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Different spatial and temporal arrangements for validating the latent heat flux obtained using the MOD16 product in a forest in the Western Amazon

Abstract

The Amazon rainforest is an important source of evapotranspiration and is essential in the global atmospheric circulation and hydrological cycle. However, measurements on vegetated surfaces are difficult, and methods such as remote sensing are promising in the micrometeorological data area. We aimed to assess the applicability of the MOD16 product to estimate evapotranspiration in a vegetated area. MOD16 data (LEMOD) derive from the Moderate Resolution Imaging Spectroradiometer sensor. For comparison, we used data from the eddy covariance system (LEEC) of the tower of the Large-scale Biosphere-Atmosphere Program in the Amazon of the Jaru Biological Reserve. To measure the linearity among variables, the Pearson correlation test (α=0.05) was used, and the T test was applied to assess the statistical significance between LEMOD and LEEC means (α=0.05); the root mean square error was also calculated. Regarding LEMOD, a similarity was found between the annual means of model and data, in which the best LEMOD estimates were obtained for annual averaging, when mean values were 96.51 W m–2 (0.7% lower than LEEC). LEMOD overestimates ranged from 1.05 W m–2 (1%) in 2007 to 15.78 W m–2 (18%) in 2005. Variations in short periods were not represented by the LEMOD product.

Keywords: energy flux, evapotranspiration, tropical forest, MODIS, eddy covariance

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Introduction

The Amazon rainforest covers half of the world's tropical forest area and constitutes one of the largest reservoirs of biodiversity.[1] Due to the magnitude of the mass and energy exchanges performed by it, it is considered the largest source of continental evapotranspiration, among other factors, which places it in a level of attention on its conservation and maintenance, such as the fact that it acts in the global atmospheric circulation and in the hydrological cycle,[2] besides having great influence on the climate and periodicity of extreme events.[3] In this sense, understanding the energy balance is essential. The latent heat flow (LE), in turn, represents an important indicator of the amount of energy used for evapotranspiration.[4,5] Measurements in water vapor flows between the surface and the atmosphere usually occur on a point scale or in a small area, in a short period of time, so that existing techniques that estimate the evapotranspiration (ET) in situ, such as the turbulent flow towers (eddy covariance), there are limitations in the representation of ET for large areas.[6] Thus, remote sensing data comes to help solve this impasse, as it is a suitable tool to obtain information in different time and spatial scales.[7,8]

Much of the remote sensing of ET models have been developed based on the Penman-Monteith models or the Priestley-Taylor equations,[9–14] in which the MOD16 algorithm stands out, developed by Mu et al.[11] and improved by Mu et al.,[8] being a combination of remote sensing data with reanalysis data to estimate global ET. ET accuracy by remote sensing varies spatially and temporally, according to factors such as season, climatic areas, altitude and land cover type. Thus, there is a need to understand the ET response generated from several models over time, in multiple scales and to quantify the uncertainty associated with the performance of the model in different ecosystems.[15,16] In this context, the objective of this study was to analyze the applicability of the MODIS product to estimate ETs in a forest area in the Western Amazon. For this purpose, the latent heat flows estimated by the MOD16 and by the eddy covariance system were analyzed, comparing the two methods using spatial distribution, seasonal and annual patterns, for a time series data from 2004 to 2009.

Material and methods

Study area and data series used

This study was carried out at the Jaru Biological Reserve (REBIO Jaru), which is an integral protection unit under the responsibility of the Chico Mendes Institute for Biodiversity Conservation (ICMBio), located east of Rondônia, approximately 80 km from the municipality of Ji-Paraná , between latitudes 09º19'52" and 10º11'46"S and longitudes 61º35'40" and 61º52'48"W. The classification of vegetation is open shoulder phile forest,[17] commonly referred to as seasonally dry or semideciduous forest,[17,18] with an average canopy height of approximately 35 m. According to the Köppen climate classification, the predominant climate in the region and its surroundings is type Aw — Rainy Tropical Climate — with climatological average air temperature of over 18°C during the coldest month (megathermal) and a well-defined dry period, from July to September, when there is a moderate deficit of water, with rainfall indexes lower than 50mm month-1.[19] According to local measurements, mean annual temperature is 24.8°C, and mean relative humidity is 79.8%;[20] the climate of the Amazon region is intrinsically characteristic, in addition to its high temperatures, by seasonality. Average precipitation from 1999 to 2010 in REBIO Jaru was 2001 mm year-1.[21]

MODIS products

MODIS system data were obtained through LPDAAC (Land Distributed Active Archive Center, https://lpdaac.usgs.gov/), with the global evapotranspiration algorithm (MOD16A2) being of interest to this study.

The MOD16A2 product, proposed by Mu et al.,[8] was an evolution of the models developed by Cleugh et al.[10] and Mu et al.,[11] and is based on the use of the Penman-Monteith equation.[9] It is composed of 8 days and a spatial resolution of 1 km. The period covered by the data set was from 2004 to 2009, totaling an "n" of 276 (46 per year). For comparison with the MOD16 product (LEMOD), we used data from the eddy covariance system (LEEC) and direction data measured by equipment installed in a meteorological tower of 61.5m (10°11'11.4"S and 61°52'29.9" W), belonging to the tower network of the Large-scale Biosphere-Atmosphere Program in the Amazon (LBA Program). Table 1 shows the examples of the data series used. Four spatial arrangements of MODIS products were compared regarding their correlation levels with field-measured ET, always with the grid cell of the meteorological tower as a center, in which (a) a nine pixel mean (3 × 3 km), as proposed by Mu et al.,[10,11,22] (b) only the central pixel (1 × 1 km), (c) 10 pixels according to the season specific predominant wind directions, as proposed by Chamers (2008), and (d) pure Forest covered pixels inthe 3 × 3 km quadrant (Table 2, Figure 1).

Table 1 Brief description of the evapotranspiration (ET) series and wind direction data

	data series		
	MODIS	**eddy covariance**	**Micrometeorological**
source/satellite/sensor	MOD16A2 (Global evapotranspiration product) MOD16A2QC (Quality control of the global evapotranspiration product) MOD12Q1 (Classification of land use and cover)	Tower installed in loco	Tower installed in loco
Duration of data series	2004 to 2009	2004 to 2009	2009
Resolution	1 km	-	-
Variables/ products	Latent heat flux (LEMOD) Quality control (QC) Land use and cover	Latent heat flux (LEEC)	Wind speed and direction

Table 2 Description of the spatial arrangements for the latent heat flux (LE) according to the pixels used

	central pixel 1×1 km	3×3 km only forest	3×3 km	North direction	South-southwest direction
pixel definition	1 pixel (61)	5 pixels (49, 50, 51, 61, 62)	9 pixels (49, 50, 51, 60, 61, 62, 71, 72, 73)	10 pixels (5, 6, 7, 16, 17, 18 28, 39, 50, 61)	10 pixels (61, 72, 82, 83, 93, 94, 104, 105, 115, 116)
LE definition	LEMOD1×1 - latent heat flux estimated by MOD16, with pixel representative of tower location	LEMODF - Latent heat flow estimated by MOD16, with representative pixels only with forested areas	LEMOD - Latent heat flow estimated by MOD16, with pixels representative of quadrant 3×3	LEMODu - Latent heat flow estimated by MOD16, with pixels representative of the prevailing wind direction, wet and dry-wet seasons	LEMODu - Latent heat flow estimated by MOD16, with pixels representative of the prevailing wind direction, dry and wet-dry seasons

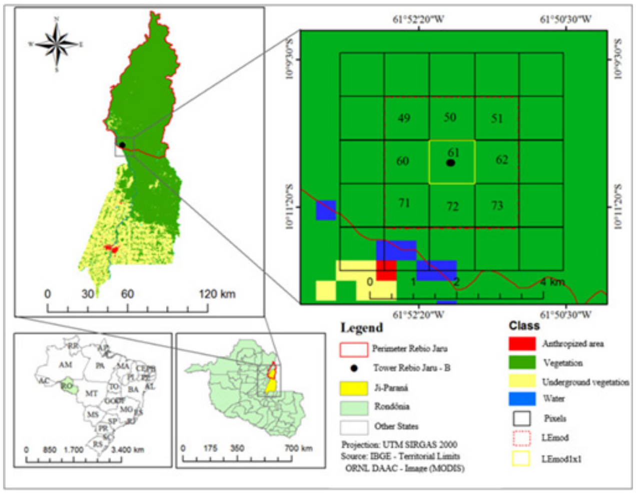

Figure 1 Classification of biomes of the MCD12Q1 product in the Jaru Biological Reserve (REBIO Jaru). Dashed squares represent the pixels, LEMOD1×1 represents the central pixel, in which the micrometeorological tower is located, and LEMOD represents an area of 3×3 pixels around the tower. Pixels numbered according to Table 2.

In all cases, quality control was used (MOD16A2QC), in which signals of cloud contamination, in each pixel, were analyzed to filter and reject data with insufficient quality.[23] By QC determination, values were assigned to each bit, in a total of 8 bits. To get to the value shown in the MOD16A2QC algorithm, codes referred to the sensor and local conditions, such as the presence of clouds and aerosols, were decoded as binary numbers, which showed as response hexadecimal values 0, 8, 16, 32, 40, 48, 97, 105, 113, 157 and 255. Values up to composition 97 are considered of acceptable quality (Andrade, 2013), which corresponds to conditions without the presence of clouds and unidentified cirrus.

Latent heat flux data measured by the eddy covariance system

Measurements of latent heat flows (LE) were determined by the turbulent vortex covariance system (eddy covariance) composed by a three-dimensional sonic anemometer (Solent 1012R2, Gill Instruments, Lymington, UK) and an open-way infrared gas analyzer (LI- 7500, LICOR Inc., Lincoln, USA). These sensors were connected to a microcomputer, which performed sensor readings at a frequency of 10.4 Hz and stored the raw data in files every 30 minutes. The collected data were processed through Alteddy.[24] The sampling time used to calculate flows was 800 s. Additionally, the accuracy of measurements of energy flows performed by turbulent vortex covariance method was evaluated by the closure of the energy balance, proposed by Moncrieff et al.[25] For this purpose, the proportion between the incident solar radiation data and the flow data was performed, and the energy flow data in the area varied from 70 to 77% of the radiation value,[26] although the standard in Amazonian forest areas is approximately 85% (Araújo et al., 2002; Rocha et al., 2004).

Statistical analyzes

Pearson correlation coefficients (r) were determined between LEEC and LEMOD data sets, an indication of the existence of linear association between two variables, for a significance level of 5% (α = 0.05). For the monthly separated data set, the T test was performed, which assesses the statistical significance of the difference between two averages of independent samples — in this case, the LEEC and LEMOD — with one special case of analysis of variance (ANOVA), which allows us to identify how large should the T value be to consider the statistically significant difference, that is, the difference is not caused by the sample variability.[27] The significance level adopted was 5% (α = 0.05). From the linear regression analysis, the coefficient of determination (r^2) was extracted, which in turn allows to assess how much the model reflects the variance of the observed data, along with the angular coefficient (b). In order to obtain the equation, the observed variables were considered as X-axis, and the simulated variables, as Y-axis. Thus, b>1 represents a model tendency to overestimate the variables in question, and b<1, a tendency to underestimate. All statistical analyzes were performed in the software SPSS® v. 21.0.

Then the root mean square error (RMSE), an indicator of the accuracy of the model, was calculated through the quadratic error difference (Wilks, 2006). LE data do not show clear temporal patterns; time series were smoothed for visual inspection by the Singular Spectrum Analysis (SSA), implemented through the Caterpillar method.[28,29] SSA is a spectral, nonparametric approach that requires neither a priori specification of models of time series nor deterministic or stochastic trends, and has shown good performance in signal extraction from short, noisy and gap-containing time series.[28,30] SSA decomposition demands a two-user-defined parameter, the window length representing the maximum lag used in the SSA autocovariance calculations, and a threshold giving the maximal sequence of missing entries values. Mathematical backgrounds of SSA are detailed in Golyanina & Osipov,[29] whereas Golyanina et al. (2010) gives recommendations for the selection of window length and missing data threshold. All statistical analyzes were performed in the software SPSS® v. 21.0.

Results

Seasonality of LEMOD and LEEC

The mean (±SD) for the entire LEMOD series was 98.42±5.28 W m–2, with a minimum of 33.33 W m–2 at Julian day 65 of 2006, (March, humid season) and a maximum of 140.10 W m– 2 at Julian day 305 in 2004 (November, wet-dry season). The mean tower measurement (LEEC) was 97.22±5.94 W m–2, which is statistically equivalent, having however a higher minimum of 57.24 W m–2, at Julian day 225 in 2005 (August, dry season), and a higher maximum of 147.85 W m–2 as well, determined at day 9 in 2006 (January, wet season). LEMOD has a full amplitude 12.10 W m-2 higher than LEEC. LEMOD and LEEC show some distinct seasonal variations during 2004 through 2009 (Figure 2). Except for the first two years, seasonality of LEMOD is monotonic (Figure 2), but even the signal is double peaking; highest values occur during the dry and dry-wet season (August through November) and lowest ones during the wet and wet-dry season (March through May). The annual phase signal containing SSA components *02 and *03 explain about 5.5% of data variations, against less than 1.4% for LEEC (Table 3). Thus, in-year amplitudes in the extracted phase signal from LEEC are lower than LEMOD, which generally has a secondary peak. Maximum values occur during the wet season (2005, 2006, 2007), but were also observed in the dry (2008) or dry-wet ones (2009). In the reconstruction phase, this results in a primary peak in the wet season (2005, 2006) or dry-wet season (2004, 2009), and a secondary one mostly during the dry season (2004, 2008) or wet-dry season (2005, 2006).

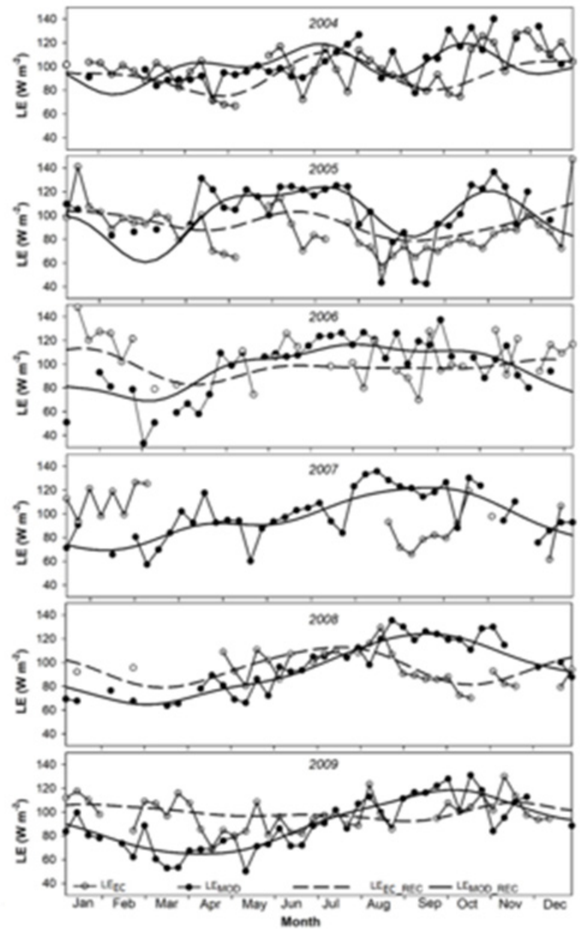

Figure 2 Values of MODIS latent heat flux (LEMOD) and 8-day mean eddy covariance latent heat flux (LEEC), according to the MOD16A2 resolution algorithm, between 2004 and 2009 for the seasonal broadleaf forest around the REBIO Jaru flux tower. SSA reconstruction (_REC) using a window length of 92 and missing values of 36 (8-day time steps).

The observed mean annual values for LEEC and LEMOD are described in Table 4. It is worth mentioning that the lowest annual LE mean, according to the EC measurements, happened in 2005, coinciding with the drought event registered in the same year in the Amazon region.[2,31] On the other hand, it is noted that the MODIS algorithm did not record this possible reduction of LE in that year, which may refer to its fragility in front of extreme events. With a higher intra-annual variability than LEEC, LEMOD showed a lower inter-annual variation than LEEC, suggesting lower sensitivity of the algorithm to detect changes in the behavior patterns of some influential variable. Both LEEC and LEMOD showed a negative trend during the six-year observation period.

Comparison of annual, seasonal and monthly LEEC and LEMOD

For further analysis of LE cyclic behavior and differences between LEMOD and LEEC measurements, the series were grouped by month, season and year. Best LEMOD estimates were obtained for annual averaging, when mean values were 96.51 W m–2 (0.7% lower than LEEC). LEMOD overestimates ranged between 1.05 W m–2 (1%) in 2007 and 15.78 W m–2 (18%) in 2005. On a monthly (Figure 3) and seasonal (Figure 4) basis, the match between LEMOD estimates and

LE flux tower measurements (LEEC) is limited. Monthly, LEMOD estimates were between 28.09 W m-2 higher (January) and 23.12 W m-2 lower (October) than LEEC; higher LEMOD overestimates occur in the dry-humid season, whereas major underestimates are seen in the wet and dry-wet season. Differences between LEMOD and LEEC were significantly higher from July to October and lower from April to May and from November to December (Figure 3). The monthly pattern observed is maintained in the seasonal comparisons. During the wet season, LEMOD underestimates LEEC (-24.64 W m-2) and overestimates LEEC (+17.95 W m-2), whereas averages and SDs are similar during the transitional periods (Figure 4).

Table 3 Percentage of explained variations in signal-containing Eigenvalues (EV) obtained from SSA decomposition (window length 92, missing values threshold 36). T (Trend), P (Phase), ACexp (Explained annual phase variance), SCexp (Explained secondary phase variance)

	EV								
	*01(T)	*02(P)	*03(P))	*04(P)	*05(P)	*08(P)	*09(P)	acexp	SCexp
LEMOD	91.31%	2.87%	2.62%	0.32%	0.30%			5.49%	0.62%
LEEC	92.60%	0.74%	0.62%	0.39%*	0.36%*	0.28%*	0.26%*	1.36%	1.29%

Note:*Week or mixed signals.

Table 4 Annual mean (±SD) of MODIS latent heat flux (LEMOD) and eddy covariance latent heat flux (LEEC) from 2004 to 2009 for the seasonal broadleaf forest around the REBIO Jaru flux tower

DATE	**YEAR**					
	2004	**2005**	**2006**	**2007**	**2008**	**2009**
LEEC (±DP) (W m–2)	99.47±10.52	86.36±12.25	104.55±14.08	99.25±17.01	95.15±11.35	98.08±9.69
LEMOD (±DP) (W m–2)	101.74±15.09	101.59±18.61	97.77±18.26	96.11±18.33	93.84±21.02	87.97±19.64

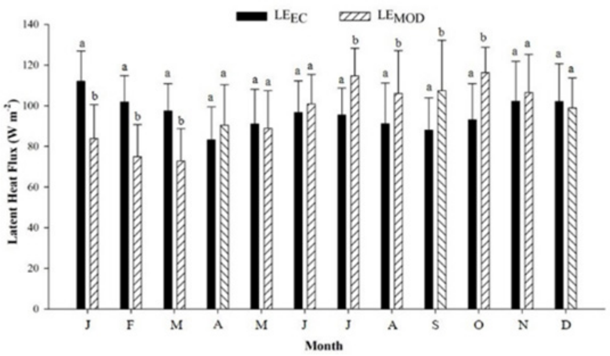

Figure 3 Monthly mean ± standard deviation of LEEC and LEMOD between 2004 and 2009. Characters (ab) indicate if there is a significant difference (α = 0.05) between averages.

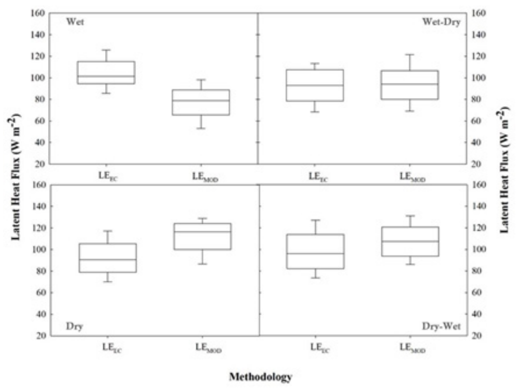

Figure 4 LEEC and LEMOD (n= 276) at the four seasons (wet, wet-dry, dry and dry-wet) from 2004 to 2009.

Factors related to spatial scale

ET dynamics is controlled by time variability in atmospheric conditions and the spatial variability of land surface conditions and climatic zones. Micro-climatological parameters, such as surface temperature, shading, wind speed and direction, atmospheric pressure, which are factors that influence ET estimates, may be altered by terrain topography and elevation.[32] Thus, ET estimation in an ecosystem must be adequate to its specific space-time heterogeneities.[33] As the relations between LEEC and LEMOD were found to be strongest for a seasonal data synthesis and annual means, these groupings were used to evaluate the influence of different MODIS pixel arrangements on the predictability of LEEC (Table 5). Highest correlations and lowest RMSE were obtained for MODIS estimates according to the predominant wind direction (LEMODu), for the wet (0.54/86.4 W m–2) and dry season (0.52/61.9 W m–2). During the dry-wet period, RMSE was low (34.7 W m–2), however, the correlation is poor, 141 (0.57) than that of LEMODF. In general, MODIS LE estimates have their highest correlations with measured LE in the dry season, with significant correlations (α<0.05) between 0.477 (LEMOD) and 0.533 (LEMOD1X1). Only LEMODu has its highest correlation in the wet season (0.535). During the dry season, there is a systematic LE overestimation from 16.6% (LEMODu) to 22.2% (LEMOD1X1), whereas LE is underestimated between 21.7% (LEMODu) and 25.0% (LEMODF).

Table 5 Mean (±SD), mean difference (%) and Pearson's correlation coefficient (including α) between LEEC and LEMOD, in different spatial arrangements (LEMOD1×1, LEMOD, LEMODF, LEMODu), percentage difference between means and monthly mean RMSE during the wet, wet-dry, dry and dry-wet seasons, and annual LE means from 2004 to 2009

Period	**spatial arrangement**	**Mean ± SD**	**Mean difference (%) regarding LEEC**	**Pearson R correlation coefficient (α)**	**RMSE ($W\ m^{-2}$)**
Wet	LEEC	103.95±13.28	–		
	LEMOD1X1	80.04 ± 27.34	–23.00	0.157(0.57)	
	LEMOD	78.33±13.42	–24.64	0.184 (0.33)	109.06

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Table Contniued...

Period	spatial arrangement	Mean ± SD	Mean difference (%) regarding LEEC	Pearson R correlation coefficient (α)	RMSE (W m^{-2})
	LEMODF	77.92 ± 19.50	–25.04	0.273 (0.30)	99.43
	LEMO Du	81.43 ± 11.31	–21.66	0.535(0.02)	98.99
Wet-Dry	LEEC	92.15± 10.37	–		86.36
	LEMOD1X1	96.50± 20.81	4.72	0.170 (0.56)	
	LEMOD	93.40±16.21	1.35	0.180 (0.23)	15.75
	LEMODF	95.09 ± 17.38	3.19	0.132 (0.65)	5.9
	LEMO Du	95.50 ± 15.98	3.63	0.050 (0.86)	13.04
dry	LEEC	93.02 ± 12.94	–		12.36
	LEMOD1X1	113.63±17.35	22.15	0.533(0.02)	
	LEMOD	109.72±16.64	17.95	0.477(0.05)	82.63
	LEMODF	111.83±16.48	20.22	0.485(0.04)	66.94
	LEMO Du	108.45±16.76	16.58	0.524(0.03)	75.41
Dry-Wet	LEEC	96.67± 13.66	–		61.88
	LEMOD1X1	112.84±16.69	16.72	0.147(0.57)	
	LEMOD	107.78±13.75	11.49	0.041(0.87)	65.48
	LEMODF	108.91±16.77	12.66	0.288(0.26)	47.15
	LEMO Du	104.70±8.73	8.3	0.141(0.57)	49.73
Annual 2004-2009	LEEC	97.22 ± 5.94	–		34.66
	LEMOD1X1	103.45± 9.78	6.4	-0.131(0.80)	
	LEMOD	98.42±5.28	1.23	-0.340(0.51)	15.24
	LEMODF	100.50±6.02	3.37	0.148(0.77)	2.92
	LEMODN	101.55±6.02	4.45	0.103(0.84)	8.81
	LEMODS	99.04±5.11	1.87	0.036 (0.94)	10.22
					4.46

Note: Latent heat flux (LE), being EC = estimated by eddy covariance system; MOD = estimated by MOD16, resolution 3×3 km; MOD1×1 = estimated by MOD16, resolution 1×1; MODF = estimated by MOD16, for forested pixels; MODu = estimated by MOD16, for pixels in the prevailing wind direction in each season; MODN = estimated by MOD16, for pixels in the direction of the North wind; MODS = estimated by MOD16, for pixels in the direction of the South-Southwest wind.

Discussion

On a yearly basis, MODIS LE data are overestimations of observed eddy covariance measurements at the REBIO Jaru tower site. Overestimations occur during the dry and dry-wet season, whereas underestimations were verified in the wet and wet-dry transition season. These findings agree with previous studies in semi-deciduous tropical forests, where LE was found to be highest during the rainy season.[34] Despite overestimating the absolute LE, correlations between LEMOD and field measurements are highest during the dry season, as previously observed by Ruhoff[35] at seven test sites in the Amazon region. Other congruent findings were reported by Cleugh et al.,[10] who verified LE overestimates of up to 100 W m–2 for a Eucalyptus predominant forest in Australia during the dry season, which is characterized by low LE due to very high deficits of vapor pressure.[36] Otherwise, during the humid seasons, MODIS estimates were between 30 and 50 W m–2 lower than field measurements, totaling an annual net overestimate of the MOD16 product algorithm.[10] Mu et al.[11] reviewed the algorithm developed by Cleugh et al.,[7] adding the soil evaporation component, and found values very close to the magnitude of the observed data regarding the annual average of 19 towers located in North America with the AmeriFlux system (measured by eddy covariance). However, the algorithm values were much lower during Spring and Summer, and closer to that observed during Fall and Winter in that region.

Yuan et al.[13] also validated ETMOD through comparison with ET measurements obtained through the eddy covariance system in 51 towers, verifying that the proposed model explained 82% of the measured evapotranspiration variations. In 2011, the algorithm proposed by Mu et al.[11] has once again examined modifications, this time including, among others, the calculation of temperatures divided into diurnal and nocturnal, and the calculation of the heat flow in the soil. The new improved algorithm reduced the mean absolute deviation of the daily mean evapotranspiration from 0.39 mm d-1 to 0.33 mm d-1 for observations in 46 towers, indicating that the new estimate better captured the magnitude of ET measures.[8] In general, we verified that the improvements ensured adequate accuracy regarding the means, however, variations that occur in smaller time scales could not yet be recorded. LEMOD showed lower inter-annual variation regarding LEEC, suggesting the algorithm had lower sensitivity to detect changes in behavior patterns of some influential variable, such as changes in ecosystem water availability in 2005. The LEMOD decrease in the rainy season in early 2006 may represent an answer to the effects of the 2005 drought, since the effects of severe drought on the canopies of the Amazon forests were persistent in the following years;[31] the decrease of water content in the soil during the year of the drought may show as a reflection the largest number of trees, among others, with consequent decrease in leaf area index, an important input parameter for the MOD16 algorithm.

Reasons for uncertainties in the LE estimation in large-scale remote sensing are associated with the parameterization model, measurement errors in meteorological towers, spatial heterogeneity within a MODIS pixel, and with the incompatibility of the relation between meteorological data and sensing data, as reported by King et al.,[37] Moreira et al.,[16] and Ruhoff[35] However, uncertainty decreased when validation analyzes were performed considering the seasons individually. In the MODIS product, the imprecise classification of land use and cover implies the incorrect use of parameters such as minimum air temperature and vapor pressure deficit (VPD) used to determine the opening and closing of stomates in the stomatal and canopy conductance.[35] This results in less precise ET estimates, as stated above, since the use of these parameters aims to simulate the stomatal and canopy conductance, even under water or temperature stress conditions, as these may result in high ET estimation errors. Errors in biome classification in the MCD12Q1 product may also result in IAF inaccuracies. The correct parameterization is so important that the good accuracy of the model was verified for sites installed in correctly classified tropical rainforest areas.[35]

In addition, some problems associated with the algorithm and the input data may occur, since the biophysical parameters used in the algorithm are considered to be constants for the same biome, and significant phenological differences might occur in it, which may result in expressive differences between the actual field conditions and the parameters used in the algorithm.[38] Cloud cover is another factor that may be related to errors in products generated by remote sensing,[39] especially during seasons with greater cloud cover, which may explain the greater accuracy of the model during drought. Furthermore, considering the inherent uncertainties to the eddy covariance system, which may vary from 20 to 30%,[40] it is not possible to attribute the totality of errors between observed and estimated LE only to the inaccuracies of the MOD16 algorithm. Comparing the different time scales, the results indicate that LEMOD showed better results when a longer time interval was considered as monthly and annual means, agreeing with Ruhoff's studies (2011). Moreover, it was important to analyze the series by season, respecting the seasonal differences existing in the locality, due to the change in the annual LEMOD pattern when compared to LEEC, an indication that the data obtained by remote sensing and by field measurements have different influence factors.

However, when considering the annual and seasonal LEMOD and LEEC means in the transition seasons (wet-dry and dry-wet), there were minor differences between them. Nevertheless, the analysis of LE means in different spatial arrangements indicates the influence of the convective transport of the surrounding area to a minimum radius of 3.5 km on the tower measurements, especially in the South-Southwest (during the dry and dry-wet seasons) and North (during the wet season) directions, since the LEMODu shows better approximation. The definition of the extension area (pixel arrangement) influenced the LEMOD mean, allowing for a better approximation to LEEC. This variation in means and its relation between LEs happen because the footprint (coverage area) of the remote sensing data varies from 1 to 110 km, while the footprint of the eddy covariance system is usually less than 1 km.[41] In this sense, the comparisons between energy flow obtained in loco and by remote sensing products becomes complex.[42]

When assessing different spatial arrangements, the best relations between the annual LEMOD and LEEC averages were observed in comparison to the relations between LEMOD1X1, LEMOD3X3F, LEMODu and LEEC. However, when considering the seasonal LE averages, the best relations were obtained with LEMODu and confirmed through linear regression analyses, with variance of 28% and 27% during the wet seasons, respectively.

These results agree with Kim et al.,[22] who, when analyzing the accuracy of the MOD16 algorithm in areas with different climatic classifications, found different correlations (r varying from 0.12 to 0.82), with a smaller r for arid areas, greater for a mixed forest in continental climate, and of 0.41 and 0.27 for tropical forests (equatorial climate). The results found in this research also agree with the correlations between LEs observed in the field and by the MOD16 product at the REBIO Jaru site and other LBA flux towers.[16] In a study comparing the MODIS ET with two models (Soil and Water Assessment Tool - SWAT and Bridging Event and Continuous Hydrological - BEACH) of the North of Vietnam, the authors concluded that the MODIS ET was very helpful for verifying the smaller scale of ET estimation by the two models, although its evapotranspiration estimates were slightly higher than those.[43–53]

Conclusion

When analyzing the applicability of the MOD16 algorithm to estimate LE at the REBIO Jaru, a good approximation of the model was verified regarding the annual averages obtained by the eddy covariance system. However, LEMOD variations in shorter time intervals did not reproduce the LEEC behavior, except for the monthly measurements of the dry season, in which a significant correlation was detected between measured and estimated data. The factors that may control the LEMOD variance are (i) related to spatiality, in which, when considering the predominant wind direction for the choice of pixels, better results where verified; (ii) factors related to micro-climatic variables and vegetation characteristics, in which the LEEC and LEMOD associations occurred with different sets of variables (except for the wet season). Also, the fact that the LEMOD 8-day and monthly data do not resemble those from LEEC may be explained by the low time MOD16 resolution (8 days), not allowing to capture daily cycle and wind effects.

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Conflicts of interest

The author declares there is no conflict of interest.

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