

# Drought and Spatiotemporal Variability of Forest Fires Across Mexico

Pompa-García MARÍN<sup>1</sup>, Camarero J. JULIO<sup>2</sup>, Rodríguez-Trejo DANTE ARTURO<sup>3</sup>, Vega-Nieva DANIEL JOSE<sup>1</sup>

(1. *Facultad de Ciencias Forestales, Universidad Juárez del Estado de Durango, Durango 34120, México*; 2. *Instituto Pirenaico de Ecología IPE-CSIC, 50059, Spain*; 3. *División de Ciencias Forestales, Universidad Autónoma Chapingo, Chapingo 56230, México*)

**Abstract:** Understanding the spatiotemporal links between drought and forest fire occurrence is crucial for improving decision-making in fire management under current and future climatic conditions. We quantified forest fire activity in Mexico using georeferenced fire records for the period of 2005–2015 and examined its spatial and temporal relationships with a multiscale drought index, the Standardized Precipitation-Evapotranspiration Index (SPEI). A total of 47 975 fire counts were recorded in the 11-year long study period, with the peak in fire frequency occurring in 2011. We identified four fire clusters, i.e., regions where there is a high density of fire records in Mexico using the Getis-Ord *G* spatial statistic. Then, we examined fire frequency data in the clustered regions and assessed how fire activity related to the SPEI for the entire study period and also for the year 2011. Associations between the SPEI and fire frequency varied across Mexico and fire-SPEI relationships also varied across the months of major fire occurrence and related SPEI temporal scales. In particular, in the two fire clusters located in northern Mexico (Chihuahua, northern Baja California), drier conditions over the previous 5 months triggered fire occurrence. In contrast, we did not observe a significant relationship between drought severity and fire frequency in the central Mexico cluster, which exhibited the highest fire frequency. We also found moderate fire-drought associations in the cluster situated in the tropical southern Chiapas where agriculture activities are the main causes of forest fire occurrence. These results are useful for improving our understanding of the spatiotemporal patterns of fire occurrence as related to drought severity in megadiverse countries hosting many forest types as Mexico.

**Keywords:** cluster; drought; forest fires; geostatistics; spatial clusters; Standardised Precipitation-Evapotranspiration Index (SPEI)

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## 1 Introduction

Fire is an integral component driving the dynamics of many forest ecosystems across the world (Moritz et al., 2014), including those located in megadiverse countries with many biomes types as Mexico. However changes in the spatiotemporal dynamics of forest fires depend on many factors (climate, fuel type, lightning, and topography, among other factors, affect fire occurrence and spread), and these drivers may trigger shifts in fire regimes with detrimental effects on the resilience of forest ecosystems (Rodríguez-Trejo, 2008). Recently, several

studies reported increases in fire frequency, burnt area, and severity in North America (Flannigan et al., 2009), as well as a recent extension of the fire season. These changes in fire activity have increased environmental concerns and awareness within society and the scientific community on possible shifts in fire activity in this region (Koutsias et al., 2013). For instance, according to the National Forestry Commission of Mexico (CONAFOR, 2016), the average fire size in Mexico during the 2005–2015 was 32.2 ha, and fires affected many forest types. Here we focus on the role that drought can play as a relevant driver of wildfire occurrence in Mexico, a

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Corresponding author: Pompa-García MARÍN. E-mail: [mpgarcia@ujed.mx](mailto:mpgarcia@ujed.mx)

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megadiverse country where fires affect many forest types and tree species.

Mexico has been forecasted to be warmer and drier in the future, and therefore it is a country particularly vulnerable to climate change (Seager et al., 2009; Williams et al., 2013). Most Mexican regions are influenced by variations of hydrological systems affected by monsoon and other global atmospheric circulation systems, which are a major component of continental, warm-season precipitation regimes (Higgins et al., 1997). There is some empirical evidence that the timing of the Mexican monsoon has shifted in recent decades (Grantz et al., 2007; Seager et al., 2007), and this can affect fire disturbance regimes (Heyerdahl and Alvarado, 2003; Román-Cuesta et al., 2003; Ray et al., 2007; Yocom et al., 2010). This climate shift could explain why Mexico experienced its most severe fire season on record in terms of affected surface area during 2011, which was a dry year. For instance, northern Coahuila (NE Mexico) experienced a fire complex comprising two forest fires that affected 317 000 ha, the largest fire in Mexico recent history (CONAFOR 2011).

There is a need for a deeper understanding of the effects of drought on the spatial and temporal patterns of fires in order to: 1) anticipate the potential effects of climate warming which could lead to more arid conditions and larger wildfires, and 2) to develop country- and site-specific mitigation and adaptation measures that can orient forest policies and managers under warmer and drier climate scenarios. Several studies have assessed the relationships between fire activity and weather anomalies (Westerling and Swetnam, 2003; Preisler et al., 2004; Yocom et al., 2010). For example, Manzo-Delgado et al. (2009) found that February temperature was a significant variable for fire risk prediction in Mexico. Consequently, some studies have forecasted future tendencies of fire activity under scenarios of warmer and drier climate conditions (Williams et al., 2001; Wotton et al., 2003; Gillett et al., 2004; Flannigan et al., 2005; 2006; Liu et al., 2012), although their conclusions have varied depending on the variables considered and the area studied.

In Mexico, several studies have explored the relationships between individual climate variables (i.e., precipitation, temperature, and evapotranspiration) and fire activity (Manzo-Delgado et al., 2004; Fulé et al., 2005; Méndez González et al., 2007; Drury and Veblen, 2008;

Skinner et al., 2008; Manzo-Delgado et al., 2009; Cerano Paredes et al., 2010; Yocom and Fulé, 2012; Navar and Lizárraga-Mendoza, 2013). However, to the best of our knowledge, no studies have specifically explored the spatial and temporal relationships of drought and fire patterns across Mexico. Most of the abovementioned studies were carried out at regional or local scales, and it is therefore necessary to develop studies that cover the diversity of climatic, ecological and environmental Mexican conditions at the national scale (González-Cabán and Sandberg, 1989; Cerano et al., 2010).

Several studies conducted in the USA have documented positive associations between drought severity and fire occurrence or severity using different drought indices, mainly the Palmer Drought Severity Index (Collins et al., 2006; Preisler and Westerling, 2007; Riley et al., 2013; Littell et al., 2016), the Keetch-Byram Drought Index (Prestemon and Burtry, 2005; Boer et al., 2009). However, recently a new drought index has been developed, the Standardized Precipitation-Evapotranspiration Index (SPEI) (Vicente-Serrano et al., 2010), which accounts for the effects of air temperature on evapotranspiration and water availability and it has not been considered in studies relating drought and fire variability. In the case of Mexico, no national-level studies have focused on drought episodes, their magnitude and frequency, and how they could be related to forest wild-fire at multiple spatial and temporal scales using the SPEI, which has been shown to drive changes in forest growth and productivity (Vicente-Serrano et al., 2013).

The use of fire record statistics is an effective method for quantifying the temporal and spatial characteristics of fire regimes (Vadrevu et al., 2013; Rocca et al., 2014). In Mexico, CONAFOR is the government agency that provides periodic information about forest fire statistics (see CONAFOR 2016), and it has just recently started efforts to develop a Mexican fire-danger rating system for which a deeper understanding of spatial and temporal fire occurrence patterns, as well as their relationships to seasonality-drought links and fire clusters (regions with high density of fire records), is required. Understanding the impact of drought on fire occurrence along spatial gradients and considering their temporal variability is useful for addressing the impact of drought on fire activity in Mexico and for improving forecasts of fire risk and developing mitigation strategies.

The ability to delineate regions with long histories of

a high clustering of frequent forest fires (Cardille *et al.*, 2001; Genton *et al.*, 2006; Yang *et al.*, 2008; Gralewicz *et al.*, 2012), and the analysis of potential causal factors of such aggregation are useful tools for effectively allocating the available resources for fire management (Batsos *et al.*, 2007; Yang *et al.*, 2008; González-Olabarria *et al.*, 2012; Wu *et al.*, 2014). Nevertheless, in Mexico, studies on the spatio-temporal patterns of fire occurrence at a national level are very scarce. Fire records associated with reliable spatial and temporal multiscale drought indices could provide robust information that could be used to improve future fire behavior models under climate change scenarios.

In this study, we use historical records of forest fires and the SPEI drought index across the Mexican territory to address the following questions regarding the spatio-temporal variability of droughts and fires: Are there any specific regions where fires cluster? Where are these clusters of fire incidence? How does the fire season vary spatially? And, are there any spatial relationships between fires and the SPEI? We hypothesized that forest fires are prone to cluster in some regions due to persistent drought-fire associations.

## 2 Materials and Methods

### 2.1 Study area

Located in tropical and subtropical regions (14°, 32°N and 86.8°, 118°W), Mexico occupies almost  $2.0 \times 10^6$  km<sup>2</sup> and it is a megadiverse country characterized by an irregular topography, with altitudes ranging from 0 to ~5000 m a.s.l. The transition between Nearctic and Neotropical biogeographical regions occurs in Mexico. This biogeographic change contributes to explain the high biodiversity of the country that is represented in tropical, semiarid, and temperate forest biomes, all of which experience wildfires. Approximately 40% of the surface area vegetation in the country is maintained by fire, and 70% of the national territory is covered by forests (Rodríguez-Trejo 2008). Mexico also is characterized by its cultural richness, as 64 native ethnic groups live in its territory as rural communities (Aguayo Quezada, 2007), and most of them use fire as an agricultural and cattle, caprine, or sheep-raising tool (Rodríguez-Trejo, 2015). These uses are the most important causes of forest fires, accounting for approximately 40% of the fires in Mexico (CONAFOR, 2016); however, many local communities

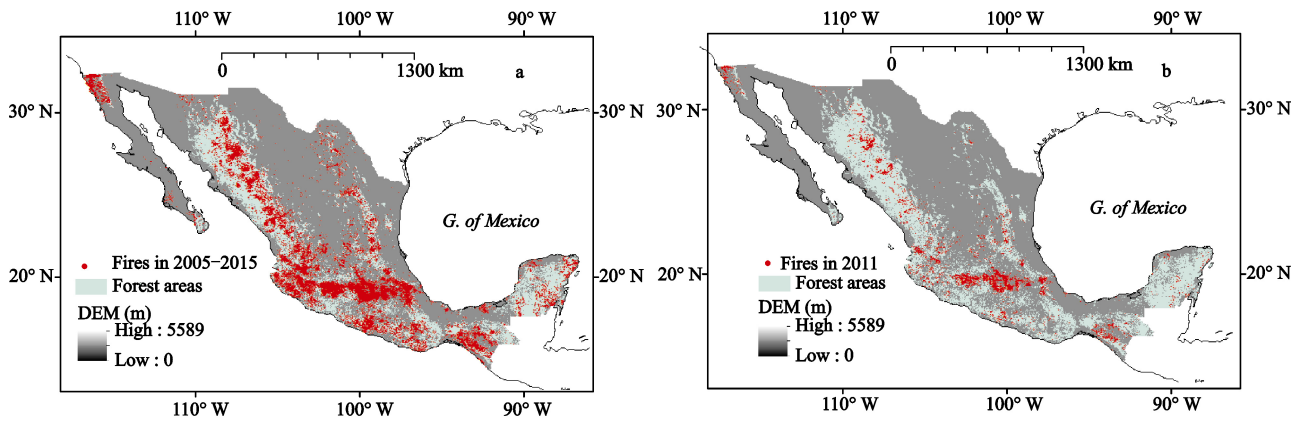
use fire as a tool for land management (Myers, 2006). The most relevant natural cause of fires, lightning, is more common in northern Mexico and in the elevated mountains and volcanoes situated in central Mexico (Rodríguez and Fulé, 2003).

### 2.2 Mexican forest fire records

We used forest fire records provided by national forestry commission of Mexico (CONAFOR) to characterize the spatiotemporal variability of fire occurrences in Mexico. These records comprise daily datasets of the fire identification, state, municipality, coordinates, and fire start and end dates, among others. For this study, we analyzed annual fires from 2005 to 2015, and we focused specifically on 2011 as a representative year of elevated fire occurrence (Fig. 1) (CONAFOR 2016). First, we filtered noisy data (outliers, disparity, out of forestry areas). Second, we downloaded the SPEI data at monthly resolution and 1- to 12-month long scales at a 0.5° spatial resolution, which is available at <http://sac.csic.es/spei/database.html>. Then, the study area was subdivided into 852 0.5° grids according to the SPEI Global Drought Monitor and based on the Climatic Research Unit 0.5°-gridded climate dataset (Harris *et al.*, 2014). The SPEI is a multiscalar drought index, calculated at several-months long scales (usually from 1 to 24 months) with positive and negative values reflecting wet and dry conditions, respectively (Vicente-Serrano *et al.*, 2010). Lastly, a forest fire database, which tracked the date information and the location of ignition within the area of study, was organized. This database layer was geo-processed with the grid data to provide a complete dataset for each pixel, including the frequency of forest fires (Fig. 1).

### 2.3 Spatial-cluster analysis

To detect fire clusters without any preconceptions about their spatial trends, we used the Getis-Ord  $G(d)$  (hereafter  $G$ ) statistic (Getis and Ord, 1992). Clustering is defined as ‘the process of collecting objects into groups whose members are similar in some way’ (Kaufman and Rousseeuw, 1990). The  $G$  statistic is especially useful in cases where other spatial statistics, such as kernel estimates,  $k$ -function analyses, Moran’s  $I$  index, and the semivariogram, do not display clear spatial patterns based on deviations from the mean (Moran’s  $I$ ) or based on deviations (Geary’s  $c$ , semivariogram), which can



**Fig. 1** Location of study area, showing fire ignitions from 2005 to 2015 recorded in Mexico and plotted on the Digital Model Terrain and forest areas (color background) (a) and fire ignitions recorded for 2011 in Mexico (b)

provide biased estimates of spatial autocorrelation when data are not normally distributed (Fortin and Dale, 2005). The equation is defined as:

$$G(d) = \frac{\sum_{i=1}^N \sum_{j=1}^N w_{ij}(d) x_i x_j}{\sum_{i=1}^N \sum_{j=1}^N x_i x_j}, i \neq j \quad (1)$$

where  $x_i$  and  $x_j$  are the measured attributes for features  $i$  and  $j$ , respectively;  $w_{ij}(d)$  is a symmetric one/zero spatial weight matrix for determining the proximity between  $i$  and  $j$  at the distance given by  $d$ . We used the standard deviation to find cluster association.

To indicate how the observed  $G(d)$  statistic is significantly different from the expected  $G_E(d)$  value (and, hence, significantly different from a random distribution), the following formula was applied:

$$Z - score = \frac{G(d) - G_E(d)}{StdDev} \quad (2)$$

The  $G$  statistic was computed for each pixel using the hotspot analysis available in ESRI ArcMap version 10.0 (ESRI, 2016). The  $G$  statistic is calculated by looking at each feature within the context of neighboring features. If a feature's value is high, and the values for all of its neighboring features are also high, it is part of a spatial hotspot. The local sum of a feature and its neighbors is compared proportionally with the sum of all features. When the local sum differs greatly from the expected local sum, and that difference is too large to be the result

of random chance, a statistically significant  $z$ -score is the result (ESRI, 2016).

## 2.4 Relating SPEI and forest fires

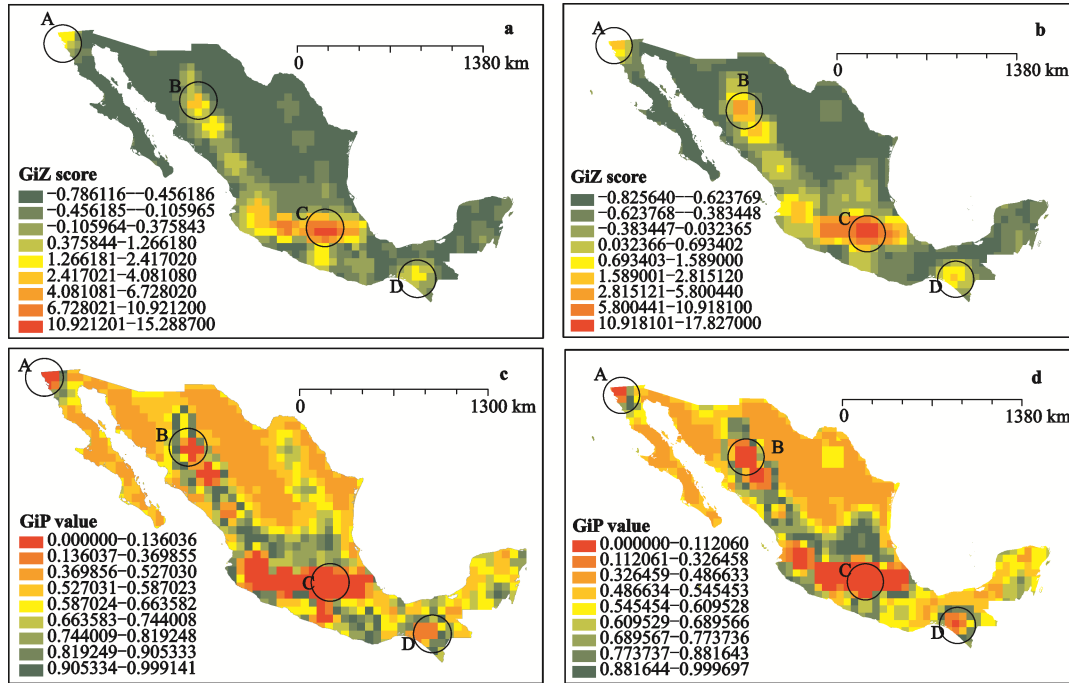
Given our hypothesis regarding the spatiotemporal relationships between fire occurrence and drought, we conducted a correlation analysis for the cluster zones to determine how the SPEI is correlated with fire frequencies (SAS Institute, 2005). We evaluated the evolution of the SPEI from 2005 to 2015 for each of 1- to 48- month long scales obtained. In addition, spatial and temporal evolutions of the SPEI and fire frequencies were calculated and analyzed for 2011 through regression analysis (SAS Institute, 2005).

## 3 Results

### 3.1 Spatiotemporal patterns of fire activity in Mexico

Spatial variations of fire counts gridded at  $0.5^\circ$  spatial resolution and for the 2005–2015 period (47 975 records) and also for 2011 (871 records) in Mexico are shown in Figs. 2a and 2c, respectively.

The large forest fires of northern Coahuila which occurred in 2001, where a complex of a few forest fires affected 316 954 ha (CONAFOR, 2011), are not evident in these figures. This is because our approach is based on the number of fires and not on the area affected by fires. The results of the clustering algorithm were useful for identifying fire spatial clusters in diverse geographical regions. The cluster map that was generated using



**Fig. 2** Map showing forest fires clusters in Mexico at a 0.5° spatial resolution for the 2005–2015 period (a), and the significant spatial clusters detected using the  $G$  statistic (c). Map showing forest fires clusters in Mexico at a 0.5° spatial resolution for the year 2011 (b) and the significant spatial clusters detected using the  $G$  statistic (d). The GiZ values shows standard deviation for  $G$  statistic, where numbers greater than zero correspond to aggregated distribution and numbers less than zero correspond to unaggregated spots. The GiP values means significance of GiZ values. When having small GiP values and a very high GiZ score value, this indicates that it is unlikely that the observed spatial pattern reflects the theoretical random pattern.

the  $G$  statistic allowed identifying clusters and their geographical locations. We found at least four regions where fires were recurrent and spatially clustered: A) northern Baja California; B) Chihuahua; C) central Mexico; and D) southern Chiapas. The Zone C showed the highest number of fire occurrences (2571 records for 2005–2015 and 443 records for 2011), followed by zone B (1015 and 188 records for 2005–2015 and 2011, respectively), zone A (366 and 58 records for 2005–2015 and 2011, respectively), and zone D (329 and 49 records for 2005–2015 and 2011, respectively). There was a similar geographical trend between decadal and annual periods. The seasonality varied across regions, ranging from February to September. In zone A, 60% of the fires occurred from May to September; the fires in zone B mainly occurred from March to June; the fires in zone C began in February and ended in April; and the fires in zone D started in March and ended by May (Fig. 3).

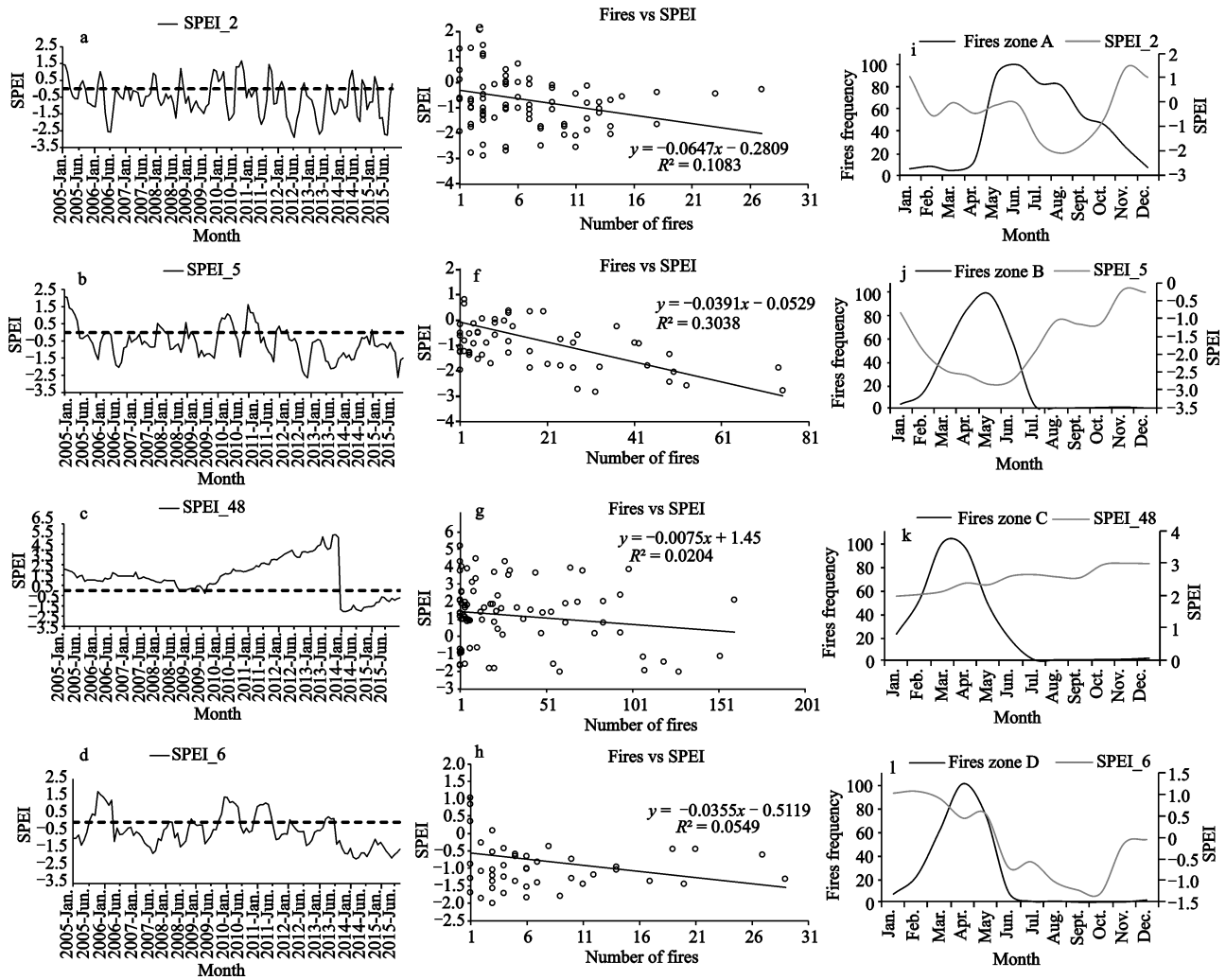
### 3.2 Relationships between forest fires and drought

Spatial variations in drought gradients according to the

SPEI for Mexico are shown in Fig. 3. These results confirmed our hypothesis, because there was a common variability between the fire frequency and the SPEI drought index. The SPEI varied among zones according to alternating dry and wet periods that occurred during the study period (Fig. 3b).

The spatiotemporal analysis indicated that the years in which more fires occurred were dry (negative SPEI values), as indicated by significantly negative correlations (Fig. 3a). The dry months that had more fire activity were associated with negative SPEI values. However, in zone C (central Mexico), the months with more fires were not associated with previous months of the SPEI, as no significant association was found between fire counts and the SPEI months. The only significant inter-month drought relationship was found for zone D (southern Chiapas), but this should be taken with caution because limited spatial data were available for this zone.

For zone A (northern Baja California), the SPEI exhibited a greater temporal relationship to fire occurrences for 2 months (first column in Fig. 3). The maximum



**Fig. 3** Relationships observed between forest fires and drought, showing spatial clusters where fires are recurring and there is a significant correlation (Pearson coefficient) between fire frequency and the Standardized Precipitation-Evapotranspiration Index (SPEI) drought index. Evolution of the long-term SPEI from 2005 to 2015 for zones A (a), B(b), C(c), and D(d). Spatial relationships between fire frequency and the SPEI for 2011 calculated using regression analysis for zones A(e), B(f), C(g) and D(h). Correspondence between the fire season and the monthly SPEI values for zones A(i), B(j), C(k) and D(l) (the last number of the SPEI indicates the scale, in months, at which maximum correlations were found)

drought occurred during September 2012, whereas the wettest period was recorded in January 2011. A regression analysis shows the influence of drought on this zone (see third column in Fig. 3). In this area, the forest fire season, which ranged from April to October, corresponded with low SPEI values. In zone B (Chihuahua), the SPEI over the previous 5 months was more highly correlated with the occurrence of fire ignitions (see last column). The wettest month was in January 2011, and the driest month was November 2012. Compared with the other zones, there was a stronger association ( $R^2 = 0.30$ ) between drought (see Fig. 3) and the fire season (March–June) in zone B. Zone C was less linked with

the SPEI over the study period. Correlation was low and not statically significant for this area. Indeed, the drought variability just showed breaks on December to November of the previous 48 months. Lastly, in zone D, fire was correlated with the previous 6 months of drought. This zone recorded its wettest period in November 2005, with synchronizing peaks of fire and drought, until it became drier in September 2014. The association between drought and fire occurrences showed low  $R^2$  values ( $R^2 = 0.05$ ), while fire frequencies and the SPEI seasonally overlapped by April. In zones C and D, the fire seasons peaked earlier (April) than elsewhere (Fig. 3d).

## 4 Discussion

### 4.1 Spatial clusters of fire occurrence

The spatial analysis presented herein allows us to test the hypothesis that forest fires are prone to cluster and are spatiotemporally associated with drought. Several clusters of fires formed in Mexico between 2005 and 2015, as was confirmed by our results, and the *G*-statistic was satisfactory as a quantitative tool for revealing those clusters of abundant and aggregated fire occurrence.

We found clusters of clusters fires, which are in agreement with our hypothesis, but not all fire clusters were driven by changes in drought severity. The results of the clustering analysis suggest that clusters occurred in different regions subjected to different topographic, climatic and socio-economic conditions, which indicates that fire clusters have diverse causes. Here we focused our study on drought responses; however, there are many other drivers of fire ignitions (e.g., type of vegetation burnt, fire regime, anthropogenic influences, type of land-use activities, among others) that are beyond the scope of this work.

In a previous study, Ávila-Flores et al. (2010a) found clustering of forest fires in the state of Durango (northwest Mexico) using a different spatial index of aggregation, the Moran's *I* index. The *G*-statistic focuses on the clustering around each locally defined area, because it does not account for the mean frequency of forest fires across the study area. This approach helps to monitor local fire behavior because the *G*-statistic is more sensitive to high than to low clustering intensity. In contrast, the Moran's *I* index is mainly affected by the scale of the clusters (Zhang and Zhang, 2007). The question of the interaction between local and global spatial statistics is important and much more research remains to be done in this direction (Ord and Getis, 1995). Additionally, it must be mentioned that an approach based on the surface area affected by forest fires may yield somewhat different results than those present here, which were based on the number of forest fires, particularly because the effect of a complex of several fires can affect very large areas, as occurred in northern Coahuila in 2011.

Despite the difficulties in interpreting their causes, the clustering metrics that were used here show the relative differences in clustering among 0.5° pixels. This approach is in line with those that hold that the cluster-

ing of fires is a function of cumulative processes occurring through time (Parisien et al., 2006; Wang and Anderson, 2010). For instance, Vázquez and Moreno (2001) showed that fires aggregate spatially and over time, producing larger, interconnected burned patches. Therefore, this finding supports the fact that climate-drought-fire interactions are dynamic and changes from year to year.

Despite revealing the most important drives of fire occurrence are beyond the scope of this study, we speculate that clustering varies with site-specific conditions. According to Vadrevu et al. (2013), the grouping of fires varies with vegetation cover. The extent and configuration of flammable vegetation and non-flammable landscape features clearly influence patterns of fire ignition (Cumming, 2001; Duncan and Schmalzer, 2004). They also speculate that these patterns are likely to respond differently to changes in spatial scales. Indeed, some studies (Flannigan et al., 2005; Parisien et al., 2006) show that splitting the clusters and, therefore, reducing the size of the study units will avoid some bias in the estimates and surely dilute the effect of clustering. In this approach, the choice of SPEI pixels as study units was not entirely arbitrary, as it was based on units for which fire activity is related to drought and depended on the availability of gridded climate datasets. However, this spatial resolution could be improved, and efforts should continue to move forward to analyze different spatial datasets and to assess and identify the spatial scales that are the most relevant for the study of spatial fire patterns (Wang and Anderson, 2010).

In addition, spatial clustering has been found in both lightning-caused fires (Díaz-Avalos et al., 2001; Genton et al., 2006) and in human-caused fires (Cardille et al., 2001, Yang et al., 2008; Gralawicz et al., 2012). The ability to locate zones with an intense and recurrent history of fire occurrence and identify their specific cause can be helpful in the implementation of measures to reduce the problem of frequent fire occurrence (González-Olabarria et al., 2012). Our results reaffirm the importance of recording historical ignitions, as well as the value of spatial characterizing fire aggregation patterns to improve decision-making in fire management. Thus, they are consistent with those documented by Van Wagner (1988) and Podur et al. (2003), who noted that historical fire records have been useful for understanding the spatial distribution of fires. Such assessments of

fire spatial patterns can provide spatially explicit information that can lead to a more effective allocation of available resources for fire suppression and for long-term fire management planning (Balatsos et al., 2007; Yang et al., 2008; González-Olabarria et al., 2012; Wu et al., 2014). Although it is not possible to ensure that this database contains all fire ignitions, it does represent the vast majority of them. Therefore, the lack of available, temporally explicit data makes it difficult to undertake a detailed study of spatial fire patterns over a considerable period of time (e.g., several decades).

#### 4.2 Drought-fire spatio-temporal associations

Whereas several studies have documented relationships between drought and fire occurrence in other countries, such as the USA (Preisler and Westerling, 2007; Westerling, 2008; Riley et al., 2013), previous studies in Mexico have focused on single climate variables as temperature or precipitation (Manzo-Delgado et al., 2004; 2009; Méndez González et al., 2007; Drury and Veblen, 2008; Manzo-Delgado et al., 2009; Navar and Lizárraga-Mendoza, 2013).

No previous study in Mexico has attempted to understand the spatial and temporal variations in a drought index such as the SPEI, which is considered to provide an integral view of the drought process (Vicente-Serrano et al. 2010). Some advantages of the SPEI dataset are that (i) it improves the spatial resolution of the unique global drought dataset at a global scale; (ii) it is spatially and temporally comparable to other datasets, given the probabilistic nature of the SPEI; and, in particular, (iii) it enables the identification of various drought types, given the multiscalar character of the SPEI (Vicente-Serrano et al., 2010; 2013). The spatial and temporal analysis results show contrasting drought tendencies and varying fire season distribution across the country. Further, the presented analyses could be done at larger spatial scales considering continental databases or even analyzing globally distributed fire ignitions.

Although consensus has been reached that forest fires could be associated with drought (Drury and Veblen, 2008), no studies have explained the links between fire occurrence and drought in Mexico. Moreira et al. (2011) reported that the effects of fire on ecosystems may vary regionally as a result of local drivers, whilst Flannigan et al. (2006) showed that the effect of climate change on fire occurrence must be viewed in a spatially-dependent

context. The fire season in Mexico mainly occurs during the dry season (March–June), and the frequencies and intensities of fires vary based on vegetation type, climate conditions, and socioeconomic drivers (Ávila-Flores et al., 2010b).

Many studies have documented that more fires occur when conditions are drier than average. Thus, it has been proven that local climate conditions influence fire activity on a regional scale, and that they can favor either high or low fire activity. Although an understanding of climate/forest fire relationships must ultimately account for large temporal and spatial scales (Skinner et al., 2008), here we focused on conditions at a smaller scale (i.e., clusters spatial zones). The approach used here found fire/drought responses at the regional scale. Other anthropogenic and physical causes were limited at this level. For instance, states with clusters with higher correlations between fire occurrence and the SPEI, such as Baja California and Chiapas, have lower populations ( $3.3 \times 10^6$  and  $3.6 \times 10^6$  people, respectively) than those with lower correlations, such as Chiapas and Estado de México ( $5.2 \times 10^6$  and  $1.62 \times 10^7$  people, respectively) (INEGI 2015). Additionally, natural causes of fires were more prevalent in northern Mexico (zones A and B) than in central and southern Mexico (zones C and D). There was a distinct contrast among these clusters, as fire occurrence in zones A and B, which are located in the northernmost part of the country and which have more natural fire regimes and lower population densities, was better explained by climatic factors. In contrast, fire occurrence in zones C and D, which are more densely populated areas that in which agricultural activities have a greater influence on fire occurrence, was better explained by non-climatic factors. In zones C and D, an earlier start to the fire season was detected as a lower SPEI-fire association which might be related to the timing of agricultural activities in these more densely populated areas of the country, which are heavily dependent on agricultural activities. Similar results were reported by Wu et al. (2014), Liu et al. (2012), and Chang et al. (2013), among others, who found climatic factors have a large influence on fire occurrence in areas of lower population density and where there is a higher occurrence of naturally caused fires, whereas climate had a smaller effect on fire occurrence in more densely populated areas where socio-economic drivers of fire occurrence prevailed.

Our results also suggest that most fires are likely to have burned in the spring to early summer. The timing of fire occurrence in zone A (northern Baja California) is similar to that found in the southern USA (Heyerdahl and Alvarado, 2003). In this region, widespread fires are generally associated with dry years that are produced by phasing patterns of global and regional atmospheric patterns, such as the Pacific-North American Teleconnection (PNA), the El Niño/Southern Oscillation (ENSO), and the Pacific Decadal Oscillation (PDO) (Manzo-Delgado *et al.*, 2004; Skinner *et al.*, 2008; Trouet *et al.*, 2010). For example, when the PNA is in a positive phase (drier winters and springs prior to the fire season), large fires occur (Cerano *et al.*, 2010; Yocom *et al.*, 2010). Therefore, the climate patterns observed in December and January prior to the fire season also drive fire occurrence in northern Mexico. Thus, when temperatures increase, the SPEI diminished, drought severity increases and many large fires occur simultaneously (Fig. 3). It should be mentioned that zone A is one of the areas with a natural fire regime in Mexico, and that fires should not always be combated there because of their beneficial effects in maintaining ecosystem structure and composition in several fire-regulated plant ecosystems of this region (see for instance Minnich and Franco, 1997).

In zone B (Chihuahua), we tight associations between fire occurrence and dry conditions. This is a region where the North American Monsoon (NAM) dominates the seasonal cycle of precipitation (Cook and Seager, 2013). Over the core region of the NAM (18°N–33°N, 112°W–102°W) the summer monsoon rainfall peaks during July–September, and it accounts for greater than 70 % of the annual rainfall total for the region. This period coincides with the end of the fire season and a decrease in the SPEI (Fig. 3). Thus, spring and early summer show precipitation reductions, which result in dry fuels and forests that are prone to fire. Consequently, when conditions are relatively dry, there is a pattern of drought-amplified fires during the early monsoon season. According to Cook and Seager (2013), monitoring monsoon timing is essential to forecast fire occurrence in this region. If there is a decline in precipitation during the early monsoon season (June and July), forests in the Sierra Madre Occidental mountain range may become drier. The fire occurrence in this zone was correlated with the drought intensity over the previous 5 months.

This can be explained because over the NAM region, the largest evapotranspiration rates start in March and extend to May when high fire activity was recorded (third column). By the time the monsoon becomes firmly established in June and July, evapotranspiration is reduced, which is in line with the SPEI trends. Therefore, in zone B, the SPEI is an important indicator of the trend of fire occurrence in response to drought, while over the southern and coastal areas of the NAM region (zone C), precipitation increases during these months.

In zone C (central Mexico), we found that areas with more fire ignitions were spatially clustered, and that fire occurrence was more likely related to human factors than to drought severity, although the study of socio-economic drivers of fire is beyond the scope of this study. In this densely populated region (e.g., >700 inhabitants km<sup>2</sup>) which accounts for 20% of Mexican population, the impact of anthropogenic pressure seems to mirror the increase of fire frequency. Previous studies have shown increasing demands for recreation and livelihood areas in this zone (Aguilar and Santos, 2011), and a somewhat similar trend was observed in western Mexico (Fig. 2). Thus, in this area, drought has relatively little effect on fire occurrence.

It has been suggested that most of the fires occurring in central Mexico are caused by humans (Rodríguez-Trejo 2008; Carrillo *et al.*, 2012; Castañeda Rojas *et al.*, 2015; Ibarra-Montoya *et al.*, 2016). Although this topic is beyond the scope of this study, widespread evidence of human-caused fires in the region (Carrillo *et al.*, 2012; Castañeda Rojas *et al.*, 2015; Ibarra-Montoya *et al.*, 2016) suggests this is an anthropogenic fire-regime type, which is mainly related to agricultural activities.

Regarding zone D (southern Chiapas), fire activity clustered and it was linked to climate seasonality. In this tropical zone, the rainy season lasts from May to October, and the dry season lasts from November until April (Fig. 3). Fires in tropical forest communities are usually linked to land use change, and during droughts, the vegetation becomes flammable (Littell *et al.*, 2016); this widespread fire activity has been shown to be associated with wetter conditions during the months immediately preceding the fire season (Rivera-Huerta *et al.*, 2016). This association with preceding wet months is due to the increased productivity of herbaceous vegetation, which responds to the high moisture availability. This increase in forest productivity is believed to lead to a rapid ac-

cumulation of flashy fuels that are easily ignited and readily carry fire during the subsequent drier months. Several studies have documented that agricultural activities are the main drivers of forest fire occurrence in this area of Mexico. For example, Román- Cuesta et al. (2003) found significant relationships between road density, agricultural land extension, and forest fires in biosphere reserves in Chiapas. In southern Mexico, many farmers use fire as the primary tool to clear land to grow basic crops, such as corn and beans, or to promote the regrowth of grasslands. As a result, fires escaping from agriculture or cattle grazing activities tend to occur more frequently in areas that are close to towns and roads (Rodríguez-Trejo and Fulé, 2003).

Although the present study was not designed to specifically address the role of non-climatic variables such as anthropogenic causes and vegetation cover, our results suggests that population density and agricultural activities are important sources of the spatial and temporal variability of fire regimes, and that they deserve further attention in future studies. Because the results of this exploratory study have helped to identify areas that exhibit different spatio-temporal relationships between fire occurrence and drought, future studies should model the spatial and temporal patterns of both climatic and non-climatic factors to determine their relationship to fire occurrence patterns in different regions of the country. This would increase our understanding of their role in fire occurrence and severity, and allow us to establish the most appropriate region- and site-specific fire management strategies under current and future climatic conditions. Lastly, the SPEI may have potential limitations that should be addressed in future investigations. For instance, the value of the SPEI for a specific location can be uncertain because of the limited availability of local climatic data necessary to adequately estimate evapotranspiration (Beguería et al., 2014).

## 5 Conclusions

Our analyses allowed us extracting relevant information on the spatio-temporal patterns of fire occurrence and how they relate to drought severity across Mexico, a megadiverse country where many forest types exist. We found that forest fires are clustered in four regions across Mexico: northern Baja California, Chihuahua, central Mexico, and southern Chiapas. The links be-

tween drought and fire occurrence varied both spatially and temporally in these clusters. We found a consistent geographical gradient of fire occurrence related to drought severity. Fire occurrence in Chihuahua was more closely related to the drought intensity over the previous 5 months, whereas fire occurrence in central Mexico was not related to drought severity. The observed spatial patterns of fire clustering across Mexico can be used to focus on other key fire drivers in those regions where the drought-fire coupling is weak (vegetation cover, fuel type, climate change, forest disturbances and human impacts), and to estimate fire patterns comparing regions with contrasting drought severity (burnt areas, combusted biomass, greenhouse gas emissions).

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