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Predicting fires for policy making: Improving accuracy of fire brigade allocation in the Brazilian Amazon

Thiago Fonseca Morello[a,*], Rossano Marchetti Ramos[b], Liana O. Anderson[c], Nathan Owen[d], Thais Michele Rosan[e], Lara Steil[b]

[a] Federal University of ABC, Brazil, Alameda da Universidade, S/N, Bairro Anchieta, São Bernardo do Campo/SP 09606-045, Brazil
[b] National Centre for Prevention and Suppression of Forest Fires (PREVFOGO/IBAMA), SCEN Trecho 2, Edifício Sede, Brasília, DF, Brazil
[c] Brazilian Centre for Monitoring and Early Warnings of Natural Disasters (Cemaden), Brazil, Estrada Doutor Altino Bondensan. Eugênio de Mello, 12247016 - São José dos Campos, SP, Brazil
[d] Land, Environment, Economics and Policy Institute, University of Exeter Business School, Xfi Building, Rennes Drive, Exeter EX4 4PU, UK
[e] Brazilian Institute for Space Research (INPE), Av. dos Astronautas, 1.758 - Jardim da Granja, São José dos Campos, SP, Brazil

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ABSTRACT

The positioning of federal fire brigades in the Brazilian Amazon is based on an oversimplified prediction of fire occurrences, where inaccuracies can affect the policy's efficiency. To mitigate this issue, this paper attempts to improve fire prediction. Firstly, a panel dataset was built at municipal level from socio-economic and environmental data. The dataset is unparalleled in both the number of variables (48) and in geographical (whole Amazon) and temporal breadth (2008 to 2014). Secondly, econometric models were estimated to predict fire occurrences with high accuracy and to infer statistically significant predictors of fire. The best predictions were achieved by accounting for observed and unobserved time-invariant predictors and also for spatial dependence. The most accurate model predicted the top 20% municipal fire counts with 76% success rate. It was over twice as accurate in identifying priority municipalities as the current fire brigade allocation procedure. Of the 47 potential predictors, deforestation, forest degradation, primary forest, GDP, indigenous and protected areas, climate and soil proved statistically significant. Conclusively, the current criteria for allocating fire brigades should be expanded to account for (i) socioeconomic and environmental predictors, (ii) time-invariant unobservables and (iii) spatial autocorrelation on fires.

1. Introduction

The fate of the Amazon remains a matter of great concern for researchers, policy makers and a wide range of private and third sector stakeholders, including traditional and indigenous populations. This remains true despite the fact that deforestation, one of the main threats to regional conservation, has been reduced by 58% in the past ten years (2007 to 2017; Prodes, 2019; Godar et al., 2014; Barlow et al., 2016). Indeed, ongoing forest degradation by timber extraction, and by fires used to manage land for (small and large scale) agriculture, remains rampant and may result in an ecological loss comparable to that of deforestation (Barlow et al., 2016; Berenguer et al., 2014). Fires not only damage flora and fauna by spreading accidentally from agricultural fields and pastures (Mendonça et al., 2004; Barlow et al., 2012), but may release more carbon than the rainforest sequesters (Balch, 2014). They also are the main source of air pollution in the rural Amazon, with major health consequences (Reddington et al., 2015; Jacobson et al., 2012; Silva et al., 2016). Over 140,000 fires were detected in both 2015 and 2017, a level last observed before 2008 when deforestation was at least twice as high (INPE, 2018). The main factors influencing recent fire occurrences are anthropogenic ignition (mainly related with changes in land cover, Carmenta et al., 2018; Cano-Crespo et al., 2015; Nepstad and Schwartzman, 1999), climate change which is making the Amazon hotter and drier (Aragão et al., 2018; Vasconcelos et al., 2013; Marengo et al., 2013; Betts et al., 2008; Coe et al., 2013) and forest degradation/fragmentation coupled with previous use of fire (Barlow et al., 2012 and 2016).

To mitigate the impacts mentioned, federal and local governments have been implementing policies targeted at preventing fires and

* Corresponding author.
E-mail addresses: fonseca.morello@ufabc.edu.br (T. Fonseca Morello), Rossano.Ramos@ibama.gov.br (R. Marchetti Ramos), liana.anderson@cemaden.gov.br (L. O. Anderson), N.E.Owen@exeter.ac.uk (N. Owen), tmrgeo@gmail.com (T.M. Rosan), larah.steil@gmail.com (L. Steil).

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suppressing forest fires.[1] Prevention policy includes partial or full bans on agricultural fire use at state level (enforced with surveillance and sanctions), subsidy to fire-free land management practices (e.g., agroforestry and non-timber forest products) and environmental education, among other minor interventions (Carmenta et al., 2013; Prevfogo, 2019a; Morello et al., 2017). Fire suppression, the largest item in the federal fire policy budget (Morello et al., 2017), is mainly targeted at uncontrolled fires spreading across forested landscapes (hereafter “forest fires”). Forest fires are tackled by state and municipal fire brigades, as well as by federal fire brigades funded by the Environment Ministry. From 2010–2014, federal fire brigades were allocated to 56 municipalities of the Legal Amazon per year, with 1900 firefighters/year being employed, representing an expenditure of US$ 3.1 million/year, 1% of the federal budget allocated to the environment (Prevfogo, 2019b). The federal, state and municipal brigades are responsible for supressing fires in the whole Legal Amazon territory (over 5 million km^2), a challenge well beyond the budget available (Morello et al., 2017; Brown et al., 2011). The gap between the area to be protected and capacity to protect (a general characteristic of Amazon conservation policy, see Boyd, 2008a,b) is being widened by the fiscal crisis across all levels of Brazilian government (Montes and Acar, 2018; WWF, 2018). The reach of fire brigades is limited, especially in remote areas, meaning that the burden of fire suppression is often left for landholders, many of them poor smallholders that lack the necessary means, yet suffer disproportionately when forests and fields are lost to wildfire (Carmenta et al., 2013 and 2018). Therefore, there is a pressing need for greater efficiency of forest fire suppression policy, due to both the considerable and nondecreasing frequency of fires and associated forest fire risk and the scarcity of budgetary resources.

One way to achieve greater efficiency is to improve the planning of fire brigade positioning. Such planning is a great challenge due to the large size of the Brazilian Amazon (five million km^2, 20% deforested), of its states (565,442 km^2 in average) and municipalities (6530 km^2 in average), and the pervasiveness of both controlled (set for farming and deforestation purposes) and uncontrolled (escaped) fires. Currently, the data and methods used for planning fire brigade positioning lag far behind the state-of-the-art of current research on Amazon fires, and fail to do justice to the size of the challenge[2] . First[3], too few variables and short time periods are considered for identifying top priority jurisdictions (states and sub-state sets of municipalities). Here, the data consists of counts of fires detected within federal-owned forested land in the previous four years, as well as the type of land (protected area, indigenous land or agrarian settlement, Ramos, 2018; Prevfogo, 2013). No further variables are considered. This fails to capture the multidimensional nature of fire predictors and their recent dynamics influenced by climate change (Arima et al., 2007; Tasker and Arima, 2016; Aragão et al., 2018; Marengo et al., 2011). Second, the interdependence among proximate municipalities, which share common levels of fire and of fire predictors, is imperfectly captured by the "mesoregion" approach. This approach consists of spatially refining the selection of priority states by assessing fire counts in sets of socioeconomically similar municipalities ("mesoregions"). However, academic studies suggest that spatial dependence is driven not only by socioeconomic factors, but also by land use, climate and physical factors (Faria and Almeida, 2016; Hansen and Naughton, 2013; Silvestrini et al., 2011). In summary, there is considerable scope for increasing the efficiency of fire brigade positioning policy by narrowing the gap between current decision making and scientific research. To contribute to this, two research questions are answered in the paper. Firstly, which econometric model most accurately predicts municipal-level fire counts? Secondly, which predictors suggested by literature have a significant effect on municipal-level fire counts?

Three main research tasks were pursued. First, a comprehensive and up-to-date review of the multidisciplinary literature on Amazonian fires was carried out to identify potential predictors of fires. Second, a panel dataset with 47 potential predictors was assembled at the Brazilian Amazon municipal scale. The dataset comprised high-resolution land use data, institutional and socioeconomic information, and satellite measurements of physical and climatic factors, including fires. Both forest and non-forest fires were considered. Four years were covered (2008, 2010, 2012 and 2014), thus capturing Amazon's recent period of lower deforestation, which has been little studied in the literature. Over 98% of the Legal Amazon territory was analyzed. Third, ten econometric panel data models were estimated, comprising standard fixed and random effects as well as their count data and spatial variants. As far as the authors are aware, this is the first study to present an analysis of Amazon fire detections incorporating all relevant predictors stressed in the literature and also the state-of-the-art of spatial panel data econometrics.

An outline of the remainder of the paper is as follows. The next section clarifies, initially, the link between brigade positioning and fire prediction. It then presents a literature review on potential predictors of satellite-detected fires, which are taken in the paper as a proxy for forest fires. The data and methodology are described in Sections 3 and 4 respectively. Results and discussion are presented in Section 5 and the paper is concluded in Section 6.

2. Literature review on the predictors of fires

2.1. Theory and main assumption of empirical analysis

To understand the precise relationship between efficient fire brigade allocation and accurate prediction of fires, a simple model of fire brigade allocation is now presented[4] . In the counterfactual situation where full information on municipal levels of fire occurrence is available a priori, the government’s problem of selecting municipalities for fire brigade allocation can be stated as follows:

$\mathrm{Max}_{\{s\}}\ B(s'F)$, s.t. $C(1's) = C$, F is given

Where B(.) is the aggregate benefit of avoiding fires in the whole Amazon. “s” is a N x 1 vector of binary variables that take value one at the position of selected municipalities and zero otherwise (its transpose is denoted by s’). “F” is the N x 1 vector of ex-post fire occurrences observed across municipalities. It is assumed, for simplicity, that (i) once fire brigades arrive in a municipality, all forest fires are extinguished and (ii) total fire detections, F, is a valid proxy for forest fires. Thus s'F is the number of avoided forest fires. C(.) is the aggregate cost, “C” is the budget, which is assumed to be fully expended. 1′ is a 1 x N vector of ones that performs the sum operation, such that 1′s is the number of municipalities selected. For simplicity, linear benefit and cost functions are assumed. This follows below, with “b” being the unitary benefit of avoiding one accidental fire, and “c” the unitary cost of establishing brigades in one municipality and $N \equiv C/c$.

[1] An important clarification must be made regarding the two main definitions of fire use in the paper, namely, (i) (accidental) forest fires and (ii) satellite fire counts which comprise forest and non-forest fires, and, thus, intended agricultural fires as well (see Section 2.2 below for detailed definitions). These two definitions have different roles in the paper which need to distinguished. First, fire brigades fight only forest fires, i.e., escaped unintended fires. Therefore all policy prescriptions here provided refer exclusively to such type of fire and the term “suppression” means, strictly, elimination of forest fires, as they bring only damage to society. Second, to identify, with econometric prediction, priority municipalities for brigade allocation, all fires are considered, including non-forest (and non-accidental) fires, as justified in Section 2.1 below.

[2] As one reviewer suggested, this gap may be due to the budgetary and technical capacity constraints faced by government personnel responsible for brigade planning and implementation, in line with Rajão and Vurdubakis (2013, p.160) findings regarding the practice of deforestation control.

[3] As local governments do not publicize information on planning criteria, the procedure here described is the one employed for federal brigades.

[4] We thank one of the reviewers for arguing on the need for an explicit formulation of this problem.

$\text{Max}_{\{s\}}$ b.s'F, s.t. 1′s = N, F is given

With the number of municipalities fixed by the constraint, the solution to this problem of maximization of total avoided forest fires is to select the top N municipalities in fire occurrences. Which is exactly the criterion currently used by the federal government. Solution will be denoted as s*(F), with s*(.) being the function that assigns ones to the positions, in the F vector, of top N municipalities and zero to the remaining positions (parameters "N" and "b" are omitted to simplify notation).

However, the true municipal levels of fire occurrences, F, are ex-post observed, after fire brigades are sent. Only fire occurrences in previous years are observed ex-ante. Thus, the (factual) problem faced by government in practice is an incomplete information problem in which F has to be predicted:

$$\text{Max}_{\{s\}}\ \text{b.s'F},\ \text{s.t.}\ 1's = N,\ F \equiv \hat{F}$$

(where the symbol "≡" indicates that predicted fire occurrences are assumed to equal true ex-post fire occurrences)

The solution, $s^*(\hat{F})$, differs from the true best allocation, s*(F). The main implication is that the aggregate (squared) allocation error, measured as $1'(s^*(\hat{F}) - s^*(F))^2$, is positively related with the aggregate (squared) fire prediction error, $1'(\hat{F}-F)^2$, whether the positions (identities) of the top N municipalities differs between F and $\hat{F}$[5] . This highlights the importance of improving fire prediction accuracy. As this requires the incorporation of all reasonable potential predictors of fires, the following subsections synthesize the knowledge on predictors accumulated in the literature, indicating potential predictors by "[P]".

Before passing to the next section, an important detail should be highlighted. In line with previous studies (Silvestrini et al., 2011; Anderson et al., 2017), the assumption that total fire detections are a valid proxy for forest fires is kept throughout the paper, what deserves further clarification. Total fire detections comprise not only forest fires but also intended agricultural fires. These are potential sources of accidental fires (Cano-Crespo et al., 2015; Anderson et al., 2017; Cochrane, 2010, chap.14, Nepstad et al., 2001). They should therefore be accounted for in the prediction of fires that aims to base the allocation of firefighting effort (Silvestrini et al., 2011; Dube, 2013). This is especially true due to the evidence of partial and minor adoption of fire control techniques by fire users (Carmenta et al., 2018; Nepstad et al., 2001; Arima et al., 2007; Carvalheiro, 2004). Notwithstanding, it must also be informed that fire brigades are not legally entitled with the duty (or prerogative) to punish (e.g., fine) the use of fire, even when the latter is conducted illegally or recklessly. This means fire suppression by brigades cannot threat food security of fire-dependent smallholders. Such is the first reason for considering all fires in the prediction exercises conducted in the paper and, in coherence, to account for the predictors of intended fires (as detailed in the next section). The second reason is that counting fire detections belonging to specific fire classes (section 2.2) is out the scope of the paper, as this would require intensive remote sensing techniques which remain prone to significant error (Cano-Crespo et al., 2015; Acevedo-Cabra et al., 2014). There is no robust method for distinguishing between categories of fire in the literature. Also, most studies do not classify fire detections before analysing them (see, for example, Tasker and Arima, 2016; Vasconcelos et al., 2013; Silvestrini et al., 2011).

2.2. Land use and land cover change (LUCC)

Fires in the Amazon can be classified according to the reason for which they are ignited and the land cover they spread through. These classes are presented below (following Fearnside, 1990, Nepstad and Schwartzman, 1999; Myers, 2006; Cochrane, 2010, chap.14). It is also relevant to highlight the spatial scale of the different fire classes. For this, the terms "farm (scale)" and "landscape (scale)" are used in brackets. The former indicates that the spread of the fire is restricted to the boundaries of the farm within which it is started, whereas the latter refers to a wider spread across multiple farms and forested areas.

1 Agricultural fires [farm]: intentional fires for agricultural purposes, specifically:
   a Deforestation fires: aimed at removing debris (slashed vegetation) resulting from the opening of new fields for agriculture.
   b Pasture fires: aimed at managing and restoring pasture.
   c Fallow fires: aimed at fertilizing, weeding and cyclically shifting secondary forest cover (of spontaneous growth) into cropland, as part of the slash and burn agricultural system.
2 Accidental fires [landscape]: unintentional fires that occur as outcomes of agricultural fires or careless human activities, namely:
   a Forest fires: accidental fires that penetrate standing forest.
   b Accidental fires on farmland: penetrates farms harming or extirpating fixed capital assets (fences, crops, pasture, facilities, etc).
3 Arson fires [landscape]: intended fires motivated by conflicts (retaliation/vendetta fires) or by vandalism.

Only class "1″ fires are directly related with land use and land cover change (LUCC), more precisely, with deforestation [P], pasture [P] and fallow-based crop growing [P]. The extents of primary [P] and secondary [P] vegetation are also relevant predictors of agricultural fires. The former is still used by farmers as natural barriers to contain fires (Carmenta et al., 2013; Carvalheiro, 2004, p.154, Toniolo, 2004, p.184, Cammelli, 2014, p.70) and the latter may in part capture fallows and also abandoned land. Besides deforestation, forest degradation [P] by timber extraction is also a relevant land use change, as it is generally conducted before slashing and burning of vegetation (Rappaport et al., 2018; Barlow et al., 2016).

2.3. Agriculture

There is wide evidence on the link between agriculture and fires. Deforestation, one of the main reasons for burning, was shown by multiple studies to be influenced by the price of agricultural commodities (Hargrave and Kis-Katos, 2013; Assunção et al., 2015; Verburg et al., 2014). Medium to large scale growers of soybean [P], one of the main export commodities of the Amazon, are also known for deforesting or buying deforested land (Morton et al., 2006; Arima et al., 2011). Smallholders rely on slash-and-burn mainly to grow annual staple crops i.e., cassava, maize, cowpea and rice (Kato et al., 1999). Planting of perennial crops, although initially less relevant among smallholders, has been increasing on small, medium and large farms, mainly due to the larger profit per hectare implied (Börner et al., 2007a; Soler et al., 2014). This higher profitability, coupled with a higher vulnerability to fire, led some authors to conjecture that the expansion of perennials may be accompanied by the reduction in fire usage (Barlow and Peres, 2004; Simmons et al., 2004; Nepstad and Schwartzman, 1999). Therefore, space and time variation of the prices of soybean, staple crops and perennials [P] should affect detected fires, both via the profitability of land and via the expected damage caused by accidental fires (Bowman et al., 2008; Scatena et al., 1996; Perz, 2003). This is also the case for the products of cattle ranching, especially the price of calves, milk and beef [P], whose relation with deforestation are clearly established by previous studies (Hargrave and Kis-Katos, 2013; Margulis, 2003; Assunção et al., 2015; Aragão et al., 2008).

Value added by primary activities [P], a measure of the economic performance of agriculture, also tends to be related with fire use but it is unclear whether the relationship is positive or negative. Firstly, if studied from the point of view of productivity, a negative relationship is expected. This is because the productivity of fire-based agriculture (i.e., slash-and-burn), a labour-intensive and small-scale activity, is generally

[5] In fact, it is both a sufficient and necessary condition for differences between s*(F) and $s(\hat{F})$ that the positions of the top N municipalities differs between F and $\hat{F}$ (i.e., the difference refers to "who" the top N are) Whereas such implies in both positive total squared prediction and allocation errors, all other differences between F and $\hat{F}$ do not imply in positive total squared allocation error.

lower than that of capital-intensive agriculture (Sauer and Mendoza-Escalante, 2007; Mburu et al., 2007; Boserup, 1965). Moreover, productivity tends to be positively correlated with value added (as synthesized in the Solow growth model, Romer, 2014). Secondly, focussing on the composition of the municipal economy, more agriculture-dependent economies may also be more reliant on fires (assuming that the variation of the share of fire-based agriculture across municipalities is small and considering that agricultural fields are opened with fire-based deforestation). However, this depends of course on the contribution of perennial crops to total agricultural value, both due to the higher value added by these crops and the incentive they create to reduce fire use (Börner et al., 2007a; Perz, 2003; Nepstad and Schwartzman, 1999). Other mechanisms relating to yield and deforestation (linked to fires, see Section 2.1) are also suggested by the literature. Ewers et al. (2008) and Marchand (2012) argue that increases in yield (introduced, for instance, by technology adoption or expansion of perennials) may decrease deforestation through a land sparing effect or increase it as further investment in agriculture is stimulated by the leap in profitability.

In addition, exports of timber [P], a proxy for the level of timber extraction[6], may also correlate with fires as the shift of land from forest to agriculture is conducted after timber is extracted (Rappaport et al., 2018; Tasker and Arima, 2016).

2.4. Municipal economy and demography

There is evidence that the size of the municipal economy and the level of development are predictors of deforestation and therefore could be related to agricultural fires (Hargrave and Kis-Katos, 2013; Rodrigues et al., 2009 and Weinhold et al., 2015). Indeed, municipal GDP [P] is, by construction, directly proportional to the levels of both agricultural production and investment on fixed capital, the latter including agricultural machinery that can be used as a substitute for fire. Alternatively, the relationship between GDP and fire occurrences may be non-linear, following a "Kuznets curve" pattern with positive and negative covariations prevailing at, respectively, low and high levels of GDP (Andela et al., 2017; Boserup, 1965). Such pattern, is consistent with the "industry life cycle theory". The latter stablishes that economic development starts with extensive agriculture as the main activity and proceeds with intensification of agriculture and an increase of manufacture and service industries (Hall and Caviglia-Harris, 2013; Boserup, 1965). In summary, the reasons for both a linear and a non-linear relationship seem plausible enough to justify the accounting of GDP as a potential predictor of fires. Also, the municipal level of human development [P] tends to be positively correlated with the level of economic development, this referring mainly to the adoption of high-productivity and capital-intensive technology, and, therefore, to the transition to fire-free agriculture (Hall and Caviglia-Harris, 2013; Andela et al., 2017; Boserup, 1965).

Previous studies suggest a feedback between (a) lack of access to preconditions for fire-free agriculture, which is associated with income poverty [P], and (b) low productivity/low capital accumulation (Coomes et al., 2011; Sorrensen, 2009; Börner et al., 2007b). Such a "fire-based poverty trap" (paraphrasing Coomes et al., 2011) is strengthened by unfavourable levels of input and output prices faced by Amazonian smallholders, who generally live in remote and road-deprived areas (Sorrensen, 2009). It should be clarified that for simplicity here, poverty is understood strictly as low income, as a multidimensional approach is beyond the scope of the paper. However, we recognize the limit of such an approach for Amazon smallholders, whose integration to market is limited by structural factors (Guedes et al., 2012).

The literature also suggests that fire has demographic predictors such as population density and degree of urbanization. The first is in accordance with the classical Boserupian argument (Boserup, 1965) that agricultural fires tend to decrease as the land becomes more densely populated [P], a process that favours agricultural intensification (Metzger, 2003; Roder, 1997). The second predictor, the degree of urbanization [P], is also expected to reduce agricultural fires. One reason for this is that, as at high levels of urbanization, the damage from externalities, such as accidental fires and air pollution, may be big enough to outweigh the benefits from fire (Shafran, 2008; Analitis et al., 2012). A more straightforward link is that the land available to be burned for agricultural purposes decreases with urbanization.

Another potential predictor is proximity to roads [P], which is a driver of agricultural profitability and, consequently, of fire-based deforestation (Arima et al., 2007; Cardoso et al., 2003; Pfaff et al., 2007; Ewers et al., 2008; Araujo et al., 2009). It should be noted that the relationship between access to roads and fire occurrences may be positive, if the effect of profitability on deforestation dominates (Pfaff et al., 2007), or negative, if the effect of profitability on the expected damage imposed by accidental fires dominates (Weinhold and Reis, 2008; Bowman et al., 2008).

2.5. Institutions

There are three types of land owned by Brazil's central government (hereafter "federal lands"), in which fires may exhibit specific behaviours: protected areas [P], agrarian settlements [P] and indigenous lands [P]. In protected areas, deforestation and agricultural fires are subjected to harsher legal constraints compared to other areas, and evidence shows that these restrictions are met (Nepstad et al., 2006; Arima et al., 2007; Nolte et al., 2013). Protected areas of all categories (i.e., both strictly protected and of sustainable use) are included in the empirical exercise. In agrarian settlements and indigenous lands, specific patterns of fire use may also be observed. Agrarian settlements are inhabited by smallholders that are mostly income poor and face multiple barriers to adopt alternatives to slash-and-burn, including remoteness, lack of access to basic public services and poor soil quality (paved roads, electricity, sanitation, etc.; Guedes et al., 2012; Peres and Schneider, 2012). Thus the utility of fires and, thus, their frequency, tends to be higher in agrarian settlements, and this is confirmed by previous research (Anderson et al., 2017; Godar et al., 2014; Carmenta et al., 2018). Indigenous communities impose a lower pressure on land-based resources (Nepstad et al., 2006) and rely on fire not only for subsistence agriculture, but also for hunting as well as cultural and religious activities (Leonel, 2000). Nepstad et al. (2006) and Arima et al. (2007) found a significantly lower number of fires in indigenous lands.

In addition, private property [P] is the type of land tenure most strongly associated with agriculture (Araujo et al., 2009), and tends to correspond with a considerable number of fire detections (Anderson et al., 2015 and 2017, Cano-Crespo et al., 2015).

Another possible predictor is whether a federal fire brigade was established in the municipalities [P] in the current year. First, because fire brigades are allocated based on the fire occurrences expected by authorities, a function of fire occurrences in previous years (as argued in the introduction). Second, fire brigades act to contain forest fires, thus reducing fire detections[7] .

[6] Exports were considered instead of the value of timber extracted, as data on the former was missing for 44 of the 719 municipalities analysed (such data is sourced by the Brazilian Institute of Geography and Statistics survey on extraction and silviculture).

[7] The potential endogeneity of fire brigades in a model explaining fires is mitigated by including, as explanatory variables, a wide range of factors (46 in total) that could be correlated with brigade allocation if left to the disturbance term. I.e., we resort to the conditioning on observables (Morgan and Winship, 2006, chap.3) against omitted variable bias. This strategy is reasonable to achieve the paper's goal of predicting fires, a task that requires incorporation of all potentially relevant predictors (including fire brigades). It should also be noted that fire brigades positioning is defined based on fire detections of previous years, whereas, in the models, fire brigades are related with the fire detections of the current year. The precautions here detailed were taken to ensure minimum accuracy in the analysis of covariates' significance but precise measurement of causal effects is out of the paper's scope.

2.6. Climate and physical factors

Temperature [P] and precipitation [P] are becoming progressively more influential on fires due to ongoing climate change (Aragão et al., 2018, Tasker and Arima, 2016, Fonseca et al., 2017; Silvestrini et al., 2011). The two variables are influential not only across time but also across space (Vasconcelos et al., 2013; Cano-Crespo et al., 2015; Marengo et al., 2011). Vasconcelos et al. (2013) found a strong negative correlation between fire detections and rainfall in the state of Amazonas. Tasker and Arima (2016) obtained the same result at the level of Amazon municipalities. Also, in the fire behaviour model presented by Cochrane (2010, 14.5 and 14.9.2, fig.14.9), both humidity and temperature enter as explanatory factors. Biophysical factors related with soil also merit attention due to their effect on the cost-benefit of fire use (Kato et al., 1999; Arima et al., 2011; Takasaki, 2011). In particular, slope of the terrain [P] and soil texture [P] drive the agricultural profitability of land and also its suitability for mechanization (Robalino and Pfaff, 2012).

3. Data

A detailed description of data sources is found in supplementary material, Section 1 (SI.1). Here, only the data that required operations and conventions to be assembled are mentioned. The $\log(1 + x)$ transformation was applied to all variables measuring area, monetary units, length and temperature (23 variables). This is because these variables had numeric scales (order of magnitudes) considerably different from the remaining variables, which were mostly constrained to the [0:1] interval. Table 1 provides the definitions and summary of all (pre-logarithm transformation) variables.

The spatial scale of the data is municipal and the temporal scale is annual with one-year gaps. The scales were dictated by the resolution of the data sources. Specifically, the spatial scale was defined by agricultural and socioeconomic data (sections 3.2,3.5 and 3.7 below). The temporal scale was defined by land use data from the TerraClass project (INPE, 2019).

3.1. Dependent variable

The dependent variable in the analysis was a count of point detections of fire (a.k.a "fire hotspots" or "hotpixels", Giglio et al., 2016). This datum came from the MODIS sensor of NASA's Terra satellite and was pre-processed by the Brazilian Institute for Space Research (INPE). All fire detections were used without a filter to isolate detections due to forest fires (as clarified in section 2.1 above).

3.2. Crop price index

Two crop price indices were calculated, based on a municipal crop survey (IBGE, 2016). The indices were a weighted average of annual and perennial crop prices, with weights given by the crop's share of total production value for main crops. For the annual crop index, the main crops consisted of soy, rice, cassava, beans and maize. The contribution of these crops to regional agriculture amounted to 87% in harvested area and 74% in produced value in the period of study (2008, 2010, 2012, 2014). For the perennial index, the main crops consisted of banana, cocoa, coffee, black pepper and rubber. These crops contributed 74% of harvested area and 73% of produced value. Prices for the years of study were converted to the purchasing power of currency in 2008 before calculation of the indices. The FAO's food price index formula (FAO, 2013, eq.1), applied to a municipality-year observation unit, is as follows:

$$price\ index_{i,t} = \sum_{k=1}^{K} (w_{k,\bar{2008}}) \frac{p_{k,i,t}}{p_{k,\bar{2008}}} = \sum_{k=1}^{K} \left(\frac{\sum_{i=1}^{I} v_{i,2008,k}}{\sum_{i=1}^{I} \sum_{k=1}^{K} v_{i,2008,k}} \right) \frac{p_{k,i,t}}{\frac{\sum_{i=1}^{I} v_{i,2008,k}}{\sum_{i=1}^{I} q_{i,2008,k}}}$$

With "k" indexing crop, "i", municipality and "t", year. The symbols "p.", "v." and "q." refer to implicit price (value/quantum ratio), value and quantum, respectively. To capture only the variation in prices, excluding the effect of the crop composition of value, the above index was based on a reference year (2008) and a reference municipality, which was the average municipality in 2008. Thus, the weight and "base price" were calculated as (weighted) averages across municipalities. A total of 13 municipalities did not produce annual crops in at least one of the years (zero value of production). For perennial crops, zero or missing production were recorded for 174 municipalities. For these cases, where possible, the average prices of contiguous municipalities were imputed. Where this was not possible (no contiguous municipalities with positive production), second other contiguity was used (following Hilber and Vermeulen, 2010, Section 4.1).

3.3. Temperature data

Land surface temperature data was taken from NASA's MODIS satellite sensor. An examination of monthly temperatures between 2003 and 2014 revealed the existence of two subannual periods of distinct temperature: January-June and August-October (see Fig. 1). These two periods approximately match the wet and dry seasons defined by Marengo et al (2011). Remaining months were assumed to be transition stages and ignored. In this work, temperature data was averaged across time into the two subannual periods and across all 5 km pixels located inside each municipality.

3.4. Soil

A map of physical classification of soil was used (IBGE, 2007 and 2012). Four main textures of soil from a total of six textures were considered: loamy, clayey, high clayey and sandy. The municipal area with soils of non-identified texture and minor textures (organic and silty) were not considered for calculating the areal share of the four main textures. As the shares are constrained to sum to one, loamy texture was omitted from models to avoid perfect collinearity.

3.5. Proxy for cattle prices and timber exports

Unfortunately, municipal-level data on cattle prices in the Amazon is only available for the state of Mato Grosso. To fill this data gap, two proxy variables were used. The number of employees in the beef processing industry was considered, which captures part of the demand for cattle. Also, cattle herd sizes were used, which is a measure for cattle supply but also for ranch productivity as whole pasture areas of municipalities were controlled for in the models.

Exports of timber in US dollars (purchasing power of 2008), were obtained from the database of Brazilian Ministry of Industry, Trade and Services (MDIC, 2018), by selecting the product class "Wood and articles of wood; wood charcoal".

3.6. Institutional variables

Institutional variables capture the extent of the three types of federal lands (see 2.4 above): protected areas, agrarian settlements, and indigenous lands. The latter was refined based on information about completion of the main stages of the administrative process of formal recognition of indigenous ownership by the federal government (as detailed in FUNAI, 2019[8]). The date in which indigenous lands were officially defined as state property ("data de regularização") was available for 82% of the lands only. Among the remaining lands, only the ones authorized by the federal parliament to be created

[8] The stages captured in the data were "estudo", "delimitação", "declaração", "homologação" and "regularização".

Table 1
Definition and summary of variables.

Category	Description [measure]	Short name	Mean [S.D]	Range
Dependent variable	Number of fire detections [count]	fires	204.7 [406]	[0:10049]
LUCC	Deforestation [km^2]	defor	9.3 [29.1]	[0:731]
LUCC	Crops: soy [km^2]	soy	56 [270.2]	[0:3620]
LUCC	Crops: fallow (crops mixed with ranching) [km^2]	fallow	23 [54.5]	[0:925]
LUCC	Pasture [km^2]	pasture	552.4 [932.9]	[0:12951]
LUCC	Primary vegetation [km^2]	pri_forest	4440.5 [12874.1]	[0:147943]
LUCC	Secondary vegetation [km^2]	sec_forest	290.5 [418.7]	[0:4400]
LUCC	Forest degradation [km^2]	degrad	16.4 [87.9]	[0:2450]
Agriculture	Annual crop price index [R$/ton]	a_price	0.6 [0.3]	[0:2]
Agriculture	Perennial crop price index [R$/ton]	p_price	0.6 [0.3]	[0:2]
Agriculture	Value added by primary sector [R$ 10^6]	v_added_prisec	47.9 [72.3]	[0:830]
Agriculture	Cattle herd [10^3 heads]	herd	105.7 [156.9]	[0:2213]
Agriculture	Employment in beef industry [count]	emp_beef	51.1 [230.2]	[0:5262]
Agriculture	Timber exports [USD 10^6]	timber_exp	0.9 [6.7]	[0:192]
Economy and demography	Municipal GDP [USD 10^6]	gpd	392 [2005.1]	[7:48149]
Economy and demography	Population [10^3 count]	pop	32.6 [104.9]	[1:2020]
Economy and demography	HDI 2010 [percent]	hdi	0.62 [0.06]	[0.4:0.8]
Economy and demography	Share of households with zero income [%]	pov_zero	0.12 [0.09]	[0:0.6]
Economy and demography	Share of rural households (RHH) with income $<$ 1/4 minimum wage [%]	povm025	0.06 [0.04]	[0:0.2]
Economy and demography	Share of RHH with 1/4 MW $<$ income $<$ = 1/2 MW [%]	povM025m05	0.08 [0.05]	[0:0.2]
Economy and demography	Share of RHH with 1/2 MW $<$ income $<$ = 1 MW [%]	povM05m1	0.24 [0.06]	[0:0.4]
Economy and demography	Urban area [km^2]	urban	6.5 [20.7]	[0:343]
Transport	Length of official roads (paved or unpaved) [km]	off_roads	113.4 [133.9]	[0:1067]
Transport	Length of unofficial roads (paved or unpaved) [km]	noff_roads	740 [1577.2]	[0:18260]
Category	Description [measure]	Short name	Mean [S.D]	Range
Institutions	Protected areas [km^2]	protected	864.5 [3895.6]	[0:56155]
Institutions	Agrarian settlements [km^2]	settlements	882.9 [2387.2]	[0:27115]
Institutions	Indigenous lands [km^2]	indigenous	1544.4 [6459]	[0:99307]
Institutions	Private properties [km^2]	acar	2602.9 [3990.3]	[0:35898]
Institutions	Presence of federal brigade (binary)	brif	0.1 [0.3]	[0:1]
Biophysical	Average annual precipitation [m/year]	av_ppt	1.9 [0.5]	[1:4]
Biophysical	Average temperature, January-June (JJ) [Kelvin]	av_temp_JJ	300.3 [2.1]	[296:309]
Biophysical	Average temperature, August-October (AO) [Kelvin]	av_temp_AJ	307 [4.6]	[299:318]
Biophysical	Slope of the terrain, first quartile [%]	slope_p25	0.01 [0.01]	[0:0.04]
Biophysical	Slope of the terrain, second quartile [%]	slope_p50	0.02 [0.01]	[0:0.09]
Biophysical	Slope of the terrain, third quartile [%]	slope_p75	0.04 [0.02]	[0:0.22]
Biophysical	Soil quality: share of sandy texture in municipal area with identified soil texture [%]	soil_sandy	0.14 [0.18]	[0:1]
Biophysical	Soil quality: share of area with clayey texture [%]	soil_clayey	0.2 [0.2]	[0:1]
Biophysical	Soil quality: share of area with high clayey texture [%]	soil_hclayey	0.07 [0.15]	[0:1]
Additional controls	Municipal area [km^2]	area	6907.5 [14009.3]	[64:159523]
Additional controls	Time [year]	time	11 [2.2]	[8:14]
Additional controls	State dummies (nine states) [binary]	d_uf	omitted	[0:1]

Note: the sample contains 2876 observations capturing 719 municipalities of Legal Brazilian Amazon for four years, 2008, 2010, 2012 and 2014. Most of the 52 municipalities excluded were at least partially outside the reach of land use data. Monetary factors (prices, v_added_pri_sec, gdp, timber_exp) are expressed in purchasing power of 2008.

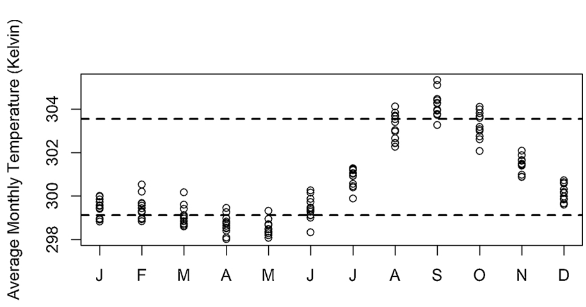

Fig. 1. Monthly temperature (dots), Legal Amazon average*, and the subannual averages (dashed lines) for January-June and August-October 2003-2014.
*The graph was computed from the average temperature of all Brazilian Legal Amazon pixels (longitude between -76° and -44° and latitude between-18° and 5°).

("declaradas") were considered. From the authorized lands, it were excluded those without information about the date when the stages before authorization were terminated, in order to avoid including lands not locally recognized as belonging to indigenous people. As the result, 352 of 376 (95%) of the total indigenous lands (September 2016) in the Legal Amazon region were included.

Aside from federal land types, the area of private property in the municipality was also considered. This was proxied by the georeferenced property boundaries retrieved from the rural-environmental land registry of federal government ("CAR", see SICAR, 2018)[9] .

3.7. Economy and demography

A range of economic and demographic variables for the municipalities were used, including GDP, population, and head-count measures for income poverty. The latter consisted in the share of households with income below one minimum wage (~US$300), using the latest population census (of 2010). This was broken down into four intervals with the thresholds of zero, one quarter, half and full minimum wage.

Two separate variables derived from different sources of road length data were considered. Firstly, information on official (i.e., government-

[9] Overlaps of property polygons were eliminated before aggregating municipal areas to avoid double counting.

owned) roads was obtained using a digital map from the Brazilian Ministry of Environment (MT, 2018). Secondly, information on unofficial (i.e., built by private landholder) roads was gained using a digital map from the NGO "Imazon" (Imazon, 2018). In both cases, paved and unpaved roads were considered.

4. Method

4.1. Econometric models

4.1.1. General approach

It is clear that the influence of social and environmental predictors on fires has both temporal and spatial dimensions (section 2). Moreover, non-observed factors may also be influential. These aspects are captured by the following general specification for panel data models:

$$Y_{it} = f(X_{it1},\dots,X_{itK};Y_{-it}) + u_{it} \quad (0.a)$$

$$u_{it} = g(\mu_i,\mu_{-i},v_{it},v_{-it}) \quad (0.b)$$

$i = 1,\dots,N,\ t = 1,\dots,T$

where Y_{it} is the number of fires detected in the i-th municipality at the t-th time instant, f(.) is a functional form approximating the true form of the conditional expectation $E[Y_{it}|X_{it1},\dots,X_{itK};\ Y_{-it}]$, and $X_{it1},\dots,X_{itK}$ are K predictors. The disturbance term u_{it} captures unobservable factors and is made up of two components (Elhorst, 2014; Baltagi, 2005; Wooldridge Jeffrey, 2002). The first, μ_i, represents time-invariant unobservables potentially correlated with covariates, and is referred as "unobserved heterogeneity". The second, v_{it}, captures space and time variant unobservables. The spatial dimension is explicitly introduced by Y_{-it}, μ_{-i} and v_{-it}, which denote the number of fires and the levels of time invariant and time variant unobservables, respectively, for proximate municipalities. For the general model to be "estimable", assumptions need to be made about f(.) and g(.). and the main possibilities, which group into three classes, are detailed in what follows.

4.1.2. Ordinary panel data models

Ordinary panel data models assume that f(.) and g(.) functions are linear and that spatial independence applies both to the dependent variable and to the disturbances, as follows (Baltagi, 2005; Wooldridge Jeffrey, 2002):

1.a $Y_{it} = X_{it}\beta + u_{it}$

1.b $u_{it} = \mu_i + v_{it}$

The general form above was estimated with pooled ordinary least squares (POLS), fixed-effects (FE) and random effects (RE) estimators.

4.1.3. Count data models

Ordinary panel data models do not account for the fact that the dependent variable, in this case the number of fires, is constrained to be a natural number. As a result, predictions from these models may return negative or fractional numbers. To generate predictions numerically consistent with the dependent variable, Poisson (2.a, 2.b, PFE and PRE) and negative binomial models (fixed-effects, 2'.a, 2'.b, NFE; and random-effects, 2''.a, 2''.b, NRE) are estimated, as specified below (Cameron and Trivedi, 2009; Wooldridge Jeffrey, 2002; Hausman et al., 1984):

2.a $Y_{it} = \exp(\beta' X_{it}) + u_{it}$

2.b $u_{it} = \mu_i + v_{it}$

2'.a $Y_{it} = \exp(\beta' X_{it})/\delta + v_{it}$

2'.b $V[Y_{it}|X] = \exp(\beta' X_{it})(1 + \delta)/\delta^2$

2''.a $Y_{it} = \mu_i \exp(\beta' X_{it})/\varphi_i + v_{it}$

2''.b $V[Y_{it}|X] = \mu_i \exp(\beta' X_{it})/\varphi_i\ (1 + \mu_i^{1/\varphi i})$

The only difference between ordinary and count panel models is that the latter assume a non-linear form for the f(.) function and, for the case of the NBFE specification, the unobserved heterogeneity is introduced as a multiplicative factor.

4.1.4. Spatial panel models

Spatial panel models assume a linear form for f(.) and g(.) functions and also assume spatially autocorrelated dependent variable and disturbances. Fixed-effects (SFE) and random-effects (SRE) estimators were used. For both approaches it is assumed that the two components of the disturbance term incorporate spatial autocorrelation in the fashion of Kapoor et al. (2007). Estimation was pursued with maximum likelihood (SFEM, SREM) and generalized method of moments (SFEG, SREG) using the R package "splm" (Millo and Piras, 2012). The functional form is as follows (Elhorst, 2014; Millo and Piras, 2012).

$$Y_{it} = \lambda \sum_{j=1}^{N} w_{ij} Y_{jt} + X_{it}\,\beta + u_{it} \quad 3.a$$

To account for spatial dependency in the unobservables, equation (0.b) is replaced by:

$$u_{it} = \rho \sum_{j=1}^{J} w_{ij} u_i + \mu_i + v_{it}; \quad 3.b$$

where "w_{ij}" is the j-th row of the (row-standardized) spatial weights matrix for which queen contiguity is assumed (i.e., neighbouring municipalities are those which share boundaries' lines or vertices). The strength of the spatial autocorrelation on the dependent variable and disturbance term are captured, respectively, by the parameters "λ" (hereafter simply "spatial effect") and "ρ".

4.2. Assessment of model performance

4.2.1. Out of sample prediction

For linear panel data models, the best linear unbiased predictor (BLUP) "S" steps ahead has the general form (Baltagi, 2008; Fingleton and Palombi, 2013; Baltagi et al., 2011):

$\hat{y}_{i,T+S} = M_i(Z_{i,T+S}'\,\hat{\beta}_T + \text{correction term}),\ S \geq 1,\ i = 1,\dots,N$

$M_i = [(I_N - \hat{\lambda}_T W_N)^{-1}]_i$ (the i-th row), for spatial models and $M_i = 1$ for non-spatial models

where Z' is a 1 x (K + 1) vector (meaning the intercept is included in the model). The "correction term" adjusts for the non-spherical (autocorrelated, Wooldridge Jeffrey, 2002, 10.4.1) structure of the residual variance-covariance matrix imposed by the presence of unobserved heterogeneity. For the random-effects spatial and non-spatial models, the correction term is as follows (Fingleton and Palombi, 2013; Baltagi et al., 2012, 2011, Appendix).

$$\textit{Correction term RE} = \left(\frac{\hat{\sigma}_\mu^2}{\hat{\sigma}_v^2 + T\hat{\sigma}_\mu^2}\right)\sum_{t=1}^{T}\hat{u}_{it}$$

where $\hat{\sigma}_\mu^2$ and $\hat{\sigma}_v^2$ are estimates for the variances of the unobserved heterogeneity and the time-variant components of disturbances respectively. The residuals are represented by $\hat{u}_{it}$.[10] For fixed-effects spatial or non-spatial models, the correction term equals the estimate for the unobserved heterogeneity (Baltagi, 2008), given by $T^{-1}\sum_{t=1}^{T}\hat{u}_{it}$.

The count data models (Poisson and negative binomial) were not considered for out-of-sample prediction for three reasons. Firstly, the

[10] In matrix notation, BLU predictions for spatial RE models are obtained from the N x 1 matrix $P(X_b, X_\tau, g) = (1-\hat{\lambda}W)^{-1}(X_\tau\hat{\beta} + f\Gamma\hat{e})$. In this equation, "f" is the variance fraction (term in parentheses in the correction term formula), "Γ" is the matrix that sums residuals for the i-th unit, "ê" is the vector of residuals, X_b is the base-data for the estimates ($\hat{\beta}$, $\hat{e}$ and $\hat{\lambda}$), X_τ is the data for predicting Y, and g is the estimator (MLE/GM).

concept of "best linear unbiased predictor" is ill-defined as they are not linear. Secondly, it was not possible to find, in the literature, formulas for the best (non-linear) predictors of the models. Finally, in-sample predictions from these models could not be obtained or were considerably less accurate compared to the other models (the only exception was the random-effects negative binomial).

The out of sample predictions are for 2014 and were based on models fit to the first three years of data. Their accuracy was assessed with the root mean squared error (RMSE), the most popular metric in the literature (Baltagi, 2008; Baltagi and Li, 2004; Chakir and Le Gallo, 2013). RMSE is reported together with another goodness of fit measure, a pseudo-R^2 statistic computed for the whole sample. The pseudo-R^2 statistic is calculated as the squared correlation between the observed and predicted dependent variable, as commonly computed by the STATA ® software (Cameron and Trivedi, 2009, chap. 8, STATA, 2016) and as recommended for spatial panels by Elhorst (2014, p.59 and Table 3.1).

4.2.2. Prediction performance and consistency

Among the three main properties of an estimator, unbiasedness, consistency and efficiency, it is generally accepted in the practice of econometrics that the second is the minimal (Wooldridge Jeffrey, 2002, 5.1). The data analysed here is subjected to two main sources of inconsistency, spatial dependence in the dependent variable, and correlation between unobserved heterogeneity and the explanatory variables[11] . To check for these inconsistencies, Moran's I and Hausman tests were applied. It should be noted that for the objectives of this work, inconsistency is only an issue for the identification of influential drivers of fire behaviour, where inaccurate estimation of parameters could lead to the incorrect inference. For the purposes of prediction, inconsistency is not a primary issue[12] . Therefore, in this work all reasonable panel models and estimators are used for prediction, but the assessment of covariate influence is mainly based on consistent models.

5. Results and discussion

The results and discussion section is organised as follows. Section 5.1 focusses on model performance, with the most accurate consistent econometric model identified in Section 5.1.1, and predictions of the relative level of fire occurrences and prediction volatility being examined in Section 5.1.2. Section 5.2 assesses and discusses the statistically significant predictors of fire. Finally, Section 5.3 considers implications for fire brigade allocation.

5.1. Prediction performance

5.1.1. Identification of the best predictive model

The spatial random effects (SREM) model delivered the most accurate predictions for 2014, followed by its non-spatial counterpart (RE). Thus, after addressing unobserved heterogeneity and spatial autocorrelation, prediction accuracy was improved. Compared with POLS, RMSE was higher for ordinary FE and 1 % lower for the RE model. The SREM model reduced RMSE further by 4 %. However, the spatial RE model estimated with generalized method of moments, SREG, had lower accuracy than POLS. This was due to unsuccessful estimation, attested by a negative estimate for the variance of the unobserved heterogeneity, an occurrence which is not limited to this paper[13] . The difference between spatial and non-spatial FE models indicated that time-invariant factors, which are accounted for only by spatial FE, provided relevant contribution for prediction. This point was reinforced by the fact that non-spatial FE, the only approach that ignores time-invariant factors, achieved the highest mean percentage error (non-spatial FE). Prediction was reasonably accurate on average, with the percent error not exceeding 29 % for the four models with the lowest RMSE, namely, POLS, RE, SREM and SREG (Table 4).

Using Hausman tests (Table 2), it was found that none of the RE models were consistent. This also means that the POLS approach was inconsistent (as it was also subjected to the heterogeneity bias driving inconsistency). Non-spatial models were also inconsistent due to the spatial dependence attested by the Moran's I test (Table 3). Therefore, based on both the RMSE and the mean percent error metrics, the most accurate consistent model was SFEG. The lowest RMSE model, SREM, besides being inconsistent, also proved unreliable for having returned a negative point estimate for the spatial effect, in contrast with the results of Moran's I test (Table 3). Similar divergences were observed by Zouabi and Peridy (2015) and Hao et al. (2016), where insignificant spatial effects in at least some econometric models were observed together with Moran's I test rejecting the null hypothesis.

It is useful to compare the discovery of the most accurate consistent econometric model in this paper with the findings of previous studies. The improvement in out-of-sample prediction performance by the explicit treatment of unobserved heterogeneity and spatial autocorrelation is a common finding. Spatial FE and RE models delivered the most accurate out-of-sample predictions for cigarette demand curve in US states in Baltagi and Li (2004). In Chakir and Le Gallo (2013), models accounting for unobserved heterogeneity and spatially correlated unobserved factors returned better out of sample predictions when predicting land use shares for French *Départements*. In fact, RMSE metrics for these models were nearly ten times smaller than those from the naïve POLS specification. The spatial RE model, which yielded one of the best predictions for fires, was used by Fingleton and Palombi (2013) to generate counterfactual predictions of skilled workers' wages for British towns in the period 1871-1890. The estimated causal effect on local economies of a macro-recession proved to be reasonable and in line with historical evidence. The superior performance of spatial RE and FE models was also detected in the Monte Carlo experiments of Baltagi et al. (2012).

5.1.2. Relative prediction performance and prediction volatility

Efficient fire brigade positioning means prioritizing locations with the highest fire counts. This does not necessarily require accurate prediction of absolute fire counts, but it does require accuracy in predicting relative fire counts. Focussing on the latter, the most accurate consistent model, SFEG, had prediction accuracy of 44 % for the penultimate quintile (Fig. 2, Table 4), with a leap in accuracy to 76 % observed for the last quintile. This reveals that accuracy increased with the degree of priority for fire brigade allocation, a convenient property of predictions. In fact, 144 out of the total 719 municipalities (20 %) were predicted with high accuracy. A number twice as larger as the count of municipalities routinely receiving federal fire brigades in the Legal Amazon (at most 70 municipalities from 2008 to 2014, Prevfogo, 2018). This proves that the models were reasonably accurate within the range of available budget - thus, the low accuracy in intermediate quintiles and the high volatility in itself are not immediate issues.

The convenient property of most accurately predicting priority municipalities seems to derive from susceptibility of predictions to both

[11] Of course, a third factor, omitted variable bias, could also be relevant. However, the economics of Amazon fires is not developed enough to reveal omitted factors correlated with the explanatory variables, and most of main factors mentioned in the literature are included in the models here (Section 2).

[12] In fact, the Monte-Carlo results by Baillie and Baltagi (1994) show that RE outperforms FE in predictions "S" periods ahead. Therefore, a relevant loss in prediction accuracy could result whether RE predictions were not generated and thus omitted based on a ex-ante Hausman test rejecting the consistency of RE.

[13] For similar poor prediction performance of spatial models, see Longhi and Nijkamp (2007) and Table 4 of Chakir and Le Gallo (2013). The computational burden of estimating spatial models, as indicated by Lesage and Pace (2009, chap.3 and 4) and Elhorst, (2014, p.18), should also be highlighted here, especially with our 47 predictors.

Table 2
Hausman tests for the hypothesis of absence of heterogeneity bias (RE vs FE).

Models compared	Chi-squared	P-value
Ordinary RE vs FE	255.76	< 0.001 %
SREM vs SFEM	74.692	< 1 %
SREG vs SFEG	1907.1	< 0.001 %

Note: function "hausman" of STATA ® was employed in models ran without any correction for non-spherical disturbances, except for the case of ordinary models for which efficient estimators were used (with the command option "sigmamore").

Table 3
Tests for the spatial independence hypothesis.

Test	Statistic	P-value
Moran's I: 2008[a]	0.329	< 0.01 %
Moran's I: 2010[a]	0.359	< 0.01 %
Moran's I: 2012[a]	0.395	< 0.01 %
Moran's I: 2014[a]	0.423	< 0.01 %

[a] Moran's I test from package spatgsa command (Pisati, 2001, p.21). It was applied to the dependent variable separately for each year, based on the same spatial weights matrix used by spatial models (queen contiguity).

high and low outliers[14], which manifested as a higher volatility of predicted fire occurrences (Table 4 shows the influence of low outliers in its fourth column and higher volatility of predictions in the sixth column [15]). High volatility came both from observed fire occurrences (whose coefficient of variation is of 1.64) and from covariates, especially the time-variant which are the only type of covariates captured by the model with the highest coefficient of variation (FE; Table 4).

The spatial variation of model performance was assessed by classifying the relationships between observed and predicted quintiles in three categories, "successful" (predicted quintile matched observed quintile), "overpredicted" (predicted quintile above observed quintile) and "underpredicted" (predicted quintile below observed quintile) (Fig. 3). Success dominated mainly in the central Amazon. Overprediction was most common in Northwest (Amazonas and part of Roraima) and South (Mato Grosso). Underprediction was more common in the Northeast, at the boundaries between the Amazon rainforest biome and the drier Brazilian Savannah biome (Pará and Maranhão states) and in the North (Amazonas).

This spatial pattern of prediction performance was highly correlated with the distribution of fires (Fig. 3), again showing the influence of top fire outliers. The statistical independence between prediction success and high level of fires was rejected (p-value < 0.01%). The success rate jumped from 40.2 % among municipalities with low to medium level of fire occurrences to 69 % among municipalities with high level.

5.2. Effective predictors

This section discusses the statistical significance of the potential predictors informed by literature and their influence on fire occurrences (detailed estimation results are found in Appendix A). For ease of expression, the phrase "influence of a particular factor on fires" will be used strictly to denote prediction power, here measured as partial correlation, and not causation. Priority is given to the SFEG model and concordance with other models is used to establish the strength of evidence regarding prediction power. Whether significance of a factor is observed only in a minority of the models (three, at most), or in majority only among the inconsistent non-spatial models, this information is omitted.

5.2.1. LUCC and agriculture

Regarding the explanatory power of land uses, only deforestation and forest degradation had significant and positive influences on fires. The relevant explanatory power of deforestation echoes previous studies (Arima et al., 2011; Cardoso et al., 2003; Aragão et al., 2008) but also contradicts a growing evidence base on the decoupling of fires from deforestation (Aragão and Shimabukuro, 2010; Vasconcelos et al., 2013; Aragão et al., 2018). Perhaps the strongest defence of the decoupling hypothesis was made by Cano-Crespo et al. (2015) with data from 2001 to 2010 for the Mato Grosso, Pará and Rondônia states (central-western Amazon). They stated that correlation between fires and deforestation was statistically insignificant across time and negligible across space. The authors' land use data was the same as used in this paper, including deforested area. However, fire data came from the NASA/MODIS burned area product "MCD45A1", which is known to considerably underestimate Amazon fires due to cloud cover (Cardozo et al., 2012; Libonati et al., 2014; see the comparison of the fire maps used by the authors and in this paper in SI.2). Nevertheless, the main difference with Cano-Crespo et al. (2015) and other previous studies is that they did not control for other sources of influence when correlating deforestation and fires. It is therefore not surprising that our results contradict previous studies. However, the finding of the present paper cannot be taken as a final word on the decoupling hypothesis, as a precise statistical test was not performed for being out of the scope.

The positive relationship found for forest degradation and fire is also expected as fire and timber extraction - this latter being the source of degradation captured by the degradation variable are the main sources of degradation (Barlow et al., 2016), and commonly act synergistically in agricultural frontier regions (Barlow et al., 2012; Morton et al., 2011; Rappaport et al., 2018). It is also reasonable that primary forest (which is the most humid and fire-repelling land cover considered) was negatively correlated with fires. This is a finding in line with Vasconcelos et al. (2013); Arima et al. (2007), and Anderson et al. (2015).

Soybeans, fallow, pasture and secondary forest had no meaningful contribution in explaining the variation of fires across municipality-years after accounting for the variation in deforestation, primary forest, degradation and the remaining covariates. This opposes the findings of Cano-Crespo et al. (2015) and Anderson et al. (2015), which detected fires mainly on lands occupied with crops and pasture. Again, the contradiction is due to the absence of controls in the cited studies which omit the prices that influence land uses and value added by agriculture. Here, by applying such controls, an irrelevant share of the variation on fires was left to be explained by land uses (except deforestation and forest).

Fires increased with the value added by primary activities, i.e., agriculture and natural resource exploitation, after controlling for the value added by all activities (GDP). This relationship was strong enough to be significant in all spatial models and in two non-spatial models, being further attested by a positive and significant (at 0.1 % level) correlation between fire and share of agriculture in GDP. Similarly, GDP was significant and negative in most models, including all spatial models. Whereas the evidence regarding primary activities indicates that a considerable fraction of Amazon agriculture remains fire-based, the finding referring to GDP suggests that many municipalities of the Amazon are no longer in the early level of development in which agriculture is dominantly fire-based. To reconcile these two findings, an explanation based in the Kuznets curve development pattern is

[14] The influence of top outliers may lead to believe that separate modelling of top-fire municipalities would lead to more accurate predictions. However, separate modelling would lead to loss in the variation captured by the parameters' estimates and associated biases. In addition, models proved flexible enough to capture the existence of both low and high fire municipalities, as revealed by the susceptibility to high and low outliers, which manifested in terms of (i) high success rates in the bottom and top quintiles, (ii) high volatility of predictions, and the (iii) trend to underestimate (Table 2), the latter revealing the influence of bottom quintiles. We thank reviewers for suggesting the introduction of this clarification.

[15] In fact, levels below 100 and above 1000 were more frequent in predicted rather than in observed counts, except for POLS and SREG models.

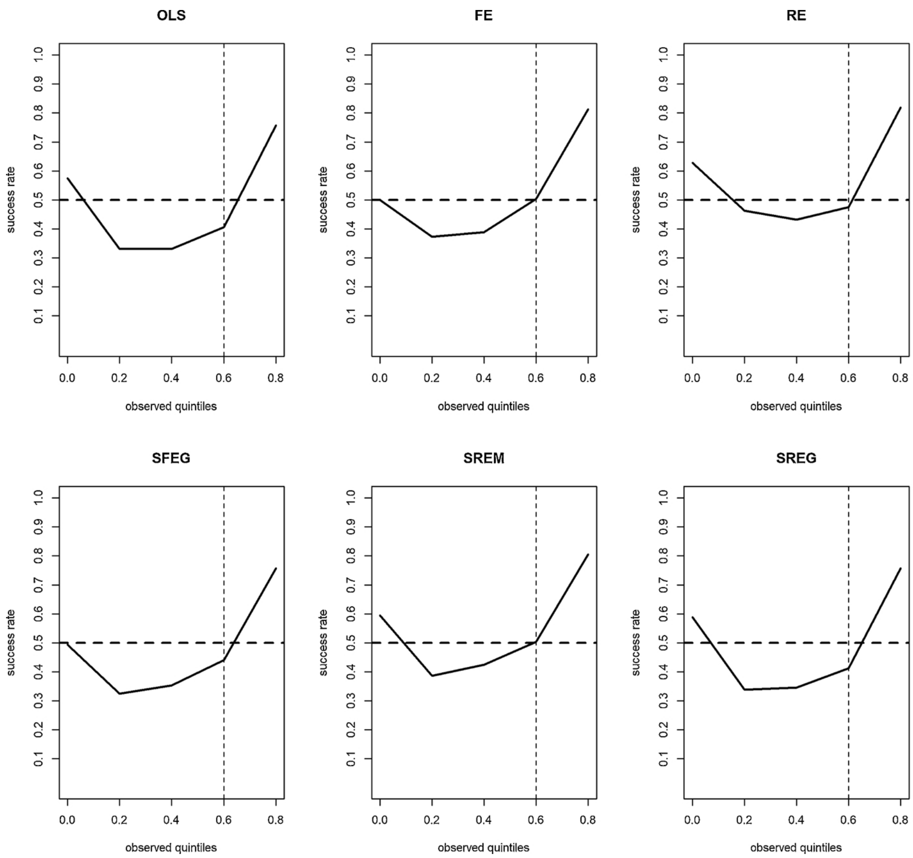

Fig. 2. Rate of observations whose rank was successfully predicted across quintiles of the dependent variable, horizontal line at 50 %, vertical line at 60 %.

Table 4
Statistics for predictions of municipal fire counts in 2014.

Model	RMSE	Mean percent error [a]	Predominant error direction [b]	Standard deviation	Coefficient of variation (predicted/ observed) [c]	Rank success rate, 60-80% [d]	Rank success rank rate, top 20% [e]
POLS	187.51	−1 %	Underestimate	279.26	1.09	41%	76 %
FE	240.82	−64 %	Underestimate	408.58	4.35	50%	81 %
RE	185.56	−29 %	Underestimate	367.73	1.98	48 %	82 %
SFEM	223.06	−7 %	Underestimate	406.70	1.68	44 %	76 %
SFEG	223.00	−5 %	Underestimate	406.71	1.66	44 %	76 %
SREM	177.54	−17 %	Underestimate	359.29	1.66	50 %	81 %
SREG	191.16	−3 %	Underestimate	287.44	1.14	41 %	76 %

Note: [a]mean percent error calculated as the mean(predicted)/mean(observed) – 1; [b]predominant error direction = sign (mean (predicted) - mean(observed)), if positive, overestimates, if negative, underestimates. [c] The ratio of the coefficients of variation of each model (denominator) and of the observed fire count (numerator), with coefficient of variation being the standard-deviation/mean ratio. [d] This is the share of observations correctly classified in the 60–80 % deciles (fourth quintile). [e] Rate of observations correctly classified in the top 20 % decile (fifth quintile).

proposed. First, the pattern applies to Amazon in a "cross-sectional" sense, i.e., different development levels were achieved by different municipalities, which explains fire perpetuation amidst fire reduction. Second, the Kuznets pattern also applies in a "time-series" sense, i.e., many municipalities pursued, in the period analysed, a path of economic expansion and fire reduction. This double explanation adheres to the evidence found by recently published articles showing that the Kuznets curve development path has been followed by Brazilian Amazon municipalities (Tritsch and Arvor, 2016; Weinhold et al., 2015, and Hall and Caviglia-Harris, 2013).

5.2.2. Institutions

Municipalities with larger extents of their territory occupied by indigenous or protected lands had a significantly higher number of fire detections. This evidence was strong, being robust to most of the econometric specifications. However, it must be emphasized that the finding refers to total fire counts without distinguishing fires inside and outside indigenous/protected lands. It is, thus, not a proof that fires are more frequently used by indigenous communities or dwellers in protected areas. In fact, the share of total fires detected within the two land types was small in the whole period: 4% for protected areas and 10 % for indigenous lands[16] . Nevertheless, the finding contradicts the studies

[16] It is possible that the positive estimate for indigenous lands is a spurious correlation. From 2008 to 2010 both fires and the area of indigenous lands had their largest increase in the period, but this seems to be a mere coincidence as fires augmented due to an extreme drought (Marengo et al., 2011), which can hardly be connected with the process of indigenous land creation. To test this "spurious coincidence" explanation, all models (except count data models) were estimated with indigenous land areas fixed in the levels of 2008. The exercise was also repeated by fixing in the levels of 2014. Spatial models still resulted in a positive and significant coefficient for indigenous lands, but the non-spatial

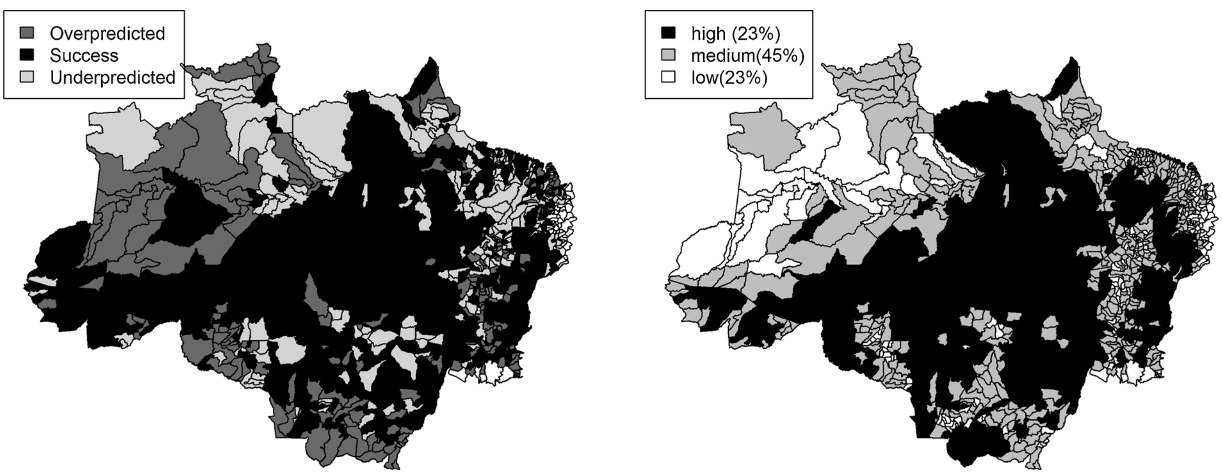

Fig. 3. Spatial distribution of classes for predicted vs observed quintiles, SFEG model, 2014 (left), fire quartiles* (right).
*Fire = Time average for fire counts. Low = first quartile (bottom 25 %), medium = second and third quartiles, high = fourth quartile (top 25 %).

of Nepstad et al. (2006), a causal analysis that resulted into negative effects for the two land types, and of Tasker and Arima (2016), who found no influence of protected areas on fires. However, the results here can only show that the municipal extents of indigenous lands and protected areas predict fires. They support no conclusions regarding underlying causations.

The fire brigade dummy was positively correlated with fires, as expected, a proof of allocation procedure based on prioritizing top-fire municipalities (belonging to the top fire count percentile and receiving a fire brigade were statistically dependent at 0.01% level).

5.2.3. Biophysical

Rain was a weakly statistically significant variable and had a negative influence on fire occurrences, as expected and in accordance with previous studies (Aragão et al., 2008; Vasconcelos et al., 2013). Temperature also had a significant role in predicting fires. The January-June subannual average was significant in all models (except for SREM) and the August-October average was significant in most models, in line with recent climatologic and ecologic research (Malhi et al., 2008; Coe et al., 2013; Brando et al., 2014). The share of clayey and high clayey soils, which are more fertile (Farella et al., 2007), and the slope of terrain, were all negatively correlated with fires. This makes sense theoretically as land with higher potential profitability is more favourable to the accumulation of capital, which is a means to finance a shift to fire-free agriculture (Coomes et al., 2011; Perz, 2003).

5.3. Implications for the improvement of fire brigade allocation

Regarding the identification of priority municipalities for fire brigade positioning, a simple exercise was conducted. Considering that fire brigades operated in 50 municipalities in 2014, two rates were calculated (for 2014). First, the success rate of fire brigade allocation was calculated as the proportion of the top 50 municipalities on observed fire occurrences that were, actually, allocated with fire brigades. Second, the success rate of the best predictive model (SFEG) was calculated as the proportion of the top 50 municipalities on observed fire occurrences which were also top 50 on predicted fire occurrences. The best predictive model was over twice as successful as the current fire brigade allocation procedure, with success rates of 70 % against 30 % (see figure B.1 in appendix B for a map of comparative accuracy; the results reported were generated with the SFEG model without the fire brigades' dummy[17]).

This result clearly demonstrates that fire brigade allocation can be improved if based on predictions from an accurate model comprising a wide range of predictors. It is a result which is consistent with previous studies. Mitsakis et al. (2014) managed to reduce average response time of Greek fire stations in at least 15 % with an allocation algorithm predicting fires from "local terrestrial and weather conditions", "experience of fire brigade", and data on the spatial propagation of the wildfire. The statistical fire model of Chevalier et al. (2012), containing multiple socioeconomic explanatory factors, based Belgium's "national reform of the fire service". Kiran and Corcoran (2017), aiming to improve the spatial allocation of urban fire stations in Australia, used quantile regression to predict response time to emergency calls based on road density and connectivity, as well as socioeconomic living condition and the presence of children and elderly in the household. The main implication of the study is that not all calls were being responded by the stations that could respond fastest. This is similar to the finding that 70 % of fire brigades were not allocated to the top fire municipalities in Amazon, suggesting that some of the main forest fire events would not be accessed as fast as needed. In Kiran and Corcoran (2017) and in this paper, the evidence on potential inefficiency of prevailing firefighting practices came from the econometric modelling of a wide range of explanatory factors. The studies mentioned in this paragraph, together with the doubling of Amazon fire brigades success rate by our analysis, are proof that fire prediction modelling is a promising path for optimizing performance of fire brigades.

(*footnote continued*)
models changed. The coefficients of the POLS and RE models, the only non-spatial and non-count data models with significant positive indigenous lands with the actual dataset, became statistically insignificant. A second source of the positive coefficient is the existence of 239 observations without indigenous lands and with low levels of fires (first percentile). These observations corresponded to a larger proportion of the sample (8 %) than observations with high levels for the two variables (3 %). Most of the former occurred in Brazilian states covered by other biomes besides the Amazon (51% are in the states of Maranhão and Tocantins). When the two sources were eliminated from the data, the positive significant relationship disappeared for both the non-spatial models and for the most accurate consistent spatial model (SFEG). Thus, the results here presented mean that the positive (partial) correlation found is probably not an indication of a positive causal relationship.

[17] For clarification, the brigades dummy is excluded to avoid capturing the current procedure of fire brigade allocation with the econometric model. This allows separation of the current procedure from the econometric modelling (otherwise, both of the success rates compared – i.e., that informed by observed and predicted allocation – would contain information on effective allocation). If the fire brigade dummy is included in the SFEG model, the success rate drops sensibly to 58 % (instead of 70 %).

6. Conclusion and implications for policy and future research

Forest fires are one of the main threats for the conservation and development of the Brazilian Amazon. Efficient forest fire suppression policy needs accurate forecasts of future fires. This paper contributed to this need by building a dataset which is unparalleled in its geographical and temporal coverage, and in the comprehensiveness of the set of potential influential factors. Screening of models revealed the importance of accounting for observed and unobserved (time-invariant) heterogeneity and also for the spatial dependence inherent to fires and to unobserved factors.

One of the main findings was that an increase in econometric sophistication, by including unobserved time-invariant factors and spatial dependence, was rewarding in terms of practical performance. The top 20 % municipalities in terms of fire detections were predicted with high accuracy and the top 50 municipalities on the 2014 level of fire detections were more successfully identified by the best model than by the current fire brigade allocation. A further result was the models' high accuracy in predicting the top municipalities up to a number that fits the federal budget. In addition, temporal and spatial variation of Amazon fires were shown to be explained by economic, institutional and climate and physical factors, attesting the systemic nature of the phenomenon.

Multiple policy recommendations may be derived from the results. Here, we focus on those that seem more compatible with the limited resources available to the government for defining fire brigade allocation, a costly activity in terms of data collection and modelling. The first recommendation, which is suggested by prominence of fixed effects estimators, is to consider not only the average fire count in the past four years but exceedances of historical averages of municipalities. This may also reveal the beginning of ascending trends that may materialize later in changes in the rank of municipal fire occurrences. The second recommendation is that a bottom-up approach of searching for fire count clusters at municipal level could better address the spatial autocorrelation on fires. This is in addition to the "nested" approach of refining priority states with priority "mesoregions". The third recommendation is that geographical units (states, mesoregions and municipalities) could be ranked based on an indicator incorporating not only fire counts, forested area and federal lands, but also deforested area, degraded forest, value added by agriculture, GDP, indigenous lands, protected areas, precipitation, temperature and soil quality.

Despite the reasonable quality of predictions there is still room for improvement, especially since inaccuracy could lead to a waste of highly scarce public funds. However, further improvements and future work would require an expansion of the knowledge available. Even accounting for a comprehensive set of factors stressed in the literature in this study, only a small proportion of the variation in fires across space and time was explained ($R^2 <= 46$ %). Adding this to the counterintuitive results obtained regarding the effects of protected and indigenous lands, it seems clear that future research efforts should be targeted in two directions. Firstly, theoretically consistent hypotheses on the mechanisms linking causal factors with fires need to be developed. Secondly, such hypotheses need to be rigorously tested with causal inference methods that eliminate confounders that still blur the published evidence available. The latter was shown to be particularly relevant regarding the relationship between fires and indigenous lands (and also protected areas), which does not seem to be fully straightforward as suggested by the results. In addition, a causal inference study of the effectiveness of fire brigades in reducing fire counts is also needed. This would be a logical complement to the identification of ways to increase the efficiency of fire brigade allocation.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.ecolecon.2019.106501.

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