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METHODOLOGY FOR MAPPING THE PROBABILITY OF FIRE OCCURRENCE IN THE BRAZILIAN CERRADO BIOME BASED ON THE DANGER OF FIRE PROPAGATION VARIABLES*

METODOLOGIA PARA MAPEAMENTO DA PROBABILIDADE DE OCORRÊNCIA DE FOGO NO BIOMA DO CERRADO BRASILEIRO BASEADA EM VARIÁVEIS RELACIONADAS AO PERIGO DE PROPAGAÇÃO DO FOGO

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ABSTRACT

The area covered by the Brazilian cerrado biome has been greatly reduced in recent years due to the expansion of agricultural land and the increased number of fire outbreaks. The objective of this paper is to propose a methodology based on geospatial analysis and logistic regression analysis (LRA) for mapping the probability of fire occurrence in Brazilian cerrado conservation units. This model was applied in the Serra da Canastra National Park (SCNP) in the Southeast of Brazil. The methodology uses the maps of the following environmental variables, which are related to the danger of fire propagation: wind effect (WIN), terrain convexity (CVX), slope (SLO), drainage density (DRD), altitude (ELV), vegetation index (NDVI), and road density (ROD). The results of the LRA showed that the variables SLO, ELV, NDVI, ROD ($p<0.0001$), DRD ($p=0.0005$) and WIN ($p=0.0007$) contributed significantly to the occurrence of fire outbreaks. The model correctly classified 94.26% of cases. We conclude that this methodology can be used to inform the planning of firefighting actions in the Brazilian cerrado biome.

Keywords: Fire outbreaks, geospatial analysis, logistic regression, Brazilian cerrado biome, Brazil.

RESUMO

As áreas cobertas pelo bioma do cerrado do Brasil têm sido extensamente reduzidas nos últimos anos devido à expansão da agricultura e ao aumento da ocorrência de eventos de fogo. O objetivo deste artigo é apresentar uma metodologia baseada em análise geoespacial e análise de regressão logística (LRA) para mapear a probabilidade de ocorrência de fogo em unidades de conservação do cerrado do Brasil. Este modelo foi aplicado no Parque Nacional da Serra da Canastra, localizado no sudeste do Brasil. A metodologia utiliza os mapas das seguintes variáveis ambientais relacionadas ao perigo de propagação do fogo: efeito do vento (WIND), convexidade do terreno (CVX), declividade (SLO), densidade de drenagem (DDR), altitude (ELV), índice de vegetação (NDVI) e densidade de estradas (ROD). Os resultados mostraram que as variáveis SLO, ELV, NDVI, ROD ($p<0,0001$); DRD ($p=0,0005$) e WIN ($p=0,0007$) contribuíram significativamente para a ocorrência de eventos de fogo. O percentual de casos corretamente classificados foi de 94,26%. Concluímos que esta metodologia pode ser utilizada em ações de planejamento do combate ao fogo no bioma do cerrado.

Palavras-chave: Eventos de fogo, análise geoespacial, regressão logística, bioma do cerrado brasileiro, Brasil.

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Introduction

Fire is a major cause of forest destruction and biodiversity loss in Brazilian biomes, especially in the Brazilian *cerrado* biome. The area covered by Brazilian *cerrado* vegetation has been greatly reduced in recent years due to the expansion of agricultural land and the increased number of fire outbreaks. Given the current vulnerability of Brazilian forests, the development of geospatial models to map the probability of fire occurrence is an important scientific goal. Tropical savannas experience a high frequency of fires because of the high production and accumulation of fuel due to the abundance of herbaceous vegetation (Rodrigues *et al.,* 2021).

Fires in the Brazilian *cerrado* biome have been occurring for 32,000 years, and they propagate on the surface vegetation of the herbaceous stratum (Miranda *et al.,* 2004). Practically all plants of the Brazilian *cerrado* have evolved to tolerate or depend on fire for their existence (Coutinho, 1990); therefore, fires are integrated into the ecosystems of this biome (Conti and Furlan, 2011).

Natural fires occur during the wet season and are mainly caused by lightning strikes. These fire types benefit some phytophysiognomies of the Brazilian *cerrado*, for example, by promoting the regrowth of several herbaceous species and acting as flowering stimuli (Conti and Furlan, 2011). Nevertheless, recurrent fires can be harmful because they may prevent woody species from having time to regenerate, affect resprouting vigour and result in changes in soil properties (Rodrigues *et al.,* 2021).

Over the last 50 years, forest fires have been concentrated at the end of the dry season and have been occurring every two or three years, which has seriously damaged fire-sensitive vegetation (Schmidt and Eloy, 2020). Fires that occur at the end of the dry season are more severe due to the larger amount of fuel available on the ground (especially dead herbaceous vegetation) and to the absence of rainfall (Gomes *et al.,* 2018).

The irrational occupation of space over decades and the increasing expansion of the agricultural frontier have worsened fires and increased their destructive power (Ramos *et al.*, 2015). Agribusiness expansion is one of the main causes of suppressing almost half of the original vegetation in the Brazilian *cerrado*, and fires are used as tools to convert natural vegetation to monocultures (Schmidt and Eloy, 2020) and as an inexpensive and quick management strategy (Conti and Furlan, 2011).

Studies have shown that several environmental factors are related to the increased danger of fire propagation in vegetation. The slope of the terrain contributes significantly to the spread of fire, with fires spreading more rapidly in areas located on steeper slopes (Ajin *et al.*, 2016; Soares Neto *et al.*, 2016). The wind acts in a more complex way because in addition to fuelling combustion, it also contributes to directing the spread of fire along slopes (Torres, 2006). The proximity of roads facilitates access to firefighting and can also act as a barrier to the spread of fires (Torres, 2006), although it can contribute to arson.

The convex forms of slopes disperse moisture on the surface and therefore tend to be drier and more favourable to fires (Coura *et al.*, 2009). Phytophysiognomies that present lower biomass densities and, therefore, lower vegetation index, such as fields, are more predisposed to the spread of fire (Messias and Ferreira, 2019a). Catry *et al.* (2009) found that population density, human accessibility, land use and altitude were the most important determinants of the spatial distribution of fire ignition in Portugal.

Among the main elements of landscapes that drive fire propagation are fuel characteristics. In the Brazilian *cerrado* biome, the main fuel load is composed of herbaceous vegetation that becomes senescent in the dry season and provides much fine and flammable fuel on the ground (Franke *et al.*, 2018). Atmospheric conditions throughout the year limit or promote the growth of fine fuel, while variations in relative humidity, wind speed and temperature may influence the ignition, intensity and propagation of fires (Ruffault *et al.*, 2017). Furthermore, the characteristics of topography, such as aspect, elevation and slope, affect fire behaviour, either directly or in association with climatic or fuel conditions (Algöwer *et al.*, 2003).

Fire elimination over a long period may cause the accumulation of fine fuel, which increases the intensity and severity of future fires (Harris *et al.*, 2016). Studies show that both frequent and rare fire occurrences may affect conservation and biodiversity in the Brazilian *cerrado* (Durigan and Ratter, 2016). Hence, protected areas in Brazil have followed an international trend of integrated fire management (IFM), which aims to reduce fire occurrence at the end of the dry season and consequently to decrease the occurrence of large magnitude events (MMA *et al,* 2017). Fire risk mapping is also an essential tool for the prevention, suppression and management of fires, as it allows the spatial visualization of areas with higher and lower ignition or propagation probabilities (Kovalsyki *et al.,* 2020).

Logistic regression is one of the most used methods for modelling fire occurrence (Catry *et al.*, 2009). The statistical method of logistic regression is used to analyse, describe and test hypotheses about the relationship between a categorical variable (the resulting event) and one or more categorical or continuous predictive variables (explanatory variables).

The simplest case is when we have a continuous predictive variable X and a dependent dichotomous variable Y (Peng *et al.*, 2002). The dichotomous or binary variable Y estimates the presence (Y = 1) or absence (Y = 0) of a phenomenon from a set of predictive explanatory variables (Panik, 2009). This method allows predicting how the probability of an event (dichotomous) is influenced or not by the presence or absence of determined variables or by their values.

The main advantages of the logistic regression method over conventional methods of simple and multiple regression are the possibility of working with dependent and independent variables that do not have a normal distribution and the use of a mixture of categorical and continuous variables (Catry *et al.*, 2009; Çokluk, 2010). For this reason, logistic regression is more efficient when working with spatial data that are not normal and have a spatially dependent distribution. The logistic regression analysis produces an equation that reveals the probabilities (measured in values of 0.0 and 1.0) of an event belonging to the yes class (it occurs) and the no class (it does not occur).

The objective of this paper is to present a methodology based on geospatial analysis and logistic regression analysis for mapping the probability of fire occurrence in Brazilian *cerrado* conservation units. Of the environmental variables related to the fire propagation, the following were selected: wind effect (WIN), terrain convexity (CVX), slope (SLO), drainage density (DRD), altitude (ELV), vegetation index (NDVI) and road density (ROD). Maps of these variables were used for the development of the methodology. This model was applied in the Serra da Canastra National Park, located in the Southeast of Brazil.

Study Area

The Brazilian *cerrado* is a savanna biome that occupies approximately two million square kilometres. This biome has a great floristic diversity and characteristic phytophysiognomies. The species of arboreal plants are generally tortuous and spaced and are adapted to extract water from deep soil. Savanna phytophysiognomies, such as *campo sujo*, *campo limpo* and *campo rupestre*, in which herbaceous species predominate, are also common (Conti and Furlan, 2011).

The Brazilian *cerrado* is humid despite its seasonality, and the annual precipitation level is above 1,000 mm (Conti and Furlan, 2011). However, the rainy and dry seasons are very set. Throughout the dry season, some main and secondary water courses become narrow or disappear temporarily. The biome contains parts of large hydrographic basins of South America, such as Paraná, Paraguai, Tocantins-Araguaia and São Francisco (Latrubesse *et al.*, 2019).

SCNP is an important protected area (conservation unit) of the Brazilian *cerrado*. SCNP is located in the southwestern part of the state of Minas Gerais, Brazil, with a defined area of 1,977.8 km² and was created by the Decree 70.355/1972. However, an area of only 715.2 km² was regulated at the time of its creation. A buffer zone around the SCNP was also created, with a perimeter of 1,493 km and a surface area of 2,695.13 km² (fig. 1) (MMA and IBAMA, 2005).

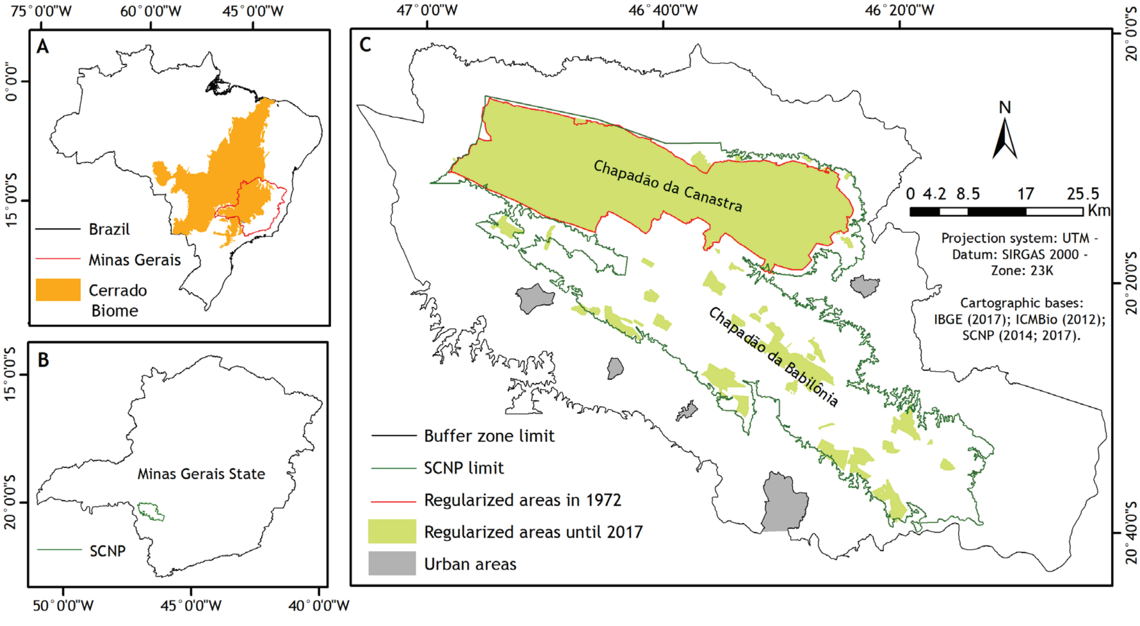

Fig. 1 - Location of the Brazilian *cerrado* biome and the state of Minas Gerais in the Brazilian territory (A); Serra da Canastra National Park in relation to the state of Minas Gerais (B); Parque Nacional da Serra da Canastra map (C).

Fig. 1 - *Localização do bioma do cerrado e do estado de Minas Gerais no território brasileiro (A); Localização do Parque Nacional da Serra da Canastra em relação ao estado de Minas Gerais (B); Mapa do Parque Nacional da Serra da Canastra (C).*

The interior of the SCNP is constituted by reliefs of *chapadas* (high reliefs with flattened tops and pronounced scarps) that form the areas referred to as *Chapadão da Canastra* and *Chapadão da Babilônia*. These are the higher zones of the SCNP, which may reach up to 1,500 m and are mainly composed of quartzite rocks. There are lower zones composed of rocks less resistant than quartzite, surrounded by the reliefs of *chapadas*, and the altitudes in these areas may range from 600 to 1,100 m (MMA and IBAMA, 2005).

The importance of the creation of the SCNP is related to its ecological relevance. The park preserves a great diversity of Brazilian *cerrado* fauna and flora, protects endemic species and endangered species (such as grebe duck), presents natural beauties, includes several water courses and waterfalls, and preserves springs of important Brazilian rivers (such as São Francisco and Araguari) (MMA and IBAMA, 2005).

Nevertheless, the preservation of the SCNP is constantly threatened by conflicting activities, such as frequent fires, deforestation, erosion development, mining and agricultural and cattle ranching activities in non-regulated areas (MMA and IBAMA, 2005; Messias and Ferreira, 2019b).

Material and Methods

The model for mapping the probability of fire occurrence is based on the following environmental variables, which are related to the danger of fire propagation: wind effect (WIN), terrain convexity (CVX), slope (SLO), drainage density (DRD), altitude (ELV), vegetation index (NDVI) and road density (ROD).

We do not use climatological variables in this research because there are no climatological stations within the park area. In addition, the available stations are located in municipalities which are quite distant from the park.

Mapping of the fire occurrence areas

The mapping of the burnt areas in the study area was carried out based on the visual interpretation of orbital images in three types of colour compositions: false-colour compositions 7R/4G/3B and 7R/5G/4B (for both Thematic Mapper — TM and Enhanced Thematic Mapper Plus — ETM+ Landsat sensors) or 5R/4G/7B and 7R/6G/5B (for Operational Land Imager — OLI Landsat sensor); and true colour composition 3R/2G/1B (for both TM-Landsat and ETM + Landsat sensors) or 4R/3G/2B (for OLI sensor).

The polygons referring to the perimeter of the burned areas were digitized on the screen within regular 5x5 km cells at an approximate scale of 1:15,000 for each year of the 1984-2015 time series. Then, the average fire frequency in the pixel in the time series was calculated. The average fire frequency map was classified by the standard deviation (SD) method.

Explanatory environmental variables

- *NDVI*. The normalized difference vegetation index map was derived from Landsat TM, ETM+ and OLI images with spatial resolution of 30 m. The SCNP is located between two Landsat scenes (paths/rows 219/74 and 220/74), and for each of them, 22 images were selected within the period from 1984 to 2015 at the beginning of the dry season in the Brazilian *cerrado*, i.e., in April or May. In the ENVI 4.2 image processing software (Exelis Visual Information Solutions, 2011), atmospheric correction of these images was performed using the Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) tool. Then, in ArcGIS 10.2 (ESRI, 2012) algebraic operations were performed on the 22 images of each scene; the median values of each pixel were calculated with the Cell Statistics tool, and a single image that represents the central trend of the reflectance in the period was obtained. The NDVI was obtained from the following expression:

$$NDVI = \frac{\rho_{NIR} - \rho_R}{\rho_{NIR} + \rho_R} \qquad \text{(Eq. 1)}$$

where ρ_{NIR} is the reflectance in the near infrared spectral band, and ρ_R is the reflectance in the red spectral band of the Landsat multispectral image;

- *Altitude*. The altitude map was obtained from the ASTER GDEM 2 Digital Elevation Model (DEM), with spatial resolution of 30 m, using ArcGIS 10.2;
- *Terrain slope*. The slope map was generated in ArcGIS 10.2 using the *Slope tool* and ASTER GDEM 2 as input data;
- *Terrain convexity*. Surface convexity index were calculated with the *Terrain Surface Convexity* tool, which is available in SAGA GIS 6.0, with ASTER GDEM 2 as input data. The higher the pixel value on the convexity index map, higher the density of convex slopes;
- *Wind effect*. The wind effect map predicts the degree of the wind effect on the terrain surface. The *wind effect* tool is available in the SAGA GIS software (Conrad *et al.*, 2015). We used ASTER GDEM 2 as input data to calculate the wind effect map, considering an azimuth of 120° as the predominant wind direction in the SCNP (MMA and IBAMA, 2005). Wind effect values lower than 1.0 are associated to areas that are not affected by the local predominant wind; wind effect values higher than 1.0 are associated to areas that are directly affected by it;
- *Road density*. The unpaved roads and the highways in the SCNP were digitized in ArcGIS 10.2 using cartographic base georeferenced satellite images

available in Google Earth. Then, the kernel density tool with a radius of 3 km was used to generate the road density map;

- *Drainage density*. The drainage density map in the SCNP was created in ArcGIS 10.2 using ASTER GDEM 2 data and hydrology and kernel density tools. All the maps built in this research have a spatial resolution of 30 m.

Model building

The model uses the multivariate logistic regression method to obtain the equation to calculate and map the probability of fire occurrence (p). In this model, we considered fire as a dichotomous variable (occurs, F=1; does not occur, F=0). The dichotomous variable was estimated from a set of explanatory environmental variables related to the danger of fire propagation, including the wind effect (WIN), slope convexity (CVX), slope (SLO), drainage density (DDR), altitude (ELV), vegetation index (NDVI) and road density (ROD) variables. The methodology used to build the model was based on the following steps:

- Mapping of 534 centroids of the polygons where the fire frequency (F=1) was greater than the annual average (> 2.5 SD) during the period from 1984 to 2015;
- Mapping of the buffers with a radius of 500 m around F=1 polygon centroids;
- Extracting the average values of each explanatory environmental variable map inside the F=1 buffer areas;
- Random selection of 1,000 points located in areas where there was no fire (F=0) from 1984 to 2015;
- Mapping of the buffers with a radius of 500 m around F=0 polygon centroids;
- Extraction of the average values of the maps for each explanatory environmental variable within the F=0 buffer areas;
- The average values for the variables WIN, CVX, SLO, DDR, ELV, NDVI and ROD calculated within the F=1 and F=0 buffer areas were organized in a spreadsheet and exported to the statistical software MedCalc (MedCalc, 2020), and the logistic regression analysis was performed. A sample of 1,534 cases was used, with 534 positives (fire or F=1) and 1,000 negatives (nonfire or F=0);
- In the logistic regression analysis, we calculated the correlation coefficients of the explanatory environmental variables and the constant and the respective levels of significance. Only variables with a significance level of less than 0.001 ($p<0.001$) were used in the model;
- A table of classification of the logistic regression was used to assess the accuracy of the model. The percentage of cases correctly classified in the fire (F=1) and nonfire (F=0) groups and the area under the ROC (receiver operating characteristics) probability curve (AUC) were calculated;
- Finally, the probability of fire occurrence equation (*p*) was obtained. This equation was used to calculate and map the probability of fire occurrence using the ArcGIS 10.2 Raster Calculator tool.

Model testing and adjustment

The model was tested and adjusted using fire foci mapped from Moderate Resolution Imaging Spectroradiometer (MODIS) orbital sensor images registered in the period from 2016 to 2020 (INPE, 2020). The fire occurrence probability map was classified into ten classes, and the density of fire foci per square kilometre was calculated in each class.

A scatter plot showing the relationship between the probability (p) calculated by the model based on the 1984 to 2015 fire data and the density of fire foci (D) mapped in the 2016-2020 period was constructed. Then, the determination coefficient (R^2) was calculated, and an equation relating p and D was obtained.

Results and discussion

The methodology for mapping the probability of fire occurrence applied in this paper was based on the explanatory variables altitude (A), slope (B), convexity index (C), wind effect (D), vegetation index (E), drainage density (F) and road density (G) in the Serra da Canastra National Park (fig. 2). However, as we do not have accurate information about the locations of such events, we do not consider the causal variables of wildfires in our study, such as lightning that occurs during spring storms and fires accidentally caused by tourists or farmers who live close to the park.

The values of the statistical parameters were obtained by the logistic regression analysis (Table I).

The chi-square value (chi-square = 1,471.817) shows that the independent variables (explanatory environmental variables) affect the dependent dichotomous variable (fire occurrence). The significance level value ($p <0.0001$) indicates that there is evidence that at least one of the independent variables contributes to the prediction of the fire event.

Analysing the values of the regression coefficients, we can see that only the terrain convexity variable (CVX) did not significantly contribute to fire prediction ($p> 0.05$). On the other hand, the variables vegetation index (NDVI),

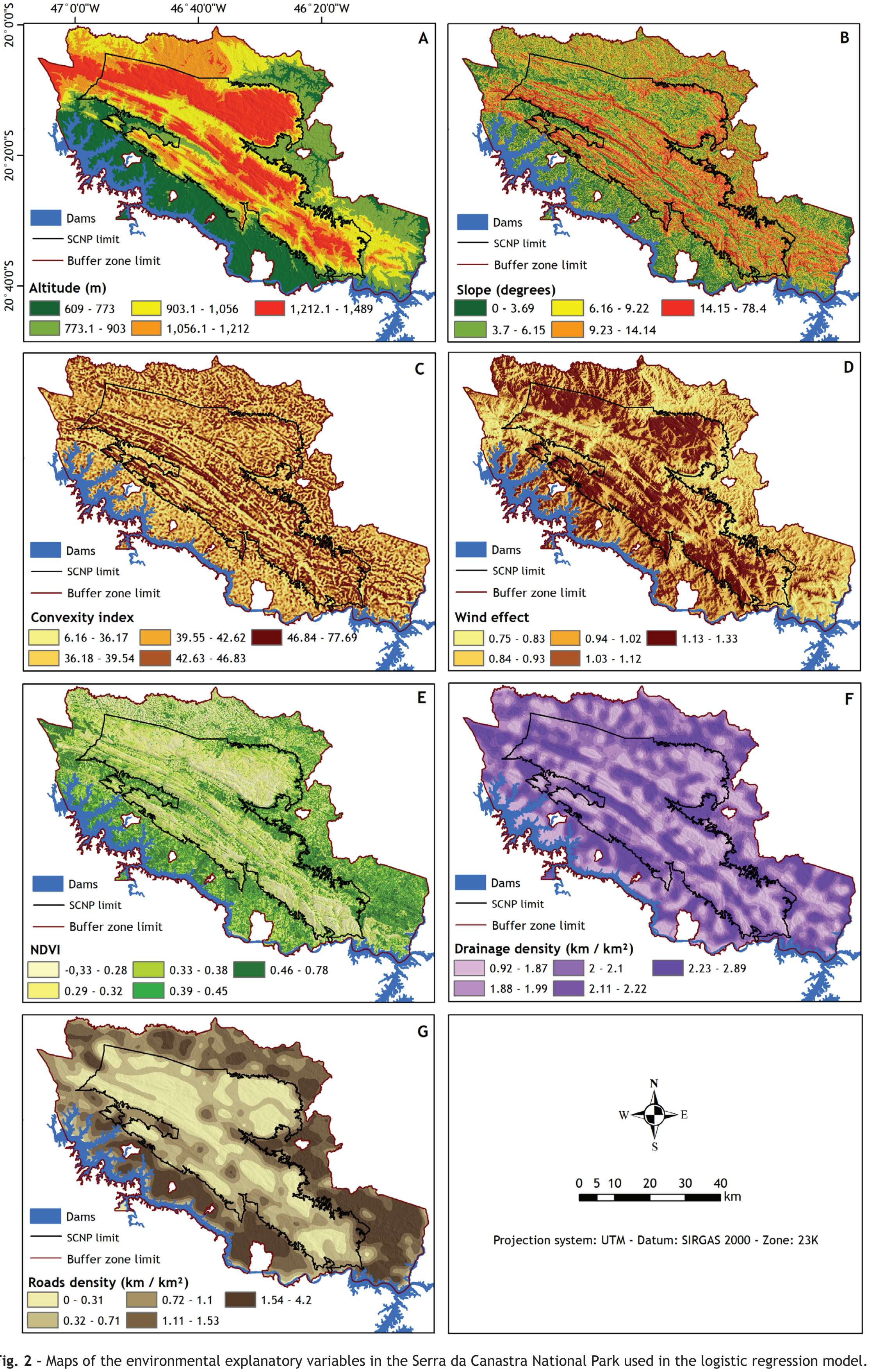

Fig. 2 - Maps of the environmental explanatory variables in the Serra da Canastra National Park used in the logistic regression model.

***Fig. 2** - Mapas das variáveis ambientais explanatórias no Parque Nacional da Serra da Canastra, utilizadas no modelo de regressão logística.*

Table I - Statistical parameters of the logistic regression model.

Tabela I - Parâmetros estatísticos do modelo de regressão logística.

Sample size

Sample size	1534
Positive cases (F=1)	534 (34.81%)
Negative cases (F=0)	1,000 (65.19%)

Overall Model Fit

Chi-squared	1,471.817
DF	7
Significance level	P<0.0001

Coefficients and Standard Errors

Variable	Coefficient	Std. Error	Wald	P
CVX	-0.042448	0.032139	1.7444	0.1866
SLO	0.15981	0.031596	25.5846	<0.0001
DDR	-2.16038	0.62402	11.9858	0.0005
ELV	0.0089268	0.00092874	92.3852	<0.0001
NDVI	-17.63823	1.87070	88.9004	<0.0001
WIN	3.59601	1.06643	11.3705	0.0007
ROD	-2.11638	0.29161	52.6731	<0.0001
Constant	-1.48865	2.35022	0.4012	0.5265

Classification table (cut-off value p=0.05)

Actual group	Predicted group		Percent correct
	0	1	
F = 0	946	54	94.60%
F = 1	34	500	93.63%
Percent of cases correctly classified			94.26%

ROC curve analysis

Area under the ROC curve (AUC)	0,980
Standard Error	0.00317
95% Confidence interval	0.971 to 0.986

slope of the terrain (SLO), altitude (ELV) and road density (ROD) contributed the most to the occurrence of fire (p <0.0001), followed by density drainage (DDR) (p = 0.0005) and wind effect (WIN) (p = 0.0007).

The classification table confirms that the percentage of cases correctly classified by the model was 94.26%, with 93.63% being fire (F=1) and 94.60% being nonfire (F=0). The area under the curve (AUC) value was 0.980 (95% CI = 0.971-0.986), and the standard error was 0.00317. The closer the AUC value is to 1.0, the greater the efficiency of the model in discriminating between negative cases (nonfire) and positive cases (fire) is. Therefore, we can affirm that the model showed a good capacity to efficiently separate these two types of events.

Equations 2 and 3 are the mathematical relationships based on the multivariate logistic regression used to calculate the fire occurrence probability (p) in the SCNP.

$$p = \frac{1}{1+e^{-logit\,(p)}} \qquad \text{(Eq. 2)}$$

where logit (p) is calculated using Eq. 3 and the constant and regression coefficient values of the explanatory variables (Table I).

$$\begin{aligned} logit\,(p) = &-1.4865 + (-0.0424\ CVX) + 0.15981\ SLO + \\ &+ (-2.603\ DRD) + 0.00892\ ELV + (-17.6382\ NDVI) + \\ &+ 3.5960\ WIN + (-2.1163\ ROD) \end{aligned} \qquad \text{(Eq.3)}$$

The total number and density of fire outbreaks recorded by class of the probability map built by the logistic regression model were calculated (Table II). Then, the adjustment curve between the values of the probability of fire occurrence calculated from 1984-2015 data and the density of fire foci observed in the orbital images in the period from 2016 to 2020, and their respective equation and determinant coefficient was performed (fig. 3).

Table II - Number and density of fire foci recorded by class of the p probability map.

Tabela II - Número e densidade de focos de fogo registrados por classe do mapa de probabilidade p.

Class	P (median of the class)	Area (km^2)	Number of fire foci (2016-2020)	Density (km^{-2})
1	0.05	2269.81	169	0.0745
2	0.15	203.51	20	0.0983
3	0.25	134.42	24	0.1785
4	0.35	113.34	23	0.2029
5	0.45	107.94	25	0.2316
6	0.55	109.37	23	0.2103
7	0.65	118.80	29	0.2441
8	0.75	141.01	31	0.2198
9	0.85	215.85	56	0.2594
10	0.95	1004.28	265	0.2639

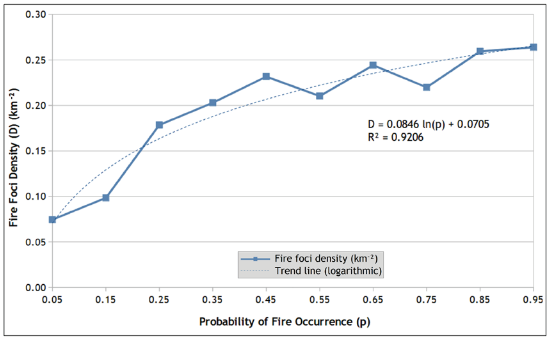

Fig. 3 - Adjustment curve of the model of the probability of fire occurrence (p) based on the 1984-2015 fire data and fire foci density data (D) from the 2016-2020 period.

***Fig. 3** - Curva de ajuste do modelo de probabilidade de ocorrência de fogo baseado em dados de fogo do período de 1984-2015 e dados de densidade de focos de fogo relativos ao período de 2016 a 2020.*

We found a positive and significant relationship (R^2 = 0.9206) between the density of fire foci identified in the 2016-2020 orbital images and the probability of fire occurrence estimated by the model (fig 3). Eq. 4, which describes the relationship between p and D (fig. 3), was modified and used to adjust the model of the fire occurrence probability p:

$$p = e^{\frac{D-0.0705}{0.0846}} \qquad \text{(Eq.4)}$$

where D is the density of fire foci recorded from 2016 to 2020, and p is the probability of fire occurrence estimated from data from the 1984-2015 period. Then, Eq. 4 was used to produce the adjusted map of the fire occurrence probability (fig. 4).

The adjusted map of the probability of fire occurrence (fig. 4) shows that the areas with a high probability of fire occurrence are spatially distributed on the geomorphological units of *Chapadão da Canastra* and *Chapadão da Babilônia* (fig. 1). The main factors that influenced the distribution of the highest values of *p* in these units were the levels of significance of the variables ELV, SLO, NDVI, WIN, and ROD, which are the variables that contributed the most to the occurrence of fire.

The areas with the highest probability of fire (fig. 4) are characterized by higher altitudes, generally above 1,200 m (fig. 2A), slopes between 3.0 and 14.0º, low vegetation index values between -0.33 and 0.28 (fig. 2E), high wind effect values between 1.13 and 1.33 (fig. 2D) and low road densities of less than 0.31 km/km^2 (fig. 2G).

Catry *et al.* (2009) found that altitude was one of the important factors associated with the spatial distribution of fire ignition in Portugal. Research carried out by Ajin *et al.* (2016) and Camelo *et al.* (2020) showed that the slope of a terrain contributes significantly to the spread of fire.

Roads make it easier to fight fires and act as a barrier to the spread of fires (Torres, 2006). In our study, the areas mapped by the model with the highest probability of fire were in areas with a low road density, indicating less accessibility to firefighting teams in the SCNP. In addition, the areas mapped with higher *p* values were located on surfaces with quartzite rock outcrops and shallow soils covered by vegetation formations such as *campo sujo*, *campo limpo* and *campo rupestre*. This type of land cover, with lower biomass densities, has a greater predisposition to the quick spread of fire (Messias and Ferreira, 2019a). Study carried out in the National Park of Brasilia by Soares Neto *et al.* (2016) showed that the risk of fire was higher in areas covered by vegetation formation of *campos*.

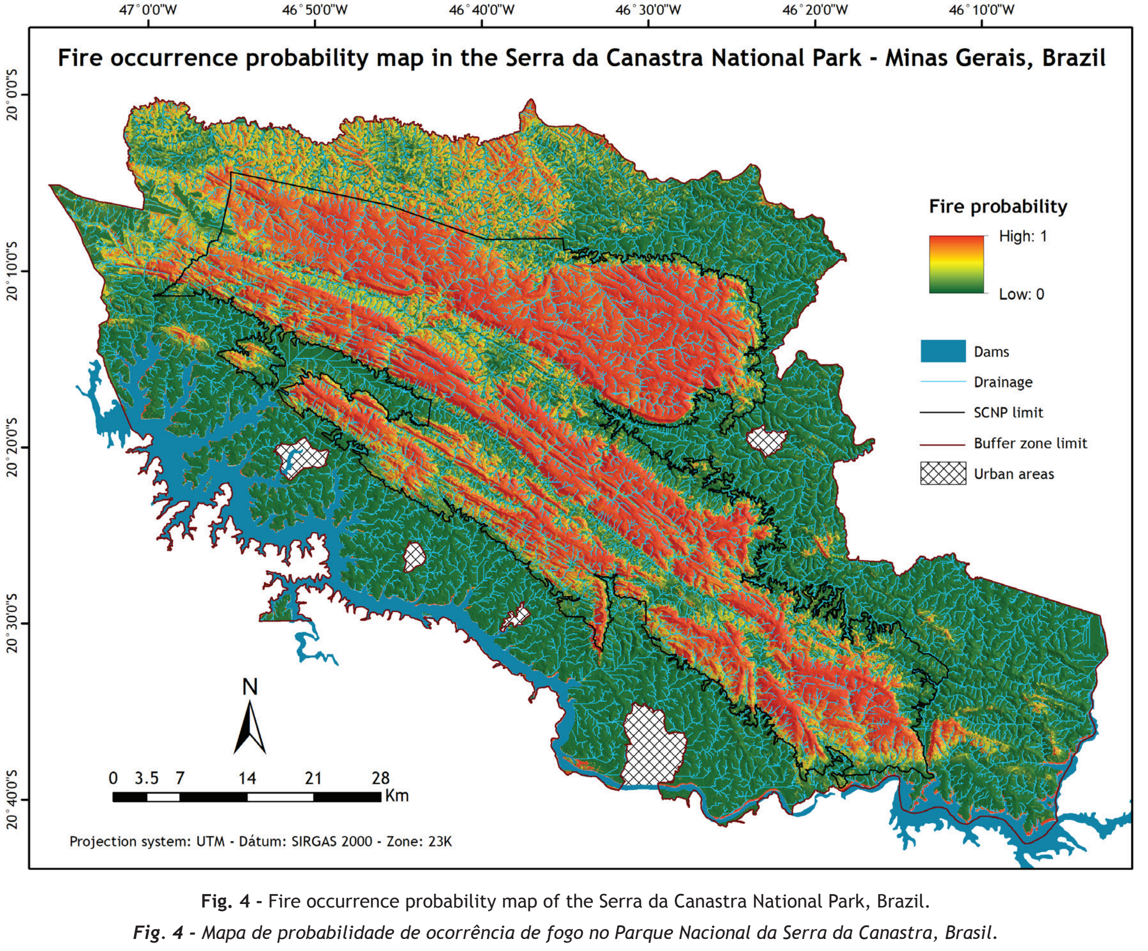

Fig. 4 - Fire occurrence probability map of the Serra da Canastra National Park, Brazil.

Fig. 4 - *Mapa de probabilidade de ocorrência de fogo no Parque Nacional da Serra da Canastra, Brasil.*

Conclusions

Our study showed that the environmental variables used in the model contributed significantly to the prediction of fire events. The variables vegetation index, slope of the terrain, altitude and road density contributed the most to the occurrence of fire.

The map of the probability of fire occurrence produced by the model was tested using real data on the density of fire foci. We found that the areas with higher probabilities of fire occurrence mapped by the model were located in areas with high densities of fire foci. This relationship was strong and statistically significant.

In addition, we noted that areas that presented the highest probability of fire were characterized by higher altitudes, flat surfaces, higher wind effects and a low density of roads. Furthermore, the areas mapped with higher *p* values were also located on surfaces with quartzite rock outcrops and shallow soils covered by herbaceous species with low vegetation index values.

Considering the percentage of cases correctly classified, we can state that this model was efficient in discriminating between fire and no-fire areas. We believe that this model can be used to map the risk of fire and as an assisting tool to prevent fire actions in conservation units located in the Brazilian *cerrado* biome.

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