Land cover change alters seasonal photosynthetic activity and transpiration of Amazon forest and Cerrado

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Abstract

Tropical vegetation influences local, regional, and global climates, largely through its relationship with the atmosphere, including seasonal patterns of photosynthesis and transpiration. Removal and replacement of natural vegetation can alter both of these processes. In the Amazon, land use/land cover change (LULCC; e.g. deforestation) started decades ago and is expected to continue, with potentially strong effects on climate. However, long-term data on tropical photosynthetic activity and transpiration are scarce, limiting our ability to estimate large-scale effects of LULCC. Here, we use remote sensing data to analyze the impact of LULCC on seasonal patterns of photosynthetic activity and transpiration in the southern Amazon. This region, naturally dominated by forest and Cerrado, has seen high rates of LULCC. Within each of these two ecosystems, we compare estimates of photosynthetic activity (from GOME-2 and GOSIF solar induced fluorescence, SIF) and transpiration (from the Global Land Evaporation Amsterdam Model, GLEAM) in paired sites with high and low rates of LULCC. In forest-dominated regions, deforestation has reduced photosynthetic activity and transpiration, particularly during the dry season, and replaced dry season greening with dry season browning. The SIF datasets disagree on wet season responses; SIF increases with deforestation according to GOME-2, but decreases according to GOSIF. In Cerrado-dominated areas, LULCC has increased photosynthetic activity during the wet season. In both ecosystems, LULCC has resulted in a higher seasonal or annual range of photosynthetic activity levels. The observed effects are often stronger in regions with more extensive LULCC. We found large differences between the two SIF products in both forest- and Cerrado-dominated pixels, with GOME-2 consistently providing higher maximum SIF values. These discrepancies merit further consideration. This analysis broadly characterizes the effects of LULCC on photosynthetic activity and transpiration in this region, and can be used to validate model representations of these effects.

1. Introduction

Tropical ecosystems provide several ecosystem services to the rest of the planet. In addition to storing large amounts of carbon in live biomass and sheltering biodiversity, they influence the regional and global climate (Nobre et al 2016). The high rates of photosynthetic activity that characterize tropical ecosystems lead to large and fast exchanges of water, energy, and carbon with the atmosphere. This strong interaction with the atmosphere influences climate in different ways. For instance, about 32% of the Amazon rainfall is produced locally, and 75% of the rainfall is returned to the atmosphere (Staal et al 2018, Lovejoy and Nobre 2019). In addition to affecting local rainfall, these forests also influence continental precipitation (Lawrence and Vandecar 2015), regional surface temperature (Alkama and...
Cescatti 2016), and atmospheric carbon concentrations (Hubau et al 2020).

Natural ecosystems of the Amazon basin and the ecosystem services they provide to the rest of the planet are threatened by high rates of anthropogenic land use and land cover change (LULCC; Nobre et al 2016). Current estimates indicate that about 17% of the tropical forests of the Amazon basin have been deforested (Lovejoy and Nobre 2019). Model projections estimate that, in a business-as-usual scenario, as much as 47% of the Brazilian Amazon could be deforested by 2050 (Soares-Filho et al 2006).

Removing and replacing native vegetation changes carbon and water cycling, among many other environmental and socio-economic effects (Spracklen and Garcia-Carreras 2015, Chambers and Artaxo 2017, Marengo et al 2018). The changes in carbon and water exchanges with the atmosphere are, in large part, the result of differences in photosynthetic rates and water-use efficiency between the original and the replacing vegetation (Butt et al 2011). In the Amazon, tropical forests ramp up photosynthetic activity and transpiration during the dry season (Saleska et al 2003, Zemp et al 2017). Deep roots enable large, old trees to access water in the deeper layers of the soil when the shallow soil dries (Nepstad et al 1994, Oliveira et al 2005a). Without hydraulic redistribution to shallower soil layers by these large trees, other vegetation types would not be able to access the water, limiting photosynthetic activity, growth and transpiration during the dry season (Oliveira et al 2005b).

A shift in the seasonality of photosynthetic activity could shift the seasonality of precipitation (Chambers and Artaxo 2017). Furthermore, changes in precipitation seasonality affect vegetation distribution, phenology, and photosynthetic activity. This feedback loop could, eventually, lead to a tipping point for ecosystems in this region (Marengo et al 2018, Lovejoy and Nobre 2019). The changes could trigger forest dieback, changes in vegetation composition due to differences in drought vulnerability among species, or even complete biome shifts (e.g. savannization) (Marengo et al 2018, Lovejoy and Nobre 2019).

In the Amazon, there have been challenges in monitoring the changing relationship between land cover and regional climate as land cover continues to change. Historically, large-scale changes in precipitation, temperature, and evapotranspiration due to LULCC in the Amazon have been studied using global climate models (GCMS) (D’Almeida et al 2007, Chambers and Artaxo 2017). Fewer studies have used field- and remote sensing-derived data to investigate these changes (Vergopolan and Fisher 2016). In addition to problems with the lack of observational studies, land surface models coupled to GCMS inaccurately represent seasonality of photosynthetic activity of tropical forests of the Amazon (Restrepo-Coupe et al 2017). Modern remote sensing datasets provide a useful tool for investigating changes in photosynthetic activity and transpiration in the Amazon.

In this study, we estimate the current effects of LULCC on seasonal photosynthetic activity, using solar induced fluorescence (SIF) data, and transpiration by evaluating differences in remote sensing-derived data products between nearby areas with low and high levels of LULCC. We answer the following questions: How does LULCC affect photosynthetic activity and transpiration in two ecosystems in the Amazon? Do these effects differ between seasons? And, do these effects get stronger as LULCC expands within an area? We hypothesized that photosynthetic activity and transpiration would decrease with LULCC, specifically during the dry season, in both ecosystems. We expected these dry season reductions would decrease annual averages and increase the range of variation of photosynthetic activity and transpiration.

2. Methods

The area of study is located in the southeastern Amazon, a region with high land cover change rates (figure S1 available online at stacks.iop.org/ERL/16/054013/mmedia). Two main natural ecosystems are found in this region; the rainforest and the Cerrado. We used land cover data from the European Space Agency Climate Change Initiative (ESA CCI) between 1992 and 2015 (ESA 2017). As a proxy of photosynthetic activity, we used SIF data from the GOME-2 sensor (Joiner et al 2011, 2013), Sensor degradation has been a problem of the GOME-2 sensor (Zhang et al 2018). Even though we expect this degradation to have a minor effect on our pixel-to-pixel comparison of seasonal data, we also analyzed SIF data from the GOSIF dataset to complement our main results. GOSIF is a global dataset developed based on SIF data from the Orbiting Carbon Observatory-2 (OCO-2), MODIS EVI and climate reanalysis data (Li and Xiao 2019). When describing our results, we use the term SIF to refer to GOME-2 (as opposed to GOSIF) data unless otherwise specified. Transpiration data were obtained from the Global Land Evaporation Amsterdam Model (GLEAM) (Martens et al 2017). Information about the timing of the dry and wet seasons was obtained from the Rainy and Dry Seasons (RADS) dataset of Bombardi et al (2019). Elevation was retrieved from the SRTM30 Digital Elevation Model data for the Amazon basin by Saatchi (2013). Details about the area of study and each of the datasets are available in the supplementary materials associated with this article.

To quantify differences in photosynthetic activity and transpiration between regions with high and low LULCC, we identified pixels with high rates of LULCC between 1992 and 2015. Because the resolution of our SIF and transpiration data was coarser than that of
the land cover data, we calculated the percentage of smaller pixels (300 m × 300 m) within a larger pixel (0.5° × 0.5°) with a change of land cover type from 1992 to 2015. For the pair selection, we first selected all the pixels in the region with ‘high’ LULCC using a threshold of > 20% of the smaller pixels within a larger pixel (figure S2). We then found a reference pixel for each of the high LULCC pixels selected. The reference pixel is a pixel with the same dominant land cover type but low LULCC (i.e. <5% of the smaller pixels within the larger pixel). A maximum distance of one degree (~100 km) was allowed between the centers of each pair of high and low LULCC pixels; if no pixel with low LULCC within such proximity (i.e. radius) was found, the high LULCC pixel was discarded. A detailed graphic explanation of the LULCC calculations and the pixels selected for the 20% threshold is provided in the supplementary information (figures S2 and S3, respectively).

We built linear mixed-effects models (LMMs) to test for significant differences in SIF and TR between low and high LULCC across all pairs of pixels. Given that SIF data are only available since 2007, we performed the comparative analyses of SIF and transpiration for the period 2007–2016. We calculated each pixel’s mean (equations (1a) and (1b)), minimum (equations (2a) and (2b)), mean maximum (equations (3a) and (3b)), and average range (equations (4a) and (4b)) for SIF and TR. Each mean value was calculated as an annual (equations (1a), (2a), (3a), and (4a)) or seasonal average (equations (1b), (2b), (3b), and (4b)), separately for the wet and the dry seasons. We calculated one additional metric to measure the mean change in SIF and transpiration from the start to the end of each season (equation (5)). The start and end dates of each season were obtained from RADIS. Equations (1)–(5) were calculated as follows:

\[ \bar{X} = \frac{1}{n} \sum_{j=1}^{n} X_j \] (1a)

\[ \bar{X} = \frac{1}{n} \sum_{p=1}^{n} X_p \] (1b)

\[ \bar{X}_{\text{min}} = \frac{1}{n} \sum_{j=1}^{n} X_{\text{min},j} \] (2a)

\[ \bar{X}_{\text{max}} = \frac{1}{n} \sum_{j=1}^{n} X_{\text{max},j} \] (3a)

\[ \bar{X}_{\text{mean}} = \frac{1}{n} \sum_{p=1}^{n} X_{\text{mean},p} \] (2b)

\[ \bar{X}_{\text{mean}} = \frac{1}{n} \sum_{p=1}^{n} X_{\text{mean},p} \] (3b)

where \( x \) represents either SIF or TR; \( S \) represents either wet or dry season; \( n_y \) and \( n_s \) represent the number of years and seasons; \( x_j \) and \( x_p \) denote annual and seasonal observations; \( x_{\text{min}} \) and \( x_{\text{max}} \) indicate the minimum and maximum values of a year or season; and \( x_{\text{mean}} \) and \( x_{\text{mean}} \) denote end and start of season values (figure S4).

LMMs are equivalent to a paired t-test, where both allow us to compare SIF and TR between our paired low and high LULCC pixels. The advantage of using LMMs is the possibility of extending the model to account for potential covariates and spatial autocorrelation. The simplest form of LMM is shown in equation (6):

\[ Y_{ij} = \alpha + \beta \cdot \text{LULCC group} + b_i + \epsilon_{ij} \] (6)

where \( Y_{ij} \) is the response of \( j \)th pixel in group \( i = 1, \ldots, m; j = 1, \ldots, n_i; m \) is the number of groups (high and low LCC), \( n_i \) is the size of group \( i \); \( \alpha \) is the intercept; \( \beta \) is the LULCC effect; \( b_i \) is the random effect; and \( \epsilon_{ij} \) is the residual error. Using the R package nlme (Pinheiro et al 2020), we were able to evaluate the effect of elevation and spatial correlation structures.

In our LMMs, the different SIF and TR metrics are the response variables for each pixel, LULCC group (i.e. high or low LULCC) is the fixed effect, elevation is a covariate, and pixel pair is a random effect. To account for the possibility of spatial autocorrelation, we also fit models that included spatial autocorrelation functions. The final model for each metric was selected based on the Akaike information criterion (AIC) value, after meeting the regression assumptions. We report the fixed-effects slope coefficient (\( \beta \); equation (6) and figure S5) from the selected LMM to indicate the difference in SIF or ET between low and high LULCC pixels and its statistical significance (p-value). We also fit LMMs separately for the two most important ecosystems in the area of study, forests (\( F \)) and Cerrado (\( C \)). LMM analyses were performed using the R package nlme (Pinheiro et al 2020).

To understand how variables were affected by increasing extents of LULCC, we fit a linear model between the difference in LULCC (independent variable) and the difference in each SIF or TR metric (dependent variable) in each pixel pair. For this analysis, we redefined our high LULCC pixels to be...
>10%, while the reference pixel threshold was kept at <5%. This redefinition allowed us to better explore the variation in the degree of LULCC. We fit models that included elevation and spatial autocorrelation, and selected the model with the lowest AIC value. For these linear models, we report the estimated change (slope, $\beta_1$) in SIF and TR with change in LULCC and its statistical significance. We also performed a binned version of this analysis that provides further information of the change with LULCC using LMM and a range of different LULCC thresholds. We varied the threshold for high-LULCC pixels, using thresholds of >10%, >30% and >40% of smaller pixels with LULCC within a larger pixel (figure S2). For each definition of ‘high-LULCC’ pixels, we identified a reference pixel (i.e. less than 5% smaller pixels with LULCC in a larger pixel) using the same criteria used in the main analyses above. Finally, we calculated the same metrics and fit the LMM for each LULCC threshold category. We compared the estimated differences and statistical significance of high vs low LULCC across the different high LULCC thresholds. The number of pairs selected under each threshold is provided in table S1.

We investigated whether any differences in photosynthesis and transpiration between high- and low-LULCC regions could be caused by different precipitation patterns, rather than LULCC. To test for differences in precipitation, we compared the annual precipitation and the dry and wet season lengths and intensities. We used the same methods to compare SIF and transpiration in corresponding pixels. Paired low- and high-LULCC pixels did not differ in mean annual precipitation, or in the durations or total precipitation of the dry and wet seasons (table S2), suggesting that any differences in photosynthetic activity and transpiration result from differences in land cover (i.e. vegetation), rather than climate.

3. Results

The effects of land cover change on SIF, as a proxy of photosynthetic activity, and on transpiration depended on the season and ecosystem type. In forests, LULCC decreased SIF and TR in the dry season (figures 1(a) and (b)). In the Cerrado, LULCC increased SIF in the wet season (figures 1(c) and (d)). The average range of SIF increased with LULCC in forests at the annual scale and in the Cerrado in both seasons and at the annual scale. The average range of TR increased with LULCC only in forests during the dry season. Most effects of LULCC were strongest in regions where a greater fraction of the landscape had been converted. The effects of LULCC on SIF sometimes depended on the dataset. This was particularly evident in forested areas in the wet season, when GOME-2 shows an increase in SIF with LULCC, but GOSIF shows a decrease. Also, GOSIF maximum values were generally lower and less variable than SIF from GOME-2.

4. Forests and land cover change

Broadleaf evergreen forests were the most common dominant land cover type in 1992 and the one with
the highest LULCC between 1992 and 2015. In forests, LULCC resulted in lower mean and minimum annual SIF in 73% and 68% of pixel pairs, respectively (figures 2(a) and (b)). The percentage of pairs of pixels with reduced (or increased) SIF and TR as a result of LULCC is represented by the dots below (or above) the 1:1 line in figures 2 and 3. In the dry season, LULCC reduced mean and minimum SIF (in 88% and 78% of pixel pairs, respectively) (figures 2(i)–(l)). In contrast to the annual and dry season decreases in SIF, LULCC increased mean and minimum SIF in the wet season (68% of the pixel pairs) (figures 2(e)–(h)). The average annual and dry season range of SIF increased with LULCC in 65% and 60% of the pixel pairs, respectively. GOSIF data yielded similar results in forest photosynthetic activity at the annual scale and during the dry season to those we observed with GOME-2 (figure 2). However, GOSIF data indicated a decrease in photosynthetic activity during the wet season. Despite the discrepancy with GOME-2 SIF in the wet season response, both data-sets suggest a stronger decrease in photosynthetic activity during the dry season than in the wet season. Also, in GOSIF, the range of variation of SIF was only significantly larger in high LULCC pixels at the annual scale, but not in the wet or dry seasons separately.

In forests, LULCC reduced transpiration; 86%, 71%, and 76% of high LULCC pixels had lower mean, minimum, and maximum annual TR, respectively.
Figure 3. Transpiration (mm m\(^{-1}\)) of paired low (x-axis) vs high (y-axis) LULCC pixels for each metric (rows) and at the annual and seasonal scale (columns). Colors and shapes correspond to forest- (green squares) and Cerrado- (gold circles) dominated pixel pairs. The 1:1 line is shown in black, and black symbols show mean values for corresponding vegetation types. LMM estimates for the difference of transpiration between low and high LULCC are represented by \(\beta_f\) and \(\beta_c\) for forest- and Cerrado-dominated pixel pairs, respectively. Asterisks (*) indicate statistically significant effects of LULCC (\(p < 0.05\)).

(figures 3(a)–(c)). The annual reductions were a result of decreased TR in the dry season, when 86%, 84%, and 76% of high LULCC pixels had lower mean, minimum, and maximum TR, respectively (figures 3(i)–(k)).

Dry season decreases in mean and minimum SIF and TR observed in high-LULCC forested pixels strongly and progressively increased in magnitude with increased difference in LULCC (figures 4(a) and (b)). The dry season range of SIF and TR consistently increased along with increased LULCC. In the wet season, increased difference in LULCC resulted in increased minimum and maximum SIF in forested pixels. At the annual scale, the maximum and the range of SIF increased, while the mean and minimum TR decreased with higher LULCC (figures 4(a) and (b); binned analyses of pixel pairs in figure S6 show similar results). For most metrics, SIF from GOSIF decreased with LULCC; these results were nearly always more negative than SIF from GOME-2. The two datasets were partially similar in the dry season, but mostly opposite in the wet season and GOSIF data were consistently more negative at the annual scale (figure 4(a)). Also, in GOSIF the range of variation of SIF significantly decreased with LULCC in the wet and dry seasons, in contrast to GOME-2 SIF. At the annual scale, there was a significant decrease in mean, minimum and maximum GOSIF SIF with increasing fractions of LULCC that was not evident in GOME-2 data (figure 4(a)).
Figure 4. Linear regression-estimated changes in the different SIF (a), (c) and transpiration (b), (d) metrics with changes in LULCC ($\beta$). Forests (a), (b) are shown in green and the Cerrado (c), (d) is shown in orange; GOME-2 results are represented by filled shapes and GOSIF by open shapes. A black ‘x’ mark indicates a statistically significant effect of LULCC on the change in SIF or TR ($p < 0.05$).

5. Cerrado and land cover change

The Cerrado, the second most common land cover in the region in 1992, often showed opposite trends to forests. In Cerrado-dominated regions, LULCC increased mean and maximum annual SIF (evident in 93% and 86% of pixel pairs; figures 2(a) and (c)). These increases were driven by wet season responses; during this time, LULCC increased mean and maximum SIF (86% of pixel pairs) (figures 2(e) and (g)). In the dry season, neither the mean, minimum, nor maximum SIF were significantly different under high LULCC. However, LULCC increased the mean range of SIF at the annual scale (86% of pixel pairs) and in both seasons (86% of pixel pairs in the wet and 79% in the dry season). According to our results from GOSIF, almost every metric of photosynthetic activity increased with LULCC in the Cerrado; only the annual and dry season minimum SIF were not significantly different between high and low LULCC (figure 2).

In the Cerrado, the mean change in transpiration was opposite to that of forests; high-LULCC pixels had higher transpiration values. However, this difference in transpiration in Cerrado-dominated pixel pairs was not significant (figure 3).

Increased differences in LULCC resulted in increased wet season mean and minimum SIF (figure 4(c)). The SIF mean annual range and maximum also increased consistently and significantly with increased LULCC (figure 4(c)). GOSIF results were in close agreement with SIF from GOME-2 at the annual scale (figure 4(c)). In the wet season, the mean, minimum and maximum values trended in the same direction, but the increase in maximum was only significant for GOSIF and the increase minimum was only significant for GOME-2. In GOSIF data, LULCC increased the maximum and the range of variation of SIF during both the dry and the wet season, whereas these were not significant trends in GOME-2 (or trended in the opposite direction, in the case of wet season range).

We did not find significant effects of increased LULCC in any TR metrics (figure 4(d)). The difficulty of detecting the effects of increased differences in LULCC on SIF and TR was likely due to the lack of pixels with LULCC greater than 30%. The small number of pixel pairs with large differences in LULCC decreased the potential of the linear models to find clear patterns in the relationship. However, in our binned analyses of pair differences, most changes in transpiration became larger as the threshold for LULCC differences increased from >10% to >20% (figure S6). This pattern was observed for annual, wet, and dry season SIF mean, maximum, and range.

TR differences between high- and low-LULCC pixels dominated by Cerrado were only significant for some metrics, and only at the >10% LULCC threshold. These TR metrics were dry season mean; annual and dry season maximum; and annual, wet, and dry season range. Other metrics, such as maximum TR across all seasons, and most metrics in the wet season, were not significantly different at any LULCC threshold. Note that the LULCC threshold analysis for the Cerrado pixels was only feasible for two thresholds because few pixels had greater than 30% LULCC.

6. Dry season ‘greening’ and land cover change

We evaluated the effect of LULCC on changes in photosynthetic activity from the beginning to the end of the dry season. In intact forests, photosynthesis and transpiration increased during the dry season and decreased during the wet season (forest-dominated pixels with low LULCC; figures 5(a) and (c)). Land cover change strongly dampened these patterns; in deforested regions, the changes in SIF and TR became less positive during the dry season and less negative during the wet season (pixels with high
Figure 5. Wet and dry season changes in GOME-2 SIF (a), (d), GOSIF (b), (e) and transpiration (c), (f) in low (tan) vs high (brown) LULCC pixels. Each boxplot shows the minimum, first quartile, median, third quartile, and maximum data points. Outliers are shown as black dots outside the boxplot. $\beta_f$ and $\beta_c$ values indicate the LMM estimate for the difference of SIF and transpiration in low and high LULCC, for forests (a)–(c) and Cerrado (d)–(f), correspondingly. Asterisks (*) indicate statistically significant effects of LULCC ($p < 0.05$).

LULCC; figures 5(a) and (c)). The decrease in SIF and TR during the dry season in forested sites significantly increased in magnitude with larger differences in LULCC (figures 4(a) and (b) ‘Delta’, figure S5). GOSIF data produced similar trends in dry season ‘greening’ and wet season ‘browning’ and the changes observed with LULCC (figure 5(b)). However, in this much less variable dataset (e.g. figures 2(d), (h) and (l)), these changes in patterns did not increase in magnitude with higher LULCC as in GOME-2 (figure 4(a)).

In contrast to forests, SIF and transpiration in the intact Cerrado increased across the wet season and decreased during the dry season (pixels with low LULCC; figures 5(d) and (f)). Also contrasting with forest, LULCC in the Cerrado amplified the seasonal changes in one of these properties; SIF increased even more in the wet season and decreased more in the dry season with high LULCC (figures 5(d) and (f)). The patterns observed in the Cerrado were not found to significantly increase with increasing LULCC (figures 4(c) and (d)). However, as mentioned before, the low number of Cerrado pixels with LULCC >30% hindered the analysis of these relationships. The increase in SIF during the wet season and decrease during the dry season increased in magnitude when comparing pixels with >10% and >20% LULCC (figure S7). The Cerrado dry and wet season patterns in GOSIF were similar to those from GOME-2 SIF, as well as the increase in magnitude caused by LULCC in those ‘greening’ and ‘browning’ patterns (figure 5(e)). Moreover, increases in the degree of LULCC intensified these changes (figure 4(c)).

7. Discussion

Our analyses of Amazonian forest and Cerrado suggest that ongoing land cover change in the region is altering the magnitude and timing of photosynthetic activity and transpiration and consequently, the water, carbon and energy feedbacks from these important ecosystems. These observed changes have the potential to strongly influence local, regional, and global climates (Lawrence and Vandecar 2015, Molina et al 2019).

In forested regions, deforestation reduced annual photosynthetic activity and transpiration, mainly by slowing these processes during the dry season. Deforested regions also switched from a pattern of dry season ‘greening’ towards dry season ‘browning’ (figure 5). Our results match previous findings of dry season greening in the Amazon tropical forests (Huete et al 2006, Doughty et al 2019) and dry season water limitation in vegetation types with shallower roots (Nepstad et al 1994, Oliveira et al 2005a, 2005b). This dry season decrease in photosynthetic activity and transpiration is of particular relevance for the local water cycling in the southern Amazon (Leite-Filho et al 2019, 2020). Forest transpiration during the dry season, through increased surface air humidity, buoyancy and a chain of atmospheric processes, directly induces the onset of the wet season (Wright et al 2017). Deforestation-induced changes in these land surface-atmosphere feedbacks can result in extended dry seasons and droughts in the region (Nobre et al 1991, Wright et al 2017, Leite-Filho et al 2019).
The effects of LULCC on Cerrado-dominated pixels were very different from those observed in forest-dominated pixels. In the Cerrado regions, photosynthetic activity was either similar (GOME-2) or higher (GOSIF) in the dry season under high LULCC, and significantly increased under high LULCC in the wet season. Unlike forests, Cerrado, croplands and pastures (if not cleared) are both expected to be water-stressed and to decrease their photosynthetic activity during the dry season. The increased photosynthetic activity with LULCC during the wet season could be explained by productivity optimization (e.g. planting time and fertilization) in human-managed vegetation during the growing season. In the wet season, high LULCC pixels’ SIF even approached that of forests. Although LULCC increased photosynthetic activity in the wet season, it had little effect on transpiration. This contrast could be explained by differences in water use efficiency of Cerrado, croplands, and pastures. However, it could also arise from the parameters used in the algorithms for transpiration estimates. In GLEAM, parameterization is done for only two vegetation types; short and tall vegetation. This categorization might result in the same parameters being used for some types of Cerrado and agricultural landscapes, given the similarity in vegetation height. To develop more accurate estimates of the impact of the Cerrado cover change on the water cycle, we recommend (a) studying differences in water use efficiency of Cerrado and common croplands and pastures in this area, and (b) closely examining the parameters used in the transpiration algorithms for these vegetation types.

LULCC increased mean photosynthetic activity in forested and Cerrado areas during the wet season. Our observations suggest that during the wet season, crops and grasses reach their productivity peaks, with SIF values and transpiration rates resembling those from forested areas. This pattern is seen in common managed vegetation in the Amazon, such as pasture or rain-fed cropland (Seymour and Harris 2019). In the dry season, these non-irrigated croplands and pastures are either cleared (e.g. annual crops) or have a natural decrease in productivity (e.g. perennial plants) (Doughty et al 2019).

We also found increases in the amplitude in the cycle of photosynthetic activity and transpiration induced by LULCC, varying for the different seasons and in the two ecosystems. These patterns are expected in human-managed vegetation, particularly with unirrigated and annual crops. Management practices in these systems promote fast plant growth and increased photosynthetic activity during the growing season (i.e. months with greater water availability) and little, if any, photosynthetic activity for the rest of the year. Neither forests nor Cerrado have such extreme changes in photosynthetic activity. These increased ranges of intraannual variation in the energy and water fluxes are likely to alter the seasonality of the local and regional climate. Precipitation, temperature, relative humidity and VPD are all influenced by the energy and water fluxes. Extreme changes in the amplitude and timing of the seasonal cycles of these climate variables are expected with changes in the amplitude and timing of vegetation seasonality.

The observed effects of LULCC on photosynthetic activity and transpiration took place without any background differences in precipitation amount and seasonality. This lack of local-scale differences in precipitation amount and variability indicates that the differences in photosynthetic activity and transpiration can be attributed to differences in vegetation ecophysiology. Furthermore, the lack of changes in precipitation rates, accompanied by decreases in the amount of water transpired back to the atmosphere, indicate a different fate for a fraction of the precipitated water. This finding supports previous modeling and observational studies that show an increase in water runoff and river discharge with LULCC (Costa et al 2003, Coe et al 2009, Swann et al 2015, Guimberteau et al 2017, Dos Santos et al 2018). Assuming unchanged precipitation regimes, most of these studies suggest that deforestation would decrease water loss through evapotranspiration, leading to increases in runoff and river discharge. This implies critical changes in the water cycling in local river basins and at the regional level for the Amazon basin.

LULCC can trigger positive feedbacks involving climate, photosynthetic activity, transpiration and the water cycle. For instance, a positive feedback can be initiated by increases in LULCC that reduce precipitation, which decreases water available to support photosynthetic activity; the feedback is then sustained as less water is transpired from the land surface to the atmosphere and precipitation subsequently declines. Continued changes and the intensification of this positive feedback can lead local and regional natural ecosystems to a tipping point (Zemp et al 2017, Marengo et al 2018); for instance, a longer and stronger dry season induced by reduced evapotranspiration can increase fire occurrence, vegetation mortality, and even lead to savannization (Marengo et al 2018, Lovejoy and Nobre 2019). In addition to these long-term and large-scale effects, the local and regional agriculture will likely be affected in the near future (Lawrence and Vandecar 2015, Coe et al 2017). The predominantly rain-fed crops of this region largely depend on the precipitation and length of the wet season, which as mentioned before is affected by the forest transpiration during the dry season. Changes in the wet season will affect those rain-dependent agricultural lands.

While SIF data provide satellite-based measurements that are closely related to photosynthetic activity (Joiner et al 2013, 2014, Li and Xiao 2019), completely accurate estimates of photosynthetic activity...
from remote sensing data are not yet possible. The currently available satellite-based SIF datasets have a variety of deficiencies, such as coarse temporal or spatial resolution or short measurement time frames. In the case of the product from GOME-2, sensor degradation is also an important issue to take into account (Zhang et al 2018). Given that our analyses are not focused on long-term changes in trend of photosynthetic activity, but are mostly based on seasonal patterns and pixel-to-pixel comparison in a relatively small area in the tropics, we believe the effect of sensor degradation to be small in our analyses. The GOSIF dataset used here to complement our analyses addresses some of the issues of the SIF products, but also introduces the uncertainty that comes with model-derived datasets (i.e. data sources and algorithms).

The two SIF datasets, GOME-2 and GOSIF, produced similar results for the most part, but there were a few clear differences between the products. Some of the conflicting results obtained here between SIF data from GOME-2 and GOSIF confirm the difficulty of using large-scale remote sensing data to study vegetation activity. GOSIF data consistently had much lower seasonal and annual maximum SIF values than GOME-2, leading to much smaller seasonal and annual ranges. Maximum annual values in GOME-2 were 1.5–2 times higher than in GOSIF, with the larger differences occurring in the wet season. This could be explained by the increased margin of error in GOSIF predictions when observed SIF values are large (e.g. maximum values) (Li and Xiao 2019). These differences in maximum values were accompanied by more subtle changes in the effects of LULCC calculated from the two datasets. Most of the disagreement on LULCC impacts appeared in forest data from the wet season, when LULCC was associated with increases in GOME-2 SIF but decreases in GOSIF values. We can only speculate about the source of these wet season discrepancies. Remote sensing is difficult during the wet season in the tropics due to an associated increase in cloudiness, and there are often gaps in the SIF data from GOME-2, which relies more heavily on direct observations. On the other hand, modeling associated with the GOSIF product might artificially constrain variability and maximum values, resulting in the larger discrepancies when compared to purely satellite-based SIF. A more in-depth comparison of the two SIF datasets is beyond the scope of this study, but our results demonstrate the need to understand the sources of the differences in the data.

Land cover detection also introduces some uncertainty. Land use and land cover delineation in the ESA CCI product is largely based on satellite-based data and algorithms that detect change in time. Both the data source and data processing introduce uncertainty to the final product. Validation efforts have shown the accuracy of this product to range between 40% and 75% in different regions of the world and at the global scale (Pérez-Hoyos et al 2017, Hua et al 2018, Samasse et al 2018, Koubodana et al 2019, Reinhart et al 2021). This implies some uncertainty associated with the land classification and land conversion detection in the dataset. A comparison of our pixel selection with a map of deforestation from the Brazilian National Institute for Space Research (Assis et al 2019) (figure S8) suggests that our pixel pair selection is likely to be robust across LULCC datasets.

Continued development of remote sensing products will overcome some of the limitations of this study. Specifically, more recent satellite missions, such as TROPOMI, will soon provide data for a longer time period and with greater spatial resolution (i.e. SIF). On the other hand, land cover data is constantly being improved by including new remote sensing products with better spectral and spatial resolution and with new classification algorithms. In addition to new technologies, current work is being done to disentangle the relationships between photosynthetic activity and transpiration in different vegetation types and plant species. This knowledge can be used to better interpret changes in remotely sensed photosynthetic activity, and to improve parameterization of models like GLEAM, and thus to increase our confidence in larger-scale analyses such as this.

We took advantage of recent growth in remotely sensed datasets to evaluate how LULCC affects annual and seasonal photosynthetic activity and transpiration across a broad region of the Amazon. As these datasets continue to expand, this information can be used to further evaluate the influence of agricultural management in the region (Voldoire and Royer 2004); for instance, by tracking larger-scale changes in SIF and transpiration under different (a) degrees of land cover change, (b) spatial patterns of land cover change, (c) agricultural land cover types, or (d) farming practices. Analyses similar to the one presented here could help monitor changes in the water cycling feedback and vegetation responses to such changes. More broadly, measuring and assessing changes in remotely-sensed photosynthetic activity and transpiration resulting from LULCC can be used to (a) characterize human-induced changes to water and carbon fluxes and their impacts on natural ecosystems, (b) evaluate the effects of different agricultural practices in the region, and (c) benchmark photosynthetic and transpiration flux simulations in land surface and climate models. Finally, the combined analysis of changes in photosynthetic activity and transpiration should also help us understand the relationship between these two processes in the different vegetation types in this region.

Data availability

The data that support the findings of this study are available upon request from the authors. The original datasets used for our analyses are all publicly available.
and the corresponding references were included in the Supplementary Materials.

The data that support the findings of this study are available upon reasonable request from the authors.

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