneous measurement of R_n, and this

E. The Problem of Temporal Scaling of ET

Yet another problem in estimating ET by Equations (1) and (11) is that H and therefore ET are calculated only at the time of satellite overpass, providing essentially an instantaneous measurement. On the other hand, surface fluxes are variable over short time periods since they are driven by the stochastic process of turbulent flow (e.g., Cooper *et al.*, 2000). Most frequently, estimates of ET are required for daily or longer time periods, and extrapolating instantaneous data to these time scales introduces error.

The most common method of extrapolating ET estimated at the time of satellite overpass to a daily time step is to express ET as the evaporative fraction (EF):

$$EF = \lambda ET/(R_n - G) = \lambda ET/(\lambda ET + H) \quad [13]$$

where R_n, G and H are all estimated at the time of satellite overpass. Several studies have suggested that for unstressed vegetation, EF can often be treated as a near constant over the daylight hours (Jackson *et al.*, 1983; Hall *et al.*, 1992; Crago, 1996). Hence, an instantaneous estimation of EF at midday (when most satellite overpasses occur) can then be scaled over a day through knowledge of R_n over 24 hours (G is usually 0 over a diurnal cycle).

Hall *et al.* (1992) in their analysis of data from the first FIFE campaign, showed that this was a reasonable approximation for 20 stations on the Konza Prairie over a four-day period. However, in an analysis of ground data from 12 flux stations in southwest France, Nichols and Cuenca (1993) reported that midday EF and all-day EF were strongly, linearly related ($r^2 = 0.80$) but were not statistically equivalent. Furthermore, all-day ET estimated from midday measurements of EF, Rn and G overestimated measured ET by 25–40%.

Wilson *et al.* (2003) determined the diurnal centroid for surface fluxes from FLUXNET sites and found that peak values for H and λET do not necessarily occur at the same time of day, and that the diurnal flux responses are dependent on factors such as horizontal advection, afternoon stomatal closure, and atmospheric stability over the course of the day. Colaizzi *et al.* (2006) tested different models for scaling instantaneous measurements of ET to daily values over bare soil and several types of crops. A single 0.5-hour measurement of ET, determined at midday in precision weighing lysimeter, was scaled over 24 hours by five models based on the quasi-sinusoidal nature of daily ET, R_n, R_s, and ET_o. Then measured total daytime ET was compared to the modeled values. The models did not perform equally, and in general errors increased as ET increased. Modeled values were generally within 10% of measured values for transpiring crops, but were over 30% for bare soil.

F. Approaches to Circumventing SEB Problems

Numerous studies have addressed the problems associated with estimating H and therefore λET by SEB methods. Hall *et al.* (1992), reviewing data from the first FIFE campaign, concluded that there is no unique relationship between LST and T_{Aero} that can be used to accurately predict H over the mixed landscape scenes and temporal and spatial scales encountered in remote sensing applications. Diak *et al.* (2004), reviewing the state of the art a decade later, came to the same conclusion. However, numerous innovative methods have been developed to circumvent, if not solve, the problems associated with the SEB approach to ET estimation. Although the approaches differ, many of them have a common element; they use information available from the scene (image area) to provide context for estimating the SEB elements. The methods fall into three overlapping groups: one-source models, that treat the landscape as a single unit; trapezoid or triangle methods, that plot VIs against LSTs to infer information on ET for each pixel in a scene; and two source models, that divide the landscape into vegetated and unvegetated units, and estimate the SEB for each separately. Examples of each approach are given in the following sections, then they are evaluated in terms of accuracy and utility.

G. SEBAL: A One-Source Model

The Surface Energy Balance Algorithm for Land (SEBAL) method is a one-source model that has been developed as a commercial product for ET estimation at the field, project and basin scales of measurement (Bastiaanssen *et al.*, 1998; Bastiaanssen, 2000). As in other SEB methods, SEBAL circumvents the problems inherent in an instantaneous estimate of ET by calculating the evaporative fraction (EF).

The most important innovation of the SEBAL method is that it circumvents the problem of estimating true values for T_{Aero} and T_a by "self-calibrating" them from information in the image or area of interest within an image. By inspection of the image, "cool" pixels are located, representing water surfaces or fully transpiring vegetated surfaces. For these pixels, SEBAL takes the apparent surface temperature of those pixels as the value at which to anchor $H = 0$ and $\lambda ET = R_n$. Then, again by inspection of the image, "hot" pixels are identified, representing dry bare soil. These pixels are assumed to have $H = R_n$-G, and their apparent surface temperature anchors the value at which $\lambda ET = 0$. An absolute value for T_{Aero} is no longer needed, and the term (T_{Aero}-T_a) in Equation 11 is replaced by ($a + bT_R$) where a and b are empirical coefficients defined by the hot and cold pixel values for each image. The fractional values for H and λET contributing to Rn-G can then be calculated for each pixel. R_n is determined for each pixel from R_s by partitioning the surface into soil and vegetation (using NDVI) then assigning albedo values to each fraction, and by estimating net longwave radiation from LST. G is determined as an empirically-derived function of albedo, LST, R_n and NDVI.

Although SEBAL circumvents the problem of requiring absolute values for T_{Aero} and T_a, it still requires an estimate of (r_h+ r_b) in Equation (11) to estimate H. These are estimated

0.62–0.74). This model has been improved and adapted to the GOES satellites. Diak (1990) and Diak and Whipple (1993) implemented a time-difference approach for portioning available energy into λET or H by using the rate of rise of LST from GOES and the growth of the atmospheric boundary layer. By using the time rate of change of LST, the need for absolute accuracy in LST is reduced. In the Atmosphere-Land Exchange Inverse (ALEXI) model, LST is measured at 1.5 h and 5.5 h after local sunrise (Anderson, 1997; Diak *et al.*, 2004). Through knowledge of LST and T_a (projected to 50 m) at two time points, and the growth in thickness of the boundary layer, H can be calculated based on the conservation of energy without absolute knowledge of LST at either time point. The ALEXI model has been further refined by incorporating higher resolution imagery to delineate the 20 individual land cover types (required to calculate roughness lengths) within each 10 km GOES pixel (Norman *et al.*, 2003). The two-source model adapted to the GOES sensor systems is being used to estimate fluxes over the continental U.S. at 10 km resolution, and the results are translated into moisture indices for soil (E) and vegetation (T) units of the landscape (Diak *et al.*, 2004).

Nishida *et al.* (2003a,b) adapted the two-source method to develop an operational model for predicting ET from MODIS VI and LST data. They used NDVI to divide the landscape into bare soil and vegetated fractions. ET for the vegetated fractions was calculated as the evaporative fraction based on a satellite-derived value of available energy and a canopy-conductance model with meteorological inputs to calculated actual ET. MODIS LST was used to estimate evaporation from bare soil. Modeled values compared to values measured at AMERIFLUX towers had an r^2 of 0.71. Venturini *et al.* (2004) found that MODIS and AVHRR sensors estimated similar values for EF over South Florida, using a simple two-source model for ET, even though absolute LST and NDVI values differed between the satellites.

J. Limitations of SEB Methods

As physically-based models, SEB methods are a powerful tool for hypotheses testing and for simulating different climate scenarios. However, like VI methods, they have limitations. These include problems of sensitivity, scaling, and equifinality, the tendency of models with different assumptions and levels of complexity to converge on the same predicted outcomes. Regarding sensitivity, SEB models often only work well within a narrow range of surface conditions for which they were developed and calibrated. As an example, Li *et al.* (2005) tested the two-source model of Norman *et al.* (1995) against a refined version during the SMACEX campaign over partially vegetated corn and soybean fields in the Great Plains region of the United States. The original model had resistances in parallel, with no interaction between vegetated and bare soil patches. The refined model had resistances in series, thereby accommodating interactions between clumps of vegetation and bare soil areas. Outputs from the two models were compared to ET measurements from 12 flux towers set in different fields in the study area. A sensitivity analysis showed that both models showed a rapid rise in predicted temperature and H at f_c above 0.4–0.6 (Figure 7). The rise in H with increasing f_c is not expected (H should decrease as vegetation cover increases) and is an artifact of the iteration procedures which adjust H and ET to conserve the energy balance. Hence, as with empirical VI methods, care must be exercised in applying an SEB model outside the range of conditions under which it was developed and validated.

The scale problem arises in part because LST measurements, on which SEB methods depend, are not scale-invariant (e.g. Hall *et al.*, 1992). LSTs measured at a fine scale cannot necessarily be aggregated to estimate LST over a larger area. McCabe and Wood (2006) investigated the scaling problem by comparing ET predictions from satellite sensor systems with different degrees of resolution. They used a SEB model that combined remote sensing and ground meteorological data to estimate R_n, G, and H, with ET calculated as the residual (Su, 2000; Su *et al.*, 2005). The model defines a wet-limit and dry-limit for H based on ground meteorological data, and uses ground data as well as LST, NDVI and other satellite data to calculate model parameters such as albedo, roughness lengths, emmissivity, LAI, and f_c. The study compared flux tower ET data to model results using data aquired by Landsat ETM + (60 m resolution), ASTER (90 m), and MODIS (1020 m) over two days on the Walnut Creek watershed in Iowa, targeting soybean and corn fields as well as the whole catchment. ETM + and ASTER ET predictions were highly consistent with each other ($r^2 = 0.96$) and fell on a 1:1 line, but the MODIS estimates were only moderately correlated with the high-resolution images, although they gave a similar estimate of ET over the whole catchment. However, the satellite predictions of ET were not highly correlated with tower predictions for any of the sensor systems (Figure 8). The authors concluded that MODIS could be used for regional-scale ET estimates but did not capture the spatial distribution of ET in the watershed.

The scale problem also arises because, as discussed in **V–E**, satellite sensors provide only a snapshot of LST at the time of overpass. Unlike foliage density, which has a dampened response to environmental factors, LST and local micrometeorological conditions are volatile over time spans of 30 minutes or less. Cooper *et al.* (2005) used a laser technique (LIDAR) to measure turbulent flux over riparian plant associations in the southwestern U.S., and reported that the 30-minute spatial variations in fluxes over the canopy were almost as large as the mean values, setting a limit to the potential accuracy of ET estimated by a single satellite overpass.

Equifinality is not just a problem in ET modeling, but confounds attempts to compare modeling approaches in all the earth sciences as well as other disciplines (Beven and Franks, 1999; Franks *et al.*, 1997; Medlyn *et al.*, 2005; Beven, 2006; Ebel and Loague, 2006). In this paper, we have seen that many of the parameters for SEB models are approximations rather than actual measurements, and that the field methods for validating the ET models have errors or uncertainties on the order of over the preceding four decades, and that even fewer of the advances had been used successfully in practice, providing "... only trivial or dubious answers to important environmental questions." The biggest problem he perceived was the inability, at the time, to make routine measurements of ET in the natural environment, leading to an over-reliance on SVAT and SEB models at the expense of actual data in predicting ET.

In our review, the succeeding thirteen years have been characterized by rapid progress in ET research and applications. Although the same SVAT and SEB models for ET that were developed fifty years ago are still used today, the difference is in the quality of data that can be applied to the models. This is seen by two examples of deficiencies cited by Morton (1994).

One example he cited was the inadequacy of the Penman-Monteith Equation in capturing plant-atmosphere feedback effects (Morton, 1994). Equation (2) shows that ET should increase as VDP increases due to higher atmospheric water demand, but in reality, plants often partially close their stomata to conserve water in response to a rise in VPD, leading to an opposite effect (Morton, 1994). Equation (2) allows the plant response to be adjusted through the stomatal resistance (r_s) term, but r_s is difficult to measure and was often treated as a constant over daily time steps in 1994. Today, flux towers provide sufficient data that Equation (2) can be inverted to provide estimates of actual stomatal resistance in half hour steps, allowing both r_s and ET to be tracked as a function of meteorological and other environmental factors. As an illustration of this methodology, Scott *et al.* (2004) used ET and micrometeorological data from eddy covariance flux towers to determine the effect of pre-monsoon and post-monsoon meteorological conditions on the stomatal resistance of riparian plants along the San Pedro River in the southwestern U.S. By inverting the Penman-Monteith equation, they were able to plot r_s as a function of VPD across seasons, and in response to changes in depth to the water table, affected by natural cycles as well as pumping of water for human use.

The second example of data deficiency cited by Morton was the inability to measure ET over spatial and temporal scales that are relevant to environmental sciences (Morton, 1994). At the time, ET_o was typically estimated by pan evaporation or limited amounts of micrometeorogical data then extrapolated through SVAT models to wide areas. Today, the hundreds of micrometeorological stations and flux tower sites distributed in agricultural and natural ecosystems can be combined with satellite remote sensing systems to project ET over local, regional, and continental scales of measurement in near-real-time, as seen in this review and others (e.g., Diak *et al.*, 2004; Nagler *et al.*, 2005c; Yang *et al.*, 2006; Scott *et al.*, 2007). These and other technical advances have allowed the interactions between plants and the soil-atmosphere system to be elucidated at environmentally-relevant scales, contributing to the emergence of the new multidisciplinary science of ecohydrology (Huxman *et al.*, 2005; Newman *et al.*, 2006).

B. Accuracy of Current ET Estimates and Prospects for Improvement

The current error or uncertainty in most wide-area ET estimates is in the range of 20–30%. This is due partly to simplifying assumptions built into SEB models for estimating parameters such as T_{Aero}, LAI, f_c, and transport coefficients (Jiang *et al.*, 2004; Overgaard *et al.*, 2005), and partly to uncertainty in the flux tower measurements, such as the unresolved issue of energy closure in eddy covariance methods, which are currently the most direct methods to measure moisture fluxes over canopies (Wilson *et al.*, 2002). On the other hand, under ideal conditions in agricultural plots, when actual ET can be measured in weighing lysimeters and meteorological variables are measured at ground micrometeorology stations, VIs calibrated with micrometerological data track ET with differences of less than 10% (e.g., Figure 4; Hunsaker *et al.*, 2005; Er-Raki *et al.*, 2007). In natural ecosystems, the r^2 between VIs and ET measured at flux towers can exceed 0.9 (Nagler *et al.*, 2005a), but decreases when data from different types of towers (Bowen ration and eddy covariance) are combined (Nagler *et al.*, 2005c). This suggests that much of the scatter between measured and predicted ET might lie with the ground measurements of ET. Therefore, as ground methods for ET measurement improve, we can expect that remote sensing estimates of wide-area ET can also be improved, due to the high fidelity between VIs and ET.

C. Comparison of VI Statistical Methods and SEB Methods for ET Estimation

Since the 1980s, SEB methods have been the preferred method for estimating wide-area ET in the remote sensing community and by atmospheric scientists (Overgaard *et al.*, 2005). The physical basis of SEB and SVAT models makes them valuable for hypothesis-testing about controls on surface fluxes, and for inclusion as components in Global Climate Models. On the other hand, now that flux towers are widely distributed in different biomes, the alternative approach of directly scaling ground measurements of ET through empirical VI methods has also become feasible. These methods work because ET and ANPP are closely correlated with foliage density as measured by VIs. On the other hand, VIs are less useful in estimating canopy attributes such as f_c, LAI, or roughness lengths of canopies, which are required in SVAT and SEB models.

Simple VI:ET models can be useful in specific applications for which ET is required, but they cannot replace SEB methods in accounting for all the surface flux components needed in land surface and climate models. The GOES SEB ensemble of models is an example of such a system, providing 10 km resolution, real-time measurements of R_s, LST, cloud cover, albedo, upward and downward longwave radiation, R_n, H, G, ET_o and λET within a consistent SVAT framework. Therefore, we project that the path forward will include high-resolution, time-series VI methods for agricultural-and-ecosystem-scale ET estimation, and continuous (GOES) or daily (MODIS) optical band and LST methods for monitoring ET and other elements of the SEB at the regional and continental scales.

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