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ORIGINAL ARTICLE

# Characterization of land cover-specific fire regimes in the Brazilian Amazon

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## Abstract
Humans profoundly alter fire regimes both directly, by introducing changes in fuel dynamics and ignitions, and indirectly, by increasing the release of greenhouse gases and aerosols from fires, which can alter regional climate and, as a consequence, modify fuel moisture and availability. Interactions between vegetation dynamics, regional climate change and anthropogenic pressure lead to high heterogeneity in the spatio-temporal fire distribution. We use the new FireTracks Scientific Dataset that tracks the spatio-temporal development of individual fires to analyse fire regimes in the Brazilian Legal Amazon over the period 2002–2020. We analyse fire size, duration, intensity and rate of spread in six different land-cover classes. Particular combinations of fire features determine the dominant and characteristic fire regime in each of them. We find that fires in savannas and evergreen forests burn the largest areas and are the most long lasting. Forest fires have the potential for burning at the highest intensities, whereas higher rates of spread are found in savannas. Woody savanna and grassland fires are usually affected by smaller, shorter, less-intense fires compared with fires in evergreen forest and savanna. However, fires in grasslands can burn at rates of spread as high as savanna fires as a result of the easily flammable fuel. We observe that fires in deciduous forests and croplands are generally small, short and low intense, although the latter can sustain high rates of spread due to the dry post-harvest residuals. The reconstructed fire regimes for each land cover can be used to improve the simulated fire characteristics by models and, thus, future projections.

**Keywords** Anthropogenic fires · Individual fires approach · Spatiotemporal fire clusters · Land-use changes · Fire burning characteristics

## Introduction

Humans influence fire occurrence and distribution decisively in the Brazilian Amazon, where fires are almost entirely ignited by humans associated with fire-driven logging, mining and deforestation processes (Aragão et al. 2008; Cochrane and Barber 2009; Curtis et al. 2018). Fire is also subsequently used for the maintenance of cattle pastures and shifting agriculture established in deforested patches, where it stimulates grass resprouting, removes shrubs and harvest remnants, controls pests, etc. (Cochrane and Laurance 2008; Nepstad et al. 2008; Lewis et al. 2015). Thus, humans have modified the spatial and seasonal niche of fire for millennia (Le Page et al. 2010; Pivello 2011; Fu et al. 2013; Marengo et al. 2018). Additionally, the Amazon region experienced frequent severe drought conditions in the last years (2005, 2010, 2015–2016), which were often associated with an extended dry season and anomalously low levels of precipitation (Marengo and Espinoza 2016; Cunha et al. 2019). Drier environmental conditions increase flammability and promote fire spread, boosting fire emissions and carbon release into the atmosphere, which accelerate warming (Brando et al. 2014; Fonseca et al. 2017; Jimenez et al. 2018). This positive fire-climate feedback loop, exacerbated by increasing anthropogenic disturbances, leads to an environment more susceptible to fire (Gutiérrez-Vélez et al. 2014; Nobre et al. 2016; Le Page et al. 2017).

Fire regimes are a generalised description of the typical fire characteristics in a particular place and time (Pausas et al. 2004; McLauchlan et al. 2020). A deviation from eco-climatic fire regimes towards anthropogenically driven regimes is being observed globally (Le Page et al. 2010;

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Pausas and Keeley 2014). Specifically, patterns of fire seasonality driven by climate or weather become greatly influenced by anthropogenic activities due to alterations in species composition and plant functioning, which induce changes in fuel loads, structure and dryness (Hantson et al. 2015; Barlow et al. 2016). This, in turn, may introduce changes in ecosystem dynamics and future biome shifts when local changes persist (Davidson et al. 2012; Boit et al. 2016). As a result, the incorporation of variables representing anthropogenic fire practices in Dynamic Global Vegetation Models (DGVMs) becomes essential to reproduce diverse fire regimes and estimate their impacts and future activity (Silvestrini et al. 2011; Mann et al. 2016; Teckentrup et al. 2019).

To analyse fire distribution and dynamics in an extensive area such as the Amazon, where ground data is scarce, remote sensing provides an opportunity to study regional patterns. Here, we employ the FireTracks (FT) Scientific Dataset (Traxl 2021, v1.0.0), which has been generated by combining network theory and the individual fires' approach. Network theory-based techniques have proven to be effective tools to examine systems in climate and geoscience by modelling the relations between their features (Goswami et al. 2013; Traxl et al. 2016; Cano-Crespo et al., 2021). The individual fires approach that separates large burned clusters that contain multiple fire events into individual fires, has recently demonstrated its potential to provide insight into global fire behaviour and dynamics (Andela et al. 2019a; Artés et al. 2019). The FT algorithm aggregates remotely sensed fire and land-cover data to produce local formations of spatio-temporal fire clusters that evolve over space and time, and computes their aggregated size, duration, intensity—for the first time in the region—and rate of spread. As the fires in the FT dataset contain information about the land cover where they occur, we characterise six land cover-specific fire regimes in the Brazilian Legal Amazon (BLA) over the period 2002–2020: croplands, deciduous forests, evergreen forests, grasslands, savannas and woody savannas. The 1-km spatial resolution of the fire data enables us to capture the heterogeneous vegetation composition at the regional scale, while the long study period makes it possible to filter out transient dynamics and focus on the long-term fire patterns that determine fire regimes. We additionally provide a comparison of the FT's fire variables in the different land-cover types with those estimated by the Global Fire Atlas (GFA, Andela et al. 2019b).

In this study, we address the following specific objectives: (1) report the spatial distribution of individual fires in the BLA over the period 2002–2020; (2) examine and evaluate properties of individual fires: size, duration, intensity and rate of spread and the relation between them to explore fire dynamics at the local scale; (3) identify and describe six land cover-specific fire regimes based on the attributes of individual fires; (4) assemble comprehensive statistical tables of key fire characteristics in different land covers that contribute to the efforts to parametrise different fire regimes in fire models.

## Methodology

### Study area

Our study area is the BLA region, which comprises the Brazilian states of Acre (AC), Amapá (AP), Amazonas (AM), Mato Grosso (MT), Pará (PA), Rondônia (RO), Roraima (RR), Tocantins (TO) and part of Maranhão (MA) (Fig. 1a). Together, they cover approximately 60% (ca. 5.1 million km$^2$) of Brazil's area. The Amazon biome spreads over two-thirds of the BLA, while smaller portions of Cerrado and Pantanal biomes are located along the southeast flank, and in the most southern part of the BLA, respectively (IBGE 2019). In 2001—at the beginning of the study period—, the BLA was mainly covered by evergreen forests (70%), open and woody savannas (19%) and grasslands (8%), while croplands and deciduous forests were less present (less than 1%) (Friedl and Sulla-Menashe 2019).

### Data and methods

We use the novel FireTracks (FT) Scientific Dataset (Traxl 2021) of individual fires. The FT algorithm employs network theory and the individual fires approach to aggregate fire events into spatio-temporal fire clusters that are tracked over space and time (Fig. S1). Individual fires are defined as the union of nearest neighbours of active fires in the discrete spacetime grid given by the spatial and temporal resolution of the Moderate Resolution Imaging Spectroradiometer (MODIS) 1-km MOD/MYD14A1 Thermal Anomalies and Fire dataset (Giglio and Justice 2015) that feeds the algorithm. Two fire events are considered neighbours if they are in the same 3-dimensional (latitude, longitude, time) Moore neighbourhood with no spatial or temporal gaps (Fig. 1b). The MOD/MYD14A1 fire product offers an indication of fire activity and has been extensively validated (Morisette et al. 2005; Csiszar et al. 2006; Hawbaker et al. 2008; de Klerk 2008). The collection 6 of the data addresses previous limitations such as frequent false alarms caused by small clearings in the Amazon forests (Friedl et al. 2010), which is particularly helpful for our purpose. The data present low levels of commission errors, but omission errors, which decrease as fire size increases, might occur with fires of short duration, small size or low intensity (Schroeder et al. 2008; Hantson et al. 2013). Also, burnings under dense vegetation cover, heavy smoke or clouds may go undetected (Giglio et al. 2016). The FT algorithm combines the MODIS

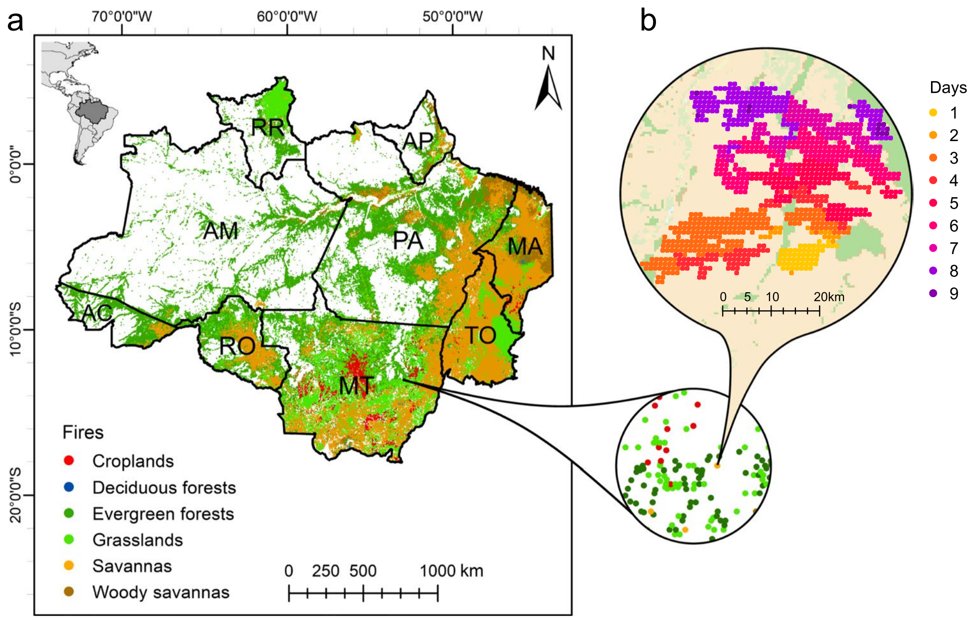


**Fig. 1** **a** Fire spatial distribution in the Brazilian Legal Amazon over the period 2002–2020 (FireTracks, $n=857{,}942$). The inserted map shows the location of the region (in dark grey) within South America. The study area comprises the states of Acre (AC), Amapá (AP), Amazonas (AM), Mato Grosso (MT), Pará (PA), Rondônia (RO), Roraima (RR), Tocantins (TO) and part of Maranhão (MA). Black lines are political boundaries. Each point in the map marks a location where a fire occurred during the 19-year period. The type of land cover where fires take place is denoted by colour. In locations when repeated burning occurs, the map shows the last land-cover information. The small number of deciduous forest fires are not visible at the scale of the map. **b** High-resolution illustration of one of the largest fires in the FireTracks dataset. Dots represent active fires within the individual fire, and colours indicate the time steps of the fire development. Background land-cover colour coding is the same as in Fig. S2 (MCD12Q1, UMD)

fire data with land-cover information from the previous year. We use the UMD classification scheme of the 500-m Land Cover Type MCD12Q1 product from MODIS (Sulla-Menashe et al. 2019). The collection 6 of the land-cover data includes new gap-filled spectro-temporal features and refinements of the algorithm, which allows a more accurate classification. However, some limitations are known, e.g. grassland areas might be misclassified as savannas, and agriculture can be underrepresented in tropical regions where agricultural fields are small (Friedl et al. 2010). Since the land-cover data has a spatial resolution twice as high as the active fires data (0.21 vs. 0.86 km$^2$), the FT algorithm associates four values of land cover with every MODIS active fire within a particular individual fire. Fires are assigned a dominant land cover when at least 80% of all the land-cover values within them belong to the same land-cover type. Fires that do not fulfil this criterion are discarded from the analysis. In this way, we ensure that the FT's fire characteristics estimated for each land-cover type are not a combination of values from different land covers.

The FT dataset registers location, time and land cover of individual fires at daily time step, as well as their estimated size, intensity, duration and rate of spread (see Text S1 for the definition of the fire variables). The smallest identifiable fire size and duration is imposed by the spatio-temporal resolution of the MODIS fire data, 0.86 km$^2$ and one day, respectively. Fires with sizes smaller than one fire-data pixel are attributed a size of 0.86 km$^2$ regardless, which may generate some overestimation of burned area. Fires of a single fire-data pixel size (0.86 km$^2$) are not considered for the calculation of rate of spread—the ratio between size and duration. We select those fires within the BLA over the time period from 2002 to 2020 in six land-cover types: croplands, deciduous forests, grasslands, evergreen forests, savannas and woody savannas (see Text S2 and Fig. S2 for the description and spatial distribution of the different land covers, respectively).

We employ the GFA dataset (Andela et al. 2019b), the most extensive study on individual fires covering the BLA so far, to perform a comparison of our estimated fire characteristics. The GFA is derived from the MODIS collection 6 500-m Burned Area MCD64A1 product (Giglio et al. 2018) and spans from 2003 to 2016. The quality of the algorithm, as for the FT's, highly depends on the inherent limitations of the data that serve as input. Fires of 0.21 km$^2$—the smallest identifiable fire size—are not taken into account when calculating rate of spread. The GFA algorithm tracks the daily progression of individual fires to produce a set of metrics on fire behaviour such as fire size, duration, daily expansion, fire line length, speed and direction of spread. We select from the FT dataset the fires identified in the BLA over the period 2003–2016—the same 14-year time window when data from the GFA is available—and compare fire size, duration and rate of spread—the variables present in both datasets—occurring in croplands, forests, grasslands and savannas (Text S2).

## Results

### Fire distribution

Of the total number of fires that FireTracks identifies in the BLA over the period from 2002 to 2020, 52% were assigned a dominant land cover type and selected for the analysis ($n = 857{,}942$). The total burned area of these fires covers approximately $3.6 \times 10^6$ km$^2$. Most of the burned area is found in evergreen forests (44%) and savannas (38%) (Fig. 2a). Smaller amounts are located in grasslands (13%) and woody savannas (5%), while we find less than 1% in croplands (0.6%) and deciduous forests (0.1%). When considering the extent covered by the different land-cover types in the BLA region, in order to ensure that the results are not consistent with homogeneous distribution, the annual fire density over the period shows a contrasting perspective, especially for evergreen forests. Although the amount of burned area is the largest in evergreen forests, fire density is one of the lowest (0.02 km$^2$ burned area per km$^2$ land cover, average of the annual values over the period) (Fig. 2b), together with deciduous forest and cropland densities. We register the highest burned area density in savannas (0.08 km$^2$/km$^2$), followed by grasslands (0.05 km$^2$/km$^2$) and woody savannas (0.04 km$^2$/km$^2$).

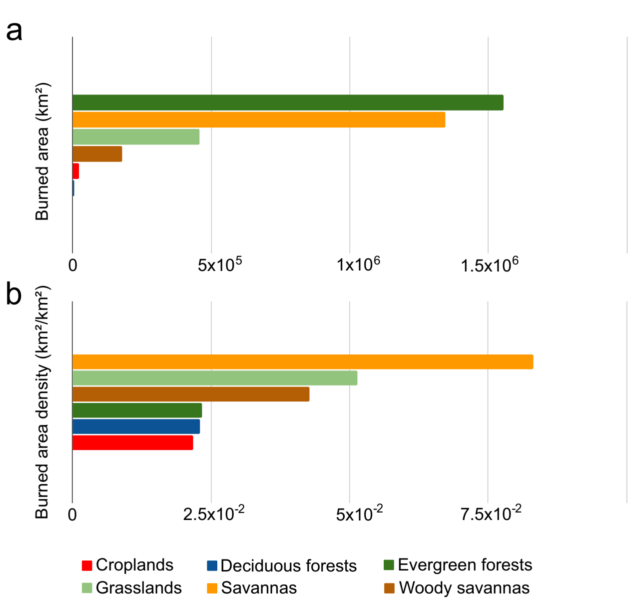


**Fig. 2** **a** Absolute amount of burned area (in km$^2$) and **b** burned area density (in km$^2$ of burned area per km$^2$ of land cover, average of annual densities over the period) in the six land-cover classes analysed in the Brazilian Legal Amazon over the period 2002–2020. Land-cover types are ordered by the magnitude of their values

Spatially, we observe a high concentration of forest fires (dark green points in Fig. 1a) on the northern side of the so-called arc of deforestation (the tropical forest-savanna frontier in Fig. S2), mainly in the states of AC, RO, AM, PA and the northern half of MT. We estimate that these states account for 92% of the total deforestation registered in the BLA over the study period (INPE 2021), and 95% of the total amount of burned area identified in evergreen forests. PA and MT are the states with the largest amount of burned area in tropical forests (37% and 20% of the total amount, respectively). The spatial aggregation of forest fires along roads and rivers can be observed in Fig. 1a, especially in the states of PA and AM, where fire distribution patterns following straight lines can be easily recognised (see the road network in Fig. S2). We find that savanna fires (orange points in Fig. 1a) occur mainly along the southeastern border of the BLA, where the states of MA, TO and PA accumulated 79% of them over the 19-year study period. Fires in woody savannas (brown points in Fig. 1a) concentrate in the most northeastern flank of the BLA, where the states of MA and PA hold 87% of them. We observe that grassland fires (light green points in Fig. 1a) are prevalent in MT, northeastern RR and eastern TO. Seventy-seven percent of the grassland fires are located in these three states. The vast majority of the agricultural fires (red points in Fig. 1a) that we identify over the study period are located in MT (83%). Lastly, we find that the few fires identified in deciduous forest (blue points in Fig. 1a) occurred predominantly in the state of MT (81%).

Temporally, we found that 71% of the total burned area registered in the BLA over the study period occurs during the dry season (April-September). The largest amounts of burned area are observed in August in evergreen and deciduous forests, while the burned area peak occurs in September in savannas, woody savannas and grasslands (Fig. S3). Burned croplands reach its maximum in April. Almost three-quarters of the burned area identified in savannas, evergreen and deciduous forests, and grasslands is detected during the dry season. Lower values were found in croplands and woody savannas (60% and 47%, respectively).

### Fire variables

We compute four key characteristics of fires that control the impacts on vegetation and emissions: size, duration, intensity and rate of spread. The frequency distribution of fire sizes is best described by a truncated power law according to a maximum likelihood estimation and maximum likelihood ratio tests (Clauset et al. 2009), a power law with an exponential cutoff at the largest fire sizes (Fig. 3a). The lowest values show the highest frequencies (mode of the distribution at 0.86 km$^2$), and few fires substantially larger than the rest result in mean values larger than median values. Fire size ranges from 0.86 to 1453.7 km$^2$ with a median of 2.6 km$^2$ over the 19-year period (Fig. 3a, Table S2). We find that 25% of the total number of fires are small and do not exceed 1 km$^2$ in size. Most of the 5% largest fires—those at the 95th percentile for size—are mostly located in evergreen forests (46%) and savannas (39%). The fire duration frequency distribution follows a power law with few dominant low values (Fig. 3b). We observe that the majority of the fires last only 1 day (91% of the sample) (Fig. 3b, Table S2), while the median value of the remaining 9% of the fires is 2 days. More than half of the 5% longest fires are identified in evergreen forests (55%), lasting up to 27 days. Fire intensity and spread show a positively skewed log-normal frequency distribution (Fig. 3c, d) that peaks at 10 MW and 1.72 km$^2$/day, respectively. Fire intensity varies between 1.7 and 418,976 MW with a median of 50 MW (Fig. 3c, Table S2). The 5% most intense fires are predominantly registered in evergreen forests (50%). Fire rate of spread ranges from 0.4 to 131 km$^2$/day, with a median value of 2.6 km$^2$/day (Fig. 3d, Table S2). Most of the 5% of fires with the highest rates of spread are found in savannas (41%) and evergreen forests (37%), with a considerable presence also in grasslands (17%).

We find a moderate positive and significant correlation between fire size and intensity ($R = 0.69$, $p < 0.05$), size and rate of spread ($R = 0.68$, $p < 0.05$) and size and duration ($R = 0.63$, $p < 0.05$) (Fig. S4), which evinces the interrelations between the fire variables. By selecting the extreme fires, i.e. those whose size, intensity, duration and rate of spread are greater than or equal to the 95th percentile of the variables' distribution, we find the highest relationship between fire intensity and size since 74% of the most intense fires are also within the 5% largest fires. Size and duration—68% of the longest fires are also the largest—and size and spread—68% of the fires with the highest rates of spread are also the largest—also show a notable relationship.

## Comparison FT vs. GFA datasets

We identify 32% more fires ($n = 652,892$) and 35% more cumulative burned area (2,714,021 km$^2$) in the FT dataset than the GFA in the BLA over the period from 2003 to 2016. The fire size probability density distribution is best described by a truncated power law for both datasets (Fig. 4a), according to a maximum likelihood estimation and maximum likelihood ratio tests. The lower median value of the GFA's size distribution indicates a higher proportion of small fires (Table S1), although the contribution of the lower half of the dataset to the cumulative burned area is very low in the GFA (6% of the total burned area) compared with the FT dataset (23%). The subset of the

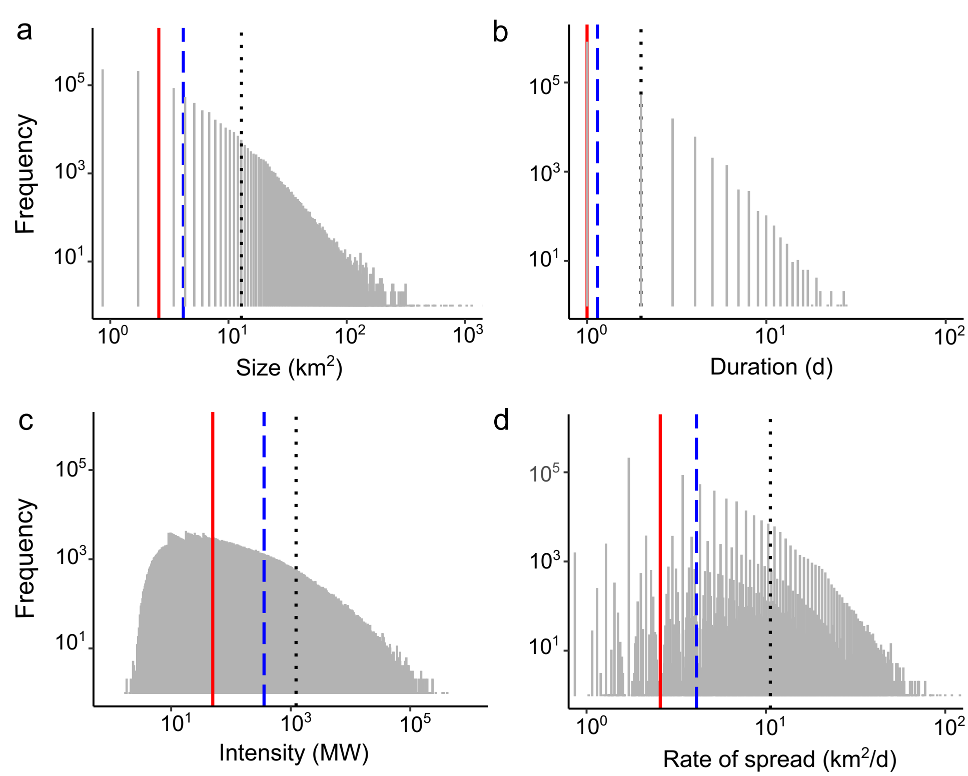


**Fig. 3** Frequency distribution of **a** fire size (in km$^2$), **b** duration (in **d**), **c** intensity (in MW) and **d** rate of spread (in km$^2$/d) in the Brazilian Legal Amazon over the period 2002–2020 ($n = 857,942$). Rate of spread is computed for fires larger than 0.86 km$^2$ ($n = 639,579$). Both axes and bins are in logarithmic scale. The red solid line, blue dashed line and black dotted line indicate the median, mean and 95th percentile values of the distribution, respectively

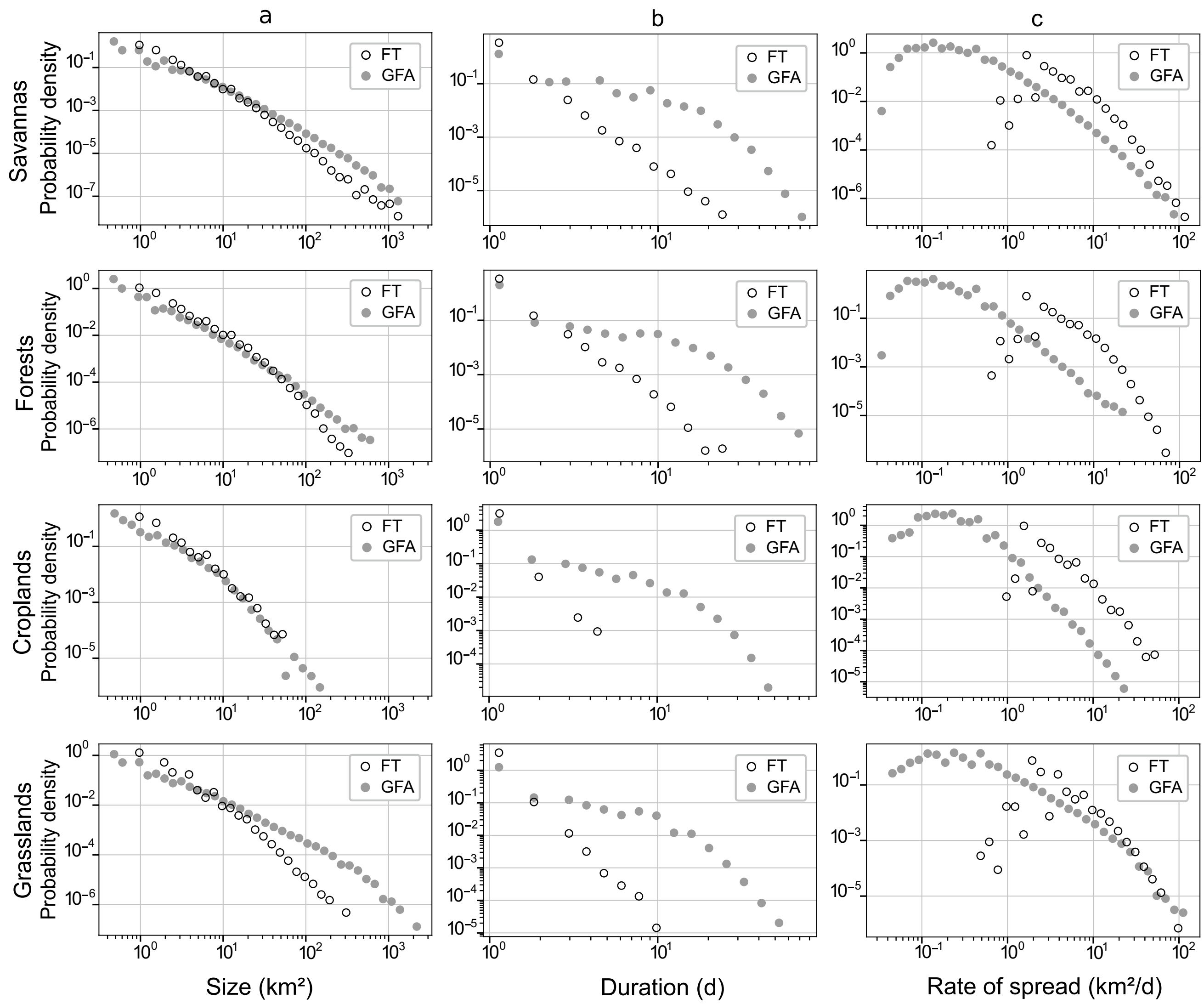


**Fig. 4** Probability density distribution of fire **a** size (in km$^2$), **b** duration (in **d**) and **c** rate of spread (in km$^2$/d) in the FireTracks ($n_{FT}$=652,892) and Global Fire Atlas ($n_{GFA}$=443,863) datasets in the Brazilian Legal Amazon over the period 2003–2016. The plots show the distribution of the fire variables in savannas ($n_{FT}$=280,885, $n_{GFA}$=295,504), forests ($n_{FT}$=278,095, $n_{GFA}$=79,613), croplands ($n_{FT}$=4,547, $n_{GFA}$=49,010) and grasslands ($n_{FT}$=89,365, $n_{GFA}$=19,736). Rate of spread is computed for fires larger than 0.86 km$^2$ ($n$=487,347) and 0.21 km$^2$ ($n$=315,648) in the FT and GFA datasets, respectively. Both axes and bins are in logarithmic scale

5% largest fires make up 30% and 60% of the cumulative burned area over the study period in the FT and GFA datasets, respectively, which demonstrates the strong effect the largest fires have on the total burned area estimated by the GFA. Regardless of the land-cover type, the FT's size distribution displays a steeper drop in the probability density with increasing size compared with the GFA (Fig. 4a). Thus, the size distribution in the GFA dataset is more skewed towards larger sizes, and it identifies the largest fires. At the lower end too, the range is usually higher in the GFA, except in savannas, where it is similar in both datasets (Fig. 4a). The largest difference in the range of fire size is found in grasslands.

Both datasets have the same temporal resolution, and therefore, the lower end of the duration range coincides at one day (Table S1). The majority of fires are very short in the FT dataset, where fires that last only for one day make up 91% of all fires. The same subset constitutes 39% of all fires in the GFA dataset, which shows higher fire duration variability. For longer lasting fires, the probability density decreases as duration increases, describing a power law distribution in the FT, and a truncated power law in the GFA datasets (Fig. 4b), where durations as long as 80 days are reached (Table S1). Longer fires are identified in the GFA dataset in all the land covers. The largest disparity in the duration range is found in croplands (Fig. 4b).

In the FT dataset, the probability density distribution of rate of spread is best described by a positively skewed log-normal distribution (Fig. 4c). Fires with the highest spreads are usually identified in the FT, except in grasslands, where the maximum value of the range is similar in both datasets (Fig. 4c, Table S1). It is not clear if the spread distribution of the GFA dataset is best described by a stretched exponential or a truncated power law distribution, a maximum likelihood ratio test finds no significant difference between the two models. The GFA dataset exhibits a wider range at the lower end of the distribution in all the land covers (Fig. 4c).

We find 44% of the FT-burned area in forests and 43% in savannas in the BLA over the study period. The amount of burned area in grasslands makes up 13% of the total, and less than 1% is located in croplands. In the GFA dataset, there is a higher proportion of burned area in savannas (75%), and seven times more burned area in croplands. Conversely, we identify almost five times more fires in forests with the FT algorithm than the GFA dataset.

## Characterization of fire regimes

We observe that the probability density distributions of the fire variables follow a similar pattern regardless of the land cover, although probabilities differ between them (Fig. 5). The size probability density distribution shows the highest probabilities concentrated at the lowest sizes in all the land covers (Fig. 5a, Table 1a). Savanna fires show the widest upper range, being the only land cover with fires that exceed 400 km$^2$ in size, followed by evergreen forests and grasslands. We observe the most limited range in deciduous forests, while croplands and woody savannas take an intermediate position (Fig. 5a). In the same way as size, the fire duration probability density results in a distribution where we find the highest probabilities at the shortest durations (Fig. 5b, Table 1b). Deciduous forests and croplands hold the shortest duration ranges, while long fires are most likely to be sustained by evergreen forests and savannas. Only fires that take place in these two land-cover types may exceed 14 days in length (Fig. 5b). The probability density of fire intensity shows a distribution whose mode is a value between 8.7 and 12.6 MW, depending on the land cover (Fig. 5c, Table 1c). From that point onwards, the distribution presents a long tail to the right in which the probability decreases as the intensity values increase. Evergreen forests display the widest intensity range, followed by savannas and grasslands. Similar to fire intensity, the spread distribution shows the highest probability densities at low to intermediate values, from where the probability continuously drops to find only few large values within the right tail (Fig. 5a, Table 1d). The highest probability density is found at 1.72 km$^2$/day in all the land covers. Fires in savannas present the broadest range of all the land covers. Fires in grasslands and evergreen forests also reach high rates of spread, while croplands and woody savannas present more limited ranges (Fig. 5d, Table 1d).

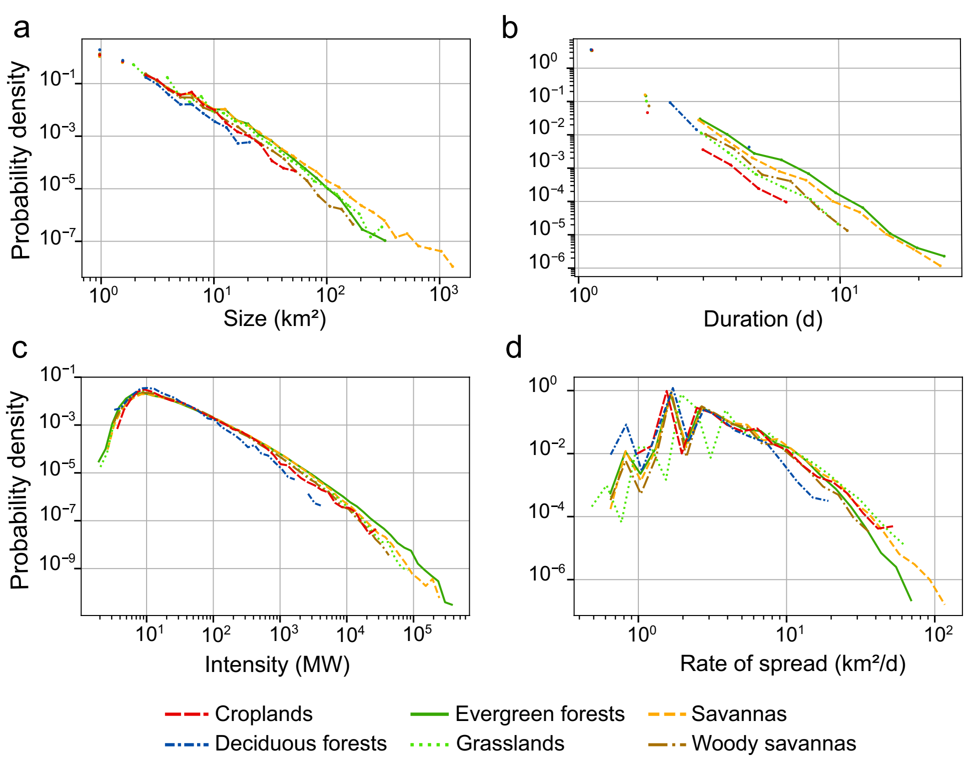


**Fig. 5** Probability density distribution of fire **a** size (km$^2$), **b** duration (**d**), **c** intensity (MW) and **d** rate of spread (km$^2$/d) in croplands ($n = 6882$), deciduous forests ($n = 2466$), evergreen forests ($n = 369{,}932$), grasslands ($n = 121{,}310$), savannas ($n = 300{,}777$) and woody savannas ($n = 56{,}575$) in the Brazilian Legal Amazon over the 19-year period (2002–2020). Rate of spread is computed for fires larger than 0.86 km$^2$ ($n = 639{,}579$). Both axes and bins are in logarithmic scale

**Table 1** Distribution of fire variables in the FireTracks dataset per land cover in the Brazilian Legal Amazon (2002–2020)

| | Min | 1st Qu | Median | Mean | 3rd Qu | 95th | Max |
|---|---|---|---|---|---|---|---|
| a) Fire size distribution (km$^2$) | | | | | | | |
| Croplands | 0.86 | 0.86 | 1.72 | 3.19 | 3.44 | 8.6 | 58.39 |
| Deciduous forests | 0.86 | 0.86 | 1.72 | 2.16 | 2.58 | 6 | 74.7 |
| Evergreen forests | 0.86 | 1.72 | 2.58 | 4.2 | 4.29 | 13.7 | 365.78 |
| Grasslands | 0.86 | 0.86 | 1.72 | 3.77 | 4.29 | 12 | 342.6 |
| Savannas | 0.86 | 1.72 | 2.58 | 4.47 | 4.29 | 13.7 | 1,453.67 |
| Woody savannas | 0.86 | 0.86 | 1.72 | 3.13 | 3.44 | 10 | 190.62 |
| b) Fire duration distribution (d) | | | | | | | |
| Croplands | 1 | 1 | 1 | 1.03 | 1 | 1 | 7 |
| Deciduous forests | 1 | 1 | 1 | 1.09 | 1 | 2 | 8 |
| Evergreen forests | 1 | 1 | 1 | 1.17 | 1 | 2 | 27 |
| Grasslands | 1 | 1 | 1 | 1.08 | 1 | 2 | 14 |
| Savannas | 1 | 1 | 1 | 1.15 | 1 | 2 | 27 |
| Woody savannas | 1 | 1 | 1 | 1.07 | 1 | 1 | 12 |
| c) Fire intensity distribution (MW) | | | | | | | |
| Croplands | 3.2 | 15.8 | 40.2 | 209.7 | 125.5 | 628.4 | 62,139.8 |
| Deciduous forests | 2.9 | 12.8 | 25.3 | 78.06 | 59.4 | 311.6 | 4,655.6 |
| Evergreen forests | 1.7 | 18.4 | 51 | 434.9 | 181.3 | 1,420.2 | 418,976.1 |
| Grasslands | 1.8 | 16.1 | 41.1 | 254.0 | 135.6 | 901.2 | 93,356.1 |
| Savannas | 2.3 | 20.2 | 53.8 | 334.9 | 183 | 1,243.6 | 343,431.7 |
| Woody savannas | 2.8 | 17.7 | 43.8 | 224.1 | 1,305.2 | 827.7 | 75,763.0 |
| d) Fire rate of spread distribution (km$^2$/d) | | | | | | | |
| Croplands | 0.86 | 1.72 | 2.58 | 3.94 | 5.15 | 9.45 | 58.39 |
| Deciduous forests | 0.57 | 1.72 | 1.72 | 2.78 | 3.44 | 6.87 | 21.47 |
| Evergreen forests | 0.57 | 1.72 | 2.58 | 4.01 | 5.15 | 10.3 | 77.28 |
| Grasslands | 0.43 | 1.72 | 2.58 | 4.27 | 5.15 | 11.59 | 109.05 |
| Savannas | 0.57 | 1.72 | 3.44 | 4.26 | 5.15 | 11.16 | 130.51 |
| Woody savannas | 0.57 | 1.72 | 2.58 | 3.55 | 4.29 | 8.59 | 50.66 |

$n_{CROPLANDS}$ = 6882; $n_{DECIDUOUS\ FORESTS}$ = 2466; $n_{EVERGREEN\ FORESTS}$ = 369,932; $n_{GRASSLANDS}$ = 121,310; $n_{SAVANNAS}$ = 300,777; $n_{WOODY\ SAVANNAS}$ = 56,575

Our results describe fires in savannas as large, long, intense and with high rates of spread (Fig. 5, Table 1). In evergreen forests, fires tend to be large, long and intense too, but they usually have much lower rates of spread than savanna and grassland fires. Compared to fires in savannas, fires in woody savannas are usually smaller, shorter, less intense and with slower rates of spread (Fig. 5, Table 1). Although grassland fires are smaller, shorter and less intense than savanna and evergreen forest fires, they may reach rates of spread close to those in savannas. Fires in croplands and deciduous forests are likely to be small and short, and spread at low rates, although cropland fires can sustain higher intensities (Fig. 5, Table 1).

## Discussion

Regional land-cover changes play a critical role in future fire regimes and their resulting impacts on ecosystems since fires behave differently depending on the land cover where they burn. Recurrent fires are a natural component in tropical savanna-type ecosystems, where they contribute to define vegetation composition and structure (Mistry 1998; Pivello 2011). As a result, woody plants and grasses have developed traits to cope with it over thousands of years (Bowman et al. 2009; Simon et al. 2009; Keeley et al. 2011). We interpret the fact that almost three-quarters of the burned area occurred during the dry season (Fig. S3), when lightning are scarce, as fire activity in savannas being largely of anthropogenic origin. Although there are important regional variations within the BA (Carvalho et al., 2021), fires caused by lightning are usually detected during the rainy season or during change-of-season storms (Ramos-Neto and Pivello 2000; Morgan et al. 2019). The herbaceous vegetation desiccated over the dry season is ignited for land clearing and soil restoring purposes (Higgins et al. 2000; Klink et al. 2020; Schmidt and Eloy 2020). This highly flammable fuel facilitates high rates of spread in open savannas, which usually result in large, long and intense fires, according to our findings (Fig. 5, Table 1). When the climate is dry enough, fires can spread freely in the absence of moist areas acting as barriers, only limited by the spatial pattern of fuel resulting from earlier fires or grazing (Archibald et al. 2012). Fire suppression has devastating effects in fire-prone savanna-type ecosystems (Berlinck and Batista 2020; Durigan 2020) since the accumulation of grassy fuels increases the risk of catastrophic large-scale wildfires jeopardising biodiversity conservation.

Woody vegetation cover may increase in savannas as the result of various local anthropogenic disturbances—livestock, management interventions, fire frequency, etc. (Bond and Keeley 2005; Baggio et al. 2021). Usually, increased grazing intensity and/or fire frequency promote the growth of woody vegetation by removing competitor grasses and fine fuels (Scholes and Archer 1997; Archer et al. 2017; Coelho et al. 2020), although the ecosystems' response can be different (Moreira 2000; Rosan et al. 2019). In woody savannas, we find smaller, shorter, less intense and slower spreading fires than in open savannas (Fig. 5, Table 1) since more scattered woody patches and individual trees contribute less than grasses to the total amount of fuel (Archibald et al. 2018).

Unlike in savannas, most plant species in evergreen forests are poorly adapted to fire (Hoffmann et al. 2012) since fire events have been rare in their evolutionary history (Barlow and Peres 2008; Balch et al. 2015). The moist understory and the scarce natural fire ignition sources preclude significant burning in dense primary forests (Kauffman and Uhl 1990; Ray et al. 2005). However, forest degradation and fragmentation caused by agriculture and ranching expansion, logging, overexploitation, etc., expose forest edges to drier conditions that favour tree mortality, canopy openings and grass invasion (Laurance et al. 2011; Silva et al. 2018; Silvério et al. 2019; Montibeller et al. 2020). In particular, increases in dry grassy vegetation beneath the trees make the forests more flammable and provide the fuel to sustain understorey fires of higher intensity and rates of spread (Silvério et al. 2013; de Faria et al. 2017). Most of the burned area happens during the dry season (Fig. S3), when natural ignition sources are rare, which points to anthropogenic pressure on evergreen forests as the most likely cause (Ramos-Neto and Pivello 2000; Morgan et al. 2019). Nevertheless, as in the case of savannas, reduced forest connectivity and fuel continuity caused by humans may contribute to a decrease in the amount of burned forest (Brando et al. 2020). Our analysis aligns with previous literature documenting the strong impact of anthropogenic activities on fire activity in tropical forests. For example, Archibald et al. (2013) identified global pyromes using satellite imagery and stated that fires in the tropical moist broadleaf forest biome fell predominantly into the pyrome with the largest Human Impact Index. The profound human-induced changes in fire regimes are also illustrated in the review of twenty-seven studies on the multiple interacting global change drivers by Rogers et al. (2020). According to our findings, we characterise forest fires as large, long, intense and with high rates of spread, although savanna fires can reach higher rates (Fig. 5, Table 1). These fire features reflect how evergreen forest fires have escalated from being naturally rare to showing characteristics more typical of savanna fires. As forest fires can spread through the ground, surface, crowns or all three together, it is important to consider that slow-moving understorey fires, which can burn for days in forests (Alencar et al. 2006; Morton et al. 2013; dos Santos Prestes et al. 2020), may go undetected if the tree canopy precludes the satellite from capturing the signal from the surface (Eva and Lambin 1998; Giglio et al. 2016; Boschetti et al. 2019).

As opposed to evergreen forests, deciduous forests shed their leaves during the dry season. They are usually interspersed with savannas (Fig. 1a) but while grasses are the predominant fuel in savannas, leaf litter constitutes the main fuel in deciduous forests (Goldammer 1993). This seasonal, surface flammable layer may be ignited by lightning or, most likely, by pastoralists and farmers towards the end of the dry season in order to remove non-desirable plant material, stimulate grass growth or facilitate the harvest of other forest products (Goldammer 2016). Just as it happens in evergreen forests, fires can escape into the deciduous forests from those shifting agricultural lands and cattle pastures. Fires in deciduous forests have been described generally as surface fires of moderate intensities (Stott et al. 1990; Nepstad et al. 1999), which may leave shrubs and trees unaffected. This is the result of a more frequent consumption of the available dry fuel in deciduous communities, e.g. the same area may sustain a grass fire at the beginning of the dry season and a leaf-litter fire in the late dry season. In agreement with that, we find smaller, shorter, less intense and less consuming fires compared to fires in evergreen tropical forests (Fig. 5, Table 1), basically as a consequence of the differences in fuel amount, structure and humidity.

Currently, all grasslands show some degree of human interference (FAO 2020). Tropical grasslands in the BLA are mostly managed grasslands, i.e. pastures (Text S2), that occur when anthropogenic and climatic disturbances trigger a change of the vegetation from forest to savanna to pasture (Pivello 2011), although also the direct clearing of tropical forests for cattle pastures has been recognised as a continuous process in the Amazon (Arvor et al. 2012; Armenteras et al. 2013; Navarrete et al. 2016), and across Latin America (Wassenaar et al. 2007). Pastures in the Brazilian Amazon may also be the result of abandoned agricultural lands (Carmenta et al. 2013). Grassland fires are sustained by the grass fuel accumulated during the growing period that desiccates from the beginning of the dry season (Soares 1990; Brunel et al.

2021). As a result of the high fire frequency to improve soil fertility and control pests, we find grassland fires to be of moderate size, duration and intensity, which are controlled by fuel availability, and to have high rates of spread associated with the easily flammable fuel (Fig. 5, Table 1). Our results are in line with the findings by Archibald et al. (2013), who described fires in tropical grasslands as frequent with variable size and duration, which we assume depends on the anthropogenic treatment of the land. It is important to note that, as it occurs in savannas, where the balance between grasses and woody vegetation can be altered by anthropogenic and climatic drivers, grasslands can also experience those shifts. Depending on the severity and frequency of burning and grazing, pasture composition and development can vary to a great extent (Rufin et al. 2015). Gutiérrez-Vélez et al. (2014) revealed how different vegetation stages in Amazonian pastures can lead to changes in fire regimes from promoting to inhibiting burnings, e.g. fires can spread rapidly in homogeneous pastures without firebreaks, while pasture heterogeneity with scattered patches of less flammable vegetation may decrease fire spread. However, if those patches are fallows or secondary forests, fire spread in that same location may increase during dry years (Schwartz et al. 2015). Intensification of livestock activity is slowly bringing along management techniques where fire is less present (Parente and Ferreira 2018; Vale et al. 2019).

The prominent human signature of the fire regime in agricultural lands was underlined by Archibald et al. (2013), who identified a pyrome characterised by small and cool fires under high human influence that occurred in regions of deforestation and agriculture. Small-scale farmers and indigenous people ignite fires regularly in the slash-and-burn cultivation technique (Sorrensen 2000; Bowman et al. 2011; Thomaz and Rosell 2020), which involves the clearing of forests or woodlands, the subsequent burning of the removed vegetation once it is dry and the exploitation of the field for several years (Junqueira et al. 2016). Regular fires provide a nutrient-rich layer of ash and control weed and pest invasion (Metzger 2002; Bonaudo et al. 2014). However, the plot's productivity decreases over time due to the progressive depletion of soil nutrients (Holscher et al. 1996), forcing farmers to move to another cultivable area systematically eroding forests inward from the forest-agricultural edges (Nobre et al. 2016; Coe et al. 2017). Thus, the ancient form of land management becomes unsustainable with intensification (Jakovac et al. 2017; Villa et al. 2018; Rebola et al. 2021). Especially in dry years, land management fires both in agriculture and grasslands may escape beyond the field limits and cause damages in the surrounding forests (Cano-Crespo et al. 2015; Aragão et al. 2018). In this line, Uriarte et al. (2012) stated that drought severity can double the fire risk in areas predominantly covered by agricultural fields in western Amazonia. We find that the fire regime in agricultural areas consists of fires of small size, short duration, moderate intensity and low rates of spread (Fig. 5, Table 1). Fire sizes and rates of spread are similar to those in deciduous forests, while intensities are usually higher in agriculture, sometimes reaching values similar to grassland fires if large amounts of dry agricultural material are burned. Nowadays, just as in cattle pastures, more intensive fire-avoiding agriculture is expanding to support growing populations by increasing production (Gollnow and Lakes 2014; Zalles et al. 2019).

The larger number of fires and amount of burned area identified by the FT dataset compared with the GFA is the result of three main factors: (1) the GFA algorithm does not allow the same pixel to burn twice in the same year, limitation that does not exist in the FT algorithm; (2) due to the lower spatial resolution of the FT's fire-data input, fires with sizes smaller than one fire-data pixel are attributed a size of 0.86 km$^2$ regardless; (3) the detection of active fires used by the FT algorithm poses an advantage over burned areas under relative cloudiness or overstorey vegetation since the former is triggered by temperature anomalies (Giglio et al. 2016) that may sometimes be captured under those circumstances (Humber et al. 2019). Our conservative approach in the delimitation of individual fires can partly explain the smaller number of large and/or long fires identified by the FT algorithm. Since it considers MODIS fire data pixels with missing data or obscured by clouds as non-fire pixels, individual fires are prevented from growing into the direction of adjacent pixels labelled as "unknown" or "clouds". This may limit potential fire expansion when clouds obscure existing fire pixels on the ground. Both the GFA's underestimation of burned area and the overestimation of fire duration, as conceded by the authors of the GFA algorithm (Andela et al. 2019a), lead to a tendency towards identifying lower rates of spread than the FT algorithm. The same behaviour was observed in the comparison Andela et al. performed between the GFA's rates of spread and those by the US Forest Service.

The larger amount of burned area detected in agricultural lands in the GFA is a result of its higher spatial resolution, which clearly poses an advantage in detecting small cropland fires. Conversely, we identify a higher number of forest fires due to the detection process of the active fires used by the FT vs. the burned areas used by the GFA. The thermal channels of the sensor may still capture active fires in the presence of canopy cover, while changes in surface reflectance are easier to be obscured. Apart from the limitations derived from the input fire data, uncertainties in the number of fires in the different land-cover types may have partly originated from the input land-cover data as well. The same land-cover product is used in both algorithms (MCD12Q1, UMD scheme), but while the GFA uses collection 5.1, FT uses collection 6. The latter includes refinements and new features that may cause significant changes in the land-cover classification maps. Moreover, the specifics of the decision process to assign a dominant land cover to the individual fires is not described in the work by Andela et al. (2019a) and may vary from the one that is applied in the FT algorithm, contributing to discrepancies in the proportion of burned area in the different land-cover types. Additional validation of our results with future individual fire datasets will contribute to a better understanding of the goodness of the FT's estimates of fire parameters. The FT algorithm will benefit from incorporating higher spatial resolution data and sub-daily fire information, as well as from evaluating the performance of the methodology in different locations and/or broader scales.

Evolving biophysical and socio-economical aspects influence the relationships between fire, vegetation, climate and human activities, which make fire regime classifications dynamic (de Faria et al. 2017; Staal et al. 2020). Thus, it is imperative to capture land-cover heterogeneity and fire regime variability to adapt the models to a rapidly changing scenario. In this regard, our study focusing on fire regimes in the BLA poses an advantage compared to global pyrome classifications since fire drivers vary depending on the scale of the measurements and the study area. Keeping track of the spatial and temporal heterogeneity of fire drivers is especially relevant in a global conservation priority hotspot like the Amazon, which is witnessing increased anthropogenic pressures. In our study, the application of the individual fires approach in the FT algorithm allows not only to estimate single fires size, duration and rate of spread, as the GFA dataset does, but also the aggregated intensity of each event for the first time in the area. Fire models show a deviation in fire activity from eco-climatic fire regimes towards anthropogenic fire regimes (Le Page et al. 2010; Chen et al. 2016; Lasslop and Kloster 2017), in which land-cover changes play a significant role. Nowadays, human representation in fire-enabled DGVMs has been identified as a research priority (Marchal et al. 2017; Forkel et al. 2019; McLauchlan et al. 2020) in order to simulate current fire patterns and emissions, and capture their impacts. The fire regimes we have identified in this study for tropical land-cover types can be used to optimise the parametrization of human ignitions and, thus, make progress in projecting the impacts of future land-cover changes on associated fire regimes. Besides, a better fuel characterization in the models means that adapted firefighting strategies can be planned, and evaluations of the current fire regimes simulated by process-based fire models can be performed.

## Conclusions

To capture the regional heterogeneity in burning characteristics is key to assess the specific impacts and further implications of different fire regimes. To this purpose, we employ the novel FT algorithm that draws upon remotely sensed fire and land-cover data and applies network theory to identify individual fires in the BLA over the period 2002–2020. The FT algorithm estimates fire size, duration, rate of spread, and intensity—provided for the first time in the Amazon—and recognises six different land cover-specific fire regimes described qualitatively as follows:

- Savanna: large, long, intense, fast-spreading fires
- Evergreen forests: large, long, intense, moderate spreading
- Grasslands: moderate size, duration, and spread, fast spreading
- Woody savannas: moderate size, duration, intensity and spread
- Croplands: small, short, moderate intensity, slow spreading
- Deciduous forests: small, short, low intensity, slow spreading

Our results align with previous studies that show how humans influence fire regimes by changing fuel type, structure and continuity as well as by controlling ignition sources, and contribute new data to the challenge of improving our understanding of the specific combination of fire attributes that define current human-dominated fire regimes. The information delivered here can help to better parametrise different fire regimes in DGVMs for more precise projections of future fire regimes and their effects.

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**Data availability** The FireTracks Scientific Dataset is available at http://doi.org/10.5281/zenodo.4461575, the Global Fire Atlas Dataset at https://daac.ornl.gov/cgi-bin/dsviewer.pl?ds_id=1642, the MODIS MCD12Q1 land-cover data at https://lpdaac.usgs.gov/products/mcd12q1v006/, and the deforestation data at http://terrabrasilis.dpi.inpe.br/downloads. Accessed 12 September 2022

## Declarations

**Conflict of interest** The authors declare no competing interests.



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