

Article

Mapping Spatial Drivers of Predicted Active Fires Kernel Density with Geographically Weighted Regression in Mexico

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Abstract

Despite the need to understand the spatial variation in human and biophysical drivers of fire spread, studies aimed at predicting remotely sensed fire kernel density at multiple scales are still relatively scarce. The current study aimed at the prediction of MODIS and VIIRS active fire kernel density (AFKD) using region-specific geographically weighted regression (GWR) in Mexico. GWR models overcame stationary models to predict AFKD at a selected 20 km optimum active fire kernel density bandwidth. Our observations confirmed, for the first time for remotely-sensed fire records, the regional variation and the non-stationarity of the human and fuel-related drivers of AFKD in Mexico. Aboveground biomass mainly showed positive relationships in low productivity areas and humped relationships in more productive areas. Contrary to previous observations for fire suppression records, road density mainly showed a negative relationship, and slope mainly showed a positive relationship with AFKD. This highlights the importance of monitoring fire spatial activity, not only from human-based suppression records, but also considering remotely-sensed AFKD, potentially improving fire prevention planning. The methodology shown in the current study can be replicated elsewhere for improving our understanding of the spatial drivers of remotely sensed fire activity.

Keywords: fire spatial driving factors; fire activity spatial patterns; fire hazard; fire occurrence; fire risk; fire danger; fire spread; MODIS; VIIRS; hotspots; GAM; GWR



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1. Introduction

The knowledge of the spatial distribution of wildfires and their driving factors is crucial for effective wildland fire management [1–3]. More specifically, it is critical to improve resource allocation for prevention and suppression, guiding fuel treatment and crew positioning to reduce fire risks and associated ecological and environmental impacts [4,5]. Consequently, there is a need to improve our understanding of the key factors driving spatial wildfire occurrence to improve forest and fire management planning [6–8].

There is an ongoing debate in the literature about the more relevant biophysical or anthropogenic factors driving fire occurrence (e.g., [9–11]). In some regions, fuel and climatic limitations appear to be the most relevant factors influencing fire occurrence (e.g., [12–14]). Contrarily, many studies have reported a major role of human-related factors in influencing fire ignition and spread (e.g., [10,15,16]). This variability seems to support theories of varying constraints of fire occurrence, which are likely region-specific (e.g., [17,18]). Accordingly, there is a need for continued research for a better understanding of the relative importance of human or biophysical drivers of fire occurrence for varying regions with different fuel, climate, and human characteristics (e.g., [9–19]).

Given the generally widespread anthropogenic cause of forest fires (e.g., [10,16]), several proxies of human activities have been explored as predictors of fire occurrence, including distance to roads (e.g., [19–21]), road density (e.g., [22–24]), population or urban area density or distance to human settlements (e.g., [14,19,23]), or agricultural or livestock density (e.g., [25–27]). However, the selection of the specific anthropogenic variables to best predict fire occurrence is still subject to continued region-specific research (e.g., [10,16,18]). Furthermore, several studies have noted that human activities can result in either positive or negative effects on fire occurrence, depending on the study area's fuels, climate, or specific human activities (e.g., [16–19]). For example, several studies have often related human pressure to increasing ignition sources (e.g., [19–27]). On the other hand, in other regions, human activities have been documented to result in indirect fire-limiting effects on fuel structure, availability, and continuity, potentially decreasing fire spread and size (e.g., [14,28,29]).

Regarding the role of fuel availability in spatial fire occurrence, previous research has more frequently relied on land use or vegetation-type maps (e.g., [28–32]). In contrast, there is a relative scarcity of studies that have explored the potential of spectral indices such as NDVI (e.g., [33–35]), or more recently available remotely sensed products of vegetation characteristics, such as leaf area index [36], tree cover [9], or aboveground biomass (e.g., [37–39]), to predict fire spatial patterns. Results from those studies have suggested either positive (e.g., [40,41]), negative (e.g., [9,36]), or humped (e.g., [35,37–39]) effects of increasing tree cover or biomass on fire occurrence, size, or intensity. Such varying relationships are possibly related to the vegetation characteristics range covered and the analyzed scale of the study area (e.g., [37–39]).

The majority of the most widely used statistical techniques for predicting fire occurrence, such as logistic regression, (e.g., [20,31,42]), classification and regression trees and random forests (e.g., [43–45]), or Bayesian modeling (e.g., [28,29]), assume coefficient stationarity, meaning that the influence of different predictors of fire ignition is constant across space (e.g., [10]). In contrast, the use of geographically weighted regression (GWR) has been increasingly explored in the literature to account for such spatially varying relationships (e.g., [10,46,47]). Nevertheless, in spite of the potential improvements observed against classic statistical techniques (e.g., [48–50]), there is still a relative scarcity of studies using GWR to predict spatial fire occurrence (e.g., [16,24,51]).

Studies using GWR have either used fire presence or absence binary point data (e.g., [50,52,53]) or aimed at fire density prediction (e.g., [10,24,51]); the latter can par-

tially account for fire ignition location uncertainty (e.g., [10,44,54]). Fire density has been calculated for administrative units such as municipalities or provinces (e.g., [23]) or at regular grids of spatial resolutions ranging from >50 km to <5 km, depending on the continental or regional scales of the area studied (e.g., [14,24,51]). However, in spite of the potential of kernel density to better account for point position inaccuracies inherent to regular grids (e.g., [10,44,54]), to our best knowledge, studies aiming at predicting fire kernel density at multiple scales using GWR are still very scarce [38].

A large body of the literature aimed at predicting fire spatial distribution has traditionally used fire suppression records (e.g., [16,22,23,31]), generally focusing on the coordinate where the fire started (fire ignition). In contrast, remotely sensed active fires have proven to provide systematic, automated daily fire records, with the potential to capture the patterns, not only of fire initiation, but also of fire spread across the landscape (e.g., [55]). However, compared to a more widespread use of human-based fire-suppression records, there are relatively fewer studies that have aimed at predicting the spatial occurrence of remotely sensed active fires (e.g., [51,56]) or burned areas (e.g., [9,14,43]). In addition, previous studies in Mexico [57,58] and in other countries (e.g., [59,60]) have highlighted discrepancies between fire suppression records and remotely sensed active fires or fire perimeters. Some reasons for this variation include positional uncertainties (e.g., [10,54,61]), together with potential accessibility biases in human-recorded fire records (e.g., [38,62,63]). Furthermore, conclusions about the role of fire drivers can largely vary depending on whether the study aims at predicting either fire ignition or fire spread (e.g., [20]).

Finally, compared to areas such as the USA, Canada, or Europe (e.g., [10–20]), there is more limited information on spatial fire drivers in Latin American countries like Mexico. Despite Mexico being a well-recognized hotspot of fire activity (e.g., [64,65]), the majority of previous studies of spatial drivers of fire occurrence in Mexico have been conducted at regional (municipalities or states) scales (e.g., [46,47,66,67]). While the previous studies by Briones-Herrera et al. [37] and Monjarás-Vega et al. [38] have aimed at predicting fire occurrence nationally, they were based on forest fire suppression records from the National Forest Commission of Mexico (CONAFOR). To our best knowledge, there is no previous study aiming at predicting the drivers of the spatial patterns of MODIS and VIIRS active fires at a national level in Mexico. Such analysis could be valuable to support forest and agricultural policies aiming at fire prevention and promotion of a sustainable integrated fire management (e.g., [68]).

Consequently, the current study aimed at the prediction of MODIS and VIIRS active fire kernel density, at varying scales, using region-specific generally additive models (GAM) and geographically weighted regression (GWR), in Mexico. We hypothesized that the drivers of active fire density (human, climatic, or fuel-related) would vary between regions of the country, likely related to the ample variations in human, climate, and vegetation characteristics. This variation is expected to reflect the substantial heterogeneity in human activities, climatic conditions, and vegetation characteristics that define Mexico's diverse environmental and socioecological landscapes. Furthermore, we hypothesized that GWR would overcome stationary techniques (GAM models), related to expected spatial variations in the sign of the fire drivers within the analyzed regions.

2. Materials and Methods

2.1. Study Area and Regions of Analysis

This study was conducted on the entire country of Mexico. A total of 10 regions of analysis (Figure 1) were considered, following the criteria outlined by [38], based on the North American level 3 ecoregions map [69], and also considering the observed spatial distribution of active fires (e.g., [57], Figure 2).

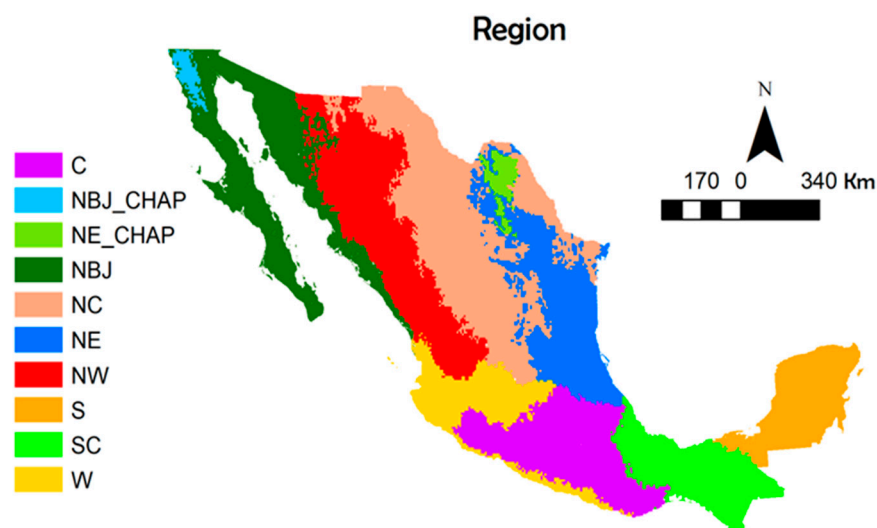


Figure 1. Regions of analysis. C: Central; NBJ_CHAP: Northern Baja California Chaparral; NE_CHAP: Northeastern Chaparral; NBJ: Northern Baja California; NC: North Central; NE: Northeastern; NW: Northwestern; S: Southern; SC: South Central; W: Western regions.

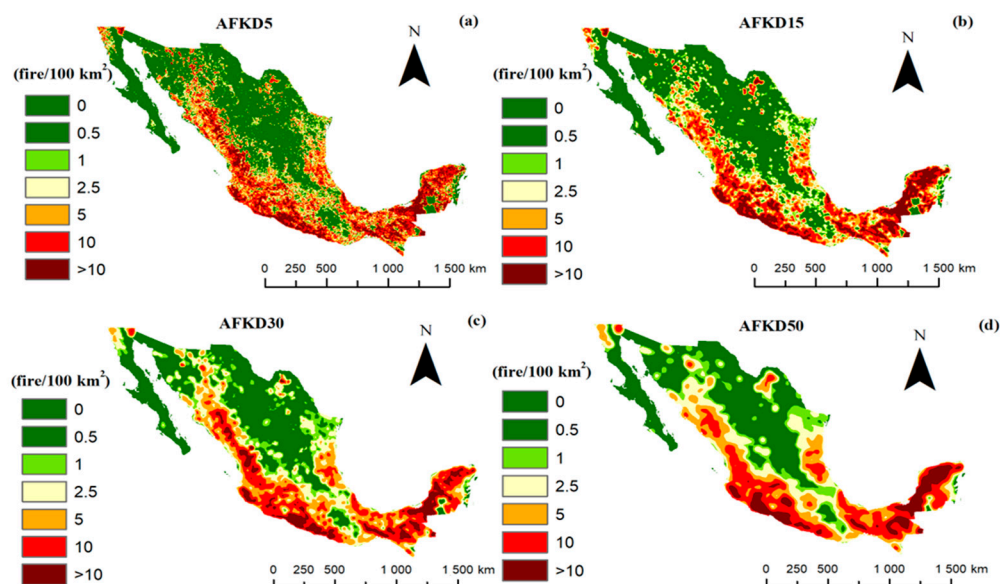


Figure 2. Observed active fire density (AFKDh) (number of fires/km²) for different h bandwidths for the calibration period (2003–2019). (a) Observed active fire density for 5 km of bandwidth. (b) Observed active fire density for 15 km of bandwidth. (c) Observed active fire density for 30 km of bandwidth. (d) Observed active fire density for 50 km of bandwidth. Pixel size is 1 km for all maps.

2.2. Active Fire Data

Active fire data for the period of 2003–2022 were downloaded for Mexico from the Fire Information for Resource Management System (FIRMS, <https://firms.modaps.eosdis.nasa.gov/download/>, accessed on 9 December 2025). Downloaded active fire detections corresponded to the sensors Moderate Resolution Imaging Radiometer Spectrum (MODIS, C6) [70] and Visible Infrared Imaging Radiometer Suite (VIIRS, V1, 375 m) [71]. Using the land use map from INEGI [72], active fires located in water bodies, volcanoes, human settlements, or industries were eliminated from the analysis. Recurrent or stationary points (corresponding to unmapped human areas) were also removed from the dataset.

2.3. Dependent and Candidate Independent Variables

Dependent variables were active fire kernel densities (KDs), calculated using the kernel density tool in ArcGIS 10.5. KDs of active fires for the period of 2003–2019 were considered for model calibration, and KDs of the remaining years (scaled by the period length) were used for independent model validation. Kernel density, a non-parametric statistical method for estimating probability densities, has the advantage of directly producing density estimates that are not influenced by regular grid impacts on localization effects [44,54]. The kernel density estimator is mathematically defined as [44] (Equation (1)):

$$f(x) = 1 / (n \cdot h) \sum_{i=1}^n K \left\{ \frac{(x - X_i)}{h} \right\} \quad (1)$$

where n is the total number of observations, X_i is the coordinates vector of the ignition point, K is the kernel function, and h is the bandwidth, or smoothing parameter.

Active fire kernel densities (AFKDs) were generated using bandwidths (h , Equation (1)) of 5, 10, 15, 15, 20, 25, 30, 30, 40, and 50 km. The selected pixel size for AFKD maps was 1 km, considering the spatial resolutions of MODIS (1 km) and VIIRS (375 m) active fires [70,71]. Examples of generated maps of active fires kernel densities at varying h bandwidths are shown in Figure 2.

Independent candidate variables to predict active fires kernel densities at the analyzed scales (5–50 km of bandwidth h) included human, fuel, topographic, and climatic variables, as detailed in Supplementary Table S1. Human variables included distance to urban areas, to roads, secondary roads, and to agricultural lands, calculated with the Euclidean distance tool in ArcGIS 10.5. The density of urban areas and population density were calculated using point density in ArcGIS 10.5, considering search windows of 5, 10, 15, 15, 20, 25, 30, 30, 40, and 50 km (selected examples shown in Figure 3). Using the same search windows, the density of roads, secondary roads, and the density of agricultural interface were calculated in ArcGIS 10.5 using the line density tool (Supplementary Table S1 and Figure 3).

Fuel-related variables included aboveground carbon density (ACD) from the Landsat- and Palsar-based map of [73] (Figure 3) and the Landsat-based tree cover (TC) map from [74]. Both ACD and TC were resampled from 30 m to resolutions of 5, 10, 15, 15, 20, 25, 30, 30, 40, and 50 km. Topographic variables included elevation, aspect, and slope (Supplementary Table S1 and Figure 3). They were calculated from the national elevation continuum of INEGI (<https://www.inegi.org.mx/app/geo2/elevacionesmex/>, accessed on 9 December 2025). Finally, we considered the climatic data of average precipitation from UNAM (<https://atlasclimatico.unam.mx/atlas/kml/>, 9 December 2025) (Supplementary Table S1). Maps of selected examples of the candidate predictive variables are shown in Figure 3.

The climatic, vegetation, and human variables for each region are summarized in Table 1. Average precipitation is <500 mm in the more arid regions (NBJ, NBJ_CHAP, NC, NE_CHAP) (Table 1), while temperate regions have an average annual precipitation of 700–800 mm for NW and NE and 1000 mm for C and W regions. Finally, the highest average precipitation, with values of >1000 and >1500 mm, is observed for S and SC regions, respectively (Table 1). Vegetation types range from chaparral and desert shrubby and pasture vegetation in the arid regions to temperate and dry to wet tropical forests (Table 1). Arid regions have average aboveground C densities (ACD) of <10 Mg C ha^{−1}, while temperate and tropical regions have average ACD > 15–20 Mg C ha^{−1} (Table 1 and Figure 3).

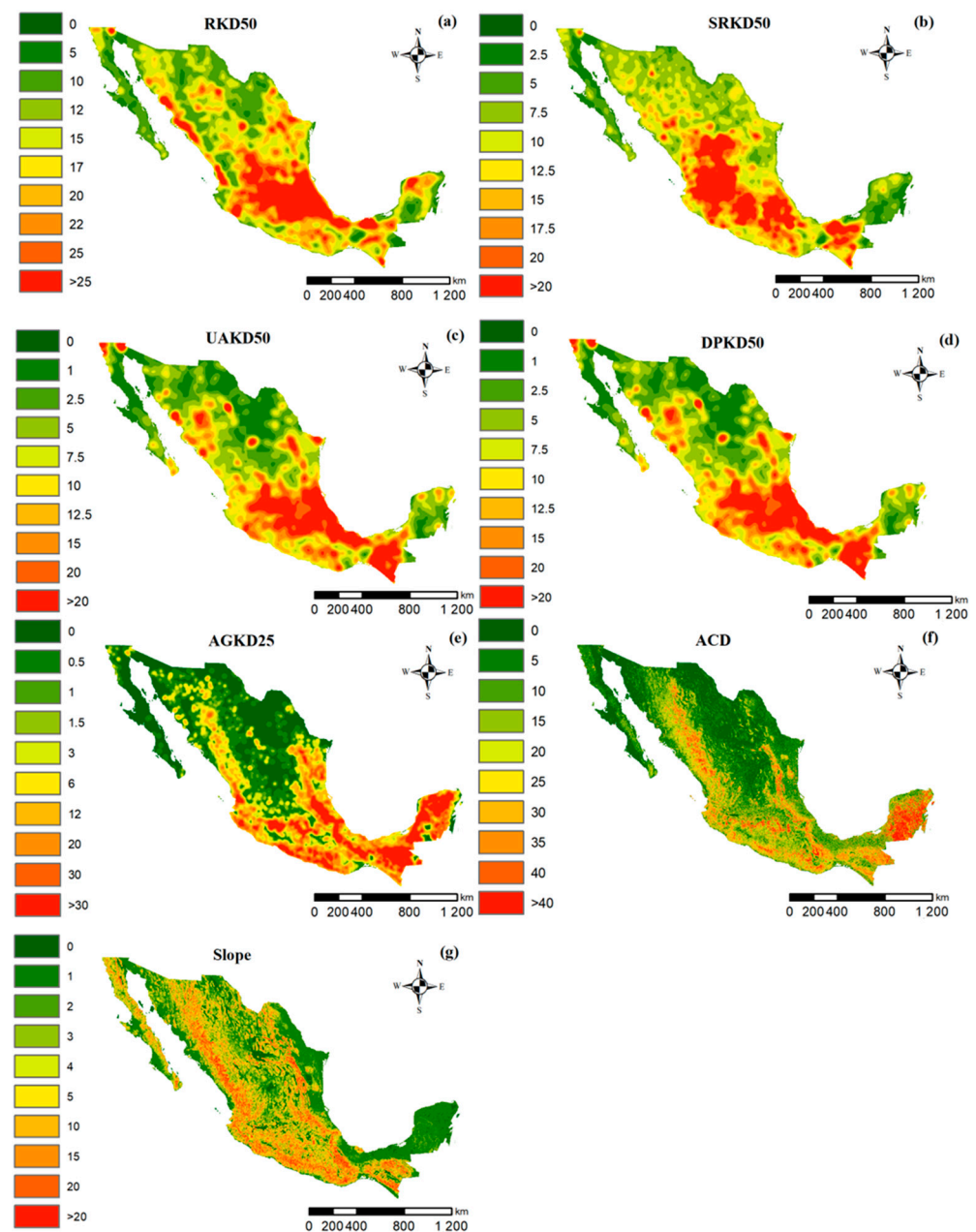


Figure 3. Selected maps of independent variables considered for the prediction of active fire density in Mexico. (a) RDKD50: road density at 50 km ($\text{km}/100 \text{ km}^2$); (b) SRKD40: secondary road density at 40 km ($\text{km}/100 \text{ km}^2$); (c) UAKD50: urban area density at 50 km (urban areas/ 100 km^2); (d) DPKD50: population density at 50 km (residents/ 100 km^2); (e) AGKD25: agricultural interface density at a distance of 25 km ($\text{km}/100 \text{ km}^2$); (f) ACD: aboveground carbon density (Mg C ha^{-1}); (g) slope (%). Pixel size is 1 km for all maps.

Regarding human factors, the most densely populated regions are C, W, and SC, while northern regions are less densely populated (Table 1 and Figure 3). The highest road density is observed for C and W regions, followed by NE and SC regions. Conversely, northern regions NBJ, NC, and NE_CHAP have the lowest road density (Table 1 and Figure 3). Finally, the highest density of forest-agriculture interface is observed in the SC and S, followed by the C and W regions (Table 1 and Figure 3).

Table 1. Main descriptive biophysical and human statistics by region.

	NBJ	NBJ_CHAP	NW	NC	NE	NE_CHAP	W	C	SC	S
AFKD20	7.5 (±1.6)	1.8 (±1.1)	3.5 (±4.8)	3.2 (±9.7)	1.5 (±1.8)	0.1 (±0.3)	6.3 (±4.1)	4.7 (±4.5)	6.1 (±3.8)	7.5 (±4.9)
UAKD50	4.6 (±6.1)	8.2 (±7.5)	6.7 (±4.9)	5.5 (±4.5)	12.5 (±11.0)	1.5 (±1.5)	16.2 (±9.8)	15.7 (±73.7)	2.8 (±1.1)	5 (±3.9)
DPKD50	201.5 (±487.9)	415.5 (±913.3)	109.4 (±288.9)	244.9 (±582.7)	543.3 (±123.3)	55.0 (±145.4)	123.5 (±181.9)	190.9 (±541.3)	7.2 (±6.9)	243.3 (±474.0)
RKD50	11.8 (±7.1)	13.3 (±3.9)	12.7 (±4.9)	15.0 (±6.9)	19.7 (±8.5)	8.7 (±3)	23.0 (±9.3)	25.1 (±13.7)	1.8 (±9.1)	13.2 (±6.5)
AGKD25	0.5 (±1.4)	0.5 (±0.8)	2.5 (±3.6)	0.4 (±1.1)	10.3 (±13.5)	0.1 (±0.2)	13.7 (±12.6)	14.0 (±11.3)	25.2 (±17.6)	23.7 (±16.0)
SRKD40	56.8 (±34.8)	66.5 (±24.9)	123.4 (±8.6)	125.3 (±103.3)	95.8 (±43.1)	6.2 (±1.9)	211.4 (±119.0)	180.0 (±66.5)	1.4 (±8.5)	50.0 (±36.4)
ACD	3.6 (±5.4)	4.6 (±3.8)	15.6 (±10)	7.3 (±5.9)	2.5 (±4.3)	10 (±10.4)	15.6 (±10.6)	18.2 (±11.4)	17.8 (±11.7)	26.2 (±16.8)
Slope	2.8 (±2.5)	6.3 (±5.1)	7.5 (±6.6)	2.4 (±3)	5 (±6.4)	6.5 (±5.8)	5.7 (±5.5)	8.2 (±6.5)	5.6 (±7.2)	0.3 (±0.6)
ELEV	328.7 (±326.7)	925.8 (±452.2)	1640.8 (±716.1)	1422.8 (±581)	876.2 (±760.6)	1097.4 (±427.9)	1298.5 (±793.9)	1524.4 (±776.5)	576.2 (±660.4)	90.8 (±381.4)
PREC	261.4 (±179.7)	298.9 (±71.1)	732.4 (±231)	371.4 (±104.4)	757.9 (±459.7)	382.5 (±76.8)	981 (±298.6)	976.5 (±343.8)	1984.4 (±754.9)	1128.9 (±129.4)
Vegetation	SH, PF	CHAP, SH, PF	POF, DTF	CHAP, PAS	POF, DTF	CHAP, SH, PAS	POF, DTF	POF, DTF	POF, DTF, WTF	DTF, WTF, WET
Climatic Zone	CT, WT, HW, WD	CT, WT, WD	CT, WT, HW, WD	CT, WT, HW, WD	CT, WT, HW, WD	CT, WT, HW, WD	CT, WT, HW, WD	CT, WT, HW, WD	CT, WT, HT	HT, WT

Values shown are average values; standard deviations are shown in brackets. NBJ, NBJ_CHAP, NW, NC, NE, NE_CHAP, W, C, SC, S: regions of study (Figure 1). AFKD20: active fire kernel density for 20 km of bandwidth (fires/100 km²); UAKD50: urban area kernel density at a distance of 50 km (urban areas/100 km²); DPKD50: population density kernel density at 50 km (residents/100 km²); RKD50: road kernel density at 50 km (km/100 km²); AGKD25: agricultural density at a distance of 25 km (km/100 km²); SRKD40: secondary road kernel density at 40 km (km/100 km²); ACD: aboveground carbon density (Mg C ha^{−1}); slope (%); ELEV: elevation (m); PREC: precipitation (mm); SH: shrubby vegetation; PF: pine forest, POF: pine and oak forest, CHAP: chaparral, PAS: natural pastureland (grasslands), DTF: dry tropical forest, WTF: wet tropical forest, WET: wetlands. Climatic zones: climatic areas [38], where CT: cold temperate; WT: warm temperate; HW: humid warm; WD: warm dry.

2.4. Variable Selection

2.4.1. Correlation Analysis

We used Pearson's correlation coefficient to assess the correlation between independent and dependent variables. The cor function in RStudio (V 1.1.442, 2015) was utilized for these calculations. Independent variables with correlation coefficients between them greater than 0.65, as frequently considered in the literature (e.g., [10,22,38]), were excluded to prevent collinearity.

2.4.2. Generalized Additive Models (GAM)

Generalized additive models were used to choose potential variables for predicting active fire kernel density across all bandwidths (5–50 km) for each region of study. A generalized additive model (GAM) is a generalized linear model with a linear predictor involving a sum of smooth functions of continuous independent variables [75]. A GAM model has the following structure [75] (Equation (2)):

$$g(E(Y)) = \beta_0 + f_1(x_1) + f_2(x_2) + \dots + f_m(x_m) \quad (2)$$

where Y is the response (dependent) variable; $E(Y)$ is the expected value of (Y) ; $g(\cdot)$ is a link function that connects the linear predictor to the mean of Y ; β_0 is the constant intercept; each $f_j(x_j)$ is a smooth spline function of the independent variable x_j .

The RStudio gam packages (V 1.1.442, 2015) were utilized for fitting GAM models. Variable selection was performed using a stepwise GAM technique [75], considering all candidate variables listed in Supplementary Table S1 (without interactions). Models were fitted using cubic regression splines. The number of knots of GAM models was defined by the criteria of minimizing the corrected Akaike information criterion (AIC) [75]. The goodness-of-fit for the GAM models was further evaluated using the root mean squared error (RMSE) and adjusted R^2 (R^2_{adj}), the latter calculated using Equation (3):

$$R^2_{adj} = 1 - \frac{(1 - R^2)(n - 1)}{n - p - 1} \quad (3)$$

where R^2 : Sample R-squared; n = number of observations (sample size), p = number of independent variables.

The selected goodness-of-fit statistics were chosen to ensure the selection of the most parsimonious models, both in terms of the number of variables selected (by penalizing models with a higher number of variables to avoid overfitting, based on stepwise selection and considering R^2_{adj} values of the selected models) and in terms of avoiding GAM knots over smoothing, the latter based on minimizing model AIC.

2.4.3. Active Fire Density Prediction with Geographically Weighted Regression (GWR)

We used the geographically weighted regression (GWR) tool in ArcGIS 10.5, incorporating the variables chosen for each region through the GAM analysis, to predict active fire kernel density for each region of study. The equation for a GWR version of the Ordinary Least Squares (OLS) regression model (e.g., [14,46]) is the following (Equation (4)):

$$y_i(u) = \beta_{0i}(u) + \beta_{1i}(u)x_{1i} + \beta_{2i}(u)x_{2i} + \dots + \beta_{mi}(u)x_{mi} \quad (4)$$

where y_i is the dependent variable; β_{0i} to β_{mi} indicate the parameters that describe the relationship around the coordinates (u) of the i th point in space (site-specific); x_{mi} is the m th variable in the i th point. In this model, active fire kernel density (AFKD) was considered as the dependent variable. The candidate independent variables x_{1i} to x_{mi} were biophysical and human variables (as described in Section 2.2 and Supplementary Table S1).

The determination of regression bandwidths in GWR relied on minimizing the corrected Akaike information criterion (e.g., [10,38]). Regional maps depicting the predicted active fire density, local R^2 , local coefficients, and model residuals for both calibration and validation periods were created in ArcGIS 10.5 by rasterizing the GWR outputs at a 1 km resolution for all regions. An inclusive mosaic encompassing all regions was constructed to provide a nationwide perspective. The efficacy of the GWR models was further assessed using adjusted R^2 (Equation (3)) and RMSE.

3. Results

3.1. Selection of Variables for Active Fire Kernel Density Prediction

The adjusted coefficient of determination increased logarithmically with increasing active fire kernel density bandwidth h (Equation (1)), as shown in Figure 4. For most regions, an inflection point in the rate of adjusted R^2 increase was observed for AFKD bandwidths approximately above 20 km (Figure 4). The variables selected by the GAM models, from the tested potential drivers (Table S1), for each region at the selected AFKD bandwidth, are shown in Table 2.

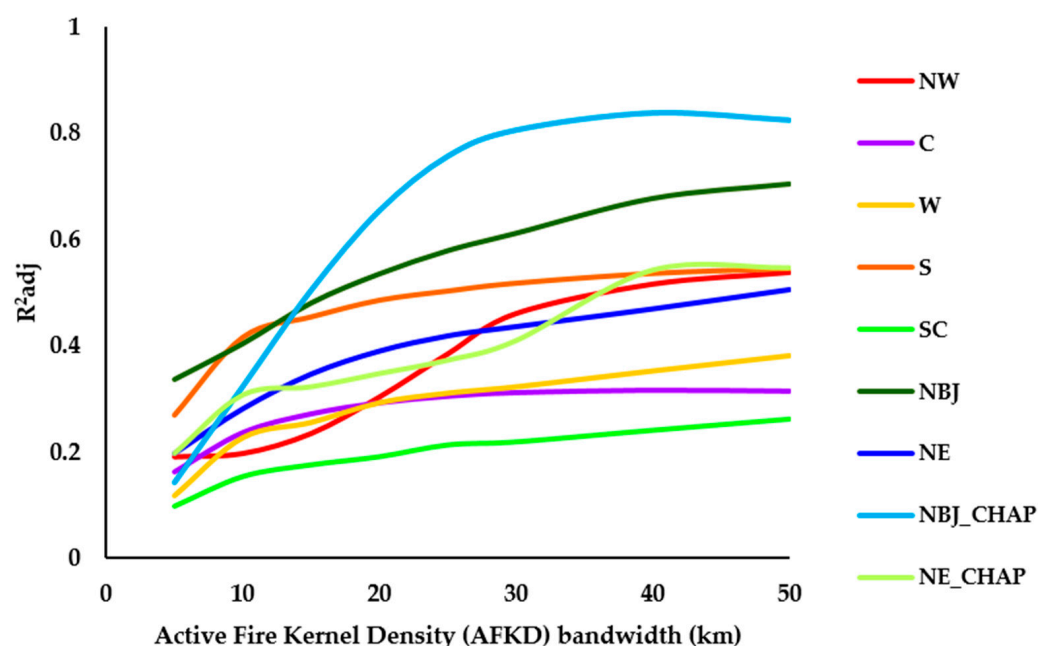


Figure 4. Goodness of fit (R^2_{adj}) of GAM models for the prediction of fire kernel density at varying bandwidths by region for the study calibration period data. C, W, NW, S, SC, NE, NBJ, Chap_NBJ, Chap_NE; regions of study (Figure 1).

Table 2. Variables selected by region GAM and GWR goodness of fit at 20 km of bandwidth.

Region	V_1	V_2	V_3	GAM		GWR_CAL		GWR_VAL	
				R^2_{adj}	RMSE	R^2_{adj}	RMSE	R^2_{adj}	RMSE
C	RKD50	ACDKD50		0.29	0.38	0.93	0.91	0.72	0.07
W	RKD50	ACDKD30	AGKD25	0.29	0.34	0.96	0.89	0.68	2.97
NW	UAKD50	ACDKD20	Slope	0.30	0.37	0.66	1.97	0.98	3.16
S	AGKD20	ACDKD10	UAKD50	0.48	0.35	0.95	0.90	0.63	4.01
SC	AGKD50	ACDKD15	DPKD30	0.19	0.34	0.93	0.90	0.99	3.75
NE	UAKD50	ACDKD40	DPKD50	0.39	0.14	0.87	0.44	0.48	2.29
NBJ	UAKD50	ACDKD20	AGKD30	0.54	0.11	0.95	0.34	0.33	0.88
NC	UAKD20	ACDKD20		0.09	0.09	0.70	0.52	0.74	0.67
Chap_NBJ	UAKD50	ACDKD15		0.65	0.06	0.82	0.48	0.13	1.49
Chap_NE	RKD40	ACDKD20	SRKD40	0.34	0.30	0.98	1.49	0.37	0.60

GAM: generalized additive model, GWR: geographically weighted regression for calibration (CAL) and validation (VAL) periods; V_1 , V_2 , V_3 : First, second and third selected variables with stepwise GAM; R^2_{adj} : adjusted R^2 ; RMSE: Root Mean Square Error; C, W, NW, S, SC, NE, NBJ, NC, Chap_NBJ, Chap_NE; regions of study (Figure 1). RKD: road density at specified distance in km; UAKD: urban area density at specified distance in km; DPKD: population density at specified distance in km; AGKD: agricultural density at specified distance in km; SRKD: secondary road density at specified distance in km; ACDKD: aboveground vegetation carbon density at specified distance in km, Slope (%).

For all regions, the first variables selected in the stepwise GAM selection were human variables: road density (RKD), urban area density (UAKD), or agricultural interface density (AGKD) (Table 2). RKD was selected for the Central and Western regions and for the Chaparral of the NE region. AGKD was selected for the Southern and South-central regions, and UAKD was the first variable selected for the remaining regions (Table 2).

For all the regions in the analysis, aboveground carbon density was the second most important variable (Table 2). Climatic variables showed strong correlation with ACD in the correlogram analysis and were not selected as the main variables to predict fire density for any of the analyzed regions. Slope was selected as a significant variable for the NW region.

The goodness of fit of the region-specific GAM models and the corresponding GWR fits are shown in Table 2. For all the analyzed regions, GWR outperformed GAM models, with higher coefficients of determination values (Table 2).

3.2. Prediction of Active Fire Kernel Density with GAM and Geographically Weighted Regression

The fitted GAM splines at a 20 km bandwidth are shown in Figure 3 and Supplementary Figures S1 and S2. Urban area density (UAKD) showed unimodal (humped) relationships with active fire kernel density for the NW region (Figure 5) and positive relationships for NBJ, NC, NBJ_CHAP, and NE regions (Supplementary Figures S1 and S2).

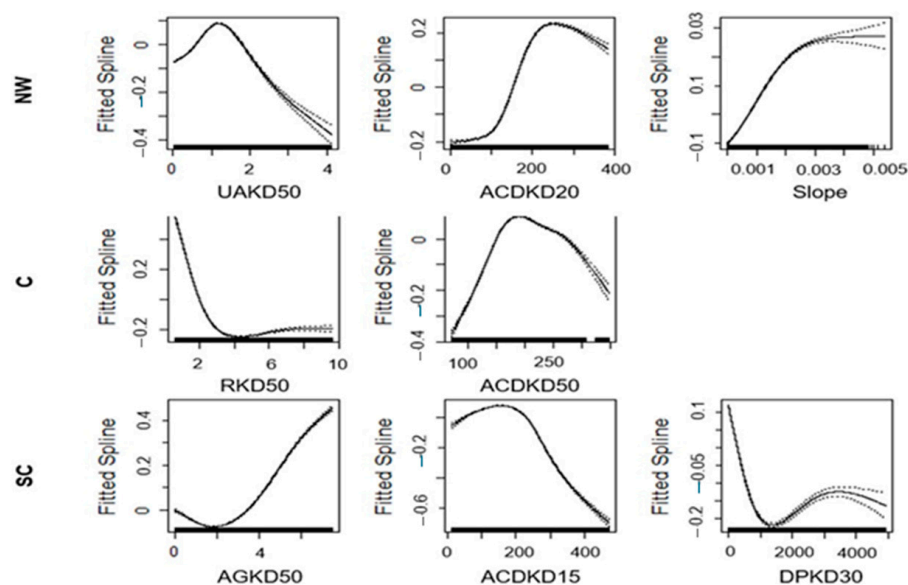


Figure 5. Fitted GAM model for the prediction of active fire kernel density with a 20 km bandwidth by region. NW: Fitted GAM model for NW region, C: fitted GAM model for C region, SC: fitted GAM model for SC region. UAKD: Urban area density at specified distance in km; RKD: road density at specified distance in km; ACDKD: aboveground vegetation carbon density at specified distance in km, Slope (%); DPKD: population density at specified distance in km (residents/100 km²). Solid lines show predicted splines and dotted lines show 95% confidence intervals of fitted splines.

Interestingly, road density (RKD) and secondary road density (SRKD) showed negative relationships with fire density for all the regions where it was selected as the main variable influencing active fire occurrence (C, W, and NE_CHAP regions) (Figure 5 and Supplementary Figure S1). For the S and SC regions, agricultural interface density emerged as the most influential variable, displaying a predominantly positive role on active fire occurrence (Figure 5 and Supplementary Figure S2). Aboveground carbon density (ACD) showed mostly a humped relationship with fire occurrence (Figure 5 and Supplementary Figures S1 and S2), except for the shrub-dominated NBJ and NBJ_CHAP regions, where the relationship was positive (Supplementary Figure S1).

3.3. Mapping of Predicted Active Fire Kernel Density with Geographically Weighted Regression

The resulting predicted active fire density map for the entire country of Mexico using the mosaic of regional GWR predictions is included in Figure 6.

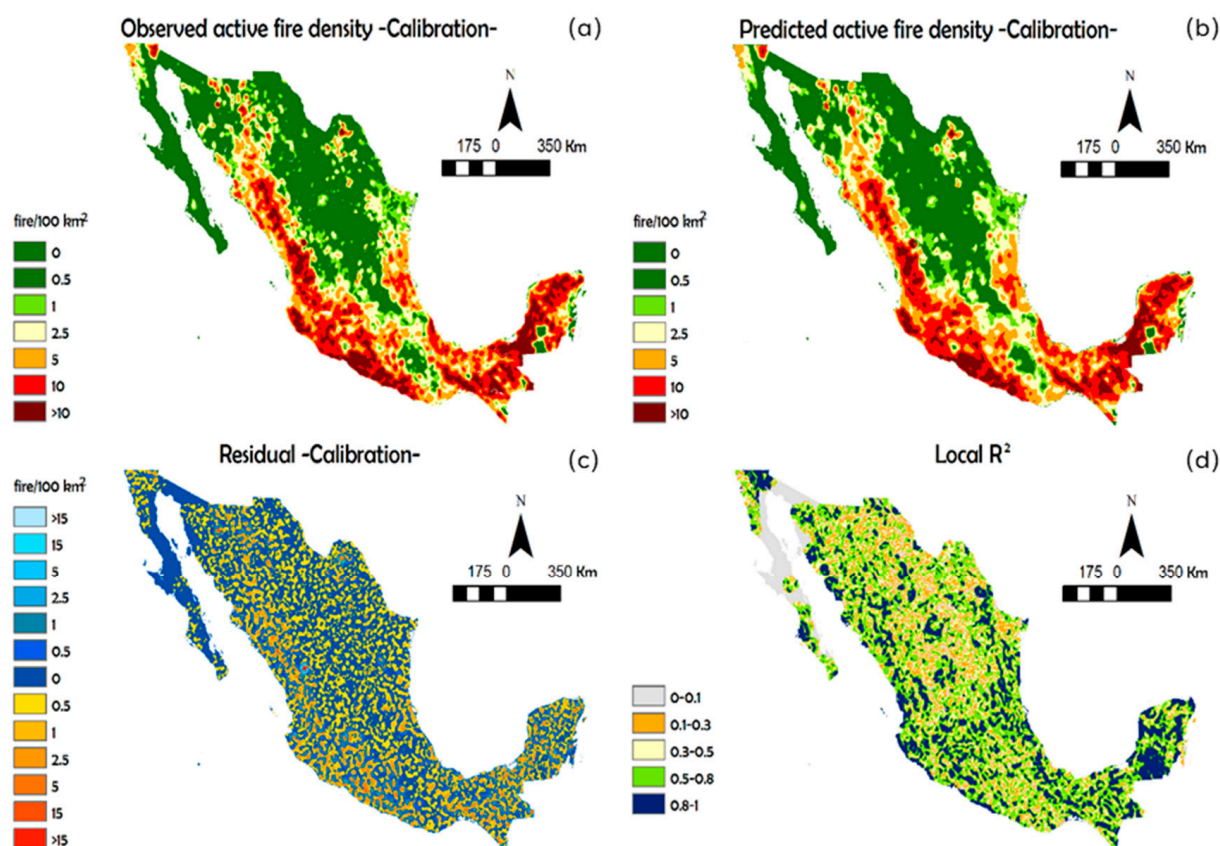


Figure 6. Observed and predicted active fire kernel density (KD) at 20 km of KD bandwidth for the calibration period (2003–2019) for Mexico. (a) Observed active fire density at 20 km, (b) predicted active fire density at 20 km, (c) Residual, (d) Local R^2 . Pixel size is 1 km for all maps.

Details of region-specific GWR observed and predicted AFKD are shown in Supplementary Figures S3–S10. For illustration purposes, we include selected examples of maps of predicted active fire kernel density using regional-specific GWR in Figures 7 and 8. For the Central region (Figure 7), the majority of active fire activity was observed in the southern part of the region, as noted in the observed and predicted fire density maps (Figure 7a,b) and in the intercept map (Figure 7e). This high fire activity in the southern part of the Central region coincided with negative GWR coefficients for road density in this area (Figure 7f), agreeing with the general negative tendency of RKD observed in the GAM models (Figure 5). Contrary to this general negative tendency, some densely populated areas with high RKD showed positive associations, pointing to varying causes of fire occurrence that were better captured with non-stationary GWR coefficients (Figure 7f).

Coefficient non-stationarity was also observed in the NW region, where positive urban area density coefficients were more pronounced in areas characterized by a higher concentration of human settlements (Figure 8f). In general, slope coefficients for the NW region were mainly positive (Figure 8h), agreeing with the general tendency described by GAM models (Figure 5). However, some parts of this region showed the contrary (negative) for this factor (Figure 8h), again confirming spatial heterogeneity in fuel drivers. This spatial non-stationarity of fuel drivers was observed for all regions of study (Supplementary Figures S3–S10).

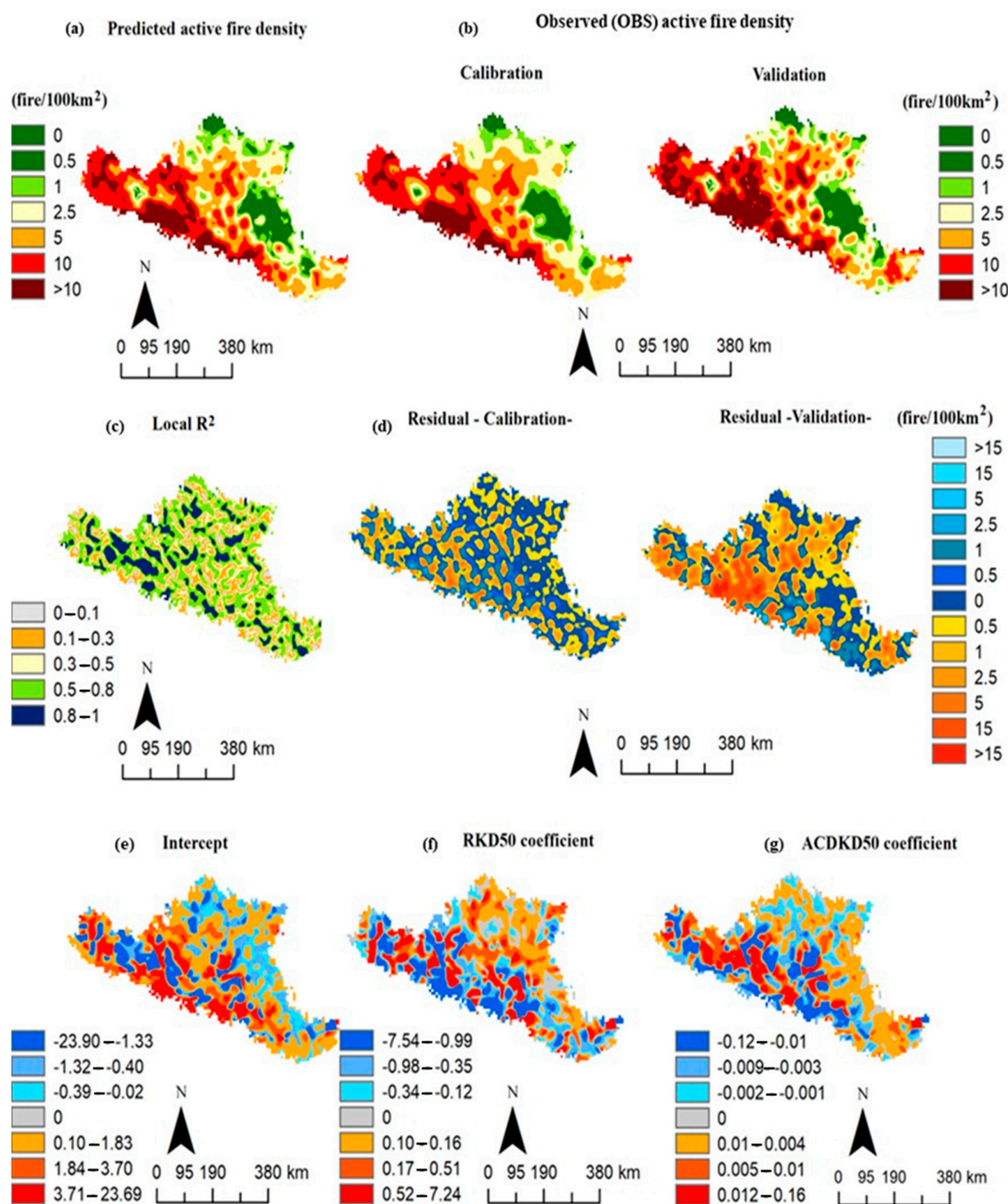


Figure 7. Predicted and observed active fire density for 20 km of bandwidth, Local R^2 , residues, and GWR model coefficients for the **Central** region. (a) Predicted active fire density observed in calibration period (2003–2019); (b) observed active fire density (fires/100 km²) with GWR model in calibration and validation period; (c) local R^2 ; (d) model residuals for calibration and validation period (fires/100 km²); (e) intercept; (f) coefficient for road density at 50 km; (g) coefficient for aboveground carbon density at 50 km. Pixel size is 1 km for all maps.

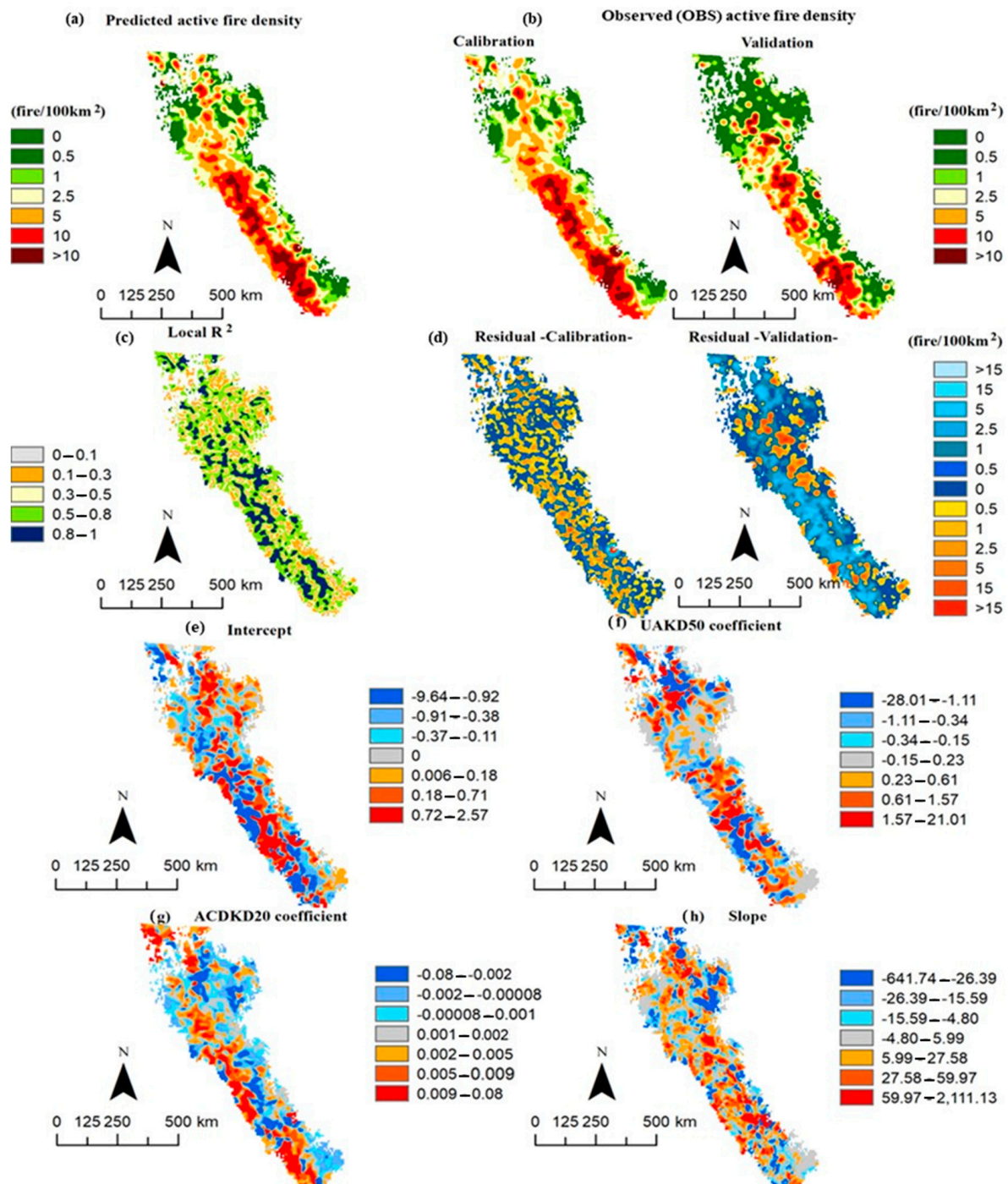


Figure 8. Predicted and observed active fire density for 20 km of bandwidth, local R², residues, and GWR model coefficients for the **Northwestern** region. (a) Predicted active fire density observed in calibration period (2003–2019); (b) observed active fire density (fires/100 km²) with GWR model in calibration and validation period; (c) local R²; (d) model residuals for calibration and validation period (fires/100 km²); (e) intercept; (f) coefficient for urban area density at 50 km; (g) coefficient for aboveground carbon density at 20 km; (h) coefficient for slope. Pixel size is 1 km for all maps.

4. Discussion

4.1. Spatial Patterns of Active Fire Density Against Fire Suppression Records

The observed regional differences in active fire density from this study support regional variations in active fire spatial patterns previously observed in Mexico (e.g., [76]). However, the spatial patterns observed here using remotely sensed MODIS and VIIRS

varied from those reported in [38] using fire suppression records. This supports previous results in Mexico (e.g., [57,58]) and in other regions (e.g., [59,60]).

Active fires can offer a more comprehensive, automated, objective view of fires that are burning at the time of satellite pass (around 12–2 pm and a second late-night pass for Mexico), given that the fire size or intensity is detectable (e.g., [71,77]). In contrast, suppression records are widely recognized to potentially have an observational bias in areas that are less accessible (e.g., [38,58,62,63]). Nevertheless, human-based suppression registers can include some small fires that were suppressed before satellite observations. In our opinion, both sources of information are complementary; considering both could better guide the prioritization of fire prevention, suppression, and post-fire restoration policies (e.g., [7,8,68]).

4.2. Variations Between Regions in the Main Drivers of Fire Occurrence

The observed differences in the selected main drivers of active fire density between regions support the observations for fire suppressions from [38] and agree with similar regional variations elsewhere (e.g., [10,18,19]). This supports the need for more local-to-regional scale analyses to understand the drivers of fire spatial occurrence. For example, [18] found through region-specific GAM analysis that the degree to which anthropogenic features predicted ignition in the Western US varied considerably by ecoregions. The studies by [10] or [19] found that both the selected variables and the sign (positive or negative) to predict fire records varied between regions in Southern Europe and suggested that different human activities determined fire activity. Our results support those observations, suggesting that this varying role of spatial fire activity drivers is probably reflecting the spatial variation in human activities across regions and the changing interactions of such different human impacts with climate, vegetation, and topography [38].

The selection of human variables (road, urban area, or agricultural density) as the main driver explaining active fire density in this study supports the observations for fire suppression records from [38]. It furthermore agrees with areas where fire activity is mainly mediated by human factors, such as the US (e.g., [11,15,18,20]) or Southern Europe (e.g., [10,19,22,23,26,31]), among other areas with large human influence on fire (e.g., [16]). Contrarily, climatic and fuel limitations have been selected as the main variables affecting fire spatial patterns in other more climate- or fuel-limited areas (e.g., [9,13,14]). These observed variations in main fire drivers between our regions of study and between previous studies elsewhere seem to support the hypotheses of varying constraints of fire activity (e.g., [6,17]). In this sense, the large anthropogenic cause of fire in Mexico, which had been previously reported in regional (e.g., [46,47,78,79]) and national [38] studies, likely explains the selection of human factors as the most limiting factor determining active fire occurrence, followed by fuel availability factors.

4.3. Effect of Aboveground Biomass on Active Fire Density

In addition to the main role of human variables, aboveground biomass carbon density significantly influenced active fire density for all the regions analyzed. This supports previous observations for fire suppression records in Mexico (e.g., [37,38]) and other countries (e.g., [33]), quantified now for the first time in Mexico with remotely sensed active fires kernel density. The latter supports observations where proxies of fuel availability, such as NDVI (e.g., [43,56]), tree cover [9], or leaf area index [36] have been related to remotely sensed active fires [56] or burned area ([9,36,43]). Aboveground carbon density, which was strongly correlated with precipitation, as previously reported in Mexico (e.g., [80]), surpassed the predictive capacity of the latter, supporting similar observations by [38] for fire suppression records prediction. The ability to reflect not only potential but current

vegetation conditions as determined by previous management, potentially at finer spatial scales, might explain this variable selection.

Relationships of active fire density against biomass (ACD) were positive for shrubby areas such as North Baja California and Northeast chaparral-dominated ecoregions, matching with expected higher fire ignition [38] and higher intensity and spread (e.g., [81,82]) with increasing shrub fuel loads. On the other hand, for the more productive ecosystems, our observed humped relationships of AKFD against biomass support the previous observations in Mexico for fire suppression records [37,38] and for remotely sensed fire intensity (Fire Radiative Power from MODIS) [39]. Our study suggests that, in the more productive ecosystems of Mexico, fire activity, as measured here by remotely sensed active fire density, is also maximum at intermediate biomass levels. At those intermediate biomass levels, the fuel complex is generally comprised of relatively open or young stands with high vertical continuity, with timber understory surface fuels, which, combined with higher wind penetration and fuel dryness, can result in high fire spread and intensity (e.g., [39,82]). Contrarily, in the denser ecosystems, fire spread is expected to be more limited by higher moisture (e.g., [76]), lower wind penetration (e.g., [37]), and the fuel complex is generally comprised of timber litter, with lower shrub and pasture loads (e.g., [39,82]). These observations also agree with studies that have documented lower burned area in the areas of highest tree cover, where fine fuel loads are lower (e.g., [9,36]).

In summary, these findings seem to support the hypothesis of maximum fire activity at intermediate biomass (e.g., [37,82,83]), now demonstrated in the current study with remotely sensed active fire density for a large variety of ecoregions. This has practical applications for fuel management: for instance, in shrub-dominated areas, higher fuel loads should be targeted to diminish fuel continuity and accordingly diminish the likelihood of large and intense fire spread (e.g., [38,39,82]). Within areas of higher tree cover, fuel treatments could aim at intermediate biomass areas, particularly those with lower tree canopy height and higher understory fuel loads, to be prioritized for fire prevention to reduce intense and fast fire spread (e.g., [37–39]).

4.4. Human Drivers of Active Fire Density

4.4.1. Role of Road Density on Fire Occurrence and Spread

Road density, which was the main human variable selected in the densely populated central and western regions, showed a negative correlation with active fire density. This supports previous observations of lower active fire activity by [29] with increasing road density or lower remotely sensed burned area in the vicinity of roads by [43]. However, these observations are contrary to the conclusions more frequently found when analyzing fire suppression records (e.g., [10,16,19–25]). Because most research on spatial patterns of fire activity has focused on fire suppression records, it is widely assumed that, in areas of denser road density or in the vicinity of roads, fires are more likely to start (e.g., [16]). This was also the case when previously analyzing fire suppression records in Mexico. Monjaras et al. [38] reported, for the same central and western regions, positive associations of fire suppression records with increasing road density, contrary to the negative relationships observed here. Furthermore, the majority of (mainly field, GPS-based) fire suppression records of CONAFOR in Mexico have been found to be within 10 km of roads [38]. Similar conclusions have been frequently found for road density (e.g., [22–24]) or road distance (e.g., [19–22,25,31]), for studies based on fire suppression records.

Two reasons might be behind this widely reported positive association of road density with fire suppression from the literature. On the one hand, more fires might actually start closer to roads (e.g., higher ignition probability), since access to the landscape of those actively starting fires for activities such as agricultural burns or land use changes, such as

urban growth (e.g., [20]), might be facilitated by roads. On the other hand, as recognized by some previous studies, fire suppression records might be affected by accessibility bias of those manually registering the position (e.g., [38,58,62,63]). This might be more relevant for older fire records (generally obtained without access to remote sensing imagery), which are known to have potential position uncertainties (e.g., [10,44,48,54]).

Remotely-sensed automated records of fire activity through active fires (e.g., [55,71,84,85]) can reduce some of those biases, potentially allowing for better characterization of which parts of the landscape are more frequently burning with a larger fire spread. For example, the previous study of [38] reported, for some regions, a negative effect of slope on fire occurrence based on human-based GPS fire-suppression records. Thus, suggesting potential accessibility limitations of those starting or suppressing the fires (e.g., [38,58,62,63]). In contrast, our observations in this study, using remotely sensed active fires, point to a positive relationship between active fire density and slope (Figure 3), agreeing with the principles of fire behavior (e.g., [81,82]). These discrepancies also seem to support the previously observed differences in the role of fire drivers when aiming at predicting either the likelihood of fire ignition (from point records of fire start or suppression) against those studies aiming to predict large fire probability (e.g., [28]), fire spread likelihood (burn probability) or fire size (from burned area perimeters) (e.g., [20]).

In summary, on the one hand, based on our previous studies and on the majority of the literature, it seems clear that fires are generally more likely to start and suppression is more likely in the vicinity of roads (e.g., [19–22,31]) and in areas of higher accessibility (e.g., higher road density) ([22–24,38]). Conversely, on the other hand, the observations from this study focusing on MODIS and VIIRS active fire density and those from literature with remotely sensed active fire records (e.g., [29]) or fire perimeters (e.g., [20,43]) suggest that fires are more likely to spread (higher burn probability) in areas with lower road density. In remote areas, fuel continuity is typically higher (e.g., [20]) and, furthermore, lower concentrations of suppression resources can be expected (e.g., [47,86]). In contrast, roads can act as fuel breaks, reducing fuel continuity and facilitating suppression (e.g., [20,47,86]), therefore decreasing the likelihood of large fires spreading (e.g., [20,47,63]). Consequently, fire prevention actions might be targeted to both diminish ignition risk (and protecting human values at risk) in the vicinity of human infrastructure, while at the same time other actions should also focus on reducing the probability of the spread of large, potentially more intense fires, as quantified by either remotely sensed observed (e.g., [39]), or simulated fire activity (e.g., [87,88]).

4.4.2. Relationships of Urban Areas and Population Density with Active Fire Occurrence

Urban areas density (UAD) was the most widely selected main driver of active fire density for the Northern regions, with a positive role, agreeing with similar observations for fire suppression records of [38] for those less populated regions of Northern Mexico. Our observations agree with the positive relationships between fire activity and UAD (e.g., [21–23]) and population density previously documented in regions such as Southern Europe, Australia, or the USA ([10,23,25,26,31]). Given the predominance of fire use linked to agricultural burns in the vicinity of human settlements in Mexico (e.g., [78,79,89]), UAD and population might be indirectly accounting for the influence of human activities such as agricultural or urban-forest interface expansion, which are the main causes of fire ignition and uncontrolled spread in Mexico (e.g., [46,47,89–91]).

However, in some of the areas where agricultural density was selected as the main variable, such as the SC region, the population density role was negative (Figure 3), agreeing in this case with regions where fire-causing agricultural activities have been documented to be away from human settlements (e.g., [9,14]). Finally, for the NW region, a humped

GAM relationship was observed for UAD in the NW region, suggesting that, for that particular region, fire-causing human activities, mainly pasture and agricultural burns, are at intermediate distances from human settlements. This resembles similar observations of humped relationships for distance to urban areas by [47] in NW Mexico. Similarly, unimodal relationships for fire activity have been previously observed for distance to urban areas or to urban interface elsewhere (e.g., [29,32,92]). Those positive, negative, or humped effects of PD or UAD observed in our GAM analysis again highlight the need for regional analyses of fire activity drivers (e.g., [10,18,19]).

4.4.3. Agricultural Interface Density

The density of agricultural interface was selected as the main variable explaining active fire density in the S and SC regions. Our observations of MODIS and VIIRS active fire density corroborated the very high activity reported using remote sensing in those regions (e.g., [76,93,94]), which represent a large hotspot of fire emissions (e.g., [58,94,95]). Fire activity in southern Mexico has been widely documented to be related to widespread use of fire in agricultural activities, including slash and burn agriculture, escaped agricultural burns, and agricultural expansion on tropical forests (e.g., [76,78,96]). Furthermore, our observed positive association of agriculture interface density agrees with similar observations in other countries (e.g., [10,25–27,48]), where agricultural activities are largely responsible for fire activity. Fire social prevention actions should focus on promoting responsible agricultural burn planning and timings, based on the cultural knowledge of sustainable fire management (e.g., [8,97,98]).

4.5. Mapping Active Fire Kernel Density with Geographically Weighted Regression

Our observed increase in the goodness of fit using GWR against GAM models supports similar previous observations of accuracy improvements of GWR against stationary linear regression techniques such as OLS (e.g., [10,24,51]). The goodness of fit increased with coarser scales, agreeing with studies that have found similar observations (e.g., [13,99,100]). Nevertheless, some studies have observed the contrary (e.g., [9]) or suggested a peak in correlation of certain variables at certain scales (e.g., [38,101]). In our study, the rate of increase in R^2 stabilized after 20 km bandwidth for active fire kernel density, agreeing with the observations nationally for Mexico by [38] or in NW Mexico [47], but in this study for the kernel density of remotely sensed active fires. This seems to agree with previous observations in Mexico [38] and NW Mexico [47] that spatial correlation of fire events was higher at distances lower than 20–30 km. In our study, the scale of 20 km is likely registering the size of the majority of clusters of spatial active fire activity. Our results support the notion that GWR modeling results are highly dependent on the choice of spatial scale and bandwidth (e.g., [38,46,47]), those parameters potentially varying for other regions of study.

Coefficient non-stationarity was found for the majority of the variables selected for all the regions analyzed, supporting similar spatial variations in the role of fire drivers across the landscape observed in previous studies exploring GWR (e.g., [24,49–53]). These variations within study regions are likely related to spatially variable interactions between different human, climatic, and fuel drivers (e.g., [10,14,38]), and their role in facilitating or limiting fire activity.

For example, some areas in the central (Figure 4) or western region (Supplementary Figure S5) showed a positive association with human presence (road density), suggesting fire-causing human activities such as urban expansion or land use changes in the vicinity of those densely populated areas (e.g., [34,102]). However, in the southernmost part of those same regions, a negative association with road density was observed, which might be explained by the pressure of agricultural expansion in the sparsely populated areas of those

regions (e.g., [79,90,91]). The latter resembles similar observations of fire activity related to agricultural expansion in areas distant from urban areas in regions such as Africa [14] or Brazil [51]. The strong variation in the majority of the GWR coefficients maps suggests that such complex interactions are better described with models that include coefficient non-stationarity. Finally, the maps of the model validation residuals allow us to identify in which areas those spatial patterns might be changing in the more recent years. New areas of agricultural or urban expansion might be identified, highlighting areas where landscape changes are being more dynamic (e.g., [3,38]).

4.6. Study Limitations and Future Work

The conclusions from this study are limited to the period of study and the analyzed variables, based on available information. Future studies should expand both the study period and the potential explanatory variables. It is important to bear in mind that exploratory tools such as GWR serve to identify spatial relationships, but do not aim at explicitly providing evidence of causation. In this sense, the previous study of [38] separately modeled fire suppression records based on CONAFOR field-recorded cause (human or natural), corroborating that, based on official fire suppression records, the vast majority of fires in Mexico are human-caused (>99%). Unfortunately, active fires lack such information on potential cause, and a match with human registers of cause might be challenging, given the well-known discrepancies between both sources of information (e.g., [57–60]). Future work in this area might point to analyzing spatio-temporal coincidences of remotely sensed active fires with recently available electric thunderstorm data, observed daily from GOES-19. This data, however, is only publicly available from Mexican fire monitoring systems since 2025 [103].

Secondly, although the majority of analyzed regions showed relatively stable spatial patterns of fire activity, as evidenced by R^2_{adj} values > 0.6 – 0.7 in the validation period for the majority of regions, several regions (mainly in NBJ and NE) showed a more limited performance in the independent (more recent) validation period. This might point to temporally changing spatial patterns of active forest degradation in those regions, which might be linked to new areas of expanding urbanization (similar to what is observed in California chaparral areas (e.g., [15,92,104]) or recent areas of agricultural expansion (e.g., [90,91]). To better capture those temporally changing spatial patterns, future studies should go beyond the use of a spatially fixed agricultural interface and aim at incorporating land use changes, based on medium resolution imagery, yearly registers of deforestation, which are required for Mexico.

Finally, as future work, future studies should aim at going beyond the separate spatial (e.g., [38]) or temporal (e.g., [76]) analysis of fire occurrence to develop space-time models of fire occurrence (e.g., [105–107]) to predict the occurrence and potential spread of individual fire events. For that goal, maps of daily weather indices (e.g., [76,108]) should be integrated with long-term spatial fire patterns, for modeling spatio-temporal fire occurrence (e.g., [105–111]) to assist in daily fire management decision-making.

5. Conclusions

The analysis of remotely sensed (MODIS and VIIRS) active fire density in Mexico revealed the following: (1) different spatial patterns and (2) different roles of human and fuel drivers, compared to the previous analysis of fire suppression records in the country. Regarding the different spatial patterns, the use of automated, remotely sensed records of fire activity might be advantageous to complement human-based field records of fire suppression, which can sometimes be subject to an accessibility bias. The observed positive role of slope in active fire density from this study, contrasting with the contrary observation

for human-based fire suppression records in previous studies, seems to confirm the utility of remotely sensed observations to describe fire spread across the entire landscape.

Active fires record not only single-point coordinates of fire ignition or fire suppression; instead, they can potentially capture both fire ignition and spread patterns. Accordingly, in contrast to the widely reported positive role of road density in facilitating fire initiation when analyzing fire records (fire ignition or fire suppression locations), our observations pointed to a role of road density in limiting fire spread when analyzing remotely sensed active fires. Our observations, therefore, corroborate the role of roads acting as fuel breaks, decreasing fuel continuity, and reducing fire spread.

This has important implications for fire management: for instance, preventive actions should aim at decreasing both fire ignition and fire spread probability. Consequently, on the one hand, fuel loads should be reduced in the vicinity of human infrastructure, aiming at protecting values at risk and at minimizing the probability of fires starting close to human locations. In addition, preventive treatments should also give priority to interrupting fuel continuity and facilitate suppression in areas with low infrastructure density, where otherwise potentially large, hard-to-suppress wildfires can occur.

While human factors (road, urban area, and agricultural interface density) were selected as the main drivers of active fire density for all the studied regions, fuel availability, indirectly considered through empirical relationships with remotely sensed aboveground biomass, significantly influenced active fire density in all regions. In shrub- and grass-dominated ecosystems, active fire density was positively correlated with biomass, suggesting that preventive actions, such as prescribed burns, should be targeted at areas with higher shrub and grass loads, especially in areas of human interface. In areas of higher tree density, a humped relationship of active fire density with total biomass was observed, suggesting that areas of intermediate tree cover (e.g., higher timber understory fuel loads, higher wind penetration, and lower moisture) should be prioritized for fuel treatments to reduce fire spread.

Our observations confirmed, for the first time, for remotely-sensed records of national fire activity, the regional variation and the non-stationarity of the human and fuel drivers of active fire density in Mexico. The latter could be successfully accounted for with geographically weighted regression, which, as expected, outperformed models assuming coefficient stationarity. Finally, our study established an optimum scale (an active fire kernel density bandwidth of 20 km) for predicting active fire kernel density at regional to national scales in our study area. The methodology shown in the current study can be replicated elsewhere for improving our understanding of the spatial drivers of remotely sensed fire activity.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/f17020264/s1>, Supplementary Figures S1 and S2. Fitted GAM model for prediction of active fire kernel density with 20 km of bandwidth by region; Figures S3–S10. Predicted and observed active fire density for 20 km of bandwidth, local R^2 , residues, and GWR model coefficients for the analyzed regions; Supplementary Table S1. Description and source of the variables analyzed.

Author Contributions: Conceptualization, D.J.V.-N.; methodology, D.J.V.-N., J.J.C.-R., M.P.-G. and P.M.L.-S.; software, J.B.-R. and C.I.B.-H.; formal analysis, N.A.M.-V., C.I.B.-H. and D.J.V.-N.; data curation, N.A.M.-V. and C.I.B.-H.; writing—original draft preparation, D.J.V.-N. and N.A.M.-V.; writing—review and editing, M.P.-G., J.C.-P., D.R.P.S., W.M.J. and E.A.-C. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: MODIS and VIIRS active fire data are freely available from NASA FIRMS (<https://firms.modaps.eosdis.nasa.gov/download/create.php>, accessed on 9 December 2025). All the cartographic variables used in the study are freely available, as detailed in Supplementary Table S1.

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