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Multi-year MODIS Active Fire Type Classification Over the Brazilian Tropical Moist Forest Biome

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Multi-year MODIS active fire type classification over the Brazilian Tropical Moist Forest Biome

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ABSTRACT

The Brazilian Tropical Moist Forest Biome (BTMFB) spans almost 4 million km^2 and is subject to extensive annual fires that have been categorized into deforestation, maintenance, and forest fire types. Information on fire types is important as they have different atmospheric emissions and ecological impacts. A supervised classification methodology is presented to classify the fire type of MODerate resolution Imaging Spectroradiometer (MODIS) active fire detections using training data defined by consideration of Brazilian government forest monitoring program annual land cover maps, and using predictor variables concerned with fuel flammability, fuel load, fire behavior, fire seasonality, fire annual frequency, proximity to surface transportation, and local temperature. The fire seasonality, local temperature, and fuel flammability were the most influential on the classification. Classified fire type results for all 1.6 million MODIS Terra and Aqua BTMFB active fire detections over eight years (2003–2010) are presented with an overall fire type classification accuracy of 90.9% (kappa 0.824). The fire type user's and producer's classification accuracies were respectively 92.4% and 94.4% (maintenance fires), 88.4% and 87.5% (forest fires), and, 88.7% and 75.0% (deforestation fires). The spatial and temporal distribution of the classified fire types are presented and are similar to patterns reported in the available recent literature.

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1. Introduction

The Brazilian Tropical Moist Forest Biome (BTMFB) supports the world's largest contiguous area of tropical forest and has experienced high rates of deforestation over the last few decades (Fearnside 2007; Numata et al. 2011) and extensive annual burning (Setzer and Pereira 1991; Giglio et al. 2006; Chen et al. 2011; Morton et al. 2013). Fire is used as the primary tool for forest and agricultural land clearing and the majority of fires are thought to be anthropogenic. Fires have been broadly classified into one of three types: (i) Maintenance fires, (ii) Deforestation fires, and (iii) Forest fires (Cochrane and Schulze 1999; Nepstad et al. 2001; Schroeder et al. 2005; Ten Hoeve et al. 2012). Maintenance fires are lit on pasture and arable land to remove crop residues, shrub, and secondary forest re-growth, to reduce pests, and to encourage nutrient recycling (Crutzen and Andreae 1990; Nepstad et al. 2001) and can burn variable amounts of biomass depending on the vegetation condition and the time since the last fire application (Cochrane et al. 1999). Maintenance fires are lit typically every two to four years, usually by burning the field perimeters and ensuring that the fire progresses across

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the pasture (Kauffman, Cummings, and Ward 1998). The fires are lit in the dry season and around midday to early afternoon when diurnal temperatures are the warmest and relative humidity the lowest; the fires burn quite rapidly (only several hours), although smoldering combustion of residual woody debris may take several days to burn (Kauffman, Cummings, and Ward 1998). Forest and deforestation fires occur in forests but have different causes. Deforestation fires are set by people to clear forested lands, typically for conversion to agricultural uses, and may burn large volumes of biomass and cause ecosystem structural change (Cochrane and Schulze 1999; Gerwing 2002) and of the three fire types they generate the most significant greenhouse and trace gas emissions (van der Werf et al. 2008). The vegetation in the forest area is slashed and left to dry for several months, large trees may be felled, sometimes the fuel is pushed into a large pile, and subsequently the dry fuel is burned typically in the late dry season by igniting the clearing/pile edges to produce energetic fires that can have flame lengths greater than 10 m and that can last for several days (Kauffman et al. 1995; Guild et al. 1998; Graça, Fearnside, and Cerri 1999; Morton et al. 2008). Forest fires are almost exclusively escaped fires lit elsewhere by people or ignited by lightning. Forest fires initially burn the forest litter, and the fires burn slowly (as little as 150 m per day) with low energy (flame heights no more than 10 cm) and are usually extinguished when the relative humidity increases in the evening, although smoldering woody debris may reignite weeks later if the conditions are conducive (Cochrane and Schulze 1998; Cochrane and Laurance 2002). In subsequent years, especially in drought years, a significant proportion of the forest biomass and not just the understory may also burn (Cochrane et al. 1999; Alencar, Solórzano, and Nepstad 2004; Alencar, Nepstad, and Diaz 2006; Aragão and Shimabukuro 2010; Alencar et al. 2011). In addition to emissions estimation, information on the timing, location and incidence of the different fire types are important for policy-makers and regulatory bodies to monitor and regulate the use of fire (Morton et al. 2008, 2013; GOFC-GOLD 2010) and to provide insights into post-disturbance land management practices and vegetation dynamics that can be difficult to infer in the region (Ramankutty et al. 2007; Laurance et al. 2011).

Satellite data have been used to monitor fire activity using active fire detection algorithms that detect the location of fires burning at the time of satellite overpass and using burned area algorithms that map the spatial extent of the area affected by fire (Lentile et al. 2006; Roy, Boschetti, and Smith 2013). Attribution of fire type to mapped burned pixels remains a research issue and has mainly been concerned with inferring the spatial extent of understory fires (Alencar, Nepstad, and Diaz 2006; Shimabukuro et al. 2010; Morton et al. 2013).

This paper develops and assesses a methodology to classify MODerate resolution Imaging Spectroradiometer (MODIS) active fire detections over the BTMFB as maintenance, forest, or deforestation fire types. Previously, satellite active fire detection fire types have been inferred using different techniques including the geographic context and proximity of satellite active fire detections relative to thematic land cover classes, roads, and forest edges (Nepstad et al. 2001; Schroeder et al. 2005; Alencar, Nepstad, and Diaz 2006; Giglio 2007; Ten Hoeve et al. 2012; Chen, Morton, et al. 2013) and by consideration of the temporal persistence of satellite active fire detections (Morton et al. 2008; Le Page et al. 2010; Chen, Morton, et al. 2013). These approaches have not been validated, and are expected to be less useful when new isolated forest areas are burned and because thematic land cover classes, roads, and forest edges may not be reliably mapped. In this study, a supervised random forest classifier is used to classify the fire type of MODIS active fire detections. Training data are defined by examination of annual Brazilian government forest monitoring program (PRODES) land cover time series and are used to provide a fire type classification accuracy assessment. The BTMFB study area and the data are first described, followed by description of the predictor variables that do not include the PRODES land cover data, and then the classification methodology. The relative importance of the predictor variables are reported in a way that accommodates correlation among variables. Results of the fire type classification of eight years (2003–2010) of 1 km MODIS Terra and Aqua active fire detections over the BTMFB and accuracy assessment, including select local comparison with Landsat data, are presented. This is followed by concluding remarks and discussion.

2. Study area

Figure 1 shows a map of the BTMFB study area covering an area of 3,982,550 km^2, equivalent to about 46% of Brazil and about 80% of the Brazilian Legal Amazon. The area lies between 5.140° N to 13.680° S and 73.67° W to 46.160° W and encompasses the Brazilian states of Rondônia, Pará, Acre, Amazonas, Roraima, Amapá, and portions of Mato Grosso. Vector shape files delineating the moist forest biome and Brazilian states were obtained from the Instituto Brasileiro do Meio Ambiente e dos Recursos Naturais Renováveis (IBAMA 2013). The roads and navigable rivers are also shown (described in Section 3.3.4) and reflect the spatial extent of surface transportation networks. The BTMFB study area is extensive, and encompasses the Equator, and so the fire seasonality varies geographically. Typically, the fire season in the Brazilian Amazon occurs from December to May for regions north of the equator and from July to December for regions south of the equator (Boschetti and Roy 2008; Morton et al. 2008). For all of the Brazilian Amazon, the peak fire month is usually August or September (Aragão et al. 2008).

3. Data

3.1. Satellite active fire data

The Collection 5, Level 2 MODIS 1 km Terra and Aqua active fire detection products (MOD14 and MYD14) (Giglio et al. 2003) were used in this study. The products define the locations of active fires detected at the time of MODIS overpass and include an estimate of the active fire detection confidence, the 4 μm and the 11 μm brightness temperatures [K] of the area around the fire detection, and the Fire Radiative Power (FRP) [MW]. All the Terra (10:30 and 22:30 Equatorial overpass times) and Aqua (13:30 and 01:30 Equatorial overpass times) active fires detected over the study

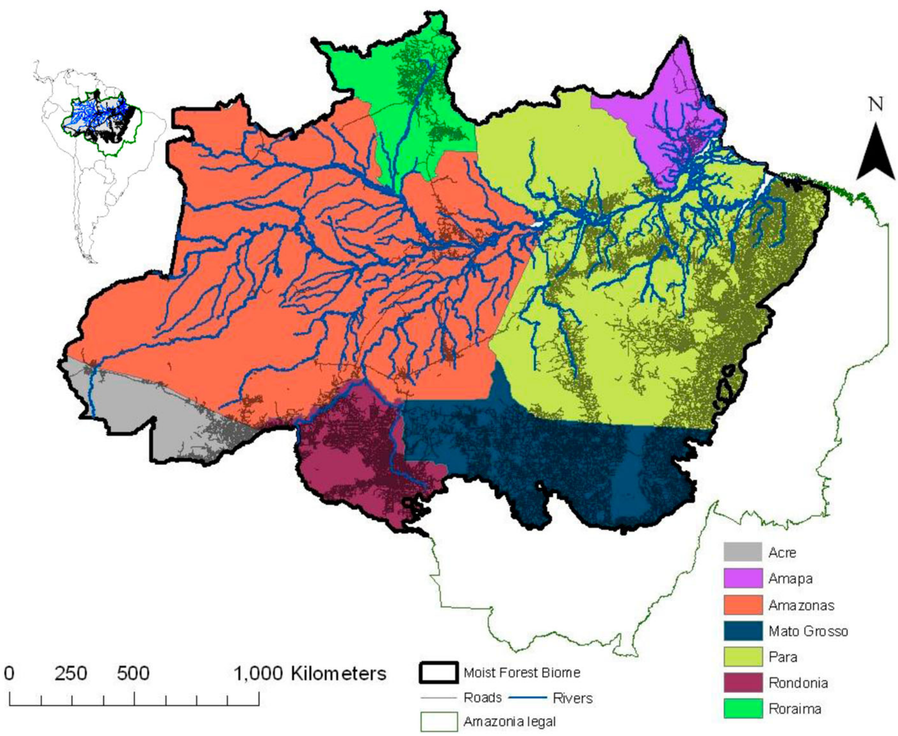

Figure 1. BTMFB study area (thick black outline) colored by states, with the official and unofficial roads (gray) and navigable river banks (blue). The limits of the legal amazon are shown by the green border.

area from 2002 to 2010 were used. The active fire detections for 2003 to 2010 were classified; the 2002 active fire detections were not classified but were used to parameterize some of the classification predictor variables.

The MODIS active fire product can only detect fires that are sufficiently hot and/or large depending on the areal proportions and temperatures of the non-burning and the smoldering and flaming fire components and is sensitive to the fire(s) sub-pixel position(s) (Kaufman et al. 1998; Giglio et al. 2003; Giglio and Justice 2003). The observed MODIS pixel footprints have elliptical shapes although the point spread function is approximately rectangular and triangular in the along-track and along-scan directions respectively (Nishihama et al. 1997; Wolfe, Roy, and Vermote 1998; Wolfe et al. 2002). The MODIS is a whiskbroom sensor and consequently, the active fire products detect fires that occur in pixel footprints that increase in area in the along-track and along-scan directions respectively from approximately 1.0 by 1.0 km at nadir to 2.0 by 4.8 km at the scan edge (Wolfe, Roy, and Vermote 1998). This causes a systematic detection omission at increasingly higher MODIS scan angles where only larger and/or hotter fires and higher FRP fires tend to be detected (Giglio, Kendall, and Justice 1999; Mottram et al. 2005; Kumar et al. 2011). Conversely, at high scan angles, the MODIS pixel footprints spatially overlap in the track direction between consecutive scans (the so-called bow-tie effect) (Nishihama et al. 1997; Wolfe, Roy, and Vermote 1998). This may result in a duplication of MODIS active fire detections at higher scan angles (Freeborn et al. 2014). However, duplicated detections cannot be distinguished from large individual fire events, from clusters of many small fires, or from long fire fronts that cover several adjacent pixels (Morisette et al. 2005; Freeborn et al. 2014). Consequently, in this study, each Level 2 MODIS active fire detection is considered as a single fire event located at the pixel center. The FRP value was divided by the pixel footprint area to give area normalized FRP [MW km^{-2}] (Kumar et al. 2011).

The Collection 5 MODIS active fire product has an estimated 3% active fire detection commission error in the Amazon occurring primarily over locations with strong thermal contrast, such as patches of bare soil surrounded by cooler dense vegetation (Schroeder, Csiszar, and Morisette 2008). Errors of omission are usually more prevalent than these commission errors due to surface obscuration by cloud and optically thick aerosols and because MODIS may not overpass when fires are occurring (Giglio 2007; Roy et al. 2008; Schroeder et al. 2008). In addition, omission errors occur due to sensor and algorithm detection limitations. MODIS active fire detection algorithm simulations indicate that the size of the smallest flaming fire having at least a 50% chance of being detected under ideal

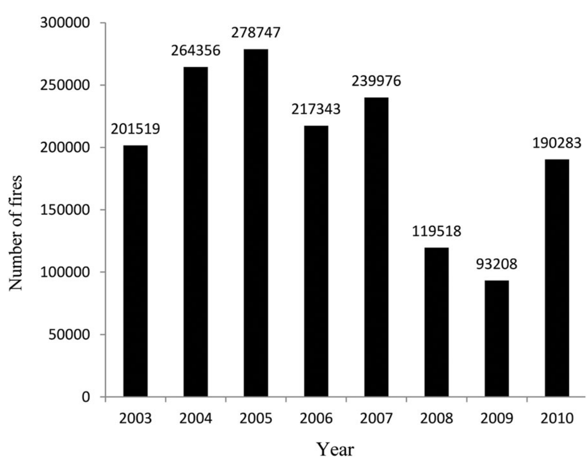

Figure 2. Total number of Level 2 MODIS Aqua and Terra, day and night, active fire detections over the study area (Figure 1) for each year. A total of 1,604,950 MODIS active fires were detected over the study area from 2003 to 2010. In 2002 (not illustrated), there were 151,085 active fire detections and were used to parameterize some of the classification predictor variables.

daytime and nighttime conditions is 100 m^2, and that nighttime detection probabilities are higher than daytime probabilities (Giglio et al. 2003).

Figure 2 summarizes the total number of annual MODIS Aqua and Terra, day and night, active fire detections for 2003–2010 over the study area, an eight-year total of 1,604,950 active fire detections. Caution in interpreting the absolute number of active fire detections is well known due to the aforementioned MODIS active fire detections issues. For this reason, we report both the absolute numbers and the relative proportions of the classified active fire types in the results section. The greatest and least number of fires occurred in 2005 and 2009, respectively. The large number of fires in 2005 has been observed by other researchers (Alencar, Nepstad, and Diaz 2006; Morton et al. 2008; Silvestrini et al. 2011) and is thought to be related to the extensive drought in that year (Espinoza et al. 2011; Lewis et al. 2011) when drier conditions increased the probability of escaped agricultural maintenance fires (Cochrane et al. 1999; Nepstad et al. 2001; Alencar, Solórzano, and Nepstad 2004; Alencar, Nepstad, and Diaz 2006) and opportunistic setting of fires to clear forested land (Araujo et al. 2009, 2010). From 2003 to 2010, deforestation decreased by almost 75% (Assunção, Gandour, and Rocha 2013; PRODES 2013; Souza et al. 2013), likely associated with the promulgation of a 2008 government deforestation policy and the transparency offered by Brazilian satellite-based forest monitoring efforts (Nepstad et al. 2009; Assunção, Gandour, and Rocha 2013). The low number of active fires in 2009 is perhaps related to this deforestation policy as a more normal number of fires were observed in the non-forest *cerrado* further south of the BTMFB (Ten Hoeve et al. 2012).

3.2. PRODES land cover data

The Brazilian government forest monitoring program produces the PRODES (Projeto de Monitoramento do Desflorestamento na Amazonia Legal) annually updated land cover classification that is used for monitoring annual deforestation across all the legal amazon (PRODES 2013). The PRODES wall-to-wall classification data over the BTMFB study area were extracted and used in this study. The PRODES classification defines the following 90 m (resampled from a 250 m × 250 m minimum mapping unit) classes: deforestation, forest, non-forest (savanna, agriculture, urban, rock, flood plain), missing data, water, and cloud. The classification has been updated annually with respect to a 1997 baseline classification using multiple remote sensing algorithms and expert opinion (PRODES 2013). Only the deforestation class is updated and the date and year of the Landsat image used for deforestation detection and the closest previous year with a non-missing forest class are available as attributes. Any location that is classified as deforested is never subsequently reclassified to another class (due to regrowth or conversion to agriculture for example). The accuracy of the PRODES data is unpublished but is considered to reflect a high level of accuracy and is the only moderate resolution wall-to-wall annual dataset that is available publically. Recently, less than a 2% difference between the PRODES Brazilian Amazon deforested area for 2000–2010 and the deforested area mapped independently using Landsat data and different techniques was reported (Souza et al. 2013).

All the PRODES data for 1997–2010 over the BTMFB were used, and in this period, about 6.4% of the study area pixels were classified as missing or persistently cloudy. As an example, Figure 3 illustrates the PRODES deforestation detected over the study area between years 2003 and 2011 (red) and regions that were classified as deforested from 1997 to 2002 (pink).

3.3. Predictor variable data and rationale for their selection

A suite of predictor variables (Table 1) were used to classify the MODIS active fire detections into forest, deforestation, and maintenance fire types. The variables were selected based on published research on the factors that drive and mediate fire in the Brazilian Amazon. The predictor variables are grouped as variables concerned primarily with fuel flammability, fuel load, fire behavior, fire

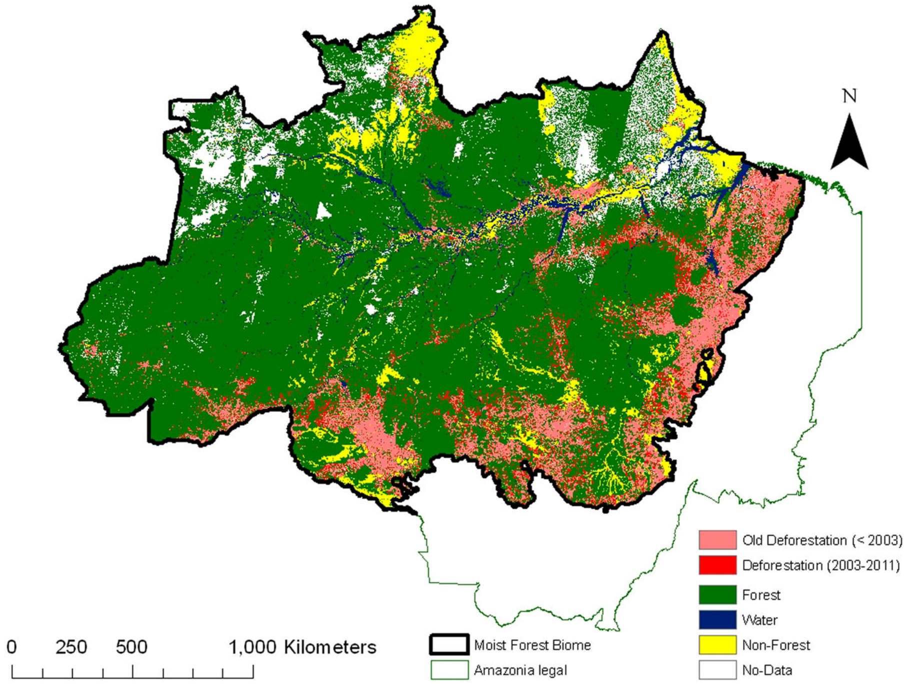

Figure 3. Illustrative 2003 PRODES 90 m derived land cover map. Deforestation detected between year 2003 and 2011 is shown in red. Deforested areas prior to year 2003 are shown in pink. The non-forest class (yellow) includes savannas, agricultural land, urban areas rocky regions, and flood plains. Clouds and missing data are shown as white.

seasonality, annual fire frequency, proximity to surface transportation, and the local temperature. The underlying premise for the variable selection is that the different fire types may occur where the fuel load and flammability are different and consequently, the fire types may have different fire behavior mediated by the local environmental conditions. In addition, the three fire types may have different fire seasonality and annual frequency. The following sub-sections detail the rationale for the predictor variable selection.

The predictor variable values were computed individually for all 1,604,950 MODIS active fire detections over the study area from 2003 to 2010. The values were derived at the center of each MODIS active fire detection location. For certain predictor variables, the values were derived as a summary statistic over a 1 km circular area centered on the pixel center. A 1 km dimension was used as fires often do not occur at the MODIS pixel center, and Morton et al. (2008) reported that 98% of MODIS Terra and Aqua active fire detections observed over one year at three static gas flares (Urucu, Amazonas, Brazil; Chuquicamata, Antofagasta, Chile; Espı'rito-Santo, Brazil) occurred within 1 km of their ground locations. Different temporal periods prior to the day of each active fire detection were used to compute the predictor variable values, up to one year prior to detection for the MODIS fire product-related variables, and up to two years prior to detection for the precipitation-related variables. Fixed calendar date ranges were not considered to avoid fire seasonality reporting issues found for extensive regions and for regions that span the Equator (Boschetti and Roy 2008).

3.3.1. Precipitation

At regional scale, the number of satellite detected fires in the Brazilian Amazon has a strong seasonality that is correlated with the amount of antecedent precipitation, with most fires occurring about three months after the end of the wet season (Kauffman and Uhl 1990; Aragão et al. 2008; Morton

Table 1. Fire type classification predictor variables.

Predictor variable name	Variable definition	Units	Descriptive group	Data with source(s) shown in parentheses
SumPrecip1m *SumPrecip2m* *SumPrecip3m* *SumPrecip6m*	Total precipitation in 1, 2, 3, and 6 month(s) prior to the active fire detection location including the month of active fire detection	[mm]	Fuel flammability	TRMM 3b43 V7 defined monthly for a 0.25° × 0.25° grid (TRMM 2014)
SumPrecip12m *SumPrecip24m*	Total precipitation in the 12 and 24 months prior to the active fire detection location including the month of active fire detection	[mm]	Fuel load	TRMM 3b43 V7 defined monthly for a 0.25° × 0.25° grid (TRMM 2014)
MaxFRP365d *SumFRP365d*	MaxFRP and SumFRP are the maximum observed FRP and the sum total FRP, respectively, of all the detections within a 1 km circular buffer around and within the previous 365 days of each detection location	[MW km^{-2}]	Fire behavior	MOD/MYD 14 Level 2 collection 5 (LAADS 2014)
DayMaxFRP365d *DayMedianFires365d*	DayMaxFRP is the day when maximum FRP was observed and DayMedian is the median day (DOY) of fire occurrences among the detections within a 1 km circular buffer around and within the previous 365 days of each detection location	[unitless, Day number]	Fire seasonality	MOD/MYD 14 Level 2 collection 5 (LAADS 2014)
#FireDays365d	The number of unique days that fire was detected among the detections within a 1 km circular buffer around and within the previous 365 days of each detection location	[unitless, count]	Annual fire frequency	MOD/MYD 14 Level 2 collection 5 (LAADS 2014)
DistRivers *DistRoads*	Closest Euclidean distance of active fire pixel center to navigable rivers (DistRiver) and to roads (DistRoads)	[km]	Proximity to surface transportation	Vector data for roads and navigable river networks (Veríssimo et al. 1998; IBAMA 2013)
LocalBrighnessTemp11 μm *MedianLocalBrighnessTemp11μm* *LocalBrighnessTemp4μm* *MedianLocalBrighnessTemp4μm*	Local brightness temperature is the mean brightness temperature in the window around each active fire detection of MODIS bands 21 (4 μm) and 31(11 μm). Median local brightness temperature is the median of the local brightness temperatures of all detections occurring within a 1 km circular buffer around and within the previous 365 days of each detection location	[K]	Local temperature	MOD/MYD 14 Level 2 collection 5 (LAADS 2014)

et al. 2008; Chen et al. 2011; Vasconcelos et al. 2013). Precipitation mediates the fuel flammability and the completeness of combustion (Rothermel and Station 1986; Carvalho et al. 2001). In addition, precipitation may influence people's decision to set fires, with opportunistic fires lit in drought periods to clear land (Cochrane et al. 1999; Nepstad et al. 1999; Cochrane 2003). The degree of biomass accumulation available for fire (i.e. the fuel load) in the Brazilian Amazon may be related to the antecedent precipitation, although the role of the seasonality of sunlight and rainfall in biomass production is subject to ongoing debate (Saleska et al. 2003; Myneni et al. 2007; Morton et al. 2014). It is unknown, however, if these precipitation factors influence the occurrence of different fire types, although as discussed earlier, different fire types are expected to have different fuel loads and may be ignited at different times of the year. To capture these different potential influences, the total precipitation during the month of active fire detection (termed for convenience one month), and for 2, 3, 6, 12, and 24 months prior to the detection were considered (*SumPrecip#m*, Table 1).

The Tropical Rainfall Measuring Mission (TRMM) monthly $0.25° \times 0.25°$ best precipitation rate estimate product (3B43, V7) (Huffman et al. 1995, 2007) for 2000–2010 (132 months) was used (TRMM 2014). Huffman et al. (1995) reported relative errors in this product of less than 20% across Amazonia. The monthly average precipitation rate [mm hr^{-1}] was converted into total monthly precipitation [mm] taking into account the different number of days in each calendar month.

3.3.2. Fire radiative power

The FRP is directly proportional to the rate of biomass combustion (Kaufman et al. 1998; Wooster et al. 2005) and so the MODIS FRP is expected to be different among the different fire types. For example, the MODIS FRP of fires occurring in a high fuel load region within the arc of deforestation in northern Mato Grosso and in a low fuel load woodland savanna in the Northern Territory of Australia were observed to have markedly different FRP distributions, with many more high FRP fires in Brazil than Australia (Kumar et al. 2011). Similarly, MODIS FRP boreal forest fire differences were observed between low fuel load surface fires in Russian and high fuel load crown fires in Alaska and Canada (Wooster and Zhang 2004). The MODIS FRP is typically under-sampled because there are only four MODIS Terra and Aqua overpasses per day at the Equator, and so fires may not be burning at the time of satellite overpass, and also because of cloud and smoke obscuration, and because the fire behavior can fluctuate rapidly in space and time (Schroeder, Csiszar, and Morisette 2008; Boschetti and Roy 2009; Kumar et al. 2011). The maximum FRP value within a 1 km buffer around the center of the active fire detection location over the previous 365 days was derived (*MaxFRP365d*, Table 1). The maximum FRP is of interest also as the maximum fire intensity affects vegetation processes like grass and tree response to fires (Archibald et al. 2010; Heward et al. 2013).

The total biomass consumed by fire is linearly related to the temporal integration of FRP over the fire duration and has been estimated from satellite by summing, or averaging, FRP over large (0.5–1°) geographic grids (Roberts et al. 2005; Roberts and Wooster 2008; Ellicott et al. 2009; Kaiser et al. 2012) or over satellite mapped burned areas (Boschetti and Roy 2009). As the different fire types are expected to consume different amounts of biomass, particularly the deforestation and maintenance fire types, the summed FRP for 365 days prior to the active fire detection was derived within a 1 km buffer around the center of the active fire pixel location (*SumFRP365d*, Table 1).

The seasonality of the FRP may be different among the fire types as the fire type may have different fuel loads and be ignited at different times. In an attempt to capture these influences, the day over the 365 days prior to each active fire detection when the maximum FRP occurred was derived within a 1 km buffer (*DayMaxFRP365d*, Table 1).

3.3.3. Annual fire frequency and seasonality

Deforestation fires may burn over several days, while maintenance typically last for a few hours within a day, and forest fires burn primarily during the day but can smolder for up to several weeks and develop active flaming fronts when conditions become favorable (Cochrane and Laurance 2002; Schroeder, Csiszar, and Morisette 2008). Morton et al. (2008) suggested that fires occurring in the same location over two or more days are likely to be deforestation fires. To capture these potential fire type persistence differences, the number of unique calendar days with at least one active fire detection, within a 1 km circular buffer, within the previous 365 days of each detection center was derived (*#FireDays365d*, Table 1). As noted previously, the three fire types may occur at predominantly different times of the fire season. In an attempt to capture this, the day of the year when 50% of the total Terra and Aqua active fire detections were detected within the 1 km circular buffer within the previous 365 days was also derived (*DayMedian365d*, Table 1). In cases where there were an even number of active fire detections, the median was randomly picked from the two middle values.

3.3.4. Distance to roads and navigable rivers

The majority of fires in the Brazilian Amazon have been observed to occur close to surface transportation networks. Adeney, Christensen, and Pimm (2009) observed that 90% of satellite active fire detections derived from a variety of polar orbiting satellites occurred within 10 km of official roads in the Brazilian Amazon. Similarly, 50% and 95% of MODIS active fire detections were found to occur within 1 and 10 km, respectively, of official and unofficial roads and navigable rivers in the BTMFB (Kumar et al. 2014). The distance to roads and navigable rivers may be different among the fire types. For example, Adeney, Christensen, and Pimm (2009) observed differences in fire to road relationships derived inside and outside of protected areas, and Kumar et al. (2014) observed regional variations in fire to road/river relationships among states that had different deforestation rates. To capture this difference, the distance of each MODIS active fire pixel center to the nearest official and unofficial road (*DistRoads*, Table 1), and to the nearest navigable river bank (*DistRivers*, Table 1) was derived following the method reported in Kumar et al. (2014). Figure 4 illustrates the official, unofficial, and navigable river data used in this study.

The red dots in Figure 4 show the 2005 MODIS active fire detections; the year that had the highest number of detections (Figure 2). It is evident that the majority of the detected fires occur close to the roads and navigable rivers (Kumar et al. 2014). The official road data were obtained from the Instituto Brasileiro do Meio Ambiente e dos Recursos Naturais Renováveis (IBAMA 2013) and define the road center lines (one dimensional line/arc segments) for federal, state, and certain private roads digitized from maps created using government sources and last updated 6 February 2007. The

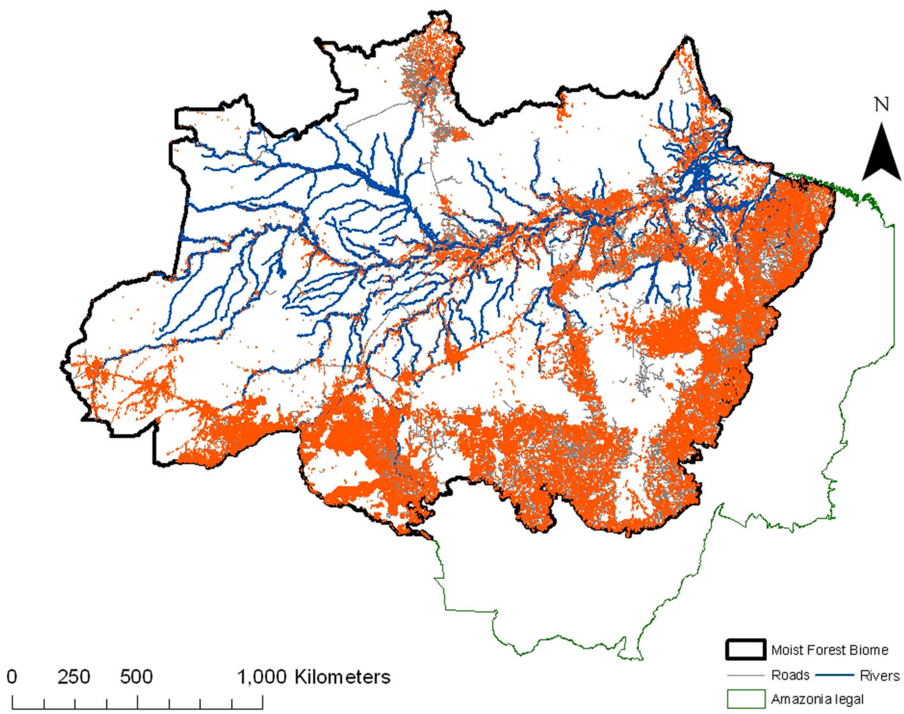

Figure 4. All MODIS Aqua and Terra day and night active fire detections for 2005 (the year of maximum active fire detections; Figure 2) with official and unofficial roads (gray) and navigable river banks (blue).

unofficial road data were derived by expert visual interpretation and digitization of wall-to-wall Amazonian Landsat imagery acquired from the *Instituto Nacional de Pesquisas Espaciais* for 1982 through 6 February 2008 obtained from the Instituto do Homem e Meio Ambiente da Amazônia (*Imazon*) (http://www.imazon.org.br). The navigable river data were also obtained from *Imazon* and define the polygons of river banks for navigable rivers wider than approximately 1000 m and river center line vectors for narrower navigable rivers. The river data were manually digitized and their navigability status established from interviews held with community leaders and river traders and by inspection of government reports and river surveys (Barros and Uhl 1995; Veríssimo et al. 1998).

3.3.5. Local brightness temperature

The local temperature of the three fire types may be different because of differences in the local surface cover (e.g. vegetation and soil cover) and condition, and the degree of char and mineral ash deposition. Forest and deforestation fire types occur in forests which, due to their vegetation cover and drainage, are likely to have different fluxes of latent and sensible heat compared to maintenance fires that occur on pasture and crop lands (Carlson, Gillies, and Perry 1994; Weng, Lu, and Schubring 2004; Bagley et al. 2013; Brando et al. 2014). The local surface temperature may be modified by any change in albedo caused by deposition of char and mineral ash (Jin and Roy 2005; Roy et al. 2010). In addition, there may be differences in the proportion of satellite observed ground and so temperature. For example, forest fires are expected to occur where there is less satellite observable bare ground due to forest canopy obscuration (Asner and Warner 2003).

Accurate spatially and temporally explicit land surface temperature estimates are difficult to derive at regional scale (Wan 2014; Jiménez-Muñoz et al. 2016) and are not always available for each MODIS active fire detection. In this study, the 4 and 11 μm brightness temperatures reported in the MODIS active fire product were used. The MODIS active fire detection algorithm is a contextual algorithm that defines candidate active fires as those with elevated 4 and 11 μm brightness temperatures, and then applies a contextual approach to reject false detections by examining the relative brightness temperatures of neighboring non-candidate non-cloudy pixels (Giglio et al. 2003). Neighboring pixels in a 3×3 km pixel window centered on the candidate pixel are considered in this process and the window dimensions are increased progressively, up to a maximum of 21×21 pixels, until there are sufficient neighboring pixels to enable a reliable brightness temperature comparison. The mean 4 and 11 μm brightness temperatures in the window around each active fire detection are reported in the MODIS Level 2 active fire product and were used in this study for each active fire detection (*LocalBrightnessTemp4μm* and *LocalBrightnessTemp11μm*, Table 1). In addition, the median 4 μm and the median 11 μm brightness temperatures were derived from all the active fire detections within a 1 km circular buffer sensed in the 365 days prior to each detection location to capture the temperatures under average burning conditions (*MedianLocalBrightnessTemp4μm* and *MedianLocalBrightness11μm*, Table 1). The median rather than the mean was used because it is robust to outliers. In cases where there were an even number of active fire detections, the median was randomly picked from the two middle values.

4. Methods

4.1. Training data definition

Supervised classification methods develop statistical classification rules using training data that consist of representative predictor variable samples and corresponding class values (Foody and Mathur 2004). For example, coarse spatial resolution land cover products, such as the global MODIS land cover product, have been derived using training data defined by visual interpretation of Landsat or higher spatial resolution imagery selected where the land cover is uniform and representative of a single class (i.e. 'pure' pixel) at both spatial scales (Friedl et al. 2010; García-Mora, Mas, and

Hinkley 2012). Definition of the optimal training data used with non-parametric supervised classifiers is complex but given sufficient samples the use of pure training data does not provide significant classification accuracy differences compared to using mixed (more than one class per pixel) training data (Foody and Mathur 2006; Egorov et al. 2015).

The scale mismatch between MODIS active fire detections and Landsat data is well known (Morisette et al. 2005; Roy et al. 2008; Hyer and Reid 2009; Boschetti et al. 2015) and is complex for MODIS because at higher scan angles a single pixel footprint covers a larger area than at nadir. Consequently, in this study, we explicitly consider the size of the MODIS active fire footprint and only derive training data for pure pixels sensed near-nadir. Only active fire detections sensed with scan angles ≤24° are used as the pixel footprint is near circular with a maximum radius of about 0.5 km (no greater than 1.10 and 1.24 km diameter in the track and scan dimensions, respectively) (Wolfe et al. 2002; Giglio 2010).

A conservative training data generation method was implemented to derive a set of unambiguous pure fire type class (forest, deforestation, maintenance) examples and their corresponding predictor variable values (Table 1). The fire type class label was defined by considering the 90 m pixel PRODES land cover classes for the year before and the year of each MODIS active fire detection within a 0.5 km buffer around the active fire pixel center as:

Forest fire type – if all 90 m pixels in the 0.5 km buffer were forest classes in both years.

Deforestation fire type – if the spatial union for both years of the 90 m pixels classified as deforestation covered the entire 0.5 km buffer, and all of the 90 m pixels had PRODES deforestation dates that occurred before the MODIS active fire detection date.

Maintenance fire type – if all 90 m pixels in the 0.5 km buffer were non-forest classes (savanna, agriculture, urban, rock, flood plain) in both years.

If the above conditions were not met, or if there were any PRODES classified cloudy or missing 90 m pixels within the 0.5 km buffer in either year, then the MODIS active fire detection was not used for training. This meant that persistently cloudy regions at the time of Landsat overpass, for example, due to stationary weather systems, were not used for training data. In addition, any MODIS active fire detections over old deforested regions (i.e. deforested prior to 2003, pink tones in Figure 3) could not be used as training data. The geolocation error between the PRODES and MODIS datasets can be considered negligible compared to the uncertainty in the position of the active fires within a MODIS pixel – the MODIS accuracy is within 50 m at nadir (Wolfe et al. 2002), and although the PRODES accuracy is unknown, it is likely to be comparable to the 30 m pixel level Landsat accuracy (Lee et al. 2004). This training data selection approach provides pure fire type training data that is internally consistent with respect to the PRODES classification scheme used by the Brazilian government for monitoring deforestation in the legal amazon.

4.2. Classification

The random forest classifier was used as it is an established supervised classifier that can accommodate non-monotonic and nonlinear relationships between predictor variables, makes no assumptions concerning the statistical distributions of the variables, and can handle correlated variables (Breiman 2001; Strobl et al. 2008). This is particularly important given the different kinds of predictor variable used (Table 1). Random forests are an ensemble form of decision tree classification where many trees are grown by recursively partitioning a random subset of the training data into more homogeneous subsets referred to as nodes. The random forest classifier provides reduced likelihood of overfitting predictor variables to the training data by independently fitting a large number of decision trees, with each tree grown using a random subset of the training data and a limited number of randomly selected predictor variables (Breiman 2001).

The R software RANDOMFOREST package (http://www.r-project.org/) was implemented on a 64-bit Linux computer with 128 GB of memory in order to accommodate the large amount of required data processing. The default random forest parameter settings were used – a total of 500 trees were grown with each tree considering 63.2% of all the training data selected at random with replacement and considering four randomly selected predictor variables per tree. All of the MODIS active fires detections sensed over the BTMFB from 2003 to 2010 were classified independently 500 times using each tree. The final classification result was assigned in the conventional way by the majority fire type cover the 500 classifications.

4.3. Classification accuracy assessment

It is well established that satellite active fire detection accuracy assessment is challenging due to the ephemeral nature of fire and difficulties in making ground-based active fire measurements at the time of satellite overpass (Cardoso et al. 2005; Morisette et al. 2005; Schroeder, Csiszar, and Morisette 2008; Roy and Boschetti 2009). The fire type classification accuracy assessment has these issues, and there are no reliable independent fire type data for the eight years over the BTMFB. Therefore, an internal unbiased error estimate of the classification accuracy was derived by bootstrapping (Breiman 1996, 2001). Specifically, after each tree was generated using 63.2% of the training data, the remaining 'out-of-bag' 32.8% was classified with the tree and the classified 'out-of-bag' results stored as a vector of class labels. The majority class label over the 500 vectors was then assigned as the fire type classification for each unique 'out-of-bag' sample. These data were used to generate a two-way confusion matrix. Conventional accuracy statistics (classification percent correct, kappa, user's and producer's accuracy) were then derived from the confusion matrix (Foody 2002).

The optimal training size and distribution for supervised classification is usually unknown (Foody and Mathur 2004, 2006). Therefore to ensure that the accuracy statistics results were not unduly influenced by the amount and distribution of the training data, the classification and accuracy assessment process was repeated four times using 25%, 33%, 50%, and 75% (selected at random without replacement) of the training data.

The described approach classifies each MODIS active fire detection into a single fire type class. The extent to which the three fire types are mixed within a MODIS active fire detection pixel is unknown and cannot be classified by the present methodology. To examine this qualitatively, and to provide confidence in the local accuracy of the classification, classified MODIS active fire detections were compared with higher spatial resolution 30 m Landsat images. Landsat 5 images were used as they do not have the scan line corrector failure that reduced the amount of useable Landsat 7 image data acquired after May 2003 by 22% (Markham et al. 2004).

4.4. Analysis of predictor variable importance

The relative importance of the predictor variables in explaining the random forest fire type classification was investigated. In this study, the Mean Decrease in Gini (MDG) was used as it provides a robust variable importance measure for random forest classification analyses (Breiman 2001; Strobl et al. 2008). The Gini is a measure of the homogeneity of subsets at each node; the MDG quantifies the mean decrease in Gini over all trees and higher MDG values imply higher predictor variable importance (Calle and Urrea 2011; Nicodemus 2011).

Several of the predictor variables were derived from the same data source (Table 1) and so are expected to be correlated. Random forest classifiers are designed to handle correlated predictor variables (Breiman 2001), but random forest measures of predictor variable importance are biased when the variables are correlated (Hothorn, Hornik, and Zeileis 2006; Strobl et al. 2008). Consequently, in this study, a straightforward approach, similar to the procedure followed by Tulbure et al. (2012), was implemented. Recall that the predictor variables are in seven groups (fuel flammability, fuel load, fire behavior, fire seasonality, annual fire frequency, proximity to surface transportation, and local temperature) (Table 1). All n possible combinations of seven predictor variables found by selecting *one* predictor variable from each of the groups were considered. If the predictor variables within any combination had an absolute Pearson's correlation coefficient greater than a certain threshold, then the combination was not considered. In this way, a smaller number of *m* combinations of uncorrelated predictor variables were considered. For each combination, the predictor variable MDG values were ranked and the ranking was assigned to the group that the variable was selected from. The percentage of times that a group was ranked a specific rank over the *m* combinations was computed to assess the importance of each predictor variable group on the fire type classification.

5. Results

5.1. Training data selection

Of the 1,604,950 MODIS active fire detections, 4.5% (72,685) were selected as training data and assigned a fire type for training (Table 2). Thus, the majority (95.47%) of the MODIS active fire detections were not used for training and therefore were subsequently classified using the random forest classifier without reference to the PRODES land cover data.

Table 2 summarizes the training data. Over the eight years, the percentage of active fire detections used for training varied from 3.05% to 7.43% of the total annual number of MODIS active fire detections. The maintenance fire type training data had the greatest proportion among the fire types for all years, except 2010, and was typically >0.5. The forest fire type proportion varied from 0.2 in 2004 and up to 0.56 in 2010. The deforestation fire type proportions declined monotonically from 0.16 (2003) to 0.002 (2010). This significant decline in the deforestation fire type training data proportion is expected and reflects the documented reductions in deforestation that are discussed at the end of Section 3.1. The reported fire type training proportions are broadly similar to those reported over different spatial and temporal spans by other researchers (Morton et al. 2008; Ten Hoeve et al. 2012) and indicate that the training data broadly reflect the underlying populations.

5.2. Classification accuracy assessment

5.2.1. Quantitative assessment

The fire type confusion matrix generated from the 500 sets of classified 'out-of-bag' training data (Section 4.3) is shown in Table 3. The overall fire type classification accuracy was 90.9% with a

Table 2. BTMFB fire type training data summary – the number of selected MODIS active fire detections and the allocated fire type proportions by year and the eight-year total.

Year	Annual number of MODIS active fires detections used for training	Percentage of all annual MODIS active fire detections (Figure 2)	Number of maintenance fire types (annual proportion in parentheses)	Number of forest fire types (annual proportion in parentheses)	Number of deforestation fire types (annual proportion in parentheses)
2003	8340	4.14	5106 (0.61)	1873 (0.22)	1361 (0.16)
2004	12,010	4.54	7672 (0.64)	2408 (0.2)	1930 (0.16)
2005	8488	3.05	5212 (0.61)	2869 (0.34)	407 (0.05)
2006	7973	3.67	5595 (0.7)	2163 (0.27)	215 (0.03)
2007	11,268	4.70	5905 (0.52)	5056 (0.45)	307 (0.03)
2008	5378	4.50	3732 (0.69)	1542 (0.29)	104 (0.02)
2009	5083	5.45	3854 (0.76)	1216 (0.24)	13 (0.003)
2010	14,145	7.43	6197 (0.44)	7919 (0.56)	29 (0.002)
All 8 years	**72,685**	**4.53**	**43,273 (0.6)**	**25,046 (0.34)**	**4,366 (0.06)**

Table 3. BTMFB fire type confusion matrix results generated by consideration of the 72,685 training data (Table 2) and the corresponding random forest classified fire types.

	Classified fire type				
Training fire type	Maintenance	Forest	Deforestation	Row total	Producer's accuracy (%)
Maintenance	**40,861**	2211	201	43,273	94.43
Forest	2912	**21,917**	217	25,046	87.51
Deforestation	428	665	**3273**	4366	74.97
Column total	44,201	24,793	3691	$n = 72,685$	
User's accuracy (%)	92.44	88.4	88.68		

Note: Overall percent correct is 90.87%, kappa = 0.824 with kappa standard error of 0.002.

kappa of 0.824 and the lowest producer's and user's fire type classification accuracies were 75% (deforestation fires) and 88% (forest fires), respectively. These results indicate quite reasonable fire type classification accuracies.

Among the three fire types, the maintenance fire type had the highest user's and producer's accuracies of 92.4% and 94.4%, respectively. This is perhaps because maintenance fires occur under quite different conditions compared to the other two fire types and are less likely to be obscured by the overstory vegetation found in forested systems. Of the 43,273 maintenance fire type training data, only 0.46% and 5.1% were misclassified as deforestation and forest fires, respectively. The forest fire type had similar user's and producer's accuracies of 88.4% and 87.5%, respectively, with 11.6% and 0.87% of the forest fire training data misclassified as maintenance and deforestation fire types, respectively. The greater relative confusion between the maintenance and forest fire types is somewhat expected as maintenance fires and forest fires may burn similar low fuel loads and so may exhibit similar fire behavior (Cochrane et al. 1999; Alencar, Solórzano, and Nepstad 2004; Alencar, Nepstad, and Diaz 2006). The deforestation fire type had the lowest producer's and user's accuracies of 75% and 88.7%, respectively. We had expected deforestation fires to be classified with relatively higher accuracy compared to the other fire types because deforestation fires are lit on large piles of dry fuel material that can burn energetically over long durations that can be observed by multiple MODIS overpasses. A total of 9.8% and 15.2% of the deforestation fire training data were misclassified as maintenance and forest fire types respectively. Greater classification confusion between the deforestation and forest fire types is expected as they both occur in forested systems and, as discussed previously, forest fires that burn more than once may consume significant amounts of biomass like deforestation fires.

To ensure that the classification results summarized in Table 3 were not unduly influenced by the amount and distribution of the training data, the classification and accuracy assessment process was repeated four times using 25%, 33%, 50%, and 75% (selected at random without replacement) of the 72,685 training data. The resulting overall fire type classification accuracy and kappa values were lower than found using 100% of the training data but were still quite high at 86.2% and 0.732 (25% sample), 87.3% and 0.754 (33% sample), 88.7% and 0.782 (50% sample), and 89.9% and 0.805 (75% sample), respectively. This indicates sufficient sample size for our training and also that the predictor variables captured the underlying variability among the fire types even under low sampling conditions.

5.2.2. Qualitative assessment by comparison with Landsat images

Figures 5 and 6 show detailed MODIS active fire detection fire type classification results for a single year (colored 500 m radius circles) superimposed over 30 m Landsat 5 Thematic Mapper images sensed in the previous year over regions in Acre and Mato Grosso, respectively. These 81 × 63 km regions were selected because they encompass fragmented landscapes and include intact forest and cleared land, and because cloud and smoke free Landsat 5 images were available. In addition, they include a smaller than usual proportion of MODIS active fire detections used as training

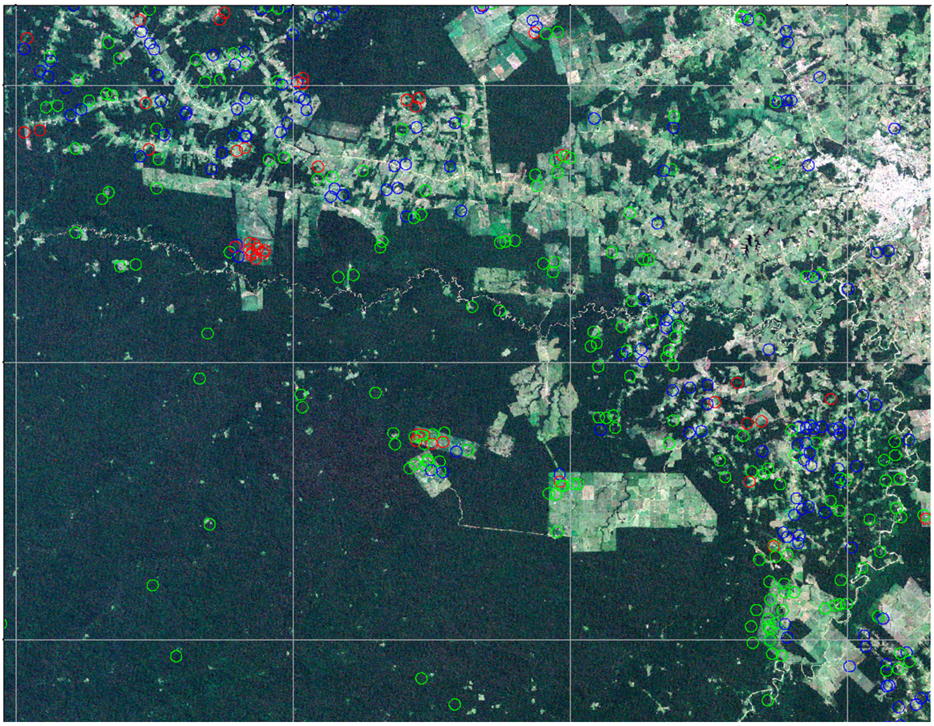

Figure 5. One year of MODIS active fire type classification results (colored circles, radius 0.5 km) superimposed on a true color 30 m Landsat image over a 81 × 63 km region in the Brazilian state of Acre (illustrated image center longitude 68.160°W, latitude 10.103° S; town of Rio Branco evident on the eastern side). The Landsat 5 Thematic image was sensed on 7 June 2005. Classified MODIS Terra and Aqua active fire detections for all of 2006 shown as green (forest fires), blue (maintenance fires), and red (deforestation fires). Of the 1279 classified MODIS active fires shown, only 22 (1.7%) were included in the classification training data. The gridded lines are spaced 25 km apart.

data because the Landsat images encompass land that PRODES classified as deforested before 2003 (pink in Figure 3). Consequently, the illustrated classification results are not overly influenced by having a larger than normal proportion of detections that were used to define training data that are expected to be more accurately classified.

The MODIS active fire type classification results are assumed to be associated with the land use evident in the illustrated previous years Landsat imagery. The results indicate that the MODIS fire type classification results are geographically plausible. In both figures, the classified forest (green) and deforestation (red) fire types occur predominantly over forest and close to forest boundaries while the classified maintenance fire types (blue) occur primarily over non-forest lands. This expected classification spatial correspondence is particularly apparent in Figure 5. However, the specific locations of fires within MODIS active fire detection pixels is unknown – fires could have occurred at the edge, or even outside, the illustrated circles, because the detection foot print, as discussed in Section 3.1, can vary from about 1.0 by 1.0 km at nadir to 2.0 by 4.8 km at the scan edge, and this has been observed by other researchers (Morisette et al. 2005). Thus, for example, in Figures 5 and 6 there are a minority of deforestation classified fire types (red) that appear to be incorrectly within cleared land but on close inspection abut forested regions where the fire may have occurred. There are a minority of obvious commission errors, for example, isolated classified maintenance fires occurring in the interiors of intact forests that are not close to clearings. This is not unexpected, however, because, although the overall classification accuracy is high (90.9%), fire types are misclassified as discussed above with, for example, 11.6% of the forest fire training data misclassified as maintenance fires (Table 3).

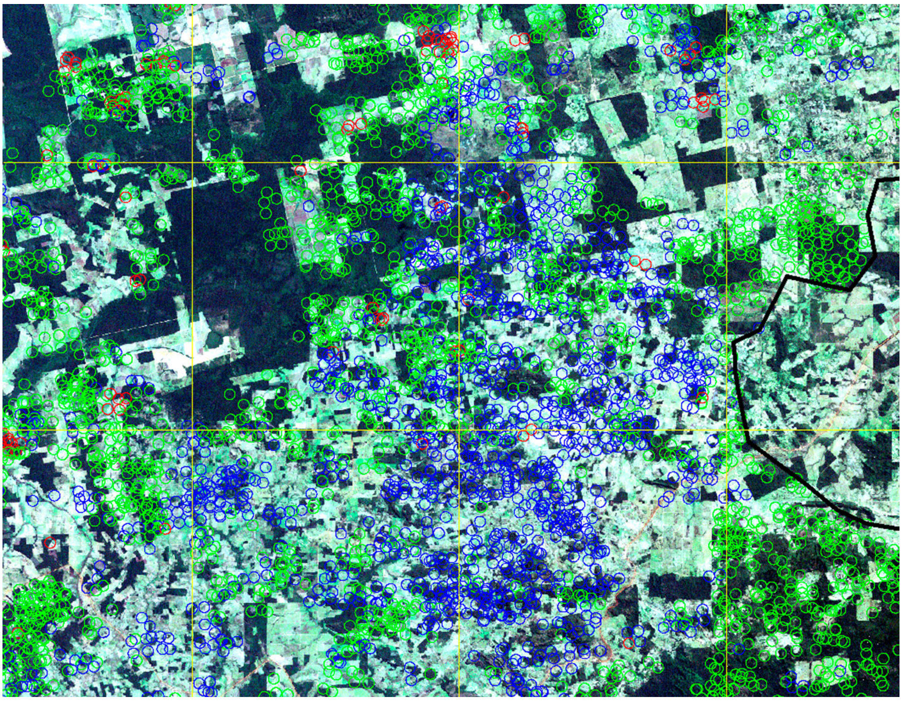

Figure 6. One year of MODIS active fire type classification results (colored circles, radius 0.5 km) superimposed on a true color 30 m Landsat image for a 81 × 63 km region in the north east of Mato Grosso (illustrated image center longitude 51.592°W, latitude 10.282°S). The Landsat 5 Thematic Mapper image background was sensed on 29 June 2006. The classified MODIS Terra and Aqua active fire detections for all of 2007 are shown as green (forest fires), blue (maintenance fires), and red (deforestation fires). Of the 3264 MODIS active fires shown, only 143 (4.4%) were included in the classification training data. The black vector shows the Eastern edge of the BTMFB study area. The gridded lines are spaced 25 km apart.

To provide further confidence in the fire type classification results, Landsat images acquired in the year *after* the MODIS active fire detections were also examined. Figure 7 shows the classified MODIS active fire detections for the Mato Grosso example (Figure 6) and the normalized difference vegetation index (NDVI) two year difference between the Landsat 5 image sensed the year before and sensed a year after the MODIS active fire detections (bottom). The NDVI differences were derived using top of atmosphere Landsat red and near infrared reflectance. Reduced and increased NDVI over the two years are shown in red and blue tones, respectively, and smaller differences are shown in gray. The gray tones show ±0.15 differences which are comparable to Brazilian NDVI seasonal variability (Morton et al. 2014; Müller et al. 2015) and to the impact of the atmosphere on Landsat NDVI over vegetated surfaces (Roy et al. 2014). In general, as expected, the classified deforestation fire types occur where there was reduced NDVI. However, regions with reduced NDVI did not always occur where there were MODIS active fire detections. This is likely because fires may not have been detected by MODIS and NDVI reductions due to forest clearing without the use of fire may have occurred. The forest fire types occurred often where there was small (±0.15) NDVI differences, which is expected because post-fire Landsat spectral signatures in Brazilian forests typically return to intact forest signatures a year after fire occurrence (Souza, Roberts, and Cochrane 2005; Alencar et al. 2011). There was no clear relationship between the NDVI differences and the location of maintenance fires which perhaps reflects the diversity of cleared land uses and vegetation conditions. Similar results were observed for the Acre site but are not illustrated. The above observations concerning Figure 7 cannot provide a definitive check because the post-fire land use trajectory may be different to the pre-fire trajectory. However, they do, with the observations concerning Figures 5 and 6, provide confidence in the local accuracy of the classification approach.

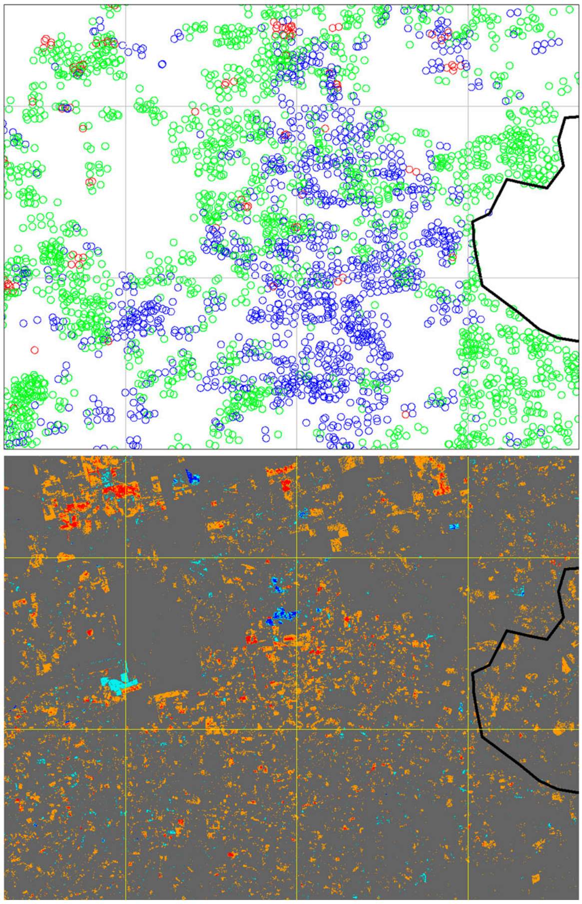

Figure 7. *Top*: Mato Grosso year 2007 classified MODIS active fire types (as Figure 6). *Bottom*: Landsat 30 m NDVI difference derived from images sensed the year before and after the MODIS active fire detections, specifically (29 June 2006 NDVI–4 July 2008 NDVI) shown colored as (−2.0 ≥ red < −0.3), (−0.3 ≥ orange < −0.15), (−0.15 ≥ gray ≤ 0.15), (0.15 < light blue ≤ 0.3), (0.3 < blue ≤ 2.0). The gridded lines are spaced 25 km apart.

5.3. BTMFB classified fire types

5.3.1. Geographic fire type distributions for years 2003 and 2010

Figures 8 and 9 show the fire type classifications results for 2003 and 2010, respectively, i.e., the beginning and end years of the study period. The individual fire type proportions (shades of gray) and the majority fire type (colors) in 7 km × 7 km grid cells are illustrated. At this synoptic scale, the overall fire type classification results appear geographically plausible. The names and locations of Brazilian states are shown in Figure 1. Maintenance classified fires occurred over non-forest and old (prior to 2003) deforested regions, noticeably over the states of Roraima, Amapá and also over certain old deforestation regions in the states of Rondônia, Pará, and portions of Mato Grosso (Figure 3). This is despite the fact that the MODIS active fires detected over old deforested regions could not be used as training data for any fire type (Section 4.1). Forest fires occurred more in the interior forested regions along navigable river and road networks, in regions of open and transitional forests (Alencar, Nepstad, and Diaz 2006), and also over old deforestation regions throughout the study area (Figure 3). Deforestation classified fires occurred primarily in the 'arc of deforestation' spanning the states of Acre, Rondônia, Pará, and Mato Grosso that are known to be the sates with the highest deforestation rates (PRODES 2013).

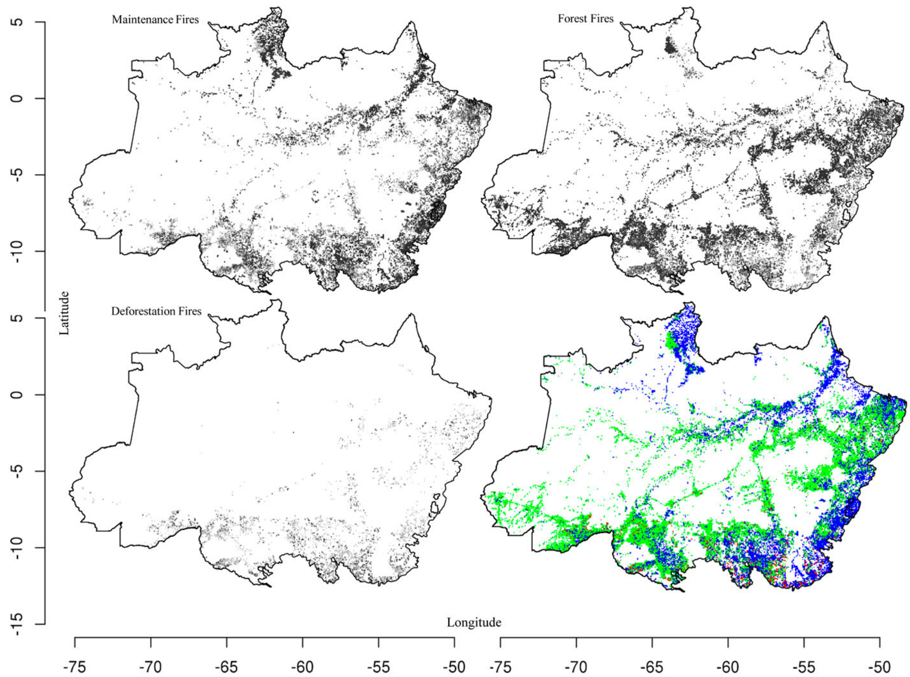

Figure 8. 2003 fire type classification results showing the majority classified fire type in 7 km × 7 km grid cells colored as maintenance fires (blue), forest fires (green), and deforestation fires (red). The grayscale images show the relative proportion of the active fire detections classified into each fire type in each grid cell (white = 0; 0 > light gray ≤ ⅓; ⅓ > medium gray ≤ ⅔; ⅔ > dark gray ≤ 1). A total of 201,519 (Figure 2) classified MODIS active fire detections are shown.

In 2003 and 2010, there were similar annual proportions of the classified maintenance fire type, 0.41 and 0.37, respectively (Table 4) and their geographic distributions appear broadly similar (Figures 8 and 9). For these two years, the annual proportions of the classified forest fire type were less similar, 0.47 (2003) and 0.61 (2010) (Table 4), and their geographic distributions are different in several regions. In 2003 and 2010, the annual proportions of the classified deforestation fire type were 0.12 and 0.03, respectively (Table 4) and this difference is very evident geographically. There were far greater incidences of classified deforestation fires over the 'arc of deforestation' in 2003 than in 2010, and this pattern has been corroborated in the literature (PRODES 2013; Souza et al. 2013).

5.3.2. Annual and seasonal fire type distributions for all eight study years

Figure 10 shows graphically the annual number of classified fire types for each year (Table 4). The likely causes of inter-annual variation in the total number of MODIS active fire detections is described in Section 3.1. In every year, there were more classified forest fires than maintenance fires, except for 2009 (the year with the fewest MODIS active fire detections) and in all years there were fewer deforestation fires. The annual number of classified forest and maintenance fires have similar temporal pattern, with a correlation of 0.85. The greatest numbers of classified forest fires occurred in 2007 and 2010 and this was also noted by Morton et al. (2013) for southern Amazonia and by Brando et al. (2014) for eastern Mato Grosso, and was suggested as being related to the drier conditions in these years (Morton et al. 2013; Brando et al. 2014). The forest and deforestation fires have a less similar temporal pattern with a correlation of 0.59. As the number of MODIS active fire detections varied among years, it is useful to consider the annual proportions of the three classified fire types (tabulated in Table 4). Most noticeably the proportion of deforestation classified fires declined from around 0.12 in 2003 to 0.03 in

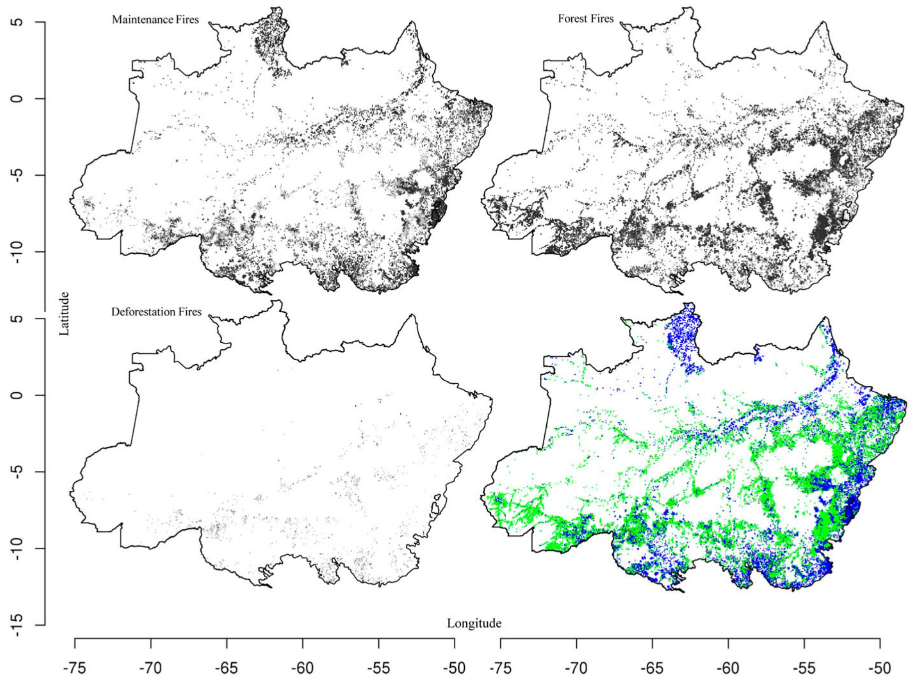

Figure 9. 2010 fire type classification results showing the majority classified fire type in 7 km × 7 km grid cells colored as maintenance fires (blue), forest fires (green), and deforestation fires (red). The grayscale images show the relative proportion of the active fire detections classified into each fire type in each grid cell (white = 0; 0 > light gray ≤ ⅓; ⅓ > medium gray ≤ ⅔; ⅔ > dark gray ≤ 1). A total of 190,283 (Figure 2) classified MODIS active fire detections.

2010 (the geographic distributions are illustrated in Figures 8 and 9). This 75% decline matches the documented 75% decrease in deforestation from 2003 to 2010 (Assunção, Gandour, and Rocha 2013; PRODES 2013; Souza et al. 2013).

Figure 11 shows the mean monthly number of MODIS active fire detections (from 2003 to 2010) that were classified into the three fire types. The majority of the fire detections occur during the southern hemisphere dry season between June and December with most inter-annual variability (vertical lines show $\pm 0.5\sigma$) in July, August, and September. As for the annual classification results (Figure 10), there were generally more classified forest fires than maintenance than deforestation fires. However, in the months January–April, the number of forest and deforestation fires are quite similar and lower than the number of maintenance fires, likely because this period is the

Table 4. BTMFB fire type classification results summarizing the annual number of MODIS active fire detections and the number and proportion classified into the three fire types by year and eight-year total.

Year	Annual number of MODIS active fires detections (see Figure 2)	Number of classified maintenance fire types (annual proportion in parentheses)	Number of classified forest fire types (annual proportion in parentheses)	Number of classified deforestation fire types (annual proportion in parentheses)
2003	201,519	82,547 (0.41)	95,549 (0.47)	23,423 (0.12)
2004	264,356	104,908 (0.4)	122,468 (0.46)	36,980 (0.14)
2005	278,747	118,386 (0.42)	131,700 (0.47)	28,661 (0.1)
2006	217,343	99,211 (0.46)	103,396 (0.48)	14,736 (0.07)
2007	239,976	90,452 (0.38)	132,891 (0.55)	16,633 (0.07)
2008	119,518	52,519 (0.44)	57,602 (0.48)	9397 (0.08)
2009	93,208	46,218 (0.5)	42,735 (0.46)	4255 (0.05)
2010	190,283	70,039 (0.37)	115,462 (0.61)	4782 (0.03)
All 8 years	1,604,950	**664,280** (**0.41**)	**801,803** (**0.50**)	**138,867** (**0.09**)

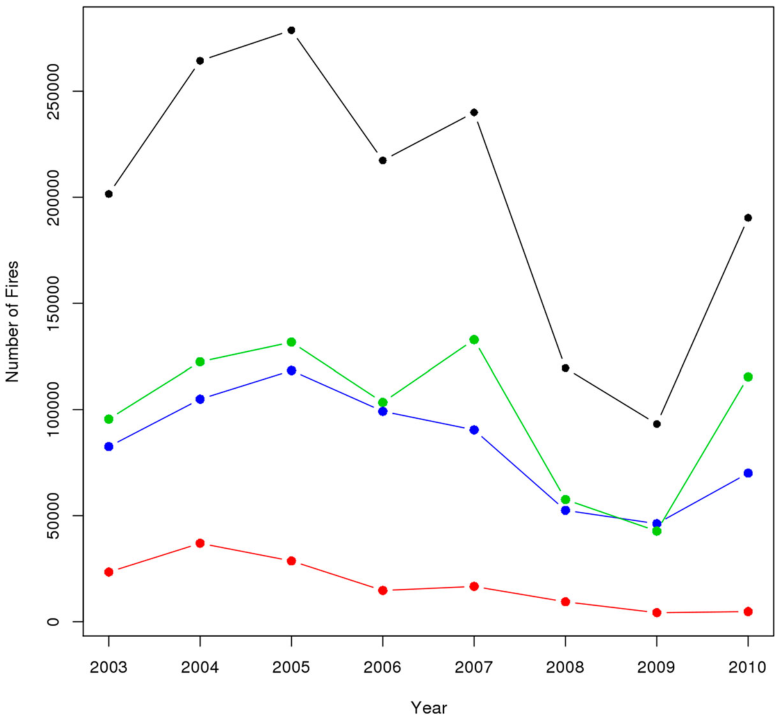

Figure 10. Annual number of MODIS active fire detections classified as forest fires (green), maintenance fires (blue), or deforestation fires (red). The total annual number of MODIS active fire detections (black) are also shown. See Table 4 for numerical values and the proportions classified into the three fire types by year and eight-year total.

southern hemisphere wet season when forest and deforestation fires are less likely to spread and burn for long periods (Morton et al. 2008; Chen, Velicogna et al. 2013; Vasconcelos et al. 2013).

5.3.3. Geographic fire type distributions for all eight study years

Figure 12 shows the majority classified fire type in 7 km × 7 km grid cells for each of the eight years classified. The same general distribution of classified fire types described earlier for the 2003 and 2010 results (Section 5.3.1) is apparent for the intervening study years. At this synoptic scale, the deforestation fires are less apparent because although deforestation classified fires can be locally clustered (Figures 5 and 6), they are often spatially interspersed with other classified fire types (Figures 8 and 9).

The deforestation fires occurred primarily in the ‘arc of deforestation’ and become less apparent later in the study period as their relative numbers decrease (Figure 10). As discussed earlier, the maintenance classified fires occurred over non-forest regions, noticeably over the states of Roraima, Amapá, and also over certain old deforestation regions in the states of Rondônia, Pará, and portions of Mato Grosso (Figure 3). The forest fires occurred more in the interior forested regions along navigable river and road networks, in regions of open and transitional forests (Alencar, Nepstad, and Diaz 2006), and over old deforestation regions throughout the study area (Figure 3). At this scale, it is difficult to describe inter-annual differences. However, notably, in north central Roraima, a distinct belt of classified forest fires along the west of the main classified maintenance fire region is apparent in 2003 and 2007 but not in the other years. This has been documented by Xaud, Martins, and Santos (2013) who noted an increased number of forest fires in this region caused by escaped agricultural maintenance fires burning the forest in 2003 and 2007 under abnormally dry conditions. Relatively, higher classified forest fire activity is

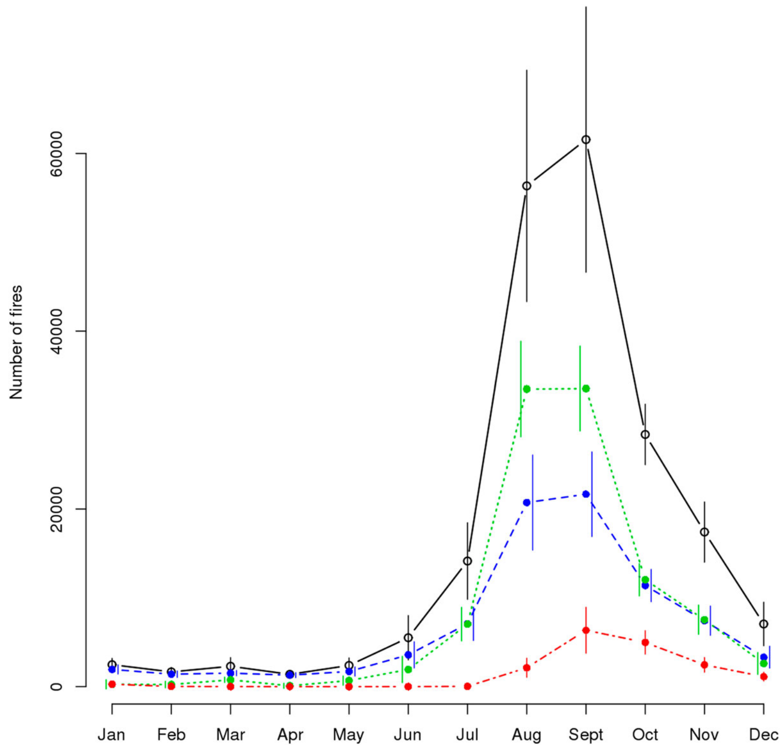

Figure 11. Mean monthly number of MODIS active fire detections (black) for 2003–2010 and the mean monthly number of detections classified as forest fires (green), maintenance fires (blue), or deforestation fires (red). The vertical lines show the monthly mean values ±0.5σ and are shown offset in the x-axis for visual clarity.

observed in 2010 over regions in eastern Mato Grosso, south east, and central Pará, and this has been documented by Brando et al. (2014).

5.3.4. Investigation of the higher incidence of forest classified fires and fire type scan angle dependency

The BTMFB results (Table 4, Figures 10–12) indicate a higher proportion of classified forest fires than the other two classified fire types. This does not necessarily mean that the BTMFB has more aerially extensive forest fires than maintenance or deforestation fires because cumulative MODIS active fire detections do not provide reliable area burned (Roy et al. 2008; Mouillot et al. 2014; Boschetti et al. 2015). Rather, the greater number of classified forest fires may be simply because the greater majority of the BTMFB study area is forested (Figure 3). Indeed, 50.4% of the MODIS active fire detections occurred where the footprint had one tenth or more forest cover. In addition, differences among the characteristic size and temperature of the three fire types may systematically affect their detection probability at different MODIS scan angles. For example, forest fires and also maintenance fires may not burn at nighttime and their sizes may be smaller than 100 m^2 so that they are less likely to be detected by MODIS. This is particularly likely at increasingly higher MODIS scan angles where only larger and/or hotter fires tend to be detected (Giglio, Kendall, and Justice 1999; Mottram et al. 2005; Kumar et al. 2011). Also, for example, the bow-tie effect may result in an over-reporting of large forest fires at high scan angles (Freeborn et al. 2014). To examine these issues, Figure 13 shows a frequency distribution of the classified MODIS active fire detections for the three fire types as a function of the MODIS scan angle. There is no systematic difference among the classified fire types as a function of scan angle suggesting no significant, or a similar MODIS active fire

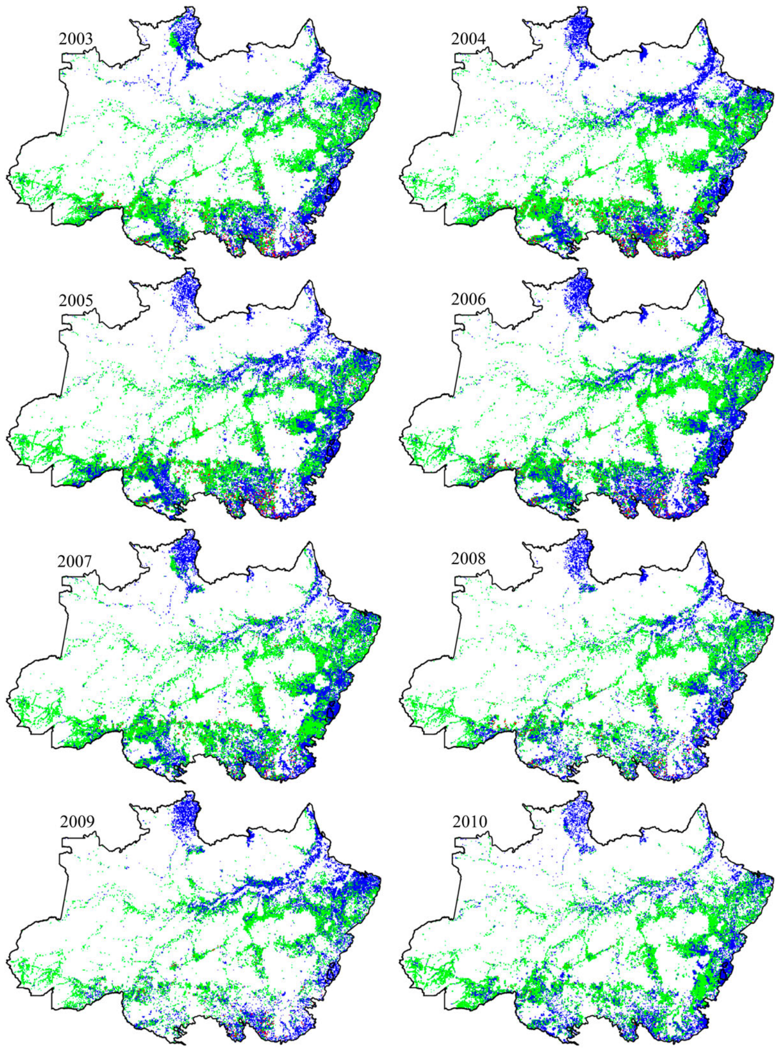

Figure 12. Annual classification results showing the majority classified fire type in 7 km × 7 km grid cells: forest fires (green), maintenance fires (blue), deforestation fires (red).

detection bias, amongst the classified fire types. These results indicate that the higher incidence of BTFBM MODIS active fire detections classified as forest fires is correct.

5.4. Analysis of predictor variable importance for fire type classification

The correlation between each of the predictor variables defined for all the MODIS active fire detections for 2003–2010 was computed. Several of the predictor variables were derived from the same data source and were quite correlated. For example, the greatest Pearson's correlation value (0.89) was between *SumPrecip2m* and *SumPrecip3m*. Considering the variables within each group (Table 1), the smallest absolute correlation values were in the fuel flammability group (0.19 correlation between *SumPrecip1m* and *SumPrecip3m*; −0.30 correlation between *SumPrecip1m* and *SumPrecip6m*) and in the proximity to surface transportation group (−0.14 correlation between *DistRivers* and *DistRoads*). The variables within the other groups had absolute correlation values >0.32. Consequently, an absolute correlation threshold of 0.3 was selected.

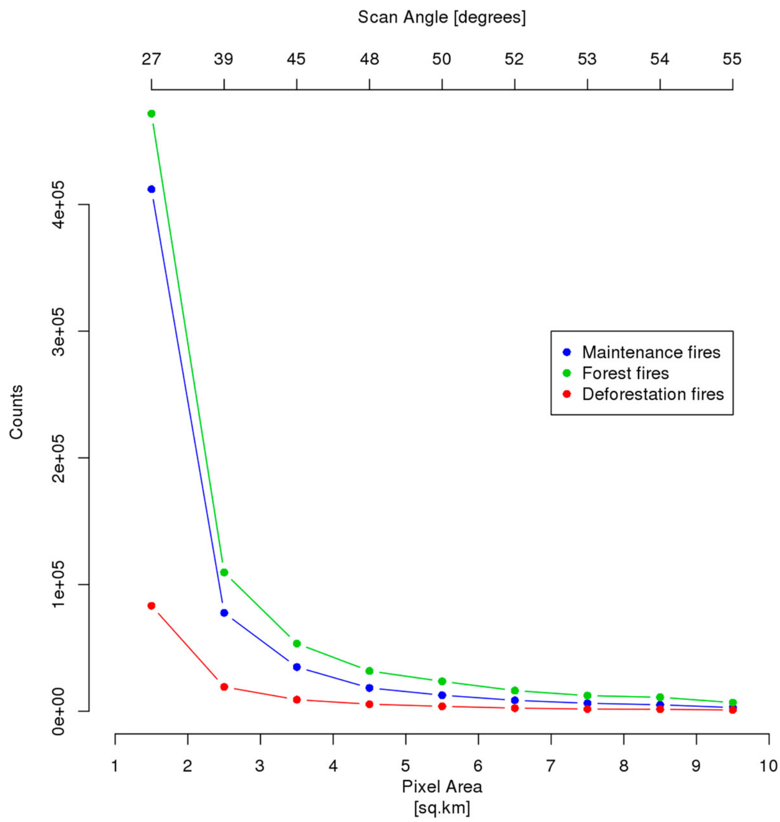

Figure 13. Frequency distribution of eight years of classified MODIS active fire detections shown with respect to MODIS 1 km^2 pixel observation area bins (from 1 to 2 km^2, 2 to 3 km^2, … , 9 to 10 km^2) and the corresponding MODIS scan angle. Only the 1,526,736 classified MODIS active detections not used for training are shown.

Recall (Section 4.4) that all the possible combinations of seven predictor variables found by selecting one predictor variable from each of the groups (Table 1) were considered. If the predictor variables within any combination had an absolute Pearson's correlation coefficient >0.3, then the combination was not considered. This meant that the predictor variables *DistRivers, SumPrecip6m*, and *SumFrp365d* were not considered because one or more of them always had an absolute correlation value >0.3 with a variable from another group. There were a total of 48 combinations considered.

Table 5 summarizes the percentage of times that a group was ranked a specific rank over the 48 combinations. The predictor variable group describing the fire seasonality variables was most frequently the most important variable group followed by the local temperature and then the fuel flammability groups. The proximity to surface transportation group was usually the fourth most important in explaining the random forest fire type classification. The fuel load and the fire behavior groups had similar and intermediate importance. The annual fire frequency group had unambiguously the least importance. The reasons for the ordering of the importance of the predictor variables in explaining the random forest fire type classification are complex as the relative variable importance may change under different conditions. We hypothesize that the fire seasonality variable group captured differences in the timing and the maximum rate of burn among the fire types and that the local temperature group was also important as it captured differences in the vegetation and soil cover and condition among the fire types.

Considering the incremental contribution of each ranked variable group to the overall fire type classification accuracy generated using all the training data indicated 2.96%, 10.83%, 2.58%, 0.06%, 0.75%, and 0.03% increases in accuracy as each ranked variable group was added. Using

Table 5. Predictor variable importance summary showing the percentage (out of 48) of uncorrelated variable combinations that a variable from a group (Table 1) had a particular MDG ranking (where rank one is the most important).

	Rank						
Predictor variable group	1	2	3	4	5	6	7
Fire seasonality	50	46	4	0	0	0	0
Local temperature	50	0	25	21	4	0	0
Fuel flammability	0	54	44	2	0	0	0
Proximity to surface transportation	0	0	23	75	2	0	0
Fuel load	0	0	4	2	94	0	0
Fire behavior	0	0	0	0	0	100	0
Annual fire frequency	0	0	0	0	0	0	100

just the highest ranked fire seasonality variables provided a 73.7% (kappa 0.484) overall fire type classification, and using all the variables from the seven ranked groups provided 90.9% (0.823 kappa) overall fire type classification accuracy. Clearly, all the variable groups have some explanatory power but all the variables in concert are needed to maximize the fire classification accuracy to the accuracy level reported in Section 5.2.

6. Conclusions

This study has demonstrated a methodology to classify MODIS active fire detections over the BTMFB into forest, deforestation, and maintenance fire types. Eight years of active fire detections (2003–2010) were classified with an overall fire type classification accuracy of 90.9% and a kappa of 0.824. The reported spatio-temporal distribution of the classified fire types was geographically plausible and in agreement over regions and periods observed and documented by previous researchers.

The fire type classification accuracy is dependent on the quality and appropriateness of the supervised classification algorithm, the predictor variables, and the training data. A random forest classifier algorithm was used to reduce overfitting of the training data and because it makes no assumptions concerning the statistical distributions of the predictor variables and can accommodate non-monotonic and nonlinear relationships among variables (Breiman 2001). The predictor variables were not selected arbitrarily but rather based on published research on the factors that drive and mediate fire in the Brazilian Amazon, concerned primarily with fuel flammability, fuel load, fire behavior, fire seasonality, annual fire frequency, proximity to surface transportation, and the local temperature. The fire type classification training data were strictly defined and internally consistent with respect to the Brazilian government forest monitoring program (PRODES) classification scheme (PRODES 2013). Of the approximately 1.6 million MODIS active fire detections that were classified, only 4.53% were used to derive training data, providing confidence that the high reported classification accuracy was not driven by the use of an excessive amount of training data.

The reported analysis of the importance of the predictor variables in classifying BTMFB fire type indicates that the variables describing the fire seasonality, local temperature, and fuel flammability are the most important. Predictor variables related to the proximity to surface transportation, fuel load, fire behavior, and annual fire frequency were less important. However, all the variables considered had some explanatory power, and using them together maximized the fire type classification accuracy.

This study described the first supervised classification of MODIS satellite fire types over the BTMFB. Other approaches have inferred fire type, for example, using geographic context and proximity to thematic land cover classes, roads, and forest edges (Nepstad et al. 2001; Schroeder et al. 2005; Alencar, Nepstad, and Diaz 2006; Giglio 2007; Ten Hoeve et al. 2012; Chen, Morton et al. 2013). Unlike other approaches, the described approach uses predictor variable information derived directly from MODIS active fire detections – the top two most important predictor variables were derived from the MODIS FRP (fire seasonality variables) and the MODIS 4 and 11 μm brightness temperatures (local temperature variables). The third most important predictor variables (fuel flammability variables) were derived from the TRMM precipitation product that is systematically generated and available for all of the tropics. We note that the random forest training is critical and dependent on the availability of the PRODES data. However, the majority (95.47%) of the MODIS active fire detections were classified without reference to PRODES, and once the random forest training has been developed, the classifier is generally applicable.

In the remote sensing, random forest classification literature spatial autocorrelation in the response and predictor variables is typically ignored. However, spatial autocorrelation violates the assumption of independence of many statistical modeling procedures and typically result in inflated accuracy estimates (Cliff and Ord 1981; Lennon 2000). Approaches to resolve this issue have been to manipulate the sampling scheme to avoid spatially autocorrelated observations or to explicitly incorporate spatial dependence into the model. For example, one approach used with random forest and decision trees is to include geographic position as a predictor variable (Mascaro et al. 2014). However, the training data should be distributed evenly in geographic space to avoid generating spurious classification accuracies (Friedl, Brodley, and Strahler 1999), which is not possible in this study as the MODIS active fire detections are sparsely distributed. In addition, unlike supervised land cover classification approaches, where training sample points inherently have high spatial autocorrelation due to the way they are collected (Egorov et al. 2015; Millard and Richardson 2015), the training data in this study were derived from a random subset of the MODIS active fire detections and therefore are less likely to be spatially autocorrelated. As observed in similar regional fire-related random forest studies (Archibald et al. 2009; Oliveira et al. 2012), spatial autocorrelation of predictor variables may occur due to various physical and biological processes but no technique to incorporate spatial dependence has been reliably demonstrated and this remains an area of active research. Certainly, the precipitation and proximity to roads and rivers predictor variables are likely to have spatial autocorrelation, but due to the sparse nature of the MODIS active fire detections, this is difficult to investigate unambiguously. The relatively low omission and commission errors reported in this study may therefore have been influenced by spatial autocorrelation effects.

Research to validate the fire type classification results is recommended. Large area fire product validation is complicated by the ephemeral nature of fire and difficulties in obtaining timely independent reference data (Cardoso et al. 2005; Morisette et al. 2005; Schroeder, Csiszar, and Morisette 2008; Schroeder et al. 2015; Roy and Boschetti 2009). In this study, qualitative assessment of some of the classified MODIS active fire types were made by visual comparison with higher resolution Landsat 5 scenes. However, more systematic comparison of the fire type classification results with ground-based observations or higher spatial resolution interpreted satellite data is recommended. In particular, the extent to which the three fire types are mixed within MODIS 1 km active fire detection pixels is unknown and cannot be classified by the present methodology. Over regions with mixed land cover classes different fire types may occur in close proximity, for example, maintenance and deforestation fires may escape into forest edges to cause forest fires (Cochrane and Laurance 2002; Ten Hoeve et al. 2012). Similar fire type classification of moderate spatial resolution satellite active fire detection data, for example, derived from ASTER or Landsat (Schroeder, Csiszar, and Morisette 2008; Schroeder et al. forthcoming) may be helpful to examine this active fire detection scale issue, particularly as the different fire types may have flame fronts with areas smaller than the approximately 100 m^2 MODIS active fire detection threshold.

The fire type classification results presented in this study may improve the regional modeling of greenhouse and trace gas emissions and their transport. Methodologies currently do not consider the fire type explicitly and typically model emissions on the basis of the dominant land cover or vegetation type where active fires are detected (Freitas et al. 2005; van der Werf et al. 2008; Ichoku and Ellison 2013; Castellanos, Boersma, and Van Der Werf 2014; Mitchard et al. 2014). The spatial distribution of the classified fire types may help provide more reliable parameterization of the biomass loading, combustion completeness, and emission factors that differ among the fire types. The temporal distribution of the classified fire types may also be useful to parameterize seasonal variations in combustion completeness and emission factors (Castellanos, Boersma, and Van Der Werf 2014). The results of this work may help policy-makers and regulatory bodies to consider the role of fire in the BTMFB. In particular, the spatial and temporal distribution of fire types may help identify regions experiencing repeated forest fires needed to reduce the incidence of future forest fires. Seasonal knowledge of the different fire type proportions may assist policy-makers more effectively regulate and limit fire to specific periods to minimize the occurrence of forest fires due to escaped maintenance and deforestation fires.

The fire type classification methodology may be applicable to other fire prone regions. However, regional differences in the factors that that drive and mediate fire would need to be taken into account, which is complex given the different interacting roles of physical, climatic, and anthropogenic factors (Nepstad et al. 1998; Cochrane et al. 1999; Archibald et al. 2009; Chen et al. 2011).

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