Spatiotemporal Distribution Patterns of Forest Fires in Northern Mexico[1]

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Abstract

Using the 2000-2011 CONAFOR databases, a spatiotemporal analysis of the occurrence of forest fires in Durango, one of the most affected States in Mexico, was conducted. The Moran's index was used to determine a spatial distribution pattern; also, an analysis of seasonal and temporal autocorrelation of the data collected was completed. The geographically weighted regression was applied to assess whether there is seasonality in the factors that influence their occurrence. The results indicate that forest fires are distributed in an aggregated manner and are not temporally correlated. It was found that precipitation, temperature, altitude, distance to roads and population severity index are non-stationary. The occurrence of fires is manifested according to population density and access roads, confirming the importance of socioeconomic factors in the distribution of these events. Low rainfall and high temperatures are climatic factors also greatly affecting fire occurrence.

Keywords: Autocorrelation, temperate forests, Durango, Mexico; Seasonality, Geographically Weighted Regression.

Introduction

In Mexico, most forest fires occur during spring and the occurrence period extends until vegetation, stimulated by the first rains, restarts its period of growth and development (Rodriguez-Trejo and Fulé, 2003; Alanís-Rodriguez *and others*, 2008). Fire occurrence depends on many climatic and topographic variables (precipitation, altitude, humidity, temperature, exposure, among others) which in turn depend on temporal variability (Drury and Veblen, 2008). Normally, wet years give rise to the formation of dense and rich vegetation that, eventually, is the ideal fuel for terrestrial wildfires of medium to relatively high intensity in the next dry year (Fulé and Covington, 1999). Similarly, areas facing north with high elevation have a lower risk

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of the presence of fire, while those facing south and southwest are generally more susceptible to the presence of fire (Fulé and Covington, 1999).

Human activities are a very important factor that influences the occurrence of forest fires in many parts of Mexico (Avila *and others*, 2010). Many farmers use fire as the main tool to clear lands which are in turn used to grow commodities such as corn and beans or to promote pasture re-growth. Misuse of fire often generates the spread of large and severe fires that destroy not only wildlife but also affect directly the general population (Rodriguez-Trejo and Fulé, 2003). When fire is used repeatedly in the same areas, it generates a low accumulation of combustible material and gives rise to low intensity fires. In contrast, when present in large and scattered areas, and sporadically, there are great chances of generating moderate to high intensity fires, able to completely remove tree cover (Fulé and Covington, 1999).

The overall objective of this paper is to analyze the spatiotemporal distribution patterns of forest fires in the State of Durango during the 2000-2011 period. In particular, the study attempts to assess spatial autocorrelation and temporal seasonality, and to identify the most important variables that influence fire occurrence.

Methods

Study area

The study was conducted in the State of Durango's temperate-cold forests. Durango is located in the north of the country and has the largest pine and pine-oak forest reserves (Figure 1) and is also one of the areas most affected by wildfires (CONAFOR, 2012). It has a great topographical diversity, making it important to study the spatial variability of fires occurrence, and its territorial extent allows noticing the role of forest landowners in the prevention, control and suppression of forest fires. About 80% of the forest area belongs to *ejidos* (communal lands) and therefore its management depends heavily on the organization of these communities.

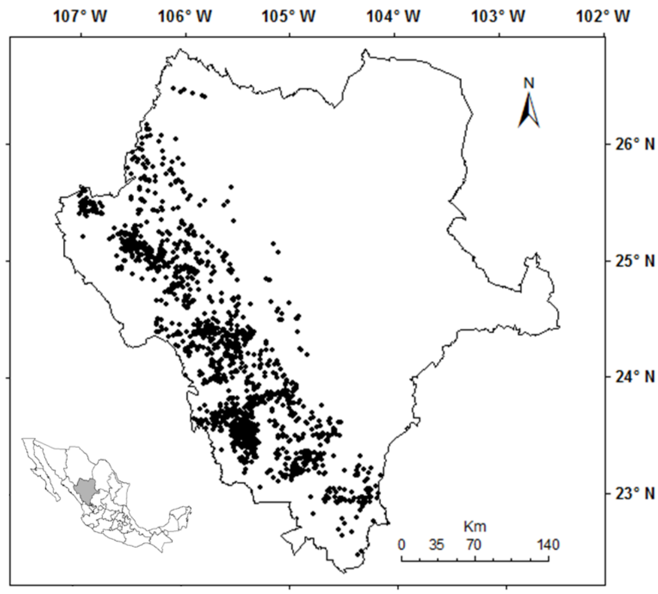

Figure 1—Location of Durango State, Mexico, and forest fires that occurred in the period 2000 to 2011.

Spatial analysis

The Moran's index (Moran, 1950) was used to estimate the spatial autocorrelation of forest fires in Durango. Autocorrelation is a measure of the distribution of a variable with itself through space (Wong and Lee, 2005); if the spatial distribution of that variable has a distinctive pattern (not random), it is said to be spatially autocorrelated. This Index may take values from -1 to 1, where negative values mean that the variable has a scattered distribution pattern and positive values have a concentrated distribution pattern. If the index is close to zero, then the variable is said to have a random distribution pattern (Wong and Lee, 2005). To test the null hypothesis of no autocorrelation, the empirical distribution is compared against a theoretical distribution, using a significance test comparing critical values at a certain level of reliability (Burt and Barber, 1996).

Temporal Analysis

Temporal analysis basically consisted of proving two properties of stochastic phenomena based on time series: seasonality and temporal autocorrelation. Temporary Seasonality is defined as those processes in which statistical moments (mean, variance, *etc.*) are not constant over time (Burt and Barber, 1996). To test this property, probability density functions of the variable of interest Y_t (*i.e.*, area affected by fire) were constructed for each year t. The temporal seasonality effect occurs if the probability functions are the same for all years. That is, if the variance σ_t^2 and mean μ_t are constant for all years. In this case,

$\sigma_t^2 = E(Y_t - \mu_t)^2$ y $\mu_t = E(Y_t)$.

As in the case of spatial autocorrelation, whether there is a dependency among observations close in time was also analyzed. Temporal autocorrelation measures the dependence degree of a variable of interest *Y* at time *t* with itself at time *t* + *k* (Burt and Barber, 1996), where *k* is the number of evaluation periods (known as lags) and can take different values. The autocorrelation for period *k* = 1, for example, means correlating variable Y_t with the same variable Y_{t+1} in which data have been shifted one time unit. The temporal autocorrelation *ρ* is then expressed as:

$$\rho(t, t+k) = \frac{E(Y_t - \mu_t)(Y_{t+k} - \mu_{t+k})}{\sigma_t \sigma_{t+k}} \qquad [1]$$

Where σ is the standard deviation (the other terms are defined above). In this case, *ρ* also takes values from 1 to -1, where the positive value indicates a high correlation and the negative value indicates that the variable *Y* tends to oscillate with above average values immediately followed by below average values. When *ρ* tends to zero, it means that there is no correlation in the time period assessed *k* (Burt and Barber, 1996). If there is no autocorrelation, then it means that its magnitude appears randomly.

Factors affecting the magnitude of fires

The RGP model was used to estimate the magnitude of fires using the affected area (*Sup*) as a function of environmental, economic and topographical variables. The RGP model has the following expression (Fotheringham *and others*, 2002):

$$Sup\ (u,v)_i = \beta_0(u,v)_i + \sum_{i=1} \beta_i(u,v)_i X + \varepsilon(u,v)_i \qquad [2]$$

Where term (*u, v*) indicates that the parameters β_0 and $ß_i$ (intercept and slope, respectively) should adjust in accordance to the location of the point (fire) *i* which has the coordinates *u* and *v*. This means that each point (fire) will have its own coefficients β_0 y β_i. The variable *X* denotes the set of factors that are related to the magnitude of the fire. The component ε (*u, v*) represents the error associated with the point with the coordinates *u* and *v*. This model (known as Geographically Weighted Regression) assumes that the points are non-stationary and that, in this case, a fire's magnitude varies depending on its location.

Model fitting was done with the support of the parameters: determination coefficient, standard error, and a coefficient named Akaike Information Criterion (CIA, for its acronym in Spanish). A Gaussian type model was used where the bandwidth was automatically identified by an adaptive iteration (see RGP model details in Fotheringham *and others*, 2002; Harris *and others*, 2011). To test the null hypothesis of no seasonality of independent variables, a Monte Carlo test was used for comparing the observed variance of the estimated parameters of each variable against a dataset randomly taken. Probability values were estimated for each of the variables and a significance level of 0.05 was utilized. The data processing was done with the program GWR3.0 ®.

Sources of information and data

The National Forestry Commission (CONAFOR, for its acronym in Spanish) database (2000-2011 period) was utilized. In addition to fire location, it includes the dependent variables affected area and number of days required for suppression of the event. Independent variables were taken from other information sources. The National Geography Institute (INEGI) digital elevation model was used to obtain the altitude and exposure data. INEGI's thematic maps were also used to obtain information on vegetation, soils, roads and towns. Climatic variables, namely average monthly rainfall and temperature, were obtained from the National Weather Service database, according to the year of fire occurrence. The variable that identifies property types was obtained from the National Agrarian Registry. With the information gathered, it was possible to make changes to them or carry out cartographic analysis on them. For example, the population severity index (IGP, for its acronym in Spanish) was calculated, expressed as:

$$IGP = \sum_{n}^{N} \frac{P_n}{D_{in}^2} \ , \forall_n : D \leq 20\ km \qquad [3]$$

Where *P* is total inhabitants in population center *n*, N the total number of towns, D is the distance (radius) from the fire *i* and town *n*, taken up to a 20 km radius of the fire. The *IGP* is a measure of the population's effect on fire occurrence. High levels (on this index) mean higher human pressure on the occurrence of fires. Table 1 shows the characteristics of the variables used in the study.

***Table 1**—Descriptive statistics in the analysis of the factors that affect the magnitude of forest fires in Durango, Mexico (Sample size = 1560).*

Variable	Description	Average	Std. Dev.	Min	Max
SUP	Surface (Ha)	84.0	215.24	0	2600
IGP	Population severity index	15.0	17.83	0	76
CAMINOS	Distance to roads (Km)	1814	1870	0	13101
LOCALID	Distance to towns (Km)	3417	2228	10	11774
PASTIZAL	Distance to grassland areas (Km)	2819	2329	0	9983
CULTIVOS	Distance to crop areas (Km)	3556	2750	0	9997
DEFOREST	Distance to deforested areas (km)	6257	5053	0	28569
PRECIP	Rainfall (mm)	607	191	174	1233
TEMP	Temperature (°C)	16.0	1.83	12	28
REGPROP	Property regime (1: *ejidos*; 2: private)	1.2	0.43	1	2
PEND	Slope (%)	11.5	9.6	0	52
EXPO	Exposure (degrees azimuths)	178	108	0	360
ALTITUD	Altitude (m. above sea level)	2437	301	753	3124

Results and discussion

Spatial analysis

Moran's index (MI) was applied to determine the existence of spatial autocorrelation of forest fires using their geographical coordinates *X* and *Y* (longitude and latitude), and in both cases the coefficient was positive with values of 0.88 and 0.74, respectively. The no autocorrelation null hypothesis test was rejected because the coefficient Z (I_M) was 6.14 ($p < 0.001$) for *X* and 5.22 for *Y* ($p < 0.001$). This means that fires present an *aggregated* distribution pattern, with high concentrations near roads and population centers.

To analyze the critical areas for fire presence, an analysis of the "hot spots" in the area affected and the number of days required for suppression was performed. Figure 2 shows the "hot spots" or places with high impact by wildfires and those "cold spots" where the effect is smaller. There are between 5 and 6 "hot spots" in the entity and they are located in inaccessible locations distant from population centers. In contrast, the "cold spots" are located near the population centers of El Salto, Pueblo Nuevo and San Miguel de Cruces, San Dimas. It is important to mention that "cold spots" are located in areas where, at present, there is greater involvement by forest landowners. The San Miguel de Cruces area, municipality of San Dimas and El Salto, municipality of Pueblo Nuevo, are characterized by high social organization in which the participation of landowners and landholders, not only in fighting fires, but in all restoration and management activities, is very positive. While it is true that there is a high frequency of fires, they are managed more efficiently, *i.e.*, in less time and with less surface area affected.

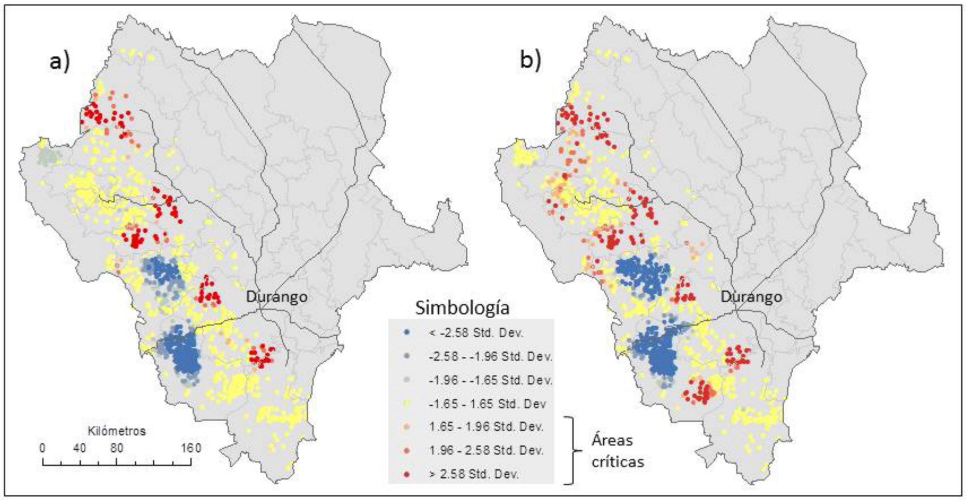

Figure 2- Critical Areas of forest fires in Durango. Red dots mean hot spots while blue ones are cold spots. Figure 2a) shows hot spots in area while Figure 2b) represents the number of days for suppression.

Temporal analysis

To evaluate temporal seasonality, probability density functions of the variable of interest were constructed (*i.e.*, area affected by fire) in each year. They estimated the average and variance, and analyzed variances' homogeneity using the Levene test. The results indicate that the most common probability density function was the Pearson Log-III, which is repeated in 5 of the 12 years comprising the study. However, the average and variance in each year are different. The Levene test and the one-way analysis of variance showed that both variance (L = 18,012, p <0.001) and the average affected area (F = 8995, p <0.001) respectively, are statistically different. The exception is observed in period 2004-2005 where the same probability density (log-Pearson III) was obtained. However, the *t*-test reveals that there are significant differences in the variances and averages of these two years. Therefore, the results show that, in the period under review, there is no homogeneity of variances in the information regarding area affected by forest fires and that this phenomenon is a non-stationary process. In other words, fire occurrenc, expressed in this case as affected surface, occurs totally randomly in each year. This phenomenon is very similar to precipitation, which can bring in a very humid year (season), but the following one is very dry.

To observe temporal variations in more detail, the temporal autocorrelation coefficient was estimated, which measures the affected area dependence degree in time t with itself at time $t + k$. Several categories and time periods k were used. A coefficient was estimated daily, monthly and yearly, and in each category up to 10 periods (lags) were used to observe the consistency of results. The results indicate that in the daily correlation a coefficient that varies between 0.08 and 0.20 ($p < 0.05$) was found, indicating the existence of autocorrelation; however, this is very low. In the case of monthly and annual autocorrelations, despite having relatively high coefficients (0.33 to -0.77), this was not statistically significant in any of the periods ($p > 0.05$). The results indicate a slight daily autocorrelation, that is, the amount of surface burning in one day has a positive effect, motivated perhaps by daily weather conditions, on the amount of surface burning in the following day. However, this does not happen in the case of monthly and annual autocorrelations. In such cases, and in accordance with Levene's test, the (variable) affected area behaves randomly.

Geographically weighted regression (RPG)

Individual analysis of the parameter means of the RPG model factors that affect fire magnitude shows that distance to grassland areas, distance to crop areas, rainfall, slope and exposure are negative. The rest of the factors' parameters assume positive values (Table 2). This table shows that, based on the Monte Carlo test, in factors population gravity index (IGP), distance to roads (ROADS), precipitation (PRECIP), temperature (TEMP) and altitude (ALTITUD) the spatial seasonality hypothesis is rejected and it is concluded that these factors are significantly non-stationary in the study area. The property of no seasonality suggests that the magnitude of forest fires does not follow a consistent pattern of variability and is influenced by the fire's geographical position. For example, fires that are geographically closer to roads have a relatively lower affected area than those where the distance is greater. This may be because in the more remote areas, fire fighting and control is more difficult and therefore fires tend to affect more surface than in those areas where access is relatively easy. Such differences could not be detected by the overall model (RLS) in which it is assumed that the distance to roads has a constant effect on the affected surface. Fires' geographical position determines the influence degree of these factors over forest fires' magnitude.

***Table 1**—Ranges of the parameters of the factors on the local regression model (RGP) for the area affected by forest fires in Durango, Mexico.*

Variable	Min	First quartile	Mean	Second quartile	Max	Monte Carlo test (*p-value*)
Intercept	-3209.9	-1612.4	-459.06	-31.697	800.56	0.06
IGP	-3.587	-0.379	-0.079	3.619	5.054	0.00***
CAMINOS	0.002	0.011	0.030	0.044	0.082	0.02*
LOCALID	0.004	0.010	0.015	0.024	0.034	0.30
PASTIZAL	-0.013	-0.005	-0.002	0.001	0.018	0.48
CULTIVOS	-0.014	-0.003	-0.001	0.002	0.008	0.32
DEFOREST	-0.011	-0.002	0.000	0.002	0.008	0.06
PRECIP	-0.365	-0.222	-0.184	-0.055	-0.024	0.02*
TEMP	-15.374	2.772	14.771	56.434	121.841	0.05*
REGPROP	-71.188	-3.483	7.907	18.228	36.430	0.64
PEND	-4.215	-2.268	-1.060	-0.562	0.002	0.35
EXPO	-0.183	-0.062	-0.018	0.028	0.239	0.80
ALTITUD	-0.173	0.008	0.094	0.327	0.647	0.05*

**** = significant at 0.1% level; ** = significant at 1%; * = significant at 5%.*

The factors distance to paths (*CAMINOS*), distance to towns (*LOCALID*) and precipitation (*PRECIP*) show consistent signs; that is to say, they remain unchanged at their maximum, intermediate and minimum values. The first two are directly related, while *PRECIP* is inversely related to the magnitude of the fires. Avila *and others*, (2010) found the most important factors that influence fire occurrence are vegetation susceptibility to fire, intensity of land-use change and precipitation. For precipitation, a common factor in this study, they found that this factor has a direct influence on the number of fires. This is somewhat contradictory since high rainfall in a given year tends to reduce the number of fires and the amount of affected area that year.

The results for the RGP model confirm that the magnitude of the fires is strongly influenced not only by environmental factors (precipitation, temperature, altitude), but also by socioeconomic factors (population severity index, distance to roads and distance to towns). There is little that can be done to mitigate the effect of the first, but there is much that can be done to reduce the effect of the second group. While it is true that fires located near roads and towns are low magnitude, their constant and recurring frequency increases the opportunity cost and decreases the likelihood of addressing other priorities. Rodriguez-Trejo and Fulé (2003) discuss a number of measures that can be implemented to reduce the negative impact of fire. Their management proposals are divided into cases where fires are excessive, normal (appropriate) or insufficient.

Finally, to observe in detail the possible variations of the combined effect of all factors, an analysis of the predicted values and residuals of the local model (RGP) was performed. Using a geographic information system, a map to indicate the differences between the affected and predicted areas was built (Figure 3). Frequency analysis revealed that 84% of the residual value of all fires are located in the middle of the table, that is between -82 and 82 hectares (-0.5 to 0.5 standard deviations). This suggests that the differences between the values of the area observed and predicted by the local model are mostly concentrated around zero and that the model is generally acceptable. The average of the residuals equals -0.94 ha, while the median is equal to -12.3 ha.

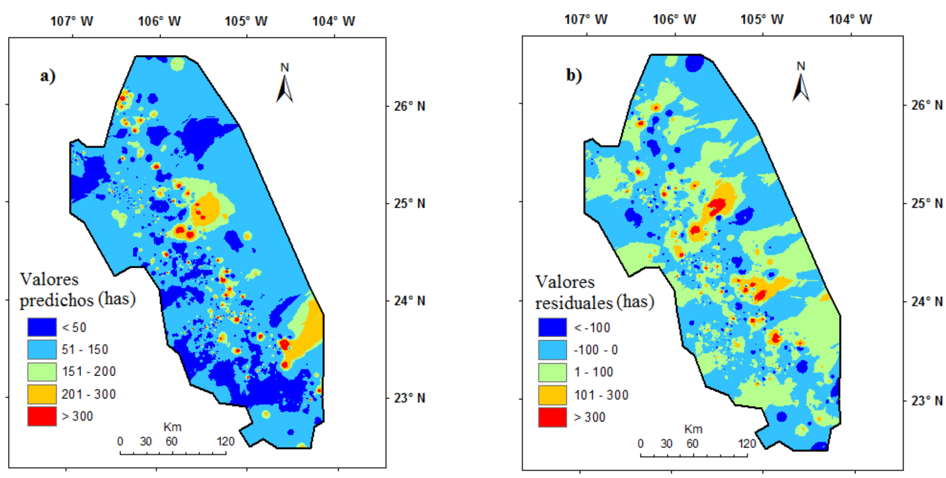

Figure 3—Spatial analysis of the RPG model results in Durango, Mexico. Figure 3a) shows predicted values while Figure 3b) shows the residuals.

Summary

According to the results, fires in the State of Durango are spatially distributed in an aggregated manner and are not temporarily stationary. The geographically weighted regression model is a suitable tool for the study of phenomena such as forest fires. This model, unlike the simple linear regression method, assigns a different weighting as observations increase their distance and become more dissimilar. It also helps to identify factors that have a constant or variable effect according to geographical location. The most important factors that influence fire magnitude can be classified as environmental (precipitation, temperature and altitude) and socioeconomic (distance to roads, distance to towns and population severity index). The population severity index (IGP), distance to roads (ROADS), precipitation (PRECIP), temperature (TEMP) and altitude (altitude) factors are not stationary in the study area nor in the time period analyzed. The geographical position of fire determines these factors' influence over the magnitude of forest fires. The use of these statistical tools in studies analyzing stochastic variables is recommended.

Acknowledgments

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