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An empirical approach to retrieving monthly evapotranspiration over Amazonia

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The extent of evapotranspiration ($E_T$) over the Brazilian Amazon rainforest remains uncertain because in situ measurement sites do not cover the entire domain, and the fetch of these sites is only of the order of $10^3$ m. In this investigation we developed an empirical method to estimate $E_T$ over the Brazilian Legal Amazon (BLA). The work was based on an improved physical understanding of what controls $E_T$ over the Amazonia rainforest resulting from analyses of recent in situ observations. Satellite data used in this study include the Enhanced Vegetation Index (EVI) from the Moderate Resolution Imaging Spectroradiometer (MODIS) and the surface radiation budget from the International Satellite Cloud Climatology Project (ISCCP). The empirical model was validated by measurements performed at four upland forest sites. The observed values and the calculated modelled values at these sites had the same mean and variance. On a seasonal scale, regional modelled $E_T$ peaks during the austral spring (September to November), as reported in the literature. In addition, the empirical model allows us to estimate the regional seasonal and interannual distributions of $E_T$/precipitation rates.

1. Introduction

Evapotranspiration ($E_T$) is a key component that links climate to the terrestrial ecosystem. At specific sites over the Amazon forest, $E_T$ contributes to about 50% of the total precipitation, as calculated by water balance methods and eddy correlation measurements (Salati 1987, Shuttleworth 1988). The geographical variation of this rate remains unknown. Results from the Anglo-Brazilian Amazonian Climate Observation Study (ABRACOS; Gash et al. 1996) and the more recent Large-Scale Biosphere-Atmosphere Experiment in Amazonia (LBA) (LBA 1996, Avisar et al. 2002, Keller et al. 2004) have provided a better understanding of the controls of forest $E_T$ at seasonal and interannual time scales. These studies have shown not only a higher $E_T$ in the dry season than in the wet season but also a higher $E_T$ over areas with less rainfall during the dry season in eastern and central Amazonia (Shuttleworth 1988, Nepstad et al. 1994, Malhi et al. 2002, Sommer et al. 2002, Sommer et al. 2002).
Souza Filho et al. 2005, Negrón Juárez et al. 2007). The maintenance of such a high rate of $E_T$ by the rainforest during the dry season plays a central role in determining when the subsequent wet season onset will occur (Fu and Li 2004, Li and Fu 2004). A higher $E_T$, as a result of the forests responding to increased solar radiation, can also mitigate the impact of moderately dry anomalies on the surface climate condition (Negrón Juárez et al. 2007). Therefore, estimation of basin-wide $E_T$ at seasonal to interannual scales is essential for determining seasonal and interannual climate variability in the Amazonian region.

Current techniques used to estimate $E_T$ (e.g. the eddy correlation technique) are limited to point measurements that represent $E_T$ within an area with a radius only of the order of $10^2$ to $10^3$ m, and as long as the surface characteristics are the same. However, heterogeneities in land surface and soil characteristics mean that extrapolation of point data beyond this area would be inaccurate because of the dynamic and regional variability of $E_T$. In more remote areas, such as the western Amazon forests, $E_T$ estimates from numerical models (Potter et al. 2001) are limited by subjective assumptions that are yet to be validated. Satellite data offer an alternative for estimation of $E_T$ over large areas by complementing previously observed measurements and numerical simulations of $E_T$. A common approach is to relate $E_T$ to remotely sensed surface temperature (Jackson et al. 1977, Hatfield 1983, Jackson 1988, Moran et al. 1989, Kustas 1990), solar irradiance (Jackson et al. 1983), vegetation indexes (Di Bella et al. 2000, Nishida et al. 2003a,b, Loukas et al. 2005, Nagler et al. 2005, Su et al. 2005) or energy balance (Blad and Rosenberg 1974, Bastiaanssen et al. 2005) by physical and statistical/semiempirical methods or the Penman–Monteith equation (PM; Monteith 1973, 1981).

Although these methods aim to provide the best possible estimate of $E_T$, their application to Amazon forests remains unknown because of the lack or inadequacy of meteorological variables required. For instance, calculation of stomatal conductance, an input in the PM equation, is frequently based on the work of Jarvis (1976), but in this case, the main weakness is the assumption that environmental constraints operate independently (Monteith 1995). In addition, values of stomatal conductance at different time scales are not easily comparable, as discussed by the American Society of Civil Engineers (ASCE) Evapotranspiration in Irrigation and Hydrology Committee (Itenfisu et al. 2000, Walter et al. 2000). Although temperature can be used to estimate $E_T$ over some areas in the Amazon, the relationship between surface temperature and $E_T$ varies in sign across Amazonia. In central-eastern Amazonia, the $E_T$ is in phase with temperature (da Rocha et al. 2004, Hutyra et al. 2005), while it is out of phase in eastern Amazonia (Sommer et al. 2002). $E_T$ is also out of phase with temperature during the wet season over southern Amazonia (Vourlitis et al. 2002). These observational results clearly suggest that a simple relationship between surface temperature and $E_T$ does not exist at the basin scale.

Most of the flux tower observations over Amazonian forests during the past two decades have suggested that $E_T$ is primarily controlled by surface radiation and vegetation condition, consistent with that originally reported by Shuttleworth (1988). More recently, Yang et al. (2006) have shown that the Enhanced Vegetation Index (EVI; Justice et al. 1998, Huete et al. 2002) is the most important driver for estimating $E_T$ at a continental scale. Compared to the Normalized Difference Vegetation Index (NDVI), the EVI can better capture canopy structural variation, seasonal vegetation variation, land cover variation, and biophysical variation for high biomass vegetation such as that in Amazonia (Gao et al. 2000, Huete et al. 2002). The EVI also performs
well under heavy aerosol and biomass burning conditions, which are frequent in the
region (Miura et al. 1998). The aim of this work was to develop an empirical approach
for the estimation of $E_T$ based on the vegetation condition inferred from the EVI and
surface net radiation from the International Satellite Cloud Climatology Project
(ISCCP; Zhang et al. 1995, 2004). The empirical model was trained and validated using
data collected at eight upland forest sites over the Brazilian Legal Amazon (BLA).

2. Methodology

2.1 Study area and model construction

The study area encompassed the nine states of the BLA (figure 1) covering about
5 x 10^6 km^2 (Brazilian Institute of Geography and Statistics, www.ibge.gov.br). Latent
heat flux ($\lambda_E$) data from eight upland sites (table 1) from the LBA experiment were used
for model construction and validation. Data from the K83 and RJA sites were used for
training the empirical model, and data from the K67 and K34 sites were used for model
validation. Other sites (CRS, DCK, SIN and BRG) were used for model comparison.

Observed data show that $\lambda_E$ has a strong linear relationship with measurements of
net radiation ($R_n$) but at different rates from site to site. For example, figure 2 shows
the relationship between daily $\lambda_E$ and $R_n$ at sites K34, K83 and RJA. Latent heat
flux represented $\sim$70% of $R_n$ at K34 and K83, but only 40% at the RJA site,
indicating that, for the Amazonia, most of $R_n$ is used to sustain $E_T$. It is worth
noting that vapour pressure deficit (VPD) and wind speed can also influence $E_T$

Our empirical model was based on the assumption that $E_T$ over the Amazonian
rainforests is primarily a function of EVI and $R_n$:

![Figure 1. Study area and sites used. The background is the climatological (1961–1990)
an annual precipitation (mm) over the Brazilian Legal Amazon. For description of sites used see
table 1. The states are: AC, Acre; AM, Amazonas; AP, Amapa; MA, Maranhao; MT, Mato
Grosso; PA, Pará; RO, Rondônia; RR, Roraima; TO, Tocantins.](image-url)
Table 1. Sites used in this study.

<table>
<thead>
<tr>
<th>Site</th>
<th>South latitude (°)</th>
<th>West longitude (°)</th>
<th>Dry season</th>
<th>Method</th>
<th>Source (period of study)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cuieiras Reserve (Manaus, Amazonas)</td>
<td>CRS</td>
<td>2.5894</td>
<td>60.1153</td>
<td>Jun–Aug</td>
<td>EC Malhi et al. (2002) (Sep 95–Aug 96)</td>
</tr>
<tr>
<td>Cuieiras Reserve (Manaus, Amazonas)</td>
<td>K34</td>
<td>2.6090</td>
<td>60.2093</td>
<td>Jun–Aug</td>
<td>EC Araújo et al. (2002) (Jul 99–Sep 00)</td>
</tr>
<tr>
<td>Ducke Reserve (Manaus, Amazonas)</td>
<td>DCK</td>
<td>2.9500</td>
<td>59.9500</td>
<td>Jun–Aug</td>
<td>PM Shuttleworth (1988) (Sep 83–Sep 85)</td>
</tr>
<tr>
<td>Tapajós National Forest (Santarém, Pará)</td>
<td>K67</td>
<td>2.8853</td>
<td>54.9205</td>
<td>Jul–Dec</td>
<td>EC Hutyra et al. (2007) (Jan 02–Jan 06)</td>
</tr>
<tr>
<td>Biological Reserve of Jarú (Ji-Paraná, Rondônia)</td>
<td>RJA</td>
<td>10.0784</td>
<td>61.9337</td>
<td>Jun–Aug</td>
<td>EC von Randow et al. (2004) (Jan 00–Dec 02)</td>
</tr>
</tbody>
</table>

EB, energy balance; EC, eddy covariance; PM, Penman–Monteith.
*Secondary vegetation: its height changed from $h=2.3$ (Apr 97) to $h=3.5$ m (Mar 98).
†Data available at ftp://ftp.as.harvard.edu/pub/tapajos/k67_flux/.
‡Data available at http://www.ess.uci.edu/%7Elba/.
§Transitional (ecotonal) tropical forest.
where $E_{VI}$ is the EVI obtained from Moderate Resolution Imaging Spectroradiometer (MODIS) data. The theoretical basis that justifies our model is composed of two factors. First, EVI has been shown to be highly correlated to canopy level CO$_2$ uptake (Huete et al. 2006), and this uptake is closely related to canopy conductance, $g_c$ (Dickinson et al. 1991, Sellers et al. 1996). Based on physical principles, $E_T$ and $g_c$ are also highly correlated (Monteith 1973, 1981). Therefore, in combination, EVI and $E_T$ should be closely related across sites. Second, $R_n$ is related to $E_T$ (figure 2) through physiological (mainly photosynthesis) and physical processes. Additionally, research has shown that greater $R_n$ increases leaf temperature, which, in turn, drives up the VPD.

Different functions were tested independently at each site. The model that best represented the observed $E_T$ at all sites ($E_{T_{site}}$, measured in mm day$^{-1}$) was

$$E_{T_{site}} = C_1 + C_2 \times E_{VI}^3 \times (R_{n_{ISCCP}} - C_4)$$

where $R_{n_{ISCCP}}$ (measured in Wm$^{-2}$) is the net radiation from the ISCCP (see section 2.3 for details) and $C_1$, $C_2$, $C_3$ and $C_4$ are constants.

The percentage error between observed and calculated $E_T$ was calculated as

$$\text{Error} = \pm \left( \frac{1}{n} \sum_{i}^{n} \frac{|Y(i) - Y'(i)|}{Y(i)} \times 100 + \sigma \right)$$

where $Y$ and $Y'$ are the observed and calculated $E_T$ values, respectively, $n$ is the number of elements in the series, and $\sigma$ is the standard deviation of errors. Constants at K83 and RJA were adjusted to obtain the maximum determination coefficient ($R^2$) between observed $E_T$ ($E_{T_{obs}}$) and modelled $E_T$ ($E_{T_{grl}}$) at these sites simultaneously. $E_{T_{grl}}$ was then used to calculate $E_T$ for the whole BLA.

2.2 MODIS EVI

The MODIS EVI products (http://edcdaac.usgs.gov/main.asp) are derived from surface reflectance from the MODIS/Terra sensor, corrected for molecular scattering, ozone absorption and aerosols (Miura et al. 2001, Vermote et al. ...
The EVI is designed to optimize signals from vegetation and is sensitive in high biomass regions (Justice et al. 1998). The MODIS EVI ($E_{VI}$) was calculated from the red, near-infrared and blue reflectances ($\rho_{\text{red}}$, $\rho_{\text{NIR}}$ and $\rho_{\text{blue}}$, respectively) as:

$$E_{VI} = \frac{G(\rho_{\text{NIR}} - \rho_{\text{red}})}{(\rho_{\text{NIR}} + a\rho_{\text{red}} - b\rho_{\text{blue}} + L)}$$  \hspace{1cm} (4)

The coefficients used in the algorithm are $L=1$, $a=6$, $b=7.5$ and $G=2.5$, with $a$ and $b$ representing the aerosol resistance. Equation (4) uses the blue band to correct the aerosol influence in the red band similar to the Atmosphere Resistant Vegetation Index (ARVI; Kaufman and Tanré 1992). The soil correction coefficient, $L$, is derived from the Soil-Adjusted Vegetation Index (SAVI; Huete 1988).

Sixteen-day MODIS EVI images with resolution of 1 km (http://modis-land.gsfc.nasa.gov/) from 2000 to 2006 were processed. Monthly data were obtained by using the number of 16-day average images that overlap the calendar month weighted by the number of actual days that overlap that month. The time series of monthly images were then smoothed on a pixel-per-pixel basis using a three-point central-moving-average. For regional estimation, the 1 km resolution data were aggregated to 0.25°. For model construction and validation, a three-pixel box centred in the tower location was used. Figure 3 shows the monthly EVI at the K67, K83, K34 and RJA sites at 1 km and 0.25° resolutions for the period 2000–2004. It was verified that EVI values after aggregation had the same mean ($t$-Student, not shown) and variance ($F$-test, not shown).

Figure 3. Comparison of monthly EVI time series at 1 km and 0.25° horizontal resolution at K67, K83, K34 and RJA sites for the period 2000–2004.
2.3 ISCCP $R_n$ data

Monthly net surface radiation ($R_{n\text{ISCCP}}$) was calculated for the period from July 1983 to December 2004, at a spatial resolution of 2.5°. The calculation was based on surface balance of shortwave (0.2–5.0 μm) and longwave (5.0–200 μm) radiative flux data at full-sky conditions from the ISCCP. Full-sky fluxes were weighted from fluxes calculated for 15 types of cloudy conditions and clear-sky fluxes by their fractional coverage for each cell. Zhang et al. (1995, 2004) have presented a complete description of this data set.

For model construction and validation, we used the $R_{n\text{ISCCP}}$ encompassing the tower coordinates. For the regional estimation of $E_T$, the $R_{n\text{ISCCP}}$ data were interpolated to a spatial resolution of 0.25° using the Kriging interpolation method (Oliver and Webster 1990). Figure 4 shows that $R_{n\text{ISCCP}}$ at 0.25° and at 2.5° agree fairly well; however, an offset was observed when compared to the observed $R_n$. The $F$-test statistics (and its probability) between observed $R_n$ and $R_{n\text{ISCCP}}$ at 0.25° for the K67, K34, K83 and RJA sites was 1.074 (0.839), 1.569 (0.392), 1.245 (0.559) and 2.667 (0.005), respectively. Except for the RJA site, $R_{n\text{ISCCP}}$ at 0.25° had the same variance with respect to the observed $R_n$. A detailed analysis of observed $R_n$ and $R_{n\text{ISCCP}}$ at RJA showed that the $F$-statistics for the period from January 2000 to

![Figure 4. Comparison between observed net radiation, $R_{n,\text{obs}}$ (W m$^{-2}$), and net radiation calculated from ISCCP data, $R_{n\text{ISCCP}}$, at 2.5° and 0.25° horizontal resolution at K67, K83, K34 and RJA sites.](image)
December 2001 is 1.9, and its probability is 0.133, indicating that the observed and satellite series had the same variance.

3. Results

3.1 Model training and validation

Figure 5 shows the observed and calculated $E_T$ at K83, RJA, K67 and K34. The empirical formula trained for best fit at each specific site ($E_{T_{site}}$) generally provided a close match with the observed data ($E_{T_{obs}}$) at seasonal and interannual scales. However, at the RJA site, $E_{T_{site}}$ overestimated the annual maximum $E_T$. The determination coefficients ($R^2$ at 95% CI, $F$-test) between $E_{T_{site}}$ and $E_{T_{obs}}$ were 0.64 at the K83 site, 0.62 at the K67 site, 0.8 at the K34 site, and 0.32 at the RJA site. The general empirical model ($E_{T_{gri}}$) used to calculate the $E_T$ over the BLA was obtained using coefficients $C_1=2.7$, $C_2=0.05$, $C_3=1.75$ and $C_4=140$. The $R^2$ values (95% CI, $F$-test) between $E_{T_{gri}}$ and $E_{T_{obs}}$ were 0.61, 0.55, 0.8 and 0.31 at the K83, K67, K34 and RJA sites, respectively. The associated errors between $E_{T_{site}}$ ($E_{T_{gri}}$) and $E_{T_{obs}}$ at these sites were $±17\%$ ($±19\%$), $±11\%$ ($±13\%$), $±6\%$ ($±9\%$), and $±12\%$ ($±20\%$), respectively. Using both RemSSC and EVI at 0.25° spatial resolution, the $E_{T_{gri}}$ errors with respect to $E_{T_{obs}}$ at K67, K83, K34 and RJA were $±18\%$, $±19\%$, $±16\%$ and $±16\%$, respectively, with an average error of $±17\%$. This shows that the 0.25° resolution did not significantly diminish the quality of the calculated $E_T$.

Figure 6 compares the seasonal mean of $E_{T_{gri}}$ for the period 2000–2004 at 1 km and 0.25° resolutions with respect to $E_{T_{obs}}$ for the sites and periods listed in table 1. At the K34, K83, K67 and RJA sites, the average difference between $E_{T_{obs}}$ and

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Figure 5. Comparison between observed, $E_{T_{obs}}$ (solid black line), and calculated values of evapotranspiration using a calibrated model for each site, $E_{T_{site}}$ (grey line and open circles) and a general model based on K83 and RJA sites, $E_{T_{gri}}$ (grey line and filled squares), for sites K83, RJA, K67 and K34.
$E_{T, grl}$ at 1 km of horizontal resolution was 8% during the wet season and 10% during the dry season. The differences at 0.25° resolution were very similar to the 1 km data, with a difference during the wet season of 8% and a difference during the dry season of 9%. At the CRS, DCK, BRG and SIN sites, the average difference between $E_{T, obs}$ and $E_{T, grl}$ during the wet season was 26% and 18% at 1 km and 0.25° resolutions, respectively. During the dry season these differences were 18% at 1 km resolution and 19% at 0.25° resolution. The best agreement, approximately 11%, occurs at the CRS site in central equatorial Amazonia, located near the K34 site. The worst agreement, about 30%, is associated with the BRG site, located near the mouth of the Amazon River, where the climate is strongly influenced by wind coming from the ocean. Thus, on seasonal and interannual scales the maximum discrepancy between $E_{T, grl}$ and $E_{T, obs}$ is about 30%, a value that is comparable to the uncertainties of in situ measurements of $E_T$ (e.g. see references in table 1).

Several factors can contribute to the discrepancies shown in figure 6. For instance, the satellite inputs associated with surface solar radiation and the EVI may be different from those at the flux towers, in part due to the lack of information on subscale structures within the satellite footprints. The observed values also have significant uncertainties due to instrumental errors, as well as the different methods involved in the calculation of $E_T$. For instance, the $E_T$ values at the DCK site were obtained from a combination of observed and calculated data using the Penman–Monteith equation, while the BRG site $E_T$ was calculated using both the Bowen ratio energy balance and the Penman–Monteith equation. The reported $E_T$ values at the SIN site were obtained using the eddy correlation system and the Priestley–Taylor model (Priestley and Taylor 1972).

![Figure 6](image-url)
3.2 Seasonal $E_T$

Figure 7 shows the average seasonal $E_T$ and precipitation for the period 2000–2004 over BLA. Precipitation data are from the Tropical Rainfall Measuring Mission (TRMM) 3B43 product (http://trmm.gsfc.nasa.gov), which uses TRMM data merged with other satellite data and available rain gauge records. This dataset has proven to be consistent with rain gauge data (Negrón Juárez et al. 2007) and has the advantage of a high spatial resolution. From December to February (DJF), the maximum values of $E_T$ ($\sim 3$ mm day$^{-1}$, figure 7(a)) appeared in the north of the Amazonas State, whereas precipitation was higher in southern BLA (>8 mm day$^{-1}$, figure 7(b)). From March to May (MAM), $E_T$ did not have extreme spatial changes over BLA, showing an average value of 2.6 mm day$^{-1}$, with some areas in Maranhão State having values of 2.9 mm day$^{-1}$. During this period, precipitation was concentrated over the northern BLA, reaching values higher than 6 mm day$^{-1}$ (lower values were observed over the north of Roraima State, RR in figure 1). The period from June to August (JJA) showed a gradient of precipitation ($E_T$) from south to north, with values ranging from 3 mm day$^{-1}$ (2 mm day$^{-1}$) to 7 mm day$^{-1}$ (2.8 mm day$^{-1}$). Maximum $E_T$ values of about 3 mm day$^{-1}$ were observed in the north of Pará State. From September to November (SON), $E_T$ ranged from 3 to 3.3 mm day$^{-1}$, except over the Cerrado domain (see figure 11) in the southern BLA, where $E_T$ ranged from 2.2 to 2.5 mm day$^{-1}$. In the eastern Amazonia $E_T$ was higher than 3.1 mm day$^{-1}$ when precipitation was lower than 3 mm day$^{-1}$, which is consistent with previous in situ observations (Nepstad et al. 1994, da Rocha et al. 2004, Oliveira et al. 2005). The increase of $E_T$ in eastern Amazonia from September to November is consistent with higher values of EVI and $R_n$, as observed by Huete et al. (2006). However, the adjacent deforested areas presented lower values of $E_T$ as well as of the EVI during the dry season, as reported in other studies (Huete et al. 2006, Myneni et al. 2007).

Figure 7. Three-month average values (DJF, MAM, JJA, SON) and annual average values of (a) calculated $E_T$ (mm day$^{-1}$) and (b) precipitation (mm day$^{-1}$), over the Brazilian Legal Amazon. Values were calculated for the period 2000–2004. Precipitation corresponds to the TRMM 3B43 data sets.
4. Discussion

4.1 Sensitivity of EVI to climate variability

In this paper, EVI is used to represent changes in vegetation, including the response of vegetation to climate variability. It is important to ask how adequate EVI is in representing the geographic seasonal to interannual variation of vegetation. The Amazon forest is dominated by its response to rainfall variation on these time scales. The capability of EVI to monitor the seasonal variation of the Amazon forest was studied by Xiao et al. (2006). To study the capability of EVI to monitor the interannual variability of Amazon forest we performed an analysis over an area in the eastern Amazon (2° S–5° S, 53° W–56° W) that experiences regular droughts from El Niño events (Stokstad 2005). In this area, the dry season lasts 5 months (consecutive months with precipitation <100 mm) centred in September (Sombroek 2001). Droughts are one of the most important climate variability events in the Amazon, having a strong influence over vegetation phenology. We diagnose these events using the Standardized Precipitation Index (SPI; McKee et al. 1993), calculated for the period 1986–2006, and based on precipitation data from the Global Precipitation Climatological Centre (GPCC). The SPI value is equal to zero if precipitation does not deviate from its climatology. Droughts begin when SPI values first fall below zero and end with positive or zero values of SPI for at least several months.

Figure 8(a) shows monthly SPI time series from 2000 to 2006. During this period, drought events with different intensities can be observed in 2002, 2003 and 2005. The 2002–2003 drought, but not the 2005 drought, can be related to an El Niño event (McPhaden 2004, Marengo et al. 2008). It can also be observed that, except for some months during the dry season, the precipitation in 2002 was below its long-term average, with a deficit starting around July 2001. Coincident with this deficit, figure 8(b) shows that, during the 2002 dry season, the EVI had the lowest values among the drought events compared. This result agrees with Hutyra et al. (2007), who reported that the gross primary productivity for the period 2002–2005 was lower during the 2002 dry season in the K67 site. As EVI is sensitive to canopy

![Figure 8](image_url)

Figure 8. Monthly spatial average values over the area 2° S–5° S and 53° W–56° W of (a) the Standardized Precipitation Index (SPI) from 2000 to 2006 and (b) the dry season EVI from 2002 to 2005. The SPI was calculated from the GPCC data (1986–2006) using a time scale of 6 months.
structure, low EVI values can be associated with a thinning of the leaf canopy or canopy openness as a consequence of drought conditions, as reported for this region by Nepstad et al. (2002). In 2003, above average precipitation started in July and continued throughout July 2004. The increase of precipitation during the 2003 dry season produced a favourable effect on vegetation (an increase in EVI values) with respect to the same period in 2002. In 2005, South America experienced below-normal precipitation anomalies, but in west-central and eastern Brazil the rainy season was slightly below normal (Shein 2006). In this year, after 6 months of wetter than normal precipitation conditions, a moderate drought event was observed in September. The EVI shows a peak in this month due to the positive response of vegetation to well-watered soil and an increase in solar radiation.

Although vegetation green-up has been reported during the dry season in the eastern Amazon (Huete et al. 2002), our results show that the intensity of this green-up depends strongly on climate variability. The EVI was capable of monitoring forest conditions related to this variability.

4.2 Uncertainties of observed and calculated $E_T$

First, in situ measurements of $E_T$ have uncertainties of about 10–30%, as suggested by the observed imbalance of 14% (K83) to 28% (RJA) (see table 1 for references), related to several factors (e.g. advection, night flux underestimations).

Second, cloud cover can reduce the quality of MODIS EVI data. Asner (2001) reported that the chance of acquiring scenes with 30% or less cloud cover over the Amazon is minimal from December to May and very limited from October to November. Annually, the probability of obtaining scenes with 30% or less cloud cover in the BLA is >90% southwards of 5° S. The MODIS science team established the Vegetation Index Usefulness Index (UI; http://edcdaac.usgs.gov/modis/moyd13_qa_v4.asp) as a quality assessment on a pixel-by-pixel basis. We used the UI to evaluate the quality of the EVI images. The values of the UI for a pixel are determined by several factors, including aerosol quantity, atmospheric correction conditions, cloud cover, shadow, and sun-target-viewing geometry. The UI has 16 levels that vary from perfect quality (level 0) to low quality (level 14). No useful data are labelled as level 15. In this work the level ‘Intermediate Quality’ (sixth in the UI scale) was used as the threshold between good and bad quality pixels. This threshold is more restrictive than the ‘Average Quality’ (eighth in the UI scale) commonly used.

The 16-day 1 km × 1 km usefulness quality data were used to calculate the percentage of pixels with quality better than the ‘Intermediate Quality’ level. The results were then converted to 0.25° resolution and are presented in figure 9. Central Pará had good quality EVI in 30–40% of images. This percentage was higher, near 50%, over western Maranhão, southern Amapá, some areas in Roraima, and the western portion of Amazonas State. The remaining areas presented EVI better than the threshold in at least 60% of the cases, with the best EVI quality being observed in the southern and western edges of the BLA. Our model represented the observations at central Pará (K83 and K67 sites) well, overcoming the effects of pixel quality. However, on the western edge of BLA, the $E_T$ values should be considered with caution because observed $E_T$ data are not available for comparison.

A third factor contributing to errors in $E_T$ are uncertainties in ISCCP-FD fluxes. The largest sources of uncertainties for South America are caused by clouds, TIROS Operational Vertical Sounder (TOVS) atmospheric temperature, ISCCP surface
temperatures, and vertical water vapour profiles (Zhang et al. 2004). Zhang et al. (2004) reported that the overall uncertainties of these fluxes are at least 10–15 W m$^{-2}$ at the surface. Although the differences between the site observations and the ISCCP-FD fluxes presented here are larger than that, the differences appears to be constant throughout the BLA (figure 4), presumably because of differences in spatial and temporal scales between satellite and flux tower measurement footprints.

4.3 ET/precipitation rates over the Amazon

The rate of $E_T$ determined with respect to precipitation across the Amazon forest is shown in figure 10. The DCK, CRS, K83 and SIN sites reported an average $E_T$/precipitation rate of 50% and the RJA site had a rate of 45%. Our results agree with these measurements but also show a regional variability in this rate. Areas of maximum precipitation (see also figure 1) had the lowest rate (<40%). These areas also show from zero to three consecutive months with precipitation <100 mm and lower daylight intensity (Sombroek 2001). High precipitation implies high cloudiness, and therefore less radiation available to promote $E_T$. These areas also have the maximum plant-available soil water (PAW) and are less susceptible to droughts than those observed during an El Niño event (Nepstad et al. 2004). $E_T$/precipitation rates with values greater than 40% were observed in southern, eastern and middle areas of the basin. These areas are characterized by annual precipitation <2000 mm (figure 1), 4–7 consecutive months of precipitation <100 mm (Sombroek 2001) and low values of maximum PAW (Nepstad et al. 2004), and their temperatures strongly correlated with

Figure 9. Areas in the Brazilian Legal Amazon with recurrent problems of MODIS EVI quality. The grey-scale indicates the frequency that pixels have better than 'Intermediate Quality' over the course of a year.

Figure 10. Percentage of evapotranspiration with respect to precipitation over the Brazilian Legal Amazon for the period 2000–2004.
the El Niño-Southern Oscillation (ENSO) index (Malhi and Wright 2004). As a result, these areas are more susceptible to drought events and fires.

4.4 $E_T$ over deforested areas

Since the early 1970s, the Amazon basin has been heavily deforested in an area along the southern and eastern edges of the basin, as delineated in figure 11. By August 2004 the accumulated deforestation was $\sim 14\%$ of the BLA (www.obt.inpe.br/prodes). After 2002, an increase in the deforestation rate was observed in response to the increased international demand for soybeans (especially in the state of Mato Grosso) and beef (Fearnside 2005). To determine whether calculated $E_T$ is adequate over deforested areas we focused our analysis over a small area within the coordinates $10^\circ$ S to $11^\circ$ S and $55^\circ$ W to $56^\circ$ W in the Mato Grosso State, where intense deforestation has occurred in recent years. During the wet and dry season our model shows $E_T$ values of $2.8 \pm 0.13$ and $2.2 \pm 0.1$ mm day$^{-1}$, respectively. These values are very close to those of $3.2$ mm day$^{-1}$ in December and $2.12$ mm day$^{-1}$ for the dry season reported by Priante et al. (2004) over a cattle pasture area located at $9.86^\circ$ S and $55.23^\circ$ W in the Mato Grosso State. These results suggest that our model may be used as a first approximation of $E_T$ over deforested areas.

5. Conclusions

The empirical model developed to calculate $E_T$, using satellite-retrieved net radiation and EVI as inputs, agrees with in situ observations within 17%. This empirical model was based on the suggestion from previous in situ observations that the distribution of $E_T$ over the Amazon is largely controlled by the surface net radiative flux and vegetation condition. Our analysis suggests that the EVI can reasonably capture the vegetation responses due to rainfall variability on a large scale. The rates of $E_T$/precipitation were very similar to those reported in the literature over the BLA; although MODIS EVI data are reduced in quality over Pará State, the calculated $E_T$ agreed well with observed $E_T$, with high values over the northern part of this state during the dry season (September to November). Our model enabled us to determine a regional pattern of the $E_T$. The model also shows a reasonable change in $E_T$ over deforested areas compared to in situ observations. However, further studies are needed to more clearly determine whether this method can be used to estimate $E_T$ over areas where change in land cover has occurred.
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