Automated mapping of evapotranspiration from irrigated crops using global climate grids and MODIS data: Comparison of energy- and vegetation-based methods with *in situ* observations

Trent W. Biggs

Michael Marshall

Alex Messina

**Abstract**

Two automated methods for estimating ET, one vegetation-based (MOD16) and one temperature-based (SEBAL) are compared over irrigated areas using only global climate grids (GMAO) and remote sensing data (MODIS) as input, validated with eddy flux correlation towers over several irrigated crops (maize, rice, cotton) in the Central Valley of California. Automated selection of wet and dry pixels in SEBAL was based on quantiles of the cumulative distribution of land surface temperature (TR) and normalized difference vegetation index (NDVI). For maize, MOD16 had lower relative mean bias in mean seasonal ET (rMB 0-10%) compared to SEBAL (rMB 14-17%) but MOD16 significantly underestimated ET from rice (rMB -50%) and cotton fields (-78%), with the largest error in the early stages of the growing season when NDVI is low but land surface wetness index (LSWI) is high. SEBAL underestimated ET from rice (rMB -24%) and cotton (-28%) but with lower rMB than MOD16. Error in SEBAL evaporative fraction (Λ=ET/Rn), which controls for errors in Rn, was lower for rice and cotton but higher for maize due to underestimation of Rn in SEBAL. Field-measured crop height, rather than fractional vegetation cover (FVC) or aboveground wet biomass (AWB), explained most of the variation in error among crops in different growth stages, though the error also correlated with Λ. Overall, MOD16 performed poorly over short crops with high Λ (cotton, rice, H<1m) but was comparable to or better than SEBAL over tall crops with low Λ (maize, H>2m). Contrary to expectation, MOD16 error did not correlate with FVC, suggesting that the error in MOD16 ET was not only due to underestimation of soil evaporation in early growth stages but also to underestimation of transpiration in mid and late parts of the growing season. SEBAL ET was sensitive to the spatial domain, the quantile used to select calibration pixels, and the parameters of the model relating NDVI to surface roughness length (z0m). We conclude that automated vegetation-based methods like MOD16 may underestimate ET from short irrigated crops with high Λ, particularly early in the growing season, while SEBAL may have difficulty in areas where the relationship between NDVI and crop height varies with crop type.

**Introduction**

Evapotranspiration (ET) is the sum of water transpired when vegetation assimilates carbon and water evaporated from soil and non-transpiring vegetation. ET is the largest term in the terrestrial water balance after precipitation, and is therefore an essential component of the global energy and water balance. ET from irrigated croplands accounts for the majority of human consumptive use of water, so understanding its spatial and temporal distribution is important for improving water management and anticipating the impacts of future climate variability and change on water resources and food production.

Given the importance of ET, various algorithms have been developed to estimate it. In agriculture, for example, models of ET are used for water resources management, to quantify consumptive water use, and for drought monitoring. Because ET varies widely spatially and temporally and *in situ* methods are expensive and difficult to scale out (Xiao et al. 2011), airborne or satellite remote sensing is often used to estimate ET. Reviews of remote sensing based methods for estimating ET can be found in Kalma et al. (2008) , Glenn et al. (2007), Glenn et al. (2010), Wang et al. (2012), Diak et al. (2004), Jimenex et al. (2011), and Mueller et al. (2011).

Remote sensing based methods of estimating ET can be categorized into two general classes: temperature or energy-based methods and vegetation-based methods. The temperature/energy-based methods typically compute latent heat (energy equivalent to ET) as a residual of the energy balance. These methods can be further classified as single source (e.g. Surface Energy Balance Algorithm for Land: Bastiaanssen 2000) or two source (e.g. Atmospheric Land Exchange Inverse Model: Anderson et al. 1997), because they handle soil evaporation in different ways. Single source methods compute sensible heat for vegetation and soil combined, while two source methods use vegetation indices to discretize the vegetation and soil components. The temperature/energy-based methods perform well over irrigated croplands for which they were initially intended (Velpuri et al. 2013), but are difficult to implement regionally/globally, because they are data intensive and/or require internal calibration dependent on landscape homogeneity. Vegetation-based methods (Nishida et al. 2003, Cleugh et al. 2007, Leuning et al. 2008, Mu et al. 2007, and Fisher et al. 2008) estimate ET as a function of a vegetation index (either the Normalized Difference Vegetation Index – NDVI or Enhanced Vegetation Index – EVI), temperature and moisture constraints, and PET. These algorithms have been gaining popularity for regional/global applications, because they are relatively easy to implement over large areas using remote sensing and surface climate reanalysis data and are comparable to temperature/energy-based methods (Ershadi et al. 2014).Single-source temperature/energy based models of ET (e.g. SEBAL) are widely used for irrigated agriculture but may be cumbersome to apply on seasonal time scales, since they require selection of calibration pixels in the imagery where ET and the associated latent heat flux are assumed to be either zero (“dry pixel”) or equal to net radiation (“wet pixel”). Automated methods can be used to select these calibration pixels in SEBAL and the closely related METRIC model, with similar performance to manual calibration (Morton et al., 2013). For regional and global applications, global gridded climate datasets should replace the need for ground-based meteorological measurements, as has been done for MOD16 and SEBS (Vinukollu et al., 2011). Automated methods can then be used to test the sensitivity of the models to parameters like the surface roughness, domain size, and sensor (Long et al., 2011). Despite the potential utility of automation of one-source models, the performance of automated SEBAL/METRIC methods has not been assessed for a heterogeneous mixture of crops types.

Several studies have compared vegetation-based and temperature-based methods for estimating ET using remote sensing. For croplands, the models show a high level of agreement, but evaluations are constrained to rain-fed systems where ET is tightly coupled to plant productivity (see Biggs et al. 2015 for a review). In Yilmaz et al. 2014, a temperature/energy-based method (ALEXI) and vegetation-based method (MOD16: Mu et al. 2011) were compared in the Nile River Basin where agriculture is primarily watered through irrigation. Unlike the rain-fed studies, MOD16 performed considerably worse than ALEXI, which was attributed to the way in which soil evaporation is computed. In temperature/energy-based methods, soil evaporation is computed, whether together or separately with transpiration, as a function of land surface temperature (LST), while vegetation-based methods compute soil evaporation as a function of relative humidity (h). Land surface temperature is particularly effective at estimating soil evaporation, because it controls the rate of heat and water exchange with the atmosphere (Nemani et al. 1993). Like soil moisture; it varies according to soil type, land use/cover type, and time of day or season. Unlike soil moisture, it can be computed from readily available thermal infrared remote sensing. Soil evaporation in vegetation-based methods is based on the Bouchet hypothesis (Bouchet 1963), which suggests that, as the soil moisture (or soil evaporation) of a target area increases, the air above it humidifies. Unlike LST, h over large areas is currently available only from surface climate reanalysis. The highest resolution reanalysis is at 0.1° (~10 km2 at the equator), which is downscaled from a suite of coarser resolution datasets (Chaney et al. 2014). At 10 km2 resolution, h can be underestimated significantly, especially where dry hot air from adjacent land use/cover forces higher ET rates from cool moist air (i.e. “oasis effect”: Stull 2009), conditions commonly found over irrigated patches. If irrigation represents a relatively small fraction of the land surface, h over irrigated fields could also be underestimated using relatively large grid cells.

ET is dominated by the transpiration component globally (Jasechko et al. 2013), so the potential errors inherent in the vegetation-based approach to soil evaporation may not be significant for global water and energy balances. However, on a regional basis, soil evaporation from irrigation can be important to energy and water balances, so addressing uncertainties in its estimation is important at that scale (Citation). Estimates of ET from irrigated cropland are also important for water resources management and quantification of the human water footprint. We therefore assemble a unique dataset of ET measured over irrigated crops using eddy flux covariance and surface renewal techniques to compare automated temperature/energy-based methods and vegetation-based methods over irrigated croplands. In doing so, we answer three critical questions:

1. How do weekly and seasonal ET estimates from MOD16 and SEBAL compare in irrigated areas?

2. Do the differences in ET estimated using MOD16 and SEBAL relate to biophysical characteristics of the crop (height, biomass, fractional cover) and/or land surface wetness?

3. Which method is best for automated regional and global monitoring of ET from irrigated croplands?

Extra text:

Two popular vegetation-based methods are 1) MOD16 (Mu) and 2) Preistely-Taylor Jet Propulsion Laboratory (PT-JPL). MOD16 has been implemented globally and is distributed as part of the MODIS suite of products. The meteorological data needed for MOD16, including air temperature, relative humidity, and net radiation, are derived from global climate grids (e.g. Global Modeling and Assimilation Office, GMAO), and no ground-level meteorological data is needed. Both MOD16 and PT-JPL have been evaluated primarily over rainfed ecosystems due to the location of the eddy flux correlation towers in the most commonly-used database (FLUXNET) (Baldocchi et al., 2001) . Less well quantified is their performance in irrigated agricultural land, which may have different relationships between vegetation indices and ET.

**Study area**

The study area is in the Central Valley of California, United States, and includes 6 eddy flux correlation towers (*Figure 1*, Table 1). Crops at the tower sites included rice (N=3), maize (N=2), and cotton (N=1). Data was available for different time periods from 2009 to 2013, with the most availability in 2011 and 2012 (Table 1). One rice site (Twt) had hourly records of ground water level, and soil moisture was available at the maize sites.

All 6 towers are bounded by a study area that is 2.5 degrees longitude by 4 degrees latitude (*Figure 1*). The modeling spatial domain was further restricted to elevations that covered the range of the tower elevations (-20 m to +100 m), which reduced the impact of adiabatic lapse rates on land surface temperature (TR) and ET. The study area can be divided into northern and southern sections defined by the locations of the towers (*Figure 1*). The southern section was further divided into a smaller section to compare the effect of different domain sizes on SEBAL ET. The various domains were used to test the impact of varying spatial domain size on SEBAL ET estimates. The upwind area of each tower or fetch was homogenous and significantly larger than eddy flux measured at each tower, making it unnecessary to calculate the footprint of the tower.

The cropping season begins in April-May and ends in September. Data on irrigation application dates were available for three sites, and ground water level data were available for three sites (Table 1). Mean annual rainfall varies from 191 mm at the southern-most site (Fiv, cotton) to 610 mm at one of the rice fields (Big). Most rainfall occurs between November and April, with minimal rainfall during the main growing season between May and September.

**Methods**

*Flux tower data: Energy balance closure*

Two techniques were used to measure ET at the towers, either singly or in combination: surface renewal (SR) (French et al., 2012) and eddy-covariance (EC) (Dabberdt et al., 1993; Twine et al., 2000). SR calculates the latent heat flux (λE) as the residual of the energy balance measured at the tower (λE =Rn-G-H, where Rn is net radiation **(W/m2)**, G is the soil heat flux **(W/m2)**, and H is the sensible heat flux **(W/m2)**. SR uses information in high frequency temperature data to model the vertical H flux. SR may be applied in both unstable and stable conditions, and does not require measurements of wind speed (French et al., 2012). EC measures all components of the energy balance separately using vertical velocity fluctuations and concentrations (Dabberdt et al., 1993).In the EC method, the sum of λE and H may not equal available energy (Rn-G) if the key assumptions are not met, such as zero net vertical advective flux (Twine et al., 2000). Closure is achieved by adjusting values of λE and/or H so that λE +H equals Rn-G. Energy balance closure can be achieved using either the latent energy closure method or the energy-balance-Bowen-ratio (EBBR) method (Twine et al., 2000). The latent energy closure method or “residual-LE closure” method assumes that all missing energy is latent heat. The Bowen ratio method assumes that the ratio of sensible heat (H) to latent heat (λE) is constant between the measured values and the actual, corrected values.

Both SR and EC were performed at two towers, EC alone at three towers, and SR alone at one tower (Table 1). For towers with EC, the latent energy closure method was used to close the energy balance. Where both SR and EC were performed, the difference between mean λE was very small (<1%), suggesting that λE values from SR and EC are comparable.

*Surface energy balance algorithm*

The surface energy balance algorithm for land (SEBAL) calculates an evaporative fraction (Ʌ) at the moment of satellite overpass as the residual in the surface energy balance equation:

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|  | ( 1 ) |

where Rn, G, and H are all for the instant of satellite overpass. G is a function of vegetation cover (NDVI) and albedo. Rn is calculated as:

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## 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) at the surface. H is calculated as:

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|  | ( 3) |

where *ρair*is the density of air (kg/m3), *Cp* is the specific heat capacity of air (J/kg/K), a and b are empirical coefficients determined for each image, TR is the radiometric surface temperature (also called the land surface temperature (LST)) from the daily product MOD11A1 v5, and Rah is the aerodynamic resistance to turbulent heat transport from the evaporating surface at height z1 to the air some distance above the evaporating surface (z2).

Determining values for the parameters a, b and Rah in ( 3) requires identifying two pixels where H and TR are known. One pixel is selected that is “wet”, where H is assumed to be 0 and λE is assumed equal to Rn-G, and another pixel is selected that is “dry”, where H is assumed to be Rn-G and λE is assumed to be 0. Initial values of a and b are based on the Rn and TR at the wet and dry pixels. H is then calculated again using ( 3), this time accounting for unstable atmospheric conditions using the Monin-Obukhov (MO) equations (Allen et al., 2011; Bastiaanssen et al., 2002; W G M Bastiaanssen et al., 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.

A stability-corrected value of Rah is calculated as:

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Where z1 and z2 are the heights of the evaporating surface and the height of the wind speed measurements, u\* is the friction velocity, k is a constant (0.41) and is the Monin-Obukhov stability correction for heat transport for stable conditions.

u\* is estimated as: (Eq 10.8 Morse):

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|  | ( 5 ) |

where U200 is wind speed at the blending height (200m), estimated from observed wind speed at some height (2-3m) and an assumed logarithmic wind speed profile. The roughness length for momentum transport (z0m) is assumed to be a fixed fraction of crop height (0.123H), and is either derived from a land use map or modelled as a function of a vegetation index (Allen et al., 2007; Bastiaanssen, 2000; Morse et al., 2000):

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|  | ( 6 ) |

where c and d are coefficients calibrated to a given region. Since land use maps showing detailed crop growth stages and type are often not available for regional applications, we used ( 6 ) to estimate z0m. We calibrated the values of c and d to crop height data collected in the field. Since several pairs of c and d values were possible and yielded different errors for different crops, we ran SEBAL with four different parameter sets of c and d, some of which were calibrated to short crops like rice, and others to tall crops like maize in different growth stages.

ET over a 24-hour period (ET24) is then calculated as ΛRn24, where Rn24 is net radiation over the 24-hour period, as G is assumed zero on a daily time step (Baastiaanssen et al. 1998). This assumes that Λ is constant over a 24-hour period. This may not be the case in some situations (Van Niel et al., 2011), but is a common assumption in applications of SEBAL.

*GMAO-MERRA data*

## Following the MOD16 algorithm, *SW↓*, *LW↓* and *LW↑* for SEBAL were taken from the Global Modeling and Assimilation Office (GMAO) Modern-Era Retrospective Analysis for Research and Applications for Land (MERRA-Land, MAT1NXRAD, <http://disc.sci.gsfc.nasa.gov/daac-bin/DataHoldings.pl>, access date Sept 11, 2013) (Reichle et al., 2011). The data includes hourly average *SW↓*, *LW↓* and *LW↑* for each day of the study period, with spatial resolution of 0.5 latitude by 0.67 degrees longitude. *SW↓*, *LW↓* and *LW↑* were extracted for the time of satellite overpass (10:30am local standard time). Daily values of *SW↓*, *LW↓* and *LW↑* were taken as the daily average of the hourly values. α was taken from the MODIS white-sky albedo product (MCD43A), which also follows the MOD16 method. Also following MOD16, wind speed at 2 m above the displacement height at the time of overpass (10:30am local time) was taken from the GMAO-MERRA dataset (MAT1NXSLV).

## All gridded GMAO data were downscaled to the resolution of the MODIS data (1 km) using bilinear interpolation on a 2x2 grid using the resample algorithm in the statistical package R. This is similar to the procedure used in MOD16 (Mu et al., 2011; Zhao et al., 2005), with the exception that MOD16 uses non-linear interpolation on a 2x2 grid. Nearest neighbor resampling was also performed but had higher errors in Rn compared with bilinear interpolation, so bilinear interpolation was used for estimating meteorological inputs to SEBAL.

*Automation of SEBAL*

Wet and dry pixels are often chosen manually given user knowledge of the area. In order to produce a time series of daily ET estimates to calculate seasonal ET, we use an automated procedure based on quantiles (q) of the observed TR and NDVI data to select the wet and dry pixels. For the wet pixel, a subset is generated where TR is lower than a given percentile (e.g. q=0.005, q=0.01), and the final wet pixel is the one with the highest NDVI within that subset. Use of NDVI assumes that vegetated surfaces better represent wet pixel conditions than water bodies. For the dry pixel, a subset is generated where TR is higher than a given percentile (e.g 0.005, 0.01), and the final dry pixel has the lowest NDVI in the subset. The impact of different quantiles for selecting wet and dry pixels was tested by using q=0.005 and q=0.01. An additional run with a very low percentile (q=10-6) was used to select the pixels with the minimum and maximum TR as the wet and dry pixels.

Several previous implementations of SEBAL have excluded different land cover types from the pixel selection and model implementation, including urban areas (Conrad et al., 2007) and water bodies (Morse et al., 2000). In our application of SEBAL, land cover data (MCD12Q1) was used to remove both urban areas and water.

The spatial domain of implementation of SEBAL can have important impacts on the resulting ET values. If a domain includes a large area, Rn-G and temperature may vary with latitude, causing underestimation of ET in locations with high Rn-G, since the relationship between TR and dT is assumed constant over the image. In order to test the impact of study area size, we first implemented SEBAL over the area that includes all towers and elevations between -20 and +100 m (*Figure 1*). Then we performed SEBAL over just the northern and southern sections separately as defined by the spatial distribution of the towers. An additional subset of the southern section that covers 1 degree latitude by 1 degree longitude was created, hereafter referred to as the “small southern” domain, due in part to an observed discontinuity in TR values at 37º N.

*Comparison of SEBAL and MOD16 with tower data*

ET estimated by both SEBAL and MOD16 was compared with ET estimated at the towers. We used both a 1x1 pixel window and a 3x3 pixel window. A 3x3 pixel window has been used in several other studies, including the primary validation study for MOD16 (Mu et al., 2011) to compensate for any issues with georeferencing of imagery, location of the tower near boundaries between two or more pixels, or heterogeneity of the land surface near the tower. Errors using a 3x3 window were slightly lower than those for a 1x1 window, though the change differed by tower; here we present the results for the 3x3 window.

Errors in ET can be due to either errors in Rn or errors in Λ. In order to remove the impact of errors in Rn, we also compared Λ from SEBAL and MOD16 with Λ from the towers.

*Vegetation and wetness indices*

Vegetation and wetness indices were used to interpret the differences between MOD16 and SEBAL estimates of ET over the growing season. The enhanced vegetation index (EVI) from 16-day MOD13A2 were used as a proxy for vegetation growth. EVI was used instead of NDVI because NDVI saturates over dense vegetation. The Land Surface Water Index (LSWI) was used as a proxy for moisture in both vegetation and soil (Xiao et al., 2005):

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|  | ( 7 ) |

where ρ is reflectance and nir1 and swir2 indicate near infrared (841-876 nm, MODIS band 2) and shortwave infrared (2105-2155 nm, MODIS band 7). The net difference water index (NDWI) (X Xiao et al., 2002) substitutes ρnir2 (1230-1250 nm, MODIS band 5) for ρswir2. LSWI and NDWI correlate with NDVI, EVI, and vegetation cover, but LSWI and NDWI are also high over wet surfaces, such as rice paddy during the flooding and transplanting stages (Xiangming Xiao et al., 2002).

*Field data*

Crop height, aboveground wet biomass (AWB) and fractional crop cover were measured in the fetch of each tower for three dates corresponding to sprouting, flowering, and grain- or bud-filling stages in 2011 and 2012. The samples were taken at regularly spaced 20 meter intervals over 60 x 60 m transects in accordance with McCoy 2005. The measurements were then averaged to produce areal estimates. The dimensions were chosen to account for geo-location error attributed to Landsat (30 m) resolution imagery, which were used in a previous study to evaluate hyperspectral narrowband and multispectral broadband vegetation indices for crop biomass (Marshall and Thenkabail 2015a). A full description of the technique is detailed in Marshall and Thenkabail 2015b. Each sample represents the average of replicates taken in 1 x 1 m2 quadrat. Replicate crop height was measured either with measuring tape (cotton and rice) or a telescoping measuring pole (maize); AWB was measured with a spring scale; and fractional crop cover was measured with a ceptometer (AccuPAR LP-80 from Decagon Devices, Inc. ®). The ceptometer captures the above and below canopy estimates of incoming shortwave radiation, which is then used to estimate the fractional crop cover. For row crops, such as these, the fractional crop cover approximately equals the green (photosynthesizing portion) fraction of the plant canopy as well.

*Irrigation practices*

Flooding and planting of rice fields occur in May. The rice site with water level data (Twt) is flooded for approximately one month prior to planting, and then drained and planted in late April (2011) or mid-May (2012). The field is flooded again within a week after planting. Flooded conditions are maintained until mid-(2011) or end-September (2012).

Maize is planted in April, but not irrigated until July. Two of the maize sites are run by the Nature Conservancy on Staten Island in the Sacramento-San Joaquin River Delta. One of the sites (StaW) was kept flooded prior to the growing season to maintain a habitat for fowl and game for hunters, while the second site (StaD) was not flooded. Cotton fields are planted in June and irrigated several times as needed during the growing season.

**Results**

*Energy balance closure*

At Twt, where the energy balance was not closed, the slope of the ordinary least square regression (OLR) line between Rn-G and H+LE was 0.58 with an intercept of 33.2 W m-2 and an R2 of 0.76. Compared to OLR statistics from other FLUXNET sites (Wilson et al., 2002), the slope (0.58) is within the lower ranges of other sites (0.55-0.99, mean 0.79), the intercept (33.2) is in the upper range of other sites (-32.9 to 32.6, mean 3.7), and the R2 is within the range (0.64-0.96) but lower than the average (0.86). The energy balance ratio (EBR) was 1.01 for 2010, 0.82 in 2011, and 0.85 in 2012 for a three-year mean of 0.89, which is slightly higher than the mean of other FLUXNET sites (0.84). The OLR slope for the daily means where Rn-G >0 was 0.64 with an intercept of 25.5 W m-2 and an R2 of 0.74. A few outlier values of Rn-G (>300 W m-2) influenced the OLR slope; removal of those outliers improved the slope to 0.73 and an intercept of 17.8 W m-2, R2 of 0.81. Overall, OLR indicates that the energy fluxes recorded at Twt are within the ranges reported by other FLUXNET sites and is acceptable for analysis.

*Net radiation and reference ET*

Rn estimated by GMAO-MERRA was lower than Rn from the towers for all towers and years except Us.Twt (*Figure 2*, Table 2). The relative mean bias (rMB) ranged from -0.30 (Wm-2) at Wil to +0.04 at Us.Twt in 2011 (Table 2). The relative RMSE (rRMSE) ranged between 0.23 and 0.55. Errors were highest in spring and early summer; excluding May and June decreased the rRMSE at Us.Twt from 0.26-0.55 to 0.18.

Reference ET (ETo) from MOD16 was very close to ETo estimated at the flux towers (Table 3). The maximum error in seasonal ETo was 15%, with an average bias of 5% and mean absolute error of 7%.

*Roughness length functions*

Field-based values of the roughness length (z0m) were calculated as a fixed fraction of measured crop height (0.123H), and compared with MODIS NDVI at the same time and location to establish the z0m-NDVI relationship (*Figure 3*). There was no consistent correlation between NDVI and z0m estimated from the field-measured crop height, and there was no optimal pair of values of c and d for the NDVI-z0m relationship. Rice and maize had very different heights and z0m for a given NDVI value (*Figure 3*). In order to test the effect of using different parameter sets in (6), we fit c and d to different crops and growth stages. Set 1 was fit to rice, set 2 to sprouting maize, set 3 to senescent maize, and set 4 to a combination of senescent rice, sprouting and flowering cotton, and sprouting and flowering maize (*Figure 3*). Formal parameter estimation minimizing least squares yielded equations did not fit targeted features in the NDVI-z0m relationship, in particular maize, so we used manual parameter adjustment and visual inspection to provide a range of NDVI-z0m relationships (*Figure 3*).

*Automated SEBAL: Pixel selection thresholds and domain effects*

Pixels selected with the automated technique occurred at the extremes of the NDVI-TR space. In the beginning of the growing season, the wet pixel sometimes had low NDVI, likely due to low vegetation cover but high soil moisture and high ET. In the middle of the growing season (xxx July, Jday 2012, 181 layer 10), the wet pixel typically had high NDVI, indicating that the wet pixel was of a vegetated surface. The automation of SEBAL resulted in high temporal variability in ET, particularly where clouds covered some fraction of the scene. Taking the 8-day moving average or seasonal averages smoothed out this variability and suggests that long time series of ET are feasible using automated pixel selection.

?? Plots of NDVI vs LST and pixels?

*SEBAL compared to tower data: Λ and ET*

Mean seasonal ET and Λ from SEBAL were similar or higher than observed at the towers for the maize sites (Figure 4b), but lower than observed at the towers for rice and cotton sites (Figure 4d, Figure 4f, Figure 4h) for all model runs (Figure 4, Table 4, Table 5). Error in Λ was smaller than error in SEBAL ET for the rice and cotton sites (Table 5) but larger than error in ET for maize, reflecting the underestimation of Rn by the GMAO data.

Using two smaller spatial domains instead of one large domain reduced error in SEBAL ET and Λ by 5.9-6.5% (*Figure 1*, Table 4, Table 5). Our objective is not to perform a systematic evaluation of the effect of domain size, but rather to test the impact of spatial domain on the comparison of SEBAL ET with tower and MOD16 ET at our particular tower sites. Implementation of SEBAL over the single large domain results in the selection of calibration pixels that do not accurately represent the relationship between TR and H over the whole domain. Future work could determine the critical maximum domain size that can be used for SEBAL with different accuracies.

The use of different percentiles (q) for selecting wet and dry pixels also affected ET and Λ values (Table 4, Table 5). Using the maximum TR in the image (q=10-5) increased ET estimates by 0-19% compared to ET estimated using q=0.01. There was no clear optimal value of q; the lowest errors in ET were obtained for q=0.01 for rice, but for q=10-5 for maize. A value q=0.005 kept all errors in mean seasonal ET less than or equal to 33%. The error in Λ was smaller (larger) than the error in ET at the rice and cotton (maize) sites due to the underestimation of Rn in the GMAO-MERRA data at most towers.

The parameters of the NDVI-z0m relationship affected the error in SEBAL ET and Λ, but there was no optimal set of c and d values that minimized the error for all crops (Table 4, Table 5). Parameters that estimate low z0m values for a given NDVI, like those associated with z0m parameter set 1, resulted in the highest errors for tall crops (maize). The NDVI-z0m parameters that resulted in the lowest error were those that best fit a range of crop types (parameter set 4), though that parameters set had higher error in some crops (maize) for some values of q than other parameter sets.

The best combination of NDOM, q, c, and d was determined as that with the minimum crop-mean relative mean bias of SEBAL ET (Table 4). The best combination for Λ was slightly different from the best combination for ET (Table 5). For simplicity, we use the same parameter set (q=0.005, NDVI-z0m parameter set 4) for both ET and Λ in the error analysis and comparison between MOD16 and SEBAL.

*MOD16 compared to SEBAL and flux towers*

MOD16 ET was slightly more accurate than SEBAL over maize, but MOD16 ET was much lower than tower ET and less accurate than SEBAL over rice (mean rMB -51%) and cotton (rMB -78%) (Figure 4, Figure 5, Table 6, Table 7). For rice, the difference between MOD16 ET and tower ET was largest in the beginning of the growing season, which coincides with low NDVI but high LSWI (Figure 4, Figure 5) and corresponds to flooding and early growth stages in rice. During this initial stage, SEBAL had a lower error than MOD16, suggesting that MOD16 underestimates soil evaporation. However, error in MOD16 ET was also high during the middle of the growing season for rice and cotton, suggesting that MOD16 also underestimates transpiration during maximum vegetation coverage for rice and cotton.

The error in seasonal ET was a function of crop height (p<0.001, Figure 6). Error in MOD16 ET was greater than 50% for crops less than 75 cm tall. For rice, error in MOD16 decreased slightly with crop height. For tall crops (maize), error in SEBAL ET was similar to error in MOD16 ET except for the later growth stage (grain-bud filling), when SEBAL overestimated ET. FVC and AWB were not significantly correlated with the error in seasonal ET (p>0.1). Maize also had a low evaporative fraction (Λ) compared to rice and cotton, so the error in ET may also be due to the relative performance of SEBAL and MOD16 over crops with low Λ.

**Discussion**

*SEBAL automation and comparison with MOD16*

The error in SEBAL evaporative fraction (Λ) was <10% for cotton and for 2 of 3 rice sites, suggesting that SEBAL performs very well for short irrigated crops. SEBAL estimated seasonal ET to between -33% and +14% of ET observed at the towers for all crops, which included errors in Rn. SEBAL ET estimates were a significant improvement from the vegetation-based MOD16 algorithm over rice and cotton, which underestimated seasonal ET by 34-78%, though MOD16 ET was slightly better than SEBAL ET over maize depending on the parameters used. If the z0m-NDVI relationship is optimized for maize (z0m parameters set 4 in Figure 3), then SEBAL ET has a similar error (7%) as MOD16, suggesting that more accurate determination of z0m over the image, perhaps by using a map of crop type or better algorithm for determining z0m from remote sensing, could improve the estimation of ET over heterogeneous crop types.

*Comparison with other studies of automated ET*

The error in seasonal mean ET from our automated SEBAL method is higher than that reported for automated METRIC implemented over alfalfa and pasture sites in western Nevada (Morton et al., 2013), where seasonal mean error was ~5% for all fields, with a range of -16% to +21%, compared to our overall error 22% for all towers with a range of -33% to +17%. The improved results for METRIC are likely due to a combination of the use of ground-level data in METRIC and the relative homogeneity of the crop type. The METRIC application included ground-based measurements of potential evapotranspiration and utilized ground-measured wind speed to determine friction velocities, compared to our implementation of SEBAL which used no ground-level data as input. The sites from Morton et al (2013) included irrigated alfalfa and pasture and non-irrigated pasture, where the parameters of the NDVI-z0m relationship may be expected to be more homogeneous over the landscape compared with the Central Valley. If only short crops are considered and the NDVI-z0m relationship fit to those crops (parameter set 1), the MODIS automated SEBAL also has a small mean error (18%), but the error over tall crops increases from 16% to 26%. The automated SEBAL results suggest that estimation of ET over irrigated sites, particularly those where Ʌ is significantly less than one, is complicated by spatial variability in crop height and the NDVI-z0m relationship. Improvements in the estimation of crop height and z0m with remote sensing could significantly improve regional ET estimates in SEBAL.

The accuracy of remote sensing methods to estimate ET is summarized in several publications (Bastiaanssen et al., 2005; Kalma et al., 2008). (Teixeira et al., 2009) found that…

Michael, can you add a few sentences about the relative performance of temp and veg-based models (e.g. SEBAL vs JPL, MOD16)? We may be able to cut and paste from the chapter.

*Implications for global mapping of ET in irrigated areas*

Vegetation-based methods like MOD16 or the related PT-JPL model perform well in rainfed areas and in irrigated sites with low land surface wetness and/or high NDVI, which includes maize. MOD16 performed poorly compared with SEBAL over plots planted in rice, particularly at the beginning of the growing season when NDVI was low but land surface wetness was high. This period coincides with inundated conditions at the surface, when ET may be high but vegetation cover low. Since the soil evaporation component from both MOD16 and PT-JPL is low when relative humidity is low, both methods may systematically underestimate ET in irrigated fields with high soil evaporation in semi-humid environments like the Central Valley. Such conditions may also be found in other major irrigated areas of the world, including India and China. Improvements to the soil evaporation component of MOD16 are recommended. MOD16 authors have incorporated LST data to better estimate soil evaporation, and this new algorithm will be tested in irrigated areas (Mu, 2013). However, MOD16 ET was also low over rice and cotton for growth periods with high fractional vegetation cover, suggesting that MOD16 also underestimates transpiration.

**Conclusion**

Automated methods for estimating seasonal evapotranspiration (ET) have a wide range of applications. This study documents that 1) automated ET algorithms based on land surface temperature (SEBAL) using only global climate grids and remote sensing data can estimate ET from irrigated crops with errors ranging from -33 to +17%; 2) automated SEBAL is sensitive to the spatial domain, the calculation of surface roughness length (z0m) from Vegetation Indices, and the quantile used to select wet and dry pixels; 3) automated algorithms based on vegetation indices alone (MOD16) underestimate ET in irrigated crops by more than 50% for rice and cotton, but perform well for maize. The difference in performance by crop type may be due to differences in the surface roughness or to differences in the evaporative fraction by crop: MOD16 performed well over tall crops with a low evaporative fraction, while SEBAL performed well over short crops with a high evaporative fraction. Further research should be focused on determining the relative effects of crop height and evaporative fraction on model performances.

The initial hypothesis, that error in ET from vegetation-based methods would be highest in the early stages of crop growth when soil evaporation is high but vegetation cover is low, was partly validated. MOD16 also underestimated ET from rice and cotton during full canopy cover, suggesting that it underestimates both evaporation and transpiration. Further research is required to improve crop height estimates and to determine the range of crop height and evaporative fraction over which each method is most valid. Future regional and global maps could use a map of crop type or height to determine which method should be used over a given pixel to produce the most accurate ET estimates at regional and global scales.

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**Figure captions**

Figure 1. Map of study area, including flux tower sites and the boundaries of the study areas where SEBAL was applied. The white boundary indicates the area between -20 m and +100 m that was used as an additional mask in defining the model domain for SEBAL.

Figure 2. Plot of Rn from GMAO-MERRA vs Rn from the towers.

Figure 3. Plot of crop height versus NDVI at the tower sites with crop height data, and the NDVI-z0m relationships (6) used in the SEBAL model.

Figure 4. Time series of LSWI, EVI and TR (top plot in each panel), water table elevation (mid plot) and ET from SEBAL, MOD16, and towers (bottom plot in each panel) at the Twt rice site, 2011 and 2012. In the ET plots, SPR, FLW and GB indicate sprouting, flowering, and grain-bud filling.

Figure 5 Time series of LSWI, EVI and TR (top plot in each panel), water level, and ET from SEBAL, MOD16, and towers (bottom plot in each panel) at the Twt rice site in 2011 and 2012. In b), DR, PL, FL indicate drained, planted, and flooded. In c), SPR, FLW and GB indicate sprouting, flowering, and grain-bud filling.

Figure 6. Error in SEBAL and MOD16 versus field-measured crop height. GB indicates maize in the grain-bud filling growth stage.

Figure xx?. Map of season total ET SEBAL (left) MOD16 (right) at the field sites.

Figure xx? TR-NDVI plot showing hot and cold calibration pixels for different values of q.

**Tables**

Table 1. Characteristics of flux towers and data. EC indicates eddy covariance and SR indicates surface renewal.

Table 2. Error statistics for net radiation (Rn) of GMAO-MERRA compared to Rn at flux towers.

Table 3. Comparison of reference evapotranspiration (ETo) from MOD16 and towers at the towers.

Table 4. Sensitivity analysis of automated SEBAL ET to the number of domains (NDOM), quantile for selecting calibration pixels (q), and the parameters of the NDVI-z0m relationship. See Figure 3 for parameter values for each parameter set.

Table 5 Sensitivity analysis of automated SEBAL evaporative fraction (Λ) to the number of domains (NDOM), quantile for selecting calibration pixels (q), and the parameters of the NDVI-z0m relationship.

Table 6. Comparison of seasonal ET from automated SEBAL and MOD16 at each tower.

Table 7. Comparison of the evaporative fraction (Λ) from SEBAL and MOD16 at each tower.