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How wildfires increase sensitivity of Amazon forests to droughts

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Abstract

The phenology of tropical forests is tightly related to climate conditions. In the Amazon, the seasonal greening of forests is conditioned by solar radiation and rainfall. Yet, increasing anthropogenic pressures (e.g. logging and wildfires), raise concerns about the impacts of forest degradation on the functioning of forest ecosystems, especially in a climate change context. In this study, we relied on remote sensing data to assess the contribution of solar radiation and precipitation to forest greening in mature and fire degraded forests, with a focus on the 2015 drought event. Our results showed that forest greening is more dependent on water resources in degraded forests than in mature forests. As a consequence, the expected increase in drought episodes and associated fire occurrences under climate change could lead to a long-term drying of tropical forests.

1. Introduction

Understanding complex interactions between climate and the functioning of Amazonian forest ecosystems is crucial for assessing the role of tropical forests in regulating global to regional biogeochemical exchanges with the atmosphere [1].

From a climate perspective, vegetation cover directly influences climate variables. The forest's canopy structure creates intense latent heat fluxes and roughness properties that slow the warming of air and ensure efficient storage of precipitation and release of water into the atmosphere as evapotranspiration (ca. two-thirds of precipitation received by mature forests), even in the dry season [2, 3]. Since forest evapotranspiration represents one-third to more than half of total precipitation in the Brazilian Amazon [4, 5], tropical forests have been conceptualized as pumps that recycle and spread moisture from the oceans [4] and from evapotranspiration. The spatial and temporal climate variability in the Amazon is related mainly to global mechanisms (e.g. displacement of the Intertropical Convergence Zone and the South Atlantic Convergence Zone, El Niño Southern Oscillation) or geographic conditions (e.g. Andes mountains). However, vegetation phenology also plays a crucial and complex role in the timing of dry-and rainy-season transitions [6, 7] with a strong climate feedback [8] (e.g. to regulate moisture, energy and gas exchanges between the surface and the atmosphere).

From a vegetation perspective, the functioning and distribution of forest ecosystems also depend on climate drivers [9]. The phenology of Amazon tropical forests is characterized by greening during the dry season due to net leaf-flushing (i.e. more new leaves appear than old leaves fall) and an increase in canopy chlorophyll content [10, 11]. During the late rainy season, photosynthetic activity decreases due to senescence, litterfall and the development of epiphylls on mature leaves [12]. This apparently homogeneous situation across the Amazon conceals high spatiotemporal variability related to two main climate factors that influence tropical forest phenology: precipitation and solar radiation [13]. Tropical forests with no limitations on water availability (i.e. at least ca. 2000 mm of annual precipitation [14]) experience rapid leaf-flushing during the dry season in response to an increase in photosynthetically active radiation. This is presumably due to the ability of deeply rooted trees to access soil water during the dry season [15]. Conversely, leaf-flushing in drier tropical forests is influenced by precipitation at the end of the dry season. Extending this gradient to savannas and pastures, a positive relationship with precipitation suggests that photosynthetic activity (i.e. higher leaf-area index (LAI) and enhanced vegetation index (EVI)) increases during the rainy season and decreases during the dry season [12, 16, 17]. Rather than a clear delineation between water- and light-limited forests, the distribution of phenological patterns follows a northwest-to-southeast moisture gradient related to dry-season length and intensity [18, 19]. Wagner *et al* [20] mapped this gradient and indicated that spatial patterns of the climate influence the leaf growing season in the Amazon.

For several decades, the Amazon rainforest has been under human pressure, due mainly to agricultural expansion and the resulting, well-known massive deforestation. Permanent land-use change to produce commodities is the main driver of deforestation in the tropics [21]. To date, most studies have focused on reporting the extent, causes and impacts of deforestation on ecosystems and climate change. Consequently, studies have reported worrying predictions of changes in mean annual precipitation [3, 22, 23], an increase in extreme droughts [24] or precipitation events [25], and changes in the beginning and end dates of the rainy season [26, 27]. Beyond deforestation, recent studies also mention the severe degradation of the Amazon rainforest due to fire, timber logging and forest fragmentation [28]. Forest degradation represents 69% of current global carbon losses in tropical forests [29] and areas of degraded forests may exceed deforested areas in certain years [30]. The frequency, nature and intensity of disturbances generate high variability in the structure, floristic composition and functioning of degraded forests over time [31], which can influence climate-vegetation interactions. As reported in many studies, phenology can be a relevant proxy for studying these climate-vegetation interactions. For example, Koltunov *et al* [32] revealed that even low forest degradation (5%–10% of canopy damage) due to selective logging can alter forest phenology, because it dries the canopy and decreases greening. Fires are the major and ultimate stage of forest degradation in the Amazon [33, 34], especially due to increased tree mortality [35–37].

Remote-sensing data are a key tool to understand spatial variations in phenology over large areas [38]. Remote-sensing time series of vegetation indices have long been used to monitor vegetation phenology. Among the many remote-sensing data available, vegetation indices based on Moderate Resolution Imaging Spectroradiometer (MODIS) are widely used to monitor phenological cycles of forests [39, 40]. The MODIS EVI measures canopy greenness, a composite property of canopy structure [41] and it is so far one of the primary data source for studies of the greening phenomenon [42]. It is not subject to saturation in high-LAI canopies [43] unlike the normalized difference vegetation index. The high temporal resolution of these products makes it possible to study phenological cycles of forests and relate them to environmental conditions. A common issue with this product is the processing and interpretation of vegetation-index time series to monitor fine-scale seasonal and interannual changes in evergreen forest phenology. Morton *et al* [42] suggested that the greening observed during the dry season [12] resulted from seasonal changes in near-infrared reflectance, which are artifacts of variations in Sun-sensor geometry. Other studies indicated that a seasonal pattern of EVI from photosynthetic activity remained after removing atmospheric contamination and considering Sun-sensor geometry effects [44]. To address this issue, Lyapustin *et al* [45] introduced Multi-Angle Implementation of Atmospheric Correction (MAIAC) to increase the performance of daily MODIS observations. Based on MAIAC, recent studies confirmed the original results that indicated dry-season greening of Amazonian forests. This was also confirmed by Doughty *et al* [11], who found a dry-season increase in solar-induced chlorophyll fluorescence (another proxy for photosynthetic activity) using TROPOMI data. The most recent results highlight that EVI is not strongly correlated with LAI or biomass, but rather with leaf-flushing [46], which may explain why greening does not appear in independent LiDAR observations that indicate no change in canopy properties during the dry season.

The phenology of Amazonian forests remains a complex subject, especially in relation to climate variations. The complex interrelationships between climate and vegetation should be considered due to the intense human pressures that impact Amazon ecosystems. Degradation must be incorporated in studies that focus on forest functioning. Currently, effects of degradation on forest phenology-climate interactions remain poorly documented [47]. In this study, we

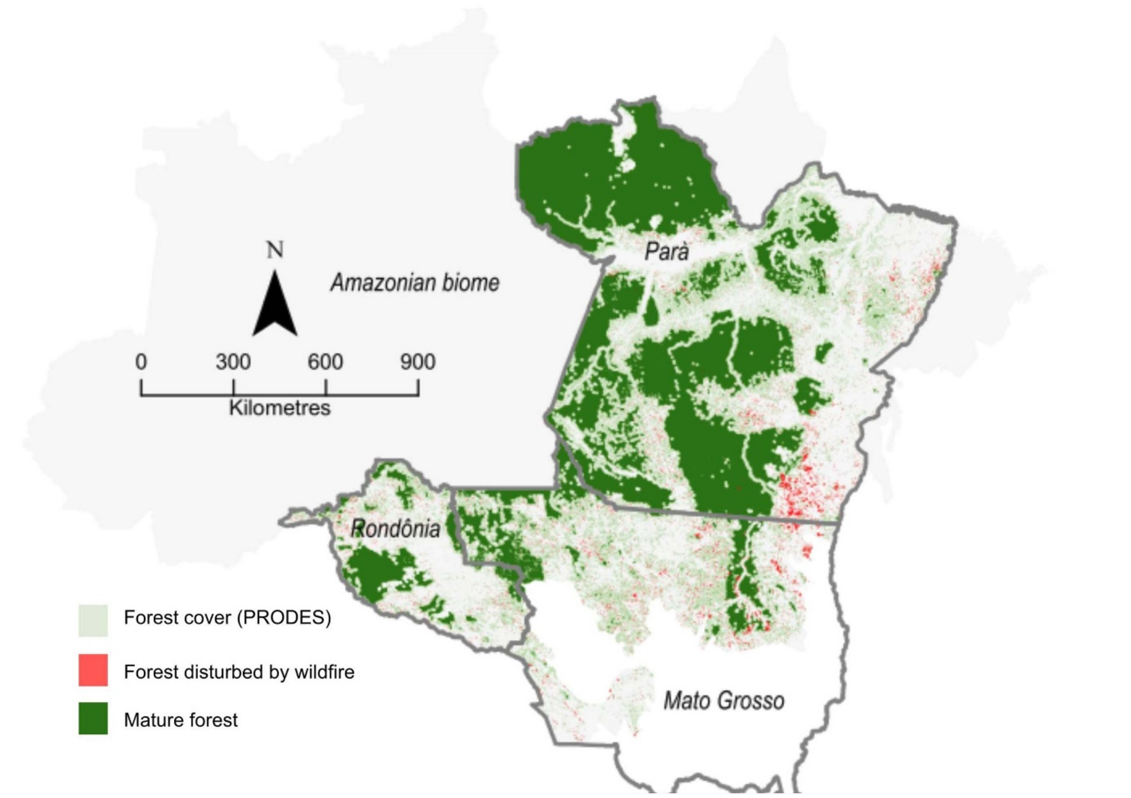

Figure 1. Study area representing the Brazilian states of Pará, Mato Grosso and Rondônia. Light green areas are forested area according to PRODES product. Inside these forest areas, mature forest are represented in dark green and FDW in red.

relied on the fact that Forests Disturbed by Wildfires [48] (FDW), as defined by Barlow *et al* [48] currently represent large areas in Amazonia and play a crucial role by releasing large amounts of carbon in the atmosphere [49]. We focused on these forest (FDW) to highlight the importance of differences in functioning between mature forests and highly degraded forest.

2. Study area, data and methods

2.1. Study area

The study focused on eastern and southern portions of the Amazon biome in three Brazilian states: Pará, Mato Grosso and Rondônia (figure 1). These states are representative of the 'arc of deforestation', with several hotspots of historic and ongoing deforestation and degradation. Forest landscapes are thus a mosaic of forests in different states of degradation. The classification used in this study to separate forest and non-forest areas is the PRODES deforestation product [50]. PRODES is a product created by INPE (Brazil's National Institute for Space Research) to monitor deforestation in Brazil. It is a combination of automated satellite images processing and expert interpretations. The result is an annual map at 30 m resolution of forest/non forest. In this paper forests disturbed by wildfires refer as in Barlow *et al* [48] to forests that have been disturbed by understory fire but not deforested according to PRODES deforestation product presented above.

2.2. Data and preprocessing

2.2.1. Mapping mature and FDW

Mature forests are considered here according to Clark's [51] definition, as primary or secondary forests that have developed the structures and species normally associated with old primary forest of that type that have sufficiently accumulated to act as a forest ecosystem distinct from any younger age class. For this purpose, a forest pixel is considered as mature forest was an non-deforested according to PRODES data, and an undisturbed forest according to Matricardi *et al* [30] and the Global Fire Atlas (figure 2). To avoid integrating the effects of borders and isolated small forest patches, riparian forests and swamp forests into the mature forest class, all pixels less than 5 km from other land uses (e.g. agriculture, water bodies) were excluded based on the Mapbiomas landcover map at 30 m spatial resolution [52].

Fire is often the ultimate stage of degradation before potential deforestation [31, 33, 34], FDW are often the most degraded forests. Burned area were extracted from the The Global Fire Atlas [53] dataset (2001–2016). It provides burned area, based on the Global Fire Atlas algorithm and from MODIS Collection 6 MCD64A1 burned area. The cumulative burned area observed over the study period was

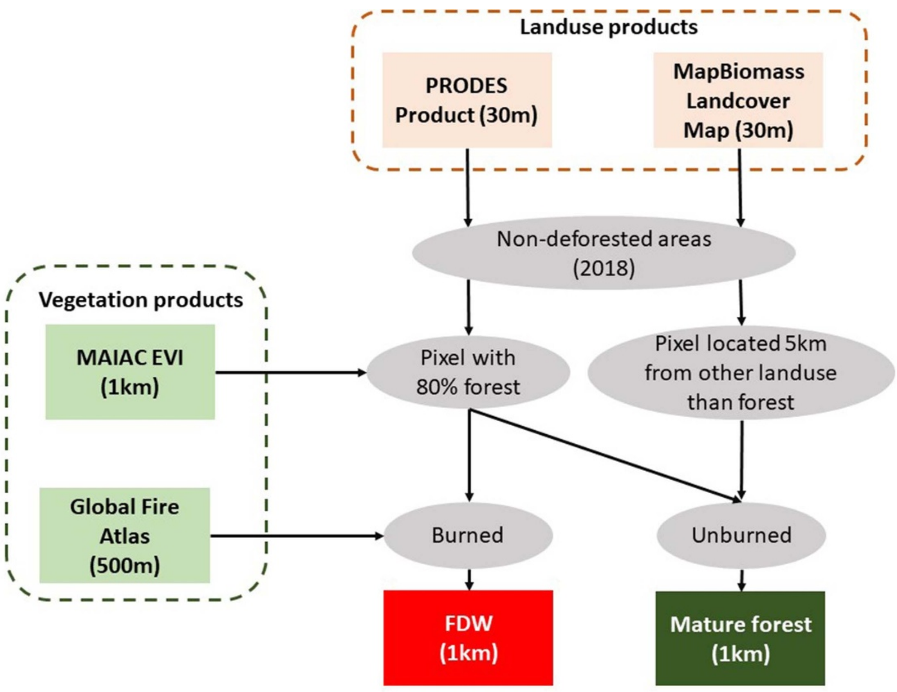

Figure 2. Workflow of preprocessing and mapping mature forest and FDW.

Table 1. Classification of mature and FDW in the study area based on PRODES data.

Forest class	Surface (in km^2)	Percentage
Total forest class	1233 215	100
Mature forest	656 011	53
FDW	99 014	8

used. A MAIAC (ca. 1 km^2) forest pixel was considered burned if it experienced a fire at least once and with at least 80% forest cover according to the latest version of the PRODES deforestation product (figure 1). Based on this classification, mature and FDW in the study area represented 53% and 8% of the pixels, respectively (table 1).

2.2.2. Vegetation data

In our study, we used the EVI from Aqua and Terra satellites, processed with MAIAC. MAIAC data are processed with advanced cloud detection and aerosol-surface retrieval, which improves the accuracy of satellite-based surface reflectance over tropical vegetation by 3–10 fold compared to that of standard MODIS products. MAIAC observations are based on MODIS Collection 6 Level 1B (calibrated and geometrically corrected) observations, which removed the main effects of sensor calibration degradation in earlier collections. We used observations from the Aqua and Terra satellites collected from 2001 to 2018 at 1 km spatial resolution. We used the same dataset as Wagner *et al* [20]: a time series of mean EVI in which interannual monthly mean EVI were filtered using a Fourier transform.

2.2.3. Precipitation and solar radiation data and preprocessing

Precipitation measurements were obtained from The Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) data. This product combines 0.05° high-spatial-resolution satellite imagery and in-situ station data, providing near-global (50° N–50° S; all longitudes) gridded daily precipitation estimates [54]. We used Version 2 data from 2001 to 2018, at a spatial resolution of 0.05° latitude × 0.05° longitude. Paca *et al* [23] observed good agreement between CHIRPS data and ground station observations over the Amazon basin, while Espinoza *et al* [22] observed very good agreement between trends of climate indexes derived from CHIRPS and the interpolated HYBAM observed precipitation (HOP) dataset. Monthly mean precipitation was calculated for 2001–2018.

Solar radiation data were obtained from The National Solar Radiation Database [55] available at 0.4° spatial resolution, from 2005 to 2015, produced by the National Renewable Energy Laboratory. We used monthly mean global irradiance on a horizontal surface (W m^{-2}). Monthly mean over the 2005–2015 period was used here.

Temperature was obtained from a monthly global climate dataset (CRU TS4.04) available at 0.5° spatial resolution, from 1901 to 2019, produced by the

Climate Research Unit (CRU) at the University of East Anglia, United Kingdom [56]. Monthly mean over the 2001–2018 period was used here.

3. Method

3.1. Mapping climatic area

We used the Köppen climate classification [57] to represent differences and in EVI profiles of FDW and mature forests as a function of climatic conditions. The Köppen classication divides terrestrial climates into five major classes (A, B, C, D and E). Temperature defines four of the classes (A, C, D and E, as B is reserved for arid climates). These classes are divided into subclasses, which are designated with additional letters representing precipitations. To assess the climatic conditions of the study period, we calculated the Köppen classification for each MAIAC pixel for each year. Then, according to the method of Dubreuil *et al* [58], the most frequent subclass per pixel during the 2001–2018 period was assigned to the pixel. Then we compare to a reference map produced by Rubel and Kottek [59] to highlight spatial shift of climate area in the last decades.

3.2. EVI greening modeling

For each Köppen subclass, we averaged monthly EVI data for FDW and mature forests. To avoid temporal shifts due to geographical variations in the beginning and end of the rainy season, each pixel started in the rainiest month. We used the same methods as Wagner *et al* [60], which in our study consisted of fitting linear regression models to the main increase in EVI as a function of two climate variables: monthly precipitation (P) and solar radiation (SR):

$$\mathrm{EVI}_{\mathrm{mat}} = f(P, SR) \tag{1}$$

$$\mathrm{EVI}_{\mathrm{deg}} = f(P, SR). \tag{2}$$

The consideration of the lag between the increase in climate parameters and the EVI was done in two steps. In the first step, the best model is selected for the whole study site with an lag of 0, 1, 2 and 3 months. In a second step, the best model per pixel is selected using lags of 0, 1, 2 and 3 months, selecting only pixels where the correlation between precipitation and solar radiation is less than 0.2 per lag, thus limiting artificial correlations between climate variables. All modeling details can be found in Wagner *et al* [60].

For each pixel, the model provided four R^2 results that represented the contribution of each climate parameter to the main increase in EVI for each type of forest: precipitation for mature forest, solar radiation for mature forest, precipitation for FDW and solar radiation for FDW. Moreover, the coefficients of rain or radiation are necessarily positive in the model, so it limits a little the compensation effect that we could have with the correlation between variables.

3.3. Extreme event: the 2015 drought

The average profiles over several years helped us to understand forest phenology/climate relationships during 'normal' climate years. However, the climate of the Amazon has high interannual variability due to larger-scale conditions, specifically El Niño and La Niña phenomena. Several intense droughts occurred during the study period; we focus on one of the most recent, which was caused by a strong El Niño event in 2015. To assess impacts of this type of event on the greening of mature and FDW, we calculated monthly EVI anomalies (i.e. differences) from the mean EVI of mature forests from 2001 to 2018, for each Köppen subclass.

4. Results

4.1. Climate classification

The study area had only one climate class (A, warm), which was subdivided into three subclasses defined by their precipitation patterns: Af (no dry season), Am (short dry season) and Aw (winter dry season) (figure 3). These three subclasses were the same in the past decades (1951–2000) (figure 3), but their spatial distribution had changed. The Af subclass (no dry season) was the smallest and was limited to a few areas in the north of Pará. The Aw subclass dominated the entire southern and eastern portion of the study area. This change in Köppen subclasses in this region was previously observed by Dubreuil *et al* [58].

4.2. EVI profile

EVI differed as a function of the climate subclass and state of the forest (mature or bruned) (figure 4). In all locations, greening of mature forests correlated more with solar radiation than that of FDW; conversely, greening of FDW correlated more with precipitation. In areas with year-round precipitation (Af), the profiles of FDW and mature forests had similar curves, with higher EVI for mature forests. Solar radiation correlated ($R^2 = 0.80$ (mature) $R^2 = 0.66$ (degraded)) more with greening than precipitation did ($R^2 = 0.05$ (mature) $R^2 = 0.12$ (degraded)). EVI peaked soon after the month of maximum solar radiation. For the climate with a more distinct dry season (Am), mean EVI was higher than that of the Af climate. For mature forests, EVI also peaked soon after the month of maximum solar radiation, while FDW reached their maximum in the middle of the rainy season, with an increase correlated with an increase in precipitation. These results were confirmed by model results, in which the relationship with solar radiation remained strong for mature forests ($R^2 = 0.60$), while the greening of FDW depended on both precipitation ($R^2 = 0.38$) and radiation ($R^2 = 0.41$). Forests had the largest differences in profiles in the Aw climate, in which the dry season and solar radiation are more intense. The EVI time series of FDW followed that of precipitation ($R^2 = 0.72$), with EVI

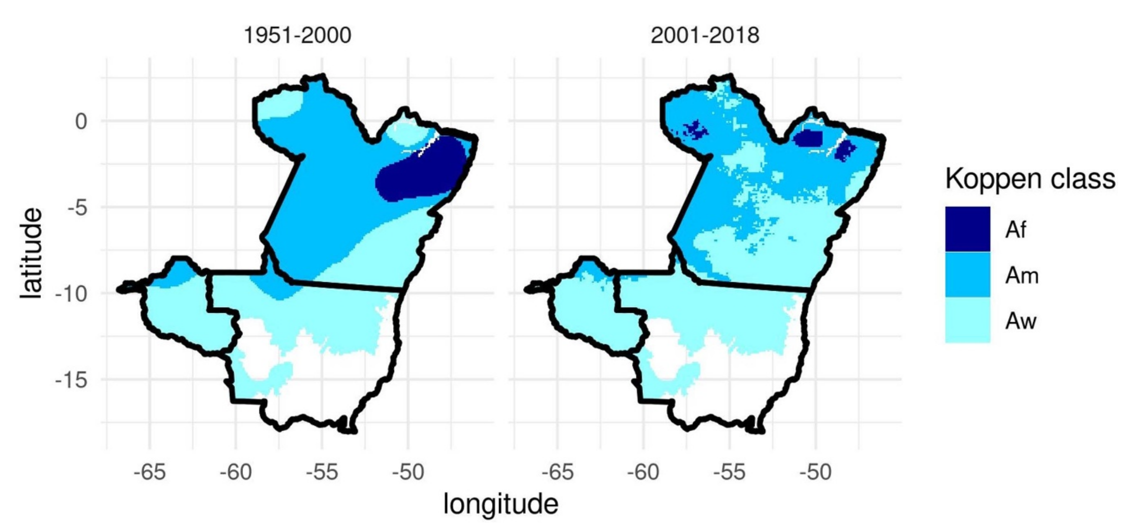

Figure 3. Dominant Köppen climate subclasses in the study area from Af (no dry season), Am (short dry season) and Aw (longer dry season in winter). Left panel represents dominant classes for 1951–2000 period (extracted from Rubel and Kottek [59]). Right panel represents the dominant classes for the studied period (2001–2018).

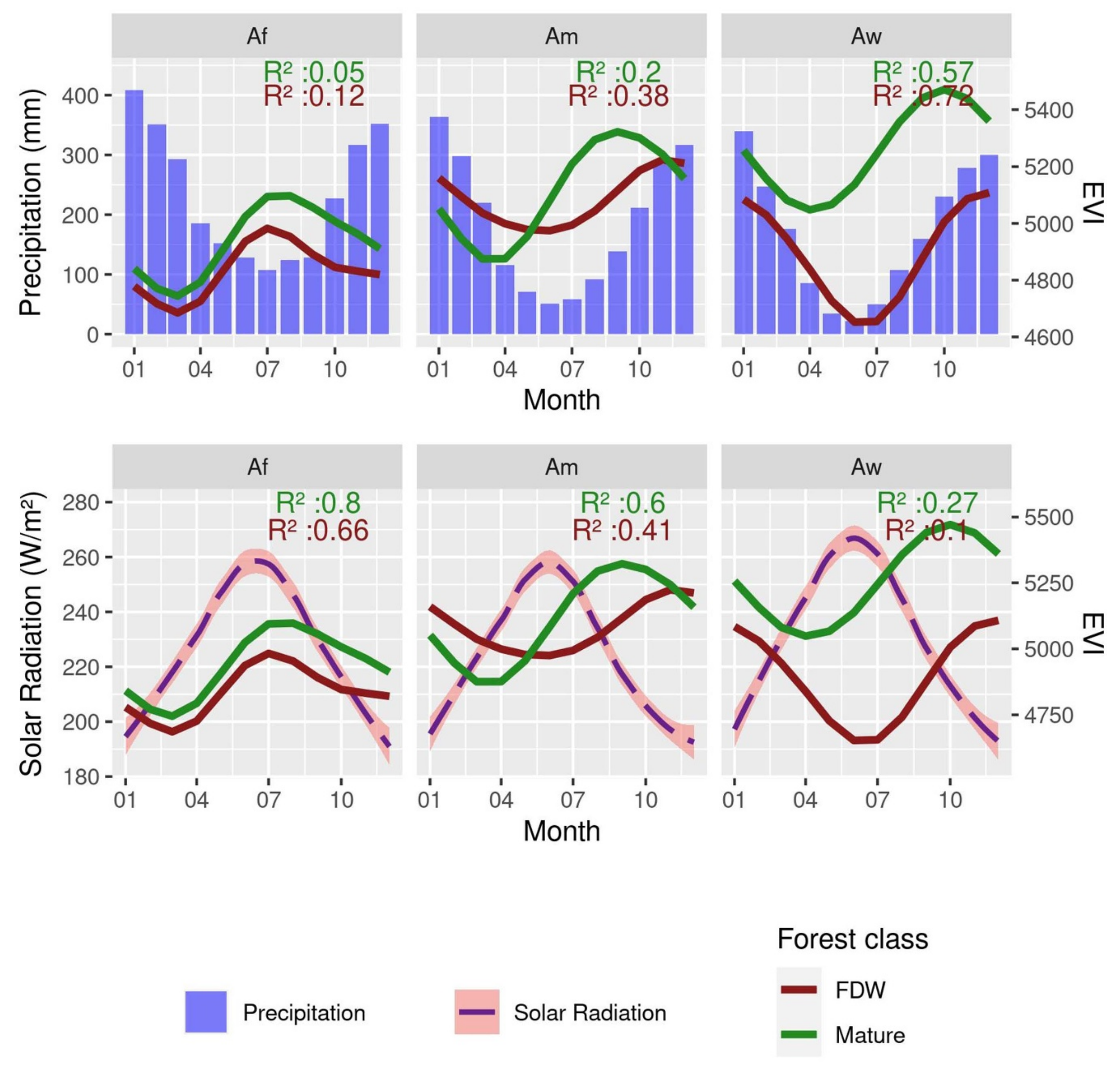

Figure 4. EVI profiles associated with precipitation and solar radiation in FDW and mature forests in the three Köppen climate subclasses (Af, Am and Aw). Month 1 is the rainiest.

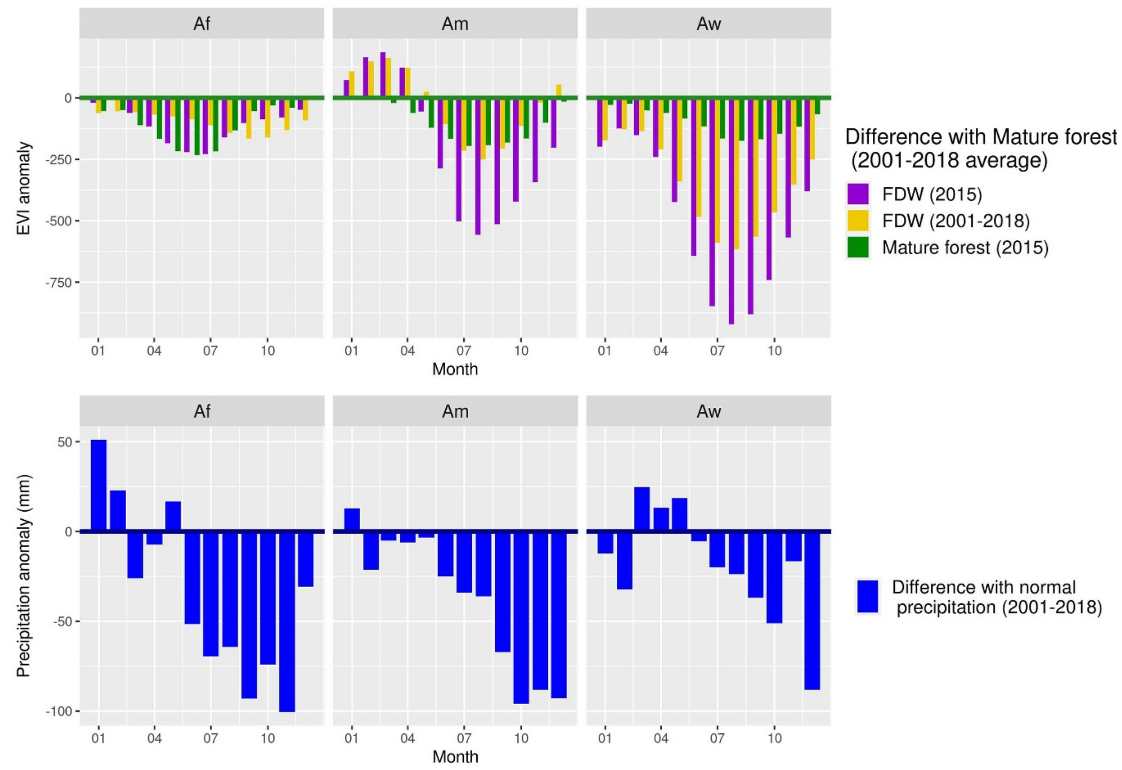

Figure 5. (Top) Anomalies between the mean EVI of mature forest (2001–2018) and those of FDW during the 2015 drought (green), FDW (2001–2018) (purple) and mature forest in 2015 (violet) in the three Köppen climate subclasses (Af, Am and Aw). (Bottom) Anomalies between precipitation in 2015 and the mean precipitation (2001–2018).

decreasing sharply in the middle of the dry season, when solar radiation had little influence on greening ($R^2 = 0.10$). Greening of mature forests was also correlated with precipitation ($R^2 = 0.57$), with a much smaller decrease during the dry season, and also depended on solar radiation ($R^2 = 0.27$). Greening resumed as soon as precipitation increased again, to reach the maximum EVI observed in the three climate subclasses.

4.3. Impact of the 2015 drought on EVI

The monthly EVI and precipitation anomalies for 2015 highlighted the effects of drought on mature and FDW. During that specific year, areas in the Af climate had alternating positive and negative precipitation anomalies at the beginning of the year (months 1–7), and then a succession of negative anomalies in the second half of the year (months 8–12) (figure 5). The same pattern occurred for the Am climate, with much larger negative anomalies at the end of the year (months 10–12). For the Aw climate, precipitation anomalies were negative in all months except for the middle of the year (months 4–8). EVI anomalies varied among the climate subclasses. For the Af climate, when precipitation anomalies were the most negative, both mature and FDW experienced roughly similar negative EVI anomalies. These anomalies differed little (<5%) from the 2001–2018 mean. For the Am climate in 2015, FDW had small positive anomalies, with values similar to their long-term mean. In the second half of the year, however, FDW had large negative anomalies (>10%), while mature forests had anomalies less than 5%. These anomalies were larger for the Aw climate, with negative anomalies greater than 15% for several consecutive months for FDW.

5. Discussion and conclusion

We observed differences between natural and FDW. The EVI of FDW tended to be lower than that of mature forests which is similar to results observed by Wang and Zhang [61] on temperate forests. They also demonstrated a shift in start and end of growing season in forest after wildfires. In this study, the maximum and minimum EVIs shifted in time in the eastern and southern portions of the deforestation arc, where the climate is drier (subclasses Am and Aw). In these areas, the greening of forests affected by fire is correlated more to precipitation. The longer and more intense the dry season, the more this aspect intensifies, which could indicate that FDW are becoming more dependent on water for leaf greening. Since EVI can be a proxy for forest functioning and productivity in the Amazon rainforest [62], our results show that understory fires reduce greening and gross primary production. These results are consistent with model predictions of Longo et al [63] which showed that degradation modifies the functioning of Amazon ecosystems. D'Amato et al [64] showed that reducing tree density could compensate for a lack of water resources by increasing water sharing. However, our results indicate that FDW Amazonian forests do not seem to benefit from this decrease in density. This difference could be because the study of D'Amato *et al* [64] focused on temperate forests, in which competition for water might be stronger and the reduction in density is chosen and controlled, rather than the result of fire.

In addition to understory fires, degraded forest landscapes are much more fragmented than mature forests [65] (e.g. forest edge represent 3% of the total surface of amazon forest [66]). Nearly 20% of tropical forests lie within 100 m of a non-forest edge [67]. This edge effect reduces the amount of carbon stored at forest edges by 25% within 500 m and by up to 10% within 1500 m of the forest edge [68]. New forest edges increase canopy desiccation, tree mortality and the frequency of fire [69, 70].

This appears to be especially true during extreme events, particularly droughts, such as the one experienced in the Amazon in 2015–2016 (El Niño event). Our results seem to show that EVIs of mature forests, which are influenced less by precipitation, are associated with much smaller negative EVI anomalies than FDW, especially in drier climate subclasses (Am and Aw). McDowell and Allen [71] showed that smaller plants are the most resistant to hotter and drier conditions, while old-growth and tall forests are particularly vulnerable. We chose to focus on the 2015–2016 drought in order to have sufficient FDW data and a long enough time series of EVI. If these results are confirmed by new studies of other extreme dry events (e.g. in another tropical rainforest), the consequences may lead to changes in vegetation patterns in the Amazon. This phenomenon could be accelerated in areas of FDW, which are even more sensitive to water stress. In addition, severe droughts increase the mortality rate of trees [72]. FDW would experience higher mortality rates with the cascade effect of a decrease in canopy cover and increased sensitivity to fire, especially during severe drought due to El Niño phenomenon [73]. Our results, based on observational data, clearly show that FDW phenology is changing, and that forests are becoming more limited by water.

The Amazon is highly vulnerable to changes in land use and the climate, especially in areas where forests are most degraded [74]. An increase in the sensitivity of FDW to precipitation could accelerate ongoing processes that could result in regional climate-tipping points [75]. Climatic trends over the past few decades reveal that climates that are rainy throughout the year (Af) are limited to a few areas of the study area [58] while the Aw climate, with a more intense dry season, has dominated the southern and eastern portion of the deforestation arc over the past 20 years. In addition, precipitation tends to decrease in the southern portion of the Amazon biome, where it transitions into the Cerrado biome [76], and the consecutive-dry-day index has increased in the south and east of the Amazon [25]. We have shown that a FDW is more sensitive to variations in precipitation when in a drier climate, and due to climate change, the area of forest in a drier climate will tend to increase. Degraded forests currently represent a large proportion of the Amazon rainforest [30], which creates a strong risk of setting up a vicious cycle in these areas: an increase in fire due to more intense and frequent drought increases sensitivity to future fires [77]. Certain areas that could change from forest to savanna could be larger than those estimated by Hirota *et al* [78].

Forests and the climate interact at different spatial and temporal scales. For the spatial scale, forests in the Aw climate in our study were more sensitive than those in wetter climates. For the temporal scale, the EVI of FDW increased more during extreme drought. Human activities, through the release of greenhouse gases at a global scale, deforestation or forest degradation, modify the climatic characteristics of the Amazon biome [79] and will result in new precipitation distribution in future decades. Gatti *et al* [80] showed that the eastern Amazon tends to be a source of greenhouse gas emissions due to the combined effect of deforestation and climate change and forest degradation has become the largest process driving carbon loss [81]. One application of our results would be to map priority areas for protection and restoration by considering current human dynamics. Another application would be to consider projected climate change in the models, including changes in Köppen climate subclasses, to determine locations of future forests that may be more sensitive to dry-season conditions, droughts and fire events. Using remote-sensing data, we have shown that fire-induced forest degradation in the deforestation arc alters phenology. Specifically, FDW depend on precipitation even in regions where mature forests are not limited by water, and where greening follows solar radiation. With the predicted climate change and increase in intensity and duration of dry seasons, this alteration in the functioning of Amazonian forests raises the issue of a potential decrease in forest productivity, as well as increased sensitivity to fire. Protecting and restoring these forests could decrease these effects, which, if they occur rapidly, could result in the loss of large areas of forest and the large amounts of the carbon they could store.

Data availability statement

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

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