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Assessing the probability of wildfire occurrences in a neotropical dry forest

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ABSTRACT

In tropical dry forests, wildfires are likely to become a major disturbance as a result of anthropogenic pressures and dryer conditions due to climate warming. Based on remote sensing techniques, this paper assesses the probability of fires occurring in the dry region of the Guanacaste Conservation Area (GCA), northwestern Costa Rica, testing the roles as fire determinants of topography, early successional forest stages, between-area susceptibility, and accessibility to human (roads and trails). Probability of fire occurrence and fire danger were determined based on a machine learning algorithm. Fire occurrence model was inferred from burned areas and fire line density; while fire danger was inferred from the probability of fire occurrence, the proportion of burned areas, and the number of fires per area. Results indicate that the presence of early successional vegetation on flat lowlands highly accessible by roads and trails are key components of fire occurrence. Three of the six investigated sectors show high probability of fire occurrence and fire danger, indicating the spatial heterogeneity of fire risk in the landscape. The results could be useful for the management of the conservation area.

RÉSUMÉ

Dans les forêts tropicales sèches, le feu deviendra vraisemblablement une perturbation majeure en raison des pressions anthropiques et des conditions plus sèches dues au réchauffement climatique. Cet article utilise des techniques de télédétection pour évaluer la probabilité d'occurrence de feux dans la région sèche de la Zone de Conservation de Guanacaste, au nord-ouest du Costa Rica, en testant les rôles de la topographie, des jeunes stades successionnels forestiers, de la susceptibilité interzone et de l'accessibilité aux humains (routes et sentiers). La probabilité d'occurrence de feu et le danger de feu ont été déterminés à l'aide d'un algorithme d'apprentissage automatique. Le modèle d'occurrence de feu a été inféré à partir de données de superficies brûlées et de densité de lignes de feux, alors que le danger de feu a été inféré à partir de la probabilité d'occurrence, de la proportion de superficies brûlées et de la densité de feux. Les résultats montrent que la présence de jeunes stades successionnels sur des terrains plats en bas de pente avec un haut degré d'accessibilité par route ou sentier sont des déterminants clés de l'occurrence de feu. Trois des six secteurs étudiés montrent une haute probabilité d'occurrence de feu et un danger de feu élevé, indiquant l'hétérogénéité du risque de feu à l'échelle du paysage. Les résultats seront utiles pour l'aménagement de l'aire protégée.

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Introduction

In tropical forests, fires are likely to become a dominant disturbance due to increasing feedbacks between land cover change and more frequent droughts (Cochrane et al. 1999; Devisscher et al. 2016). The long-term consequences of fires on biodiversity and forest carbon stocks depend on fire frequency and intensity (Keeley 2009; Morton et al. 2013). Tropical forests respond to recurrent fires with a shift in tree species composition, where already present fire-tolerant species will become more dominant in the future, generating a possible long-term change in vegetation composition and carbon loss (Lee et al. 2011).

In Costa Rica, most wildfires occur in heathlands or moors (also known as *páramos*) and tropical dry forests (TDF) as a result of changes in the national productive structure and agricultural policy between 1950 and 1980 (Calvo 1990). In 1957, meat exports increased to the United States, providing a major economic incentive to the cattle industry (Calvo 1990). This incentive encouraged a significant conversion of forest and other ecosystems to grasslands (Calvo 1990). The creation of the National Parks Department in the 1970s and the Costa Rican Ministry of Natural Resources in the 1980s set the bases for new environmental laws and policies. The number and extent of new conservation areas, such as national parks and wildlife refuges have thus increased

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due to economic incentives such as tax deduction, reforestation loans, and payments for environmental services (Arroyo-Mora et al. 2005).

Fire is a major disturbance agent playing a significant role in the carbon dynamics of forests and many ecosystems on Earth, but the extent to which fire regulates plant communities in the Neotropical dry forest still remains unknown. For instance, in TDF, fires are widely considered by people as destructive, and scientists argue that they pose the largest threat to dry forest conservation (Otterstrom et al. 2006) while the ecological functions of fire have not been demonstrated.

Generally, fire regimes are variable in time and space depending on climate, vegetation, topography, and human activities. Weather and climate determine the availability and moisture content of fuels, because they influence wind, water balance and heat transfer (Guo et al. 2017). Topographic features such as elevation and slope are linked to spatial variations in meteorological variables such as temperature and wind. Elevation and slope also influence fuel distribution and its availability to burn (Sharples 2009). Anthropogenic activities have been reported to be essential fire sources. Notably, in tropical dry forests, hunting, and negligence in land preparation are linked to fires (Otterstrom et al. 2006; Aleman et al. 2017). Moreover, accessible roads and trails play a significant role in fire occurrence (Ngoc Thach et al. 2018).

For decades, the detection and monitoring of land cover and fires have relied on remotely sensed data acquisition through aircraft and satellites. However, there are still uncertainties about potential underestimations of wildfire areas using satellite data (Allison et al. 2016). Fire detection from satellites poses challenges related to spatial resolution and the ground scale of the fire event (Kennedy 2015). Until 2017, with the launch of the MODIS Collection 6, sensors such as the Advanced Very High-Resolution Radiometer (AVHRR) and the Moderate Resolution Imaging Spectroradiometer (MODIS) offer daily data but were not suitable to detect wildfires smaller than 200 ha (Hawbaker et al. 2008; Giglio et al. 2018). Moderate-resolution sensors such as Landsat, Sentinel, SPOT are not completely suitable for their low temporal resolution, especially for tropical regions, which tend to have high cloud cover and rapid vegetation cicatrisation (Bowman et al. 2003; Chuvieco et al. 2019). The combination of remote sensing imagery and field data was shown to measure wildfire dynamics more accurately (Anderson and Gaston 2013) and to offer very accurate results, especially on the estimation of tropical burned areas (Zhang et al. 2016).

In the last decade, machine learning (ML) applied to remote sensing has also gained relevance, thanks to the capacity of these algorithms to efficiently learn from given features and incorporate prior knowledge into the identification process (Li et al. 2018). Random Forest (RF) is among the most intuitive and simple to use ML algorithms due to its flexibility, intuitive simplicity, and computational efficiency. RF is a well-suited classifier to address fire mapping problems and it is well suited for fire severity (Collins et al. 2018).

There are two terms used in wildfires assessment: fire occurrence and fire danger. Fire occurrence measures fire start or ignition in a given area over a given time, and is a process modeled separately from fire spread, which may or may not take place after ignition depending on environmental conditions (Costafreda-Aumedes et al. 2017). Fire danger is a general term used to determine the ease of ignition (Costafreda-Aumedes et al. 2017). In this paper, we assess the probability of wildfire occurrence in the dry region of the Guanacaste Conservation Area in northwestern Costa Rica. We test the hypothesis that fire occurrence depends on topography, early successional forest stages, between-area susceptibility and accessibility to humans. Fire danger could thus be assessed from relationships between fire occurrence and these potential drivers.

Methods

The study area is located in in six sectors of the tropical dry forest ecosystem of the Guanacaste Conservation Area (GCA): Santa Rosa, Murciélago, Santa Elena, Junquillal, El Hacha, and Pocosol (Figure 1). These sectors contain most of the tropical dry forest frequently affected by wildfire in the GCA (Vargas-Sanabria and Campos-Vargas 2018a). Climatically, two seasons, rainy and dry, are present with an annual rainfall of about 1500 mm. Between 85% and 97% of precipitations fall between May and November during the rainy season (Calvo-Alvarado et al. 2018). The dry season extends from approximately late December to mid-May with less than 10 mm per month, producing ideal conditions for wildfire occurrence.

The current vegetation cover of the GCA is a mosaic of successional stages of secondary forests, abandoned pastures, and mangroves (Li et al. 2017). Most forests are dominated by broadleaved trees where at least 50% of the trees are deciduous during the dry season. Pastures and early successional TDF are the areas most susceptible to get burned due to illegal hunting practices inside the protected area, and negligence on private lands contiguous to the protected area (Janzen 2000). Early successional TDF contain a high percentage of

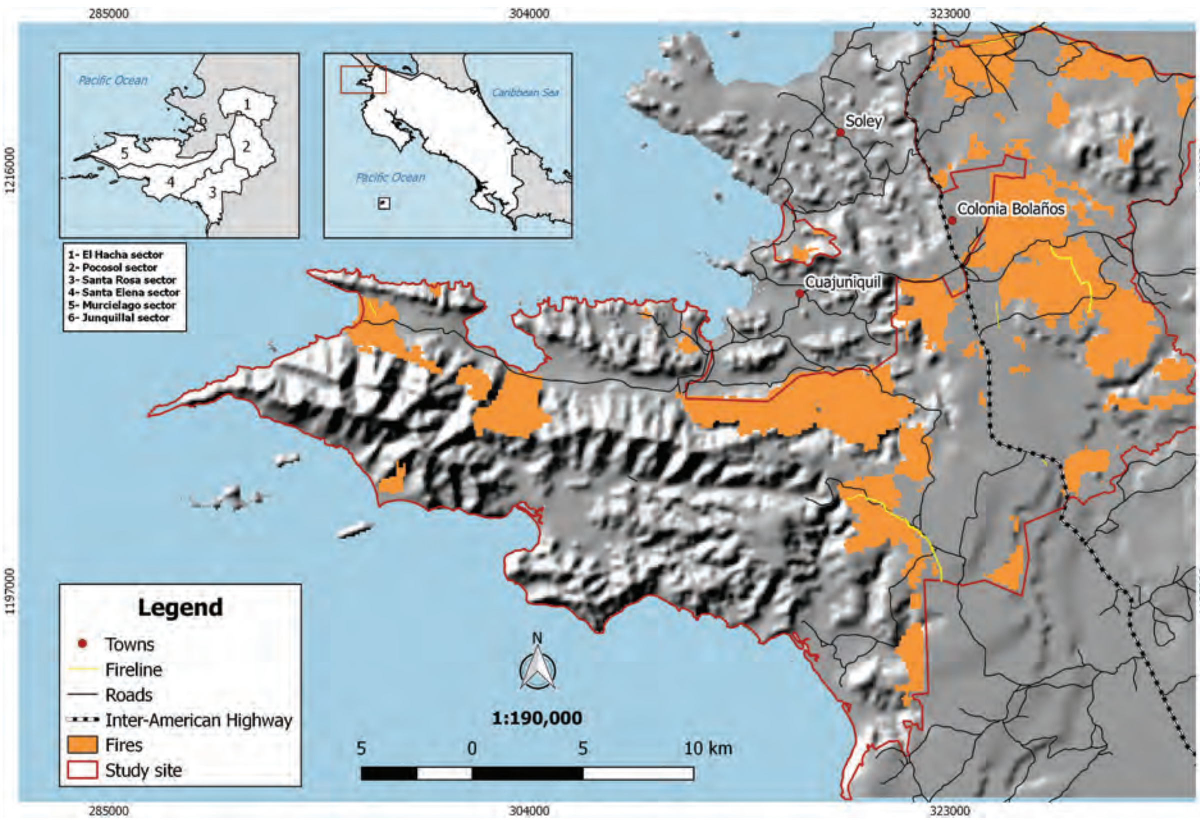

Figure 1. Study area (red perimeter) and burned areas (1997–2015) in the dry tropical forest of the Guanacaste Conservation Area, Costa Rica.

deciduous trees with many shrubs, small trees, grasses, and bare soil in open areas (Hilje et al. 2015). Pastures are mainly covered by *jaragua* grass (*Hyparrhenia rufa*), an East African exotic grass; and a few areas are dominated by *Bulbostylis paradoxa*, a fire-tolerant native grass.

Sampling design

The sampling design is based on 25-ha hexagonal-grids (Vargas-Sanabria and Campos-Vargas 2020) to cover the landscape pattern of the GCA. The study area was thus divided into 2280 hexagons. The values recorded in each hexagon were: (i) the ratio of burned areas over the period 1997–2020 (ii) the ratio of areas covered by early successional TDF; (iii) the sum of slope values: (iv) the sum of fire line density; and (v) the sum of road and trail density. A few hexagons had an area < 25 ha because they were situated along the coastline.

Data acquisition

The burned area polygons were generated through fieldwork using the tracking option of a global positioning system (GPS) device for mapping the perimeter of the areas affected by fire as soon as the fires were extinguished. This procedure was performed by the Fire Management Program (FMP) of the GCA each year during the 'Fire Season', i.e. between December and May. To create the variable burned area, all areas affected by fire over the period 1997 to 2020 were recorded as a burned area. However, to create the model, only data from 1997 to 2015 were used. Data from 2016 to 2020 were reserved for validation purposes. Then, a ratio between the burned area and the effective sampling area was estimated. This ratio provided values from 0 to 1, where 0 represents areas that had never burned over the period 1997–2015, and 1 represents areas that had burned at least once from 1997 to 2015.

The fire lines are areas inside the GCA that are annually burned during the first months of the dry season to generate a discontinuity on the fuel bed. These fire lines were strategically designed to split the GCA into major blocks, separating the *jaragua* grasslands from the different successional stages of TDF (Janzen 1986). The fire lines were identified by the FMP using a GPS. The accessibility data were gathered following all the roads and trails in the GCA using the tracking option of the GPS. The accessibility and fire line data were transformed to line density values at 100 m cell size using the function Line density in ArcMap (ESRI. 2011. ArcGIS Desktop. 10.3).

The slope values in degrees were obtained through a Digital Elevation Model using the contour information at a scale of 1:5000 available from the National System of Territorial Information (SNIT) of the Costa Rica government (www.snitcr.go.cr). The slope values were spatially resampled to a cell size of 100 m in ArcMap.

To obtain the extent of early successional TDF, the land cover data was generated using field data and a Landsat 8 OLI image acquired in April 2015 with a resolution of 900 m^2 (Vargas-Sanabria and Campos-Vargas 2018b). The Landsat image was radiometrically and atmospherically corrected following the approach of Kalacska et al. (2016). The image was classified with supervised classifications using the ENVI program (Exelis Visual Information Solutions 5.1). The classes 'early successional TDF' and 'grassland with shrubs' were merged into one class called early successional stages (Figure 2). The ratio of area covered by early successional stages to effective sampling area was estimated for each hexagon.

Data transformation

Data transformation was applied to the ratio of area burned, the ratio of early successional stages, the sum of road and trail density values, the sum of fire line density; and the sum of slope density. The values were transformed through a Box-Cox transformation using the MASS package of the R program.

Probability of fire occurrence model

To select the most significant variables, we used the function 'bootStepAIC' of the MASS package. The 'bootStepAIC' function is a bootstrap method used in model selection through the estimation of selection frequencies (Beier et al. 2001). Specifically, the selection was based on the Akaike Information Criterion (AIC), the number of times the variable was selected, and the statistical significance.

The response variable was the difference between burned area and fire lines, while the independent variables were the transformed data of early successional stages ('early stages'), slope, accessibility, and all their interactions. To fit the model, the response variable was the difference between burned area and fire lines, whereas the independent variables were early stages, accessibility, slope and the interaction of slope and accessibility.

The difference between burned area and fire lines was chosen as a response variable because the lack of fuel bed in the fire lines prevents fire occurrence, and the discontinuity of the forest cover generated by the fire lines prevents fire propagation. Consequently, in areas close to fire lines the probability of fire occurrence is reduced. The bootstrapping indicated that early stages,

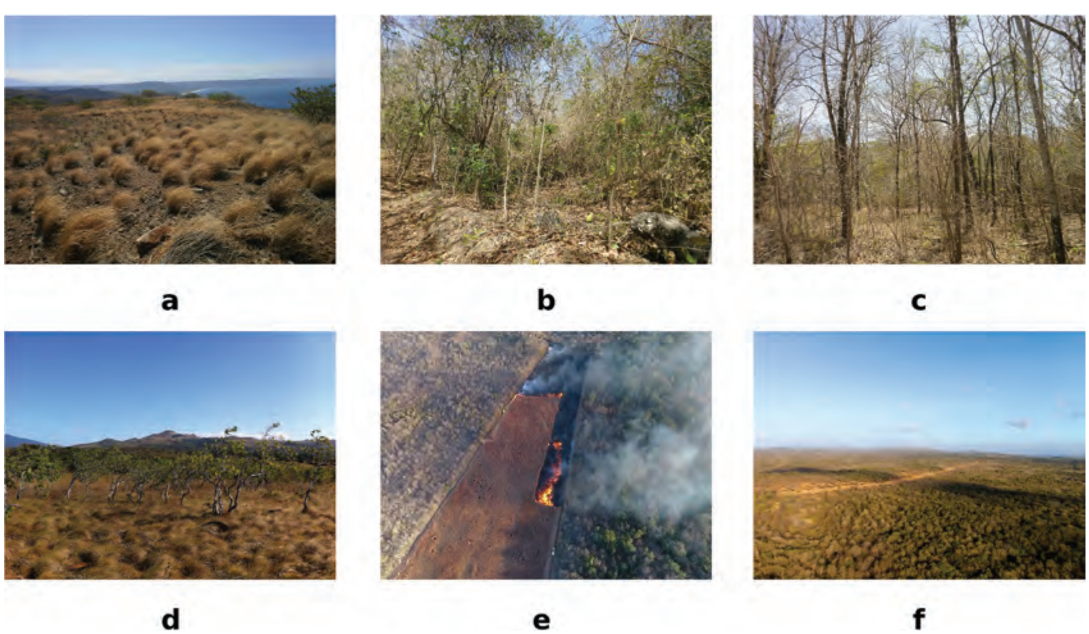

Figure 2. Successional stages of the tropical dry forest of the Guanacaste Conservation Area (GCA), Costa Rica: (a) grasslands covered with *jaragua* grass; (b) early successional stage in the *Murciélago* sector; (c) early successional stage in the *Santa Rosa* sector, (d) grasslands covered with *jaragua* grass and *Byrsonima crassifolia*, a fire-tolerant tree; (e) prescribed burning of a fireline; (f) aerial view of the dry forests of the GCA.

slope, accessibility, and the interaction of slope and accessibility were chosen in all cases with a statistical significance of 100%. Contrary to the interactions of early stages and accessibility, and the interaction of early stages, slope and accessibility that were selected 39% and 28% of times with statistical significance of 13.9% and 33.7% (Table 1).

To estimate the probability of fire occurrence a Generalized Least Squares (GLS) model was implemented using Equation 1 as a linear model. The GLS is a method that fits a linear regression model to estimate unknown parameters while accounting for spatial autocorrelation (Kissling and Carl 2008). The GLS model was implemented in the nlme package of the R program with a linear spatial correlation:

$$burnedarea - firelineyoung + accessibility - slope + slope/accessibility \tag{1}$$

Fire danger model

Even though the output from the GLS model takes values from 0 to 100% for fire occurrence probability, it remains difficult to determine at what percentage a fire is likely to occur. Consequently, a ML model was used to generate two fire danger classes that facilitate the identification of burning susceptibility or fire danger. The Random Forests (RF) algorithm ('CARET' package in the R program) was applied to classify the low and high fire danger classes. Three variables were provided to RF to classify these classes: the probability of fire occurrence, the proportion of burned area, and the number of times an area had burned. A conservative approach was used to select high and low danger samples that were supplied to the RF algorithm. The high danger samples were areas affected by at least one fire event over the period 1997–2015. In contrast, the low danger samples were picked in areas that had not been affected by fires since 1997. The optimal number of samples to avoid overfitting of the classification was selected employing the bootstrap '632 method'. The optimal tune-up parameters of RF were estimated with the functions 'expand.grid' and 'tuneGrid' of the 'CARET' package. These functions estimate the best parameters based on the Receiver Operating Characteristic (ROC) curve, classification accuracy, and sensitivity. The RF was trained using 500 samples from the hexagonal grid generated previously, 250 tagged as high danger, and 250 tagged as low danger.

Fire danger model validation

To validate the wildfire danger model, the two danger categories were compared with remotely sensed and field data from 2016 to 2020. The remotely sensed data used for the validation were gathered from NASA's Fire Information for Resource Management System (FIRMS). The FIRMS data provides satellite observation of active fire collected by the Moderate Resolution Imaging Spectroradiometer (MODIS) and the Visible Infrared Imaging Radiometer Suite (VIIRS). The burned area reserved to validate the model results was transformed from polygons to centroids in QGIS. A total of 245 active fires were used to validate the wildfire danger map. Data and validation period were different from those used for model generation to ensure the independence of the validation exercise.

Finally, the inclusion, exclusion, and general errors of the fire danger map were estimated using an error matrix that employed predicted and unpredicted fire events. The predicted fire events were defined as fire points that coincided with the high-danger class, while the unpredicted fire events were fire points that fell under the low-danger class.

Results

Probability of fire occurrence

The results show that the probability of fire occurrence is mainly determined by the presence of early successional stages (GLS estimate = 0.354, $p < 0.001$), which correspond to grasslands and early successional TDF. Variables such as slope (GLS estimate = −1.217, $p = 0.001$), accessibility (GLS estimate = 0.195, $p < 0.001$),

Table 1. Results of the bootstrap process to select the most significant variables to estimate the probability of fire occurrence.

		Coefficients (%)		Significance
Covariates	Selected(%)	Positive	Negative	(%)
early successional forest	100	100	0	100
slope	100	0	100	100
accessibility	100	100	0	100
early:slope	75.3	63.2	36.8	40.8
early:accessibility	39.4	44.9	55.0	13.9
slope:accessibility	100	100	0	100
early:slope:accessibility	27.9	99.6	0.4	33.7

Table 2. Significance of the variables tested to estimate the probability of fire occurrence in the Guanacaste Conservation Area, Costa Rica.

Variables	Estimate	Std error	t	p
burned area-fire line	9.82	0.89	11.07	0.000
early successional forest	0.35	0.07	5.18	0.000
slope	−1.22	0.18	−6.63	0.000
accessibility	0.19	0.03	7.27	0.000
slope:accessibility	0.02	0.00	4.22	0.000

and the interaction of slope and accessibility (GLS estimate = 0.020, $p < 0.001$) also drive wildfire occurrence (Table 2). Burned areas positively respond to the presence of early successional stages and accessibility. The slope displayed a negative relation with burned areas, which indicates that the lower the slope, the higher the probability of fire occurrence.

The results also suggest that in the dry region of the GCA, there are no areas with very high danger probability or null fire occurrence because the probability of fire occurrence ranges from 20% to 95% (Figure 3). The mean probability of fire occurrence is 61%, while the median corresponds to 62% suggesting a normal distribution. The fitted values show a non-uniform distribution, with peaks around 20%, 30%, 40%, 60%, and 80% (Figure 3).

At the sector level, the probability of fire occurrence exhibited the highest average values (82%) in the Junquillal sector (Table 3). The El Hacha, Pocosol, and Santa Rosa sectors had lower, but nevertheless high average values (76%, 72% and, 67%, respectively). Even though the El Hacha, Pocosol, and Santa Rosa sectors registered lower average values than Junquillal, the maximum values within the sectors were higher than at Junquillal. The Murciélago and Santa Elena sectors had the lowest average values (53% and 49%, respectively). The minimum values indicate that the Murciélago, Santa Elena, and Santa Rosa sectors recorded the lowest scores (21%, 22% and 24%, respectively). The minimum values in Junquillal, El Hacha, and Pocosol were 43%, 43%, and 33% (Table 3).

The probability of fire occurrence shows a non-uniform distribution across the six sectors (Figure 4). Generally, the Junquillal, Santa Rosa, Murciélago, El Hacha, and Pocosol sectors had a high number of hexagons with probability of fire occurrence higher than 50%, contrary to the Santa Elena sector which showed the opposite tendency, with most values below 50% (Figure 4).

Table 3. Descriptive statistics of the probability of fire occurrence in six sectors of the Guanacaste Conservation Area, Costa Rica.

Sectors	Average	Maximum	Minimum
Junquillal	81.9	93.9	42.7
El Hacha	75.6	96.1	42.4
Pocosol	71.5	95.9	32.8
Santa Rosa	67.5	96.8	23.5
Murcielago	53.2	90.2	21.4
Santa Elena	49.2	94.4	21.9

The lower values in the Pocosol sector coincide with a transition area from dry forest to wet forest. Furthermore, the occurrence of early successional forest stages in this area was low (Figure 4). The low values in the El Hacha sector were on a hill only accessible through a walking path. The low values in the Santa Elena, Santa Rosa and Murciélago sectors coincide with

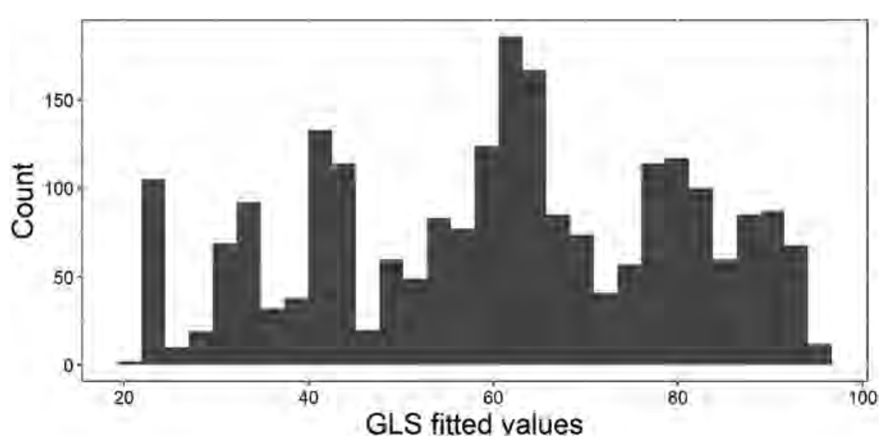

Figure 3. Distribution of generalized least square (GLS) fitted values to estimate the probability of fire occurrence in the Guanacaste Conservation Area, Costa Rica.

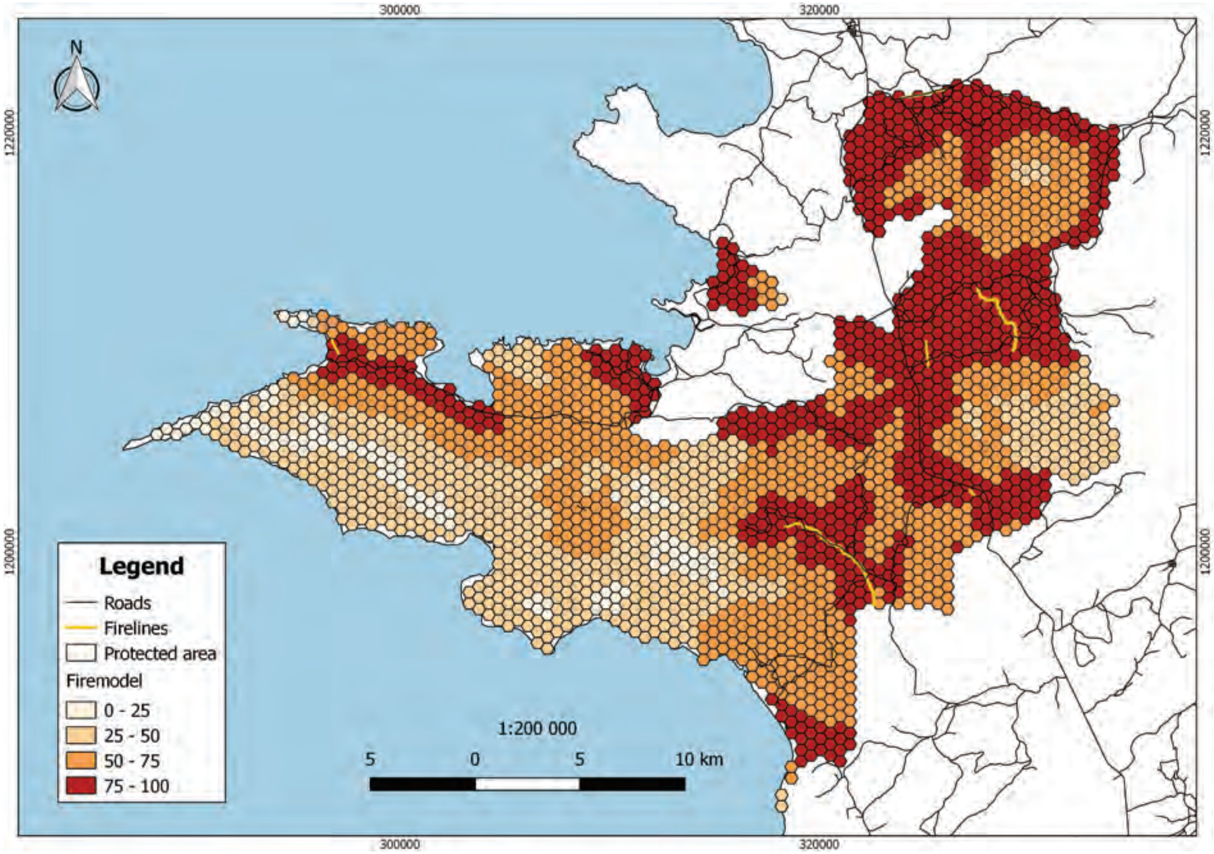

Figure 4. Generalized least square (GLS) model-based probability distribution of fire occurrence among sectors of the Guanacaste Conservation Area, Costa Rica.

inaccessible areas associated with cliffs and steep terrains.

Wildfire danger

The validation process revealed that the wildfire danger model had a general accuracy of 99%. Specifically, from a total of 245 points of active fires spotted over the period 2016–2020, 242 active fire points fell into high probability. Three active fires fell into low probability representing an omission error of 1.2% (Figure 5).

In terms of fire danger, the results show that Junquillal is the sector most susceptible to fire danger with 97% of its area classified as high danger. Likewise, Pocosol and El Hacha also showed high susceptibility to fire with 78% and 70% of their area classified as high. In the Murciélago, Santa Rosa, and Santa Elena sectors, the high-danger areas only comprise 37%, 36%, and 24% of the total area, respectively (Table 4).

Discussion

The present analysis of fire occurrence and danger showed that early successional forest stages on flat terrain with accessibility through roads and trails are key components of fire occurrence in the Guanacaste Conservation Area (GCA). The probability of fire occurrence was higher in the sectors of Junquillal, El Hacha, and Pocosol than in Santa Rosa, Santa Elena, and Murciélago. This could be explained by the presence of adjacent pastures and agricultural lands that are maintained with human-driven fires. The introduction of the *jaragua* grass in the 1940s changed the fire dynamics in the whole region because people used fire to regenerate the grass rhizomes (Janzen 2000). During the dry season, grasslands are controlled with fires to remove competitor plants, such as trees and shrubs, and to regenerate grass rhizomes. However, negligence and extreme weather conditions such as high temperature, wind speed, and low humidity can result in fires in neighboring grasslands penetrating into the protected area. These

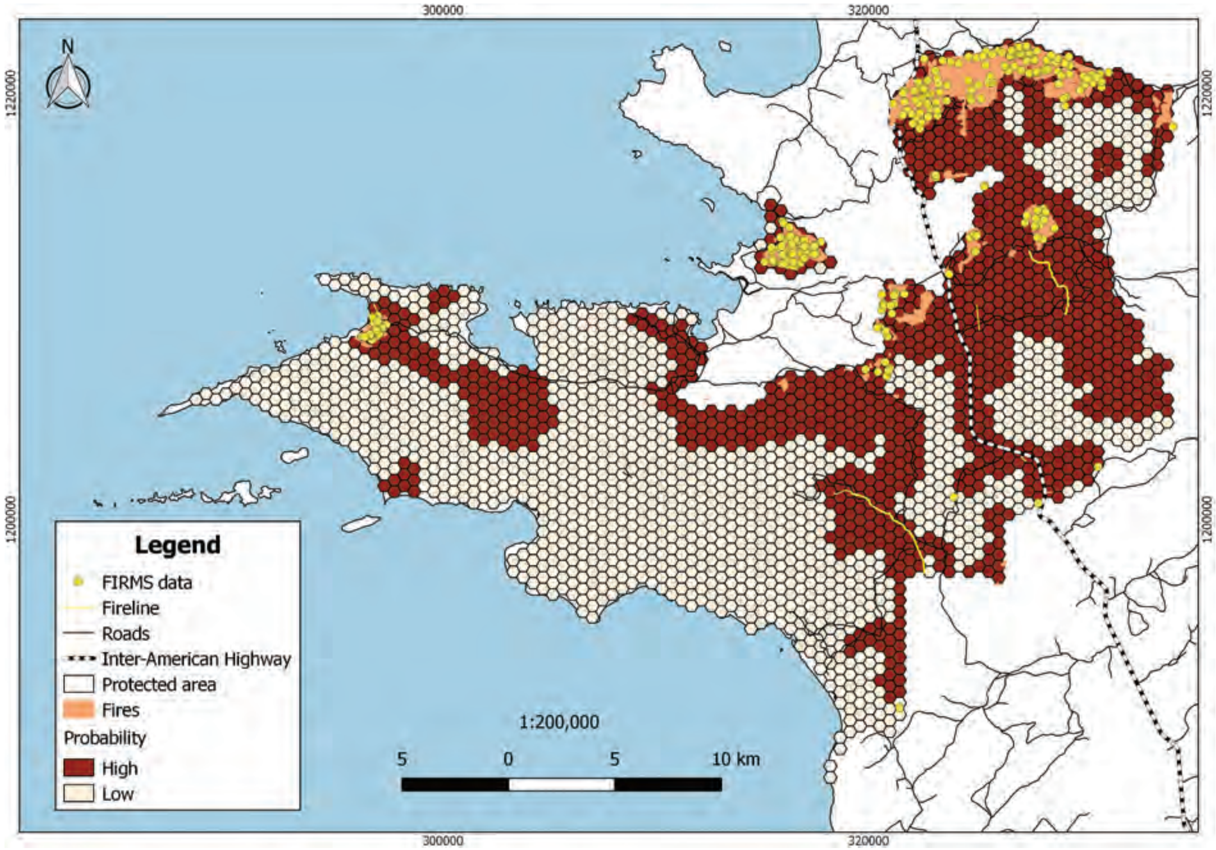

Figure 5. Fire danger in the Guanacaste Conservation Area, Costa Rica. The red areas represent high fire danger areas. The orange polygons show the distribution of fires, and the yellow points represent all active fires detected from NASA's Fire Information for Resource Management System (FIRMS) over the period 2016–2020.

Table 4. Area covered by each fire danger class in sectors of the Guanacaste Conservation Area, Costa Rica.

	high		low		
Sector	ha	%	ha	%	Total area (ha)
Junquillal	424	97.2	12	2.8	436
El Hacha	5434	70.1	2318	29.9	7752
Murcielago	4476	36.7	7729	63.3	12205
Pocosol	7530	77.7	2162	22.3	9692
Santa Elena	3495	23.5	11363	76.5	14858
Santa Rosa	3835	35.8	6879	64.2	10714

observations support the results of Cochrane and Schulze (1999) who found that a significant amount of burned forests in Brazil is often adjacent to fire-maintained grasslands for husbandry and croplands. In tropical dry regions, forests near edges are more vulnerable to fire incursion because fires are used first to clear the forest and later to maintain the cattle pastures established after deforestation (Cochrane 2001). Furthermore, slope and accessibility are key drivers of fire occurrence in the GCA. Slope showed an inverse relation with the probability of fire occurrence, which means that the higher the slope values, the lower the probability of fire occurrence. This fact coincides with the findings of Vázquez and Moreno (2001), who found that fires aggregated at low elevations and on lower slopes in central Spain (dry mountain Mediterranean woodlands). A possible explanation is that intentional fires are often related to arsonists who access and escape protected areas through existing routes (Maingi and Henry 2007). Flat terrains facilitate accessibility, contrary to terrains with steep slopes. Unintentional fires can also occur close to human structures, such as roads and buildings, where humans often inadvertently provoke ignition through campfires (Maingi and Henry 2007).

The high number of high-danger polygons in the Junquillal, El Hacha, and Pocosol sectors is alarming in terms of tourism and ecological restoration. In the case of the Junquillal sector, tourism augments the complexity of the consequences of fires, because a fire event could cause life losses. Furthermore, fire occurrence and susceptibility result in positive feedbacks. Consequently, the recurrence of fires in the El Hacha, and Pocosol sectors could lead to colonization by invasive non-forest plants such as grasses and weedy vines. Fires can drastically alter species diversity (Fournier et al. 2020), affect pollinator communities (Lazarina et al. 2019), and balk forest regeneration (Kodandapani 2013).

In the southwestern Amazon, it has been determined that wildfires accelerate forest degradation, especially when combined with fragmentation and logging, which cause drastic depletion of biodiversity and carbon stocks (Alvarado et al. 2018). Even more, tropical dry forests are often degraded to early successional stages, mostly by fire (Schmerbeck and Fiener 2015). While the understanding of fire behavior and ecology has significantly increased over the decades, there is still a gap between science and fire policies largely conceived in classical conservation terms (Mistry et al. 2019). Likewise, it has been widely recognized that complete fire suppression at the landscape scale is not possible due to social and economical issues (Mistry et al. 2016). It is therefore imperative to generate scenarios that support fire management and policy-making inspired from nature-based solutions. This study contributes to the understanding of fire occurrence in a neotropical dry region where fire role and behavior had been poorly studied. Furthermore, it provides outputs useful for wildfire field units and other researchers, such as danger maps or vulnerability maps (Vargas-Sanabria and Campos-Vargas 2018a), which support the Fire Management Program at GCA.

Conclusion

The present study demonstrates that fire occurrence at the GCA is mainly determined by the extent of early successional forest stages on flat or gentle slope terrains that are accessible by people through trails and roads. Likewise, it demonstrated that burned areas positively respond to the presence of early successional stages, accessibility and low landscape slope. Fire danger and probability of fire occurrence are higher in three of the six studied sectors (Junquillal, El Hacha, and Pocosol), suggesting that fire detection and preparedness for early firefighting response must be reinforced in these areas.

Finally, this work is an initial tool to support decision-making associated with fire control in the GCA by providing numerical and categorized maps showing that some areas are more susceptible to fire than assumed so far. The following step includes an upscaling of the generated models to the regional or national level to contribute to the national firefighting authorities. However, to conduct such work it will be necessary to rely on burned areas exclusively estimated by remotely sensed data that could be translated into a potential sub-estimation of burned areas because, in neotropical dry tropical regions, fire is usually restricted to the forest floor that could be partially shaded or hidden from spaceborne sensors.

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