Surface energy dynamics and canopy structural properties in intact and disturbed forests in the Southern Amazon

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Key points

- Evapotranspiration, surface temperature and forest structure data can inform about the effects of canopy cover changes in the Amazon
- Forest disturbances affect evapotranspiration-temperature relationships differently across wet and dry seasons and disturbance levels
- Forest structure showed moderate relationship with evapotranspiration in heavily disturbed forests and weak correlation at intact forests

Abstract

The Brazilian Amazon has been a focus of land development with large swaths of forests converted to agriculture. Forest degradation by selective logging and fires has accompanied the advance of the frontier and has resulted in significant impacts on Amazonian ecosystems. Changes in forest structure resulting from forest disturbances have large impacts on the surface energy balance, including on land surface temperature (LST) and evapotranspiration (ET). The objective of this study is to assess the effects of forest disturbances on water fluxes and canopy structural properties in a transitional forest site located in Mato Grosso State, Southern Amazon. We used ET and LST products from MODIS and Landsat 8 as well as GEDI-derived forest structure data to address our research questions. We found that disturbances induced seasonal water stress, more pronounced and earlier in croplands and pastures than in forests, and more pronounced in second-growth and recently burned areas than in logged and intact forests. Moreover, we found that ET and LST were negatively related, with a more consistent relationship across disturbance classes in the dry season than the wet season, and that forest and cropland and pasture classes showed contrasting relationships in the dry season. Finally, we found that canopy structural properties exhibited moderate relationships with ET and LST in the most disturbed forests, but negligible correlations in the least disturbed forests. Our findings help to elucidate degraded forests functioning under a changing climate and to improve estimates of water and energy fluxes in the Amazon degraded forests.

Plain Language Summary

Deforestation, selective timber extraction and forest fires are the main causes of forest disturbances in the Amazon region. These disturbances alter how forests function. Forest degraded by logging and fires may exchange less water and absorb less carbon dioxide from the atmosphere during photosynthesis. We used satellite-based observations on the amount of water transpired to the atmosphere by trees (known as evapotranspiration), land surface temperature, and forest structural properties such as canopy cover and height over a region in the Southern Amazon to understand the differences in function between disturbed and intact forests. We found that disturbances induced stronger and earlier water stress in the dry season in croplands and pastures than in forests, and stronger water stress in second growth and recently burned areas than in logged and intact forests. We also found that structural properties show a moderate relationship with evapotranspiration and temperature in the most disturbed forests, but weak relationships in the least disturbed forests. Our findings highlight the importance of intact forests in maintaining water balance in the Amazon region and suggest that disturbed forests may have limited ability to cope with the changing climate.

Keywords

Amazon; forest degradation; forest structure; evapotranspiration; land surface temperature

1. Introduction

Changes in tree cover and forest structure have large impacts on energy balance and ecosystem properties, altering components of the biosphere-atmosphere interactions that operate from the leaf (plant physiology) to global (atmospheric circulation) scales. Deforestation and forest degradation can alter rainfall regimes, water availability, and surface-atmosphere flux of water and energy of tropical forests (Davidson et al., 2012; Jucker et al., 2018; Longo et al., 2020; Spracklen et al., 2018). These impacts are particularly pronounced in ecotonal, semi-deciduous tropical forests of the southern Amazon Basin, which have experienced rapid regional warming and deforestation over the last three decades (Vourlitis et al., 2008). However, integrated assessments linking structural and functional changes resulting from forest disturbances are still lacking, and climate and forecast models are incipient in representing the influence of canopy structure on energy and water balances in degraded Amazon forests (Huang et al., 2020; Longo et al., 2020).

Chief among the water balance variables, evapotranspiration (ET) is a multi-faceted variable controlled by a combination of vegetation, atmospheric, and radiative drivers. ET measurements need to ensure that the abiotic and biotic controls are adequately captured: net radiation and land surface temperature provide the physical drivers for the state change of water and the subsequent impact on latent and sensible heat partitioning; humidity and air temperature regulate the transfer of water from the land into the air, and phenology and vegetation cover information are necessary for seasonal dynamics and relative magnitudes of ET fluxes (Fisher et al., 2008). One critical measurement to the estimation of remotely-sensed ET is the land surface temperature (LST), as it can capture fine spatial and temporal dynamics associated with heterogeneous land surface processes controlling ET (Fisher et al., 2017).

Variability in the strength of ET drivers may be linked to different degrees of the canopy–atmosphere coupling (Jarvis & McNaughton, 1986). The control of ET can be viewed as complex supply-demand interactions, where net radiation and soil moisture represent the supply and the atmospheric vapor pressure deficit (VPD) represents the demand. This supply-demand interaction accelerates the biophysical feedbacks in ET. The degree of biophysical control is a function of the ratio of canopy conductance (an aggregated measure of canopy control on transpiration) to aerodynamic conductance. When the canopy and aerodynamic conductance ratio is very small (i.e., water-stress conditions), stomata principally control the water loss and a change in canopy conductance results in a nearly proportional change in transpiration. Such conditions trigger a strong biophysical control on transpiration. In this case, vegetation is believed to be fully coupled to the atmosphere. In contrast, for a high canopy and aerodynamic conductance ratio (i.e., high water availability), changes in canopy conductance will have little effect on the transpiration rate, and transpiration is predominantly controlled by net radiation (Mallick et al., 2016).

In the Amazon basin, ET exerts a large influence on regional and global climate patterns, and provides a significant source of rainfall water in South America (Maeda et al., 2017; Spracklen et al., 2012; van der Ent et al., 2010), by returning to the atmosphere between 50 and 75% of the regional precipitation (Lathuillière et al., 2012; Malhi et al., 2002). The major environmental controls driving spatial and temporal variability of ET in the Amazon are solar radiation (accounting for more than 80% of ET variability), atmospheric VPD, vegetation cover, and precipitation (Fisher et al., 2009), but complex interactions resulting from local climatic and biotic conditions generate highly heterogeneous patterns across the region (Fisher et al., 2009; Hasler & Avissar, 2007; Maeda et al., 2017). Synergies between climate and forest structure and functioning control much of the spatial variability in water and energy balances in the Amazon (Coe et al., 2016). While forest ET increases during the dry season in equatorial Amazonian forests, seasonally dry forests at the southern fringe of the biome present the opposite trend (da Rocha et al., 2009; Hasler & Avissar, 2007; Restrepo-Coupe et al., 2013).

Land cover changes alter vegetation cover and structure and land surface properties such as albedo, emissivity, and surface roughness (Bonan, 2008; Bright et al., 2015). Ultimately, the conversion of natural areas to urban or agricultural development affects gas and energy exchange processes between the land surface and the atmosphere, by changing how incoming precipitation and radiation are partitioned among sensible and latent heat fluxes and run-off (Coe et al., 2016). Decreased forest cover increases surface albedo and reduces net radiation and ET (Costa & Foley, 1997). Based on eddy covariance data collected in the Western Amazon, von Randow et al. (2004) found evapotranspiration rates 20-41% lower in pastures compared to forests. Silvério et al. (2015) showed, for a large river basin in the southern Amazon, that abrupt transitions in land uses such as forest/crops and forest/pastures decreased ET by 32% and 24%, respectively. These authors also found that LST was 6.4°C higher over croplands and 4.3°C higher over pasturelands, compared to the forests they replaced. Using an ecosystem demography model calibrated with tropical forest parameters, Longo et al. (2020) estimated that severely degraded forests experience water-stress with ET declines up to 34% and increases in daily mean ground temperatures (up to 6.5° C) relative to intact forests. Seasonality of water and energy fluxes also amplifies differences among disturbed and intact vegetation, due to their differential capability to access subsurface water during seasonal drought (von Randow et al., 2004; Zemp et al., 2017).

Disturbed forests in the Amazon are expected to transpire substantially less compared to old-growth forests, because of the potential reductions in LAI and rooting depth (Silvério et al., 2015), but recent research has shown contrasting results. Some degraded forests have shown ET levels similar to intact forests' or even increased ET after a few years after fires or start of the secondary growth, with no corresponding recovery in structural attributes such as biomass or leaf area index (LAI) (Brando et al., 2019; Von Randow et al., 2020). Canopy structural properties are intrinsically affected by disturbance type, intensity, and time since events. Given that changes in tree cover and structure have large impacts on energy balance and ecosystem properties, there is an urgent need to quantify these properties not only for mature forests but also for forests with lower, less complex cover and structure.

Active and optical remote sensing approaches have been widely used to directly observe or estimate LST, ET and forest structural properties. The ET product from the Moderate Resolution Imaging Spectroradiometer (MODIS) is estimated using the Penman-Monteith equation (Monteith, 1965) and utilizes other MODIS products and meteorological inputs. While MODIS has long run and well-established ET products, its coarse resolution may not be adequate to capture the ET variability associated with small scale disturbances. Therefore, we also used ET derived from Landsat 8 data, retrieved as a residual of the surface energy balance (SEBAL algorithm; Bastiaanssen et al., 1998), and using LST observations as the most important input. Landsat is distinguished by being both the first medium resolution Earth observation satellite as well as the longest running continuous program, with the recent Landsat launches showing improved geometric and radiometric properties (Wulder et al., 2019). Laser scanning, an active form of remote sensing commonly known as lidar, is suitable to characterize three-dimensional forest structural properties (Lefsky et al., 2002). The Global Ecosystem Dynamics Investigation (GEDI) spaceborne lidar instrument has been providing unprecedented three-dimensional information of tropical and temperate forests worldwide (Dubayah et al., 2022; Dubayah et al., 2020; Duncanson et al., 2022) and has made it possible to investigate forest structure over large areas in the Amazon.

The objective of this study is to assess the effects of forest disturbances (both deforestation/total canopy cover removal and degradation/partial canopy cover removal) on the seasonal ET fluxes and canopy structural properties in a transitional forest site located in Mato Grosso State, Southern Amazon. We use ET and LST data from MODIS and Landsat 8 OLI and TIRS sensors, taking advantage of their well-established record in the investigation of water fluxes (Anderson et al., 2012; Mu et al., 2011), as well as the novel GEDI forest structure data (Dubayah et al., 2022) to address the following questions: a) What is the effect of forest disturbances on the seasonal water stress of the canopy? b) How are variations in seasonal water stress manifested in LST-ET relationships across the study site, and do these relationships vary with season and disturbance severity levels? c) What is the contribution of canopy structural properties to ET and LST? Table 1 summarizes our research questions and related hypotheses, and the datasets used to address each of them.

Table 1. Hypotheses and datasets for the research questions.

Research questions	Hypotheses tested	Datasets used
Q1. What is the effect of forest disturbances on the seasonal water stress of the canopy?	H1. Areas with decreased vegetative cover exhibit reduced ET earlier in the dry season, with equivalent water stress	MODIS MYD16A2 product (Total Evapotranspiration and Total Potential Evapotranspiration layers), 1 year of 8-day composites at 500-m resolution.
Q2a. How are variations in seasonal water stress manifested in LST and ET relationships in the study site?	H2.a. LST is higher in areas with low ET and canopy cover	Landsat 8 LST, Landsat 8 ET (derived from the METRIC model), wet and dry season single dates at 30-m resolution
Q2b. Do these relationships vary with seasons and disturbance level?	H2.b. The negative ET-LST relationship will be stronger in more severely disturbed forests and during periods of greater water stress	
Q3.a. What is the contribution of canopy structural properties to ET and LST?	H3.a. ET and LST covaries with structural properties in Amazon disturbed forests	Landsat 8 LST, Landsat 8 ET (derived from the METRIC model), dry season single date at 30-m resolution Structural properties (canopy cover, plant area index, top-of-canopy height, and foliage height diversity) from GEDI at 25-m footprint

2. Material and methods

2.1. Study area

The study area covers approximately 100,000 km^2 at the southern and drier flank of closed-canopy Amazon forests in the Brazilian state of Mato Grosso (Figure 1), including the municipality of Feliz Natal. The area is covered by evergreen broadleaf forests (IBGE, 2021). A five-month dry season (May to September) accounts for only 6% of mean annual precipitation (inset in Figure 1).

This site is located in the ‘Arc of deforestation’, a region that surrounds the southern edge of the Amazon biome, where conventional practices include land clearing for cattle ranching, small-scale subsistence farming, logging, and, increasingly, soybean production for global markets. Decades of agricultural expansion (which includes fire as a land clearing technique) and selective logging have left a mosaic of fragmented and degraded forests in the area (Matricardi et al., 2010; Morton et al., 2013; Souza et al., 2005), with the majority of intact forests remaining inside the indigenous reserves (Figure 1).

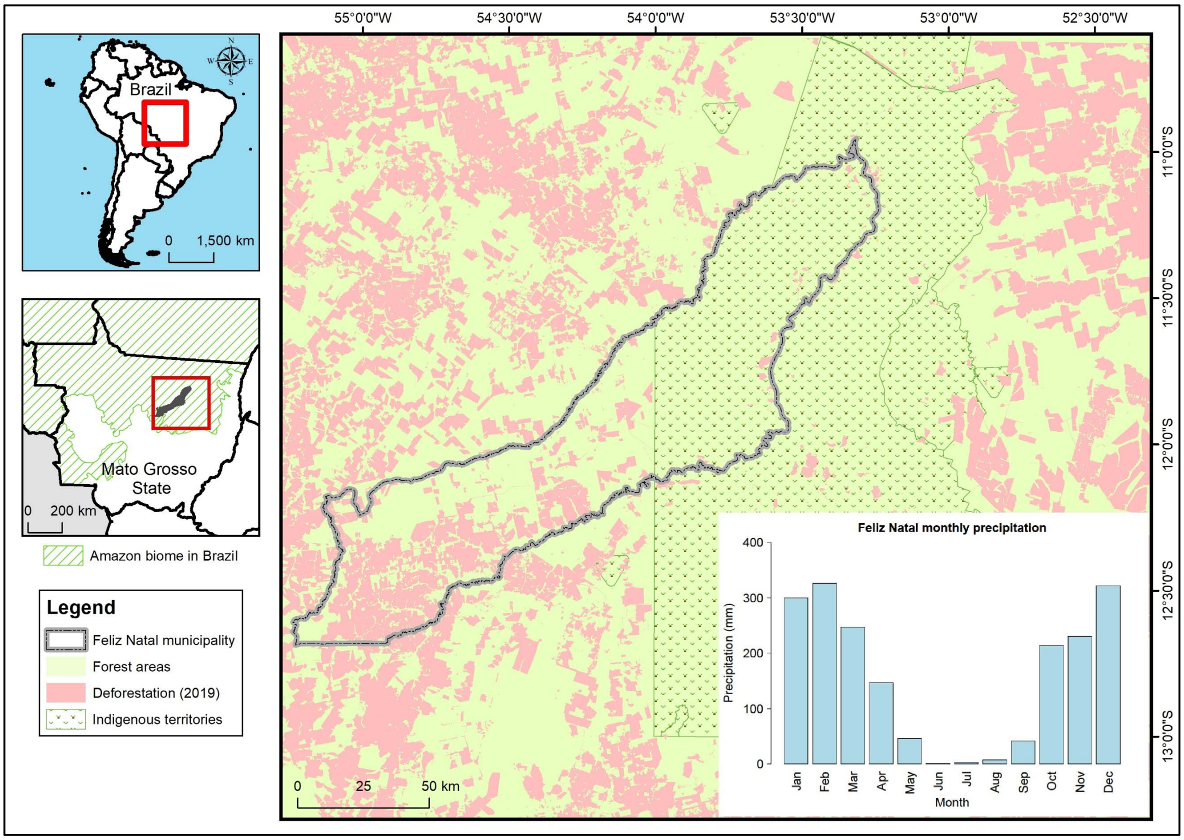

Figure 1. Location, forest cover and monthly precipitation (inset) of the study area. Source of precipitation data: climate-data.org. Source of deforestation data: INPE (2020).

2.2. Disturbance history assessment

We mapped the land cover/land use of the Feliz Natal region from 2000 to 2018, including both disturbances that lead to degradation of standing forests (selective logging and fires) and classes of land use that follow stand-replacement disturbances (croplands, pastures and secondary forests). To map forest degradation, we masked out accumulated deforestation until 2019 (INPE, 2020) and areas of alluvial vegetation. Subsequently, we mapped logged and burned areas on the forest remnants based on visual interpretation of yearly fitted Normalized Burn Ratio (NBR) images derived from Landsat 5, 7, and 8 observations. To differentiate forests experiencing variable degrees of disturbance, we classified degraded forests into six classes: 0-3 years (L1), 4-7 years (L2), and 8-14 (L3) years after logging, and 0-3 years (B1), 4-7 years (B2), and 8-14 (B3) years after burning, while forested areas with no signs of logging or fires in the time-series were classified as intact forests (IN). Polygons that experienced multiple degradation events in the time-series were classified according to the latest event. Details of the methodology for mapping intact and degraded forests can be found in Rangel Pinagé et al. (2022).

Subsequently, we included classes of land cover following deforestation in the disturbance history. Crop (CR) and pasture (PA) polygons for 2019 were obtained from the MapBiomas Collection 5 data of Brazil's annual land cover and use maps, based on Landsat images

(MapBiomas Project, 2019). Also from MapBiomas data, we extracted a land cover class representing the transition of pasture and crops to forest cover from 2015 to 2019 to represent young secondary forests (SFN). Next, we extracted data for the old secondary forest class (SFO) from the TerraClass dataset, which classifies land uses following deforestation in the Amazon, based on Landsat and MODIS data. We chose to use TerraClass until 2014 instead of the regeneration data from MapBiomas because the former is more consistent with the INPE methodology for deforestation mapping (Almeida et al., 2016).

The consolidated layer of disturbance history was generated by merging the forest degradation, old secondary forest (from TerraClass), and crop/pasture and young secondary forest (from MapBiomas) individual layers (Figure 2). We eliminated isolated polygons with areas smaller than 50 hectares to be consistent with MODIS resolution.

2.3. Remote sensing data

The remote sensing data employed in this study includes ET modelled from MODIS observations, ET (modeled) and LST from Landsat 8 observations, and forest structural properties from GEDI observations.

2.3.1. MODIS data

Due to its high temporal resolution and compositing scheme, MODIS data allow for the generation of consistent seasonal patterns. To address Q1, we used the MYD16A2 Version 6 Evapotranspiration/Latent Heat Flux product, an 8-day composite dataset produced at 500-m resolution (Running et al., 2017). The layers ET_500m (for total evapotranspiration) and PET_500m (for total potential evapotranspiration) were selected, along with the quality control flag layer to filter out low-quality data. The improved algorithm of product MYD16A2 is based on the logic of the Penman-Monteith equation, which includes inputs of daily meteorological reanalysis data along with MODIS data products such as vegetation property dynamics, albedo, and land cover. The pixel values for the ET and PET layers represent the sum of all eight days within the composite period.

To test the hypothesis that areas with low forest cover experience water stress earlier in the dry season (H1), we applied the concept of Evaporative Stress Index (ESI, Fisher, 2013), computed from the ratio between actual and potential evapotranspiration. Any ET less than the PET is an indicator that water supply is limited; plants may close stomata to conserve water, and productivity may therefore be less than optimal. Hence, the actual-to-potential ET ratio (ET/PET) is a key indicator of plant water stress (low values of ESI are associated with increased water stress, and high ESI values are associated with lack of water stress). Moreover, anomalies to ET/PET can provide valuable information about water stress without requiring precipitation or soil moisture information (Anderson et al., 2012). We divided the ET by the PET layer, extracted the pixels over the polygons of each disturbance class, and finally, extracted their mean values for each 8-day composite to build the 2019 annual profile of ESI.

2.3.2. Landsat 8 OLI and TIRS data

While MODIS ET estimates are valuable for understanding spatially integrated regional ET patterns and seasonality, they are not able to capture fine-scale spatial dynamics associated with heterogeneous land surface processes controlling ET. Hence, to address Q2 and Q3, which are related to relationships of ET with LST and forest structure, we used Landsat data at 30-m resolution over a ~ 300,000-hectare subset (approximately 3.5% of the total area, yellow outline polygon in Figure 2) within the same image scene. Using one single scene minimizes inconsistency of ET values across disturbance classes. For Q2, we compared ET and LST relationships across disturbance classes at single dates at the wet (January 31st, 2019) and dry (September 28th, 2019) seasons. For Q3, we used the ET and LST data from September only along with structural variables from GEDI (described in the next section). We used only one dry season date to compare ET and LST relationships with forest structure data because the latter is not expected to change seasonally or daily, unlike process variables such as evapotranspiration or gross primary productivity.

Land surface temperature and evapotranspiration data were derived from Landsat 8 observations. The images were obtained through the Earth Engine Evapotranspiration Flux (EEFlux version 0.20.3, described at Allen et al. (2015)). EEFLUX is based on the Mapping Evapotranspiration at High Resolution Internalized Calibration (METRIC) (Allen et al., 2007). Within EEFLUX workflow, LST data is generated using a fixed atmospheric calibration, where the near-surface temperature gradients are an indexed function of radiometric surface temperature, thereby eliminating the need for absolutely accurate surface temperature and the need for air-temperature measurements. Actual evapotranspiration is derived from the Landsat images representing the 24-hour actual ET, via the standard automated calibration within EEFlux. In this framework, actual ET is calculated as a residual of the surface energy balance, according to the following equation:

$$LE = \mathrm{R}_n - H - G$$

where: LE is the latent heat flux (energy spent in the evapotranspiration process (W m^{-2}); $\mathrm{R_n}$ is net radiation (W m^{-2}); G is the heat flux in the soil (W m^{-2}), and H is the sensible heat flux (W m^{-2}). The EEFlux calibration uses the Landsat thermal band and shortwave bands to estimate the surface energy balance and to estimate the amount of vegetation, albedo and surface roughness. Version 0.20.3 of EEFlux employs automated image calibration by assigning values for EToF (which represents ET as a fraction of the reference evapotranspiration) for the 'hot' and 'cold' pixels of the surface temperature spectrum of the scene. LE is estimated at the exact moment of the passage of the satellite for each pixel and instantaneous ET is then calculated by dividing the LE by the latent heat of vaporization, according to the following equation:

$$ET_{inst} = 3600\ LE/\lambda\rho w$$

where: ET_{inst} is the instant evapotranspiration (mm h^{-1}); 3600 converts seconds to hours; λ is the latent heat of vaporization (J kg^{-1}), and ρw is the density of water (~1000 kg^{-3}). Numata et al. (2017) assessed the accuracy of METRIC ET estimates for the Amazon region and found good agreement between METRIC and flux tower-derived ET ($R^2 > 0.7$).

To assess the ability of Landsat data to capture the seasonal water stress detected with MODIS, we chose two Landsat images of a subset of the study area (yellow polygon in Figure 2) from the wet and late dry seasons with the least cloud coverage and extracted the equivalent of an ESI (ratio of actual and reference ET).

2.3.3. GEDI data

GEDI produces high resolution 3D observations of Earth's forests and topography (Dubayah et al., 2020). GEDI's precise measurements of forest canopy height, canopy vertical structure, and surface elevation at a 25-meter footprint can characterize important carbon and water cycling processes, biodiversity, and habitat (Dubayah et al., 2020).

To address Q3, we extracted four structural properties from GEDI Level 2A and 2B data: top of canopy height (TCH, m), plant area index (PAI, m^2/m^2), canopy cover (CC, %) and foliage height diversity (FHD, unitless). TCH was derived from level 2A data (GEDI L2A Canopy Elevation and Height Metrics). The RH98 (the 98th percentile return height) was used as a proxy for TCH. PAI, CC and FHD were derived from Level 2B (GEDI L2B Footprint Canopy Cover and Vertical Profile Metrics) (Tang & Armston, 2019).

We processed the version 2 of GEDI Level 2A and Level 2B data for the study area, for the period between May 5 and November 11, 2019. To filter low-quality data, we only kept laser shots with the recommended quality flags (i.e., sensitivity ≥ 0.95, quality flag = 0, and degrade ≠ 0; Hofton et al., 2019). We implemented an additional filter to remove data in the adjacency of low-quality data, by keeping the shots along a single beam that were part of a continuous strike of at least 30 good quality filtered shots. Finally, we excluded additional shots within fire scars detected in 2019 according to the DETER-B datasets (Diniz et al., 2015) and without associated values of ET or LST (i.e., due to cloud on Landsat observations). After the application of all filters, a total of 12.551 shots from the subset of the study area were retained (Figure 2). GEDI data processing was performed in a Geographic Information System (GIS) platform and the R statistical software (R Core Team, 2021), with the aid of the rGEDI package (Silva et al., 2020).

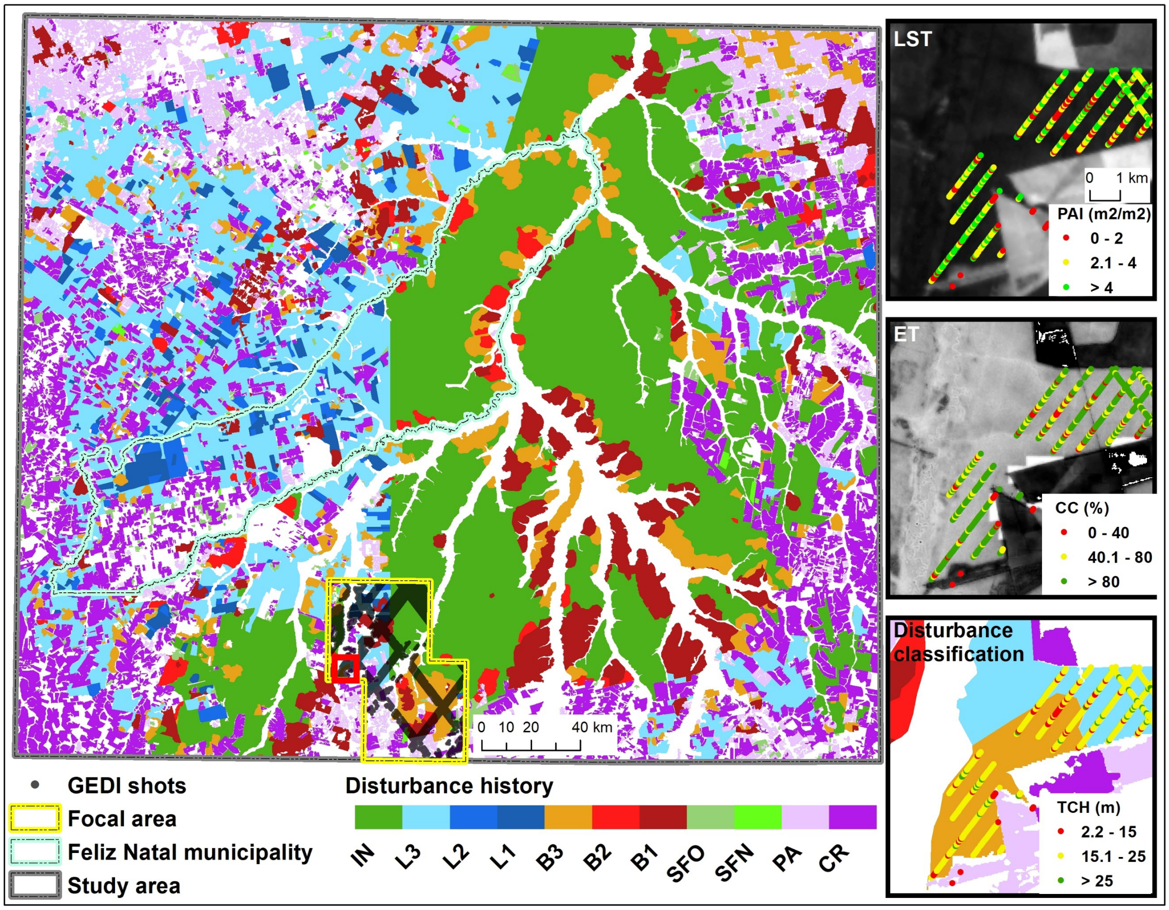

Figure 2. Disturbance classification at Feliz Natal region and post-filtered GEDI shots over the focal area (yellow outline polygon). Insets are zooms from the red outline polygon in the main map and show GEDI structural properties (PAI, CC and TCH). Inset background images are LST and ET from Sep-2019. Higher values of LST and ET are brighter. Unclassified areas (over alluvial vegetation or savannas, or due to mismatch among input datasets) are shown in white in the disturbance classification.

2.4. Statistical analysis

To compare ET and LST among the disturbance classes and across seasons, we applied the Tukey's Honestly Significant Difference test (henceforth Tukey's test) (Tukey, 1977) to identify statistically distinct groups.

To assess ET-LST relationships, we developed linear regression models with ET as the dependent variable. The models were fit at the pixel level for dry and wet seasons for the disturbance classes separately. We did not fit models for the data encompassing all classes because the ET-LST relationship in that case was clearly nonlinear. In addition, we tested the differences in slope coefficients between wet and dry seasons for each group to evaluate how seasonal moisture stress influences the relationship between ET and LST. Only 1/500 pixels were included in the regression models, and observations falling below the 2.5^{th} and above the

97.5th percentiles were excluded, to minimize outliers that are likely to occur in the edges of polygons from the different classes.

To compare GEDI-derived structural properties among the disturbance classes, we also used violin plots and the Tukey's test to compare all possible pairs of means. Next, we fitted linear regression models at the GEDI footprint level with ET and LST as dependent variables and each structural attribute as the independent variable, to assess the relationship between ET or LST with structural variables. We made no assumptions on the normality or transformation of the data due the large sample size (> 1000 observations). All statistical tests, analysis and plotting were performed in the R statistical environment (R Core Team, 2021).

3. Results

3.1. Seasonal water stress

The 2019 annual profile of the ESI showed that forest and non-forest classes in Feliz Natal region experience year-round ESI < 1(Figure 3). The disturbance classes showed varied evaporative stress in the dry season (May through September) and could be distinguished into two groups with well-marked water stress signals: croplands and pastures and forests (Figure 3).

Croplands and pastures exhibited the sharpest ESI decline at the onset of the dry season, with ESI almost reaching zero (meaning maximum evaporative stress or no vegetation cover) at the end of the dry season (Figure 3A). Pastures showed a similar annual pattern to that of croplands but with a less pronounced ESI decrease.

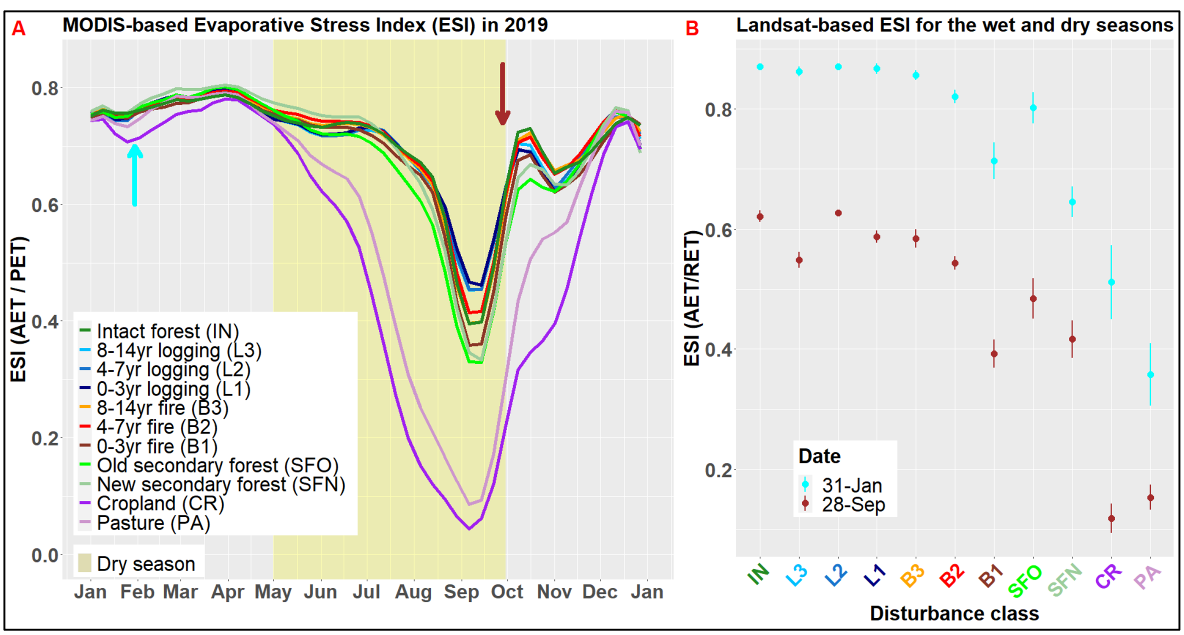

Figure 3. Annual profile of the MODIS Evaporative Stress Index for the disturbance classes for Feliz Natal region (A). The cyan and brown arrows in A indicate the dates that the Landsat-based ESI for a subset of the study area was extracted (B). A sample of 100 Landsat pixels was included for each class. The error bars in B represent 95%

confidence interval of the mean. Labels in the x-axis in B represent the disturbance classes and are in the same order and color of the legend in (A).

ESI from the different forest classes declined sharply later in the dry season, and with a much weaker descent than crops and pastures. Among the forest classes, logged forests showed higher ESI than intact forests at the time of the most severe water stress signal in early September (0.45-0.46 and 0.39, respectively). Recently burned forests showed lower ESI than intact forests (0.36), whereas the older burned classes showed similar or higher ESI compared to intact forests (0.39-0.41). Meanwhile secondary forests showed slightly lower ESI values compared to the other forest classes (~ 0.33). Interestingly, pastures and croplands showed similar MODIS-based ESI levels as that of forests during most of the wet season (Figure 3A).

Water stress in the late dry season (in September) is also detected by Landsat data (Figure 3B), but with improved water stress discrimination among classes (e.g., larger differences within burned and secondary forests). However, Landsat data showed larger differences between the least and most disturbed classes in both seasons with substantially lower ESI values for croplands and pastures, while MODIS ESI showed little divergence in the wet season (Figure 3A). Landsat's finer spatial resolution is likely producing this better discrimination, but it could be due to different sensor's characteristics and ET retrieval algorithms.

3.2. ET-LST relationships

By using Landsat observations of land surface temperature (LST) and evapotranspiration (ET), we found that some areas of croplands and pasturelands show moderate ET in January (wet season), comparable to degraded forests, and that ET differences within degraded and intact forests are amplified in September (dry season). LST in the other hand shows higher values in crop and pasturelands in both analyzed periods, but with notably higher differences compared to forests in the dry season (Figure 4).

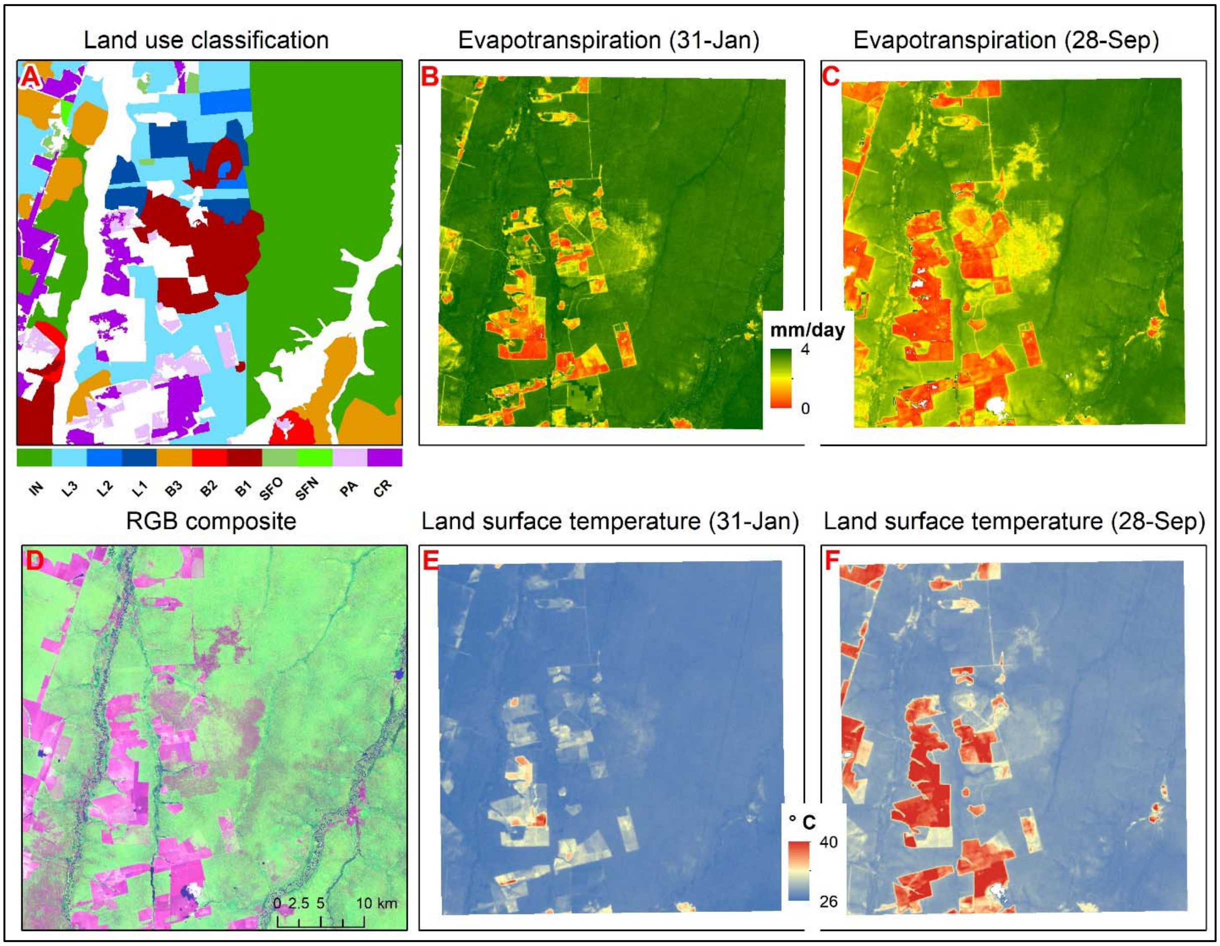

Figure 4. Disturbance classification (A), evapotranspiration in wet and dry seasons (B-C), a false-color RGB composite (D), and land surface temperature in wet and dry seasons (E-F) over a subset of the study area. RGB composite image info: Landsat 8, path/row 225/069, date 28-Sep-2019, R6G4B5. ET and LST data are from EEFLUX.

The seasonal variation in ET and LST was largely consistent with the continuum of disturbance intensity (Figure 5, sorted from intact forests to crops). ET and LST were inversely correlated, showing opposite trends in both wet and dry season dates. In January, most forest classes showed similarly high ET ranges (median: 3.4-3.8) , except for the most recent burned and secondary forests (median: 3.2 and 2.9, respectively) (Figure 5A). Croplands and pastures showed greater variability than forests, but croplands exhibited a high proportion of pixels with high ET as well (median:2.6 and 13, respectively). Toward the end of the dry season (e.g., September), following maximum evaporative stress (Figure 3), ET and LST in pasture and croplands patterns were distinct from all forest classes. Forests also showed increased differentiation in the dry period compared to the wet season. LST showed a similar pattern of differentiation among the classes, but an opposite trend of values (higher in those classes with lower ET estimates, Figure 5B).

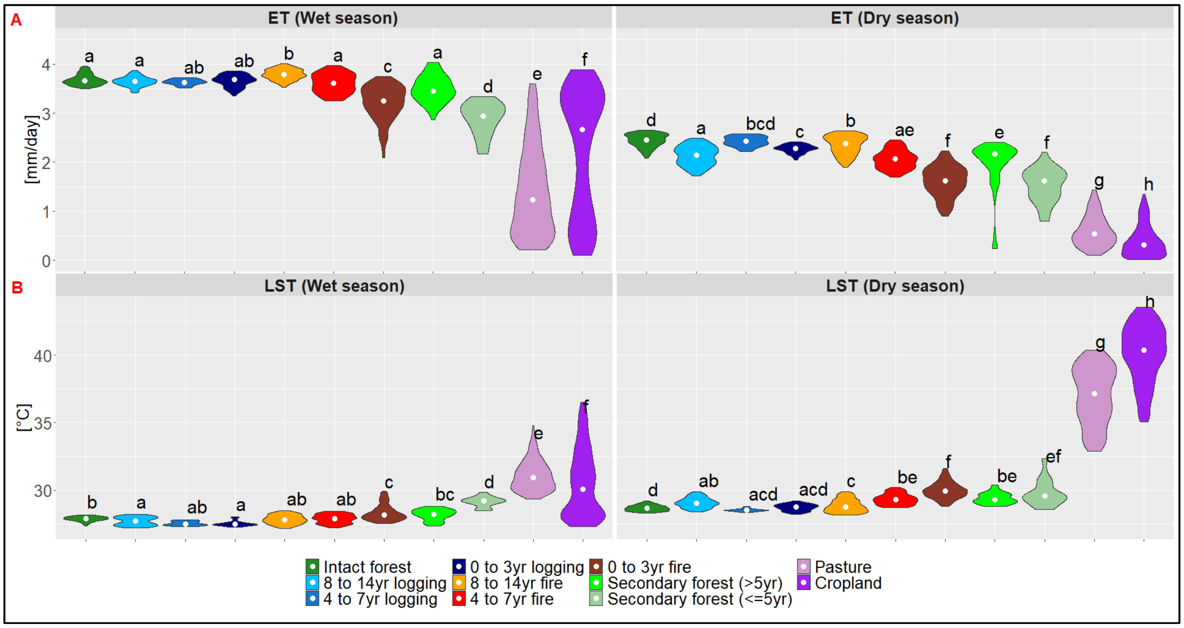

Figure 5. Distribution of ET (A) and LST (B) in the wet and dry seasons across the disturbance classes. Only 1/500 pixels were included, and observations falling below the 2.5th and above the 97.5th percentiles were excluded. Violin plots show the kernel probability density of the data at different values. All violins have the same width, and the median of each group is indicated by the white dots. Groups labelled with the same letter are not significantly different at a confidence level of 95% (Tukey's HSD test). The wet season image date is January 31st, 2019, and the dry season image date is September 28th, 2019.

We found a strong negative relationship between ET and LST across disturbance classes, with a global correlation coefficient of -0.81 (Figure 6). Two clusters of points were observed in the dry season data: forest classes at one end (with intact forests at the edge of this cluster), and crops and pastures at the other end. In the wet season data, there is no such clear differentiation: ET from cropland and pastures is more variable, with the highest values being like those observed in forests. Moreover, the secondary forest classes mostly had their points spread in the transition between the two clusters in the dry season.

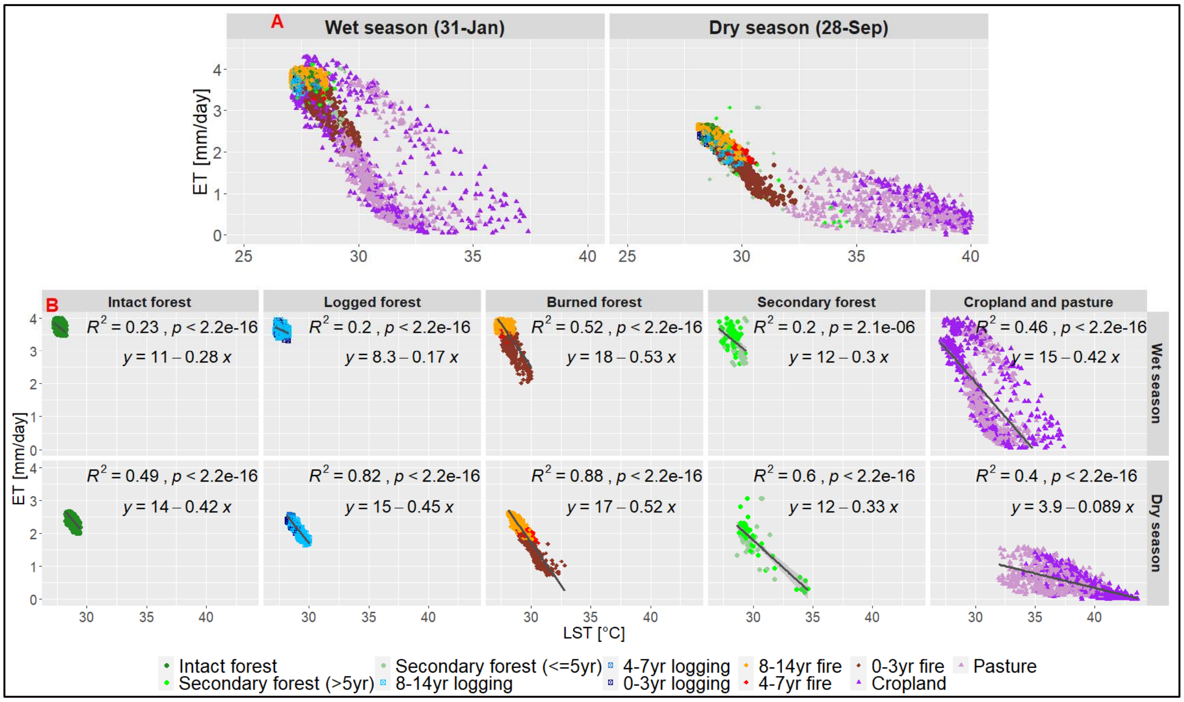

Figure 6. Relationship between ET and LST in wet and dry seasons for all classes (A), and for the broad disturbance classes separately (B). 1/500 pixels were randomly included, and observations falling below the 2.5th and above the 97.5th percentiles were excluded. Black lines represent the best fit line.

To assess ET and LST relationships over different land cover types, we merged the disturbance classes into five broad classes, namely intact, logged, burned and secondary forests, and crops and pastures (Figure 6B). All the regression models were significant, but the regression coefficients varied widely. Dry season conditions strengthened ET-LST relationship (i.e., increased the coefficient of determination, R^2) in intact, logged, burned and secondary forests. Nevertheless, in terms of sensitivity of the relationship (i.e., the slope coefficient), burned and secondary forest classes showed very small or not significant differences in slope across seasons (Table 2). Croplands and pastures were the only class that showed a lower coefficient of determination, and a much lower slope in the dry season.

All classes showed significantly different slopes between wet and dry seasons (p-value < 0.05), except secondary forests (p-value = 0.72), whereas the largest difference was observed at the cropland and pasture class (Table 2). A significant finding is that intact and logged forests showed a positive difference in trend (significantly higher slope in the dry season), whereas burned and secondary forests showed a negative trend (implying smaller slopes in the dry season, but with non-significant or marginally significant differences).

Table 2. Estimates of slope differences between wet and dry season in ET and LST relationship for the broad disturbance classes. P-values of pairwise comparisons > 0.05 (highlighted in gray) indicate non-statistically significant differences in slope at 95% confidence level.

Pair	Difference in trend	SE	df	t.ratio	p.value
Intact forest	0.149	0.0182	2577	8.205	<.0001
Logged forest	0.282	0.0149	1248	18.948	<.0001
Burned forest	-0.041	0.0133	2917	-3.087	0.002
Secondary forest	-0.025	0.0710	202	-0.358	0.720
Cropland and pasture	-0.350	0.0138	1992	-25.363	<.0001

3.3. Structure-function relationships

Forest structural properties derived from GEDI observations over all disturbance classes were significantly affected by disturbances. Classes following deforestation (secondary forests, croplands, and pastures) showed the most pronounced responses in the structural properties assessed (Figure 7). For both canopy cover (CC) and plant area index (PAI), intact forests showed the highest values, crops and pastures showed the lowest values and the least dispersed range, whereas young secondary forests showed intermediate values and the broadest range. Burned and logged forests clearly responded to time since disturbance and disturbance type, as indicated by increasing CC and PAI with time since disturbance. Young secondary forests (≤ 5 years) showed CC and PAI similar to the most recent burns. FHD, a measure of structural complexity, showed very little variability among intact and logged forests, whereas burned and secondary forests and crops/pastures differed significantly from those classes. Except for the FHD metric, young secondary forests had all GEDI structural metrics not significantly different from crops and pastures.

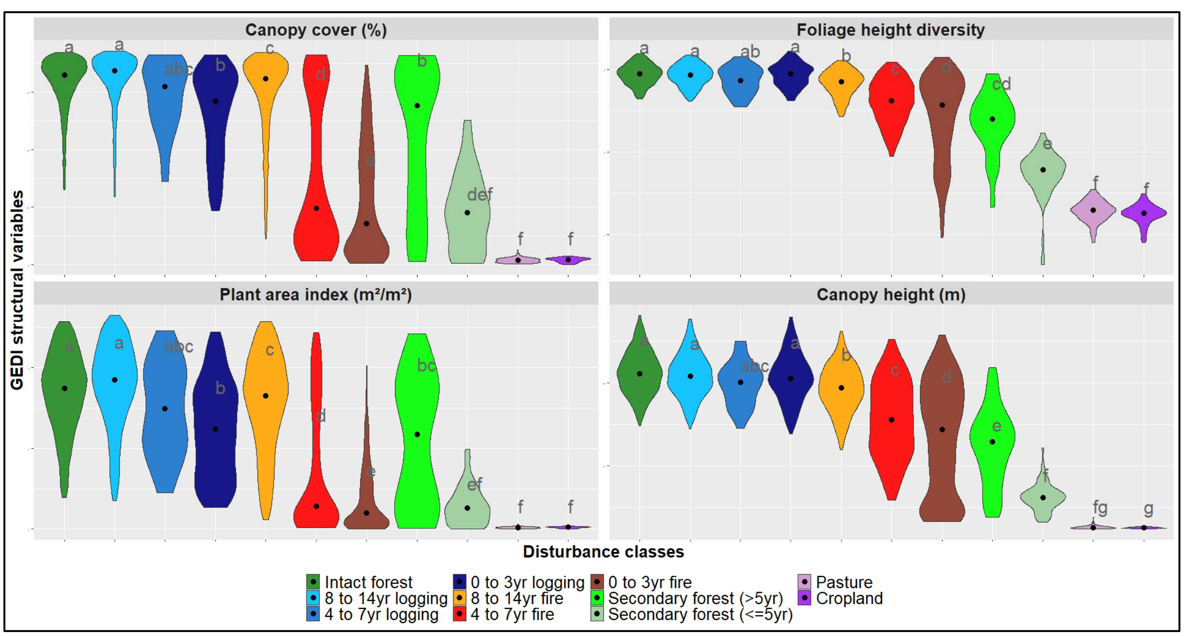

Figure 7. Structural properties derived from GEDI data for the disturbance classes. Groups labelled with the same letter are not significantly different at a confidence level of 95% (Tukey's HSD test). Observations falling below the 2.5th and above the 97.5th percentiles were excluded.

To assess the relationships between structural properties and ET and LST, we grouped the disturbance classes into four broad categories: intact, logged, burned and secondary forests. Croplands and pastures were excluded from this analysis because the structure in these classes might be ephemeral (i.e., crops are harvested), making the examination of relationships of structure to ET and LST less meaningful.

Structural properties showed moderate to high correlations with ET (positively correlated, coefficients from 0.50 to 0.59) and LST (negatively correlated, coefficients from -0.50 to -0.76) (Table 3). The strongest relationships between structure and ET and LST were observed in the most intensively disturbed classes (burned and secondary forests), whereas intact and logged forests showed no significant slopes in the relationships. For instance, CC explained 28 and 44% of ET and LST in burned forests, and PAI explained 25% of ET in burned and secondary forests. The greater regression slope for burned and secondary forests compared to intact and logged forests was consistent across all GEDI-derived structural properties (Figure 8).

Table 3. Correlation matrix of structural properties with ET and LST. All correlations are significant at 99% confidence. Positive coefficients are shown in blue and negative coefficients are shown in red.

	Canopy height	**Canopy cover**	**PAI**	**FHD**	**ET**	**LST**
Canopy height	**1.00**	**0.79**	**0.71**	**0.93**	**0.56**	**-0.67**
Canopy cover		**1.00**	**0.95**	**0.74**	**0.59**	**-0.62**
PAI			**1.00**	**0.63**	**0.50**	**-0.50**
FHD				**1.00**	**0.58**	**-0.76**
ET					**1.00**	**-0.77**
LST						**1.00**

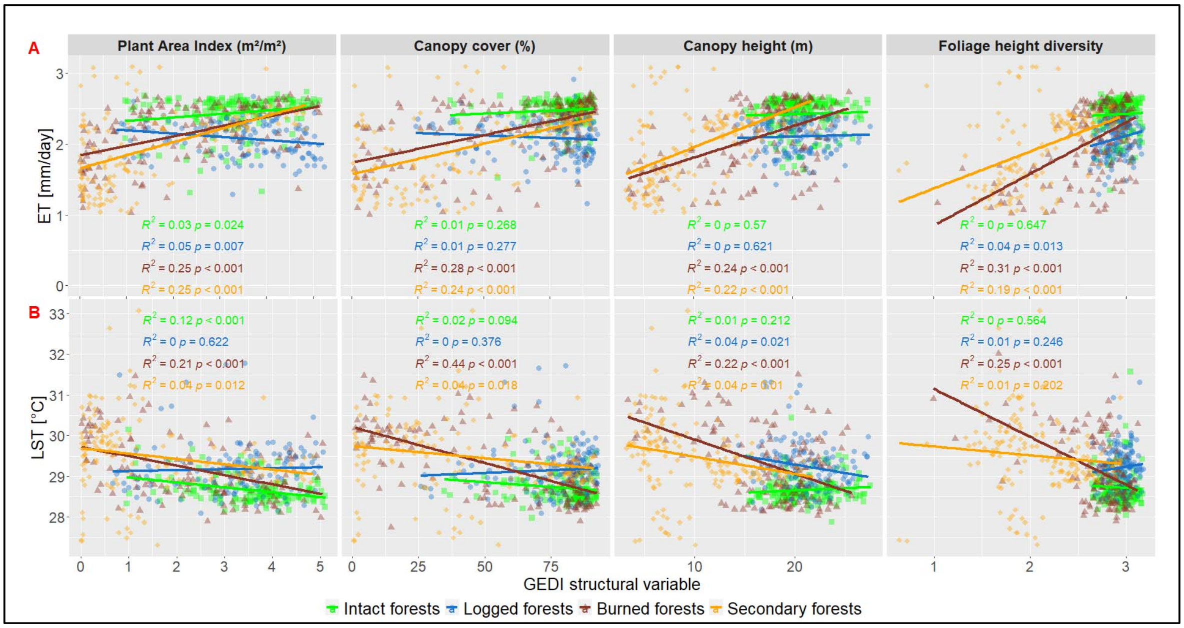

Figure 8. Relationship between GEDI structural properties and evapotranspiration (A) and land surface temperature (B) for the broad forest classes. Lines represent the best fit from the linear regression models.

ET and LST varied substantially among classes at the lower end of forest structure (short or low PAI forests), but not at the upper end (tall or high PAI forests) (Figure 8). There was a separation across the classes because intact and logged forests do not have the extremely low PAI, CC, canopy height and FHD. Interestingly, ET and LST have different ranges between intact and logged versus secondary and burned forests with similar PAI or canopy cover at the intermediate values. Moreover, the regression analysis suggests that most variation in ecosystem function (ET and LST) from these heavily disturbed forests can be explained by structure, whereas there is much lower variation in the least disturbed forests explained by structure and disturbance.

4. Discussion

In this study, we employed a novel combination of MODIS, Landsat and GEDI observations to compare seasonal water stress and ET-LST relationships over a continuum of disturbance conditions; and to quantify the contribution of forest structure properties to ET and LST variability in secondary, degraded and intact forests. The results showed that disturbances increased seasonal water stress, earlier and more pronounced in croplands and pastures than in forests, and more pronounced in second-growth and recently burned areas than in logged and intact forests. Moreover, we found that the negative ET- LST relationships were more consistent across disturbance classes in the dry season, and that the forest and cropland & pasture classes showed contrasting relationships in the dry season. Finally, we found that structural properties of the canopy such as plant area index, canopy cover, canopy height, and foliage height diversity exhibited moderate relationships with ET and LST in the most disturbed forests, but negligible correlations at the least disturbed forests.

4.1. Water stress, ET and LST variability across a disturbance continuum

The ESI seasonal profile analysis indicated that, while forest classes still showed some divergence in water stress especially at the end of the dry season, pastures and croplands in our study region are highly seasonal with a growing season-dependent exclusively on rainfall (Arvor et al., 2014) (Figure 3). This contrasting pattern occurs because the maximum rooting depth of these crops and grasses is far shallower than those of forests (Nepstad et al., 1994; O'Connor et al., 2019). But certainly, the most novel results of our study are those related to the behavior of secondary-growth and burned forests, showing that they experienced moderate and delayed water stress compared to intact and logged forests, related to changes in structural properties of these forests caused by disturbances (assessed with GEDI data) and potentially to species composition shifts (not assessed in this study).

ET generally increased and LST generally increased in the disturbance classes along a disturbance intensity continuum (intact forests < logged forests < burned forests < secondary forests < croplands & pastures). Although studies assessing ET and LST relationships in tropical forests are rare, the dry season declines in ET and increases in LST observed in this study (Figure 5 and Figure 6) agree with similar comparisons in the southern Amazon. Hasler and Avissar (2007) found 5-10% decreases in flux tower -measured ET in the dry season at sites in Rondônia and Mato Grosso States, while (von Randow et al., 2004) found 25% less ET in pastures in Rondonia state during the dry season. In general, we found similar trends, but more pronounced ET declines from January to September (33-40% at intact and least disturbed sites, and even greater declines (~50%) for the most heavily degraded forests, with crops and pastures showing the largest differences (60-80%), and greatest variability (Figure 4, Figure 5, Figure 6). These differences in magnitude could be due to the different methods of data acquisition (e.g., flux tower data versus satellite-based estimates, or single flux tower sites versus patch averages within a large area). Other plausible explanation for these differences is that the aforementioned studies used data from the early 2000's, while we looked at data from 2020. Temperatures and VPD increased in this interval, which could be adding more stress to these forests (Barkhordarian et al., 2019; Da Silva et al., 2019).

Despite slightly reduced PAI (Figure 7), the least disturbed forests such as logged and oldest burns showed ET and LST comparable to intact forests during both seasons (Figure 5), suggesting that albedo and net radiation on these forests recovered or never shifted from that of intact forests. Classes with intermediate levels of disturbance (4-7 yr fires and old secondary forests) showed stronger ET depletion during the dry season, and the most heavily degraded classes (0-3yr fire and young secondary forests) exhibited significantly lower LST and ET compared to intact forests on both seasons. These results agree with Miller et al. (2011), that found modest and ephemeral effects on the water and heat fluxes in a logged forest site in Central Amazon, with changes due to logging smaller than the interseasonal and interannual variability; these authors also found albedo not being significantly affected by logging activities. Similar to our results for burned forests, Brando et al. (2019) found that ET had fully recovered seven years after experimental fires in the same region. Comparing ET between intact and 20-years old secondary forests in Central Amazon, Von Randow et al. (2020) found that secondary forests showed ET approximately 20% higher than primary forests over wet and dry seasons. Given the shorter and less severe dry season in Central Amazon compared to Feliz Natal region, it is reasonable to expect lower ET in the dry season in Feliz Natal. Moreover, our samples include a much larger spatial variability of secondary forest conditions.

The strongest (negative) ET-LST relationships were observed at the disturbance classes with larger ranges of ET and LST values (e.g., burned and secondary forests), rather than at the most severely disturbed classes (e.g., crops and pastures, Figure 6). Among the forest classes, variations in seasonal water stress manifested in ET-LST relationships in different ways: burned and secondary forests showed little change from wet to dry season (differences in trend from -0.04 to -0.02), whereas the dry season substantially improved ET-LST relationships at intact and logged forests (differences in trend from 0.15 to 0.28; Figure 6, Table 2). These findings, along with the ESI profile from Landsat (Figure 3B), suggest that patches of burned and secondary forests, especially the most recent ones, experience year-round moisture stress (e.g., patches with low ET and high LST even in the wet season). Therefore, strong inverse correlations between ET and LST in wet periods could be used as an indicator of water stress and inform about the functioning of disturbed forests.

Patchy mosaics are prominent following fires and can include severely disturbed patches adjacent to fragments with substantial residual vegetation and organic matter (Chazdon, 2003). In this sense, Landsat fine-scale ET and LST estimates showed improved discrimination of the internal ET and LST variability of these patches. While MODIS data showed similarly low water stress across all forest classes in January (Figure 3A), Landsat finer-scale data showed larger differences among those classes even in the wet season (Figure 3B). These larger differences in the Landsat-based ESI may imply that MODIS-based assessments of water fluxes or water-use efficiency (e.g., Brunsell et al., 2020) are underestimating moisture deficit in these more degraded and patchier areas such as burned forests.

Taken together, these results highlight the wide range of forest functional responses to disturbances from a continuum of canopy structure and energy balance. This is a bi-directional gradient, resulting from deforestation and degradation in one direction, and forest regeneration or succession in the other. The characteristics of these disturbance gradients are integrally linked to canopy structural properties and may influence energy balance components and associated microclimates in linear or non-linear ways (Breshears, 2006; Stark et al., 2020). For example, as woody plant cover decreases, albedo and near-ground solar radiation increase, which increases the Bowen ratio (von Randow et al., 2004). Additionally, these patterns may also manifest nonlinearly, displaying threshold-type responses. Near-ground solar radiation, for instance, decreases nonlinearly with increasing canopy cover. Similarly, surface roughness and associated wind flow category change nonlinearly with increasing cover (Breshears, 2006; Stark et al., 2020).

4.2. Forest structure controls on energy balance

Although radiation controls on water and energy cycles prevail over our study area, forest structure seems to be an important secondary control of transpiration in degraded and secondary forests. Building on the Landsat-based ET and LST characterization during the dry season and the structural characterization provided by GEDI data, we showed that forest structure moderately explained ET and LST variability in the most heavily disturbed forests (burned and secondary), whereas forest structure provided little or no ET and LST predictive power in the least disturbed logged and intact forests (Figure 8). These findings suggest that disturbances enhance ET biophysical controls (from forest structure) and that the contribution of canopy structural properties to ET and LST is modulated by disturbances and the associated water stress. Also, forest structure's contribution to ET decreased with time since disturbance, pointing to the functional recovery of these forests, with decreasing water stress and biophysical control over time as regeneration takes place.

Previous modelling studies converge with our findings. Using a land surface model, Mallick et al. (2016) quantified the controls on evaporation and transpiration across representative plant functional types in the Amazon and found enhanced biophysical influence on ET during the dry season, especially over pastures and dry forest functional types. This same effect was observed on the diurnal cycle, which shows higher VPD in the afternoon than in the morning, and during the strong 2005 drought. Longo et al. (2020) investigated the effects of forest degradation on ET using an ecosystem demography model, and found that the magnitude and seasonality of fluxes were modulated by changes in forest structure caused by degradation. During the dry season and under typical conditions, severely degraded forests (biomass loss $\geq$ 66%) experienced water stress with declines in ET (up to 34%) and daily mean ground temperatures (up to 6.5°C) relative to intact forests.

Studies using observational data such as satellite observations and flux tower measurements also show degrees of agreement with our results. von Randow et al. (2012) found enhanced biophysical control on ET for pastures during the dry season, whereas the findings from Oliveira et al. (2019) suggested that the control of canopy stomatal conductance and root depth on vegetation water use is stronger in agricultural systems than in primary and secondary forests in the Amazon.

We observed larger ET and LST variability in the dry season for the majority of the forest classes (Figure 5). Hasler and Avissar (2007) also found a larger scatter of ET values during dry season throughout the Amazon and suggested that this effect is due to the increasing importance of secondary drivers of latent heat flux in the dry period, such as VPD and water availability. The ESI annual profile (Figure 3) showing increasing evaporative stress towards the end of the dry season for all classes corroborates this. In contrast, the most recent classes (and likely, the most impacted) of logged, burned and secondary forests showed larger ET variability in the wet season (Figure 5), suggesting that these classes may be experiencing the dry season enhanced biophysical controls during the wet season as well. This hypothesis is also supported by the strong ET-LST relationships in these forests during both seasons (Figure 6).

Forest structure plays an essential role in determining roughness lengths and aerodynamic conductance to heat, moisture, and momentum between the canopy and atmospheric (Bright et al., 2015). Supporting the strong influence of forest structure on the canopy and aerodynamic conductances, we found that ET and LST were strongly correlated with FHD, TCH, CC, and PAI (Table 3). Moreover, the FHD metric (an indirect measure of surface roughness given by structural complexity) was significantly lower in burned and secondary sites compared to intact forests (Figure 7) likely leading to decreased canopy conductance to heat and moisture and consequent lower ET and higher LST in these forests (Figure 5, Figure 6).

Due to their larger aerodynamic properties, forests are more efficient at dissipating sensible heat away from the surface and into the boundary layer relative to areas with shorter vegetation, particularly during the daytime (Bright et al., 2015; Hoffmann & Jackson, 2000). Our detailed characterization of ET, LST and forest structure relationships strongly supports these statements, as the classes with lower stature and complexity (described by CC and FHD metrics in Figure 7) showed the highest temperatures on both wet and dry seasons (Figure 5). Moreover, the highest correlation of the FHD metric with surface temperature also suggests that structural complexity plays an important role in cooling the canopy.

4.3. Implications for vegetation modelling

Land cover changes (Davidson et al., 2012) and their positive feedbacks in the precipitation variability in the Amazon Basin (Hilker et al., 2014; Wang et al., 2011) are expected to increase the canopy–atmosphere coupling of forest systems under drier conditions by altering the ratio of the biological and aerodynamic conductances. Our observational findings support previous model-based and eddy-covariance findings showing that under drier conditions, the canopy-atmosphere coupling increases, and so the biophysical controls on ET amplify as well. An increase in biophysical control is an indicator of a potential transpiration shift from an energy-limited to a water-limited regime (due to the impact of air and surface temperatures and VPD on the canopy and aerodynamic conductance ratio), with further consequences for the global surface water balance and rainfall recycling.

The implications of these findings to vegetation models in tropical forests are significant. The largely aggregated 'big-leaf' vegetation models, which represent forests with single functional types, may not be able to characterize complex and heterogeneous structure-climate interactions across different forest types and disturbance conditions. Cohort-based vegetation models (CBVM) stand between 'big leaf' and individual-based models and can efficiently represent structural and functional diversity within forest ecosystems at regional and global scales (Fisher et al., 2018). CBVM may provide a more appropriate way to account for forest responses to the changes in the micro-environment caused by disturbances (Longo et al., 2020). Explicitly incorporating forest structure information into CBVM to inform about the degradation status and the degree of vegetation canopy coupling to the atmosphere could certainly improve estimates of seasonal water and energy fluxes at heterogeneous forests such as those in the Southern Amazon.

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Data Availability Statement

All remote sensing data utilized in this study is freely available for users. MODIS and GEDI data can be accessed at the Land Processes Distributed Active Archive Center (LP DAAC - https://lpdaac.usgs.gov/). Landsat ET and LST data can be accessed at the EEFLUX page (http://eeflux-level1.appspot.com/).

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