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Modeling the Influence of Eucalypt Plantation on Wildfire Occurrence in the Brazilian Savanna Biome

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Abstract: In the last decades, eucalypt plantations are expanding across the Brazilian savanna, one of the most frequently burned ecosystems in the world. Wildfires are one of the main threats to forest plantations, causing economic and environmental loss. Modeling wildfire occurrence provides a better understanding of the processes that drive fire activity. Furthermore, the use of spatially explicit models may promote more effective management strategies and support fire prevention policies. In this work, we assessed wildfire occurrence combining Random Forest (RF) algorithms and cluster analysis to predict and detect changes in the spatial pattern of ignition probability over time. The model was trained using several explanatory drivers related to fire ignition: accessibility, proximity to agricultural lands or human activities, among others. Specifically, we introduced the progression of eucalypt plantations on a two-year basis to capture the influence of land cover changes over fire likelihood consistently. Fire occurrences in the period 2010–2016 were retrieved from the Brazilian Institute of Space Research (INPE) database. In terms of the AUC (area under the Receiver Operating Characteristic curve), the model denoted fairly good predictive accuracy (AUC $\approx$ 0.72). Results suggested that fire occurrence was mainly linked to proximity agricultural and to urban interfaces. Eucalypt plantation contributed to increased wildfire likelihood and denoted fairly high importance as an explanatory variable (17% increase of Mean Square Error [MSE]). Nevertheless, agriculture and urban interfaces proved to be the main drivers, contributing to decreasing the RF's MSE in 42% and 38%, respectively. Furthermore, eucalypt plantations expansion is progressing over clusters of high wildfire likelihood, thus increasing the exposure to wildfire events for young eucalypt plantations and nearby areas. Protective measures should be focus on in the mapped Hot Spot zones in order to mitigate the exposure to fire events and to contribute for an efficient initial suppression rather than costly firefighting.

Keywords: modeling; wildfire occurrence; eucalypt plantation; machine learning; spatial pattern; Brazilian savanna

1. Introduction

The market demand for bioproducts has increased during the last decades, prompting the expansion of forest plantation worldwide [1]. Brazil is one of the largest hotspots of eucalypt plantation expansion due to the high productivity and the short-term rotation of this tree species under local environmental conditions [2,3]. From 2010 to 2016 the area planted with eucalypt has grown 15.8% per year in Brazil [4]. The south-western Brazilian savanna, recently labeled as the 'new forestry frontier' due to the large concentration of forest fast-growing plantations, has led this expansion, with an increase of 499,600 hectares over this period, representing a yearly area growth of 22% [3,5].

The savanna is a very important biome due to its large geographic extent, high levels of biodiversity and intense fire activity [6,7], being among the most frequently burned ecosystems in the world [8,9]. At the same time, this fire-prone biome is perceived as favorable land for agricultural expansion, which has emerged as a key factor transformation for this region [10]. Recently, Brazilian savanna, also known as 'Cerrado', is experiencing a significant land use transformation, with the native vegetation being replaced by intensive forestry, agricultural lands and urban areas [11]. The probability of a fire to occur depends on the occurrence of an ignition source (either human-related or natural) and favorable burning conditions within the environment [12]. In the Brazilian savanna, fire is used by humans as a management tool for vegetation removal, maintain grasslands, burn off agricultural residues or clean farm borders [6,13]. Nonetheless, fire is also a side-effect arising from the accidental and unintentional ignitions or arson fires [6,14]. Wildfire events are connected to the expansion of urban interfaces and increasing accessibility into the wildlands [15–17]. The proximity to those features increases the probability of a fire to occur [15]. In this sense, agriculture and forestry expansion in conjunction with socio-economic development of the region have the potential to increase human pressure on wildlands, thus increasing fire incidence.

Wildfire is one of the main threats to eucalypt forests [18,19]. Eucalypt plantations are responsible for fast accumulation of larger amounts of both litter and biomass above the ground, consequently increasing the wildfire hazard likelihood, due to the increased fuel load [20]. In addition, eucalypt plantations in Brazil are valuable investments due the high rates of biomass growth in the short term [21]. Annual economic losses caused by wildfires in these planted forests are quite high. In Brazil, the exact number of fires occurrence is difficult to obtain due to the lack of an official database, however, Santos [22] estimated that 5,832 fires occurred between 1998 and 2002 in eucalypt plantations across the country. This amount represented 30% of all fire occurrence recorded in Brazil. Nevertheless, little is known about the causes and spatial distribution of wildfires in the Brazilian eucalypt planted forest [22]. Furthermore, despite the large fire activity in the 'Cerrado' biome, there is still a lack of studies that analyze the driving forces of wildfire ignition likelihood on this biome [23]. Understanding the role of driving factors of fire ignitions and predicting where wildfires are most likely to start is essential to design strategies for wildfire impact mitigation or to identify regions at risk [24]. In this context, wildfire occurrences have been extensively investigated, with researchers attempting to identify which environmental and socioeconomic factors foster fire occurrence, using broadly approaches and goals, such as fire prevention, supporting strategies and policies for fire, forest or land management [16]. Wildfire occurrence is considered one of the main components of wildfire risk assessment [25]. Additionally, the use of spatially explicit models may promote more effective management strategies and support better fire prevention policies [26].

The first steps in modeling wildfire occurrence begun with Ordinary Least Squares (multiple linear regression) and Generalized Linear Models (logistic regression) methods [27–30]. Statistical regression methods became very popular in Human-Caused Fire (HCF) predictions, as they are simple to use and understand [31]. Nevertheless, the increase of computer power and the availability of detailed spatial datasets promoted the use of complex techniques, such as classification and regression trees, artificial neural networks, support vector machines and other machine learning algorithms. These robust methods have been introduced as alternatives to traditional statistical methods, especially when dealing with large datasets, non-linear relationships, and variables that are highly correlated or not normally distributed [16]. Wildfire occurrences have also been analyzed with spatial-temporal points processes statistical tools to model wildfire spatial-likelihood. The spatial point processes framework has the advantage to deal with micro-geographic data and to model, parametrically or not, the spatial-temporal trend and the interaction structure between the points [16,32–35]. Random Forest (RF) has been extensively used to model wildfire occurrence for large datasets. RF is a tree-based machine learning algorithm able to explore complex relationships among covariates [36], attaining high predictive performance in data mining while being able to capture fine-grained spatial patterns compared with other modeling methods [37–40]. Rodrigues and de la Riva [37] compared RF with traditional methods like Logistic Regression for the assessment of human-caused wildfire occurrence in Spain. As a result, RF algorithms improved the prediction accuracy of traditional regression methods on a country scale. Oliveira [40] has tested traditional Multiple Linear Regression and RF to model the likelihood of fire occurrence at the European scale. Accordingly, RF showed a higher predictive ability than traditional modeling methods. Guo [39] applied Logistic Regression and RF to evaluate drivers of fire occurrence on a provincial scale in China. The RF model was able to identify significant driving factors and demonstrated a higher predictive ability than logistic regression on a regional scale.

Within this context, this work focuses on modeling the relative influence of eucalypt plantation on wildfire occurrence in the Brazilian savanna biome comparing its influence to traditional ignition drivers such as agricultural and urban interfaces. To this end, a RF model was trained using several explanatory factors related to fire ignition, selecting variables potentially associated with wildfire ignition in the Brazilian savanna: accessibility, infrastructure, proximity to agricultural lands, human activities, and land tenure. Specifically, we introduced the progression of eucalypt plantations on a two-year basis, in order to capture the influence of land cover changes in the fire likelihood. We considered a two-year gap to mitigate the potential error in the land cover mapping, derived by the use of remote sensing data in the classification process. Moreover, retrieving land changes in a longer period may represent more effectively the complexity of land conversion across 'Cerrado' and, consequently their impacts on local fire regime [41,42]. The dependent variable was retrieved from remote sensing data of the Brazilian National Institute for Space Research Hot Spot Database in the period 2010–2016. The spatial distribution of occurrence probability was analyzed by means of Cluster and Outlier Analysis to identify and outline areas with increased chance to hold a fire (Hot Spots), thus related to the identification of priority intervention areas for wildfire management. The results of this study may be used to (i) understand the driving forces of wildfire ignition and (ii) assess the influence of eucalypt plantations expansion in the wildfire occurrence likelihood by means of its importance as an explanatory variable. In addition, the analysis of the spatial distribution of wildfire likelihood on the landscape and the identification of risk cluster zones may promote valuable information for support of effective wildfire management strategies on the regional scale.

2. Materials and Methods

2.1. Study Area

The study area is located in the Brazilian savanna biome, in western Brazil (Figure 1). This region covers 56,842 km^2 accounting for 15% of the national eucalypt plantation area [4]. The climate is mainly tropical with dry winter [43]. The area is very homogeneous in terms of biogeographic, dominated by natural 'Cerrado' vegetation, pasture and eucalypt planted forest. The relief is mostly flat with elevation above sea level ranging from 253 m to 785 m [44]. Nevertheless, the study area is heterogeneous in terms of socioeconomic features. From the depopulated areas in the northern, western and southern edges of the region to more populated urban areas in the eastern of the study area, we find a wide range of rural-to-urban conditions [45].

During the last decade, land cover changes have taken place in the region, mainly related to the expansion of eucalypt plantation over pastures and grasslands (Figure 2). The progression of plantation has altered the landscape structure with increasing fuel load produced by the eucalypt forest plantation. The shift from a grazing system dominated by pasture lands to woody vegetation alters the amount and structural complexity of fuel available to burn in a wildfire [46]. Agriculture is the main activity in the region, represented by livestock, sugarcane, soy, and corn as the main activities [45]. The region is dominated by low population densities with a predominance of the rural population. Despite that, in the last decade, the region has grown demographically an average of 2% per year due to the economic development of the region promoted mainly by the expansion of industrial plantation [4,47].

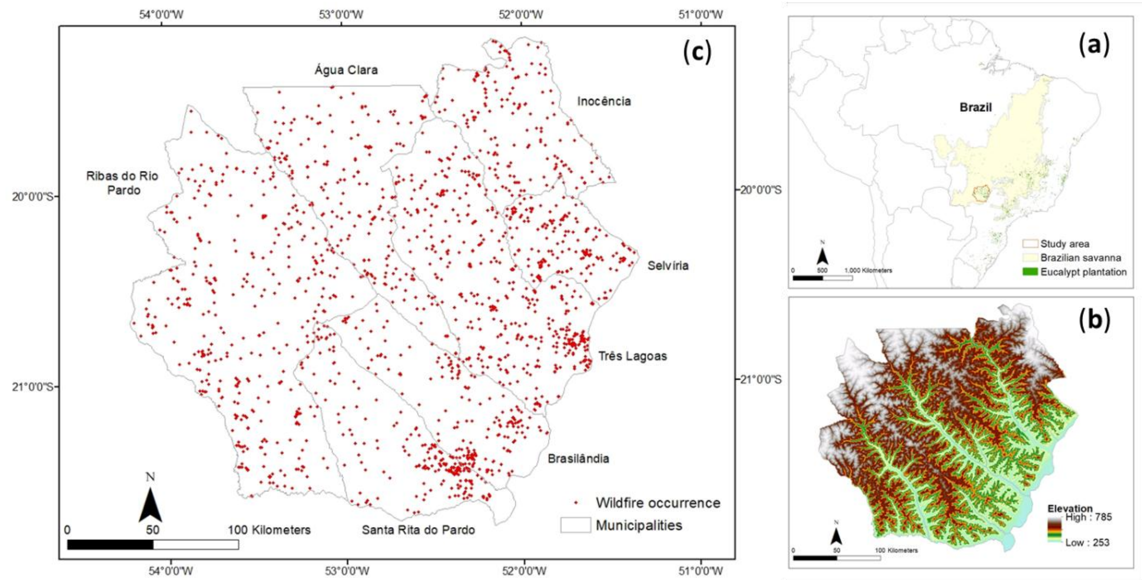

Figure 1. (**a**) Study area location, Brazilian savanna biome, and eucalypt plantation distribution in Brazil (2016). (**b**) Elevation gradient of the study area. (**c**) Spatial distribution of wildfires occurrence (2010–2016; Brazilian Institute of Space Research [INPE]) over municipalities limits.

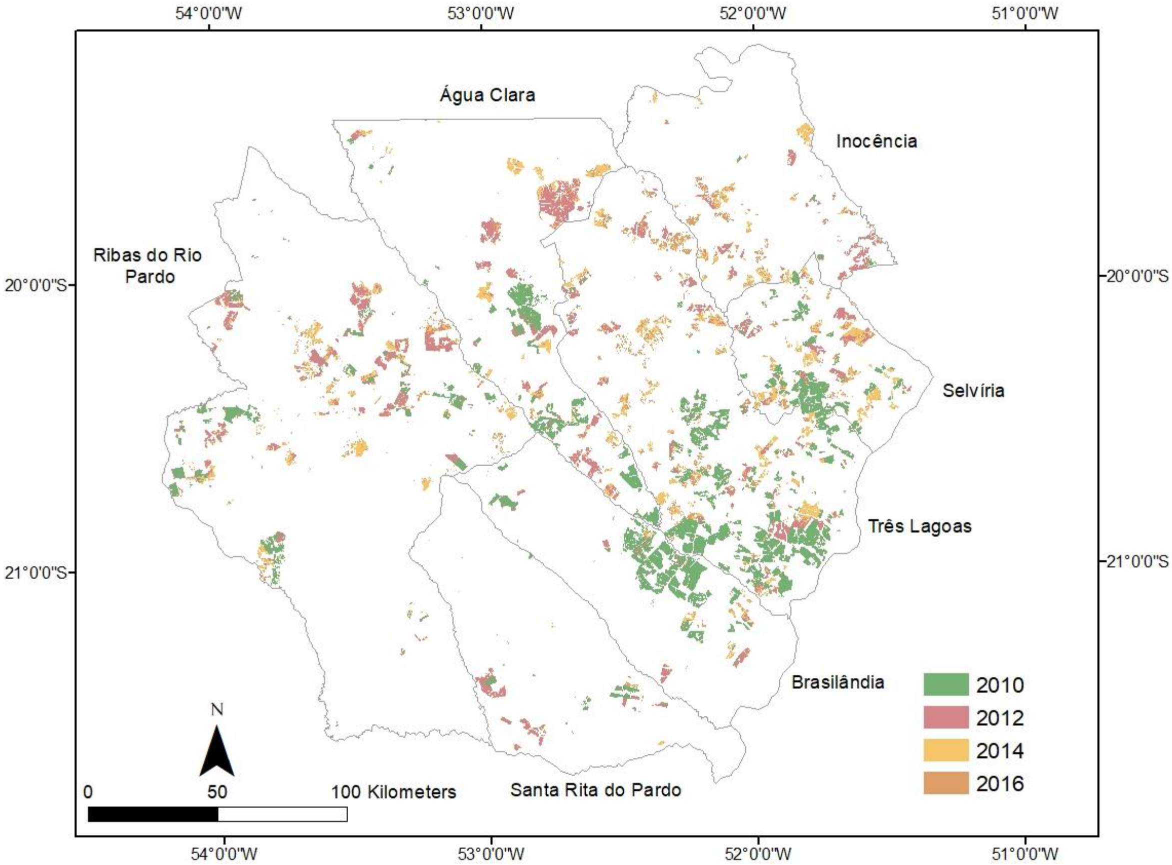

Figure 2. Eucalyptus plantation expansion areas across Brazilian savanna by year over the study period (2010 to 2016).

2.2. Methods

The overall procedure was based on spatial modeling of wildfire occurrence, combining Random Forest algorithms and Cluster and Outlier Analysis through the Anselin's Local Moran's I to detect changes in the spatial pattern of ignition probability over time and to predict areas at risk (Figure 3). The RF model was trained using several explanatory drivers related to wildfire ignition. Specifically, we introduced the progression of eucalypt plantations on a two-year basis. Fire occurrences in the period 2010–2016 were retrieved from remote sensing data of the Brazilian Institute of Space Research.

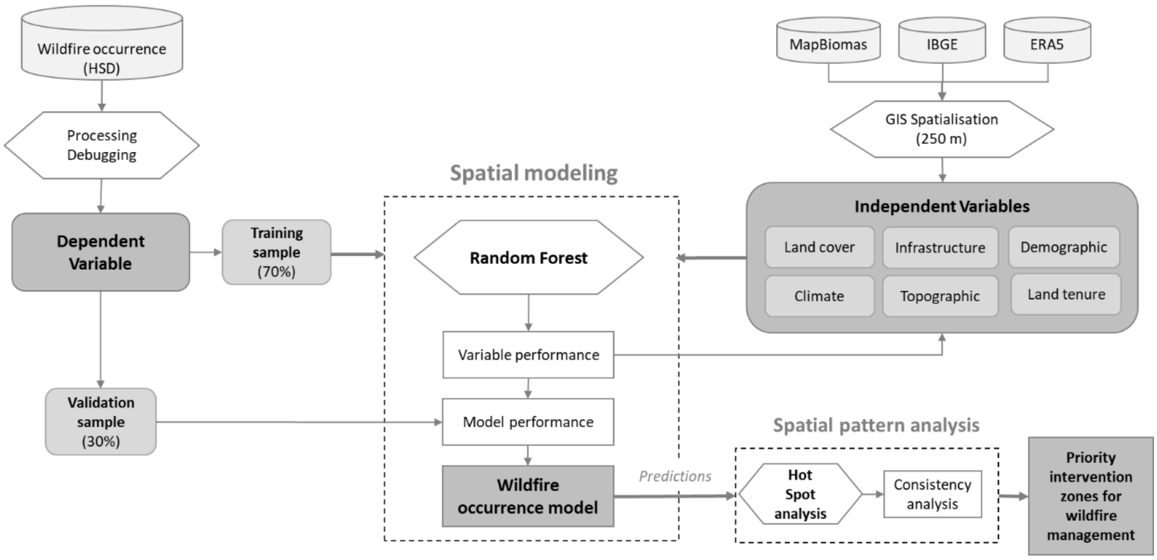

Figure 3. The general workflow for modeling and mapping the probability of wildfire occurrence in the Brazilian savanna.

2.3. Dependent Variable

Wildfire occurrence was modeled as a presence or absence of fire. The fact that fires were rare events that rarely started more than once within the period of analysis in the same spatial location allows modeling them as binary process [48,49]. In our dataset 2.4% of all fire's events occurred twice in the same location over the studied period, this is represented by a maximum number of 2 points in the same location. The dependent variable wildfire occurrence was built from the Hot Spot Database (HSD) of the Brazilian Institute of Space Research (INPE). The HSD was based on active fire detection by using remote sensing data from MODIS sensor (Terra and Aqua satellites), NOAA-15, NOAA-18, NOAA-19, METOP-B, and VIIRS sensor (NPP-Suomi satellite). The radiant flux received by the satellites sensor is emitted by the target itself and the emissions tend to increase after the occurrence of the fires due to the elevation of the temperature, characterizing a heat source [50,51]. The HSD is characterized by high temporal resolution (30 min to 3 days), and spatial resolution, ranging from 375 m to 4 km [52]. In order to mitigate the wildfire detection error heat sources must be processed so they can be interpreted as fire occurrences [53,54].

HSD data were analyzed on a two-year basis, from 2010 to 2016, to match data about land use change. Figure 4 represents the fire occurrences distribution by month over the studied period. In order to identify the actual location of fire ignition from the successive pulses of active fire we first ordered temporally all the active fires and considered the first detected pulse as the ignition point. Furthermore, in order to model the fire occurrence with RF, it was necessary to create a set of fire absence points for the study area. In order to create a balanced dataset, the number of absence and presence points was considered to be the same (1693 points) and equally distributed by year (423 points) [55]. The absence sample was randomly distributed across the studied area, following a uniform distribution. The module Random Points Generation in ArcGIS 10.5.1 was used to build the sample of absence points. The final binary dependent variable was created joining fire presence with fire absence, totalizing 3,386 points. The distribution of fire occurrences along the year in the study area is presented in Figure 4. During the period of analysis, it was found a minimum of 6 and maximum of 115 fires events per month, with 35.27 as mean numbers of wildfire ignitions identified per month.

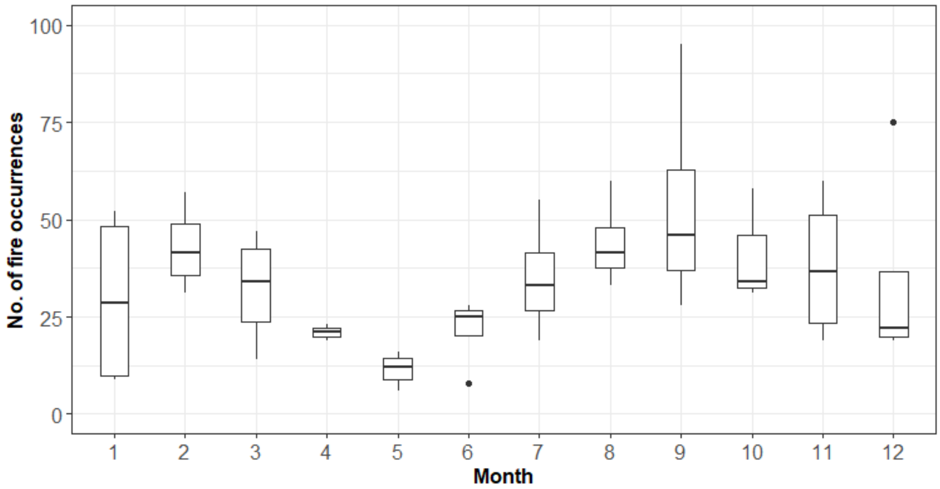

Figure 4. Distribution of fire events (dependent variable) by month between the study period (2010 to 2016) across the studied area in the Brazilian savanna region.

2.4. Explanatory Variables

In most countries, human activities are the main responsible for fire ignition [56]. In the Brazilian savanna region, fire ignition was caused mainly by agricultural activities, when the fire is used to promote fresh regrowth of grass in pastures for livestock, and to clear land for crop cultivation [6,57,58]. Land cover type and anthropic land management technique also play an important role in wildfire occurrence across 'Cerrado' region, which seems to be able to increase fire occurrence frequency on a regional scale [17]. Other anthropogenic wildfires, related to increasing human pressure on wildlands (e.g., population density, distance to roads, distance to urban) and human socioeconomic variables (e.g., census data), include both arson and accidental fires [52,58]. Despite the importance of the issue, there are no updated statistical data to understand the profile of wildfires in Brazil and few environmental agencies have kept a reliable record of fire events. According to Soares [59], the main sources of wildfires in Brazil are burning for cleaning agricultural fields and pasturelands, which corresponds to 63.7% of the total burned area, followed by arson fires, with 14.7%, accidental fires representing 11.6% and other sources represent about 10% of total burned area in the country. Environmental factors such as topographic (e.g., elevation, slope, and aspect) and weather variables (e.g., temperature, wind speed, and humidity) influence wildfire regime, due to its relations to drought or vegetation moisture, both influencing ignitability [16,23].

The approach to consider human factors in wildfire modeling has been commonly based on statistical models, which aim at explaining the historical human-caused fire occurrence from a set of independent variables [16,55,60–62]. For this study, the analysis of factors related to wildfires (i.e., human activities, land cover, weather) was firstly based on selecting the potential variables associated with the ignitions in Brazilian savanna, following a detailed review of specialized literature [16]. We described all the potential explanatory variables related to fire occurrence likelihood, their units, sources, and resolution in Table 1.

General explanatory factors commonly identified by previous studies (e.g., human pressure into wildlands) needed to be approached using single variables (e.g., distance to urban), which should be available for all study area over the study period. Area characterized by mixed occupation of land uses (e.g., agriculture and pasture) associated with natural vegetation, where an individualization of its components is not possible by the available remote sensing techniques was approached using single variable interface (e.g. mosaic of agriculture and pasture) [63]. All the potential explanatory variables were spatialized in raster grids with the same spatial resolution (250 m) on a two-year basis, in order to capture the influence of land cover changes on the fire ignition likelihood over the study's period. Variables' interfaces were retrieved from the spatialized dataset.

As a preliminary step towards the final set of covariates, we evaluated variable importance in RF models by calculating the percentage increase in the Mean Square Error (IncMSE). For this purpose, the RF algorithm replaces the actual values of each covariate at a time with a 'dummy' variable constructed using random values and calculates the ratio of IncMSE from the out-of-bag sample (33% of training dataset). The higher the IncMSE, the larger the contribution of that variable to the RF model. We established a threshold of 10% as the minimal necessary IncMSE contribution of each potential explanatory variables to be selected indeed as the model's explanatory variables.

2.5. Model Calibration and Evaluation

In order to estimate the fire occurrence likelihood, a RF algorithm was fitted and evaluated using the *caret* package [64] in the *R* environment for statistical computing [65]. In addition, we used *raster* [66] and *plotmo* [67] packages for predictions and plotting the RF outputs.

RF is an ensemble algorithm and uses decision/regression trees as base classifiers. RF can be parameterized according to the number of trees averaged in the ensemble forest (*ntree*), the number of predictor variables randomly selected at each iteration (*mtry*), and the minimum number of observations at end nodes (node size), which can decrease the length of nodes in tree branches and simplify trees [37]. The node size parameter was left at its default value for regression (5) [68]. Per each tree in the forest (*ntree*) the calibration sample is randomly split keeping 67% of observations to fit the model and the remaining 33% (*Out-of-Bag*, OOB) to estimate the error of the model and the importance of the predictive variables.

The total sample (3,386 points) obtained from the spatial distribution of the presence and absence of fire compiled in the HSD database was separated into a training sample (70% of the population) and a testing sample (30% of the population). Consequently, the calibration sample was made up of 2,358 fire records and the validation sample of 1,028. All combinations of *ntrees* levels (from 100 to 1000 at 100 intervals) and *mtry* levels (from 1 to 5) were tested, retaining the combination that minimized the error in the OOB samples. The *nodesize* parameter was left at its default value for regression (5). The values of the parameters in the final model were *mtry* 4 and *ntrees* 1000. Models with higher values of these parameters did not improve accuracy.

To evaluate the predictive performance of the model, we calculated the area under the receiver operating characteristic (ROC) curve [69]. The ROC curve is a graphical representation of the false-positive error versus the true positive rate, that is referred as sensitivity or the proportion of correct predictions for a binary classifier system [70]. The AUC is considered a threshold-independent metric because it evaluates the performance of a model at all possible threshold values [71]. AUC values ranged from 0.5 to 1. An AUC value of 0.5 indicates random predictions, a value above 0.7 indicates good performance, and a value of 1 indicates a perfect fit [37,72,73]. The potential explanatory variables were considered or not considered, according to the value of the area under the receiver operating characteristic curve (AUC) of the trained model. Variables were introduced when they improved the AUC value and dropped when the AUC remained at the same or lesser value.

2.6. Spatial Analysis of the Ignition Probability Patterns

Changes in the spatial ignition probability patterns were addressed through local Hot Spot analysis [38,71]. The assessment of changes in the spatial pattern of predicted probability was based on the assumption that one of the key factors in wildfire management was guiding stakeholders or responsible authorities through prioritization across sites and resources at risk [72]. We considered those areas with high occurrence probability (Hot Spot) as priority intervention areas for wildfire risk management [62].

The assessment of the changes in the spatial pattern of the RF model's prediction over the study period is carried out by Cluster and Outlier Analysis through the Anselin's Local Moran's I [74]. This spatial analysis allows identifying and allocating Hot Spot areas as well as characterizing the type of cluster. Given a set of weighted features, the Cluster and Outlier Analysis tool identifies clusters of features with similar values in magnitude [38]. The threshold established for the cluster detection was defined by spatial autocorrelation analysis of the dependent variable semivariogram, evidenced by 16 km distance of spatial autocorrelation. In order to save computing time and avoid unnecessary spatial autocorrelation it was necessary to resample the model's predictions to raster resolutions of 2 km. The tool calculates a Local Moran's I value, a Z score, a p-value, and a code representing the cluster type for each feature. The results were mapped according to the significantly detected cluster typology: Hot Spot (HH), Hot Spot surrounded by Cold Spot (HL), Cold Spot (LL), and Cold Spot surrounded by Hot Spot (LH), where HL and LH are spatial outliers.

Table 1. Description of initial explanatory variables for modeling the wildfire occurrence likelihood.

Category	*Code*	*Name*	*Description*	*Unit*	*Reference*
Land cover	Savanna	Brazilian savanna	Euclidian distance to variable	Meters	[5]
	Grassland	Grasslands	Euclidian distance to variable	Meters	[5]
	Annual_crop	Annual crop	Euclidian distance to variable	Meters	[5]
	Forest_p	Eucalypt forest plantation	Euclidian distance to variable	Meters	[5,75]
	Mosaic_agric	Mosaic agriculture/pasture	Euclidian distance to variable	Meters	[5]
	Other_urban	Other urban areas	Euclidian distance to variable	Meters	[5]
	Perennial_crop	Perennial crop	Euclidian distance to variable	Meters	[5]
	Indg	Indigenous territory	Euclidian distance to variable	Meters	[76]
	Water	Water bodies	Euclidian distance to variable	Meters	[5]
	Urban	Urban	Euclidian distance to variable	Meters	[5]
Infrastructure	P_roads	Paved roads	Euclidian distance to variable	Meters	[77]
	Unp_roads	Unpaved roads	Euclidian distance to variable	Meters	[77]
	Eletric_ln	Electric power lines	Euclidian distance to variable	Meters	[78]
	Train_ln	Train lines	Euclidian distance to variable	Meters	[77]
Climate	Temp	Temperature	Daily temperature	K	[79]
	wSpeed	Wind speed	Daily wind speed	$m\ s^{-1}$	[79]
	Rel_umd	Relative humidity	Daily humidity	%	[79]
Topography	Elev	Elevation	Terrain elevation	Meters	[44]
	Asp	Aspect	Relief aspect	Class	[44]
Land tenure	Public_ld	Public land	Euclidian distance to variable	Class	[76]
	Ld_tenure	Land tenure	Euclidian distance to variable	Class	[76]
	Prop_size	Rural properties size	Euclidian distance to variable	Class	[76]
Demographic	Pop_den	Population density	Population density	Inhabitant per km^2	[47]

Additionally, in order to identify the priority intervention zones for wildfire management, we mapped the change in cluster type, i.e., clusters areas that have changed their classification over time (2010–2016). As an outcome of this analysis, a map of stable cluster zones over time was produced for the study area.

3. Results

3.1. Model Performance and Variable Importance

The RF model achieved a fairly good predictive accuracy with an AUC value of 0.72. Figure 5 shows the importance of the explanatory variables considered in the RF model. According to both model-specific procedures and to AUC estimation, the proximity of mosaic of agriculture and pasture lands and urban interfaces were the most important explanatory variable for the RF wildfire occurrence model (IncMSE > 35%). Urban areas, paved roads, and perennial crops interfaces also played an important role as a model's explanatory variables (IncMSE > 20%). Even though eucalypt plantations were not the main explanatory factor (IncMSE > 17%), it also contributed to increasing wildfire likelihood. The variable's importance results show how the increase in human presence and pressure near wildlands, contribute to wildfire occurrence in the studied area.

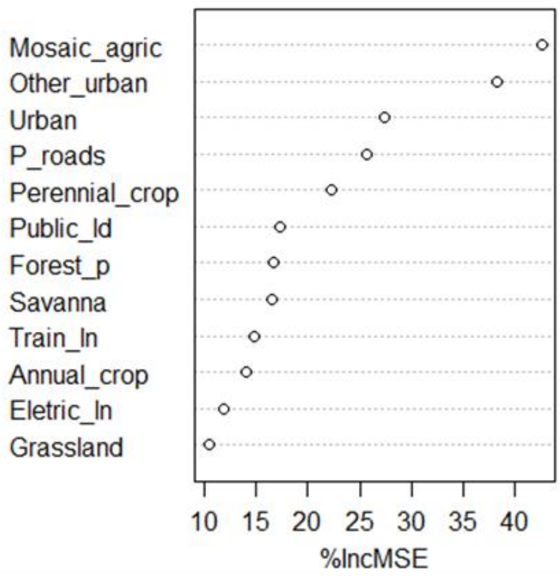

Figure 5. Percentage increase in the Mean Square Error (IncMSE) of the explanatory variables selected in the Random Forest (RF) model. The higher the IncMSE, the larger the contribution of that variable to the model.

3.2. Spatial Distribution of Occurrence Probability

The results suggested that there were no significant changes in the spatial pattern of wildfire ignition probability over the studied period (Figure 6 and Table 2). Hot Spot clusters (HH; i.e., clusters gathering pixels with a high predicted probability of wildfire ignition) were mainly distributed on the eastern part of the study area (Figure 7). The HH zones were dominated mainly by clusters of agriculture lands and urban interface. On the other hand, Cold Spot clusters (LL), with a low probability of wildfire occurrence, were concentrated mostly on the western part. The LL regions were occupied by natural vegetation (e.g. grasslands and natural forest). Hot Spot zones surrounded by Cold Spot (HL) and Cold Spot surrounded by Hot Spot (LH) were very rare in the study region, revealing a consistent spatial pattern of fire probability across the study area, which is related with the current land cover distribution and human pressure into the Brazilian savanna.

Table 2. Predicted fire ignition probability classes over the studied period.

Ignition Likelihood (%)	2010 Area (ha)	%	2012 Area (ha)	%	2014 Area (ha)	%	2016 Area (ha)	%
0.00–0.10	42,625.0	*0.7*	24,237.5	*0.4*	25,093.8	*0.4*	15,262.5	*0.3*
0.11–0.25	991,843.8	*17.4*	663,200.0	*11.7*	721,675.0	*12.7*	678,281.3	*11.9*
0.26–0.50	3,731,675.0	*65.6*	3,170,775.0	*55.8*	3,173,193.8	*55.8*	3,189,231.3	*56.1*
0.51–0.85	917,731.3	*16.1*	1,785,450.0	*31.4*	1,723,256.3	*30.3*	1,753,662.5	*30.9*
0.86–1.00	406.3	*0.0*	40,618.8	*0.7*	41,062.5	*0.7*	47,843.8	*0.8*

The consistency and persistence over time of Hot Spot areas (2010–2016) identified priority intervention zones for wildfire management. There was a noticeable predominance of HH clusters (558,380 ha), representing 10% of the total area; followed by LL cluster (470,031 ha), representing 8% of the total study area (Figure 8). The analysis of eucalypt plantation progression through the study area revealed that the expansion is increasingly progressing over clusters of high wildfire likelihood (Figure 9). During the study period, 66,822 ha of planted forest expansion took place on HH zones, that represents 13.4% of the total expansion area. In contrast, 10,855 ha were planted on LL zones, representing only 2% of the total expansion in the study area.

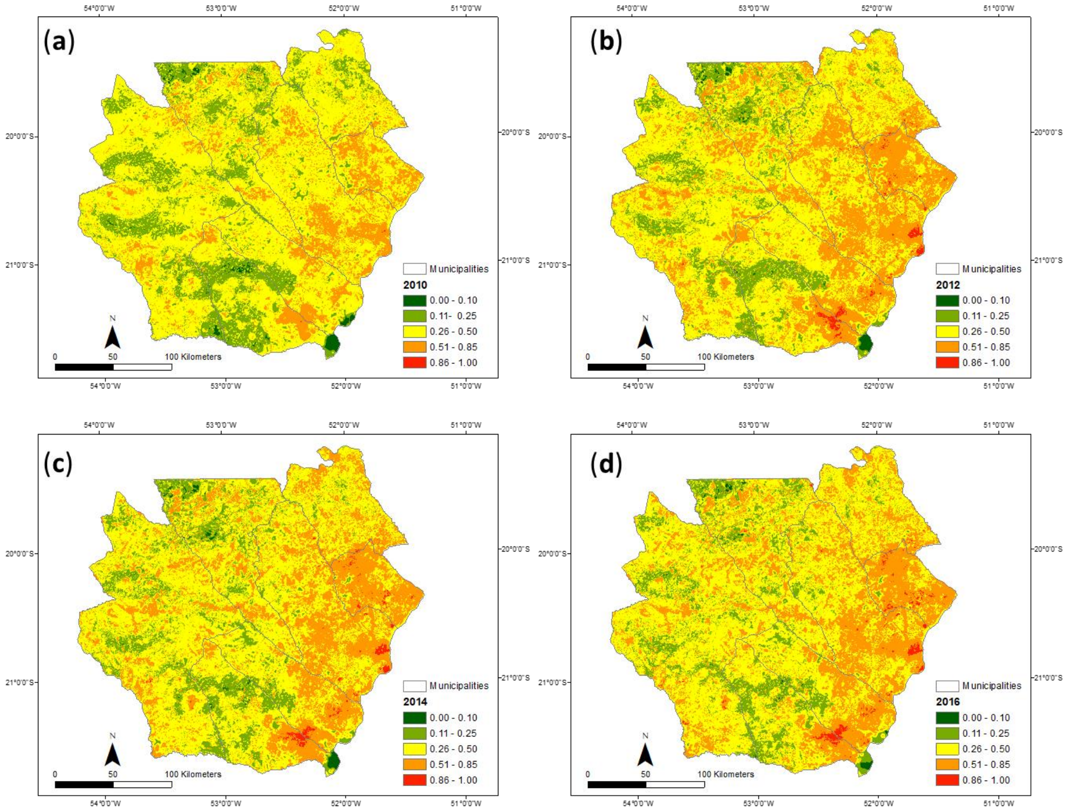

Figure 6. Predictions of fire ignition likelihood considering the land cover changes over the study period. (**a**) Predicted probability for 2010 (mean: 0.37). (**b**) Predicted probability for 2012 (mean: 0.43). (**c**) Predicted probability for 2014 (mean: 0.43). (**d**) Predicted probability for 2016 (mean: 0.44).

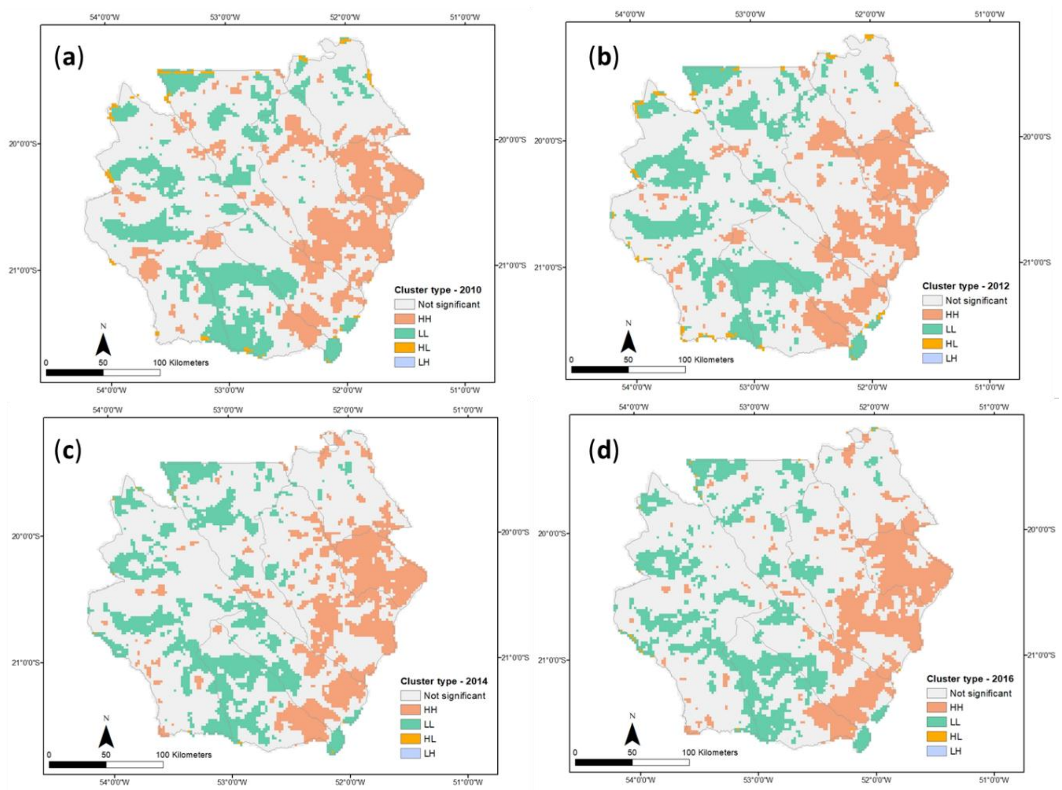

Figure 7. Spatial distribution of the cluster type: Hot Spot (HH), Hot Spot surrounded by Cold Spot (HL), Cold Spot (LL), and Cold Spot surrounded by Hot Spot (LH). (**a**) Cluster's distribution in 2010 (**b**) Cluster's distribution in 2012. (**c**) Cluster's distribution in 2014. (**d**) Cluster's distribution in 2016.

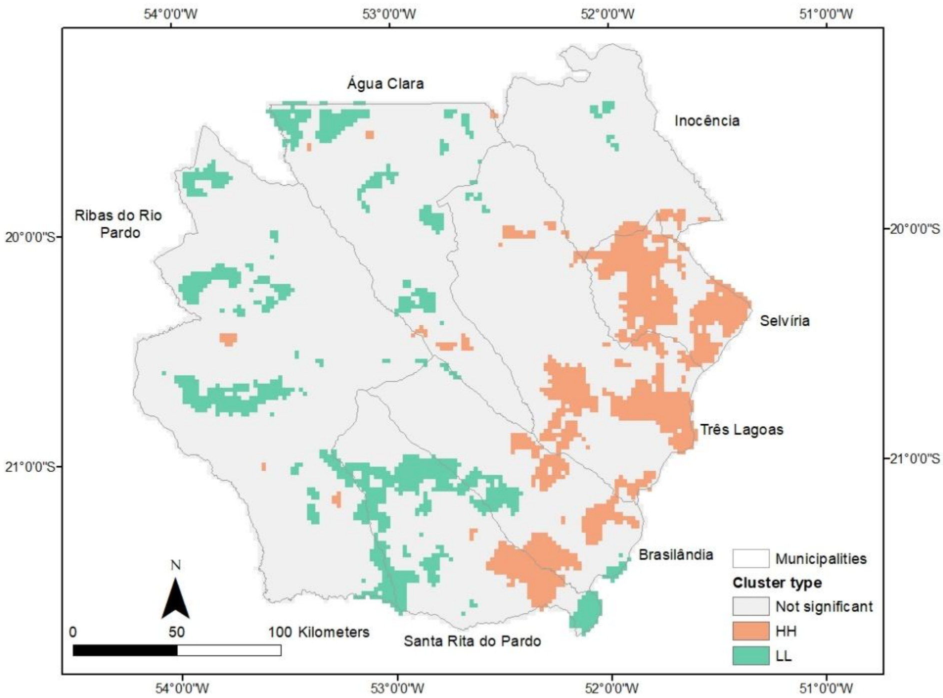

Figure 8. Consistency analysis of cluster's mapped areas over time (2010–2016).

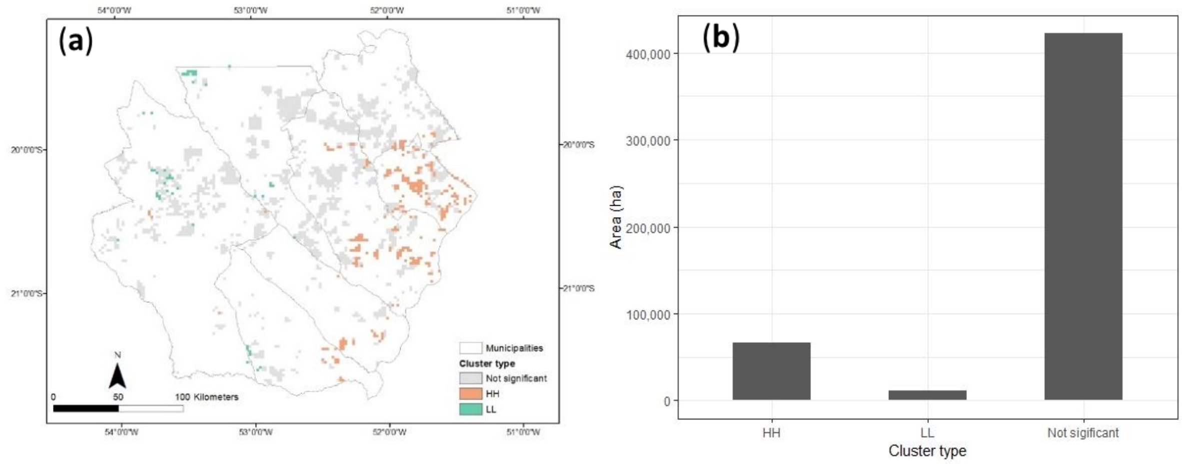

Figure 9. (**a**) Eucalypt expansion areas over fire likelihood occurrence cluster type over in the study period (2010–2016). (**b**) Distribution of eucalypt expansion area (ha) in the study period (2010–2016) classified by cluster type.

4. Discussion

In this work, we extended our understanding about the driving forces of wildfire occurrence across a eucalypt plantation hotspot on a fire-prone region of Brazil. We leveraged wildfire ignition modeling (Random Forest algorithm) and spatial distribution (Hot Spot analysis) to conduct a spatially explicit fire occurrences probability model at landscape scale. Our modeling framework provides clear guidance for fire risk management and it can be applied for quantifying wildfire ignition likelihood elsewhere.

Even though multiple sources of uncertainty remain with regard to modeling wildfire occurrence [26], the fitted RF model for fire occurrence presented a fairly good accuracy (AUC $\approx$ 0.72). Nevertheless, the model accuracy could be improved with the refinement of the spatial accuracy of the response variable, the expansion of the temporal resolution or considering the causes (human-related versus naturally caused) behind wildfire into the modeling framework [38,80], limitations that were imposed by data availability and its features.

In this study, land cover and socioeconomic variables were highly contributing in explaining the wildfire ignition likelihood, while governing the broad spatial pattern. We found that human-related activities close to wildlands, especially agriculture and urban activities, seemed to promote wildfire occurrence. The explanatory variables were in agreement with other wildfire studies carried out in the Brazilian savanna [6,17,58,81] and also in accordance with the literature about modeling wildfire occurrence [20]. Croplands [82,83] or proximity to agricultural plots [60] are associated with a higher chance of fire ignitions due to the use of either machinery or traditional practices like slash-and-burn. Urban interfaces and proximity to roads also played an important role in increasing fire events due to their relationship with increased human presence, granting accessibility into wildlands [15,17].

Climate often plays an important role in fire ignition by altering fuel moisture, fostering fuel availability, or boosting fire spread [16,84,85]. Nevertheless, climate variables (temperature, relative humidity, and wind speed) presented a low contribution to wildfire occurrence likelihood in this work (see Supplementary material Figure S1). The minor relevance of climate as explanatory variables in the RF model is most likely related to the fact that wildfire size was disregarded since it cannot be retrieved from the HSD. The role of climate and weather is often more relevant to model the ultimate size of fires that to determine the chance of a fire to occur, especially in human-dominated landscapes. Nonetheless, Nogueira [86] found good correlations between fire danger indices and the seasonal pattern of burned areas in the Brazilian savanna. Other studies reported a temporal and spatial pattern resulting from climate interactions, identifying a main fire season between July and November, which is the drier season in the Brazilian savanna [23]. The fire occurrence distribution across the studied area is characterized by a peak of fire events during the wet season between January and March (Figure 4), thus supporting the hypothesis that fire occurrence is better related to anthropogenic activities than weather factors. Human-related drivers can substantially alter the seasonal fire pattern according to local fire practices [87]. Our findings support this hypothesis, suggesting that explanatory factors are rather stationary, i.e., related to fixed relationships over space and time, mainly linked to human-related drivers or landscape structure. The spatial pattern of fire probability and HH distribution across the study area evidence this behavior.

In particular, mosaic of agriculture and pasture, other urban, urban, paved roads, and perennial crops interfaces have proved to be the variables most closely related to fire occurrence in the studied savanna area (Figure 5). These land covers coexist in the landscape and their intermix seems to favor wildfire occurrence. The mix of land covers may increase fire occurrence at distinct spatial-temporal scales (e.g., burning season for agriculture and accidental fires in the road), then make it hazardous and difficult to mitigate [6,17]. Furthermore, the heterogeneity of wildfire drives across the landscape increases the complexity of building an effective fire policy to control the risk.

Apart for the grasslands and savanna interface, all the explanatory variables have positive behavior on the fire occurrence, it means they increase ignition likelihood with increasing proximity of the variable's interface (Figure 10). The proximity to these interfaces is related to increased human presence, related to both accidental (use fire as a management tool) and arson fires, thus increasing the occurrence of fire events in the Brazilian savanna. The presence of eucalypt plantations areas also contributed to increasing wildfire likelihood, most likely due to the increased human presence and forest-fuel availability in the plantations. The response curve of the annual crop presented the steepest slope (-8.046×10^{-6}), representing that this variable makes an important contribution for fire ignition in a short distance (up to 5 km) region. This behavior may be explained by the fire management in the agricultural fields, that is inventively used to eliminate annual crop harvesting wastes and to clean cropland borders [6,57]. On the other hand, the grasslands and savanna formations seem to have an inverse relationship, with decreasing fire occurrence likelihood when increasing proximity of the variable's interface. Their response curves presented positive linear slope 2.220×10^{-5} and 6.555×10^{-5}, in a range up to 3 km and 1.5 km distance respectively for grasslands and savanna interfaces. This behavior is directly linked with low human presence and with low accessibility across remote areas of natural vegetation.

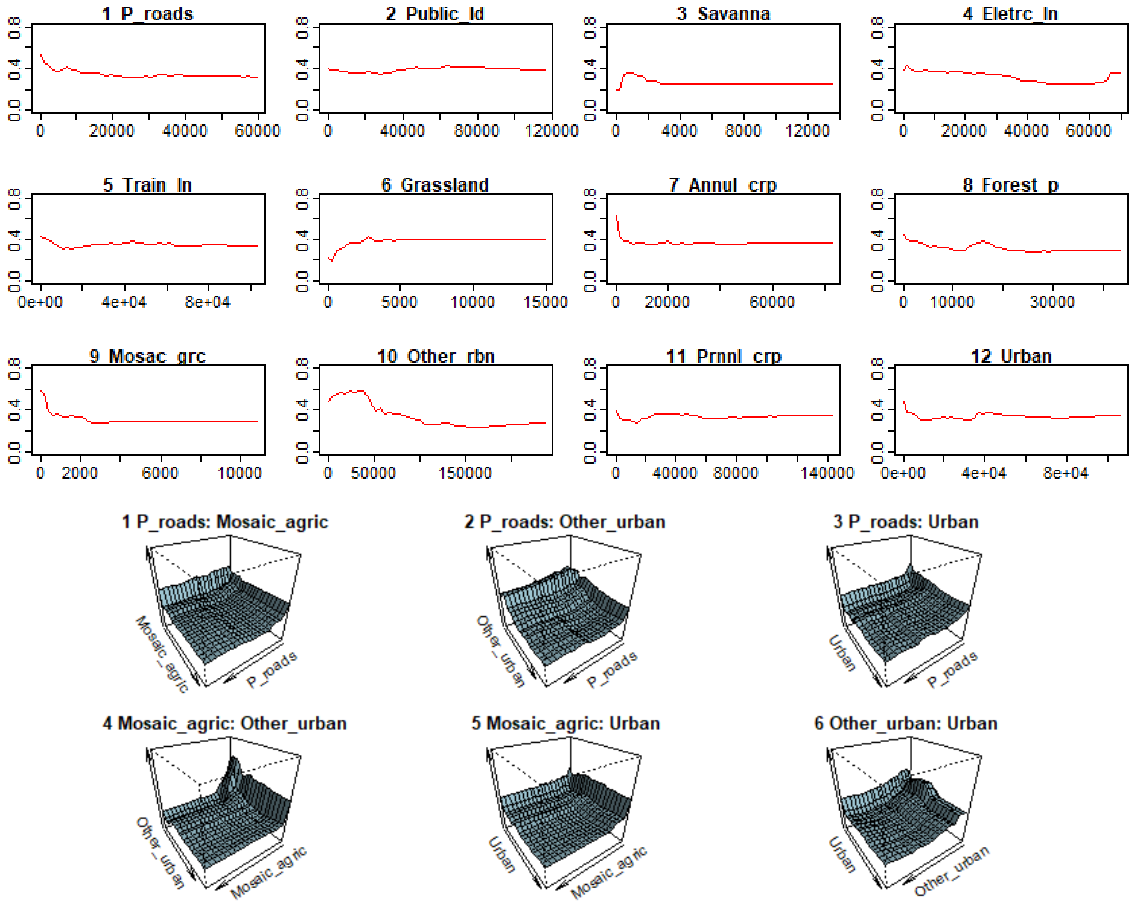

Figure 10. Response curves (top) and variable interactions (bottom) for predictive variables of RF.

The response of the explanatory variables is related to the spatial pattern of ignition likelihood, which is observed in the probability and clusters maps (Figure 6, Figure 7, and Figure 8). Western zones of the studied area are dominated by low ignition likelihood and are consequently dominated by natural vegetation and wildlands. On the other hand, eastern areas that are dominated by high ignition likelihood and are occupied by intensive agriculture, eucalypt plantations, and urban interfaces, demonstrating the impacts of human pressure on fire events. In this sense, land cover changes, and specifically the expansion of agriculture and forest plantations, may impact even more the fire regime across the studied area in a near future.

Eucalypt plantations are increasingly dominating the study landscape, with an average area growth of 22% per year (2010 to 2016) and future projections showed an increasing trend indicating that the forest plantations area is going to continue increasing over time due to the increasing demand for bioproducts [1,4,88]. Besides the landscape-level changes, the expansion of eucalypt forest increases the amount of stocked carbon and alter the structural complexity of fuel available to burn during a wildfire event [89]. The particular fuel characteristics and highly flammable nature of eucalypt forests have long been recognized and studied in the fire science [90]. Cheney and Richmond [91] highlighted eucalypts' fire potential demonstrated by the bark, a rapidly established gap between the understory and overstorey layers due to self-pruning, and fast build-up of uniformly compacted litter. Eucalypt plantations may increase fuel load to hazardous levels, as shown by the total fuel load of 11 t ha^{-1} in eucalypt plantation in Brazil [92]. Forest plantations of flammable species managed to optimize wood yields are essentially vulnerable to wildfires, and risk management is advised when ignitions are likely to occur in fire-prone ecosystems [91]. Therefore, it is essential to understand how eucalypt forest behaves regarding wildfire occurrence in order to promote wildfire policy and management actions to mitigate risks.

Fire effects on the vegetation were mainly influenced by factors related to both fire damage and individual tree characteristics. Hence, it is important to understand the impact on each tree under local weather and managerial conditions [26,93]. Response functions related to fire intensity levels indicate tree mortality (%) at the stand level and were developed for the main commercial tree species *Quercus spp., Pinus spp., Eucalyptus spp.* in Europe and US [93–97]. The development of site species-specific mortality curves provides valuable information for accurate risk assessments [98]. Nevertheless, fire effects modeling efforts are still required for Eucalyptus spp. plantations in Brazil.

In this regard, the prediction of wildfire occurrence probability overlaid with eucalypt expansion areas demonstrated that the eucalypt plantation expansion is taking place over clusters of high wildfire likelihood (HH). When comparing eucalypt expansion on HH and LL clusters, HH represents 86% of the expansion area (Figure 8). Thus, the increasing concentration of a forest fuel load on HH zones consequently increases the exposure to wildfire events for young eucalypt forests and, potentially, for nearby forest stands and wildland areas. The potential impact may be estimated by further studies that assess potential wildfire economic losses and transmission to other eucalypt stands, rural communities, and urban areas.

Our findings suggest an increasing exposure to fire of the eucalypt plantations, which may drive to higher fire risk, causing economic and environmental loss. Thus, the mapped clusters may be used as a reference for the establishment of new eucalypt plantations, as well for fire ignition mitigation and firefighting resource allocation. Nevertheless, in order to build a broad wildfire policy and fire risk management, it is essential to assess the fire behavior across the studied area. Fire behavior models can provide detailed and site-specific wildfire risk assessments, measuring wildfire risk at the regional scale to provide meaningful outcomes to forest managers and policymakers [24,98–100].

5. Conclusions

This study presents a first attempt at generating a wildfire occurrence probability model on the Brazilian savanna biome based on socio-economic and environmental variables, addressing specifically the role of eucalypt forest plantations. Thus, it contributed to developing fire science knowledge in one of the most active world fire areas that still requires modeling efforts [16]. The model could be particularly useful not only for evaluating the current occurrence likelihood distribution and unravel fire occurrence driving forces across the studied landscape, but also for assessing and defining critical areas for further improvements in wildfire management planning. Furthermore, our findings may be used as a reference for strategic planning of furthers eucalypt plantations expansion, in order to mitigate potential fire risk for the new plantations across the region.

The model denoted a fairly good performance (AUC $\approx$ 0.72). Nevertheless, it still can be improved by enhancing the spatial resolution of explanatory variables and expanding the temporal resolution of analysis in order to improve the prediction power and to support a better understanding of wildfire trends. The analysis of land cover changes across the study area increased the modeling complexity, although the land cover changes were essential for a better understanding of how human-related factors, which are progressively present on Brazilian savanna landscape, influence wildfire occurrence. In addition, cartographic outputs were a valuable and useful asset to support local wildfire managerial actions.

Regarding the explanatory factors, humans were the main drivers of wildfire in the region. Socio-economic variables, such as agriculture (mosaic agriculture and pasture), rural villages and cities interfaces (other urban and urban), and accessibility (paved roads) were strong predictors of wildfire ignition likelihood. The low explanatory power of climate-related variables may be linked to being forced to disregard wildfire size since it cannot be retrieved from the fire database. Eucalypt plantations played an important role in both increasing wildfire likelihood and its area expansion across the Brazilian savanna landscape.

Finally, the results suggest that preventive measures should be applied in most critical mapped areas (Hot Spots) and special attention should be given to the eucalypt plantation stands, due to their potential risk of burning. Protective measures (e.g., widening of firebreaks, reorganization of forest management practices, optimization of resource allocation for firefighting, and media campaigns) could be relatively easily implemented in Hot Spot zones in order to mitigate the risks. The removal of eucalypt forest residues (litter and harvest residues), as a by-product, would be an efficient way to prevent forest fires, nevertheless, it is considered not environmentally feasible due to physical and biological damage to the soil [3,101]. Furthermore, wildfire detection systems from forestry companies may prioritize the HH zones in the monitoring framework to facilitate early fire ignition detection and to focus on efficient initial suppression rather than costly firefighting. Fuel metrics and potential fire behavior changes across the eucalypt plantation must be better understood and further studies should be carried out to support an effective wildfire risk management in the Brazilian savanna.

Supplementary Materials: The Supplementary Materials are available online at http://www.mdpi.com/1999-4907/10/10/844/s1.

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